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Research Article

Joint User Association and Energy Offloading in Downlink Heterogeneous Cellular Networks

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As a key technology in Long-Term Evolution-Advanced (LTE-A) mobile communication systems, heterogeneous cellular networks (HCNs) add low-power nodes to offload the traffic from macro cell and therefore improve system throughput performance. In this paper, we investigate a joint user association and resource allocation scheme for orthogonal frequency division multiple access- (OFDMA-) based downlink HCNs for maximizing the energy efficiency and optimizing the system resource. The algorithm is formulated as a nonconvex optimization, with dynamic circuit consumption, limited transmit power, and quality-of-service (QoS) constraints. As a nonlinear fractional problem, an iteration-based algorithm is proposed to decompose the problem into two subproblems, that is, user association and power allocation. For each iteration, we alternatively solve the two subproblems and obtain the optimal user association and power allocation strategies. Numerical results illustrate that the proposed iteration-based algorithm outperforms existing algorithms.

1. Introduction

Shortage of power resource and scarcity of spectrum resource are two major factors in restricting communication development, and thus, green-oriented communication system design has gradually attracted attention of academics particularly in wireless communication filed. Energy consumption in information and communication technology (ICT) industry accounts for about 2%–6% of global total consumption, 60% of which are consumed on base stations (BSs). In recent years, innovations in this area facilitate the unprecedented growth of traffic data which accelerates the problem more seriously [1–4]. In order to improve resource efficiency, energy harvesting can be used [5], but more effectively wireless systems are prone to miniaturization and heterogeneity, which may be composed of various types of networks to support growth of traffic demand. For instance, coordinating with macro cell, for example, pico BSs and femto BSs are used to offload the traffic and energy consumption from the large-scaled BSs. The layout of heterogeneous cellular networks (HCNs) is more reasonable and economical than that of macro-only networks. However, extreme densification of BSs would bring a new challenge: cochannel interference is introduced by spectrum sharing in a local-area, which has significantly negative impact on system capacity [6]. Considering its high spectrum efficiency and flexibility in allocating radio resource, orthogonal frequency division multiple access- (OFDMA-) based HCNs system is a good candidate to achieve better performance wireless communications [7].

Resource allocation for HCNs is investigated from different perspectives in one/multi-cell scenarios. In previous researches, studying of user association is more attractive in HCNs [8–11], as user allocation have an impact on the interference as well as capacity. Power consumption is also a factor that affects the communication performance especially for intra- and intercell interference suppression in networks [12–15]. However, capacity and coverage enhancement are not always achieved by increasing transmit power. Increased transmit power may generate more interference to neighboring cells which has became a challenging issue. As a result, energy-efficient designs have recently attracted a lot of interest to exploit the potential performance gains toward green wireless communication systems [16–18]. Energy efficiency is defined as the ratio of system throughput to total energy consumption. In [19], the authors proposed a utility-based energy-efficient (UEE) resource allocation algorithm with mixed traffic in downlink HCNs which only achieves a suboptimal solution. Zhou et al. [20] proposed a fractional programming framework, by solving the weighted energy efficiency problem iteratively consisting of channel allocation and power allocation. A non-cooperative resource competition game was introduced in [21] for energy efficiency optimization in dense networks under traffic-related minimum rate requirement. Cheng et al., Zhou et al., and Wang et al. [19–21] focused on jointly channel allocation and power control where the set of users associated with the BS were predetermined in the optimal process. In most of the previous works, they only consider either user association or subchannel allocation but not both of them. However, the system performance is affected by both of them. Additionally, for the above works, system power consumption only involves the transmit power and static circuit power. For energy efficient resource allocation, circuit power is also accounted in addition to the transmitted power with the increasing demand for high-capacity networks, which is more practical and general [22, 23]. The novelty of this work is to consider both user association and subchannel allocation in the optimization of energy efficiency with circuit power. These practical conditions have not been studied together in the literature.

In this paper, we formulate an energy efficiency maximization problem via jointly optimizing user association, subchannel association, and power control for OFDMA-based downlink HCNs in terms of QoS requirement and available power constraints. In particular, the circuit power consumption is modeled as a function of system rate, not just as a constant. We address the nonconvex mixed integer optimization problems by applying proposed iteration-based algorithm. By utilizing the Dinkelbach method, it transforms the primary problem to a subtractive form problem. The EE maximization problem is decomposed equivalently into two subproblems which can then be solved by using the iterative method alternatively. Compared with the previous algorithms, simulation results demonstrate that the proposed scheduling strategy gains a tradeoff between system capacity and overall consumption and then obtains an optimal resource allocation.

The remainder of the paper is formulated as follows: Section 2 briefly introduces the system model and formulates the energy efficiency maximization problem. Based on this model, an iteration-based algorithm is proposed to solve the three-layer problems alternatively; then the algorithm complexity is also analyzed in Section 3. The numerical results are discussed in Section 4. Finally, the conclusion is drawn in Section 5.

2. System Model

A range of area may be randomly deployed with numerous small hotspots, providing flexibility and quick access, along with a larger base station (BS) located at the center of cellular covering the entire macro cell space, as shown in Figure 1. In this section, we design a two-layer OFDMA-based downlink HCNs system, which consists of macro base stations (MBSs) and pico base stations (PBSs), as alternative wireless access points for user equipments. In a time slot, channel resources are allocated to users for information interaction according to the user association rule. We assume that each subchannel only can be allocated to a single user at the same time; thus, no interchannel interference exists among user groups. In the following, the set of $\mathcal{N} = \mathcal{N}_m \cup \mathcal{N}_p = \{1, 2, 3, \ldots, N\}$ and $\mathcal{K} = \{1, 2, 3, \ldots, K\}$ represent the index of BSs and users in the considered scenario, respectively. Based on the OFDMA model, we equally divide the bandwidth into S orthogonal spectrum bands and denote $\mathcal{S} = \{1, 2, 3, \ldots, S\}$ as the subchannel index set. In this paper, the received signal to interference and noise ratio (SINR) of terminate $k \in \mathcal{K}$ from BS $n \in \mathcal{N}$ on subchannel $s \in \mathcal{S}$ can be expressed as

$$\mathrm{SINR}_{n,k,s} = \frac{P_{n,s} g_{n,k}^{s}}{\sigma_{k,s}^{2} + \sum_{m \in \mathcal{N}/n} \left(P_{m,s} g_{m,k}^{s} \right)}, \tag{1}$$

where $P_{n,s}$ and $g_{n,k}^{s}$ represent the transmit power and channel gain from BS n on subchannel s to user k, respectively. $\sigma_{k,s}^{2}$ is the additive white Gaussian noise (AWGN) power received at the terminal k of the link from subchannel s. When transmitting to BS n on subchannel s, user k is interfered by other cochannel signals from the neighboring cellular. Thus, we can denote the received data rate when user k is associated with BS n on channel s as

$$r_{n,k,s} = \log_2\left(1 + \frac{1}{\Gamma}\mathrm{SINR}_{n,k,s}\right), \tag{2}$$

where Γ is the SINR gap to capacity involving in the bit error ratio (BER) expectation, coding gain, and noise margin [12].

Hence, the total amount of bits delivered by the users and BSs is given by

$$R_{\mathrm{tot}} = \sum_{k \in \mathcal{K}} A_{n,k,s} r_{n,k,s}, \tag{3}$$

where $A_{n,k,s} \in \{0, 1\}$ is the resource allocation indicator. $A_{n,k,s} = 1$ indicates that the subchannel s of BS n is assigned to user k and $A_{n,k,s} = 0$ indicates that, the subchannel s of BS n is not assigned to the user k in this time slot. In this case, the subchannel s of BS n is either assigned to another user or not assigned to any user. Considering the energy efficient resource allocation design, we model the energy consumption as

$$P_{\mathrm{tot}} = \sum_{n \in \mathcal{N}} \left(\sum_{s \in \mathcal{S}} \rho_n P_{n,s} + P_{\mathrm{c}} \right), \tag{4}$$

where ρ_n is the amplifier factor of BS transmit power. P_{c} is the total circuit consumed power. Considering the approach presented in [24], it is reasonable to relate the circuit power consumption to the sum-data rate which can be defined as

$$P_{\mathrm{c}} = P_{\mathrm{s}} + \gamma R_t, \tag{5}$$

where P_{s} is the static circuit consumed power, and the dynamic circuit consumed power is proportional to the unit data rate where γ is an constant of proportionality.

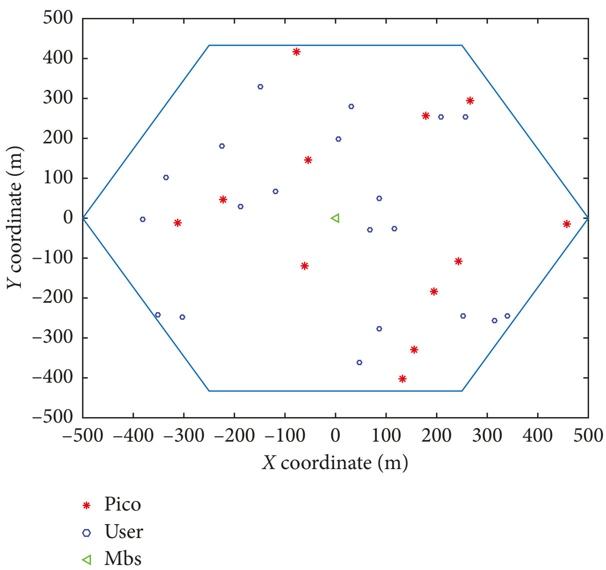

FIGURE 1: Illustration of BS deployment model of HCNs.

The overall energy efficiency (Bits-Hz-Joule) is defined as the ratio of system throughout and total energy consumption. As a result, the maximum energy efficiency optimization problem can be obtained by

$$E(\mathbf{A}, \mathbf{P}) = \frac{R_{\text{tot}}(\mathbf{A}, \mathbf{P})}{P_{\text{tot}}(\mathbf{A}, \mathbf{P})} = \frac{\sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}}\sum_{s\in\mathcal{S}} A_{n,k,s} r_{n,k,s}}{\sum_{n\in\mathcal{N}}\left(\sum_{s\in\mathcal{S}} \rho_n P_{n,s} + P_c\right)}, \quad (6)$$

$$\text{s.t.} \quad \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} A_{n,k,s} r_{n,k,s} \geq r_{k,\min}, \quad \forall k \in \mathcal{K}, \quad (6a)$$

$$0 \leq \sum_{s\in\mathcal{S}} P_n^s \leq P_{n,\max}, \quad \forall n \in N, \quad (6b)$$

$$\sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} A_{n,k}^s = 1, \quad \forall k \in \mathcal{K}, \quad (6c)$$

$$\sum_{s\in\mathcal{K}} A_{n,k}^s \leq 1, \quad \forall n \in \mathcal{N}, \quad \forall s \in \mathcal{S}, \quad (6d)$$

$$A_{n,k,s} \in \{0, 1\}, \quad \forall k \in \mathcal{K}, \quad \forall n \in N, \quad \forall s \in \mathcal{S}, \quad (6e)$$

where $r_{k,\min}$ in (6a) is the minimum received data rate that the user k required. $P_{\max}$ in (6b) is the maximum transmit power allowance for each BS used to control the cochannel interference. (6c) and (6d) are imposed to guarantee that each user exclusively associates to one BS to avoid the cross-user interference and one subchannel can serve at most one UE.

3. Solution to the Problem

The objective function (6) is a nonlinear one, coupled with discrete and continuous variables which add the level of computationally complexity. In the following, an iteration-based algorithm is proposed to decouple it into two subproblems, including user-BS association and subchannel power control, which can be solved alternatively.

Since the combinatorial problem is difficult to solve directly, the first step is to simplify the fractional optimization to a linear objective function using Dinkelbach approach [25, 26]. Thus, it can be proved that the maximum EE can be obtained only if

$$F(\eta^*) = \max_{A^*,P^*}\{R_{\text{tot}}(A^*, P^*) - \eta^* P_{\text{tot}}(A^*, P^*)\} = 0, \quad (7)$$

where η^* is the optimal energy efficiency and A^*, P^* is the optimal resource allocation scheme. Therefore, the original problem is transformed into an objective function in subtractive form and has a unique solution [27]. The Dinkelbach method is widely used to solve (7) with the character of super-linear convergence speed [28]. The proposed algorithm is summarized in Table 1, and the proof of convergence is illustrated in Appendix. In each iteration in main loop, we solve the inner problem: user association and subchannel power allocation alternatively for a specific η and then update the value of η each iteration and repeat the process until convergence.

3.1. User Association with a Given Subchannel Power Allocation

For a given η, we focus on the solution for inner problem in the rest of section. The above problem involves user association and subchannel power allocation; therefore, it can be resolved by alternative iteration method. For a given power control, the optimization problem is generalized for maximizing system capacity under considered constraints, which is given by

$$\max_{A} \quad F(A) = \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} A_{n,k,s} r_{n,k,s}, \quad (8)$$

$$\text{s.t.} \quad \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} A_{n,k,s} r_{n,k,s} \geq r_{k,\min}, \quad \forall k \in \mathcal{K}, \quad (8a)$$

$$\sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} A_{n,k,s} = 1, \quad \forall k \in \mathcal{K}, \quad (8b)$$

$$\sum_{s\in\mathcal{K}} A_{n,k}^s \leq 1, \quad \forall n \in \mathcal{N}, \quad \forall s \in \mathcal{S}, \quad (8c)$$

$$A_{n,k,s} \in \{0, 1\}, \quad \forall k \in \mathcal{K}, \quad \forall n \in \mathcal{N}, \quad \forall s \in \mathcal{S}. \quad (8d)$$

Since link capacity is limited by interference especially from the cochannels of different BSs, an heuristic user allocation scheme is applied to the cellular system, shown in Table 2. Initially, we assume that each subchannel of BSs is allocated with equal transmit power and modeled as identically Rayleigh distributed channel. Each user is assigned to the BSs with the highest SINR. The subchannel allocation follows the cognitive rules that users are associated with good channel conditions and suffering small interference. $\mathcal{S}_0$ is a set of available subchannel which is not occupied. It

Table 1: An iteration-based algorithm.

Algorithm 1: An alternative iteration algorithm.

(1) Initialization: Set $t = 0$, $\eta_0 = 1$, flag $= 0$, T_1;
(2) **Repeat**:
(3) find the optimal solution of user association A^* and subchannel allocation P^* alternatively for a given η_t,
(4) update η by $\eta^{t+1} = R_{\text{tot}}(A^*, P^*)/P_{\text{tot}}(A^*, P^*)$;
(5) **if** $(|\eta_{t+1} - \eta_t| \leq \varepsilon)$ **then**
(6) return η_{t+1}, flag $= 1$;
(7) **else**
(8) set $t = t + 1$, flag $= 0$;
(9) **end if**
(10) **Until**:
(11) flag $= 1$ or $t = T_1$.

Table 2: User association for HCNs.

Algorithm 2: An heuristic user allocation scheme.

(1) Initialization: Set $P_{n,s} = (1/S)P_{n,\max}$, $\mathcal{S}_0 = \mathcal{S}$;
(2) **For** $i = 1$ to K
(3) Find $n^* = \arg\max\{r_{n,k}\}$ for all of $k \in \mathcal{K}$;
(4) Find $k(n^*, s^*) = \arg\max r_{n,k,s}$, $\forall s \in \mathcal{S}_t$;
(5) Update $\mathcal{S}_t = \mathcal{S}_t/s^*$;
(6) Set $A_{n^*,k^*,s^*} = 1$
(7) **Endfor**

will be updated after each iteration according to the decisions, which can guarantee the subchannel cannot be reused by other users.

3.2. Subchannel Power Resource Allocation with Given User Association.

3.2. Subchannel Power Resource Allocation with Given User Association. This subsection details the power allocation procedure. For the case with fixed user allocation set, the optimization problem can be reformulated into

$$\max_{P} \; F(P) = \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} \sum_{k\in K} A_{n,k,s} r_{n,k,s} - \eta \sum_{n\in N} \left(\sum_{s\in S} \rho_n P_{n,s} + P_{\mathrm{c}} \right), \tag{9}$$

$$\text{s.t} \quad \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} A_{n,k,s} r_{n,k,s} \geq r_{k,\min}, \quad \forall k \in \mathcal{K}, \tag{9a}$$

$$0 \leq \sum_{s\in\mathcal{S}} P_{n,s} \leq P_{n,\max}, \quad \forall n \in \mathcal{N}. \tag{9b}$$

Notably, constraint (9a) is nonconvex to P because of the presence of cochannel interference, which makes the objective function rather difficult [29]. Specifically, we first set a concave lower bound to relax r by referring the following inequality [30]:

$$\log(1 + z) \geq \log(1 + z^*) + \frac{z^*}{1 + z^*} \left(\log(z) - \log(z^*)\right). \tag{10}$$

The equality is true only when $z = z^*$. With this relaxation, r is redefined as

$$r^*_{n,k,s} = \alpha_{n,k,s} \log_2\left(\mathrm{SINR}_{n,k,s}(P)\right) + \beta_{n,k,s}, \tag{11}$$

where

$$\alpha_{n,k,s} = \frac{\mathrm{SINR}(P_0)}{1 + \mathrm{SINR}(P_0)}, \tag{12}$$

$$\beta_{n,k,s} = \log_2\left(1 + \mathrm{SINR}(P_0)\right) - \alpha_{n,k,s} \log_2\left(\mathrm{SINR}(P_0)\right), \tag{13}$$

where P_0 is a reference value. Since the transformed problem is still nonconvex with respect to P, we follow the approach in [31] and define q where $e^{q_{n,s}} = P_{n,s}$ for convexification. Thus, the subchannel power allocation is given by

$$\max_{P} \quad \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} \sum_{k\in\mathcal{K}} A_{n,k,s} r^*_{n,k,s} - \eta \sum_{n\in\mathcal{N}} \left(\sum_{s\in\mathcal{S}} \rho_n e^{q_{n,s}} + P_{\mathrm{c}} \right), \tag{14}$$

$$\sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} A_{n,k,s} r^*_{n,k,s} \geq r_{k,\min}, \quad \forall k \in \mathcal{K}, \tag{14a}$$

$$0 \leq \sum_{s\in\mathcal{S}} e^{q_{n,s}} \leq P_{n,\max}, \quad \forall n \in \mathcal{N}. \tag{14b}$$

Then, we solve the subchannel power allocation optimization problem using the Lagrangian dual-decomposition approach for a given user association set with the value of η. The Lagrangian dual function which absorbs the boundary constraints (14a) and (14b) is given as

$$\begin{aligned} \min_{\lambda,\upsilon} \max_{P} \quad & \mathcal{L}(\mathbf{P}, \boldsymbol{\upsilon}) \\ = & \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} \sum_{k\in\mathcal{K}} (1 - \eta\gamma) A_{n,k,s} r^*_{n,k,s}\left(e^{q_{n,s}}\right) \\ & - \eta \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} \rho_n e^{q_{n,s}} + \sum_{n\in\mathcal{N}} \lambda_n \left(P_{n,\max} - \sum_{s\in S} e^{q_{n,s}} \right) \\ & + \sum_{k\in\mathcal{K}} \upsilon_k \left(\sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} A^s_{n,k} r^*_{n,k,s}\left(e^{q_{n,s}}\right) - r_{k,\min} \right), \end{aligned} \tag{15}$$

where $\boldsymbol{\lambda}$ and $\boldsymbol{\upsilon}$ are the Lagrange multiplier vectors. With respect to Karush–Kuhn–Tucker (KKT) conditions, we take the derivative of the objective function (15), which yields

$$\frac{\partial \mathcal{L}(\mathbf{P}, \boldsymbol{\upsilon})}{\partial q^s_n} = \sum_{k\in\mathcal{K}} \omega_k A_{n,k,s} \alpha^*_{n,k,s} - Q^s_k - \eta\rho_n e^{q_{n,s}} - \lambda_n e^{q_{n,s}}, \tag{16}$$

where

$$Q^s_k = \sum_{m\in\mathcal{N}, m\neq n} \frac{\omega_k A_{m,k,s} \alpha^*_{m,k,s} g^s_{n,k} e^{q_{n,s}}}{\sum_{j\in\mathcal{N}, j\neq m} e^{q_{j,s}} g^s_{j,k} + \sigma^2_{k,s}}, \tag{17}$$

where $\omega = (1 - \eta\gamma + \upsilon_k)/(\ln 2)$. Thus, the optimal subchannel power allocation on subchannel s of BS n for user k is obtained from (16), as follows:

$$P_{n,s}^{t+1} = \frac{\sum_{k\in\mathscr{K}} \omega_k A_{n,k,s} \alpha_{n,k,s}^*}{\sum_{m\in\mathscr{N},m\neq n} \sum_{k\in\mathscr{K}} \left(\left(\omega_k A_{m,k}^s \alpha_{m,k,s}^* g_{n,k}^s \right) / \left(\sum_{j\in\mathscr{N},j\neq m} P_{j,s}^t g_{j,k}^s + \sigma_j^2 \right) \right) + \eta\rho_n + \lambda_n}. \tag{18}$$

We update $\boldsymbol{\upsilon}$ and $\boldsymbol{\lambda}$ using the gradient descent method as

$$\upsilon_k^{t+1} = \left[\upsilon_k^t - \xi_1 \left(\sum_{n\in\mathscr{N}} \sum_{s\in\mathscr{S}} A_{n,k,s} r_{n,k,s}^* - r_{k,\min} \right) \right]^+, \quad \forall k \in \mathscr{K}, \tag{19}$$

$$\lambda_n^{t+1} = \left[\lambda_n^t - \xi_2 \left(P_{n,\max} - \sum_{s\in\mathscr{S}} e^{q_{n,s}} \right) \right]^+, \quad \forall n \in \mathscr{N}, \tag{20}$$

where index t is the number of iterations and $[x]^+ = \max\{0, x\}$. The positive descent gradient ξ_1 and ξ_2 are small enough to guarantee the convergence of the algorithm. The subchannel power allocation problem can be solved via the Lagrangian dual-decomposition approach which is summarized in Table 3. Specifically, within each iteration, we update the P and dual Lagrange multipliers according to the duality-based algorithm, and the process repeats until problem converges.

4. Numerical Results

In the following, we consider two-layer heterogeneous networks where the fixed node MBS is located at the center of a radius of 500 meters, and PBSs are randomly scattered in the cellular. K users are uniformly distributed in the range of service area. It is assumed that the system bandwidth is 6 MHz and the number of subchannels is 32. Users are subjected to −128 dBm/Hz AWGE power spectral density, giving the SINR gap $\Gamma = 0$ dBm. The maximum transmit power of MBS is 46 dBm. The coefficient of power amplifier of MBS and PBS are 4 and 2, and the constant power consumption values are 10 W and 0.1 W, separately. The path loss model of MBS and PBS is set to $l_{nk} = 128.1 + 37.6\log 10(d)$ and $l_{nk} = 140.7 + 37.6\log 10(d)$, where d (in km) represents the distance between BS n and user k. Besides, the shadowing fading of all links is set to 0 dB. In addition, assumed system parameters can easily be modified to any other values to demonstrate the energy efficiency in different scenarios.

4.1. Convergence of the Proposed Algorithm. Figure 2 illustrates the convergence properties of the proposed iteration-based algorithm. The maximum transmit power of PBSs is 32 dBm and the sum-rate factor is 0.38. The number of PBS and amount users is set as 10 and 30. It can be observed from Figure 2(a) that the objective as a function of q converges within 15 iterations in considered scenarios. Figure 2(b) shows that the value of η is converging to the optimal EE within 5 times, demonstrating that the convergence rate of proposed algorithm is high. In summary, the validity of the proposed algorithm is confirmed, and it is efficient for multivariable dynamic programming.

Table 3: Subchannel transmit power allocation for HCNs.

Algorithm 3: Lagrangian dual-decomposition approach.
(1) Initialization: Set $e^q = (1/S)P_{n,\max}$, $i = 0$, $t = 0$, α_0, β_0, T_2, T_3;
(2) **Repeat**
(3)   **Repeat**
(4)   Update P according to (18);
(5)   Update $\boldsymbol{\upsilon}$ and $\boldsymbol{\lambda}$ according to (19) and (20), respectively;
(6)   Set $t = t + 1$;
(7)   **Until** $\|\nu^{t+1} - \nu^t\| \le \varepsilon$ or $t = T_2$
(8)   Set $P_0 = P$;
(9)   Update α and β according to (12) and (13), respectively;
(10) **Until** $\|q^{i+1} - q^i\| \le \varepsilon$ or $i = T_3$

4.2. Energy Efficiency and Power Consumption. We compare the performance of proposed iteration-based algorithm for maximizing energy efficiency (MEE) with MTP proposed in [14] for different number of users versus increasing QoS requirement in Figures 3 and 4. For MTP, its objective is to minimize the power consumption for subchannel assignment and power distribution. We assume that the maximum transmit power of PBS is 32 dBm and the sum-rate coefficient is 0.38. Figure 3 shows that MEE is much better than MTP in energy efficiency. For MEE and MTP, as the increasing dense subscribers, the EE increases at first and then remains stable for all schemes. This is because the cochannel interference would have less impact when the user density was low. However, since more subchannels being allocated, performance is restricted by the limited system resources as the number of users in the system increases. We also observe that the EE declines with the growing minimum data rate requirement in MEE and MTP since the BSs require to enhance the transmit power of subchannel to maintain the throughput requirements which impairs the system energy efficiency.

As seen in Figure 4, the corresponding power consumption of MEE versus different number of users is less than that of MTP, due to our proposed power allocation policy strongly control the unassigned subchannel transmit power resulting in lower transmit power levels. As the user density increases, the spectrum is shared by different tiers, and thus, the cochannel interference will become significant. Hence, extra power consumption is required to narrow the gap of QoS requirements. It simultaneously shows that the EE increases with the descending minimum rate targets for MEE and MTP, while the rate of rise declines. This is because when the threshold is high, more users are unable to meet the requirements, which consumes the excessive transmission to improve the performance of the system. For MEE and MTP, it concluded that the performance improvement of our proposed algorithm outperforms previous research.

Figure 5 investigates the impact of circuit power on the energy efficiency versus the number of users. The maximum transmit power of PBSs is set as 36 dBm. For a fixed factor γ, when the number of users is smaller and EE increases significantly for both algorithms, but then progressively slows with the user density increases adequately. This is because that the increasing sum-rate will also make the system consume

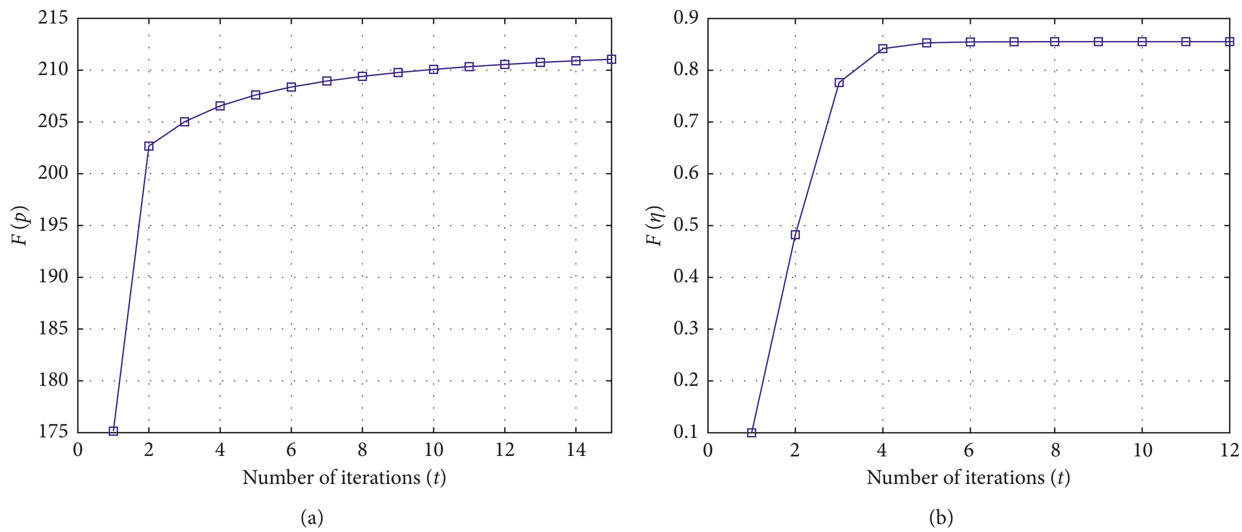

Figure 2: Convergence of proposed iteration-based algorithm: (a) iteration of power allocation algorithm; (b) iteration of Dinkelbach's algorithm.

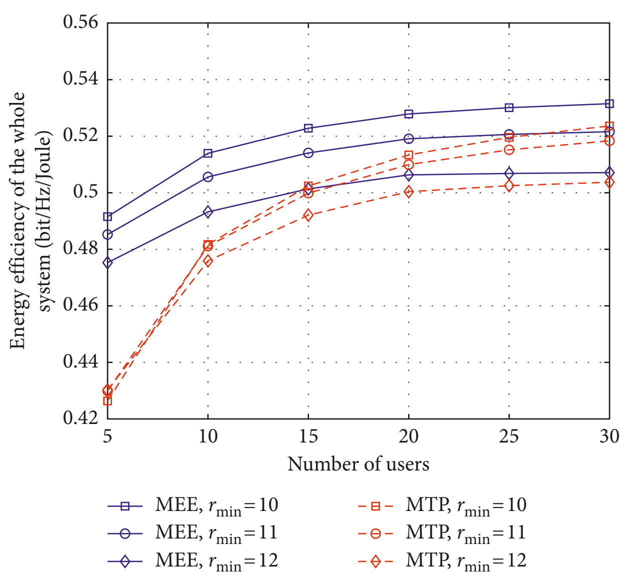

Figure 3: Performance comparison versus different user density for different QoS requirements.

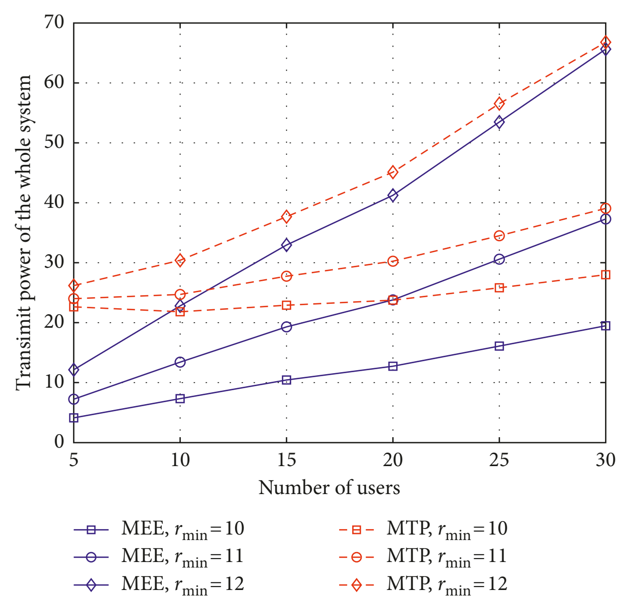

Figure 4: Transmit power consumption versus different user density for different QoS requirements.

more extra power for circuit power per unit data rate, which restricts the EE growth. It can be seen from Figure 5 that the EE decreases with the increase of γ resulting in higher power consumption. In conclusion, the energy efficiency is influenced by the sum-data rate of the links and decreases with the increase of circuit power consumption.

Figure 6 illustrates the change of EE of the system under the number of small cells in the network, and we consider the number of users in each cell is 4. It can be seen from the figure that the energy efficiency of MEE is higher than that of MTP in considered scene, due to the proposed maximum EE-based power strategy policy. As the number of cell increases, more users are associated to the network to increase system throughout as well as increase the power consumption on dynamic circuit power.

5. Conclusion

In this paper, we have studied the jointly the user association and subchannel power allocation problem in the downlink OFDMA-based HCNs under minimum QoS requirement and available power constraints. To tradeoff between throughout and energy consumption, the conception of maximum energy efficiency is introduced. We solved the fractional programming by transferring it into two subproblems, that is, user association subproblem and power allocation subproblem, and further proposed an iteration-based algorithm to handle the subproblems alternatively. Simulation results demonstrated that a higher

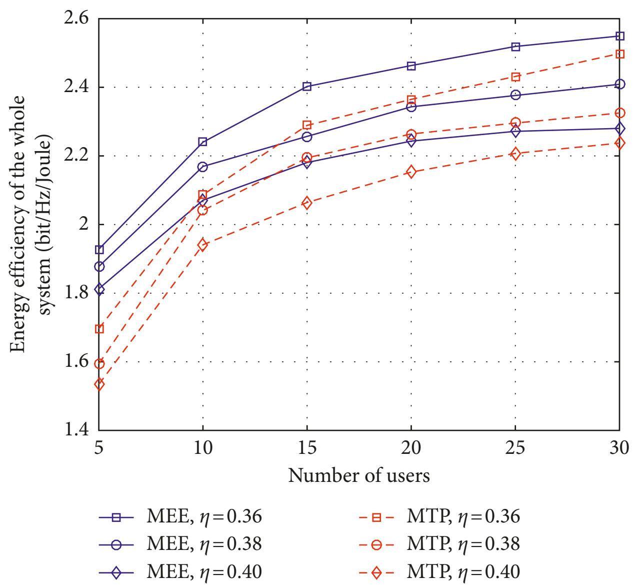

Figure 5: Energy efficiency versus dense of users for different circuit power.

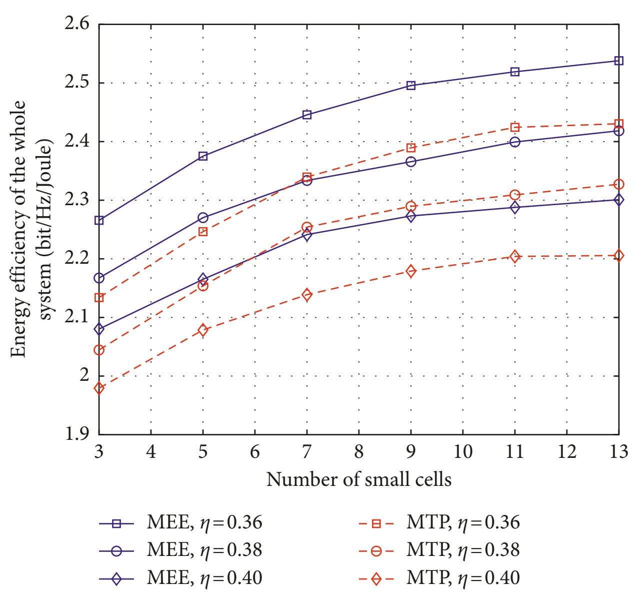

Figure 6: Energy efficiency versus different numbers of small cells in the network.

energy efficiency compared with previously proposed algorithms is obtained.

Appendix

Proof of the Rate of Convergence

The alternative iteration algorithm super-linearly converges to the optimal energy efficiency.

Firstly, it has been proved that if the number of iterations is large enough, the sequence of $\{\eta_t\}$ converges to the optimal η^* [24, 28]. Then, the further proof of convergence speed is detailed as follows.

Let $\{A', P'\}$ and $\{A'', P''\}$ be the optimal solution of $F(\eta')$ and $F(\eta'')$, respectively, where $F(\eta') = \max\{R_{\text{tot}}(A', P') - \eta' P_{\text{tot}}(A', P')\}$. Therefore, we could have

$$R_{\text{tot}}(A', P') - \eta' P_{\text{tot}}(A', P') \geq R_{\text{tot}}(A'', P'') - \eta' P_{\text{tot}}(A'', P''). \tag{A.1}$$

Dividing both sides by $P_{\text{tot}}(A', P') > 0$,

$$\frac{R_{\text{tot}}(A', P')}{P_{\text{tot}}(A', P')} - \eta' \geq \frac{R_{\text{tot}}(A'', P'')}{P_{\text{tot}}(A', P')} - \eta' \frac{P_{\text{tot}}(A'', P'')}{P_{\text{tot}}(A', P')}. \tag{A.2}$$

Denoting $Q = R_{\text{tot}}/P_{\text{tot}}$, and taking (A.2) to the next step,

$$\begin{aligned} Q(A'', P'') - Q(A', P') &= \frac{R_{\text{tot}}(A'', P'')}{P_{\text{tot}}(A'', P'')} - \frac{R_{\text{tot}}(A', P')}{P_{\text{tot}}(A', P')} \\ &\leq \frac{R_{\text{tot}}(A'', P'')}{R_{\text{tot}}(A'', P'')} - \frac{R_{\text{tot}}(A'', P'')}{P_{\text{tot}}(A', P')} \\ &\quad - \eta' \left[1 - \frac{P_{\text{tot}}(A'', P'')}{P_{\text{tot}}(A', P')}\right] \\ &= \left(-R_{\text{tot}}(A'', P') + \eta' P_{\text{tot}}(A'', P')\right) \\ &\quad \cdot \left(\frac{1}{P_{\text{tot}}(A', P')} - \frac{1}{P_{\text{tot}}(A'', P'')}\right) \\ &= \left[-F(\eta'') + (\eta' - \eta'') P_{\text{tot}}(A'', P'')\right] \\ &\quad \cdot \left(\frac{1}{P_{\text{tot}}(A', P')} - \frac{1}{P_{\text{tot}}(A'', P'')}\right). \end{aligned} \tag{A.3}$$

We assume that $\eta'' = \eta^*$, where η^* satisfies $F(\eta^*) = 0$ and $Q(A^*, P^*) = \eta^*$. From (A.3), we have

$$\eta^* - Q(A', P') \leq (\eta^* - \eta') \left(1 - \frac{P_{\text{tot}}(A^*, P^*)}{P_{\text{tot}}(A', P')}\right). \tag{A.4}$$

η is updated by the previous value of $Q(A, P)$ in each iteration, for example, $\eta_{t+1} = Q(A_t, P_t)$. From (A.4), the algorithm converges at the rate of $(1 - (P_{\text{tot}}(A^*, P^*)/P_{\text{tot}}(A_t, P_t)))$. Therefore, the updated values rapidly get close to the optimal solution with respect to t.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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