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Thesis for the Degree of Doctor of Philosophy in Engineering

A Decentralized Resource Allocation for Small Cells in Heterogeneous Networks

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February, 2017
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Abstract

Small cell networks are envisioned as a promising solution to enhance the capacity and coverage for indoor and cell edge users with less capital expenditure and maintenance cost in the heterogeneous networks (HetNets). To reap the benefits of small cell network deployment, we target optimization-based approaches to employ the resource allocation problems for small cells with various enabling technologies in the future wireless network. Accordingly, the overall small cell network is modeled by an optimization problem. This problem integrates multiple constraints such as transmit powers, backhaul link capacities, radio resources, interference management, and the users' quality of service (QoS) demands into a unified optimization problem. To solve this problem, we exploit the frameworks of the coalitional game, matching theory, and optimization theory to find sub-optimal solutions in a decentralized manner.

In this thesis, we particularly investigate two optimization problems for resource allocation in small cells with the cognitive radio and wireless virtualization technologies. These technologies are identified as some of the key emerging technologies for future wireless networks.

At first, we consider a resource allocation in the uplink of the cognitive femtocell network (CFN). The goal is to maximize the uplink sum-rate under constraints of intra-tier and inter-tier interference while maintaining the average delay requirement for femtocell users and protecting the macrocell base station. In the solution section, we aim at developing distributed algorithms in which the CFN implementation is self-organized and
self-optimized. To this end, we first propose an autonomous framework, in which the femtocell users self-organize into disjoint groups (DJGs). Then, we examine the coalitional game aspects of the subchannel and power allocations in each DJG. We show that the optimization problem can be formulated as a coalitional game in partition form. This game captures realistic inter-coalition effects that are formed by players who are seeking to cooperate and to form coalitions. By using the recursive core method and optimization theory, we develop a distributed algorithm for the power and channel allocations. We prove that the proposed algorithm always converges to a Nash-stable partition.

Then, we study resource allocation for small cell networks with the wireless virtualization considering both the backhaul capacity of the infrastructure provider (InP) and the users’ QoS requirements. The optimization problem focuses on the profit gained by a mobile virtual network operator (MVNO) which is a middleman who buys physical resource from the InP, bundling them into virtual resources called slides before selling off the service providers. To solve this problem, we propose a distributed solution framework based on Lagrangian relaxation to find a suboptimal decision about slice and transmit power allocations. Furthermore, by exploiting the concept of a matching game, we propose a low complexity solution that makes our proposal much more practical and robust in the virtualized wireless network environment.

In all of these scenarios, the proposed frameworks are evaluated based on the simulation results. We show that the proposed frameworks can be implemented in a distributed manner and require a small number of iterations to converge. The experimental results show that the proposed frameworks are better than those of the other frameworks.

Thesis Supervisor: Choong Seon Hong
Title: Professor
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## 3.1 Background and contribution

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### 3.2.1 System Model

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Chapter 1

Introduction

1.1 Background

To fulfill the presumptions and challenges of the near future, the current wireless-based networks will have to advance in various ways. To this end, some of the key emerging technologies have been discussed that can be used in next generation wireless network like spectrum sharing with cognitive radio spectrum access, wireless virtualization, small cell networks, cloud technologies and multi-radio access technology association solutions [1, 2]. In this thesis, we address the results of optimization-based approaches for resource allocation in small cell networks in HeNets. Specifically, we focus on studying small cell networks integrating cognitive radio and wireless virtualization technologies.

1.1.1 Small cell network

Nowadays, wireless networks face coverage issues at busy locations such as airports, shopping malls, and sporting/concert venues in which 80% volume is emitted from indoor & hotspots already now. Additionally, wireless networks also face the proliferation of new applications with high data rate services such as web meeting, video conferencing, Internet of Things, and 4K video, which potentially cause growing data traffic in near future. It is
predicted that the mobile data traffic expected to grow by a factor of 500-1000 times by 2020 [3]. Clearly, this type of network density, coupled with high user demand, is the leading contributor to small cell growth in the near future. Besides, with emerging markets, such as the Internet of Things (IoT), Vehicle to x, and smart cities, small cell growth is beginning in every market category [1].

In general, small cells are required to deploy mini-base stations with the plug-and-play capability [4] which could be operator or user installed, but will always be managed by carriers and tied into the macro-cell network. Small cells may provide a fast, flexible, and cost-efficient solutions to accomplish the gap between capacity and demand to cope with the fast growth in wireless traffic of the indoor (home, enterprises) and cell edge users. Small cell functioning as mini-base stations (such as picocells, microcells, and femtocells), operates at a much low-power and low-cost [5]. Small cells have coverage radii from several tens to several hundreds of meters. They can offload data traffic to decrease the overloading in macrocells, and improve users’ QoS. Small cells can be overlaid on any existing wireless technology [3].

Depending on the size and functionality, small cells can be categorized into femtocells, microcells, picocells, and metro-cells. In the small cell networks deployment, depending on the small cells’ characteristic, they have private attributes. The femtocell network concentrates on the small areas bounded by small base stations for residential indoor applications, and managed by the customers. Some important femtocells’ attributes are composed of self-optimization, low power consumption, ease of deployment (user-deployed), and closed/open/hybrid accesses [3]. In the picocell network, they are low-power base stations, used in enterprise or public indoor areas, and sometimes involves outdoor small cells. Key attributes are composed of the wired or wireless backhaul, deployed by operators, self-optimization, and open access. The microcells are outdoor short-range base stations aiming
at enhancing coverage for both indoor and outdoor users. Key attributes are composed of the wired or wireless backhaul, self-optimization, low power consumption, open access. In this thesis, we first address specific attributes of the femtocell network with a closed-access mode for low-power and low-cost femtocell base stations. After that, a closed-access mode model is addressed for the small cell network with wireless virtualization technologies. Next, we introduce in details about cognitive femtocell networks.

1.1.2 Cognitive small cell network

In the channel deployment, small cells can be realized with three ways: dedicated-channel, partial-channel-sharing, and co-channel deployments [3]. In the dedicate-channel deployment, small cell base stations are allocated a dedicated carrier frequency different from the macrocell base station. In the partial-channel-sharing deployment, the overall bandwidth is divided into two parts. One part is exclusively allocated to macro users, and the another part is shared by the macrocell and small cells. In the co-channel or spectrum sharing deployment, spectral usage is high because small cells are deployed in the same carrier frequency as macrocells without bandwidth segmentation. This method is more attractive due to easy implementation and more efficient utilization of spectrum [6]. Cognitive radio can be an emerging technology for realizing such flexible interference management. There are two types of spectrum access methods: overlay and underlay. The overlay access method enables the secondary user transmitting data when the primary user is not transmitting. In the underlay spectrum access method, the secondary user is allowed to operate in the band of the primary network when the overall interference power of secondary users at the primary receiver is less than the interference power threshold. This thesis addresses the spectrum access in the femtocells based on underlay spectrum access method. Consequently, the macrocell can be considered as the primary network and small
cells can be regarded as the secondary cognitive network. A small cell network reusing sub-channels based on the cognitive radio technology is commonly known as the cognitive small cell network [6, 7]. Generally, the cognitive radio is motivated due to the spectrum scarcity problem in ultra-dense networks. Our thesis addresses problems of resource allocation in the cognitive femtocell networks.

1.1.3 Wireless network virtualization

In general, significant design efforts are made to new applications (such as IoT, 4K television, M2M, and live streaming services) and the explosion of mobile devices will make a nervousness the data traffic in the near future wireless network. These challenges require a natural process the current network to new network paradigms technologies with flexible management in the next generation networks. In order to handle this tremendous growth of network traffic and services, the wireless virtualization is proposed as an emerging technology bring the upcoming fifth generation (5G) to realization [2].

With the wireless virtualization technology, the all-embracing cost of wireless network deployment and operation can be decreased markedly contingent upon abstracting, sharing, isolating, and slicing of radio spectrum and infrastructure resources [8]. The concept "virtualization" has become alluring in various areas of the information and communication technology (ICT) sector. The virtualization given a set of physical entities in which it is able to bundle a set of logical architecture that can transparent to the user. It enables dissociates the network infrastructure from the network services it provides. In addition, various services can coexist on the same physical infrastructure, whereas a physical infrastructure can be shared among numerous service providers. Moreover, wireless virtualization can reduce the progress of Research and Development for newly admitted technologies without seeing the complicated interfaces and essences of physical infrastructures. Our proposal
expresses abstracting, sharing, isolating, and slicing problems. We first split physical resources from multiple services providers into virtual resources (or virtual slice). Then, we address solutions for allocating virtual resources to users of multiple service providers.

Generally, after wireless network virtualization, the question is who parties are. With aspects in the commercial market, business models can be constructed depending on the composition of the aspects in the wireless network market and the main function of these aspects. The roles in the business models can be separated into two logical roles including the mobile network operator (MNO) and services provider (SP) [8]. Additionally, we can further separate the business models with four logical roles: Infrastructure provider (InP), the mobile virtual network provider (MVNP), the mobile virtual network operator (MVNO) and SP [9, 10]. In some approaches, the MVNO plays a role for both MVNO and MVNP in the business model. Our thesis focuses on the business model in which the MVNO plays a role for both MVNO and MVNP. In this model, the InP owns the infrastructure (base station equipments, antennas, backhaul links) and wireless network resources (radio resources). SPs focuses on providing services to its subscribers based on the virtual resources that are bundled and provided by MVNOs. Our work focuses on to maximize the benefit of MVNO in a business model by isolating, creating, and allocating virtual resources to guarantee mobile users’ QoS demands.

1.1.4 Motivation

In the small cell network deployment, many technical challenges should be addressed such as resource allocation, interference management, cell association, admission control, network performance analysis, hand-off and mobility management, self-organization, self-optimization, backhaul for small cells, security and synchronization [3, 6]. Moreover, the small cell network deployment with the wireless virtualization faces more significant chal-
lenges such as isolation, virtual resource allocation, and business models [8]. With a highly
dynamic wireless channel, it is very challenging to achieve the reliable bandwidth and net-
work efficiency in small cell networks. It has been accepted in the community that efficient
resource allocation is also one of the key components to address these challenges.

Besides, the operators and researchers should pay more attention to uplink traffic model
to adapt the inevitable traffic explosion in future mobile networks. This is because of the
integration of cloud-enabled technologies in wireless networks, the convergence of Internet
of things system, the development of M2M and M2C platforms, and the increase in the
number of mobile devices [11]. In this thesis, we focus on the resource allocation for uplink
transmission in small cell networks.

To reap the benefits of small cell network deployment, we target optimization-based
approaches to employ the resource allocation problems for small cell network paradigms.
Accordingly, the overall small cell network is modeled by an optimization problem. This
problem integrates multiple constraints such as transmit powers, backhaul links, radio re-
sources, interference management, and the users’ QoS demands into a unified optimization
problem. To solve this problem, we exploit the frameworks of the coalitional game, match-
ing theory, and optimization theory, to find sub-optimal solutions in distributed manner
corresponding to the network entities behavior.

Our goal is to effectively allocate network resources for the uplink of two small cell
networks (i.e., cognitive femtocell and virtualized small cell wireless networks) considering
the problems of small cells’ attributes as well as the characteristics of the cognitive small
cells and wireless virtualization. Especially, we need to establish new optimization-based
approaches and framework to develop distributed algorithms for high performance in small
cell networks.
2.2 Methodology

Technical challenges in small cell deployment

Network utility maximization

Optimization-based approaches:
- Coalition game
- Two-side matching game
- Optimization theory

Distributed optimal solutions:
- Distributed manner
- Network entities behavior

Evaluations

Figure 1.1: Methodology structure to solve optimization problems

1.2 Methodologies

In the wireless network, many network resource allocations problem can be formulated as optimization problems in which the purpose is to maximize utility functions with constraints. To solve maximization problem efficiency, researchers seek solutions with two main purposes for the non-convex optimization problem. The first purpose is how to find optimal solutions, which may have high complexity in a centralized manner. The second purpose is designing sub-optimal solutions with low-complexity. For the second purpose, depending on optimization problem, researchers have many ways to solve the non-convex optimization. In this thesis, our methodology is represented as Figure 1.1.

In our methodology, we focus on properties of the various small cells to formulate op-
timization problems. Corresponding to each small cells paradigm, the specific technical challenges are taken into consideration as constraints of formulated optimization problems. Then, a network utility maximization corresponding to each small cells paradigm and service providers are considered under the constraints. In order to solve the optimization problem in the distributed manner, the sub-optimal solutions are taken into consideration with a combination of both aforementioned approaches and our novel proposed approaches. Specifically, the coalitional game and two-side matching game are combined with optimization theory to obtain sub-optimal solutions. By these combinations, distributed solutions can be designed corresponding the network entities behavior. In addition, the proposed algorithms must guarantee some characteristics such as the small optimality gap, fast convergence speed, low-complexity, and in distributed manner.

1.2.1 Coalitional game

Game theory is a solution for analyzing framework to study the complex interactions among reasonable players. Game theory has a wide range applications such as economics, engineering, and even psychology [12]. Specifically, it has also been used for analyzing communication networks. The benefits obtain from game theory application are come from developing distributed, autonomous, and flexible algorithms for mobile networks. Moreover, using game theory we can design low-complexity distributed algorithms representing competitive or collaborative behaviors between network entities. Based on players behavior, game theory can be separated into two arms: non-cooperative [13] and cooperative game theory [12]. In the non-cooperative game, players strategy is interacted to enhance its own utility or decrease costs. For the cooperative game, it accommodates analytical methods to treat the behavior of conscious players with cooperative actions [12]. This arm addresses the formation of groups or coalitions of the cooperative players. These cooper-
ations can make new communication models that are very useful for self-organizing and
distributed networks.

The coalitional game is a type of the cooperative game. This game defines a set of
cooperative players in which individual payoffs of players are arranged in a payoff vector.
The player always finds coalitions to attain the total benefit or value of the coalitions.
There are three basic forms in the coalitional game: characteristic form, partition form,
and graph form. In the characteristic form, the value of the formed coalition is only effected
the coalition’s internal structure. In the partition form, the value of the coalition depends
on the network partition. In the graph form, coalition formation depends on a graph
structure that associates the coalitional members. In this thesis, we exploit respects of the
coalitional game in partition form to the resource allocation in the uplink of the cognitive
femtocell network. We further exploit the recursive core method to the solution of the
proposed game.

1.2.2 Two-side matching game

The two-side matching game is a promising solution to find sub-optimal of the maximum
weighted matching problem. Basically, this game includes two sides: proposal and accep-
tance sides. Player behaviors are selfish and rational that are operated based on preference
lists. The marriage markets is a most popular example to address this game. In the mar-
riage markets, each man has strict preferences over women and vice versa. In the matching
processes, a woman is acceptable to a man if the man prefers women to being unmatched.
The purpose of this design is to find a stable matching.

The classical classification of the two-side matching game is based on the values of the
player quotas as follows:

- One-to-one matching: Each player can be matched to at most one player from the
opposite side.

- Many-to-one matching: Here, in one of the sets, at least one player can be matched to multiple players of the opposing side, while in the other set, every player has exactly one match.

- Many-to-many matching: At least one player within each of the two sets could be matched to more than one member in the other set.

In this thesis, we exploit the aspects of the one-to-one matching game for the resource allocation problem in the small cell network with wireless virtualization.

1.3 Related work

1.3.1 Distributed resource allocation for cognitive femtocell networks: A coalitional game approach

Several recent studies have considered the resource allocation and user association problem in the uplink CFN \([3, 4, 23–36]\). These works, however, have only studied power control, subchannel allocation, or user association problems separately.

For power control, existing works focus on efficient sharing of a single channel through adaptively adjusting the power levels in uplink two-tier femtocell networks \([23–26]\). The studies in \([23–25]\) only considered access control and power control to minimize the number of secondary users to be removed and to maximize the overall network throughput for efficient sharing of a single channel. The distributed power control for spectrum-sharing femtocell networks using the Stackelberg game approach is also presented in \([26]\). However, the proposals in \([23–26]\) do not consider the subchannel allocation issue.

There have been some existing works studying the subchannel assignment for uplink
OFDMA-based femtocell networks, but they do not consider power control in their designs [27–32, 36]. In [28], the authors proposed two approaches to mitigate the uplink interference for OFDMA femtocell networks. In the first approach, FUEs are only allowed to use dedicated subchannels if they produce strong interference for the MUEs. In the second approach, the channel assignment for both tiers is performed based on an auction algorithm. Moreover, some other works address the joint subchannel allocation and power control [30–32, 36]. A distributed power control and centralized matching algorithms for subchannel allocation are proposed in [31], which lead to fair resource allocation for uplink OFDMA femtocell networks. A distributed auction game is employed to design the joint power control and subchannel allocation in OFDMA femtocell networks [32]. Additionally, the authors in [36] investigated the joint uplink subchannel and power allocation problem in cognitive small cells using cooperative Nash bargaining game theory but ignoring interference among small cells. Nonetheless, the system models in [30–32, 36] are based on closed access models, where only the registered FUEs are allowed to communicate with FBSs.

There have also been some existing works on the user association design for the uplink CFN [34, 35]. In [34], the authors studied resource sharing and femtocell access control in OFDMA femtocell networks, in which incentive mechanisms are proposed to encourage FUEs to share their FBSs with MUEs. However, this work considers only resource sharing without power control. In [35], the authors propose a cross-layer resource allocation and admission control framework in a downlink CFN in which MUEs can establish connection with FBSs to mitigate the excessive cross-tier interference and achieve a better throughput.

Some ideas presented in this chapter for the interference management are related to those works in [27, 37]. In [27], authors presented an uplink capacity analysis and interference avoidance strategy for a shared spectrum two-tier DS-CDMA network. In [37],
Chapter 1: Introduction

authors proposed the non-collaborative intercell interference avoidance method in order to ensure fairness for cell edge users in the OFDMA network. The interference avoidance method in [37] is not applicable for the spectrum sharing network. Moreover, differently from these works, this chapter studies the interference management strategy based on matching algorithm that captures on FUEs and FBSs’ behaviors to find the sub-optimal strategies of the proposed optimization problem in the two-tier network.

Recently, the application of the matching theory to engineer the future wireless network has received increasing attention [38–40]. A concise introduction and survey on matching theory applications is provided in [38]. A framework that jointly associates user equipment to the FBSs and allocates FBSs to the service provider using the matching game approach was proposed in [39]. This work does not, however, consider the underlay spectrum sharing approach between macro-tier and femto-tier. In addition, the algorithms developed in [39] do not ensure QoS guarantees for the served user equipments and the feasible solution of the formulated optimization problem in case of the resource limitation. An admission game for uplink user association in wireless small cell networks is addressed in [40]. The studies in [40] only considered the problem of user association based on a college admissions game by utilizing the matching and coalition game approach for the small cell network that does not consider the spectrum sharing with the macrocell network.

It first can be seen that none of the existing works study joint channel allocation and power control considering intra-tier interference and self-organization, self-optimization. This thesis address the joint design problem based on the coalitional game in partition form. Moreover, it can be seen that none of the existing works study joint user association, channel allocation, and power control considering intra-tier interference in cognitive femtocell networks. This thesis aims to address this joint design problem based on the coalitional game in partition form.
1.3.2 Resource allocation in virtualized wireless networks with backhaul constraints

The design of an efficient virtualized resource allocation plays an important role in the virtualized cellular network deployment [77–79]. However, the works in [77] and [78] ignore backhaul link constraints that should be carefully studied for dense small-cell deployment scenarios with possible bottleneck in various backhaul solutions, e.g., xDSL, non-line-of-sight (NLOS) microwave, and wireless mesh networks [80].

Unlike [77] and [78], the study of [79] incorporates a business model for the profit of MVNOs. In this model, the MVNOs rent the network resources from the wireless physical infrastructure providers (InPs) to create virtual resources. In turn, the service providers (SPs) rent virtualized resources from MVNOs to provide specific services to the end users. However, it is noted that works in [77–79] do not study virtual resource allocation for uplink transmissions, which enables user equipments to use power more efficiently to meet their QoS requirements for the given scheduled radio resources. Besides, it should pay more attention to adapt the inevitable uplink traffic explosion in future mobile networks [11].

1.4 Contribution

In this thesis, we consider two network utility maximization problem for the small cell networks in the future HetNets. All two problems have different kinds of constraints corresponding to different network models. Additionally, these network utility maximization problem have different kinds of constraints corresponding to different the entities behavior of the wireless networks.
1.4.1 Distributed resource allocation for cognitive femtocell networks: A coalitional game approach

In this work, we study the joint subchannel- and power-level allocation in the uplink of the two-tier CFN comprised of a conventional macrocell and multiple femtocells using underlay spectrum access. The contribution can be summarized as follows:

We first propose a resource allocation problem, which is addressed via an optimization problem, in which we maximize the uplink sum-rate under constraints of intra-tier and inter-tier interferences while maintaining the average delay requirement for cognitive femtocell users. Specifically, the aggregated interference from cognitive femto users to the macrocell base station is also kept under an acceptable level. We show that this optimization problem is NP-hard and propose an autonomous framework, in which the cognitive femtocell users self-organize into disjoint groups (DJGs).

Then, instead of maximizing the sum-rate in all cognitive femtocells, we only maximize the sum-rate of each DJG. After that, we formulate the optimization problem as a coalitional game in partition form, which obtains sub-optimal solutions. Moreover, we propose algorithms to allocate resources in a distributed way, in which the CFN implementation is self-organized and self-optimized.

Finally, the proposed framework is tested based on the simulation results and shown to perform efficient resource allocation.

1.4.2 Resource allocation in virtualized wireless networks with backhaul constraints

In this part, we move to the study resource allocation for the virtualized wireless network. We formulate the network utility maximization problem as an NP-hard optimization problem that jointly allocates power and slices in a business model. The design objective is to
maximize the mobile virtual network operator (MVNO) profit while guaranteeing the users’ QoS requirements and the InP’s backhaul constraints. Here, the chunk-based radio resource allocation approach (subcarrier aggregation) is used to isolate the slices for uplink transmissions in an orthogonal frequency division multiple access (OFDMA)-based system [41,42].

The considered joint slice and power allocation complicate any optimization-based design due several coupled constraints: i) slice isolation, ii) backhaul limitation, and iii) chunk allocation for heterogeneous users’ QoS. Our research contributions are summarized as follows:

We first propose a slice isolation approach for the uplink of a virtualized cellular network in which the virtualized resources or slices are isolated by base stations and chunk-based radio resources owned by different InPs. This isolation ensures that each slice is uniquely determined and that the customization in one slice will not interfere with other slices.

Then, we propose a distributed algorithm based on Lagrangian relaxation to find the suboptimal decision on slice and transmit power allocations. The problem is solved in two different phases of power allocation and slide allocation through updating the sequence of primal and dual variables. The optimal power is derived from Karush-Kuhn-Tucker (KKT) conditions, whereas the Hungarian method is applied to solve the slice allocation in a centralized manner.

To circumvent the requirement of global information, we further propose a distributed algorithm based on the concept of the matching game. This algorithm is shown to converge to a suboptimal solution.

Finally, numerical results show that our proposed approaches require a small number of iterations to converge.
1.5 Thesis outline

The remainder of the thesis is organized as follows:

- Chapter 2 investigates a resource allocation that consists of subchannel- and power-level allocation in the uplink of the two-tier CFN comprised of a conventional macro-cell and multiple femtocells using underlay spectrum access. A coalitional game approach is applied to implement the distributed resource allocation with self-organization and self-optimization.

- In Chapter 3, besides describing virtualized resources in the virtualized wireless network, this chapter also presents the distributed resource allocations scheme in which backhaul constraints are carefully considered.

- Finally, conclusions are drawn in Chapter 4.
Chapter 2

Distributed resource allocation for cognitive femtocell networks: A coalitional game approach

2.1 Background and contribution

In recent years, the number of mobile applications demanding high-quality communications have tremendously increased. For instance, high-quality video calling, mobile high-definition television, online gaming, and media sharing services always have connections with high-quality of services (QoS) requirements among devices and service providers [43]. In order to adapt to these requirements, the Third Generation Partnership Project (3GPP) Long-Term Evolution Advanced (LTE-Advanced) standard has been developed to support higher throughput and better user experience. Moreover, in order to accommodate a large amount of traffic from indoor environments, the next mobile broadband network uses the heterogeneous model, which consists of macrocells and smallcells [44,45]. The smallcell...
model (such as femtocells) is one way of increasing coverage in dead zones in indoor environments, reducing the transmit power and the size of cells and improving spectrum reuse [3, 4].

In practice, a two-tier femtocell network can be implemented by spectrum-sharing between tiers, where a central macrocell is underlaid with several femtocells [26]. This network model is also called the cognitive femtocell network (CFN) [6, 27]. The CFN can be deployed successfully and cost-efficiently via two different spectrum-sharing paradigms: overlay and underlay [6, 46, 47]. The overlay access paradigm enables the cognitive femtocell user equipment (secondary user) to transmit their data only in spectrum holes where macrocell users (primary users) are not transmitting. A femtocell user equipment (CFUE) vacates its channel if it detects an occupancy requirement of a macro user equipment (MUE). In the underlay access, CFUEs are allowed to operate in the band of the macrocell network, while the overall interference from CFUEs occupancy on the same channel should be kept below a given threshold. Moreover, in this paradigm, entities in CFN are assumed to have knowledge of the interference caused by transmitters in the macrocell network [26, 46]. In this chapter, we focus on the resource allocation in underlay CFN where the channel usages are based on the underlay cognitive transmission access paradigm [6, 26, 48].

In the CFN deployment, interference is a major challenge caused by overlapping area among cells in a network area and co-channel operations. The interference can be classified as: intra-tier (interference caused by macro-to-macro and femto-to-femto) or inter-tier (interference caused by macro-to-femto and femto-to-macro) [49, 50]. Specifically, the inter-tier interference, which is caused by using the underlay spectrum access, needs to be considered to protect the macrocell network [26]. In order to mitigate interference, some works have studied the downlink direction [49, 51–53]. Suppression of intra-tier interference using the coalitional game is studied in [49]. In [51], the authors employed frequency division multiple
access in terms of the area spectral efficiency and subjected to a sensible QoS requirement. The power and sub-carrier allocations for OFDMA femtocells based on underlay cognitive radios in a two-tier network are mentioned in [52]. A self-organization strategy for physical resource block allocation with QoS constraints to avoid co-channel and co-tier interference is investigated in [53]. However, the CFN uplink using the underlay paradigm is also an important challenge that needs to be considered [3, 4, 45]. In the uplink direction, the uplink capacity and interference avoidance for two-tier femtocell network were developed by Chandrasekhar et al. [27]. In [54], an interference mitigation was proposed by relaying data for macro users via femto users, based on the coalitional game approach and leasing channel. The power control under QoS and interference constraints in femtocell networks was studied in [55]. The distributed power control for spectrum-sharing femtocell networks using the Stackelberg game approach was presented in [26]. However, most of the above mentioned works only focus on single-channel operation and do not mention the channel allocation to the femto users. In [28], the uplink interference is considered in OFDMA-based femtocell networks with partial co-channel deployment without the femtocell users power control. Additionally, channel allocations are based on an auction algorithm for macrocell users and femtocell users. Clearly, the channel allocation in [28] is not efficient where users can reuse the channels by power control, as in [26,55].

In this chapter, we study an efficient distributed resource allocation for the CFN uplink in two-tier networks to overcome the drawbacks of the existing literature. The efficient distributed resource allocation in the multiple channel environment is represented by solving an optimization problem. The objective of this optimization problem is the uplink sum-rate. The intra-tier and inter-tier interference are considered with constraints in the optimization problem. Additionally, the guaranteed average delay requirements are at the minimum for the connected cognitive femtocell users, and the total interference at the
MBS is kept under acceptable levels as well. We show that this optimization problem is an NP-hard optimization problem. Motivated by the design of self-optimization networks [3, 4, 6, 56], we propose a self-organizing framework in which CFUEs self-organize into disjoint groups (DJGs). By doing so, instead of maximizing the sum-rate in whole cognitive femtocells, we only maximize the sum-rate of each DJG where the computation of the original optimization is decomposed to the formed DJGs. Then, in order to solve the optimization problem at each DJG, we formulate this optimization problem as a coalitional game in the partition form, which obtains near-optimal solutions along with efficient resource allocation in a distributed way. The coalitional game is defined by a set of players who are the decision makers seeking to cooperate to form a coalition in a game [21, 49]. One kind of game expression is the coalitional game in the partition form that captures realistic inter-coalition effects in many areas, particularly in wireless communication networks [21, 57]. In this chapter, CFUEs can join and leave a coalition to obtain the maximum data rate (denoted by individual payoff). The joining and leaving of CFUEs have to satisfy some constraints of the above mentioned optimization problem. Specifically, the proposed game is solved based on the recursive core method [21, 57]. Throughout this method, the stability of the coalition formation is a result of the optimal channel and power allocation. The optimal power allocation to CFUEs corresponding to the network partition is obtained from sharing payoffs of CFUEs in a coalition. The geometric programming and dual-decomposition approaches, which are based on [55, 58–60], are proposed to determine the optimal power allocation in the coalition. Simulation results show that the proposed framework can be implemented in a distributed manner with an efficient resource allocation. Furthermore, the social welfare of the usable data rate in CFN under our solution is also examined via our simulation results. In addition, we also estimate the gap between the global optimal solution and the sub-optimal solution using proposed cooperative approach.
The main contributions of this chapter are summarized as follows:

- We investigate an efficient resource allocation for the underlay CFN uplink that is addressed via a NP-hard optimization problem.
- The NP-hard optimization problem is simplified by dividing the network into DJGs. Then, it is solved by formulating the optimization problem as a coalition game in a partition form.
- We propose algorithms to allocate resources in a distributed way, in which the CFN implementation is self-organized and self-optimized.

The remainder of this chapter is organized as follows: section 2.2 explains the system model and problem formulation. The optimization problem of the efficient resource allocation is formulated in section 2.3, as is the DJGs formation. In section 2.4, we address the solutions to solve this optimization problem based on a coalitional game in the partition form approach. Section 2.5 provides simulation results. Finally, conclusions are drawn in section 2.6.

2.2 System model and problem formulation

Firstly, we provide the system model followed by the problem formulation of primary network protection. Secondly, we consider the data transmission model in the uplink of CFUEs. Thirdly, we analyze a queuing model of CFUEs. Finally, we discuss some problems of licensed subchannel reuse among CFUEs in the CFN.

2.2.1 System model

We consider an uplink CFN based on the underlay spectrum access paradigm, in which $N$ CFBSs are deployed as in Fig. 2.1. These CFBSs are under-laid to the macrocell frequency spectrum and reuse the set of licensed subchannels of the uplink OFDMA macrocell. In
the primary macrocell, there exist $M$ subchannels which are correspondingly occupied by $M$ macrocell user equipments (MUEs) in the uplink direction. Let $\mathcal{N} = \{1, ..., N\}$ and $\mathcal{M} = \{1, ..., M\}$ denote a set of all CFBSs and MUEs, respectively. A subchannel can be contain one resource block or a group resource with the single carrier frequency division multiple access (SC-FDMA) technology in LTE system [61]. Every CFBS $n \in \mathcal{N}$ is associated to the same $L$ number of CFUEs. Let $\mathcal{L}_n = \{1, ..., L\}$ denote the set of CFUEs served by a CFBS $n \in \mathcal{N}$. Furthermore, cognitive modules are added to CFUEs and CFBSs to support self-organization, self-optimization as in [6]. Moreover, CFUEs and CFBSs exchange information via dedicated reliable feedback channels or wired back-hauls.
2.2.2 Primary network protection

In the underlay CFN, the MBS of the macrocell needs to be protected against overall interference from CFUEs, as in [62–64]. The protection on subchannel $m$ at the MBS is addressed as follows:

$$\sum_{l \in \mathcal{L}_n, n \in \mathcal{N}} \alpha_{ln}^m h_{ln,0} P_{ln}^m \leq \zeta_0^m, \quad \forall m \in \mathcal{M},$$  \hspace{1cm} (2.1)$$

where $\alpha_{ln}^m$ is a subchannel allocation indicator defined as

$$\alpha_{ln}^m = \begin{cases} 1, & \text{if } l \in \mathcal{L}_n \text{ is allocated to subchannel } m, \\ 0, & \text{otherwise}, \end{cases}$$  \hspace{1cm} (2.2)$$

$h_{ln,0}^m$ denotes the channel gain between CFUE $l \in \mathcal{L}_n$ and the primary MBS, $P_{ln}^m$ is the power level of CFUE $l \in \mathcal{L}_n$ using subchannel $m$, and $\zeta_0^m$ is the interference threshold at the primary receiver MBS on subchannel $m$.

2.2.3 Data transmission model in uplink

In our considered model, the data transmission of CFUEs is affected by the interference from the MUE and other CFUEs in other femtocells. Each CFUE is assumed to be assigned to one subchannel for a given time. The transmission rate of CFUE $l \in \mathcal{L}_n$ on subchannel $m$ follows the Shannon capacity as follows:

$$R_{ln}^m = B_w \log (1 + \Gamma_{ln}^m),$$  \hspace{1cm} (2.3)$$

where $B_w$ is the bandwidth of subchannel $m$, $\forall m \in \mathcal{M}$, and $\Gamma_{ln}^m$ is the Signal-to-interference-plus-noise ratio (SINR) of the CFUE $l \in \mathcal{L}_n$ using subchannel $m$ as follows:
\[ \Gamma_{ln}^m = \frac{h_{ln}^m P_{ln}^m}{I_n^m + n_0}. \]  

In (2.4), \( I_n^m \) denotes the total interference at CFBS \( n \) on subchannel \( m \):

\[ I_n^m = \sum_{l' \in L_{n'}, n' \in N} h_{l'n'}^m P_{l'n'}^m + h_{m,n}^m P_{m0}^m. \]  

where \( n' \neq n \); \( h_{ln}^m, h_{l'n'}^m \) and \( h_{m,n}^m \) are the channel gains between CFUE \( l \) and CFBS \( n \), CFUE \( l' \) and CFBS \( n \), and MUE \( m \) and CFBS \( n \), respectively; \( n_0 \) is the noise variance of the symmetric additive white Gaussian noise; \( h_{m,n}^m P_{m0}^m \) is the inter-tier interference at CFBS \( n \) from MUE \( m \); and \( \sum_{l' \in L_{n'}, n' \in N} h_{l'n'}^m P_{l'n'}^m \) is total intra-tier interference from CFUEs at the other CFBSs that use the same subchannel \( m \).

In order to successfully decode the received signals at the CFBS of the CFUE transmission, the SINR at CFBS \( n \) from CFUE \( l \in L_n \) has to satisfy [65]:

\[ \Gamma_{ln}^m \geq \gamma, \]  

where \( \gamma \) is the SINR threshold to decode received signals at the CFBS, \( \forall n \in N, \forall m \in M \).

Because the transmission on the CFUE-CFBS link can be dropped due to a certain outage event, the successful transmission of CFUEs can be computed based on the probability of maintaining the SINR above a target level \( \gamma \), given by:

\[ \xi_{ln} = \Pr(\Gamma_{ln}^m > \gamma). \]  

This outage value can be reduced by employment of the Hybrid Automatic-Repeat-Request protocol with Chase Combining at the medium access layer [66]. According to this protocol, packets will be re-transmitted if they have not been successfully received at the receiver. This re-transmission can occur up to \( K_{max} \) times until the successful data
transmission. Hence, if arrivals to CFUE $l \in L_n$ follow a Poisson process with arrival rate $\lambda_{ln}$, the effective arrive rate $\tilde{\lambda}_{ln}$ with a maximum of $K_{max}$ re-transmissions is computed as follows:

$$\tilde{\lambda}_{ln} = \lambda_{ln} \sum_{k=1}^{K_{max}} \xi_{ln}(1 - \xi_{ln})^{k-1},$$

(2.8)

where $(1 - \xi_{ln})$ is the error packet transmission probability of the connected link CFUE $l \in L_n$ to CFBS $n$, which is calculated based on (2.7), and $\sum_{k=1}^{K_{max}} \xi_{ln}(1 - \xi_{ln})^{k-1}$ is the successful transmission probability of a data packet of CFUE $l$ with a maximum of $K_{max}$ re-transmissions.

Clearly, through (2.8), congestion at the queue of the CFUE occurs when the departure rate or data rate on the CFUE-CFBS link is lower than the acceptable threshold. This congestion leads to delaying data packets in the queueing model of the CFUE data transmission. The queueing model for CFUEs will be discussed in the next subsection.

### 2.2.4 Queueing model analysis for guaranteeing the CFUE demands

In this subsection, we address the data transmission of the CFUE using the M/D/1 queuing model [67], as shown in Fig. 2.2. In this queueing model, the arrival rate $\lambda_{ln}$ depends on the data rate from the upper layer of CFUE $l$. Based on Little’s law, the average waiting time of a packet in CFUE $l$ can be calculated as follows:

$$D_{ln}^{m} = \frac{\tilde{\lambda}_{ln}}{2R_{ln}^{m} \left( R_{ln}^{m} - \tilde{\lambda}_{ln} \right)},$$

(2.9)

where $R_{ln}^{m}$ is considered as the service rate in the M/D/1 queuing model determined by (2.3).

Assuming that, at the beginning of each time slot, the maximum delay requirement for
each CFUE $l \in \mathcal{L}_n$ is given by $D_{\text{in}}^m \leq D_{\text{in}}^{\max}$, the condition
\[ R_{\text{in}}^m \geq R_{\text{th}}^m \]  
(2.10)

has to be guaranteed. From (2.9) and the maximum delay value requirement $D_{\text{in}}^m = D_{\text{in}}^{\max}$, the data rate requirement $R_{\text{in}}^{\min}$ is calculated as follows:
\[
R_{\text{in}}^{\min} = \frac{\left( (D_{\text{in}}^{\max} \tilde{\lambda}_{\text{in}})^2 + 2D_{\text{in}}^{\max} \tilde{\lambda}_{\text{in}} \right)^{1/2} + D_{\text{in}}^{\max} \tilde{\lambda}_{\text{in}}}{2D_{\text{in}}^{\max}}.
\]  
(2.11)

From (2.3), (2.4) and (2.10), we have the constraint of total interference to guarantee the minimum delay requirement of each CFUE as follows:
\[
I_{\text{in}}^m + n_0 \leq h_{\text{in}}^m R_{\text{in}}^m \chi_{\text{in}},
\]  
(2.12)

where $\chi_{\text{in}} = \left( \frac{R_{\text{in}}^{\min}}{h_{\text{in}}^{\frac{1}{2}} - 1} \right)$.

Intuitively, from (2.3) and (2.10), in order to satisfy the minimum average delay requirement, the CFUE needs to increase its power greater than a power level threshold. However, this increase may produce harmful interference to other CFUEs, which leads to a
reduced data rate of other CFUEs using the same subchannel, as in (2.3). Additionally, the increasing power level at the CFUEs using the same subchannel $m$ will increase the overall interference at the MBS, as mentioned in (2.1). Therefore, when the power allocation to CFUEs cannot satisfy constraints (2.1), (2.3), and (2.10), CFUEs have an incentive to find another opportunity for selecting the subchannel from a set of subchannels.

2.2.5 Channel reuse in the CFN

In the CFN, a subchannel $m$ that allocated to a CFUE $n$ can be reused at other CFUEs if it overcomes the intra-tier interference constraints as considered in [53]. Certainly, in order to allocate a subchannel efficiently, the unlicensed subchannels need to be reused among CFUEs that are based on parameter $\alpha_{m}^{ln}$ as follows:

$$
\alpha_{m}^{ln} = \begin{cases} 
0, & \text{if } l' \in \mathcal{L}_{n'}, n' \in T_{m}^{l} \cap \mathcal{M}, \\
1, & \text{if } l', n' /\in \mathcal{L}_{m} \cup T_{m}^{l}, m \in \mathcal{M},
\end{cases}
$$

(2.13)

where $T_{m}^{l}$ is a set of the CFBSs lying within the interference range of CFUE $l \in \mathcal{L}_{n}$ on subchannel $m$. The CFBS $n' \in T_{m}^{l}$ if and only if:

$$
IR_{m}^{ln, n'} \geq \gamma,
$$

(2.14)

where the interference range $IR_{m}^{ln, n'}$ is determined based on the SINR level from observing the surrounding CFBSs of CFUE $l \in \mathcal{L}_{n}$ as follows:

$$
IR_{m}^{ln, n'} = \frac{h_{ln}^{l}P_{m, \text{max}}^{l}}{h_{mn}'P_{m0} + n_{0}},
$$

(2.15)

and $P_{m, \text{max}}^{l}$ is the maximum transit power of CFUE $l \in \mathcal{L}_{n}$ that can be allocated on subchannel $m$. 
In order to illustrate the reuse of subchannels among CFUEs and to form table $T_{ln}^m$, we present a simple example as follows.

**Example 1.** Let us consider reusing a licensed subchannel $m = 1$ among three CFUEs as shown in Fig. 2.3, in which each CFBS serves one CFUE. The table $T_{ln}^m$ of each CFUE is constructed by considering the interference range of the CFUEs based on (2.14), (2.15). Then, the CFBSs that belong to the table of CFUEs 11, 12 and 13 are $T_{11}^1 = \{1, 2\}$, $T_{12}^1 = \{2\}$ and $T_{13}^1 = \{2, 3\}$, respectively. From (2.13), if subchannel $m = 1$ is allocated to CFUE 11, then $\alpha_{11}^1 = 1$, $\alpha_{12}^1 = 0$, and $\alpha_{13}^1 = 1$. This means that subchannel 1 cannot be reused at CFUE 12 from CFUE 11 but CFUE 13 can reuse this subchannel. Similarly, we consider principles for CFUEs 12 and 13, respectively. The detail of the table $T_{ln}^m$ formation is discussed in section 2.3.2.

In order to illustrate the subchannel and power allocation efficiently and optimally, we address an optimization problem in the next section.
2.3 Optimization problem and DJG formulation

In this section, we first discuss an optimization problem that represents an efficient resource allocation for the underlay CFN uplink. Secondly, we address the network partition into DJGs to decompose the computation of the optimization problem into distributed computations at DJGs.

2.3.1 Optimization problem formulation

The objective is to maximize the uplink sum-rate of the whole CFN. The constraints include minimization of the intra-tier and inter-tier interference levels with similarly minimal average delay requirements for connected CFUEs. Specifically, the total interference at the MBS is also kept under acceptable levels. Moreover, the subchannels are efficiently reused among CFUEs. From the discussion of our considered problems in section 2.2, the optimization problem is formulated as follows:

\[ \text{OPT-2:} \]

\[
\max_{(\alpha_{ln}^m, P_{ln}^m)} \sum_{m \in M} \sum_{n \in N} \sum_{l \in \mathcal{L}_n} \alpha_{ln}^m R_{ln}^m
\]

subject to: \( (2.1), (2.12), (2.13), \)

\[ 0 \leq \sum_{m \in M} \alpha_{ln}^m \leq 1, \quad n \in N, \quad l \in \mathcal{L}_n, \quad (2.17) \]

\[ \alpha_{ln}^m = \{0, 1\}, \quad m \in M, n \in N, l \in \mathcal{L}_n, \quad (2.18) \]

\[ P_{ln}^{m, \text{min}} \leq P_{ln}^m \leq P_{ln}^{m, \text{max}}, \quad \forall m, n, l. \quad (2.19) \]

The purpose of OPT-2 is to allocate the optimal subchannels and power levels for CFUEs in order to maximize the CFN uplink sum-rate. The constraints \( (2.1), (2.6), (2.12), (2.13) \) are addressed in section 2.2. Moreover, some conditions of subchannel allocation indicator \( \alpha_{ln}^m \) are represented in \( (2.17), (2.18) \) and \( (2.19) \). Constraint \((2.17)\) shows that each
CFUE $l \in \mathcal{L}_n$ is only assigned one subchannel at a given time, and (2.18) is represented as in (2.2). Constraint (2.19) represents the power range of each CFUE $l \in \mathcal{L}_n$, which has to be within the threshold range. The thresholds $P_{\text{max}}^{m,\text{max}}$ and $P_{\text{min}}^{m,\text{min}}$ indicate the limitations of the power range of CFUE $l \in \mathcal{L}_n$ on each licensed subchannel $m$.

Clearly, **OPT-2** is an NP-hard optimization problem because, in order to find the optimal solution, we must allocate subchannels with mixed integer variable $\alpha_{\text{in}}^m$ and non-integer variable $P_{\text{in}}^m$ along with mixed linear and nonlinear constraints [68, 69]. The NP-hard optimization problem along with the huge number of CFUEs makes it infeasible to find an optimal solution. In order to solve **OPT-2**, we propose a solution that is based on the DJGs’ formation and coalitional game in the partition form approach. A sketchy summary of the proposed solution is illustrated in Fig. 2.4. Firstly, CFUEs in the network self-organize into DJGs using Algorithm 2.1 (to be discussed in section 2.3.2), in which the interference from CFUEs transmission in a DJG is not affected by CFUEs transmission among other DJGs. The purposes of this division are to reduce feedback among network entities and decompose the computation in **OPT-2** into distributed computations at DJGs. Secondly, CFUEs in DJGs will be considered as players in the coalitional game. CFUE cooperates with other CFUEs to choose subchannel and power levels in order to form stable coalitions using Algorithms 2.2 and 2.3 (described in section 2.4.3). In the next subsection, we simplify the optimization problem **OPT-2** by addressing DJGs formation.

### 2.3.2 DJGs formation

In the CFN deployment, depending on the aims of network designers and mobile user equipments, the locations of CFBSs and CFUEs are distributed randomly in a network area. Some femtocells less be affected by interferences from others femtocells. Thus, CFUEs can self-organize into DJGs as addressed in Algorithm 2.1.
Figure 2.4: The proposed structure for solving OPT-2 based on the DJGs’ formation and coalitional form in the partition form.

At the beginning of each period, the CFBS broadcasts a message that contains CFBS identification (ID) and interference from MUEs (Step 2). The CFUE decodes the received messages (Step 4,5) and detects the surrounding CFBSs within the interference range (IR) using (2.14) and (2.15). The detected CFBSs are stored in table $T_{ln}^m$ and then form table $T_{ln} = \{t_{ln'}\}_{M \times |N_l|}$ (Step 6); here, $t_{ln'} = 1$ if $n' \in T_{ln}^m$, else $t_{ln'} = 0$, and $N_l$ is the set of CFBSs detected by CFUE $l$. Then, the CFUE sends its information $T_{ln}$ to its CFBS $n$ (Step 7). The CFBS $n$ collects information $T_{ln}$ of all its CFUEs and constructs table $T_n = \{t_{lmn'}\}_{M \times \max(|N_l|) \times L_n}$ (Step 9). Here, $\{t_{lmn'}\}$ equals to 1 if $n' \in T_{ln}$; otherwise, it equals to 0. Simultaneously, the CFBSs exchanges information the table $T_n$ with the CFBSs $n' \in T_n$ to form a disjoint group $g$ (Step 10). Then, the CFBSs build a subchannel reuse table among CFUEs based on (2.13) (lines 11, 12). For convenience, let denote $T_g = \{a_{ln}^m\}_{(|L_g| \times |L_g| \times M}$
Algorithm 2.1: The self-organization of CFUEs into DJGs

**Inputs:** $\mathcal{M}$, $\mathcal{N}$, $\mathcal{L}_n$, $\forall n \in \mathcal{N}$,

1. * Initialize: $T_{ln} = \emptyset$, $P_{ln}^m = P_{ln}^{m, \text{max}}$, $\forall m \in \mathcal{M}$, $\forall n \in \mathcal{N}$, $l \in \mathcal{L}_n$.

2. The CFBSs broadcast TxCFemtoBS-ID messages based on pilot channels as discussed in [53].

3. * At the CFUE, $\forall l \in \mathcal{L}_n, \forall n \in \mathcal{N}$, do:
   4. Decodes TxCFemtoBS-ID message of the surrounding CFBSs.
   5. Estimates $h_{ln'}$, $n' \neq n$ based on received RSSIs.
   6. Constructs table $T_{ln}$ based on (2.14).
   7. Sends table $T_{ln}$ to its CFBS.

8. * At the CFBS $n$, $\forall n \in \mathcal{N}$, do:
   9. Collects $T_{ln}$ from its CFUEs.
   10. Constructs table $T_n$ based on table $T_{ln}$, $\forall l \in \mathcal{L}_n$.
   11. Exchanges $T_n \leftrightarrow T_{n'}$, $\forall n' \in T_n$.
   12. Self-organizes into groups.
   13. Constructs tables $T_g$ based on condition (2.13), then sends it to the network coordinator.

**Output:** DJGs formation

The reuse table of CFUEs at DJG $g$. Here, denoting by $\mathcal{L}_g = \bigcup_{n \in \mathcal{N}_g} \mathcal{L}_n$ is the set of CFUEs in DJG $g$, and $\mathcal{N}_g$ is the set of CFBSs belonging group $g$. Clearly, some CFUEs can be self-organized into disjoint group $g$.

After CFUEs form DJGs, CFUEs only exchange information for group formation if and only if the network has new events such as the CFUEs’ location or new joining CFUEs. In addition, exchanging information among CFBSs in the DJG formation can be processed via asynchronous inter-cell signaling [70, 71]. A femtocell signals its status information to
neighbor femtocells periodically and updates its CFUEs local information upon reception of the other femtocells signaling. For clear understanding of DJG formation, we provide Example 2 as below.

**Example 2.** Let us consider a CFN model consisting of five CFBSs, as shown in Fig. 2.5, in which each CFBS contains an CFUE. Assume that the interference ranges (IRs) of CFUEs are determined and exist as shown in Fig. 2.5 (Steps 2-5). Intuitively, table $T_m$ is constructed as in Table 2.1 (Step 6), where “1” indicates the CFBS belongs to the CFUE’s IR, “0” represents the CFBS does not belong to the IR of the CFUE, and $\emptyset$ indicates that the CFUE does not receive the CFBS’s pilot signals. Because we only consider one subchannel, the tables $T_1$, $T_2$, $T_3$, $T_4$ and $T_5$ are also represented as $T_{11}$, $T_{12}$, $T_{13}$, $T_{14}$ and $T_{15}$ as in Table 2.2, respectively. In order to obtain databases of tables of the surrounding CFBSs, the CFBS $n$ exchanges table $T_n$ with other CFBSs $n' \in T_n$. By doing so, the CFUEs $\{1\}$, $\{12\}$ and $\{13\}$ have the same database as in Table 2.2 and form a disjoint group, namely DJG-1. Moreover, DJG-2 is formed by CFUEs $\{14\}$ and $\{15\}$. After finishing disjoint group formation, subchannel reuse tables for DJGs are formed based on (2.13) and exist.
as shown in Table 2.2. Here, “1” denotes two CFUEs that can reuse subchannel 1, “0”
denotes two CFUEs that cannot reuse subchannel 1, and the ∅ denote two CFUEs belonging
to different DJGs.

Table 2.1: The table $T_{ln}$ formulation of all CFUEs.

<table>
<thead>
<tr>
<th>Table $T_{ln}$</th>
<th>CFemtoBS_ID</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CFBS-1</td>
</tr>
<tr>
<td>$T_{11}$</td>
<td>1</td>
</tr>
<tr>
<td>$T_{12}$</td>
<td>0</td>
</tr>
<tr>
<td>$T_{13}$</td>
<td>0</td>
</tr>
<tr>
<td>$T_{14}$</td>
<td></td>
</tr>
<tr>
<td>$T_{15}$</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.2: The subchannel reuse table $T_g$ among CFUEs.

<table>
<thead>
<tr>
<th>Subchannel 1</th>
<th>CFUEs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$i_1$</td>
</tr>
<tr>
<td>$i_1$</td>
<td>1</td>
</tr>
<tr>
<td>$i_2$</td>
<td>0</td>
</tr>
<tr>
<td>$i_3$</td>
<td>1</td>
</tr>
<tr>
<td>$i_4$</td>
<td>1</td>
</tr>
<tr>
<td>$i_5$</td>
<td>0</td>
</tr>
</tbody>
</table>

After establishing DJGs, without loss of generality, we find the local optimal solution
of $\text{OPT-2}$ by finding an optimal solution of $\text{OPT-2}_g$ in each DJG $g$, which is taken from
$\text{OPT-2}$ as follows:
**OPT-2g**: 

\[
\max_{(\alpha_{ln}^m, P_{ln}^m)} \sum_{m \in \mathcal{M}} \sum_{n \in \mathcal{N}_g} \sum_{l \in \mathcal{L}_n} \alpha_{ln}^m R_{ln}^m
\]  

s.t. 

\[
\sum_{l \in \mathcal{L}_n, n \in \mathcal{N}_g} \alpha_{ln}^m h_{ln, gn} P_{ln}^m \leq \zeta_n^m, \quad m \in \mathcal{M}, \quad (2.20)
\]

\[
P_{ln}^m + n_0 \leq h_{ln, gn} P_{ln}^m \chi_{ln}, \forall n, m, l, \quad (2.21)
\]

\[
\alpha_{ln}^m = \begin{cases} 
0, & \text{if } l' \in \mathcal{L}_{n'}, \ n' \in T_{ln}^m, \ m \in \mathcal{M}, \\
1, & \text{if } l' \in \mathcal{L}_{n'}, \ n' \notin T_{ln}^m, \ m \in \mathcal{M}, 
\end{cases} \quad (2.22)
\]

\[
0 \leq \sum_{m=1}^M \alpha_{ln}^m \leq 1, \quad n \in \mathcal{N}_g, l \in \mathcal{L}_n, \quad (2.23)
\]

\[
\alpha_{ln}^m = \{0, 1\}, \quad n \in \mathcal{N}_g, l \in \mathcal{L}_n, m \in \mathcal{M}, \quad (2.24)
\]

\[
P_{ln}^{m, \text{min}} \leq P_{ln}^m \leq P_{ln}^{m, \text{max}}, \forall n, m, l, \quad (2.25)
\]

where let \(\mathcal{N}_g\) denote the set of CFBSs that belong to the DJG \(g\). Constraint (2.23) is taken from (2.13), and \(n, n' \in \mathcal{N}_g\). Herein, the network size is decreased, but **OPT-2g** is still an NP-hard optimization problem. In the next section, we discuss in detail how to find the optimal solution of **OPT-2g**.

We note that, the intra-tier interference \(I_{ln}^m\) in (2.22) is determined based on (2.3) as follows:

\[
I_{ln}^m = Z_{ln, g}^{m} + Z_{ln, gn}^{m} + h_{ln, gn}^{m} P_{ln}^m.
\]  

where \(Z_{ln, g}^{m} = \sum_{l' \in \mathcal{L}_{n'}, n' \in \mathcal{N}_g} h_{ln', gn}^{m} P_{ln'}^{m}\) is the intra-tier interference from CFUEs inside DJG \(g\) to CFBS \(m\) on subchannel \(m\); \(Z_{ln, gn}^{m} = \sum_{l' \in \mathcal{L}_{n'}, n'' \in \mathcal{N}_g \setminus \mathcal{N}_g} h_{ln', gn}^{m} P_{ln'}^{m}\) is the intra-tier interference from CFUEs outside DJG \(g\) to CFBS \(n\) on subchannel \(m\).
2.4 Resource allocation based on coalitional game in partition form.

Herein, the problem \( \text{OPT}-2 \) is solved based on coalition game approach where CFUEs are players as follows. Firstly, the \( \text{OPT}-2_g \) of each DJG \( g \) is formulated as a coalitional game in partition form. Secondly, we present the recursive core method to solve the proposed game. Thirdly, we address an implementation of the recursive core method to determine the optimal subchannel and power allocation in a distributed way. Finally, we consider the convergence and existence of the Nash-stable coalitions in the game.

2.4.1 Formulation \( \text{OPT}-2_g \) as a coalitional game in partition form

The coalitional game is a kind of cooperative game that is denoted by \( (\mathcal{L}_g, U^{\mathcal{L}_g}) \), in which individual payoffs of a set of players \( \mathcal{L}_g \) are mapped in a payoff vector \( U^{\mathcal{L}_g} \). The players have incentives to cooperate with other players, in which they seek coalitions to achieve the overall benefit or worth of the coalitions. The coalitional game in partition form is one such game expression, which is studied and applied in [14,21,22]. The worth of coalitions depend on how the players outside of the coalition are organized and on how the coalitions are formed. In the coalitional game, the cooperation of players to form coalitions is represented as the non transferable utility (NTU) game which is defined as follows [14]:

**Definition 1.** A coalitional game in partition form with NTU is defined by the pair \( (\mathcal{L}_g, U^{\mathcal{L}_g}) \). Here, \( U^{\mathcal{L}_g} \) is a mapping function such that every coalition \( \mathcal{S}_{m,g} \subset \mathcal{L}_g \), \( U^{\mathcal{L}_g} (\mathcal{S}_{m,g}, \phi_{\mathcal{L}_g}) \) is a closed convex subset of \( \mathbb{R}^{|\mathcal{S}_{m,g}|} \), which contains the payoff vectors available to players in \( \mathcal{S}_{m,g} \).

The mapping function \( U^{\mathcal{L}_g} \) is defined as follows:
Chapter 2: RA for CFNs: A Coalitional Game in Partition Form Approach

\[ U_{\mathcal{L}_g}(\mathcal{S}_{m,g}, \phi_{\mathcal{L}_g}) = \left\{ x \in \mathbb{R}^{\mathcal{S}_{m,g}} \mid x_{ln}(\mathcal{S}_{m,g}, \phi_{\mathcal{L}_g}) = R^m_{ln}(\mathcal{S}_{m,g}, \phi_{\mathcal{L}_g}) \right\} \]

(2.28)

where \( x_{ln}(\mathcal{S}_{m,g}, \phi_{\mathcal{L}_g}) \) is the individual payoff of player \( l \in \mathcal{L}_n \), which corresponds to the benefit of a member in \( \mathcal{S}_{m,g} \) in partition form \( \phi_{\mathcal{L}_g} \) of group \( g \). The CFUE \( l \in \mathcal{L}_n \) belongs to coalition \( \mathcal{S}_{m,g} \) depending on the partition \( \phi_{\mathcal{L}_g} \) in a feasible set \( \Phi_{\mathcal{L}_g} \) of players joining coalitions.

**Remark 1.** The singleton set \( U_{\mathcal{L}_g}(\mathcal{S}_{m,g}, \phi_{\mathcal{L}_g}) \) is closed and convex [58].

In summary, the players make individual distributed decisions to join or leave a coalition to form optimal partitions that maximize their utilities and bring the overall benefit of coalitions. Based on the characteristics and principles of this game, we model the OPT-2\(_g\) as a coalitional game in partition form. Instead of finding the global optimal that cannot be solved directly, CFUEs will cooperate with other CFUEs to achieve sub-optimal solution of the optimization problem OPT-2\(_g\).

**Proposition 1.** The optimization problem OPT-2\(_g\) can be modeled as a coalitional game in partition form \((\mathcal{L}_g, U_{\mathcal{L}_g})\).

**Proof.** CFUE \( l \in \mathcal{L}_n \) and its data rate \( R^m_{ln} \) in a certain DJG \( g \) are considered as player \( l \in \mathcal{L}_n \) and individual payoff \( x_{ln}(\mathcal{S}_{m,g}, \phi_{\mathcal{L}_g}) \) in the game, respectively. A set of CFUEs that belong to DJG \( g \) is represented as \( \mathcal{L}_g \). The data rate \( R^m_{ln} \) is mapped in a payoff vector \( U_{\mathcal{L}_g} \) as in (2.28). In order to address formation of a certain coalition \( \mathcal{S}_{m,g} \), we assume that there are only \( M + 1 \) candidate coalitions \( \mathcal{S}_{m,g} \) that CFUEs can join, \( m \in \mathcal{M} \cup \{0\} \). Here, \( \mathcal{S}_0 \) means that CFUEs in this coalition are not allocated to any subchannel. Furthermore, each joining or leaving coalition of CFUEs has to satisfy the constraints of the optimization problem OPT-2\(_g\). The total data rate of CFUEs using the same subchannel bring the
overall benefit or worth of a coalition. In order to find a sub-optimal value in $\text{OPT} - 2_g$, CFUEs have incentives to cooperate with other CFUEs. The cooperation information consists of the subchannels and power levels allocated to CFUEs. Intuitively, if CFUEs do not exchange their information with other CFUEs, the system performance will be degraded due to unsatisfied constraints (2.21)-(2.26), as mentioned in 2.3.1. Moreover, from (2.27), the individual payoff of each CFUE depends on CFUEs belong to $L_g$ using the same subchannels. In addition, the individual payoff of CFUEs depend on using subchannels of CFUEs at other DJGs. Hence, in order to improve the individual payoff value of CFUEs, incentives to cooperate among CFUEs are necessary [14, 49, 72]. Therefore, the $\text{OPT} - 2_g$ can be solved based on modeling as a coalitional game in partition form.

In order to solve this game, we simplify the coalition formation by assuming the value of the coalition depends on the outside coalitions, which is intra-tier interference from other DJGs. Then, we apply the recursive core method that is introduced in [22, 57] to solve this proposed game. Different from the core of Shapley value in the characteristic form, recursive core allows modeling of externalities for games in partition form [57]. The details of the solution are discussed in the following subsection.

2.4.2 Recursive core solution

As discussed in [22, 57], the NTU game in partition form is very challenging to solve. However, we can use the concept of a recursive core to solve the proposed game [57]. Normally, the recursive core is defined for games with transferable utility (TU), where a real function captures the benefit of a coalition instead of mapping [22, 57]. Moreover, since the mapping function in (2.28) is a singleton set, we can define an adjunct coalition game as $(L_g, v)$ for the proposed game in which the benefit of each coalition $S_{m,g}$ is captured over a real line $v(S_{m,g})$. By doing so, the original game $(L_g, U_{L_g})$ is solved via the adjunct coalition
game \((L_g, v)\) that is similar to games with transferable utility as studied in [49, 54, 72].

Whenever a CFUE detects a coalition \(S_{m,g}\) that it can join, it compares its payoff in the current coalition and payoff in coalition \(S_{m,g}\). If the payoff in \(S_{m,g}\) is greater than the current then CFUE will join it; otherwise will stay in the current coalition. In the NTU game, payoffs are a direct by product of the game itself due to power allocation of CFUEs on subchannel \(m\) to avoid violation of MBS protection (2.21) and providing guaranteed QoS to CFUEs in coalition as in (2.22). However, the payoff values of players are not determined solely by the data rate that CFUEs can achieve because of the CFUEs are the subscribed users of the wireless service providers. Meanwhile, the wireless service providers are the operators of the networks, so they can control the payoffs of the players via network coordinator from two aspects. First, service providers can physically provide different services to cooperative and non-cooperative users using rewards and punishment. Second, the CFUEs are stimulated to act cooperatively and improve the overall performance of the formed coalition \(S_{m,g}\) or network while guaranteeing the MBS protection and CFUEs’QoS, which can be obtained via division of the single TU value \(v(S_{m,g})\) [22, 57]. Whenever \(S_{m,g}\) belongs to \(\phi_{L_g}\), the function value \(v(S_{m,g}, \phi_{L_g}) \in v\) of our game is determined as follows:

\[
v(S_{m,g}, \phi_{L_g}) = \begin{cases} 
\sum_{ln \in S_{m,g}} x_{ln}, & \text{if } (2.21), (2.22), \text{ and } |S_{m,g}| \geq 1, \\
0, & \text{otherwise.}
\end{cases}
\]

We can see that the mapping vector of the individual payoff value of CFUEs in (2.28) is uniquely given from (2.29) and the core in TU game is non-empty [22]. Thus, we are able to exploit the recursive core as a solution concept of the original game \((L_g, U_{L_g})\) by solving the game \((L_g, v)\) while restricting the transfer of payoffs according to the unique mapping in (2.28). Here, the value \(v(S_{m,g}, \phi_{L_g})\) is the sum-rate of CFUEs allocated to the same subchannel \(m\) in partition \(\phi_{L_g}\). Through cooperating and sharing the payoff among
CFUEs in the coalition $m$, CFUEs achieve their optimal power allocation to maximize each coalition $S_{m,g}$ to which they belongs (details are discussed in Algorithm 2.2 of section 2.4.3). Then, based on the results in each coalition, the optimal subchannel allocations are determined by finding the core of the game using the recursive core definition.

Before describing the recursive core definition, we define a residual game that is an important intermediate problem. The residual game $(R, v)$ is a coalitional game in partition form that is defined on a set of CFUEs $R = L_g \setminus S_{m,g}$. CFUEs outside of $R$ are deviators, while CFUEs inside of $R$ are residuals [22, 57]. The residual game is still in partition form and can be solved as an independent game, regardless of how it is generated [14]. For instance, when some CFUEs are deviators that reject an existing partition, they have incentives to join another coalition that satisfy (2.23), (2.24), (2.25) and subchannel reuse table $T_g$. Naturally, their decisions will affect the payoff values of the residual CFUEs. Hence, the residual game of CFUEs forms a new game that is a part of the original game. CFUEs in the residual game still have the possibility to divide any coalitional game into a number of residual games which, in essence, are easier to solve. The solution of a residual game is known as the residual core [22, 57], which is a set of possible game outcomes, i.e. possible partitions of $R$. The recursive core solution can be found by recursively playing residuals games, which are defined as follows (mentioned in [57], definition 4):

**Definition 2.** The recursive core $C(L_g, v)$ of a coalitional formation game $(L_g, v)$ is inductively defined as follows:

1) **Trivial Partition.** The core of a game with $L_g$ is only an outcome with the trivial partition.

2) **Inductive Assumption.** Proceeding recursively, consider all CFUEs belonging to the DJG $g$, and suppose the residual core $C(R, v)$ for all games with at most $|L_g| - 1$ CFUEs has been defined. Now, we define $A(R, v)$ as follows: $A(R, v) = C(R, v)$, if $C(R, v) \neq \emptyset$; $A(R, v) = \emptyset$. \end{definition}
\( \Omega(\mathcal{R},v) \), otherwise. Here, let \( \Omega(\mathcal{R},v) \) denote a set of all possible outcomes of game \((\mathcal{R},v)\).

3) Dominance. An outcome \((x,\phi_{\mathcal{L}_g})\) is dominated via coalition \(S_m\) if at least one \((y_{\mathcal{L}_g}\setminus S_{m,g},\phi_{\mathcal{L}_g}\setminus S_{m,g}) \in A(\mathcal{L}_g\setminus S_{m,g},v)\) there exists an outcome \(((y_{S_{m,g}},y_{\mathcal{L}_g}\setminus S_{m,g}),\phi_{S_{m,g}} \cup \phi_{\mathcal{L}_g}\setminus S_{m,g}) \in \Omega(\mathcal{L}_g,v), \text{ such that } (y_{S_{m,g}},y_{\mathcal{L}_g}\setminus S_{m,g}) \succ S_{m,g} x. \) The outcome \((x,\phi_{\mathcal{L}_g})\) is dominated if it is dominated via a coalition.

4) Core Generation. The recursive core of a game of \(|\mathcal{L}_g|\) is a set of undominated partitions, denoted by \(C(\mathcal{L}_g,v)\).

In Step 1, the core of a trivial partition is initialized with CFUEs belonging to coalition 0. Step 2 is an inductive assumption that establishes the dominance for a game of \(|\mathcal{L}_g|\)-1 CFUEs through inductive steps of the formed coalitions. For instance, subchannel allocation permits assigning subchannels to CFUEs to bring dominance. Step 3 is the main step for checking and finding dominant coalitions, which captures the value of a coalition depending on partitions. We define \(x\) as the payoff vector of players and \(\phi_{S_{m,g}}\) as the partition of the user set \(\mathcal{L}_g\). The payoff vector \(x\) is an undominated coalition if there exists a way to partition that brings an outcome \(((y_{S_{m,g}},y_{\mathcal{L}_g}\setminus S_{m,g}),\phi_{S_{m,g}} \cup \phi_{\mathcal{L}_g}\setminus S_{m,g})\) that achieves greater reward to CFUEs of \(S_{m,g}\), compared to \(x\). Corresponding to each DJG partition, the individual payoffs of all CFUEs in the game are uniquely determined and undominated. Furthermore, the coalitions in the recursive core are formed to provide the highest individual payoffs or data rates of CFUEs, as detailed in Step 4.

### 2.4.3 Implementation of the recursive core at each coalitional game formation in partition form at DJGs

We address implementation of the recursive core method to solve the proposed game, which is sketched in Fig. 2.6. As discussed in the above subsection, the game \((\mathcal{L}_g,U_g)\) is solved via the game \((\mathcal{L}_g,v)\). According to this alternative, the coalition \(S_{m,g}\) in a partition \(\phi_{\mathcal{L}_g}\) is
represented by a real function $v(S_{m,g,\phi_L})$ as in (2.29). Corresponding to the subchannel allocation of CFUEs, some CFUEs can be allocated into the same subchannel $m$, which forms a coalition $S_{m,g}$. Then, CFUEs optimize their individual payoffs by sharing with other CFUEs in the same coalition $S_{m,g}$. In this case, CFUEs cooperate with others in coalition $m$ to maximize the individual payoff and value $v(S_{m,g,\phi_L})$. Sharing is achieved by finding optimum power values of each CFUE in the following optimization problem:

**OPT-2**$_{S_{m,g,\phi_L}}$:

$$\text{maximize } \quad v(S_{m,g,\phi_L})$$

subject to:

$$\sum_{ln \in S_{m,g}} h_{ln,0}^m P_{ln}^m \leq \zeta_0^m,$$  

$$Z_{m,g}^n + Z_{m,g}^n + h_{ln,n}^m P_{ln}^m + n_0 \leq h_{ln}^m P_{ln}^m \chi_{ln}, \quad l \in L_n, ln \in S_{m,g},$$

$$P_{ln}^m,\min \leq P_{ln}^m \leq P_{ln}^m,\max, \quad ln \in S_{m,g}, l \in L_n.$$  

The constraint (2.32) is taken from (2.22) and (2.27). When CFUE $l \in L_n$ belongs the coalition $S_{m,g}$, $\alpha_{ln}^m$ is set to 1, otherwise is set to 0. Therefore, without loss of generality, we ignore parameter $\alpha_{ln}^m$ in **OPT-2**$_{S_{m,g,\phi_L}}$. By finding the optimal power allocation to CFUEs, they will achieve an optimum individual payoff value that maximizes the worth of coalition $S_{m,g}$. The optimal solution of **OPT-2**$_{S_{m,g,\phi_L}}$ can be found in a centralized or distributed way. We find the optimal solution in a distributed way. We solve the optimization problem by modeling as a geometric convex programming problem [55, 59, 64]. Then, the optimum values can be found using Karush–Kuhn–Tucker (KKT) conditions [55, 58, 59, 73], as follows:

$$P_{ln}^m = e^{h_{ln}^m} = \frac{1 + \mu_{ln}}{\beta h_{ln,0}^m + \eta_{ln} - s_{ln}},$$  

(2.34)
Algorithm 3

The partition of the DJG-g into coalitions under partition.

Each coalition $m$ corresponds to the partition that finds optimum $P^m$ power level through Algorithm 2 to maximize $OP1_{s_i}$. 

algorithm

Check convergence based on conditions of recursive core.

no

yes

Optimal values $a_{ln}^{m*}, P_{ln}^{m*}$

Figure 2.6: The determination of the optimal solution of $OPT-2_g$ based on the coalitional game in partition form.

where $[a]^+ = \max\{a, 0\}$; the Lagrange multipliers $\beta, \mu_{ln}, \eta_{ln}, \varsigma_{ln}$ and the consistency price $\vartheta_{ln}$ for all CFUE $ln \in S_{m,g}$ are updated as (2.35), (2.39), (2.36), (2.37) and (2.38), respectively.
\[
\beta(t) = \left[ \beta(t-1) + s_1(t) \left( \sum_{\forall \ln \in S_{m,g}} h_{ln,0}^m e^{y_{ln}^m} - \zeta_0^m \right) \right]^+, \quad (2.35)
\]

\[
\eta_{ln}(t) = \left[ \eta_{ln}(t-1) + s_2(t) \left( y_{ln}^m(t) - \log P_{ln}^{m,\text{max}} \right) \right]^+, \quad (2.36)
\]

\[
\varsigma_{ln}(t) = \left[ \varsigma_{ln}(t-1) + s_3(t) \left( -y_{ln}^m(t) + \log P_{ln}^{m,\text{min}} \right) \right]^+, \quad (2.37)
\]

\[
\vartheta_{ln}(t) = \left[ \vartheta_{ln}(t-1) + s_4(t) \left( Z_{n,g}^m - e^{z_{n,g}^m} \right) \right]^+. \quad (2.38)
\]

\[
\mu_{ln}(t) = \left[ \mu_{ln}(t-1) + s_5(t) \log \left( \frac{e^{-y_{ln}^m} \left( e^{z_{n,g}^m} + Z_{n,g}^m \right) + h_{ln,n}^m P_{ln}^m + n_0}{h_{ln}^m} \right) - \log(\chi_{ln}) \right]^+. \quad (2.39)
\]

We use the changing logarithm of the variables \( y_{ln}^m = \log P_{ln}^m \). The parameter \( s_i(t) \) represents the step size satisfying

\[
\sum_{t=0}^{\infty} s_i(t)^2 < \infty, \quad \text{and} \quad \sum_{t=0}^{\infty} s_i(t) = \infty, \quad \forall i = 1, 2, 3, 4, 5, \quad (2.40)
\]

which leads to the convergence of algorithms [58]. Additionally, the variable \( z_{n,g}^m \) is also calculated from the KKT necessary conditions as follows:

\[
e^{z_{n,g}^m} = \frac{\vartheta_{ln} \left( Z_{n,g}^m + h_{ln,n}^m P_{ln}^m + n_0 \right)}{1 - \vartheta_{ln} + \mu_{ln}}, \quad (2.41)
\]

where \( z_{n,g}^m = \log(Z_{n,g}^m) \).

The details of finding the optimum value \( P_{ln}^m \) and \( e^{z_{n,g}^m} \) in OPT-2_{S_{m,g},\phi_{\mathcal{L}}} is expressed in Appendix A. The updating of values \( e^{z_{n,g}^m} \) and \( P_{ln}^m \) are expressed in Algorithm 2.2.

In Algorithm 2.2, the information being exchanged among CFUEs and CFBSs is based on feedback, such as ACK/NACK. This information can be exchanged in forms such as wired back-hauls, dedicated control channels, or pilot signals. The CFBS measures the
Algorithm 2.2 Distributed power allocation for CFUEs in the coalition \( S_{m,g} \subseteq \phi\mathcal{L}_g \)

**Inputs:** \( P_{ln}^m(t) \in \left[ P_{ln}^{m,\min}, P_{ln}^{m,\max} \right], \forall ln \in S_{m,g} \)

1: Initialize \( t = 0, \beta_0 > 0, \mu_{ln}(0) > 0, \eta_{ln}(0) > 0, \varsigma_{ln}(0) > 0, \vartheta_{ln}(0) > 0, \)
\( P_{ln}^m(0) \in \left[ P_{ln}^{m,\min}, P_{ln}^{m,\max} \right], \chi_{ln}, \forall ln \in S_{m,g} \).

2: *At the CFBS* \( n, \forall n \in S_{m,g}:*

3: Measures the interference \( I_{m,n,g}^m \).

4: Calculates the variable \( e_{n,g}^m \) as in (2.41).

5: Updates the Lagrange multiplier \( \mu_{ln}(t + 1) \) and consistency price \( \vartheta_{ln}(t + 1) \) using (2.39) and (2.38), respectively.

6: Transmits \( \mu_{ln}(t + 1) \) to CFUE \( l \in \mathcal{L}_n \).

7: *At the CFUE* \( l \in \mathcal{L}_n, ln \in S_{m,g}:*

8: Estimates channel gain \( h_{ln,0}^m \) and compute the total interference at the MBS; Receives the updated value \( \mu_{ln}, \vartheta_{ln} \).

9: Updates the Lagrange multipliers \( \beta, \eta_{ln}, \) and \( \varsigma_{ln} \) from (2.35), (2.36), and (2.37), respectively.

10: Calculates the power value \( P_{ln}^m(t + 1) \) as in (2.34).

11: Sends power value \( P_{ln}^m(t + 1) \) and \( h_{ln,0}^m(t + 1) \) to other CFUEs in the coalition \( S_{m,g} \).

**Output:** Optimal transmit power level \( P_{ln}^{m,*} \) and optimal value \( v(S_{m,g}, \phi\mathcal{L}_g)^{m,*} \) of the formed coalition \( m \).

intra-tier interference and inter-tier interference on subchannel \( m \) (Step 3). Then, the CFBS updates the value \( e_{n,g}^m(t + 1) \) (Step 4). The Lagrange multiplier \( \mu_{ln}(t + 1) \) and consistence price \( \vartheta_{ln}(t + 1) \) are updated (Step 5). After that, the CFBS transmits \( \mu_{ln}(t + 1) \) to CFUE \( l \) (Step 6). CFUE \( l \in \mathcal{L}_n \) estimates channel gain \( h_{ln,0}^m(t + 1) \) and the aggregated interference at the MBS (Step 8). Simultaneously, CFUE \( l \in \mathcal{L}_n \) gets updated values of \( \beta(t + 1), \vartheta_{ln}(t + 1) \) from CFBS \( n \). We note that the value threshold \( \xi_0^m \) is updated from MBS via
a weighted interference vector depending on the formed coalition. Then, the remaining
Lagrange multipliers are updated via (2.35), (2.36), (2.37) (Step 9). After that, the CFUE
updates the power value at time $t+1$, as in Step 10. Then, the CFUE sends its the newest
power value $P_{m}^{n}(t+1)$ and newest channel gain $h_{m,n}^{n}(t+1)$ to other CFUEs that belong
to coalition $S_{m,g}$ (Step 11). $\text{OPT-2}_{S_{m,g},\phi_{L_{g}}}$ is transformed to the convex optimization
problem, the optimal duality gap is equal to zero, and step-sizes satisfy (2.40). Therefore,
the solution $P_{m}^{n}$ will converge to the optimal solution under Algorithm 2.2.

After finishing Algorithm 2.2, in general, coalition $S_{m,g}$ guarantees the optimal sharing
payoffs among members CFUEs. Simultaneously, we also find the optimum worth $v(S_{m,g},\phi_{L_{g}})$ of coalition $S_{m,g}$. Based on the steps in the Definition 2, we propose Al-
gorithm 2.3 to find recursive core which leads to the distributed subchannel and power
allocation.

To obtain a partition in the recursive core, the CFUEs in $L_{g}$ use Algorithm 2.3. In
the initial step, the information on subchannel reuse table $T_{g}$ of DJG $g$ is formed at the
network coordinator (Step 1). The network coordinator makes decision to allocate sub-
channel to CFUEs with the assurance to protect MBS and provide guaranteed QoS to
CFUEs. The individual payoff values of CFUEs in (2.28) are mapped to the formed coalitions via (2.29). Then, in the coalition formation, the value of whole game in group $g$
$(\sum_{m\in M\cup\{0\}} v(S_{m,g},\phi_{L_{g}}))$ is captured at the network coordinator. Network partitions of
DJG $g$ are controlled by network coordinator that makes a decision to assign CFUEs into
coalition $S_{m,g}$, $\forall m \in M \cup \{0\}$ (Step 3). Additionally, network partitions of DJG $g$ have
to satisfy the principles in the subchannel reuse table $T_{g}$ and Steps 4, 5, and 6. After that
CFUEs find the optimal transmit power and individual payoff value based on Algorithm 2.2
in order to adopt their delay requirement and the MBS protection (Step 7). The network
coordinator updates the undominance partition via Step 3 of Definition 2 (Steps 8 and 9).
**Algorithm 2.3** Distributed algorithm for subchannel and power allocation in cognitive femtocell network.

1: * Initialization: CFUEs and CFBSs form DJGs ← Algorithm 2.1; Forms table $T_g$;  
   \[ \phi_{L_g}^{(0)} = \{ \{1\}, \{2\}, \ldots, \{|L_g|\} \} \]
   in which CFUEs are randomly allocated subchannel and transmit power with non-cooperative among FUEs.

2: * Coalition formation at each DJG $g$:

3: CFUEs operate in cooperative mode and join into potential coalitions $\phi_{L_g} = \{ \{0\}, \{1\}, \ldots, \{|M|\} \}$ that satisfy the table $T_g$.

4: for player \(\{nl\} \in L_g\) do
   
5:     for $S_{m,g} \in \{\phi_{L_g}^{(k-1)} \setminus \{nl\}\}$ do
   
6:         Set $\phi_{L_g}^{(k)} := \{\phi_{L_g}^{(k-1)} \setminus S_{m,g} \cup \{nl\}\}$.

7:         Find $v(S_{m,g}, \phi_{L_g}^{(k)}) \leftarrow$ based on (2.29) and Algorithm 2.2.

8:         if $\sum_{m \in M \cup \{0\}} v(S_{m,g}, \phi_{L_g}^{(k)}) > \sum_{m \in M \cup \{0\}} v(S_{m,g}, \phi_{L_g}^{(k-1)})$, then
   
9:             Set $\phi_{L_g}^{(k)} = \phi_{L_g}^{(k-1)}$.

10:            Update $\alpha_{ln}^{m*}$, $P_{ln}^{m*}$.

11:        end if

12:     end for

13: end for

**Output:** Output the stable core of game $(L_g, v)$ consisting of both the final partition $\phi_{L_g}^{*}$, subchannel allocation decision $\alpha_{ln}^{m*}$, and transmit power level $P_{ln}^{m*}$.

The algorithm is repeated until it converges to the stable partition $\phi_{L_g}^{(k)*}$, which results in an undominated partition in the recursive core. Whenever undominated partition $\phi_{L_g}^{(k)*}$ is updated at time $k$, the network coordinator updates subchannel allocation to CFUEs (Step 10). CFBS of each femtocell shares the resource usage information among each other when...
they get the updated information from its CFUEs. Sharing of these confirmation causes overhead in the system. However, we have mitigated the amount of messages exchange by forming DIGs. By doing this, only CFUEs inside a DJG are permitted to exchange information. In addition, observation of the value $v(S_m, \phi_{L_g})$ is done by network coordinator such as the femtocell gateway [72]. We note that the subchannel and power allocation of CFUEs are updated whenever a network partition is transferred from partition $(k - 1)$ to partition $(k)$, which produces Pareto dominates $S^{(k)}_{m,g}$. The convergence and Nash-stable coalitions in Algorithm 2.3 are discussed in the next subsection.

2.4.4 Convergence and stable analysis of the proposed game

Convergence of the proposed game through four steps of the recursive core method is guaranteed as follows:

**Propriety 1.** Starting from any initial partition $\phi_{L_g}$, using the Algorithm 2.3, coalitions of CFUEs merge together by Pareto dominance, which results in a stable network partition and lies in the non-empty recursive core $C(L_g, v)$.

Proof. Let $\phi^{(k)}_{L_g}$ be the formed partition at iteration $k$ that is based on principles of residual game (Steps 5 and 6 of Algorithm 2.3). The individual payoff of CFUE $l \in L_n$ via a function $v^{(k)}(S^{(k)}_{m,g}, \phi^{(k)}_{L_g})$ as (2.29) is denoted by $x^{(k)}(S^{(k)}_{m,g}, \phi^{(k)}_{L_g})$. Therefore, each distributed decision made by the CFUE in Algorithm 2.3 can be seen as a sequential transformation of the composition of the network partition as follows:

$$
\phi^{(0)}_{L_g} \rightarrow \phi^{(1)}_{L_g} \rightarrow \phi^{(2)}_{L_g} \rightarrow \ldots \rightarrow \phi^{(k)}_{L_g} \rightarrow \ldots,
$$

(2.42)

where the decision of making a partition is managed by the network coordinator; and $\phi^{(k)}_{L_g}$ is the network partition in DJG $g$ after $k$ transfers. Every transfer operation from partition
(k − 1) to partition (k) is an inductive step, which produces Pareto dominates $S_{m,g}^{(k)}$ as follows:

$$\phi_{L_g}^{(k-1)} \rightarrow \phi_{L_g}^{(k)} \Leftrightarrow \sum_{S_{m,g}^{(k)} \in \phi_{L_g}^{(k)}} v(S_{m,g}^{(k)}, \phi_{L_g}^{(k)}) > \sum_{S_{m,g}^{(k-1)} \in \phi_{L_g}^{(k-1)}} v(S_{m,g}^{(k-1)}, \phi_{L_g}^{(k-1)}).$$  \quad (2.43)

We note that, each CFUE gradually selects the coalition based on reuse table $T_g$ and conditions (2.23), (2.24) and (2.25). Hence, the value of coalition will be set to zero if any condition of the formed coalition is violated, and the value of other coalitions remains unchanged. Therefore, in Algorithm 2.3, when any two successive steps k − 1 and k are successful, then we have $v(\phi_{L_g}^{(k)}) = \sum_{S_{m,g}^{(k)} \in \phi_{L_g}^{(k)}} v(S_{m,g}^{(k)}, \phi_{L_g}^{(k)})$ is Pareto dominated by $\phi_{L_g}^{(k)}$.

Therefore, Algorithm 2.3 ensures that the overall network utility sequentially increases by Pareto dominance. In addition, the sum of values of the coalitions in each group $g$ increases without decreasing the payoffs of the individual CFUEs and the whole network as well. Since the number of partitions of $L_g$ CFUEs into $M + 1$ coalitions is a finite set given by the Bell number [22], thus the number of transmission steps in (2.42) is finite. Hence, the sequence in (2.42) will terminate after a finite number of inductive steps and will converge to a final partition.

After DJG $g$ partition converges to a final partition $\phi_{L_g}$, it is still not guaranteed analytically that the partition is Nash-stable. A partition $\phi_{L_g}$ is Nash-stable if no player can get benefit in transferring from its coalition $(S_{m,g}, \phi_{L_g})$ to another existing coalition $S_{m'}$, which can be mathematically formulated based on [74] as follows:

**Definition 3.** The partition $\phi_{L_g}$ is Nash-stable with Pareto dominance if $\forall \ln \in L_g$, such that $\ln \in S_{m,g}, S_{m,g} \in \phi_{L_g}$; thus, $(S_{m,g}, \phi_{L_g}) \succeq_{\ln} (S_{m', \ln} \cup \{ln\}, \phi'_{L_g})$ for all $S_{m'} \in \phi_{L_g} \cup \emptyset$ with $\phi'_{L_g} = (\phi_{L_g} \setminus \{S_{m,g}, S_{m'}\}) \cup \{S_{m,g} \setminus \{ln\}, S_{m'} \cup \{ln\}\}$.

Hence, the stability of partition $\phi_{L_g}$ in the proposed game can be considered as below.
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Proposition 2. Any final partition \( \phi_{L_g} \) belongs to the core \( C(L_g, v) \) of the DJG in Algorithm 2.3 and always converges to a Nash-stable partition.

Proof. Consider a partition \( \phi'_{L_g} \) belongs to core \( C(L_g, v) \), that is found according to the four steps in Definition 2. If this partition is not Nash-stable, then there exists a CFUE \( ln \in L_g \) with \( ln \in S_{m,g} \), \( S_{m,g} \in \phi'_{L_g} \), and a coalition \( S_{m'} \in \phi'_{L_g} \) such that \( y(S_{m'} \cup \{ln\}, \phi'_{L_g}) >_{ln} x(S_{m,g}, \phi_{L_g}) \), and CFUE \( l \in L_n \) can move to coalition \( S_{m'} \). Here, \( \phi_{L_g} = (\phi_{L_g} \setminus \{S_{m,g}, S_{m'}\} \cup \{S_{m,g} \setminus \{ln\}, S_{m'} \cup \{ln\}\}) \). However, this contradicts with the final partition \( \phi_{L_g} \) in Property 1. On the other hand, after finishing the recursive core formation, we can see that CFUEs have no incentive to abandon their coalitions, because any deviation can be detrimental. As a result, a partition \( \phi_{L_g} \) in the recursive core is also stable since it ensures the highest possible payoff for each CFUE with no incentive to leave this partition, as studied in [75]. Thus, any partition \( \phi_{L_g} \) that belongs to the core of Algorithm 2.3 is Nash-stable.

Obviously, the recursive core method applied to our proposed game always converges to a final DJG partition. Moreover, the network partition based on residual game always converges to a Nash-stable partition.

2.4.5 Computational complexity analysis

With respect of computational complexity, related to centralized solution, it is worth mentioning that finding a partition is strongly challenged by the exponentially growing number of required iterations and the signaling overhead traffic which would rapidly congest the backhaul and dedicate channels. Moreover, femtocell does not have reliable centralized control due to unreliable backhaul [46]. Due to these characteristics, femtocell deployment needs distributed solutions with automatic channel selection, power adjustment for autonomous interference coordination and coverage optimization. In our distributed solution, the complexity can be significantly reduced by considering follows aspects. First, in
our game, the network partition is managed by network coordinator of each DJG. Moreover, cooperation is established only among those CFUEs who are using the same subchannel in their DJG is often small. Further, the network partition formation does not depend on the order in which the CFUEs in coalition are evaluated, the number of iterations is further reduced. Second, the network partition is obtained by running residual games in each DJG with checks in subchannels reusing table, significantly reducing the search space and amount of exchanged information.

2.5 Simulation Results

As shown in Fig. 2.7, we simulate an MBS and 16 CFBSs with the coverage radii of 500 m and 30 m, respectively. In order to allocate subchannels to the femtocells, we utilize three SC-FDMA licensed subchannels, which are allocated to uplink transmission of three MUEs, each with bandwidth $B_w = 360$ kHz (by using two sub-carriers for each licensed subchannel) and a fixed power level of 500 mW. Moreover, the interference threshold at the MBS for each licensed subchannel equals to -70 dbmW. Each CFBS has two CFUEs, a pilots signal with power equals to 500 mW. Each CFUE has an arrival rate equals to 1.5 Mb/s, and the delay must be less than or equal to 10 ms. In addition, each CFUE has a maximum power level constraint ($P_{\text{max}}$) of 100 mW. We assume that distance-dependent path loss shadowing according to the 3GPP specifications [76] affects the transmissions.

After the network is initialized, the CFBS and MBS periodically broadcast the pilot signal to CFUEs. CFUEs measure RSSI of the pilot signals and estimate channel gain to the surrounding CFBSs. Additionally, the CFUE also estimates its channel gain to the MBS based on the messages broadcast from the MBS. Independently, the CFUE estimates the maximum power level for each licensed subchannel based on its own observed channel gain to the MBS and (2.1), in which the maximum power level on each licensed subchannel
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Figure 2.7: Self-organization of CFUEs in the CFN to six DJGs according to Algorithm 2.1. DJG-1, DJG-2, DJG-3, DJG-4, DJG-5 and DJG-6 are composed of CFUEs belonging to the groups CFBS \{1\}, \{2, 3, 12, 14\}, \{4, 15\}, \{5, 11, 13\}, \{6, 7, 8, 9, 10\} and \{16\}, respectively.

is determined by $P_{in,\text{max}} = \min(P_{\text{max}}, \zeta_m / h_{in,0})^+, \forall m \in \{1, 2, 3\}$.

The maximum power level of CFUEs on licensed subchannels are shown in Fig. 2.8. CFUEs in CFBS-16 have the highest maximum power level because the distance to MBS is too far from CFUEs where the MBS lies outside the interference threshold range.

In order to find DJGs, we run Algorithm 2.1. The self-organization DJGs are shown in Fig. 2.7, in which CFUEs self-organize into six DJGs. Simultaneously, the subchannel reuse tables among CFUEs of DJGs are also formed. The subchannel reuse tables of all DJGs are depicted in Fig. 2.9, in which value “0” means two CFUEs cannot be reused, else it has a value equal to “1”.

In Fig. 2.10, we compare our proposal to a random subchannel allocation scheme.
Specifically, we consider DJGs 1 and 5. Intuitively, by using Algorithm 2.3, DJG-5 needs 20 time steps, and DJG-1 needs 5 time steps to converge to the optimum value. On the other hand, by randomly allocating the subchannels, the sum-rate of each DJG-1 and DJG-5 is not stable and are lower than the optimum value. This examination is the same for all DJGs in the network. We also see that the sum-rate in each DJG using our scheme is greater than that of the random subchannel allocation scheme. Therefore, our scheme is more efficient than the random subchannel allocation scheme.

The convergence of DJGs after applying coalitional game approach via Algorithm 2.3 is shown in Fig. 2.11. By using the coalitional game, in each time step, all CFUEs will cooperate with other CFUEs in its formed coalition and form DJGs with joining and leaving principles to maximize the sum-rate of DJGs. Clearly, using the coalitional game approach, we can achieve a local optimum. We also see that the convergence of Algorithm 2.3 is achieved after around 18 time steps, as shown in Fig. 2.11.
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Figure 2.9: The subchannel reuse tables among CFUEs in DJGs of the CFN. The value “0” means two CFUEs cannot be reused the subchannels, else it has a value equal to “1”.

The results of the subchannel and power allocation based on the core of the game are shown in Figs. 2.12 and 2.13, respectively. In each group, some CFUEs may not be allocated to any subchannel because these allocations do not satisfy the constraints of the minimum delay and protection at the MBS. Additionally, the power of CFUEs in CFBS-16 are allocated with the maximum power level because the MBS is outside of the interference range of CFUEs in CFBS 16. Furthermore, this group is not affected by interference from other CFUEs in other DJGs or by interference from the MUEs.

To leverage subchannel variations and network stochastic realizations, the results are averaged over a large number of simulations. We consider our problem in 30 periods, and we estimate the social welfare of CFUEs by the utilitarian measure \( \left( \frac{1}{N \times L} \sum_{l=1}^{L} \sum_{n=1}^{N} R_{ln} \right) \) for each period. There are three schemes considered: our proposal given in Algorithm...
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The sum rate of the CFUEs in the DJGs (Mb/s)

Optimal channel allocation in DJG−1
Random channel allocation in DJG−1
Optimal channel allocation in DJG−5
Random channel allocation in DJG−5

Figure 2.10: The optimal subchannel allocation in DJG-1 and DJG-5.

The sum rate (Mbps)

DJG−1
DJG−2
DJG−3
DJG−4
DJG−5
Formation a new partition in DJG−5

Figure 2.11: The convergence of each disjoint group.
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The indexes of the CFBSs

Subchannel indexes

CFUE−2 of CFBS−6 is assigned to subchannel 1
CFUE−1 in CFBS−6 is assigned to subchannel 3

Figure 2.12: The optimal subchannel allocation of CFUEs.

The indexes of the CFBSs

Power (mW)

CFUE−1
CFUE−2
no subchannel and power level allocation
Maximum power allocation

Figure 2.13: The optimal power allocation of CFUEs.
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2.3, subchannel allocation using Algorithm 2.3 with the fixed maximum power level of CFUE (CA + maximum power allocation), and subchannel allocation using Algorithm 2.3 with random power level allocation to each CFUEs (CA + random power allocation). The results are shown in Fig. 2.14. Intuitively, our proposed scheme always achieves a higher social welfare utilities for all CFUEs compared to the other methods. Hence, sharing the individual payoff among CFUEs using Algorithms 2.2 is necessary to find the optimal solution of OPT-2.

Next, we estimate the social welfare of CFUEs \( \left( \sum_{i=1}^{L} \sum_{n=1}^{N} R_{in} \right) \) with respect to different interference thresholds of the MBS. Fig. 2.15 shows that for any interference threshold at the MBS, the social welfare of the proposed approach is always higher than those of the (CA + maximum power allocation) and (CA + random power allocation) schemes. Further, in Fig. 2.15, we have numerically compared the proposed approach with the optimal solution, in which CFUEs are allocated subchannel and transmit power in a centralized
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Figure 2.15: The social welfare of CFUEs in OPT-2 versus the interference threshold at the MBS.

fashion. The social welfare of all the schemes grows with the increase in interference
thresholds at the MBS. The comparison shows that performance of the proposed is close
to centralized solution. In addition, gaps between the proposed approach and centralized
solution are 4.56% and 4.96% when the interference thresholds are of -70 dBmW and -40
dBmW, respectively.

In order to see the social welfare versus the numbers of licensed subchannels, we fix the
positions of CFUEs and CFBSs. Then, we increase the number of licensed subchannels
that are allocated to CFN in the uplink direction. We examine OPT-2 with different
methods, as shown in Fig. 2.16. When the number of subchannels is less than or equal
to 11, the social welfare of CFUEs in our scheme is higher than that of the other two
schemes. With increasing number of licensed subchannels, the social welfare is increased
because more CFUEs are allocated to subchannels. The saturation point is achieved when
the number of subchannels is greater than or equal to 11 because, at this point, all CFUEs are allocated to the optimal subchannel and power level formed in the core of the proposed game. The scheme “Optimal CA + random power allocation” always has the smallest value because some CFUEs which are allocated with random power level do not satisfy the conditions to protect MBS or the minimum delay requirement of each CFUE. In such cases, the subchannel is not allocated to these CFUEs, which dramatically decreases the sum rate of all CFUEs, as well as the the social welfare in the network.

2.6 Summary

In this chapter, we investigated an efficient distributed resource allocation scheme for uplink underlay CFN. The efficient resource allocation is characterized via an optimization problem. We identified the optimal subchannels and power levels for CFUEs to maximize
the sum-rate. The optimization problem guaranteed the inter-tier and inter-tier interference thresholds. Specifically, the aggregated interference from femtocell users to the MBS and the maximum delay requirement of the connected CFUE are kept under the acceptable level. In order to solve the optimization problem, we simplified the CFN by forming DJGs and suggested a formulation optimization problem as a coalitional game in partition form in each formed disjoint group. The convergence of algorithms was also carefully investigated. Simulation results showed that the CFUEs can be self-organized into DJGs. Additionally, the sum-rate in the proposed framework is achieved by the optimal subchannel and power allocation policy with all CFUEs’ average delay constraints being satisfied. Moreover, the efficient resource allocation is tested, with the sum-rate of the proposed framework always being close to optimal solution and better than those of the other frameworks.
Chapter 3

Resource Allocation for
Virtualized Wireless Networks
with Backhaul Constraints

3.1 Background and contribution

The wireless network virtualization has recently been considered as a promising solution to increase the spectrum and infrastructure efficiency [8]. Using virtualization, the same infrastructure can be shared for differentiated services. Moreover, it provides easier migration to newer technologies while supporting legacy technologies by isolating part of the network.

In the current mobile wireless networks, in most of the applications, the backhaul capacity can be much larger than that of the last wireless hop from base station to users or from the users to the base station. However, this may not true in the future mobile networks because of the following reasons.
Firstly, nowadays, we are witnessing the proliferation of many new applications and services, mostly through cloud architecture and technologies [81]. Some applications require the same amount of upload and download capacity such as web meeting (cloud-based, video conferencing, tele-medicine, Internet of Things, virtual office and connected vehicle safety applications). Hence, the proliferation of new applications exacerbates the demand for high data rate services with a possible bottleneck in various backhaul solutions, e.g., xDSL, non-line-of-sight (NLOS) microwave, and wireless mesh networks [80].

Secondly, the considerably higher number of small cells in which backhaul links will mostly be inexpensive wired or wireless [82, 83]. In the case that multiple base stations might have to share the capacity of a single backhaul link causing a congestion at the backhaul link. Furthermore, the increased backhaul signaling traffic required for Coordinated Multi-Point (CoMP) transmission/reception [84], as well as the upcoming cloud-RAN (C-RAN) [85] technologies, are expected to further stress the backhaul network [83]. Hence, as the radio access technologies are constantly improving, it is argued that the backhaul network will emerge as a major performance bottleneck, and user association algorithms that ignore the backhaul load and topology can lead to poor performance [86].

Finally, in our work, we focus on the profit gained by a mobile virtual network operator (MVNO) which is a middleman who buys physical resources from the InP, bundling them into virtual resources called slides before selling off the service providers [87]. In order to guarantee the benefit at the MVNO side, the MVNO can mainly focus on assigning virtualized resources for subscribed users to the lowest cost InP. Hence, this assignment can cause a bottleneck at the backhaul links of the InP that has the lowest cost. This in turn can cause delay for the backhaul network assuming it is wireless or heterogeneous (i.e., a combination of wired and wireless technologies) [83].

Therefore, in order to guarantee the benefit of the MVNO and the subscribed users'
QoS demand, it is necessary to consider the backhaul constraint in the wireless network virtualization for future mobile network, as has also been considered in [82,83,86,88–90].

To fill the gap in the existing literature (backhaul and uplink considerations in the virtualized wireless network), we study the virtual resource allocation in an uplink virtualized cellular network. The resource allocation is formulated as an NP-hard optimization problem that jointly allocates power and slices in a business model. The design objective is to maximize the MVNO profit while guaranteeing the users' QoS requirements and the InP's backhaul constraints. Here, the chunk-based radio resource allocation approach (subcarrier aggregation) is used to isolate the slices for uplink transmissions in an orthogonal frequency division multiple access (OFDMA)-based system [41, 42]. The considered joint slice and power allocation complicate any optimization-based design due several coupled constraints: i) slice isolation, ii) backhaul limitation, and iii) chunk allocation for heterogeneous users’ QoS. Our research contributions are summarized as follows:

- We propose a slice isolation approach for the uplink of a virtualized cellular network in which the virtualized resources or slices are isolated by base stations and chunk-based radio resources owned by different InPs. This isolation ensures that each slice is uniquely determined and that the customization in one slice will not interfere with other slices.

- We propose a distributed algorithm based on Lagrangian relaxation to find suboptimal decision on slice and transmit power allocations. The problem is solved in two different phases of power allocation and slide allocation through updating the sequence of primal and dual variables. The optimal power is derived from Karush-Kuhn-Tucker (KKT) conditions, whereas the Hungarian method is applied to solve the slice allocation in a centralized manner.
To circumvent the requirement of global information, we further propose a distributed algorithm based on the concept of the matching game. This algorithm is shown to converge to a suboptimal solution.

Numerical results show that our proposed approaches require a small number of iterations to converge.

3.2 System model and problem formulation

3.2.1 System Model

We consider an OFDMA-based virtualized cellular network for uplink transmissions as shown in Fig. 3.1. The MVNO rents network resources from a set of $B = \{1, 2, ..., B\}$ InPs. For simplicity, we focus on a small area overlapped by multiple InPs, in which each InP provides infrastructure services including one small-cell base station (SBS), chunk-based wireless resources, and a wireless backhaul link underlay an InP’s macro-cell base station (MBS). The MVNO then provides virtual resource services to a set of $I = \{1, 2, ..., I\}$ SPs. Each SP $i \in I$ has a set $U^i = \{1, 2, ..., U_i\}$ subscribed users. Let $U$ be the set of all users of all SPs. The radio resources owned by InP $b$ consisting of a set of $L_b = \{1, 2, ..., L_b\}$ subcarriers are divided into $C_b = \{1, 2, ..., C_b\}$ chunks, each of which is aggregated by $L_{b,c} = \{1, 2, ..., L_b/C_b\}$ subcarriers. Each of these narrowband orthogonal subcarriers has a bandwidth of $W$. Additionally, we assume there is no interference among the small-cells from the same InP and among different InPs.

Virtualized resource. The infrastructure services are isolated by a set of $S$ slices. Each slice is uniquely determined by a pair of base station and chunk. We denote $\alpha = [\alpha_{b,c}^u]_{U \times (C_b \times B)}$ as the slice allocation matrix. Here, $\alpha_{b,c}^u$ is a binary indicator variable with $\alpha_{b,c}^u = 1$ if user $u$ is allocated to slice $\{b, c\}$ ($b \in B$, $c \in C_b$), and $\alpha_{b,c}^u = 0$ otherwise.
3.2.2 Problem Formulation

a. Slice-based data transmission rate. When user $u$ of the SP $i$ transmits data with the slice-based allocation scheduled by the MVNO, its data rate is given by

$$R_i^u(\alpha, P) = \sum_{b \in B} \sum_{c \in C_b} \alpha_{b,c}^u r_{b,c}^u(P_{b,c}^u),$$

where $r_{b,c}^u(P_{b,c}^u) = \sum_{l \in \mathcal{L}_{b,c}} W \log_2(1 + \gamma_{u,l}^{b,c} P_{u,l}^{b,c})$ is the chunk-based data rate of user $u$ associated to SBS $b$ and chunk $c$; $W$ is the bandwidth of each subcarrier $l \in \mathcal{L}_b$, $\forall b$; $\gamma_{u,l}^{b,c} = \frac{g_{u,l}^{b,c} \sigma_b^2}{\sigma_b^2}$ in which the additional interference from macrocell network is absorbed into the background noise $\sigma_b^2$; $g_{u,l}^{b,c}$ represents the instantaneous channel gain on subcarrier $l$ of chunk $c$ from user $u$ to the SBS $b$; $P_{b,c}^u = [P_{b,c}^u]_{1 \times |\mathcal{L}_{b,c}|}$ is the transmit power vector on all sub-carriers of chunk $c$; $P = [P_{b,c}]_{|\mathcal{U}| \times (|\mathcal{C}_b| \times B)}$ is the transmit power matrix of users on all slices of all subscribed users.
b. **User’s QoS demand.** In order to guarantee the minimum rate requirement $R_{u,\text{min}}^i$ for user $u$ subscribed to the specific service of the SP $i$, the following constraint is imposed:

$$R_{u}^i(\alpha, P) \geq R_{u,\text{min}}^i, \quad \forall u \in \mathcal{U}, \forall i \in \mathcal{I}. \quad (3.2)$$

c. **Backhaul link constraint.** In order to avoid congestion at the capacity-limited backhaul links of InPs’ SBSs, the aggregated data rate aggregation from all the users needs to satisfy the following constraint:

$$\sum_{i \in \mathcal{I}} \sum_{u \in \mathcal{U}_i; \alpha_{u,c}^i = 1} R_{u}^i(\alpha, P) \leq Z_{b,\text{bh}}, \quad \forall b \in \mathcal{B}, \forall c \in \mathcal{C}_b, \quad (3.3)$$

where $Z_{b,\text{bh}} \geq 0$ is a predefined backhaul capacity of SBS $b$.

d. **Network utility function.** We consider the following network utility of the MVNO achieved from allocating the slice and transmit power to SPs’ users:

$$U_{\text{MVNO}}(\alpha, P) = U_{\text{rev}}(\alpha, P) - U_{\text{cost}}(\alpha, P), \quad (3.4)$$

where $U_{\text{rev}}(\alpha, P) = \sum_{i \in \mathcal{I}} \sum_{u \in \mathcal{U}_i} \varphi_{i}^{sp} R_{u}^i(\alpha, P)$ is the MVNO network revenue resulting from providing virtual resources to SPs; $U_{\text{cost}}(\alpha, P) = \sum_{b \in \mathcal{B}} \sum_{c \in \mathcal{C}_b} (\varphi_{b}^{bh} \alpha_{b,c}^u r_{b,c}^u(P_{b,c}^u) + \varphi_{b,c}^{\text{slice}} \alpha_{b,c}^u)$ is total cost incurred as the MVNO leases physical resource from the InPs; $\varphi_{i}^{sp}$ is the payment (in units/Mbps) of each SP $i$ to the MVNO; $\varphi_{b}^{bh}$ is the unit price (in units/Mbps) of the backhaul set by InP $b$ for SBS $b$; $\varphi_{b,c}^{\text{slice}}$ is the unit price of the slice set by InP $b$ for the chunk $c$ of the SBS $b$.

The design problem is mathematically formulated as follows:
(OP-4): 

$$\max_{(\alpha, P)} U_{\text{MVNO}}(\alpha, P) \quad (3.5)$$ 

s.t. (3.2), (3.3),

$$\sum_{b \in B} \sum_{c \in C_b} \alpha_{b,c} \sum_{l \in L_c} P_{b,c}^{u,l} \leq \bar{P}_u, \quad \forall u \in U, \quad (3.6)$$

$$P_{b,c}^{u,l} \geq 0, \quad \forall b \in B, \forall c \in C_b, \forall u \in U, \quad (3.7)$$

$$\alpha_{b,c}^u \in \Pi_{\alpha}, \quad \forall b \in B, \forall c \in C_b, \forall u \in U, \quad (3.8)$$

where the total amount of transmit power ($\bar{P}_u$) of user is constrained by (3.6); $\Pi_{\alpha}$ is the following non-convex set:

$$\sum_{u \in U} \alpha_{b,c}^u \leq 1, \quad \forall c \in C_b, \forall b \in B, \quad (3.9)$$

$$\sum_{b \in B} \sum_{c \in C_b} \alpha_{b,c}^u \leq 1, \quad \forall u \in U, \quad (3.10)$$

$$\sum_{u \in U} \sum_{c \in C_b} \alpha_{b,c}^u \leq 1, \quad \forall b \in B, \quad (3.11)$$

$$\sum_{u \in U} \sum_{b \in B} \alpha_{b,c}^u \leq 1, \quad \forall c \in C_b, \quad (3.12)$$

$$\alpha_{b,c}^u = \{0,1\}, \quad \forall u \in U, \forall b \in B, \forall c \in C_b. \quad (3.13)$$

Here, constraint (3.9) implies that each slice is allocated to at most one user. Constraint (10) indicates that each user is allocated at most one slice (i.e., at most one chunk and one SBS). Constraints (3.11) and (3.12) represent the slice isolation, which is uniquely determined in the MVNO.

The problem (OP-4) is a mixed integer non-convex optimization problem, which is computationally intractable. In next section, a suboptimal solution of the problem (OP-4) is proposed using the Lagrangian relaxation.
3.3 Proposed joint slice and power allocation

The partial Lagrangian of problem (OP-4) is obtained by augmenting its objective function with a weighted sum of constraints (3.2), (3.3), (3.6) as follow:

\[
L(\alpha, P, \lambda, \beta) = U_{MVNO}(\alpha, P) + \sum_{i \in I} \sum_{u \in U_i} \lambda_u \left( R_u^i(\alpha, P) - R_{u, \text{min}}^i \right) - \sum_{b \in B} \beta_b \left( \sum_{i \in I} \sum_{u \in U_i} R_u^i(\alpha, P) \right) - Z_{b, bh} - \nu \left( \sum_{b \in B} \sum_{c \in C_b} \sum_{l \in L_c} P_{u,l}^{u,l, b,c} - \bar{P}_u \right),
\]

where \( \lambda = [\lambda_u]_{1 \times (|U|)}, \beta = [\beta_b]_{1 \times B} \) and \( \mu = [\mu_u]_{1 \times (|U|)} \) are Lagrangian nonnegative multipliers associated with constraints (3.2), (3.3) and (3.6), respectively.

Then, the Lagrangian dual function of the dual problem for the problem (OP-4) is

\[
(D-4) \max_{(\alpha, P)} \sum_{i \in I} \sum_{u \in U_i} \sum_{b \in B} \sum_{c \in C_b} \Omega_{b,c}^u \left[ \Omega_{b,c}^u(P_{b,c}^u) - \varphi_{\text{slice}}^b \right]
\]

s.t. (3.7), (3.8),

where \( \Omega_{b,c}^u(P_{b,c}^u) = (\varphi_{b,c}^{sp} - \varphi_{b,c}^{bh} + \lambda_u - \beta_b)P_{b,c}^u - \mu_u \sum_{l \in L_{b,c}} P_{b,c}^{u,l} \).

**Power control (PA) phase:** Regardless of slice allocation \( \alpha \) and Lagrangian multiplier values, the optimal power can be determined based on the KKT condition for optimality [91] by taking the first derivative of \( \Omega_{b,c}^u(P_{b,c}^u) \) with respect to \( P_{b,c}^{u,l} \) as:

\[
P_{b,c}^{u,l} = \left[ \frac{\varphi_{b,c}^{sp} - \varphi_{b,c}^{bh} + \lambda_u - \beta_b}{(\ln 2)\mu_u} - \frac{1}{\gamma_{b,c}} \right]^+, \quad (3.16)
\]

where \( (x)^+ = \max(x, 0) \).
Slice allocation (SA) phase: Given the power allocation in (3.16), problem (D-4) reduces to a maximum weighted matching problem as:

\[
(D-4.1) \quad \max_{(\alpha, P)} \sum_{i \in I} \sum_{u \in U} \sum_{b \in B} \sum_{c \in C} \alpha_{b,c}^u \left[ \Omega_{b,c}^u (P_{b,c}^u) - \varphi_{b,c}^{\text{slice}} \right] \\
\text{s.t.} \quad (3.9), (3.10), (3.13). 
\]

Here, an optimal slice allocation can be obtained using the Hungarian algorithm [92] in which each slice \{b, c\} is weighted by \[ \Omega_{b,c}^u (P_{b,c}^u) - \varphi_{b,c}^{\text{slice}} \] for user \( u \).

In Algorithm 3.1, we propose a distributed algorithm for the JSPA problem, which is referred to as the JSPA-HSA algorithm. Given the allocations \( \alpha \) and \( P \), the optimal value of Lagrangian multipliers can be obtained by the projected gradient-descent method [91] according to (3.18), (3.19) and (3.20) with positive step sizes \( s_1(t), s_2(t) \) and \( s_3(t) \). The convergence of the JSPA-HSA algorithm can be proved using the gradient-based standard technique [91]. An optimal solution in the SA phase is found by the Hungarian method with a computation complexity of \( O(|U| \times |S|)^3 \). Moreover, the MVNO needs global information about \( \Omega_{b,c}^u (P_{b,c}^u) \) on all the slices from the users via dedicated reliable feedback channels [8]. Due to the high complexity of this algorithm, we next propose a low-complexity distributed algorithm in the SA phase.

### 3.4 Matching-based low-complexity algorithm

Herein, we present a low-complexity solution for the problem (OP-4) in which the SA phase is formed as a two-side matching game [93] including subscribed users and slices to maximize objective function (3.17).

We consider a two-side matching game \((U, S, \succ_U, \succ_S)\) for the slice allocation. Here, \( \succ_U = \{ \succ_u \}_{u \in U} \) and \( \succ_S = \{ \succ_{b,c} \}_{(b,c) \in S} \) denote the preference relations of the users and...
Algorithm 3.1 JSPA-HSA: JSPA with Hungarian-based Slice Allocation.

1: **Initialization**: $I, B, C_b, U_i, P(0), \lambda(0), \mu(0), \text{and } \beta(0)$.

2: **Repeat**:

3:  * Power allocation phase:

4:  *At the subscribed user $u$:

5:      Update $\lambda_u$ as:

\[
\lambda_u(t+1) = [\lambda_u(t) - s_1(t)(R_u^i(\alpha, P) - R_u^{\text{min}})]^+; \tag{3.18}
\]

6:      Update $\mu_u$ as:

\[
\mu_u(t+1) = [\mu_u(t) - s_2(t)\left(\sum_{b \in B} \sum_{c \in C_b} \sum_{l \in L_c} \alpha_{b,c} P_{u,l}^{u,l} - \bar{P}_u\right)]^+; \tag{3.19}
\]

7:      Update transmit power $P_{u,l}^{u,l}(t+1)$ by (3.16);

8:  *At the SBS $b$:

9:      Update congested backhaul link price $\beta_b(t+1)$:

\[
\beta_b(t+1) = [\beta_b(t) + s_3(t)(\sum_{i \in I} \sum_{u \in U_i} R_u^i(\alpha, P) - Z_{b,bh})]^+; \tag{3.20}
\]

10:  * Slice allocation phase:

11:  *At the MVNO:

12:      Update $\alpha_{b,c}^u(t+1)$ using the Hungarian algorithm to maximize (3.17).

13: **Until** $|\lambda_u(t+1) - \lambda_u(t)| \leq \epsilon_1$, $|\mu_u(t+1) - \mu_u(t)| \leq \epsilon_2$, and $|\beta_b(t+1) - \beta_b(t)| \leq \epsilon_3$ are simultaneously satisfied.

slices, respectively. The two-side matching game is defined as a function $\mu: U \mapsto S$ such that:

(i) $u = \mu(\{b, c\}) \leftrightarrow \{b, c\} = \mu(u), \forall u \in U, \{b, c\} \in S$;
Algorithm 3.2 MSA: Matching-based Slice Allocation.

1: \textbf{while} $\sum_{u,\{b,c\}} b_{u,\{b,c\}} \neq 0$ or convergence not achieved \textbf{do}

2: \hspace{1em} \textit{At the subscribed users:}

3: \hspace{2em} Send a bid for the slice $\{b,c\}^* = \arg \max_{\{b,c\} \in \succ_u} \phi_u(\{b,c\})$.

4: \hspace{1em} \textit{At the MVNO:}

5: \hspace{2em} Construct $\succ_{\{b,c\}}$ based on (3.21).

6: \hspace{2em} Update $\{b,c\}^* = \mu(\{b,c\}) | u^* = \arg \max_{u \in \succ_{\{b,c\}}} \phi_{\{b,c\}}(u)$.

7: \hspace{2em} Update the rejected user lists on the slices and the preference $\succ_u$.

8: \textbf{end while}

(ii) $|\mu(\{b,c\})| \leq 1$ and $|\mu(u)| \leq 1$, $u \in U$, $\{b,c\} \in S$.

In the matching $\mu$, user $u$ prefers slice $\{b,c\}$ to $\{b,c\}'$ is denoted by $\{b,c\} \succ_u \{b,c\}'$ ($\{b,c\}, \{b,c\}' \in S$). Additionally, slice $\{b,c\}$ prefers user $u$ to $u'$ is represented by $u \succ_{\{b,c\}} u'$ ($u, u' \in U$). A pair $(u, \{b,c\})$ is a blocking pair for $\mu$ if there exists $\{b,c\} \succ_u \{b,c\}'$ or $u \succ_{\{b,c\}} u'$, $\forall u, b, c, i$.

In the matching $\mu$, utility functions $\phi_u(\{b,c\})$ and $\phi_{\{b,c\}}(u)$ form the preference relations $\succ_u$ and $\succ_{\{b,c\}}$ of the users and the MVNO, respectively. In the proposed two-side matching game, the utilities of user $u$ for different available slices are estimated based on the utility value $\phi_u(\{b,c\}) = \Omega_{b,c}^u(P_{b,c}^u)$. Additionally, user $u$ always seeks to maximize its utility value, which means that it will bid the slice $\{b,c\}^* := \arg \max_{\{b,c\} \in S} \Omega_{b,c}^u(P_{b,c}^u)$ in its preference list. In response to the request from the users for occupying certain slices, the MVNO wishes to maximize a utility function on each slice defined as follows:

$$\phi_u(\{b,c\}) = \Omega_{b,c}^u(P_{b,c}^u) - \varphi_{b,c}.$$  \hspace{1em} (3.21)

To maximize the objective function (3.17), the distributed slice allocation strategy is
Algorithm 3.3 JSPA-MSA: JSPA with Matching-based Slice Allocation.

1: **Initialization**: $\mathcal{I}$, $\mathcal{B}$, $\mathcal{C}_b$, $\mathcal{U}_i$, $P_i^{(0)}$, $\lambda^{(0)}$, $\mu^{(0)}$, and $\beta^{(0)}$.

2: **Repeat**:

3: - **Power allocation phase**:

4: *At the subscribed user $u$*:

5: Update $\lambda_u$ as:

$$\lambda_u(t+1) = [\lambda_u(t) - s_1(t)(R_u^i(\alpha, P) - R_u^{\min})]^+;$$  \hspace{1cm} (3.22)

6: Update $\mu_u$ as:

$$\mu_u(t+1) = [\mu_u(t) - s_2(t) \left( \sum_{b \in \mathcal{B}} \sum_{c \in \mathcal{C}_b} \sum_{l \in \mathcal{L}_c} \alpha_{b,c} P_{b,c}^{u,l} - \bar{P}_u \right)]^+;$$  \hspace{1cm} (3.23)

7: Update transmit power $P_{b,c}^{u,l}(t+1)$ by (3.16);

8: *At the SBS $b$*:

9: Update congested backhaul link price $\beta_b(t+1)$:

$$\beta_b(t+1) = [\beta_b(t) + s_3(t) \left( \sum_{i \in \mathcal{I}} \sum_{u \in \mathcal{U}_i} R_i^u(\alpha, P) - Z_{b,bh} \right)]^+;$$  \hspace{1cm} (3.24)

10: - **Slice allocation phase**:

11: *At the MVNO*:

12: Update $\alpha_{b,c}^u(t+1)$ using the MSA algorithm.

13: **Until** $|\lambda_u(t+1) - \lambda_u(t)| \leq \epsilon_1$, $|\mu_u(t+1) - \mu_u(t)| \leq \epsilon_2$, and $|\beta_b(t+1) - \beta_b(t)| \leq \epsilon_3$ are simultaneously satisfied.

presented in Algorithm 2, which is referred to as the MSA algorithm. The MSA algorithm operates based on the conventional deferred acceptance algorithms [93]. It always converges to the stable matching $\mu^*$ if no blocking pairs exits at the both proposal (users) and
acceptance (slices) sides. Additionally, the computation complexity of this algorithm can be determined with an upper bound of $O(|U|^2(|S|-1))$. The processes of acceptance and rejection in the MSA algorithm capture the value $\phi_{(b,c)}(u)$ on each slice $\{b,c\}$. This execution leads to an increase in the objective value of (3.17). Hence, the MSA algorithm converges to a maximal value of problem (D-4.1). However, since the MSA algorithm execution is stopped at the stable matching $\mu^*$, only a suboptimal solution is achieved.

From above analysis, we now develop a low-complexity distributed algorithm to solve problem (OP-4). Referred to as JSPA-MSA, this algorithm is formed by substituting the Hungarian method by the MSA algorithm in Step 12 of the JSPA-HSA algorithm. In this algorithm, the slice and power allocations are assumed to be performed in different timescales. In the SA phase, the MVNO need not share the cost information of the slices to the users, whereas users only share the slice information with the most preferred slice in its preference list to the MVNO. The convergence of the JSPA-MSA algorithm can be proved using a gradient-based standard technique [91]. The duality gap is nonzero because the low-complexity algorithm MSA is suboptimal.

### 3.5 Computation complexity analysis

To find the suboptimal values of $P$ and $\alpha$ in the JSPA-HSA algorithm, the Lagrangian multipliers need to be updated via the sub-gradient update method. Additionally, sub-channel allocations need to be determined based on Hungarian method at the MVNO. In the sub-gradient update method, $|U|$ QoS demand prices, $|B|$ congestion price, and $|U|$ power prices are needed to update at each iteration with steps sizes (3.18), (3.19), and (3.20), and (3.20), respectively. However, at the users side, they only need information of the backhaul congestion that are transmitted from the SBSs. Thus, the total computation complexity of the sub-gradient iterative method is approximately $O(U \times |B|)$. Addition-
ally, the computation in the subchannel allocation phase based on Hungarian matching algorithm, the computation complexity is $O(|U| \times |S|)^3$. Therefore, the total computation complexity in the $JSPA-HSA$ algorithm is $O(U \times |B| + |U| \times |S|)^3$.

In the sup-optimal solution using the $JSPA-MSA$, the subchannel allocation computation is updated based on matching game. Because the $JSPA-MSA$ algorithm depends on private information, it is hard to determine the exact computational complexity. However, we can find an upper bound on the maximum number of communication messages passing between the users-InPs’ base stations-MVNO in the $JSPA-MSA$ algorithm by considering the worst case. According to the $JSPA-MSA$ algorithm between users and MVNO, the worst case scenario occurs when all of the users have the same preference relations for all subchannels. Additionally, at the MVNO side, the list order of the users is exactly opposite of the list order of subchannels in the MVNO. Hence, given that the MVNO have $|S|$ slices to serve $|U|$ users, in each round in the $JSPA-MSA$ algorithm, $|U| - 1$ users will be rejected by the MVNO and this occurs for $|S| - 1$ rounds. Thus, the computation complexity of this algorithm can be determined with an upper bound of $O(|U|^2(|S| - 1))$. Therefore, the total computation complexity for the $JSPA-MSA$ algorithm is $O(|B| \times |U| + |U|^2(|S| - 1))$.

Additionally, for the users demand consideration in the proposed algorithms $JSPA-MSA$ and $JSPA-HSA$, we can see that, whenever an user request more resources, it can obtain a higher data rate that is controlled by the MVNO. Actually, in order to maximize the MVNO’s profit, the SP’s users should pay more cost and overhead in the proposed algorithm before they are assigned resources. However, these costs are integrated with the price (units/Mbps) that service providers have to pay for the MVNO via agreements.
3.6 Numerical results

We consider $B = 3$ InPs each having an SBS with a coverage radius of 100 m and signal bandwidth of 3 MHz. Each SBS contains 10 chunks and each chunk contains 12 subcarriers. The bandwidth of each subcarrier is $W = 15$ kHz. The MVNO rents InPs’ network resources to serve two SPs, each of which has 10 users. The SP $i$ has the minimum target rate of $200 \times i$ kbps ($i = 1, 2$). The small-scale channel gains are assumed to be independent and identically distributed Rayleigh random variables with unit mean. The large-scale path loss in dB for distance $d$ (between a user and an SBS) is assumed to be $L_d = 38.46 + 20 \log_{10}(d)$. The noise power is set to -174 dBm/Hz. Each user $u$ has $P_u^{\text{max}} = 100$ mW. We set $\varphi_{1}^{\text{sp}} = 2.5$ and $\varphi_{2}^{\text{sp}} = 3.5$ units/Mbps for SPs 1 and 2, respectively. The backhaul prices for InPs 1, 2 and 3 are 0.2, 0.4 and 0.6 units/Mbps, respectively. The slices price of InPs 1, 2, and 3 are 0.1, 0.2, and 0.3 units/slice, respectively. Moreover, we set the error tolerance as $\epsilon = 10^{-3}$ for all concerned algorithms.

Fig. 3.2a show that two proposed algorithms converge in a few iterations, whereas backhaul links are protected by the JSPA-MSA scheme as shown in Fig. 3.2b. In Fig. 3.2a, the JSPA-MSA scheme approaches the JSPA-HSA scheme at a gap of 3.98%.

Fig. 3.3a compares the profits attained by the MVNO with the proposed algorithms where we also include the baseline algorithm Max-Rate. Similar to the JSPA-HSA, this Max-Rate algorithm allocates the virtual resources without considering the business model as in [77] and [78]. However, this benchmark algorithm only focuses on maximizing the sum rate $\sum_{i \in I} \sum_{u \in U_i} R_u^{i}(\alpha, P)$ in problem (OP-4). As seen, our proposed algorithms outperform the Max-Rate solution. The gain is observed for the JSPA-MSA scheme with an improvement of up to 9.8% over the baseline, whereas 4.1% over the JSPA-HSA scheme. The gain is slightly less for the JSPA-HSA scheme at the benefit of carrying out the computation in a distributed fashion.
Figure 3.2: Evaluation results of the proposed algorithms with $B = 3$ InPs, $I = 2$ SPs, $U_i = 10$ users, $S = 30$ slices.

Figure 3.3: Evaluation results with $Z_{b,bh} = 10$ Mbps.
In Fig. 3.3b, we show the network utility versus the number of SPs’ users for different schemes with backhaul rate of 10 Mbps. The number of subscribed users $|\mathcal{U}|$ increases from 4 to 20 users, and each SP has $|\mathcal{U}|/2$ users. As the number of users increases, the network utilities of all schemes are improved since data traffic grows. Moreover, the proposed schemes outperform the $\text{Max-Rate}$ solution in terms of network utility. The results of the low-complexity $\text{JSPA-MSA}$ scheme follow those of the $\text{JSPA-HSA}$ counterpart.

3.7 Summary

In this chapter, we have proposed efficient virtual resource allocations in the uplink of a virtualized cellular network. A mixed integer nonconvex optimization problem is formulated considering the backhaul constraint. An algorithm based on Lagrangian relaxation has been proposed to solve the formulated problem. Additionally, a low-complexity distributed algorithm based on the concept of the matching game has been developed to reduce computation complexity. Numerical results have confirmed that the devised algorithms quickly converge and guarantee higher profits for the MVNO compared to those of the existing designs.
Chapter 4

Conclusion

To reap the benefits of small cell network deployment, we have addressed optimization-based approaches to employ the resource allocation problems for small cell network paradigms. We particularly have investigated two optimization problems for resource allocation in the small cell networks with cognitive radio-based spectrum access and wireless virtualization.

In the first optimization problem, we have studied a resource allocation in the uplink of the cognitive femtocell network. We have maximized the uplink sum-rate under constraints of intra-tier and inter-tier interferences while maintaining the average delay requirement for femtocell users and protecting the macrocell base station. In the solution section, we have developed distributed algorithms in which the CFN implementation is self-organized and self-optimized. To this end, we first have proposed an autonomous framework, in which the femtocell users self-organize into disjoint groups (DJGs). Then, we have examined the coalitional game aspects of the subchannel and power allocations in each DJG. We have shown that the optimization problem can be formulated as a coalitional game in partition form. By using the recursive core method and optimization theory, we have developed a distributed algorithm for the power and channel allocations. We have proved that the
proposed algorithm always converges to a Nash-stable partition.

We next have considered resource allocation in the virtualized small cell network considering both the backhaul capacity of the infrastructure provider (InP) and the users’ QoS requirements. The optimization problem has focused on the profit gained by a mobile virtual network operator (MVNO) which is a middleman who buys physical resource from the InP, bundling them into virtual resources called slides before selling off the service providers. To solve this problem, we have proposed a distributed solution framework based on Lagrangian relaxation to find suboptimal decision about slice and transmit power allocations. Furthermore, by exploiting the concept of a matching game, we have proposed a low complexity solution that makes our proposal much more practical and robust in the virtualized wireless network environment.

In all of these scenarios, the proposed frameworks have tested based on the simulation results. We have shown that the proposed frameworks can be implemented in a distributed manner and require a small number of iterations to converge. The experimental results have shown that the proposed frameworks are better than those of the other frameworks.
Bibliography


Appendix A

Proof of (2.34) and (2.41)

In this section, we solve $\text{OPT}_1\mathcal{S}_{m,g,\phi_L}$ based on the geometric programming method [59, 60, 64] and KKT conditions [58, 59, 94]. Since the signal levels at the receivers CFBSs to guarantee QoS of FUEs are much higher than the interference level or $\Gamma_m \ln \gg 1$, $B_w \log(1 + \Gamma_m)$ is approximated to $B_w \log(\Gamma_m)$, and $\nu(S_{m,g}, \phi_{\mathcal{L}_g})$ is approximated to $B_w \log \left( \prod_{\forall \ln \in \mathcal{S}_{m,g}} \Gamma_m \right)$. Thus, $\text{OPT}_1\mathcal{S}_{m,g,\phi_L}$ can be approximated as follows:

$$\text{OPT}_2\mathcal{S}_{m,g,\phi_L} : \begin{array}{l}
\text{maximize} \log \prod_{\forall \ln \in \mathcal{S}_{m,g}} \Gamma_m \\
\text{subject to } (2.31), (2.32), (2.33).
\end{array} \tag{A.1}$$

Since the objective (A.1) is similar to minimizing $\prod_{\forall \ln \in \mathcal{S}_{m,g}} (\Gamma_m)^{-1}$, $\text{OPT}_2\mathcal{S}_{m,g,\phi_L}$ is equivalent to the following problem:

$$\text{OPT}_3\mathcal{S}_{m,g,\phi_L} : \begin{array}{l}
\text{min.} \prod_{\forall \ln \in \mathcal{S}_{m,g}} \Gamma_m^{-1} \\
\text{s.t. }
\end{array} \tag{A.2}$$
Appendix A: Proof of (2.34) and (2.41)  

\[
\sum_{\forall l_n \in S_{m,g}} h_{l_n}^m P_{l_n}^m \leq 1, \quad (A.3)
\]

\[
\frac{Z_{n,g}^m + Z_{n,g'}^m + h_{m,n}^m P_{m0}^m + n_0}{h_{l_n}^m P_{l_n}^m \chi_{l_n}} \leq 1, \quad l \in \mathcal{L}_n, l_n \in S_{m,g} \quad (A.4)
\]

\[
\frac{P_{l_n}^m \text{min}}{P_{l_n}^m} \leq 1, \quad \forall l_n \in S_{m,g}, \quad (A.5)
\]

\[
\frac{P_{l_n}^m \text{max}}{P_{l_n}^m} \leq 1, \quad \forall l_n \in S_{m,g}. \quad (A.6)
\]

This optimization has become a standard form of the geometric programming problem but still not a convex optimization problem. However, by applying some logarithmic changes to the variables \( y_{l_n}^m = \log P_{l_n}^m \) and a logarithmic operation to the function, \( \text{OPT3}_{S_{m,g}, \phi_{L_g}} \) becomes:

\[
\text{OPT4}_{S_{m,g}, \phi_{L_g}} : \quad \min_{y_{l_n}^m, z_{m,n,g}^m} \sum_{\forall l_n \in S_{m,g}} \log \left( \frac{e^{-y_{l_n}^m}}{h_{l_n}^m} \left( e^{z_{m,n,g}^m} + Z_{n,g}^m + h_{m,n}^m P_{m0}^m + n_0 \right) \right) \quad (A.7)
\]

s.t.

\[
\sum_{\forall l_n \in S_{m,g}} h_{l_n}^m e^{y_{l_n}^m} - z_{0}^m \leq 0, \quad (A.8)
\]

\[
\log \left( \frac{e^{-y_{l_n}^m}}{h_{l_n}^m} \left( e^{z_{m,n,g}^m} + Z_{n,g}^m + h_{m,n}^m P_{m0}^m + n_0 \right) \right) - \log \left( \chi_{l_n} \right) \leq 0, \quad \forall l_n \in S_{m,g} \quad (A.9)
\]

\[
e^{y_{l_n}^m} - \frac{P_{l_n}^m \text{max}}{P_{l_n}^m} \leq 0, \quad \forall l_n \in S_{m,g}, \quad (A.10)
\]

\[
-e^{y_{l_n}^m} + \frac{P_{l_n}^m \text{min}}{P_{l_n}^m} \leq 0; \quad \forall l_n \in S_{m,g}, \quad (A.11)
\]

\[
\log \left( Z_{n,g}^m \right) - z_{n,g}^m \leq 0, \quad \forall l_n \in S_{m,g}. \quad (A.12)
\]

In this optimization problem, we assume that each CFBS has the capability to estimate the intra-tier interference via an auxiliary variable that is generated by other CFUE transmissions on subchannel \( m \). Based on that, we introduce a new variable \( z_{n,g}^m = \log(Z_{n,g}^m) \). Moreover, we relax the equality constraint \( \sum_{l_n \in S_{m,g}} h_{l_n}^m e^{y_{l_n}^m} - e^{z_{n,g}^m} = 0 \) by an inequality \( \log \left( Z_{n,g}^m \right) - z_{n,g}^m \leq 0 \), which becomes a convex inequality constraint. According to [58], the problem \( \text{OPT4}_{S_{m,g}, \phi_{L_g}} \) is a convex problem. Thus, \( \text{OPT4}_{S_{m,g}, \phi_{L_g}} \) can be solved by its dual problem. The Lagrangian dual problem of
Appendix A: Proof of (2.34) and (2.41)

OP4$_{S_{m,g}}$ is given as follows:

\[
L_{\forall \ln \in S_{m,g}} (y_{\ln}^m, z_{n,g}^m, \beta, \mu_{\ln}, \eta_{\ln}, \varsigma_{\ln}, \vartheta_{\ln}) = \sum_{\forall \ln \in S_{m,g}} \log \left( e^{y_{\ln}^m/h_{\ln}^m} \left( e^{z_{n,g}^m} + Z_{n,g}^m + h_{m,n}^m P_{0}^m + \eta_0 \right) \right) \\
+ \beta \sum_{\forall \ln \in S_{m,g}} h_{\ln,0}^m e^{y_{\ln}^m} - \zeta_{\ln}^m \\
+ \sum_{\forall \ln \in S_{m,g}} \mu_{\ln} \log \left( e^{y_{\ln}^m/h_{\ln}^m} \left( e^{z_{n,g}^m} + Z_{n,g}^m + h_{m,n}^m P_{0}^m + \eta_0 \right) \right) - \log (\chi_{\ln}) \\
+ \sum_{\forall \ln \in S_{m,g}} \eta_{\ln} \left( e^{y_{\ln}^m} - P_{\ln}^{m,\max} \right) \\
+ \sum_{\forall \ln \in S_{m,g}} \varsigma_{\ln} \left( -e^{y_{\ln}^m} + P_{\ln}^{m,\min} \right) \\
+ \sum_{\forall \ln \in S_{m,g}} \vartheta_{\ln} \left( Z_{n,g}^m - e^{z_{n,g}^m} \right),
\]

where $\beta, \mu_{\ln}, \eta_{\ln}, \varsigma_{\ln}$ are Lagrange multipliers, and $\vartheta_{\ln}$ is the consistency price. To enable the distributed algorithm, we solve OPT4$_{S_{m,g}, \varphi_{Lg}}$ by applying the decomposition method based on the Lagrange relaxation of the coupling constraints, as in [59]. OP4$_{S_{m,g}, \varphi_{Lg}}$ can be separated into $|S_{m,g}|$ sub-problems, each of which is given by:

\[
L_{\forall \ln \in S_{m,g}} (y_{\ln}^m, z_{n,g}^m, \beta, \mu_{\ln}, \eta_{\ln}, \varsigma_{\ln}, \vartheta_{\ln}) = \log \left( e^{y_{\ln}^m/h_{\ln}^m} \left( e^{z_{n,g}^m} + Z_{n,g}^m + h_{m,n}^m P_{0}^m + \eta_0 \right) \right) + \beta h_{\ln,0}^m e^{y_{\ln}^m} \\
+ \mu_{\ln} \log \left( e^{y_{\ln}^m/h_{\ln}^m} \left( e^{z_{n,g}^m} + Z_{n,g}^m + h_{m,n}^m P_{0}^m + \eta_0 \right) \right) \\
+ \eta_{\ln} e^{y_{\ln}^m} - \varsigma_{\ln} e^{y_{\ln}^m} - \vartheta_{\ln} e^{z_{n,g}^m}.
\]

Then, OP4$_{S_{m,g}, \varphi_{Lg}}$ can be solved by each CFUE $\ln \in S_{m,g}$. The dual problem becomes

\[
\max. \min. \ L (y_{\ln}^m, z_{n,g}^m, \beta, \mu_{\ln}, \eta_{\ln}, \varsigma_{\ln}, \vartheta_{\ln}) \quad (A.15)
\]

\[
\text{s.t.} \ y_{\ln}^m, z_{n,g}^m, \beta, \mu_{\ln}, \eta_{\ln}, \varsigma_{\ln} \geq 0. \quad (A.16)
\]

By using the sub-gradient method that updates the Lagrange multipliers, consistency prices as (2.35)-(2.39), and the KKT conditions, the optimum power of each CFUE and the auxiliary variable $z_{n,g}^m$ can be achieved as in (2.34) and (2.41), respectively.
Appendix B

List of Publications

B.1 Journal Papers


[J3] Tuan LeAnh, Nguyen H. Tran, Walid Saad, Long Bao Le, Dusit Niyato, Tai Manh Ho, and Choong Seon Hong, “Matching-based Distributed User Association and Resource Allocation in Cognitive Femtocell Network” (It was accepted with Major Revision in the IEEE Transactions on Vehicular Technology).
B.2 Conference Papers

International Conference


[C7] Tuan LeAnh, Seon Hyeok Kim, and C. S. Hong, ”Joint Base Station Association and Power Control for Uplink Cognitive Small Cell Network,” was accepted in IEEE Network Operations and Management Symposium (APNOMS), Kanazawa, 2016


Appendix B: list of publications

[C15] Tra Huong Thi Le, Nguyen H. Tran, Tuan LeAnh and Choong Seon Hong, “User Matching Game in Virtualized 5G Cellular Networks,” was accepted in the IEEE Network Operations and Management Symposium (APNOMS), 2016 18th Asia-Pacific, Kanazawa, 2016,

Domestic Conference


[C17] Tuan LeAnh, Choong Seon Hong, “Improving data transmission rate for SU in CR Network with multi-radio by using Q-learning method,” (KIISE 2012), 2012.11.23 24 (23)


[C19] Tuan LeAnh, Choong Seon Hong, “Coalitional Game Formulation for Multi-channel cooperative in Heterogeneous Cognitive Wireless Networks,” KIISE 2013, 2013.11.15 16(16)


[C24] Tuan LeAnh, Tra Huong Thi Le, Kyi Thar, Seung II Moon, Choong Seon Hong, “Optimal joint Subchannel and Power Allocation for Green Underlay Device-to-Device Communication”, 2016 (KCC 2016), 2016.06.29. 07.01. (the Best Paper Award)


[C28] Kyi Thar, Tuan LeAnh, Choong Seon Hong, “Applying Multi-Armed Bandit Problem into Cache Decision Algorithm for Content Centric Networking”, 2016 (KCC 2016), 2016.06.29. 07.01