Message-Passing-Based Joint User Association and Time Allocation for Wireless Powered Communication Networks

Hongju Lee, *Graduate Student Member, IEEE*, Jihwan Moon, *Member, IEEE*, Changick Song, *Senior Member, IEEE*, Sang Hyun Lee, *Member, IEEE*, and Inkyu Lee, *Fellow, IEEE*

***Abstract*— This work develops a joint design of user association and time allocation for wireless powered communication networks. A harvest-then-transmit protocol is applied with base stations (BSs) transfer wireless energy to users in the first downlink phase. Then, the users utilize the harvested energy for their information transmission to the BS in the subsequent uplink phase. In this configuration, we employ a general α–fair utility to maximize the network throughput. In particular, the maximization of sum-rate, proportional fairness and minimum rate are investigated individually. We introduce a new message-passing based framework to provide an efficient distributed solution for the user association and optimize the time allocation between the downlink and uplink phase. To achieve this joint goal, each user selects a BS in a distributed manner to maximize the α–fair utility. After identifying the user association, the time allocation is determined by an efficient line search technique. Simulation results show that the proposed algorithm outperforms existing approaches.**

***Index Terms*— Wireless powered communication networks, message-passing algorithm, user association, time allocation.**

I. Introduction

WIRELESS energy transfer (WET) technologies based on radio frequency (RF) signals have recently attracted considerable interests in applications of energy-constrained communication networks such as wireless sensor networks [1]–[6]. By applying the energy harvesting (EH) technique [7], users can store the harvested energy in rechargeable batteries and prolong the battery lifetime. Simultaneous wireless information and power transfer (SWIPT) [8] and wireless powered communication network (WPCN) [2] have been investigated as two major approaches for the WET system. In the SWIPT, users harvest energy and receive the data simultaneously from a hybrid access point (H-AP) in the downlink (DL). By contrast, users in the WPCN are powered by the energy harvested from the DL WET by the H-AP and perform the wireless information transfer (WIT) operation in the uplink (UL). The WPCN has been applied in various systems in literature [9]–[11]. The authors in [9] have studied a two-user interference channel WPCN and optimized the time allocation and the transmit power to maximize the UL sum throughput. The system is then extended to generalized multi-user scenarios in [10] and [11] as well. The WPCN can also be considered in multi-tier heterogeneous networks (HetNets).

There have been a number of studies that handle resource allocation problems for multi-tier HetNets with EH [12]–[19]. To enhance the WET capability of user devices collecting only small amount of the energy, small BSs (SBS) which transmit a relatively lower energy signal than the macro BS (MBS) are deployed in a hot-spot area. Thus, a multi-tier HetNet approach proves to be a promising means which extends the lifetime of battery-powered devices. In [12], sub-carrier and power allocation schemes have been presented to minimize the DL sum transmit power of both MBS and SBS. Also, energy-efficient power control for SBSs in two-tier HetNets has been examined in [13]. In addition, various energy efficient designs have been proposed to control power of SBSs and user scheduling in [14] and [15].

In contrast to a single tier network, load balancing among BSs in HetNets involves several important issues such as different capabilities and unequal power budget of the MBS and SBSs. Thus, numerous user association policies have been designed to deal with various network utilities [16]. To maximize the system throughput, a biased factor that balances traffic loads in the BS-tier pair is adjusted. The user association that maximizes the sum throughput has also been found in a multi-cell WPCN where information and energy access points are separately located [17]. The optimization for the user association has been solved by relaxing discrete variables, and thus the resulting solution becomes obviously suboptimal. The time allocation has been considered

Manuscript received July 29, 2020; revised May 3, 2021; accepted June 22, 2021. Date of publication July 7, 2021; date of current version January 10, 2022. This work was supported in part by the National Research Foundation of Korea (NRF) Grant through the Ministry of Science and ICT (MSIT), Korea Government, under Grant 2017R1A2B3012316 and Grant 2019R1A2C1084855, in part by the Basic Science Research Program through the Ministry of Education under Grant 2021R1I1A3050126, in part by the Information Technology Research Center (ITRC) supervised by the Institute of Information Communications Technology Planning and Evaluation (IITP) under Grant IITP-2020-0-01749, and in part by the Korea University Grant. The associate editor coordinating the review of this article and approving it for publication was K. Tourki. *(Corresponding authors: Sang Hyun Lee; Inkyu Lee.)*

Hongju Lee, Sang Hyun Lee, and Inkyu Lee are with the School of Electrical Engineering, Korea University, Seoul 02841, South Korea (e-mail: honglee2335@korea.ac.kr; sanghyunlee@korea.ac.kr; inkyu@korea.ac.kr).

Jihwan Moon is with the Department of Information and Communication Engineering, Chosun University, Gwangju 61452, South Korea (e-mail: anschino@chosun.ac.kr).

Changick Song is with the Department of Electronic Engineering, Korea National University of Transportation, Chungju 27469, South Korea (e-mail: c.song@ut.ac.kr).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TWC.2021.3093317.

Digital Object Identifier 10.1109/TWC.2021.3093317

along with the user association in [18] to maximize the sum throughput of users in a multi-cell WPCN. In addition, EH models have also been analyzed with respect to the energy efficiency in [19].

Meanwhile, the WPCN incurs a doubly near-far effect [2]. To be specific, users located farther away from the BS need more energy in the UL WIT phase while lower energy is harvested in the DL WET phase, which gives rise to a user fairness issue and motivates to resorts to α–fairness [17], [20]–[23]. In literature, a class of the α–fair utility, such as maximum sum, max-min and proportional fairness, has been addressed in various fairness problems. For a wireless powered sensor network, a BS power control and UL/DL resource allocation strategy for the maximum sum α–fairness is developed for a single-cell WPCN [24]. Also, the load balancing based on the α–fairness is considered for HetNets [25], [26] as well as massive multiple-input multiple-output (MIMO) systems [27], [28].

This work addresses a self-organizing joint user association and time allocation technique operating in a fully distributed manner for a two-tier WPCN. A macro and multiple pico BSs (PBS) first transmit energy signals to users in the DL phase. Subsequently, each user utilizes the harvested energy for information transmission to their corresponding BS in the UL based on the time division multiple access (TDMA) protocol. We aim to maximize the UL WIT utility performance by associating each user with an appropriate BS and determining the optimal DL and UL time allocation. As a result, the traffic and energy load can be balanced among BSs while minimizing the service outage of individual users.

The challenge of this problem lies in that the duration of the DL phase that a BS can supply energy to each user varies with the number of users associated with the BS and subsequently affects the UL data rate of individual users. Furthermore, the DL and UL time allocation is subject to a careful adjustment, since the overall rate of users highly depends on the allocated time allocation. A centralized user association algorithm inherently requires a central management agent which knows the information about all users and BSs information, which normally brings up heavy computational loads to the central unit. Thus, the user association should conduct only with local information in practice for the reduced system complexity. This naturally poses a self-organizing solution for the joint task.

We employ a state-of-the-art technique based on the message-passing framework [29]–[33], [35] to develop a distributed load balancing strategy. The previous work in [35] considered the user association and the resource blanking ratio in HetNets to maximize the log sum utility in the message-passing algorithm. Since it is not easy to tackle continuous variables in the message-passing framework, the authors defined a discrete set of the resource blanking ratio values as a suboptimal approach. Then, the message-passing algorithm was repeatedly applied as many as the number the resource blanking ratio candidates. Furthermore, such a heuristic strategy required an additional message-passing operation for determining the discretized resource blanking ratio variable.

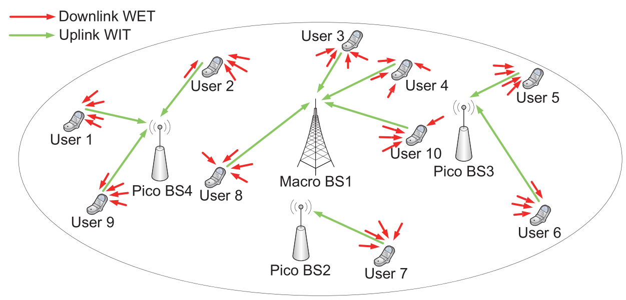
A main difference point of our study from the aforementioned previous work is that we treat general α–fair utilities and determine the user association and the time allocation jointly in a single round of the message-passing algorithm. We first present a user and BS association method based on the message-passing algorithm with given time allocation. The optimal time allocation can be determined in a distributed manner by applying a simple one-dimensional search technique. The simulation results show that the proposed algorithm provides sum-rate and minimum-rate improvements of more than 30% over existing techniques. Also, the proposed algorithm balances the user throughput between the sum and the minimum in low complexity which exhibits the potential of viability for self-organizing WPCN management.

The remainder of this paper is organized as follows: Section II provides the description of the system model and its optimization formulation for joint user association and time allocation. Section III develops a message-passing based distributed algorithm for the user association and an one-dimensional search technique for the time allocation along with practical implementation issues including computational complexity and convergence. After simulation results are presented in Section IV, the paper is concluded in Section V.

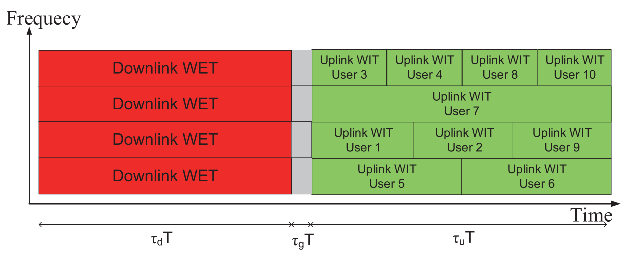
II. System Model

We consider a two-tier heterogeneous wireless network consisting of a single macro BS (MBS), multiple pico BSs (PBSs) with set $\mathcal{B} \in \{1, \ldots, B\}$, and users with set $\mathcal{K} \in \{1, \ldots, K\}$ as shown in Fig. 1 (a). Without loss of generality, the index $i = 1$ indicates the MBS, and PBSs are indexed with $i \in \{2, \ldots, B\}$. Individual BSs have their own fixed energy sources and do not share the energy among them. Thus, a network of multiple clusters can be formed around individual BSs as the corresponding cluster heads and their associated users as members, respectively.

Fig. 1 (b) illustrates a TDMA-based transmission frame structure for the WPCN. Wireless channels are assumed to remain constant during the block transmission time T_0. The block transmission time T_0 is made up with the optimization time $\tau_o T_0$, the guard time $\tau_g T_0$, the transmission times for DL phase $\tau_d T_0$ and UL phase $\tau_u T_0$. During the optimization time, the throughput maximization proceeds to identify the user association along with UL and DL phases. Guard time intervals are spared to avoid the interference at each phase change. Since the time durations for optimization time and guard time are fixed, it suffices to adjust UL and DL phase time intervals. For simple representation, the total transmission time duration of WET and WIT operations is denoted by T. During the total transmission time duration, the perfect channel state information is available at each BS, and each user has sufficient energy to exchange simple control messages. In the WET phase of duration $\tau_d T$ $(\tau_d \in [0, 1])$, all BSs broadcast the energy over the network and users harvest the received energy signal. Then, in the WIT phase, each user transmits the information to its associated BS using the harvested energy in a TDMA manner. The TDMA protocol in the WPCN requires the synchronization between WET and WIT operation for different BSs [9].



(a) Two-tier WPCN



(b) Transmission frame structure

Fig. 1. Example of a system model.

Since the signal traveling distance varies from a user-BS pair, different energy and data signal arrival times among users cause the interference problem. In particular, the energy signal transmitted to a distant user interferes with the data signal transmitted by a nearby user if the WIT is allowed immediately after the WET for each user. Thus, a constant guard time interval $\tau_g T_0$, corresponding to the signal traveling time for cell-edge users, is introduced in-between for the separation of the DL WET phase and the UL WIT phase, and the guard time interval is inserted before the WET phase. Since the location of each BS is fixed and low-energy devices move slowly, the channel state changes slowly, and the resource allocation phase is relatively small compared to the whole block transmission time [34].

The DL channel from the i-th BS to the a-th user and the corresponding UL channel are characterized by the channel power gains h_{ia} and g_{ia}, respectively. In each block, the first time duration of $\tau_d T$ is assigned to the DL phase for all BSs, while the UL phase occupies the remaining time duration $\tau_u T$ such that $\tau_u + \tau_d = 1$. It is assumed that equally divided amount of time is allocated to a set of individual users associated with each BS, since the optimal resource allocation has been shown to be uniform in [25]. Thus, the duration of a time slot allocated to the a-th user to the i-th BS is equal to $\tau_{ia} T = (1 - \tau_d)T/u_i$ if u_i is the total number of users associated with the i-th BS.[1] For simplicity, the time block is normalized to unity, i.e., $T = 1$, in the sequel. In addition, to avoid inter-user interference in the WIT phase, the total frequency band is uniformly divided into B sub-channels, and all users associated with the same BS transmit the information on the same frequency band.

To avoid the service outage, a positive integer U is introduced to limit the maximum number of served users for an individual BS and is set greater than K/B to accommodate K users within B BSs of the network. In the DL phase, the j-th BS sends the energy signal with power P_j. If the receiver noise is neglected for EH, and η stands for the energy conversion efficiency in the energy-harvesting circuit, the amount of the harvested energy of the a-th user in WET becomes $\tau_d \eta \sum_{j=1}^{B} P_j h_{ja}$.[2]

In the subsequent UL WIT phase, each user transmits independent information to the corresponding BS during the allocated time slot using the harvested energy. Note that since the users operate in a TDMA manner during the UL WIT, no inter-user interference occurs in the WIT phase [10]. The average transmit power of the a-th user to the j-th BS during the UL transmission is $(\tau_d \eta \sum_{j=1}^{B} P_j h_{ja})/\tau_{ia}$. Therefore, the corresponding UL throughput from the a-th user to the i-th BS is expressed in bits/second/Hz as

$$r_{ia}(\tau_d, u_i) = \frac{1-\tau_d}{u_i} \log_2\left(1 + \frac{u_i \tau_d \eta g_{ia} \sum_{j=1}^{B} P_j h_{ja}}{(1-\tau_d)\Gamma\sigma^2}\right), \tag{1}$$

where Γ stands for the signal-to-noise (SNR) margin for practical modulation and coding schemes [2].

We desire to find a load-balancing solution for the set of user-BS pairing and the time allocation which maximizes the network-wide $\alpha-$fair utility. The utility of the throughput r is evaluated based on $\alpha-$fair utility as

$$U(r, \alpha) = \begin{cases} \dfrac{r^{1-\alpha}}{1-\alpha} & \text{if } 0 \le \alpha < 1, \\ \log r & \text{if } \alpha = 1, \\ -\dfrac{r^{1-\alpha}}{\alpha - 1} & \text{if } \alpha > 1. \end{cases} \tag{2}$$

The $\alpha-$fair utility functions with $\alpha = 0, 1$, and ∞ correspond to the maximum sum, the proportional fairness, and the max-min utility, respectively [22]. The value of α is chosen in order to achieve a desired balance between the network-wide performance and the user fairness, such that no users are given zero throughput. For a concrete formulation, a binary variable x_{ia} is introduced to represent the association between the i-th BS and the a-th user, i.e., $x_{ia} = 1$ indicates that the a-th user is associated with the i-th BS. The overall objective function is the sum of individual utilities denoted by $\mathcal{R}_{ia}^{\alpha}(\tau_d, u_i) \equiv U(r_{ia}(\tau_d, u_i), \alpha)$.

By considering several constraints, an optimization problem that determines the values of x_{ia} and τ_d is formulated as

$$\max_{\{x_{ia}\}, \tau_d} \sum_{i \in \mathcal{B}} \sum_{a \in \mathcal{K}} x_{ia} \mathcal{R}_{ia}^{\alpha}(\tau_d, u_i) \tag{3a}$$

$$\text{subject to } \sum_{i=1}^{B} x_{ia} = 1, \quad x_{ia} \in \{0, 1\}, \ \forall a \in \mathcal{K}, \tag{3b}$$

$$\sum_{a=1}^{K} x_{ia} = u_i, \quad u_i \in \{0, \ldots, U\}, \ \forall i \in \mathcal{B}, \tag{3c}$$

$$\mathcal{R}_{ia}^{\alpha}(\tau_d, u_i) \ge r_{\min}, \quad \forall a \in \mathcal{K}, \ \forall i \in \mathcal{B}, \tag{3d}$$

$$\tau_d \in [0, 1], \tag{3e}$$

[1] The variable u_i is introduced to represent the number of the associated users $\sum_{a \in \mathcal{K}} x_{ia}$ for compact notation.

[2] The BS transmit power is set under the consideration of the energy consumption by signal processing of the user message, which is reflected in energy efficiency η.

where (3b) represents the constraint that each user is served by only one BS, (3c) indicates that the number of users associated with the i-th BS equals the sum of nonzero binary variables for the i-th BS, (3d) addresses the minimum rate requirement with minimum user data rate $r_{\min}$ which is necessary, in particular, for sum-rate maximization i.e., $\alpha = 0$, and (3e) accounts for the time slot allocated to users in the DL phase.

The resulting optimization is in a form of nonlinear mixed-integer programming. The UL throughput of an individual user in WIT depends on the number of other user connections with the same BS, which leads to a highly nonlinear combinatorial objective. Thus, identifying an efficient solution readily turns out to be computationally demanding. To handle this, a message-passing strategy is applied to find the user association along with the time allocation for UL and DL phases.

III. Proposed Algorithm

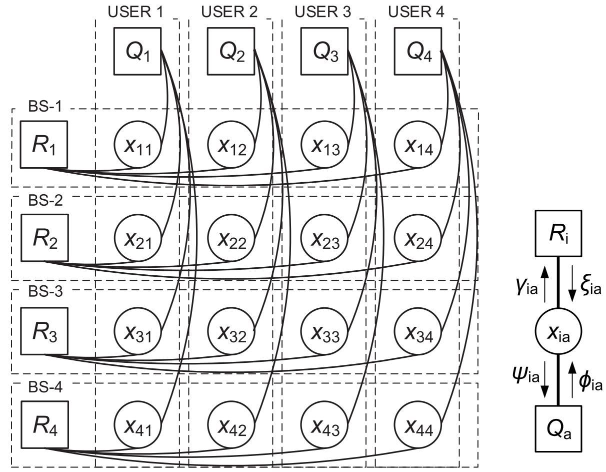
It is known that the message-passing algorithm itself consolidates necessary conditions which a feasible solution satisfies to guarantee the global optimality. Once the algorithm converges to a fixed point, the corresponding point is associated with the global solution. We adopt this property of the message-passing algorithm to identify the optimum user association for a given time phase. To jointly optimize the user association and the time phase, the optimum user association should be determined for all possible time phases, and the one with the highest utility function will be selected as in [35]. However, such an exhaustive search is obviously prohibitive. Instead, in our problem, the message-passing algorithm is applied only once for obtaining the user association. The objective function in (1) is concave with respect to τ_d for a given configuration of user association, and the α–fair utility is a strictly monotonic increasing function with respect to α. Thus, the objective function in (3a) is a still concave function with respect to the τ_d. The maximum of a unimodal concave function can be found in a computational complexity of order $O(\log \frac{1}{\epsilon})$ within error tolerance ϵ by means of line search algorithms [36]. Thus, the time phase is computed with a simple line search by exploiting the convex property.

A. User Association

Note that the original formulation in (3) can be decomposed to address individual operations of a BS and a user. A factor graph [29] can be used to facilitate to visualize this task with a graphical representation of the optimization. It is a bipartite graph with two classes of variables and factors interconnected by edges. To obtain a factor graph for the formulation in (3), two factors associated with the constraints and the objective in (3) are introduced as

$$Q_a(\mathcal{X}_a) = \begin{cases} -\infty & \text{if } \sum_{i\in\mathcal{B}} x_{ia} \neq 1, \\ 0 & \text{else}, \end{cases} \tag{4}$$

$$R_i(\mathcal{X}_i) = \begin{cases} -\infty & \text{if } \sum_{a\in\mathcal{K}} x_{ia} \neq u_i, \\ & \text{or } \mathcal{R}^{\alpha}_{ia}(\tau_d, u_i) < r_{min} \\ \sum_{a\in\mathcal{K}} x_{ia}\mathcal{R}^{\alpha}_{ia}(\tau_d, u_i), & \text{else}. \end{cases} \tag{5}$$



(a) Factor graph (b) Messages

Fig. 2. Example of a factor graph for 4-BS and 4-user network.

where $\mathcal{X}_a \equiv \{x_{ia} : i \in \mathcal{B}\}$ and $\mathcal{X}_i \equiv \{x_{ia} : a \in \mathcal{K}\}$. Here, $Q_a(\mathcal{X}_a)$ is associated with the first constraint in (3), while $R_i(\mathcal{X}_i)$ corresponds to the combination of the constraints (3c) and (3d). Furthermore, $R_i(\mathcal{X}_i)$ takes an input of x_{ia} only, since u_i is a function of x_{ia} when all variables have a valid assignment of values. We see that upon satisfying individual constraints, $Q_a(\mathcal{X}_a)$ permits each user to choose a single BS and $R_i(\mathcal{X}_i)$ produces the uplink data rate for the a-th user when connected to the i-th BS. Otherwise, the output values of both factors become infinite, and the optimization is no longer valid. From these facts, the constrained formulation in (3) can be recast into an unconstrained one as

$$\max_{x_{ia}\in\{0,1\}} \sum_{a\in\mathcal{K}} Q_a(\mathcal{X}_a) + \sum_{i\in\mathcal{B}} R_i(\mathcal{X}_i). \tag{6}$$

Then, it is sufficient to identify a solution for (6). To find a distributed solution, individual factors are maximized separately, and their maximizing assignment of variables are exchanged among factors to obtain a consistent global solution. Fig. 2 (a) illustrates a factor graph corresponding to the WPCN with 4 BSs and 4 users. The factor $Q_a(\cdot)$ and $R_i(\cdot)$ are connected to variables in the same row and column associated with the a-th user and the i-th BS, respectively. Thus, the a-th user and the i-th BS are responsible for the maximization of $Q_a(\cdot)$ and $R_i(\cdot)$, respectively. The maximizing assignments of individual variables are negotiated among nodes to take consistent values.

We derive a message-passing algorithm for (6) (See [29], [30] for details on the message-passing algorithm). In the message-passing algorithm, all factors and variables exchange a real number quantity, which is called a message, repeatedly in two directions of edges interconnecting them. A message transferred from node a to node b about variable c is denoted by $\mu_{a\to b}(c)$. Two constraints in (3) result in four different types of messages about variable x_{ia}. The corresponding four different types of the message are defined as $\mu_{x_{ia}\to Q_a}(\cdot)$, $\mu_{Q_a\to x_{ia}}(\cdot)$, $\mu_{x_{ia}\to R_i}(\cdot)$, and $\mu_{R_i\to x_{ia}}(\cdot)$, respectively.

As depicted in Fig. 2 (b), for compact notations, we denote the differences of four messages between two cases of x_{ia}

taking one and zero as

$$\begin{aligned}\psi_{ia} &= \mu_{x_{ia}\to Q_a}(x_{ia}=1) - \mu_{x_{ia}\to Q_a}(x_{ia}=0),\\ \phi_{ia} &= \mu_{Q_a\to x_{ia}}(x_{ia}=1) - \mu_{Q_a\to x_{ia}}(x_{ia}=0),\\ \gamma_{ia} &= \mu_{x_{ia}\to R_i}(x_{ia}=1) - \mu_{x_{ia}\to R_i}(x_{ia}=0),\\ \xi_{ia} &= \mu_{R_i\to x_{ia}}(x_{ia}=1) - \mu_{R_i\to x_{ia}}(x_{ia}=0). \end{aligned} \tag{7}$$

Here, messages ψ_{ia} and γ_{ia} encode the evidence for how well-suited the i-th BS is to serve for the a-th user upon the maximization of two factor functions, $Q_a(\mathcal{X}_a)$ and $R_i(\mathcal{X}_i)$, respectively. By contrast, messages ϕ_{ia} and ξ_{ia} reflect the evidence for how appropriate it would be for the a-th user to choose the i-th BS to meet two constraints in (3), respectively [30]. The outgoing messages emanating from a variable to neighboring factors at time instant t are simply the sum of all incoming messages and thus are given by

$$\psi_{ia}^{(t+1)} = \xi_{ia}^{(t)}, \tag{8}$$
$$\gamma_{ia}^{(t+1)} = \phi_{ia}^{(t)}. \tag{9}$$

To obtain the outgoing message from a factor node, the maximizer of the factor function is identified according to the max-sum message computation rule. First, the message ψ_{ia} is expressed so that the values of the factor $Q_a(\cdot)$ are maximized with respect to the variable node set $\mathcal{X}_a$ excluding x_{ia}, which can be set to either 0 or 1. The corresponding message can be represented in a compact form and its detailed derivation is presented in Appendix A. The final form of the a-th user message ϕ_{ia} can be simplified as

$$\begin{aligned}\phi_{ia}^{(t)} &= \mu_{Q_a\to x_{ia}}(x_{ia}=1) - \mu_{Q_a\to x_{ia}}(x_{ia}=0)\\ &= \max_{\mathcal{X}_a\backslash x_{ia}} \Big(Q_a(x_{ia}=1,\mathcal{X}_a\backslash x_{ia})\\ &\qquad + \sum_{j\in\mathcal{B}\backslash i} \mu_{x_{ja}\to Q_a}(x_{ja})\Big)\\ &\quad - \max_{\mathcal{X}_a\backslash x_{ia}} \Big(Q_a(x_{ia}=0,\mathcal{X}_a\backslash x_{ia})\\ &\qquad + \sum_{j\in\mathcal{B}\backslash i} \mu_{x_{ja}\to Q_a}(x_{ja})\Big)\\ &= -\max_{j\in\mathcal{B}\backslash i} \psi_{ja}^{(t)}. \end{aligned} \tag{10}$$

The factor function $Q_a(\cdot)$ is evaluated such that it takes a finite value when x_{ia} is set to either one or zero. If $x_{ia}=1$, no other BS can be chosen, meaning that the i-th BS needs to serve the a-th user,i.e., $\phi_{ia}>0$. On the other hand, if $x_{ia}=0$, another BS should be chosen for the service of the a-th user, implying that the i-th BS may not be associated with the a-th user, i.e., $\phi_{ia}<0$. The substitution of (9) into (16) leads to a new message update rule as

$$\gamma_{ia}^{(t+1)} = -\max_{j\in\mathcal{B}\backslash i} \xi_{ja}^{(t)}. \tag{11}$$

Next, we derive the message update rule associated with the factor $R_i(\mathcal{X}_i)$. The i-th BS calculates the maximization task pertaining to $R_i(\mathcal{X}_i)$ which addresses the objective function for the BS. The computation of the factor function becomes quite challenging since it requires a complete enumeration of all feasible assignments of a binary variable x_{ia} and corresponding to different values of u_i. The corresponding message can be represented in a compact form and its detailed derivation is presented in Appendix B. The final form of the i-th BS message ξ_{ia} can be simplified as

$$\begin{aligned}\xi_{ia}^{(t)} &= \mu_{R_i\to x_{ia}}(x_{ia}=1) - \mu_{R_i\to x_{ia}}(x_{ia}=0)\\ &= \max_{\mathcal{X}_i\backslash x_{ia}} \Big(R_i(x_{ia}=1,\mathcal{X}_i\backslash x_{ia}) + \sum_{b\in\mathcal{K}\backslash a} \mu_{x_{ib}\to R_i}(x_{ib})\Big)\\ &\quad - \max_{\mathcal{X}_i\backslash x_{ia}} \Big(R_i(x_{ia}=0,\mathcal{X}_i\backslash x_{ia}) + \sum_{b\in\mathcal{K}\backslash a} \mu_{x_{ib}\to R_i}(x_{ib})\Big)\\ &= \Xi_{ia}(1) - (\Xi_{ia}(0))^+, \end{aligned} \tag{12}$$

where $(\cdot)^+$ is $\max(0,\cdot)$, and

$$\begin{aligned}\Xi_{ia}(x) \triangleq \max_{u_i\in\{1,\ldots,U\}} \Big(&\mathcal{R}_{ia}^{\alpha}(\tau_d,u_i) + \sum_{k=1}^{u_i-x} \operatorname{rank}^k_{b\in\mathcal{K}\backslash a}\\ &\times[\mathcal{R}_{ib}^{\alpha}(\tau_d,u_i)+\gamma_{ib}]\Big). \end{aligned} \tag{13}$$

Here $\operatorname{rank}^k[A]$ is the k-th largest value in the input set A. The message $\mu_{R_i\to x_{ia}}(x_{ia}=1)$ indicates which users can maximize the objective when the i-th BS is associated with the a-th user. Similarly, $\mu_{R_i\to x_{ia}}(x_{ia}=0)$ decides which users to maximize the objective when the a-th user is not served by the i-th BS. If it becomes zero, no user is allowed to associate with the i-th BS. Since the message ξ_{ia} is the difference of the two messages, ξ_{ia} is interpreted as the preference of the i-th BS and the a-th user over the unconnected links of other users. For a positive ξ_{ia}, the i-th BS desires to support the a-th user, and the a-th user evaluates the BSs based on ϕ_{ia}.

Since all messages are expressed in terms of $\xi_{ia}^{(t)}$ and $\gamma_{ia}^{(t)}$ at time instant t, an iterative algorithm is constructed so that BSs and users are in charge of updating messages $\xi_{ia}^{(t)}$ and $\gamma_{ia}^{(t+1)}$, respectively. For the enhancement of convergence and stability with messages, a damping technique [32], [33] is applied to take linear combinations of the previous messages and the updated messages with a positive parameter $\delta\in(0,1]$. The resulting iterative message update rules become

$$\xi_{ia}^{(t)} = (1-\delta)\xi_{ia}^{(t-1)} + \delta(\Xi_{ia}(1) - (\Xi_{ia}(0))^+), \tag{14}$$
$$\gamma_{ia}^{(t+1)} = (1-\delta)\gamma_{ia}^{(t)} - \delta\max_{j\in\mathcal{B}\backslash i} \xi_{ja}^{(t)}. \tag{15}$$

Note that a low value of δ results in conservative updates of messages. This improves the stability of message dynamics while it causes the time elapsed to approach the solution to increase.

In summary, the i-th BS computes message $\xi_{ia}^{(t)}$ to transfer to the a-th user, and the a-th user calculates message $\gamma_{ia}^{(t)}$ to send it back to the i-th BS. Upon completion of the message exchange among users and BSs, a tentative decision of user association is made at each iteration. The a-th user evaluates a decision metric calculated using $\xi_{ia}^{(t)}+\gamma_{ia}^{(t)}$ and asks the association for such a BS with the largest decision metric. To see this more carefully, we consider the convergence of all messages. Since users have limited energy source and harvest the energy supplied from BSs, saving in energy consumption for message calculation is also necessary so that as much energy as possible is spared for uplink transmission. Since each BS picks up at most U users, it suggests the association to users with the first U largest positive sum message. A user suggested by multiple BSs grants one of their suggestions based on the largest decision metric. Using such a protocol, each user can save the energy consumption for the decision of the user association.

B. Time Allocation

We address the identification of the optimal time allocation for τ_u and τ_d. Recall that the message-passing algorithm can efficiently determine user association for a given time phase. To lift the computational burden, the following observation allows the development of a further simplified algorithm. In calculating message $\xi_{ia}^{(t)}$, the evaluation of the function $\Xi_{ia}(x)$ at $x = 0, 1$ involves sorting the sums of incoming messages and utility function $\mathcal{R}_{ia}^{\alpha}(\tau_d, u_i)$. Although different values of τ_d lead to different $\Xi_{ia}(x)$, the maximizing BS-user pair indices of $\Xi_{ia}(x)$ are found to be identical. Assuming that two users a and b are associated with the same i-th BS, the α-fair utilities of $r_{ia}(\tau_d, u_i)$ and $r_{ib}(\tau_d, u_i)$ depend on the uplink channel gains and the harvested energy in the downlink, and their relationship of which user has a larger value of the utility remains invariant. Since the associated user population at the i-th BS and the time phase τ_d are the same for both utilities, the maximizer of $\Xi_{ia}(x)$ is not affected by the time phase. This implies that the user association configurations obtained with distinct τ_d are not different. Using this observation, we can develop a simplified strategy that does not require repeating message-passing algorithms for multiple time phases without any performance degradation.

If the user association is obtained with a given τ_d, the α-fair utility $\mathcal{R}_{ia}^{\alpha}(\tau_d, u_i)$ is calculated. Then, the improved time allocation τ_d is found with the current user association configuration by the golden section search. This strategy allows us to identify the optimal time phase such that the user associations are robust to different initial time phases. Once the user association is determined using the message-passing algorithm with an initial time phase, all BSs calculate their α-fair utilities. To obtain the total objective with distributed operations, individual utilities along with the time phase need to be shared by all BSs via backhaul links and subsequently configure the total objective $\mathcal{R}_{ia}^{\alpha}(\tau_d, u_i)$ for each BS. Since the golden section search chooses the next candidate value with the fixed ratio $(1 + \sqrt{5})/2$, all BSs are simultaneously aware of the next τ_d and identify the optimal time phase. Upon the determination of the time phase, the BSs conduct the WET and WIT operations with their associated users. In this simplified technique, the best time allocation is found in a single round of the message-passing operation. As shown in the simulation results, this yields the identical performance to the optimal strategy with lower complexity. Algorithm 1 summarizes the overall procedures of the proposed algorithm.

C. Computational Complexity and Implementation

Now, we address the computational complexity of the message-passing algorithm. At users' side, each user processes incoming messages from at most B BSs. Thus, the computation of the factor node $Q_a(\cdot)$ becomes $O(B)$, normally scaling with $O(K)$. Thus, the overall complexity mainly depends on the calculation of $\xi_{ia}^{(t)}$, which involves the sort operations in determining several largest input messages. U incoming messages are sorted in the decreasing order, which costs $O(U \log U)$ complexity. In (13), l ranges from 1 to U, and the sort operation is repeated for $O(U)$ times. Thus, $\phi_{ia}^{(t)}$ requires $O(U^2 \log U)$ operations. Hence, the overall complexity of the factor node $R_i(\cdot)$ is $O(U^2 \log U)$ in a single iteration, which is a manageable computational load for a distributed operation at an individual BS. Since the maximum number of users associated with a BS becomes as large as the total number of users, the worst complexity is $O(K^2 \log(K))$ at a single iteration of the message-passing operation. According to empirical observations from intensive simulation, the average number of iterations necessary to obtain efficient solutions suffices to scale with the logarithm of the number of users. Thus, the effective complexity of the overall algorithm becomes $O(K^2 (\log K)^2)$, since the time allocation is found using a line search having a linear complexity. Therefore, the overall computational cost of the proposed algorithm is manageable with the distributed operations among network nodes.

We compare the computational complexity with existing techniques. Both maximum-SNR and equal-loading techniques associate users with the highest uplink channel gains. Especially, the equal-loading technique tries to distribute the overall loads uniformly over all BSs with the maximum number of users allowed for a BS equal to U. The sort operations over BSs for both techniques result in the computational complexity of $O(KB \log B)$. Another popular user association technique is K-medians clustering (KM) algorithm [30]. Upon the equal-loading results, the user association is changed repeatedly with other BSs to improve the overall objective until convergence. Since the number of required iterations scales with $O(K)$, its complexity becomes $O(KB \log K \log B)$. Furthermore, in a special case of $\alpha = 1$, a primal-dual algorithm [28] can be applied using a Lagrange dual formulation with a relaxed binary constraint. Since individual users choose their serving BSs with linear processing of the information for each BS, the complexity equals $O(KB \log K)$ For all above algorithms, the time allocation is obtained by a line search method for a given user association result. Thus, the overall complexity is multiplied by the number

Algorithm 1 The Proposed Message-Passing Algorithm

Set initial τ_d, $\gamma_{ia}^{(1)} = 0$ for all (i, a) and $t = 1$.
Repeat
Use (14) to update message $\xi_{ia}^{(t)}$ at BS i for $a \in \mathcal{K}$ and send it back to user a.
Use (15) to update message $\gamma_{ia}^{(t+1)}$ at user a for $i \in \mathcal{B}$ and send it back to BS i.
Set $t \leftarrow t + 1$.
Until convergence of all messages
Decide user association using pair (i, a) with the largest $\xi_{ia}^{(t)} + \gamma_{ia}^{(t)}$.
Obtain the best τ_u and τ_d by golden-section search.

TABLE I

COMPUTATIONAL COMPLEXITY OF THE PROPOSED AND CONVENTIONAL ALGORITHMS

Algorithm	Complexity
Proposed	$O(K^2(\log K)^2)$
Optimal	$O(TK^2(\log K)^2)$
maximum-SNR	$O(TK^2 \log K)$
Equal-loading	$O(TK^2 \log K)$
K-medians	$O(TK^2(\log K)^2)$
Primal-dual	$O(TK^2 \log K)$

of time phase samples T for obtaining an efficient solution. Although B is in general small as compared to K, it has a linear relationship, i.e., $B = O(K)$. Considering this relationship, the corresponding complexities of all techniques are summarized in Table I. This indicates that the overall computational costs may vary according to the resolution of the time allocation.

Next, we discuss the energy consumption relevant to the processing of the proposed algorithm. The harvested energy is consumed mostly for the calculation of messages and the transmission of the signal. According to [37], the energy dissipation of EH circuits and the message transmission for one bit are measured as 50 nJ/bit and 10 pJ/bit/m^2, respectively. For the payload data of 32 bits and the message of 5 bits, the user energy consumptions for the payload data transmission and the user association message processing amount to 2.4 μJ and 0.37 μJ, respectively. Thus, about 15 % of additional energy is transmitted by a BS for compensating the energy dissipation at users, which is reflected by the energy efficiency η for simulation. Since this amount of the extra energy is relatively small as compared to the BS transmit power, the proposed algorithm is affordable in low energy devices.

D. Optimality and Dynamic Behaviors of Messages

The optimality and the convergence dynamics of the proposed algorithm are briefly addressed in this subsection. Recall that since the message-update rules are necessary conditions, if the algorithm converges to a fixed point the corresponding point becomes one of the optimal solutions. Thus, the convergence is crucial in the analysis of the proposed algorithm, while the convergence of the message passing algorithm over a loopy graph has not been fully understood in literatures yet. In this vein, a complete theoretical condition for the convergence of the proposed algorithm is still quite challenging to establish, although its convergence can be observed empirically from intensive simulations. Nevertheless, some analytical results are obtained based on theory and experiments using the notion of nonexpansive mapping [32]. According to the result, the algorithm reaches a fixed assignment of messages asymptotically as the node population grows with a certain value of the damping parameter δ. The detailed discussion is presented in Appendix C.

IV. SIMULATION RESULTS

A. Simulation Setup

To test the proposed algorithm, a simulation setup of two-tier WPCN with a single MBS and 6 PBSs is considered.

TABLE II

AVERAGE THROUGHPUT PERFORMANCE OF THE PROPOSED ALGORITHM

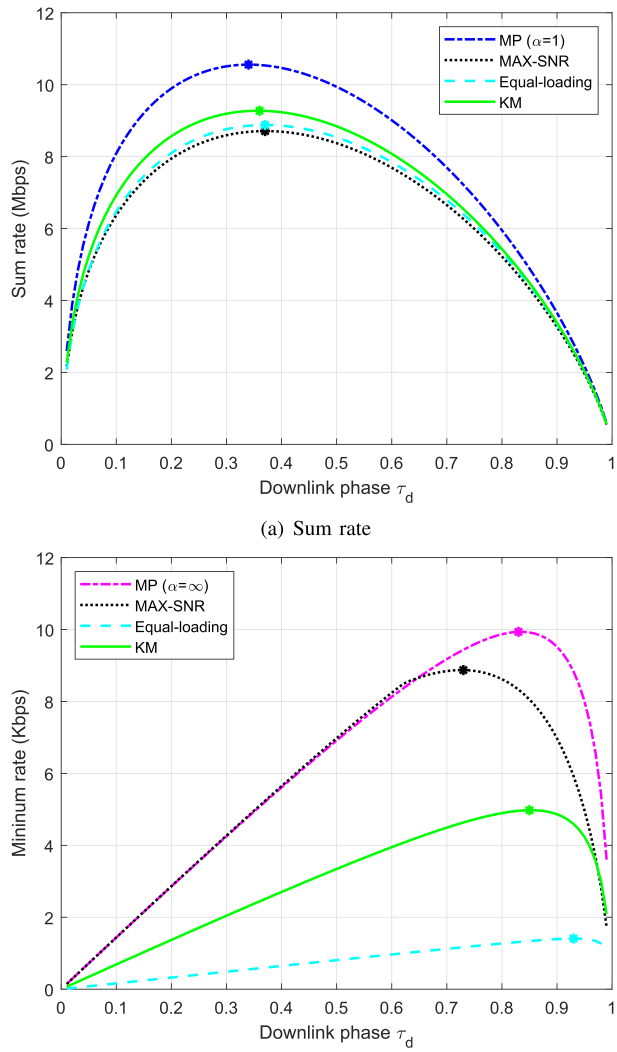
	$K = 14$		$K = 21$	
	Optimal	Proposed	Optimal	Proposed
$\alpha = 1$	0.12	0.12	0.16	0.16
$\alpha = 0$	7.23 Mbps	7.23 Mbps	12.46 Mbps	12.44 Mbps
$\alpha = \infty$	8.80 Kbps	8.80 Kbps	11.83 Kbps	11.80 Kbps

The MBS is located at the center of the network, and all PBSs are uniformly located within the radius of 50 m around the MBS. Users are uniformly distributed within the coverage area of the MBS and PBSs. The transmit power of the MBS and a PBS are set to 40 dBm and 30 dBm, respectively, and the bandwidth is equal to 1 MHz. The channel gain is modeled as $h_{ia} = g_{ia} = \rho_{ia}^2 d_{ia}^{-\zeta}$, where ρ_{ia}^2 represents a short-term fading channel corresponding to an exponentially distributed random variable with mean 10^{-3} [2]. Here, d_{ia} and ζ stand for the distance between BS i and user a and the path-loss exponent, respectively. The path-loss exponent between the MBS and a user, and a PBS and a user are given by 2.2 and 2.7, respectively [12]. The EH efficiency and the noise power are equal to $\eta = 0.4$ and -160 dBm/Hz, respectively [2]. The simulation results are averaged over 5000 independent instances of random user configurations.

B. Performance Evaluation

The performance with sum-rate, proportional fairness and minimum-rate utilities are compared with the global optimum with 14 and 21 users in Table II. The global optimal results are obtained by searching for the user association solutions with 100 different time phase values in the interval [0, 1]. In contrast, the proposed strategy conducts a single round of the message-passing algorithm for the user association with an initial time phase and subsequently searches for the optimal time allocation with a line search based on the user association configuration obtained by the message-passing algorithm. For all utilities, at least 98.98% of the cases finds the optimal solution.

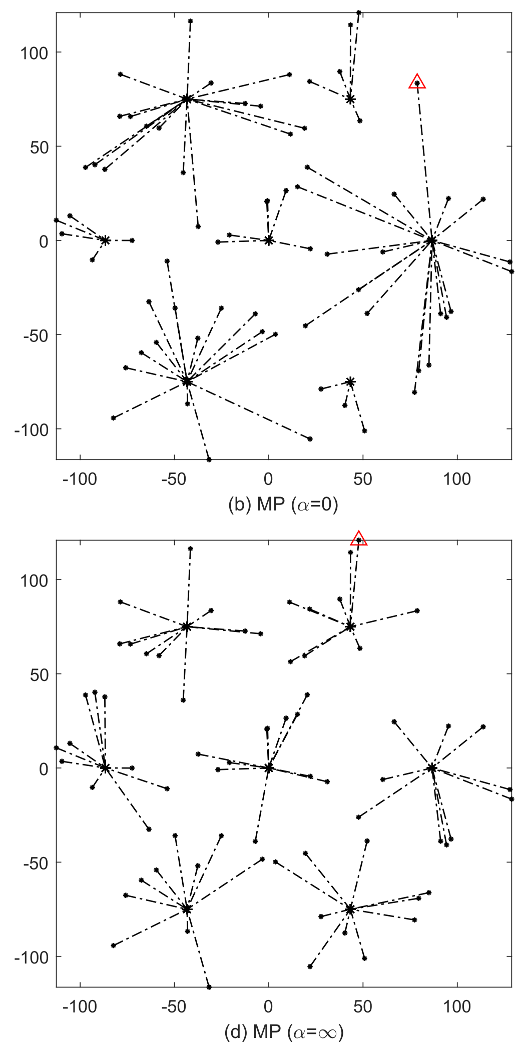
Fig. 3 shows sum rate and minimum rate throughputs for various values of τ_d. The solid dots indicate the best UL sum rates associated with the optimal time phase τ_d. The sum rate maximization as shown in Fig. 3 (a) finds the optimal DL phase around 0.35 for all techniques in comparison, while MP shows the best throughput performance. It is also observed that the user association results are distinct among compared techniques for a given τ_d, implying that the user association plays a more important role than the time allocation in the overall throughput performance. Since the sum rate maximization usually tries to maximize the throughput of users located near each BS having large channel gains g_{ia} and h_{ia}, there exist one group of high-rate connections made by nearby users and another group of low-rate connections made by remote users in the user association results. On the other hand, the minimum rate maximization achieves uniform throughput values for all user connections by establishing pairings between each BS and users. In Fig. 3 (b), the optimal DL phase turns out to be 0.83 for MP, while other techniques shows different DL



(a) Sum rate

(b) Minimum rate

Fig. 3. Rate throughput with respect to τ_d for $K = 70$.



(b) MP (α=0)

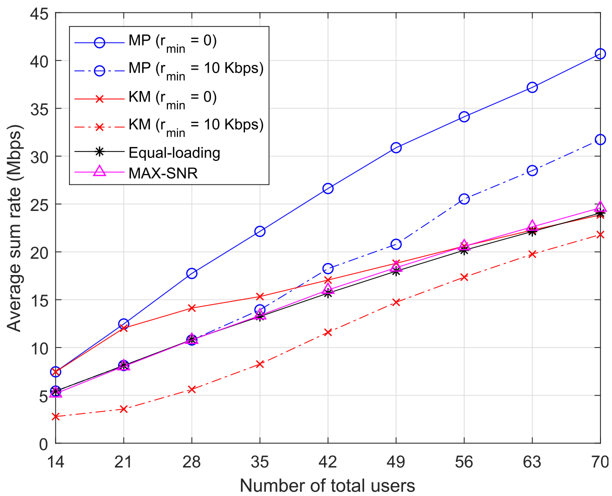
(d) MP (α=∞)

Fig. 4. Simulation results for different user associations ($K = 70$).

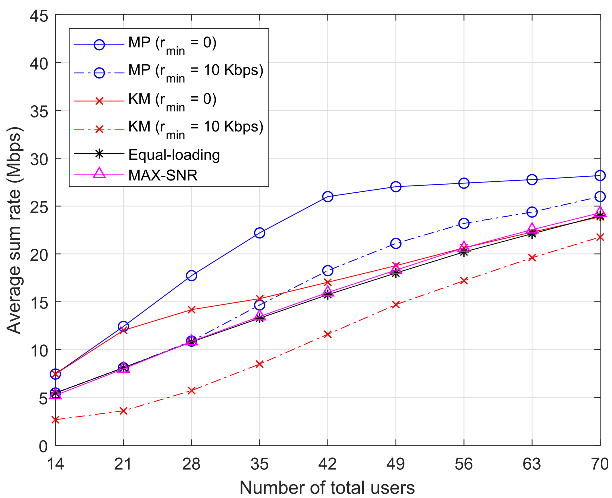
phases. Since the minimum rate performance is determined by the worst-case user connection, the DL phase depends on the user association. This means that other strategies cannot identify the worst-case user connection, and the DL phases are inconsistent.

Fig. 4 illustrates the user association results of the MP strategy for a given channel realization. The circles represent users and the dashed lines indicate the connections between a user and a BS, and the triangle points out the minimum-rate user. In case of the sum rate maximization, the proposed approach achieves 8.52 Mbps, while the max-SNR algorithm provides 7.05 Mbps. In particular, MP allows the MBS to support nearby users to achieve a high sum-rate, since far connected users do not contribute to the sum rate performance. Thus, users located between the MBS and PBSs are associated with PBSs to lower the number of associated users at the MBS. However, the UL rate of a far connected user supported by the PBS decreases, which accounts for a doubly near-far effect [2], and this degrades the minimum rate performance. In case of the minimum rate maximization, the proposed approach and the max-SNR method yield 12.6 and 7.61 Kbps, respectively. Furthermore, MP with $\alpha = \infty$ allows the PBS supporting the minimum rate user to offload users to other BSs, which, in turn, leads neighboring BSs to accommodate additional users to reduce the number of associated users.

Fig. 5 shows how the constraint on the number of users per cell affects the overall performance. The sum rate maximization is considered for two cases of no constraint on the number of users in each BS and 30 users allowed to access to each BS. In addition, the minimum rate constraints are imposed on PBS users. Fig. 5 (a) presents the average sum rates when BSs do not have the limit on the number of serving users. The proposed algorithm exhibits a large gap in the average sum rate performance over other techniques regardless of the minimum rate constraint. KM algorithm has similar performance to the proposed algorithm for small user population of the WPCN, while its performance deviates from the proposed algorithm to approach the MAX-SNR algorithm as the network population increases. If KM algorithm obtains initial solution with sufficiently good quality, it would not make a large change from the current configuration, and its performance does not improve considerably. In the sum rate maximization, the contribution of nearby users around MBS

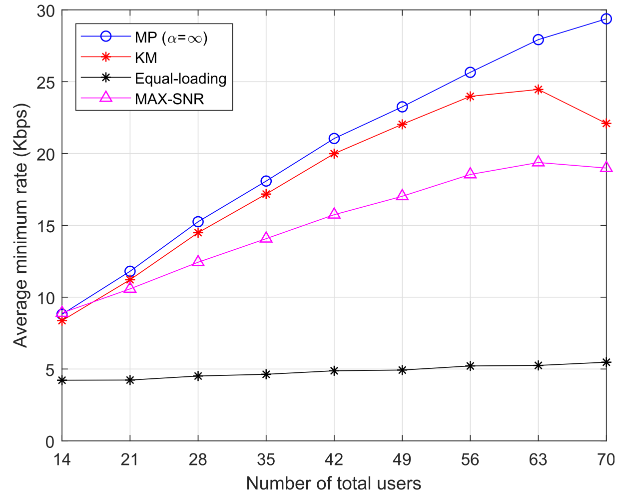


(a) $U = 70$

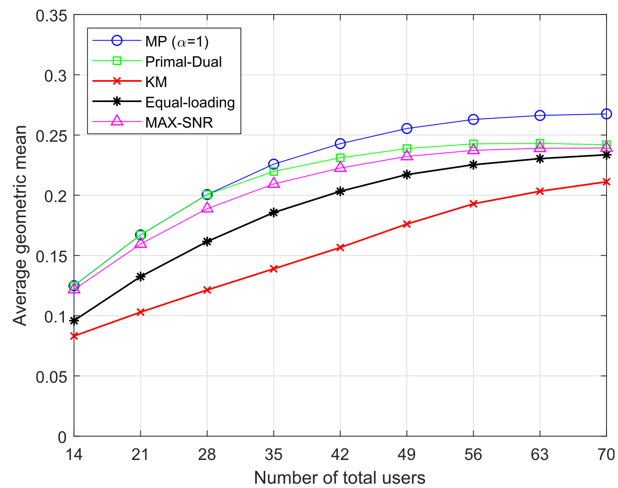


(b) $U = 30$

Fig. 5. Average sum throughput with respect to the number of users.



(a) Minimum rate



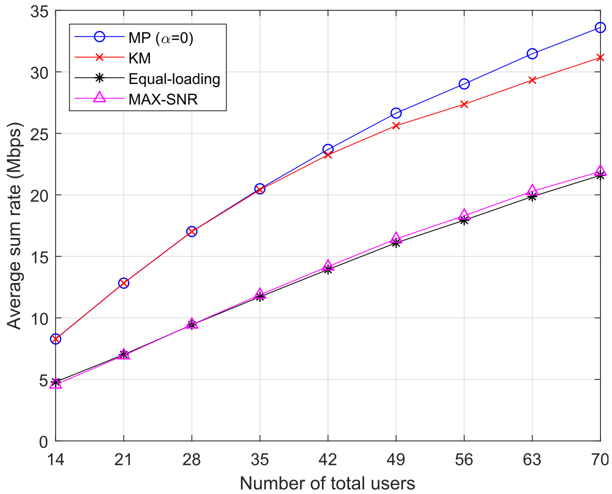
(b) Proportional fairness

Fig. 6. Average throughput performance with respect to the number of users.

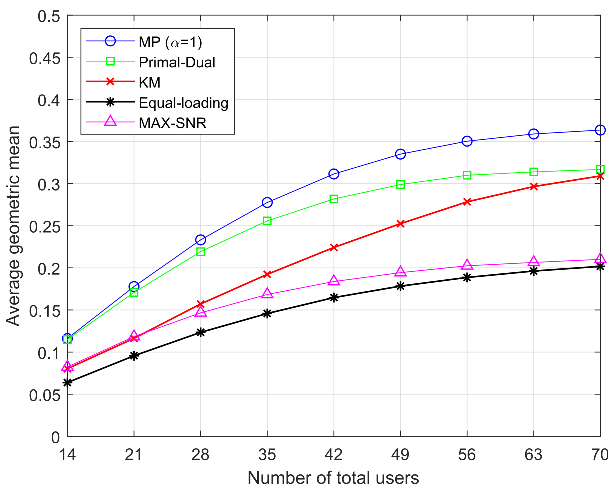
contributes to the overall objective is critical. If there is no constraint on the number of MBS users, many users adjacent to MBS are connected to it, and the remaining users are supported by PBSs. If the minimum rate constraint is imposed, the users attached to PBSs are detached to guarantee the minimum rate. Thus, the detached users access to MBS that is relatively of long distance and the user population in MBS increases, resulting in the degradation in the performance. On the other hand, if the number of users which can access to BSs is limited, the overall performance becomes saturated for increasing number of users as shown in Fig. 5 (b). The constraint prohibits users from accessing to MBS. A number of users are connected to PBS, thereby incurring the overall performance degradation. If the minimum rate constraint is imposed, cell-edge users in PBSs connect to the MBS to avoid the service outage. It increases the load of the MBS resulting in the loss of the MBS throughput and sum rate performance.

Fig. 6 depicts the average minimum rate and geometric mean performance of the proposed algorithm along with existing techniques with respect to the number of users. Unlike the sum throughput maximization, both cases are not affected by the minimum rate of the user and maximum number of associated users at BS constraints. Fig. 6 (a) compares the average minimum rates of MP and other strategies. The minimum rate with $\alpha = \infty$ provides 48.7% improvement as compared to the MAX-SNR strategy for the 10-user case. In addition, KM and Equal-loading find local solutions but failing to improve the minimum rate performance. The MBS cannot support more users located in overlap coverage in BS-tiers. Then, PBSs bear the burden of more users, resulting in minimum performance loss. Fig. 6 (b) exhibits the geometric mean of MP with $\alpha = 1$ and other strategies. As the number of users per cell increases, the proposed algorithm shows improved throughput performance. If the number of user equals 10, MP with $\alpha = 1$ provides 9.5% improvement over the max-SNR strategy. On the other hand, KM exchanges user pairings between BSs sequentially and does not consider all BSs' balance. Thus, the KM scheme does not mitigate user loads between BSs, and its performance is worse than the equal-loading scheme. In addition, the primal-dual method provides similar performance compared to the max-SNR strategy.

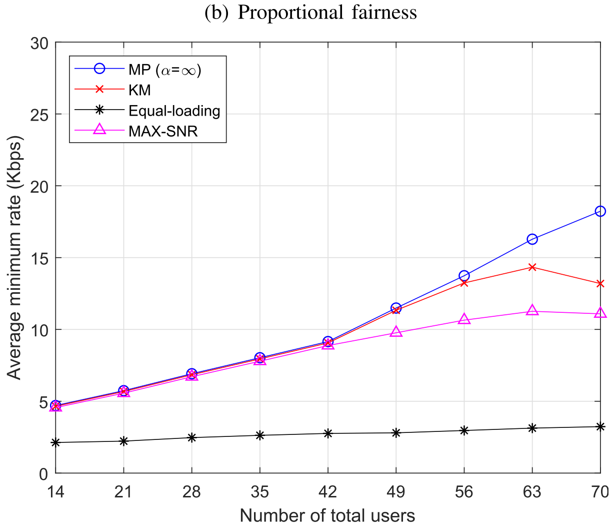
The proposed algorithm can be applied in a non-linear EH model [38]. The proposed algorithm outperforms conventional techniques for all cases in Fig. 7. Since the maximum



(a) Sum rate ($U = 70, r_{\min} = 0$)



(b) Proportional fairness



(c) Minimum rate

Fig. 7. Average throughput performance with respect to the number of users in non-linear EH model.

harvested energy of users is limited in EH circuits, the users located near the BSs cannot utilize more received energy. Then, the performance of the users in the MBS and PBSs do not show much difference. In the sum rate maximization, the number of associated users in each BS-tier is not critical to

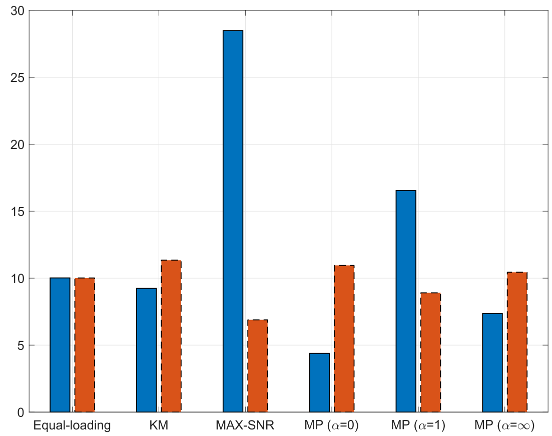


Fig. 8. Average number of users with different techniques.

improve the sum throughput. Thus, KM shows similar performance to MP for small number of users. In the proportional fairness optimization, the non-linear energy conversion efficiency polarizes the harvested energy in users. Far-connected users experience low energy efficiency for low input power region in the EH circuit, while users located near BSs exploit most of received energy for high energy efficiency. It becomes intractable to balance the performance between users in conventional schemes. In the minimum rate maximization, the minimum performance of users is degraded due to lower energy efficiency. Therefore, all techniques shows the performance degradation compared to the linear EH model case.

Fig. 8 compares the average load balancing performance when the number of users per BSs is 10. We can see that the MAX-SNR strategy results in unbalanced loads. In MP with $\alpha = 0$, the MBS supports less than 5 users to allocate more energy to only nearby users. In the proportional fairness case with $\alpha = 1$, the MBS accommodates additional users to balance the performance of users in different BS-tiers as compared to MP with $\alpha = 0$. In addition, both BSs subject to MP with $\alpha = \infty$ allocate similar user loads to balance among PBSs. The KM and Equal-loading strategies exchange one or two user pairs which cannot efficiently alleviate the load imbalance in the network.

V. Conclusion

This paper investigates joint user association and time allocation to maximize various utilities, including maximum sum, proportional fairness and max-min rate, for wireless powered communication networks. A message-passing algorithm is developed to solve the user association in a distributed manner to maximize the α–fair utility. The proposed message-passing algorithm is conducted for the user association at given time allocation. Subsequently, the optimal time allocation is solved by a simple one-dimensional search technique. The simulation results verify the effectiveness of the proposed algorithm and its performance improvement over existing techniques. For a work worthwhile further investigation in the future, the proposed algorithm can be developed in the case of the WPCN with the inter-cell interference, resulting from the network configuration where users share the resources instead of the dedicated time slots in the WIT phase.

Appendix A
Derivation of the Message ϕ_{ia}

In the message ϕ, the values of the factor $Q_a(\cdot)$ are maximized with respect to the variable node set $\mathcal{X}_a$ for both cases of $x_{ia} \in \{0,1\}$ as

$$\begin{aligned}
&\phi_{ia}^{(t)} \\
&= \mu_{Q_a \to x_{ia}}(x_{ia}=1) - \mu_{Q_a \to x_{ia}}(x_{ia}=0) \\
&= \max_{\mathcal{X}_a \backslash x_{ia}} \Big(Q_a(x_{ia}=1, \mathcal{X}_a \backslash x_{ia}) + \sum_{j \in \mathcal{B} \backslash i} \mu_{x_{ja} \to Q_a}(x_{ja}) \Big) \\
&\quad - \max_{\mathcal{X}_a \backslash x_{ia}} \Big(Q_a(x_{ia}=0, \mathcal{X}_a \backslash x_{ia}) + \sum_{j \in \mathcal{B} \backslash i} \mu_{x_{ja} \to Q_a}(x_{ja}) \Big) \\
&= \sum_{j \in \mathcal{B} \backslash i} \mu_{x_{ja} \to Q_a}(0) \\
&\quad - \max_{j \in \mathcal{B} \backslash i} \Big(\mu_{x_{ja} \to Q_a}(1) + \sum_{k \in \mathcal{B} \backslash \{i,j\}} \mu_{x_{ka} \to Q_a}(0) \Big) \qquad (16a) \\
&= -\max_{j \in \mathcal{B} \backslash i} \Big(\mu_{x_{ja} \to Q_a}(1) - \mu_{x_{ja} \to Q_a}(0) \Big) \qquad (16b) \\
&= -\max_{j \in \mathcal{B} \backslash i} \psi_{ja}^{(t)}, \qquad (16c)
\end{aligned}$$

In (16a), if $x_{ia} = 1$, all other variables in $\{x_{ja} : j \in \mathcal{B} \backslash i\}$ should take zero. Otherwise, another variable in $\{x_{ja} : j \in \mathcal{B} \backslash i\}$ should take one for the satisfaction of the constraint. The corresponding maximum values of the messages are given as such. Note that the first term is constant and can be canceled out with the remaining terms. The resulting message becomes (16b) and, by definition, the final simplified message in (16c) is obtained.

Appendix B
Derivation of the Message ξ_{ia}

In the message ξ, the values of the factor $R_i(\cdot)$ are maximized with respect to the variable node set $\mathcal{X}_i$ excluding x_{ia}. Since the factor $R_i(\cdot)$ depends on the number of associated user u_i, the message ξ can be expressed as (17), shown at the bottom of the page. Note that $\mathcal{R}_{ia}^{\alpha}(\tau_d, 0) = 0$. Thus, the comparison of messages among possible values of u_i proceeds with computational complexity of order $O(U^2 \log U)$. Cancelling out all terms with the constant value $\sum_{b \in \mathcal{K}} \mu_{x_{ib} \to R_i}(0)$ invokes the appearance of γ_{ib} as (18), shown at the bottom of the next page.

Appendix C
Discussion on Convergence Dynamics

The existence of a fixed point can be addressed by the notion of contraction mapping [39]. A mapping $\boldsymbol{\xi}^{(t+1)} = \mathbb{T}(\boldsymbol{\xi}^{(t)})$ is called a contraction if $\|\mathbb{T}(\boldsymbol{y}^{(t)}) - \mathbb{T}(\boldsymbol{z}^{(t)})\| \le \|\boldsymbol{y}^{(t)} - \boldsymbol{z}^{(t)}\|$ for input vectors $\boldsymbol{y}$ and $\boldsymbol{z}$. For the proposed algorithm, $\mathbb{T}(\cdot)$ is obtained by plugging (11) into (12) instead of handling the damped form in (14) and (15), because both forms of the algorithm have the identical fixed points and the original form is favorable to the analysis. Let $\boldsymbol{y^t}$ and $\boldsymbol{z^t}$ be the vectorized collections of messages $\{\xi_{ia}^t : i \in \mathcal{K}, a \in \mathcal{B}\}$ with different initializations. Also, let $\mathbb{F}(\boldsymbol{y^t})$ denote the collection of a message mapping function from the i-th BS to users, i.e., $\mathbb{F}(\boldsymbol{y^t}) = [\ldots, \mathbb{F}_{ia}(\boldsymbol{y^t}), \ldots]$. Since $\mathbb{F}_{ia}(\cdot)$ consists of the difference between $\xi_{ia}^{(t)}(x_{ia})$ with x_{ia} status, two variables l_i and $\bar{l}_i$ are introduced as the selected number of associated users at the i-th BS for the two cases with the previous message $\boldsymbol{y^t}$. Likewise, m_i and $\bar{m}_i$ can also be defined with respect to another previous version of the message $\boldsymbol{z^t}$. We assume $l_i > \bar{l}_i$ and $m_i > \bar{m}_i$ for simplicity, since the remaining two cases can also be addressed similarly. Furthermore, we define v_{k_1} and w_{k_2} as the indices of the k_1-th and k_2-th largest input values of $\mathcal{R}_{iv}^{\alpha}(\tau_d, l_i) + y_{iv}^t$ and $\mathcal{R}_{iw}^{\alpha}(\tau_d, m_i) + z_{iw}^t$, respectively. The resulting function $\mathbb{F}_{ia}(\boldsymbol{y^t})$ is

$$\begin{aligned}
\xi_{ia}^{(t)} &= \mu_{R_i \to x_{ia}}(x_{ia}=1) - \mu_{R_i \to x_{ia}}(x_{ia}=0) \\
&= \max_{\mathcal{X}_i \backslash x_{ia}} \Big(R_i(x_{ia}=1, \mathcal{X}_i \backslash x_{ia}) + \sum_{b \in \mathcal{K} \backslash a} \mu_{x_{ib} \to R_i}(x_{ib}) \Big) - \max_{\mathcal{X}_i \backslash x_{ia}} \Big(R_i(x_{ia}=0, \mathcal{X}_i \backslash x_{ia}) + \sum_{b \in \mathcal{K} \backslash a} \mu_{x_{ib} \to R_i}(x_{ib}) \Big) \\
&= \max_{\mathfrak{X}_i \backslash x_{ia}} \Big(\mathcal{R}_{ia}^{\alpha}(\tau_d, 1) + \sum_{b \in \mathcal{K} \backslash a} \mu_{x_{ib} \to R_i}(x_{ib}=0), \\
&\qquad \mathcal{R}_{ia}^{\alpha}(\tau_d, 2) + \max_{b \in \mathcal{K} \backslash a} (\mathcal{R}_{ib}^{\alpha}(\tau_d, 2) + \mu_{x_{ib} \to R_i}(x_{ib}=1) + \sum_{b \in \mathcal{K} \backslash a} \mu_{x_{ib} \to R_i}(x_{ib}=0)), \\
&\qquad \mathcal{R}_{ia}^{\alpha}(\tau_d, 3) + \sum_{k=1}^{2} \operatorname*{rank}^k_{b \in \mathcal{K} \backslash a} [\mathcal{R}_{ib}^{\alpha}(\tau_d, 3) + \mu_{x_{ib} \to R_i}(x_{ib}=1) + \sum_{c \in \mathcal{K} \backslash \{a,b\}} \mu_{x_{ic} \to R_i}(x_{ic}=0)], \ldots, \\
&\qquad \mathcal{R}_{ia}^{\alpha}(\tau_d, U) + \sum_{k=1}^{U-1} \operatorname*{rank}^k_{b \in \mathcal{K} \backslash a} [\mathcal{R}_{ib}^{\alpha}(\tau_d, U) + \mu_{x_{ib} \to R_i}(x_{ib}=1) + \sum_{c \in \mathcal{K} \backslash \{a,b\}} \mu_{x_{ic} \to R_i}(x_{ic}=0)] \Big) \\
&\quad - \max_{\mathfrak{X}_i \backslash x_{ia}} \Big(\sum_{b \in \mathcal{K} \backslash a} \mu_{x_{ib} \to R_i}(x_{ib}=0), \mathcal{R}_{ia}^{\alpha}(\tau_d, 1) + \max_{b \in \mathcal{K} \backslash a} (\mathcal{R}_{ib}^{\alpha}(\tau_d, 1) + \mu_{x_{ib} \to R_i}(x_{ib}=1) + \sum_{b \in \mathcal{K} \backslash a} \mu_{x_{ib} \to R_i}(x_{ib}=0)), \\
&\qquad \mathcal{R}_{ia}^{\alpha}(\tau_d, 2) + \sum_{k=1}^{2} \operatorname*{rank}^k_{b \in \mathcal{K} \backslash a} [\mathcal{R}_{ib}^{\alpha}(\tau_d, 2) + \mu_{x_{ib} \to R_i}(x_{ib}=1) + \sum_{c \in \mathcal{K} \backslash \{a,b\}} \mu_{x_{ic} \to R_i}(x_{ic}=0)], \ldots, \\
&\qquad \mathcal{R}_{ia}^{\alpha}(\tau_d, U) + \sum_{k=1}^{U} \operatorname*{rank}^k_{b \in \mathcal{K} \backslash a} [\mathcal{R}_{ib}^{\alpha}(\tau_d, U) + \mu_{x_{ib} \to R_i}(x_{ib}=1) + \sum_{c \in \mathcal{K} \backslash \{a,b\}} \mu_{x_{ic} \to R_i}(x_{ic}=0)] \Big). \qquad (17)
\end{aligned}$$

expressed as

$$\begin{aligned}&\mathbb{F}_{ia}(\boldsymbol{y^t})\\&\quad=\mathcal{R}^{\alpha}_{ia}(\tau_d,l_i)\\&\qquad+\Big((\mathcal{R}^{\alpha}_{iv_1}(\tau_d,l_i)+y^t_{iv_1})+\ldots+(\mathcal{R}^{\alpha}_{iv_{l_i}}(\tau_d,l_i)+y^t_{iv_{l_i}})\Big)\\&\qquad-\Big((\mathcal{R}^{\alpha}_{iv_1}(\tau_d,\bar{l}_i)+y^t_{iv_1})\\&\qquad\qquad+\ldots+(\mathcal{R}^{\alpha}_{iv_{\bar{l}_i}}(\tau_d,\bar{l}_i+1)+y^t_{iv_{\bar{l}_i}})\Big).\end{aligned}\tag{19}$$

We consider $\mathbb{F}_{ia}(\boldsymbol{y^t})-\mathbb{F}_{ia}(\boldsymbol{z^t})$ since this provides an upper bound of the difference between the actual messages (12) with different initializations and yields a simpler expression. Subsequently, (19) is also upper bounded by the difference between the maximum of $\mathbb{F}_{ia}(\boldsymbol{y^t})$ and the minimum of $\mathbb{F}_{ia}(\boldsymbol{z^t})$ as (20), shown at the bottom of the page, if it holds that $l_i-\bar{l}_i>m_i-\bar{m}_i$ and $l_i>m_i>\bar{l}_i>\bar{m}_i$. Except (20a), all other terms can be made small regardless of the message value and the network population at the current iteration. We examine this by evaluating their statistics with simulation. The numerical evaluation turns out that the utilities $\mathcal{R}^{\alpha}_{ia}(\cdot)$ in (20b), (20c) and (20d) all have zero mean and variance less than 0.01, which is only 2 % of the variance of message differences. Furthermore, the mean and the variance of $(m_i-\bar{m}_i)-(l_i-\bar{l}_i)$ are found to be almost zero. A lower bound can also be obtained similarly, and the resulting expression yields

$$\begin{aligned}(m_i-\bar{m}_i)(y^t_{iv_{l_i}}-z^t_{iw_{\bar{m}_i+1}})&\le\mathbb{F}_{ia}(\boldsymbol{y^t})-\mathbb{F}_{ia}(\boldsymbol{z^t})\\&\le(m_i-\bar{m}_i)(y^t_{iv_{\bar{l}_i+1}}-z^t_{iw_{m_i}}).\end{aligned}\tag{21}$$

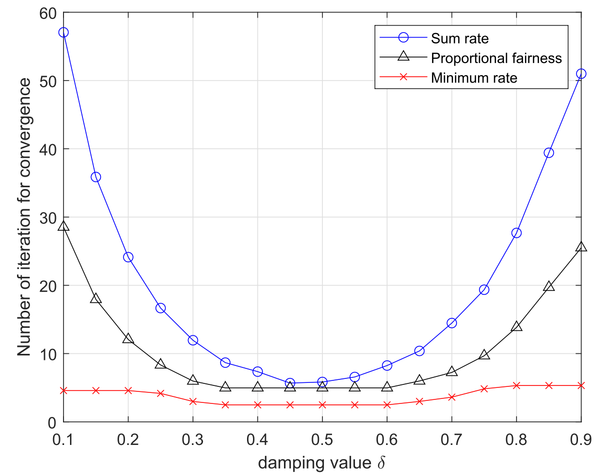


Fig. 9. Number of iterations for the convergence.

Applying the ∞-norm of the message difference, it can be postulated as

$$\|\mathbf{F}(\boldsymbol{y}^t)-\mathbf{F}(\boldsymbol{z}^t)\|_\infty\le(m_i-\bar{m}_i)\|\boldsymbol{y}^t-\boldsymbol{z}^t\|_\infty.\tag{22}$$

Since the overall mapping function is given by $y^{t+1}_{ia}=\mathbb{T}_{ia}(\boldsymbol{y}^t)=-\max_{j\in\mathcal{B}\setminus i}F_{ja}(\boldsymbol{y}^t)$ and $\|\max_{i,a}y_{ia}-\max_{i,a}z_{ia}\|\le\max_{i,a}|y_{ia}-z_{ia}|$, $\|\mathbb{T}_{ia}(\boldsymbol{y}^t)-\mathbb{T}_{ia}(\boldsymbol{z}^t)\|_\infty$ is also bounded by

$$\|\mathbb{T}_{ia}(\boldsymbol{y}^t)-\mathbb{T}_{ia}(\boldsymbol{z}^t)\|_\infty\le(m_i-\bar{m}_i)\|\boldsymbol{y}^t-\boldsymbol{z}^t\|_\infty.\tag{23}$$

Thus, for a range of $\delta\in(0,1/(m_i-\bar{m}_i))$, the mapping function $\mathbb{T}$ can be considered as a contraction. To verify this, the proposed algorithm is simulated with various values of δ

$$\begin{aligned}\xi^{(t)}_{ia}&=\max_{\mathfrak{X}_{ia}}\Big(\mathcal{R}^{\alpha}_{ia}(\tau_d,1),\mathcal{R}^{\alpha}_{ia}(\tau_d,2)+\max_{b\in\mathcal{K}\setminus a}(\mathcal{R}^{\alpha}_{ib}(\tau_d,2)+\gamma_{ib}),\mathcal{R}^{\alpha}_{ia}(\tau_d,3)+\sum_{l=1}^{2}\operatorname*{rank}^l_{b\in\mathcal{K}\setminus a}[\mathcal{R}^{\alpha}_{ib}(\tau_d,3)+\gamma_{ib}],\ldots,\\&\qquad\qquad\mathcal{R}^{\alpha}_{ia}(\tau_d,U)+\sum_{l=1}^{U-1}\operatorname*{rank}^l_{b\in\mathcal{K}\setminus a}[\mathcal{R}^{\alpha}_{ib}(\tau_d,U)+\gamma_{ib}]\Big)\\&\qquad-\max_{\mathfrak{X}_i\setminus x_{ia}}\Big(0,\mathcal{R}^{\alpha}_{ia}(\tau_d,1)+\max_{b\in\mathcal{K}\setminus a}(\mathcal{R}^{\alpha}_{ib}(\tau_d,1)+\gamma_{ib}),\mathcal{R}^{\alpha}_{ia}(\tau_d,2)+\sum_{l=1}^{2}\operatorname*{rank}^l_{b\in\mathcal{K}\setminus a}[\mathcal{R}^{\alpha}_{ib}(\tau_d,2)+\gamma_{ib}],\ldots,\\&\qquad\qquad\mathcal{R}^{\alpha}_{ia}(\tau_d,U)+\sum_{l=1}^{U}\operatorname*{rank}^l_{b\in\mathcal{K}\setminus a}[\mathcal{R}^{\alpha}_{ib}(\tau_d,U)+\gamma_{ib}]\Big)\\&=\Xi_{ia}(1)-(\Xi_{ia}(0))^+.\end{aligned}\tag{18}$$

$$\begin{aligned}\mathbb{F}_{ia}(\boldsymbol{y^t})-\mathbb{F}_{ia}(\boldsymbol{z^t})\le{}&(m_i-\bar{m}_i)(y^t_{iv_{\bar{l}_i+1}}-z^t_{iw_{m_i}}) &&\text{(20a)}\\&+\Big((l_i-\bar{l}_i)-(m_i-\bar{m}_i)\Big)\Big(\mathcal{R}^{\alpha}_{iv_{\bar{l}_i+m_i-\bar{m}_i+1}}(\tau_d,l_i)+y^t_{iv_{\bar{l}_i+m_i-\bar{m}_i+1}}\Big) &&\text{(20b)}\\&+\mathcal{R}^{\alpha}_{ia}(\tau_d,l_i)-\mathcal{R}^{\alpha}_{ia}(\tau_d,m_i)+(m_i-\bar{m}_i)(\mathcal{R}^{\alpha}_{iv_{\bar{l}_i+1}}(\tau_d,l_i)-\mathcal{R}^{\alpha}_{iw_{m_i}}(\tau_d,m_i)) &&\text{(20c)}\\&+\bar{l}_i\Big(\mathcal{R}^{\alpha}_{iv_1}(\tau_d,l_i)-\mathcal{R}^{\alpha}_{iv_1}(\tau_d,\bar{l}_i)\Big)-\bar{m}_i\Big(\mathcal{R}^{\alpha}_{iv_{\bar{m}_i}}(\tau_d,m_i)-\mathcal{R}^{\alpha}_{iv_{\bar{m}_i}}(\tau_d,\bar{m}_i)\Big) &&\text{(20d)}\\={}&(m_i-\bar{m}_i)(y^t_{iv_{\bar{l}_i+1}}-z^t_{iw_{m_i}})+o(m_i-\bar{m}_i). &&\text{(20e)}\end{aligned}$$

when the number of BSs and users are 7 and 70 in Fig. 9. The number of iterations for the convergence of the messages are determined when $|\boldsymbol{y}^{t+1} - \boldsymbol{y}^{t}|$ is less than 10^{-3}. For a small or a large value of δ, the algorithm converges slowly. If δ becomes close to the reciprocal of the mean value of $m_i - \bar{m}_i$, the convergence speed is improved. The damping value of $\delta \in [0.35, 0.65]$ ensures the convergence within 10 iterations. It is revealed empirically that upon the convergence to a fixed point, the resulting user association normally obtains an optimal solution. In this sense, the proposed algorithm provides a convergent optimal solution.

References

[1] S. Bi, C. K. Ho, and R. Zhang, "Wireless powered communication: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 53, no. 4, pp. 117–125, Apr. 2015.

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

[3] Z. Wang, L. Duan, and R. Zhang, "Adaptively directional wireless power transfer for large-scale sensor networks," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1785–1800, May 2016.

[4] X. Lu, P. Wang, D. Niyato, D. I. Kim, and Z. Han, "Wireless charging technologies: Fundamentals, standards, and network applications," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 1413–1452, 2nd Quart., 2016.

[5] P. Nintanavongsa, U. Muncuk, D. R. Lewis, and K. R. Chowdhury, "Design optimization and implementation for RF energy harvesting circuits," *IEEE J. Emerg. Sel. Topics Circuits Syst.*, vol. 2, no. 1, pp. 24–33, Mar. 2012.

[6] F. Zhao, H. Lin, C. Zhong, Z. Hadzi-Velkov, G. K. Karagiannidis, and Z. Zhang, "On the capacity of wireless powered communication systems over Rician fading channels," *IEEE Trans. Commun.*, vol. 66, no. 1, pp. 404–417, Jan. 2018.

[7] H. Lee, K.-J. Lee, H. Kim, B. Clerckx, and I. Lee, "Resource allocation techniques for wireless powered communication networks with energy storage constraint," *IEEE Trans. Wireless Commun.*, vol. 15, no. 4, pp. 2619–2628, Apr. 2016.

[8] H. Lee, S.-R. Lee, K.-J. Lee, H.-B. Kong, and I. Lee, "Optimal beamforming designs for wireless information and power transfer in MISO interference channels," *IEEE Trans. Wireless Commun.*, vol. 14, no. 9, pp. 3817–3822, Sep. 2015.

[9] H. Kim, H. Lee, L. Duan, and I. Lee, "Sum-rate maximization methods for wirelessly powered communication networks in interference channels," *IEEE Trans. Wireless Commun.*, vol. 17, no. 10, pp. 6464–6474, Oct. 2018.

[10] H. Lee, K.-J. Lee, H.-B. Kong, and I. Lee, "Sum-rate maximization for multiuser MIMO wireless powered communication networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 11, pp. 9420–9424, Nov. 2016.

[11] J. Kim, H. Lee, C. Song, T. Oh, and I. Lee, "Sum throughput maximization for multi-user MIMO cognitive wireless powered communication networks," *IEEE Trans. Wireless Commun.*, vol. 16, no. 2, pp. 913–923, Feb. 2017.

[12] M. Z. Sarwar and K.-W. Chin, "On supporting legacy and RF energy harvesting devices in two-tier OFDMA heterogeneous networks," *IEEE Access*, vol. 6, pp. 62538–62551, Oct. 2018.

[13] Y. Jiang *et al.*, "Energy-efficient noncooperative power control in small-cell networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 8, pp. 7540–7547, Aug. 2017.

[14] S. Samarakoon, M. Bennis, W. Saad, M. Debbah, and M. Latva-Aho, "Ultra dense small cell networks: Turning density into energy efficiency," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1267–1280, May 2016.

[15] J. Zhang, L. Xiang, D. W. K. Ng, M. Jo, and M. Chen, "Energy efficiency evaluation of multi-tier cellular uplink transmission under maximum power constraint," *IEEE Trans. Wireless Commun.*, vol. 16, no. 11, pp. 7092–7107, Nov. 2017.

[16] D. Liu *et al.*, "User association in 5G networks: A survey and an outlook," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 1018–1044, 2nd Quart., 2016.

[17] C. Guo, B. Liao, and L. Huang, "Time allocation and load balancing in multi-cell wireless powered communication networks," *IEEE Access*, vol. 4, pp. 7795–7805, 2016.

[18] C. He, J. Liang, G. Qian, C. Guo, and D. Feng, "Optimal time allocation in multi-cell wireless powered communication networks," *IEEE Access*, vol. 7, pp. 26519–26526, 2019.

[19] T. Lv, H. Gao, Z. Shi, and X. Su, "Energy efficiency of two-tier heterogeneous networks with energy harvesting," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2017, pp. 1–6.

[20] D. Bethanabhotla, O. Y. Bursalioglu, H. C. Papadopoulos, and G. Caire, "Optimal user-cell association for massive MIMO wireless networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 3, pp. 1835–1850, Mar. 2016.

[21] P. Xu and K. Cumanan, "Optimal power allocation scheme for non-orthogonal multiple access with α-fairness," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 10, pp. 2357–2369, Oct. 2017.

[22] J. Mo and J. Walrand, "Fair end-to-end window-based congestion control," *IEEE/ACM Trans. Netw.*, vol. 8, no. 5, pp. 556–567, Oct. 2000.

[23] C. Guo, B. Liao, L. Huang, Q. Li, and X. Lin, "Convexity of fairness-aware resource allocation in wireless powered communication networks," *IEEE Commun. Lett.*, vol. 20, no. 3, pp. 474–477, Mar. 2016.

[24] Z. Yang, W. Xu, Y. Pan, C. Pan, and M. Chen, "Optimal fairness-aware time and power allocation in wireless powered communication networks," *IEEE Trans. Commun.*, vol. 66, no. 7, pp. 3122–3135, Jul. 2018.

[25] Q. Ye, B. Rong, Y. Chen, M. Al-Shalash, C. Caramanis, and J. G. Andrews, "User association for load balancing in heterogeneous cellular networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 6, pp. 2706–2716, Jun. 2013.

[26] V. Singh, N. Prasad, M. Y. Arslan, and S. Rangarajan, "Optimizing user association and activation fractions in heterogeneous wireless networks," in *Proc. 13th Int. Symp. Modeling Optim. Mobile, Ad Hoc, Wireless Netw. (WiOpt)*, May 2015, pp. 283–290.

[27] D. Bethanabhotla, O. Y. Bursalioglu, H. C. Papadopoulos, and G. Caire, "User association and load balancing for cellular massive MIMO," in *Proc. Inf. Theory Appl. Workshop (ITA)*, Feb. 2014, pp. 1–10.

[28] Y. Lin, Y. Wang, C. Li, Y. Huang, and L. Yang, "Joint design of user association and power allocation with proportional fairness in massive MIMO HetNets," *IEEE Access*, vol. 5, pp. 6560–6569, 2017.

[29] F. R. Kschischang, B. J. Frey, and H.-A. Loeliger, "Factor graphs and the sum-product algorithm," *IEEE Trans. Inf. Theory*, vol. 47, no. 2, pp. 498–519, Feb. 2001.

[30] B. J. Frey and D. Dueck, "Clustering by passing messages between data points," *Science*, vol. 315, no. 5814, pp. 972–976, Feb. 2007.

[31] I. Sohn, S. H. Lee, and J. G. Andrews, "Belief propagation for distributed downlink beamforming in cooperative MIMO cellular networks," *IEEE Trans. Wireless Commun.*, vol. 10, no. 12, pp. 4140–4149, Dec. 2011.

[32] M. Moretti, A. Abrardo, and M. Belleschi, "On the convergence and optimality of reweighted message passing for channel assignment problems," *IEEE Signal Process. Lett.*, vol. 21, no. 11, pp. 1428–1432, Nov. 2014.

[33] I. Sohn and S. H. Lee, "Distributed load balancing via message passing for heterogeneous cellular networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 11, pp. 9287–9298, Nov. 2016.

[34] J. Chen, L. Zhang, Y.-C. Liang, X. Kang, and R. Zhang, "Resource allocation for wireless-powered IoT networks with short packet communication," *IEEE Trans. Wireless Commun.*, vol. 18, no. 2, pp. 1447–1461, Feb. 2019.

[35] S. H. Lee and I. Sohn, "Message-passing strategy for joint user association and resource blanking in HetNets," *IEEE Trans. Wireless Commun.*, vol. 17, no. 2, pp. 1026–1037, Feb. 2018.

[36] W. H. Press, S. A. Teukolsky, W. T. Vetterling, and B. P. Flannery, *Numerical Recipes in C: The Art of Scientific Computing*. New York, NY, USA: Cambridge Univ. Press, 2007.

[37] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," *IEEE Trans. Wireless Commun.*, vol. 1, no. 4, pp. 660–670, Oct. 2002.

[38] E. Boshkovska, D. W. K. Ng, N. Zlatanov, and R. Schober, "Practical non-linear energy harvesting model and resource allocation for SWIPT systems," *IEEE Commun. Lett.*, vol. 19, no. 12, pp. 2082–2085, Dec. 2015.

[39] D. P. Bertsekas and J. N. Tsitsiklis, *Parallel and Distributed Computation: Numerical Methods*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1989.

Hongju Lee (Graduate Student Member, IEEE) received the B.S. degree in electrical engineering from Korea University, Sejong, South Korea, in 2016, and the M.S. degree in electrical engineering from Korea University, Seoul, South Korea, in 2018, where he is currently pursuing the Ph.D. degree with the School of Electrical Engineering. His research interests include signal processing, information theory, and optimization techniques for the next-generation wireless communications, such as mobile edge computation networks and energy harvesting communication systems.

Jihwan Moon (Member, IEEE) received the B.Eng. and Ph.D. degrees in electrical engineering from Korea University, Seoul, South Korea, in 2014 and 2019, respectively. In 2018, he visited King's College London, U.K., to conduct a collaborative research. In 2019, he was with the Research Institute for Information and Communication Technology (RICT), Korea University, as a Post-Doctoral Research Associate, and subsequently joined the affiliated institute of Electronics and Telecommunications Research Institute (ETRI), Daejeon, South Korea, as a Researcher. Since 2020, he has been with Chosun University, Gwangju, South Korea, as an Assistant Professor. His research interests include optimization techniques, energy harvesting, physical-layer security, wireless surveillance, covert communications, and machine learning for wireless communications.

Changick Song (Senior Member, IEEE) received the B.S., M.S., and Ph.D. degrees in electrical engineering from Korea University, Seoul, South Korea, in 2007, 2009, and 2012, respectively. He worked as a Visiting Researcher with the University of Southern California, Los Angeles, CA, USA, in 2009, and Queen's University, Kingston, ON, Canada, in 2011. From September 2012 to April 2013, he was a Research Professor with Korea University. From May 2013 to August 2014, he was with the Communications and Signal Processing Group, Imperial College London, U.K., as a Post-Doctoral Research Associate. In September 2014, he joined the faculty of the Korea National University of Transportation (KNUT), Chungju, South Korea, where he is currently an Associate Professor with the Department of Electronic Engineering. His research interests include machine learning theory and signal processing for wireless communications and security.

Sang Hyun Lee (Member, IEEE) received the B.S. and M.S. degrees from the Korea Advanced Institute of Science and Technology in 1999 and 2001, respectively, and the Ph.D. degree from The University of Texas at Austin in 2011. He is currently with the School of Electrical Engineering, Korea University, Seoul, South Korea. His research interests include communication theory, optimization, inference, learning and their applications to wireless communication systems, and cross-disciplinary areas in natural and social sciences.

Inkyu Lee (Fellow, IEEE) received the B.S. degree (Hons.) in control and instrumentation engineering from Seoul National University, Seoul, South Korea, in 1990, and the M.S. and Ph.D. degrees in electrical engineering from Stanford University, Stanford, CA, USA, in 1992 and 1995, respectively. From 1995 to 2002, he was a member of the Technical Staff with Bell Laboratories, Lucent Technologies, Murray Hill, NJ, USA, where he studied high-speed wireless system designs. Since 2002, he has been with Korea University, Seoul, where he is currently a Professor with the School of Electrical Engineering. He has also served as the Department Head of the School of Electrical Engineering, Korea University, from 2019 to 2021. In 2009, he was a Visiting Professor with the University of Southern California, Los Angeles, CA, USA. He has authored or coauthored more than 190 journal articles in IEEE publications and holds 30 U.S. patents granted or pending. His research interests include digital communications, signal processing, and coding techniques applied for next-generation wireless systems. He was elected as a member of the National Academy of Engineering of Korea in 2015. He was a recipient of the IT Young Engineer Award at the IEEE/IEEK Joint Award in 2006, the Best Paper Award at the Asia–Pacific Conference on Communications in 2006, the IEEE Vehicular Technology Conference in 2009, the Best Research Award from the Korean Institute of Communications and Information Sciences in 2011, the IEEE International Symposium on Intelligent Signal Processing and Communication Systems in 2013, the Best Young Engineer Award from the National Academy of Engineering of Korea in 2013, and the Korea Engineering Award from the National Research Foundation of Korea in 2017. He served as an Associate Editor for the IEEE TRANSACTIONS ON COMMUNICATIONS from 2001 to 2011 and the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS from 2007 to 2011. In addition, he was a Chief Guest Editor of the IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS Special Issue on "4G wireless systems" in 2006. He also serves as the Co-Editor-in-Chief for the *Journal of Communications and Networks*. He is also a Distinguished Lecturer of IEEE.