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Joint Time and Power Allocation in Multi-Cell Wireless Powered Communication Networks

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ABSTRACT This paper investigates the joint time and power allocation in a multi-cell wireless powered communication network (WPCN) with successive interference cancellation. In the WPCN, the hybrid access points broadcast wireless energy to all users and then the users utilize the harvested energy to transmit information simultaneously in a spectrum-sharing fashion. The max–min fairness throughput optimization and max-sum throughput optimization problems are formulated to analyze the system performance. However, both of the two optimization problems are nonconvex due to the complicated co-channel interference and the coupled time and power variables. To deal with this challenge, efficient two-stage approaches are proposed to transform them into more tractable ones. Specifically, for the max–min fairness throughput optimization problem, we first convert the power allocation problem into geometric programming (GP) problem for given time allocation and then optimize the time allocation. For the max-sum throughput optimization problem, we first transform the power allocation problem into a signomial programming problem with fixed time allocation, which is further approximated as a GP one. Then, time allocation is optimized. The simulation results validate the effectiveness of the two proposed approaches. In addition, it is shown that the ''doubly near-far'' issue can be well addressed by the max–min fairness throughput optimization.

INDEX TERMS Time allocation, power allocation, max-min throughput, max-sum throughput, wireless powered communication network (WPCN).

I. INTRODUCTION

With the ever-accelerating progress of information and communications technology, increasing wireless devices are being connected to the Internet and it gives rise to ''Internet-of-Things (IoT)''. However, IoT devices face a tremendous challenge in battery lifetime due to the size and space constraints. Moreover, the conventional battery is difficult to maintain operation because of the high cost of battery replacement as well as environmental concerns [1]–[3]. Thus, energy harvesting has been considered as a promising technology to address this issue. Nevertheless, energy harvesting from the environment (e.g., solar or wind) is an uncontrollable process [4]. As a result, radio-frequency (RF) energy harvesting technology which can provide stable and continuous energy to wireless devices in communication networks has attracted considerable attention from researchers. One typical direction of RF energy harvesting is wireless powered communication network (WPCN) [2], [5]. WPCN mainly focuses on uplink (UL) information transmission, where users are harvested energy in the downlink (DL) stage and then transmit information to the hybrid access point (HAP) in the UL stage.

Ju and Zhang [6] proposed a ''harvest-then-transmit'' protocol with time-division-multiple-access (TDMA) in a single-cell WPCN. Hadzi-Velkov *et al.* [7] jointly optimized HAP broadcasting power and time sharing among users to maximize the sum throughput. To further maximize the

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sum throughput in full-duplex WPCN for OFDM systems, the work [8] jointly optimized subcarrier and power allocation. Noting that in [6], the 'doubly near-far' phenomenon is illustrated. It is shown that users far away from HAP which need more wireless energy to transmit information harvest less wireless energy than near users. To overcome the 'doubly near-far' problem, a plenty of methods have been proposed in the literatures, such as adaptive time and power allocation [7], [9], multi-antenna beamforming [10], [11], and user cooperation [12], [13].

With the explosive growth of wireless devices, improving spectrum efficiency is also an imperative issue. To this end, non-orthogonal multiple access (NOMA) has been proposed to support efficient spectrum sharing in the future wireless networks. In the NOMA systems, through successive interference cancellation (SIC) technology, multiple users can transmit information simultaneously and multi-access interference can be reduced. Specifically, the signal of strongest channel is decoded first, then the receiver subtracts the decoded strongest signal and decodes the signal of weakest channel in the uplink [14]. In [15], NOMA scheme was applied to a single-cell WPCN to improve the max-min fairness rate and spectrum efficiency. In [16], the fairness-aware resource allocation in WPCN was investigated, where the utility maximization problems with TDMA and NOMA were formulated, respectively. In [17], the SIC technique was applied for information decoding in a multiple-input multiple-output (MIMO) WPCN. The work [18] studied the energy-efficient NOMA based in WPCN. In [19], the individual data rate optimization and fairness improvement by fixed decoding order and time sharing strategies in WPCN with NOMA were investigated. The literature in [20] globally optimized power and time allocation for achieving max-min, proportional and harmonic fairness in SIC-enabled WPCN.

All the aforementioned works focus on a single-cell WPCN. However, the multi-cell WPCNs are more practical and can accommodate the increasing number of network devices. In [21], homogeneous Poisson Point Processes (PPPs) was adopted to analyze the performance of a large-scale WPCN. It is showed that increasing the number of users can bring higher sum throughput but lead to increased interference. In [22], the jointly intra-cell time allocation and inter-cell load balancing were studied in a multi-cell WPCN. In [23], asynchronous protocol was proposed to maximize weighted sum throughput with interference channels in a multi-cell WPCN. He *et al.* [24] presented a multi-cell WPCN with load coupling to optimize time allocation.

However, none of the above works considers multi-cell WPCN and SIC simultaneously. In the SIC-enabled multi-cell WPCN, the intra-cell and inter-cell co-channel interference greatly complicates the resource allocation problem. In this paper, we aim to address this issue. The detailed contributions of this paper are summarized as follows:

- We propose a framework for the resource optimization in a multi-cell WPCN with NOMA under the "harvest-then-transmit" protocol. DL wireless energy transfer (WET) and UL wireless information transfer (WIT) share the same frequency band in a time division manner and operate at different time. In the WET stage, the HAPs broadcast wireless energy to users within their converge range. And then in the WIT stage, all the users utilize the harvested energy to transmit their information to the associated HAP simultaneously by using the same frequency band. In addition, we adopt ideal SIC demodulation receivers at all HAPs so that the intra-cell interference can be decreased.
- The jointly time and power allocation optimization problems to maximize the minimum throughput of all users (max-min fairness throughput) and the sum throughput among all users (max-sum throughput) are formulated, respectively. Both of the two problems are nonconvex due to the complicated intra-cell and inter-cell interference and the coupled time and power variables. To deal with this issue, we introduce auxiliary variables to transform the original problems into more tractable ones. In particular, for the max-min fairness throughput problem, we first transform the power allocation problem into a geometric programming (GP) problem for given time allocation; then use the Hopfinger golden section search method to find the optimal time allocation. For the max-sum throughput problem, we first transform it into a signomial programming (SP) power allocation problem with fixed time allocation. This SP problem can be turned into an approximate GP problem based on geometric mean approximations. Then, the optimal time solution is obtained by the same method in max-min throughput optimization.
- Through simulation, we validate the effectiveness of the proposed resource allocation methods in the multi-cell WPCN. It is shown that the 'doubly near-far' issue can be well addressed by max-min fairness throughput scheme.

The rest of this paper is organized as follows. A multi-cell WPCN model is introduced in section II. Then, the max-min fairness throughput optimization and the max-sum throughput optimization are discussed in Sections III and IV, respectively. Numerical analysis is presented in section V to compare the two proposed schemes and demonstrate their effectiveness. Finally, we conclude this paper in section VI.

II. SYSTEM MODEL

We consider a multi-cell WPCN consisting of N SIC-enabled HAPs and K single-antenna users as shown in Fig. 1, where the sets of HAPs and users are denoted by $\mathcal{N} = \{1, 2, \cdots, N\}$ and $\mathcal{K} = \{1, 2, \cdots, K\}$, respectively. Each cell deploys a HAP in the cell center. The HAPs can broadcast energy in the DL and harvest information in the UL. Each user can harvest energy from all HAPs which is stored in a rechargeable battery and then transmit individual information with the harvested energy.

Define $x_{k,n} = \{0, 1\} (k \in \mathcal{K}, n \in \mathcal{N})$ as the user association indicator. When user k is associated with HAP n, $x_{k,n} = 1$;

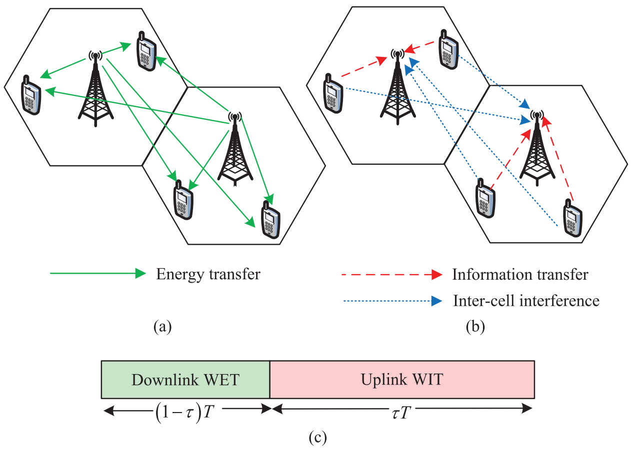

FIGURE 1. **Multi-cell WPCN model. (a) Downlink WET. (b) Uplink WIT. (c) "harvest-then-transmit" protocol.**

otherwise $x_{k,n} = 0$. Each user can be associated with only one HAP and association constraint is denoted as $\sum_{n=1}^{N} x_{k,n} \leq 1$ $(k \in \mathcal{K})$. HAP n associates one unique set of users in cell n, denoted by set $X_n = \{k|\ x_{k,n} = 1, k \in \mathcal{K}\}$. In this paper, each user is associated with HAP n^* with the best UL channel power gain. Let $g_{k,n}$ denotes the UL channel power gain from user k to HAP n, then $n^* = \arg\max_{n \in \mathcal{N}} g_{k,n}$, $x_{k,n^*} = 1$.

The multi-cell WPCN works on the "harvest-then-transmit" protocol [6]. We also assume that the WET and WIT are operated on the same frequency band with different time. A time period of length T is strictly divided into two stages: the DL WET stage with time length $(1-\tau)T$ and the UL WIT stage with time length τT $(0 \leq \tau \leq 1)$. Without loss of generality, we further assume $T = 1$ as in [6]. In the DL WET stage, all HAPs broadcast energy signal with fixed transmit power $P_n^{(0)} (n \in \mathcal{N})$ to each user [22]. In the UL WIT stage, each user transmits individual information simultaneously to the associated HAP by employing NOMA.

During the DL WET stage, the broadcasting signal from HAP n is denoted by $s_n^{(0)}(t)$ satisfying $\mathbb{E}[|s_n^{(0)}(t)|^2] = P_n^{(0)}$. The received signal of user k can be given by

$$y_k^{(0)}(t) = \sum_{n=1}^{N} \sqrt{h_{n,k}} s_n^{(0)}(t) + z_k, \tag{1}$$

where $\sqrt{h_{n,k}}$ denotes channel coefficient from HAP n to user k, and z_k is the noise at user k. The DL channel power gain from HAP n to user k is denoted by $h_{n,k}$. The harvested energy of user k from all HAPs can be expressed as

$$E_k = \eta(1-\tau)\mathbb{E}\left[|y_k^{(0)}(t)|^2\right] = \eta(1-\tau)\sum_{n=1}^{N} h_{n,k} P_n^{(0)}, \tag{2}$$

where the noise power is negligible [6] and $0 < \eta \leq 1$ denotes the energy harvesting efficiency. In addition, we assume that both DL channels and UL channels are quasi-static flat-fading and independent, $h_{n,k}$ and $g_{k,n}$ are considered to be constant during a time period.

Consider SIC demodulation receivers at all HAPs for reducing intra-cell interference and obtaining better throughput. Prior to SIC, intra-cell users are arranged in descending order according to their signal strength, so that the SIC receiver can decode the stronger signal first and subtract it from the combined signal [14]. With SIC, the HAP first decodes information of the user with the strongest signal (i.e., the highest UL channel power gain) by treating the remaining lower signal of intra-cell users as interference. Then the HAP subtracts the decoded signal and then successively decodes information of remaining intra-cell users. Therefore, intra-cell interference of user k only comes from users with lower channel power gain (i.e., $\sum_{j \in X_n, g_{j,n} < g_{k,n}} p_j^{(1)} g_{j,n}$). As a result, the weakest channel gain user suffers no intra-cell interference since all the interference from other users is cancelled by SIC. Assuming all demodulation is correct, there is no error propagation. The signal-to-interference-plus-noise ratio (SINR) of user k associated with HAP n can be expressed as

$$\phi_{k,n} = \frac{p_k^{(1)} g_{k,n}}{\sum\limits_{\substack{j \in X_n \\ g_{j,n} < g_{k,n}}} p_j^{(1)} g_{j,n} + \sum\limits_{j' \notin X_n} p_{j'}^{(1)} g_{j',n} + \sigma_n}, \tag{3}$$

where $p_k^{(1)}$ is the transmit power of user k and σ_n is the white Gaussian noise power at HAP n. The first term and the second term in denominator express intra-cell interference with SIC and inter-cell interference without SIC, respectively. The achievable throughput of user $k \in X_n$ associated with HAP n can be expressed as:

$$R_k = \sum_{n=1}^{N} x_{k,n} \tau \log_2\left(1 + \phi_{k,n}\right). \tag{4}$$

When $x_{k,n} = 0$, $x_{k,n}\tau\log_2\left(1+\phi_{k,n}\right) = 0$. Actually, the value of R_k is valid only when $x_{k,n} = 1$ (i.e., $k \in X_n$). In the following, for simplicity, we let $\boldsymbol{P}^{(1)} = \left\{p_k^{(1)} |\ k \in \mathcal{K}\right\}$.

III. MAX-MIN FAIRNESS THROUGHPUT OPTIMIZATION

In this section, we consider the max-min throughput optimization to achieve user fairness. In general, user unfairness issue caused by the 'doubly near-far' phenomenon is pretty severe in WPCNs. Therefore, we consider the max-min fairness throughput optimization to address 'doubly near-far' issue. When the minimum throughput of the whole network is increased, the quality-of-service (QoS) of all users can be guaranteed. The max-min fairness throughput problem can be presented as

$$\max_{\tau, \boldsymbol{P}^{(1)}} \ \min_{k=1,2,\cdots K} \sum_{n=1}^{N} x_{k,n}\tau\log_2\left(1+\phi_{k,n}\right) \tag{5}$$

$$\text{s.t. } 0 \leq \tau \leq 1, \tag{5a}$$

$$0 \leq p_k^{(1)} \leq P_k^{\max}, \quad \forall k \in \mathcal{K}, \tag{5b}$$

$$\tau p_k^{(1)} \leq \eta(1-\tau)\sum_{n=1}^{N} P_n^{(0)} h_{n,k}, \quad \forall k \in \mathcal{K}. \tag{5c}$$

The constraint (5b) guarantees the power of all users is within the maximum allowed transmit power. The constraint (5c) implies that, the energy of transmitting information of each user in the WIT stage is not more than its harvested energy in the WET stage. The co-channel interference is highly complex. Since variables τ and $\boldsymbol{P}^{(1)}$ are complexly coupled in the objective function of (5), it is of great challenge to solve the problem (5) directly. In the following, we will transform the optimization problem into a more tractable one.

By introducing an auxiliary variable $\overline{S}$, the problem (5) can be equivalently transformed into the following form.

$$\max_{\tau,\boldsymbol{P}^{(1)},\overline{S}} \overline{S} \tag{6}$$
$$\text{s.t. } 0 \le \tau \le 1, \tag{6a}$$
$$0 \le p_k^{(1)} \le P_k^{\max}, \quad \forall k \in \mathcal{K}, \tag{6b}$$
$$\tau p_k^{(1)} \le \eta(1-\tau)\sum_{n=1}^{N} P_n^{(0)} h_{n,k}, \quad \forall k \in \mathcal{K}, \tag{6c}$$
$$\sum_{n=1}^{N} x_{k,n}\tau \log_2\left(1+\phi_{k,n}\right) \ge \overline{S}, \quad \forall k \in \mathcal{K}. \tag{6d}$$

Since the value of R_k is valid only when $k \in X_n$. To facilitate analysis, the constraint (6d) can be further constructed as

$$\tau \log_2\left(1+\phi_{k,n}\right) \ge \overline{S}, \quad \forall n \in \mathcal{N},\ \forall k \in X_n. \tag{7}$$

Although the original max-min problem (5) is simplified to the maximum problem (6), it is still hard to be solved due to the coupling of time and power variables. To deal with this challenge, we propose a two-stage method. We first derive the optimal power allocation $\boldsymbol{P}^{(1)}$ for a given τ and then optimize the time allocation τ.

Let $\overline{Q} = 2^{\frac{\overline{S}}{\tau}} - 1$. The $\boldsymbol{P}^{(1)}$ and $\overline{Q}$ optimization problem with fixed τ can be written as

$$\max_{\boldsymbol{P}^{(1)},\overline{Q}} \overline{Q} \tag{8}$$
$$\text{s.t. } 0 \le p_k^{(1)} \le P_k^{\max}, \quad \forall k \in \mathcal{K}, \tag{8a}$$
$$p_k^{(1)} \le \frac{\eta(1-\tau)\sum_{n=1}^{N} P_n^{(0)} h_{n,k}}{\tau}, \quad \forall k \in \mathcal{K}, \tag{8b}$$
$$\frac{p_k^{(1)} g_{k,n}}{\sum\limits_{\substack{j\in X_n \\ g_{j,n}<g_{k,n}}} p_j^{(1)} g_{j,n} + \sum\limits_{j'\notin X_n} p_{j'}^{(1)} g_{j',n} + \sigma_n} \ge \overline{Q}, \quad \forall n \in \mathcal{N},\ \forall k \in X_n. \tag{8c}$$

It can be easily verified that the problem (8) is nonconvex. However, the problem (8) can be transformed into a GP problem as following,

$$\min_{\boldsymbol{P}^{(1)},\overline{Q}} \overline{Q}^{-1} \tag{9}$$
$$\text{s.t. } 0 \le \frac{p_k^{(1)}}{P_k^{\max}} \le 1, \quad \forall k \in \mathcal{K}, \tag{9a}$$
$$\frac{\tau p_k^{(1)}}{\eta(1-\tau)\sum_{n=1}^{N} P_n^{(0)} h_{n,k}} \le 1, \quad \forall k \in \mathcal{K}, \tag{9b}$$
$$\left(\sum_{\substack{j\in X_n \\ g_{j,n}<g_{k,n}}} p_j^{(1)} g_{j,n} + \sum_{j'\notin X_n} p_{j'}^{(1)} g_{j',n} + \sigma_n\right) \times \frac{\overline{Q}}{p_k^{(1)} g_{k,n}} \le 1, \quad \forall n \in \mathcal{N}, \quad \forall k \in X_n. \tag{9c}$$

It can be observed that the constraint (9c) is a posynomial function. Define $y_k = \ln\left(p_k^{(1)}\right)$ and $Q = \ln\left(\overline{Q}\right)$. By substituting new variables y_k and Q, the problem (9) can be reformulated as

$$\min_{\{y_k\},Q} -Q \tag{10}$$
$$\text{s.t. } \ln\left[\frac{\exp(y_k)}{P_k^{\max}}\right] \le 0, \quad \forall k \in \mathcal{K}, \tag{10a}$$
$$\ln\left[\frac{\tau \exp(y_k)}{\eta(1-\tau)\sum_{n=1}^{N} P_n^{(0)} h_{n,k}}\right] \le 0, \quad \forall k \in \mathcal{K}, \tag{10b}$$
$$\ln\left[\frac{e^{Q-y_k}}{g_{k,n}}\left(\sum_{\substack{j\in X_n \\ g_{j,n}<g_{k,n}}} g_{j,n}e^{y_j} + \sum_{j'\notin X_n} g_{j',n}e^{y_{j'}} + \sigma_n\right)\right] \le 0, \quad \forall n \in \mathcal{N},\ \forall k \in X_n. \tag{10c}$$

Since (10c) is a log-sum-exp function which is convex [25], the problem (10) is a convex one. Therefore, the problem (10) can be solved effectively using interior-point methods [25]. Thus, we can derive the optimal solutions $\{y_k(\tau)\}$ and $Q(\tau)$ for a given τ.

Once the problem (10) is solved for y_k, the power allocation is simply given by $p_k^{(1)} = \exp(y_k)$. The process of the optimal power allocation is showed in Algorithm 1. Then, the optimal time allocation can be identified by $\tau^* = \arg\max_{\tau\in[0,1]} \bar{S}(\tau)$, where $\bar{S}(\tau) = \tau\log_2(1+\exp(Q(\tau)))$.

Algorithm 1 Power Allocation of Max-Min Optimization Algorithm

1: For a given τ in the problem (10), using interior-point methods to obtain the optimal solution $\{y_k(\tau), Q(\tau)\}$ for $k = 1, 2, \cdots, K$.
2: Calculating $\bar{S}(\tau) = \tau\log_2(1+\exp(Q(\tau)))$.
3: Return $p_k^{(1)}(\tau) = \exp(y_k(\tau))$ for $k = 1, 2, \cdots, K$ and the minimum throughput $R_{min}(\tau) = \bar{S}(\tau)$.

We observe that $\bar{S}$ is linear with respect to τ in (7) and τ is restricted by (6a) and (6c). Here, we adopt the Hopfinger golden section search method [26] to apply the line search to find the optimal time allocation. The whole procedure of the optimal time allocation is showed in Algorithm 2. For more details of the Hopfinger golden section search method, interested readers may refer to [26].

IV. MAX-SUM THROUGHPUT OPTIMIZATION

In this section, we focus on the max-sum throughput optimization. Mathematically, the optimization problem can be

Algorithm 2 Max-Min Fairness Throughput Optimization Algorithm

Initialization the iteration index $c = 1$, the search interval $\left[a_1^c, a_4^c\right]$, $a_1^c = 0$, $a_4^c = 1$, $\gamma = (-1+\sqrt{5})/2$ and tolerance $\epsilon > 0$.
Let $a_1^c < a_2^c < a_3^c < a_4^c$ and $b^c \in \{1, 2, 3, 4\}$ denotes the index number of the maximum throughput of $\{R(a_1^c), R(a_2^c), R(a_3^c), R(a_4^c)\}$.
Set $a_2^c = a_4^c - \gamma(a_4^c - a_1^c)$ and $a_3^c = a_1^c + \gamma(a_4^c - a_1^c)$.
Obtain the throughput $R(a_1^c)$, $R(a_2^c)$, $R(a_3^c)$, $R(a_4^c)$ by Algorithm 1, then $[R_{\max}^c, b^c] = \max\{R(a_1^c), R(a_2^c), R(a_3^c), R(a_4^c)\}$.
repeat
  if $b^c \in \{1, 2\}$, **then**
    set $a_1^{c+1} = a_1^c$, $a_3^{c+1} = a_2^c$, $a_4^{c+1} = a_3^c$ and $a_2^{c+1} = a_4^{c+1} - \gamma(a_4^{c+1} - a_1^{c+1})$.
    Substituting a_2^{c+1} into Algorithm 1, and then return $R(a_2^{c+1})$.
    If $R(a_2^{c+1}) > R_{\max}^c$, then $b^{c+1} = b^c$, else $b^{c+1} = b^c + 1$.
  else
    set $a_1^{c+1} = a_2^c$, $a_2^{c+1} = a_3^c$, $a_4^{c+1} = a_4^c$ and $a_3^{c+1} = a_1^{c+1} + \gamma(a_4^{c+1} - a_1^{c+1})$.
    Substituting a_3^{c+1} into Algorithm 1, and then return $R(a_3^{c+1})$.
    If $R_{\max}^c \geq R(a_3^{c+1})$, then $b^{c+1} = b^c - 1$, else $b^{c+1} = b^c$.
  end if
  $c = c + 1$.
until $\left|a_4^c - a_1^c\right| < \epsilon$.
Obtain $\tau^* = \frac{a_4^c + a_1^c}{2}$. Substituting τ^* into Algorithm 1, and then return $\left\{p_k^{(1)}(\tau^*), R(\tau^*)\right\}$ for all users.

formulated as

$$\max_{\tau, \boldsymbol{P}^{(1)}} \sum_{n=1}^{N} \sum_{k \in X_n} \tau \log_2\left(1 + \phi_{k,n}\right) \tag{11}$$

$$\text{s.t. } 0 \leq \tau \leq 1, \tag{11a}$$

$$0 \leq p_k^{(1)} \leq P_k^{\max}, \quad \forall k \in \mathcal{K}, \tag{11b}$$

$$\tau p_k^{(1)} \leq \eta(1-\tau) \sum_{n=1}^{N} P_n^{(0)} h_{n,k}, \quad \forall k \in \mathcal{K}. \tag{11c}$$

The optimization problem in (11) is also nonconvex due to the coupled variables. Thus, we adopt the similar method in the max-min fairness optimization. We first optimize power allocation $\boldsymbol{P}^{(1)}$ for a given τ, and then optimize τ by the Hopfinger golden section search method.

First, the power optimization problem in (11) with fixed τ can be presented as

$$\max_{\boldsymbol{P}^{(1)}} \sum_{n=1}^{N} \sum_{k \in X_n} \log_2\left(1 + \phi_{k,n}\right) \tag{12}$$

$$\text{s.t. } 0 \leq p_k^{(1)} \leq P_k^{\max}, \quad \forall k \in \mathcal{K}, \tag{12a}$$

$$p_k^{(1)} \leq \frac{\eta(1-\tau)\sum_{n=1}^{N} P_n^{(0)} h_{n,k}}{\tau}, \quad \forall k \in \mathcal{K}. \tag{12b}$$

The optimization problem (12) is still a nonconvex problem. Let $f_{k,n}(\boldsymbol{P}^{(1)}) = p_k^{(1)} g_{k,n} + \sum\limits_{j \in X_n, g_{j,n} < g_{k,n}} p_j^{(1)} g_{j,n} + \sum\limits_{j' \notin X_n} p_{j'}^{(1)} g_{j',n} + \sigma_n$. By introducing an auxiliary variable Z, the problem (12) can be equivalently transformed to be a SP minimum problem as following,

$$\min_{\boldsymbol{P}^{(1)}, Z} Z \tag{13}$$

$$\text{s.t. } 0 \leq \frac{p_k^{(1)}}{P_k^{\max}} \leq 1, \quad \forall k \in \mathcal{K}, \tag{13a}$$

$$\frac{\tau p_k^{(1)}}{\eta(1-\tau)\sum_{n=1}^{N} P_n^{(0)} h_{n,k}} \leq 1, \quad \forall k \in \mathcal{K}, \tag{13b}$$

$$\prod_{n=1}^{N} \prod_{k \in X_n} \frac{\sum\limits_{\substack{j \in X_n \\ g_{j,n} < g_{k,n}}} p_j^{(1)} g_{j,n} + \sum\limits_{j' \notin X_n} p_{j'}^{(1)} g_{j',n} + \sigma_n}{f_{k,n}\left(\boldsymbol{P}^{(1)}\right)} \leq Z. \tag{13c}$$

According to [27] and [28], the problem (13) can be further transformed into an approximate GP problem using the classic arithmetic geometric mean inequality [29]. Therefore, posynomial denominator of (13c) has an arithmetic geometric mean inequality as

$$\begin{aligned} & p_k^{(1)} g_{k,n} + \sum_{\substack{j \in X_n \\ g_{j,n} < g_{k,n}}} p_j^{(1)} g_{j,n} + \sum_{j' \notin X_n} p_{j'}^{(1)} g_{j',n} + \sigma_n \\ & \geq \left(\frac{p_k^{(1)} g_{k,n}}{\beta_{k,n}^k}\right)^{\beta_{k,n}^k} \times \prod_{\substack{j \in X_n \\ g_{j,n} < g_{k,n}}} \left(\frac{p_j^{(1)} g_{j,n}}{\beta_{j,n}^k}\right)^{\beta_{j,n}^k} \\ & \quad \times \prod_{j' \notin X_n} \left(\frac{p_{j'}^{(1)} g_{j',n}}{\beta_{j',n}^k}\right)^{\beta_{j',n}^k} \times \left(\frac{\sigma_n}{\beta_{0,n}^k}\right)^{\beta_{0,n}^k}, \end{aligned} \tag{14}$$

where

$$\beta_{j,n}^k = \frac{p_j^{(1)}(0) g_{j,n}}{p_k^{(1)}(0) g_{k,n} + \sum\limits_{\substack{j \in X_n \\ g_{j,n} < g_{k,n}}} p_j^{(1)}(0) g_{j,n} + \sum\limits_{j' \notin X_n} p_{j'}^{(1)}(0) g_{j',n} + \sigma_n}, \tag{15}$$

and

$$\beta_{0,n}^k = \frac{\sigma_n}{p_k^{(1)}(0) g_{k,n} + \sum\limits_{\substack{j \in X_n \\ g_{j,n} < g_{k,n}}} p_j^{(1)}(0) g_{j,n} + \sum\limits_{j' \notin X_n} p_{j'}^{(1)}(0) g_{j',n} + \sigma_n}, \tag{16}$$

and $p_k^{(1)}(0)$ is the initialization value.

Let $\tilde{f}_{k,n}(\boldsymbol{P}^{(1)}) = \left(\frac{\sigma_n}{\beta_{0,n}^k}\right)^{\beta_{0,n}^k} \times \left(\frac{p_k^{(1)} g_{k,n}}{\beta_{k,n}^k}\right)^{\beta_{k,n}^k} \times \prod\limits_{j \in X_n, g_{j,n} < g_{k,n}} \left(\frac{p_j^{(1)} g_{j,n}}{\beta_{j,n}^k}\right)^{\beta_{j,n}^k} \times \prod\limits_{j' \notin X_n} \left(\frac{p_{j'}^{(1)} g_{j',n}}{\beta_{j',n}^k}\right)^{\beta_{j',n}^k}$. By substituting (14) into (13c), an GP approximation of the SP problem in (13) using a monomial based on the above geometric mean can be written as

$$\min_{\boldsymbol{P}^{(1)},Z} Z \tag{17}$$

$$\text{s.t. } 0 \leq \frac{p_k^{(1)}}{P_k^{\max}} \leq 1, \quad \forall k \in \mathcal{K}, \tag{17a}$$

$$\frac{\tau p_k^{(1)}}{\eta(1-\tau)\sum_{n=1}^{N} P_n^{(0)} h_{n,k}} \leq 1, \quad \forall k \in \mathcal{K}, \tag{17b}$$

$$\prod_{n=1}^{N}\prod_{k\in X_n} \frac{\sum\limits_{\substack{j\in X_n \\ g_{j,n}<g_{k,n}}} p_j^{(1)} g_{j,n} + \sum\limits_{j'\notin X_n} p_{j'}^{(1)} g_{j',n} + \sigma_n}{\tilde{f}_{k,n}\left(\boldsymbol{P}^{(1)}\right)} \leq Z. \tag{17c}$$

The constraint (17) is a posynomial function and the problem (17) becomes a GP problem. Thus, it can be converted into a convex problem and solved by interior-point methods [25]. The whole procedure of the proposed power allocation of max-sum throughput optimization is showed in Algorithm 3. And the optimal time allocation of max-sum throughput optimization is same as the max-min throughput optimization. It is not described in detail here. For the convergence, we have the following Lemma 1.

Algorithm 3 Power Allocation of Max-Sum Throughput Optimization Algorithm

1: Initialization $i = 1$, error tolerance $\delta = 10^{-4}$ and for a given τ in the problem (17), $p_k^{(1)}(i) = \eta \sum_{n=1}^{N} P_n^{(0)} h_{n,k}$ for $k = 1, 2, \cdots, K$.

2: $i = i + 1$, calculate $\beta_{j,n}^k(i) = \frac{p_j^{(1)}(i-1)g_{j,n}}{f_{k,n}(\boldsymbol{P}^{(1)}(i-1))}$, $\beta_{0,n}^k(i) = \frac{\sigma_n}{f_{k,n}(\boldsymbol{P}^{(1)}(i-1))}$.

3: Substituting $\beta_{j,n}^k(i)$ and $\beta_{0,n}^k(i)$ into the problem (17), then using interior-point methods to obtain $p_k^{(1)}(i)$.

4: If $\sum_{k=1}^{K}\left(\left|p_k^{(1)}(i) - p_k^{(1)}(i-1)\right|\right) \leq \delta$, save $p_k^{(1)}(i)$, and go to Step 5; Otherwise, go to Step 2.

5: $p_k^{(1)}(\tau) = p_k^{(1)}(i)$. Calculate the SINR $\phi_{k,n}(\tau) = \frac{p_k^{(1)}(\tau)g_{k,n}}{\sum\limits_{\substack{j\in X_n \\ g_{j,n}<g_{k,n}}} p_j^{(1)}(\tau)g_{j,n} + \sum\limits_{j'\notin X_n} p_{j'}^{(1)}(\tau)g_{j',n} + \sigma_n}$, and the sum throughput $R_{sum}(\tau) = \sum\limits_{n=1}^{N}\sum\limits_{k\in X_n} \tau \log_2(1+\phi_{k,n}(\tau))$.

Lemma 1: The optimal solution of GP in (17) can converge to the optimal solution of SP in (13).

Proof: $f_{k,n}(\boldsymbol{P}^{(1)})$ and $\tilde{f}_{k,n}(\boldsymbol{P}^{(1)})$ meet the following three conditions.

1) $f_{k,n}(\boldsymbol{P}^{(1)}) \geq \tilde{f}_{k,n}(\boldsymbol{P}^{(1)})$ for $n = 1, 2, \cdots, N$ and $k \in X_n$. This inequality can be derived from (14) directly.
2) $f_{k,n}(\boldsymbol{P}^{(1)}(0)) = \tilde{f}_{k,n}(\boldsymbol{P}^{(1)}(0))$. For fixed power allocation $\boldsymbol{P}^{(1)}(0)$, we can obtain $\beta_{j,n}^k$ and $\beta_{0,n}^k$. Therefore, we further derive $f_{k,n}(\boldsymbol{P}^{(1)}(0)) = \tilde{f}_{k,n}(\boldsymbol{P}^{(1)}(0))$.
3) $\nabla f_{k,n}(\boldsymbol{P}^{(1)}(0)) = \nabla \tilde{f}_{k,n}(\boldsymbol{P}^{(1)}(0))$. This equation can be attested from derivatives of $f_{k,n}(\boldsymbol{P}^{(1)})$ and $\tilde{f}_{k,n}(\boldsymbol{P}^{(1)})$.

TABLE 1. Simulation parameters.

Parameters	Value
Each cell radius	8 m
Path loss exponent α	2
The noise power σ_n	-100 dBm
The transmit power of HAP n $P_n^{(0)}$	10 W
The energy harvesting efficiency η	1
The maximum allowed transmit power $P_k^{\max}$	30 dBm
The tolerance ϵ	10^{-4}

According to the successive convex approximation method [28]–[30], the optimal solution of GP in (17) can converge to that of SP in (13) satisfying the Karush-Kuhn-Tucker (KKT) conditions and the proof ends. ■

V. SIMULATION RESULTS

In this section, we analyze the performance of multi-cell WPCN. The simulation parameters are listed in Table I. The bandwidth is set as 1MHz. With channel reciprocity, we assume that all channels are Rayleigh distributed and the DL and UL channel power gains are denoted by $h_{n,k} = g_{k,n} = 10^{-3}\rho_{n,k}d_{n,k}^{-\alpha}$ [6], where $d_{n,k}$ is the distance between HAP n and user k, α is the path loss exponent, $\rho_{n,k}$ represents short-term fading gain and is exponentially distributed with unit mean. There are K users uniformly distributed in the multi-cell WPCN. Furthermore, for comparison, we consider a heuristic scheme by using the time allocation $\tau = 0.5$ and the power allocation $p_k^{(1)} = \eta\sum_{n=1}^{N} P_n^{(0)} h_{n,k}$ for all users. In addition, we adopt Jain's Fairness Index to evaluate the fairness of users, denoted as $J = \frac{\left(\sum_{k=1}^{K} R_k\right)^2}{K\sum_{k=1}^{K} {R_k}^2}$. A greater J implies a more fair allocation [31].

Fig. 2 illustrates the sum throughput, the minimum throughput and Jain's Fairness Index for different number of users. From Fig. 2(a), the sum throughput increases as K increases. Besides, the max-sum optimization has a larger sum throughput than the max-min fairness optimization. This is because the max-sum optimization allocates stronger WIT time and more transmit power to users with good channel. In addition, the max-min fairness optimization is directly affected by the users close to the cell edge. From Fig. 2(b), the minimum throughput decreases as K increases since increasing the number of users results in increased interference and lower throughput for each user. When $K \leq 15$, the max-min fairness optimization achieves over 150% higher minimum throughput than the max-sum optimization. Moreover, from Fig. 2(c), the fairness index graph can directly find that the max-min fairness optimization is better than the max-sum optimization. These verify that the max-min fairness optimization can address the 'doubly near-far' issue.

When $K \leq 18$, the sum throughput increases with adding number of users from Fig. 2(a). However, the minimum throughput is very low from Fig. 2(b). It means that the current number of HAPs is no longer sufficient for the communication needs of a large number of users.

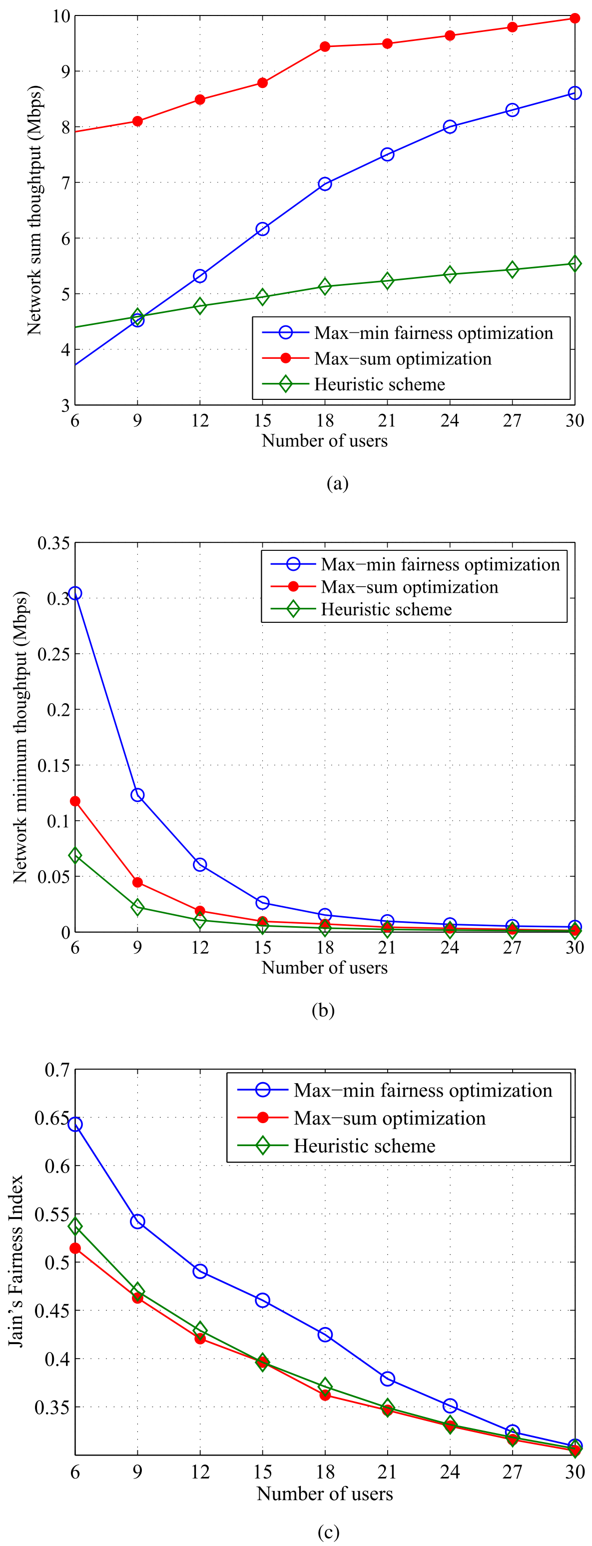

FIGURE 2. Sum throughput, minimum throughput and Jain's fairness index with varying number of users, where $N = 3$. (a) Sum throughput vs. number of users. (b) Minimum throughput vs. number of users. (c) Jain's Fairness Index vs. number of users.

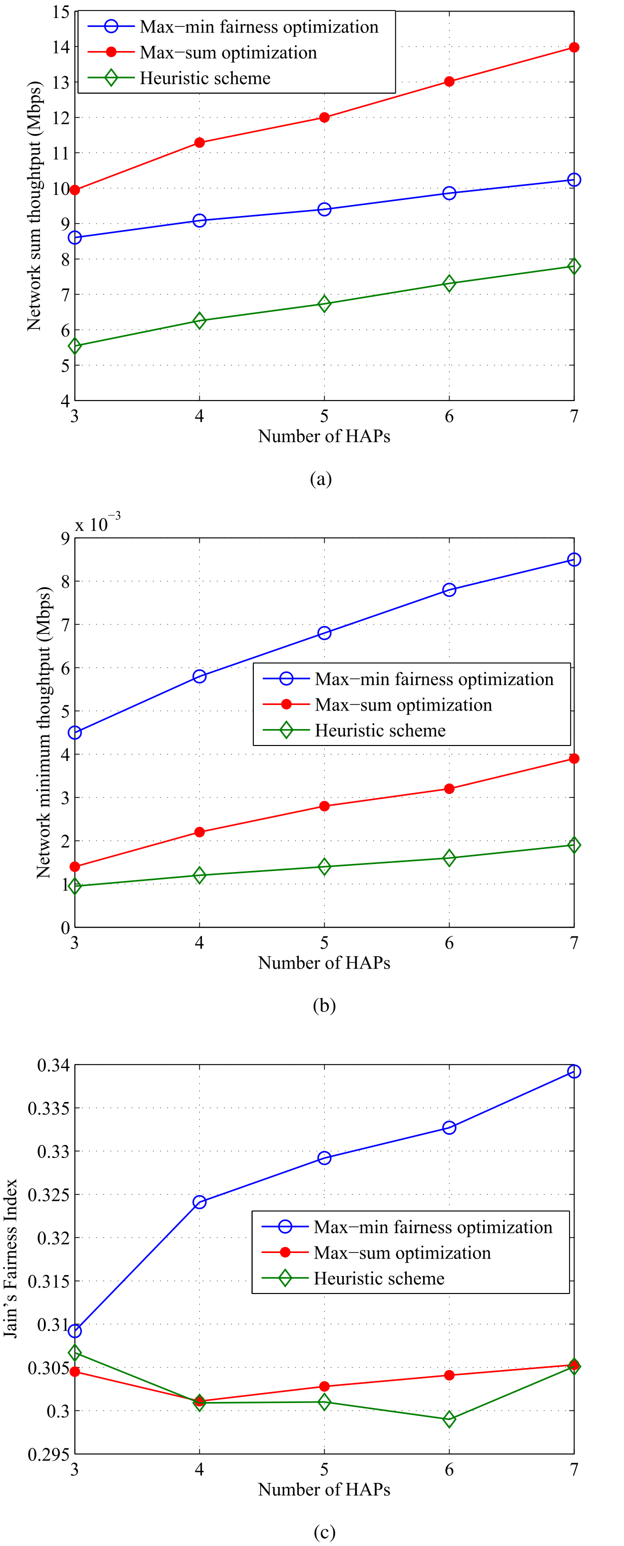

FIGURE 3. Sum throughput, minimum throughput and Jain's fairness index with varying number of HAPs, where $K = 30$. (a) Sum throughput vs. number of HAPs. (b) Minimum throughput vs. number of HAPs. (c) Jain's Fairness Index vs. number of HAPs.

Fig. 3 illustrates the sum throughput, the minimum throughput and Jain's Fairness Index versus the amount of HAPs. From Fig. 3(a) and Fig. 3(b), the sum throughput and the minimum throughput both increase as the number of HAPs increases. The sum throughput and the minimum throughput increase over 19% and 89%, respectively, in the max-min fairness optimization. This illustrates that deploying more HAPs is conducive to provide better QoS for increasing users. Furthermore, as shown in Fig. 3(b), the max-min fairness optimization increases by 118% compared with the max-sum optimization when $N = 7$. From Fig. 3(c), it can be also observed that the max-min fairness optimization achieves much better fairness to the worst channel user than other schemes. Therefore, the 'doubly near-far' issue can be efficiently addressed by the max-min fairness optimization scheme.

VI. CONCLUSION

In this paper, we study the max-min and max-sum optimization problems in the multi-cell WPCN by jointly optimal time and power allocation. To deal with the nonconvexity due to the complicated co-channel interference and the coupled time and power variables, we utilize two-stage methods to convert the original problems into more tractable ones. For given time allocation, we first transform two power allocation problems into a GP problem and a SP problem, respectively. And then we optimize time allocation by the Hopfinger golden section search method. In addition, we demonstrate the effectiveness of the two proposed approaches through simulation results. It is showed that the max-min fairness throughput optimization scheme is conducive to overcome 'doubly near-far' problem.

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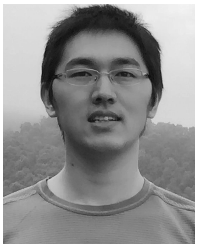

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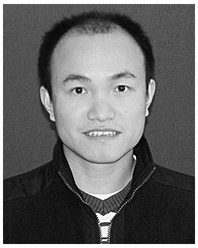

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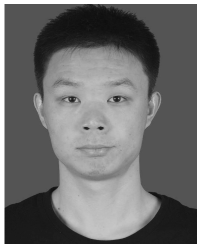

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