Joint Power and Admission Control for Spectral and Energy Efficiency Maximization in Heterogeneous OFDMA Networks

Wei-Sheng Lai, *Student Member, IEEE*, Tsung-Hui Chang, *Member, IEEE*, and Ta-Sung Lee, *Fellow, IEEE*

***Abstract*—This paper studies the joint power and admission control (JPAC) problem for orthogonal frequency division multiplexing access (OFDMA) based heterogeneous networks. We consider a small-cell network coexisting with a macro-cell network. Small cells are not only subject to constraints imposed by interference with the macro-cell network but also by the minimum achievable rates of secondary user equipment (SUE). The goal is to admit as many SUE as possible to satisfy the minimum rate requirements while maximizing a certain network utility associated with the admitted SUE. To this end, we formulate two JPAC problems aimed at maximizing the network spectral efficiency (SE) and network energy efficiency (EE), respectively, where the latter has not been considered before. In light of the NP-hardness of the admission control and SE maximization problems, prior works have often treated the two problems separately without considering OFDMA constraints. In this paper, we propose a novel joint optimization framework that is capable of considering power control, admission control, and resource block assignment simultaneously. Via advanced convex approximation techniques and sequential SUE deflation procedures, we develop efficient algorithms that jointly maximize the SE/EE and the number of admitted SUE. Simulation results show that the proposed algorithms yield substantially higher SE/EE and admit more SUE than existing methods.**

***Index Terms*—Small cell, heterogeneous networks, joint power and admission control, orthogonal frequency division multiplexing access (OFDMA), energy efficiency.**

I. INTRODUCTION

THE need for high transmission rates and guaranteed quality of service (QoS) for indoor and cell edge mobile users requires the deployment of complementary low-power nodes, namely, small cells [1], [2], within an existing macro-cellular network, a combination which results in a two-tier heterogeneous network. In particular, small cells can improve the traffic capacity and provide uniform QoS for mobile users at a low implementation cost and therefore have been recognized as an essential technology for the future 5G network [3], [4]. In general, these small cells are randomly deployed and share the spectrum with the macro-cell network, which however results in severe co-tier and cross-tier interference. Therefore, interference management is one of the most important issues in heterogeneous networks [5] and has drawn significant attention, see, e.g., [6]–[8]. To address the issue, a heterogeneous cloud radio access network (H-CRAN) architecture has been proposed for the 5G network to integrate the heterogeneous nodes (e.g., base stations and small cells etc.) through a cloud-based network. The H-CRAN architecture allows for cooperative radio resource management (RRM) in which the network radio resources of all heterogeneous nodes are managed in a centralized fashion [3], [4].

One important feature of the future 5G communication network is that users in the network are required to experience a guaranteed QoS [9], [10]. To this end, the current 4G standards [11] have specified minimum rate constraints on the users. For example, according to [11], the spectral efficiency is required to be at least 3 bps/Hz and 2.25 bps/Hz for downlink and uplink transmission, respectively, for indoor users, whereas for users in an outdoor environment with low mobility, the data rate has to be at least 1 bps/Hz. Unfortunately, due to complex co-tier and cross-tier interference, not all the secondary user equipment (SUE) in the small cells can achieve the minimum rate requirements, especially when the number of SUE is large and when the small cells are densely deployed. To overcome this issue, a mechanism of admission control has been introduced for heterogeneous networks [12]–[19]. Specifically, an SUE is admitted to the network only if it can achieve the specified minimum QoS; otherwise, it is dropped. The goal of admission control is to admit as many SUE as possible that satisfy the minimum rate requirement, while maximizing certain utilities associated with the admitted SUE. For example, [12], [15], [17] proposed to first perform admission control followed by maximizing the SE (e.g., the proportional fairness rate, max-min-fairness rate and sum rate) of the admitted SUE. Specifically, [17] used a semi-Markov decision process method for admission control and a game approach for distributed power control. The works [13], [14] have proposed to optimize the SE sequentially by employing some SUE deflation procedures. Yet the works [18], [19] considered a different power minimization formulation and proposed to combine the admission control problem and power minimization problem as a single joint optimization formulation. However, these existing

Manuscript received August 29, 2015; revised December 12, 2015; accepted January 19, 2016. Date of publication January 28, 2016; date of current version May 6, 2016. The work of W.-S. Lai and T.-S. Lee was supported by the MOST, Taiwan (R.O.C.) under Grant MOST-104-2221-E-009-081. The work of T.-H. Chang was supported by NSFC, China, under Grant 61571385. The associate editor coordinating the review of this paper and approving it for publication was M. Rossi.

W.-S. Lai and T.-S. Lee are with the Department of Electrical and Computer Engineering, National Chiao Tung University, Hsinchu 30013, Taiwan (e-mail: lws816.cm97g@g2.nctu.edu.tw; tslee@mail.nctu.edu.tw).

T.-H. Chang is with the School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen 518172, China (e-mail: tsunghui.chang@ieee.org).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TWC.2016.2522958

approaches assumed a single-carrier system with each small cell only containing one SUE (i.e., the interference channel model). Therefore, these formulations cannot be applied to multi-carrier-based systems, e.g., orthogonal frequency division multiple access (OFDMA) systems [20], [21].

In this paper, we consider the joint power and admission control (JPAC) problem for OFDMA-based heterogeneous networks with minimum rate constraints on the SUE. In each small cell, the subcarriers are grouped into several physical resource blocks (PRBs) and, according to the OFDMA, each PRB is allowed to be occupied by one SUE exclusively. Therefore, the JPAC problem for OFDMA-based networks not only involves both power and admission control, but also PRB assignment. Thus, in comparison with [12]–[16], [18], [19], the proposed OFDMA-based JPAC (OFDMA-JPAC) problem is more challenging due to the OFDMA constraints. When comparing to the conventional OFDMA resource allocation problems [20]–[22], the considered problem is also more challenging since it additionally involves admission control. In addition, unlike [12]–[16], in which only the spectral efficiency (SE) maximization is considered, we consider two respective JPAC problems, one for SE maximization and the other for network energy efficiency (EE) maximization. The network EE is defined as the ratio of the achievable sum rate and the total power consumed by the SUE (including the power required for transmission and basic circuit power). The EE is regarded as an important performance metric in 5G communication networks; see [23], [24] and also [25]–[30] for related EE maximization problems[1]. Note that none of [25]–[30] has considered joint power and admission control for EE maximization.

In this paper, we propose a JPAC optimization framework that transforms the admission control and SE/EE maximization problems into a single joint optimization problem. Considering that both of these problems are NP-hard [18], [31], we apply advanced successive convex approximation (SCA) techniques and a sequential SUE deflation procedure to solve the JPAC problems. Because SUE deflation is based on solutions of the joint optimization formulation that explicitly account for the minimum rate constraints and admission control mechanism, the proposed algorithms can yield higher SE/EE and are capable of admitting more SUE than existing methods. We begin the study by assuming that each small cell contains one SUE only and subsequently extend the proposed optimization framework to include multiple SUE per cell subject to the OFDMA constraint. Our main contributions are summarized as follows:

- For the JPAC problem for SE maximization (JPAC-SEM), we propose a novel joint optimization formulation that is equivalent to solving the admission control and SE maximization problems simultaneously (Theorem 1). Then, we propose an SCA algorithm (Algorithm 1) and an adaptive SUE deflation algorithm (Algorithm 2) to solve the JPAC-SEM problem. We show that the proposed JPAC optimization framework is sufficiently flexible to accommodate most of the popular utilities, including the sum rate, proportional fairness rate, harmonic mean rate, and max-min-fairness rate.
- For the JPAC problem for EE maximization (JPAC-EEM), we propose to reformulate both the admission control and EE maximization problems as a single joint optimization problem (Theorem 2). Note that solving the EE maximization problem without admission control would already be difficult. Unlike existing methods [28], [29] which rely on Dinklebach's procedure [32], we propose to solve the problem by judicious problem reformulation and SCA techniques (Algorithm 3). It is shown that Algorithm 3 is computationally more efficient than existing methods. Subsequently, by extending the proposed reformulation and approximation, we further develop an adaptive SUE deflation algorithm (Algorithm 4) for solving the JPAC-EEM problem. We should mention that, to the best of our knowledge, the proposed algorithm is the first to consider joint power and admission control for EE maximization.
- Finally, the proposed JPAC optimization framework is extended to a scenario with multiple SUE per cell subject to OFDMA constraints. In particular, we employ the ℓ_q-norm minimization method in [22] to account for the OFDMA constraints. We show that the ℓ_q-norm minimization method can be seamlessly integrated with the JPAC optimization framework, and the same SCA and SUE deflation techniques can be applied to the OFDMA-constrained joint optimization problem (Algorithm 5).

For all the scenarios described above, we focus on centralized algorithms by assuming that the JPAC optimization is implemented over a CRAN knowing the CSI of all the SUE. The simulation results show that the proposed algorithms are either computationally more efficient or significantly outperform existing methods in terms of both SE/EE and the number of admitted SUE.

The remainder of this paper is organized as follows. Section II presents the signal model of the two-tier heterogeneous network and problem statement. Section III presents the JPAC problem for SE maximization and the proposed algorithms, whereas the JPAC problem for EE maximization is studied in Section IV. Section V extends the JPAC formulation and algorithms to include OFDMA constraints. The efficacy of the proposed algorithms is demonstrated in Section VI via computer simulations. Finally, conclusions are drawn in Section VII.

II. Signal Model and Problem Statement

Consider a two-tier heterogeneous network consisting of a macro-cellular system and a set of coexisting small-cell systems. The MBS serves a set of macro user equipments (MUEs). In the service region of MBS, there are N_s small cells deployed nearby, denoted by the set $\mathcal{N}_s$. These small cells adopt co-channel deployment with a frequency reuse factor equal to one, and also share the same spectrum with the macro-cellular system. Each small cell j is composed of one small-cell access point (SAP) and N_j small-cell UEs, which are denoted by the

[1]It is worthing noting that works [25], [26], [28]–[30] have considered a different EE criterion. Specifically, they instead aimed to optimize the (weighted) sum of the EE of individual users (which is the sum of ratios of the achievable rate and the power consumption of each user). Such design criterion may be suitable for distributed optimization without channel state information (CSI) exchange, although it does not necessarily optimize the network EE considered in the current paper.

set $\mathcal{N}_j$. The set of all the SUE is denoted by $\mathcal{N}_u \triangleq \mathcal{N}_1 \cup \mathcal{N}_2 \cup \cdots \cup \mathcal{N}_{N_s}$. As in the 4G LTE standard [33], the subcarriers are grouped into $N_{\rm rb}$ PRBs (denoted by the set $\mathcal{N}_{\rm rb}$), and each small cell employs the OFDMA technique; that is, each PRB can only be accessed by one SUE from each small cell. However, SUE in different cells may share one common PRB.

In this paper, we focus on the uplink transmission of a two-tier heterogeneous network[2]. Let SAP_j denote the jth SAP, and let SUE_{k_j}, where $k_j \in \mathcal{N}_j$, denote the kth SUE in cell j. For ease of exposition here, let us first assume that each SAP serves one SUE, i.e., $N_j = 1$; thus, $\text{SUE}_{k_j} = \text{SUE}_j \forall j \in \mathcal{N}_s$ and $\mathcal{N}_s = \mathcal{N}_u$. In Section V, the considered design problems are extended to the general case with $N_j > 1$. Under this assumption, the signal received by the SAP_j over the PRB n is given by

$$y_j^n = h_j^n s_j^n + \sum_{j' \neq j} h_{j',j}^n s_{j'}^n + z_j^n + v_j^n, \tag{1}$$

where s_j^n is the information signal sent from the SUE_j over the PRB n; h_j^n denotes the channel from SUE_j to SAP_j over PRB n; $h_{j',j}^n$ denotes the co-tier (inter-cell) interference channel from $\text{SUE}_{j'}$ to SAP_j; z_j^n represents the cross-tier interference from MUE to SUE_j, and v_j^n is the additive Gaussian noise. Assume that each SAP_j employs the single-user detection technique (which detects s_j^n by treating $s_{j'}^n$ for all $j' \neq j$ as interference). Then the achievable information rate of SUE_j over PRB n is given by

$$\begin{aligned} r_j^n &= \log_2\left(1 + \frac{p_j^n \left|h_j^n\right|^2}{\sum_{j'\neq j} p_{j'}^n \left|h_{j',j}^n\right|^2 + \sigma_{j,n}^2}\right) \\ &= \log_2\left(1 + \frac{p_j^n g_j^n}{\sum_{j'\neq j} p_{j'}^n g_{j',j}^n + 1}\right), \end{aligned} \tag{2}$$

where $p_j^n \triangleq \mathbb{E}[|s_j^n|^2]$ denotes the transmission power of SUE_j; $\sigma_{j,n}^2 \triangleq \mathbb{E}[|z_j^n|^2] + \mathbb{E}[|v_j^n|^2] > 0$ represents the cross-tier interference power plus the additive Gaussian noise power; and $g_j^n \triangleq |h_j^n|^2/\sigma_{j,n}^2$ and $g_{j',j}^n \triangleq |h_{j',j}^n|^2/\sigma_{j,n}^2$ are normalized channel gains. From (2), the achievable rate of SUE_j is given by

$$\begin{aligned} r_j(\boldsymbol{p}) &= \sum_{n=1}^{N_{\rm rb}} r_j^n = \sum_{n=1}^{N_{\rm rb}} \log_2\left(\frac{\sum_{j'=1}^{N_s} p_{j'}^n g_{j',j}^n + 1}{\sum_{j'\neq j} p_{j'}^n g_{j',j}^n + 1}\right) \\ &= \sum_{n=1}^{N_{\rm rb}} \left(\log_2\left(1 + \sum_{j'=1}^{N_s} p_{j'}^n g_{j',j}^n\right)\right. \\ &\qquad \left. - \log_2\left(1 + \sum_{j'\neq j} p_{j'}^n g_{j',j}^n\right)\right), \end{aligned} \tag{3}$$

where $\boldsymbol{p} = [\boldsymbol{p}_1^T, \ldots, \boldsymbol{p}_{N_s}^T]^T$ and $\boldsymbol{p}_j \triangleq [p_j^1, \ldots, p_j^{N_{\rm rb}}]^T$.

[2]Note that in the 3GPP-LTE standard, single-carrier frequency division multiple access (SC-FDMA) has been used for the uplink access scenario. The major difference between SC-FDMA and OFDMA is the PRB contiguity allocation constraint (i.e., adjacent PRBs are grouped into blocks and each block is assigned to one UE [34]). The proposed methods may be extended to the SC-FDMA system as well by adding the contiguity allocation constraint.

In addition to performing co-tier interference control within the small cells, these cells have to control the cross-tier interference to maintain the operation of the macro-cellular system [13], [14]. In particular, the SUE would interfere with the MBS during uplink transmission. Over PRB n, this interference is given by $\sum_{j=1}^{N_s} p_j^n \tilde{g}_j^n, \forall n \in \mathcal{N}_{\rm rb}$, where $\tilde{g}_j^n$ denotes the channel gain from SUE_j to the MBS. We assume that the small cells and the macro cell are maintained by different operators and thus do not consider joint small-cell and macro-cell power control. However, we ensure that the traditional macro cellular system is under protection and suffers at most interference $I_n^{\max}$ over PRB n due to the small cells, i.e., $\sum_{j=1}^{N_s} p_j^n \tilde{g}_j^n \leq I_n^{\max}$.

Given the above signal models, a typical system design problem would consist of optimizing the small-cell throughput subject to the interference constraint on the MBS and the SUE power constraint. Specifically, the following power control problem may be considered [13], [20]

$$\max_{p_j^n \geq 0, \forall j,n} \sum_{j=1}^{N_s} w_j r_j(\boldsymbol{p}_j) \tag{4a}$$

$$\text{s.t.} \sum_{n=1}^{N_{\rm rb}} p_j^n \leq P_j^{\max}, \quad \forall j \in \mathcal{N}_s, \tag{4b}$$

$$\sum_{j=1}^{N_s} p_j^n \tilde{g}_j^n \leq I_n^{\max}, \quad \forall n \in \mathcal{N}_{\rm rb}, \tag{4c}$$

where $w_j > 0$ is a priority weight, (4b) is the maximum power constraint on the SUE.

Although problem (4) aims to maximize the small-cell throughput, it cannot guarantee a minimum QoS (e.g., minimum rate) for the SUE as requested by 4G and B4G communication networks. This is particularly true when the small cells are densely deployed as the user rates would be limited by cross-tier and co-tier interference. One simple way to address this issue is to impose *minimum rate constraints* in problem (4), as in [12]–[14]. However, this could make the problem infeasible. Therefore, it is essential to introduce the mechanism of *SUE admission control* [12]–[15], [18], [19]. In the next section, we propose a novel joint optimization framework for the JPAC problem for SE maximization.

III. JPAC for Spectral Efficiency Maximization (JPAC-SEM)

In this section, we formulate the JPAC problem for spectrum efficiency maximization (SEM) and present the proposed JPAC-SEM algorithm.

A. Problem Reformulation

In general, the JPAC problem can be described as a two-stage design problem [15]. In particular, the first stage involves searching for a maximum number of SUE that can meet their minimum rate requirements under the power constraint (4b) and the cross-tier interference constraint (4c). In the second stage, given the selected subset of SUE, the network spectral efficiency (e.g., the sum rate) is maximized. Mathematically, we can formulate two optimization problems according to this two-stage design. Let $R_j^{\min} > 0$ be the minimum rate requirement of SUE_j, and let β_j be an indicator variable representing whether SUE_j satisfies the minimum rate, i.e.,

$$\beta_j \triangleq \begin{cases} 1 & \text{if } r_j(\boldsymbol{p}) \geq R_j^{\min}, \\ 0 & \text{otherwise}, \end{cases} \tag{5}$$

If $\beta_j = 1$, then SUE_j is admitted by the small cell; otherwise, SUE_j is dropped. By (5), the first stage problem is given by

$$\max_{\substack{p_j^n \geq 0 \\ \beta_j \in \{0,1\}, \forall j,n}} \sum_{j=1}^{N_s} \beta_j \tag{6a}$$

$$\text{s.t.} \quad \beta_j = \begin{cases} 1, & \text{if } r_j(\boldsymbol{p}) \geq R_j^{\min}, \\ 0, & \text{otherwise}, \end{cases} \quad \forall j \in \mathcal{N}_s, \tag{6b}$$

$$\sum_{n=1}^{N_{\text{rb}}} p_j^n \leq \beta_j P_j^{\max}, \quad \forall j \in \mathcal{N}_s, \tag{6c}$$

$$\sum_{j=1}^{N_s} p_j^n \tilde{g}_j^n \leq I_n^{\max}, \quad \forall n \in \mathcal{N}_{\text{rb}}. \tag{6d}$$

As seen above, problem (6) seeks a maximum subset of SUE for which the desired minimum rates $R_j^{\min}$ can be achieved under the power and interference constraints (6c) and (6d). Denote $\mathcal{B}^\star = \{j | \beta_j^\star = 1\}$ as the set of SUE selected by (6). The second stage is to maximize the throughput of SUE in $\mathcal{B}^\star$, i.e.,

$$\max_{p_j^n \geq 0, \forall j,n} \sum_{j \in \mathcal{B}^\star} w_j r_j(\boldsymbol{p}) \tag{7a}$$

$$\text{s.t.} \quad r_j(\boldsymbol{p}) \geq R_j^{\min}, \quad \forall j \in \mathcal{B}^\star, \tag{7b}$$

$$\sum_{n=1}^{N_{\text{rb}}} p_j^n \leq P_j^{\max}, \quad \forall j \in \mathcal{B}^\star, \tag{7c}$$

$$\sum_{j \in \mathcal{B}^\star} p_j^n \tilde{g}_j^n \leq I_n^{\max}, \quad \forall n \in \mathcal{N}_{\text{rb}}, \tag{7d}$$

$$p_j^n = 0, \quad \forall n \in \mathcal{N}_{\text{rb}}, j \notin \mathcal{B}^\star. \tag{7e}$$

Note that (7b) guarantees that the admitted SUE satisfy the minimum rate constraints. It has been shown that both the admission control problem (6) [12], [18] and the weighted sum rate maximization problem (7) [31] are NP-hard problems in general. Therefore, we focus on suboptimal but efficient approximation algorithms. Specifically, we adopt a similar philosophy as in [18], [19] to transform the above two-stage problems into a single-stage problem which jointly performs admission control and SE optimization. Let us consider the following problem

<u>JPAC Problem for Spectral Efficiency Maximization (JPAC-SEM):</u>

$$\max_{\substack{p_j^n \geq 0 \\ \beta_j \in \{0,1\}, \forall j,n}} \lambda \sum_{j=1}^{N_s} w_j r_j(\boldsymbol{p}) + (1-\lambda) \sum_{j=1}^{N_s} \beta_j \tag{8a}$$

$$\text{s.t.} \quad r_j(\boldsymbol{p}) + \delta_j^{-1}(1-\beta_j) \geq R_j^{\min}, \quad \forall j \in \mathcal{N}_s, \tag{8b}$$

$$\sum_{n=1}^{N_{\text{rb}}} p_j^n \leq \beta_j P_j^{\max}, \quad \forall j \in \mathcal{N}_s, \tag{8c}$$

$$\sum_{j=1}^{N_s} p_j^n \tilde{g}_j^n \leq I_n^{\max}, \quad \forall n \in \mathcal{N}_{\text{rb}}, \tag{8d}$$

where $\lambda \in [0, 1]$ is a weighting parameter and $\delta_j > 0$ is a constant. The following theorem shows that solving problem (8) is equivalent to solving the two-stage problems in (6) and (7) as long as appropriate values are chosen for λ and δ.

Theorem 1: *Assume that*

$$\lambda^{-1} \geq \frac{1}{\lambda^{\max}} \triangleq \sum_{j=1}^{N_s} w_j R_j^{\max} - \min_{j \in \mathcal{N}_s} w_j R_j^{\min} + 1, \tag{9}$$

$$\delta_j^{-1} \geq R_j^{\min}, \forall j \in \mathcal{N}_s, \tag{10}$$

where $R_j^{\max} \triangleq \sum_{n=1}^{N_{\text{rb}}} \log_2(1 + g_j^n P_j^{\max})$ and $R_i^{\min} \neq R_j^{\min}$, if $i \neq j$. Then, solving problem (8) is equivalent to solving the two-stage problems in (6) and (7). Moreover, if $\mathcal{B}^\star$ of (6) is not unique, then problem (8) yields the optimal subset of SUE with the highest SE.

Proof: See Appendix. ■

Theorem 1 implies that we can simply focus on solving the JPAC-SEM problem (8) as long as λ and δ follow (9) and (10), respectively. Moreover, the JPAC-SEM problem (8) can yield the best subset of SUE that achieves the highest system throughput.

It is interesting to compare the JPAC-SEM problem (8) with the methods proposed in [12]–[15], [18], [19]. In particular, in contrast to (8) which jointly performs admission control and SE maximization, the methods presented in [12], [15] solve the two problems separately. Therefore, the subset of SUE selected based on problem (6) may not be the one that yields the highest SE, no mention that the methods used to solve (6) are suboptimal. The methods in [13], [14] perform SE maximization and admission control in an iterative manner through a conservative deflation procedure. However, SUE deflation is based on the solution of problem (4) which neither accounts for minimum rate requirements nor does it consider admission control. In the next subsection, we propose a novel adaptive deflation algorithm based on the JPAC-SEM problem (8). As shown in Section VI, the proposed algorithm significantly outperforms existing approaches in terms of both SE and the number of served SUE.

We should also compare the JPAC-SEM problem (8) with the JPAC formulations studied in [18, eqs. (15)-(18)] and [19, eq. (7)]. First, both [18], [19] considered a different formulation which aimed at minimizing the total transmission power subject to minimum signal-to-interference-plus-noise ratio (SINR) constraints. Second, the approach we use in (8b) for reformulating the admission constraint (6b) is distinct from that in [19] and [18] because we constrain the minimum achievable rates of the SUE, whereas [18], [19] constrain their minimum SINRs. Third, the SE maximization design is inherently more challenging to solve than the power minimization design; therefore, additional approximation techniques have to be applied to (8), as shown in Section III-B. Finally, the JPAC framework is flexible to accommodate other system utilities including the network energy efficiency. This aspect will be further studied in Remark 1 and Section IV.

B. Successive Convex Approximation and Adaptive SUE Deflation

The JPAC-SEM problem (8) is difficult to solve because of 1) the binary variables β_j and 2) the non-convex rate function (i.e., (3)). Our approach employs simple convex approximation techniques for handling (8) efficiently. First, let us relax the binary constraint $\beta_j \in \{0, 1\}$ to the box constraint $\beta_j \in [0, 1]$. Then, to handle the non-convex rate functions, we write problem (8) as

$$\max_{\substack{p_j^n \geq 0 \beta_j \in [0,1], \\ R_j \geq 0, \forall j, n}} \lambda \sum_{j=1}^{N_s} w_j R_j + (1-\lambda) \sum_{j=1}^{N_s} \beta_j \tag{11a}$$

$$\text{s.t.} \sum_{n=1}^{N_{\text{rb}}} \left[\log_2 \left(1 + \sum_{j'=1}^{N_s} p_{j'}^n g_{j',j}^n \right) - \log_2 \left(1 + \sum_{j' \neq j} p_{j'}^n g_{j',j}^n \right) \right] \geq R_j, \quad \forall j \in \mathcal{N}_s, \tag{11b}$$

$$R_j + \delta_j^{-1}(1-\beta_j) \geq R_j^{\min}, \quad \forall j \in \mathcal{N}_s, \tag{11c}$$

$$\text{constraints(8c), (8d),} \tag{11d}$$

where R_j are the introduced slack variables. It is easy to verify that the inequality constraint (11b) always holds with equality at the optimal solution. Hence, (11) is equivalent to (8) (with β_j relaxed to [0, 1]). Problem (11) is not convex because the second term on the left-hand side (LHS) of (11b) (the minus-logarithm term) is convex rather than concave. Thus, we propose a successive convex approximation (SCA) method [35], [36], which iteratively solves a sequence of convex approximation counterparts of (11). Specifically, suppose that, at the ith iteration, we are given $\boldsymbol{p}_j[i]$ for all $j \in \mathcal{N}_s$ where $\boldsymbol{p}_j[i] \triangleq [p_j^1[i], \ldots, p_j^{N_{\text{rb}}}[i]]^T$. We consider the first-order approximation of $-\log_2\left(1 + \sum_{j' \neq j} p_{j'}^n g_{j',j}^n\right)$, i.e.,

$$-\log_2\left(1 + \sum_{j' \neq j} p_{j'}^n g_{j',j}^n\right) \geq -\log_2(\eta_j^n[i]) - \frac{1}{\ln(2)\eta_j^n[i]} \sum_{j' \neq j} g_{j',j}^n \left(p_{j'}^n - p_{j'}^n[i]\right) \tag{12}$$

where

$$\eta_j^n[i] \triangleq 1 + \sum_{j' \neq j} p_{j'}^n[i] g_{j',j}^n, \tag{13}$$

and the inequality is due to the fact that $-\log(y) \geq -\log(x) - \frac{1}{x}(y - x) \; \forall x, y > 0$. By using the right-hand side (RHS) of (12), we obtain the following problem

$$\max_{\substack{p_j^n \geq 0 \beta_j \in [0,1], \\ R_j \geq 0, \forall j, n}} \lambda \sum_{j=1}^{N_s} w_j R_j + (1-\lambda) \sum_{j=1}^{N_s} \beta_j \tag{14a}$$

$$\text{s.t.} \; u_j(\boldsymbol{p}, \boldsymbol{p}[i]) \geq R_j, \quad \forall j \in \mathcal{N}_s, \tag{14b}$$

$$\text{constraints (11c), (8c), (8d),} \tag{14c}$$

where

$$u_j(\boldsymbol{p}, \boldsymbol{p}[i]) \triangleq \sum_{n=1}^{N_{\text{rb}}} \left[\log_2 \left(1 + \sum_{j'=1}^{N_s} p_{j'}^n g_{j',j}^n \right) - \log_2(\eta_j^n[i]) - \frac{1}{\ln(2)\eta_j^n[i]} \sum_{j' \neq j} g_{j',j}^n \left(p_{j'}^n - p_{j'}^n[i]\right) \right]. \tag{15}$$

As seen, $u_j(\boldsymbol{p}, \boldsymbol{p}[i])$ is a concave function, and thereby problem (14) is a convex optimization problem which is efficiently solvable by off-the-shelf solvers such as CVX [37]. Suppose that, after solving (14), $\{\beta_j[i+1], \boldsymbol{p}_j[i+1]\}_{j \in \mathcal{N}_s}$ is obtained as the optimal solution. Then, the next iteration is performed and the steps are repeated until convergence is achieved. We summarize the SCA method for solving problem (11) in Algorithm 1. The convergence property of Algorithm 1 is built as follows.

Algorithm 1. Proposed SCA method for solving (11)

1: **Given** a set of initial powers $p_j^n[0] \geq 0 \forall j, n$, and compute $\{\eta_j^n[0]\}$ by (13).
2: Set $i := 0$.
3: **repeat**
4: Solve (14) to obtain $\{p_j^n[i+1], \beta_j[i+1]\}$ and compute $\{\eta_j^n[i+1]\}$ by (13).
5: Compute the objective value $F(\boldsymbol{p}[i+1], \boldsymbol{\beta}[i+1])$ in (8a) achieved by $\{p_j^n[i+1], \beta_j[i+1]\}$ (i.e., (3)).
6: $i := i + 1$.
7: **until** $\dfrac{|F(\boldsymbol{p}[i+1], \boldsymbol{\beta}[i+1]) - F(\boldsymbol{p}[i], \boldsymbol{\beta}[i])|}{F(\boldsymbol{p}[i], \boldsymbol{\beta}[i])} \leq \epsilon$.

Proposition 1: *Let $F(\boldsymbol{p}, \boldsymbol{\beta})$ denote the objective function in (8a), where $\boldsymbol{\beta} \triangleq [\beta_1, \ldots, \beta_{N_s}]^T$. Then, $F(\boldsymbol{p}[i+1], \boldsymbol{\beta}[i+1])$ converges as $i \to \infty$. Moreover, $\{\boldsymbol{p}[i+1], \boldsymbol{\beta}[i+1]\}$ has limit points as $i \to \infty$, and any regular limit point[3] is a Karush-Kuhn-Tucker (KKT) point of problem (11).*

Proof: See Appendix. ■

As the admission control variables β_j obtained by (14) are not necessarily equal to zero or one, the set of admissible SUE has to be decided manually. In [12]–[15], [18], [19], this is usually implemented by a heuristic *deflation* procedure which removes unqualified SUE sequentially until all the remaining SUE satisfy the minimum rate constraints.

[3]For an optimization problem $\min_{\boldsymbol{x}} f(\boldsymbol{x})$s.t.$h_i(\boldsymbol{x}) \leq 0, i = 1, \ldots, N$. we say that $\boldsymbol{x}^\star$ is regular if $\{\nabla h_i(\boldsymbol{x}^\star)\}_{i \in \mathcal{J}}$ are linearly independent, where $\mathcal{J} \triangleq \{i = 1, \ldots, N | h_i(\boldsymbol{x}^\star) = 0\}$.

Algorithm 2. Proposed adaptive SUE deflation algorithm for JPAC-SEM problem (8)

1: **Given** the set of SUE $\mathcal{N}_s$, a set of initial powers $\{p_j^n[0]\}$ and a parameter $\epsilon > 0$.
2: Compute $\{\eta_j^n[0]\}$ by (13). Set $\mathcal{N}_{\text{adm}} \leftarrow \mathcal{N}_{\text{SUE}}$ and $m := 0$.
3: **repeat**
4: $\quad m := m + 1$.
5: $\quad$ **For** $i = 0, \ldots, L-1$
6: $\quad\quad$ Solve (14) for SUE in $\mathcal{N}_{\text{adm}}$ to obtain $\{p_j^n[i+1]\}$ and compute $\{\eta_j^n[i+1]\}$ by (13).
7: $\quad$ **End**
8: $\quad$ Compute the rates $\{\hat{r}_j[m]\}$ achieved by $\{p_j^n[L]\}$ (i.e., (3)).
9: $\quad$ Let $\hat{j} = \arg\min_{j\in\mathcal{N}_{\text{adm}}} \hat{r}_j[m]/R_j^{\min}$. If $\hat{r}_{\hat{j}}[m]/R_{\hat{j}}^{\min} < 1$, then set $\mathcal{N}_{\text{adm}} \leftarrow \mathcal{N}_{\text{adm}} \backslash \{\hat{j}\}$.
10: **until** $\hat{r}_j[m] \geq R_j^{\min} \forall j \in \mathcal{N}_{\text{adm}}$ and $\frac{|\sum_{j\in\mathcal{N}_{\text{adm}}} w_j\hat{r}_j[m] - \sum_{j\in\mathcal{N}_{\text{adm}}} w_j\hat{r}_j[m-1]|}{\sum_{j\in\mathcal{N}_{\text{adm}}} w_j\hat{r}_j[m-1]} \leq \epsilon$
11: Output $\mathcal{N}_{\text{adm}}$ as the set of admissible SUE and $\{p_j^n[L]\}$ as the associated transmit powers.

Interestingly, the successive approximation nature of Algorithm 1 enables us to develop an efficient and high-performance deflation procedure. In particular, we do not allow Algorithm 1 to run until it reaches convergence for SUE deflation; instead, we only implement this algorithm for a small number of iterations (e.g., 5 to 8 iterations)[4], after which one unqualified SUE is removed, based on the approximate solution. This is because the "worst" SUE (which violates the minimum rate constraint to the largest extent) can usually be identified long before the SCA algorithm reaches the convergence condition. Thus, one can considerably reduce the computational overhead of the deflation procedure. Besides, the proposed SUE deflation algorithm is "adaptive" in the sense that it takes into account the varying subset of SUE due to deflation, and continues refining the solutions to achieve a higher SE when all remaining SUE have met their minimum rate requirement. We present the proposed adaptive SUE deflation algorithm in Algorithm 2. As seen from Algorithm 2, the SCA steps (from Step 5 to Step 7) are only run L times (e.g., $L = 5 \sim 8$), and the result is used to identify and remove the single worst unqualified SUE from $\mathcal{N}_{\text{adm}}$ (Step 9). Further, note that when all admitted SUE in $\mathcal{N}_{\text{adm}}$ satisfy their minimum rate constraints, the algorithm continues optimizing the SE performance of the admitted SUE until the conditions in Step 10 are satisfied. Therefore, when Algorithm 2 converges, the best subset of qualified SUE is selected and their SE is optimized at the same time.

The following two remarks relate to JPAC-SEM problem (8) and Algorithm 2.

Remark 1: It is easy to extend problem (8) and Algorithm 2 to other utilities, such as the proportional fairness rate, harmonic mean rate, and the max-min-fairness rate [35]. For example, by simply replacing $\sum_{j=1}^{N_s} w_j R_j$ in (14) with $\sum_{j=1}^{N_s} w_j \log(R_j)$ and $\sum_{j=1}^{N_s} -w_j/R_j$, the JPAC formulations for maximizing the proportional fairness rate and the harmonic mean rate, respectively, are obtained. Because the max-min-fairness (MMF) criterion would enforce all SUE to have the same achievable rate (i.e., $R = R_1 = \ldots = R_{N_s}$), it is natural to directly optimize the system throughput, i.e., $R\sum_{j=1}^{N_s} \beta_j$. Therefore, for MMF rate maximization, problem (14) is replaced by the following convex problem

$$\max_{\substack{R\geq 0,\, p_j^n \geq 0,\\ \beta_j\in[0,1]\forall j,n}} \quad \log(R) + \log\left(\sum_{j=1}^{N_s} \beta_j\right) \tag{16a}$$

$$\text{s.t.} \quad u_j(\boldsymbol{p}, \boldsymbol{p}[i]) \geq R, \quad \forall j \in \mathcal{N}_s, \tag{16b}$$

$$R + \delta_j^{-1}(1-\beta_j) \geq R_j^{\min}, \quad \forall j \in \mathcal{N}_s, \tag{16c}$$

$$\text{constraints (8c), (8d).} \tag{16d}$$

Remark 2: According to Theorem 1, for any two different pairs of $(\lambda_1, \{\delta_{j1}\})$ and $(\lambda_2, \{\delta_{j2}\})$ both satisfying (9) and (10), problems of (8) associated with the two pairs of parameters are equivalent to the two-stage problems (6) and (7) and will have the same optimal solution. In practice, however, Algorithm 2 can yield different solutions for different pairs of $(\lambda, \{\delta_j\})$ since Algorithm 2 solves the relaxed problem (11) rather than problem (8). This is particularly the case when one changes the value of λ. As seen from the objective value of (11), when $\lambda > \lambda_{\max}$ and increases to one, Algorithm 2 would tend to yield solutions that improve the weighted sum rate only; whereas when $\lambda < \lambda_{\max}$ and reduces to zero, Algorithm 2 would tend to improve the number of admitted SUE.

Remark 3: The system models and problem formulations considered in [12]–[15] are different from those in this paper, and therefore are not applicable to problems (6) and (7). However, the overall approach in [12]–[15] could still be used to develop several methods and benchmark them against the proposed Algorithm 2. These algorithms are described as follows.

- *One-step removal algorithm [14]:* First solve the SE maximization problem without the minimum rate constraints, i.e., (4). Based on the solution of (4), simply remove all the SUE that do not meet the minimum rate constraints. Then, solve problem (4) again for the remaining SUE.
- *One-by-one removal algorithm [14]:* This method is similar to Algorithm 2 in which only one worst SUE is removed each time. Specifically, first solve the SE maximization problem (4). If some of the SUE do not satisfy the minimum rate constraints, then drop the worst SUE that violates the minimum rate constraint most. Repeat these two steps until all the remaining SUE satisfy the minimum rate.
- *Dual-based one-by-one removal algorithm [13]:* This method is the same as the above one-by-one removal algorithm except that minimum rate constraints $r_j(\boldsymbol{p}_j) \geq R_j^{\min}, \forall j \in \mathcal{N}_s$ are added to problem (4). To avoid infeasibility issues, the Lagrange dual method [38], which relaxes the minimum rate constraints, is used to approximately solve the problem, followed by the removal of the single worst SUE at each iteration.

The performance comparison results are presented in Section VI.

[4]The numbers are obtained based on our simulation experience in Section VI. It may change when a different setting (e.g., the number of SUE, the number of PRBs) is considered.

IV. JPAC for Energy Efficiency Maximization (JPAC-EEM)

In this section, we consider the JPAC formulation for network EE maximization. The network EE for the uplink network is defined as

$$\mathcal{E} = \frac{\sum_{j=1}^{N_s} w_j r_j(\boldsymbol{p}_j)}{\sum_{j=1}^{N_s}\sum_{n=1}^{N_{rb}} p_j^n + N_s P_c} \text{bits/joule}, \tag{17}$$

where $P_c > 0$ represents the basic circuit power of each SUE. Next, we show how the JPAC problem for EE maximization can be efficiently handled via judicious problem reformulation and approximation.

A. Problem Reformulation

Analogous to the JPAC-SEM problem in Section III, we start by describing the problem as a two-stage design problem. The first stage is problem (6), i.e., we search for a maximum possible subset of SUE capable of satisfying the minimum rate constraints. Given the optimal subset of SUE $\mathcal{B}^\star = \{j|\beta_j^\star = 1\}$ from (6), the second stage of the problem requires the EE in (17) to be maximized:

$$\text{(EEM)} \max_{p_j^n \ge 0, \forall j,n} \frac{\sum_{j=1}^{N_s} w_j r_j(\boldsymbol{p})}{\sum_{j=1}^{N_s}\sum_{n=1}^{N_{rb}} p_j^n + N_s P_c} \tag{18a}$$

$$\text{s.t. constraints (7b), (7c), (7d), (7e).} \tag{18b}$$

Consider the following problem

JPAC Problem for Energy Efficiency Maximization (JPAC-EEM):

$$\max_{\substack{p_j^n \ge 0 \\ \beta_j \in \{0,1\}, \forall j,n}} \lambda \left(\frac{\sum_{j=1}^{N_s} w_j r_j(\boldsymbol{p})}{\sum_{j=1}^{N_s}\sum_{n=1}^{N_{rb}} p_j^n + N_s P_c} \right) + (1-\lambda)\sum_{j=1}^{N_s} \beta_j \tag{19a}$$

$$\text{s.t.} \quad r_j(\boldsymbol{p}) + \delta_j^{-1}(1-\beta_j) \ge R_j^{\min}, \quad \forall j \in \mathcal{N}_s, \tag{19b}$$

$$\sum_{n=1}^{N_{\text{rb}}} p_j^n \le \beta_j P_j^{\max}, \quad \forall j \in \mathcal{N}_s, \tag{19c}$$

$$\sum_{j=1}^{N_s} p_j^n \tilde{g}_j^n \le I_n^{\max}, \quad \forall n \in \mathcal{N}_{\text{rb}}, \tag{19d}$$

We have the following result analogous to Theorem 1:

Theorem 2: *Solving the JPAC-EEM problem (19) is equivalent to solving the two-stage problems in (6) and (18), if*

$$\lambda^{-1} \ge \frac{\sum_{j=1}^{N_s} w_j R_j^{\max}}{N_s P_c} - \frac{\min_{j\in\mathcal{N}_s} w_j R_j^{\min}}{\sum_{j=1}^{N_s} P_j^{\max} + N_s P_c} + 1, \tag{20}$$

$$\delta_j^{-1} \ge R_j^{\min}, \forall j \in \mathcal{N}_s. \tag{21}$$

Moreover, if $\mathcal{B}^\star$ of (6) is not unique, then problem (19) yields the subset of SUE with the highest EE.

Proof: The proof follows the same approach as Theorem 1 and is omitted here. ■

Theorem 2 implies that we can focus on solving the JPAC-EEM problem (19). Since the JPAC-EEM problem (19) has the same constraint set as the JPAC-SEM problem (8) and both problems involve the same non-convex rate function, the approximation techniques developed for the former in the previous section may be applicable to the latter. However, due to the fractional structure of the EE function, the JPAC-EEM problem (19) requires additional techniques and is more complex to handle. In the literature (see, e.g., [28], [29]), problems involving EE maximization are usually solved by the Dinkelbach's procedure [32]. However, this would result in a two-layer optimization algorithm and it may not be computationally efficient when the problem dimension is large. Thus, we present a simple SCA method for solving the JPAC-EEM problem (19) via judicious problem reformulation. To illustrate the proposed SCA method, we first consider the EE maximization problem (18), following which the proposed SCA method is extended to the JPAC-EEM problem (19).

B. Proposed SCA Method for Solving EEM Problem (18)

Let us consider problem (18). By using the same ideas as in (11) to (14), we have the following approximation problem for (18)

$$\max_{\substack{p_j^n \ge 0, R_j \ge 0, \\ \forall j,n}} \frac{\sum_{j=1}^{N_s} w_j R_j}{\sum_{j=1}^{N_s}\sum_{n=1}^{N_{rb}} p_j^n + N_s P_c} \tag{22a}$$

$$\text{s.t.} \quad u_j(\boldsymbol{p}, \boldsymbol{p}[i]) \ge R_j, \quad \forall j \in \mathcal{B}^\star, \tag{22b}$$

$$R_j \ge R_j^{\min}, \quad \forall j \in \mathcal{B}^\star, \tag{22c}$$

$$\text{constraints (7c), (7d), (7e),} \tag{22d}$$

where R_j are the introduced slack variables, and $u_j(\boldsymbol{p}, \boldsymbol{p}[i])$ and $\eta_j^n[i]$ are defined in (15) and (13), respectively. However, unlike [28], [29], in which Dinkelbach's procedure or its variant is used, we employ a simple change of variables to directly reformulate (22) as a convex problem. This can be illustrated as follows. Define $\gamma = \sum_{j=1}^{N_s}\sum_{n=1}^{N_{rb}} p_j^n + N_s P_c$. Then, (22) can be expressed as

$$\max_{\substack{p_j^n \ge 0, R_j \ge 0, \\ \forall j,n}} \frac{\sum_{j=1}^{N_s} w_j R_j}{\gamma} \tag{23a}$$

$$\text{s.t.} \quad \sum_{j=1}^{N_s}\sum_{n=1}^{N_{rb}} p_j^n + N_s P_c = \gamma, \tag{23b}$$

$$\text{constraints (22b), (22c), (7c), (7d), (7e).} \tag{23c}$$

By defining $\hat{R}_j = R_j/\gamma$, $\hat{p}_j^n = p_j^n/\gamma, \forall j \in \mathcal{N}_s$ and $\hat{\gamma} = 1/\gamma$. and applying them to (23), we obtain the following problem

$$\max_{\substack{\hat{p}_j^n \geq 0, \hat{R}_j \geq 0, \\ \hat{\gamma} \geq 0, \forall j,n}} \sum_{j=1}^{N_s} w_j \hat{R}_j \tag{24a}$$

$$\text{s.t.} \sum_{n=1}^{N_{\text{rb}}} \left[\hat{\gamma} \log_2 \left(1 + \sum_{j=1}^{N_s} \frac{\hat{p}_j^n \bar{g}_j^n}{\hat{\gamma}} \right) - \hat{\gamma} \log_2(\eta_j^n[i]) - \frac{1}{\ln(2)\eta_j^n[i]} \sum_{j' \neq j} \bar{g}_{j',j}^n \times \left(\hat{p}_{j'}^n - \hat{\gamma} p_{j'}^n[i] \right) \geq \hat{R}_j \right], \forall j \in \mathcal{B}^\star, \tag{24b}$$

$$\hat{R}_j \geq \hat{\gamma} R_j^{\min}, \quad \forall j \in \mathcal{B}^\star, \tag{24c}$$

$$\sum_{n=1}^{N_{\text{rb}}} \hat{p}_j^n \leq \hat{\gamma} P_j^{\max}, \quad \forall j \in \mathcal{B}^\star, \tag{24d}$$

$$\sum_{j=1}^{N_s} \hat{p}_j^n \tilde{g}_j^n \leq \hat{\gamma} I_n^{\max}, \quad \forall n \in \mathcal{N}_{\text{rb}}, \tag{24e}$$

$$\sum_{j=1}^{N_s} \sum_{n=1}^{N_{rb}} \hat{p}_j^n + \hat{\gamma} N_s P_c = 1, \forall j \in \mathcal{B}^\star, \tag{24f}$$

$$p_j^n = 0, \quad \forall n \in \mathcal{N}_{\text{rb}}, j \notin \mathcal{B}^\star. \tag{24g}$$

Thus, it becomes clear that, with the change of variables, the objective function (24a) and constraints (24d)-(24g) are all linear. Moreover, as $\hat{\gamma} \log_2 \left(1 + \sum_{j=1}^{N_s} \frac{\hat{p}_j^n \bar{g}_j^n}{\hat{\gamma}} \right)$ is the perspective function [38] of the concave function $\log_2 \left(1 + \sum_{j=1}^{N_s} \hat{p}_j^n \bar{g}_j^n \right)$, $\hat{\gamma} \log_2 \left(1 + \sum_{j=1}^{N_s} \frac{\hat{p}_j^n \bar{g}_j^n}{\hat{\gamma}} \right)$ is concave and thereby constraint (24b) is a convex constraint. Therefore, (24) is a convex optimization problem, which is efficiently solvable. The proposed SCA method for solving the EEM problem (18) is summarized in Algorithm 3. Analogous to Proposition 1, we have the convergence property for Algorithm 3:

Algorithm 3. Proposed SCA method for solving (18)

1: **Given** a set of initial powers $p_j^n[0] \geq 0 \forall j, n$, and compute $\{\eta_j^n[0]\}$ by (13).
2: Set $i := 0$.
3: **repeat**
4: Solve (24) to obtain $p_j^n[i+1] = \hat{p}_j^n[i+1]/\hat{\gamma} \forall j, n$ and compute $\{\eta_j^n[i+1]\}$ by (13).
5: Compute the energy efficiency $\mathcal{E}c[i+1]$ (i.e., (17)).
6: $i := i + 1$.
7: **until** $\frac{|\mathcal{E}c[i+1] - \mathcal{E}c[i]|}{\mathcal{E}c[i]} \leq \epsilon$

Proposition 2: *Let $G(\boldsymbol{p})$ denote the objective function in (18a). Then, $G(\boldsymbol{p}[i+1])$ converges as $i \to \infty$. Moreover, $\{\boldsymbol{p}[i+1]\}$ has limit points as $i \to \infty$ and any regular limit point of is a KKT point of problem (18).*

In Section VII, it will be shown that the proposed Algorithm 3 is computationally more efficient than the existing methods based on Dinkelbach's procedure [28], [29].

C. SCA and Adaptive SUE Deflation for JPAC-EEM Problem (19)

The above Algorithm 3 cannot be directly applied to solving JPAC-EEM problem (19) due to the additional term $(1 - \lambda) \sum_{j=1}^{N_s} \beta_j$ in the objective function and constraints (19b) and (19c). Thus, let us first introduce an equivalent formulation of (19), which is more amenable to efficient approximation. Like (23), we introduce the slack variable γ as the network power consumption, which enables us to equivalently present problem (19) as

$$\max_{\substack{\gamma \geq 0, p_j^n \geq 0 \\ \beta_j \in \{0,1\}, \forall j,n}} \lambda \left(\frac{\sum_{j=1}^{N_s} w_j r_j(\boldsymbol{p}_j)}{\gamma} \right) + (1 - \lambda) \sum_{j=1}^{N_s} \beta_j \tag{25a}$$

$$\text{s.t.} \sum_{j=1}^{N_s} \sum_{n=1}^{N_{rb}} p_j^n + N_s P_c = \gamma, \tag{25b}$$

$$\text{constraints (19b), (19c), (19d).} \tag{25c}$$

Let us consider the following problem

$$\max_{\substack{\gamma \geq 0, p_j^n \geq 0 \\ \beta_j \in \{0,1\}, \forall j,n}} \lambda \left(\frac{\sum_{j=1}^{N_s} w_j r_j(\boldsymbol{p}_j)}{\gamma} \right) + (1 - \lambda) \sum_{j=1}^{N_s} \beta_j \tag{26a}$$

$$\text{s.t.} \frac{r_j(\boldsymbol{p}_j)}{\gamma} + \frac{\delta_j^{-1}}{N_s P_c}(1 - \beta_j) \geq \frac{R_j^{\min}}{\gamma}, \quad \forall j \in \mathcal{N}_s, \tag{26b}$$

$$\sum_{n=1}^{N_{\text{rb}}} p_j^n \leq P_j^{\max}, \quad \forall j \in \mathcal{N}_s, \tag{26c}$$

$$\frac{r_j(\boldsymbol{p}_j)}{\gamma} \leq \beta_j \frac{R_j^{\max}}{N_s P_c}, \quad \forall j \in \mathcal{N}_s, \tag{26d}$$

$$\sum_{j=1}^{N_s} p_j^n \tilde{g}_j^n \leq I_n^{\max}, \quad \forall n \in \mathcal{N}_{\text{rb}}, \tag{26e}$$

$$\sum_{j=1}^{N_s} \sum_{n=1}^{N_{rb}} p_j^n + N_s P_c = \gamma. \tag{26f}$$

Note that, in comparison with problem (25), constraints (26b) and (26c) are different from (19b) and (19c), respectively, whereas constraint (26d) is new. Interestingly, (26b)-(26f) actually describe the same feasible set as (19b)-(19d), and therefore problem (26) is equivalent to problem (25):

Lemma 1: *Assume $\delta_j^{-1} \geq R_j^{\min}, \forall j \in \mathcal{N}_s$. Then, problems (26) and (25) are equivalent to each other.*

Proof: See Appendix. ■

The reformulated problem (26) is amenable to efficient approximation. Specifically, by applying the approximations and change of variables in (22)-(24) to problem (26), we obtain the following approximation problem for JPAC-EEM problem (19)

$$\max_{\substack{\hat{p}_j^n \geq 0 \beta_j \in [0,1], \\ \hat{R}_j \geq 0, \hat{\gamma} \geq 0, \forall j,n}} \lambda \sum_{j=1}^{N_s} w_j \hat{R}_j + (1-\lambda) \sum_{j=1}^{N_s} \beta_j \quad (27a)$$

$$\text{s.t.} \sum_{n=1}^{N_{\text{rb}}} \Bigg[\hat{\gamma} \log_2 \left(1 + \sum_{j=1}^{N_s} \frac{\hat{p}_j^n \bar{g}_j^n}{\hat{\gamma}} \right) - \hat{\gamma} \log_2(\eta_j^n[i]) - \frac{1}{\ln(2)\eta_j^n[i]} \sum_{j' \neq j} \bar{g}_{j',j}^n \times \left(\hat{p}_{j'}^n - \hat{\gamma} p_{j'}^n[i] \right) \Bigg] \geq \hat{R}_j, \quad \forall j \in \mathcal{N}_s, \quad (27b)$$

$$\hat{R}_j + \frac{\delta_j^{-1}}{N_s P_c}(1-\beta_j) \geq \hat{\gamma} R_j^{\min}, \quad \forall j \in \mathcal{N}_s, \quad (27c)$$

$$\hat{R}_j \leq \beta_j \frac{R_j^{\max}}{N_s P_c}, \quad \forall j \in \mathcal{N}_s, \quad (27d)$$

$$\sum_{n=1}^{N_{\text{rb}}} \hat{p}_j^n \leq \hat{\gamma} P_j^{\max}, \quad \forall j \in \mathcal{N}_s, \quad (27e)$$

$$\sum_{j=1}^{N_s} \hat{p}_j^n \tilde{g}_j^n \leq \hat{\gamma} I_n^{\max}, \quad \forall n \in \mathcal{N}_{\text{rb}}, \quad (27f)$$

$$\sum_{j=1}^{N_s} \sum_{n=1}^{N_{rb}} \hat{p}_j^n + \hat{\gamma} N_s P_c = 1, \quad \forall j \in \mathcal{N}_s. \quad (27g)$$

As can be seen, problem (27) is a convex optimization problem. Analogous to Propositions 1 and 2, by iteratively solving (27), it is possible to reach a KKT point of problem (19) (with β_j's relaxed to [0, 1]). By following the same approach as in Algorithm 2, we can also develop an adaptive SUE deflation algorithm as shown in Algorithm 4. Assume that the set of admitted SUE $\mathcal{N}_{\text{adm}}$ converges when m is sufficiently large. Then, $\{\boldsymbol{p}[m], \boldsymbol{\beta}[m]\}$ generated in Algorithm 4 (i.e., $\{p_j^n[L], \beta_j^n[L]\}_{j,n}$ at iteration m) have limit points and any regular limit point is a KKT point of problem (19) with β_j's relaxed to [0, 1] and for SUE in $\mathcal{N}_{\text{adm}}$. We should remark that, to the best of our knowledge, the proposed Algorithm 4 is the first for solving the JPAC problem for network EE maximization.

V. JPAC Under OFDMA Constraints

In this section, we consider scenarios in which $N_j > 1$ (i.e., one SAP serves multiple SUE) and extend the previous JPAC formulations to OFDMA small-cell systems. We only present the extension of the JPAC-SEM problem (8) to the OFDMA scenario. The extension of the JPAC-EEM problem to the OFDMA scenario can be obtained in a similar way and the details are omitted here due to limited space.

A. OFDMA-Constrained JPAC-SEM

Assume that each SAP_j serves N_j SUE. In particular, denote the kth SUE in cell j as SUE_{k_j}, for $k \in \mathcal{N}_j$ and $j \in \mathcal{N}_s$.

Algorithm 4. Proposed adaptive SUE deflation algorithm for JPAC-EEM problem (19)

1: **Given** the set of SUE $\mathcal{N}_s$, a set of initial powers $\{p_j^n[0]\}$ and a parameter $\epsilon > 0$.
2: Compute $\{\eta_j^n[0]\}$ by (13). Set $\mathcal{N}_{\text{adm}} \leftarrow \mathcal{N}_{\text{SUE}}$ and $m := 0$.
3: **repeat**
4: $m := m + 1$.
5: **For** $i = 0, \ldots, L-1$
6: Solve (27) to obtain $p_j^n[i+1] = \hat{p}_j^n[i+1]/\hat{\gamma} \forall j, n$ and compute $\{\eta_j^n[i+1]\}$ by (13).
7: **End**
8: Compute the rates $\{\hat{r}_j[m]\}$ achieved by $\{p_j^n[L]\}$ (i.e., (3)) and compute the EE $\mathcal{E}c[m]$ (i.e., (17)).
9: Let $\hat{j} = \arg\min_{j \in \mathcal{N}_{\text{adm}}} \hat{r}_j[m]/R_j^{\min}$. If $\hat{r}_{\hat{j}}[m]/R_{\hat{j}}^{\min} < 1$, then set $\mathcal{N}_{\text{adm}} \leftarrow \mathcal{N}_{\text{adm}} \backslash \{\hat{j}\}$.
10: **until** $\hat{r}_j[m] \geq R_j^{\min} \forall j \in \mathcal{N}_{\text{adm}}$ and $\frac{|\mathcal{E}c[m] - \mathcal{E}c[m-1]|}{\mathcal{E}c[m-1]} \leq \epsilon$
11: Output $\mathcal{N}_{\text{adm}}$ as the set of admissible SUE and $\{p_j^n[L]\}$ as the associated transmit powers.

Moreover, define $\mathcal{N}_u \triangleq \mathcal{N}_1 \cup \mathcal{N}_2 \cup \cdots \cup \mathcal{N}_{N_s}$ as the set of all the SUE, i.e., $k_j \in \mathcal{N}_u$. For OFDMA transmission, we introduce the binary variables $\alpha_{k_j}^n \in \{0,1\}$ to indicate if SUE_{k_j} is scheduled to access the nth PRB. If not, i.e., $\alpha_{k_j}^n = 0$, then $p_{k_j}^n = 0$. According to the OFDMA constraint, each PRB can only be accessed by one SUE in each cell, that is, $\sum_{k \in \mathcal{N}_j} \alpha_{k_j}^n = 1$. As SUE in different cells may access a common PRB, these SUE continue to suffer from co-tier interference. By taking into account these constraints in the JPAC-SEM problem (8), we propose the following JPAC formulation for OFDMA systems:

OFDMA-Constrained JPAC-SEM (OFDMA-JPAC-SEM) Problem:

$$\max_{\substack{p_{k_j}^n \geq 0, \alpha_{k_j}^n \geq 0, \\ \beta_{k_j} \in \{0,1\}, \forall k,j,n}} \left\{ \lambda \sum_{j=1}^{N_s} \sum_{k \in \mathcal{N}_j} w_{k_j} r_{k_j}(\boldsymbol{p}) + (1-\lambda) \sum_{j=1}^{N_s} \sum_{k \in \mathcal{N}_j} \beta_{k_j} \right\} \quad (28a)$$

$$\text{s.t.} \quad r_{k_j}(\boldsymbol{p}) + \delta_{k_j}^{-1}(1-\beta_{k_j}) \geq R_{k_j}^{\min}, \quad \forall k, j, \quad (28b)$$

$$\sum_{n=1}^{N_{\text{rb}}} p_{k_j}^n \leq \beta_{k_j} P_{k_j}^{\max}, \quad \forall k, j, \quad (28c)$$

$$\sum_{j=1}^{N_s} \sum_{k \in \mathcal{N}_j} p_{k_j}^n \tilde{g}_{k_j}^n \leq I_n^{\max}, \quad \forall n, \quad (28d)$$

$$p_{k_j}^n \leq \alpha_{k_j}^n P_{k_j}^{\max}, \quad \forall n, k, j, \quad (28e)$$

$$\sum_{k \in \mathcal{N}_j} \alpha_{k_j}^n = 1, \alpha_{k_j}^n \in \{0,1\}, \quad \forall j, n, \quad (28f)$$

where, with a slight abuse of notation, $r_{k_j}(\boldsymbol{p})$ denotes the rate achievable by SUE_{k_j} and is given by

$$r_{k_j}(\boldsymbol{p}) = \sum_{n=1}^{N_{\text{rb}}} \left(\log_2 \left(1 + \sum_{\ell \in \mathcal{N}_u} p_\ell^n g_{\ell,j}^n \right) - \log_2 \left(1 + \sum_{\ell \in \mathcal{N}_u, \ell \neq k_j} p_\ell^n g_{\ell,j}^n \right) \right). \quad (29)$$

We have used (28e) to enforce $p_{k_j}^n = 0$ if $\alpha_{k_j}^n = 0$ and used (28f) to enforce the OFDMA constraints. Similar to Theorem 1, if the parameters λ and $\{\delta_{k_j}\}$ are set to

$$\lambda^{-1} \geq \sum_{k_j \in \mathcal{N}_u} w_{k_j} R_{k_j}^{\max} - \min_{k_j \in \mathcal{N}_u} w_{k_j} R_{k_j}^{\min} + 1, \quad (30)$$

$$\delta_{k_j}^{-1} \geq R_{k_j}^{\min}, \forall k_j \in \mathcal{N}_u, \quad (31)$$

then solving (28) is equivalent to solving the admission control problem (6) followed by solving the OFDMA-constrained SEM problem [20], [21]

$$\max_{\substack{p_{k_j}^n \geq 0, \alpha_{k_j}^n \geq 0, \\ \forall k,j,n}} \sum_{j=1}^{N_s} \sum_{k \in \mathcal{N}_j} w_{k_j} r_{k_j}(\boldsymbol{p}) \quad (32a)$$

$$\text{s.t.} \quad r_{k_j}(\boldsymbol{p}) \geq R_{k_j}^{\min}, \quad \forall k, j, \quad (32b)$$

$$\sum_{n=1}^{N_{\text{rb}}} p_{k_j}^n \leq P_{k_j}^{\max}, \quad \forall k, j, \quad (32c)$$

$$\text{constraints (28d), (28e), (28f).} \quad (32d)$$

In general, OFDMA-constrained power control problems are NP-hard [39]. Therefore, suboptimal solutions based on simple relaxation [40], alternating optimization [20], [21], [28], or a Lagrange dual decomposition [41], [42] were previously proposed. However, these methods cannot be efficiently applied to OFDMA-JPAC-SEM problem (28) because this problem not only involves power control and PRB assignment, but also SUE admission control. In the Section V-B, we adopt the q-norm minimization framework proposed in [22] for handling OFDMA constraints (28f). As will be seen shortly, the ℓ_q-norm minimization framework can be perfectly integrated with the proposed JPAC techniques in Section III, leading to an efficient algorithm for solving the OFDMA-JPAC-SEM problem (28).

B. SCA and Adaptive SUE Deflation for OFDMA-JPAC-SEM

The ℓ_q-norm minimization method is based on the observation that any $\{\alpha_{k_j}^n\}$ satisfies the OFDMA constraints (28e) if and only if $\{\alpha_{k_j}^n\}$ is an optimal solution to the following optimization problem

$$\min_{\alpha_{k_j}^n \forall k,j,n} \sum_{j=1}^{N_s} \sum_{k \in \mathcal{N}_j} \sum_{n=1}^{N_{\text{rb}}} (\alpha_{k_j}^n + \varepsilon)^q \quad (33a)$$

$$\text{s.t.} \sum_{k \in \mathcal{N}_j} \alpha_{k_j}^n = 1, \forall k, j, n. \quad (33b)$$

where $q \in (0, 1)$ and $\varepsilon \geq 0$ are given parameters[5]. This observation motivates the following reformulation problem for (28):

$$\max_{\substack{p_{k_j}^n \geq 0, \alpha_{k_j}^n \geq 0, \\ \beta_{k_j} \in [0,1], \forall k,j,n}} \left\{ \lambda \sum_{j=1}^{N_s} \sum_{k \in \mathcal{N}_j} w_{k_j} r_{k_j}(\boldsymbol{p}) + (1-\lambda) \sum_{j=1}^{N_s} \sum_{k \in \mathcal{N}_j} \beta_{k_j} - \nu \sum_{j=1}^{N_s} \sum_{k \in \mathcal{N}_j} \sum_{n=1}^{N_{\text{rb}}} (\alpha_{k_j}^n + \varepsilon)^q \right\} \quad (34a)$$

$$\text{s.t. constraints (28b), (28c), (28d), (28e),} \quad (34b)$$

$$\sum_{k \in \mathcal{N}_j} \alpha_{k_j}^n = 1, \quad \forall j, n. \quad (34c)$$

In (34), the binary constraints $\alpha_{k_j}^n \in \{0, 1\}$ are removed from (33b), and the penalty term $-\nu \sum_{j=1}^{N_s} \sum_{k \in \mathcal{N}_j} \sum_{n=1}^{N_{\text{rb}}} (\alpha_{k_j}^n + \varepsilon)^q$ is added to the objective, where $\nu > 0$ is a weighting parameter. It can be seen that, when $\nu \to \infty$, variables $\{\alpha_{k_j}^n\}$ obtained by solving problem (34) would satisfy the OFDMA constraint (28e) due to (33).

In [43], an iterative reweighted minimization (IRM) framework is used to solve problems with the same form as (33). Such an IRM method is essentially an SCA method where the concave function $(\alpha_{k_j}^n + \varepsilon)^q$ is successively approximated by its first-order approximation. Because the proposed approximation method in (11)-(14) for solving the JPAC-SEM problem (8) is also based on a successive first-order approximation, the IRM framework can seamlessly be combined with the proposed adaptive SUE deflation framework. Specifically, assume that $\{\alpha_{k_j}^n[i]\}$ are given at iteration i. Then, each concave function $(\alpha_{k_j}^n + \epsilon)^q$ is upper bounded by its first-order approximation

$$(\alpha_{k_j}^n + \varepsilon)^q \leq (\alpha_{k_j}^n[i] + \varepsilon)^q + q(\alpha_{k_j}^n[i] + \varepsilon)^{q-1}(\alpha_{k_j} - \alpha_{k_j}^n[i]). \quad (35)$$

By substituting the RHS of (35) into (34) as well as applying the approximations in (11)-(14) to problem (34), we obtain the following convex approximation problem

$$\max_{\substack{p_{k_j}^n \geq 0, \alpha_{k_j}^n \geq 0, \\ R_{k_j} \geq 0 \\ \beta_{k_j} \in \{0,1\}, \forall k,j,n}} \left\{ \lambda \sum_{j=1}^{N_s} \sum_{k \in \mathcal{N}_j} w_{k_j} R_{k_j} + (1-\lambda) \sum_{j=1}^{N_s} \sum_{k \in \mathcal{N}_j} \beta_{k_j} - \nu \sum_{j=1}^{N_s} \sum_{k \in \mathcal{N}_j} \sum_{n=1}^{N_{\text{rb}}} \rho_{k_j}^n[i] \alpha_{k_j}^n \right\} \quad (36a)$$

[5]As the constraint set (33b) is a simplex and the objective function (33a) is concave, the optimal solution of problem (33) must be one of the extreme points in the simplex. Therefore, the optimal solution is an OFDMA solution satisfying (28e).

$$\text{s.t. } u_{k_j}(\boldsymbol{p}, \boldsymbol{p}[i]) \geq R_{k_j}, \forall k, j, \tag{36b}$$

$$R_{k_j} + \delta_{k_j}^{-1}(1 - \beta_{k_j}) \geq R_{k_j}^{\min}, \forall k, j, \tag{36c}$$

$$\text{constraints (28c), (28d), (28e), (34c),} \tag{36d}$$

where

$$\rho_{k_j}^n[i] \triangleq q(\alpha_{k_j}^n[i] + \varepsilon)^{q-1}, \tag{37}$$

and, with a slight abuse of notation,

$$u_{k_j}(\boldsymbol{p}, \boldsymbol{p}[i]) \triangleq \sum_{n=1}^{N_{\text{rb}}} \Bigg[\log_2\Bigg(1 + \sum_{\ell \in \mathcal{N}_u} \sum p_\ell^n g_{\ell,j}^n\Bigg) - \log_2(\eta_{k_j}^n[i]) - \frac{1}{\ln(2)\eta_{k_j}^n[i]} \sum_{\ell \in \mathcal{N}_u, \ell \neq k_j} g_{\ell,j}^n (p_\ell^n - p_\ell^n[i]) \Bigg], \tag{38}$$

$$\eta_{k_j}^n[i] \triangleq 1 + \sum_{\ell \in \mathcal{N}_u, \ell \neq k_j} p_\ell^n[i] g_{\ell,j}^n. \tag{39}$$

Based on problem (36), we develop the adaptive SUE deflation algorithm in Algorithm 5 for solving the JPAC-OFDMA-SEM problem (28). Different from Algorithm 2, in Step 7 of Algorithm 5, an additional PRB assignment is performed for fulfilling the OFDMA constraint. The SUE deflation (step 8) is then executed based on rates achieved by $\{p_{k_j}^n[L], \alpha_{k_j}^n[0]\}$.

Algorithm 5. Proposed adaptive SUE deflation algorithm for JPAC-OFDMA-SEM problem (28)

1: **Given** the set of SUE $\mathcal{N}_u$, initial powers $\{p_{k_j}^n[0]\}$, and parameters $q \in (0, 1)$, $\varepsilon > 0$, and $\epsilon > 0$. Compute the initial achievable rates $\{r_{k_j}^n[0]\}$. Set $m := 0$, $\mathcal{N}_{\text{adm}} \leftarrow \mathcal{N}_u$ and

$$\alpha_{k_j}^n[0] = \begin{cases} 1 & \text{if } k_j = \arg\max_{k_j \in \mathcal{N}_j} r_{k_j}^n[0], \\ 0 & \text{otherwise}, \end{cases} \quad \forall n, k, j. \tag{40}$$

2: **repeat**
3: **for** $i = 0, \ldots, L - 1$ **do**
4: Compute $\{\rho_{k_j}^n[i]\}$ by (37) and $\{\eta_{k_j}^n[i]\}$ by (39).
5: Solve problem (36) for SUE in $\mathcal{N}_{\text{adm}}$ to obtain $\{p_{k_j}^n[i+1], \alpha_{k_j}^n[i+1]\}$.
6: **end for**
7: Set

$$\alpha_{k_j}^n[0] = \begin{cases} 1 & \text{if } k_j = \arg\max_{k_j \in \mathcal{N}_j} \alpha_{k_j}^n[L], \\ 0 & \text{otherwise}, \end{cases} \quad \forall n, k, j. \tag{41}$$

Compute the rates $\{\hat{r}_{k_j}[m]\}$ achieved by $\{p_{k_j}^n[L], \alpha_{k_j}^n[0]\}$ (i.e., (29)).
8: Let $\hat{k}_j = \arg\min_{\ell \in \mathcal{N}_{\text{adm}}} \hat{r}_\ell[m]/R_\ell^{\min}$. If $\hat{r}_{k_j}[m]/R_{\hat{k}_j}^{\min} < 1$, then set $\mathcal{N}_{\text{adm}} \leftarrow \mathcal{N}_{\text{adm}} \backslash \{\hat{k}_j\}$.
9: $m := m + 1$.
10: **until** $\hat{r}_{k_j}[m] \geq R_{k_j}^{\min}$ $\forall k_j \in \mathcal{N}_{\text{adm}}$, and $\frac{|\sum_{k_j \in \mathcal{N}_{\text{adm}}} w_{k_j}\hat{r}_{k_j}[m] - \sum_{k_j \in \mathcal{N}_{\text{adm}}} w_{k_j}\hat{r}_{k_j}[m-1]|}{\sum_{k_j \in \mathcal{N}_{\text{adm}}} w_{k_j}\hat{r}_{k_j}[m-1]} \leq \epsilon$.
11: Output $\mathcal{N}_{\text{adm}}$ as the set of admissible SUE and $\{p_{k_j}^n[L], \alpha_{k_j}^n[0]\}$ as the associated transmit powers and PRB assignment.

VI. Simulation Results

The two-tier heterogeneous network was simulated by following the channel model in [44], [45] which not only considers small-scale channel fading, but also large-scale fading effects such as shadowing and path loss. Within a macro cell, the MBS has a hexagonal service region with a size of 500×500 m^2 and serves 15 MUE which are uniformly located within the service region. If not mentioned specifically, the SAPs are uniformly located in a region with a radius of 200 m, and the distance between the center of the region and the MBS is randomly set within the range 400 to 450 m. Each SAP has a service range with a radius of 20 m, serving one or multiple SUE, which are randomly distributed along the cell edge of the associated small cell. The signal bandwidth of each small cell was set to 3 MHz, including a total of 15 PRBs ($N_{\text{rb}} = 15$) [45]. The signal-to-noise ratio (SNR) is defined as $\frac{1}{\sum_{j=1}^{N_s} N_j}\left(\sum_{j=1}^{N_s} \sum_{k_j \in \mathcal{N}_j} P_{k_j}^{\max}\mathbb{E}[g_{k_j,j}]\right)/(BN_0)$, where B denotes the PRB bandwidth, N_0 is the one-sided spectral density of the Gaussian noise, and $\mathbb{E}[g_{k_j,j}]$ is the average power of the channel coefficient. Further, the weight coefficients w_{k_j} are set to one for all k, j, the minimum rate requirements are set to $R_{k_j}^{\min} = 1$ bps/Hz for all k, j, the interference threshold of MBS is $I_n^{\max} = -120$ dBw, and the maximum transmitting power of each SUE is $P_{k_j}^{\max} = 26$ dBm. When the network EE is considered, the circuit power P_c is set to 100 mW (20 dBm). The other simulation parameters are detailed in [44, Annex A]. For Algorithms 1 to 5, all the associated convex problems (e.g., problems (14), (27), (24), and (36)) are solved by the convex solver CVX [37]. The parameters L and ϵ are set to 8 and 10^{-5}, respectively; the parameters δ_j and λ follow (9) and (10) for JPAC-SEM, and follow (20) and (21) for JPAC-EEM. The presented performance results are obtained by averaging over 1,000 channel realizations.

A. Comparison of Algorithms for Solving JPAC-SEM Problem (8)

We first examine the performance of the proposed Algorithm 2 for solving the JPAC-SEM problem (8) and compare it with the one-step removal algorithm [14], one-by-one removal algorithm [14], and dual-based one-by-one removal algorithm [13] mentioned in Remark 3. In the one-step and one-by-one removal algorithms, the associated problem (4) is solved by an SCA algorithm similar to Algorithm 1 (by removing

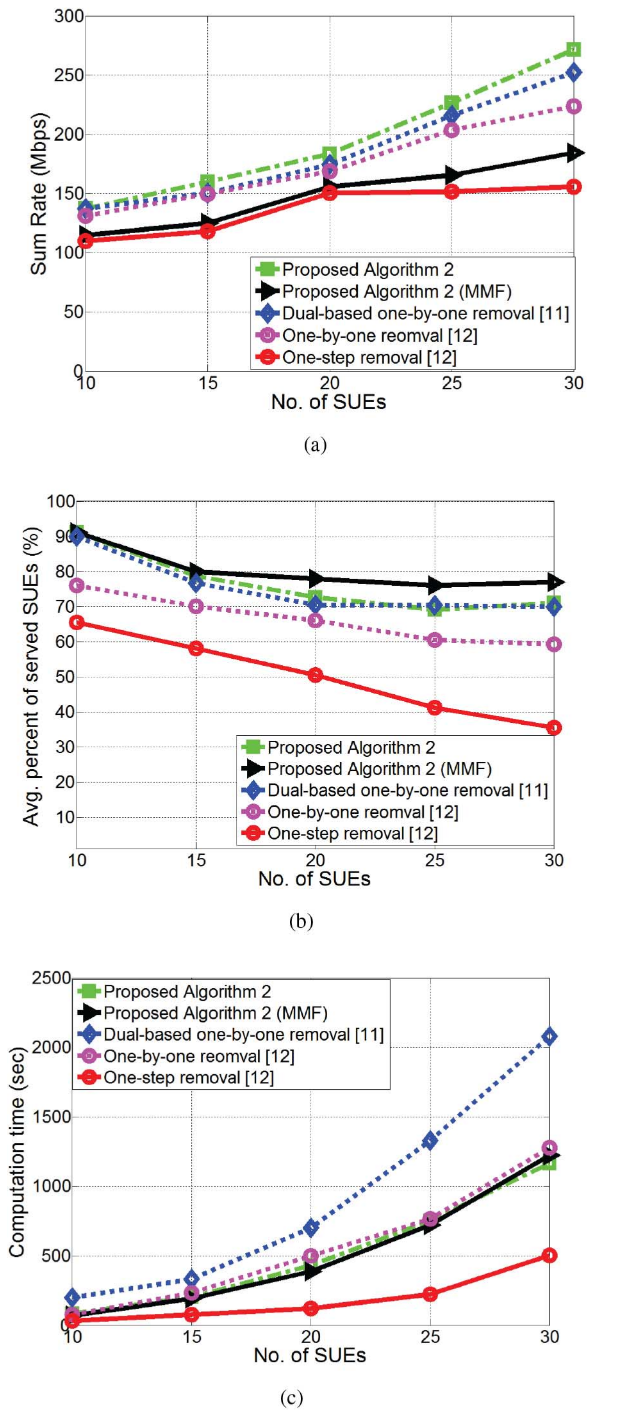


Fig. 1. Performance comparison results of the proposed Algorithm 2 with existing methods for SNR = 25 dB by varying the number of SUE.

the minimum rate constraints and β_j). For the dual optimization method employed in the dual-based one-by-one removal algorithm, the primal subproblem is also solved by an SCA algorithm similar to Algorithm 1; the stopping condition of the dual optimization method requires the improvement of the dual objective value to be less than 0.01.

Fig. 1 displays the performance comparison results for SNR = 25 dB as a function of the number of SUE. In Fig. 1(a), one can observe that the proposed Algorithm 2 consistently yields higher sum rates than the existing methods. More importantly, as shown in Fig. 1(b), Algorithm 2 has the ability to support a larger percentage of SUE than the three existing methods. This is because the proposed Algorithm 2 is based on the JPAC-SEM problem (8), which accounts for both power control and admission control. The figures indicate that the performance of the dual-based one-by-one removal algorithm is comparable to that of the proposed Algorithm 2. However, as shown in Fig. 1(c), the computational time (in seconds)[6] of the proposed Algorithm 2 is about 40% less than that of the dual-based one-by-one removal algorithm when the number of SUE exceeds 25.

In addition, Fig. 1(c) shows that Algorithm 2 is almost as fast as the one-by-one removal algorithm but slower than the one-step removal algorithm. In Fig. 1 we have also presented the performance of the proposed Algorithm 2 for MMF rate maximization which is discussed in Remark 1. Interestingly, the JPAC-MMF formulation can admit even more SUE.

B. Comparison of Algorithms for Solving EE Maximization Problem (18)

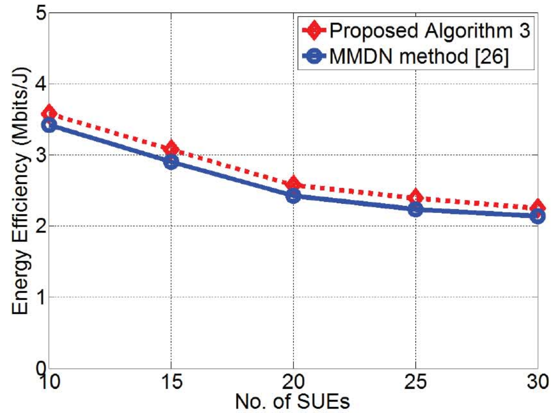
Let us examine the performance of the proposed Algorithm 3 for solving the EE maximization problem (18) (without the minimum rate constraints). In particular, we compare the proposed Algorithm 3 with the minorization-maximization and damped Newton (MMDN) method in [29, Algorithm 2]. The damped Newton method can be interpreted as an improved implementation of Dinkelbach's procedure [32], whereas the minorization-maximization method is essentially the same as the convex approximation used in problem (22). Fig. 2 shows the comparison results for SNR = 25 dB by varying the number of SUE. Fig. 2(a) shows that the proposed Algorithm 3 only performs slightly better than the MMDN method in terms of the achievable EE. However, as shown in Fig. 2(b), the computational time (in seconds) of the proposed Algorithm 3 is about 40% that of the MMDN method when the number of SUE exceeds 25.

One can observe from Fig. 2(a) that the network EE decreases with the number of SUE N_s. While the system sum rate can increase with the number of SUEs, the improvement is limited due to the co-tier interference. Moreover, since the network circuit power consumption $N_s P_c$ always increases with N_s, the overall EE of the network decreases with N_s. Note that this is different from the weighted sum of EE of individual SUE considered in [26], [29], which increases with the number of SUEs.

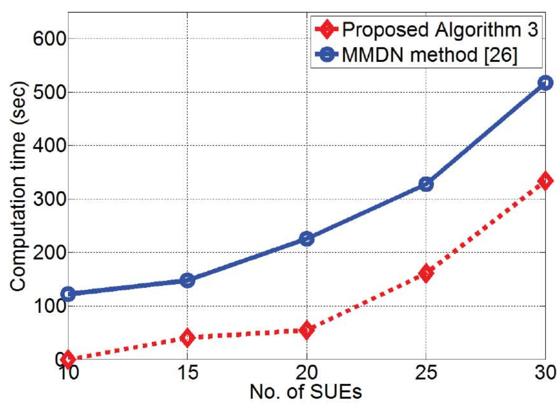
C. Comparison of Algorithms for Solving JPAC-EEM Problem (19)

Next, we evaluate the performance of the proposed Algorithm 4 for solving the JPAC-EEM problem (19). As there is no existing result for this problem, i.e., none of the works

[6]The simulations are performed on a desktop computer with a core i7 @ 3.6 GHz CPU and 16 GB RAM.

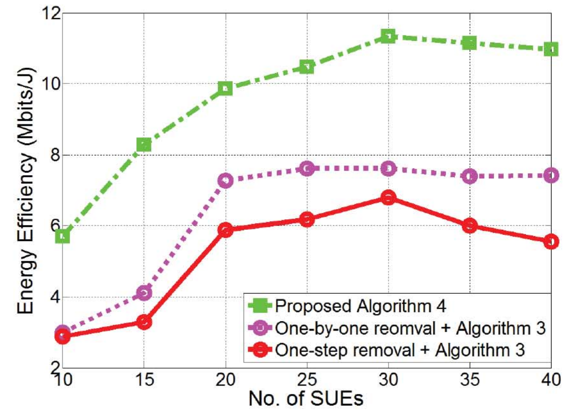


(a)

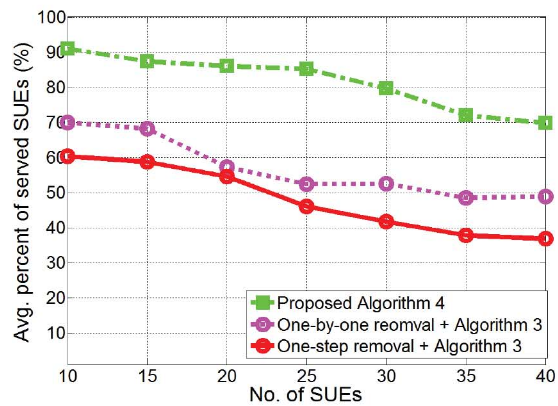


(b)

Fig. 2. Performance comparison results of the proposed Algorithm 3 with the MMDN method in [29, Algorithm 2], for SNR = 25 dB by varying the number of SUE.



(a)



(b)

Fig. 3. Performance comparison results of the proposed Algorithm 4 with the existing methods, for SNR = 25 dB by varying the number of SUE.

cited in Remark 3 considered this problem, we compare the proposed Algorithm 4 with the one-step removal and one-by-one removal algorithms in Remark 3, by replacing the SEM problem (4) with the EEM problem (18) (without the minimum rate constraints and with all SUE in $\mathcal{N}_s$). The proposed Algorithm 3 is used to solve (18). As seen in Fig. 3, in terms of both the EE and the number of admitted SUE, the proposed Algorithm 4 significantly outperforms the heuristic one-step removal and one-by-one removal algorithms.

By comparing 3(a) with Fig. 2(a), one can also see how the admission control can improve the network EE. Specifically, it is interesting to see that the values of network EE in Fig. 3(a) are not only larger than those in Fig. 2(a) but also increase with the number of SUE as long as the number of SUE is less than 30. However, when the number of SUE is large enough (larger than 30 in Fig. 3(a)), the circuit power consumption $N_s P_c$ would become more dominant than the transmission power and moreover it increases in a faster rate than the network sum rate. Therefore, the network EE eventually decreases with the number of SUE as observed in Fig. 3(a). Note that the number of SUE for which the EE starts to decrease (30 in Fig. 3(a)) depends on system parameters (e.g., P_c, number of SUE and number of PRBs etc.) and channel conditions, and can change from one scenario to another.

D. Comparison of Algorithms for Solving JPAC-OFDMA-SEM Problem (28)

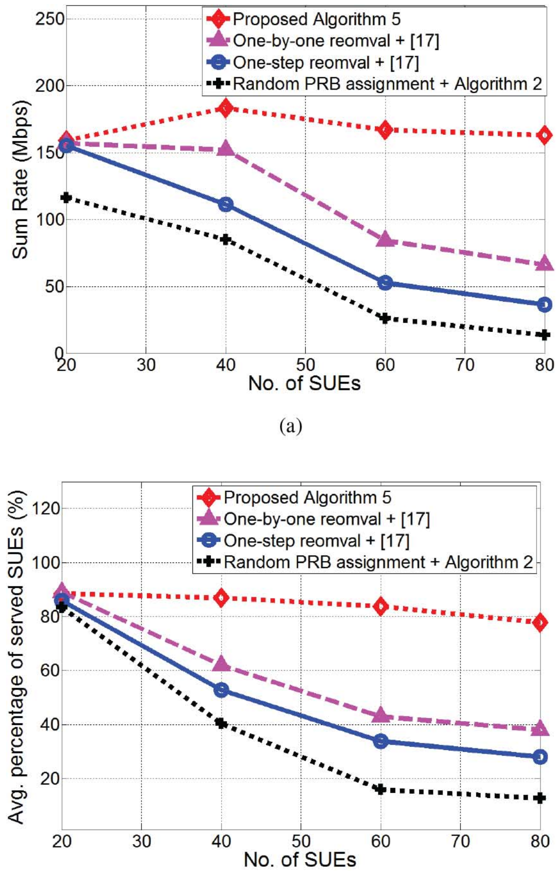
We now examine the performance of the proposed Algorithm 5 for solving the JPAC-OFDMA-SEM problem (28). Instead of setting the parameter ε as a constant and updating $\{\rho_{k_j}^n\}$ by (37) in Algorithm 5, we follow [22] to update ε and $\{\rho_{k_j}^n\}$ as follows:

$$\varepsilon[i+1] = \min[i]\left\{\varepsilon, 0.01\left[\left\{\frac{p_\ell^n[i]}{P_\ell^{\max}}\right\}_{\ell\in\mathcal{N}_u}\right]_2\right\}, \quad (42)$$

$$\rho_{k_j}^n[i+1] = q\left(\frac{p_{k_j}^n[i]}{P_{k_j}^{\max}} + \varepsilon[i+1]\right)^{(q-1)}, \quad (43)$$

where the initial $\varepsilon = 10^{-4}$, $\rho_{k_j}^n[0] = q(\alpha_{k_j}^n[0] + \varepsilon)^{q-1}$, and $[\{p_\ell^n[i]/P_\ell^{\max}\}_{\ell\in\mathcal{N}_u}]_2$ denote the second largest value in the set $\{p_\ell^n[i]/P_\ell^{\max}\}_{\ell\in\mathcal{N}_u}$. In particular, the update rule (43) was empirically found to speed up the convergence of the algorithm in [22] as well as in our Algorithm 5. The parameters q and ν are set to 0.8 and $\max_{\ell\in\mathcal{N}_u} N_\ell P_\ell^{\max}$, respectively.

To assess the performance of proposed Algorithm 5, we consider using a method that randomly assigns the PRBs to the SUE as a benchmark exercise. Once the PRBs are assigned, problem (28) is reduced to a problem analogous to problem (8)



(a)

(b)

Fig. 4. Performance comparison results of the proposed Algorithm 5 with the existing methods, for $N_{\text{SAP}} = 10$, SNR $= 25$ dB by varying the number of SUE.

which can be processed via Algorithm 2. In addition, we also consider the one-step removal and one-by-one removal algorithms, in which the SEM problem (4) is replaced by the OFDMA-constrained SEM problem (32). We adopt the alternating optimization method proposed in [20, Table 1] to solve problem (32).

Fig. 4 presents the simulations results for a scenario with 10 small cells and various numbers of SUE per cell ($N_j = 2, 4, 6, 8$). The SAPs are uniformly located in a region with a radius of 100 m. As shown in the figure, the proposed Algorithm 5 significantly outperforms the other three methods under evaluation. Interestingly, the performance gap becomes larger when the number of SUE in the small-cell network increases. This clearly demonstrates the ability of the proposed Algorithm 5 to exploit all the degrees of freedom (provided by power control, admission control, and PRB assignment) to mitigate the co-tier interference. In addition, the proposed Algorithm 5 was shown capable of optimizing both the system throughput and the number of served SUE.

VII. Conclusion and Future Direction

In this paper, we have proposed a JPAC framework for solving the two-stage admission control and power allocation problem in an OFDMA-based heterogeneous network. In particular, we propose to reformulate the two-stage design problem as a single JPAC problem and solve the JPAC problem via SCA techniques and adaptive SUE deflation. Both JPAC formulations for SE maximization and EE maximization were respectively considered. For the EE maximization problem without admission control (i.e., (18)), we have also proposed an approximation algorithm (Algorithm 3) which is shown computationally more efficient than the conventional methods based on Dinkelbach's procedure. By imposing OFDMA constraints upon the small cells, we also showed that the classical IRM method for ℓ_q-norm minimization can easily be integrated into the proposed JPAC formulation to perform joint power control, PRB assignment, and SUE admission control. The presented simulation results have shown that, for both SE and EE maximization, the proposed algorithms can significantly outperform the existing methods not only in terms of the achievable SE/EE but also in terms of the number of served SUE.

There are several interesting directions for future research. First, while the current paper focuses on centralized solutions to the JPAC problems, it is worth studying distributed and parallel algorithms. In decentralized scenarios, distributed algorithms not only allow for SAPs to make decision by themselves but also avoid excessive CSI exchange. In a centralized scenario, distribtued algoirithms enable efficient parallel implementation and thus are particularly suitable for solving resource allocation problems due to large numbers of small cells. Second, robust JPAC algorithms that account for imperfect CSI are of great importance for providing guaranteed QoS in practical scenarios. Third, as the current work is interested in the network EE in (17), it is worthwhile to study JPAC algorithms for maximizing the weighted sum of EE of individual SUE as is considered in [17], [25], [26], [28]–[30]. Finally, while efficient JPAC algorithms for both SE and EE have been respectively proposed in the paper, the connection between JPAC-SEM and JPAC-EEM solutions is not studied. Recently, [30] has analyzed the connection between beaforming solutions of SEM and EEM without admission control, and used it to develop efficient algorithms. It is therefore interesting to see if the JPAC-SEM and JPAC-EEM problems can have similar connection and insights which may improve the algorithm efficiency further.

Appendix

Proof of Theorem 1: We first show that (8b)-(8d) are equivalent to (6b)-(6d). Let $\{\hat{\beta}_j, \{\hat{\boldsymbol{p}}_j\}\}_{j\in\mathcal{N}_s}$, where $\hat{\boldsymbol{p}}_j = [\hat{p}_j^1, \ldots, \hat{p}_j^{N_{\text{rb}}}]^T$, be a feasible point of (8b)-(8d), and denote $\hat{\mathcal{B}} = \{j|\hat{\beta}_j = 1\}$ and $\{\hat{r}_j\}_{j\in\hat{\mathcal{B}}}$ as the achievable rates of the admitted SUE. Notice that $\hat{r}_j = 0 \forall j \notin \hat{\mathcal{B}}$ due to (8c). Then it is easy to see that $\{\hat{\beta}_j, \{\hat{\boldsymbol{p}}_j\}\}_{j\in\mathcal{N}_s}$ is also feasible to (6b)-(6d). Analogously, let $\{\bar{\beta}_j, \{\bar{\boldsymbol{p}}_j\}\}_{j\in\mathcal{N}_s}$, where $\bar{\boldsymbol{p}}_j = [\bar{p}_j^1, \ldots, \bar{p}_j^{N_{\text{rb}}}]^T$, be a feasible point of (6b)-(6d), and denote $\bar{\mathcal{B}} = \{j|\bar{\beta}_j = 1\}$ and $\{\bar{r}_j\}_{j\in\bar{\mathcal{B}}}$ as the achievable rates of the admitted SUE ($\bar{r}_j = 0 \forall j \notin \bar{\mathcal{B}}$). Then, $\{\bar{\beta}_j, \{\bar{\boldsymbol{p}}_j\}\}_{j\in\mathcal{N}_s}$ is also feasible for (8b)-(8d) provided that $\delta_j^{-1} \geq R_j^{\min}$ (i.e., (10)). Thus, (8b)-(8d) and (6b)-(6d) describe the same feasible set.

Next, we show that the subset of SUE selected by the JPAC-SEM problem (8) is optimal to the admission control problem (6). Assume that $\{\hat{\beta}_j, \{\hat{\boldsymbol{p}}_j\}\}_{j\in\mathcal{N}_s}$ is an optimal solution to problem (8), and that $\{\bar{\beta}_j, \{\bar{\boldsymbol{p}}_j\}\}_{j\in\mathcal{N}_s}$ is an optimal solution to problem (6). Further, suppose that $\{\hat{\beta}_j, \{\hat{\boldsymbol{p}}_j\}\}_{j\in\mathcal{N}_s}$ is not optimal to problem (6). Then, it must be

$$\sum_{j\in\bar{\mathcal{B}}} \bar{\beta}_j \geq \sum_{j\in\hat{\mathcal{B}}} \hat{\beta}_j + 1. \tag{A.1}$$

Equation (A.1) implies that

$$\begin{aligned}(1-\lambda)&\sum_{j\in\bar{\mathcal{B}}} \bar{\beta}_j + \lambda \sum_{j\in\bar{\mathcal{B}}} w_j \bar{r}_j \\ &\geq (1-\lambda)\left(\sum_{j\in\hat{\mathcal{B}}} \hat{\beta}_j + 1\right) + \lambda \sum_{j\in\bar{\mathcal{B}}} w_j \bar{r}_j \\ &\geq (1-\lambda)\sum_{j\in\hat{\mathcal{B}}} \hat{\beta}_j + (1-\lambda) + \lambda \min_{j\in\mathcal{N}_s} w_j R_j^{\min}, \end{aligned} \tag{A.2}$$

where the last inequality is due to (6b). We can then bound the optimal objective value of problem (8) as follows:

$$\begin{aligned}(1-\lambda)&\sum_{j\in\hat{\mathcal{B}}} \hat{\beta}_j + \lambda \sum_{j\in\hat{\mathcal{B}}} w_j \hat{r}_j \\ &= (1-\lambda)\sum_{j\in\hat{\mathcal{B}}} \hat{\beta}_j \\ &\quad + \lambda \sum_{j\in\hat{\mathcal{B}}} w_j \sum_{n=1}^{N_{\text{rb}}} \log_2\left(1 + \frac{\hat{p}_j^n g_j^n}{\sum_{j'\neq j} \hat{p}_{j'}^n g_{j',j}^n + 1}\right) \\ &< (1-\lambda)\sum_{j\in\hat{\mathcal{B}}} \hat{\beta}_j + \lambda \sum_{j=1}^{N_s} w_j R_j^{\max}, \\ &\leq (1-\lambda)\sum_{j\in\bar{\mathcal{B}}} \bar{\beta}_j + \lambda \sum_{j\in\bar{\mathcal{B}}} w_j \bar{r}_j + \frac{\lambda}{\lambda^{\max}} - 1, \end{aligned} \tag{A.3}$$

where the first inequality is due to (8c) and the definition of $R_j^{\max} \triangleq \sum_{n=1}^{N_{\text{rb}}} \log_2(1 + g_j^n P_j^{\max})$, and the last inequality is obtained by applying (A.2) and the definition of $\lambda^{\max}$ in (9). By choosing $\lambda \leq \lambda^{\max}$, one obtains that $(1-\lambda)\sum_{j\in\hat{\mathcal{B}}} \hat{\beta}_j + \lambda \sum_{j\in\hat{\mathcal{B}}} w_j \hat{r}_j < (1-\lambda)\sum_{j\in\bar{\mathcal{B}}} \bar{\beta}_j + \lambda \sum_{j\in\bar{\mathcal{B}}} w_j \bar{r}_j$, which however contradicts with the optimality of $\{\hat{\beta}_j, \{\hat{\boldsymbol{p}}_j\}\}_{j\in\mathcal{N}_s}$ to problem (8). Therefore, $\{\hat{\beta}_j, \{\hat{\boldsymbol{p}}_j\}\}_{j\in\mathcal{N}_s}$ is also optimal to problem (6) and $\hat{\mathcal{B}}$ is an optimal subset of SUE. By fixing $\hat{\mathcal{B}}$ in problem (8), the remaining power control problem becomes the same as problem (6). As a result, solving problem (8) is equivalent to solving the two-stage problems (6) and (7). Finally, if problem (6) has multiple $\mathcal{B}^\star$, problem (8) would provide the best subset of SUE which gives the largest SE, because problem (8) jointly searches the optimal subset of SUE and optimizes the associated SE. ■

Proof of Proposition 1: It is easy to verify that inequality constraints (14b) must hold with equality for the optimal solution. Therefore, problem (14) is actually equivalent to the following problem

$$(\boldsymbol{\beta}[i+1], \boldsymbol{p}[i+1]) = \arg \max_{\substack{p_j^n \geq 0 \beta_j \in [0,1], \\ \forall j,n}} \mathcal{U}(\boldsymbol{\beta}, \boldsymbol{p}|\boldsymbol{p}[i]) \tag{A.4a}$$

$$\text{s.t.} \quad u_j(\boldsymbol{p}, \boldsymbol{p}[i]) + \delta_j^{-1}(1-\beta_j) \geq R_j^{\min}, \forall j \in \mathcal{N}_s, \tag{A.4b}$$

$$\text{constraints (8c), (8d),} \tag{A.4c}$$

where $\mathcal{U}(\boldsymbol{\beta}, \boldsymbol{p}|\{\boldsymbol{p}[i]\}) \triangleq \lambda \sum_{j=1}^{N_s} w_j u_j(\boldsymbol{p}, \boldsymbol{p}[i]) + (1-\lambda) \sum_{j=1}^{N_s} \beta_j$. Note that $r_j(\boldsymbol{p}_j) \geq u_j(\boldsymbol{p}, \boldsymbol{p}[i])$ and $r_j(\boldsymbol{p}_j) = u_j(\boldsymbol{p}_j, \boldsymbol{p}_j)$ according to (12). Moreover, $u_j(\boldsymbol{p}, \boldsymbol{p}[i])$ in (15) is strongly concave on the feasible set of (A.4) [46, Lemma 3.1]. Denote $\boldsymbol{x} = [\boldsymbol{\beta}^T, \boldsymbol{p}^T]^T$. Thus, for some constant $c > 0$, we have

$$\begin{aligned} F(\boldsymbol{x}[i]) &= \mathcal{U}(\boldsymbol{x}[i]|\boldsymbol{p}[i]) \\ &\leq \mathcal{U}(\boldsymbol{x}[i+1]|\boldsymbol{p}[i]) + \nabla\mathcal{U}(\boldsymbol{x}[i+1]|\boldsymbol{p}[i])^T \\ &\quad \times (\boldsymbol{x}[i] - \boldsymbol{x}[i+1]) - \frac{c}{2}\|\boldsymbol{x}[i+1] - \boldsymbol{x}[i]\|_2^2 \\ &\leq \mathcal{U}(\boldsymbol{x}[i+1]|\boldsymbol{p}[i]) - \frac{c}{2}\|\boldsymbol{x}[i+1] - \boldsymbol{x}[i]\|_2^2 \\ &\leq F(\boldsymbol{x}[i+1]) - \frac{c}{2}\|\boldsymbol{x}[i+1] - \boldsymbol{x}[i]\|_2^2 \end{aligned} \tag{A.5}$$

where the second inequality is true by the first-order optimality condition of (A.4), i.e., $\nabla\mathcal{U}(\boldsymbol{x}[i+1]|\boldsymbol{p}[i])^T(\boldsymbol{x} - \boldsymbol{x}[i+1]) \leq 0$ for all $\boldsymbol{x}$ feasible (A.4). Since $F(\boldsymbol{\beta}[i+1], \boldsymbol{p}[i+1])$ must be upper bounded due to constraints (8c) and (8d), (A.5) shows that $F(\boldsymbol{\beta}[i+1], \boldsymbol{p}[i+1])$ converges as $i \to \infty$. To show that any regular limit point of $(\boldsymbol{\beta}[i+1], \boldsymbol{p}[i+1])$ is a KKT point of problem (11), we extend the analysis in [46, Proposition 3.2] to problem (A.4). Obverse from (A.5) that $\|\boldsymbol{x}[i+1] - \boldsymbol{x}[i]\|_2 \to 0$ as $i \to \infty$. Then, by following similar steps as the proof of [46, Proposition 3.2], one can conclude the desired claim in Proposition 1. ■

Proof of Lemma 1: Let $\{\tilde{\gamma}, \tilde{p}_j^n, \tilde{\beta}_j\}$ be a feasible solution of (26b)-(26f) and denote $\tilde{r}_j$ as the corresponding achievable rates (i.e., (3)). Consider the index subset $\mathcal{B}_0 = \{j|\tilde{\beta}_j = 0\}$. Then, (26d) implies $\tilde{r}_j = 0\ \forall j \in \mathcal{B}_0$, and thus $\tilde{p}_j^n = 0 \forall n \in \mathcal{N}_{\text{rb}}, j \in \mathcal{B}_0$, which implies that (19c) is satisfied for all $j \in \mathcal{B}_0$. Because $\tilde{r}_j = 0$ and $\tilde{\beta}_j = 0\ \forall j \in \mathcal{B}_0$, and given $\delta_j^{-1} \geq R_j^{\min}$, (19b) is also satisfied for all $j \in \mathcal{B}_0$. On the other hand, consider indices j in $\mathcal{B}_1 = \{j|\tilde{\beta}_j = 1\}$. It is obvious that (26c) implies that (19c) holds for all $j \in \mathcal{B}_1$. Because (26b) with $\tilde{\beta} = 1$ implies $\tilde{r}_j \geq R_j^{\min}$, we have that (19b) holds for all $j \in \mathcal{B}_1$. Therefore, we conclude that $\{\tilde{\gamma}, \tilde{p}_j^n, \tilde{\beta}_j\}$ is also feasible for (19b)-(19d). Conversely, it can also be shown that any feasible point of (19b)-(19d) is also feasible for (26b)-(26f). ■

REFERENCES

[1] Small Cell Forum, "Interference management in UMTS femtocells," White Paper, Feb. 2010.

[2] T. Quek, G. De, I. Guvenc, and M. Kountouris, *Small Cell Networks: Deployment, PHY Techniques, and Resource Management*. Cambridge, U.K.: Cambridge Univ. Press, 2013.

[3] M. Peng, Y. Li, J. Jiang, J. Li, and C. Wang, "Heterogeneous cloud radio access networks: A new perspective for enhancing spectral and energy efficiencies," *IEEE Wireless Commun.*, vol. 21, no. 6, pp. 126–135, Dec. 2014.

[4] M. Gerasimenko *et al.*, "Cooperative radio resource management in heterogeneous cloud radio access networks," *IEEE Access*, vol. 3, no. 6, pp. 397–406, Apr. 2015.

[5] T. Zahir, K. Arshad, A. Nakata, and K. Moessner, "Interference management in femtocells," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 1, pp. 293–311, Feb. 2013.

[6] R. Zhang, Y. Liang, and S. Cui, "Dynamic resource allocation in cognitive networks," *IEEE Signal Process. Mag.*, vol. 27, no. 3, pp. 102–114, May 2010.

[7] E. Yaacoub and Z. Dawy, "A survey on uplink resource allocation in OFDMA wireless networks," *IEEE Commun. Surveys Tuts.*, vol. 14, no. 2, pp. 332–337, May 2012.

[8] M. Naeem, A. Anpalagan, M. Jaseemuddin, and D. C. Lee, "Resource allocation techniques in cooperative cognitive radio networks," *IEEE Commun. Surveys Tuts.*, vol. 16, no. 2, pp. 729–744, May 2014.

[9] IMT, "IMT vision towards 2020 and beyond," IMT-2020 (5G) Promotion Group, Feb. 2014.

[10] 4G Americas, "4G Americas recommendations on 5G requirements and solutions," Oct. 2014.

[11] International Telecommunication Union Radio communication Sector (ITU-R), "Guidelines for evaluation of radio interface technologies for IMT-Advanced," Tech. Rep. ITU-R M.2135, 2008 [Online]. Available: http://www.itu.int/en/ITU-R/Pages/default.aspx.

[12] L. Le and E. Hossain, "Resource allocation for spectrum underlay in cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 7, no. 12, pp. 5306–5315, Dec. 2008.

[13] A. Leith, D. I. Kim, M.-S. Alouini, and Z. Wu, "Distributed optimization of a multisubchannel ad hoc cognitive radio network," *IEEE Trans. Veh. Technol.*, vol. 61, no. 4, pp. 1786–1800, May 2012.

[14] D. I. Kim, L. Le, and E. Hossain, "Joint rate and power allocation for cognitive radios in dynamic spectrum access environment," *IEEE Trans. Wireless Commun.*, vol. 7, no. 12, pp. 5517–5527, Dec. 2008.

[15] M. Monemi, M. Rasti, and E. Hossain, "On joint power and admission control in underlay cellular cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 14, no. 1, pp. 265–278, Jan. 2015.

[16] H.-Y. Gu, C.-Y. Yang, and B. Fong, "Low-complexity centralized joint power and admission control in cognitive radio networks," *IEEE Commun. Lett.*, vol. 13, no. 6, pp. 420–422, Jun. 2009.

[17] L. Le, D. Niyato, E. Hossain, D. Kim, and D. Hoang, "QoS-aware and energy-efficient resource management in OFDMA femtocells," *IEEE Trans. Wireless Commun.*, vol. 12, no. 1, pp. 180–194, Jan. 2013.

[18] I. Mitliagkas, N. D. Sidiropoulos, and A. Swami, "Joint power and admission control for ad-hoc and cognitive underlay networks: Convex approximation and distributed implementation," *IEEE Trans. Wireless Commun.*, vol. 10, no. 12, pp. 4110–4121, Dec. 2011.

[19] Y.-F. Liu, Y.-H. Dai, and Z.-Q. Luo, "Joint power and admission control via linear programming deflation," *IEEE Trans. Signal Process.*, vol. 61, no. 6, pp. 1327–1338, Feb. 2013.

[20] L. Venturino, N. Prasad, and X. Wang, "Coordinated scheduling and power allocation in downlink multicell OFDMA networks," *IEEE Trans. Veh. Technol.*, vol. 58, no. 6, pp. 2835–2848, Jul. 2009.

[21] T. Wang and L. Vandendorpe, "Iterative resource allocation for maximizing weighted sum min-rate in downlink cellular OFDMA systems," *IEEE Trans. Signal Process.*, vol. 59, no. 1, pp. 223–234, Jan. 2011.

[22] P. Liu, Y.-F. Liu, and J. Li, "An iterative reweighted minimization framework for joint channel and power allocation in the OFDMA system," in *Proc. IEEE Int. Conf. Acoust. Speech Signal Process. (ICASSP)*, Brisbane, QLD, Australia, Apr. 19–24, 2015, pp. 3068–3071.

[23] D. Sabella *et al.*, "Energy efficiency benefits of ran-as-a-service concept for a cloud-based 5G mobile network infrastructure," *IEEE Access*, vol. 2, no. 99, pp. 265–278, Jan. 2015.

[24] C.-L. I, C. Rowell, S. Han, Z. Xu, G. Li, and Z. Pan, "Toward green and soft: A 5G perspective," *IEEE Commun. Mag.*, vol. 52, no. 2, pp. 66–73, Feb. 2014.

[25] G. W. Miao, N. Himayat, G. Y. Li, A. T. Koc, and S. Talwar, "Interference-aware energy-efficient power optimization," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Dresden, Germany, Jun. 2009, pp. 1–5.

[26] G. Miao, N. Himayat, G. Li, and S. Talwar, "Distributed interference aware energy-efficient power optimization," *IEEE Trans. Wireless Commun.*, vol. 10, no. 4, pp. 1323–1333, Apr. 2011.

[27] A. Aijaz, X. Chu, and A. H. Aghvami, "Energy efficient design of SC-FDMA based uplink under QoS constraints," *IEEE Trans. Wireless Commun. Lett.*, vol. 3, no. 2, pp. 149–152, Apr. 2014.

[28] L. Venturino, A. Zappone, C. Risi, and S. Buzzi, "Energy-efficient scheduling and power allocation in downlink OFDMA networks with base station coordination," *IEEE Trans. Wireless Commun.*, vol. 14, no. 1, pp. 1–14, Jan. 2015.

[29] R. Ramamonjison and V. K. Bhargava, "Energy efficient maximization framework in cognitive downlink two-tier networks," *IEEE Trans. Wireless Commun.*, vol. 14, no. 3, pp. 1468–1478, Mar. 2015.

[30] L. Venturino and S. Buzzi, "Energy-aware and rate-aware heuristic beamforming in downlink MIMO OFDMA networks with base station coordination," *IEEE Trans. Veh. Technol.*, vol. 67, no. 7, pp. 2897–2910, Jul. 2015.

[31] Z.-Q. Luo and S. Zhang, "Dynamic spectrum management: Complexity and duality," *IEEE J. Sel. Topics Signal Process.*, vol. 2, no. 1, pp. 57–73, Feb. 2008.

[32] W. Dinkelbach, "On nonlinear fractional programming," *Manage. Sci.*, vol. 13, no. 7, pp. 492–498, Mar. 1967.

[33] 3GPP, "Evolved universal terrestrial radio access (E-UTRA) and evolved universal terrestrial radio access network (E-UTRAN); Overall description," 3GPP TS-36.300 v11.2.0, Jun. 2012.

[34] I. C. Wong, O. Oteri, and W. McCoy, "Optimal resource allocation in uplink SC-FDMA systems," *IEEE Trans. Wireless Commun.*, vol. 8, no. 5, pp. 2161–2165, May 2009.

[35] W.-C. Li, T.-H. Chang, C. Lin, and C.-Y. Chi, "Coordinated beamforming for multiuser MISO interference channel under rate outage constraints," *IEEE Trans. Signal Process.*, vol. 61, no. 5, pp. 1087–1103, May 2013.

[36] S.-J. Kim and G. B. Giannakis, "Optimal resource allocation for MIMO ad hoc cognitive radio networks," *IEEE Trans. Inf. Theory*, vol. 57, no. 5, pp. 3117–3131, May 2011.

[37] M. Grant and S. Boyd. (2010, Jul.). *CVX: Matlab Software for Disciplined Convex Programming*, version 1.21 [Online]. Available: http://cvxr.com/cvx

[38] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[39] Y.-F. Liu and Y.-H. Dai, "On the complexity of joint subcarrier and power allocation for multi-user OFDMA systems," *IEEE Trans. Signal Process.*, vol. 62, no. 3, pp. 583–596, Feb. 2014.

[40] C. Y. Wong, R. S. Cheng, K. B. Letaief, and R. D. Murch, "Multiuser OFDM with adaptive subcarrier, bit and power allocations," *IEEE J. Sel. Areas Commun.*, vol. 17, no. 10, pp. 1747–1758, Oct. 1999.

[41] K. Seong, M. Mohseni, and J. Cioffi, "Optimal resource allocation for OFDMA downlink systems," in *Proc. IEEE Int. Symp. Inf. Theory*, Seattle, WA, USA, Jul. 2006, pp. 1394–1398.

[42] W. Yu and R. Lui, "Dual methods for nonconvex spectrum optimization of multicarrier systems," *IEEE Trans. Commun.*, vol. 54, no. 7, pp. 1310–1322, Jul. 2006.

[43] J. Nocedal and S. J. Wright, *Numerical Optimization*, 2nd ed. New York, NY, USA: Springer, 2006.

[44] 3GPP, "Evolved universal terrestrial radio access (E-UTRA); Further advancements for E-UTRA physical layer aspects," 3GPP TR-36.814 v9.0.0, Release 9, Mar. 2010.

[45] 3GPP, "Evolved universal terrestrial radio access (E-UTRA); Base station (BS) radio transmission and reception," 3GPP TS-36.104 v10.2.0, Relase 10, May 2011.

[46] A. Beck, A. Ben-Tal, and L. Tetruashvili, "A sequential parametric convex approximation method with applications to nonconvex truss topology design problems," *J. Global Optim.*, vol. 47, pp. 29–51, Jul. 2009.

Wei-Sheng Lai received the B.S. degree in electrical engineering from National Taipei University of Technology, Taipei, Taiwan, in 2002, and the Master's degree in electrical engineering from National Sun Yat-Sen University, Kaohsiung, Taiwan, in 2004. He is currently pursuing the Ph.D. degree at the Institute of communication engineering, National Chiao Tung University, Hsinchu, Taiwan. He is also an Assistant Researcher with the National Chung-Shan Institute of Science and Technology (NCSIST), Taoyuan, Taiwan. His research interests include wireless communication and network, signal processing, and moving target estimation, deployment of small cell networks, heterogeneous networks, optimal resource allocation design, and game-theoretic models for communication networks.

Tsung-Hui Chang (S'07–M'08) received the B.S. degree in electrical engineering and the Ph.D. degree in communications engineering from National Tsing Hua University (NTHU), Hsinchu, Taiwan, in 2003 and 2008, respectively. He is currently an Assistant Professor with the School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen, China. From 2012 to 2015, he was an Assistant Professor with the Department of Electronic and Computer Engineering, National Taiwan University of Science and Technology (NTUST), Taipei, Taiwan. He held research positions with the NTHU, from 2008 to 2011, and the University of California, Davis, CA, USA, from 2011 to 2012. His research interests include signal processing and optimization problems in data communications, smart grid, and machine learning.

Dr. Chang currently serves as an Associate Editor of the IEEE TRANSACTIONS ON SIGNAL PROCESSING and the IEEE TRANSACTIONS ON SIGNAL AND INFORMATION PROCESSING OVER NETWORKS. He was the recipient of the Young Scholar Research Award of NTUST in 2014 and the IEEE ComSoc Asian-Pacific Outstanding Young Researcher Award in 2015.

Ta-Sung Lee (S'88–M'89–SM'05–F'16) received the B.S. degree from National Taiwan University, Taipei, Taiwan, in 1983, the M.S. degree from University of Wisconsin-Madison, Madison, WI, USA, in 1987, and the Ph.D. degree from Purdue University, West Lafayette, IN, USA, in 1989, all in electrical engineering. In 1990, he joined the Faculty of National Chiao Tung University (NCTU), Hsinchu, Taiwan, where he holds a position as a Professor of the Department of Electrical and Computer Engineering. From 1999 to 2001, he was the Director of Communications and Computer Continuing Education Program, NCTU. From 2005 to 2007, he was the Chairman of the Department of Communication Engineering, and from 2007 to 2008 and 2012 to 2013, he was the Dean of Student Affairs, NCTU. From 2008 to 2010, he was the Commissioner of the National Communications Commission (NCC), a regulatory agency of Taiwan similar to the FCC, and responsible for the strategic planning, policy making, and technical regulation for the telecommunications and broadcasting services. He has been the Chairman of Telecom Technology Center, a government funded agency for telecommunications R&D, since 2013. His research interests include signal processing and system design for wireless communications. He was the Vice Chairman and the Chairman of the IEEE Communications Society Taipei Chapter from 2005 to 2008, a Board Member of the IEEE Taipei Section from 2007 to 2010, an Associate Editor of the IEEE TRANSACTIONS ON SIGNAL PROCESSING from 2009 to 2013, and the IEEE Signal Processing Society Regional Director-at-Large for R10 from 2011 to 2013. He is currently an Area Editor of *Journal of Signal Processing Systems*. He was the recipient of several awards for his research, engineering, and education contributions including Young Electrical Engineer Award of the Chinese Institute of Electrical Engineering (CIEE), Distinguished Electrical Engineering Professor Award of CIEE, NCTU Distinguished Scholar Award, and NCTU Teaching Award.