

Chapter 2

Bandwidth-Efficient Joint User-Association and Resource-Allocation in Multi-Cell VWN

This chapter addresses the user association and resource allocation problem in a multi-cell VWN where users belong to different slices with each slice requiring a minimum reserved rate from the network. We formulate a bandwidth-efficient joint user-association and resource-allocation scheme that assigns users to BS and allocates the sub-carriers and power to maximize the total achieved sum-rate of the network subject to the rate reservation per slices. The original problem is converted into computationally tractable form using variable relaxation and complementary geometric programming (CGP). The simulation results demonstrate the performance improvement obtained with the proposed iterative algorithm compared to the conventional max SINR-based approach for user association.

2.1 Introduction

In a *virtualized wireless network* (VWN), the physical resources of one network provider, e.g., spectrum, power, and infrastructure are shared among different service providers, also called slices [1, 2]. Generally, each slice comprises of a set of users, and has its own quality-of-service (QoS) requirements. To harvest the potential advantages of VWN, effective resource allocation is a major concern which has been addressed in a number of works.

For instance, in [1], a resource management scheme is studied by introducing two types of slices, including rate-based and resource-based slices, where the minimum rate and minimum network resources are preserved for each slice, respectively. Furthermore, in [3], interactions among slices, network operator, and users are modeled as an auction game where the network operator is responsible for spectrum management on a higher level, and each slice focuses on QoS management for its own users. To preserve the QoS of slices from wireless channel fading, the admission control policy is proposed in [4] where the requirement of each slice

is adjusted by the channel state information (CSI) of its own users. To extend the feasibility condition of VWN in order to support diverse QoS requirements, Jumba et al. [5] consider the use of massive MIMO where the access point is equipped with a large number of antennas. In [6], the combination of time, space and elastic resource allocation for OFDMA system is considered. Advantages of full-duplex transmission relay in VWN have been investigated in [7].

Generally, these works have focused on analyzing the resource allocation problem in a single-cell VWN scenario. However, in practice, the coverage of a specific region may require a set of BSs, in a multi-cell VWN scenario. The key question in such a multi-cell VWN scenario is how to allocate the resources to maintain the QoS of each slice, while improving the total performance of VWN over a specific region. In this chapter, we consider a multi-cell OFDMA based VWN where the coverage of a specific region is provided by a set of BSs serving different groups of users belonging to different slices. The QoS of each slice is represented by its minimum reserved rate. Each user of each slice can be only served by one BS and this BS is not predetermined by the distance or by measuring the average received signal strength of BSs. Consequently, in this setup, the resource sets in the related optimization problem involve the *set of BSs, sub-carriers* and *power* for each user belonging to each slice.

In the problem considered in this chapter, the objective of proposed resource allocation problem is to maximize the total throughput of VWN in the specific region subject to power limitation of BSs, minimum required rate of each slice, and sub-carrier and BS assignment limitations. Based on the limitations of downlink OFDMA transmission, each sub-carrier can be assigned to one user within a cell and each user can be associated to only one BS. Since in this optimization problem, the sub-carrier assignment and BS association are inter-related, we introduce the user association factor (UAF) that jointly determines the BS assignment and sub-carrier allocation as the optimization variable vector. Due to this user-association constraint and the inter-cell interference, the proposed optimization problem is non-convex and NP-hard, suffering from high computational complexity [8]. We apply the frameworks of complementary geometric programming (CGP) and the successive convex approximation (SCA) [9–12] to develop an efficient, iterative, two-step algorithm to solve the proposed problem. For a given power-allocation, the first step derives the optimum user-association solution, and subsequently, with this obtained user-association solution, the second step finds the optimal power allocation. This two-step optimization process is repeated until convergence. It can be shown that the simplified problem of each step still involves non-convex optimization problem. By applying various transformation and convexification techniques, we develop the analytical framework to transform the non-convex optimization problems encountered in each step into the equivalent lower-bound geometric programming (GP) problems, [11], which can be solved by available software packages, e.g., CVX [13].

Simulation results demonstrate that the proposed approach can significantly outperform the traditional scenario where the BS assignment is based on the largest average signal-to-interference-plus-noise ratio (SINR), and subsequent sub-carrier

and power allocation is derived for the users of each cell. The simulation results reveal that considering UAF can increase the feasibility of resource allocation problem (the required rate of each slice will be satisfied with a higher probability as compared to the traditional approach). Specifically, the proposed algorithm can significantly increase the probability of achieving higher rates for the cell-edge users, resulting better coverage for the VWN.

The rest of this chapter is organized as follows: Sect. 2.2 presents the system model considered in this problem along with the problem formulation. The proposed algorithm is discussed in Sect. 2.3 followed by Sect. 2.4 where we present the numerical results with concluding remarks in Sect. 2.5.

2.2 System Model and Problem Formulation

We consider the downlink transmission of a VWN where the coverage of a specific area is provided by a set of BSs, i.e., $\mathcal{L} = \{1, \dots, L\}$. The total bandwidth of W Hz is divided into a set of sub-carriers, $\mathcal{N} = \{1, \dots, N\}$ and shared by all BSs through orthogonal frequency-division multiple-access (OFDMA). The bandwidth of each sub-carrier, i.e., $\frac{W}{N}$, is assumed to be much smaller than the coherent bandwidth, W_c , of the wireless channel so that the channel response in each sub-carrier is flat. This set of BSs serves a set of slices, $\mathcal{S} = \{1, \dots, S\}$, where the slice s has a set of users $\mathcal{K}_s = \{1, \dots, K_s\}$ and requests for a minimum reserved rate of R_s^{rsv} and $K = \sum_{s \in \mathcal{S}} K_s$ is the total number of users. An illustration of the system model with 3 BSs is presented in Fig. 2.1.

Let $h_{l,k_s,n}$ and $P_{l,k_s,n}$ be the channel power gain (also representing the channel state information (CSI)), and the allocated power, respectively, of the link from BS $l \in \mathcal{L}$ to user k_s of slice s on sub-carrier n . Due to the OFDMA limitation, each user is assigned to one BS, and to avoid intra-cell interference, orthogonal sub-carrier assignment is assumed among users in a cell. The binary-valued user association factor (UAF) $\alpha_{l,k_s,n} \in \{0, 1\}$ represents both sub-carrier allocation and BS assignment indicator for user k_s of slice s on sub-carrier n of BS l , i.e., $\alpha_{l,k_s,n} = 1$ when BS l allocates sub-carrier n to user k_s , and $\alpha_{l,k_s,n} = 0$, otherwise.

Consider $\mathbf{P} = [P_{l,k_s,n}]_{\forall l,s,k_s,n}$ and $\boldsymbol{\alpha} = [\alpha_{l,k_s,n}]_{\forall l,s,k_s,n}$ as the vectors of all transmit powers and UAFs of users, respectively. The rate of user k_s at sub-carrier n of BS l can be expressed as

$$R_{l,k_s,n}(\mathbf{P}) = \log_2 \left[1 + \frac{P_{l,k_s,n} h_{l,k_s,n}}{\sigma^2 + I_{l,k_s,n}} \right], \quad (2.1)$$

where

$$I_{l,k_s,n} = \sum_{\forall l' \in \mathcal{L}, l' \neq l} \sum_{\forall s \in \mathcal{S}} \sum_{\forall k'_s \in \mathcal{K}_s, k'_s \neq k_s} P_{l',k'_s,n} h_{l',k'_s,n}$$

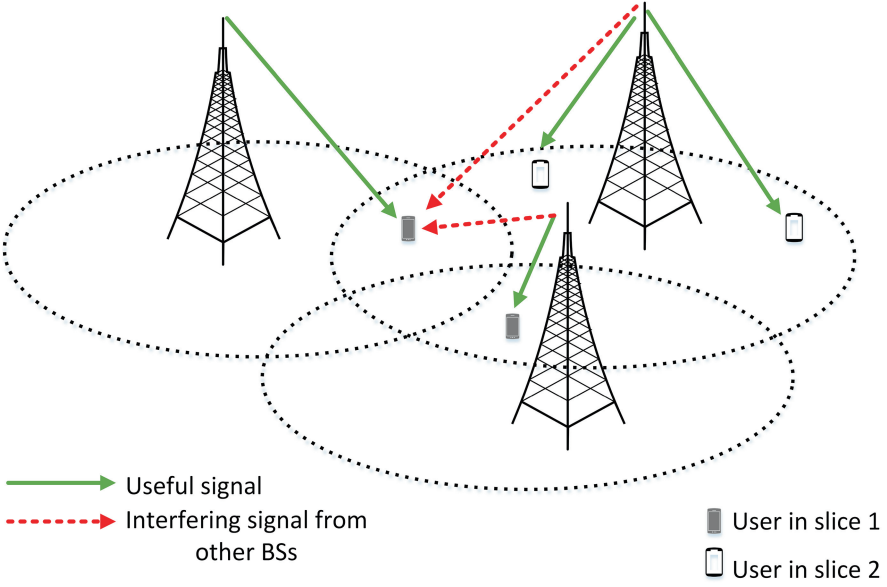


Fig. 2.1 Illustration of a multi-cell VWN with BSs serving users of different slices

is the interference to user k_s in BS l and sub-carrier n , and σ^2 is the noise power. Without loss of generality, noise power is assumed to be equal for all users in all sub-carriers and BSs. From (2.1), the required minimum rate of slice $s \in \mathcal{S}$ can be represented as

$$\text{C2.1 : } \sum_{l \in \mathcal{L}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n} R_{l,k_s,n}(\mathbf{P}) \geq R_s^{\text{rsv}}, \forall s \in \mathcal{S}.$$

We consider the maximum transmit power limitation of each BS as

$$\text{C2.2 : } \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} P_{l,k_s,n} \leq P_l^{\max}, \quad \forall l \in \mathcal{L},$$

where $P_l^{\max}$ is the maximum transmit power of BS l . Furthermore, the OFDMA exclusive sub-carrier allocation within each cell l can be expressed as

$$\text{C2.3 : } \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \alpha_{l,k_s,n} \leq 1, \quad \forall l \in \mathcal{L}, \quad \forall n \in \mathcal{N}.$$

In this setup, due to the limitation of multi-cell OFDMA, we restrict the access of each user by the following constraint

$$\text{C2.4 : } \left[\sum_{n \in \mathcal{N}} \alpha_{l,k_s,n} \right] \left[\sum_{\forall l' \neq l} \sum_{n \in \mathcal{N}} \alpha_{l',k_s,n} \right] = 0, \quad \forall k_s \in \mathcal{K}_s, \quad \forall s \in \mathcal{S}, \quad \forall l \in \mathcal{L}.$$

C2.4 implies that each user can be associated to only one BS. More specifically, C2.4 ensures when any sub-carrier n is assigned to user k_s by BS l , that user would not be assigned any sub-carriers by other BSs l' .

The joint power, sub-carrier and BS assignment can be formulated as

$$\begin{aligned} \max_{\alpha, \mathbf{P}} \quad & \sum_{l \in \mathcal{L}} \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n} R_{l,k_s,n}(\mathbf{P}), \\ \text{subject to: } & \text{C2.1--C2.4.} \end{aligned} \quad (2.2)$$

The optimization problem (2.2) has a non-convex objective function due to inter-cell interference and involves non-linear constraints with combination of continuous and binary variables, i.e., $\mathbf{P}$ and α . In other words, (2.2) is a non-convex mixed-integer, NP-hard optimization problem [8]. Therefore, proposing an efficient algorithm with reasonable computational complexity is desirable.

2.3 Proposed Two-Level Iterative Algorithm

To tackle the computational complexity of (2.2), we adopt the iterative approach to iteratively find the UAF and power allocation for each user in two steps as shown in Algorithm 2.1. In the first step, for a given power allocation vector, the UAF is considered as the variable of the user-association problem and solved by sub-algorithm 2.1.A (to be discussed in detail in Sect. 2.3.1).

This derived UAF is then used in the second step to find the corresponding allocated power as the solution of the power-allocation optimization problem by sub-algorithm 2.1.B (to be discussed in detail in Sect. 2.3.2). Both these steps are iteratively executed until both the current UAF and power allocation vector solutions are not much different from their values obtained in the previous iteration. In other words, the sequence of the UAF and power allocation vector solutions can be expressed as

$$\underbrace{\alpha(0) \rightarrow \mathbf{P}(0)}_{\text{Initialization}} \rightarrow \dots \underbrace{\alpha^*(t) \rightarrow \mathbf{P}^*(t)}_{\text{Iteration } t} \rightarrow \underbrace{\alpha^* \rightarrow \mathbf{P}^*}_{\text{Optimal solution}}, \quad (2.3)$$

where $t > 0$ is the iteration number and $\alpha^*(t)$ and $\mathbf{P}^*(t)$ are the optimal values at the iteration t from convex transformation of related optimization problems in each step. The iterative procedure is stopped when

$$||\alpha^*(t) - \alpha^*(t-1)|| \leq \varepsilon_1 \text{ and } ||\mathbf{P}^*(t) - \mathbf{P}^*(t-1)|| \leq \varepsilon_2$$

where $0 < \varepsilon_1 \ll 1$ and $0 < \varepsilon_2 \ll 1$.

Notably, both the user-association and power-allocation optimization problems are still non-convex and suffer from high computational complexity. To solve them

Algorithm 2.1 Iterative joint user-association and resource-allocation algorithm

Initialization: Set $t = 0$, and $\mathbf{P}(t = 0)$ such as power in each sub-carrier of BS l is $P_l^{\max}/K$.

Repeat: Set $t = t + 1$.

Step 1.A User Association:

Initialization for Step 1.A: Set $t_1 = 0$, $\alpha(t_1) = \alpha(t)$, $\mathbf{P}(t_1) = \mathbf{P}(t)$ and set arbitrary initial for $s_{k_s, n}(t_1)$.

Repeat: Set $t_1 = t_1 + 1$.

Step 1.A.1: Update $\lambda_{l, k_s}(t_1)$, $\xi_{l, k_s}(t_1)$, $v_{l, k_s, n}(t_1)$, $\eta_{l, k_s, n}(t_1)$ and $\varphi_{l, k_s, n}(t_1)$ using (2.5)–(2.8) and (2.15)–(2.17),

Step 1.A.2: Find optimal UAF in (2.14) using CVX [13],¹

Until $\|\alpha^*(t_1) - \alpha^*(t_1 - 1)\| \leq \varepsilon_1$,
set $\alpha(t) = \alpha^*(t_1)$.

Step 1.B Power Allocation:

Initialization for Step 1.B: Set $t_2 = 0$, $\alpha(t_2) = \alpha(t)$.

Repeat: Set $t_2 = t_2 + 1$.

Step 1.B.1: Update $\kappa_{l, k_s, n}(t_2)$, $\kappa_o(t_2)$ using (2.22),

Step 1.B.2: Find optimal power allocation according to (2.23) using CVX [13, 14]

Until $\|\mathbf{P}^*(t_2) - \mathbf{P}^*(t_2 - 1)\| \leq \varepsilon_2$,
set $\mathbf{P}(t) = \mathbf{P}^*(t_2)$.

Until $\|\alpha^*(t) - \alpha^*(t - 1)\| \leq \varepsilon_1$, and $\|\mathbf{P}^*(t) - \mathbf{P}^*(t - 1)\| \leq \varepsilon_2$.

efficiently, we apply complementary geometric programming (CGP) for each step [11] in which via different transformations and convexification approaches, the sequence of lower bound GP based approximation of relative optimization problem is solved as described next.

2.3.1 User-Association Problem

At the iteration t , with given $\mathbf{P}(t)$, we formulate the following user association optimization problem to maximize the sum rate,

$$\begin{aligned} \max_{\alpha} \quad & \sum_{l \in \mathcal{L}} \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} \alpha_{l, k_s, n} R_{l, k_s, n}(\mathbf{P}(t)), \\ \text{subject to:} \quad & \widetilde{\text{C2.1}}, \text{C2.3, C2.4,} \end{aligned} \quad (2.4)$$

where $R_{l, k_s, n}(\mathbf{P}(t))$ is computed by (1) with $\mathbf{P}(t)$ and

$$\widetilde{\text{C2.1}} : \sum_{l \in \mathcal{L}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} \alpha_{l, k_s, n} R_{l, k_s, n}(\mathbf{P}(t)) \geq R_s^{\text{rsv}}, \quad \forall s \in \mathcal{S}.$$

¹CVX chooses its own initialize value for vector α [13], which is applied for our algorithm to check the convergence condition.

In (2.4), the only optimization variable is α , and therefore, (2.4) has lower computational complexity than (2.2). However, it still suffers from the integer optimization variable α . In addition, due to C2.4 and the objective function, (2.4) is still a non-convex optimization problem. To overcome the computational complexity of (2.4), we follow the following steps: We first relax the UAF variable to be continuous as $\alpha_{l,k_s,n} \in [0, 1]$. Then, we apply the technique as described in **Proposition 1** to convert (2.4) into the GP formulation by transforming C2.4 into its related linear constraints, and the objective function to the monomial function from **Proposition 2**. Specifically, to have a standard GP formulation, the equality constraint in C2.4 should only involve monomial functions. In the following, we first relax C2.4 and then apply iterative AGMA approximation (as shown in (A.9) and (A.10) in the Appendix) to get the monomial approximation for C2.4.

Proposition 1 *At iteration t_1 in solving (2.4), define $x_{l,k_s}(t_1) = \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n}(t_1)$ and $y_{k_s}(t_1) = \sum_{l \in \mathcal{L}} \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n}(t_1)$. C2.4 can be approximated by the following constraints.*

$$C2.4.1: \quad z_{l,k_s}^{-1}(t_1) + x_{l,k_s}(t_1)y_{k_s}(t_1)z_{l,k_s}^{-1}(t_1) \leq 1, \quad \forall k_s \in \mathcal{K}_s, s \in \mathcal{S}, \forall l \in \mathcal{L},$$

$$C2.4.2: \quad \lambda_{l,k_s}(t_1)\lambda_{l,k_s}^{\lambda}(t_1)z_{l,k_s}(t_1) \times \left[\frac{x_{l,k_s}^2(t_1)}{\xi_{l,k_s}(t_1)} \right]^{-\xi_{l,k_s}(t_1)} \leq 1, \quad \forall k_s \in \mathcal{K}_s, \forall s, \forall l,$$

$$C2.4.3: \quad x_{l,k_s}(t_1) \prod_{n \in \mathcal{N}} \left[\frac{\alpha_{l,k_s,n}(t_1)}{v_{l,k_s,n}(t_1)} \right]^{-v_{l,k_s,n}(t_1)} = 1, \quad \forall k_s \in \mathcal{K}_s, s \in \mathcal{S}, \forall l \in \mathcal{L},$$

$$C2.4.4: \quad y_{k_s}(t_1) \prod_{l \in \mathcal{L}, n \in \mathcal{N}} \left[\frac{\alpha_{l,k_s,n}(t_1)}{\eta_{l,k_s,n}(t_1)} \right]^{-\eta_{l,k_s,n}(t_1)} = 1, \quad \forall k_s \in \mathcal{K}_s, \forall s, \forall l \in \mathcal{L},$$

where $z_{l,k_s}(t_1)$ is an auxiliary variable, and,

$$\lambda_{l,k_s}(t_1) = \frac{1}{x_{l,k_s}^2(t_1 - 1) + 1}, \quad (2.5)$$

$$\xi_{l,k_s}(t_1) = \frac{x_{l,k_s}^2(t_1 - 1)}{x_{l,k_s}^2(t_1 - 1) + 1}, \quad (2.6)$$

$$v_{l,k_s,n}(t_1) = \frac{\alpha_{l,k_s,n}(t_1 - 1)}{\sum_{n \in \mathcal{N}} \alpha_{l,k_s,n}(t_1 - 1)}, \quad (2.7)$$

$$\eta_{l,k_s,n}(t_1) = \frac{\alpha_{l,k_s,n}(t_1 - 1)}{\sum_{l \in \mathcal{L}} \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n}(t_1 - 1)}, \quad (2.8)$$

for all $k_s \in \mathcal{K}_s$, $s \in \mathcal{S}$, and $\forall l \in \mathcal{L}$.

Proof From the definition of $x_{l,k_s}(t_1)$ and $y_{k_s}(t_1)$, C2.4 can be rewritten as for all $k_s \in \mathcal{K}_s$, $s \in \mathcal{S}$ and $l \in \mathcal{L}$,

$$x_{l,k_s}(t_1)[y_{k_s}(t_1) - x_{l,k_s}(t_1)] = 0, \quad (2.9)$$

which is not a monomial function. Equation (2.9) can be rewritten as $x_{l,k_s}(t_1)y_{k_s}(t_1) = x_{l,k_s}^2(t_1)$ and by adding 1 to both the left and right hand sides, we have $x_{l,k_s}(t_1)y_{k_s}(t_1) + 1 = 1 + x_{l,k_s}^2(t_1)$ for all $k_s \in \mathcal{K}_s$, $s \in \mathcal{S}$, and $l \in \mathcal{L}$. We define $z_{l,k_s}(t_1) \geq 0$ as an auxiliary variable to relax and convert (2.9) into the posynomial inequalities as follows [9]

$$x_{l,k_s}(t_1)y_{k_s}(t_1) + 1 \leq z_{l,k_s}(t_1) \leq 1 + x_{l,k_s}^2(t_1), \quad \forall k_s \in \mathcal{K}_s, \forall s \in \mathcal{S}, \forall l \in \mathcal{L}. \quad (2.10)$$

The above inequalities can be written as

$$\frac{x_{l,k_s}(t_1)y_{k_s}(t_1) + 1}{z_{l,k_s}(t_1)} \leq 1, \quad \frac{z_{l,k_s}(t_1)}{1 + x_{l,k_s}^2(t_1)} \leq 1.$$

Now, the above constraints can be approximated using AGMA approximation as

$$\text{C2.4.1: } z_{l,k_s}^{-1}(t_1) + x_{l,k_s}(t_1)y_{k_s}(t_1)z_{l,k_s}^{-1}(t_1) \leq 1, \quad (2.11)$$

$$\text{C2.4.2: } z_{l,k_s}(t_1) \left[\frac{1}{\lambda_{l,k_s}(t_1)} \right]^{-\lambda_{l,k_s}(t_1)} \left[\frac{x_{l,k_s}^2(t_1)}{\alpha_{l,k_s}(t_1)} \right]^{-\alpha_{l,k_s}(t_1)} \leq 1, \quad (2.12)$$

where $\lambda_{l,k_s}(t_1) = \frac{1}{x_{l,k_s}^2(t_1)-1}+1$ and $\alpha_{l,k_s}(t_1) = \frac{x_{l,k_s}^2(t_1)-1}{x_{l,k_s}^2(t_1)+1}$. Now, C2.4 can be replaced by the following constraints

$$\text{C2.4.1: } z_{l,k_s}^{-1}(t_1) + x_{l,k_s}(t_1)y_{k_s}(t_1)z_{l,k_s}^{-1}(t_1) \leq 1,$$

$$\text{C2.4.2: } z_{l,k_s}(t_1) \left[1/\lambda_{l,k_s}(t_1) \right]^{-\lambda_{l,k_s}(t_1)} \left[\frac{x_{l,k_s}^2(t_1)}{\alpha_{l,k_s}(t_1)} \right]^{-\alpha_{l,k_s}(t_1)} \leq 1,$$

$$\widehat{\text{C2.4.3: }} x_{l,k_s}(t_1) = \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n}(t_1),$$

$$\widehat{\text{C2.4.4: }} y_{k_s}(t_1) = \sum_{l \in \mathcal{L}, n \in \mathcal{N}} \alpha_{l,k_s,n}(t_1),$$

Note that via (2.10), the positive condition for the constraints of GP is met [15]. However, the equality constraints in $\widehat{\text{C2.4.3}}$ and $\widehat{\text{C2.4.4}}$ are not monomial functions since we have $x_{l,k_s}(t_1) - \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n}(t_1) = 0$ and $y_{k_s}(t_1) - \sum_{l \in \mathcal{L}, n \in \mathcal{N}} \alpha_{l,k_s,n}(t_1) = 0$, and, they have negative constraints. To convert $\widehat{\text{C2.4.3}}$ and $\widehat{\text{C2.4.4}}$ to the monomial functions, we again apply AGMA approximation as

$$\text{C2.4.3: } x_{l,k_s}(t_1) \prod_{n \in \mathcal{N}} \left[\frac{\alpha_{l,k_s,n}(t_1)}{v_{l,k_s,n}(t_1)} \right]^{-v_{l,k_s,n}(t_1)} = 1, \quad (2.13)$$

$$\text{C2.4.4: } y_{k_s}(t_1) \prod_{l \in \mathcal{L}, n \in \mathcal{N}} \left[\frac{\alpha_{l,k_s,n}(t_1)}{\eta_{l,k_s,n}(t_1)} \right]^{-\eta_{l,k_s,n}(t_1)} = 1$$

where $v_{l,k_s,n}(t_1)$ and $\eta_{l,k_s,n}(t_1)$ are defined in (2.7) and (2.8), respectively. $\square$

Based on C2.4.1–C2.4.4, C2.4 is transformed and represented by the approximated monomial equalities and posynomial inequalities. Next, we show how we can transform the objective function into the monomial function to reach the GP-based formulation for (2.4).

Proposition 2 Consider the auxiliary variable $x_0 > 0$ and $\Xi_1 \gg 1$. The user association problem (2.4) at each iteration t_1 can be transformed into the following standard GP problem

$$\min_{\alpha(t_1), x_0(t_1), z_{l,k_s}(t_1), x_{l,k_s}(t_1), y_{k_s}(t_1)} x_0(t_1), \quad (2.14)$$

subject to : C2.4.1–C2.4.4,

$$\Xi_1 \left[\frac{x_0(t_1)}{c_0(t_1)} \right]^{-c_0(t_1)} \prod_{l \in \mathcal{L}, s \in \mathcal{S}, k_s \in \mathcal{K}_s, n \in \mathcal{N}} \left[\frac{\alpha_{l,k_s,n}(t_1) R_{l,k_s,n}(\mathbf{P}(t))}{c_{l,k_s,n}(t_1)} \right]^{-c_{l,k_s,n}(t_1)} \leq 1,$$

$$\widetilde{\text{C2.1.1}} : R_s^{rsv} \times \prod_{l \in \mathcal{L}, k_s \in \mathcal{K}_s, n \in \mathcal{N}} \left[\frac{\alpha_{l,k_s,n}(t_1) R_{l,k_s,n}(\mathbf{P}(t))}{\varphi_{l,k_s,n}(t_1)} \right]^{-\varphi_{l,k_s,n}(t_1)} \leq 1, \quad \forall s \in \mathcal{S},$$

$$\text{C2.3.1: } \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \alpha_{l,k_s,n}(t_1) \leq 1, \quad \forall l \in \mathcal{L}, \forall n \in \mathcal{N},$$

where

$$\varphi_{l,k_s,n}(t_1) = \frac{\alpha_{l,k_s,n}(t_1 - 1) R_{l,k_s,n}(\mathbf{P}(t))}{\sum_{l \in \mathcal{L}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n}(t_1 - 1) R_{l,k_s,n}(\mathbf{P}(t))}, \quad \forall s \in \mathcal{S}, \quad (2.15)$$

$$c_{l,k_s,n}(t_1) = \frac{\alpha_{l,k_s,n}(t_1 - 1) R_{l,k_s,n}(\mathbf{P}(t))}{x_0(t_1 - 1) + \sum_{l \in \mathcal{L}} \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n}(t_1 - 1) R_{l,k_s,n}(\mathbf{P}(t))}, \quad (2.16)$$

$$c_0(t_1) = \frac{x_0(t_1 - 1)}{x_0(t_1 - 1) + \sum_{l \in \mathcal{L}} \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n}(t_1 - 1) R_{l,k_s,n}(\mathbf{P}(t))}. \quad (2.17)$$

Proof To reach the GP based formula for (2.4), we should have minimization over the objective function, i.e.,

$$\min_{\alpha(t_1)} \sum_{l \in \mathcal{L}} \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} -\alpha_{l,k_s,n} R_{l,k_s,n}(\mathbf{P}(t)).$$

Clearly, we have negative elements on the objective function similar to our general formulation of Appendix (A.8). To meet the positive conditions of objective function in GP, we consider $\mathcal{E}_1 \gg 1$ and rewrite objective function as

$$\mathcal{E}_1 - \sum_{l \in \mathcal{L}} \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n}(t_1) R_{l,k_s,n}(\mathbf{P}(t))$$

which is always positive. Then, consider a positive auxiliary variable x_0 , and rewrite the objective function with this new auxiliary variables

$$\frac{\mathcal{E}_1}{x_0 + \sum_{l \in \mathcal{L}} \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n}(t_1) R_{l,k_s,n}(\mathbf{P}(t))} \leq 1. \quad (2.18)$$

Now, (2.18) can be rewritten as the product of monomial functions based on the AGMA (discussed in Appendix A.1.2) as

$$\mathcal{E}_1 \left[\frac{x_0}{c_0(t_1)} \right]^{c_0(t_1)} \prod_{l \in \mathcal{L}, s \in \mathcal{S}, k_s \in \mathcal{K}_s, n \in \mathcal{N}} \left[\frac{\alpha_{l,k_s,n}(t_1) R_{l,k_s,n}(\mathbf{P}(t))}{c_{l,k_s,n}(t_1)} \right]^{c_{l,k_s,n}(t_1)} \leq 1, \quad (2.19)$$

where $c_{l,k_s,n}(t_1)$ and $c_0(t_1)$ are updated from (2.16) and (2.17), respectively. Therefore, the total optimization problem can be transformed into (2.14). $\square$

Now, at each iteration, the optimization problem can be replaced by its GP approximation in (2.14). Iteratively, (2.14) will be solved until achieving the optimal value of UAF value as shown in Step 1.A of Algorithm 2.1.

Proposition 3 *With AGMA, the above mentioned approach (Step 1.A) converges to a locally optimal solution that satisfies the KKT conditions of the original problem.*

Proof In [10], it is shown that the conditions for the convergence of the SCA are satisfied and guarantee that the solutions of the series of approximations by AGMA converges to a point that satisfies the KKT conditions of (2.4), i.e., a local maximum is attained [16]. $\square$

2.3.2 Power-Allocation Problem

For a given set of UAFs obtained from Step 1.A, the optimization problem can be formulated as

$$\max_{\mathbf{P}(t_2)} \sum_{l \in \mathcal{L}} \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n}(t) R_{l,k_s,n}(\mathbf{P}(t_2)) \quad (2.20)$$

subject to:

$$\widetilde{\text{C2.1.2}} : \sum_{l \in \mathcal{L}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n}(t) R_{l,k_s,n}(\mathbf{P}(t_2)) \geq R_s^{\text{rsv}}, \forall s \in \mathcal{S},$$

$$\widetilde{\text{C2.2.2}} : \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} P_{l,k_s,n}(t_2) \leq P_l^{\max}, \quad \forall l \in \mathcal{L},$$

where t_2 is the iteration index. Due to interference in the objective function of $R_{l,k_s,n}(\mathbf{P}(t_2))$, (2.20) is a non-convex optimization problem. In order to approximate it to the corresponding GP form, first, we rewrite the objective of (2.20) as

$$\max_{\mathbf{P}(t_2)} \prod_{l \in \mathcal{L}, s \in \mathcal{S}, k_s \in \mathcal{K}_s, n \in \mathcal{N}} \gamma_{l,k_s,n}(\mathbf{P}(t_2)) \quad (2.21)$$

where

$$\gamma_{l,k_s,n}(\mathbf{P}(t_2)) = \frac{\sigma^2 + I_{l,k_s,n}(t_2) + P_{l,k_s,n}(t_2)h_{l,k_s,n}}{\sigma^2 + I_{l,k_s,n}(t_2)},$$

$$I_{l,k_s,n}(t_2) = \sum_{\forall l' \in \mathcal{L}, l' \neq l} \sum_{\forall s \in \mathcal{S}} \sum_{\forall k'_s \in \mathcal{K}_s, k'_s \neq k_s} P_{l',k'_s,n}(t_2) h_{l,k_s,n}.$$

Now, using AGMA, $\gamma_{l,k_s,n}^{-1}(\mathbf{P}(t_2))$ can be approximated as

$$\widehat{\gamma}_{l,k_s,n}(\mathbf{P}(t_2)) = (\sigma^2 + I_{l,k_s,n}(t_2)) \left(\frac{\sigma^2}{\kappa_o(t_2)} \right)^{-\kappa_o(t_2)} \prod_{\forall l,s,k_s,n} \left(\frac{P_{l,k_s,n}(t_2)h_{l,k_s,n}}{\kappa_{l,k_s,n}(t_2)} \right)^{-\kappa_{l,k_s,n}(t_2)},$$

where

$$\kappa_{l,k_s,n}(t_2) = \frac{P_{l,k_s,n}(t_2 - 1)h_{l,k_s,n}}{\sigma^2 + \sum_{l \in \mathcal{L}, k_s \in \mathcal{K}_s, s \in \mathcal{S}} P_{l,k_s,n}(t_2 - 1)h_{l,k_s,n}}, \quad (2.22)$$

$$\kappa_o(t_2) = \frac{\sigma^2}{\sigma^2 + \sum_{s \in \mathcal{S}, k_s \in \mathcal{K}_s, s \in \mathcal{S}} P_{l,k_s,n}(t_2 - 1)h_{l,k_s,n}}.$$

Consequently, (2.20) is transformed into the following standard GP problem

$$\min_{\mathbf{P}(t_2)} \prod_{l \in \mathcal{L}, s \in \mathcal{S}, k_s \in \mathcal{K}_s, n \in \mathcal{N}} \widehat{\gamma}_{l,k_s,n}(\mathbf{P}(t_2)) \quad (2.23)$$

subject to:

$$\widetilde{\text{C2.1.2}} : \prod_{l \in \mathcal{L}, k_s \in \mathcal{K}_s, n \in \mathcal{N}} \widehat{\gamma}_{l,k_s,n}(\mathbf{P}(t_2)) \leq 2^{-R_s^{\text{rsv}}}, \quad \forall s \in \mathcal{S},$$

$$\widetilde{\text{C2.2.2}} : \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} P_{l,k_s,n}(t_2) \leq P_l^{\max}, \quad \forall l \in \mathcal{L},$$

The overall optimization problem is iteratively solved as described in Step 1.B until the power vector converges, i.e., $\|\mathbf{P}(t_2) - \mathbf{P}(t_2 - 1)\| \leq \varepsilon_2$ where $0 < \varepsilon_2 \ll 1$. Note that Proposition 3 holds for Step 1.B.

2.4 Numerical Results and Discussions

2.4.1 System Parameters

We consider a multi-cell VWN scenario with $L = 4$ BSs and $N = 4$ sub-carriers serving $S = 2$ slices in a 2×2 square area. The 4 BSs are located at coordinates: (0.5, 0.5), (0.5, 1.5), (1.5, 0.5) and (1.5, 1.5). The channel power gains are based on the path loss and Rayleigh fading model, i.e., $h_{l,k_s,n} = \chi_{l,k_s,n} d_{l,k_s}^{-\zeta}$ where $\zeta = 3$ is the path loss exponent, $d_{l,k_s} \in [0.1, 1]$ is the distance between the BS l and user k_s normalized to the cell radius and $\chi_{l,k_s,n}$ is the exponential random variable with mean of 1 [17]. We use the noise power in a sub-carrier bandwidth as reference (i.e., normalized to 1 or 0 dB) and hence express transmit power or interference power in dB relative to noise power. For all of the simulations, we set $\mathcal{E}_1 = 10^7$ and $\varepsilon_1 = 10^{-5}$, $\varepsilon_2 = 10^{-6}$. In all of the following simulations, for each realization of network, when there exists no feasible solution for the system, i.e., C2.1–C2.4 cannot be hold simultaneously, the corresponding total rate is set to be zero. The simulation results are taken over the average of 100 different channel realizations. For all the following simulations, we set $R^{\text{rsv}} = R_s^{\text{rsv}}$ for all $s \in \mathcal{S}$ and $P^{\max} = P_l^{\max}$ for all $l \in \mathcal{L}$.

2.4.2 Reference Resource Allocation

For performance comparison, we take as reference, the traditional SINR-based joint sub-carrier and power allocation algorithm as summarized in Algorithm 2.2. Under the SINR criterion, the users are assigned to the BSs that yields the highest average received SINR. In this case, the resource allocation problem is formulated as

$$\max_{\alpha', \mathbf{P}} \sum_{l \in \mathcal{L}} \sum_{s \in \mathcal{S}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} \alpha'_{l,k_s,n} R_{l,k_s,n}(\mathbf{P}) \quad (2.24)$$

subject to: C2.1–C2.3,

Algorithm 2.2 Reference resource-allocation algorithm

Initialization: Set $t_3 = 0$, BS assignment: user k_s is assigned to BS l based on the average received SINR.

Repeat: Set $t_3 = t_3 + 1$.

Step 2.A: Compute $\alpha'^*(t_3)$ by using Step 1.A of Algorithm 2.1 except that the BS is assigned based on the signal strength.

Step 2.B: For a fixed $\alpha'^*(t_3)$, find the optimal power allocation $\mathbf{P}'(t_3)$ by using Step 1.B of Algorithm 2.1.

Until $\|\alpha'^*(t_3) - \alpha'^*(t_3 - 1)\| \leq \varepsilon_1$ and $\|\mathbf{P}'(t_3) - \mathbf{P}'(t_3 - 1)\| \leq \varepsilon_2$.

where $\alpha' = [\alpha'_{l,k_s,n}]_{\forall l,k_s,n}$ and $\alpha'_{l,k_s,n}$ shows the sub-carrier allocation of user k_s on sub-carrier n when it is allocated to the BS l . Clearly, (2.24) is still highly non-convex. In order to show the importance and effects of defining UAF in this context, we apply the similar approach based on CGP to solve (2.24). In other words, Algorithm 2.2 is based on CGP and similar to Algorithm 2.1, except that, in Algorithm 2.2, (2.14) contains only C2.1–C2.3, i.e., C2.4 is removed, since BS-user association is based on the highest average received SINR. When the sub-carrier assignment is solved, the optimal power is derived from Step 1.B similar to Algorithm 2.1, for (2.24). This iterative algorithm is terminated when the convergence conditions are met as summarized in Algorithm 2.2.

2.4.3 Total Rate and Rate-Outage Evaluation

Primarily, we evaluate and compare the total rates achieved by Algorithms 2.1 and 2.2 versus the number of sub-carriers and maximum transmit power in Fig. 2.2a and b, respectively. We set $K_s = 4$ and the eight users in two slices are randomly located in the 2×2 square area according to a uniform distribution. The results in both Fig. 2.2a and b indicate that Algorithm 2.1 considerably outperforms Algorithm 2.2 for different values of R_s^{rsv} , N and P_l^{max} .

From Fig. 2.2a, it can be observed that the total rate is increased by increasing the total number of sub-carriers, N , due to the opportunistic nature of fading channels in wireless networks. As expected, with increasing P_l^{max} , the total achievable rate is also increased as shown in Fig. 2.2b. Both figures indicate that by increasing the value of R_s^{rsv} , the total rate decreases because the feasibility region of resource allocation in (2.24) is reduced leading to less total average achieved rate. However, from Fig. 2.2b, increasing R_s^{rsv} has considerable effect on the performance of Algorithm 2.2 as compared to Algorithm 2.1. It can be interpreted as Algorithm 2.1 can efficiently control interference between different cells compared to Algorithm 2.2. Therefore, the chance of feasible power allocation for larger values of R_s^{rsv} is increased by Algorithm 2.1.

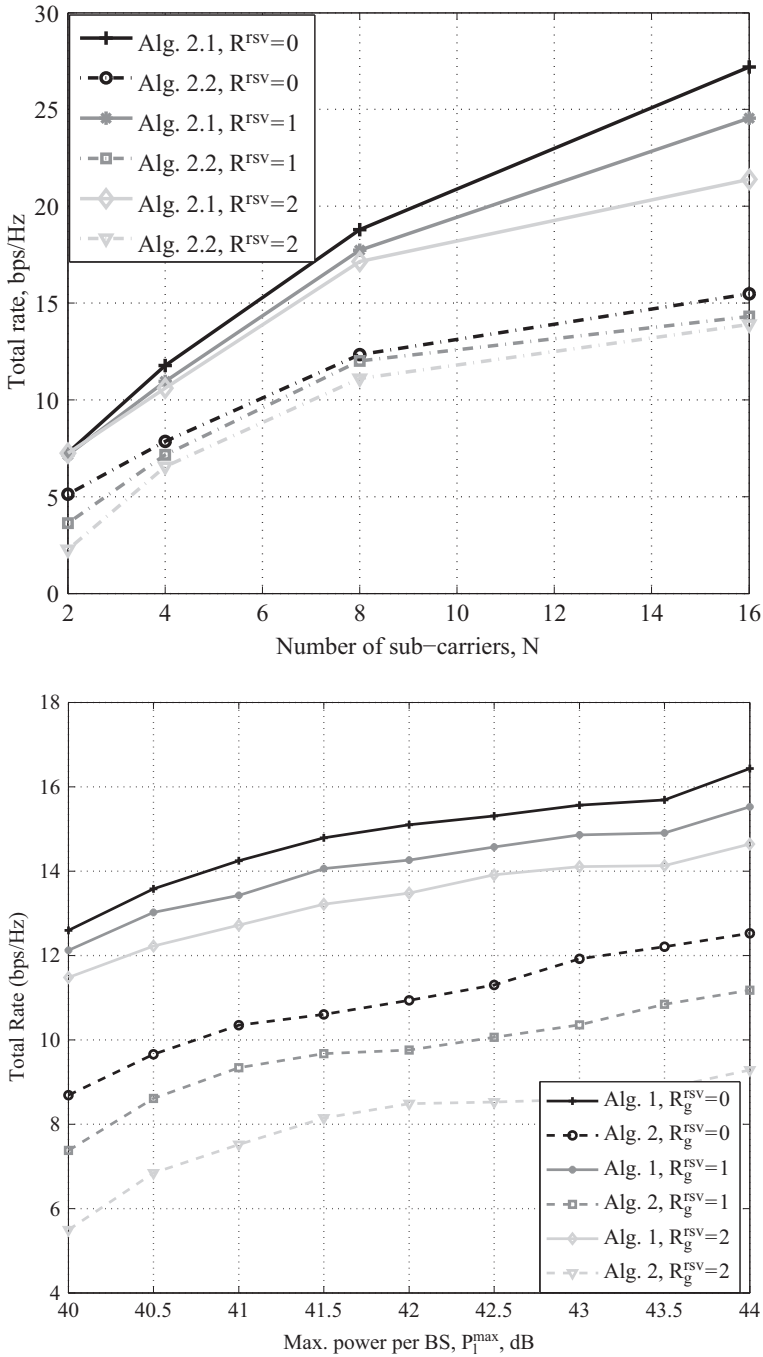


Fig. 2.2 Total rate versus (a) N , and (b) maximum transmit power per BS, P^{max} (in dB)

To study this point further, we consider the rate-outage probability of C2.1, expressed as

$$\text{Pr}(\text{rate-outage}) = \Pr\left\{\sum_{l \in \mathcal{L}} \sum_{k_s \in \mathcal{K}_s} \sum_{n \in \mathcal{N}} \alpha_{l,k_s,n} R_{l,k_s,n}(\mathbf{P}, \boldsymbol{\alpha}) \leq R_s^{\text{rsv}}\right\}, \quad \forall s \in \mathcal{S}.$$

Via Monte Carlo simulation, we compute $\text{Pr}(\text{rate-outage})$ of both Algorithms 2.1 and 2.2 for the above-mentioned simulation setting, as depicted in Fig. 2.3a with $N = 8$ and $P_l^{\text{max}} = 40$ dB for all $l \in \mathcal{L}$. The results demonstrate that as the rate reservation per slice R_s^{rsv} increases, the rate-outage probability of both Algorithms 2.1 and 2.2 increases. However, Algorithm 2.2 has larger rate-outage probability compared to the outage probability of Algorithm 2.1, implying that the feasibility region of Algorithm 2.2 is smaller than that for Algorithm 2.1. On the other hand, Algorithm 2.1 can efficiently manage interference in the specific region between different cells as compared to Algorithm 2.2. It is mainly because Algorithm 2.1 has more degrees of freedom to choose the BS and allocate the sub-carriers among users of different slices while the BS assignment is predetermined in Algorithm 2.2. Therefore, the achieved rate of Algorithm 2.2 is less than that of Algorithm 2.1. With increasing R_s^{rsv} , the rate reduction of Algorithm 2.2 is greater than that of Algorithm 2.1, since Algorithm 2.2 cannot manage the interference between different BSs. Hence, Algorithm 2.2 cannot satisfy the minimum rate requirements of slices, leading to reduced VWN efficiency.

For the same setup, in Fig. 2.3b, the total rate of Algorithms 2.1 and 2.2 are plotted for different values of R_s^{rsv} . Figure 2.3b clearly shows that Algorithm 2.1 yields higher rate than Algorithm 2.2. Note that in all the simulation results, when the problem is infeasible, i.e., there is no power and sub-carrier vectors that can meet the constraint C2.1 for all $s \in \mathcal{S}$, the achieved total rate is set to zero. These simulations highlight the importance of introducing UAF as the joint BS assignment and sub-carrier allocation in the multi-cell wireless networks to manage and control the interference between different cells.

2.4.4 Coverage Analysis

In any cellular network, the coverage can be measured by SINR or achieved total rate of users at the cell boundaries. To study the performance of Algorithm 2.1 in terms of coverage, we consider the simulation setup similar to Fig. 2.4 where the majority of users are located in the cell-edge region, consequently, these users experience high interference from other BSs. Therefore, the achieved rate of each user is decreased, which can be considered as the worst-case scenario of coverage analysis.

The cumulative distribution function (CDF) of the total throughput of cell-edge users and cell-center users is depicted in Fig. 2.5a and b, respectively, for both Algorithms 2.1 and 2.2. It can be seen that Algorithm 2.1 outperforms Algorithm 2.2

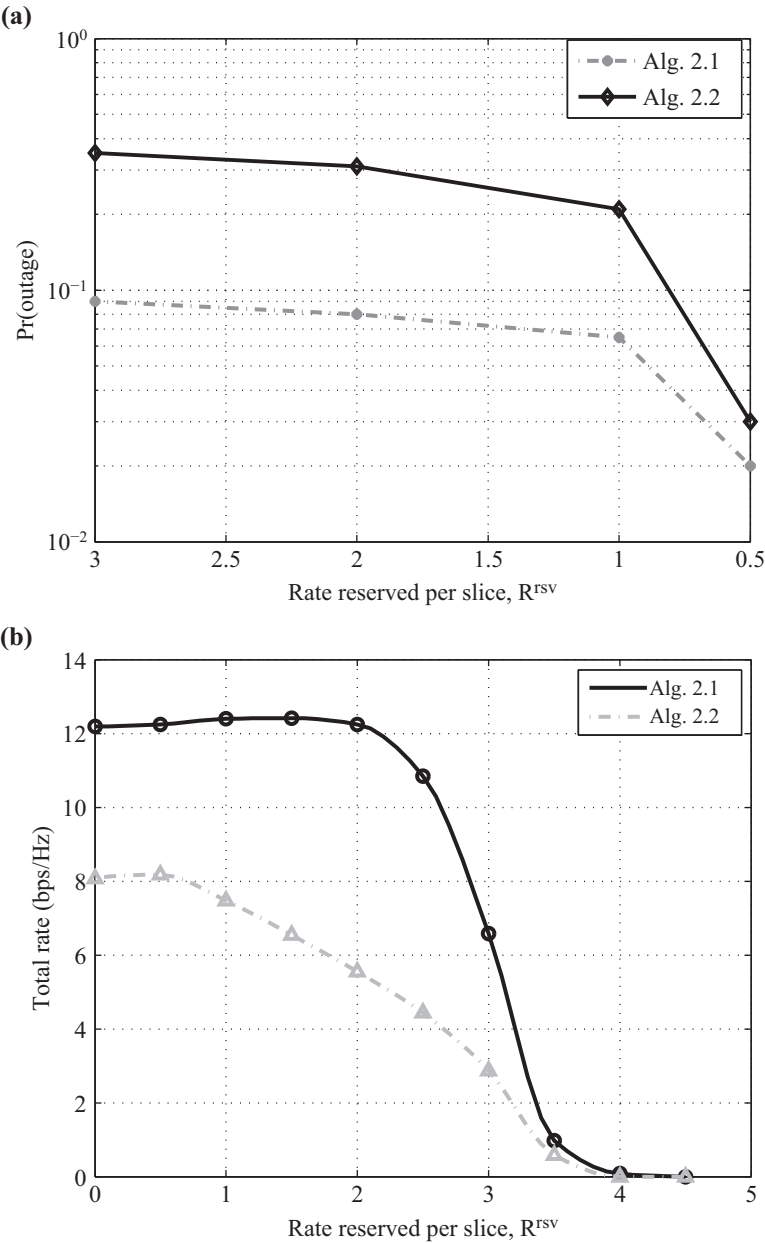


Fig. 2.3 (a) Outage probability, and (b) total rate versus R^{rsv}

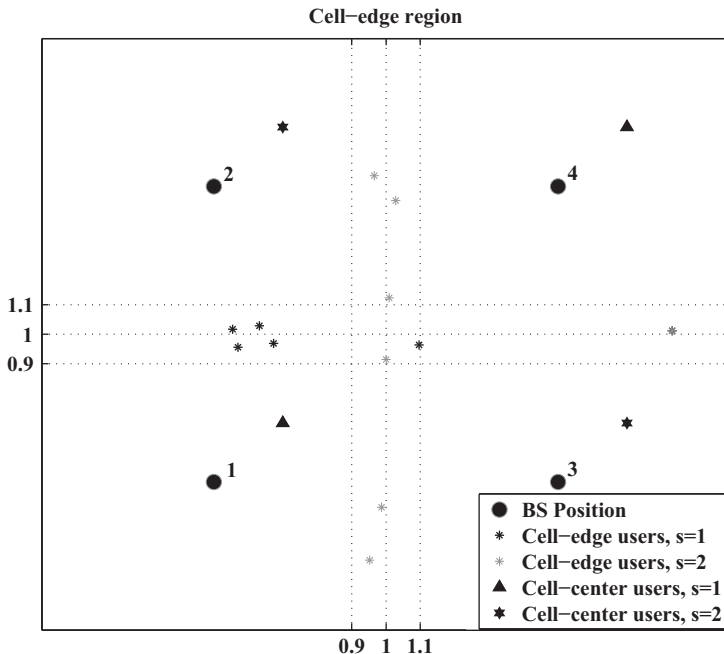


Fig. 2.4 Illustration of network setup to investigate the coverage of multi-cell VWN

for the cell-edge users where 50% of users in the cell-edge achieve a rate of 2.5 bps/Hz by Algorithm 2.1, and around 1.5 bps/Hz via Algorithm 2.2. However, the performance of both algorithms are similar for the cell-center users. It is because via user-association in Algorithm 2.1, the interference among different cells can be controlled while Algorithm 2.2 cannot control the interference through the connectivity of users to different BS and it is pre-determined by the received SINR of reference signal. In other words, Algorithm 2.1 can provide better coverage for cell-edge users for multi-cellular VWN which is desirable from implementation perspective.

The performance is further investigated with respect to the number of users in the cell-edge in Fig. 2.6a, b. Algorithm 2.1 can consistently improve the performance of cell-edge users and maintain desirable rate of each slice regardless of the user deployment density as compared to the Algorithm 2.2. For instance, with $K = 18$, for the uniform user distribution, the total rate is increased by 57% from 7 bps/Hz (by Algorithm 2.2) to 11 bps/Hz (by Algorithm 2.1) for cell-edge users and by 33% from 24 bps/Hz (by Algorithm 2.2) to 32 bps/Hz (by Algorithm 2.1) for cell-center users. For non-uniform user distribution, when $K = 32$, the rate is increased by 71% from 7 bps/Hz (by Algorithm 2.2) to 12 bps/Hz (by Algorithm 2.1) for cell-edge users and by 50% from 18 bps/Hz (by Algorithm 2.2) to 27 bps/Hz (by Algorithm 2.1) for cell-center users. These results show the efficiency of applying Algorithm 2.1 in increasing the coverage over the whole network.

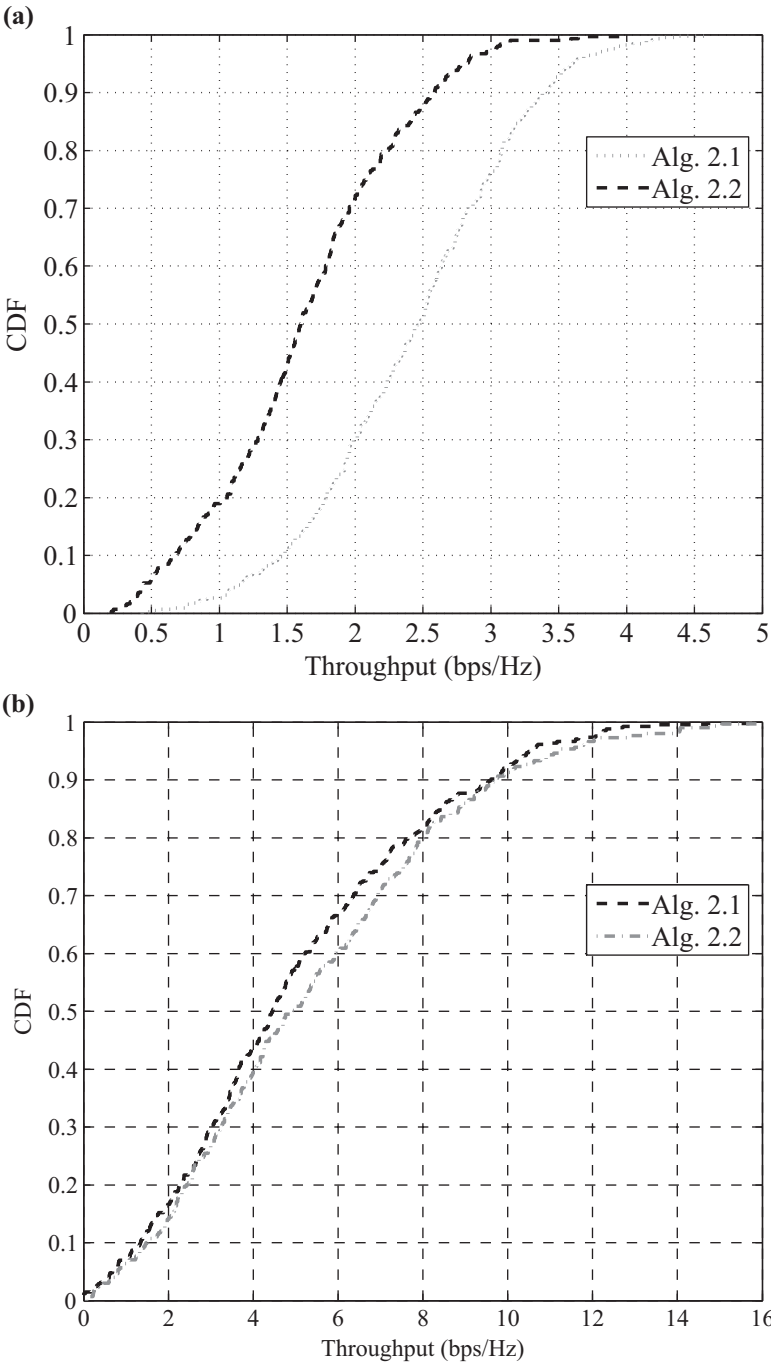


Fig. 2.5 Rate distribution for (a) cell-edge, and (b) cell-center users

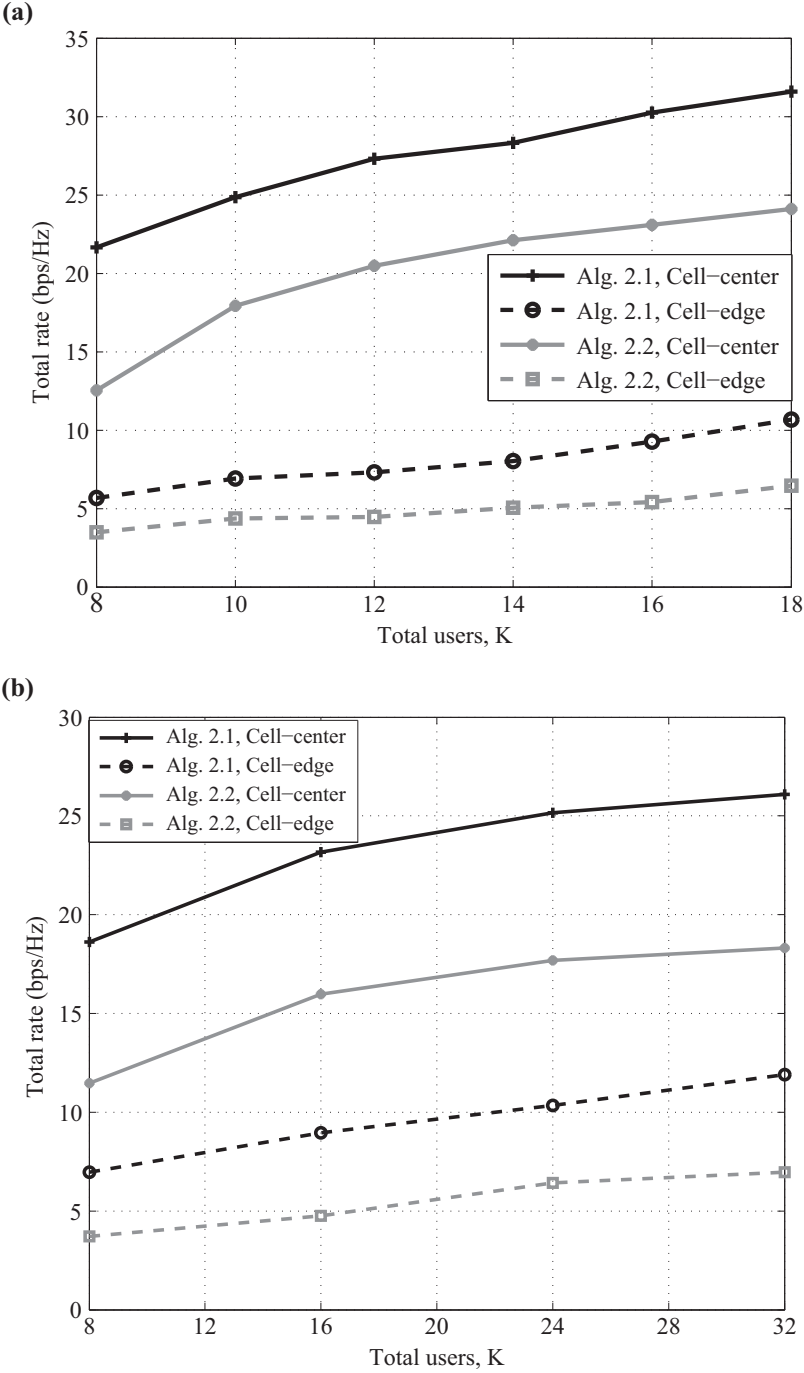


Fig. 2.6 Total rate for (a) uniform user distribution, and (b) non-uniform user distribution

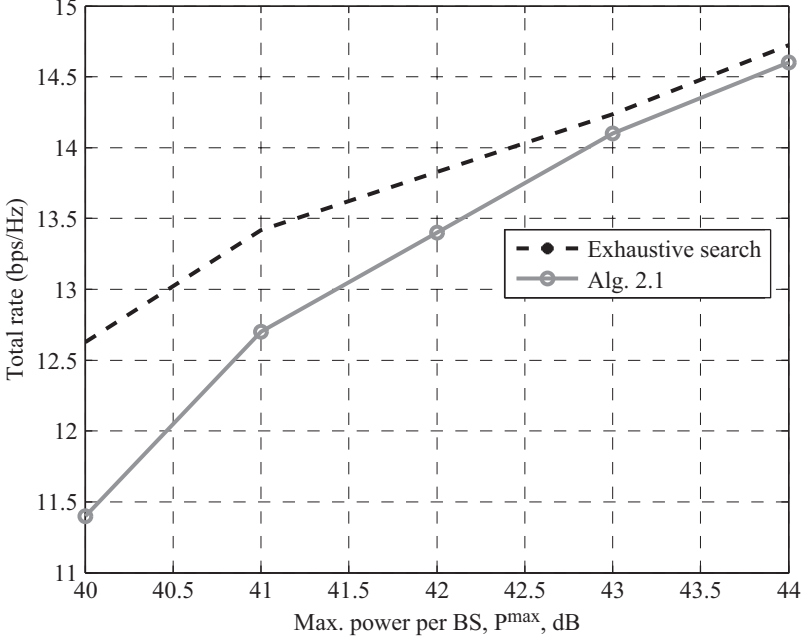


Fig. 2.7 Total rate versus $P^{\max}$ for both exhaustive search and Algorithm 2.1

2.4.5 Optimality Gap Study

We investigate the performance gap between the optimum solution (by exhaustive search) and the proposed Algorithm 2.1 for $N = 2$ sub-carriers and $K = 4$ users. Figure 2.7 plots the total rate versus $P^{\max}$ for both Algorithm 2.1 and the exhaustive search. As seen in the figure, the performance of Algorithm 2.1 approaches the performance of exhaustive search as $P^{\max}$ increases because the AGMA approach to convexify the rate is the best fit approximation for the high SINR scenario.

2.4.6 Computational Complexity and Convergence Analysis

In this section, we investigate the computational complexity and the convergence of Algorithm 2.1. First, we focus on deriving the computational complexity of Algorithm 2.1 analytically. Since CVX is used to solve GP sub-problems with the interior point method in Step 1.A (User-Association problem) and Step 1.B (Power-Allocation problem), the number of required iterations is $\frac{\log(c/(r^0 \varrho))}{\log(\xi)}$ [14], where c is the total number of constraints in (2.14), r^0 is the initial point to approximate the accuracy of interior point method, $0 < \varrho \ll 1$ is the stopping criterion for

interior point method, and ξ is used for updating the accuracy of interior point method [14]. As previously discussed, the numbers of constraints in (2.14) are $c_1 = S + LN + 4LK + 1$ for Step 1.A and $c_2 = S + L$ for Step 1.B.

Moreover, in Steps 1.A and 1.B, for each iteration, the number of computations required to convert the non-convex problems using AGMA into (2.14) and (2.21) is $i_1 = NL^2K + 6NLK + LNSK$ and $i_2 = SLNK + 2LNK$, respectively. Therefore, the order of computational complexity for each step is

- $i_1 \times \frac{\log(c_1/(r_1^0 \varrho_1))}{\log(\xi_1)}$ for Step 1.A,
- $i_2 \times \frac{\log(c_2/(r_2^0 \varrho_2))}{\log(\xi_2)}$ for Step 1.B.

Based on this analysis, the computational complexity of Step 1.A is significantly higher than that of Step 1.B. Moreover, Step 1.A is more sensitive to N and K than Step 1.B. Since Algorithm 2.1 is a type of block SCA algorithm [18], when (2.2) is feasible, the outer loop of Algorithm 2.1 is converged (Proposition 6 in [19] and Theorem 2 in [18]). For further investigation by simulation, in Fig. 2.8a, the number of iterations required for convergence for Steps 1.A and 1.B versus the total number of sub-carriers, N , is plotted for $K = 8$ and $R^{\text{rsv}} = 2$ bps/Hz. Similarly, in Fig. 2.8b, the number of iterations required for convergence versus the total number of users, i.e., K , for $N = 4$ sub-carriers is plotted in the case of Steps 1.A and 1.B. As N and K increase, the number of iterations required for convergence also increases. The computational complexity of Step 1.A is higher than that of Step 1.B because the total number of constraints for Step 1.A is higher than that for Step 1.B.

The major issue of Algorithm 2.1 is that (2.2) can be infeasible, e.g., due to deep fades and/or high interference and C2.1 cannot be met. Therefore, a potential extension work of this chapter could be to consider the admission control policy to adjust R_s^{rsv} .

2.5 Concluding Remarks

Joint user association and resource allocation problem for multi-cell OFDMA based VWNs was considered in this chapter. In the proposed setup, we have considered a set of slices (service providers), each has a set of their own users and require a minimum reserved rate. We formulated the related optimization problem based on the new defined optimization variable, called user association factor (UAF), indicating the joint sub-carrier and BS assignment. To solve the proposed non-convex and NP-hard optimization problem, we followed an iterative approach where in each step, one set of optimization variables is derived. However, in each step, the optimization problem is non-convex and NP-hard. To derive the efficient algorithm to solve them, we apply the framework of iterative successive convex approximation via complementary geometric programming (CGP) to transform the non-convex optimization problem into the convex one. Simulation results reveal that, via the

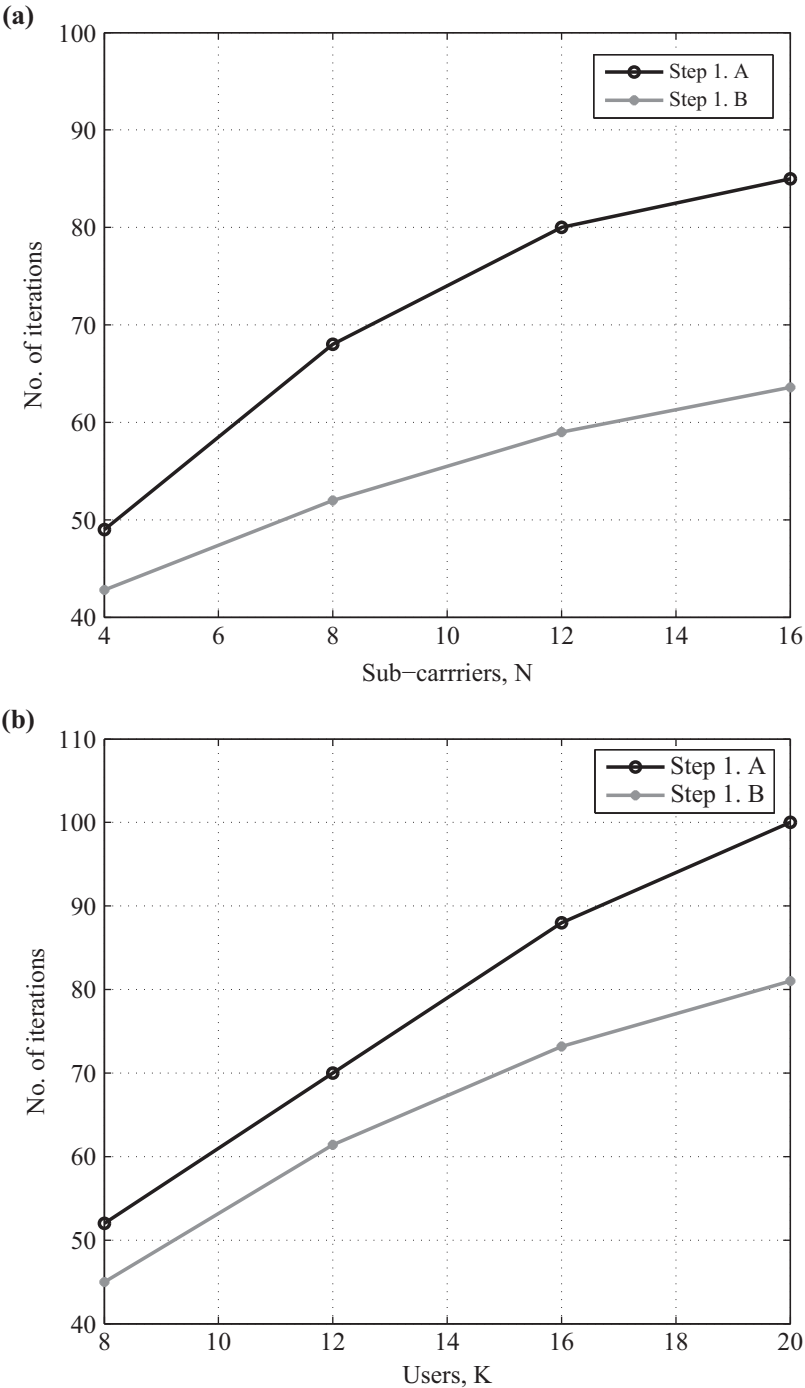


Fig. 2.8 Number of required iterations for lower-level iterative algorithms versus (a) number of sub-carriers, N , and (b) total number of users, K

proposed approach, the throughput and coverage of VWN, especially for the cell-edge users, are considerably improved as compared to the traditional scenario where the BS is assigned based on the maximum value of SINR.

References

1. R. Kokku, R. Mahindra, H. Zhang, and S. Rangarajan, "NVS: A substrate for virtualizing wireless resources in cellular networks," *IEEE/ACM Trans. Netw.*, vol. 20, no. 5, Oct. 2012.
2. C. Liang and F. Yu, "Wireless network virtualization: A survey, some research issues and challenges," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 99, pp. 358–380, Aug. 2014.
3. F. Fu and U. Kozat, "Stochastic game for wireless network virtualization," *IEEE/ACM Trans. Netw.*, vol. 21, no. 1, pp. 84–97, Feb. 2013.
4. S. Parsaefard, V. Jumba, M. Derakhshani, and T. Le-Ngoc, "Joint resource provisioning and admission control in wireless virtualized networks," in *IEEE Wireless Commun. Netw. Conf. (WCNC)*, Mar. 2015, pp. 2020–2025.
5. V. Jumba, S. Parsaefard, M. Derakhshani, and T. Le-Ngoc, "Resource provisioning in wireless virtualized networks via massive-MIMO," *IEEE Wireless Commun. Lett.*, vol. 4, no. 3, pp. 237–240, Feb. 2015.
6. X. Zhang, Y. Li, D. Jin, L. Su, L. Zeng, and P. Hui, "Efficient resource allocation for wireless virtualization using time-space division," in *IEEE Intl. Conf. on Wireless Commun. and Mobile Comp. (IWCMC)*, Aug. 2012, pp. 59–64.
7. G. Liu, F. Yu, H. Ji, and V. Leung, "Distributed resource allocation in full-duplex relaying networks with wireless virtualization," in *IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2014, pp. 4959–4964.
8. Z.-Q. Luo and S. Zhang, "Dynamic spectrum management: Complexity and duality," *IEEE J. Sel. Topics in Signal Processing*, vol. 2, no. 1, pp. 57–73, Feb. 2008.
9. M. Chiang, "Geometric programming for communication systems," *Foundations and Trends in Communications and Information Theory*, vol. 2, no. 1–2, pp. 1–154, 2005.
10. M. Chiang, C. W. Tan, D. Palomar, D. O'Neill, and D. Julian, "Power control by geometric programming," *IEEE Trans. Wireless Commun.*, vol. 6, no. 7, pp. 2640–2651, July 2007.
11. G. Xu, "Global optimization of signomial geometric programming problems," *European Journal of Operational Research*, vol. 233, no. 3, pp. 500–510, 2014.
12. M. Derakhshani, X. Wang, T. Le-Ngoc, and A. Leon-Garcia, "Airtime usage control in virtualized multi-cell 802.11 networks," in *IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2015, pp. 1–6.
13. M. Grant and S. Boyd, "CVX: Matlab software for disciplined convex programming, version 2.1," <http://cvxr.com/cvx>, 2014.
14. S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2009.
15. M. Avriel and A. Williams, "Complementary geometric programming," *SIAM Journal on Applied Mathematics*, vol. 19, no. 1, pp. 125–141, 1970.
16. B. Marks and G. Wright, "A general inner approximation algorithm for nonconvex mathematical programs," *Journal of Operations Research*, vol. 26, no. 8, pp. 681–683, 1978.
17. A. Goldsmith, *Wireless Communications*. Cambridge University Press, 2004.
18. M. Razaviyayn, "Successive convex approximation: Analysis and Applications," in *IEEE Wireless Commun. Netw. Conf. (WCNC)*, May 2014.
19. D. T. Ngo, S. Khakurel, and T. Le-Ngoc, "Joint subchannel assignment and power allocation for OFDMA femtocell networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 1, pp. 342–355, Jan. 2014.

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