Doctoral Dissertation

Fair and Energy-Efficient Resource Allocation Optimization in Wireless Networks

Pham Quoc Viet

Department of Information and Communications Systems

Graduate School, Inje University

Advisor: Prof. Won-Joo Hwang

Fair and Energy-Efficient Resource Allocation Optimization in Wireless Networks

Pham Quoc Viet

Department of Information and Communications Systems

Graduate School, Inje University

A dissertation submitted to the Graduate School of
Inje University in partial fulfillment of the requirements
for the Degree of Doctor of Engineering

Advisor: Prof. Won-Joo Hwang

Jun. 2017

Approved by Committee of the Graduate School of Inje University in partial fulfillment of the requirements for the Degree of Doctor of Engineering

Chairman of Committee: 김 철 수 (signature)

Committee: 김 희 철 (signature)

Committee: 이 숭 희 (signature)

Committee: 진 교 홍 (signature)

Committee: 황 원 주 (signature)

Graduate School, Inje University

Jun. 2017

To my family

for their unconditional love and affection on me.

Acknowledgements

Foremost, I would like to express my deep gratitude to my supervisor Prof. Won-Joo Hwang for guiding and supporting throughout my M.S. and Ph.D. studies. In pursuing my Ph.D., I simply appreciate the inspiration and freedom he has given to me, which ultimately help me to complete my work. I would also like to express my deep appreciation to my thesis committee members; your comments and feedback are absolutely invaluable.

I am grateful to members and alumni of the WINE Lab. for their helps during my academic life at the Inje University. Thank you for sharing your knowledge and expertise with me. I also want to thank staffs of the graduate school, especially Mr. Kim Hee Kyu, for assisting me in official documents and giving me chances to study Korean culture.

I am very much thankful to friends in Korea, who share with me sadness, happiness, and warm memories during the 4-year staying from the time I started my Master studies. Especially, many thanks to friends of the "Xom Lieu" group for the great time we have spent together and for inspiring me to relieve stresses at research and overcome obstacles in life. Thank you all for being a piece of my life. It is my heart full feeling to thank my friends who are thousands of miles away from me, but always beside to encourage and make me less homesick.

My greatest love goes to my family; this thesis would never have been completed if I were not received the constant love and continuous support from my family. The heartiest thank is for my special friend, Le Thi Mai, who simply stands by me at every difficult moment. Last but not least, I would like to dedicate this thesis to my lovely paternal grandfather, who went missing and passed away last year, as he will remain forever in my heart and memories.

ABSTRACT

Fair and Energy-Efficient Resource Allocation Optimization
in Wireless Networks

Quoc-Viet Pham
(Advisor: Prof. Won-Joo Hwang)
Department of Information and Communication Systems
Graduate School, Inje University

The use of network utility maximization (NUM) paradigm for the overall performance of communication networks is to decompose the whole problem into sub-problems at various network layers, i.e., cross-layer design. Among the problems addressed in cross-layer designs, congestion control has been regarded as the key issue, since appropriate congestion control schemes can ensure network stability and acceptable performance. For a part of the Ph.D. studies, we survey the state of the art cross-layer congestion control in wireless networks and propose two congestion control schemes in multipath lossy wireless networks and complex communications systems. This part is however not covered in this thesis and can be found in our articles in the section Publications.

The rapid expansion of wireless communication networks drives the research community to design wireless networks with higher spectral efficiency and energy efficiency. Besides, fairness among mobile users in wireless networks is of critical importance. To satisfy QoS requirements and guarantee fairness in next-generation networks, many of technology and network architecture evolution have been proposed, for example, heterogeneous networks (HetNets), device-to-device (D2D) communication, massive multiple-input-multiple-output (massive-MIMO), and non-orthogonal multiple access (NOMA). This thesis considers three fair and energy-efficient resource allocation problems in such kinds of wireless networks. In particular, various power control schemes are proposed for interference management in HetNets, for the

tradeoff between spectral efficiency and energy efficiency in spectrum-sharing wireless networks, and for fairness in NOMA systems.

Our first work considers energy-efficient power control schemes for interference management in uplink spectrum-sharing heterogeneous networks, consisting of a higher-tier macrocell and multiple lower-tier smallcells, where the optimization problem is formulated based on the multi-objective formulation subject to constraints on rate outage probability and maximum tolerable interference at the macro base station. In the first scenario, the objective function is defined as the weighted sum of the energy efficiencies and the optimization problem is in a sum-of-ratios form, which cannot be conventionally solved by the Dinkelbachs procedure; we develop an efficient global optimization algorithm with global linear and local quadratic rate of convergence to solve the considered problem. To ensure fairness among individual UEs in term of energy efficiency, we consider the max-min problem, where the objective is defined as the weighted minimum of the energy efficiencies and a fractional programming theory and the dual decomposition method are jointly used to solve the problem and investigate an iterative algorithm. We further discuss the global energy efficiency problem and consider near optimal schemes. Numerical examples are provided to demonstrate significant improvements of the proposed algorithms over existing ones.

The second work introduces a fair and energy-efficient resource allocation framework in spectrum-sharing wireless networks with quality-of-service guarantees. Consider the tradeoff between energy efficiency and spectral efficiency, the multiobjective problem of spectral efficiency and energy efficiency is transformed into a problem that minimizes the total power consumption and maximizes the achievable utility, subject to power constraints and rate outage probability constraints. We then analyze the complexity of the considered problem; particularly, the optimization problem is NP-Hard when $0 < \alpha < 1$ and $\alpha = 0$ and is convex for other values of the fairness index α. After that, we adopt the successive convex approximation approach to approximate and transform the NP-hard nonconvex optimization problem into a sequence of convex programs and propose two iterative successive convex approximation (SCA) based resource allocation algorithms. Extensive simulation results are presented to demonstrate the effectiveness and outperformance of the proposed algorithms over existing frameworks.

NOMA is now considering as a promising radio access technique for next-generation networks owing to its offered benefits, e.g., spectral efficiency improvement. Due to the successive interference cancellation (SIC) order at receivers, fairness among users in NOMA may not be guaranteed. Our third work focuses on -fair resource allocation in NOMA. The complexity of the considered problem is then analyzed. In particular, the problem is shown to be convex when $1 \leq \alpha < \infty$ and $\alpha = \infty$, NP-Hard when $0 < \alpha < 1$, and polynomial time solvable when $\alpha = 0$. Finally, simulation results are provided to examine effects of the fairness degree on the system performance and verify the effectiveness of our proposed algorithms.

Keywords: Fairness, Energy Efficiency, Spectral Efficiency, Power Allocation, Heterogeneous Networks, Non-Orthogonal Multiple Access, Spectrum-Sharing Networks.

Contents

List of Figures

Chapter 1

Introduction

Firstly, this chapter provides the brief to key technologies in 5G communication networks. Then, motivations behind and contributions of the approaches proposed in this thesis are explained. Finally, the organization of this thesis is given at the end of this chapter.

1.1 Background

We are approaching the fifth-generation wireless network, which will be able to provide a 1000 times increase in data traffic and one millisecond round trip latency compared to current cellular networks [1]. It is anticipated that there are more than 100 billion devices with approximately 8.0 billion mobile subscribers in 2016 due to the proliferation of electronic devices such as smartphones and tablets and many new personal applications [2, 3]. Smartphones accounted only 45 percent of total mobile devices and connections in 2016; however, smartphones represented 82 percent of total mobile traffic [3]. The Cisco white paper [3] also presents some milestones of mobile data traffic through 2021, for example, annual global mobile data traffic will exceed half a zettabyte, mobile will represent 20 percent of total IP traffic by 2021, the number of mobile-connected devices per capita will reach 1.5 by 2021, and smartphones will account for over 50 percent of global devices and connections by 2021. As a result, it is important to find feasible solution and develop disruptive technologies for the stringent throughput requirement in 5G wireless networks, which according to [1, 4] are:

- Millimeter wave (mmWave): the enormous chunk of spectrum at mmWave frequencies can be used in order to transmit digital signal at a rate of gigabits per second for 5G networks.
- Massive multiple-input-multiple-output (massive MIMO): massive MIMO is a system, where the BS is equipped with hundreds or thousands of antennas. The very large number of antennas is used to multiplex signals of several mobile users at the same time-frequency resource.
- Device-centric architecture: The cell-centric architecture in 1G, 2G, 3G, and 4G should be changed to the device-centric architecture, where a mobile user is served and connected a set of network nodes.
- Smarter devices: mobile devices are designed and integrated with new technologies such that they will be more responsible for transmission and reception of digital data signals. Device-to-device (D2D) communication and local caching are two examples of smarter devices.
- Native support for machine-to-machine (M2M) communication: M2M communication is supported in 5G communication with three main requirements: ability to support a large number of connected devices, extremely high link reliability, and very low-latency and real-time data transmission.

The demand for higher data rates in wireless networks has also triggered the development of multi-tier heterogeneous wireless networks (HetNets) in 4G and ultra-dense HetNets in 5G. A HetNet is defined as an integration of higher-tier macrocells and lower-tier smallcells. There are a number of kinds of smallcells in HetNets, for example: picocells, femtocells, relays, and remote radio heads (RRHs). Picocells are small base stations (BSs) with a coverage of hundreds of meters which are deployed by network operators; smallcells are installed by users to serve a small number of users a indoor spots; relays are access points which are deployed by network operators in order to cover dead zones and cell edges of macrocells in HetNets;

and RRHs are radio frequency units which are install by operators to extends the coverage of the macro BS to remote areas. With the deployment of smallcells, the network capacity significantly increases, which is attributed by reduced distance among femtocells and users, lower transmit power, smaller interference from neighboring macrocells, and a large portion of resources. However, the interference management problem becomes critical in HetNets due to the new existences of macrocell-to-femtocell interference, femtocell-to-femtocell interference, and femtocell-to-macrocell interference.

An active research direction in 5G networks is on multiple access schemes. Various radio access technologies have been applied in the previous network generations, for example, frequency-division multiple access (FDMA) for the 1G network, time-division multiple access (TDMA) for the 2G network, code-division multiple access (TDMA) for the 3G network, and orthogonal frequency-division multiple access (OFDMA) for the 4G network. A common point in above multiple access scheme is that each user is served on and assigned to an exclusively allocated resource. Now, non-orthogonal multiple access (NOMA) is considered as a promising multiple access (NOMA) technique in 5G networks. The fundamental idea of NOMA is the use of superposition coding technique at the BS side and multiple user detection at the user side, and a set of users share the same time-frequency resource. NOMA can be classified into power-domain NOMA and code-domain NOMA; power-domain NOMA do multiplexing in power domain while code-domain NOMA do multiplexing in code domain. Typical examples of code-domain are low-density spreading CDMA, low-density spreading-based OFDMA, and sparse code multiple access. A comparison between OMA and NOMA can be summarized in Table. 1.1 [5]. Although NOMA is able to support a large number of users at a time instance and improve spectral efficiency and fairness, various technical issues associated with NOMA must be addressed before its use in real networks. Islam *et al.* in [6] provide some research directives for NOMA in their survey: dynamic user pairing, impact of transmission distortion, impact of interference, resource allocation, NOMA with multiple antenna, NOMA with HetNets, outage probability analysis, uniform fairness, NOMA with antenna selection, and carrier aggregation.

In another viewpoint, the problem of energy efficiency in wireless networks is critical and has become a

Table 1.1: Comparison between OMA and NOMA

	Frameworks	Evaluation
OMA	- Simpler receiver detection	- Lower spectral efficiency - Limited number of users - Unfairness for users
NOMA	- Higher spectral efficiency - Higher connection density - Enhanced user fairness - Lower latency - Supporting diverse QoS	- Increased complexity of receivers. - Higher sensitivity to channel uncertainty.

very popular research topic in recent years. There are three main reasons for the focus on energy efficiency problems [7]

- The huge number of connected devices poses sustainable growth concerns. The 1000 times increase in higher data rate should be achieved with the same level of energy consumption, i.e, the 5G network targets at a 1000 times increase in the energy efficiency.

- The exponential growth of wireless networks causes environmental concerns. It was showed in [8] that information and communication technology (ICT) products and services account for 3.9% in 2007 and 4.6% in 2012 of the world-wide energy and that percentage is still increasing. More than half of the ICT energy is consumed at the BS, which causes about 2% of the world-wide CO_2 emission. In addition, electromagnetic pollution and improper disposal of end-of-life electronic devices are considered as ecological concerns.

- Energy-efficient wireless networks are also driven by economical reasons. From the operator's viewpoint, a large amount of money for electricity bill and maintenance costs can be saved by maximizing energy efficiency.

Possibly, energy efficiency can be improved by other technologies, for example, hardware and RF front-ends, resource allocation, and adaptive network management and network planning. In [9], the authors showed that the issue of energy efficiency in wireless communication networks can be addressed in two directions; the first is communication technology perspective where energy-efficient resource allocation schemes are proposed for implementation at different layers; and the second is system design perspective which includes network infrastructure deployment, design of low-power processors among network nodes, and power consumption policies. The combination of the two above approaches may result in different energy efficiency tradeoff for energy-efficient wireless networks. In this thesis, we however focus on energy-efficient resource problems for wireless networks.

In designing energy-efficient wireless networks, the energy efficiency metric is of importance. Currently, there exist two main approaches to define the energy efficiency for a communication network: global energy efficiency (GEE) and multi-objective energy efficiency. To review two kinds of the energy efficiency metric, we consider a wireless network with L nodes, each with transmit power p_l, signal-to-interference-plus-noise-ratio (SINR) $\gamma_l(\boldsymbol{P})$, and throughput $R_l(\boldsymbol{P}) = \log_2(1+\gamma_l(\boldsymbol{P}))$, where $\boldsymbol{P}$ is the power allocation vector. The global energy efficiency is defined as the ratio between the bits transmitted per unit power consumption of a network, that is

$$\text{GEE} = \frac{\sum_{l=1}^{L} R_l(\boldsymbol{P})}{\sum_{l=1}^{L} \rho_l p_l + P_c},$$

where P_c is the total circuit power and ρ_l is the constant that accounts for the inefficiency of the power amplifier of the link l. As definition, while the global energy efficiency is to maximize the network energy efficiency, it does not allow to tune the energy efficiency of individual link and faces challenges of fairness among individual links. That can be occurred in the case where the energy efficiency of a link is really high while those of other links are low. This issue can be tackled by considering another energy efficiency metric, that is, multi-objective energy efficiency. The second technique is to define the energy efficiency metric by using the concept of multi-objective optimization problem. First, let us define individual energy efficiency of a network link, that is

$$\text{EE}_l = \frac{R_l(\boldsymbol{P})}{\rho_l p_l + P_{l,c}},$$

where $P_{l,c}$ is the circuit power consumption of the link l. The multi-objective energy efficiency can be formulated, as follows:

$$\text{EE} = \max_{\boldsymbol{P}} f\left(\text{EE}_1, ..., \text{EE}_L\right).$$

In practice, there are many choices of the objective function $f(\cdot)$. In the related literature on energy efficiency in wireless networks, the function $f(\cdot)$ can be: the weighted sum of the energy efficiencies (WSEE), the weighted minimum of the energy efficiencies (WMEE), and the weighted product of the energy efficiencies (WPEE). In details, the WSEE, WMEE, and WPEE are respectively defined as the three following equations

$$\text{WSEE} = \sum_{l=1}^{L} \omega_l \text{EE}_l = \sum_{l=1}^{L} \omega_l \frac{R_l(\boldsymbol{P})}{\rho_l p_l + P_{l,c}},$$

$$\text{WMEE} = \min_{l=1,\dots,L} \omega_l \text{EE}_l = \min_{l=1,\dots,L} \omega_l \frac{R_l(\boldsymbol{P})}{\rho_l p_l + P_{l,c}},$$

$$\text{WPEE} = \prod_{l=1}^{L} (\text{EE}l)^{\omega_l} = \prod_{l=1}^{L} \left(\frac{R_l(\boldsymbol{P})}{\rho_l p_l + P_{l,c}}\right)^{\omega_l}.$$

where ω_l is the priority of the link l. Three above EE metrics can address the problem of link fairness as well as individual link energy efficiency, they does not maximize the network benefit, e.g., the network (global) energy efficiency. Therefore, we must consider the network scenario when designing a communication system to select the appropriate energy efficiency metric. Over past few years, a huge number of literature have been dedicated to the optimization problem of spectral efficiency and energy efficiency separately. However, there is another direction that intends to maximize spectral efficiency and energy efficiency simultaneously. Maximizing spectral efficiency/energy efficiency does not mean energy efficiency/spectral efficiency is maximized. When energy efficiency is selected as the objective function and is maximized, it often leads to a low performance of spectral efficiency, and vice versa. Therefore, there is a need to learn and research into the problem of spectral- and energy-efficiency tradeoff.

As network resources are allocated to and shared by a number of users to optimize the design objective, fairness is required for the network or all users. The consequence of an unfair resource allocation among different users causes resource starvation, wastage or redundant allocation [10]. The concept of fairness can be considered from the system or user level (individual level). The system fairness is achieved when resource allocation to all users are fair; however, it becomes unfair if one or more users are allocated unfairly. In this thesis, we consider a well-known family of utility functions that has been discussed in [11]

$$U_\alpha(r_i) = \begin{cases} (1-\alpha)^{-1} r_i^{1-\alpha} & \text{if } \alpha \geq 0, \alpha \neq 1, \\ \ln(r_i) & \alpha = 1. \end{cases} \tag{1.1}$$

Accordingly, the fairness degree can range from zero to infinity. There are 3 special cases: if $\alpha = 0$, the utility is the sum rate; if $\alpha = 1$ (proportional fairness), the utility is the sum logarithmic utility of user rate; if $\alpha = \infty$ (max-min fairness), the utility is the minimum achievable user rate. In addition, as the fairness degree increases, transmit power is allocated in a more fair manner. Considering the design objective, an appropriate value of the fairness degree can be selected. For example, if we just care about the total performance, e.g., sum rate of all users, we should set the fairness degree to zero, i.e., $\alpha = 0$. In the case of considering fairness among pairs in the network, the max-min fairness is a suitable option; however, the performance, e.e., sum rate and energy efficiency, has to be sacrificed to reserve fairness.

1.2 Contributions

As aforementioned, spectral efficiency, energy efficiency, and fairness are three important criteria for the design of next-generation networks. In this thesis, we put our focus on developing fair and energy-efficient resource allocation in wireless networks. Firstly, in chapter 2, we consider HetNets with one macrocell and multiple smallcells. Since the battery of mobile users is still limited while demand of energy consumption for many energy-hungry services and applications is significantly increasing, the uplink instead of the downlink in HetNets is considered. Moreover, in the uplink of HetNets, the macrocell should be protected against cross-tier interference from femtocells and while QoS requirements for FUEs are guaranteed. Therefore, we introduce two energy-efficient problems; the first is the weighted sum of the energy efficiencies and the second is the weighted minimum of the energy efficiencies; and the interference power constraint or interference temperature constrain is imposed at the BS to guarantee that the total cross-tier interference from smallcell users is below a threshold. We conduct extensive simulation results and showed that our proposed energy-efficient algorithms are superior to the existing frameworks. This work has been under a minor revision of International Journal of Communication Systems since Jun. 2017.

Secondly, in chapter 3, we shift our focus to the problem of α-fairness in interference-limited wireless networks with the objective of finding the optimal solution to the multiobjective problem of spectral efficiency and energy efficiency. With five distinct cases of the fairness index, we show that the considered optimization problem has different complexity. In particular, the problem is convex when $1 \leq \alpha \leq \infty$ and NP-Hard when $0 \leq \alpha < 1$. Based in these complexity analysis, we proposed two iterative algorithms for the two cases of NP-Hardness. In addition, simulation results show that by adjusting the priority parameter for spectral efficiency and energy efficiency while considering the fairness degree and the design objective, the tradeoff between spectral efficiency and energy efficiency can be achieved. This work has been accepted by IEEE Transactions on Vehicular Technology in Jun. 2017.

Due to a massive number of connected devices in 5G networks, conventional multiple access schemes, for example TDMA, FDMA, CDMA, and OFMDA in 4G and before, become inappropriate. Hence, the research on non-orthogonal multiple access has become a hot topic for last few years in wireless networks communities. The key idea of NOMA is the use of superposition coding technique at the base station side and the interference cancellation techniques at the receiver side. One of the most popular interference cancellation technique is NOMA. It is usually assumed in the literature that the decoding order is in order of channel gains; hence, users in NOMA systems may achieve different rates and fairness is not obtained. In addition, fairness in NOMA can be improved and supported through an appropriate power allocation [12]. We therefore shift our focus in the last chapter (chapter 4) to the problem of α-fair power allocation in NOMA systems. It is shown from simulation results that there is a tradeoff between the fairness and the number of users on a cluster in NOMA systems and our proposed power control scheme outperforms two baseline methods. This work has been under review of IET Communications since Mar. 2017.

1.3 Thesis Outline

The rest of the thesis is organized as follows. In chapter 2, we study the power control problem for energy efficiency in uplink HetNets. In chapter 3, we turn our attention to the multi-objective problem of spectral efficiency and energy efficiency in interference-limited wireless networks while consider fairness. In chapter 4, we study the problem of α-fairness in NOMA systems. In chapter 5, a conclusion of this thesis is given and some limitations of the work are also pointed out with potential solutions, which may drive research efforts in the future.

Chapter 2

Energy-Efficient Power Control for Uplink Spectrum-Sharing Heterogeneous Networks

2.1 Introduction

Heterogeneous network (HetNet), defined as an integration of higher-tier macrocells and lower-tier smallcells, e.g., picocells and femtocells, has been considered as a technological evolution for LTE 4G networks and beyond networks due to the potentials of significantly increasing performance, coverage, and energy efficiency for indoor and outdoor hot-spots [13]. In such multi-tier HetNets, there are two scenarios of spectrum allocation between the macrocell and smallcells: spectrum sharing and spectrum splitting. Macrocells and smallcells use orthogonal resource in a spectrum splitting policy [14]; therefore, they are free from macro-to-femto and femto-to-macro interference. In addition, a spectrum splitting policy requires the optimal splitting, which in turns depends on configuration of cells. In comparison to spectrum splitting, spectrum-sharing is usually preferred due to scarce availability of spectrum, absence of coordination between tiers, and high requirement on end users [15]. However, the performance in spectrum-sharing scenario can be significantly affected by cross-tier and co-tier interference [16]. Therefore, a great number of researches have been devoted to power control for interference management in spectrum-sharing HetNets [14–18]. Recently, energy efficiency has been an important metric in wireless networks due to sustainable growth concerns, ecological concerns, and economic concerns [7, 19].

The energy-efficient resource allocation in HetNets has prompted significant research efforts. Reference [20] considered a problem to minimize the network power consumption of a multicarrier small cell network, subject to constraints on minimum rate requirements. Applying the KKT optimality conditions, the authors proposed a distributed algorithm based on dynamic pricing, which is to capture effects of other users. In [21], the global energy efficiency maximization problem was studied for optimizing transmit beamforming and allocating transmit power under a heterogeneous traffic model including both non-real time traffic and real time traffic. The work of [22] modeled the energy-efficient power control for HetNets in non-cooperative and cooperative games, where the locations of BSs are followed a stationary Poisson point process; this work is however not applicable if a minimum rate requirement is imposed [23]. In [24], the energy-efficient beamforming and weighted sum rate maximization problems in coordinated heterogeneous multicell networks were addressed, where the objective function is defined as the weighted sum per-cell energy efficiencies. The authors in [25] formulated an optimization problem to maximize the sum energy-efficiency of the secondary-users in cognitive downlink two-tier networks while limiting the total interference at each primary user. Then they solved the optimization problem [25] in two network scenarios: orthogonal transmission scheme and spectrum-sharing scheme, and proposed iterative resource allocation algorithms. One difference between [25] and our work is that the authors of [25] considered the instantaneous SINR and rate of users, not statistical values. Therefore, the proposed algorithms in [25] must update required parameters whenever the channel meanders from one fading state to another state. This is however extremely difficult for practical wireless networks, especially for networks with very low channel coherence time, and may create a significant amount of communication overhead [26]. While the aforementioned literature established comprehensive frameworks for understanding energy efficiency in HetNets, none of them is focused on uplink scenarios. A power control algorithm for interference management in uplink HetNets with QoS consideration was proposed by the authors in [18] in order to maximize the system capacity; this work can obtain high system capacity, the resulted energy efficiency however can be degraded due to excessive power consumption. In [15], Kang *et al.* proposed two pricing schemes using power control: non-uniform pricing and uniform pricing, for the problem of interference management in spectrum-sharing femtocell networks; however, the proposed algorithms do not guarantee the QoS requirements for users. Ha *et al.* in [17] proposed a joint framework of base station association and hybrid power control scheme for interference management, which is able to support users with various QoS requirements. This work however does not take the MBS protection into consideration. An interference management scheme with low complexity and singaling overhead was proposed in [14]; however, the QoS requirements are not taken into consideration. It was definitely established in [27] that for the uplink scenario, the energy-efficient objective function should be defined via the multi-objective formulation, e.g., weighted sum per-user energy efficiencies (WSEE) and weighted minimum per-user energy efficiencies (WMEE), instead of defining as the ratio between the network sum rate and total consumed power, i.e., the GEE optimization problem.

In sum, interference management using power control is of importance for spectrum-sharing HetNets and energy efficiency is the suitable metric for the uplink of HetNets. However, to the best of the authors' knowledge, none of existing literature is dedicated to the power control problem for interference management that maximizes the energy efficiency of users in the uplink of HetNets, protects the MBS, and supports femtocell users (FUEs) with QoS consideration. Therefore, in this chapter, we seek two power allocation schemes that maximize the energy efficiency of of uplink users in spectrum-sharing HetNets while protecting the MBS from interference of FUEs and satisfying QoS requirements on FUEs. Toward this end, we first present the system model and formulate the problem as a sum-of-ratios program where the objective is the WSEE, resource constraints on QoS requirements of femtocell user equipment (FUE) by considering the concept of rate outage probability and on BS protection by limiting interference from FUE are taken into consideration (Section 2.2). Different from conventional literature, where the objective function is defined as the ratio of the network throughput and total power consumption and the problem can be efficiently solved by the Dinkelbach's procedure, we make use of an efficient global optimization algorithm to address the original problem by first transforming into an equivalent problem and a parametric subtractive optimization problem and showing their equivalent relationship (Section 2.3). The proposed algorithm is proved to have global linear and local quadratic rate of convergence. Second, we formulate the problem of the max-min energy efficiency under the same set of constraints in order to balance fairness among individual UEs in term of energy efficiency, where the objective is defined as the WMEE. Exploiting the relationship between the fractional programming and parametric programming and using the Lagrangian duality technique, we investigate an iterative algorithm for the max-min energy-efficient problem (Section 2.4). Furthermore, as by-products, we also discuss the GEE maximization problem and extend the considered problems into the near-optimal (NOP) cases where the upper bound and lower bound between the certainly-equivalent margin (CEM) and the outage probability is taken into consideration. Finally, in Section 2.6, we conduct numerical simulations to show the convergence and advantages of the proposed algorithms over existing ones.

Notation: For the rest of the chapter, we use the italic characters to denote variables, the bold symbols to represent vectors, and the notation $*$ to indicate optimal values. Notations Pr$(\cdot)$ and $e^{(\cdot)}$/$\exp(\cdot)$ represent the probability function and exponential function, respectively. $\log(\cdot)$ denotes the natural logarithm. Mathematical notations $\geq$, $\leq$, and $=$ for vectors are defined as element-wise operations.

2.2 Network Model and Problem Formulation

We consider the uplink of a two-tier HetNet with a higher-tier macrocell and N lower-tier femtocells. Similar to frameworks of interference management in spectrum-sharing HetNets [15, 18, 25], we make two following assumptions: first, femtocells are assumed to utilize the same and single frequency band* as the macrocell; second, there is exactly one scheduled user during each signaling time-slot in each femtocell. The problem formulation and methods under these assumptions can be straightforwardly extended to spectrum-sharing HetNets with multiple and parallel frequency subchannels. Denote by $\mathcal{N} = \{1, ..., N\}$ the set of FAPs. For a given time slot, an example of the considered network consisting of one central MBS and three FAPs is described in Fig. 2.1.

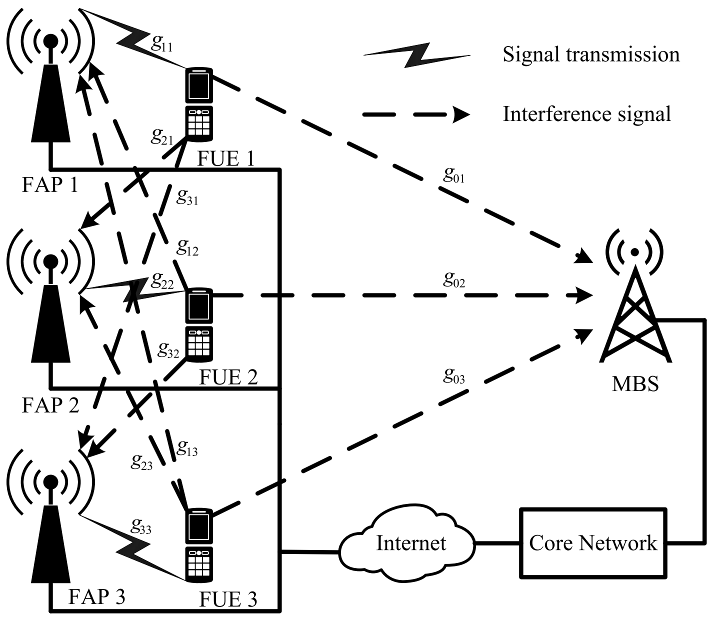


Figure 2.1: A HetNet consisting of one MBS and three FAPs.

The SINR of FUE n at FAP n can be written as

$$\gamma_n(\boldsymbol{P}) = \frac{p_n g_{nn} F_{nn}}{\sigma_n^2 + \sum\limits_{m \in \mathcal{N}/\{n\}} p_m g_{nm} F_{nm}},$$

where F_{nm} and g_{nm} are the fast-fading and slow-fading channel gain from FUE m in femtocell m to FAP n, respectively, σ_n^2 is the background noise at FAP n, and interference from the MBS is treated as additive

*A frequency band can be a frequency sub-channel in OFDMA.

noises and integrated into σ_n^2. Similar to [26], we consider the Rayleigh fading model, where the channel gain component F_{nm} is assumed to be exponentially independent and identically distributed (i.i.d) with unit mean and the corresponding average SINR is

$$\bar{\gamma}_n(\boldsymbol{P}) = \frac{p_n g_{nn}}{\sigma_n^2 + \sum\limits_{m \in \mathcal{N}/\{n\}} p_m g_{nm}}.$$

The data rate attained by FAP n can be written as $C_n(\boldsymbol{P}) = W \log_2(1+\zeta\bar{\gamma}_n(\boldsymbol{P}))$, where W is the baseband bandwidth and ζ is the SINR-gap that depends on particular modulation, coding scheme, and bit-error-rate.

Traditional resource allocation schemes that maximize the system throughput or minimize the total power consumption only focus on the radiated transmit power p_n; however, the consumed power attributed by circuit components can significantly affect the network energy efficiency [28]. Here, the consumed power P_n of transmitting C_n-bits is the sum of the transmission-consumed power p_n and circuit power consumption $p_{n,c}$, e.g., $P_n = \varrho_n p_n + p_{n,c}$, where ϱ_n is the power-inefficient factor of the amplifier. In the case of using different values of ϱ_n for different FUEs, the update of optimal power allocation for the WSEE algorithm in step 2 of Algorithm 1 and for the WMEE algorithm in (2.31) are a little bit different from current updates. For example, in (2.31), the component $\varphi_n(t)q\varrho$ should be changed to $\varphi_n(t)q\varrho_n$. Therefore, for simplicity and fair comparison with the existing framework [18], we assume that the value ϱ_n is ϱ, constant and the same for all FUEs. Then, we concentrate on the individual energy efficiency of FUE n (b/J/Hz) which is defined as the ratio of the user throughput to the user power consumption

$$\eta_n(\boldsymbol{P}) = \frac{C_n(\boldsymbol{P})}{P_n} = \frac{W \log_2(1+\zeta\bar{\gamma}_n(\boldsymbol{P}))}{\varrho p_n + p_{n,c}}.$$

With the aim of maximizing the weighted energy efficiency subject to constraints on maximum tolerable interference at the MBS and rate outage probability of UEs, the optimization problem can be mathematically formulated, as follows:

$$
\begin{aligned}
&\max_{\boldsymbol{P}} \left[\sum_{n\in\mathcal{N}} \omega_n \eta_n(\boldsymbol{P}) = \sum_{n\in\mathcal{N}} \omega_n \frac{W \log_2(1+\zeta\bar{\gamma}_n(\boldsymbol{P}))}{\varrho p_n + p_{n,c}} \right] \\
&\text{s.t. (C1): } \sum_{n\in\mathcal{N}} p_n g_{0n} \le I_{\max}, \\
&\quad \text{(C2): } \Pr\left(\gamma_n(\boldsymbol{P}) \le \gamma_n^{th}\right) \le \epsilon_n,\ \forall n \in \mathcal{N}, \\
&\quad \text{(C3): } \mathcal{P} = \{p_n, n\in\mathcal{N} | p_n^{\min} \le p_n \le p_n^{\max}\},
\end{aligned}
\tag{2.1}
$$

where the weight ω_n, for $n \in \mathcal{N}$, may potentially account for certain level of priority and/or fairness among all the UEs, $p_n^{\min}$ and $p_n^{\max}$ are the minimum and maximum transmit power of UE n, respectively. $I_{\max}$ is the maximum tolerable interference inducing at the MBS, i.e., the aggregate power of the interference from all of the FUEs should not exceed $I_{\max}$ [15]. The constraint (C1) is first derived from cognitive radio networks and is known as the *interference power constraint* or *interference temperature constraint* [15]. The interference power constraint (C1) has been applied in HetNets for interference management [15, 18]. The constraint (C2) is, the communication channel declares an outage, e.g., FAP n cannot correctly decode the received signal whenever the SINR γ_n is not greater than the minimum SINR requirement γ_n^{th} [26] and ϵ_n is a preassigned threshold that indicates the maximal allowed outage probability of UE n. Finally, the constraint (C3) ensures that the transmit power p_n should be within the bounds of the minimum transmit power $p_n^{\min}$ and the maximum transmit power $p_n^{\max}$. In the problem (2.1), the optimization objective is defined as the sum of the energy efficiency of all the UEs instead of the network energy efficiency, this metric has been proved to be reasonable for uplink and heterogeneous network scenarios [27,29]. According to [26, 30], the constraint (C2) can be equivalently expressed as $\prod_{m\in\mathcal{N}/\{n\}}\left(1+\gamma_n^{th}\frac{p_m g_{nm}}{p_n g_{nn}}\right) \le \Omega_n(p_n)$, where $\Omega_n(p_n) = (1-\epsilon_n)^{-1}\exp\left(-\frac{\sigma_n^2\gamma_n^{th}}{p_n g_{nn}}\right)$. The recent problem formulation in [25] is partially close to our optimization problem; however, as mentioned previously, the authors focused on the downlink of a cognitive two-tier network. In addition, the application scope of [25] is restricted to slowly varying wireless channels due to the assumption of static-fading channels, where power allocation must be updated once channel states change and it is required to retrack the instantaneous SINR and rerun the algorithm to seek new optimal solution [26]. As a result, proposed algorithms in [25] can lead to an excessive amount of message exchange in the network [26].

Remark 1. *The problem in* (2.1) *is NP-hard in general and non-convex due to the sum-of-ratios form of the objective function and the rate outage constraints, it is therefore very difficult to solve directly. We also note that the Dinkelbach's procedure used in [27, 31, 32] cannot be applied since it only solves a single-ratio fractional program.*

In Section 2.5, we also discuss extensive problems as compared methods which aim at maximizing the objective of global energy efficiency and taking the lower and upper bounds between the certainly-equivalent margin and the outage probability into consideration as outage constraints.

Let us introduce the Successive Convex Approximation for Low ComplExity (SCALE) method [33] as $\alpha \log(z) + \beta \leq \log(1+z)$, which is tight at $z = \tilde{z} \geq 0$ when the approximation coefficients are as follows

$$\alpha = \frac{\tilde{z}}{1+\tilde{z}}, \tag{2.2}$$

$$\beta = \log(1+\tilde{z}) - \frac{\tilde{z}}{1+\tilde{z}} \log(\tilde{z}). \tag{2.3}$$

We then make a logarithmic change of variable, i.e., $\boldsymbol{\rho} = \log \boldsymbol{P}$ and take the logarithm of both sides of the second constraint, the problem (2.1) can be relaxed to the following problem

$$\begin{aligned}
&\max_{\boldsymbol{\rho}} \sum_{n\in\mathcal{N}} \omega_n \frac{W\left(\alpha_n \log_2(\zeta\bar{\gamma}_n(e^{\boldsymbol{\rho}})) + \beta_n\right)}{\varrho e^{\rho_n} + p_{n,c}} = \sum_{n\in\mathcal{N}} \omega_n \frac{\check{C}_n(\boldsymbol{\rho})}{P_n(\rho_n)} \\
&\text{s.t.} \sum_{n\in\mathcal{N}} e^{\rho_n} g_{0n} \le I_{\max}, \\
&\quad \sum_{m\neq n} \log\left(1 + \gamma_n^{th}\frac{e^{\rho_m} g_{nm}}{e^{\rho_n} g_{nn}}\right) \le \log \Omega_n(e^{\rho_n}),\ \forall n\in\mathcal{N}, \\
&\quad \mathcal{Y} = \{\rho_n, n\in\mathcal{N} | \log p_n^{\min} \le \rho_n \le \log p_n^{\max}\},
\end{aligned} \tag{2.4}$$

where $\boldsymbol{\alpha} = [\alpha_1, ..., \alpha_N]$ and $\boldsymbol{\beta} = [\beta_1, ..., \beta_N]$.

Proposition 1. *The problem (2.4) is still not a convex problem due to the sum-of-ratios form of the objective function. However, for given $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, the feasible set is convex and the individual energy efficiency in the objective function is quasiconcave in $\boldsymbol{\rho}$.*

Proof. We can refer to [26] for the convexity proof of the feasible set. Then, the remaining work is to prove the objective function is quasiconcave in $\boldsymbol{\rho}$. We have $\log_2(\zeta\bar{\gamma}_n(e^{\boldsymbol{\rho}})) = \log_2(\zeta e^{\rho_n} g_{nn}) - \log_2(\sigma_n^2 + \sum_{m\neq n} e^{\rho_m} g_{nm})$, which is concave due to the subtraction of linear and log-sum-exp terms [34], $\check{C}_n(\boldsymbol{\rho})$ is therefore a concave function. The denominator is a convex function due to the exponential and constant terms. Let define $\check{\eta}_n(\boldsymbol{\rho}) = \check{C}_n(\boldsymbol{\rho})/P_n(\rho_n)$ and its superlevel sets $S_a = \{\rho_n \in \mathcal{Y}, \forall n | \check{\eta}_n(\boldsymbol{\rho}) \ge a\},\ \forall a \in R$. When $a \le 0$, $\check{\eta}_n(\boldsymbol{\rho}) \ge a$ for all $\boldsymbol{\rho}$; hence, S_a is convex. For the case $a > 0$, the set S_a can can be equally expressed as $S_a = \{\rho_n \in \mathcal{Y}, \forall n | \check{C}_n(\boldsymbol{\rho}) - aP_n(\rho_n) \ge 0\}$. Let define $f_n(\boldsymbol{\rho}) = \check{C}_n(\boldsymbol{\rho}) - aP_n(\rho_n)$. According to [34], S_a is a convex set if for any $\boldsymbol{\rho}_1$, $\boldsymbol{\rho}_2 \in S_a$ and any θ with $1 \ge \theta \ge 0$, we have

$$\theta\boldsymbol{\rho}_1 + (1-\theta)\boldsymbol{\rho}_2 \in S_a. \tag{2.5}$$

The condition (2.5) is satisfied when $f_n(\theta\boldsymbol{\rho}_1 + (1-\theta)\boldsymbol{\rho}_2) \ge 0$ Actually, $\check{C}_n(\boldsymbol{\rho}) - aP_n(\rho_n)$ is a concave function due to the subtraction of a concave function and a linear function. By definition, $f_n(\theta\boldsymbol{\rho}_1 + (1-\theta)\boldsymbol{\rho}_2) \ge$

$\theta f_n(\boldsymbol{\rho}_1)+(1-\theta)f_n(\boldsymbol{\rho}_2)$. Due to $\boldsymbol{\rho}_1, \boldsymbol{\rho}_2 \in S_a$, we have $f_n(\boldsymbol{\rho}_1) \geq 0$ and $f_n(\boldsymbol{\rho}_2) \geq 0$, the condition (2.5) is satisfied, and S_a is a convex set. As a result, the individual energy efficiency is quasiconcave in $\boldsymbol{\rho}$ and the Proposition 1 holds. □

The objective function is the sum-of-ratio form and sum of quasiconcave functions, which is however not guaranteed to be quasiconcave. Hence, it is difficult to obtain the globally optimal solution to the problem (2.4) by the conventional method, e.g., Dinkelbach's procedure. To circumvent it, based on the application of an efficient global optimization algorithm proposed in [35], we first transform the problem (2.4) into a parametric convex programming problem and then find the optimal solution to the underlying problem.

2.3 Energy-Efficient Algorithm

By introducing new auxiliary variable $\boldsymbol{\kappa} = \{\kappa_1, ..., \kappa_N\}$, the problem in (2.4) is equivalent to

$$\begin{aligned}
&\max_{\boldsymbol{\rho},\boldsymbol{\kappa}} \sum_{n\in\mathcal{N}} \kappa_n \\
&\text{s.t. } \kappa_n \leq \omega_n \frac{\check{C}_n(\boldsymbol{\rho})}{P_n(\rho_n)}, \ \forall n \in \mathcal{N} \\
&\quad \sum_{n\in\mathcal{N}} e^{\rho_n} g_{0n} \leq I_{\max}, \\
&\quad \sum_{m\neq n} \log\left(1+\gamma_n^{th}\frac{e^{\rho_m} g_{nm}}{e^{\rho_n} g_{nn}}\right) \leq \log \Omega_n(e^{\rho_n}), \ \forall n \in \mathcal{N}, \\
&\quad \mathcal{Y} = \{\rho_n, n \in \mathcal{N} | \log p_n^{\min} \leq \rho_n \leq \log p_n^{\max}\}.
\end{aligned} \tag{2.6}$$

We have the following Lemma to describe the equivalence between the weighted sum maximization problem (2.6) and its corresponding parametric subtractive optimization problem.

Lemma 1. *If $(\boldsymbol{\rho}^*, \boldsymbol{\kappa}^*)$ is the optimal solution to the problem (2.6), then there exists $\boldsymbol{\lambda}^* = [\lambda_1, ..., \lambda_N]$ such that $\boldsymbol{\rho}^*$ is the optimal solution to the following problem, i.e., satisfies its KKT optimality conditions, for*

$\boldsymbol{\lambda} = \boldsymbol{\lambda}^*$ *and* $\boldsymbol{\kappa} = \boldsymbol{\kappa}^*$

$$\begin{aligned}
&\max_{\boldsymbol{\rho}} \sum_{n \in \mathcal{N}} \lambda_n \left(\omega_n \check{C}_n(\boldsymbol{\rho}) - \kappa_n P_n(\rho_n) \right) \\
&\textit{s.t.} \sum_{n \in \mathcal{N}} e^{\rho_n} g_{0n} \leq I_{\max}, \\
&\quad \sum_{m \neq n} \log \left(1 + \gamma_n^{th} \frac{e^{\rho_m} g_{nm}}{e^{\rho_n} g_{nn}} \right) \leq \log \Omega_n(e^{\rho_n}) \; \forall n \in \mathcal{N}, \\
&\quad \mathcal{Y} = \{ \rho_n, n \in \mathcal{N} | \log p_n^{\min} \leq \rho_n \leq \log p_n^{\max} \}.
\end{aligned} \tag{2.7}$$

The optimal solution $\boldsymbol{\rho}^*$ *also satisfies the following system of equations for* $\boldsymbol{\lambda} = \boldsymbol{\lambda}^*$ *and* $\boldsymbol{\kappa} = \boldsymbol{\kappa}^*$

$$\lambda_n = \frac{1}{P_n(\rho_n)}, \; \forall n \in \mathcal{N}, \tag{2.8}$$

$$\kappa_n = \omega_n \frac{\check{C}_n(\boldsymbol{\rho})}{P_n(\rho_n)}, \; \forall n \in \mathcal{N}. \tag{2.9}$$

Inversely, if $\boldsymbol{\rho}^*$ *is the optimal solution to* (2.7) *and satisfies the system* (2.9) *and* (2.8) *for* $\boldsymbol{\lambda} = \boldsymbol{\lambda}^*$ *and* $\boldsymbol{\kappa} = \boldsymbol{\kappa}^*$*,* $(\boldsymbol{\rho}^*, \boldsymbol{\kappa}^*)$ *is the optimal solution to the problem* (2.6) *with* $\boldsymbol{\lambda} = \boldsymbol{\lambda}^*$ *being the dual variable associated with the first constraint.*

Proof. In (2.6), the first constraint is equivalent to $\omega_n \check{C}_n(\boldsymbol{\rho}) - \kappa_n P_n(\rho_n) \geq 0$. Let us define the function for the problem (2.6), as follows:

$$\begin{aligned}
L(\boldsymbol{\rho}, \boldsymbol{\kappa}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu}) = {}& \vartheta \sum_{n \in \mathcal{N}} \kappa_n + \sum_{n \in \mathcal{N}} \lambda_n \left(\omega_n \check{C}_n(\boldsymbol{\rho}) - \kappa_n P_n(\rho_n) \right) \\
&+ \mu \underbrace{\left(I_{\max} - \sum_{n \in \mathcal{N}} e^{\rho_n} g_{0n} \right)}_{f(\boldsymbol{\rho})} + \sum_{n \in \mathcal{N}} \nu_n \underbrace{\left(\log \Omega_n(e^{\rho_n}) - \sum_{m \neq n} \log \left(1 + \gamma_n^{th} \frac{e^{\rho_m} g_{nm}}{e^{\rho_n} g_{nn}} \right) \right)}_{h_n(\boldsymbol{\rho})},
\end{aligned}$$

where $\boldsymbol{\lambda}$, μ, and $\boldsymbol{\nu}$ are the Lagrange multipliers associated with the first, second, and third constraints in (2.6), respectively. By Fritz-John optimality condition [36], there exist ϑ^*, $\boldsymbol{\lambda}^*$, μ^*, and $\boldsymbol{\nu}^* = [\nu_1^*, ..., \nu_N^*]$ such that

$$\frac{\partial L}{\partial \rho_n} = \sum_{n\in\mathcal{N}} \lambda_n^* \frac{\partial \left(\omega_n \check{C}_n(\boldsymbol{\rho}^*) - \kappa_n^* P_n(\rho_n^*)\right)}{\partial \rho_n} + \mu^* \frac{\partial f(\boldsymbol{\rho}^*)}{\partial \rho_n} + \sum_{n\in\mathcal{N}} \nu_n^* \frac{\partial h_n(\boldsymbol{\rho}^*)}{\partial \rho_n} = 0,\ \forall n \in \mathcal{N}, \tag{2.10}$$

$$\frac{\partial L}{\partial \kappa_n} = \vartheta^* - \lambda_n^* P_n(\rho_n^*) = 0,\ \forall n \in \mathcal{N}, \tag{2.11}$$

$$\lambda_n^* \frac{\partial L}{\partial \lambda_n} = \lambda_n^* \left(\omega_n \check{C}_n(\boldsymbol{\rho}^*) - \kappa_n^* P_n(\rho_n^*)\right) = 0,\ \forall n \in \mathcal{N},$$

$$\mu^* \frac{\partial L}{\partial \mu} = \mu^* f(\boldsymbol{\rho}^*) = 0, \tag{2.12}$$

$$\nu_n^* \frac{\partial L}{\partial \nu_n} = \nu_n^* h_n(\boldsymbol{\rho}^*) = 0,\ \forall n \in \mathcal{N}, \tag{2.13}$$

$$\omega_n \check{C}_n(\boldsymbol{\rho}^*) - \kappa_n^* P_n(\rho_n^*) \geq 0, \lambda_n^* \geq 0,\ \forall n \in \mathcal{N}, \tag{2.14}$$

$$f(\boldsymbol{\rho}^*) \geq 0, \mu^* \geq 0, \tag{2.15}$$

$$h_n(\boldsymbol{\rho}^*), \nu_n^* \geq 0,\ \forall n \in \mathcal{N}, \tag{2.16}$$

$$\vartheta^* \geq 0, (\vartheta^*, \boldsymbol{\lambda}^*, \mu^*, \boldsymbol{\nu}^*) \neq (0, \mathbf{0}, 0, \mathbf{0}), \tag{2.17}$$

where $\mathbf{0}$ is the zero vector. If we suppose $\vartheta^* = 0$, we have $\boldsymbol{\lambda}^* = \mathbf{0}$ according to (2.11) since $P_n(\rho_n) > 0$, $\forall n$ for all feasible solutions $\boldsymbol{\rho}$. Define $I(\boldsymbol{\rho}^*) = \{n | h_n(\boldsymbol{\rho}^*) = 0, n \in \mathcal{N}\}$; hence, it follows from (2.10), (2.12), (2.13), (2.15), (2.16), and (2.17) that

$$\mu^* \nabla f(\boldsymbol{\rho}^*) + \sum_{n\in I(\boldsymbol{\rho}^*)} \nu_n^* \nabla h_n(\boldsymbol{\rho}^*) = 0, \tag{2.18}$$

$$\mu^* + \sum_{n\in I(\boldsymbol{\rho}^*)} \nu_n^* > 0, \mu^* \geq 0, \nu_n^* \geq 0, n \in I(\boldsymbol{\rho}^*). \tag{2.19}$$

By Slater's condition, there must exist a value $\boldsymbol{\rho}'$ such that

$$f(\boldsymbol{\rho}') > 0, h_n(\boldsymbol{\rho}') > 0, n \in \mathcal{N}. \tag{2.20}$$

Due to (2.20) and the concavity of $h_n(\boldsymbol{\rho}), n \in \mathcal{N}$ and $f(\boldsymbol{\rho})$, we have

$$\nabla f(\boldsymbol{\rho}^*)^T(\boldsymbol{\rho}' - \boldsymbol{\rho}^*) \geq f(\boldsymbol{\rho}') - f(\boldsymbol{\rho}^*), \tag{2.21}$$

$$\nabla h_n(\boldsymbol{\rho}^*)^T(\boldsymbol{\rho}' - \boldsymbol{\rho}^*) \geq h_n(\boldsymbol{\rho}') - h_n(\boldsymbol{\rho}^*) > 0, n \in I(\boldsymbol{\rho}^*). \tag{2.22}$$

If we assume $\nabla f(\boldsymbol{\rho}^*) = 0$, $\mu^* > 0$ and $\nabla f(\boldsymbol{\rho}^*)(\boldsymbol{\rho}' - \boldsymbol{\rho}^*) > 0$, otherwise $\mu^* = 0$. Now, let $\boldsymbol{d} = \boldsymbol{\rho}' - \boldsymbol{\rho}^*$, from (2.19), (2.21), and (2.22), we have

$$\left[\mu^* \nabla f(\boldsymbol{\rho}^*) \quad \sum_{n \in I(\boldsymbol{\rho}^*)} \nu_n^* \nabla h_n(\boldsymbol{\rho}^*)\right]^T \boldsymbol{d} > 0, \tag{2.23}$$

since either $\nabla f(\boldsymbol{\rho}^*)$ or μ^* must be zero. Clearly, (2.18) contradicts (2.23). Consequently, we have $\vartheta^* > 0$

Assign $\vartheta^* = 1$ or $\boldsymbol{\lambda}^* = \boldsymbol{\lambda}^*/\vartheta^*$, $\mu^* = \mu^*/\vartheta^*$, and $\boldsymbol{\nu}^* = \boldsymbol{\nu}^*/\vartheta^*$. Equations (2.11) and (2.14) are, respectively, equivalent to $\lambda_n^* = 1/P_n(\rho_n^*)$ and $\kappa_n^* = \omega_n \check{C}_n(\boldsymbol{\rho}^*)/P_n(\rho_n^*)$, $\forall n \in \mathcal{N}$. Moreover, for given $\boldsymbol{\lambda} = \boldsymbol{\lambda^*} > \boldsymbol{0}$ and $\boldsymbol{\kappa} = \boldsymbol{\kappa^*} \geq \boldsymbol{0}$, (2.10), (2.12), (2.13), (2.15), and (2.16) are just the KKT conditions for the problem (2.7). Note that (2.7) is a convex problem; therefore, the KKT conditions are also the sufficient optimality conditions and $\boldsymbol{\rho}^*$ is the optimal solution for given $\boldsymbol{\lambda} = \boldsymbol{\lambda^*} > \boldsymbol{0}$ and $\boldsymbol{\kappa} = \boldsymbol{\kappa^*} \geq \boldsymbol{0}$. This completes the proof of the first statement. The second statement is proved similarly. The proof ends. □

As proved in the Proposition 1, the function $\check{C}_n(\boldsymbol{\rho})$ is concave and the function $P_n(\rho_n)$ is convex in $\boldsymbol{\rho}$. Accordingly, for given $\boldsymbol{\lambda}$ and $\boldsymbol{\kappa}$, the objective function of (2.7) is concave. In addition, the feasible set is convex. Hence, the problem (2.7) is a convex optimization problem for given $\boldsymbol{\lambda}$ and $\boldsymbol{\kappa}$ and then the globally optimal solution to (2.7) can be guaranteed. We exploit this idea to investigate the algorithm for seeking the optimal solution to the parametric subtractive optimization problem, as described in Algorithm 1, where we

Algorithm 1 Solutions to the parametric subtractive approximation problem (2.7) (WSEE Algorithm)

1: Set ε, $t = 0$, $\xi \in (0, 1)$, $\chi \in (0, 1)$, choose arbitrary value $\boldsymbol{\rho}^{(t)}$ which satisfies all the constraints, and initialize $\boldsymbol{\lambda}^{(t)}$ and $\boldsymbol{\kappa}^{(t)}$ as

$$\lambda_n^{(t)} = \frac{1}{P_n(\rho_n^{(t)})}, \ \kappa_n^{(t)} = \omega_n \frac{\check{C}_n(\boldsymbol{\rho}^{(t)})}{P_n(\rho_n^{(t)})}, \ \forall n \in \mathcal{N}.$$

2: Obtain the optimal value $\boldsymbol{\rho}^{(t+1)}$ of the following problem

$$\begin{aligned} \max_{\boldsymbol{\rho} \in \mathcal{Y}} & \sum_{n \in \mathcal{N}} \lambda_n^{(t)} \left(\omega_n \check{C}_n(\boldsymbol{\rho}) - \kappa_n^{(t)} P_n(\rho_n) \right) \\ \text{s.t.} & \sum_{n \in \mathcal{N}} e^{\rho_n} g_{0n} \le I_{\max}, \\ & \sum_{m \neq n} \log \left(1 + \gamma_n^{th} \frac{e^{\rho_m} g_{nm}}{e^{\rho_n} g_{nn}} \right) \le \log \Omega_n(e^{\rho_n}) \ \forall n \in \mathcal{N}. \end{aligned}$$

3: **if** $\left| \kappa_n^{(t)} P_n \left(\rho_n^{(t+1)} \right) - \omega_n \check{C}_n(\boldsymbol{\rho}^{(t+1)}) \right| \le \varepsilon$ and $\left| \lambda_n^{(t)} P_n \left(\rho_n^{(t+1)} \right) - 1 \right| \le \varepsilon$ **then**

4: $\quad$ $\boldsymbol{\rho}^{(t+1)}$ is a globally optimal solution to the problem (2.6) and then stop the Algorithm.

5: **else**

6: $\quad$ Find i_n the smallest non-negative integer satisfying

$$\begin{aligned} & \sum_{n \in \mathcal{N}} \left(\left| \psi_n^{\lambda} \left(\lambda_n^{(t)} - \xi^i \psi_n^{\lambda} \left(\lambda_n^{(t)} \right) \left[\Delta_n \left(\rho_n^{(t+1)} \right) \right]^{-1} \right) \right|^2 \right. \\ & \left. + \left| \psi_n^{\kappa} \left(\kappa_n^{(t)} - \xi^i \psi_n^{\kappa} \left(\kappa_n^{(t)} \right) \left[\Delta_n \left(\rho_n^{(t+1)} \right) \right]^{-1} \right) \right|^2 \right) \\ & \le \left(1 - \chi \xi^i \right)^2 \sum_{n \in \mathcal{N}} \left(\left| \psi_n^{\lambda} \left(\lambda_n^{(t)} \right) \right|^2 + \left| \psi_n^{\kappa} \left(\kappa_n^{(t)} \right) \right|^2 \right). \end{aligned}$$

7: $\quad$ Update $\boldsymbol{\lambda}^{(t+1)}$ and $\boldsymbol{\kappa}^{(t+1)}$, as follows:

$$\begin{aligned} \lambda_n^{(t+1)} &= \lambda_n^{(t)} - \xi^{i_n} \psi_n^{\lambda} \left(\lambda_n^{(t)} \right) \left[\Delta_n \left(\rho_n^{(t+1)} \right) \right]^{-1}, \ \forall n \in \mathcal{N}, \\ \kappa_n^{(t+1)} &= \kappa_n^{(t)} - \xi^{i_n} \psi_n^{\kappa} \left(\kappa_n^{(t)} \right) \left[\Delta_n \left(\rho_n^{(t+1)} \right) \right]^{-1}, \ \forall n \in \mathcal{N}. \end{aligned}$$

8: $\quad$ Set $t = t + 1$.

9: $\quad$ Go to step 2.

10: **end if**

define

$$\psi_n^{\lambda}(\lambda_n) = -1 + \lambda_n P_n(\rho_n),\ \forall n \in \mathcal{N},$$

$$\psi_n^{\kappa}(\kappa_n) = -\omega_n \check{C}_n(\boldsymbol{\rho}) + \kappa_n P_n(\rho_n),\ \forall n \in \mathcal{N},$$

$$\Delta_n(\rho_n) = P_n(\rho_n),\ \forall n \in \mathcal{N},$$

and update auxiliary variables $\boldsymbol{\lambda}$ and $\boldsymbol{\kappa}$ based on the Newton's method.

The Algorithm 1 is composed of two main steps: the first one is to seek the optimal solution to the problem (2.7) for given $\boldsymbol{\lambda}$ and $\boldsymbol{\kappa}$ and choose the one satisfying the system (2.8) and (2.9) among optimal values, the second step is to update $\boldsymbol{\lambda}$ and $\boldsymbol{\kappa}$, and these two steps are repeated until convergence. The output of the Algorithm 1 is just the optimal solution to the problem (2.4) for given $\boldsymbol{\alpha}(\tau)$ and $\boldsymbol{\beta}(\tau)$, i.e., we are trying to maximize the lower bound of the total achievable data rate. To obtain the final solution, we iteratively update $\boldsymbol{\alpha}(\tau+1)$ and $\boldsymbol{\beta}(\tau+1)$ according to (2.2) and (2.3), respectively, with $\tilde{z} = \zeta\bar{\gamma}_n\left(e^{\boldsymbol{\rho}^{(\tau)*}}\right)$, where $\boldsymbol{\rho}^{(\tau)*}$ is the optimal solution of Algorithm 1. These new approximation values $\boldsymbol{\alpha}(\tau+1)$ and $\boldsymbol{\beta}(\tau+1)$ will be used as the input of Algorithm 1 in the next iteration $(\tau+1)$ and these processes are repeated until the maximum number of iteration τ reaches or the stopping criterion satisfies. With the logarithmic approximation, the objective function of (2.4) is improved for each iterative update of approximation coefficients and the optimal solution to the approximation problem finally converges to the Karush-Kuhn-Tucker (KKT) optimal point of the original problem (2.1) [33]. Together with the result in Theorem 1, the whole algorithm (the SCALE procedure to update approximation coefficients $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ and Algorithm 1) finally converges to an optimal solution to the optimization problem (2.1).

Theorem 1. *The Algorithm 1 has global linear and local quadratic rate of convergence.*

Proof. Refer to [35, Corollary 3.2 and Remark 3.1] for the detailed proof. □

2.4 Max-Min Energy Efficiency

In section 2.2 and section 2.3, the formulation and algorithm of the weighted sum energy-efficient problem are respectively presented; however, this scenario only targets at the energy efficiency of the entire network, which can be improved at the cost of individual energy efficiency and therefore leads to blatant unfairness among individual UEs. Consequently, in this section we study the energy-efficient problem for the max-min scheme under the same set of constraints so as to ensure fairness among individual UEs in term of energy efficiency. The problem is formulated, as follows:

$$\begin{aligned}
&\max_{\boldsymbol{P}} \min_{n\in\mathcal{N}} \left[\omega_n \eta_n(\boldsymbol{P}) = q = \omega_n \frac{W\log_2(1+\zeta\bar{\gamma}_n(\boldsymbol{P}))}{\varrho p_n + p_{n,c}}\right] \\
&\text{s.t.} \sum_{n\in\mathcal{N}} p_n g_{0n} \leq I_{\max}, \\
&\quad \Pr\left(\gamma_n(\boldsymbol{P}) \leq \gamma_n^{th}\right) \leq \epsilon_n,\ \forall n \in \mathcal{N}, \\
&\quad \mathcal{P} = \{p_n, n\in\mathcal{N} | p_n^{\min} \leq p_n \leq p_n^{\max}\},
\end{aligned} \tag{2.24}$$

Remark 2. *Even with the concavation of the numerator of the objective function and of the feasible set, (2.24) is still a non-convex problem due to the max-min nature and fractional form of the objective function.*

Define q^* as the maximum energy efficiency which is achieved with the optimal solution $\boldsymbol{P}^*$, as follows:

$$q^* = \max_{\boldsymbol{P}\in\mathcal{F}} \min_{n\in\mathcal{N}} \left[\omega_n \eta_n(\boldsymbol{P})\right],$$

where $\mathcal{F}$ is the feasible set of constraints (C1), (C2), and (C3). The following Theorem specifies conditions to reach the optimal energy efficiency to (2.24).

Theorem 2. *The optimal solution $\boldsymbol{P}^*$ achieves the optimal energy efficiency q^* if and only if*

$$\max_{\boldsymbol{P}\in\mathcal{F}} \min_{n\in\mathcal{N}} \left[\omega_n C_n(\boldsymbol{P}) - q^* P_n(\boldsymbol{P})\right] = \min_{n\in\mathcal{N}} \left[\omega_n C_n(\boldsymbol{P}^*) - q^* P_n(\boldsymbol{P}^*)\right] = 0.$$

In other words, if we know the value q^* in advance, we can seek the optimal solution to the problem (2.24) by equivalently tackling the following problem

$$\max_{\boldsymbol{P}\in\mathcal{F}} \min_{n\in\mathcal{N}} \left[\omega_n C_n(\boldsymbol{P}) - q^* P_n(\boldsymbol{P})\right]. \tag{2.25}$$

The detailed proof of Theorem 2 is shown in [37]. This proof gives a simple condition to choose the optimal solution parameter q^* for which the problem (2.24) and (2.25) are equivalent, i.e., they have the same optimal solution. However, generally the optimal value q^* is not specified in advance. Therefore, we propose an algorithm, in which we achieve the solution of (2.25) for a given q and then update q iteratively.

Algorithm 2 Iterative algorithm of the max-min energy-efficient problem (2.24) (WMEE Algorithm)

1: Set ε and $T_{\max}$, and initialize $t = 0$, FLAG $= 0$, and $q^{(t)} = 0$.
2: **repeat**
3: For a given $q^{(t)}$, solve the problem (2.25) to obtain $\boldsymbol{P}^{(t)}$.
4: **if** $\left|\min_{n\in\mathcal{N}}\left[\omega_n C_n(\boldsymbol{P}^{(t)}) - q^{(t)} P_n(\boldsymbol{P}^{(t)})\right]\right| \leq \varepsilon$ **then**
5: $\boldsymbol{P}^* = \boldsymbol{P}^{(t)}$ and $q^* = q^{(t)}$.
6: FLAG $= 1$.
7: **else**
8: Set $t = t + 1$.
9: Set $q^{(t)} = \min_{n\in\mathcal{N}} \frac{C_n\left(\boldsymbol{P}^{(t-1)}\right)}{P_n\left(\boldsymbol{P}^{(t-1)}\right)}$.
10: **end if**
11: **until** FLAG $= 1$.

On the basis of Theorem 2, we develop an algorithm to find the optimal solution to the problem (2.24). The main step of the Algorithm 2 lies in line 3, which is targeted at solving the problem (2.25) for a given

$q^{(t)}$. Specifically, for a given q, the problem (2.25) can be recast, as follows:

$$\begin{aligned}
&\max_{\boldsymbol{P}} \min_{n\in\mathcal{N}} \left[\omega_n C_n(\boldsymbol{P}) - qP_n(\boldsymbol{P})\right] \\
&\text{s.t.} \sum_{n\in\mathcal{N}} p_n g_{0n} \le I_{\max}, \\
&\quad \Pr\left(\gamma_n(\boldsymbol{P}) \le \gamma_n^{th}\right) \le \epsilon_n,\ \forall n \in \mathcal{N}, \\
&\quad \mathcal{P} = \{p_n, n \in \mathcal{N} | p_n^{\min} \le p_n \le p_n^{\max}\}.
\end{aligned} \tag{2.26}$$

Using the SCALE method [33] and introducing new variable u, problem in (2.26) boils down to

$$\begin{aligned}
&\max_{\boldsymbol{\rho},u} u \\
&\text{s.t.} \sum_{n\in\mathcal{N}} e^{\rho_n} g_{0n} \le I_{\max}, \\
&\quad \sum_{m\neq n} \log\left(1+\gamma_n^{th}\frac{e^{\rho_m} g_{nm}}{e^{\rho_n} g_{nn}}\right) \le \log \Omega_n(e^{\rho_n}),\ \forall n \in \mathcal{N}, \\
&\quad \mathcal{Y} = \{\rho_n, n \in \mathcal{N} | \log p_n^{\min} \le \rho_n \le \log p_n^{\max}\}, \\
&\quad u \le \omega_n \check{C}_n(\boldsymbol{\rho}) - qP_n(\boldsymbol{\rho}),\ \forall n \in \mathcal{N},
\end{aligned} \tag{2.27}$$

which is formulated for given $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. Based on the Theorem 2, we have the following Propositions for the problem (2.27).

Proposition 2. *For given $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, problem (2.27) is a jointly convex problem in $\boldsymbol{\rho}$ and u.*

Proof. According to Proposition 1, the first, second, and third constraint are all convex. Obviously, the last constraint is convex due to concavity of its right-hand side and linearity of its left-hand side. Consequently, (2.27) is a jointly convex problem that maximizes a concave objective function over a convex set. □

Proposition 3. *For any feasible $\boldsymbol{\rho}$, the auxiliary variable $u \ge 0$ when the energy efficiency $q \le q^*$.*

Due to convexity of (2.27), in the following, we use the Lagrangian duality technique to solve (2.27). Let μ, $\boldsymbol{\nu}$, and $\boldsymbol{\varphi}$ are respectively the Lagrange multipliers associated with the first, second, and fourth constraint of (2.27), the Lagrangian function is defined as

$$L(\boldsymbol{\rho}, u, \mu, \boldsymbol{\nu}, \boldsymbol{\varphi}) = u + \mu\left(I_{\max} - \sum_{n\in\mathcal{N}} e^{\rho_n} g_{0n}\right) + \sum_{n\in\mathcal{N}} \nu_n \left(\log \Omega_n(e^{\rho_n}) - \sum_{m\neq n} \log\left(1 + \gamma_n^{th}\frac{e^{\rho_m} g_{nm}}{e^{\rho_n} g_{nn}}\right)\right) + \sum_{n\in\mathcal{N}} \varphi_n \left(\omega_n \check{C}_n(\boldsymbol{\rho}) - qP_n(\boldsymbol{\rho}) - u\right) \quad (2.28)$$

In (2.28), μ can be interpreted as the interference price while $\boldsymbol{\nu}$ and $\boldsymbol{\varphi}$ can be viewed as the outage price and energy price, respectively. Then, the Lagrange dual function is

$$g(\mu, \boldsymbol{\nu}, \boldsymbol{\varphi}) = \max_{\boldsymbol{\rho}, u} L(\boldsymbol{\rho}, u, \mu, \boldsymbol{\nu}, \boldsymbol{\varphi}), \quad (2.29)$$

which can be specified as the maximum of the Lagrangian function (2.28). Accordingly, the Lagrange dual problem is

$$\min_{\mu\geq 0, \boldsymbol{\nu}\geq \mathbf{0}, \boldsymbol{\varphi}\geq \mathbf{0}} g(\mu, \boldsymbol{\nu}, \boldsymbol{\varphi}). \quad (2.30)$$

First, for given μ, $\boldsymbol{\nu}$, and $\boldsymbol{\varphi}$, we can obtain the update value of transmit power by taking the first derivative of $L(\boldsymbol{\rho}, u, \mu, \boldsymbol{\nu}, \boldsymbol{\varphi})$ with respect to (w.r.t.) ρ_n, $\forall n$ and setting the result to zero. After some algebraic manipulation and transformation of the result back to the $\boldsymbol{P}$-space, the power update formula is given by the following

$$p_n(t+1) = \left[\frac{\nu_n(t)\frac{\sigma_n^2 \gamma_n^{th}}{p_n(t) g_{nn}} + \frac{\varphi_n(t)}{\log 2}\omega_n W \alpha_n}{\mu(t) g_{0n} + \varphi_n(t) q \varrho + \sum\limits_{m\neq n}\left[\nu_m(t)\frac{M_m(t) g_{mn}}{1 + M_m(t) g_{mn} p_n(t)} + \Lambda_m(t) g_{mn}\right]}\right]_{p_n^{\min}}^{p_n^{\max}}, \quad (2.31)$$

where $[x]_a^b = \max\{\min\{x, b\}, a\}$, $M_m = \gamma_m^{th}(p_m g_{mm})^{-1}$, and $\Lambda_m = \frac{\varphi_m}{\log 2}\omega_n W \alpha_m(\sigma_m^2 + \sum_{l\neq m} p_l g_{ml})^{-1}$. Observe in (2.31) that message passing among FAPs is required to update power, for example, to update

p_n, FAP n needs message passing of ν_m, M_m, and Λ_m from other FAPs $m \neq n$. In addition, FAP n has to estimate channel gain from itself to other FAPs.

Next, the auxiliary variable u can be computed by solving the following problem

$$\max_{u} \left(1 - \sum_{n\in\mathcal{N}} \varphi_n\right) u$$
$$\text{s.t.} u \leq \omega_n \check{C}_n(\boldsymbol{\rho}) - qP_n(\boldsymbol{\rho}), \ \forall n \in \mathcal{N}.$$

Here, we use the idea from [38] to update u. In particular, if $1 < \sum_{n\in\mathcal{N}} \varphi_n$, $u(t) = 0$ due to u's property in Proposition 3; otherwise,

$$u(t) = \min_{n\in\mathcal{N}} \{\underbrace{\omega_n \check{C}_n(\boldsymbol{\rho}(t+1)) - qP_n(\boldsymbol{\rho}(t+1))}_{g_n(\boldsymbol{\rho})}\},$$

where $\boldsymbol{\rho}(t+1) = \log \boldsymbol{P}(t+1)$ with $\boldsymbol{P}(t+1)$ obtained from (2.31). To update u, we can assign this calculation to one of any FAPs, then the assigned FAP sends new value of u to other FAPs.

Finally, we update the Lagrangian multipliers by the subgradient projection method as

$$\mu(t+1) = [\mu(t) - \delta_\mu(t)\Delta\mu]^+ , \tag{2.31}$$
$$\nu_n(t+1) = [\nu_n(t) - \delta_\nu(t)\Delta\nu_n]^+ , \tag{2.32}$$
$$\varphi_n(t) = [\varphi_n(t) - \delta_\varphi(t)\Delta\varphi_n]^+ , \tag{2.33}$$

where $[z]^+ = \max\{0, z\}$, t is the iteration index, and $\delta_\mu(t)$, $\delta_\nu(t)$, and $\delta_\varphi(t)$ are sufficiently positive small step sizes*, which are chosen to guarantee the convergence of aforementioned updates. Here, $\Delta\mu$, $\Delta\mu_n$, $\Delta\varphi_n$ is a subgradient of the Lagrange dual function $g(\mu, \boldsymbol{\nu}, \boldsymbol{\varphi})$, which can be specified by the Proposition 4. The whole procedure to solve the problem (2.27) is summarized in Algorithm 3.

*Typical step size criteria are constant and square summable but not summable, which refer to the step size $\delta(t)$ satisfying the diminishing rule, i.e., $\delta(t) \geq 0$, $\sum_{t=1}^{t=\infty} \delta(t)^2 < \infty$, and $\sum_{t=1}^{t=\infty} \delta(t) = \infty$

Proposition 4. *For the dual problem* (2.30) *with the primal problem established in* (2.27)*, a subgradient of* $g(\mu, \boldsymbol{\nu}, \boldsymbol{\varphi})$ *is*

$$\Delta\mu = I_{\max} - \sum_{n\in\mathcal{N}} p_n^* g_{0n}$$
$$\Delta\nu_n = \log\Omega_n(p_n^*) - \sum_{m\neq n} \log\left(1 + \gamma_n^{th}\frac{p_m^* g_{nm}}{p_n^* g_{nn}}\right)$$
$$\Delta\varphi_n = \omega_n \check{C}_n(\boldsymbol{P}^*) - qP_n(\boldsymbol{P}^*) - u^*,$$

where $\boldsymbol{P}^* = \exp(\boldsymbol{\rho}^*)$*, and* u^* *and* $\boldsymbol{\rho}^*$ *denote the optimal solution of* (2.29) *for given* μ*,* $\boldsymbol{\nu}$*, and* $\boldsymbol{\varphi}$*.*

Proof. The proof is similar to [38,39]. By definition, a subgradient of $g(\mu, \boldsymbol{\nu}, \boldsymbol{\varphi})$ is any vector t that satisfies the following inequality, $\forall(\mu', \boldsymbol{\nu}', \boldsymbol{\varphi}')$

$$g(\mu', \boldsymbol{\nu}', \boldsymbol{\varphi}') \geq g(\mu, \boldsymbol{\nu}, \boldsymbol{\varphi}) + t^T \begin{bmatrix} \mu' - \mu \\ \boldsymbol{\nu}' - \boldsymbol{\nu} \\ \boldsymbol{\varphi}' - \boldsymbol{\varphi} \end{bmatrix}.$$

We have

$$g(\mu', \boldsymbol{\nu}', \boldsymbol{\varphi}') = \max_{\boldsymbol{\rho}, u} L(\boldsymbol{\rho}, u, \mu', \boldsymbol{\nu}', \boldsymbol{\varphi}') = u^* + \mu'\left(I_{\max} - \sum_{n\in\mathcal{N}} e^{\rho_n^*} g_{0n}\right)$$
$$+ \sum_{n\in\mathcal{N}} \nu_n' \left(\log\Omega_n(e^{\rho_n^*}) - \sum_{m\neq n}\log\left(1 + \gamma_n^{th}\frac{e^{\rho_m^*} g_{nm}}{e^{\rho_n^*} g_{nn}}\right)\right) + \sum_{n\in\mathcal{N}} \varphi_n' \left(\omega_n \check{C}_n(\boldsymbol{\rho}^*) - qP_n(\boldsymbol{\rho}^*) - u^*\right)$$
$$= g(\mu, \boldsymbol{\nu}, \boldsymbol{\varphi}) + t^T \begin{bmatrix} \mu' - \mu \\ \boldsymbol{\nu}' - \boldsymbol{\nu} \\ \boldsymbol{\varphi}' - \boldsymbol{\varphi} \end{bmatrix}.$$

Therefore, a subgradient of $g(\mu, \boldsymbol{\nu}, \boldsymbol{\varphi})$ is $t = [\Delta\mu \; \{\Delta\nu_n\}_n \; \{\Delta\varphi_n\}_n]^T$. This ends the proof. □

For given $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, the fixed-point power update (2.31) always converges to the maximizer of Lagrangian (2.28) with Lagrange multipliers fixed [33, Lemma 3]. The updates of Lagrange multipliers μ, ν_n, and φ_n via (2.31), (2.32), and (2.33), respectively, are also guaranteed to converge by appropriately choosing step sizes δ_μ, δ_ν, and δ_φ [34]. As pointed out in the previous section, the logarithmic approximation ensures the monotonic increase of the objective function. In addition, it has been shown in [37] that the update sequence of energy efficiency q (line 9 in Algorithm 2) is convergent. Therefore, it can be concluded that Algorithm 2 is guaranteed to eventually converge to the optimal solution to the optimization problem (2.24).

2.5 Discussion and Extension

As by-products, this section derives algorithms to compute the optimal solution to the problems that maximize the global energy efficiency and utilize simple rate outage constraints by considering the relationship between certainly-equivalent margin (CEM) and outage probability.

2.5.1 Global Energy Efficiency Maximization

Considering the objective function of the global energy efficiency, the optimization problem is specified as

$$
\begin{aligned}
&\max_{\boldsymbol{P}} \frac{\sum\limits_{n\in\mathcal{N}} \omega_n W \log_2(1+\zeta\bar{\gamma}_n(\boldsymbol{P}))}{\sum\limits_{n\in\mathcal{N}} (\varrho p_n + p_{n,c})} \\
&\text{s.t.} \sum_{n\in\mathcal{N}} p_n g_{0n} \le I_{\max}, \\
&\quad \Pr\left(\gamma_n(\boldsymbol{P}) \le \gamma_n^{th}\right) \le \epsilon_n, \ \forall n \in \mathcal{N}, \\
&\quad \mathcal{P} = \{p_n, n\in\mathcal{N} | p_n^{\min} \le p_n \le p_n^{\max}\}.
\end{aligned}
\tag{2.34}
$$

Algorithm 3 Optimal solution to the max-min energy-efficient problem (2.27)

Set ε and $T_{\max}$, and initialize $t = 0$, FLAG $= 0$, $\mu(t)$, $\boldsymbol{\nu}(t)$, $\boldsymbol{\varphi}(t)$, $\boldsymbol{\alpha} = \mathbf{1}$, and $\boldsymbol{\beta} = \mathbf{0}$

repeat {To update $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$}

  repeat {To solve (2.27) for given $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$}

    Allocate transmit power $\boldsymbol{P}$ according to (2.31).

    Update the auxiliary variable u as

$$u(t) = \begin{cases} 0 & 1 < \sum\limits_{n\in\mathcal{N}} \varphi_n, \\ \min\limits_{n\in\mathcal{N}} g_n(\boldsymbol{\rho}) & \text{otherwise.} \end{cases}$$

    Update dual variables by (2.31), (2.32), and (2.33).

    if

$$\begin{cases} |\mu(t+1) - \mu(t)| \le \varepsilon, \\ \max\limits_{n\in\mathcal{N}} |\nu_n(t+1) - \nu_n(t)| \le \varepsilon, \\ \max\limits_{n\in\mathcal{N}} |\varphi_n(t+1) - \varphi_n(t)| \le \varepsilon. \end{cases}$$

then

      FLAG $= 1$.

    else

      Set $t = t + 1$.

    end if

  until FLAG $= 1$.

  FAP n updates α_n and β_n according to (2.2) and (2.3), respectively, with $\tilde{z}_n = \zeta\bar{\gamma}_n(e^{\boldsymbol{\rho}(t)})$.

until $\boldsymbol{P}$ converges.

In comparison to the problem (2.1) whose objective is in a sum-of-ratios form and cannot be conveniently transformed into the subtractive form by the conventional Dinkelbach's procedure, by using the SCALE method and logarithmic changes of variables and introducing a new energy-efficient variable q, the problem (2.34) can be transformed into the following form

$$\begin{aligned} &\max_{\boldsymbol{\rho}} \sum_{n\in\mathcal{N}} \omega_n \check{C}_n(\boldsymbol{\rho}) - q \sum_{n\in\mathcal{N}} P_n(\rho_n) \\ &\text{s.t.} \sum_{n\in\mathcal{N}} p_n g_{0n} \le I_{\max}, \\ &\quad \sum_{m\neq n} \log\left(1+\gamma_n^{th}\frac{e^{\rho_m} g_{nm}}{e^{\rho_n} g_{nn}}\right) \le \log \Omega_n(e^{\rho_n}),\ \forall n\in\mathcal{N}, \\ &\quad \mathcal{Y} = \{\rho_n, n\in\mathcal{N} | \log p_n^{\min} \le \rho_n \le \log p_n^{\max}\}. \end{aligned} \tag{2.35}$$

For a given q, (2.35) is a convex optimization problem; its optimal solution is therefore can be obtained efficiently by any convex solvers [34] (here we use the Lagrangian duality technique as in section 2.4). The procedure to solve the problem (2.34) is summarized in Algorithm 4 with convergence.

Algorithm 4 Solution to the problem (2.34) (GEE Algorithm)

Set ε and $T_{\max}$, and initialize $t=0$, FLAG $=0$, and $q^{(t)}=0$.
repeat
  For a given $q^{(t)}$, solve the problem (2.35) to obtain $\boldsymbol{P}^{(t)}$.
  if $\left|\sum_{n\in\mathcal{N}} \omega_n \check{C}_n(\boldsymbol{P}^{(t)}) - q^{(t)} \sum_{n\in\mathcal{N}} P_n(\boldsymbol{P}^{(t)})\right| \le \varepsilon$ **then**
    $\boldsymbol{P}^* = \boldsymbol{P}^{(t)}$ and $q^* = q^{(t)}$.
    FLAG $=1$.
  else
    Set $t=t+1$.
    Set $q^{(t)} = \sum_{n\in\mathcal{N}} \check{C}_n\left(\boldsymbol{P}^{(t-1)}\right) \Big/ \sum_{n\in\mathcal{N}} P_n\left(\boldsymbol{P}^{(t-1)}\right)$.
  end if
until FLAG $=1$.

2.5.2 Near-Optimal Energy Efficiency

We define CEM as the ratio of the average SINR to the corresponding SINR threshold, i.e., CEM $=\gamma_n/\gamma_n^{th}$. According to the relationship between the CEM and the outage probability [40], the upper bound and lower bound between the CEM and the outage probability are given as

$$\frac{1}{1+\text{CEM}} \leq \Pr(\gamma_n(\boldsymbol{P}) \leq \gamma_n^{th}) \leq 1-\exp(-1/\text{CEM}). \tag{2.36}$$

For simplicity, we consider the lower bound of (2.36), which with condition of the rate outage probability (cf. the second constraint in (2.1)) results in

$$\gamma_n(\boldsymbol{P}) \geq \gamma_n^{th}\left(\frac{1}{\epsilon_n}-1\right). \tag{2.37}$$

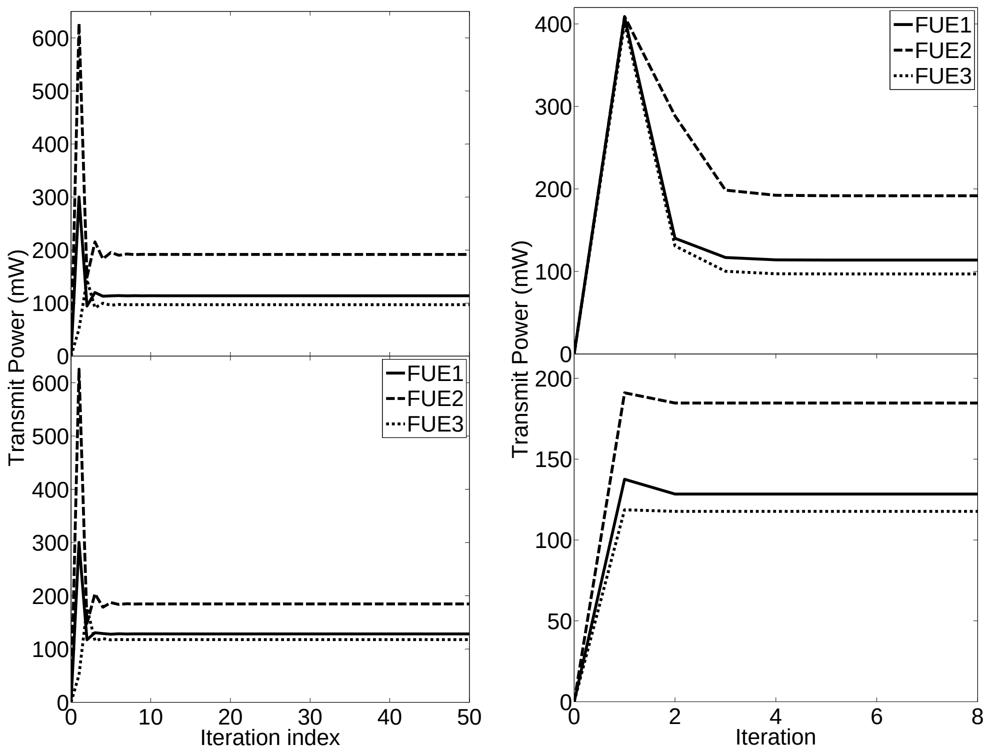
Taking the logarithm of both sides of (2.37) and substituting the result for the second constraint in (2.1) and (2.24), respectively we have two corresponding problems. From this point, all derivations, algebraic manipulations, and algorithms are carried out similarly.

2.6 Simulation Results

In this section, numerical results are presented to evaluate the performance of the proposed procedures in comparison with existing power control schemes for interference management.

2.6.1 Simulation Settings

We consider a HetNet as illustrated in Fig. 2.1, where the MBS has the coverage area of 200 meters, three femtocells are positioned inside the coverage area of the MBS. The distance between three FUEs and the MBS are 50, 100, and 200 m, respectively. The outage probability thresholds and SINR thresholds are respectively set to $(0.20, 0.15, 0.10)$ and $(30.0, 20.0, 10.0)$ dB. The fast-fading channel gain is assumed to



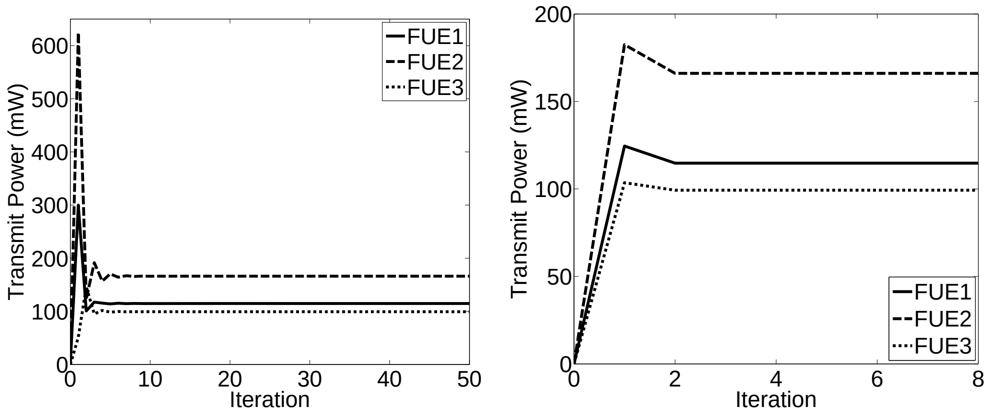
(a) Convergence of the inner loop. (b) Convergence of the outer loop.

Figure 2.2: Convergence of the WSEE Algorithm and WMEE Algorithm. Upper figures: WSEE Algorithm; Lower figures: WMEE Algorithm.

be i.i.d with mean $\mathrm{E}[F_{nm}] = 1$ while the slow-fading channel gain is $g_{nm} = g_0(d_{nm}/100)^{-\mathrm{AF}}$, where d_{nm} is the distance between FUE m in femtocell m and FAP in femtocell n, $\mathrm{AF} = 4$ is the path loss attenuation factor, and $g_0 = 0.25$ is the reference channel gain. The distance vector $\boldsymbol{D} = \{d_{nm}\}$ between FUEs and FAPs is

$$D = \begin{bmatrix} 10 & 50 & 150 \\ 50 & 15 & 50 \\ 150 & 50 & 10 \end{bmatrix}.$$

Although the distance vector D is fixed, this has been selected from a large number of network instances to correctly reflect the performance of the proposed algorithms as well as the compared frameworks. In



(a) Convergence of the inner loop. (b) Convergence of the outer loop.

Figure 2.3: Convergence of the GEE algorithm.

literature, a number of research works have used the same method of simulation as ours, for example, [41–43]. The thermal noise power at all FAPs is assumed to be 0.005 dB and the maximum tolerable interference inducing at the MBS is $I_{\max} = 0.05$ dB. Without loss of generality, weight ω_n is assumed to be 1. The baseband bandwidth $W = 32$ kHz and SINR-gap $\zeta = -1.5/\log(5\text{BER})$ where $\text{BER} = 10^{-3}$ for MQAM modulation [44]. The minimum and maximum power, i.e., $p_n^{\min}$ and $p_n^{\max}$ are set to 0 W and 1 W, respectively. The fixed circuit power is set to $p_{n,c} = 1$ W and the drain efficiency of power amplifier is 50%, that is, $\varrho = 1/0.50 = 2$. Furthermore, the same step size $\delta = 10^{-3}/iter$ with $iter$ being the iteration index is used for all proposed as well as compared algorithms, the error tolerance is $\varepsilon = 10^{-6}$, and the numerical simulation runs on MATLAB R2013a and a Window-based personal computer with a core i7-3.40GHz and 8 GB RAM memory.

2.6.2 Performance of the Proposed Algorithms

In the first experiment, we examine the convergence of the WSEE algorithm and of the WMEE algorithm. Note that both of these algorithms can be regarded as two-loop operations, more in details, the inner-loop of the WSEE algorithm lies in the step 2 and the corresponding outer-loop is to update $\boldsymbol{\lambda}$ and

$\boldsymbol{\kappa}$ of the Algorithm 1 while the outer loop and inner loop of the WMEE algorithm are actually the Algorithm 2 and Algorithm 3, respectively. It is observed from Fig. 2.2a and Fig. 2.2b that the outer loops of these algorithms can converge within only few iterations, 8 iterations under the error tolerance $\varepsilon = 10^{-6}$ for the Algorithm 1 and 4 iterations for Algorithm 2, and similarly the inner loops* converge within ten iterations. Similarly, as shown in Fig. 2.3, the GEE algorithm can converge to the optimal point within ten of iterations. Therefore, the total number of iterations is $10 * 8 = 80$ iterations and the real simulation time is really short, i.e., the computational complexity of our proposed algorithms is cost-effective. Due to the small number of iterations, the proposed algorithms can well adapt to fast-fading wireless networks. In addition, higher the rate outage probability means that the adaptability of the proposed algorithms also increases since the probability that the algorithms need to update parameters is low.

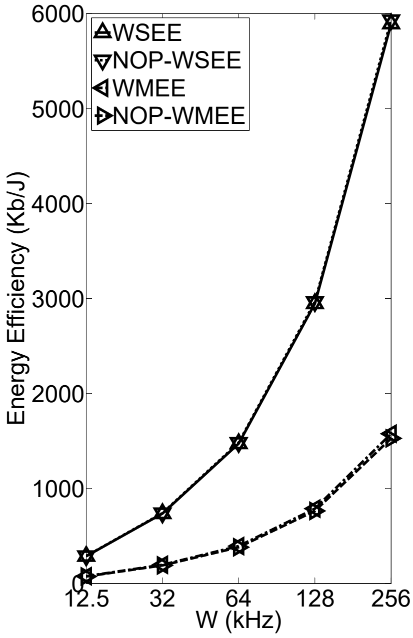


Figure 2.4: The optimal energy efficiency versus the baseband bandwidth W.

In Fig. 2.4, we plot the optimal energy efficiency of the proposed schemes as a function of the baseband

*For the sake of simplicity in running simulation, we show the convergence of the inner loops corresponds to the last outer loops. Arbitrary inner loops have the same convergence properties.

bandwidth W. It is remarked that the optimal energy efficiency of the WSEE problem is defined as the sum of the per-UE energy efficiencies and that of the WMEE problem is just equal to the minimum of the per-UE energy efficiencies. We can see that the optimal energy efficiency increases apparently with the increment of the baseband bandwidth W, since more bandwidth resource can open up more opportunities to improve the energy efficiency [45]. We also observe that near-optimal schemes can achieve close performance compared to the optimal ones, therefore it is practical to use the near-optimal algorithms instead of optimal procedures in order to reduce the amount of message passing in the network.

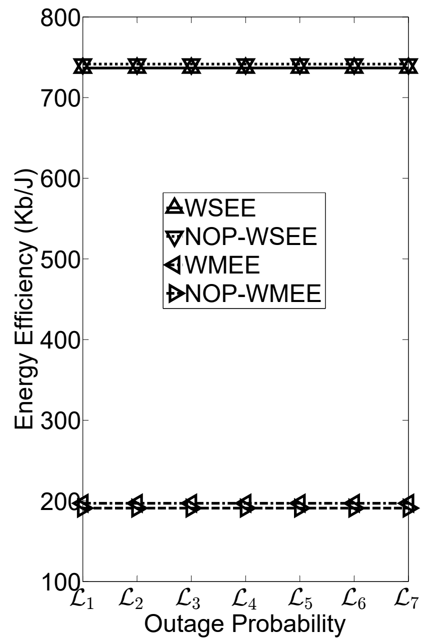


Figure 2.5: The optimal energy efficiency versus the rate outage probability. There are seven scenarios $\mathcal{L}_i = \{\epsilon_1, 0.15, 0.10\}$, where $\epsilon_1 = 0.10 + 0.05(i-1)$.

Fig. 2.5 investigates the energy efficiency of the proposed schemes when we keep the second and third FUEs' rate outage probabilities fixed and changes the outage threshold of the first FUE. In this context, it is observed that the optimal energy efficiency is almost the same when the outage probability threshold varies. This result can be explained as the following. Actually, FUE 1 should increase its transmission power to compensate for the increasing link outage and then both the FUE's capacity and total consumed power increase. However, if the outage constraints of all the FUEs are stricter, i.e., the outage probability is lower, the decrease in the capacity is much larger than that of the consumed power and then the energy efficiency tends to be reduced as the outage constraints become stricter. Although the optimal EE does not change much as the outage probability varies, schemes with more power consumption are not preferred and therefore, the FUE's outage should be kept under a small value as much as possible.

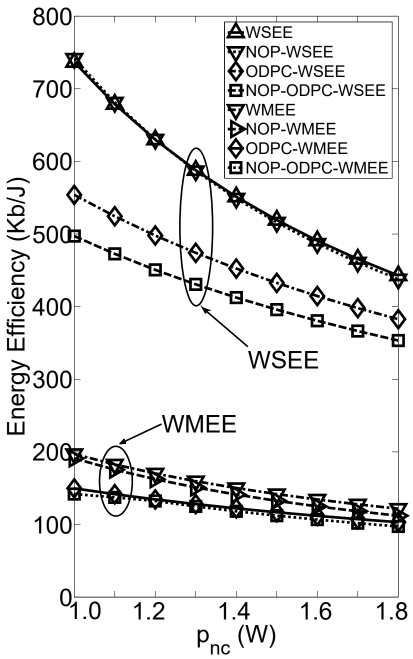


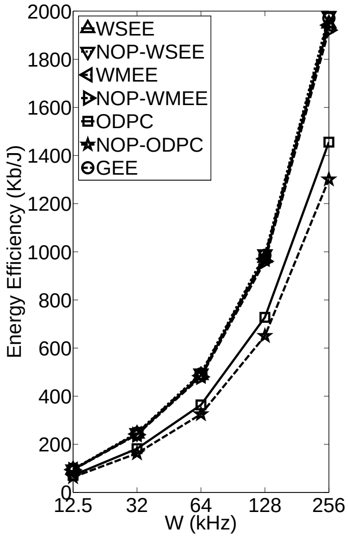
Figure 2.6: The optimal energy efficiency versus the fixed circuit power consumption p_{nc}.

Fig. 2.6 illustrates the optimal energy efficiency of the considered algorithms compared with the weighted sum rate maximization (WSR)-based algorithms, i.e., Optimal Distributed Power Control (ODPC) algorithm and NOP-ODPC algorithm [18] when the fixed circuit power consumption is different. Since the weighted-sum approach maximizes the weighted-sum rate of all users, its energy efficiency with the WSEE approach (ODPC-WSEE and NOP-ODPC-WSEE) and with the WMEE approach (ODPC-WMEE and NOP-ODPC-WMEE) can be computed by definition as in the problem (2.1) and (2.24), respectively.

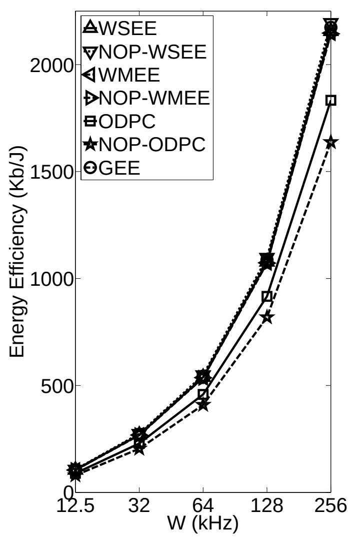
From the figure, the optimal energy efficiency of WSEE algorithms, i.e., WSEE and NOP-WSEE, WMEE algorithms, i.e., WMEE and NOP-WMEE, and compared frameworks, i.e., ODPC and NOP-ODPC reduces as the fixed power consumption increases and the proposed algorithms yield higher energy efficiency than the compared frameworks. In addition, the performance gap in energy efficiency between the proposed algorithms and the compared ones gets smaller when the fixed circuit power consumption increases. This is suitable since the fixed power is increasingly dominant over the transmit power in determining the energy efficiency and the energy efficiency optimization problem becomes the WSR maximization problem. Again, the near-optimal schemes converge close to the optimal values of the energy efficiency.

Fig. 2.7 compares the energy efficiency of the proposed algorithms with the ODPC and NOP-ODPC algorithm and with the GEE algorithm. Due to different objectives of different frameworks, we compare here the same objective for all framework alternatives, for example, the global energy efficiency, the best (maximum) and worst (minimum) individual energy efficiency, and the weighted sum of the energy efficiencies. Fig. 2.7 depicts that the proposed algorithms outperform the corresponding compared ones for all considered cases. This is since in [18], the aggregate data rate is maximized regardless of the EE, which maybe results in high and not optimal transmission power at each FUE, meaning that the high EE obtained by the proposed algorithms is sacrificed by the total transmission rate. Note that the performance of the GEE problem is actually the performance of the ODPC problem. Moreover in the ODPC problem, the optimal EE gap between ODPC and NOP-ODPC is significant, which is opposed to the proposed procedures.

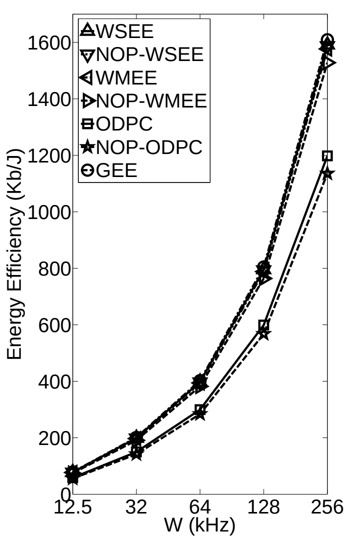
In Fig. 2.8, we compare the EE performance of the WSEE algorithm, the WMEE algorithm, the GEE algorithm, and the ODPC algorithm, by varying the number of FUEs. It is generally observed that the WSEE, WMEE, and GEE algorithms outperform the ODPC algorithm and the performance difference among these algorithms become smaller when the number of FUEs increases. Although the performance gap gets smaller, from Fig. 2.9, the compared ODPC approach consumes more power than the proposed methods. The reason is that the objective of the ODPC approach is to maximize the weighted-sum rate of all users, to increase the energy efficiency, the throughput performance (spectral efficiency) needs to be



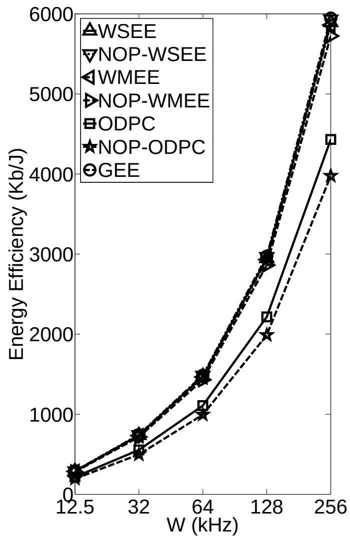
(a) GEE vs W.



(b) Maximum EE vs W.



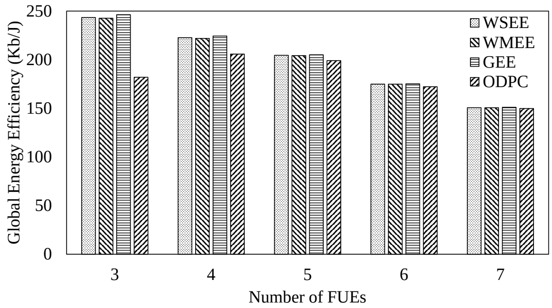
(c) Minimum EE vs W.



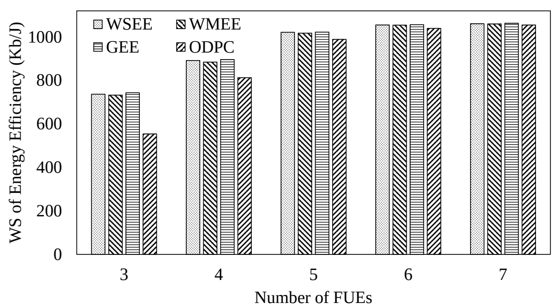
(d) WSEE vs W.

Figure 2.7: Comparison of different EE aspects among framework alternatives.

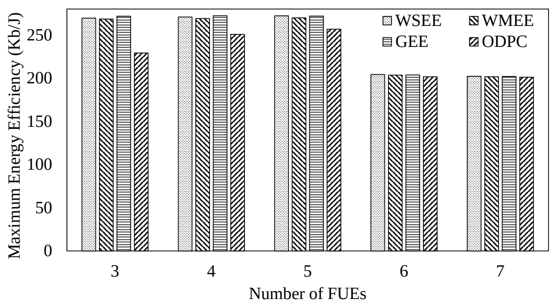
reduced and the total power consumption is higher. Fig. 2.8a illustrates that the GEE algorithm can achieve the best GEE in comparison with the other algorithms since its optimization objective is to maximize the



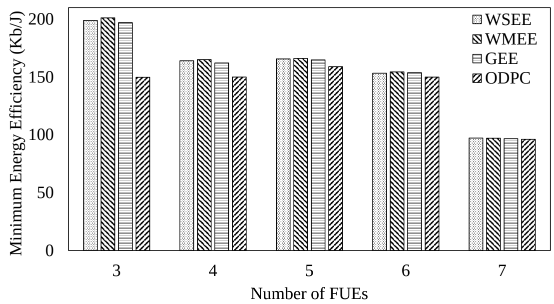
(a) GEE vs number of FUEs.



(b) WSEE vs number of FUEs.



(c) Maximum EE vs number of FUEs.



(d) Minimum EE vs number of FUEs.

Figure 2.8: Comparison of different EE aspects among framework alternatives when the number of FUEs varies. The baseband bandwidth $W = 32$ kHz and the fixed circuit power is $p_{n,c} = 1$ W.

global energy efficiency. Fig. 2.8b shows that the WSEE algorithm can obtain the better weighted sum of the energy efficiencies than that of the WMEE algorithm due to its optimization objective. In addition, as shown in Fig. 2.8c, the best energy efficiency obtained by the WSEE algorithm and the GEE algorithm is higher than that of the WMEE algorithm. However, the WMEE algorithm is targeted at maximizing the worst energy efficiency, therefore it can ensure and improve the fairness among FUEs compared to the others; Fig. 2.8d verifies that the WMEE yields the highest-worst energy efficiency. Actually, each of the proposed algorithms has a specific optimization objective and which algorithm is used depends on the practical systems.

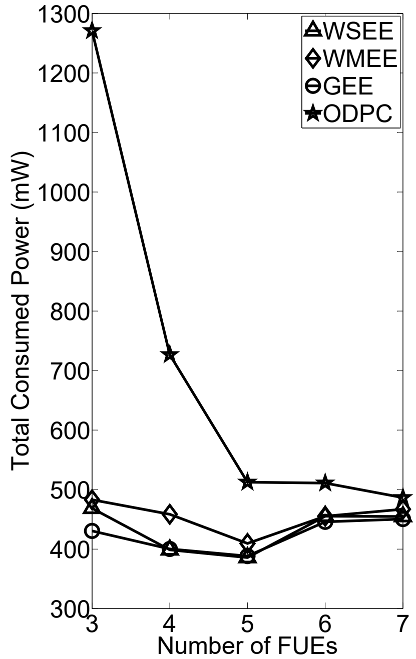


Figure 2.9: Comparison of total power consumption among approaches when the number of FUEs varies. The baseband bandwidth $W = 32$ kHz and the fixed circuit power is $p_{n,c} = 1$ W.

2.7 Conclusion

In this chapter, we developed two energy-efficient power control schemes for interference management in uplink spectrum-sharing HetNets. In particular, the optimization objectives are to maximize either the weighted sum of the energy efficiencies (WSEE) or the weighted minimum of the energy efficiencies (WMEE) while the interference from FUEs to the MBS is controlled and QoS on rate outage of each FUE is guaranteed. To circumvent the sum-of-ratios problem, we make use of an efficient global optimization algorithm. Meanwhile, the WMEE problem can be solved by exploiting the relationship between the fractional programming and parametric programming and using the Lagrangian duality technique. We also discussed the global energy efficiency (GEE) maximization problem and near-optimal schemes. Through extensive numerical experiments, we solidified the validity of the proposed algorithms.

Chapter 3

Fairness-Aware Spectral and Energy Efficiency in Spectrum-Sharing Wireless Networks

This chapter presents the problem of α-fair resource allocation problem for the tradeoff of spectral efficiency and energy efficiency in spectrum-sharing wireless networks.

3.1 Introduction

Energy-fficient wireless communications, often called as green networks, have recently drawn much attention from research communities, both academia and industry, due to the dramatic increase in network infrastructure and traffic demand [27, 38, 45, 46]. In spectrum-sharing wireless networks, i.e., interference-limited wireless networks, a key example of resource allocation for interference management and network performance improvement, for example, sum rate maximization and energy efficiency (EE) [42, 43, 47, 48], is power control. Although energy efficiency is a major metric for environment-friendly wireless networks, it does always conflict with spectral efficiency. Therefore, the tradeoff issue between spectral efficiency (SE) and energy efficiency should be studied. On the other hand, fairness is an important issue in wireless networks, which is usually related to resource allocation problems [10]. Moreover, it has been recognized that one should optimize SE and EE simultaneously while considering fairness among wireless links [49, 50].

The energy-efficient resource allocation in wireless networks has prompted significant research attention [27,38,42,43,45,50–53]. Optimization of energy-efficient resource allocation, where energy efficiency can be defined as the global energy efficiency, the weighted sum of the energy efficiencies, the weighted minimum of the energy efficiencies, and the exponentially-weighted product of the energy efficiencies, in wireless networks, has been widely studied, e.g., single-cell networks [38, 45], uplink heterogeneous cellular networks in chapter 2, and coordinated multicell networks [27]. Some energy-efficient frameworks have been studied for 5G cellular networks, e.g., a scheme for energy efficiency with statistical QoS constraints in MIMO-OFDM networks [54], a joint baseband and RF precoding scheme for energy efficiency in 5G RF chain systems [55], and a model of random cellular networks for spectrum and energy efficiency [56]. A distributed algorithm for maximizing the weighted sum of the energy efficiencies in wireless ad hoc networks was investigated in [51]. The SE-EE tradeoff problem has been studied in [42, 43, 50, 52, 53, 57, 58]. In [42], the authors investigated the tradeoff between SE and EE in interference-limited wireless networks, where the objective is to maximize the global energy efficiency subject to minimum rate requirements. Similar to [42], the SE-EE tradeoff problem, where the objective function is the minimum of the energy efficiencies, was studied in [43]. Li and Jiang [52] introduced an energy-rate tradeoff index (EI) that captures the relative importance of transmit power and transmit rate, and considered an optimization problem to maximize the EI subject to power constraints in spectrum-sharing wireless networks. The authors in [53] proposed a new system metric called resource efficiency to control the tradeoff between EE and SE by balancing consumed power and occupied bandwidth. An SE-EE tradeoff analysis in the uplink of multiuser

OFDMA heterogeneous networks was studied in [50]. A unified resource metric for the SE-EE tradeoff has been proposed in a point-to-point link [57] and OFDMA multicell wireless networks [58]. However, the aforementioned literature on optimization of EE or SE-EE tradeoff do not discuss fairness issues among users, implicitly restrict fairness in the objective function, and is not able to study the impact of α-fairness on resource allocation.

Some recent works have been devoted to fair and energy-efficient resource allocation problems in wireless networks [47–49]. The authors in [49] considered the problem of joint power allocation and scheduling and investigated the SE-EE tradeoff in the downlink of OFDMA networks, where α-fair utility function is used to study the problem of rate fairness among users. The tradeoff between link fairness and system sum-rate in spectrum-sharing networks was studied in [48], where the authors showed that different values of α-fairness index can result in either convexity or NP-hardness of the original problem. It is however only focused on SE maximization and does not examine the impact of EE as well as SE-EE tradeoff. The proportional fair EE, max-min fair EE, and harmonic fair EE were discussed in [47], where the original problem can be cast to convex ones by introducing auxiliary variables, changing variables and transforming the objective and constraint functions. The globally optimal solution is then obtained by the interior-point method. However, the application scope of such works [47–49] is restricted to slowly varying wireless channels due to the assumption of static-fading channels, where power allocation must be updated once channel states change and it is required to retrack the instantaneous SINR and compelled to rerun the algorithm to seek new optimal solution [26]. As a result, proposed algorithms in [47–49] can lead to an excessive amount of message exchange in the network and waste processing energy due to a frequent update of power allocation [59].

In order to best utilize network resources and meet design criteria in spectrum-sharing wireless networks, fundamental problems need to be addressed (1) balance between SE and EE simultaneously (2) guarantee a reasonable level of fairness among users, and (3) adapt to fast-fading channels of wireless networks. None of the existing research is able to address the above problems jointly. In light of the aforementioned observations, in this chapter, we consider the SE-EE tradeoff problem in interference-limited wireless networks, where rate fairness and fading-induced outage probability are considered as resource constraints. In a nutshell, the summary of features and contributions offered by this chapter can be listed, as follows:

- In Section 3.2, we consider an interference-limited wireless network, present the system model, and then formulate the optimization problem. The problem is to allocate transmit power so as to jointly maximize EE and SE when jointly considering fairness. Consider the tradeoff between energy efficiency and spectral efficiency, the multiobjective problem (MOP) of the spectral efficiency and energy efficiency is transformed into a problem that minimizes the total power consumption and maximizes the achievable utility, subject to power constraints and rate outage probability constraints.

- For each case of the α-fairness index, we analyze the complexity of and specify the method to solve the considered optimization problem. In particular, the problem is NP-hard when $0 < \alpha < 1$ and $\alpha = 0$ and is convex for other values of the fairness index α (Section 3.3).

- For $\alpha = 0$, we exploit the SCALE method to transform and approximate the original problem into a sequence of convex ones. To tackle the problem with $0 < \alpha < 1$, we exploit the Difference in Convex (D.C.) structure of the objective function and simplify the outage constraint in order to convexify the optimization problem. Iterative resource allocation algorithms are proposed with a guarantee to converge to a locally optimal solution to the underlying problem (Section 3.4).

- Finally, extensive simulation results are provided in Section 3.5 to verify the effectiveness of the proposed algorithm as well as showing the performance comparison in in term of the SE-EE tradeoff with those reported in the references. It is shown that the SE-EE tradeoff can be achieved by considering the network scenarios such as the outage probability threshold and data rate requirement and adjusting the fairness index and priority parameter.

3.2 Problem Formulation

We consider a spectrum-sharing wireless network with I distinct node pairs. Each pair* is composed of one dedicated transmitter and one dedicated receiver. The considered network can be an ad-hoc network or cellular network, where all the pairs simultaneously operate on the same frequency band. Different from literature considering imperfect channel state information (CSI), for example, channel estimation in [60], effective interference channel in [61], and the bounded and probabilistic CSI error models in [62], we assume that perfect CSI is available at the transmitter and receiver. In addition, global CSI is required to be available at the central controller to implement the proposed centralized algorithms. Research of the considered problem under imperfect CSI is left for future work. Let $\mathcal{I}$ denote the set of node pairs and i denote the pair index. The instantaneous capacity of user i is modeled by the Shannon capacity $r_i(\boldsymbol{p}) = W \log_2 (1 + \zeta\gamma_i(\boldsymbol{p}))$, where W is the baseband bandwidth, ζ is the SINR-gap that depends on particular modulation coding scheme, and bit-error-rate [44], and $\boldsymbol{p} = [p_1, ..., p_I]^T$ is the transmit power vector. For simplicity, we assume that $W = 1$ and $\zeta = 1$. When node i obtains the data rate $r_i(\boldsymbol{p})$, it will receive the utility $U_\alpha (r_i(\boldsymbol{p}))$, where α is the fairness index and $U_\alpha(\cdot)$ is the utility function (1.1). The instantaneous signal-to-interference-plus-noise ratio (SINR) is $\gamma_i(\boldsymbol{p}) = p_i g_{ii} f_{ii} / \left(\sigma_i^2 + \sum_{j\neq i} p_j g_{ij} f_{ij}\right)$, where p_i is the transmit power of node i, $g_{ij} f_{ij}$ is the channel gain from the transmitter j to the receiver i, and σ_i^2 is the thermal noise power at the receiver on pair i. We consider the non-line-of-sight propagation and use the average SINR $\bar{\gamma}_i(\boldsymbol{p})$ instead of $\gamma_i(\boldsymbol{p})$. Then, $\bar{\gamma}_i(\boldsymbol{p}) = p_i g_{ii} / \left(\sigma_i^2 + \sum_{j\neq i} p_j g_{ij}\right)$,where fast-fading channel gains f_{ij} are assumed to be i.i.d. and $E[f_{ij}] = 1, \forall i, k$.

The power consumption $P_{i,T}$ of each user i is attributed by the transmission-consumed power p_i and the circuit power consumption $p_{i,ct}$ at the transmitter and $p_{i,cr}$ at the receiver. Here, $P_{i,T} = \varrho_i p_i + p_{i,ct} + p_{i,cr}$, where ϱ_i is the power-inefficient factor of the amplifier. For simplicity, we assume that all pairs have the same value ϱ, p_{ct}, and p_{cr}. Hence, the total power consumption is $P_T = \sum_{i=1}^I P_{i,T} = \varrho \sum_{i=1}^I p_i + I(p_{ct} + p_{cr})$.

*We will use "pair" and "user" interchangeably throughout this chapter.

With the goal of finding the SE-EE tradeoff, the objective function should jointly maximize the SE and EE. Denote by $\eta_{SE}(\boldsymbol{p})$ and $\eta_{EE}(\boldsymbol{p})$ the spectral efficiency and energy efficiency, respectively. Then, the multiobjective optimization problem of SE and EE is given by $\{\min_{\boldsymbol{p}} \eta_{SE}^{-1}(\boldsymbol{p}), \min_{\boldsymbol{p}} \eta_{EE}^{-1}(\boldsymbol{p})\}$. Actually, there exist many approaches for a multiobjective problem, for example, weighted sum method, lexicographic method, weighted max-min method, and weighted product method; however, the objective sum method is one of the most computationally efficient, easy-to-use, and common approaches [63]. Therefore, we exploit the weighted sum method to deal with the multiobjective problem of the SE and EE. According to [64], the multiobjective problem of SE and EE can be obtained by solving a simple multiobjective problem that minimizes the total power consumption and maximizes the achievable rate utility, i.e., $\min_{\boldsymbol{p}} \psi_{EE} P_T - \psi_{SE} \sum_{i \in \mathcal{I}} U_i(r_i)$ or $\max_{\boldsymbol{p}} \{-P_T, \sum_{i \in \mathcal{I}} U_i(r_i)\}$, where $\boldsymbol{\psi} = [\psi_{SE} \;\; \psi_{EE}]$ is the priority parameter. The optimization problem now can be mathematically formulated as

$$\begin{aligned} &\max_{\boldsymbol{p}} \;\; \psi_{SE} \sum_{i \in \mathcal{I}} U_\alpha(r_i) - \psi_{EE} P_T, \\ &\text{s.t.} \quad \Gamma = \left\{p_i | p_i^{\min} \le p_i \le p_i^{\max}\right\} \; \forall i \in \mathcal{I}, \\ &\qquad\;\; \Pr\left(\gamma_i \le \gamma_i^{th}\right) \le \epsilon_i \; \forall i \in \mathcal{I}, \end{aligned} \tag{3.1}$$

where γ_i^{th} is the target minimum SINR below which performance becomes unacceptable, and $\epsilon_i \in (0,1)$ is the outage probability threshold of node i. Actually, once channel states change, it is required to re-track the instant SINR and compelled to rerun the algorithm to seek the optimal solution [26]. For fast-fading networks where the channel might change very fast, it is not efficient and impractical. With the outage probability, the optimal solution to the problem does not need to change when the channel state wanders from one fading state to another one for a fraction of time. According to [26], the second constraint in (3.1) can be equivalently expressed as $\prod_{j \in \mathcal{I}/\{i\}} \left(1 + \gamma_i^{th} \frac{p_j g_{ij}}{p_i g_{ii}}\right) \le \Omega_i(\boldsymbol{p})$, where $\Omega_i(\boldsymbol{p}) = (1-\epsilon_i)^{-1} \exp\left(-\frac{\sigma_i^2 \gamma_i^{th}}{p_i g_{ii}}\right)$.

3.3 Complexity Analysis

In what follows, we consider five cases of the fairness index α, where for each case we specify the method to solve the optimization problem and investigate the corresponding algorithm.

3.3.1 $\alpha = 0$

When $\alpha = 0$, the utility is the weighted-sum rate (WSR) and the optimization problem becomes

$$\begin{aligned}
&\max_{\boldsymbol{p}} \ \psi_{SE} \sum_{i \in \mathcal{I}} \log_2 \left(1 + \frac{p_i g_{ii}}{\sigma_i^2 + \sum\limits_{j \neq i} p_j g_{ij}} \right) - \psi_{EE} P_T \\
&\text{s.t.} \quad \Gamma = \left\{ p_i | p_i^{\min} \leq p_i \leq p_i^{\max} \right\} \ \forall i \in \mathcal{I}, \\
&\qquad\quad \Pr\left(\gamma_i \leq \gamma_i^{th}\right) \leq \epsilon_i \ \forall i \in \mathcal{I}.
\end{aligned} \tag{3.2}$$

Based on the proof of the Theorem 5 and of the Theorem 1 in [65], we can prove that the problem (3.2) is NP-hard, the problem is, therefore, difficult to solve. In Subsection 3.4.1, we will apply the SCALE method [33] to approximate the problem (3.1) into a sequence of convex programs and to propose an iterative two-loop algorithm.

3.3.2 Proportional fairness, $\alpha = 1$

The optimization problem now becomes

$$\begin{aligned}
&\max_{\boldsymbol{p}} \ \psi_{SE} \sum_{i \in \mathcal{I}} \log \left(\log_2 \left(1 + \frac{p_i g_{ii}}{\sigma_i^2 + \sum\limits_{j \neq i} p_j g_{ij}} \right) \right) - \psi_{EE} P_T, \\
&\text{s.t.} \quad \Gamma = \left\{ p_i | p_i^{\min} \leq p_i \leq p_i^{\max}, \ \forall i \in \mathcal{I} \right\}, \\
&\qquad\quad \Pr\left(\gamma_i \leq \gamma_i^{th}\right) \leq \epsilon_i \ \forall i \in \mathcal{I}.
\end{aligned} \tag{3.3}$$

Theorem 3. *The problem (3.3) is a convex optimization problem.*

Proof. Let us introduce auxiliary variables t_i satisfying constraints $\exp(t_i) \leq \log_2(1 + \gamma_i(\boldsymbol{p}))$ and auxiliary variables $\rho_i = \log(p_i)$. The above inequality is equivalent to

$$\log\left(\frac{\sigma_i^2}{g_{ii}}e^{-\rho_i} + \sum_{j\neq i}\frac{g_{ij}}{g_{ii}}e^{\rho_j-\rho_i}\right) + \log\left(2^{\exp(t_i)} - 1\right) \leq 0.$$

Let $\boldsymbol{t} = [t_1, ..., t_I]^T$, the problem (3.3) can be rewritten, as follows:

$$\begin{aligned} &\max_{\boldsymbol{p},\boldsymbol{t}} \ \psi_{SE}\sum_{i\in\mathcal{I}} t_i - \psi_{EE}P_T(e^{\boldsymbol{\rho}}), \\ &\text{s.t.} \quad \mathcal{L} = \left\{\rho_i | \log\left(p_i^{\min}\right) \leq \rho_i \leq \log\left(p_i^{\max}\right), \forall i \in \mathcal{I}\right\}, \\ &\qquad \sum_{j\neq i}\log\left(1 + \gamma_i^{th}e^{\rho_j-\rho_i}\frac{g_{ij}}{g_{ii}}\right) \leq \log\left(\Omega_i(e^{\boldsymbol{\rho}})\right), \ \forall i \in \mathcal{I}, \\ &\qquad \log\left(\frac{\sigma_i^2}{g_{ii}}e^{-\rho_i} + \sum_{j\neq i}\frac{g_{ij}}{g_{ii}}e^{\rho_j-\rho_i}\right) + \log\left(2^{\exp(t_i)} - 1\right) \leq 0. \end{aligned} \tag{3.4}$$

Since the total power consumption $P_T(e^{\boldsymbol{\rho}})$ is the summation of a sum-exp function and a constant, it is convex. As a result, the objective function is jointly concave in $\boldsymbol{t}$ and $\boldsymbol{\rho}$ due to the subtraction of a linear term and a convex term. The second and third constraints are concave according to [26] and [65], respectively. Therefore, it is concluded that the problem (3.4) is a convex optimization problem. The proof ends. □

3.3.3 Max-min fairness, $\alpha = \infty$

The objective now is $H(\boldsymbol{p}) = -\psi_{EE}P_T + \psi_{SE} \min_{i\in\mathcal{I}} r_i$ and the problem (3.1) becomes

$$
\begin{aligned}
\max_{\boldsymbol{p}} \; & -\psi_{EE}P_T + \psi_{SE} \min_{i\in\mathcal{I}} \log_2\left(1 + \frac{p_i g_{ii}}{\sigma_i^2 + \sum_{j\neq i} p_j g_{ij}}\right) \\
\text{s.t.} \quad & \Gamma = \left\{p_i | p_i^{\min} \leq p_i \leq p_i^{\max}\right\} \; \forall i \in \mathcal{I}, \\
& \Pr\left(\gamma_i \leq \gamma_i^{th}\right) \leq \epsilon_i \; \forall i \in \mathcal{I}.
\end{aligned} \tag{3.5}
$$

Introducing a new variable u and auxiliary variables $\rho_i = \log(p_i)$, the problem (3.5) can be rewritten, as follows:

$$
\begin{aligned}
\max_{\boldsymbol{p},u} \; & -\psi_{EE}P_T(e^{\boldsymbol{\rho}}) + \psi_{SE}u \\
\text{s.t.} \quad & \mathcal{L} = \left\{\rho_i | \log\left(p_i^{\min}\right) \leq \rho_i \leq \log\left(p_i^{\max}\right), \forall i \in \mathcal{I}\right\}, \\
& \sum_{j\neq i} \log\left(1 + \gamma_i^{th} e^{\rho_j - \rho_i} \frac{g_{ij}}{g_{ii}}\right) \leq \log\left(\Omega_i(e^{\boldsymbol{\rho}})\right), \; \forall i \in \mathcal{I}, \\
& u \leq \log_2\left(1 + \frac{e^{\rho_i} g_{ii}}{\sigma_i^2 + \sum_{j\neq i} e^{\rho_j} g_{ij}}\right) \; \forall i \in \mathcal{I}.
\end{aligned} \tag{3.6}
$$

The objective function of the above problem is concave due to the subtraction of a linear term and a convex term, the first and second constraints are convex according to the proof of Theorem 3. The third constraint can be equivalently expressed as

$$
\log\left(\frac{\sigma_i^2}{g_{ii}} e^{-\rho_i} + \sum_{j\neq i} \frac{g_{ij}}{g_{ii}} e^{\rho_j - \rho_i}\right) + \log\left(2^u - 1\right) \leq 0,
$$

which can be easily verified to be neither convex nor concave. In order to convexify as well as easily solving the problem (3.6), we apply an iterative approach, where we deal with the problem of power allocation $\boldsymbol{p}$

and auxiliary variable u separately and the subproblem becomes convex in power allocation and linear in auxiliary variable u. At first, we need to find a feasible solution $(u(0), \boldsymbol{p}(0))$. At the iteration t, we find the optimal solution $u(t)$ for a given $\boldsymbol{p}(t-1)$ from the previous iteration t, then, we find the optimal power allocation $\boldsymbol{p}(t)$ for the fixed $u(t)$ (i.e., Gauss-Seidel fashion). The above process is iteratively repeated until there is no improvement in the optimal solution.

3.3.4 Fairness with $1 < \alpha < \infty$

For the α-fair utility function, the network utility is

$$U(\boldsymbol{p}) = \sum_{i \in \mathfrak{I}} (1-\alpha)^{-1} \left(\log_2\left(1+\gamma_i(\boldsymbol{p})\right)\right)^{1-\alpha}.$$

The problem (3.1) becomes

$$\begin{aligned} \max_{\boldsymbol{p}} \ & \psi_{SE} \sum_{i \in \mathfrak{I}} \frac{1}{1-\alpha} \left(\log_2\left(1+\gamma_i(\boldsymbol{p})\right)\right)^{1-\alpha} - \psi_{EE} P_T \\ \text{s.t.} \ & \Gamma = \left\{p_i | p_i^{\min} \le p_i \le p_i^{\max}\right\} \ \forall i \in \mathfrak{I}, \\ & \Pr\left(\gamma_i \le \gamma_i^{th}\right) \le \epsilon_i \ \forall i \in \mathfrak{I}. \end{aligned} \tag{3.7}$$

Theorem 4. *The problem (3.7) is a convex problem.*

Proof. Introducing auxiliary variables $\boldsymbol{t}$ and $\boldsymbol{\rho}$, we can reformulate the problem (3.7) as

$$
\begin{aligned}
\max_{\boldsymbol{p},\boldsymbol{t}} \ & \psi_{SE} \sum_{i\in\mathcal{I}} \frac{1}{1-\alpha} \left(\exp(t_i)\right)^{1-\alpha} - \psi_{EE} P_T(e^{\boldsymbol{\rho}}), \\
\text{s.t.} \quad & \mathcal{L} = \left\{ \rho_i | \log\left(p_i^{\min}\right) \le \rho_i \le \left(p_i^{\max}\right), \forall i \in \mathcal{I} \right\}, \\
& \sum_{j\neq i} \log\left(1 + \gamma_i^{th} e^{\rho_j - \rho_i} \frac{g_{ij}}{g_{ii}}\right) \le \log\left(\Omega_i(e^{\boldsymbol{\rho}})\right), \ \forall i \in \mathcal{I}, \\
& \log\left(\frac{\sigma_i^2}{g_{ii}} e^{-\rho_i} + \sum_{j\neq i} \frac{g_{ij}}{g_{ii}} e^{\rho_j - \rho_i}\right) + \log\left(2^{\exp(t_i)} - 1\right) \le 0.
\end{aligned}
\tag{3.8}
$$

Since $1 < \alpha < \infty$, the second-order derivative of the objective function $H(\boldsymbol{t}, \boldsymbol{\rho})$ w.r.t. t_i is negative, which means that the first term in the objective function is concave [66]. Hence, the objective function is jointly concave in $\boldsymbol{t}$ and $\boldsymbol{\rho}$. In addition, according to the proof of Theorem 3, the feasible set is convex. Consequently, the problem (3.8) is a convex optimization problem. The proof ends. □

Remark 3. *A special fairness index is $\alpha = 2$. In that case, the network utility is actually the harmonic-rate utility function and the optimization problem is convex. Similarly in [65], the authors also proved that the problem of maximizing the harmonic-rate utility function under power constraints in single frequency band systems is convex.*

3.3.5 Fairness with $0 < \alpha < 1$

The problem is actually the problem (3.7) with $0 < \alpha < 1$.

Theorem 5. *The problem (3.7) with $0 < \alpha < 1$ is NP-hard.*

Proof. For simplicity of proof, we consider $\gamma_i^{th} = 0$, $p_i^{\min} = 0$, $p_i^{\max} = 1$, $\forall i \in \mathcal{I}$ and omit some constants in the objective function, the optimization problem (3.7) can be reformulated, as follows:

$$\max_{\boldsymbol{p}} \ \psi_{SE} \sum_{i \in \mathcal{I}} \frac{1}{1-\alpha} \left(\log_2\left(1+\gamma_i(\boldsymbol{p})\right)\right)^{1-\alpha} - \psi_{EE} \varrho \sum_{i \in \mathcal{I}} p_i,$$
$$\text{s.t.} \quad \Gamma = \left\{p_i | 0 \leq p_i \leq 1, \ \forall i \in \mathcal{I}\right\}. \tag{3.9}$$

Define $A_i = \sigma_i^2/g_{ii}$ and $\beta_{ij} = g_{ij}/g_{ii}$. For each vertex $v_i \in \mathcal{V}$, let $\beta_{ij} = \infty$ if v_i is adjacent to v_j and $\beta_{ij} = 0$ otherwise.

In what follows, we show a polynomial transformation of the maximum independent set problem on a graph to the problem (3.9). Consider a connected undirected graph $G = (\mathcal{V}, \mathcal{E})$; here $|\mathcal{V}| = I$. It is known that an independent set of the graph G is a subset of $\mathcal{V}$, i.e., a set of vertices of $\mathcal{V}$, such that there is no connecting edge between any two vertices. Assume that there are possibly $S = |\mathcal{S}|$ feasible simplices of $\mathcal{V}$. For a feasible simplex $\mathcal{S}_k$, let $0 \leq p_i \leq 1$ if $v_i \in \mathcal{S}_k$ and $p_i = 0$ otherwise.

Now, we consider the feasible simplex $\mathcal{S}_k$ and suppose that p_i^* and H_k^* are respectively the optimal solution and the optimal value to the problem in the simplex $\mathcal{S}_k$, which can be achieved by solving the following problem

$$\max_{\boldsymbol{p}} \sum_{i \in \mathcal{I}} \left[\frac{\psi_{SE}}{1-\alpha} \left(\log_2 \left(1 + \frac{p_i}{A_i + \sum\limits_{j \neq i} \beta_{ij} p_j} \right) \right)^{1-\alpha} - \psi_{EE} \varrho p_i \right],$$
$$\text{s.t.} \quad 0 \leq p_i \leq 1 \ \forall v_i \in \mathcal{S}_k,$$
$$p_i = 0 \ \forall v_i \notin \mathcal{S}_k.$$

Since $\beta_{ij} = \infty$ if two vertices are adjacent and $p_i = 0$ for all $v_i \notin \mathcal{S}_k$, the above problem is cast as

$$\max_{\boldsymbol{p}} \sum_{i \in \mathcal{F}(\mathcal{S}_k)} \left[\psi_{SE} \frac{1}{1-\alpha} \left(\log_2 \left(1 + \frac{p_i}{A_i} \right) \right)^{1-\alpha} - \psi_{EE} \varrho p_i \right],$$
$$\text{s.t.} \quad 0 \leq p_i \leq 1 \; \forall v_i \in \mathcal{S}_k, \tag{3.10}$$

where $\mathcal{F}(\mathcal{S}_k)$ is the subset of $\mathcal{S}_k$ such that no two nodes in $\mathcal{S}_k$ are connected. Assuming $A_i = A$ for all nodes and solving the problem (3.10), we obtain a unique optimal solution* $p_i^* = f(\psi_{SE}, \psi_{EE}, \alpha, A)$, which is further identical for all feasible simplices. Similarly, we have

$$H_k^* = |\mathcal{F}(\mathcal{S}_k)| \left[\psi_{SE} \frac{1}{1-\alpha} \left(\log_2 \left(1 + \frac{p_i^*}{A} \right) \right)^{1-\alpha} - \psi_{EE} \varrho p_i^* \right].$$

The maximum simplex contained in $\mathcal{S}$ is obtained by

$$\max_{k \in \mathcal{S}} H_k^* = \max_{k \in \mathcal{S}} \; |\mathcal{F}(\mathcal{S}_k)| \left[\psi_{SE} \frac{1}{1-\alpha} \left(\log_2 \left(1 + \frac{p_i^*}{A} \right) \right)^{1-\alpha} - \psi_{EE} \varrho p_i^* \right],$$

which is equivalent to the following one

$$\max_{k \in \mathcal{S}} \; |\mathcal{F}(\mathcal{S}_k)|. \tag{3.11}$$

Obviously, maximizing the objective function in (3.7) is equivalent to maximizing the maximum simplex (3.11), which is further equal to the problem of finding the maximum independent set in the graph $G = (\mathcal{V}, \mathcal{E})$. In addition, the maximum independent set problem is known to be NP-hard, implying that maximizing the optimization problem (3.7) with $0 < \alpha < 1$ is NP-hard. The proof ends. □

*Suppose that the problem (3.10) is always feasible.

3.4 Optimal Resource Allocation

Since the optimization problems (3.2) and (3.7) with $0 < \alpha < 1$ are both NP-Hard, algorithms with polynomial time to find the optimal solution to the problems are not possible, and the globally optimal solution has to be found by using global optimization approaches. However, finding the global optimum of the power allocation problem may take an unrealistically long time and highly computational complexity. In this section, the SCA approach is adopted to approximate and transform the NP-hard nonconvex optimization problem to a sequence of convex programs and then propose two iterative SCA-based resource allocation algorithms. The convergence of the proposed algorithms are also analyzed. Effectiveness of SCA-based algorithms for several resource allocation problems in wireless networks was verified in [23, 41–43] to have the same optimal values as the globally optimal algorithms can achieve.

3.4.1 SCA-based Resource Allocation with Logarithmic Approximation

For the problem with $\alpha = 0$, instead of solving the highly non-convex optimization problem, we exploit the SCALE method [33] to resort the objective function. Applying the SCALE method, making use of a logarithmic change of variables $\rho_i = \log(p_i)$, and taking the logarithm of both sides of the second constraint, the problem (3.2) can be boiled down to

$$\begin{aligned}
&\max_{\boldsymbol{\rho}} \ \psi_{SE} \sum_{i\in\mathcal{I}} \check{r}_i(e^{\boldsymbol{\rho}}, \alpha_i, \beta_i) - \psi_{EE} P_T\left(e^{\boldsymbol{\rho}}\right), \\
&\text{s.t.} \quad \mathcal{L} = \left\{\rho_i \middle| \log\left(p_i^{\min}\right) \le \rho_i \le \log\left(p_i^{\max}\right), \forall i \in \mathcal{I}\right\}, \\
&\qquad \sum_{j\neq i} \log\left(1 + \gamma_i^{th} e^{\rho_j - \rho_i} \frac{g_{ij}}{g_{ii}}\right) \le \log\left(\Omega_i(e^{\boldsymbol{\rho}})\right), \ \forall i \in \mathcal{I},
\end{aligned} \tag{3.12}$$

where $\check{r}_i(e^{\boldsymbol{\rho}}, \alpha_i, \beta_i) = \alpha_i \log_2\left(\gamma_i(e^{\boldsymbol{\rho}})\right) + \beta_i$.

Lemma 2. *For a given $(\boldsymbol{\alpha}, \boldsymbol{\beta})$, (3.12) is a convex problem.*

Proof. As proved in the previous section, the feasible set is convex. The first term in the objective function is concave since the log-sum-exp function is convex [66] while the second one is obviously convex; the objective function is, therefore, concave. As a result, (3.12) is a convex optimization problem. □

In the following, we utilize the Lagrangian duality technique to solve the problem (3.12) and then propose an iterative algorithm. Denote by $\boldsymbol{\lambda}$ the Lagrangian multiplier associated with the second constraint in (3.12), the Lagrangian function is defined as

$$\begin{aligned} L(\boldsymbol{\rho}, \boldsymbol{\lambda}) =& \psi_{SE} \sum_{i \in \mathcal{I}} \check{r}_i(e^{\boldsymbol{\rho}}, \alpha_i, \beta_i) - \psi_{EE} P_T\left(e^{\boldsymbol{\rho}}\right) \\ &+ \sum_{i \in \mathcal{I}} \lambda_i \left(\log\left(\Omega_i(e^{\boldsymbol{\rho}})\right) - \sum_{j \neq i} \log\left(1 + \gamma_i^{th} e^{\rho_j - \rho_i} \frac{g_{ij}}{g_{ii}}\right)\right), \end{aligned}$$

where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are two fixed approximation vectors. The dual function of which is given by $g(\boldsymbol{\lambda}) = \max_{\boldsymbol{\rho} \in \mathcal{L}} L(\boldsymbol{\rho}, \boldsymbol{\lambda})$. Accordingly, the dual problem is

$$\max_{\boldsymbol{\lambda} \geq \mathbf{0}} L(\boldsymbol{\lambda}). \tag{3.13}$$

Upon solving the stationary condition $\partial L(\boldsymbol{\rho}, \boldsymbol{\lambda})/\partial \rho_i = 0$ and transforming of the result back to the original solution space, we obtain the following fixed-point equation

$$p_i(t+1) = \left[\frac{\psi_{SE}\alpha_i (\ln 2)^{-1} + \lambda_i(t)\sigma_i^2 N_i(t)}{\psi_{EE}\varrho + \sum_{j \neq i}\left(\psi_{SE}\Lambda_j(t) g_{ji} + \lambda_j(t)\frac{N_j(t) g_{ji}}{1 + N_j(t) g_{ji} p_i(t)}\right)} \right]_{p_i^{\min}}^{p_i^{\max}}, \tag{3.14}$$

where $[z]_a^b = \max\{a, \min\{z, b\}\}$, $N_i(t) = \gamma_i^{th}(p_i(t) g_{ii})^{-1}$, and $\Lambda_i(t) = \alpha_i \gamma_i(\boldsymbol{p}(t))(g_{ii} p_i(t) \ln 2)^{-1}$.

The solution to the dual problem (3.13) can be obtained by the subgradient method [66] as

$$\lambda_i(t+1) = \left[\lambda_i(t) - \delta(t) \times \left(\log\left(\Omega_i(\boldsymbol{p}(t))\right) - \sum_{j \neq i} \log\left(1 + \gamma_i^{th} \frac{p_j(t) g_{ij}}{p_i(t) g_{ii}}\right)\right)\right]^+, \tag{3.15}$$

Algorithm 5 SCA-based Power Allocation with Logarithmic Approximation for the Problem with $\alpha = 0$

Set $\varepsilon_{in} > 0$, $\varepsilon_{out} > 0$, $\tau = 1$, FLAG$_{out}$ = 0, $\boldsymbol{\alpha}(\tau) = \mathbf{1}$, and $\boldsymbol{\beta}(\tau) = \mathbf{0}$.
repeat {To update $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$}
  Set FLAG$_{in}$ = 0 and $t = 1$
  repeat {To solve (3.12) for a given $(\boldsymbol{\alpha}, \boldsymbol{\beta})$}
    Allocate transmit powers according to (3.14).
    Update dual variables λ_i via (3.15).
    if $\max_{i \in \mathcal{I}} |\boldsymbol{p}(t) - \boldsymbol{p}(t-1)|/\boldsymbol{p}(t) \leq \varepsilon_{in}$ **then**
      $\boldsymbol{p}(\tau) = \boldsymbol{p}(t)$ and FLAG$_{in}$ = 1.
    else
      Set $t = t + 1$
    end if
  until FLAG$_{in}$ = 1
  if $\max_{i \in \mathcal{I}} |\boldsymbol{p}(\tau) - \boldsymbol{p}(\tau-1)|/\boldsymbol{p}(\tau) \leq \varepsilon_{out}$ **then**
    $\boldsymbol{p}^* = \boldsymbol{p}(\tau)$ is the optimal solution.
    FLAG$_{out}$ = 1.
  else
    Let $z(\tau) = \gamma_i(\boldsymbol{p}(\tau))$, update $\alpha_i(\tau)$ and $\beta_i(\tau)$ as in (2.2) and (2.3), respectively.
    Set $\tau = \tau + 1$
  end if
until FLAG$_{out}$ = 1

$\forall i \in \mathcal{I}$, where t is the iteration index and $[z]^+ = \max\{0, z\}$, and $\delta(t)$ is the step size, which is further required to satisfy the diminishing rule, i.e, $\delta(t) > 0$, $\sum_{t=1}^{t=\infty} \delta(t)^2 < \infty$, $\sum_{t=1}^{t=\infty} \delta(t) = \infty$.

For a given $(\boldsymbol{\alpha}, \boldsymbol{\beta})$, transmit powers and dual variables can be updated by (3.14) and (3.15), respectively. Let τ denote the iteration index of the outer loop. We continue to investigate an iterative SCA-based algorithm to solve the optimization problem (3.3) as presented in Algorithm 5.

Remark 4. *Let $\mathcal{T}$ be the number of iterations required to update the approximation vectors $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. Also, denote by L the number of iterations to solve the problem (3.12) in the dual domain, i.e., the number of iterations to update the transmit power according to (3.14). Then, the computational complexity of each iteration of Algorithm 5 is $\mathcal{O}(\mathcal{T}LI)$.*

Theorem 6. *With the logarithmic approximation, each outer loop of Algorithm 5 monotonically improves the objective function. In addition, the optimal solution $\boldsymbol{p}^*$ obtained by Algorithm 5 converges to an optimal point, which satisfies the KKT optimality conditions of the underlying problem (3.3).*

Proof. Define $V(\boldsymbol{p}) = \psi_{SE} \sum_{i \in \mathcal{I}} \log_2 \left(1 + \frac{p_i g_{ii}}{\sigma_i^2 + \sum_{j \neq i} p_j g_{ij}}\right) - \psi_{EE} P_T(\boldsymbol{p})$. We have

$$
\begin{aligned}
V(\boldsymbol{p}(\tau-1)) &\overset{(a)}{=} \sum_{i \in \mathcal{I}} \check{r}_i(e^{\boldsymbol{\rho}(\tau-1)}, \alpha_i(\tau), \beta_i(\tau)) - \psi_{EE} P_T\left(e^{\boldsymbol{\rho}(\tau-1)}\right) \\
&\overset{(b)}{\leq} \sum_{i \in \mathcal{I}} \check{r}_i(e^{\boldsymbol{\rho}(\tau)}, \alpha_i(\tau), \beta_i(\tau)) - \psi_{EE} P_T\left(e^{\boldsymbol{\rho}(\tau)}\right) \\
&\overset{(c)}{\leq} V(\boldsymbol{p}(\tau)).
\end{aligned}
\tag{3.16}
$$

In (3.16), we show (a) and (c) by the SCALE approximation. Inequality (b) is suitable since $\boldsymbol{p}(\tau)$ is the optimal solution to the problem (3.12) for a given $(\boldsymbol{\alpha}, \boldsymbol{\beta})$. In addition, because the feasible region of (3.2) is compact, $V(\boldsymbol{p})$ is bounded in its domain and then the solution obtained by Algorithm 5 eventually converges. Similar to [33], the second part of Theorem 6 can be proved by listing KKT optimality conditions of (3.2) and (3.12) and comparing between the corresponding conditions. □

3.4.2 SCA-based Resource Allocation with D.C. Approximation

The rate function $r_i(\boldsymbol{p})$ can be expressed as a D.C. function of power allocation vector $\boldsymbol{p}$ as $r_i(\boldsymbol{p}) = f_i(\boldsymbol{p}) - h_i(\boldsymbol{p})$, where both $f_i(\boldsymbol{p})$ and $h_i(\boldsymbol{p})$ are concave w.r.t. $\boldsymbol{p}$, which are respectively given as $f_i(\boldsymbol{p}) = \log_2\left(\sigma_i^2 + \sum\limits_{j\in\mathcal{I}} p_j g_{ij}\right)$ and $h_i(\boldsymbol{p}) = \log_2\left(\sigma_i^2 + \sum\limits_{j\neq i} p_j g_{ij}\right)$, for any node $i \in \mathcal{I}$.

Theorem 7. *α-fair utility function $U_\alpha(r_i(\boldsymbol{p}))$ can be rewritten as*

$$U_\alpha(r_i(\boldsymbol{p})) = U_\alpha(f_i(\boldsymbol{p}) - h_i(\boldsymbol{p})) = u_i(\boldsymbol{p}) - v_i(\boldsymbol{p}),$$

where $u_i(\boldsymbol{p})$ and $v_i(\boldsymbol{p})$ are respectively given as $u_i(\boldsymbol{p}) = U_\alpha(r_i(\boldsymbol{p})) + \chi_i h_i(\boldsymbol{p})$ and $v_i(\boldsymbol{p}) = \chi_i h_i(\boldsymbol{p})$), where χ_i is a constant satisfying $\chi_i \geq C_i^{-\alpha}$ with $C_i > 0$.

Proof. Refer to [48] for the proof. □

For given $\boldsymbol{p}(t)$ at the iteration t, we approximate $v_i(\boldsymbol{p})$ by its first-order Taylor expansion as $v_i(\boldsymbol{p}) \approx v_i(\boldsymbol{p}(t)) + \nabla v_i^T(\boldsymbol{p}(t))(\boldsymbol{p} - \boldsymbol{p}(t))$. Here, $\nabla v_i(\boldsymbol{p}(t))$ is the gradient of $v_i(\boldsymbol{p})$ at $\boldsymbol{p}$ and given by $\nabla v_i(\boldsymbol{p}(t)) = \frac{\chi_i}{\sigma_i^2 + \sum\limits_{j\neq i} p_j g_{ij}} \boldsymbol{e}_i$, where $\boldsymbol{e}_i$ is a $I-$dimensional column vector with $\boldsymbol{e}_i(i) = 0$ and $\boldsymbol{e}_i(j) = \frac{\chi_i}{\ln 2} g_{ij},\ j \neq i$. Then, the network utility can be represented as

$$\begin{aligned}\sum_{i\in\mathcal{I}} U_\alpha(r_i(\boldsymbol{p})) &= \sum_{i\in\mathcal{I}} (u_i(\boldsymbol{p}) - v_i(\boldsymbol{p})) = \sum_{i\in\mathcal{I}} u_i(\boldsymbol{p}) - \sum_{i\in\mathcal{I}} v_i(\boldsymbol{p}) \\ &\approx u(\boldsymbol{p}) - \left(v(\boldsymbol{p}(t)) + \nabla v^T(\boldsymbol{p}(t))(\boldsymbol{p} - \boldsymbol{p}(t))\right),\end{aligned}$$

where $u(\boldsymbol{p}) = \sum_{i\in\mathcal{I}} u_i(\boldsymbol{p})$. Therefore, if we initialize from the iteration 0 and iteratively update the power allocation, the optimal value at the iteration $(t+1)$ is derived from the following optimization problem

$$\begin{aligned}
&\max_{\boldsymbol{p}} \ \psi_{SE}\left[u(\boldsymbol{p}) - \left(v(\boldsymbol{p}(t)) + \nabla v^T\left(\boldsymbol{p}(t)\right)\left(\boldsymbol{p}-\boldsymbol{p}(t)\right)\right)\right] - \psi_{EE}P_T(\boldsymbol{p}) \\
&\text{s.t.} \quad \Gamma = \left\{p_i | p_i^{\min} \leq p_i \leq p_i^{\max},\ \forall i \in \mathcal{I}\right\}, \\
&\qquad \Pr\left(\gamma_i \leq \gamma_i^{th}\right) \leq \epsilon_i \ \forall i \in \mathcal{I},
\end{aligned} \tag{3.17}$$

where $\boldsymbol{p}(t)$ has been already obtained from the previous iteration. The objective function and first constraint of (3.17) are actually concave; however, the problem (3.17) is still not a convex problem due to the nonconvexity of the second constraint. To convexify (3.17), we simplify the second constraint by exploiting the relationship between the certainty-equivalent margin (CEM), which is CEM $= \bar{\gamma}_i/\gamma_i^{th}$, and outage probability. According to [26, 40], the upper bound and lower bound of the rate outage probability is given, as follows:

$$\frac{1}{1+\text{CEM}} \leq \Pr\left(\gamma_i \leq \gamma_i^{th}\right) \leq 1 - \exp\left(-1/\text{CEM}\right). \tag{3.18}$$

For simplicity, we consider the lower bound of (3.18), which with the condition of the rate outage probability ϵ_l results in

$$\bar{\gamma}_i^{th} \leq \bar{\gamma}_i, \tag{3.19}$$

where $\bar{\gamma}_i^{th} = \gamma_i^{th}\left(1/\epsilon_i - 1\right)$. The rate outage constraints (3.19) can be equally expressed by the following linear constraints $p_i g_{ii} - \bar{\gamma}_i^{th}\left(\sigma_i^2 + \sum_{j\neq i} p_j g_{ij}\right) \geq 0$. Now, the optimization problem can be formulated as

$$\begin{aligned}
&\max_{\boldsymbol{p}} \ \psi_{SE}\left[u(\boldsymbol{p}) - \left(v(\boldsymbol{p}(t)) + \nabla v^T\left(\boldsymbol{p}(t)\right)\left(\boldsymbol{p}-\boldsymbol{p}(t)\right)\right)\right] - \psi_{EE}P_T(\boldsymbol{p}) \\
&\text{s.t.} \quad \Gamma = \left\{p_i | p_i^{\min} \leq p_i \leq p_i^{\max},\ \forall i \in \mathcal{I}\right\}, \\
&\qquad p_i g_{ii} - \bar{\gamma}_i^{th}\left(\sigma_i^2 + \sum_{j\neq i} p_j g_{ij}\right) \geq 0 \ \forall i \in \mathcal{I}.
\end{aligned} \tag{3.20}$$

Since the above problem is a convex optimization problem, we can use any convex solver [66] to solve (3.20). The procedure to solve the problem (3.7) is summarized in Algorithm 6. A remark on Algorithm 6 is made

Algorithm 6 SCA-based Power Allocation with D.C. Approximation for Problem with $0 < \alpha < 1$

Set $\varepsilon > 0$, $t = 0$, FLAG = 0 and initialize $\boldsymbol{p}(t)$.
repeat
  Solve the problem (3.20) to obtain $\boldsymbol{p}^*$.
  if $\max_{i \in \mathcal{I}} |\boldsymbol{p}^* - \boldsymbol{p}(t)|/\boldsymbol{p}^* \leq \varepsilon$ **then**
    $\boldsymbol{p}^*$ is the optimal solution.
    FLAG = 1.
  else
    Set $t = t + 1$.
    Set $\boldsymbol{p}(t) = \boldsymbol{p}^*$.
  end if
until FLAG = 1

as the following.

Remark 5. *At each step of Algorithm 6, $v_i(\mathbf{p})$ is approximated by its first-order Taylor expansion $v_i(\mathbf{p}(t)) + \nabla v_i^T(\mathbf{p}(t))(\mathbf{p} - \mathbf{p}(t))$, which is concave w.r.t. power allocation $\mathbf{p}$ and very close to $v_i(\mathbf{p})$ at fairly large neighborhood of $\mathbf{p}(t)$. The performance of this approximation has been verified in previous literature, for example, [23, 41, 42, 48].*

Theorem 8. *With the D.C. approximation, the sequence of power allocation $\{\mathbf{p}(t)\}$ generated by Algorithm 6 monotonically improves the objective function and eventually, converges to a locally optimal solution to the problem (3.7).*

Proof. Let $g(\boldsymbol{p}) = \psi_{SE} u(\boldsymbol{p}) - \psi_{EE} P_T(\boldsymbol{p})$. Since $u(\boldsymbol{p})$ is concave and $P_T(\boldsymbol{p})$ is linear, $g(\boldsymbol{p})$ is concave. In addition, due to the concavity of $v(\boldsymbol{p})$, $v(\boldsymbol{p}) \leq v(\boldsymbol{p}(t)) + \nabla v^T(\boldsymbol{p}(t))(\boldsymbol{p} - \boldsymbol{p}(t))$. We have the following relations

$$\begin{aligned} g(\boldsymbol{p}(t)) - \psi_{SE} v(\boldsymbol{p}(t)) &\geq g(\boldsymbol{p}(t)) - \psi_{SE} v(\boldsymbol{p}(t-1)) - \psi_{SE} \nabla v^T \left(\boldsymbol{p}(t-1)\right)\left(\boldsymbol{p}(t) - \boldsymbol{p}(t-1)\right) \\ &= \max_{\boldsymbol{p}} \left[g(\boldsymbol{p}) - \psi_{SE} v(\boldsymbol{p}(t-1)) - \psi_{SE} \nabla v^T \left(\boldsymbol{p}(t-1)\right)\left(\boldsymbol{p} - \boldsymbol{p}(t-1)\right) \right] \\ &\geq g(\boldsymbol{p}(t-1)) - \psi_{SE} v(\boldsymbol{p}(t-1)) - \psi_{SE} \nabla v^T \left(\boldsymbol{p}(t-1)\right)\left(\boldsymbol{p}(t-1) - \boldsymbol{p}(t-1)\right) \\ &= g(\boldsymbol{p}(t-1)) - \psi_{SE} v(\boldsymbol{p}(t-1)). \end{aligned}$$

In the above system, the first inequality is from the concavity of $v(\boldsymbol{p})$, the second equality is actually step 3 of Algorithm 6, the third inequality is suitable since $\boldsymbol{p}(t)$ is the optimal solution to the problem (3.20) for given $\boldsymbol{p}(t-1)$, the last one is obviously true. Clearly, the objective monotonically increases or remains unchanged after each update of power allocation $\boldsymbol{p}(t)$. Moreover, the feasible region of (3.7) is compact, the sequence of power allocation $\{\boldsymbol{p}(t)\}$ generated by Algorithm 6 therefore will eventually converge to a locally optimal solution to (3.7).

$\square$

3.5 Simulation Results

In this section, we evaluate the performance of the proposed algorithms (ProA) in Section 3.4 by extensive numerical results. The noise power and the circuit power consumption are respectively set to $\sigma_i^2 = 0.1$ μW and $(p_{i,ct} + p_{i,cr}) = 0.1$ mW [42, 43], and the power amplifier efficiency $\varrho = 50\%$ is set. The stopping criteria ε is set to 10^{-6}. Unless other stated, the rate outage probability for all users is 0.15, i.e., $\epsilon_i = 0.15, \forall i$, the data rate requirement for all users is 0.5 bps, i.e., $\gamma_{th} = 0.4142, \forall i$, and the priority parameter $\boldsymbol{\psi} = [0.2 \;\; 0.8]$ is set.

To evaluate the convergence of the proposed algorithms, we use the same network scenarios in [67]. Specifically, a random network topology with 10 users and the coverage area of 100 m x 100 m is considered. Transmitters are randomly positioned according to a uniform distribution and receivers are located randomly within a 20 m x 20 m area around their corresponding transmitters. The channel gains $g_{ij} = d_{ij}^{-4}$, where d_{ij} is the distance from the transmitter j to the receiver i. The noise power spectral density is 174 dBm/Hz. Other parameters are, $p_{cr} = 10.0$ mW, $p_{ct} = 10.0$ mW, $\varrho = 50\%$, $\epsilon_i = 0.1$ and $\gamma_i^{th} = 6.5$ dB for all i. Note that Algorithm 5 can be regarded as a two-loop operation, more in details, the inner loop lies in step 5, which is to find the optimal power allocation for a given $(\boldsymbol{\alpha}, \boldsymbol{\beta})$ and the outer loop is to update the approximation coefficients $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. From Fig. 3.1, the inner loop of the ProA with $\alpha = 0$ converges within few dozens of iterations. Meanwhile, the outer loop usually converges within few iterations, which depends on initial conditions, for example, initial power allocation. Therefore, the ProA with $\alpha = 0$ is numerically convergent and cost-effective in term of computational complexity.

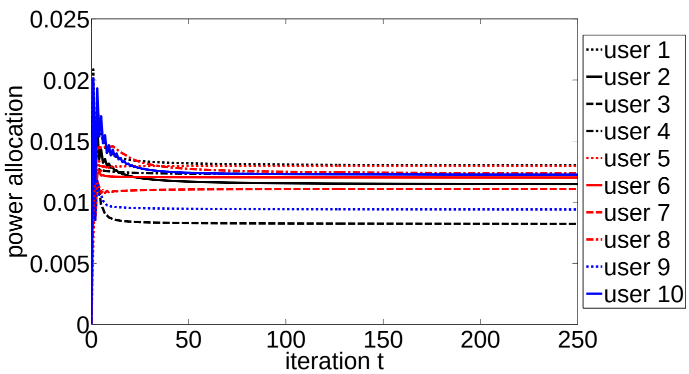


Figure 3.1: Convergence of the transmit powers.

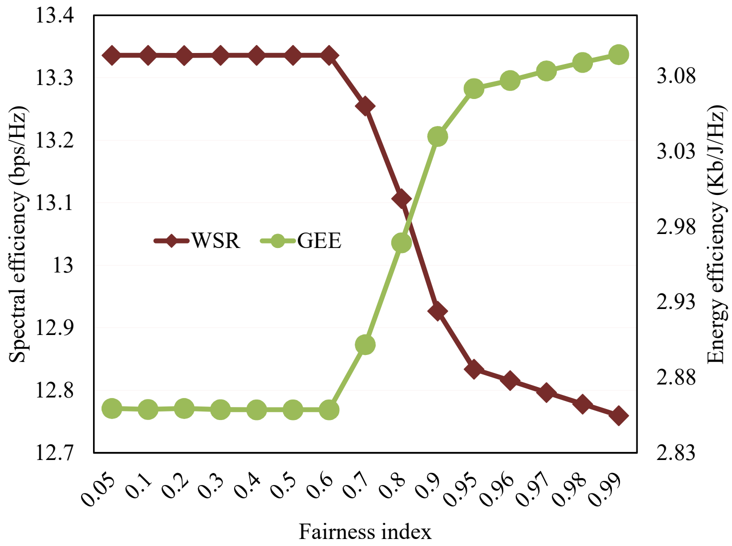
For the ease of evaluation of the ProAs and convenience of comparison with existing frameworks, we consider the simulation scenario as in [41–43, 52] and the weight $w = [1/6\ 1/6\ 1/3\ 1/3]$ in [41] is changed to $w = [1\ 1\ 1\ 1]$. Specifically, $I = 4$, $\boldsymbol{P}^{\max} = \left[\{p_i^{\max}\}_i\right] = [0.7\ 0.8\ 0.9\ 1.0]$ mW, $\boldsymbol{P}^{\min} =$

$\left[\{p_i^{\min}\}_i\right] = [0.0\ \ 0.0\ \ 0.0\ \ 0.0]$ mW, and the channel gain matrix $G = \{g_{ij}\}$*

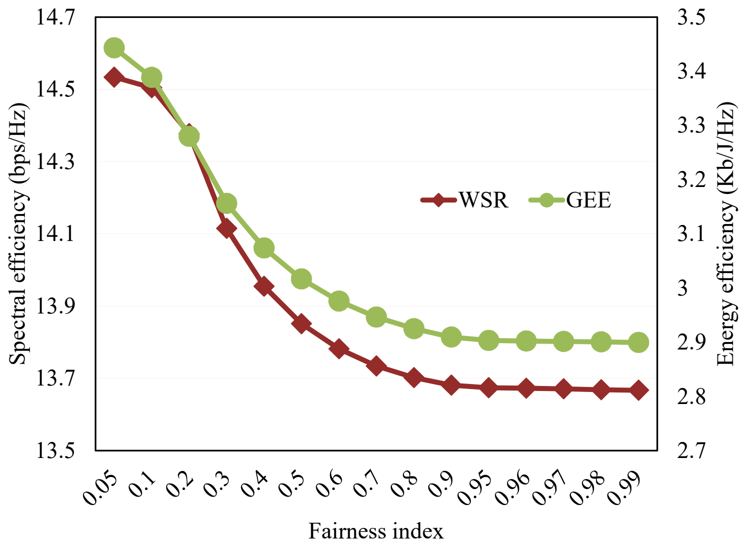
$$G = \begin{bmatrix} 0.4310 & 0.0002 & 0.0129 & 0.0011 \\ 0.0002 & 0.3018 & 0.0005 & 0.0031 \\ 0.2605 & 0.0008 & 0.4266 & 0.0099 \\ 0.0039 & 0.0054 & 0.1007 & 0.0634 \end{bmatrix}.$$

In the first experiment, we vary values of the fairness index α and rate outage threshold ϵ_i (from $\epsilon_i = 0.05$ to $\epsilon_i = 0.50$) and show their impacts on the spectral efficiency and energy efficiency. As can be seen from Fig. 3.2 and Fig. 3.3, when ϵ_i is small, the smaller the fairness index α is ($\epsilon \leq 0.15$ in the current simulation settings), the larger and smaller spectral efficiency and energy efficiency, respectively, are. In the meanwhile, when ϵ_i is large enough ($\epsilon \geq 0.20$), both spectral efficiency and energy efficiency decrease as the fairness index α increases. This is reasonable since when the outage constraint is not strict, i.e., the outage probability is high, as the fairness degree increases, there is a drop in the sum rate utility and an increase in the total power consumption. Our observation is similar to one in relay-aided cooperative OFDMA networks [68] that for the same value of spectral efficiency, a lower energy efficiency is achieved as the fairness level increases or a higher fairness results in a worse SE-EE tradeoff. However, when the outage probability is low, the most energy efficient design is to fulfill the rate outage constraint, i.e., low SINR and less interference to the other pairs. Under this context, the total power consumption reduces as the fairness degree increases and its decrease is much faster than that of the spectral efficiency. As a result, when the maximal outage probability is low, the higher the fairness degree, the higher the energy efficiency. In summary, the spectral efficiency and energy efficiency are conflicting when the outage constraint is strict and vice versa. It can also be seen from Fig. 3.3a and Fig. 3.3b that the performance gap approaches zero as ϵ_i increase, e.g., the spectral efficiency and energy efficiency in the case of $\epsilon_i = 0.40$ and $\epsilon_i = 0.50$ are almost the same.

*The channel gain matrix G is generated by considering a four-link network where the links are randomly positioned in a 10 m x 10 m area and $g_{ij} = d_{ij}^{-4}$.



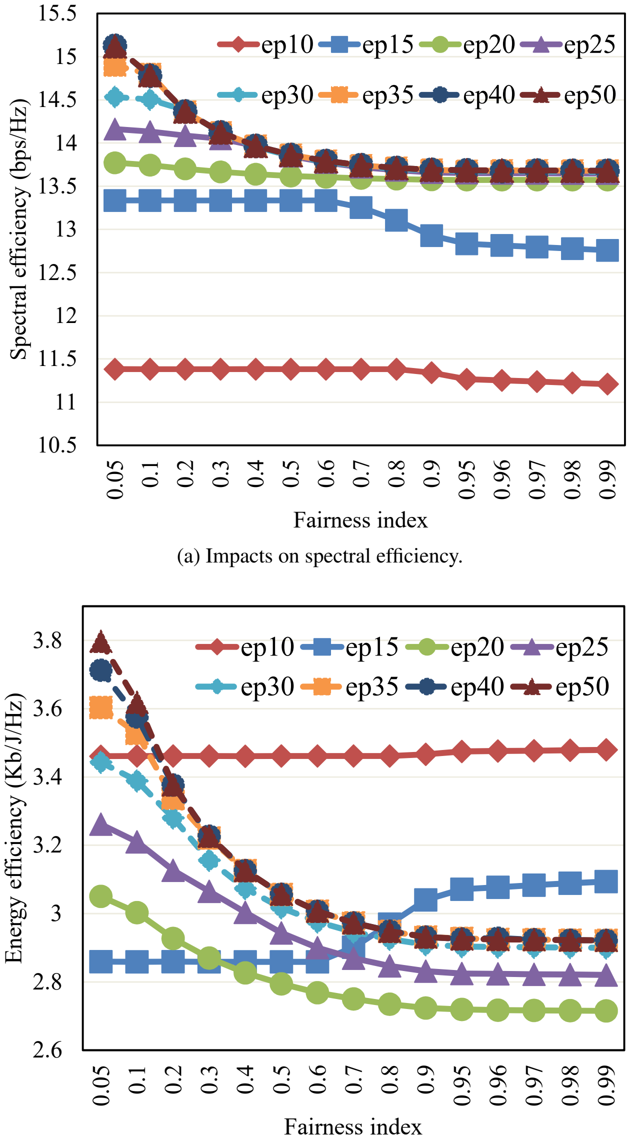
(a) Rate outage probability $\epsilon_i = 0.15$.



(b) Rate outage probability $\epsilon_i = 0.30$.

Figure 3.2: Impacts of the fairness index and rate outage probability on the performance.

In Fig. 3.4, we evaluate the performance of the ProA with $0 < \alpha < 1$ as the SINR threshold and fairness index change. In this context, let r_i^{req} be the data rate requirement of user i, its target minimum SINR is



(a) Impacts on spectral efficiency.

(b) Impacts on energy efficiency.

Figure 3.3: Impacts of the fairness index and rate outage probability on the performance, where epxx means $\epsilon_i = 0.xx, \forall i$.

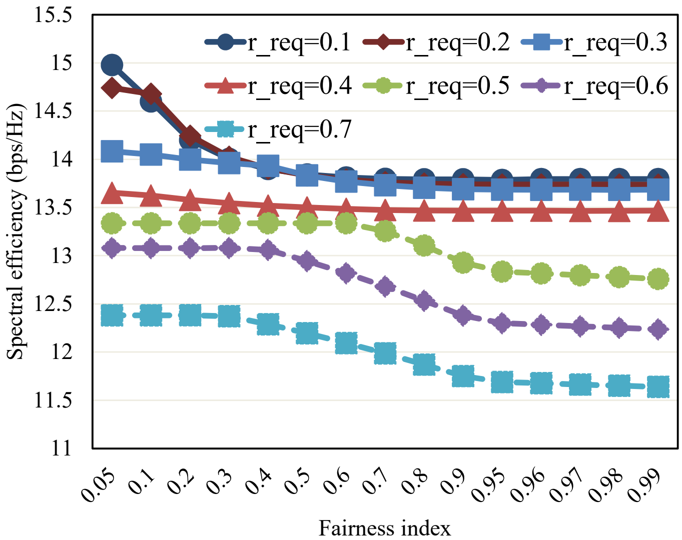
$\gamma_i^{th} = 2^{r_i^{req}} - 1$. Similar to the case of varying ϵ_i, spectral efficiency decreases as the SINR threshold γ_i^{th} increases (for a given fairness index α) and the fairness index increases (for a given SINR threshold

γ_i^{th}) and the gap gets closer and becomes zero when the SINR threshold is large enough. In term of energy efficiency, when γ_i^{th} is less than a critical value (correspondingly, $r_i^{req} \leq 0.4$ bps in the current simulation settings), energy efficiency decreases as γ_i^{th} increases. In contrast, when γ_i^{th} is large ($r_i^{req} \geq 0.5$ bps), energy efficiency increases as γ increases. Another observation from Fig. 3.3 and Fig. 3.4 is that $\epsilon_i = 0.15$ and $r_i^{req} = 0.5$ can be used to have a reasonable performance of the SE-EE tradeoff, we therefore simply consider $\epsilon_i = 0.15$ and $r_i^{req} = 0.5$ in the default setting.

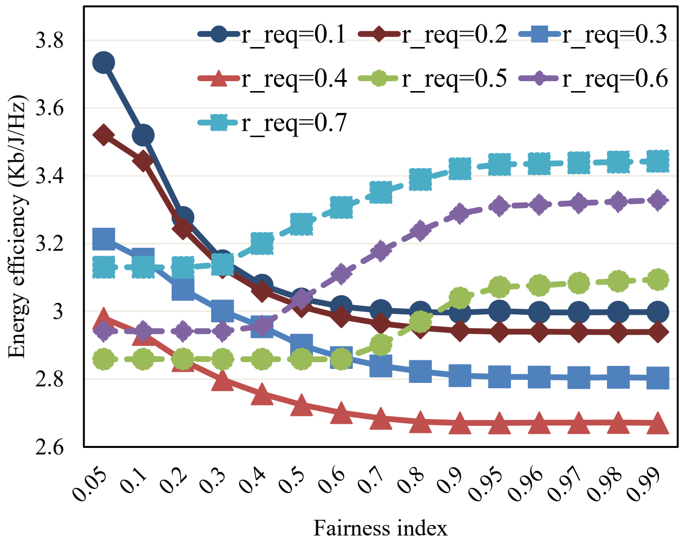
Now, we compare the ProA with $0 < \alpha < 1$ with three alternatives; the first one, SRM, was proposed in [48], which is to maximize the sum of α-fair sum rate ($0 < \alpha < 1$) subject to constraints on data rate requirements and power budget; the second one, SRMO, is to maximize the sum of α-fair sum rate ($0 < \alpha < 1$) subject to constraints on rate outage probability and power budget, which is the optimization problem (3.7) with $\boldsymbol{\psi} = [1\ \ 0]$; and the last one, NPM, is to the optimization problem (3.7) with $\boldsymbol{\psi} = [0\ \ 1]$. As can be seen from Fig. 3.5, the NPM achieves the highest energy efficiency, which is sacrificed by the lowest spectral efficiency. The SRMO yields higher spectral efficiency, but lower energy efficiency than the ProA, which is able to adjust the priority parameter to balance between energy efficiency and spectral efficiency. In addition, as the fairness index α increases, both energy efficiency and spectral efficiency obtained from the SRM proposed in [48] decreases. Although the SRM outperforms the ProA in term of spectral efficiency, which is reasonable since its objective is to maximize the sum of α-fair sum rate, energy efficiency, yielded by the ProA, increases steadily and is higher than that of SRM when the fairness index α is around 0.75. The drop in energy efficiency of the ProA is due to the use of near-optimal scheme with the lower bound of the rate outage probability (3.18). Therefore, it is recommended to use a hybrid scheme, which is composed of the SRM [48] ($\alpha \leq 0.75$) and the ProA ($\alpha \geq 0.75$)*.

Next, we evaluate performance of the ProA with $\alpha = 0$. Note that the optimization problem in 3.2 reduces to the total power minimization problem at $\boldsymbol{\psi}1 = [0.0\ \ 1.0]$ and to the weighted sum rate maximization problem at $\boldsymbol{\psi}11 = [1.0\ \ 0.0]$. Since the multi-objective problem of the SE-EE tradeoff is transformed to

*The value of the fairness index α, below which we use the SRM and above which we use the ProA, depends on the simulation settings, for example, the channel gain matrix and the data rate requirement.



(a) Impacts on spectral efficiency.



(b) Impacts on energy efficiency.

Figure 3.4: Impacts of the fairness index and data rate requirement on the performance, where r_req $= 0.x$ means $r_i^{req} = 0.x$ bps, $\forall i$.

the problem of maximizing the sum-rate and minimizing the total power consumption, the highest spectral efficiency and lowest energy efficiency are achieved at $\psi 1$ and vice versa at $\psi 11$. Moreover, from Fig. 3.6,

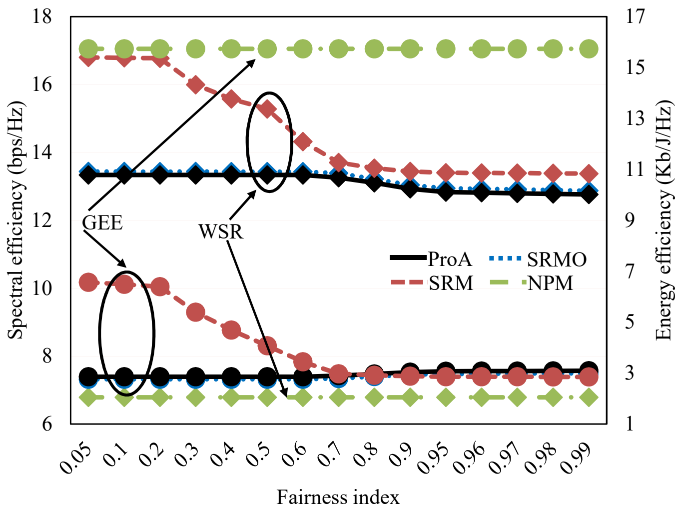


Figure 3.5: Comparison of the ProA with existing alternatives.

spectral efficiency and energy efficiency increases and decreases monotonically when the priority parameter changes from $\psi 1$ to $\psi 11$. This is reasonable since (1) at $\psi 1$, the objective function is to maximize the sum-rate of all users; (2) at $\psi 11$, the objective is the total power minimization; and (3) as the priority goes from $\psi 1$ to $\psi 11$, the priority for maximizing spectral efficiency is higher while that for maximizing energy efficiency is smaller. Therefore, comparing to the sum-rate maximization and total power minimization schemes, our proposed algorithm outperforms in term of the SE-EE tradeoff.

In Fig. 3.7, we study impacts of both the priority parameter and outage probability threshold on spectral efficiency and energy efficiency of the ProA with $\alpha = 0$. From Fig. 3.7 and as observed in Fig. 3.6, for a given rate outage probability, spectral efficiency and energy efficiency increases and decreases monotonically when the priority parameter changes from $\psi 2$ to $\psi 10$. Also, for a given priority parameter, spectral efficiency increases and energy efficiency decreases as the higher outage probability threshold is imposed*. The reason is that when ϵ_i increases, more power consumption is needed to compensate effects of rate out-

*Note that the left figure is for the *spectral efficiency*, not the *spectrum*, and the right figure is for the *energy efficiency* with the unit of Kb/J/Hz. In addition, a large set of the priority parameter is used in the experiment, from ψ_2 to ψ_{10}. Therefore, the gap between the maximum and minimum value of spectral efficiency and energy efficiency is relatively large and the performance gap looks minimal and the observation should be seen from the two enlargements.

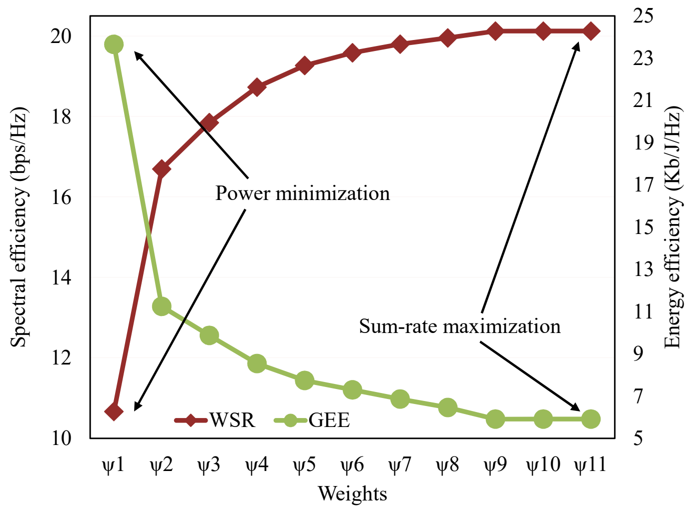
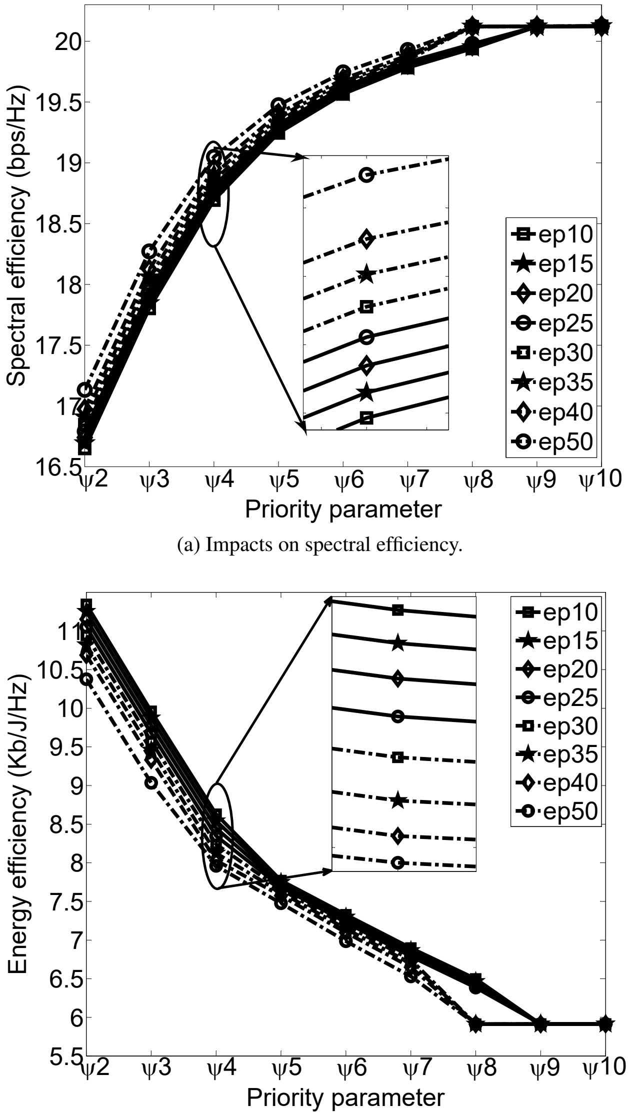


Figure 3.6: Impacts of the priority parameter on spectral efficiency and energy efficiency with $\alpha = 0$, where $\boldsymbol{\psi} i = [0.1 \times (i-1) \;\; 1 - 0.1 \times (i-1)]$.

age as well as meeting QoS requirements. However, due to the limitation on the power budget and fixed SINR threshold, increment in outage probability cannot be fully compensated by allocating more transmit power and therefore, the performance gap in spectral efficiency and energy efficiency between different schemes of outage probability thresholds becomes smaller and larger, respectively.

Finally, we vary the data rate requirement from 0.1 bps to 0.8 bps with a step of 0.1 and compare the performance of the ProA with $\alpha = 0$ with the weighted sum rate maximization (WSRM) scheme in [41] and the general algorithm procedure (GAP) embedded with an iterative power allocation algorithm in [42]. For a fair comparison, as r_i^{req} is the data rate requirement of user i in [41, 42], the SINR threshold of user i in the current simulation is $\gamma_i^{th} = 2^{r_i^{req}} - 1$, which is defined similarly to the case $0 < \alpha < 1$. As can be seen from Fig. 3.8, the energy efficiency and spectral efficiency yielded by the ProA increases and decreases monotonically as the higher data rate is required. Similarly, the spectral efficiency of the WSRM and GAP decreases as the data rate requirement increases; however, the corresponding energy efficiency varies differently when the data rate requirement changes. Moreover, the ProA is distinctly superior to the WSRM and GAP in term of the SE-EE tradeoff. In particular, in the GAP scheme, the



(a) Impacts on spectral efficiency.

(b) Impacts on energy efficiency.

Figure 3.7: Impacts of the priority parameter and outage probability threshold on the performance, where epxx means $\epsilon_i = 0.xx, \forall i$.

highest energy efficiency is sacrificed by the lowest spectral efficiency; this is reasonable since its objective is to maximize the global energy efficiency. In the meanwhile, both spectral efficiency and energy efficiency of the WSRM approach are lower than those of the ProA. In addition to high performance on the SE-EE tradeoff, the ProA can also vary ψ to adjust the priority of either spectral efficiency or energy efficiency as illustrated in Fig. 3.6. In order to show the better tradeoff of the ProA, we present the spectral efficiency and energy efficiency in a single value by defining two types of performance functions, the first type of utility is $U_1 = w(\eta_{SE}/\eta_{SE}^{\max}) + (1-w)(\eta_{EE}/\eta_{EE}^{\max})$ and the second type of utility is defined as $U_2 = (\eta_{SE}/\eta_{SE}^{\max})^w(\eta_{EE}/\eta_{EE}^{\max})^{(1-w)*}$, where w is the priority parameter of the spectral efficiency, $\eta_{SE}^{\max}$ and $\eta_{EE}^{\max}$ are respectively the maximal spectral efficiency and energy efficiency. For any value of the priority parameter, the utilities of the ProA are clearly higher than those of the WSRM. Although the GAP method achieves higher energy efficiency than the ProA, the ProA can adjust the priority parameter so that the obtained utilities are higher than those of the GAP. These facts can be illustrated by sampling w as 0.8 and seen from Fig. 3.9, where the first and second types of utility functions are denoted by solid lines and dashed lines, respectively. The comparison for the case of $0 < \alpha < 1$ can be explained similarly.

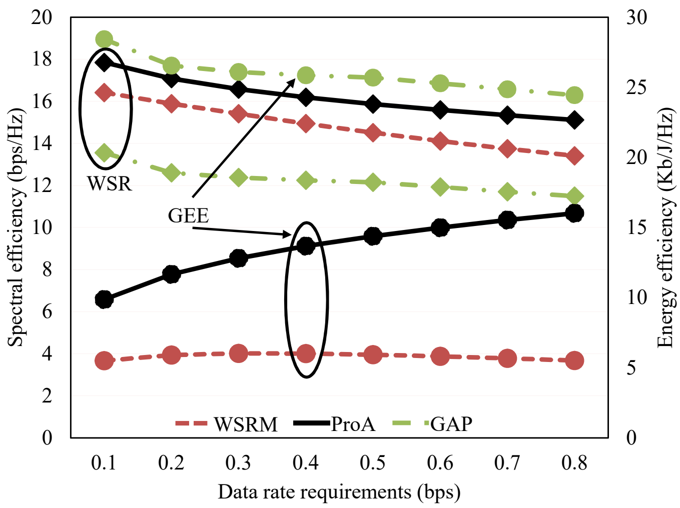


Figure 3.8: Comparison of the ProA with existing frameworks.

*According to [63], to present both the spectral efficiency and energy efficiency in a single numerical value for comparison, it is important to make both the spectral efficiency and energy efficiency comparable without associated physical units, i.e., the spectral efficiency and energy efficiency should be transformed such that they are dimensionless

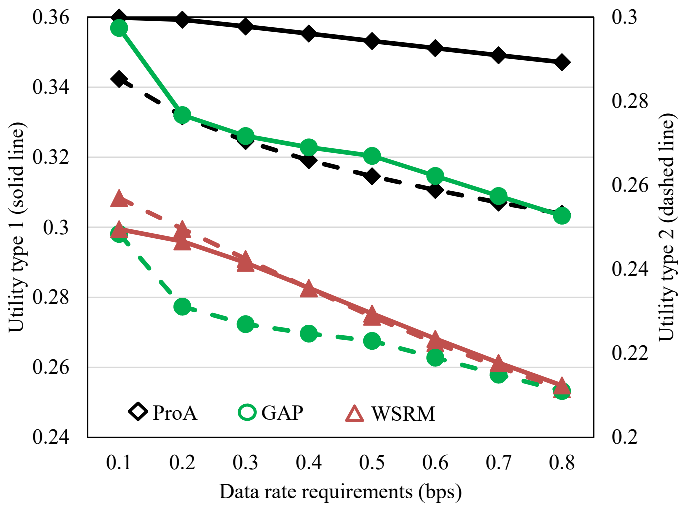


Figure 3.9: Comparison of the ProA with existing frameworks with 2 types of utility function.

3.6 Conclusion

This chapter devised the formulation and analyzed the complexity of the optimization problem of the SE-EE tradeoff in spectrum-sharing wireless networks. In particular, the problem is NP-Hard when $0 < \alpha < 1$ and $\alpha = 0$ and is convex for other values of the fairness index α. Accordingly, two algorithms were proposed for NP-Hard cases. Numerical examples demonstrated that the proposed algorithms outperform the compared alternatives in term of the SE-EE tradeoff.

Chapter 4

α-Fair Resource Allocation in Non-Orthogonal Multiple Access Systems

As an extension of chapter 3, this chapter considers and analyzes the complexity of the α-fair power control problem in NOMA systems.

4.1 Introduction

Non-orthogonal multiple access, namely NOMA, has been considered as a promising multiple access technology in 5G networks due to the superior spectral efficiency by introducing a new domain, the power domain, compared to conventional orthogonal multiple access (OMA). With NOMA, multiple users are enabled to pair in and share the same frequency radio resource at the same time. At the receiver side, multi-user detection algorithms such as successive interference cancellation (SIC) are used to detect the desired signals. Due to the SIC order, the users in NOMA can achieve different rates and fairness is therefore not obtained. However, fairness can be improved and supported through an appropriate power allocation [12].

Great attention has been devoted to the fair resource allocation in NOMA systems, for example, proportional fairness in [69] and max-min fairness in [12]. Actually, there is a tradeoff between the sum-rate and fairness degree, i.e., improving the sum-rate results in decreasing the fairness degree and vice versa. While the min-rate problem [12] offers the most fairness, the sum-rate is low. In addition, the proportional sum-rate [69] cannot provide a reasonable tradeoff between the sum-rate and fairness degree. α-fair resource allocation was studied in [70] for the sum-rate maximization problem and in chapter 3 for the problem of spectral- and energy-efficient tradeoff in spectrum-sharing wireless networks. However, to the best of the authors' knowledge, there is no existing work devoted to α-fair resource allocation problem in NOMA systems.

In this chapter, we consider and analyze the complexity of the α-fair resource allocation problem in NOMA systems. Specifically, the problem is shown to be convex when $1 \leq \alpha < \infty$ and $\alpha = \infty$, NP-Hard when $0 < \alpha < 1$, and polynomial-time solvable when $\alpha = 0$. Despite of the NP-Hardness for the case $0 < \alpha < 1$, the power allocation problem is formulated as a difference of two concave functions (DC). The problem is therefore approximated to a convex program and then the sub-optimal solution can be achieved by solving a sequence of convex programs. The numerical simulation is also provided so as to verify the performance of our proposed algorithms.

4.2 System Model and Problem Formulation

Consider the downlink of a NOMA system with one base station (BS) and N users, each one is equipped with only one antenna. The set of users is $\mathcal{N} = \{1, ..., N\}$. Denote by g_n the channel response from the BS to the user n and channel gains of all users are sorted in an ascending order, i.e., $|g_1| \leq |g_2| \leq ... \leq |g_N|$. The total bandwidth is normalized to unity.

The NOMA system serves multiple users at the same time over the entire bandwidth by allowing the BS to use the superposition coding technique. Hence, the received signal at the user n is given as $y_n = g_n \sum_{i\in\mathcal{N}} \sqrt{p_i} s_i + z_n$, where p_i is the transmit power allocated to the user i, s_i is the data symbol for the user i, and z_n is the additive white Gaussian noise, which is assumed to be i.i.d. and the noise variance is σ_n^2.

For NOMA, the user n implements the successive interference cancellation (SIC) technique in order to decode the signal of users with lower channel gain. As a result, the SINR at the user n to decode signals from users with lower channel gains is

$$\gamma_n(\boldsymbol{p}_n) = \frac{|g_n|^2 p_n}{\sigma_n^2 + |g_n|^2 \sum\limits_{i=n+1}^{N} p_i},$$

where $\boldsymbol{p}_n = [p_n, p_{n+1}, ..., p_N]$. Correspondingly, the achievable rate at the user n is $R_n(\boldsymbol{p}_n) = \log_2(1 + \gamma_n(\boldsymbol{p}_n))$ and the utility is $U_\alpha(R_n(\boldsymbol{p}_n))$, where α is the fairness index and $U_\alpha(\cdot)$ is the utility function (1.1).

The objective is to maximize the total α-fair utility of all users, the optimization problem is therefore formulated as

$$\begin{aligned} \max_{\boldsymbol{p}} \quad & \sum_{n\in\mathcal{N}} U_\alpha(R_n) \\ \text{s.t.} \quad & p_n \geq 0 \; \forall n \in \mathcal{N}, \\ & \sum_{n\in N} p_n \leq P, \end{aligned} \tag{4.1}$$

where P denotes the maximum transmit power at the BS.

4.3 Complexity Analysis and Algorithm

We consider five cases of the fairness index α and analyze the complexity of the problem (4.1).

4.3.1 $\alpha = 0$

When $\alpha = 0$, the optimization problem (4.1) becomes

$$\begin{aligned} \max_{\boldsymbol{p}} \quad & \sum_{n \in \mathcal{N}} \log_2 \left(1 + \gamma_n(\boldsymbol{p}_n)\right) \\ \text{s.t.} \quad & p_n \geq 0 \ \forall n \in \mathcal{N}, \\ & \sum_{n \in N} p_n \leq P. \end{aligned} \tag{4.2}$$

The problem (4.2) is equivalent to the R-JPCAP in single-carrier NOMA systems [71]. In particular, the problem (4.2) is polynomial-time solvable and power can be consecutively allocated in their channel gains, i.e., an ascending order since we have assumed that channel gains are sorted in an ascending order. Since there is no fairness among users in this case, user with the highest channel gain is enabled to transmit at its maximum power and the remaining power is used for the other users; the process is repeated until power is allocated to all of users or there is no power to allocate.

4.3.2 Proportional fairness, $\alpha = 1$

When $\alpha = 1$, proportional fairness, the optimization problem (4.1) becomes

$$\begin{aligned} \max_{\boldsymbol{p}} \quad & \sum_{n \in \mathcal{N}} \log \left(\log_2 \left(1 + \gamma_n(\boldsymbol{p}_n)\right)\right) \\ \text{s.t.} \quad & p_n \geq 0 \ \forall n \in \mathcal{N}, \\ & \sum_{n \in N} p_n \leq P. \end{aligned} \tag{4.3}$$

Introducing auxiliary variables $\rho_n = \log(p_n)$ and t_n such that $\exp(t_n) \leq \log_2 \left(1 + \gamma_n(\boldsymbol{p}_n)\right)$, we can easily prove that the problem (4.3) is a convex optimization problem and the globally optimal solution to (4.3) can be obtained by the interior-point method. Slightly different from our approach, Yang *et al.* introduced η_n

such that $\eta_n \leq \gamma_n(\boldsymbol{p}_n)$ and transformed the problem (4.3), with the unique intensity constraint for visible light communication systems, to a convex problem. The optimal solution in [69] is however obtained by using the the duality technique with low complexity in a comparison with the interior-point method.

4.3.3 Max-min fairness, $\alpha = \infty$

The optimization problem now becomes

$$\begin{aligned} &\max_{\boldsymbol{p}} \min_{n \in \mathcal{N}} \ \log_2 \left(1 + \gamma_n(\boldsymbol{p}_n)\right) \\ &\text{s.t.} \quad p_n \geq 0 \ \forall n \in \mathcal{N}, \\ &\qquad \sum_{n \in N} p_n \leq P. \end{aligned} \tag{4.4}$$

Timotheou and Krikidis proved in [12] that the objective function with proportional fairness is quasi-concave and transformed the problem (4.4) into a series of linear programs by introducing new auxiliary variables, which can be found through a bisection procedure.

Similarly, Luo and Zhang [65] proved that the spectrum management problem in single frequency band systems is polynomial time solvable, i.e., it can be solved by parametric linear programming. In chapter 3, the SE-EE tradeoff problem in interference-limited wireless networks is verified to be neither convex or concave. However, the authors showed that the solution can be achieved by dealing with variables separately in a Gauss-Seidel fashion.

4.3.4 Fairness with $1 < \alpha < \infty$

For the case of $0 < \alpha < 1$ and $1 < \alpha < \infty$, the problem is

$$\begin{aligned} \max_{\boldsymbol{p}} \quad & \sum_{n \in \mathcal{N}} \frac{1}{1-\alpha} \left(\log_2\left(1 + \gamma_n(\boldsymbol{p}_n)\right)\right)^{1-\alpha} \\ \text{s.t.} \quad & p_n \geq 0 \ \forall n \in \mathcal{N}, \\ & \sum_{n \in N} p_n \leq P. \end{aligned} \tag{4.5}$$

The complexity of (4.5) with $1 < \alpha < \infty$ is now analyzed and that for $0 < \alpha < 1$ will be analyzed in the next subsection.

Theorem 9. *The problem* (4.5) *is a convex optimization problem.*

Proof. Introducing new auxiliary variables $\boldsymbol{t}$ and $\boldsymbol{\rho}$ such that $\exp(t_n) \leq \log_2\left(1 + \gamma_n(\boldsymbol{p}_n)\right)$ and $\rho_n = \log(p_n)$, the problem (4.5) can be reformulated as

$$\begin{aligned} \max_{\boldsymbol{\rho}, \boldsymbol{t}} \quad & \sum_{n \in \mathcal{N}} \frac{1}{1-\alpha} \left(\exp(t_n)\right)^{1-\alpha} \\ \text{s.t.} \quad & \exp(t_n) \leq \log_2\left(1 + \gamma_n(\exp(\boldsymbol{\rho}_n))\right) \ \forall n \in \mathcal{N}, \\ & \sum_{n \in N} \exp(\rho_n) \leq P. \end{aligned} \tag{4.6}$$

The second-order derivative of the objective function w.r.t. t_n is $(1-\alpha)(\exp(t_n))^{1-\alpha}$; therefore, when $1 < \alpha < \infty$, the objective function is a concave function. The second constraint in (4.6) is convex. Let $h_n = |g_n^2|$, the first constraint can be equivalently transformed into

$$\log\left(\frac{\sigma_n^2}{h_n} e^{-\rho_n} + \sum_{i=n+1}^{N} e^{\rho_i - \rho_n}\right) + \log\left(2^{e^{t_n}} - 1\right) \leq 0.$$

The log-sum-exp function is convex [66], the second term $\log\left(2^{e^{t_n}} - 1\right)$ can be proved to be convex by taking the second-order derivative and showing that the result is non-negative. Hence, the third constraint is convex. Therefore, the problem (4.6) is a convex problem. The proof ends. □

Remark 6. *A special case is $\alpha = 2$. In this case, the objective function is actually the harmonic-rate utility function. Similarly, Luo and Zhang [65] proved that the problem of maximizing the harmonic-rate utility subject to power constraints in single frequency band systems is convex.*

4.3.5 Fairness with $0 < \alpha < 1$

The optimization in this case is actually the problem (4.5) with $0 < \alpha < 1$. We have the following theorem.

Theorem 10. *The optimization problem (4.5) with $0 < \alpha < 1$ is NP-Hard.*

Proof. Assume $0 \leq p_n \leq 1$, i.e., the second constraint in (4.5) is simply $\sum_{n \in \mathcal{N}} p_n \leq N \leq P$. Then, the problem (4.5) with $0 < \alpha < 1$ can be represented as the following

$$\begin{aligned} &\max_{\boldsymbol{p}} \sum_{n \in \mathcal{N}} \frac{1}{1-\alpha} \left(\log_2 \left(1 + \frac{h_n p_n}{1 + h_n \sum\limits_{i=n+1}^{N} p_i} \right) \right)^{1-\alpha} \\ &\text{s.t.} \quad 0 \leq p_n \leq 1 \; \forall n \in \mathcal{N}. \end{aligned}$$

The problem of optimizing the multiobjective problem of spectral efficiency and energy efficiency while considering fairness in spectrum-sharing networks with $0 < \alpha < 1$ in chapter 3 is, as follows:

$$\begin{aligned} &\max_{\boldsymbol{p}} \; \psi_{SE} \sum_{i \in \mathcal{N}} \frac{1}{1-\alpha} \left(\log_2 \left(1 + \gamma_i(\boldsymbol{p}) \right) \right)^{1-\alpha} - \psi_{EE} \varrho \sum_{i \in \mathcal{I}} p_i, \\ &\text{s.t.} \quad 0 \leq p_i \leq 1, \; \forall i \in \mathcal{N}, \end{aligned} \tag{4.7}$$

where ψ_{SE} and ψ_{EE} are respectively the priority parameter of spectral efficiency and energy efficiency, and

ϱ is the power-inefficient factor of the amplifier. The problem (4.7) can be proved to be NP-hard by showing a polynomial transformation of the maximum independent set problem on a graph to the problem (4.7). A special case of the problem (4.5) has the same structure as the problem (4.7). As a result, the problem (4.5) with $0 < \alpha < 1$ is NP-Hard. The proof ends. $\square$

Due to NP-Hardness, an algorithm with polynomial time to find the optimal solution to the problem is not possible and the globally optimal solution has to be found by using global optimization approaches. However, we latterly prove that the objective function of the problem (4.5) with $0 < \alpha < 1$ can be represented as the difference of two concave (D.C.) functions. Then, we utilize the D.C. programming to propose a procedure to find the suboptimal solution to the problem (4.5).

The utility function of the user n can be rewritten as

$$\begin{aligned} U_\alpha\left(R_n(\boldsymbol{p}_n)\right) &= U_\alpha\left(\underbrace{\log_2\left(1 + h_n \sum_{i=n}^{N} p_i\right)}_{f_n(\boldsymbol{p}_n)} - \underbrace{\log_2\left(1 + h_n \sum_{i=n+1}^{N} p_i\right)}_{g_n(\boldsymbol{p}_{n+1})}\right) \\ &= \underbrace{\left(U_\alpha\left(f_n(\boldsymbol{p}_n) - g_n(\boldsymbol{p}_{n+1})\right) + \chi_n g_n(\boldsymbol{p}_{n+1})\right)}_{u_n(\boldsymbol{p}_n)} - \underbrace{\chi_n g_n(\boldsymbol{p}_{n+1})}_{v_n(\boldsymbol{p}_{n+1})}, \end{aligned}$$

where $\chi \geq \theta^{-\alpha}$ with θ being a small positive number and f_n, g_n, and v_n are all concave functions w.r.t. $\boldsymbol{p}$. Therefore, our remaining task is to prove that u_n is concave w.r.t. $\boldsymbol{p}$. We have the following relationships

$$\begin{aligned} &U_\alpha\left(f_n(\boldsymbol{p}_n) - g_n(\boldsymbol{p}_{n+1})\right) + \chi_n g_n(\boldsymbol{p}_{n+1}) \\ &\leq U_\alpha(\theta_n) + \theta_n^{-\alpha}\left(f_n(\boldsymbol{p}_n) - g_n(\boldsymbol{p}_{n+1}) - \theta_n\right) + \chi_n g_n(\boldsymbol{p}_{n+1}) \\ &= \underbrace{U_\alpha(\theta_n)}_{\text{concave}} - \underbrace{\theta^{-\alpha+1}}_{\text{a number}} + \underbrace{\theta_n^{-\alpha} f_n(\boldsymbol{p}_n)}_{\text{concave}} + \left(\chi_n - \theta_n^{-\alpha}\right) g_n(\boldsymbol{p}_{n+1}), \end{aligned}$$

where the inequality is due to the concavity of U_α. In particular, since the function U_α is a concave function, $U_\alpha(y) \leq U_\alpha(x) + \nabla U_\alpha(x)^T(y - x)$ [66]. The inequality is then showed by replacing $f_n(p_n) - g_n(p_{n+1})$

for y, θ_n for x, and using the α-utility function in (1.1). It is observed that the right hand side of the above relationships is concave if and only if $(\chi_n - \theta^{-\alpha})\, g_n(\boldsymbol{p}_{n+1})$ is concave. It is true because we assume that $\chi_n \geq \theta^{-\alpha}$. As a result, u_n is concave since it is equivalent to the infimum of concave functions w.r.t. θ_n. Moreover, the objective function of the problem (4.5) can be represented as the D.C. function. Consequently, we can utilize an iterative algorithm to find the suboptimal solution to the problem (4.5). Specifically, for given $\boldsymbol{p}(t)$ at the iteration t, we approximate $v(\boldsymbol{p})$ by its first-order Taylor expansion, i.e., $v(\boldsymbol{p}(t)) + \nabla v(\boldsymbol{p}(t))(\boldsymbol{p} - \boldsymbol{p}(t))$. Then, we find the power allocation at the iteration $(t+1)$ by solving the following concave optimization problem

$$\begin{aligned} &\max_{\boldsymbol{p}} \; u(\boldsymbol{p}) - (v(\boldsymbol{p}(t)) + \nabla v(\boldsymbol{p}(t))(\boldsymbol{p} - \boldsymbol{p}(t))) \\ &\text{s.t.} \quad p_n \geq 0 \; \forall n \in \mathcal{N}, \\ &\qquad \sum_{n \in N} p_n \leq P. \end{aligned} \tag{4.8}$$

The procedure to solve the problem (4.5) is summarized in Algorithm 7. It is noted that with the D.C. approximation, the sequence of power allocation $\{\boldsymbol{p}(t)\}$ generated by Algorithm 7 monotonically improves the objective function and eventually converges to a locally optimal solution to the problem (4.8). Similar to chapter 3, we can prove the locally optimal solution of Algorithm 7.

4.4 Simulation Results

In this section, we provide numerical simulation results to verify the proposed algorithms. Consider a single-cell with one base station (BS) and a number of users. The BS is located in the center of the cell and users are uniformly distributed with an annulus with the inner and outer of 500 m and 1000 m, respectively. The path loss is modeled as $33.1 + 36.7 \log(10d)$, where d is the distance between the BS and a user in kilometers. The noise variance -160 dBm is assumed to be the same for all users, the large-scale

Algorithm 7 SCA-based Power Allocation with D.C. Approximation for Problem with $0 < \alpha < 1$

1: Set $\varepsilon > 0$, $t = 0$, FLAG = 0 and initialize $\boldsymbol{p}(t)$.
2: **repeat**
3: Solve the problem (4.8) to obtain $\boldsymbol{p}^*$.
4: **if** $\max_{i \in \mathcal{I}} |\boldsymbol{p}^* - \boldsymbol{p}(t)|/\boldsymbol{p}^* \leq \varepsilon$ **then**
5: $\boldsymbol{p}^*$ is the optimal solution.
6: FLAG = 1.
7: **else**
8: Set $t = t + 1$.
9: Set $\boldsymbol{p}(t) = \boldsymbol{p}^*$.
10: **end if**
11: **until** FLAG = 1

shadowing part is modeled by a log-normal distribution with zero mean and standard deviation 8 dB, and the small-scale fading coefficients are distributed as Rayleigh random number variables with unit variances. Each following plot is average over 100 channel realizations.

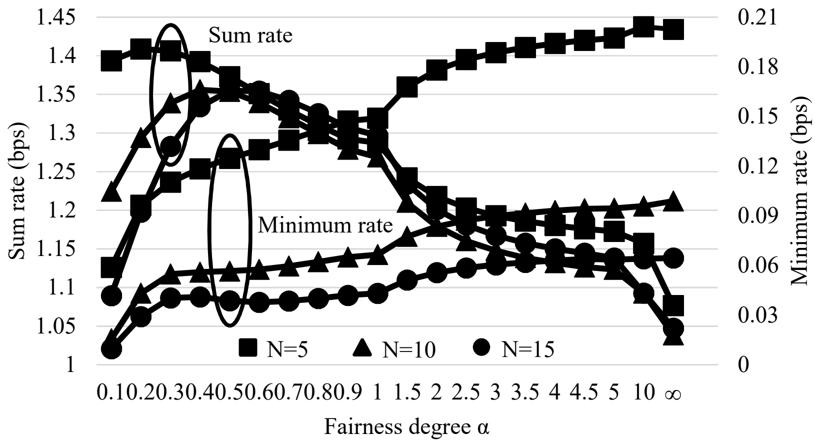


Figure 4.1: Impact of the fairness degree on the performance.

In the first experiment, we set the maximum transmit power at the BS P to 6 W and examine impact of the fairness degree on the sum rate and minimum rate. From Fig. 4.1, the minimum rate increases almost linearly as the fairness degree increases and eventually approaches the highest value at $\alpha = \infty$, i.e., max-min fairness. Moreover, for a given fairness degree, reducing the number of users increases the minimum rate, which is similar to the observation in [12] for the case of max-min fairness. Another observation from Fig. 4.1 is that the sum rate tends to reduce as the fairness degree increases. However, when the fairness degree is low, both the sum rate and minimum rate increase as the fairness degree increases, which is different from the fairness for maximizing the sum-rate in spectrum-sharing wireless networks [70], where a more fair power allocation often results in a reduction in the sum-rate. It can be explained, as follows. The use of superposition coding technique for a large number of users is unfair. For example, the sum rates for $N = 5$, $N = 10$ and $N = 15$ first increase and then reduce; and the inflection point* in term of the fairness degree for $N = 15$ ($N = 10$) is higher than that of $N = 10$ ($N = 5$). As a result, there is a tradeoff between fairness and the number of users sharing the same time-frequency resource block†, and for the low fairness degree, both the sum rate and minimum rate can be obtained, i.e., they do not conflict each other. In addition, the performance gap between $N = 5$ and $N = 10$ is larger than that between $N = 10$ and $N = 15$, i.e., the performance gap gets closer as the number of users increases.

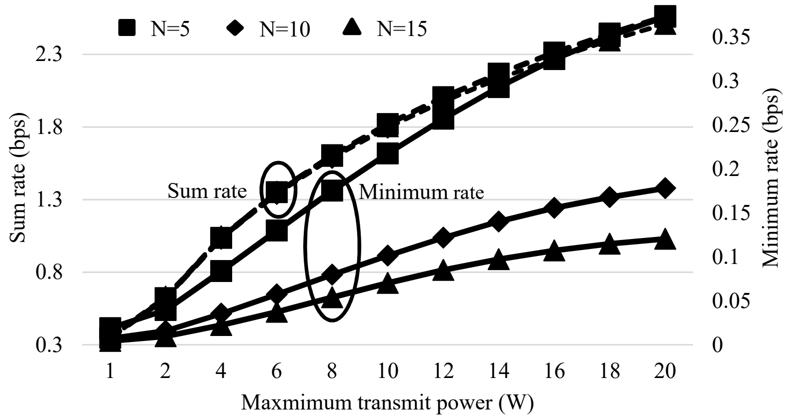


Figure 4.2: Impact of the fairness degree on the performance when the fairness degree $\alpha = 0.6$.

In Fig. 4.2, we plot the sum rate and minimum rate as functions of the maximum transmit power avail-

*A point below which the sum rate increases and above which the sum rate decreases.

†A resource block can be the entire bandwidth if all users are allowed to use the entire bandwidth or a sub-carrier in OFDMA-based NOMA systems, where users, using the same sub-carrier, compose a cluster.

able at the BS. It is shown that both the minimum rate and sum rate increases with the increment of the maximum transmit power at the BS increases. Moreover, the performance gap between $N = 5$ and $N = 10$, and $N = 10$ and $N = 15$ becomes larger and it is verified gain that increasing the number of users reduces the performance.

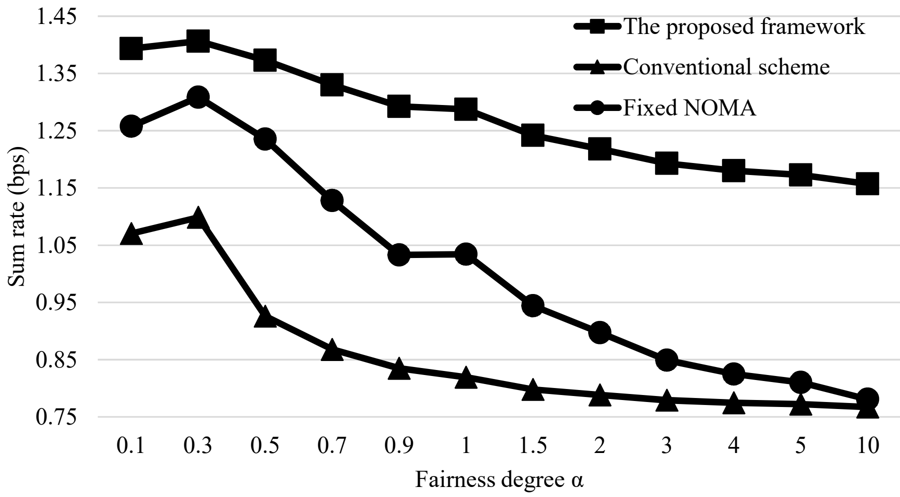


Figure 4.3: Comparative performance between the proposed framework, fixed NOMA, and conventional scheme in term of the total achievable rate.

In Fig 4.3., we compare the performance of the proposed framework with two different ones: the fixed NOMA, where the transmit power is equally assigned among users, and the conventional scheme, where the SIC capability is not supported at the receiver side. The number of users is fixed as $N = 5$ and the maximum transmit power at the BS P is $P = 6$ W. It is observed that the proposed framework always outperforms the fixed NOMA and conventional scheme in all cases of the fairness degree.

4.5 Conclusion

This chapter considered and analyzed the complexity of α-fair resource allocation problem in NOMA systems. In particular, the problem is shown to be convex when $1 \leq \alpha < \infty$ and $\alpha = \infty$, NP-Hard when

$0 < \alpha < 1$, and tractable when $\alpha = 0$. The simulation results verified that there is a tradeoff between the number of users in a cluster and fairness degree, and the proposed framework is superior to the conventional scheme and fixed NOMA scheme.

Chapter 5

Conclusion and Future Work

The final chapter summarizes the important contributions of this thesis and highlights the future research directions. In sum, this thesis proposes three fair and energy-efficient resource allocation frameworks in wireless networks. In particular, our first work considers energy-efficient power control schemes for interference management in the uplink of spectrum-sharing heterogeneous networks. In the first scenario, the objective function is defined as the weighted sum of the energy efficiencies and the optimization problem is in a sum-of-ratios form and we develop an efficient global optimization algorithm with global linear and local quadratic rate of convergence to solve the considered problem. We consider the max-min problem to improve fairness among individual UEs in term of energy efficiency, where the objective is defined as the weighted minimum of the energy efficiencies. A fractional programming theory and the dual decomposition method are jointly used to solve the problem and develop an iterative algorithm. Moreover, we discuss the global energy efficiency problem and consider near optimal schemes. Open issues of this work for the future development include: 1) reducing the amount of message passing in the networks; 2) addressing the joint subchannel assignment and power allocation for energy efficiency maximization in uplink OFDMA-based HetNets; 3) developing a systematic design where both of the uplink and downlink energy-efficient resource allocation are jointly optimized; and 4) extending this work to multiple antenna systems.

In the second work, we introduce a fair and energy-efficient resource allocation framework in interference-limited wireless networks. Consider the tradeoff between energy efficiency and spectral efficiency, the multiobjective problem of spectral efficiency and energy efficiency is transformed into a problem that minimizes the total power consumption and maximizes the achievable utility, subject to power constraints and rate outage probability constraints. The complexity of the considered problem is then analyzed; particularly, the optimization problem is NP-Hard when $0 \leq \alpha < 1$ and is convex for other values of the fairness index α. Regarding the complexity analysis, we adopt the SCA approach to approximate and transform the NP-hard nonconvex optimization problem into a sequence of convex programs and propose two iterative SCA-based resource allocation algorithms. The obtained results in this work can be served as a useful reference in order to achieve the SE-EE tradeoff with the fairness consideration. In addition, this work is a basis for future developments of the problem of α-fairness and the SE-EE tradeoff in D2D communications and NOMA systems.

The final problem we consider is the problem of α-fairness in NOMA-based wireless networks. We consider the α-fair power control problem and point out that the problem is convex when $1 \leq \alpha \leq \infty$, NP-Hard when $0 < \alpha < 1$, and polynomial time solvable when $\alpha = 0$. The key result from this work is that there is a tradeoff between the fairness and the number of users in a cluster in NOMA systems. Regarding this important conclusion, we will focus on the problem of -fair resource allocation for OFDMA-based NOMA systems. An extension of our work to visible light communications (VLCs) is interesting. The current work can be significantly improved if users have capability to harness energy from renewable resources, e.g., solar and wind, and RF signals, e.g., television signals and interference signals.

Bibliography

[1] Q. Wu, G. Y. Li, W. Chen, D. W. K. Ng, and R. Schober, "An overview of sustainable green 5g networks," *arXiv preprint arXiv:1609.09773*, 2016. 1, 2

[2] J. G. Andrews, S. Buzzi, W. Choi, S. V. Hanly, A. Lozano, A. C. K. Soong, and J. C. Zhang, "What will 5g be?" *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 6, pp. 1065–1082, Jun. 2014. 1

[3] Cisco. (2017, Mar.) Cisco visual networking index: Global mobile data traffic forecast update, 2016-2021, white paper. [Online]. Available: www.cisco.com 1

[4] F. Boccardi, R. W. Heath, A. Lozano, T. L. Marzetta, and P. Popovski, "Five disruptive technology directions for 5g," *IEEE Communications Magazine*, vol. 52, no. 2, pp. 74–80, Feb. 2014. 2

[5] Z. Wei, J. Yuan, D. W. K. Ng, M. Elkashlan, and Z. Ding, "A survey of downlink non-orthogonal multiple access for 5g wireless communication networks," *ZTE Communications*, vol. 14, no. 4, pp. 17–25, Oct. 2016. 3

[6] S. M. R. Islam, N. Avazov, O. A. Dobre, and K. s. Kwak, "Power-domain non-orthogonal multiple access (noma) in 5g systems: Potentials and challenges," *IEEE Communications Surveys Tutorials*, vol. 19, no. 2, pp. 721–742, Second Quarter 2017. 3

[7] A. Zappone and E. Jorswieck, "Energy efficiency in wireless networks via fractional programming theory," *Foundations and Trends in Communications and Information Theory*, vol. 11, no. 3-4, pp. 185–396, Jun. 2015. 4, 11

[8] B. Lannoo, "Energy consumption of ict networks," in *TREND Final Workshop*, Oct. 2013, pp. 1–30. 4

[9] R. Mahapatra, Y. Nijsure, G. Kaddoum, N. U. Hassan, and C. Yuen, "Energy efficiency tradeoff mechanism towards wireless green communication: A survey," *IEEE Communications Surveys Tutorials*, vol. 18, no. 1, pp. 686–705, First Quarter 2016. 4

[10] H. Shi, R. V. Prasad, E. Onur, and I. G. M. M. Niemegeers, "Fairness in wireless networks:issues, measures and challenges," *IEEE Communications Surveys Tutorials*, vol. 16, no. 1, pp. 5–24, First Quarter 2014. 7, 45

[11] J. Mo and J. Walrand, "Fair end-to-end window-based congestion control," *IEEE/ACM Transactions on Networking*, vol. 8, no. 5, pp. 556–567, Oct. 2000. 7

[12] S. Timotheou and I. Krikidis, "Fairness for non-orthogonal multiple access in 5g systems," *IEEE Signal Processing Letters*, vol. 22, no. 10, pp. 1647–1651, Oct 2015. 8, 77, 80, 86

[13] Y. S. Soh, T. Quek, M. Kountouris, and H. Shin, "Energy efficient heterogeneous cellular networks," *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 5, pp. 840–850, May 2013. 10

[14] K. Son, S. Lee, Y. Yi, and S. Chong, "Refim: A practical interference management in heterogeneous wireless access networks," *IEEE Journal on Selected Areas in Communications*, vol. 29, no. 6, pp. 1260–1272, Jun. 2011. 10, 11, 12

[15] X. Kang, R. Zhang, and M. Motani, "Price-based resource allocation for spectrum-sharing femtocell networks: A stackelberg game approach," *IEEE Journal on Selected Areas in Communications*, vol. 30, no. 3, pp. 538–549, Apr. 2012. 11, 12, 13, 16

[16] V. Chandrasekhar, J. G. Andrews, and A. Gatherer, "Femtocell networks: a survey," *IEEE Communications Magazine*, vol. 46, no. 9, pp. 59–67, Sep. 2008. 11

[17] V. N. Ha and L. B. Le, "Distributed base station association and power control for heterogeneous cellular networks," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 1, pp. 282–296, Jan. 2014. 11, 12

[18] T. M. Ho, N. Tran, C. Do, S. Ahsan Kazmi, E.-N. Huh, and C. S. Hong, "Power control for interference management and qos guarantee in heterogeneous networks," *IEEE Communications Letters*, vol. 19, no. 8, pp. 1402–1405, Aug. 2015. 11, 12, 13, 15, 16, 39, 40

[19] D. Feng, C. Jiang, G. Lim, J. Cimini, L.J., G. Feng, and G. Li, "A survey of energy-efficient wireless communications," *IEEE Communications Surveys Tutorials*, vol. 15, no. 1, pp. 167–178, First Quarter 2013. 11

[20] F. Ahmed, A. A. Dowhuszko, O. Tirkkonen, and R. Berry, "A distributed algorithm for network power minimization in multicarrier systems," in *2013 IEEE 24th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*. IEEE, 2013, pp. 1914–1918. 11

[21] J. Tang, D. So, E. Alsusa, K. Hamdi, and A. Shojaeifard, "Resource allocation for energy efficiency optimization in heterogeneous networks," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 10, pp. 2104–2117, Oct. 2015. 11

[22] Y. Kwon, T. Hwang, and X. Wang, "Energy-efficient transmit power control for multi-tier mimo hetnets," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 10, pp. 2070–2086, Oct. 2015. 11

[23] D. T. Ngo, S. Khakurel, and T. Le-Ngoc, "Joint subchannel assignment and power allocation for ofdma femtocell networks," *IEEE Transactions on Wireless Communications*, vol. 13, no. 1, pp. 342–355, Jan. 2014. 11, 57, 63

[24] S. He, Y. Huang, H. Wang, S. Jin, and L. Yang, "Leakage-aware energy-efficient beamforming for heterogeneous multicell multiuser systems," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 6, pp. 1268–1281, Jun. 2014. 11

[25] R. Ramamonjison and V. Bhargava, "Energy efficiency maximization framework in cognitive downlink two-tier networks," *IEEE Transactions on Wireless Communications*, vol. 14, no. 3, pp. 1468–1479, Mar. 2015. 11, 13, 16, 17

[26] Q.-V. Pham, H.-L. To, and W.-J. Hwang, "A multi-timescale cross-layer approach for wireless ad hoc networks," *Computer Networks*, vol. 91, pp. 471 – 482, Nov. 2015. 12, 15, 16, 17, 18, 46, 49, 51, 62

[27] L. Venturino, A. Zappone, C. Risi, and S. Buzzi, "Energy-efficient scheduling and power allocation in downlink ofdma networks with base station coordination," *IEEE Transactions on Wireless Communications*, vol. 14, no. 1, pp. 1–14, Jan. 2015. 12, 16, 17, 44, 45

[28] Q.-D. Vu, L.-N. Tran, M. Juntti, and E.-K. Hong, "Energy-efficient bandwidth and power allocation for multi-homing networks," *IEEE Transactions on Signal Processing*, vol. 63, no. 7, pp. 1684–1699, Apr. 2015. 15

[29] H. Ye, G. Lim, L. Cimini, and Z. Tan, "Energy-efficient scheduling and resource allocation in uplink ofdma systems," *IEEE Communications Letters*, vol. 19, no. 3, pp. 439–442, Mar. 2015. 16

[30] Q.-V. Pham, H. Kim, and W.-J. Hwang, "Globally optimal solutions for cross-layer design in fast-fading lossy delay-constrained manets," *Journal of Korea Multimedia Society*, vol. 18, no. 2, pp. 168–177, Feb. 2015. 16

[31] J. Bastos, K. M. S. Huq, S. Mumtaz, J. Rodriguez, and C. Verikoukis, "Energy efficiency optimization for downlink ofdma system in heterogeneous network with qos constraints," *International Journal of Communication Systems*, vol. 30, no. 2, pp. e2969–n/a, Jan. 2017, e2969 dac.2969. 17

[32] L. Zhou, C. Zhu, R. Ruby, X. Wang, X. Ji, S. Wang, and J. Wei, “Qos-aware energy-efficient resource allocation in ofdm-based heterogenous cellular networks,” *International Journal of Communication Systems*, vol. 30, no. 2, pp. e2931–n/a, Jan. 2017, e2931 dac.2931. 17

[33] J. Papandriopoulos and J. Evans, “Scale: A low-complexity distributed protocol for spectrum balancing in multiuser dsl networks,” *IEEE Transactions on Information Theory*, vol. 55, no. 8, pp. 3711–3724, Aug. 2009. 17, 24, 27, 31, 50, 57, 60

[34] S. Boyd and L. Vandenberghe, *Convex optimization*. Cambridge university press, 2009. 18, 31, 33

[35] Y.-C. Jonga, “An efficient global optimization algorithm for nonlinear sum-of-ratios problem,” *Jong*, May 2012. [Online]. Available: http://www.optimization-online.org/DB_FILE/2012/08/3586.pdf 19, 24

[36] M. S. Bazaraa, H. D. Sherali, and C. M. Shetty, *Nonlinear programming: theory and algorithms*. John Wiley & Sons, 2013. 21

[37] J. Crouzeix, J. Ferland, and S. Schaible, “An algorithm for generalized fractional programs,” *Journal of Optimization Theory and Applications*, vol. 47, no. 1, pp. 35–49, Sep. 1985. 26, 31

[38] Y. Li, M. Sheng, C. W. Tan, Y. Zhang, Y. Sun, X. Wang, Y. Shi, and J. Li, “Energy-efficient subcarrier assignment and power allocation in ofdma systems with max-min fairness guarantees,” *IEEE Transactions on Communications*, vol. 63, no. 9, pp. 3183–3195, Sep. 2015. 29, 30, 44, 45

[39] W. Yu and R. Lui, “Dual methods for nonconvex spectrum optimization of multicarrier systems,” *IEEE Transactions on Communications*, vol. 54, no. 7, pp. 1310–1322, Jul. 2006. 30

[40] S. Kandukuri and S. Boyd, “Optimal power control in interference-limited fading wireless channels with outage-probability specifications,” *IEEE Transactions on Wireless Communications*, vol. 1, no. 1, pp. 46–55, Jan. 2002. 34, 62

[41] H. Kha, H. Tuan, and H. Nguyen, “Fast global optimal power allocation in wireless networks by local d.c. programming,” *Wireless Communications, IEEE Transactions on*, vol. 11, no. 2, pp. 510–515, Feb. 2012. 36, 57, 63, 65, 72

[42] Y. Li, M. Sheng, C. Yang, and X. Wang, “Energy efficiency and spectral efficiency tradeoff in interference-limited wireless networks,” *Communications Letters, IEEE*, vol. 17, no. 10, pp. 1924–1927, Oct. 2013. 36, 44, 45, 57, 63, 64, 65, 72

[43] Y. Li, M. Sheng, X. Wang, Y. Zhang, and J. Wen, “Max-min energy-efficient power allocation in interference-limited wireless networks,” *Vehicular Technology, IEEE Transactions on*, vol. 64, no. 9, pp. 4321–4326, Sep. 2015. 36, 44, 45, 57, 64, 65

[44] A. Goldsmith, *Wireless communications*. Cambridge university press, 2005. 36, 48

[45] L. Xu, G. Yu, and Y. Jiang, “Energy-efficient resource allocation in single-cell ofdma systems: Multi-objective approach,” *IEEE Transactions on Wireless Communications*, vol. 14, no. 10, pp. 5848–5858, Oct. 2015. 38, 44, 45

[46] D. Feng, C. Jiang, G. Lim, J. Cimini, L.J., G. Feng, and G. Li, “A survey of energy-efficient wireless communications,” *IEEE Communications Surveys and Tutorials*, vol. 15, no. 1, pp. 167–178, First Quarter 2013. 44

[47] C. Guo, B. Liao, L. Huang, X. Lin, and J. Zhang, “On convexity of fairness-aware energy-efficient power allocation in spectrum-sharing networks,” *IEEE Communications Letters*, vol. 20, no. 3, pp. 534–537, Mar. 2016. 44, 46

[48] C. Guo, Y. Zhang, M. Sheng, X. Wang, and Y. Li, “α-fair power allocation in spectrum-sharing networks,” *IEEE Transactions on Vehicular Technology*, vol. 65, no. 5, pp. 3771–3777, May 2016. 44, 46, 61, 63, 69

[49] Z. Song, Q. Ni, K. Navaie, S. Hou, and S. Wu, "Energy- and spectral-efficiency tradeoff with alpha -fairness in downlink ofdma systems," *IEEE Communications Letters*, vol. 19, no. 7, pp. 1265–1268, Jul. 2015. 45, 46

[50] H. Pervaiz, L. Musavian, Q. Ni, and Z. Ding, "Energy and spectrum efficient transmission techniques under qos constraints toward green heterogeneous networks," *IEEE Access*, vol. 3, pp. 1655–1671, Oct. 2015. 45, 46

[51] C. Pan, W. Xu, W. Zhang, J. Wang, H. Ren, and M. Chen, "Weighted sum energy efficiency maximization in ad hoc networks," *IEEE Wireless Communications Letters*, vol. 4, no. 3, pp. 233–236, Jun. 2015. 45

[52] Y. Li and T. Jiang, "Fixed-point algorithms for energy-efficient power allocation in spectrum-sharing wireless networks," in *2016 IEEE Global Communications Conference (GLOBECOM)*, Dec. 2016, pp. 1–6. 45, 65

[53] J. Tang, D. So, E. Alsusa, and K. Hamdi, "Resource efficiency: A new paradigm on energy efficiency and spectral efficiency tradeoff," *IEEE Transactions on Wireless Communications*, vol. 13, no. 8, pp. 4656–4669, Aug. 2014. 45

[54] X. Ge, X. Huang, Y. Wang, M. Chen, Q. Li, T. Han, and C. X. Wang, "Energy-efficiency optimization for mimo-ofdm mobile multimedia communication systems with qos constraints," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 5, pp. 2127–2138, Jun. 2014. 45

[55] R. Zi, X. Ge, J. Thompson, C. X. Wang, H. Wang, and T. Han, "Energy efficiency optimization of 5g radio frequency chain systems," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 4, pp. 758–771, Apr. 2016. 45

[56] X. Ge, B. Du, Q. Li, and D. S. Michalopoulos, "Energy efficiency of multiuser multiantenna random cellular networks with minimum distance constraints," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 2, pp. 1696–1708, Feb. 2017. 45

[57] L. Deng, Y. Rui, P. Cheng, J. Zhang, Q. Zhang, and M. Li, "A unified energy efficiency and spectral efficiency tradeoff metric in wireless networks," *IEEE Communications Letters*, vol. 17, no. 1, pp. 55–58, Jan. 2013. 45, 46

[58] W. Jing, Z. Lu, X. Wen, Z. Hu, and S. Yang, "Flexible resource allocation for joint optimization of energy and spectral efficiency in ofdma multi-cell networks," *IEEE Communications Letters*, vol. 19, no. 3, pp. 451–454, Mar. 2015. 45, 46

[59] N. Tran, C. S. Hong, and S. Lee, "Cross-layer design of congestion control and power control in fast-fading wireless networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 24, no. 2, pp. 260–274, Feb. 2013. 46

[60] F. Gao, T. Cui, and A. Nallanathan, "On channel estimation and optimal training design for amplify and forward relay networks," *IEEE Transactions on Wireless Communications*, vol. 7, no. 5, pp. 1907–1916, May 2008. 48

[61] R. Zhang, F. Gao, and Y. C. Liang, "Cognitive beamforming made practical: Effective interference channel and learning-throughput tradeoff," *IEEE Transactions on Communications*, vol. 58, no. 2, pp. 706–718, Feb. 2010. 48

[62] F. Zhou, Z. Li, J. Cheng, Q. Li, and J. Si, "Robust an-aided beamforming and power splitting design for secure miso cognitive radio with swipt," *IEEE Transactions on Wireless Communications*, vol. 16, no. 4, pp. 2450–2464, Apr. 2017. 48

[63] R. Marler and J. Arora, "Survey of multi-objective optimization methods for engineering," *Structural and Multidisciplinary Optimization*, vol. 26, no. 6, pp. 369–395, 2004. 49, 74

[64] O. Amin, E. Bedeer, M. H. Ahmed, and O. A. Dobre, "Energy efficiency - spectral efficiency tradeoff: A multiobjective optimization approach," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 4, pp. 1975–1981, Apr. 2016. 49

[65] Z.-Q. Luo and S. Zhang, "Dynamic spectrum management: Complexity and duality," *IEEE Journal of Selected Topics in Signal Processing*, vol. 2, no. 1, pp. 57–73, Feb. 2008. 50, 51, 54, 80, 82

[66] S. Boyd and L. Vandenberghe, *Convex optimization*. Cambridge university press, 2009. 54, 58, 63, 81, 83

[67] Q.-V. Pham, M. Hasegawa, and W.-J. Hwang, "An energy-efficient resource allocation in ad hoc networks," in *4th Korea-Japan Joint Workshop on Complex Communication Sciences*, 2016, pp. 1–2. 64

[68] Z. Song, Q. Ni, K. Navaie, S. Hou, S. Wu, and X. Sun, "On the spectral-energy efficiency and rate fairness tradeoff in relay-aided cooperative ofdma systems," *IEEE Transactions on Wireless Communications*, vol. 15, no. 9, pp. 6342–6355, Sep. 2016. 66

[69] Z. Yang, W. Xu, and Y. Li, "Fair non-orthogonal multiple access for visible light communication downlinks," *IEEE Wireless Communications Letters*, vol. 6, no. 1, pp. 66–69, Feb. 2017. 77, 80

[70] C. Guo, Y. Zhang, M. Sheng, X. Wang, and Y. Li, "alpha-fair power allocation in spectrum-sharing networks," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 5, pp. 3771–3777, May 2016. 77, 86

[71] L. Lei, D. Yuan, C. K. Ho, and S. Sun, "Power and channel allocation for non-orthogonal multiple access in 5g systems: Tractability and computation," *IEEE Transactions on Wireless Communications*, vol. 15, no. 12, pp. 8580–8594, Dec. 2016. 79

Curriculum Vitae

Personal

Name	Pham Quoc Viet
Date of birth	April 05th, 1990
Nationality	Vietnamese
Contact	vietpq90 AT gmail DOT com

Education

Aug. 2008 - Jul. 2013	Bachelor of Engineering
	School of Electronics and Telecommunications
	Hanoi University of Science and Technology, Hanoi, Vietnam
	Adviser: Assoc. Prof. Nguyen Van Duc
Aug. 2013 - Jul. 2015	Master of Science, Computer Networks Lab. (CNL Lab.)
	Department of Information and Communication Systems
	Inje University, Gimhae, Korea
	Academic Supervisor: Prof. Won-Joo Hwang
Aug. 2015 - Jul. 2017	Doctor of Engineering, Wireless Networks Lab. (WINE Lab.)
	Department of Information and Communication Systems
	Inje University, Gimhae, Korea
	Academic Supervisor: Prof. Won-Joo Hwang

Field of Research Interest

Major	Electronics and Telecommunications
Specialization	Cross-Layer Designs for Wireless Networks
	Network Optimization for Wireless Networks
	Resource Allocation for Wireless Networks

List of Research Achievements

Journal Papers

1. **Q.-V. Pham**, H. To, W.-J. Hwang, *A Multi-Timescale Cross-Layer Approach for Wireless Ad Hoc Networks*, Computer Networks, vol 18, pp. 471-482, Sep. 2015.

2. **Q.-V. Pham** and W.-J. Hwang, *Resource Allocation for Heterogeneous Traffic in Complex Communication Networks,* IEEE Transactions on Circuits and Systems II: Express Briefs, vol 63, no. 10, pp. 959-963, Oct. 2016.

3. F. Boabang, H. Nguyen, **Q.-V. Pham**, W.-J. Hwang, *Network-assisted Distributed Fairness-aware Interference Coordination for Device to Device Communication Underlaid Cellular networks*, Mobile Information Systems, vol 2017, pp. 1-11, 2017.

4. **Q.-V. Pham**, W.-J. Hwang, *Network Utility Maximization in Multipath Lossy Wireless Networks*, International Journal of Communication Systems, vol 30, no. 5, pp. 1-18, Mar. 2017.

5. **Q.-V. Pham**, W.-J. Hwang, *Network Utility Maximization based Congestion Control over Wireless Networks: A Survey and Potential Directives*, IEEE Communications Surveys & Tutorials, vol. 19, no. 2, pp. 1173-1200, Second Quarter 2017.

6. **Q.-V. Pham**, W.-J. Hwang, *Fairness-Aware Spectral and Energy Efficiency in Spectrum-Sharing Wireless Networks*, IEEE Transactions on Vehicular Technology, **Accepted**, Jun. 2017.

7. **Q.-V. Pham**, W.-J. Hwang, *Energy-Efficient Resource Allocation in Uplink Spectrum-Sharing Heterogeneous Networks*, International Journal of Communication Systems, **Under minor revision**, 2017.

8. **Q.-V. Pham**, W.-J. Hwang, *Fairness-Aware Resource Allocation in Non-Orthogonal Multiple Access Systems*, IET Communications, **Under review**, 2017.

Conferences

1. **Q.-V. Pham**, W.-J. Hwang, *Distributed Power Control for Interference Management in Uplink Heterogeneous Networks*, Proceedings of The 2017 Spring Conference of KMMS (Korea MultimediaSociety), vol 20, no. 1, May 2017.

2. **Q.-V. Pham** and W.-J. Hwang, *Outage Constrained Resource Allocation for Energy Efficiency in Coordinated Multicell OFDMA Networks,* Japan-Korea Joint Workshop on Complex Communication Sciences (KJCCS2016), Oct. 2016. (**Best paper award**)

3. **Q.-V. Pham**, and W.-J. Hwang, *Fair and Energy-Efficient Power Control in Spectrum-Sharing Wireless Networks,* The 12th International Conference on Multimedia Information Technology and Applications (MITA2016), Jun. 2016.

4. **Q.-V. Pham**, M. Hasegawa and W.-J. Hwang, *An Energy-Efficient Resource Allocation in Ad Hoc Networks,* Korea-Japan Joint Workshop on Complex Communication Sciences (KJCCS2016), Jan. 2016.

5. **Q.-V. Pham**, A. Radwan, W.-J. Hwang, *Optimal Resource Allocation for Energy Efficiency in Uplink*

Heterogeneous Networks, Proceedings of The 2015 Fall Conference of KMMS (Korea MultimediaSociety), vol 18, no. 2, Nov. 2015.

Awards

1. **Q.-V. Pham**, and W.-J. Hwang, Best paper awards, The 2014 Fall Conference of Korea Multimedia Society, 2014.

2. **Q.V.- Pham**, Prize for excellent students, Vietnamese Students' Association in Korea, 2015.

3. **Q.-V. Pham**, and W.-J. Hwang, Best paper awards, Japan-Korea Joint Workshop on Complex Communication Sciences, 2016.