Resource allocation in heterogeneous networks using game theory

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RESOURCE ALLOCATION IN HETEROGENEOUS NETWORKS USING GAME THEORY

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Abstract

The proposed infrastructure of the next generation wireless networks not only contains the centralized control but also enables the mobile devices to make distributed decisions. The focus of this thesis is to investigate the application of game theoretic approaches in distributed solutions to resource allocation problems in wireless networks. As a useful analytical tool to find distributed solutions to various practical problems, game theory has great potential to be applied in modeling various wireless communication problems, such as spectrum allocation, interference management, accessing mode selection, etc.. Furthermore, it gives us an insight into the behavior and interaction among the independent autonomous mobile nodes.

Our work reported in this thesis is focused on two emerging fields in wireless network research: the spectrum-sharing based heterogeneous networks (HetNets) and the device-to-device communication enabled mobile networks. The former has been included in the Long Term Revolution Advanced (LTE-A) standard as a promising technique in enhancing the network capacity. The latter is considered to be a competitive technique to further improve the quality of service (QoS) and latency in the mobile network. Geared with the game theoretic tools, we investigate some fundamental problems in the spectrum-sharing based heterogeneous networks, and provide practical and distributed algorithms to solve a series of resource allocation problems.

In Chapters 1 and 2, we first give brief introduction to the background knowledge in HetNets and game theory. Then we discuss the problems we face in HetNets, and give literature review to various applications of game theory in wireless networks. We also highlight the structure of this thesis and the major contributions.

In Chapter 3, we first investigate the joint power control and sub-band allocation issues in the spectrum-sharing based heterogeneous network using a non-cooperative game theoretical model. The licensed spectrum of the macro-cell

operator is divided into non-overlapping sub-bands, each of which can be utilized by several unlicensed subscribers (ULS). We propose a Stackelberg game theoretical approach to simultaneously solve the interference management problem of the macro-cell, and the resource allocation problems of the femto-cells. Our approach is modeling the macro-cell base station (MBS) as a game leader and the unlicensed subscribers as followers. We have two purposes in designing the pay-off functions. One is to give sufficient protection to the licensed subscribers (LS), e.g., the macro-cell users, and the other one is to maximize the achieved rate of the unlicensed subscribers. To balance these two purposes, we establish the connection between the pay-off functions of the MBS and unlicensed subscribers by assuming that the unlicensed subscribers should pay for occupying the spectrum of the MBS operator. The unlicensed subscribers also compete for the limited sub-bands in a distributed manner. The proposed algorithm ensures that the interference of the small cell users towards macro-cell base station is kept under a tolerable level, while the unlicensed subscribers achieve the Nash Equilibrium of the resource allocation sub-game.

In Chapter 4, under the same system setup, we further explore the application of the cooperative game model in the above problem. The interference control is still accomplished using pricing scheme under the Stackelberg game model. However, the unlicensed users utilize the sub-bands shared by the MBS in a cooperative way. The nearby unlicensed users can send and receive signals cooperatively by forming virtual multiple-input-multiple-output (MIMO) channels, in order to improve the pay-off sum of the unlicensed users. The cooperation among the unlicensed users is modeled as an overlapping coalition formation game (OCF-game). The OCF-game together with the Stackelberg game form a hierarchical game framework to jointly solve the interference control problem on the macro-cell side and the resource allocation problems on the unlicensed users side.

Different from the previous chapters in which we discuss the interaction between the MBS and the ULSs, in Chapter 5 we focus on the interaction between the small cell base station (SBS) and the LSs. More specifically, we discuss about how the LSs can benefit by smartly shifting between different tiers of heterogeneous network. We explore the potential benefit of cooperation between the small cells and the licensed subscribers, and model the accessing mode selection problem of the licensed subscribers as a Stackelberg game. We show the capacity of small cell can be guaranteed, while the energy efficiency of the licensed subscribers can be improved if they properly cooperate. Furthermore, the proposed approach copes with the distributed nature of the user-deployed small cell networks, and requires no inter-cell coordination. The proposed approach is flexible in practice, by adjusting the objective functions, the benefit gained via cooperation can be balanced between the capacity gain of small cells and the energy efficiency improvement of the licensed subscribers. Therefore it can be applied flexibly for various design purposes.

So far the cellular networks are operated mainly under a central controller, and the signals are forwarded and relayed by the base stations. However to establish the direct link among mobile devices may improve the transmission rate and latency in particular scenarios. Furthermore, in modeling the previous games, we assume that all the players know the historical and current information of their opponents, which results in *dynamic games with perfect information*, since the base station (BS) can act as a coordinator to forward the information. However, in D2D networks this information is difficult to obtain, so they mainly make decisions based on their private beliefs about others' actions. In Chapter 6, we introduce the Bayesian dynamic game to model the problem of carrier aggregation (CA) among D2D links in this scenario. More specifically, we assume that there are several D2D links and each of them obtains an exclusive sub-band. To improve the performance, each of the D2D links contacts each other to aggregate their sub-bands. We model the CA problems of D2D links as a Bayesian coalition formation game, in which each of the players is blind with their opponents' actual behaviors and properties, but can only make decision based on their beliefs. We find that the uncertainties of the belief about the types of other D2D links will affect the D2D link's decision-making. Therefore a two-loop algorithm is developed to enables the players to iteratively update their belief and converge to a stable structure of the CA.

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List of Abbreviations

3GPP: 3rd Generation Partnership Project

BS: base station

CA: carrier aggregation

CDMA: code division multiple access

CF: coalition formation

D2D: device-to-device

FDMA: frequency division multiple access

GSM: Global System for Mobile Communications

HetNet: heterogeneous network

HBS: home base station

IMT-Advanced: International Mobile Telecommunications-Advanced

ITU-R: International Telecommunication Union Radio-communication Sector

IWF: iterative water filling

LS: licensed subscriber

LTE: Long Term Evolution

MBS: macro-cell base station

MCO: macro-cell operator

MIMO: multiple-input-multiple-output

MU: macro-cell user

NBSS: narrow-band spectrum-sharing

NE: Nash equilibrium

NTU: non-transferable utility

OCF-game: overlapping coalition formation game

OFDMA: orthogonal frequency division multiple access

OSA: orthogonal spectrum assignment

PU: primary user

QoS: quality of service

SBS: small-cell base station

SE: Stackelberg equilibrium

SINR: signal-to-noise-ratio

SU: secondary user

TDMA: time division multiple access

TU: transferable utility

UMTS: Universal Mobile Telecommunications System

ULS: unlicensed subscriber

WiMax: Worldwide Interoperability for Microwave Access

WLAN: wireless local-area-network

Chapter 1

Introduction and Outline

1.1 Heterogeneous Networks: An Overview

The next generation wireless systems will include many heterogeneous networks (HetNets) which are complementary to each other. For example, the device-to-device (D2D) communications for establishing short range direct links, the wireless local-area-network (WLAN) provides high-data-rate local-area access, the cellular networks provide data and voice service covering a wide area, the satellite communication networks cover an ultra-wide area for special purpose in military and commercial applications. As the next generation mobile networks, e.g., the Long Term Evolution (LTE), tend to merge into an all-IP-based infrastructure [23], it is interesting to investigate the issues that the mobile devices can achieve global roaming among a variety of networks, and enjoy high data rate in an energy efficient way. The landscape of the future wireless systems is sketched in Fig.1.1.

More specifically, in this thesis, we investigate the heterogeneous wireless networks which evolve from the traditional large scale cellular networks. In the rest of thesis, we denote the terminology of HetNets to be wireless networks with multiple tiers which consist a variety of wireless networks with different coverage

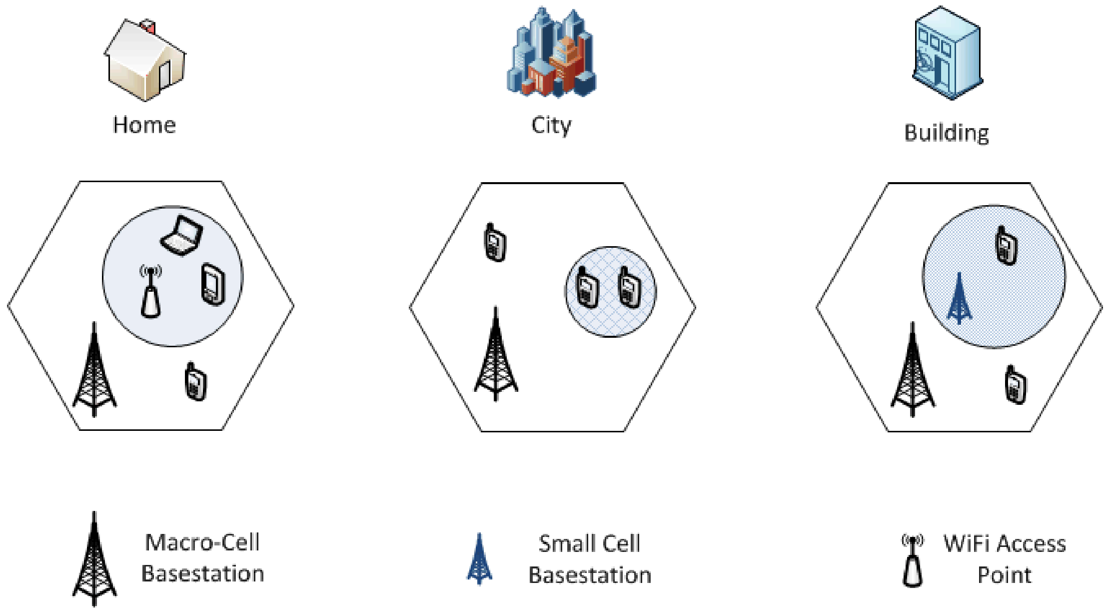

Figure 1.1: The heterogeneous wireless networks.

ranges and capacities, but all under the same radio access technology. The HetNets have been included in Long Term Evolution Advanced (LTE-A) standard as a part of the next generation mobile networks. A typical HetNets could be a number of co-located macro-cells, micro-cells, pico-cells and femto-cells, which result in various wireless coverage zones, ranging from outdoor to indoors. Apart from these techniques in which the communications should be conducted by the corresponding base stations (BS) of the cells, the D2D communications which enable the direct link between cellular subscribers also drives attention in recent years. The D2D communications is expected to improve the network capacity and latency as the demand for proximity-based services are increasing. Hence, the D2D layer is expected to be another component in the HetNets. However, the infrastructure of the D2D-enabled HetNets will be more complex and the standardization of the D2D communications is still under discussion.

1.1.1 Cellular Network: From Homogeneous to Heterogeneous

The cellular structure has been adopted as the radio system deployment methodology for decades, from the analog 1G systems to digital systems such as 2G (e.g., GSM, IS-95), 3G (e.g., UMTS, CDMA2000), and the current 3.5G (e.g., LTE, WiMax). The name of cell comes from the coverage area division scheme: the area which requires the wireless communication service is divided into regular shaped cells, centered in each cell there is a BS which provides the radio links to the mobile users in this cell. The shapes of the cells are usually hexagon, sometimes square or circle. The radio spectrum of the operator is divided and assigned to the cells orthogonally: the adjacent cells are assigned with different frequency bands and the non-adjacent cells can reuse a same frequency band.

In conventional cellular networks such as the 2G and 3G systems, the layouts of the network are in a fully planned manner, and the cells are identical with each other. Each cell contains a centered macro BS covering a relatively large area and offers unrestricted access to the subscribers of its operator. All the BSs share an identical design, from the transmit power levels, antenna patterns, to the backhaul connectivity to the core network. The mobile devices carry similar data flows with similar QoS requirements [41]. We call this kind of cellular network the homogeneous wireless network.

However, there seems an endless desire for higher data rate transmission, especially in the last decade when the online multimedia based services become popular. The International Telecommunication Union Radio-communication Sector (ITU-R) has proposed the International Mobile Telecommunications-Advanced (IMT-Advanced) as the requirements for the next generation wireless network, which is usually marketed as the 4G mobile phone and internet services[33]. The IMT-Advanced requires the data rate to achieve 1Gbits/s for stationary mobile devices and 100Mbits/s for high speed moving mobile devices, which are almost ten times of that in current LTE systems. However, the spectrum suitable for wireless transmission is limited and people should find ways to utilize the licensed spectrum more efficiently. This becomes the main motivation driving the development of HetNets.

The goal of using HetNets is to improve the data rate and network coverage, support more subscribers and data services by reusing the existing frequency bands allocated to the network operators. During the last decades, the population of the mobile devices experiences a steep increasing, while more applications become data-hungry and require always online, e.g., the multimedia content streaming service, the online game, the real-time video chat, etc.. These applications require much more bandwidth which exceeds the capacity of the traditional homogeneous large scale network. Our goal is to fulfill such demand for high-speed-connections while considering the practical constraint of limited radio resources. The frequency reuse, or spectrum-sharing among different cells in the HetNets becomes an emerging topic. Furthermore, the distribution of the mobile devices becomes rather unbalanced. For some sites so called 'hot spots' in urban area, a single macro cell can not provide enough bandwidth to the crowded mobile devices, and this burden can be off-loaded by the deployment of underlying small cells.

1.1.2 Capacity Gain: From Radio Access to Network Topology

The wireless communication networks have been developed and commercialized for almost 30 years, for every generation there are evolutionary advances in different technical aspects. From 1G to 2G, the key technical advance is the shifting from analog modulation to digital modulation, which has greatly improved the network capacity and robustness. From 2G to 3G, the spectral efficiency (i.e., bps/Hz) is improved by tens of times for adopting advanced modulation and coding techniques, e.g., the wide-band CDMA and MIMO. In the mean time more radio spectrum is assigned for wireless communication in the 3G standard, hence the over all data rate of the 3G network is improved dramatically. However, during the further evolution form 3G standards to the 3.5G (e.g.,LTE), nothing more for improving the spectral efficiency is added. The better performance of LTE is simply achieved by allowing the mobile devices to utilize more bandwidth if possible, e.g., the scalable bandwidth technique allows the mobile devices to use the bandwidth form 1.4MHz to 20MHz. It is noted that the improvement of the spectral efficiency per link is approaching to the theoretical limits with 3G and LTE [41]. However, it does not mean that the further improvement of data rate can be only achieved by assigning more spectrum. As the radio spectrum is more and more scarce nowadays, researchers and engineers try to find alternative ways for improving the network capacity from a different angle. In the 4G candidate standard, e.g., the LTE-Advance, new techniques are utilized to further improve the performance.

1) The higher order MIMO. In 3G network, the 2×2 MIMO has already been used to achieve spatial multiplexing and spatial diversity, which shows a great advantage in improving the spectral efficiency and robustness in the LTE network. In LTE-Advanced network, the launch of 4×2 MIMO is expected to give more spectral efficiency at the cost of the complexity of network configuration.

2) The carrier aggregation. In the LTE, a single sub-band can have as much as 20MHz bandwidth, however in the LTE-Advanced the carrier aggregation is enabled to support more data-hungry services, e.g., the online high-definition (HD) video streaming. In the 3GPP Release 12 [3], up to 5 sub-bands can be aggregated together to form a 100MHz band for ultra-high speed transmission.

3) The heterogeneous networks. Apart from the conventional macro cell, an other important component of HetNets is small cell, such as the micro cell, pico-cell, and femto-cells. These small cells are either deployed by the

operator (the micro and pico cells) or deployed by the end user (the femtocell). Furthermore, since the deployment of small cells is non-uniform but demand driven, they appear in the network in a non-planned manner.

The performance of LTE-Advanced is improved from three different aspects. The higher order MIMO further explores the spatial diversity gain brought by the MIMO technique, which improves the spectral efficiency. However, the higher order MIMO brings challenging work in antenna design, and increases the computational complexity for both transmitter and receiver. The carrier aggregation can be considered as an instance of the opportunistic spectrum access, and its performance depends on scenarios: when there are only a few active mobile devices in a cell, they can achieve a very high data rate through carrier aggregation, when the cell is fully loaded with many active mobile devices, there is no idle subbands available for carrier aggregation. The HetNets introduce more flexible and smart BS deployment methodologies, which help to improve the performance by increasing the spectral efficiency per unit area.

The concept of HetNets is a break through in the network topology of the wireless communications networks. It opens a door and shows a new way for improving the network performance from a new perspective. As the performance of an isolated radio systems (i.e., a single cell) approaches information theoretic capacity limits, the further improving of performance will be made by reducing the distance between the BSs and the mobile devices. Hence, at the cost of deploy a set of diverse cells in the same area, the spectral efficiency per unit area is expected to be improved.

1.1.3 Key Features and Challenge Problems

Table 1.1 lists the key features of different cells.

We conclude that the key features of the small cells are:

a) Small coverage area.

Table 1.1: The Comparison of Different Cells

	Macro-cell	Micro-cell	Pico-cell	Femto-cell
Coverage	$2-35$km	≤ 2km	≤ 200m	≤ 50m
Tx-power	$5-40$W	≤ 5W	≤ 2W	≤ 200mW
Backhaul	Dedicated wire Micro-wave	Dedicated wire Micro-wave	Internet	Internet
Deployment	Planned	Ad-hoc	Ad-hoc	Ad-hoc
Spectrum usage	Licensed	Licensed/Shared	Shared	Shared

b) Low transmit power.

c) Flexible deployment.

d) Low cost backhaul connection.

In Table 1.1, the micro and pico-cells are deployed in an ad-hoc manner, which means the deployment is not precisely planned but just based on some roughly knowledge, such as there are coverage holes or hot spots. The femto-cell is purchased and used by the end user, therefore the deployment totally depends on the user. Unlike the bulky and powerful macro BS, the BSs of these small cells (especially the pico and femto cells) are small in size and do not require special power supply. Furthermore, the small cells cover a small area, so that the BSs can be easily deployed in road side or inside buildings, unlike the macro BS which needs to put on top of towers or high buildings. These properties give the small cells more flexibilities in site acquisition.

However, introducing the small cells complicates the infrastructure of the cellular network, and raises more problems in the radio resource allocation and interference management. The following reasons make the optimization of the spectrum-sharing based HetNets a challenging work.

a) The traditional cellular network is a fully BS-controlled wireless system, which means the macro-cell BS (on behalf of the operator) controls everything of the subscribers, from the mobility management, transmit power to sub-band allocations. However, in the HetNets with multiple co-located cells, the subscribers are only controlled by the BS of the corresponding cell. In this case, performing centralized control requires the macro-cell operator (MCO) to obtain global information of all the mobile devices in its covering area, which will introduce a huge communication overhead and generally an intractable task. Hence it is interesting to find simple and distributed solution to the optimization problems in the HetNets.

b) Due to the intra-macro-cell frequency reuse, the time variant wireless environment in HetNets is more unpredictable compared to that in the traditional cellular network. For example, it is easy to assign different sub-bands to the macro-cell subscribers by the MCO in a single cell network. However in the HetNets, if two small cells are sharing the same spectrum, the mutual interferences between them become a main problem which degrades the performance of both cells. Furthermore, the subscribers attached with different cells are lack of coordination, therefore distributed interference management and sub-band allocation algorithms are demanded to optimize the individual performance as well as that of the entire network.

c) New problems are brought by the co-located small cells and D2D links. For example, in a D2D-enabled network, whether to select D2D communication or communicating via the BS is referred as the mode selection problem of the subscribers. In small cell networks, there is an open or closed access problem, when a subscriber of cell A travels to cell B, whether it should be handed over to cell B. These new problems incorporate many decision making process, and the mobile nodes are possible to make decisions instead of executing the command of BS only.

In this thesis, we mainly consider the spectrum-sharing based HetNets to maximize the possibilities of spectrum reuse. The spectrum-sharing based HetNets can be considered as an instance of the primary-secondary network in cellular network, where the primary user (PU) is subscriber of the MCO and the secondary user (SU) is the unlicensed subscriber. The spectrum reuse issues in the primary-secondary networks have been inspected and concluded in [85]. There are two ways the secondary users can access the licensed spectrum of the primary users: a) spectrum underlay means that the SU is allowed to transmit on the spectrum of PU simultaneously, while the PU is being protected by an interference constraint, which is also called spectrum-sharing; b) spectrum overlay means that the SU is able to sense the spectrum of the PU's, and transmit whenever it finds the spectrum is idle, which is also called opportunistically spectrum access.

However, the co-existing cells or communication links result in a complicated wireless network infrastructure, and how to optimally allocate the resources among different entities is still an open question. The centralized control methodology used by the traditional homogeneous cellular network can not be simply transplanted to the HetNets for two reasons: 1) The difficulties for parameter acquisition. Since lack of the central controller (e.g., the MBS), the collection of network parameters for centralized optimization becomes a challenging work. 2) As the complexity of the network topology grows, e.g., the number of heterogeneous mobile nodes and the dimension of network tiers increases, the computational complexity for centralized optimization becomes extremely difficult. Therefore, it is interesting to investigate decentralized approach for network performance optimization.

1.2 The Research Focus in This Thesis

In this thesis, we focus on the applications of dynamic games in analyzing different issues in wireless communication networks. More specifically, the following research problems are investigated.

1.2.1 Resource Allocation in HetNets

One of the essential problems in HetNets is how to efficiently utilize the spectrum. It has been concluded in [44] that there are two ways to allocate the spectrum resources in the spectrum-sharing based wireless networks: the orthogonal and the non-orthogonal assignments. In the orthogonal assignment, the spectrum resource is divided into disjoint frequency bands (e.g., in FDMA), time slots (e.g., in TDMA), or resource blocks (e.g., in OFDMA), and each cell obtains a distinct portion of spectrum to support its subscribers' transmission. This approach is simple for implementation but at the cost of inefficient spectrum utilization. In contrast, the non-orthogonal assignment allows multiple co-located cells to share the same spectrum, and the overall capacity is improved due to the spectrum reuse. However, the mutual interference constitutes the main problem which degrades the quality of service. Hence efficient interference management scheme is required to solve this problem. We can brought some light from the studies in cognitive radio about the interference management issue. In [25], energy efficiency transmission of the secondary network in a primary-secondary network is considered. Using TDMA to avoid co-tier interfering, they resolves the transmission time and beamforming vector for optimal transmission in the secondary network.

Recently, the carrier aggregation has been proposed to support relatively large peak data rate in LTE-A standard [29], this technique can be considered as an instance of the spectrum underlay. The main idea of the carrier aggregation is allowing the entities (e.g., small cells) in the HetNets to aggregate their spectrum together, so as to obtain an ultra wide bandwidth for high-data-rate transmission. For example, in LTE-A, the bandwidth can be expanded up to 100MHz through carrier aggregation, which is much wider than the 20MHz bandwidth in LTE [3] [7]. By aggregating the sub-bands from different cells, it is possible to support very high peak data rate when facing the data burst in some applications. This approach further explores the intra-macro-cell spectrum reuse (comparing to the spectrum reuse between macro-cells), and coordination is required for avoiding the collision and fatal interferences.

We consider a scenario that multiple femto-cells are deployed in the coverage area of a macro-cell. The spectrum is licensed to the MCO. The MCO is willing to lease the spectrum to the co-located femto-cells to generate revenue, e.g., monetary payment. The femto-cells compete for the total spectrum licensed to the MCO. The subscribers in this network are classified into two categories: the licensed subscribers (LSs) and the unlicensed subscribers (ULSs). The LSs are the macro-cell subscribers which are only under the instruction of the operator. The ULSs are the subscribers of the femto-cells, which are controlled by the femto-cell BSs. They can share the sub-bands occupied by the LSs of the operator under the condition that the resulting interference should be maintained below a tolerable level. Furthermore, the femto-cells can aggregate their sub-bands leased by the macro-cell together to further expand the bandwidth. In other words, the ULSs may access multiple sub-bands, while each sub-band can be accessed by multiple users simultaneously. We assume frequency-selective-fading in different sub-bands, therefore the ULSs need to optimally allocate their power. We utilize a game theoretical approach to map the sub-band allocation problem into an overlapping coalition formation (OCF) game. In the OCF-game, each ULS has an amount of resource (power) to distribute in different tasks (sub-bands), the outcome of each task depends on not only the properties of the task (channel information) but also the action of other co-band ULSs and the MCO. We jointly investigate the interference management and sub-band allocation problems through a hierarchical game framework. The further detail is provided in Chapters 3 and 4.

1.2.2 Accessing Mode Selection in HetNets

Apart form the interference management issues, there are also mobility management issues in spectrum-sharing based HetNets. More specifically, in this thesis we focus on the 'open or closed' access problem of the user deployed small cells, which investigates whether the small cell should accept the ULSs in a HetNets. Moreover, we enable both the small cell BS and the ULSs to be a decision-maker in the handover game, and aim at an agreement between them towards a win-win result.

Comparing with the florescent research in the interference management in the spectrum-sharing HetNets, limited achievement has been made in smart access strategy selection. The benefits of open access versus closed access in cellular networks were discussed in [68] based on the spatial distribution analysis of the small cells. However, their work was based on the statistical model only, and missed the participation of the BSs and mobile devices. A discontinuous game formulation was presented in [40] with a pay-off secured solution, in which the small cells competed for allocating their spectrum to macro-cell users (MUs) in the coverage area. Their approach required collecting channel state information of all MUs, as well as a centralized controller to deal with the conflict of interest.

The future mobile devices with advanced hardware will be environmentally aware and can adapt their behavior correspondingly. They will take part in the decision-making process in the access mode selection. We propose a Stackelberg game in which the small cell BS acts as the leader; the ULS acts as the follower. We investigate the demand-driven behavior in the access mode selection game. The small cell BS concerns with improving the capacity by eliminating the interference. The MU concerns with saving the battery life while satisfying transmission task. Only if open access is beneficial to both of them, the MU will hand-over to the small cell. Otherwise, the small cell remains closed. This dynamic access strategy selection is built on the 'cognition' capability of both small cell BS and MU. We here refer the 'open access' to partially assigning the spectrum of the small cell to the MU, which means the MU being handed over to the small cell BS is scheduled with the spectrum orthogonal to the small cell subscribers.

To this end, we analyze the demand-driven behavior of both small cell BS and MU, and propose one practical algorithm to cope with the self-governed nature of small cell networks. Our approach enables the small cell BS and MUs to choose their access strategies distributively. Both the small cell BS and MU take part in the access strategy selection game, for the purpose of obtaining a win-win result. Further details are discussed in Chapter 5.

1.2.3 Carrier Aggregation in Device-to-device Communications

The device-to-device communications enable the nearby mobile devices communicate directly without relaying by the BS. It is a promising technique to improve data rate in short range transmission [21]. Driven by the demands of proximity-based services, for example, the media sharing or social network based applications [1], and the rapidly growing of mobile devices density; the chances of local communications within a cell range in the future network are significantly increased. The short range D2D communication reduces the signal attenuation caused by propagation loss, which subsequently improves the quality of the local communication service, such as the transmission latency, the network spectral/energy efficiency, and off-loads the burden of BS. However, some fundamental problems need to be discussed when the D2D communications being enabled to the cellular networks, for example, the D2D devices discovering problem [20], the accessing mode selection problem [49], and also the resource allocation problem [21].

One of the important issues in D2D communications is to efficiently assign the spectrum resources to the D2D devices. Most of the previous work [21] [49] [79] considered the spectrum sharing approach between cellular network and

D2D network. In [21][49], the authors proposed the spectrum sharing approach between the D2D devices and the cellular devices. However, these approaches incorporated the cross-layer coordination between the D2D network and the cellular network, which requires a significant cost for centralized control, especially when the network size is large. The authors in [21] considered the D2D devices transmit in the cellular uplink slot only to mitigate the interference, which limits the chances for D2D transmission. In [79], spectrum sharing in both uplink and downlink was taken into consideration, wherein the transmit powers of cellular and D2D links were jointly optimized in both cases. In [72], the authors proposed a carrier aggregation scheme to improve the data rate of D2D links, and modeled the D2D pairing problem as a matching game. In this thesis, we propose a scheme to let the D2D devices efficiently coordinate their spectrum resources. We suppose the mode selection of D2D devices is achieved with the help of the BS. Each of the D2D pairs is assigned by the BS an exclusive frequency band for their transmission. Therefore we can neglect the interference between the LSs and the D2D links and concentrate on the carrier aggregation pair forming problem between D2D links. In our setup, the D2D links are able to aggregate their carriers to expand their transmission bandwidth and share the spectrum between each other to achieve better pay-off sum. We model the D2D carrier aggregation problem as a coalition formation game. However, due to lack of coordination between independent D2D links, it is difficult to obtain the information from other D2D links, therefore each D2D links can only make decision based on their beliefs about other D2D links. In this case, a Bayesian dynamic coalition formation game is formulated, and algorithms to update the beliefs and find stable coalition structure are provided. More details will be discussed in Chapter 6.

1.2.4 The Connection Among Research Topics

In this thesis, we focus on solving the technical problems in HetNets using game theory. Although the research topics in this thesis contribute to different research areas in HetNets, the consistency of our research work exhibits in both the relationship between topics and the underlying mathematical models. The connection of aforementioned problems are underlined as follows. In Chapter 3, we use the Stackelberg game to model the interference management problem in a spectrum-sharing based two-tier network, in which the ULSs compete in a non-cooperative manner. In Chapter 4, based on the Stackelberg game for interference control, we explore the benefit of cooperation between the ULSs by modeling an overlapping coalition formation game (OCF-game). The problems considered in Chapters 3 and 4 focus on the interaction between the MCO and the ULSs. In Chapters 5, the Stakelberg game is utilized to model the open/closed access problem, which studies the interaction between the small cell and the LSs (of the MCO). In Chapter 6 we further extend the coalition formation game model to a Bayesian coalition formation game, which considers the uncertainty of the independent D2D links. Generally speaking, this thesis is outlined by the use of Stackelberg game and coalition formation game in HetNets. The connections among the research topics are sketched in Fig.1.2.

1.3 Major Contributions

The major contributions of this thesis are:

1) In Chapters 3 and 4, the sub-bands allocation and the power control issues in the carrier-aggregation-enabled heterogeneous networks are studied. We propose a hierarchical game framework to jointly solve the power and sub-band allocation problems under the constraints of the power cap and maximum tolerable interference level. The upper level Stackelberg game regulates the transmit power of the ULSs so as to give sufficient protection

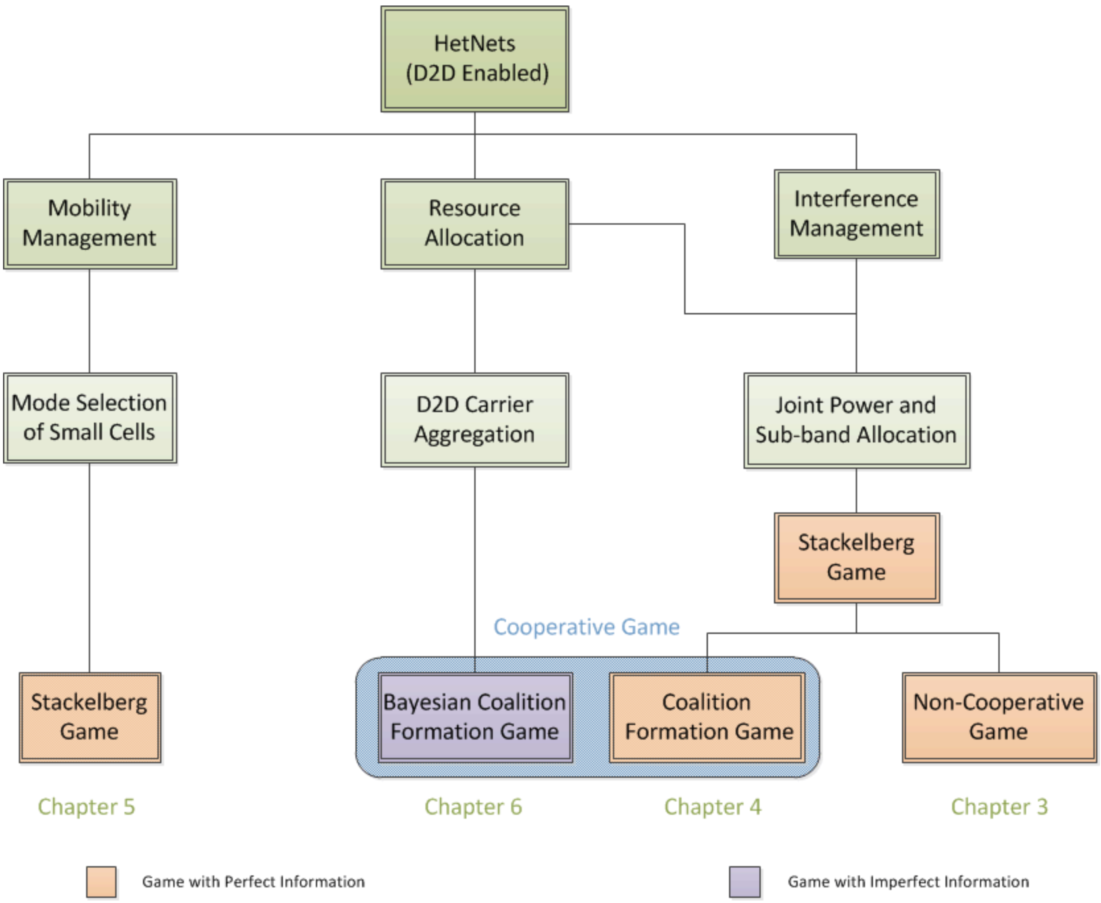

Figure 1.2: The research focus in this thesis.

to the LSs while optimizing the pay-off of the ULSs. The lower level non-cooperative or OCF-game enables the ULSs to distributely perform power allocation and sub-band selection. We have proposed a simple distributed algorithm to let the ULSs iteratively search the the Stackelberg equilibrium (SE) of the hierarchical game, where the transmit power and the sub-band allocations are stable, and no players can profitably deviate from it by acting alone.

The ideas presented in these two chapters deal with more complicated problem comparing to previous literature. We allow multiple users to share one sub-band, and also allow one user to utilize multiple sub-bands simultaneously. In contrast, in [17], [34] and [65] the authors only consider a wide-band spectrum to be shared by all users. Furthermore, the key difference between the proposed algorithm and that in [17] is that our solution is provided in a distributed manner.

Furthermore, we have addressed the problem of sub-band and power allocation problem under two dimensional constraints in Chapter 4 by using overlapping coalition game model, while in [44] and [53] only non-overlapping coalition was considered. We have asked the fundamental question about the existence of a stable and Pareto optimal solution of sub-band allocation and the power allocation by proving that the core of the OCF-based power allocation game exists. The proposed framework can also be expanded to more complex network with multiple BSs to cooperatively share their sub-bands or the downlink cases that multiple LSs need to be protected.

2) In chapter 5, the choice of access strategy in small cells is investigated. We introduce a novel demand-driven mode selection scheme. We analyze the benefits of open mode for the overall networks, which motivates small cell to choose open mode and MUs to join the small cells. We formulate the interaction between the small cells and the MUs as a Stackelberg game, and provide simple algorithms in multiple small cells multiple MU scenario. We

propose simple algorithms that, both the small cell BSs and MUs can improve their performances by making smart choices to the access strategies. Our algorithm requires no inter-cell coordination and guarantees the overall network will always be benefited from choosing the open access mode. Furthermore, the overall benefits can be flexibly balanced between the capacity gain of small cells and the energy efficiency gain of the MUs due to the designing of algorithm. Comparing with previously literature with fixed accessing mode [41] or using empirical model of traffic statistics to decide the accessing mode [64], this chapter discusses the scenario that the MUs also take part in the game.

3) In chapter 6, we investigate the application of coalition formation game in self-organizing spectrum-sharing based D2D networks. We first model the carrier aggregation problem of the D2D link as a coalition formation game with perfect information, and introduce a simple algorithm which enables the D2D links to self-organize into disjoint coalitions. We then discuss a more general case, where the D2D links are blind with the mutual channel information and sub-band allocation of other D2D link, i.e., D2D links knowing imperfect information. We formulate a Bayesian dynamic game to model the decision making process of D2D link in this case. In both scenarios, we give the sufficient conditions of the existence of the spectrum-sharing structure in the core of the proposed game. Simple distributed algorithms which lead to the solution in the core are proposed and proven to be convergent and stable. Our experimental results show significant performance improvements in both scenarios compared with the non-spectrum-sharing case, especially when the D2D pairs are sparsely distributed. Previous literature, such as in [19] [20] [46], whose analysis are built on fixed parameters which is assumed ready-to-be- obtained, we consider a D2D network which is lack of central coordination. Hence, each of the D2D pairs should establish the knowledge about others' behavior based on its own observation.

Chapter 2

Background on Game Theory & Related Applications in HetNets

2.1 Basic Elements in Game Theory

Game theory provides the mathematical model to study the conflict and cooperation between rational decision-makers [50]. A typical game model contains the follow elements:

- *Players*: a set of rational decision makers.
- *Strategies*: the actions available to the players in the game.
- *Information*: the knowledge of the players about the game to make decision.
- *Pay-off*: a mapping from the outcome of the game to a real value.

Furthermore, in Bayesian game, there are other terms:

- *Type*: The type of the player specifies the pay-off functions. A player may have a probability distribution over different types.
- *Belief*: The belief is held by each of the players, which is a probability distribution over the possible types for a player.

2.2 The Types of Games

The game can be classified into many categories using different criteria.

2.2.1 Static Game and Dynamic Game

- *Static Game*: A static game is a game model that contains only one decision point, i.e., the players make the decisions simultaneously in the game.
- *Dynamic Game*: A dynamic game is a game model that the players move sequentially. At each decision point, the players make the decision based on the previous and current information.

2.2.2 Non-cooperative Game and Cooperative Game

- *Non-cooperative Game*: A non-cooperative game is a game in which the players make decisions independently and selfishly.
- *Cooperative Game*: A cooperative game is a game in which the players may form coalitions, the cooperation is enforced within a coalition, while the competition occurs only among coalitions.

2.2.3 Non-Bayesian Game and Bayesian Game

- *Non-Bayesian Game*: The non-Bayesian game, which is also referred as game with *perfect information*, is a game in which the players know all the actions and pay-offs of their opponents.
- *Bayesian Game*: A Bayesian game is a game in which the players know incomplete information (i.e., pay-off) about the other players. In dynamic games, the pay-off of the players may be affected by the process of the game (i.e., the historical information), therefore the game with imperfect information (i.e., the game process) also falls in to the Bayesian Game.

2.3 Solution Concepts of Games

The solution concept is defined as a formal rule to predict how the game is played, which depends on the game structure. For example, for a game with only one player, the solution concept is solving an optimization problem. In this thesis, we consider two solution concepts related to non-cooperative game and cooperative game, respectively.

2.3.1 Nash Equilibrium

A Nash equilibrium (NE) is a solution concept of a non-cooperative game involving two or more players, in which each of the player is given the strategies of others. If a state is reached, in which no player can benefit by changing its own strategies while the others keep their unchanged, then this state (i.e., the strategy set of all players and the corresponding pay-offs) constitutes an NE.

Definition 2.1. *Denote $\pi_i s^i, \boldsymbol{s}_{-i}$ where the subscript $-i$ denotes all players except i and s_i denotes the strategy of player i. A strategy profile $\boldsymbol{s}^*$ is an NE if, for every player $i, i \in [1, K]$, and $s_i^*, s_i \in \boldsymbol{s}^*$, it always holds i $\pi_i(s_i^*, \boldsymbol{s}_{-i}^*) \geq \pi_i(s_i^{'}, \boldsymbol{s}_{-i}^*)$.*

2.3.2 The Core

The core is the solution concept of a cooperative (i.e., coalition) game. More specifically, in this thesis we consider the coalition formation game which aims to find a stable coalition structure, in which no players can benefit by leaving the current coalition and join another one. Hence we formally define the core as:

Definition 2.2. *A tuple $(\mathcal{C}_{\mathcal{S}}, \boldsymbol{x}_{\mathcal{S}})$ is the core of a coalition formation game $G = (\mathcal{K}, \boldsymbol{v})$, if for any set of player $\mathcal{J} \subseteq \mathcal{K}$, any coalition structure $\mathcal{C}_{\mathcal{J}}$ on $\mathcal{J}$, and any imputation $\boldsymbol{y}_{\mathcal{J}} \in I(\mathcal{C}_{\mathcal{J}})$, we have $\pi_j(\mathcal{C}_{\mathcal{J}}, \boldsymbol{y}_{\mathcal{J}}) \leq \pi_j(\mathcal{C}_{\mathcal{S}}, \boldsymbol{x}_{\mathcal{S}})$ for some agent $j \in J$.*

2.4 The Main Game Models Used In this Thesis

We provide the basic definitions of the game models used in this thesis.

2.4.1 Stackelberg game

Definition 2.3. *[9] A Stackelberg game is a game played by a leader and followers. In each round, the leader commits to a strategy based on the best responses of the followers in previous round, and the followers observe the leaders move and respond with the optimal actions, which maximize their pay-off accordingly.*

2.4.2 Overlapping coalitional game

Definition 2.4. *A coalition $\mathcal{C}$ is a non-empty sub-set of the set of all players $\mathcal{K}$. A coalitional game is defined by $(\mathcal{C}, v)$ where $v = v(\mathcal{C})$ is the value function mapping a coalition structure to a real value. Given two coalitions $\mathcal{C}_1$ and $\mathcal{C}_2$, we say $\mathcal{C}_1$ and $\mathcal{C}_2$ are overlapping if $\mathcal{C}_1 \cap \mathcal{C}_2 \neq \emptyset$.*

2.5 Application of Game Theory in HetNets

Game theory is a study of conflict. It is to provide mathematical basis for modeling and analyzing the decision-making problem between interactive players who may have conflict of interests. Different from the optimization problems which focus on maximizing the utility of one player or multiple players with the same objective, the game theory deals with the optimal decision-making problem for multiple-players with difference objectives. For example, in traditional large scale homogeneous wireless network, the only player is the macro-cell BS which is the controller of the whole network, hence its optimal strategy of resource allocation can be answered by solving an optimization problem. However, in HetNets, due to the heterogeneity of different types of cells, i.e., those cells or communication links are different in coverage, capacity, air-interface, deployment, etc., the macrocell is no longer the only player. The presence of other players (e.g., the small cells or D2D links) result in a scenario that all players mutually influence each other by their actions in a dynamical manner, which makes static information based optimization impossible.

However, game theory may give us some light in investigating interactions of the autonomous players. The game theory which analyzes the interaction and decision-making process between multiple players with different kind of interests shows great potential in applying to HetNets. The different kind of mobile nodes in HetNets can be modeled as different players in the game, and using various game theoretical tools we can predict the possible outcome (i.e., pay-off) of the players and find an equilibrium in which the players satisfy the outcome and hence their actions become stable. There are various game models available for use and how to choose the suitable game model depends on the problem structure.

2.5.1 The application of non-cooperative game

The non-cooperative game model is usually used to model the problems of competition for limited resources. In a non-cooperative game, the players are selfish and only cares about their own profits. The actions which can maximize players' own pay-off functions are regarded as optimal and will be adopted. The outcome of such games is called NE which is formally defined in Section 2.1.

In [66], the authors point out that usually the efficiency of the NE would be degraded by the competition among players. Hence, they suggested ways which could help to improve the performance of non-cooperative game. A variety of non-cooperative game approaches for distributed interference control have been proposed to solve the above interference management problems. Usually the pricing scheme is utilized to trade-off between the power consumption and the data rate improvement. For example, the linear pricing scheme was used in [17] and non linear pricing function was proposed in [34].

Using the Stackelberg game model to handle the interference control problem was first proposed in [4]. The sub-band price was introduced to regulate the receiving power at the base station (BS) in code division multiple access (CDMA) network. The author designed a mechanism which minimized the information exchange during the power control process between the BS and the mobile nodes. Similar game model has been applied in [38], the authors extended the problem to a femto-cell network where the LS and ULS shared a common spectrum. They modeled the distributed interference control problem as a non-cooperative game. They proposed two different pricing schemes and discussed the impact to the pay-offs using different pricing schemes. They studied two scenarios in which the femto-cells are sparsely and densely deployed respectively. In [69], the authors considered the setup that the spectrum is divided into sub-bands, and they proposed a non-cooperative game model to enable the ULS join the sub-bands sequentially while the interference to the MCO was controlled by pricing. However, the selfish-behaved subscriber may cause inefficient equilibrium in the non-cooperative game. Moreover, the Stackelberg game can be also utilized to study the traffic control game between the macro-cell and the femto-cell. In [22], how the pricing strategy will influence the choice of mobile subscribers between macro or femto-cell are studied. By varying the conditions on frequency, operation cost, and femto-cell coverage, the authors give an comprehensive study on the trad-off in a two-tier network which helps the operator in optimal network planning.

2.5.2 The application of cooperative game

The efficiency of the whole system may be degraded by competition in non-cooperative game. In some problems, exploring the benefits gained by cooperation among the players may improve the performance of the wireless communication systems. In cooperative game, the players are no longer behave selfishly but care about the overall performance of the whole system. A widely used cooperative game model in the study of wireless communications is the coalitional game.

The coalitional game is usually utilized to investigate the cooperative behaviors and interactions among the nodes in the wireless communication systems, where the mobile subscribers seek to form coalitions in case they can make more profits than acting alone. In [57], three kinds of coalitional games and their applications in wireless communications have been summarized. More specifically, a special kind of coalitional game - the coalition formation game drives attention in analyzing the self-organizing mobile nodes in HetNets. In [31], the coalition formation game had been used to model the cooperation between the mobile nodes at different locations in a cell. The authors proposed a mechanism that the mobile nodes located near the BS can help to improve the QoS of the mobile nodes at the cell boundary. Coalition was formed between them and the overall performance of the network was improved. In [42], the rate allocation problems for Gaussian multiple access channels was investigated using coalitional game model, the authors proposed a transferable utility (TU) game therefore the mobile nodes can cooperate to improve the sum rate while improving its own performance. In [71] the authors considered a coalition formation game among the secondary users in the cognitive network. The ULSs formed disjoint coalitions to cooperatively utilize the spectrum. Together with the Stackelberg game between the MCO and ULSs, the authors provided a hierarchical game framework towards the solution to jointly optimize the resource allocation problem in cognitive networks.

2.5.3 The game with imperfect information

The information in the game refers to the actions or pay-offs of other players, which is used by the player in the game to predict its pay-off and take certain action. Sometimes this information is not perfectly known by the player, or is not deterministic. For example, in a non-cooperative game the independent mobile nodes may not know the pay-off of other players, or may not have precise observation about others' actions. In this case, each of the players should keep a private information about other players. We formally define the private information about the players as *types*. When one player takes actions, it may receive different pay-offs when facing different players. If a player wants to determine its action to maximize its pay-off, it should first make a prediction about the type of the other players. Hence, a player must have its private knowledge about *types* of other players, which is formally defined as $beliefs$. The belief can be considered as a probability distribution over the types of other players, but is not necessarily to be the true type. More specifically, the player needs to establish an initial belief about the types of other players, and may update the beliefs based on the Bayes' rule during the play takes part in the game. Therefore, we call this kind of game the Bayesian game. In Bayesian game, the player evaluates its benefit by the expected pay-off which averages out the beliefs, i.e., $\mathbb{E}(\pi) = \sum_{b_i \in \mathcal{B}} \pi(a|b_i)p(b_i)$, where b_i is a belief about the other player's types, and a is the action. The solution concept related to this kind of game is the Bayesian equilibrium, which is obtained based on the expected pay-off instead of the pay-offs in obtaining NE.

We assume that in future wireless communication networks the mobile nodes are intelligent and have the ability to observe and adapt to the radio environment. Hence, the Bayesian game can be applied to model the interactive behavior between mobile nodes when complete information is not available. Each mobile node keeps a belief which can be updated dynamically based on learning during the game play process. The objective of them is to find a Bayesian Equilibrium in which their beliefs approach the true types of other players, and the expected pay-off is optimal based on this belief.

The Bayesian game has been used in study of the wireless communications problems in recent years. In [46], the Bayesian learning was used to investigate the dynamic spectrum access problem in cognitive radios. The mobile nodes using learning scheme to get knowledge about the transmit behavior of others, therefore they can take best strategies to maximize the pay-off. In [28] the Bayesian game was used to model the resource allocation problems in a fading multiple access channels among selfish users, and the proof of the Bayesian NE and sub-optimal algorithm are given to optimize the sum rate of the network. In [76], the authors studied the application of Bayesian bargaining game in a primary-secondary cognitive network. The primary users shared their spectrum with the secondary users while the latter helps the former for their transmission in return. The authors design an non-cooperative bargaining game model to study the division of capacity gain between the primary and secondary networks. They show that using their model, the game between the primary and secondary users reach the equilibrium and achieve a win-win situation. In [72], the authors proposed a Bayesian coalition formation game to model the carrier aggregation problem in D2D communications. The author proposed a scenario that the D2D links first chose the mobile operator to access and then opportunistically performed carrier aggregation among D2D links accessing the same operator. The D2D carrier aggregation was modeled as a coalition formation game. Each of the D2D links kept a private preference order about the operators, but did not know the preference of others. During the game play process, each of the D2D links updated its preference order about the operators to maximize its pay-off, based on the belief about other D2D links' preference order. Furthermore, the D2D links would also update its belief about other D2D links' preference order based on its observation using the Bayesian learning. The author proved that their approach converged to a stable coalition formation structure where no D2D links will deviate it solely.

Chapter 3

Resource Allocation using Non-Cooperative Game

3.1 Introduction

We consider the resources allocation issues in a spectrum-sharing based two-tier Network, where the femto-cell subscribers act as the secondary user to access the spectrum owned by the MCO. The femto-cell technology has been proposed to improve the QoS of indoor mobile users by the deployment of home base station (HBS) [16]. The HBS connects to the core network using the IP network (e.g., DSL or home broadband) as backhaul, thus it is cost efficient to deploy.

Two rapidly growing demands driving the research in femto-cell networks are, 1) providing faster connections for mobile internet devices, 2) improving the coverage and releasing the burden of macro-cells. Under the spectrum-sharing model, a variety of game theoretical approaches based on pricing have been proposed [17], [37], [82]. By imposing the interference price as a policy to regulate the actions of unlicensed subscribers (ULS), the spectrum owner, i.e., the MCO, protects its licensed subscribers (LS) from harmful interference. Under this policy, both the MCO and the ULS sought to improve their pay-offs. Although these reported works utilized different game models and considered different trade-off

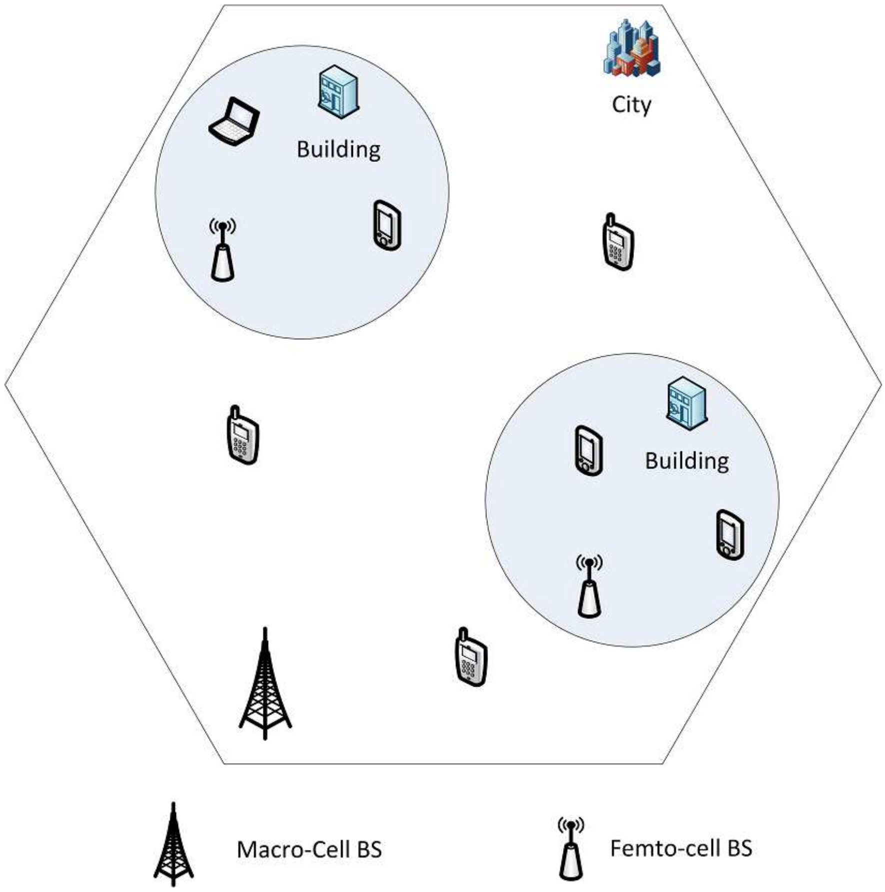

Figure 3.1: Illustration of a femto-cell network.
The spectrum sharing based two-tier femto-cell network contains a macro-cell and two femto-cell providing in-door service.

pairs, they shared the same concept that both the MCO and the ULS participate in the game.

In this chapter, we consider a scenario that the macro-cell partially shares its sub-bands with femto-cells, while being protected by the interference temperature constraint applied in each sub-band. We assume that each ULS can access multiple sub-bands to maximize the data rate. Furthermore, each sub-band can be shared by multiple users to further improve the overall network capacity by spectrum reuse. We formulate the resource allocation problem in this scenario as a Stackelberg game, in which the players (ULSs) act individually to maximize their own utilities without any coordination. To the best of the author's knowledge, this is the first game model which considers the multiple-user multiple-access problem in the femto-cell networks. We establish the connection between the game leader (the MCO) and the followers (the ULSs) by embedding the pricing term into the pay-off functions to follow the same line as [4] [38] [82] [71]. The pricing function is taken as a penalty to the ULSs for interfering the MCO. Therefore the leader can interact with the followers by adjusting the price. We will also prove the existence and uniqueness of Nash Equilibrium (NE), and provide distributed algorithm converging to the NE. With the help of the pricing function, the ULSs allocate their transmit powers considering both the channel gain and the interference to MCO.

3.2 System Setup

Table 3.1: The Notations

π_{S_k}	pay-off function of ULS S_k
π_{mo}	pay-off function of MCO
$\gamma_{S_k}^m$	receving SINR of ULS S_k
$\boldsymbol{l}_{S_k}$	sub-band allocation vector of ULS S_k
μ^m	interference price in sub-band m
$h_{S_k}^m$	channel gain from ULS S_k to macro-cell BS in sub-band m
$p_{S_k}^m$	transmit power of ULS S_k in sub-band m
$g_{S_k,k}^m$	the channel gain between ULS S_k and BS k
$\lambda_{S_k}^m$	the pay-off division factor for ULS S_k in sub-band m
$\boldsymbol{P}$	the power allocation matrix of all ULSs

We consider a two-tier network that constitutes a macro-cell and K femto-cells. The spectrum is owned by the MCO and divided into sub-bands. The macro-cell shares K sub-bands with the femto-cells, where the shared sub-band set is denoted by $\mathcal{K}$. We take frequency selective fading channel into consideration and one sub-band refers to a frequency bin. In the rest of the section, we interchangeably use the term 'channel' and 'sub-band' for the same meaning. The additive noise is assumed to be white Gaussian with variance σ^2. We denote $g^m_{S_k,k}$ as the channel gain between ULS S_k i and HBS k via sub-band l. We denote $h^m_{S_k}$ as the channel gain between ULS transmitter i and the MCO receiver via sub-band m. We assume $g^m_{S_k,k}$ and $h^m_{S_k}$ are time-invariant in one time slot, i.e., $h^m_{S_k}(t) = h^m_{S_k}$. We consider uplink channel while the femto-cells and macro-cell are assumed to be synchronized, i.e., they are in the same transmit or receive mode.

Figure 3.1 illustrates the proposed two-layers networks where the femto-cells underlay the macro-cell. In this research, we set up the game with *perfect information*, i.e., we assume that, 1) both the MCO and ULSs can precisely measure the noise-plus-interference levels at their receivers in each channel, 2) each ULS can estimate the channel gains in both signal link and interfering link, 3) the ULSs can receive the instantaneous price broadcast by the MCO. For simplicity, we assume that at each time slot there is only one active user in a femto-cell.

The ULSs are mobile devices, therefore the transmit power is bounded by the hardware limitation. Without loss of generality, we assume that for each ULS, there is a power cap constraint applied,

$$\sum_{m=1}^{M} p^m_{S_k} \leq \overline{p}, \tag{3.1}$$

where $p^m_{S_k}$ is the transmit power of user S_k on sub-band m and $\overline{p}$ is the total power. For the sake of fairness, we assume that all ULSs have the same total transmit power constraint.

On the other hand, the LSs of the MCO should be protected. More specifically, we apply an interference power constraint in each sub-band at the MCO receiver to guarantee the QoS of the LSs,

$$\sum_{k=1}^{K} p_{S_k}^m h_{S_k}^m \leq \overline{Q}, \tag{3.2}$$

where $p_{S_k}^m h_{S_k}^m$ is the interference from S_k in sub-band m.

Because each ULS is assumed to access arbitrary sub-bands and transmit over multiple sub-bands simultaneously, the power allocation over each sub-band is supposed to be efficient. In another word, we face a joint sub-band and power allocation problem. The ULS should not only choose suitable set of sub-bands to access but also need to properly allocate the transmit power over these sub-bands.

Traditional power allocation problems such as the water-filling solution usually consider the power cap constraint only. When applying to the spectrum-sharing based wireless network, a spectral mask constraint P_{mask} is imposed to limit the interference in a single sub-band [60]. However, the spectrum mask constraint is uniformly applied to each sub-band which does not consider the difference in channel gains. Here we use the interference power constraint which is aware of the fact that the ULSs may have different 'abilities' to interfere the MCO due to different spatial distributions and fading states.

3.3 Problem Formulation

In this section, we focus on developing fully distributed resource allocation scheme to avoid the information exchange among ULSs.

The Stackelberg game is a game type which can be classified as extensive game [53] [52]. The leader and the follower in the Stackelberg game move sequentially, and they can study the situation change and modify the decision to optimally adapt to this change. Subsequently, the Stackelberg equilibrium (SE) is equivalent to the subgame perfect equilibrium of the Stackelberg game. Formally, we refer the definition the Stackelberg game in Chapter 2.3 and define the SE as follows,

Definition 3.1. *A Stackelberg equilibrium is a solution of a Stackelberg game,* *in which the leader is making the best decision given the the followers' optimal actions, and the followers are making the optimal actions taking into account the leader's decision. Neither the leader nor the followers can benefit by deviating from the current action while the others remain unchanged.*

Particularly, the Stakelberg game model for interference management is described as follows,

- *Player*: The MCO (Leader) and the femto-cells (Follower).
- *Actions*:
  - Action of the leader is to decide the interference prices in each sub-bands, which is given by $\boldsymbol{\mu} = [\mu^1, \mu^2, ..., \mu^M]$.
  - Action of follower S_k is to select sub-bands to transmit from $\mathcal{K}$, which is given by the power allocation vector $\boldsymbol{p}_{S_k} = [p^1_{S_k}, p^2_{S_k}, ..., p^M_{S_k}]^T$.
- *Pay-offs*:
  - Pay-off of the leader is the payment collected from all the followers.
  - Pay-off of the follower S_k is the transmit rate r_{S_k} minus the payment c_{S_k} submitted to the leader.

As we mentioned in previous section, the LSs are given sufficient protection by the interference power constraint. It is more preferred to allow the less interfering ULS to transmit with priority. However, the instantaneous aggregated interference at the MCO receiver is difficult to be obtained by the ULSs, therefore the pricing scheme is utilized to regulate the transmission of the ULSs. The payment of S_k for using m is a positive valued function given by $c^m_{S_k}(\mu^m, h^m_{S_k} p^m_{S_k})$, which means that the ULS is penalized for interfering the MCO. Furthermore, $c^m_{S_k}(\mu^m, h^m_{S_k} p^m_{S_k})$ should increase with the interference $h^m_{S_k} p^m_{S_k}$, because the ULSs who bring heavy interference are not welcomed by the MCO.

We define the pay-off functions of the MCO as,

$$\pi_{mo}(\boldsymbol{p}, \boldsymbol{\mu}) = \sum_{k=1}^{K} c_{S_k}, \tag{3.3}$$

where the c_{S_k} denotes the payment collected from S_k.

We define the pay-off functions of the ULS S_k as,

$$\pi_{S_k}(\boldsymbol{p}_{S_k}, \boldsymbol{\mu}) = r_{S_k} - c_{S_k}, \tag{3.4}$$

where r_{S_k} is the revenue gained by S_k for transmission.

We seek a stable operation point (i.e., an equilibrium point) as the solution of the aforementioned game model. Once the equilibrium point is reached, both the MCO and the femto-cells have no incentive to leave. This equilibrium is the SE of the proposed Stackelberg game, which is formally defined as,

Definition 3.2. *The price vector* $\boldsymbol{\mu}^* = [\mu^{1*}, \mu^{2*}, ..., \mu^{M*}]$ *and the power allocation matrix* $\boldsymbol{P}^* = [\boldsymbol{p}^*_{S_1}, \boldsymbol{p}^*_{S_2}, ..., \boldsymbol{p}^*_{S_K}]$ *together form an SE if the constraints in (3.1) and (3.2) are satisfied, while*

$$\boldsymbol{\mu}^* = \arg\max_{\mu^m \geq 0} \pi_{mo}(\boldsymbol{p}, \boldsymbol{\mu}), \tag{3.5}$$

and

$$\boldsymbol{p}^*_{S_k} = \arg\max_{p^m_{S_k} \geq 0} \pi_{S_k}(p_{S_k}, \boldsymbol{p}^*_{-S_k}, \boldsymbol{\mu}). \tag{3.6}$$

3.4 Game Theoretical Analysis

In this section, we provide the solutions to the problems defined in Section II. We will show that if we define the cost function using linear pricing, and the revenue function using the Shannon capacity, the proposed game model will achieve a stable and unique sub-band allocation, and the SE is unique and optimal. Furthermore, we provide simple algorithm to achieve the SE of the game in certain condition.

3.4.1 The Individual Pay-off of ULSs

We define the revenue function of the S_k as the Shannon Capacity,

$$r_{S_k} = \sum_{m=1}^{M} \log\big(1 + \gamma_{S_k}^m\big). \tag{3.7}$$

To the signal to interference and noise ratio (SINR) in a multiple access channel contains two parts, the additive white noise and the interference come from co-channel subscribers, therefore the SINR $\gamma_{S_k}^m$ is given by,

$$\gamma_{S_k}^m = \frac{g_{S_k}^m p_{S_k}^m}{\sigma^2 + g_{S_0,k}^m p_{S_0}^m + \sum_{l=1,l\neq k}^{K} g_{S_l,k}^m p_{S_l}^m}, \tag{3.8}$$

where S_0 denotes the LS of the operator and S_l is other ULSs, $g_{S_l,k}$ is the channel gain between ULS S_l to femto-cell base station k.

In our system setup, the noise variance σ^2 is constant, and the LS is protected by the fixed interference constraint. So the LS can always transmit using the optimal power. Hence we only need to consider the power allocation of the ULSs. Using the linear pricing scheme, we take the payment to be proportional to the interference level. Hence we have the cost function,

$$c_{S_k} = \sum_{m=1}^{M} \mu^m h_{S_k}^m p_{S_k}^m. \tag{3.9}$$

Subsequently the pay-off function of S_k is defined as,

$$\pi_{S_k}(\boldsymbol{p}_{S_k}, \boldsymbol{p}_{-S_k}) = \sum_{m=1}^{M} \big[\log\big(1 + 1 + SINR_{S_k}^m\big) - \mu^m h_{S_k}^m p_{S_k}^m\big]. \tag{3.10}$$

With the explicit expression of the pay-off function defined above, the ULS

S_k is to individually solve the following optimization problem, while being constrained by the power cap constraint $\overline{p}$ and interference power constraint $\overline{Q}$.

$$\max\ \pi_{S_k}(\boldsymbol{p}_{S_k}, \boldsymbol{P}_{-S_k}) \tag{3.11}$$

$$\text{s.t.} \sum_{m=1}^{M} p_{S_k}^m \leq \overline{p}, \tag{3.12}$$

$$\sum_{k=1}^{K} p_{S_k}^m h_{S_k}^m \leq \overline{Q}. \tag{3.13}$$

$$p_{S_k}^m \geq 0. \tag{3.14}$$

The above problem is a maximization problem with multiple linear inequality constraints. However, (3.13) requires the knowledge of the transmit power and channel gain of other players which is difficult to be obtained by S_k. Furthermore, in the pay-off function (3.10), $\boldsymbol{P}_{-S_k}$ is also unknown by the S_k since lack of coordination with peers. Therefore distributed approaches avoiding the information exchange among ULSs is desired.

Fortunately, the proposed game model design can successfully avoid the problem of obtaining the global information, Firstly, the participation of the MCO as the game leader can be a 'bridge' among the independent ULSs to help them make decision. More specifically, if the adjustment of the interference price in each sub-band is related to the interference level, then the information of interference is actually embedded in the pricing factor μ^m. Hence, through properly adjusting the μ^m in each sub-band, the MCO can regulate the transmit behavior of the ULSs by two means, 1) control the interference at a safe level, 2) implicitly inform the ULSs about the interference level in each sub-band. Therefore, all the ULSs only need to optimize their power allocation based on μ^m broadcast by the MCO, and (3.13) is automatically satisfied. This is an exciting result that we can hence remove (3.13) from above problem. Secondly, although the interference components are written separately in (3.8), The S_k actually does not need to identify which is the interference source and how much interference it contributes. It can simply ask the femto-cell BS k to measure the aggregated interference at its receiver, then take it as noise to allocate the power by using conventional approach such as water-filling. Based on above two facts, the problem (3.14) is reduced to:

$$\max \ \pi_{S_k}(\boldsymbol{p}_{S_k}, \boldsymbol{P}_{-S_k}) \tag{3.15}$$

$$\text{s.t.} \sum_{m=1}^{M} p_{S_k}^m \leq \overline{p}, \tag{3.16}$$

$$p_{S_k}^m \geq 0. \tag{3.17}$$

which can be totally solved locally by each S_k itself using standard convex optimization technique. The detailed solution step is omitted and here we only provide the result. The best power allocation strategy for S_k is a water-filling alike solution, which is,

$$p_{S_k}^m = \max\left(0, W^m - N_{-S_k}^m\right). \tag{3.18}$$

In (3.18),

$$W^m = \frac{1}{\beta_{S_k} + \mu^m h_{S_k}^m}, \tag{3.19}$$

which is the water-level, and β_{S_k} is chosen to satisfy the power cap constraint (3.1).

$$N_{-S_k}^m = \frac{\sigma^2 + g_{S_0,k}^m p_{S_0}^m + \sum_{l=1,l\neq k}^{K} g_{S_l,k}^m p_{S_l}^m}{g_{S_k}^m}, \tag{3.20}$$

which is the ratio of the interference plus noise level to the channel gain at the receiver of femto-cell BS k.

In the following paragraphs we give some analysis on (3.18). The water-filling is only a one-time solution with the given interference status. The optimal power allocation at time t may not be optimal at time $t+1$ in the multiple access scenario, since the interference may change. Therefore, the ULSs should adjust its transmit strategy frequently to catch the dynamics of interference. Since the optimal solution for power allocation requires an exhaustive search and is generally mathematically intractable, low cost sub-optimal solutions have been proposed in [80] [60] [62]. These solutions can be classified as variations of the iterative water-filling (IWF) algorithm. As the name suggests, the IWF algorithm aims to solve the power allocation problem in multiple access channel by performing the water-filling procedure iteratively. The IWF extended the standard water-filling methods to the multiple access channel, and the mutual interferences therein are considered as noise.

However, the key difference between our setup and the scenario where conventional IWF algorithm applied in is the presence of the spectrum owner. Hence, the power allocation of ULSs will not only be affected by the channel gain and mutual interference, but also the interference constraints to protect the macro-cell subscribers. As a result, the water-filling like solution in (3.18) contains the channel dependent factor $\mu^m h^m_{S_k}$. The term $\mu^m h^m_{S_k}$ changes the water level in each channel, resulting in a non-uniform water-level comparing to the uniform water level in conventional IWF algorithms. The reason is that the cost term added to the pay-off function makes the ULSs not only to consider the noise level, but also care about the interference to the MCO while allocating the power in each channel.

The power allocation of ULSs is modeled as a non-cooperative game, in which each player S_k treats the measured $N^m_{-S_k}$ and received μ^m as the information of other player's action. Then it takes the *best response* towards this observation, saying $B(P_{-S_k})$, which is actually the water-filling solution for $N^m_{-S_k}$ and μ^m, respectively. If such a game has an NE, the following equation will be satisfied,

$$\boldsymbol{p}^*_{S_k} = B(\boldsymbol{P}^*_{-S_k}), \tag{3.21}$$

where $\boldsymbol{p}^*_{S_k}$ and $\boldsymbol{P}^*_{-S_k}$ represent the power allocations of player S_k and other players, respectively. Equation (3.21) indicates that each player's *best response* to other players' action is also the optimal action. In this case, no player is willing to deviate from the NE point solely, since this is the best choice if other users do not change their strategies [26].

3.4.2 The Pay-off Sum of ULSs

Based on the individual pay-off optimization problem defined in (3.17), we discuss maximizing the sum pay-off of all the ULSs,

Problem 3.4.1.

$$\max \sum_{k=1}^{K} \pi_{S_k}(\boldsymbol{p}_{S_k}, \boldsymbol{P}_{-S_k}) \tag{3.22}$$

$$s.t. \sum_{m=1}^{M} p_{S_k}^m \leq \overline{p}, k = 1, 2, ..., K. \tag{3.23}$$

$$p_{S_k}^m \geq 0 . k = 1, 2, ..., K. \tag{3.24}$$

Theorem 3.1. *In the proposed K ULSs M sub-bands multiple access channel, $\boldsymbol{p}_{S_k}$ is an optimal solution to the pay-off sum maximization problem (3.4.1) if and only if $\boldsymbol{p}_{S_k}$ is the water-filling solution vector when taking the interference sum as noise in each sub-band.*

Proof:

1) The if part can be obtained directly from the problem structure of the (3.4.1). As shown in (3.18), the solution of an individual subscriber is given by

$$p_{S_k}^m = \left(\frac{1}{\beta_{S_k} + \mu^m h_{S_k}^m} - \frac{\sigma^2 + g_{S_0,k}^m p_{S_0}^m + \sum_{l=1, l\neq k}^{K} g_{S_l,k}^m p_{S_l}^m}{h_{S_k}^m} \right)^+ . \tag{3.25}$$

The solution structure is exactly the same as the single subscriber scenario except an additive interference term $g_{S_0,k}^m p_{S_0}^m + \sum_{l=1, l\neq k}^{K} g_{S_l,k}^m p_{S_l}^m$. Hence, if we consider the interference as noise, there are no correlation between the optimal power allocation of each ULS. Then problem (3.4.1) is just a linear combination of a series of individual pay-off maximization problem, i.e., $\max\limits_{\boldsymbol{P}} \sum_{k=1}^{K} \pi_{S_k} = \max\limits_{\boldsymbol{p}_{S_1}} \pi_{S_1} +, ... + \max\limits_{\boldsymbol{p}_{S_K}} \pi_{S_K}$. Therefore if each of the $\boldsymbol{p}_{S_k}$ optimizes π_{S_k}, then the collection of $\boldsymbol{p}_{S_1}, \boldsymbol{p}_{S_2}, ...\boldsymbol{p}_{S_K}$ will optimize $\sum_{k=1}^{K} \pi_{S_k}$.

2) Then we proof the only if part. Suppose at the optimum of the pay-off sum in which all the ULSs allocate their power optimally, there exists a ULSs S_k, and its power allocation $\boldsymbol{p}'_{S_k}$ is equal to the one-time water-filling solution of (3.17). Since it is the optimum point and all other ULSs have fixed their power allocation, then the interference term in (3.17) becomes constant. Subsequently, we take the interference as noise and the optimal solution of problem (3.17) is given by $\boldsymbol{p}^*_{S_k}$, which is the water-filling solution, and will satisfy $\boldsymbol{p}^*_{S_k} > \boldsymbol{p}'_{S_k}$. Hence, it contradicts with our assumption. Therefore the power allocation of S_k should be the water-filling solution if the interference sum is taken as noise.

□

3.4.3 The Pay-off of MCO

As shown in previous section, the pay-off sum function of the MCO is simply defined as the payment collecting from all the ULSs in all sub-bands, hence the maximization problem is given by,

Problem 3.4.2.

$$\max_{\boldsymbol{\mu}} \sum_{m=1}^{M} \mu^m \sum_{k=1}^{K} h^m_{S_k} p^m_{S_k}, \tag{3.26}$$

$$s.t. \sum_{k=1}^{K} h^m_{S_k} p^m_{S_k} \leq \overline{p}, m = 1, 2, ..., M. \tag{3.27}$$

Proposition 3.1. *The problem (3.4.2) can be decomposed into a series of individual problems which are to maximize the pay-off in each sub-band. The problem in sub-band m is given by,*

Problem 3.4.3.

$$\max_{\mu^m} \ \mu^m \sum_{k=1}^{K} h_{S_k}^m p_{S_k}^m, \tag{3.28}$$

$$s.t. \sum_{k=1}^{K} h_{S_k}^m p_{S_k}^m \leq \overline{Q}. \tag{3.29}$$

Proof: In each time slot, for given $h_{S_k}^m$ and $_{S_k}^m$, the MCO tries to find optimal μ^m to maximize the pay-off. Since the power allocation of the ULSs is determined by themselves, the channel gains are the fixed physical parameters, and the interference prices in all sub-bands are independent with each other. Hence, the pay-off sum function (3.27) is actually the summation of a series of individual pay-off functions with independent variables. Such that $\max\limits_{\boldsymbol{\mu}} \sum_{m=1}^{M} \mu^m \sum_{k=1}^{K} h_{S_k}^m p_{S_k}^m = \max\limits_{\mu_1} \mu^1 \sum_{k=1}^{K} h_{S_k}^1 p_{S_k}^1 +, ..., + \max\limits_{\mu_M} \mu^M \sum_{k=1}^{K} h_{S_k}^M p_{S_k}^M$. □

We rewrite the result of (3.25) as,

$$p_{S_k}^{m*} = \left(\frac{1}{\beta_{S_k} + \mu^m h_{S_k}^m} - \frac{I_{S_k}^m}{g_{S_k}^m} \right)^+, \tag{3.30}$$

where $I_{S_k}^m = \sigma^2 + g_{S_0,k}^m p_{S_0}^m + \sum_{l=1,l\neq k}^{K} g_{S_l,k}^m p_{S_l}^m$ represents the interference plus noise.

Then we substitute the result of (3.30) into problem (3.4.2) and obtain the following problem.

Problem 3.4.4.

$$\max_{\mu^m} \ \mu^m \sum_{k=1}^{K} h_{S_k}^m \left(\frac{1}{\beta_{S_k} + \mu^m h_{S_k}^m} - \frac{I_{S_k}^m}{g_{S_k}^m} \right)^+, \tag{3.31}$$

$$s.t. \sum_{k=1}^{K} h_{S_k}^m \left(\frac{1}{\beta_{S_k} + \mu^m h_{S_k}^m} - \frac{I_{S_k}^m}{g_{S_k}^m} \right)^+ \leq \overline{Q}. \tag{3.32}$$

The centralized optimization of problem (3.4.4) requires the global information (i.e., $\beta_{S_k}, h_{S_k}^m, p_{S_k}^m$), and can be obtained by standard optimization process. In this section we are interested in developing fast algorithm to achieve the optimal solution. From problem 3.4.4, we can derive the following proposition,

Proposition 3.2. *The objective function of problem 3.4.4 monotonically decreases with μ^m in the range $\mu^m \in [\mu^{m'}, +\infty)$ if $\mu^{m'}$ satisfies,*

$$\sum_{k=1}^{K}\left[\frac{\mu^{m\prime}_{S_k}\beta_{S_k}}{(\mu^{m'}h^m_{S_k}+\beta_{S_k})^2}-\frac{I^m_{S_k}}{g^m_{S_k}}\right]<0. \tag{3.33}$$

$$\sum_{k=1}^{K}h^m_{S_k}\left(\frac{1}{\mu^{m'}h^m_{S_k}+\beta_{S_k}}-\frac{I^m_{S_k}}{g^m_{S_k}}\right)=\overline{Q}. \tag{3.34}$$

In the following paragraph we will give analysis of problem 3.4.4 and the proof of proposition 3.2.

It is easy to verify that, (3.3) (which we briefly write as $\pi_{mo}(\mu^m)$) is concave function of μ^m since,

$$\frac{\partial^2\pi_{mo}(\mu^m)}{\partial\mu^{m2}}=-2\sum_{k=1}^{K}\frac{h^{m2}_{S_k}\beta_{S_k}}{\mu^m h^m_{S_k}+\beta_{S_k}}<0. \tag{3.35}$$

Therefore, the objective function (3.3) is maximized without the constraint when the first-order derivation equations to zero, hence the optimal μ^{m*} satisfies,

$$\sum_{k=1}^{K}\frac{h^m_{S_k}\beta_{S_k}}{(\mu^{m*}h^m_{S_k}+\beta_{S_k})^2}=\sum_{k=1}^{K}\frac{h^m_{S_k}I^m_{S_k}}{g^m_{S_k}}. \tag{3.36}$$

Then we look at the constraint (3.32). Obviously (3.32) is a monotonically decreasing function of μ^m, we assume (3.32) takes equality when $\mu^m = \mu^{m'}$, i.e.,

$$\sum_{k=1}^{K}h^m_{S_k}\frac{1}{\mu^{m'}h^m_{S_k}+\beta_{S_k}}-\sum_{k=1}^{K}\frac{h^m_{S_k}I^m_{S_k}}{g^m_{S_k}}=\overline{Q}. \tag{3.37}$$

In the following we only consider the case that $\mu^{m'} > 0$ and $\mu^{m*} > 0$ are feasible since the price should be positive, otherwise it is only a trivial result that $\mu^m = 0$. Substitute (3.36) into (3.37) and after some derivations, we have,

$$\sum_{k=1}^{K}\frac{h^m_{S_k}\beta_{S_k}}{(\mu^{m'}h^m_{S_k}+\beta_{S_k})^2}+\sum_{k=1}^{K}\frac{\mu^{m'}h^{m2}_{S_k}}{(\mu^{m'}h^m_{S_k}+\beta_{S_k})^2}=\sum_{k=1}^{K}\frac{h^m_{S_k}\beta_{S_k}}{(\mu^{m*}h^m_{S_k}+\beta_{S_k})^2}+\overline{Q}. \tag{3.38}$$

Since (3.3) is concave, it is a decreasing function when $\mu^m \in [\mu^{m*}, +\infty)$. Hence, it also decrease in $[\mu^{m'}, +\infty)$ if $\mu^{m'} \geq \mu^{m*}$. Considering the case $\mu^{m'} \geq \mu^{m*}$, we can derive the following inequality from (3.38),

$$\sum_{k=1}^{K} \frac{\mu^{m'} h_{S_k}^{m2}}{(\mu^{m'} h_{S_k}^{m} + \beta_{S_k})^2} \geq \overline{Q}. \tag{3.39}$$

Substitute (3.37) into (3.39), we obtain,

$$\sum_{k=1}^{K} \left[\frac{\mu_{S_k}^{m\prime} \beta_{S_k}}{(\mu^{m'} h_{S_k}^{m} + \beta_{S_k})^2} - \frac{I_{S_k}^{m}}{g_{S_k}^{m}} \right] < 0. \tag{3.40}$$

which directly leads to the proposition 3.2, which is very useful in algorithm design. When the conditions in proposition 3.2 are satisfied, we can make use of the monotone property of the pay-off function of MCO, such that, the MCO can just maximize his pay-off by simply decreasing the interference price μ^m from a large value without obtaining any information from the ULSs.

3.5 Distributed Algorithm

In this section, we provide our algorithm for solving problem (3.17). We will prove that the proposed algorithm will converge to the SE. Furthermore, the proposed algorithm gives the optimal solution under proposition 3.2 and is sub-optimal otherwise.

In the previous section, a non-cooperative game of femto-cell resource allocation is formulated. We are interested in developing a fully distributed algorithm which converges to the NE of the resource allocation game. We will prove that for any given Q^m and P_{max} pair, the existence and uniqueness of NE coincide with the convergence of the proposed algorithm.

The proposed algorithm contains two-layered loops, the inner loop is a price based IWF algorithm. Different from the conventional water-filling updating function, here the $WF(\boldsymbol{p}_{-i}, \mu^m)$ is time-varying due to the time-varying μ^m. Thus the convergence proof of traditional IWF based on the contract-mapping theorem

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Algorithm 3.1: Two-Layer Iterative Water-Filling Algorithm

Consider a K-user system with M sub-bands, we denote the power cap constraint as $\overline{p}$ and the interference power constraint as $\overline{Q}$. We denote ϵ, δ, η and ζ as small constants and $\boldsymbol{u}$ as a unit vector of length M.

Initialization:

$P = \overline{p}$, $\mu^m = \mu_0$.

WHILE $\forall m, Q^m > \overline{Q}$

WHILE $\|\boldsymbol{\mu}(t+1) - \boldsymbol{\mu}(t)\| \leq \zeta$

WHILE $\|\boldsymbol{p_i}(t+1) - \boldsymbol{p_i}(t)\| \leq \epsilon$

FOR $i = 1$ to N,

FOR $m = 1$ to K,

$N_{-i}^m(t) = \sum_{j=1,j\neq i}^{N} p_j^m(t-1)H_{ji}^m + \sigma^2$

$p_i^m(t) = WF(N_{-i}^m(t), \mu^m(t-1))$,

$Q^m(t) = \sum_{i=1}^{N} g_{i0}^m p_i^m(t)$.

END.

If $Q^m(t) > \overline{Q}$

Set $\mu^m(t) = \mu^m(t-1) * (1-\delta)$,

ELSE IF $Q^m(t) < \overline{Q} - \epsilon$ Set $\mu^m(t) = \mu^m(t-1) * (1+\delta)$,

END.

If μ^m does not converge in a limited iterations.

Set $\overline{p} = \overline{p} - \eta$

END.

---

[10] can not be directly applied. However, the simulation results still support the convergence.

The outer loop controls the pricing factor and the amount of transmit power per-user. At first, the MCO admits the initial power of ULSs and adjusts the sub-band price μ^m to balance the interference in each of the sub-bands. If $\sum_{m=1}^{M} p_{S_k}^m h_{S_k}^m \geq \overline{Q}$, the sub-band m is overloaded and the MCO increases the price μ^m to push the ULSs away to allocate their powers to other sub-bands. On the other hand, the MCO decreases μ^m if sub-band m is not fully loaded. However, if only considering the inner-loop, adjusting price μ^m only makes the ULS to allocate different portion of total power in different sub-bands, which does not affect the total transmit power. If the initial power is too large, no mater how the MCO adjusts the interference price, the interference will not meet the constraint. In this case, a positive power allocation satisfying the interference constraint is infeasible. To avoid this situation, we should also adjust the amount of transmit power for each user so as to fit the interference constraint. It is observed in simulation that if a power allocation based on given P_{max} and $\overline{Q}$ is feasible, the price factor $\boldsymbol{\mu}$ will converge in just a few iterations, as shown in figure 3.2. If the price does not converge in a limited number of iterations, the MCO will consider the positive power allocation not being obtained with the current total power constraint. Then the MCO informs the ULSs to reduce the total transmit power in order to obtain a feasible power allocation. The step-size η can be set as a constant or user-dependent. For example, setting η_i proportional to the interference caused by i_{th} user results in heavier penalty to the stronger interfering user.

Theorem 3.2. *For a given interference and power constraint pair, and an initial price vector $\boldsymbol{\mu}$, the power allocation calculated by the proposed algorithm will converge to a fixed point.*

Lemma 3.1. *For any given fixed linear pricing function, the water-filling updating function $WF(\boldsymbol{p}_{-i}, \mu^m)$ converges to a fixed point if the channel gain of the* *interfering channel gain* $g^m_{S_l,k}$*,* $l \neq k$*, is sufficiently weak compared with the signal channel gain* $g^m_{S_k,k}$*. More specifically, it is given by,*

$$\sum_{k=1,k\neq k\prime} \max_{m\in l_{S_k}\cap l_{k\prime}} \left\{ \frac{g^m_{S_k,k\prime}}{g^m_{S_k,k}} \right\} \leq 1, \forall k\prime \in \mathcal{N}, \tag{3.41}$$

$$\sum_{k\prime=1,k\prime\neq k} \max_{m\in l_{S_k}\cap l_{k\prime}} \left\{ \frac{g^m_{S_k,k\prime}}{g^m_{S_k,k}} \right\} \leq 1., \forall k \in \mathcal{N} \tag{3.42}$$

Proof: From the convergence proof in [60], we can see that adding a linear pricing function with a fixed price does not affect the convergence [67]. Therefore if the time-varying price controlled by the outer loop is to be fixed over a few iterations, then the convergence proof can be applied again. Going through various sufficient conditions for the convergence of IWF in [80], [62] and [60], we can summarize that, if the interfering channel gain $g^m_{S_l,k}$, $j \neq i$ is, sufficiently weak compared to the signal channel gain $h^m_{S_k,k}$, or if the SINR at receiver is sufficiently small, the IWF algorithm will converge. This conclusion is useful in the femto-cell network, since the ULSs always have good channel condition with its nearby HBS, while experiencing serious path loss and penetration loss to other base stations. □

Lemma 3.2. *The interference price* μ^m *always converges to a non-negative value if a non-negative power allocation for a given* P_{max} *and* $\overline{Q}$ *pair exists.*

Proof: The MCO adjusts the channel price μ^m according to the measured interference in channel l. If the interference level is below the threshold, the MCO keeps decreasing the price until the channel is fully loaded or the price is decreased to zero. Conversely, if the interference level exceeds the threshold, the MCO keeps increasing the price to scare away the ULSs to other channels until approaching the upper bound. So there are only two cases that the MCO will stop adjusting the channel price, 1) the interference in the channel approaches the upper bound, 2) the price is reduced to zero. □

From lemma 3.2 we conclude that, for any given P_{max} and Q^m, the proposed algorithm will converge to a fixed NE. Simulations in next section also support this conclusion.

Algorithm 3.1 can be implemented in a distributed manner. The MCO does not need to know exactly the interfering link gain $h^m_{S_k}$ and corresponding transmit power $p^m_{S_k}$. It just measures the aggregated interference in each channel and then adjusts the price accordingly and broadcasts it. The price μ^m together with the local information N^m_{-i} and $h^m_{S_k}$ are enough for them to perform the self-updating procedure. $h^m_{S_k}$ can also be calculated using some empirical path loss model if real-time estimation value is not valid. Note that femto-cell's coverage is very small compared to the macro-cell, we consider the HBS and its active ULS at the same point in the macro-cell map. The position of HBS is easy to obtain by the mobile service provider since its deployment is fixed.

The complexity of the propose algorithm in each iteration is linearly scaled with the number of ULSs within the macro-cell. Since each ULS will only measures the interference by itself and there are only one MCO and N ULSs in total, therefore the complexity is given by $\mathcal{O}(N)$.

3.6 Numerical Results

We set the number of users $N = 4$ and the number of shared sub-bands $K = 8$. The signal channel gain h^m_{ii} is in the range of $[0.5, 1]$, and the interfering channel gain g^m_{i0}, $h^m_{i,j}$, $i \neq j$ is in $[0.01, 0.06]$. The setup is reasonable to femto-cell network, since the HBS is from the corresponding ULS while the other base stations are far away. We assume the maximum transmit power due to the hardware limitation of a mobile device is $P_{max} = 50$, where ULS is not necessarily transmitted on that level. The initial channel price $\mu^m = 0$.

Figure 3.2 shows an example of the convergence of the prices in each of the eight channels, with $P_{max} = 50$ and $\overline{Q} = 0.85$. We can observe that the prices

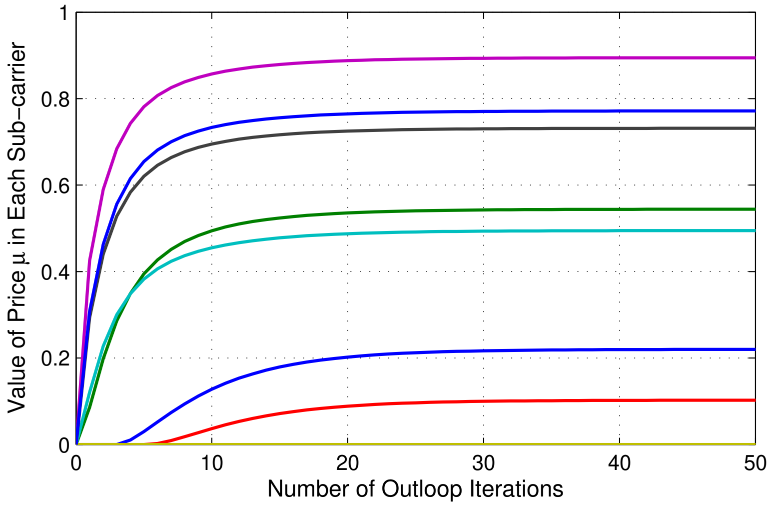

Figure 3.2: Convergence performance of the interference prices. the eight curves illustrate the converging prices in eight channels. $\overline{p} = 50$, $\overline{Q} = 0.85$.

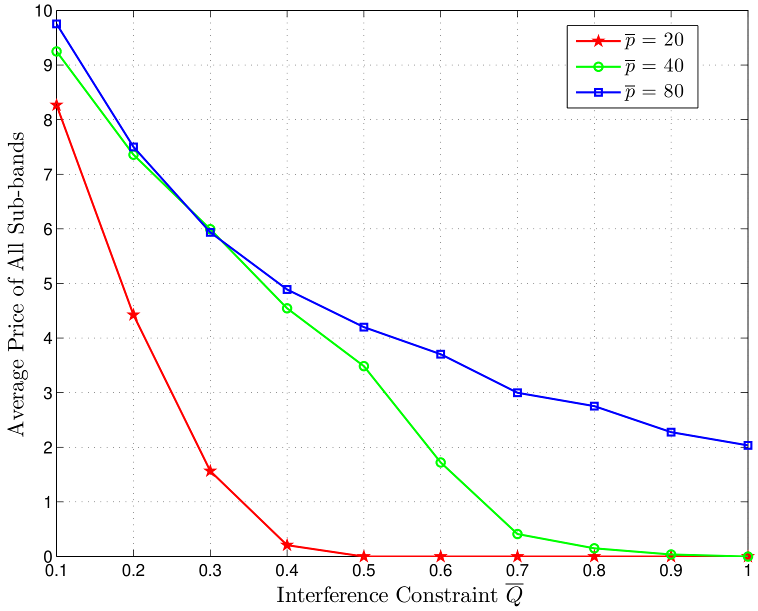

Figure 3.3: The impacts of interference constraint on price. Average price $\overline{\mu}$ decreases with $\overline{Q}$.

converge in a few iterations. Note that the price directly affects the power allocation on all sub-bands, hence the oscillation of interference price in one sub-band will also prevent the prices in other sub-bands to converge. Another observation is that the prices converge to different values, which means the price is adjusted by MCO according to the total interference, such that it is channel dependent.

Figures 3.3 and 3.4 illustrate the choice of $\overline{Q}$ against the average price over all sub-bands $\bar{\mu}$ and sum rate of femto-cell networks R. The average price $\bar{\mu}$ decreases with $\overline{Q}$, as shown in Figure 3.3. This interesting observation can be explained by an economics point of view, $\overline{Q}$ here is the amount of goods the MCO holds. If the amount of goods is small, it can be sold at a high price. Otherwise, if the vendor has a lot of goods to sell, he tends to sell them at a cheap price. Figure 3.4 shows the increasing trend of R with $\overline{Q}$. The slope of R decreases gradually and then converges. When $\overline{Q}$ is small, the amount of transmit power is limited by

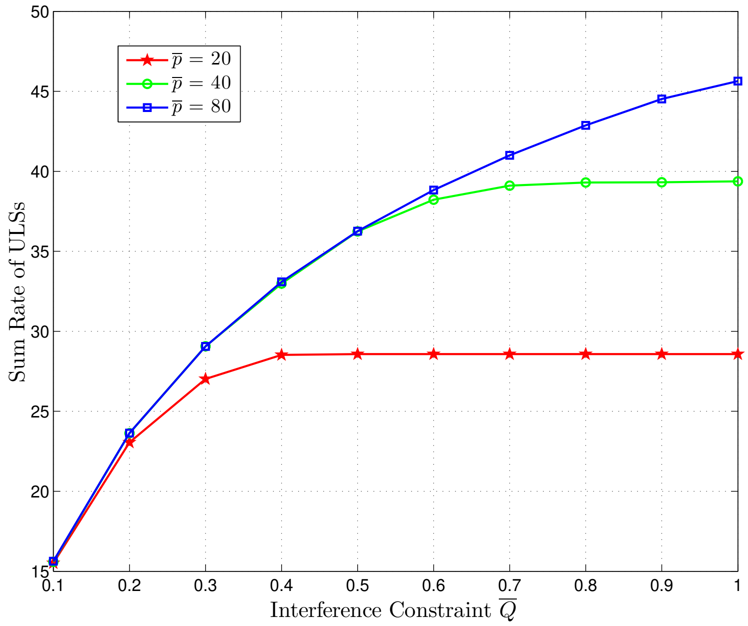

Figure 3.4: The impacts of interference constraint on sum rate. Sum rate R increases with $\overline{Q}$.

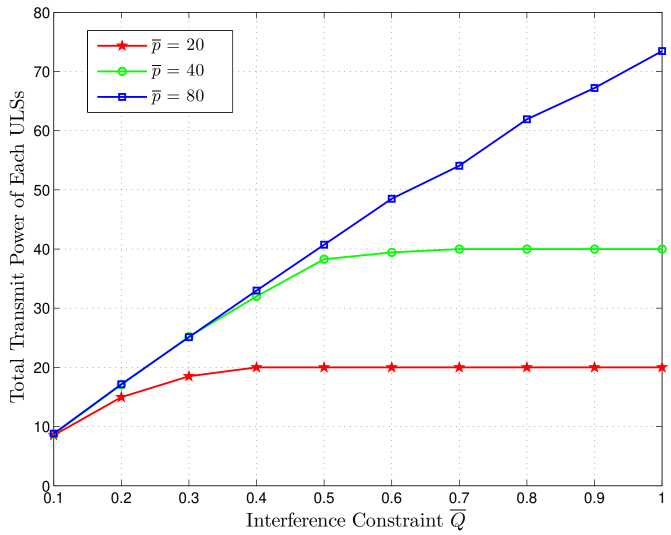

Figure 3.5: The impacts of interference constraint on sum rate. Sum rate R increases with $\overline{Q}$.

the interference constraint, resulting in the sum rate increases with $\overline{Q}$. When $\overline{Q}$ is high enough, the transmit rate will only be limited by the maximum transmit power constraint.

Figure 3.5 shows the actual power consumption versus the interference power constraint $\overline{Q}$. We can see that from the beginning to $\overline{Q} = 0.4$, the total transmit power increases with $\overline{Q}$. In this range the power allocation is jointly determined by the two constraints. When $0.4 \leq \overline{Q} < 0.7$, the curves of $\overline{p} = 40$ and $\overline{p} = 80$ keep increasing but the curve of $\overline{p} = 20$ keeps at a constant, which means the main limitation when $\overline{p} = 20$ is determined by the total power constraint. When $\overline{Q} \geq 0.7$, only the curve of $\overline{p} = 80$ increases while those of $\overline{p} = 20$ and $\overline{p} = 40$ remain to be constant. This figure gives a straightforward view about how the two power constraints jointly affect the transmit power.

Figure 3.6 shows the convergence curves of the total interference at MCO. We can see that when $\overline{Q} = 0.2$ and $\overline{Q} = 0.4$, the corresponding curves reach the interference after a few rounds of fluctuation. However when $\overline{Q} = 1$ the corresponding curve converges to a value which is slightly smaller than the constraint. This observation indicates that if $\overline{Q}$ is not stringent or the ULSs are far away from MCO, they can transmit with their maximum power but still satisfying the interference constraint. In this case, the resulted interference will not reach the upper bound.

Figure 3.7 compares the proposed algorithm with two other schemes as well as the benchmark in [19]. The first one is the narrow-band spectrum-sharing (NBSS) which is similar to [37]. In NBSS, multiple ULSs may share one common sub-band, however one ULS can access only one sub-band at the same time. The other one is the orthogonal spectrum allocation (OSA), in which each of the ULS exclusively occupies a sub-band for transmission. In all three scenarios the spectrum is shared by the MCO, while a common interference constraint $\overline{Q}$ is applied to protect the LSs. We fix $\overline{Q}$ while increasing the $\overline{p}$. We can see that the OSA has the worst performance since it totally loses the spectral efficiency gained by the spectrum reuse among ULSs. The NBSS performs better than OSA all the way. The NBSS performs similarly to the proposed scheme but it is outperformed by the proposed scheme when $\overline{p}$ becomes large. Because the proposed scheme can use more power to transmit on more sub-bands.

The proposed scheme can be simply implemented. For the information exchange between the MCO and the ULSs, there is a need for only one dedicated channel for the MOC to broadcast the interferences prices. A time frame for data transmission can be divided into two phases: the power control phase and the data transmission phase. In the power control phase, the time is divided into several time slots, which corresponds to an iteration in the proposed interference control algorithm. In each time slot, the MCO first measures the interference it is suffering, then adjusts the interference prices in each sub-band. Upon receiving the interference prices, the ULSs re-allocate their power in each sub-band based on the prices and the measured mutual interference. After several iterations when

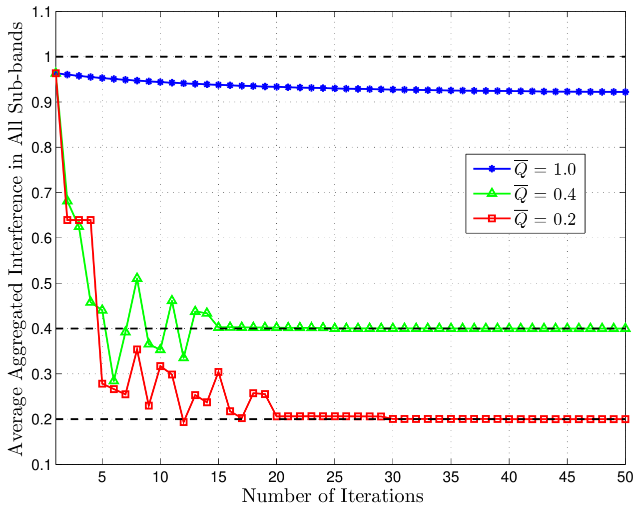

Figure 3.6: The convergence of average interference in each channel Q_{avg}. Q_{avg} may not approaching the $\overline{Q}$ if the power cap $\overline{p}$ is tight.

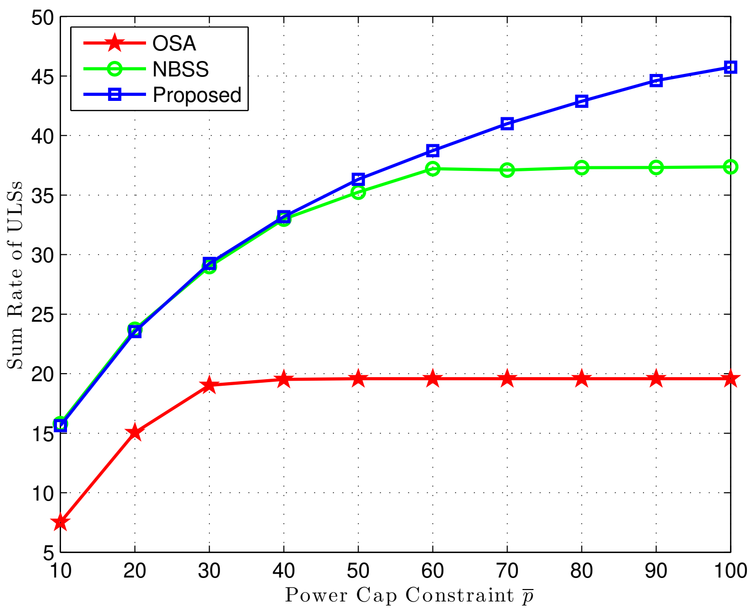

Figure 3.7: The comparison between OSA, NBSS and proposed scheme.

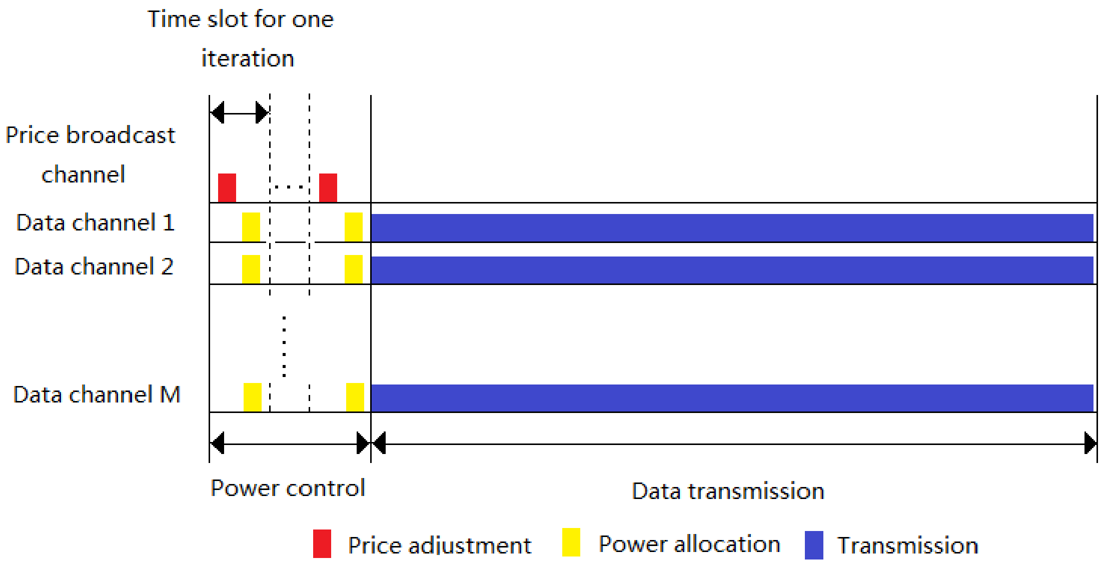

Figure 3.8: A time frame of proposed algorithm.

the prices and power allocation are stable, each of the ULSs uses its power allocation in the last time slot to perform data transmission. Suppose the price and power allocation will converge after L time slots, each time slot duration is τ, and the data transmission time is t, then the overhead of the proposed algorithm should be $\frac{t}{K\tau+t}$. The implementation is illustrated in Figure 3.8.

3.7 Conclusion

In this chapter, we have studied the resource allocation issues for spectrum-sharing based femto-cell networks on a multiple users multiple sub-bands basis. Different from previous literature which limited the spectrum-sharing in a narrow band, we have proposed a multiple ULS multiple sub-band spectrum-sharing scheme to further improve the spectrum efficiency. While the LS of MCO is protected by the interference power constraint, the resource allocation among the ULSs is formulated as a price-based Stackelberg game, and the existence and uniqueness of NE have been proved. A fully distributed algorithm which converges to the NE has been proposed. Experimental results show that the proposed algorithm outperforms the conventional OSA scheme all the way, and performs better than the NBSS scheme when there is spare power to transmit on more sub-bands. The proposed algorithm can be implemented with a low complexity in a distributed manner. It is shown to be a practical way of dealing with the interference issues in spectrum-sharing based two-tier networks without cooperation and centralized control.

The limitation of the proposed scheme is that it requires sparse spacing of the ULSs, otherwise the proposed algorithm would not converge. Furthermore, the proposed algorithm it is not always guaranteed to be optimal, and the optimality depends on the power and interference constraints.

Chapter 4

Resource Allocation Using Hierarchical Game

4.1 Introduction

A heterogeneous network is a multiple tier network consisting of co-located macro-cells, micro-cells and femto-cells, which is illustrated in Figure 4.1. It has been included in Long Term Evolution Advanced (LTE-A) standard as a part of the next generation mobile technology. One of the main motivations driving the development of HetNets is to improve the spectrum utilization efficiency by reusing the existing frequency band. With rapid growth of the popularity of mobile devices and multimedia contents in data services, there is an urgent need for mobile networks of a large capacity. Due to the scarcity of radio resources, it is important to seek an efficient way to improve the network capacity with the limited radio resources.

Recently, the carrier aggregation is proposed to support relatively large peak data rate in LTE-A standard [29], which is an instance of spectrum-sharing in practice. The carrier aggregation [73] [74] technique is introduced in the emerging LTE-A standard. It refers to the process of aggregating different blocks of spectrum to form larger transmission bandwidths to support high data rate. The technical challenges in the implementation issues of carrier aggregation are discussed in [81]. In [82], the spectrum shared by the MCO is divided into sub-bands, and frequency-selective-fading is considered. The authors proposed a heuristic algorithm to achieve the Nash equilibrium of the proposed game. The game theoretical based resource allocation has also been used to study the HetNets [77], [8], the authors therein consider the interference management issues and focus on the distributed intra-operator resource allocation schemes.

As the deployment of the femto-cells has been made by the end-user, centralized control is generally difficulty to achieve. Game theory provides useful tools to study the distributed optimization for multi-user network systems. Various game theoretical models have been proposed to solve power control problems in spectrum-sharing networks[17], [38]. For instance, using the Stackelberg game model to handle the interference control problem was first proposed in [4]. The sub-band price is introduced to regulate the receiving power at the BS in CDMA network. Similar game model has been applied in [38], the authors modeled the distributed interference control problem as a non-cooperative game and discussed the impact to the pay-offs using different pricing schemes in a scenario that the LS and ULSs sharing a common spectrum. However they assumed that all ULSs can only access one communication channel with flat-fading, which is not always held in practical scenario. In [69], the authors considered the setup that the spectrum is divided into sub-bands, and they proposed a non-cooperative game model to enable the ULS to join the sub-bands sequentially while the interference to the MCO is controlled by pricing.

However, in crowded place where the spacing of small cells are close, simply spectrum sharing using non-cooperative model will cause inefficiency pay-off due to serious mutual interference. Hence we seek cooperation between nearby ULSs by cooperatively transmit and receive signals.

To release the potential benefit gained from the cooperation in the mobile network, the coalitional game was introduced to investigate the behavior and interactions among the nodes in the wireless communication systems [57]. In this game the subscribers can form coalitions if they can make more profits than acting along. In [31], the coalition between the cellular subscribers located at the middle and boundary of each cell was formed to improve the performance of the network. In [42], the rate allocation problem for Gaussian multiple access channels was investigated using coalitional game model. In [71] the authors considered a coalitional game among the secondary users in the cognitive network. The ULSs form disjoint coalitions to cooperatively utilize the spectrum.

Although the coalitional game has been widely used to study the problems in wireless communications, most of the game model only considers forming disjoint coalitions. In other words, denoting $\mathcal{C}_j$ as a coalition, then $\mathcal{C}_1$ and $\mathcal{C}_2$ are disjoint coalitions if $\mathcal{C}_1 \cap \mathcal{C}_2 = \emptyset$. In contrast, $\mathcal{C}_1$ and $\mathcal{C}_2$ are overlapping coalitions if $\mathcal{C}_1 \cap \mathcal{C}_2 \neq \emptyset$. In practical communication systems, enabling the overlapping of coalitions may further improve the performance. For example, one user D_k forms coalition with D_j to cooperatively transmit in sub-band m. If D_k still has spare power, it may cooperative with D_i on the sub-band l to support more data rate. However, so far only some limited works have been reported for overlapping coalitional game. In [84], the authors considers the small cells form overlapping coalitions to coordinate their transmission, and they aimed to find a stable coalition structure.

In this chapter, we consider a scenario that the spectrum is licensed to the MCO and can be shared to the co-located femto-cells with payment. The femto-cells compete with each other for spectrum licensed to the MCO. The macro-cell subscribers are LSs who have been controlled by the operator. The femto-cell subscribers are ULSs who are controlled by the femto-cell BSs. The ULSs can share the sub-bands occupied by the LSs on condition that the resulting interference should be maintained below a tolerable level. Upon obtaining the spectrum from the MCO, the femto-cells can aggregate their sub-bands together to further expand the bandwidth. In other words, the ULSs may access multiple sub-bands, while each sub-band can be accessed by multiple users simultaneously. We utilize a game theoretical approach to map the sub-band allocation problem into an OCF-game. In the proposed game, each ULS has an amount of power resource to distribute in different sub-bands, and the achieved data rate depends on the parameters of the sub-bands and the transmit strategies of other ULSs.

We establish a hierarchical game framework to investigate the interaction between the MCO and the ULS. To the best of the author's knowledge, this is the first work which applies hierarchical game model in the analysis of HetNets. Furthermore, we further extend the hierarchical game model introduced in [71] by allowing ULSs to access multiple sub-bands simultaneously, and each sub-band can be shared by multiple ULSs. Hence the sub-band allocation problem in this new scenario can be modeled as an OCF-game, in which the ULSs in the same sub-bands act cooperatively to maximize the pay-off sum. The most important issue in the proposed OCF-game is to find an optimal coalition structure to maximize the pay-off sum of the femto-cell network.

On the other hand, the essential problem in a spectrum-sharing based network is to give sufficient protection to the LS of the MCO. The maximum tolerable interference level constraint or interference power constraint [32] is usually applied to regulate the transmit of the spectrum occupier, and the Stackelberg game is a useful tool to model the interaction between the MCO and the ULSs [38] [4] . The MCO acts as the leader to control the game play and the ULSs as followers play the best response to the leader's action.

The main contributions of this chapter are summarized follows.

1) We first consider a spectrum-sharing model in which the MCO share its spectrum to multiple ULSs. In contrast, the former works [71] [38] set that the spectrum to be accessed by only one ULS.

2) We first apply the OCF-game model to study the scenario that the cooperative ULSs can dedicate their power resources to multiple sub-bands. To the best of the author's knowledge, this is among the first few works which

introduce the overlapping coalition formation game into the HetNets.

3) We prove that the proposed OCF-game is 2^n-finite and hence the existence of the core of the game is presented, which makes finding the optimal coalition formation structure possible.

4.2 System Setup

Table 4.1: The Notations

$\pi_{S_k}(\boldsymbol{p}_{S_k}, \boldsymbol{\mu})$	pay-off function of ULS S_k
$\boldsymbol{v}(\boldsymbol{p}^m, \mu^m)$	value function of partial coalition m
$\boldsymbol{l}_{S_k}$	sub-band allocation vector of ULS S_k
$\boldsymbol{\mu}$	interference price vector
$h^m_{S_k}$	channel gain from ULS S_k to macro-cell BS in sub-band m
$p^m_{S_k}$	transmit power of ULS S_k in sub-band m
$g^m_{i,j}$	the ratio of the channel gain between ULS i and BS j to the interference power at k in sub-band m
$\lambda^m_{S_k}$	the pay-off division factor for ULS S_k in sub-band m
$\boldsymbol{P}$	the power allocation matrix of all ULSs

Consider an orthogonal frequency-division multiple access (OFDMA) based two-tier network where the spectrum owned by MCO is divided into M sub-bands, each of which can be accessed by one of the K femto-cells. We denote the set of sub-bands as $\mathcal{B}$ and the set of femto-cells as $\mathcal{K}$. Here the concept of *underlay* borrowed from the cognitive radio means that the secondary user (i.e., ULS) is allowed to transmit on the spectrum of primary user (i.e., LS) simultaneously, while the latter is being protected by an interference constraint [85]. The frequency selective fading is considered in this chapter, i.e., channel fading in different sub-bands is independent. We assume the channel state is time-invariant in each time block. The additive noise in each sub-band is assumed to

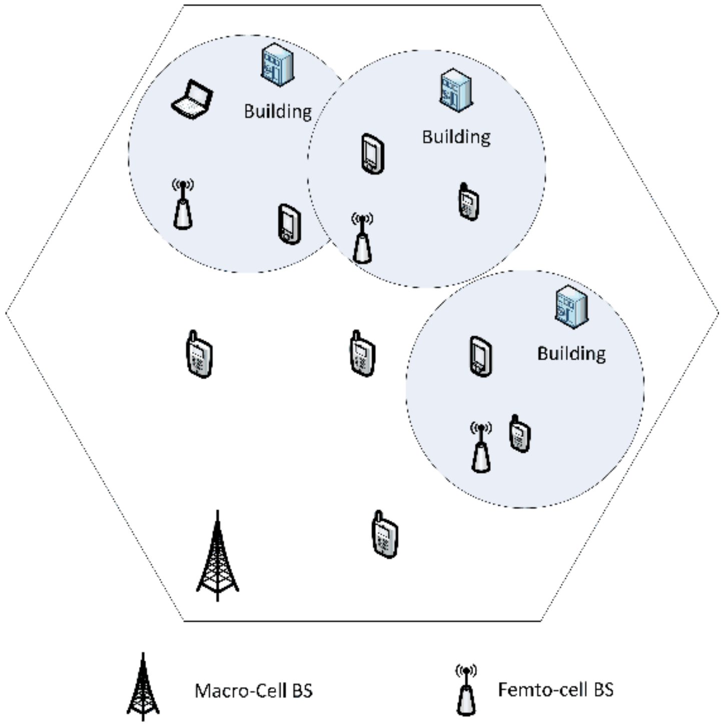

Figure 4.1: A spectrum sharing multi-tiers heterogeneous network. The spectrum is owned by the macro cell and shared to other tiers.

be white Gaussian. We further assume that the mobile devices are equipped with multiple antennas, therefore it is capable to transmit over multiple sub-bands simultaneously. Furthermore, multiple ULSs are allowed to share the same sub-band in order to fully utilize the spectrum. Each femto-cell can apply multiple sub-bands to support the services of its subscriber, i.e., the same portion of sub-bands can be reused by more than one femto-cell.

We assume that in each time slot there is only one active subscriber S_k in femto-cell k. Note that this assumption is just adopted to simplify the analysis, in fact there are no difference in applying the proposed scheme in multi-subscribers case. The reason is the follows: if we assume that the small cell multiplexes the ULSs using TDMA, then it can be always considered that there is virtually only one active user in one time slot in the small cell. If there are n ULSs in a small cell which are multiplexed using OFDMA, then it is equivalent to virtually n small cells with a single ULS.

Let h_k^m be the channel gain between S_k and the macro-cell BS receiver in sub-band m, and g_{kj}^m be the channel gain between S_k and jth femto-cell BS. Let $\boldsymbol{p}_{S_k} = [p_{S_k}^1, ..., p_{S_k}^M]$ be the power allocation vector of small cell subscribers, where $p_{S_k}^m = 0$ implies that sub-band m is not used by S_k.

On the other hand, multiple femto-cells can apply for the same sub-band at the same time. We denote the set of femto-cells utilizing the same sub-band m as $\mathcal{L}_m$, i.e., $\mathcal{L}_m = \{k : p_{S_k}^m > 0\}$. $\mathcal{L}_m = \emptyset$ means no ULS uses sub-band m, $\mathcal{L}_m = S_k$ means sub-band m is exclusively occupied by femto-cell k, $|\mathcal{L}_m| \geq 2$ means sub-band m has been shared by two or more femto-cells.

Different from the previous works which consider the non-cooperative spectrum-sharing scheme [82], the ULSs can cooperatively transmit the signal with co-channel peers to improve their pay-offs. Since the femto-cells may be deployed in an area without the coverage of the macro-cell, they are given the chance to aggregate their spectrum. The ULSs of different femto-cells in one sub-band m can cooperate by forming a virtual $|\mathcal{L}_m|$-input $|\mathcal{L}_m|$-output MIMO channel [47]. More specifically, at the beginning of each time slot, a portion of time is assigned for the ULSs to obtain the channel state information. When ULSs in the same coalition forms a virtual MIMO channel, S_k needs to estimate the channel gains of all the femto-cell BSs in the same coalition.

We follow the same line as [27] and consider the following two power constraints applied in the proposed system.

1) Interference power constraint of each sub-band,

$$\sum_{k=1}^{K} p_{S_k}^m h_{S_k}^m \leq \overline{Q}, \tag{4.1}$$

where the maximum tolerable interference $\overline{Q}$ is introduced to protect the LS.

2) The power cap of the mobile devices,

$$\sum_{m=1}^{M} p_{S_k}^m \leq \overline{p}, \tag{4.2}$$

where $p_{S_k}^m$ is the transmit power of S_k on sub-band m and $\overline{p}$ is the power cap. This constraint specifies the maximum transmit power of each subscriber, due to the hardware limitation and the battery life. Similar setup considering both the total power and per-band power constraints is investigated in [27].

Remark: These two power constraints together limit the number of ULSs accessing each sub-band. How they jointly affect the sub-band and power allocation of the ULSs depends on the particular network realization. For example, if $\overline{p}$ and $h_{S_k}^m$ are large, ULS S_k may cause interference that is close to $\overline{Q}$, then it will be the only active ULS in sub-band m. On the other hand, if $\overline{p}$ and $h_{S_k}^m$ are small, multiple ULSs can simultaneously transmit at the same sub-band, and the aggregated interference is still below $\overline{Q}$. The number of sub-bands used by an individual ULS is affected by the power cap given in (4.2), but the total number of the active ULSs in each sub-band is limited by the maximum tolerable interference level constraint (4.1).

The maximum tolerable interference level constraint reflects the fact that the randomly distributed ULSs usually cause different levels of interference to the macro-cell BS. Due to the frequency selective fading, even the interferences from the same ULS could be different in different sub-bands. Hence the ULSs are preferred to transmit in those frequency bands with weak channel gains between the ULSs and the macro-cell BS.

An important problem is how ULSs can smartly form the overlapping coalitions to maximize their pay-off. We propose an overlapping coalition formation game to study this problem. In this game, a group of ULSs can form coalitions, in which they behave cooperatively to coordinate their actions. Hence the coalition formation game focuses on two questions: 1) How the coalition members coordinate with each other, 2) How a coalition formation structure can be established among ULSs.

To answer the first question, we introduce the virtual MIMO technique as the cooperation scheme among the ULSs in the same coalition. We choose the virtual MIMO as the cooperation strategy for two reasons: 1) it is shown to achieve the upper-bound of the rate for a multiple access channel [64], 2) it is shown to satisfy the proportional fairness [71]. More specifically, the ULSs in the same sub-band m form a coalition to transmit and receive signal cooperatively. Using the virtual MIMO technique, we can convert the communication within one coalition into a virtual $\mathcal{L}_m$-input $\mathcal{L}_m$-output channel following the same line as [64] and [71]. Therefore we obtain that the capacity sum of all ULSs in the virtual MIMO channel m as,

$$\sum_{S_k \in \mathcal{L}_m} r_{S_k} = \sum_{S_k \in \mathcal{L}_m} \log\left(1 + \lambda^m_{S_k} p^m_{S_k}\right), \tag{4.3}$$

where $\lambda^m_{S_k}$ is the k_{th} non-zero eigenvalue of matrix $\boldsymbol{G}^T_{\{S_k \in \mathcal{L}_m\}} \boldsymbol{G}_{\{S_k \in \mathcal{L}_m\}}$, and $\boldsymbol{G}_{\{S_k \in \mathcal{L}_m\}}$ is the channel gain matrix of ULSs in the same sub-band. For example, if $\{S_1, ..., S_n\}$ are in the same sub-band m, then the matrix is given by

$$\boldsymbol{G}_{\{S_k \in \mathcal{L}_m\}} = \begin{bmatrix} g^m_{11} & g^m_{12} & \cdots & g^m_{1n} \\ g^m_{21} & g^m_{22} & \cdots & g^m_{2n} \\ . & . & . & . \\ . & . & . & . \\ g^m_{n1} & g^m_{n2} & \cdots & g^m_{nn} \end{bmatrix}. \tag{4.4}$$

In above matrix, g^m_{jk} is the ratio of the channel gain between ULS S_j and femtocell BS k to the received interference power at k in sub-band m_{S_k}. We will give analysis and propose distributed algorithm to answer the second question in section 4.4.

To simplify the analysis, we consider the uplink transmission. In the uplink, the receiver of macro-cell BS is interfered by the signal from ULSs, therefore there is only one leader when it applies price-based interference control. However, our model can be directly extended into the downlink scenario. In that case randomly distributed LSs act as a group of leaders and decide the sub-band prices of the sub-bands cooperatively. The main objective of this chapter is to solve the following problems:

1) *Power control problem*: we investigate the schemes to give sufficient protection to the LSs of the MCO.

2) *Sub-band allocation problem*: we investigate the strategies of ULSs for sub-band accessing.

3) *Coalition formation problem*: we investigate how the ULSs form overlapping coalitions to improve the data rate.

We formulate the first problem as an Stackelberg game and the second and third problems as an OCF-game, which together form a hierarchical game.

4.3 The Hierarchical Game Formulation

The Stackelberg game between the LSs and ULSs is a multiple leaders game. The cooperation among the leaders is investigated in [71]. The femto-cell and macro cell are assumed to be synchronized, i.e., they are in the same transmit or receive mode in each time slot.

Our goal is to jointly solve the protection problem of the LSs and resource allocation problems of the ULSs. Firstly, there is a trade-off between the sum capacity of the femto-cell network and quality of service (QoS) of the macro cell. If the ULSs transmit at high/low power to get high data rate, the interference to the macro-cell BS is large/small. Since sufficient protection to the LSs should be guaranteed in the first place, the MCO is the ruler who imposes the policy to regulate the behavior of the ULSs. Therefore, this is an power control problem between the MCO and ULSs. Secondly, given the limited spectrum and power resources, we should consider how the ULSs can behavior cooperatively to allocate the sub-band and power. This results in the resource allocation problem among the ULSs.

We model a hierarchical game in which the two sub games respectively deal with the above mentioned problems. In the proposed game model, the macro-cell operator and femto-cell BSs are the *players*, which refer to the participators of the game. The way the players play the game is defined as *actions*. In the proposed game model, the action of the MCO is to decide the interference prices, and the actions of the ULSs are to decide which sub-bands to access and how much power they allocate in these sub-bands.

We use the Stackelberg game to formulate the power control problem between the macro-cell and the femto-cells. In the proposed Stackelberg game, the *leader* is the MCO and the *followers* are the femto-cell BSs who control the ULSs. We follow a commonly adopted game theoretic setup [38] [70] [54] to define the pay-off functions of the ULSs, in which the *benefit* is the data rate and the *cost* is the payment for the interference. Both the follower and leader are selfish and try to maximize their pay-off. We denote μ^m as the unit price of interference in sub-band m. The price in all sub-bands is denoted by vector $\boldsymbol{\mu} = [\mu^1, \mu^2, ..., \mu^M]$. We adopt linear pricing scheme hence the payment from S_k for interfering the macro-cell BS receiver in sub-band m is proportional to the received interference power, say $\mu^m h^m_{S_k} p^m_{S_k}$. The ULS is benefited from transmitting on the sub-bands shared by the macro-cell, and the resulting data rate contributes to the profit term in the pay-off function, while the payment to MCO contributes to the cost term. We can hence rewrite the pay-off of S_k as,

$$\pi_{S_k}(\boldsymbol{p}_{S_k}, \boldsymbol{\mu}) = r_{S_k}(\boldsymbol{p}_{S_k}) - c_{S_k}(\boldsymbol{p}_{S_k}, \boldsymbol{\mu}), \tag{4.5}$$

where $c_{S_k}(p_{S_k,\mu}) = \sum_{m=1}^{M} \mu^m h^m_{S_k} p^m_{S_k}$ is the cost function. Furthermore, since S_k can transmit in multiple sub-bands at the same time, it aims to maximize the sum of the pay-offs obtained from all the active sub-band, under the constraints given in (4.2) and (4.1).

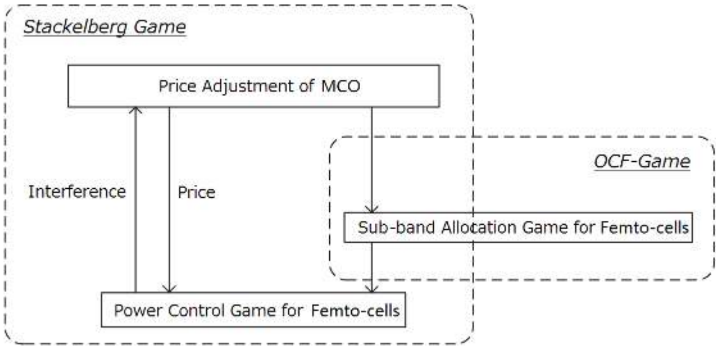

Figure 4.2: The hierarchical game structure.

The MCO collects the payment from all the ULSs occupying the sub-bands and only cares about the aggregated revenue. From these points we define the pay-off functions of the MCO as,

$$\pi_{MCO}(\boldsymbol{p}_{S_k}, \boldsymbol{\mu}) = \sum_{k=1}^{S_k} c_{S_k}(\boldsymbol{p}_{S_k}, \boldsymbol{\mu}). \tag{4.6}$$

The SE of our proposed Stackelberg game is defined as follows.

Definition 4.1. *Let $\boldsymbol{\mu}^*$ be the interference price vector and $\boldsymbol{p}^*_{S_k}$ be the power allocation vector of ULS S_k. Then, the point $(\boldsymbol{\mu}^*, \boldsymbol{P}^*)$ is an SE for the proposed Stackelberg game if for any non-negative $(\boldsymbol{\mu}, \boldsymbol{P})$, the following conditions are satisfied,*

$$\pi_{S_k}(\boldsymbol{p}^*_{S_k}, \boldsymbol{\mu}^*) \geq \pi_{S_k}(\boldsymbol{p}_{S_k}, \boldsymbol{\mu}^*), \tag{4.7}$$

$$\pi_{MCO}(\boldsymbol{P}^*, \boldsymbol{\mu}^*) \geq \pi_{MCO}(\boldsymbol{P}^*, \boldsymbol{\mu}). \tag{4.8}$$

The structure of the hierarchical Game is shown in figure 4.2. On the MCO side, the price is adjusted to maximize the pay-off in (4.6). In the analysis in Section 4.3.2 we will show that the maximization of the pay-off can be achieved by catching the dynamic of the aggregated interferences in each sub-band, therefore the task of obtaining global information for centralized optimization is avoided. On the femto-cells side, they cooperate and self-organize into coalitions based on the interference prices given by the MCO. The member subscribers in the same coalition coordinate their transmission to improve the sum of pay-off. The details will be provided in Section 4.4.

4.3.1 The pay-off of ULS

We start from introducing the pay-off functions of the proposed hierarchical game. Assuming that the overlapping coalition formation structure is fixed, i.e., each S_k already obtained a fixed λ_{S_k}, then each ULS, i.e., S_k, will obtain a pay-off defined by,

$$\pi_{S_k}^m(p_{S_k}^m, \mu^m, \lambda_{S_k}^m) = \log\left(1 + \lambda_{S_k}^m p_{S_k}\right) - \mu^m h_{S_k}^m p_{S_k}^m \tag{4.9}$$

The optimal power allocation of S_k is obtained by solving the following maximization problem,

Problem 4.3.1.

$$\begin{aligned} &\max_{\boldsymbol{p}} \pi_{S_k}(\boldsymbol{p}_{S_k}, \boldsymbol{\mu}, \boldsymbol{\lambda}_{S_k}) \\ &= \sum_{m=1}^{M} \left(\log\left(1 + \lambda_{S_k}^m p_{S_k}\right) - \mu^m h_{S_k}^m p_{S_k}^m\right), \\ &s.t. \quad \sum_{m=1}^{M} p_{S_k}^m \leq \overline{p}. \end{aligned} \tag{4.10}$$

In the proposed Stackelberg game framework, the maximum tolerable interference in (4.2) is omitted in problem 4.3.1 because it is embedded in the interference μ^m and thus is autonomously satisfied. Hence we only need to consider constraint in (4.1). Note that we can not directly apply (4.1) to problem 4.3.1 to obtain the power allocation using water-filling solution. Because the power value does not satisfy the requirement to form a virtual MIMO channel.

To deal with the above mentioned problem, we first solve problem 4.3.1 individually in each sub-band,

$$p_{S_k}^{m\dagger} = \arg\max_{p} \pi_{S_k}^{m}(p_{S_k}^{m}, \mu^m, \lambda_{S_k}^{m}), \tag{4.11}$$

$$= \left(\frac{1}{\mu^m h_{S_k}^m} - \frac{1}{\lambda_{S_k}^m}\right)^+. \tag{4.12}$$

The power allocated by each ULS S_k in each sub-band m should be given by $p_{S_k}^{m\dagger}$ only. In other words, if S_k decides to access sub-band m, it can only transmit at the power $p_{S_k}^{m\dagger}$, or it will cause the failure of the coalition. Then the sub-bands accessed by S_k are chosen to satisfy the constraint in (4.1).

For $m = [1, 2, ..., M]$, we have $\boldsymbol{p}_{S_k}^{\dagger} = [p_{S_k}^{1\dagger}, p_{S_k}^{2\dagger}, ..., p_{S_k}^{m\dagger}]$. Due to the power cap constraint in (4.1), the final power allocation will fall into the following two cases.

Case 4.1. $\sum_{m=1}^{M} p_{S_k}^{m\dagger} \leq \bar{p}$. *In this case, S_k can access all sub-bands without violentting in (4.1). The power allocation of S_k is purely decided by constraint (4.2). Hence we can removed (4.1) and the power allocation of the ULS solely depends on the sub-band prices. Each of the ULSs tries to solve (4.24) for the optimal power allocation and obtain $p_{S_k}^{m\dagger}$ to maximize the pay-off.*

Case 4.2. $\sum_{m=1}^{M} p_{S_k}^{m\dagger} > \bar{p}$. *In this case, only selected sub-bands can be utilized by the ULS S_k. More specifically, the solution is achieved by searching a sub-set $\mathcal{N}_i \subset \mathcal{M}$ such that the following conditions are satisfied:*

$$\begin{cases} \sum\limits_{m \in \mathcal{N}_i} p_{S_k}^{m\dagger} \leq \bar{p} \\ \sum\limits_{m \in \mathcal{N}_i} \pi(p_{S_k}^{m\dagger}) \geq \sum\limits_{n \in \mathcal{N}_j, j \neq i} \pi(p_{S_k}^{n\dagger}), \end{cases} \tag{4.13}$$

where $\{\mathcal{N}_j\}$ denote all other sub-sets of $\mathcal{M}$ other than $\mathcal{N}_i$. This case implies that, once the price is fixed, the number of sub-bands accessed by one ULS is bounded by the power cap constraint.

We conclude from case 4.1 and 4.2 that, the optimal power allocation of S_k is given by,

$$\boldsymbol{p}^*_{S_k} = \{p^{m*}_{S_k}, m = 1, 2, ..., M.\},$$
$$p^{m*}_{S_k} = \begin{cases} p^{m\dagger}, \text{if } m \in \mathcal{N}_i \\ 0, \text{otherwise.} \end{cases} \tag{4.14}$$

The corresponding sub-band allocation indicator is,

$$\boldsymbol{l}^*_{S_k} = \{l^{m*}_{S_k}, m = 1, 2, ..., M.\},$$
$$l^{m*}_{S_k} = \begin{cases} 1, \text{if } \boldsymbol{l}^*_{S_k} > 0, \\ 0, \text{otherwise.} \end{cases} \tag{4.15}$$

From the results above we see that the optimal solution of the transmit power in $\boldsymbol{p}_i$ only depends on the sub-band prices μ^m and $\lambda^m_{S_k}$, which are two key outcomes of the proposed hierarchical game. The prices are decided by the MCO through the Stackelberg game, and the $\lambda^m_{S_k}$ is obtained from the coalitional game between ULSs. In the following subsection we consider how to obtain optimal μ^m and $\lambda^m_{S_k}$.

4.3.2 The Pay-off of the MCO

The MCO controls the interference in each sub-band by simply adjusting the interference price $\boldsymbol{\mu}$, and the ULSs only need to care about the interference prices. We will show that the MCO can maximize its pay-off by adjusting the prices based on the dynamic of the aggregated interference at the macro-cell BS receiver. Hence the proposed algorithm greatly reduces the communication overhead and makes the distributed power allocation approach possible.

The revenue gained by the MCO by sharing sub-band m is given by,

$$\pi_{MCO}(\boldsymbol{p}^m, \mu^m) = \mu^m \sum_{k=1}^{K} h^m_{S_k} p^m_{S_k}. \tag{4.16}$$

Hence the MCO is to find the optimal sub-band price to maximize its revenue in each sub-band under the maximum tolerable interference constraint.

Problem 4.3.2.

$$\max_{\mu^m} \ \pi_{MCO}(\boldsymbol{p}^m, \mu^m) \tag{4.17}$$

$$s.t. \ \sum_{k=1}^{K} p_{S_k}^m h_{S_k}^m \leq \overline{Q}, \tag{4.18}$$

$$p_{S_k}^m \geq 0. \tag{4.19}$$

Substitute (4.12) into problem 4.3.2, we obtain,

Problem 4.3.3.

$$\max_{\boldsymbol{\mu}} \ \sum_{k=1}^{K} \left(\frac{1}{h_{S_k}^m} - \frac{\mu^m}{\lambda_{S_k}^m} \right)^+ h_{S_k}^m \tag{4.20}$$

$$s.t. \ \sum_{k=1}^{K} \left(\frac{1}{\mu^m h_{S_k}^m} - \frac{1}{\lambda_{S_k}^m} \right)^+ h_{S_k}^m \leq \overline{Q}. \tag{4.21}$$

The optimal μ^m can be obtained by solving above problem using standard convex optimization approach. However, it requires MCO to obtain the transmit power and channel gains of the ULSs. Fortunately, problem 4.3.3 has a nice property which enables us to search the optimal μ^m using fast numerical method. The objective and constraint functions both monotonically decrease with μ^m, hence the objective function will be maximized when the constraint in (4.21) takes equality. Note that the left side of (4.21) corresponds to the aggregated interference at the macro-cell BS receiver in sub-band m. Therefore the MCO can simply keep decreasing the price from a large value, and stops when observing that the interference approaches $\overline{Q}$.

Based on the analysis in subsection 4.3, we notice that the Stackelberg game model enables simple and distributed pay-off optimizations. The MCO optimizes price μ^m by simply catching the dynamic of interferences, while the femto-cells negotiate with each other to form overlapping coalitions and adjust the transmit power adapting to the price.

4.4 Coalition Formation Game Analysis

Our main contribution is presented in this section. We first present formal definitions of the coalition and imputation.

Definition 4.2 ([51], chapter 9)**.** *Denote the set of all players as $\mathcal{K}$, we define a coalition $\mathcal{C}$ is a non-empty sub-set of $\mathcal{K}$, i.e., $\mathcal{C} \subseteq \mathcal{K}$. Specially, $\mathcal{K}$ is referred as the grand coalition. A coalitional game is defined as $(\mathcal{C}, v)$ where v is the value function mapping a coalition structure $\mathcal{C}$ to a real value $v(\mathcal{C})$. If for any two disjoint coalitions $\mathcal{C}_1$ and $\mathcal{C}_2$ in a coalition game, $\mathcal{C}_1 \cap \mathcal{C}_2 = \emptyset$, $\mathcal{C}_1 and \mathcal{C}_2 \subset \mathcal{K}$, we have,*

$$v(\mathcal{C}_1 \cup \mathcal{C}_2) \geq v(\mathcal{C}_1) + v(\mathcal{C}_2), \tag{4.22}$$

then we say this game satisfies the super-additive property. Given two coalitions $\mathcal{C}_1$ and $\mathcal{C}_2$, we say $\mathcal{C}_1$ and $\mathcal{C}_2$ overlaps if $\mathcal{C}_1 \cap \mathcal{C}_2 \neq \emptyset$.

Definition 4.3. *We define an imputation as a pay-off vector satisfying both group and individual rationalities. A pay-off vector $\boldsymbol{\pi}$ is a division of the value $v(\mathcal{C})$ to all the coalition members, i.e., $\boldsymbol{\pi} = [\pi_{S_1}, \cdots, \pi_{S_K}]$. We say $\boldsymbol{\pi}$ is group rational if $\sum_{k=1}^{K} \pi_{S_k} = v(\mathcal{C})$ and individual rational if $\pi_{S_k} \geq v(\{S_k\}), \forall S_k \in \mathcal{C}$.*

If a coalitional game satisfies the super-additive condition, then the grand coalition is formed, and the game focuses on finding the optimal imputation to form the grand coalition. However if the super-additive condition does not hold, then the game focuses on finding optimal partition of the grand coalition. In this case, a core of the coalitional game is defined as a set of stable coalition formation structures in which no player can profitably deviate from them. This is different from the one defined in the coalitional game which is a set of imputations stabilizing the grand coalition. In the proposed OCF-game, given the fixed interference price, we focus on finding optimal coalition formation structure, i.e., we investigate the optimal coalition partitioning of the grand coalition.

When overlapping is enabled among coalitions, the coalitions are no longer disjoint sub sets of the player set as defined in a non-overlapping coalitional game. In the OCF-game, the concept *partial coalition* is utilized:

Definition 4.4. *The partial coalition is defined on a vector* $\boldsymbol{p}^m = (p_{S_1}^m, p_{S_2}^m, ..., p_{S_K}^m)$*, where* $p_{S_k}^m$ *is the fractional resource of* S_k *dedicated to coalition* m*. Note that* $p_{S_k}^m = 0$ *means* S_k *not being in this coalition. A coalition structure is a collection* $\boldsymbol{P} = (\boldsymbol{p}^1, ..., \boldsymbol{p}^M)$ *of partial coalitions.*

Remark 4.1. *In a non-overlapping coalition formation game, a coalition is just a subset of the player set. For a player set of size* N*, the number of coalition formation structure is given by the Bell number* B_N*, where* $B_N = \sum_{k=0}^{N-1} \binom{N-1}{k} B_k$ *is the possible number of coalition structures and* B_k *is the number of ways to partition the set into* k *items.*

For example, given the player set $\{S_1, S_2\}$*, the coalitions set is* $\{\{S_1\}, \{S_2\}, \{S_1, S_2\}\}$*, hence the resulting coalition structure is* $\{S_1, S_2\}$ *or* $\{\{S_1\}, \{S_2\}\}$*. However, in OCF-game the concept of partial coalition not only shows who joins the coalition, but also indicates how much resource each player contributes to this coalition. If the resource is continuous, there are generally infinite number of partial coalitions. For example, for players set* $\{S_1, S_2\}$*, the set of partial coalitions may be* $\{\{0, 1\}, \{0.2, 0.3\}, \{1, 1\}, \{0.5, 0\}, ...\}$*. It means that the concept of coalition is considered as a special case of the partial coalition, where each player join only one coalition with all its resource.*

Definition 4.5. *An OCF-game is denoted by* $G = (\mathcal{K}, \mathcal{M}, \boldsymbol{P}, \boldsymbol{v})$*, where*

- $\mathcal{K} = \{1, 2, ..., K\}$ *is the set of players which are the femto-cells.*

- $\mathcal{M} = \{1, 2, ..., M\}$ *is the set of sub-bands.*

- $\boldsymbol{P}$ *is the power allocation matrix, which the row* $\boldsymbol{p}_{S_k} = (p_{S_k}^1, p_{S_k}^2, ..., p_{S_k}^M)$ *represents how player* S_k *assign its power on different sub-bands, and the column* $\boldsymbol{p}^m = (p_{S_1}^m, p_{S_2}^m, ..., p_{S_K}^m)$ *represent the power each player spends on sub-band* m*.* $\boldsymbol{p}^m = (p_{S_1}^m, p_{S_2}^m, ..., p_{S_K}^m)$ *also corresponds to a partial coalition.*

- $\boldsymbol{v}(\boldsymbol{C}^m) : \mathbb{R}^n \longrightarrow \mathbb{R}^+$ *is the value function, which represents the total pay-off of a partial coalition* $\boldsymbol{C}^m$.

Definition 4.6. *We define a game to be U-finite if for any coalition structure that arises in this game, the number of all possible partial coalitions is bounded by* U.

Figure 4.3 illustrates one example of the overlapping coalition formation of our model. The spectrum of the MCO is divided into six sub-bands $\{1, 2, 3, 4, 5, 6\}$ which can be allocated to three mobile devices $\{M1, M2, M3\}$. A coalition is formed on the sub-band if it is accessed by two or more mobile devices. Each mobile device may belong to multiple coalitions, since it may access multiple sub-bands at the same time. We say the coalitions containing a common member player are overlapping. For example, in figure 4.3, we denote the coalition formed by the devices accessing sub-band k as $\mathcal{C}_k$, Then we have, $\mathcal{C}_1 = \{M1\}$, $\mathcal{C}_2 = \{M1, M3\}$, $\mathcal{C}_3 = \{M3\}$, $\mathcal{C}_4 = \{M1, M2, M3\}$, $\mathcal{C}_6 = \{M2, M3\}$, $\mathcal{C}_5 = \emptyset$. Hence, $\mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_4$ are overlapping since $\mathcal{C}_1 \cap \mathcal{C}_2 \cap \mathcal{C}_4 = M1$, $\mathcal{C}_3, \mathcal{C}_4, \mathcal{C}_6$ are overlapping since $\mathcal{C}_3 \cap \mathcal{C}_4 \cap \mathcal{C}_6 = M2$, $\mathcal{C}_2, \mathcal{C}_4 and \mathcal{C}_6$ are overlapping since $\mathcal{C}_2 \cap \mathcal{C}_4 \cap \mathcal{C}_6 = M3$.

The sum rate achieved by forming coalition is given by (4.3), and the pay-off sum of a ULS equals to the sum rate minus payment to the MCO. Hence the value function of the partial coalition $\boldsymbol{p}^m$ is defined as the pay-off sum on sub-band m. Given the fixed price vector $\boldsymbol{\mu}$, the value function of the partial coalition $\boldsymbol{p}^m$ is given by,

$$\boldsymbol{v}(\boldsymbol{p}^m, \boldsymbol{\lambda}^m) = \sum_{S_k \in \mathcal{L}_m} r_{S_k} - \sum_{S_k \in \mathcal{L}_m} \mu^m h^m_{S_k} p^m_{S_k}. \tag{4.23}$$

It is proved in [71] that the pay-off division among coalition members satisfies the proportional fairness [39], if the benefit allocated to each member equals to its contribution to the overall rate in sub-band m, i.e.,

$$r^m_{S_k} = \log\left(1 + \lambda^m_{S_k} p^m_{S_k}\right). \tag{4.24}$$

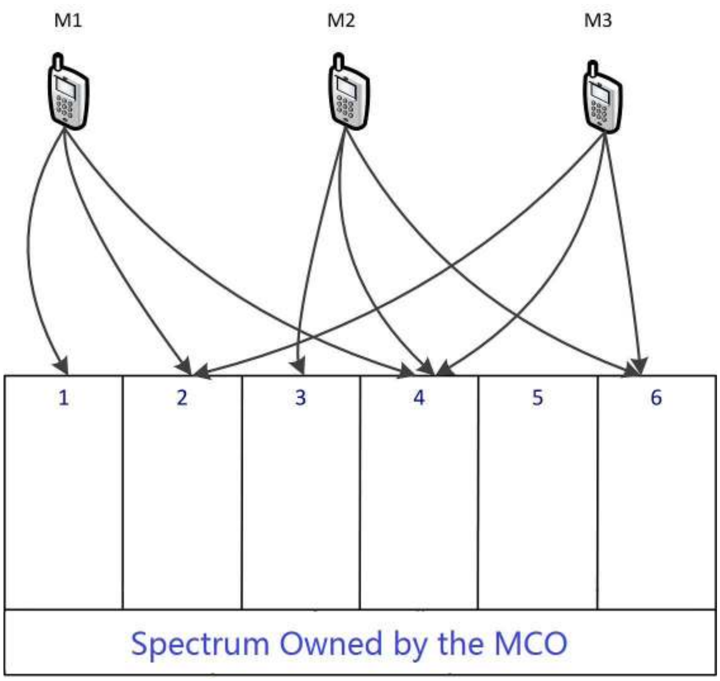

Figure 4.3: The illustration of the overlapping coalitions in our proposed game.

The solution of the optimal power vector $p^m_{S_k}$ of S_k is given in (4.14), which is jointly decided by $\lambda^m_{S_k}$ and μ^m. Since $\boldsymbol{\mu}$ is maintained by the MCO, the ULSs can optimize the pay-off sum by choosing $\lambda^m_{S_k}$ only. Furthermore, since $\lambda^m_{S_k}$ depends on the coalition structure, then finding optimal $\lambda^m_{S_k}$ is equivalent to choosing an optimal coalition structure. Therefore, the power allocation of the ULS side can be equivalently achieved by the coalition formation game.

There are two actions of the players in an OCF-game, which are the coalitional action and the overlapping action. The former defines how the resource being allocated among the member players in one coalition, and the latter defines how resource being allocated between players in the overlapping parts of multiple coalitions. These are the key features to differentiate the OCF-game from the non-overlapping coalition formation game.

In the proposed system setup, the femto-cell subscribers accessing the same sub-band form a coalition. The cooperation among the member players is achieved by forming a virtual MIMO channel. The pay-off division relies on assigning $\boldsymbol{\lambda}$ to the players, which can be considered as the contribution of each coalition member to the sum rate. Since the ULSs can join multiple coalitions, the proposed game becomes an OCF-game. As the resources of a ULS is the total transmit power, the profit is the pay-off sum obtained from all coalitions. The ULSs need to distribute the resources in each sub-band properly to maximize the pay-off. For the proposed OCF-game, we have the following definition.

Definition 4.7. *For a set of ULSs $\mathcal{S}$, a coalition structure on $\mathcal{S}$ is a finite list of vectors (partial coalitions) $\boldsymbol{P} = (\boldsymbol{p}^1, ..., \boldsymbol{p}^M)$ that satisfies (i) $\sum_{k=1}^{K} h_{S_k}^m p_{S_k}^m \leq \overline{Q}$, (ii) $\sup \boldsymbol{p}^m \subseteq \mathcal{S}$ for all $m = 1, ..., M$, and (iii) $\sum_{m=1}^{M} p_{S_k}^m \leq \overline{p}$ for all $j \in \mathcal{S}$.*

The power allocation matrix also indicates the utilization status of sub-bands. The constraint (i) states that the transmit power of ULS in each sub-band is bounded, (ii) states that the overlapping coalition is a sub set of the grand coalition, and (iii) states that the sum of transmit power is upper bounded.

Proposition 4.1. *The proposed OCF-game is 2^n-finite.*

Proof: Suppose the a partial coalition $\boldsymbol{p}^{m*} = \{p_{S_k}^{m*} : k = 1, 2, ...K\}$ is formed on sub-band m, in which the positive power $p_{S_k}^{m*}$ is given by (4.14), i.e.,

$$\boldsymbol{p}^{m*} = \arg\max_{\boldsymbol{p}^m} \pi(\boldsymbol{p}^m). \tag{4.25}$$

We define the support of $\boldsymbol{p}^{m*}$ as,

$$\text{supp}(\boldsymbol{p}^{m*}) = \{S_k : p_{S_k}^{m*} > 0, k = 1, 2, ...K\}^m, \tag{4.26}$$

which defines a coalition of ULSs regardless the resource distribution. Hence, for any other partial coalition $\boldsymbol{p}^{m'}$ with the support $\text{supp}(\boldsymbol{p}^{m*})$, we have

$$\pi(\boldsymbol{p}^{m*}) \geq \pi(\boldsymbol{p}^{m'}), \tag{4.27}$$

i.e., the partial coalition $\boldsymbol{p}^{m*}$ *blocks* all other partial coalitions formed on sub-band m which involves with $\text{supp}(\boldsymbol{p}^{m*})$.

Therefore, we can say that the partial coalition $\boldsymbol{p}^{m*}$ in our proposed game is one-to-one correspondent to the coalition $\{S_k : p^{m*}_{S_k} > 0, k = 1, 2, ...K\}^m$ formed on sub-band m. Since $\{S_k\}^m \subseteq \mathcal{K}$, i.e., $\{S_k\}^m$ is a subset of $\mathcal{K}$, the number of all possible partial coalitions equals to the number of subset of $\mathcal{K}$, which is given by,

$$\sum_{n=1}^{K} \binom{K}{n} = 2^n - 1. \tag{4.28}$$

Hence the proposed game is 2^n-finite. □

This is a significant result since the coalition structure is reduced to a finite set, which enables us to find the core of the proposed game. In traditional coalitional game which studies the grand coalition which is a finite set of all players, the core is a set of imputations, i.e., efficient pay-off division vectors which satisfy individually rationality, which stabilizes the grand coalition. However, many practice problems are naturally inefficient with the cooperation of all players. We are interested in investigating a stable coalition structure which optimizes the pay-off sum, i.e., to find an optimal partitioning of the grand coalition. Following the same line in [14], we define the core of the OCF-game for the sub-bands allocation,

Definition 4.8. *For a set of player $\mathcal{I} \subseteq \mathcal{K}$, a tuple $(\boldsymbol{P}_{\mathcal{I}}, \boldsymbol{\pi}_{\mathcal{I}})$ is the core of an OCF-game $G = (\mathcal{K}, \boldsymbol{v})$. If for any other set of player $\mathcal{J} \subseteq \mathcal{K}$, any coalition structure $\boldsymbol{P}_{\mathcal{J}}$ on $\mathcal{J}$, and any imputation $\boldsymbol{y}_{\mathcal{J}}$, we have $p_j(\mathcal{C}_{\mathcal{J}}, \boldsymbol{y}_{\mathcal{J}}) \leq p_i(\mathcal{C}_{\mathcal{I}}, \boldsymbol{\pi}_{\mathcal{I}})$ for some player $j \in J$.*

Theorem 4.1. *[14] Given an OCF-game $G = (\mathcal{K}, \boldsymbol{v})$, if $\boldsymbol{v}$ is continuous bounded, monotone and U-finite for some $U \in \mathbb{N}$, then an outcome $(\mathcal{C}_{\mathcal{S}}, \boldsymbol{\pi})$ is in the core of $(\mathcal{K}, \boldsymbol{v})$ iff $\forall S \in N$,*

$$\sum_{j \in S} p_j(\mathcal{C}_{\mathcal{S}}, \boldsymbol{\pi}) \leq v^*(S), \tag{4.29}$$

where $v^*(S)$ is the least upper bound on the value that the members of S can achieve by forming the coalition.

Proposition 4.2. *The proposed OCF-game of sub-band allocation has non-empty core.*

Proof:

1) Continuous: The value function in (4.23) is the difference between a log function and a linear function, which is obviously continuous.

2) Monotone: The interference power constraint in (4.2) limits the total transmit power in sub-band m indirectly by pricing in the Stackelberg game. Hence the power allocated in sub-band m by S_k is bounded by $p_{S_k}^{m*}$. Since the pay-off function of S_k $\pi(p_{S_k}^{m})$ is concave, then for any $\pi(p_{S_k}^{m'}) \in [0, p_{S_k}^{m*}]$ we have $\pi(p_{S_k}^{m'}) \leq \pi(p_{S_k}^{m*})$. Therefore for any $\boldsymbol{p}^{m'}$, $\boldsymbol{p}^{m*}$, such that $p_{S_k}^{m'} \leq p_{S_k}^{m*}$, we have $\boldsymbol{v}(\boldsymbol{p}^{m'}) \leq \boldsymbol{v}(\boldsymbol{p}^{m*})$, i.e., the value function is monotone.

3) Bounded: According to the proof of in 2), the value function is bounded by $\boldsymbol{v}(\boldsymbol{p}^{m*})$, where $\boldsymbol{p}^{m*} = (p_{S_1}^{m}, p_{S_2}^{m}, ..., p_{S_K}^{m})$ satisfies $\sum_{k=1}^{K} h_{S_k}^{m} p_{S_k}^{m} = \overline{Q}$.

4) U-finite: The proof can be referred to proposition 4.1.

5) The equality: The equality of (4.29) is always taken in the proposed game since the value function is the summation of individual pay-off of the member players.

□

Because enabling the overlapping in the coalition formation game will greatly increase the complexity of the game, hence the overlapping coalition structure is sometimes unstable as there may exist cycles in the game play. For example, suppose three players S_1, S_2 and S_3, and two available sub-bands l_1 and l_2. We denote $\pi_{S_j}[m|S_i]$ as the pay-off obtained by S_j when it forms a coalition with S_i on sub-band m, and $\pi_{S_j}[m|\emptyset]$ is the pay-off obtained by S_j when it exclusively occupies m. Initially ,since $\pi_{S_1}[l_1|\emptyset] > \pi_{S_1}[l_2|\emptyset]$, $\pi_{S_2}[l_2|\emptyset] > \pi_{S_2}[l_1|\emptyset]$ and $\pi_{S_3}[l_2|\emptyset] > \pi_{S_3}[l_1|\emptyset]$, S_1 joins l_1, S_2 and S_3 join l_2. However, if we assume the following statements respectively hold for the three devices, 1) $\pi_{S_1}[l_2|S_2] > \pi_{S_1}[l_1|S_3]$ and $\pi_{S_1}[l_1|S_2] > \pi_{S_1}[l_2|S_3]$, 2) $\pi_{S_2}[l_1|S_3] > \pi_{S_2}[l_2|S_2]$ and $\pi_{S_2}[l_2|S_3] > \pi_{S_2}[l_1|S_2]$, 3)$\pi_{S_3}[l_1|S_1] > \pi_{S_3}[l_2|S_2]$, $\pi_{S_3}[l_2|S_1] > \pi_{S_3}[l_1|S_2]$, then we can easily illustrate that the game play of the coalition formation will be stuck in a cycle. To avoid this situation, a history of the coalition structure is maintained in proposed algorithm. If the rotation is detected, it will be removed from the coalition formation flow.

4.5 Algorithm

In this section, we discuss the algorithms which can reach the coalition structure in the core of the coalition formation game and the SE of the hierarchical game. To reduce the number of iterations, we can use the similar way to that in [71] to drive the feasible region of the sub-band price μ_j, which is given by $\mu_j \in [0, \overline{\mu}]$. Given $\overline{v}$ be the upper bound of v_{S_k} and $\underline{h}$ be the lower bound of $|h_{jk}|^2$ where $\overline{\mu} = \frac{\overline{v}}{\underline{h}}$.

In each iteration, each of the ULSs will at most negotiate with $K-1$ other ULSs in a single sub-band, and there are K ULSs and M sub-bands, therefore the complexity is $\mathcal{O}((K-1)KM)$.

Algorithms 4.1 and 4.2 are proposed to find the SE of the hierarchical game, For any given $\overline{Q}$, $\overline{p}$ pair and the channel gains, the algorithms achieve the SE which contains a stable overlapping coalition structure, and an optimized power allocation of each ULS. We have the following proposition about the SE of the game.

Proposition 4.3. *The interference price μ^m always converges to a non-negative value if a non-negative power allocation for a given $\overline{p}$ and $\overline{Q}$ pair exists.*

Proof: It is proved in previous section that finding $\mu^{m*} = \arg\max_{\mu^m} \pi_{MCO}(\boldsymbol{p}^*, \mu^m)$ is equivalent to solving $\sum_{k=1}^{K} \left(\frac{1}{\mu^{m*} h_{S_k}^m} - \frac{1}{\lambda_{S_k}^m} \right)^+ h_{S_k}^m = \overline{Q}$. Hence the pay-off maximizing for MCO is equivalently achieved by adjusting the price to control the

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Algorithm 4.1: OCF Algorithm for Sub-band Allocation

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1) *Initialization:*

a) The ULSs sequentially send the pilot signal to obtain the channel information. Upon receiving the interference prices in all available sub-bands from the MCO, they can estimate their pay-offs in each of the sub-bands when the sub-bands are exclusively used by S_k.

b) Each ULS S_k broadcasts the sub-band combination $\boldsymbol{l}^*_{S_k}$ that maximizes its pay-off sum,

$$\boldsymbol{l}^*_{S_k} = [l^{(1)}_{S_k}, l^{(2)}_{S_k}, ..., l^{(n)}_{S_k}], \tag{4.30}$$

Let $\mathcal{R}^* = \{\boldsymbol{l}^*_{S_k} : k \in \{1, ..., K\}\}$.

2) *Negotiating:*

- a) The active ULSs in the same sub-bands, i.e., all the active ULSs in $\mathcal{R}^*$ must negotiate with each other about the pay-off division factor $\lambda^m_{S_k}$.

- b) After negotiation, each ULS S_k obtains a set of $\lambda^m_{S_k}$ corresponding to each sub-bands. S_k solves problem (4.3.1) and obtains a new sub-band allocation which maximizes its pay-off. All the S_k update and broadcast their optimal sub-bands allocation. Step 2) is repeated until no ULS wants to change its occupied sub-bands.

Algorithm 4.2: Distributed Interference Control Algorithm

Definitions: At iteration t, let

- $\mu^m(t)$ be the pricing coefficient in sub-band m,

1) *Initialization:*

   - Set $\mu^m \geq \overline{\mu}, \forall m \in \{1, 2, ..., M\}$.

   - Set $\epsilon > 0$ to be a small positive constant.

2) *Price Adjustment:*

   a) At iteration t, MCO updates and broadcasts $\boldsymbol{\mu}(t) = (1 - \epsilon)\boldsymbol{\mu}(t - 1)$.

   b) Each S_k senses the sub-bands and negotiates with other active ULSs in the same sub-bands to determine the sub-band allocation $\boldsymbol{l}^{m*}(t)$ and power allocation $\boldsymbol{p}^{m*}(t)$.

   c) All active ULSs repeat Step 2-b) to update their optimal sub-bands, and the outcome is a coalition structure $\boldsymbol{P}^m(t)$.

   d) The MCO monitors the aggregated interference in each sub-band. If $N_j > \overline{Q}$, the price adjustment in sub-band j stops. If $N_j \leq \overline{Q}$, go to Step 2a).

3) *Termination:*

The algorithm ends with solution $\boldsymbol{\mu}^* = \boldsymbol{\mu}(t - 1), \boldsymbol{P}^* = \boldsymbol{P}(t - 1)$ in which the element $p^{(}m*)_{S_k}(\mu^{m*})$ is given by (4.14).

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interference approaching $\overline{Q}$. In other words, therefore only two cases that the MCO will stop adjusting the channel price, 1) $\sum_{k=1}^{K} p_{S_k}^m h_{S_k}^m \leq \overline{Q}$ and 2) $\mu^m = 0$. Hence the interference price μ^m always converges to a fixed price. □

From propositions 4.2 and 4.3 we conclude that, for any given $\bar{p}$ and $\overline{Q}$, the proposed algorithm will converge to the SE of the hierarchical game. The simulation results provided in section IV support this claim.

Remark 4.2. *The hierarchical game works in this way. During each iteration two games are played. At the beginning of iteration, the MCO (leader) starts a Stackelberg game by broadcasting the interference price $\boldsymbol{\mu}$. Based on $\boldsymbol{\mu}$, the ULSs (followers) start to play an OCF-game of which the outcome is an optimal coalition structure (i.e., power allocation matrix) $\boldsymbol{P}$. Subsequently, the interference brought by $\boldsymbol{P}$ is considered as the followers' move in the Stackelberg game, the MCO will adjust the price based on the interference. Then go to the next iteration.*

The proposed algorithms can be implemented in a distributed manner. On the MCO side, it does not need to inquire any information from the ULSs, e.g., the interfering link gain $h_{S_k}^m$ or corresponding transmit power $p_{S_k}^m$. It just measures the aggregated interference at its receiver in each channel, and adjusts and broadcasts the price accordingly. On the ULSs side, with the channel price and the link gain information measured with in a coalition, they can easily derive the potential pay-off gained by joining different coalitions. Therefore each of them can choose the best profited coalition combination to take part in.

4.6 Numerical Results

In this section we follow the setup up described above to investigate the performance of the proposed hierarchical game framework in the spectrum-sharing based femto-cell network. To better illustrate that the proposed algorithm adapts to various network environment, we test on different sets of interference and power constraints, as well as different number of ULSs K and available sub-bands M

combinations. The result shows that the proposed algorithm can automatically fit the constraints, no matter which one dominates or both of them jointly apply.

From Figure 4.4 to 4.6 we show an instance of the convergence performance of the sub-band prices as well as the pay-offs of the MCO and ULSs network. The test network contains 8 ULSs and 16 sub-bands, with $\overline{p} = 100$ and $\overline{Q} = 6$. In Figure 4.4 the trend of the curve shows that the prices converge quickly in a few iterations. Furthermore, it is noted that the prices converge in similar speeds. This is because the sub-band prices directly control the power allocation, so the price in each sub-band will be affected by other oscillating prices, i.e., no one can converge solely. However, an interesting observation is that some of the price curves oscillate and have sharp turning, because the coalition structure changes (which means a big change on the value of $\lambda_{S_k}^m$). Therefore the interference level has a sudden change in the sub-bands. At last, the price converges to different values since they are channel dependent, which coincides with the definition in (4.19).

Figure 4.5 shows the pay-offs of the MCO and the ULSs versus the interference and power constraints. Assuming the channel coefficients are fixed, we increase one constraint while fixing the other one. It is observed that at the beginning the pay-offs will increase with the constraint before they become steady. The reason for this phenomenon is that initially the varying constraint is much tighter, which becomes the main limitation of the transmit power. However, when the varying constraint becomes larger, the transmit power is then jointly limited by the two constraints. At last when the varying constraint becomes very loose, the transmit power is limited by the fixed constraint, so the system performance will not change.

Figure 4.6 illustrates the choice of interference $\overline{Q}$ against the average price $\overline{\mu}$ over all sub-bands. The average price $\bar{\mu}$ generally reflects the willingness of the MCO to sell its interference quota. It is observed that the sub-band prices decrease with the interference constraint. This interesting observation can be

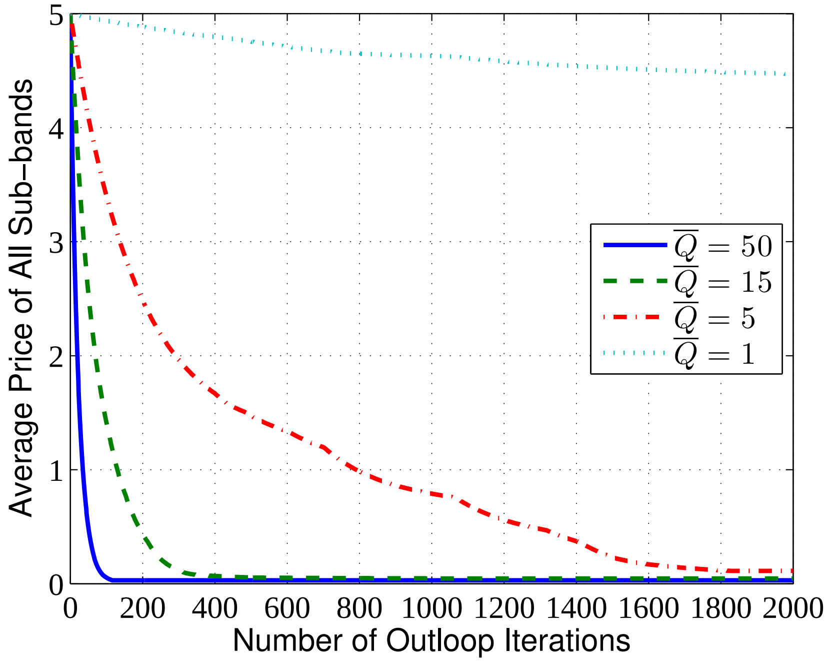

Figure 4.4: Convergence performance of the price.

explained by an economics point of view: $\overline{Q}$ here is the amount of goods the MCO holds. If the amount of goods is small, it can be sold at a high price. Otherwise, if the vendor has a lot of goods to sell, he tends to sell them at a cheap price.

Figure 4.7 to 4.10 show the impact of the number of available sub-bands to the propose game. Figure 4.7 and 4.8 show the number of active ULSs and the number of coalitions versus the number of sub-bands. We can see that the active ULSs are always lower than the total number of ULSs, since if the channels gains of some ULSs are highly correlated, the ULSs with low pay-off is forced to leave the coalition. From Figure 4.7 we illustrate that, the larger the value of Q the more active ULSs. Since larger Q enables more chances for the ULS to transmit. From Figure 4.8 we can see that the number of coalition formed by proposed algorithm increases with the number of available sub-bands, because when overlapping is enabled, the only limitation for the number of coalitions is

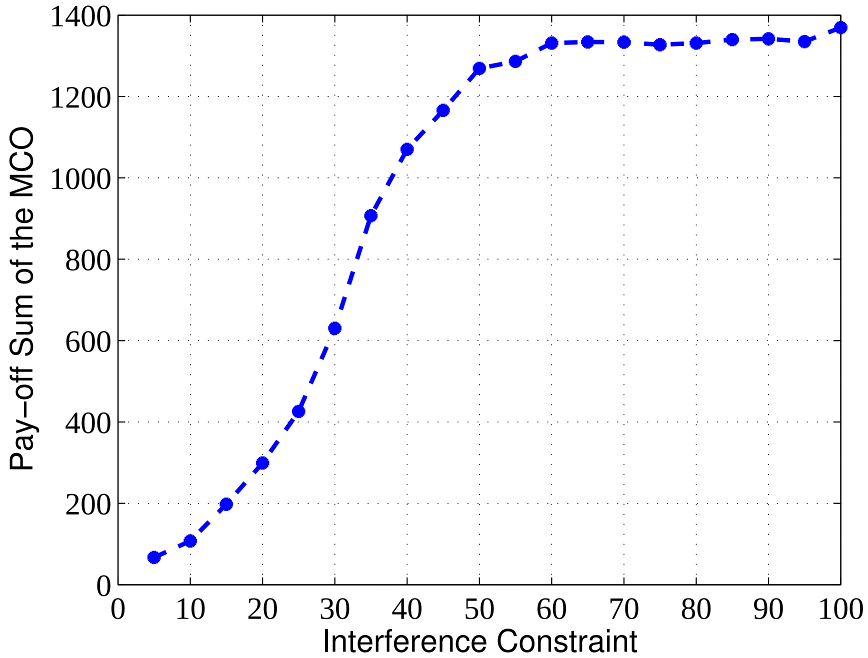

Figure 4.5: The impacts of varying the interference constraint: the pay-off sum increases with $\overline{Q}$.

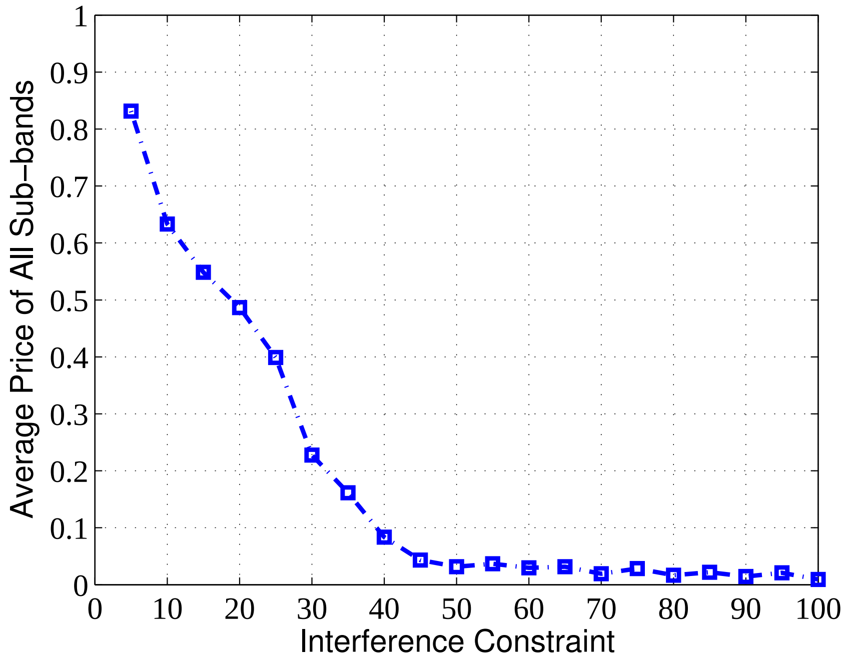

Figure 4.6: The impacts of interference constraint:
The average price $\overline{\mu}$ decreases with $\overline{Q}$.

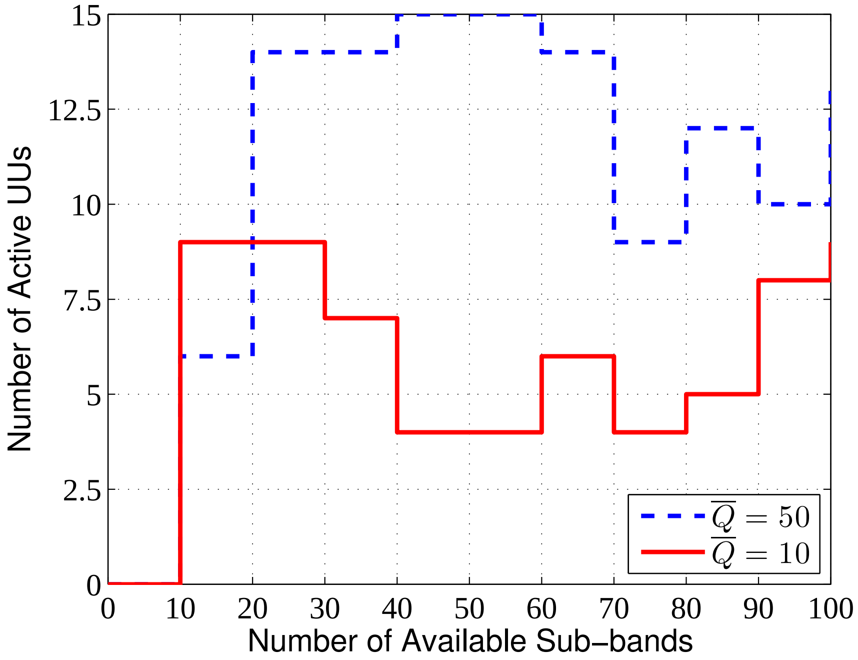

Figure 4.7: Comparison 1A of $\overline{Q} = 10$ and $\overline{Q} = 50$.
No. of active ULSs versus No. of sub-bands.

the number of sub-bands.

Figure 4.9 and 4.10 show the average number of coalitions each ULS joins and the average sub-band prices of sub-bands, versus the number of sub-bands. From Figure 4.9 we can see that the ULS tends to join more coalitions when the number of available sub-bands increases, since in this case the players with lower pay-off in a crowded coalition may better-off if joining a new coalition. From Figure 4.10 we can see that the sub-band prices tend to decrease with number of available sub-bands. When the ULSs spread their power across more sub-bands, the aggregated interference in a single sub-band will be lower, which resulting a lower sub-band prices. Another observation is that the price at $Q = 10$ is higher than that at $Q = 50$, this is because the tolerated interference is 'rarer' when Q is smaller, so the price is accordingly larger.

Note that the actually price depends on the following parameters: (1) the

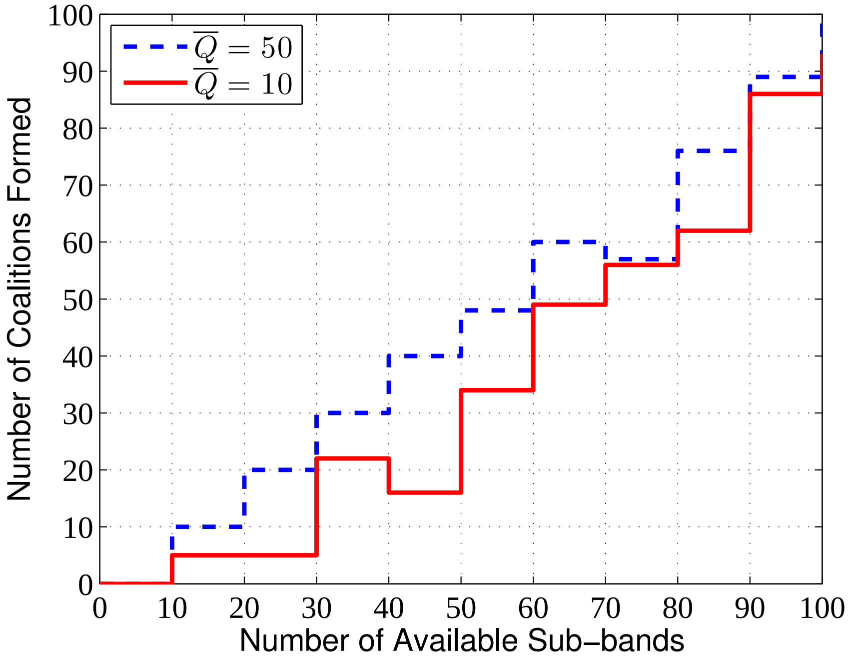

Figure 4.8: Comparison 1B of $\overline{Q} = 10$ and $\overline{Q} = 50$.
No. of coalitions versus No. of sub-bands.

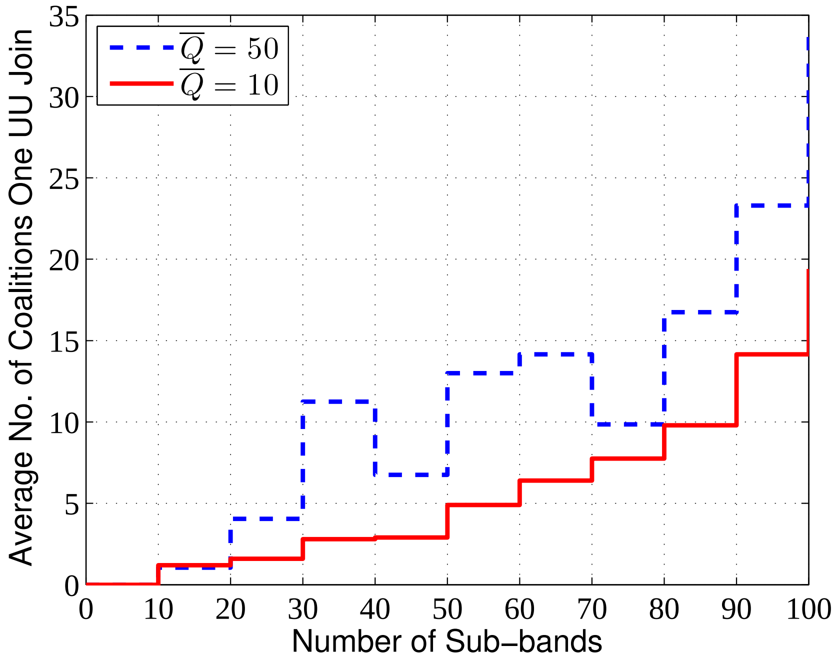

Figure 4.9: Comparison 2A of $\overline{Q} = 10$ and $\overline{Q} = 50$.
The average No. of coalitions one ULS join versus No. of sub-bands.

channel gains between the ULSs and BSs, and among the ULSs. (2) the coalition formation structure. Increasing or decreasing the number of sub-bands will lead to a totally different coalition structure. Since in the simulation presented in Figure 4.9 we generate random channel gain matrix when simulating different number of sub-bands. In general, it can be observed that there is a trend that the interference price decreases with upper bound of interference power constraint. However, since it is sensitive to the channel gains as well as the interactively actions among the players, it observes a fluctuation when the number of channels increases with a small amount (14.28% from 70 to 80).

The increasing of number of sub-bands only gives a probability of new choice. Generally speaking, if the condition of the added sub-bands is better than the previous ones, the ULS will certainly try to assign power to the new sub-bands which will cause the interference price drops in the previous bands. On the other hand, if the condition of added sub-bands is much worse than the previous ones, the ULS will choose to stay in the previous sub-bands. Since the number of total sub-bands increases, the average interference price in each sub-band will still decrease. The plot in Figure 4.11 shows the result in this case.

Figure 4.12 compares the proposed OCF algorithm with the coalition formation (CF) without overlapping. It is illustrated directly in the figure that the improvement of data rate by enabling overlapping. When the power available for transmit goes high, the ULSs in OCF scheme are benefited by exploring more chances to transmit on multiple sub-bands while in the CF schemes each of the ULS can only access a single sub-band.

4.7 Conclusion

The sub-bands allocation and the power control issues in the carrier-aggregation-enabled heterogeneous networks are studied in this chapter. We proposed a hierarchical game framework to jointly solve the power and sub-band allocation

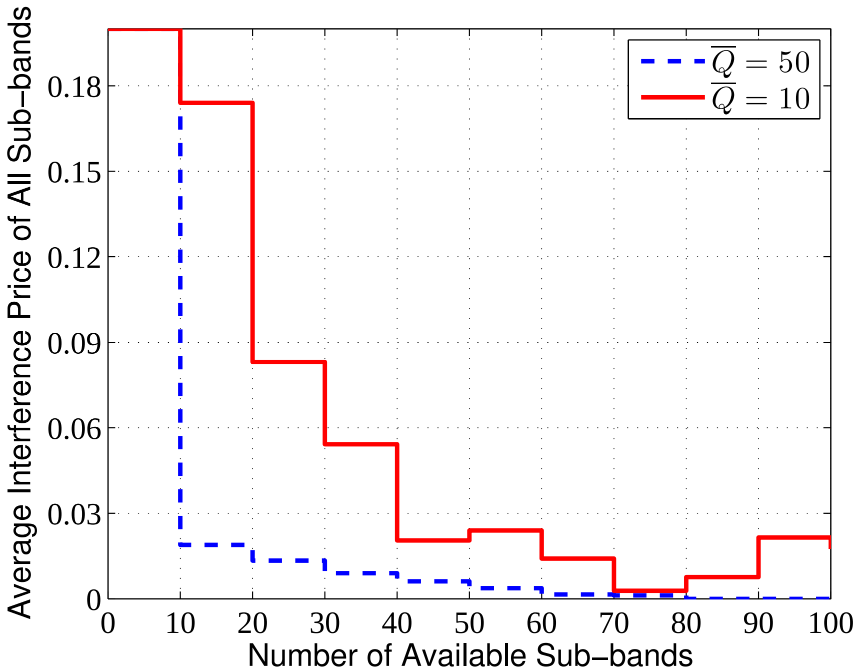

Figure 4.10: Comparison 2B of $\overline{Q} = 10$ and $\overline{Q} = 50$.
The average sub-band prices versus No. of sub-bands, random channel coefficient.

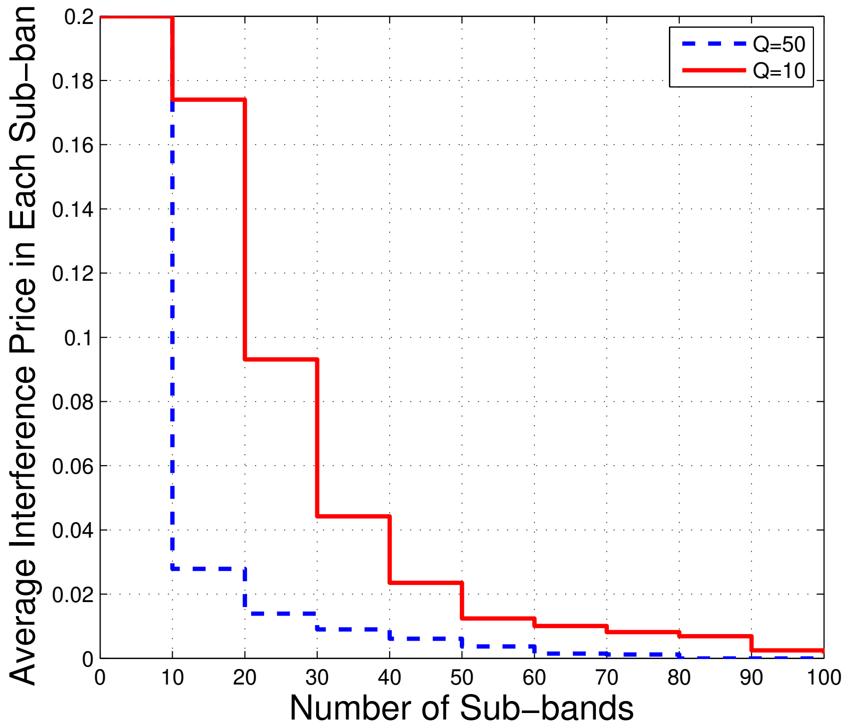

Figure 4.11: Comparison 2C of $\overline{Q} = 10$ and $\overline{Q} = 50$.
The average sub-band prices versus No. of sub-bands, the channel coefficients of previously existing sub-bands keep the same when new sub-bands is added.

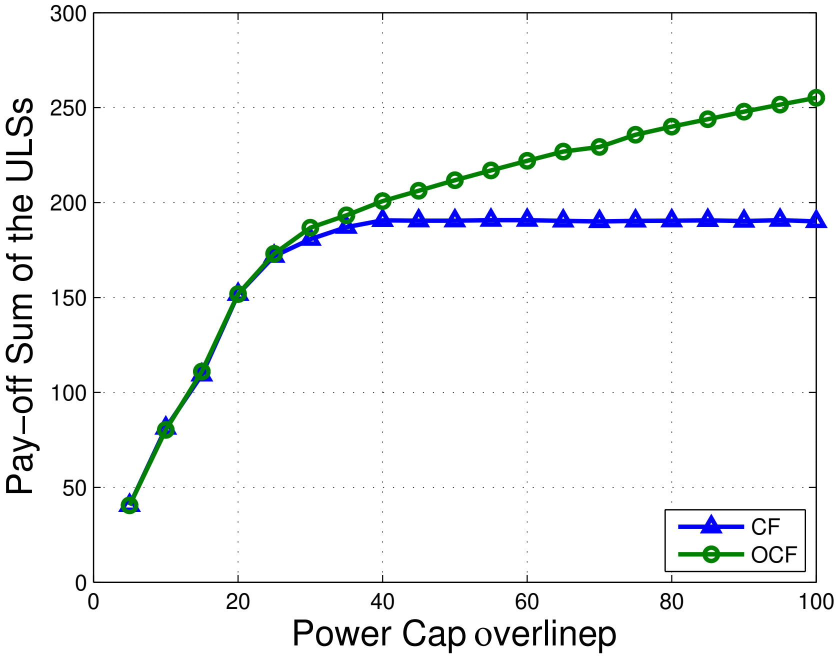

Figure 4.12: The comparison between CF and OCF schemes.

problems under the constraints of the power cap and maximum tolerable interference level. The upper level Stackelberg game regulates the transmit power of the ULSs so as to give sufficient protection to the LSs while optimizing the pay-off of the ULSs. The lower level OCF-game enables the ULSs to self-organize into overlapping coalitions, and the ULSs in the same coalition transmit cooperatively to improve the performance. We have proposed a simple two-layer algorithm to let the ULSs iteratively search for the optimal coalition structure and the power allocations, under the dynamic prices adjusted by the macro cell. It was proved that the proposed algorithm can always achieve the SE of hierarchical game, where the transmit power and the sub-band allocations are stable, and no players can profitably deviate from it by acting alone. Furthermore, by allowing the overlapping coalitions, we have addressed the problem of sub-band and power allocation problem under two dimension constraints. The proposed framework can also be expanded to more complex network with multiple BSs to cooperatively share their sub-bands or the downlink cases that multiple LSs need to be protected. The experimental result shows that enabling overlapping among coalition can further increase the performance.

Note that the propose scheme only applies to the scenario in which the transmitting and/or receiving nodes of the cooperative ULSs are near with each other, otherwise there is no cooperation gain by forming virtual-MIMO channel.

Chapter 5

Dynamic Access Mode Selection in Small Cell Network

5.1 Introduction

In previous sections, we have investigated the application of both cooperative and non-cooperative game models to solve the resource allocation problems in a spectrum sharing based mobile network. In other words, we investigate how the macro-cells share their resources with small cells to help improve the service quality of the unlicensed subscribers. On the other hand, the small cells can also help the macro-cell users (MU) with their transmission in particular scenarios. For instance, a MU in an area with weak coverage by the macro-cell BS may seek the help from nearby small cells to improve the performance. More specifically, we investigate an open/closed accessing mode selection problem in this chapter from the game theory perspective view. Generally speaking, a user-deployed small cell (e.g., femto-cell) can operate in two modes.

- open access - The small cell BS allows any mobile subscriber who travels into its coverage area to access.
- closed access - The small cell BS only grants its service to the registered

mobile subscribers.

The small cell operating in closed access mode has the risks of the harmful interferences from the nearby macro-cell subscribers in the uplink or to which in the downlink. To avoid the transmission failure caused by the cross-tier interference, previous studies have considered the frequency assignment [30] [45] [18], power control [17] [78] [35] [36], and spectrum sensing approach [43] [65]. An alternative way to avoid the cross-tier interference is that the small cell BS allows the nearby co-channel mobile subscribers to access. The small cell BS schedules the unregistered subscribers as its own subscribers, at the expense of the its radio spectrum (i.e., frequency-band or time slot) and bandwidth resources (i.e., backhaul connection). The benefits of open access versus closed access in cellular networks are discussed in [68] based on the spatial distribution analysis of the small cells. However, their work is only based on the statistical model, thus missing the participation of the base stations (BS) and mobile devices. A discontinuous game formulation is presented in [40] with a pay-off secured solution, in which the small cells compete for allocating their spectrum to MUs in the coverage area. However, their approach requires collecting channel state information of all MUs, and a centralized controller to deal with the conflict of interests.

Today's mobile devices with advanced hardware make the application of cognitive radio possible. The cognitive devices can observe the radio environments and adjust their behaviors. Therefore they are given chances to take part in the access strategy selection. We propose a Stackelberg game in which the small cell BS acts as the leader and the MU as the follower. We are interested in mining their motivations to support their actions. The small cell BS concerns with improving the capacity by eliminating the interference. The MU concerns with saving the battery life while doing transmission task. Only if open access is beneficial to both of them, the MU will be handed over to the small cell. Otherwise, the small cell remains closed. This dynamic access strategy selection is built on the 'cognition' capability of both small cell BS and MU. We here refer the 'open access' to partially assigning the spectrum of the small cell to the MU, which means the MU being handed over to the small cell BS is scheduled with the spectrum orthogonal to the small cell subscribers.

To this end, we analyze the demand-driven behavior of both small cell BS and MU, and propose one practical algorithm to cope with the self-governed nature of small cell networks. We are interested in investigating two fundamental problems in the access mode selection problem of the small cell: 1) When it should allow the unregistered subscribers to access, 2) How many unregistered subscribers it should take. We propose a Stackelberg game based approach, which enables the small cell BS and MU to improve their performances by establishing direct links. The designed approach enables the small cell BS and MU to choose their access strategies distributively, which copes with the distributed nature of the user-deployed small cell networks, and requires no inter-cell coordination. Both the small cell BS and MU take part in the access strategy selection game, for the purpose to obtain a win-win result. Experimental results show that the proposed approach can guarantee the capacity gain of the small cells, while improving the energy efficiency of the MUs. Furthermore, by adjusting the objective function, the benefits of open access can be balanced between the capacity gain of small cells and the energy efficiency improvement of the MUs. Therefore it can be applied flexibly for various design purposes.

5.2 System Setup and Problem Formulation

In this section, we first describe the system setup and then formulate the mode selection problem following a game theoretical way. We define the related game model and provide formal mathematical descriptions of the problem. The analysis of the problem will be provided in the next section.

5.2.1 System Setup

Suppose we have a spectrum-sharing based two-tier network wherein several users deploying small cells are underlying with a macro-cell. The small cell shifts between the open and closed access modes: it may allow the MUs in its coverage area to link to it directly if the resulting pay-off is higher.

We assume that the orthogonal frequency-division multiple access (OFDMA) is adopted by the network, where the basic medium for transmission is sub-bands. We denote the set of BS as $\mathcal{B} = \{B_0, B_1, ..., B_N\}$ and $|\mathcal{B}| = N$. Specifically, B_0 stands for the macro-cell BS and $B_i, i \neq 0$ stand for the set of small cell BSs. We denote the set of macro-cell subscribers as $\mathcal{U} = \{U_0, U_1, ..., U_K\}$, where $|\mathcal{U}| = K$. We assume slow fading channel here, i.e., the fading state will not change in a time slot. The noise power variance is assumed to be σ^2. The spectrum-sharing based two-tier network is implemented by letting each small cell utilizes a fraction of the spectrum shared by the macro-cell, i.e., a sub-set of the spectrum of the macro-cell. Each of the MUs is also assigned with a set of sub-bands which are not necessarily the same with that of the small cell's. Therefore, the spectrum of MU and small cell may overlap when some of the sub-bands are simultaneously used by each other. In this case, serious interference could be generated if the MU travels into the coverage area of a co-channel small cell.

For the single small cell BS/single MU case, it can be assumed that the overlapped portion of spectrum is λ, but remaining $1 - \lambda$ portion is interference free, where $\lambda \in [0, 1]$. This assumption is realistic for the modern cellular networks, since both LTE and LTE-advanced standards have adopted the scalable bandwidth and carrier aggregation for mobile devices to meet various wireless service demands [61]. Therefore, it is reasonable to consider the general case that the shared spectrum may be partially rather than entirely overlapped. This is consistent with the scenario discussed in [45].

The notations used in the following sections are listed in Table 5.1.

Assumptions: (1) The mobile devices have the capability to estimate the channel gain. (2) There is a dedicated channel for information exchange between the MUs and the small cell BS. (3) The small cell BS receiver can monitor the interference level in each sub-band.

5.2.2 Problem Formulation

In a spectrum-sharing based two-tier network, the MUs may mutually interfere with the nearby small cell BSs if they share the same radio resources. In the uplink, the transmission of the MUs will interfere the small cell BSs. In the downlink, the signal from the macro-cell BS may interfere the subscribers of the small cells. Hence, an MU is a potential 'loud neighbor' of nearby small cell BSs if their spectra are overlapped or partially overlapped. We consider a scenario that the small cell BSs can opportunistically select the accessing mode between open or closed. Hence there are the following cases:

- If no co-band MU is presented, the small cell will work in the closed mode, i.e., the access permissions are exclusively granted to their own subscribers.
- If a co-band MU is presented nearby, however the interference caused is tolerable to the small cell BS, the small cell will also choose to close. This

Table 5.1: The Notations

g_{ki}	channel gain between U_k and B_i
h_{ji}	channel gain between B_j's subscriber to B_i
p_k^c	transmit power per unit bandwidth of U_k in closed access mode
p_k^o	transmit power per unit bandwidth of U_k in open access mode
p_i	transmit power per unit bandwidth of B_i's subscriber
p_0^k	total transmit power per unit bandwidth of U_k
λ_i^k	overlapped portion of spectrum between U_k and B_i
ρ_i^k	spectrum assigned to the U_k by B_i in open access mode
I_i	aggregated interference at the BS receivers

case usually occurs if the portion of overlapped spectrum is small or the MUs transmit at low power.

- If a co-band MU is presented nearby, and cause harmful interference which is intolerable to the small cell BS, it will shift to open mode, i.e., it will admit the MU to the small cell network temporarily, so as to schedule them as its own subscribers to avoid the interferences.

In the last case listed above, the small cell benefits from open mode due to the elimination of interference. On the other hand, the MU also has the potential to benefit from hand-over to the small cell. In practice, the coverage area of the user deployed small cell is usually at indoor area, so the MUs in the same area usually experience penetration loss which results in weak link gains with its home network BS. Therefore, they usually have to transmit high power to fulfill the rate requirements. In this case, The MU may potentially reduce the power consumption if it hands over to a nearby small cell BS.

We assume that both the MU and the small cell BS are rational, that is, they will make decisions only if it is profitable. Hence the open access mode will be triggered on only if both the MU and small cell are benefited. The small cell BS directly experience the interference from a nearby MU, then it makes decision to choose the accessing mode. After the small cell's move, the MU is acknowledged to have chance to hand-over to the small cell network. It will subsequently make the decision to hand-over or not. Therefore the model of Stackelberg game which investigates the interaction between leader and followers is a suitable tool for analyzing the access strategy selection of both small cell BS and the MU, where small cell BS is the leader and the MU is the follower.

We formally define the proposed Stackelberg game for accessing mode selection as follows.

Definition 5.1. *A Stackelberg game is denoted by $G = (\mathcal{L}, \mathcal{F}, \mathcal{A}, \boldsymbol{\pi})$, where the formulation of the game is given as follows.*

- *Leaders.* $\mathcal{L} = [1, 2, ..., N]$ is the set of leaders which are small cell BSs.

- *Followers.* $\mathcal{F} = [1, 2, ..., K]$ is the set of followers which are MUs.

- *Actions.* The action space $\mathcal{A}$ can be divided into two subspace corresponding to the leaders and followers, respectively.

  $\mathcal{A}_L = \{\mathcal{A}_L^1 \times \cdots \times \mathcal{A}_L^M\}$ denotes the action spaces of the leaders. $\mathcal{A}_L^i = \{0, \rho_i\}$ of the small cell BS i denotes its possible actions - 0 for remaining in closed mode and ρ_i for opt to open mode, and offer an amount of ρ_i radio resources to the MUs.

  $\mathcal{A}_F = \{\mathcal{A}_F^1 \times \cdots \times \mathcal{A}_F^K\}$ denotes the action spaces of the followers. The action $\mathcal{A}_F^k = \{0, i\}$ of MU U_k corresponds to the decision of not hand-over to a small cell, or hand-over to small cell i.

- *Pay-offs.* The pay-offs are also defined differently to leaders and followers. The pay-off of the leader is the increase of capacity by shift to the open access mode, which is defined as:

$$\pi_{B_i} = C_{B_i}^{open} - C_{B_i}^{close}, \tag{5.1}$$

  where $C_{B_i}^{open}$ and $C_{B_i}^{close}$ are the Shannon capacity in open and closed mode, respectively.

  The pay-off of the follower is defined as the improvement of energy efficiency. In the setup of this chapter, we assume that each of the MU U_k maintains a target rate $R_{U_k}^T$, hence the improvement is reflected as the decrease of power consumption.

$$\pi_{U_k} = p_k^c - p_k^o - \epsilon, \tag{5.2}$$

  where ϵ is a small constant which can be considered as a cost term. We will discuss about ϵ in the next section.

5.3 Game Theoretical Analysis

In this section, we will start from a single small cell and a single MU case to discuss the interaction between the leader and follower in the proposed game model. We give the explicit form of both pay-off functions and show the existence of the equilibrium.

5.3.1 The Pay-off of the Small Cell BS

We denote $\gamma_{B_i}^0$ and $\gamma_{B_i}^k$ as the SINR at the small cell BS receiver when no presence of the MU and a co-band MU U_k is presented, respectively.

$$\gamma_{B_i}^0 = \frac{p_i h_{ii}}{\sigma^2 + \sum_{j \in \mathcal{N} \setminus i} p_j h_{ji}}, \tag{5.3}$$

$$\gamma_{B_i}^k = \frac{p_i h_{ii}}{\sigma^2 + p_0^k g_{0i} + \sum_{j \in \mathcal{N} \setminus i} p_j h_{ji}}. \tag{5.4}$$

For simplicity, we assume the small cell schedules its subscribers using time-division-duplex, hence in each time slot there is only one active subscriber in each small cell. In closed access mode, the capacity of i_{th} small cell is,

$$C_{B_i}^{close} = \lambda_i^k \log_2 \left(1 + \gamma_{B_i}^k\right) + (1 - \lambda_i^k) \log_2 \left(1 + \gamma_{B_i}^0\right), \tag{5.5}$$

where C_i^{close} is monotonically decreasing with p_0^k. As we consider flat fading channels, the transmit power spreads equally over the spectrum.

For open access with a sharing of ρ_i^k portion of radio resources to the MU, the capacity of i_{th} small cell BS becomes (in this case the interference from MU disappears):

$$C_i^{open} = (1 - \rho_i^k) \log_2 \left(1 + \gamma_{B_i}^0\right). \tag{5.6}$$

Note that C_i^{open} is the achievable data rate of the small cell's own subscriber and excludes that of the accepted MU. The transmit power p_i and channel gain h_{ii}

are well known by the corresponding small cell BS. We define the pay-off function of the small cell as the difference of capacity in open and closed modes,

$$\pi_{B_i} = C_{B_i}^{open} - C_{B_i}^{close}. \tag{5.7}$$

If $\pi_{B_i} \geq 0$, the small cell has a capacity gain going to open mode. In this case, the small cell BS is willing to accept the MU for the positive reward. Hence the range of ρ_i^k is given by:

$$0 \leq \rho_i^k \leq \rho_i^{total}, \tag{5.8}$$

where $\rho_i^{total} = \lambda^k \left[1 - \frac{\log_2\left(1+\gamma_i^k\right)}{\log_2\left(1+\gamma_i^0\right)}\right]$. This inequality implies that, given the current transmit power of the MU, the small cell BS can always get a non-negative reward by sharing ρ_i^k portion of spectrum. We have two observations from (5.7):

1. The π_{B_i} monotonically increases with λ_i^k. Large λ_i^k indicates large interference from the MU, so the small cell BS is more likely to choose open access in this situation.

2. π_{B_i} monotonically decreases with ρ_i^k. However, if current ρ_i^k can not improve MU's pay-off, the MU does not hand-over. Then the small cell BS offers larger ρ_i^k. After a few rounds of negotiations, they will make or break a contract when hitting the upper bound of ρ_i^k.

The illustration of the negotiation between one MU and one small cell BS is shown in Figure 5.1. Note that the motivation of small cell BS to accept an MU is to improve its own pay-off, and it does not know at which point the MU will agree to join it. However, the bottom line is that the capacity of open access mode should not be less than closed mode. In Figure 5.1, the horizontal axis is the amount of radio resources the small cell BS offers to the MU. We assume that the MU will agree to join the small cell if the offer reaches ρ_c. Hence the pay-off of small cell BS remains the same until ρ_i^k reaches the critical point ρ_c, which is the point MU chosen to join the small cell. Then the pay-off of small

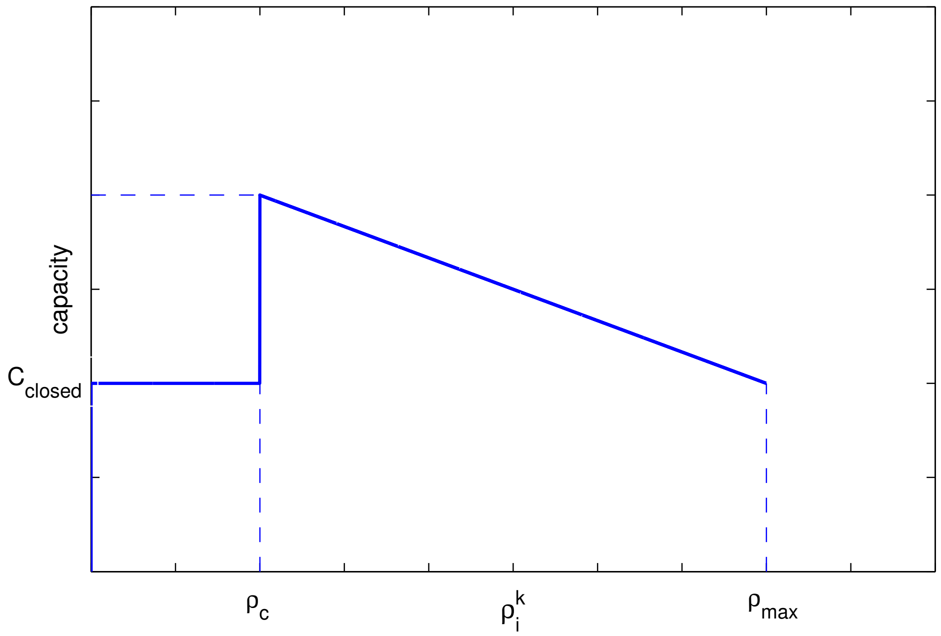

Figure 5.1: Small cell capacity versus ρ_i^k.
A sample plot illustrating the relationship between ρ_i^k and capacity of small cell. At ρ_c the SBS and MU make the agreement of open access and the capacity reaches the maximum.

cell will drop if ρ_i^k continuously increases, since the data rate of its owe subscriber decreases with ρ_i^k in open access mode. Therefore, the best strategy for small cell BS is to terminate at ρ_c.

5.3.2 The pay-off of the MU

The mobile devices have two main targets: (1) meeting certain wireless service requirement, (2) slowing down the battery draining, which leads to a rate constrained energy saving problem.

When MU does not hand over to the nearby small cell BS, the transmit power should satisfy:

$$R_{U_k}^T = \log_2\left(1 + \frac{p_k^c h_{k0}}{\sigma^2 + I_0}\right), \tag{5.9}$$

where $R_{U_k}^T$ is the target rate. Here I_0 is the aggregated interference at the macro-cell receiver.

On the other hand, if the MU is informed that it can join the small cell, it will evaluate the performance gain after hand-over. Assuming that the target rate keeps unchanged when accessing certain service, the estimated power consumption p_k^o should satisfy:

$$R_{U_k}^T = \rho_i^k \log_2 \left(1 + \frac{p_k^o h_{ki}}{\sigma^2 + I_i}\right), \tag{5.10}$$

where I_i is the potential aggregated interference at the small cells BS B_i. Obviously, $p_k^o(\rho_i^k)$ is a decreasing function of ρ_i^k. If I_i is bounded and known as a prior, the MU can estimate the transmit power paired with the target rate after hand-over. Hence the energy consumptions before and after hand-over are obtained.

The definition of the MU's pay-off is either purely based on the transmit power level or combined with other efficient functions, such as the one proposed in [59]. About the real time implementation, we just take the energy consumption into consideration. The pay-off function formulation is given by:

$$\pi_{U_k} = p_k^c - p_k^o - \epsilon, \tag{5.11}$$

where p_k^c and p_k^o represent the power consumption of user i to maintain the target rate in closed or open access mode, respectively and ϵ is a small constant.

Based on equation (5.11), the MU will make a decision of two corresponding actions: (1) Accept the offer of ρ_i^k if $\pi_{U_k} \geq 0$, (2) Reject if $\pi_{U_k} < 0$.

Remark: ϵ here can be considered as the compensation for cost of the energy consumption during the hand-over and the negotiation procedure. When the transmission time $T \to \infty$, this energy cost can be ignored, so we can set $\epsilon = 0$. From another angle of view, since ϵ impacts the breaking of the deal, i.e., the value ρ_c, it can be set as a parameter to adjust the pay-off gains distributed between the small cell and the MU. If setting $\epsilon = 0$, the capacity improvement of small cell is maximized and the MU has no energy efficiency gain. Also it is easy to verify that when $\epsilon = p_k^c - p_k^o(\rho_i^{total})$ the MU gets the most improvement of battery saving. Only if ϵ is set in this range, a successful deal between the k_{th} MU and i_{th} small cell BS is enabled.

5.3.3 Discussion on Parameters

It is observed that the interference value of I_0 and I_i are two key parameters for MU to evaluate the performance before and after hand-over. However, in practice it is trivial to measure I_0. Since the MU knows its currently transmit power, and whether the target rate R_T^k is reached can be directly obtained by the feedback from the macro-cell BS, then the exact transmit power paired with the target rate is ready to be obtained. Hence only I_i is needed for the MU to obtain the expected power consumption after joining the small cell. Assume that I_i is a random variable, and the aims to optimize the long term pay-off. Rewriting (5.10) and taking the expectation we obtain,

$$\begin{aligned}\mathbb{E}[p_k^o(I_i)] &= \mathbb{E}[\frac{(\exp^{\frac{R_T^k}{\rho_i^k}} - 1)(\sigma^2 + I_i)}{h_{ki}}] \\ &= \frac{(\exp^{\frac{R_T^k}{\rho_i^k}} - 1)(\sigma^2 + \mathbb{E}[I_i])}{h_{ki}},\end{aligned} \tag{5.12}$$

where $\mathbb{E}[\cdot]$ denotes the expectation. Hence, the value of $\mathbb{E}[I_i]$ can be obtained from statistic information, which can be approximately considered as the average interference of small cell that B_i experiences. This value is maintained by each of the small cell, and will be broadcast to the MUs together with the offered amount of radio resources ρ_k.

5.4 Multiple Small Cell BSs and Multiple MUs Case

In previous section we analyzed the single BS single MU scenario. In practice we face the communication systems that contain multiple small cells and multiple MUs. For example, in the Scenario 2 of LTE release 12 networks [2], multiple small cells are deployed densely in an area. In this case, the cross-tier interferences at the small cell BS receivers are contributed by multiple users. However, a useful assumption can be made is that no MUs co-exist in the same spectrum in the mean time, which is based on the fact that most of modern mobile communication standards assigns orthogonal frequency band to users.

The capacity of the i_{th} small cell BS in closed access mode interfered by multiple MUs is given by:

$$C_i^{close} = \sum_k \lambda_i^k \log_2\left(1+\gamma_i^k\right) + (1-\sum_k \lambda_i^k)\log_2\left(1+\gamma_i^0\right), \tag{5.13}$$

where λ_i^k is the portion of spectrum overlapped with k_{th} MU. Thus $\sum_k \lambda_i^k \in [0,1]$ and $\lambda_i^k \geq 0$, the case $\lambda_i^k = 0$ implies there is no spectrum overlapping and no interference is generated. The BS can easily obtain the portion of interfered radio spectrum by counting the number of interfered resource blocks in an OFDMA based communication system.

5.4.1 A Two-Sided Many-to-One Matching Market

In the multiple small cells multiple MUs scenario, each small cell BS temporarily admits the MU as its subscriber to eliminate the interference. This problem can be modeled as the two-sided many-to-one matching market, which is also known as the *stable admission market*. In this market, a set of students (or, in our model, the MUs) applies for a set of universities (or, in our model, the small cells), each of the MUs can choose only one small cell to join and each of the small cells only has limited vacancies, or *quota*. Note that in our model, the *quota* is not a fixed number but a portion of spectrum ρ_k which changes with the network topology. This means if one interfering MU presents or leaves, the value of ρ_k should be updated correspondingly.

Definition 5.2. *The small cell selection market is defined as (two sided many-to-one) matching market $\mathcal{G}^{M1} = \{\mathcal{U}, \mathcal{B}, \succ\}$, in which $\mathcal{U}$ is a set of MUs, $\mathcal{B}$ is a set of small cell BSs, and $\succ$ is the preference of each MU (or small cell BS) over the small cell BS (or MU).*

In above definition, the $M(\cdot)$ denotes 'be matched to'. For example, $M(i)$ denotes all the MUs access the small cell BS i. An important property of a matching M is the *stability*. We refer the term 'm-stable' as the stability of a matching. In other parts of the thesis there are concepts of stability in coalition game, and the meanings are essentially different from that in matching, so here we use the specified term m-stable to describe the stability concept in matching.

Definition 5.3. *A matching M between $\mathcal{U}$ and $\mathcal{B}$ is said to be m-stable if it can not be strictly improved by any of the player or pair.*

The above definition implies that, if we say a matching between an MU U_k and a small cell i is stable, then U_i or B_i can not improve their pay-offs by matching to another partner $B_{i'}$ or $U_{k'}$.

Each of the members in $\mathcal{U}$ should build a preference order towards $\mathcal{B}$, and vice versa. We denote the preference order of the MUs as $\boldsymbol{\mathcal{R}}^b = \mathcal{R}_k^b, k \in \mathcal{U}$, and the preference order of the small cell BS as $\boldsymbol{\mathcal{R}}^u = \mathcal{R}_i^u, i \in \mathcal{B}$. The rank in preference $\mathcal{R}_k^b$ is determined by the interference level caused by the MUs. The rank in preference $\mathcal{R}_i^u$ is determined by the amount of spectrum the small cell BS will to share. For MU U_k, its preference is a rank of the small cells, we denote $r_{U_k}^i$ as the label of rank order, then we have,

$$\mathcal{R}_k^b =< r_k^1, ..., r_k^N > \tag{5.14}$$

For example, if $r_{U_1}^1 = B_2$, $r_{U_1}^2 = B_1$, then we say B_2 is preferred to B_1 by U_1, and B_2 is the most preferred small cell.

We design a matching algorithm to pair the small cell and the MUs.

Algorithm 5.1: A Matching Algorithm

1 **Initialization**:

a) Each small cell BS i measures λ_i^k and γ_i^k, to calculate ρ_i^k. For a small constant δ, calculate $\rho_i^{k\prime} = (1-\delta)\rho_i^k$, as well as the corresponding preference $\mathcal{R}_i^u$.

b) Each MU U_k inquires the $\rho_i^{k\prime}$ from the small cell i to calculate its pay-off π_{U_k} followed up by the preference $\mathcal{R}_k^b$.

WHILE: at least one MU has not been admitted by a small cell,

a) Denote the set of MUs who prefer to access BS i as $\{\tilde{U}_1, \cdots, \tilde{U}_n\}$, i.e., $r^1_{\tilde{U}_1} = \cdots = r^1_{\tilde{U}_n} = i$, and $\tilde{U}_1 \succ_i \cdots \succ_i \tilde{U}_n$. The corresponding radio resources are written as $\{\tilde{\rho}_i^1, \cdots, \tilde{\rho}_i^n\}$. Suppose there is a positive number m satisfying $1 \le m < n$, $\sum_{j=1}^m \tilde{\rho}_i^j \le \rho_i^{total}$ and $\sum_{j=1}^{m+1} \tilde{\rho}_i^j > \rho_i^{total}$. Then the small cell picks the first m MUs according to the preference order R_i^u, and rejects the rest.

a) Each of the MUs U_k received a reject acknowledgment removes i from its preference list $\mathcal{R}_k^b$, then goes to step 2-a).

The proposed algorithm is a modified version of the deferred acceptance algorithm in [55], which gives the stable and optimal solution of the matching. We sketch the proof of this property as follows: Suppose a small cell i accepts a set of MUs n_i in the matching results. According to the step in proposed algorithm, any of the MUs U_k in n_i should be strictly preferred by the small cell i than any other MU $U_{k\prime}$ which is not in n_i. Otherwise the match between small cell BS i and the MU U_k will not be stable. Therefore, we say that there are no more MUs other than n_i that is preferred by the small cell BS i. On the other hand, there is no more other small cell BS j which is preferred by the MU U_k than small cell BS i, otherwise, the MU U_k will send the request to small cell BS j other than small cell BS i. From the two points listed above, we can say that the matching result obtained by the proposed algorithm is $m - stable$.

The implementation of the deferred acceptance algorithm requires a time block for the MU admission. In each iteration, each MU will at most send K applications to the small cell BSs, in case that before it is rejected by the $N - 1$ BSs before being admitted; and in worst case, each MU will send request to $N - 1$ BSs and be rejected by all of them, hence for total K MUs the complexity of the proposed algorithm is given by $\mathcal{O}(KN)$.

5.4.2 A Sequentially Joining Algorithm

A two-sided one-to-one matching market model requires each of the players at both sides to collect the global information. Furthermore, as illustrated in Figure 5.1, the small cell may not necessarily assign ρ_i^k to the MU U_k, since the MU may agree to join small cell i at a point ρ_i^k which satisfies $\rho_i^k \leq \overline{\rho}_i^k$. If we assume that each small cell BS is rational and selfish, then we can easily illustrate that every small cell expects other small cells to accept the interfering MUs, since in this case the interference is eliminated and it will not cost its own radio resources.

In the small cell and MU matching algorithm in subsection 5.4.1, to build the preference order $\mathcal{R}_k^u$ over the MUs, the small cell BS i should contact each of the MU U_k to obtain λ_i^k and γ_i^k, and the MU U_k needs to inquire ρ_i^k from each of the small cell BS i. However sometimes it is impractical for the small cell to find the exact interference sources.

In this subsection, we propose an algorithm that enables the MUs to make the decision autonomously on selecting the small cell. The framework of the proposed algorithm builds on the Stackelberg game, in which the small cell BS avoids to gather the global information. Furthermore, as the leader of the game, the small cell BSs control the game play and try to maximize their own pay-offs. Let us impose the following policies to the proposed algorithm first:

a) The MUs join the small cells sequentially. Since once an MU leaves its home network and joins a small cell, the network topology as well as other parameters (e.g., the resulting interference, the amount of bandwidth each small cell wants to share) are changed, hence an updating of these information is required.

b) The MUs who make the decision to join a small cell will not change their decision until it leaves this small cell. The MU always chooses the small cell whose offer maximizes its pay-off, and its target data rate is satisfied, so it does not have any motivation to change the decision.

c) The MUs can not hand-over from one small cell to another small cell, i.e., they first leave the current small cell and go back to its home network, then join other small cells if necessary. This is because the MU is controlled by the BS of its home network, hence each move will be approved by the macro-cell BS.

The implementation of the sequential joining algorithm requires a dedicated channel for the broadcast of current bandwidth offer, which will not scale with the number of mobile nodes. In each iteration, there are at most N BSs should be coordinated to broadcast the bandwidth offer, and there are at most K MUs are accepted in each iteration, therefore the complexity is $\mathcal{O}(KN)$.

Since the network status changes when MUs sequentially join the small cell, the resulting algorithm works in an iterative manner. In each iteration, the problem becomes one MU to pick the favorable one to join from many candidate small cells. Hence, we propose a parallel updating algorithm that directly solves this problem based on matching theory [55]. The proposed algorithm is designed based on the following propositions.

Proposition 5.1. *: The small cell can always provide a 'clean' spectrum for the* *accepted MU, and the shared spectrum only depends on the parameters of the MUs being considered. Here 'clean' stands for no interference from other MUs.*

Proof: When the offered ρ_i^k is from the clean spectrum, the maximum spectrum for establishing the agreement between small cell BS and l_{th} MU satisfies $C_i^{open} = C_i^{close}$, which means:

$$\begin{aligned}&\sum_k \lambda_i^k \log_2\left(1+\gamma_i^k\right) + (1-\sum_k \lambda_i^k)\log_2\left(1+\gamma_i^0\right) \\ &= \sum_{k\in\mathcal{K}\setminus l} \lambda_i^k \log_2\left(1+\gamma_i^k\right) + (1-\sum_{k\in\mathcal{K}\setminus l} \lambda_i^k - \rho_i^l)\log_2\left(1+\gamma_i^0\right),\end{aligned} \tag{5.15}$$

which can be simplified as:

$$-\lambda_i^l \log_2\left(1+\gamma_i^0\right) + \rho_i^k \log_2\left(1+\gamma_i^k\right) + \lambda_i^l \log_2\left(1+\gamma_i^k\right) = 0, \tag{5.16}$$

therefore, we obtain the maximum portion of spectrum resource that can be shared to l_{th} MU,

$$\rho_i^l = \lambda_i^l \left[1 - \frac{\log_2\left(1+\gamma_i^l\right)}{\log_2\left(1+\gamma_i^0\right)}\right]. \tag{5.17}$$

It is obvious that $\gamma_i^0 \geq \gamma_i^k > 0$ such that $0 < 1 - \frac{\log_2\left(1+\gamma_i^l\right)}{\log_2\left(1+\gamma_i^0\right)} < 1$, which implies $\rho_i^l < \lambda_i^l$. When the l_{th} MU shifts from the macro-cell to the small cell, the λ_i^l spectrum of the small cell is no longer being interfered. Therefore, the small cell BS can always provide enough 'clean' spectrum to the accepted MUs, which completes our proof. □

Proposition 5.2. *The total available spectrum resource ρ_i^{total} can be calculated directly by the small cell BS, without separately considering each MU's interference in each sub-band.*

Proof: The maximum possible ρ_i^{total} offered by the small cell BS should satisfy the following equation, where all the interfering MUs are assumed to be accepted by the current small cell BS:

$$\sum_k \lambda_i^k \log_2\left(1+\gamma_i^k\right) + (1-\sum_k \lambda_i^k)\log_2\left(1+\gamma_i^0\right) \\ = (1-\rho_i^{total})\log_2\left(1+\gamma_i^0\right), \tag{5.18}$$

which is followed by:

$$\rho_i^{total} = \sum_k \left[\lambda_i^k \left(1 - \frac{\log_2\left(1+\gamma_i^k\right)}{\log_2\left(1+\gamma_i^0\right)}\right)\right]. \tag{5.19}$$

Recall the result of equation (5.17), we obtain:

$$\rho_i^{total} = \sum_l \rho_i^l. \tag{5.20}$$

Therefore, instead of considering the MUs one by one, it is equivalent to calculate the overall possibly offered spectrum directly. □

Now we are ready to develop our dynamic access strategy selection algorithm for the general case. Figure. 5.1 implies that the small cell BS may potentially get a better pay-off if it increases ρ from a small value. Proposition 5.1 and 5.2 show that the small cell BS can determine its maximum amount of resources to share without regard the individual MU. Hence, we can design an algorithm that, the small cell BS B_i gradually increases and broadcasts the amount of resources ρ_i it is willing to share, and the MUs who satisfy with the offer sequentially join the small cells.

Let us provide Algorithm 5.2 as follows.

The Algorithm 5.2 update the ρ in a synchronized manner, i.e., the small cell BSs offer the same ρ at the same time. This ensures the fairness between the BS, while ensures the MU to always join its most preferred BS if available. If the increasing of ρ is small enough, there will be at most one MU with pay-off improvement joining one of the small cells in an iteration. Once an MU joins a small cell, it will no longer be considered for succeeding iterations. Therefore, the convergence of the proposed algorithm is guaranteed. However, ρ may be set

Algorithm 5.2: Dynamic Access Strategy Selection Algorithm

1 **Initialization**:

a) Set the offer of spectrum as $\rho = 0$.

b) Set ζ to be a small positive constant.

WHILE at least one MU are not admitted by the small cells

a) At iteration t, the small cell BSs update spectrum budget $\rho_i(t)^{total} = 1 - \frac{R_i(t)}{\log_2 1+\gamma_i^0}$.

b) All small cell BSs broadcast current offer $\rho(t)$. If current offer $\rho(t) > \rho_i^{total}(t)$. The i_{th} small cell BS is kicked out.

c) MUs perceive ρ and calculate $\pi_{U_k}(B_i)$. If $\pi_{U_k}(B_i) > 0$, and $\pi_{U_k}(B_i) > \pi_{U_l}(B_j)$. $\forall k, l \in \mathcal{K}, l \neq k$ and $i, j \in \mathcal{N}, j \neq i$ then let U_k connect with B_i.

d) Update network topology and $\rho(t+1) = \rho(t) + \zeta$. If $\forall i, \rho(t) > \rho_i^{total}(t)$ **BREAK** larger to reduce the interaction times. In this case the macro-cell BS may choose multiple MUs based on its preference order.

In standard Stackelberg game, the leader is assumed to know the pay-off functions of all followers. It decides the best action in advance by predicting the reactions of the followers. However, in the two-tier network, there is limited information from the MUs. Therefore, small cell BSs consider the MUs with equal possibilities to accept or reject it. It is worthless to discuss the latter case since no change occurs. For the former case, the small cell achieves a pay-off gain $\pi^i_{SBS}(\rho)$, which is decreasing with ρ. Therefore by backward deduction, the small cell BS is willing to choose the smallest amount under the current budget. Then an iterative way of increasing ρ for it to find the deal point is a good choice. It starts betting from a small value of ρ, then increases it gradually until accepted by one MU. It keeps increasing the offer to attract more MUs unless running out of the budget. This is the motivation of using an iterative way in algorithm 5.2. It helps reducing the complexity especially when there are many small cell BSs and MUs.

5.5 Numerical Results

In this section, the increasing trend of the interference level against the amount of spectrum the small cell BS granted is shown under the single small cell BS/single MU scenario, followed by the multiple small cell BSs/multiple MUs case which illustrates how the proposed approach can be beneficial to both the small cell and MUs.

The simulation carries out on a system contains of 3 small cell BS and 6 MUs. The target rates of MUs are set between $[0.1, 0.5]$. The link gain between the corresponding SU and small cell BS is $h_{ii} = 1$, between the k_{th} MU and macro-cell BS is $g_{k0} = 0.01$ and the link gain between the MUs and nearby small cell BSs are set in the range of [0.6, 1.0]. The overlapped portion of spectrum satisfies

$\sum_k \lambda_i^k \leq 1, \lambda_i^k \geq 0$. The background noise variance is $\sigma^2 = 1$. The cross/co-tier interferences power at the macro-cell BS and i_{th} small cell BS receivers are assumed to be bounded to 1.

Here the choice of parameter follows these assumptions: (1) the channel gain between the MCU and the HBS is much better than which between the MCU and the MBS. (2) the spectrum utilized by the MCU overlaps with the small cell. Hence, in any of the following scenarios the dynamic accessing mode selection is not needed: (1) the MCU travels into the small cell using a totally difference sub-band, hence it won't hurt the performance of the small cell and the small cell has no willing to let it hand-off. (2) the MCU satisfies with the receiving SNR to the MBS, which implies its channel gain to the MBS is not much worse than that to the HBS.

Figure 5.2 shows the performance of the two-sided matching algorithm. We vary the value of δ to investigate the impact of the pay-off to the coalition formation. It is observed that, when δ is zero, the MU achieves its best pay-off, since the small cells give their best offer about ρ_i^k. However, the pay-off sum of the small cell network is not zero. This observation reflects an interesting fact that, when MU U_k is admitted by the small cell i, the small cell i is at least not worse-off, and other small cells $\{-\boldsymbol{i} : j \in -\boldsymbol{k}, \lambda_j^k \neq 0\}$ will be better-off. Furthermore, we see that when δ goes large, the pay-off sum of the small cells increases while that of the MUs decreases. Therefore we can conclude that algorithm 5.1 maximize the pay-off of MUs without the parameter δ. However, we can assign more pay-off to the small cells by introducing δ.

Figure 5.3 shows the increasing trend of the agreed ρ_i^k against the target rate of the MU. On one hand, higher target rate requires the small cell to offer more spectrum, and on the other hand, higher target rate makes the MU transmitting at a larger power, which results in a larger interference to the small cell BS receiver. Therefore the small cell is willing to offer more spectrum to compensate for the capacity loss, which coincides with the common sense.

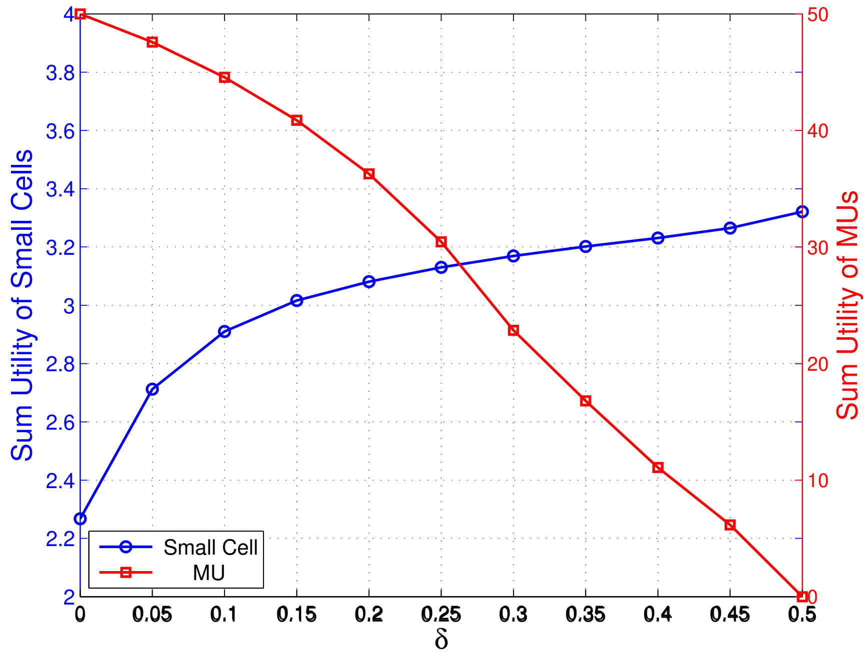

Figure 5.2: The pay-offs against δ.

δ adjusts the pay-offs of small cells and MUs.

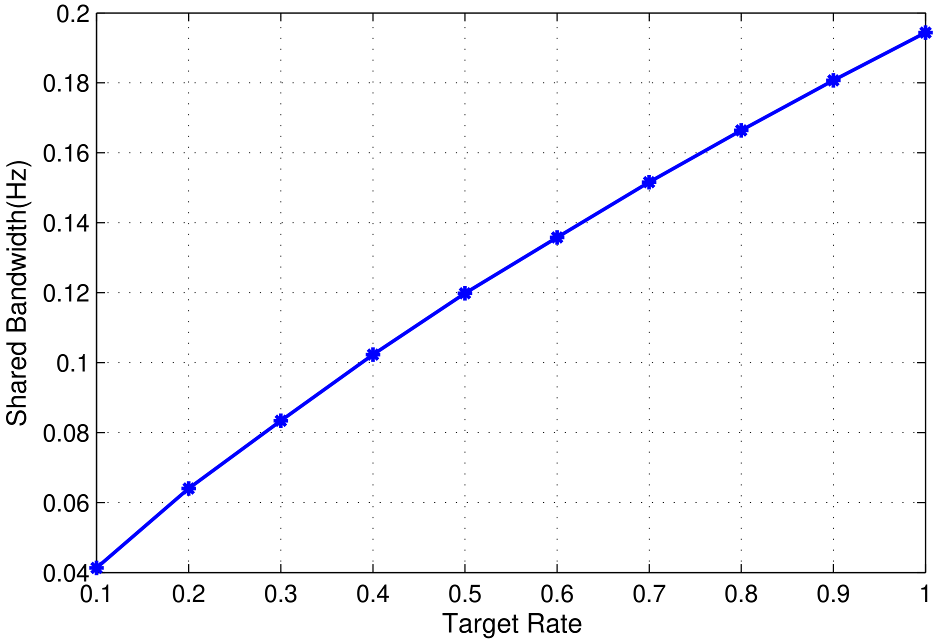

Figure 5.3: Relationship between ρ_i^k and R_T^k.
The shared spectrum resource ρ_i^k grows with the target rate R_T^k. Overlapped portion of spectrum $\lambda = 0.5$.

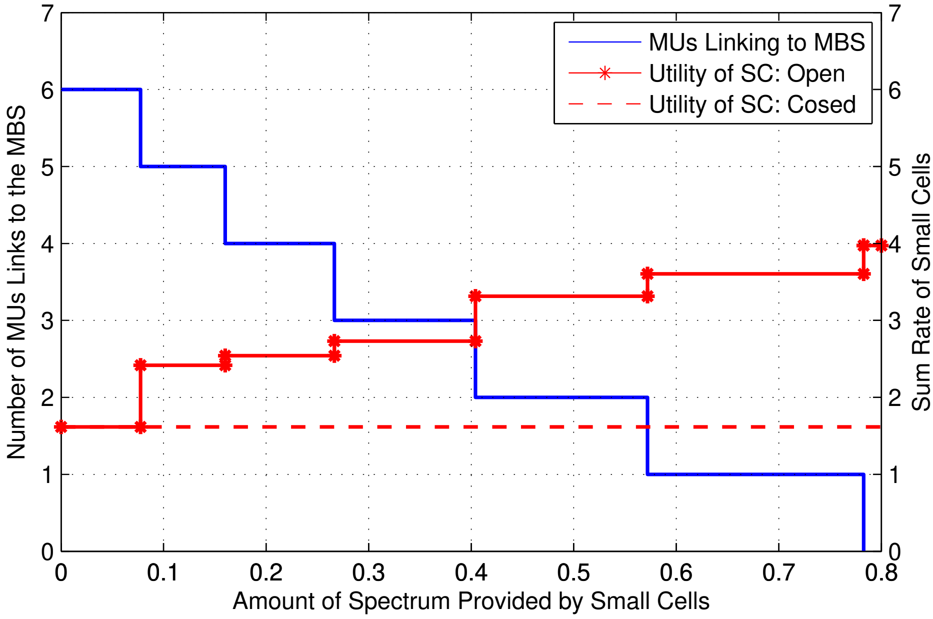

Figure 5.4: The dynamic of algorithm 5.2.
As the amount of offered spectrum $\sum \rho_i^k$ grows, more interfering MUs would like to join the small cell BS while the sum capacity of small cells increases for elimination of interference sources.

Figure 5.4 shows the dynamic of the sequentially joining algorithm. As the offered $\sum \rho_i^k$ grows, the candidate MUs sequentially join the small cells, while the sum capacity of small cells increases. As shown in the blue solid curve, the number of MUs linking to the macro-cell BS decreases with $\sum \rho_i^k$. Meanwhile, the sum capacity of small cells increases, as illustrated by the red star curve. The dash line as a comparison is the small cell BS's capacity under closed access mode. Obviously, the proposed algorithm guarantees that the sum capacity gained by the small cell BSs is improved by smartly choosing the open access mode. It can be observed that there is a great capacity increase for open access in an multiple small cell BSs/multiple MUs scenario. Because in this scenario, one MU may interfere multiple small cell BSs, therefore eliminating one interfering MU may be beneficial to multiple small cells.

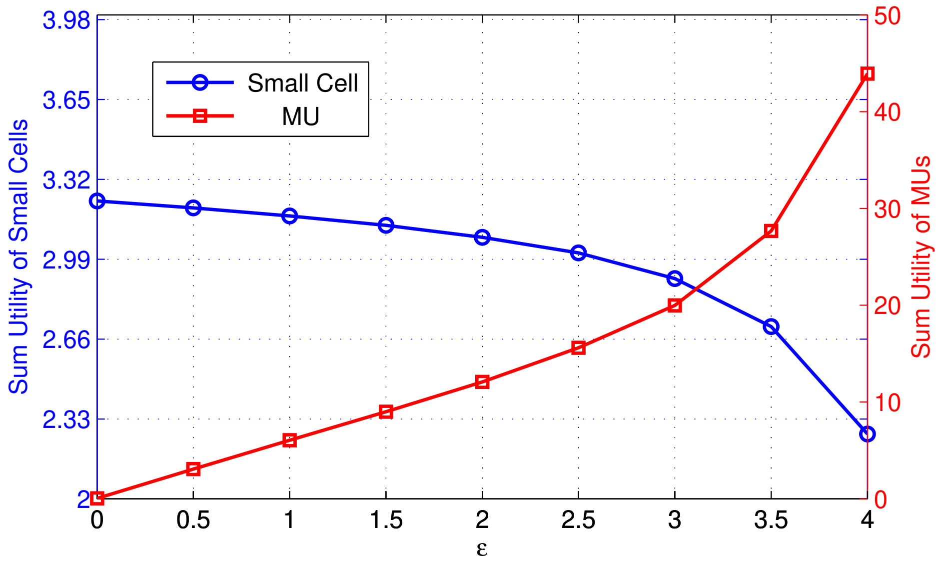

Figure 5.5: A trade-off between small cells and MUs.
ϵ adjusts the pay-offs of small cells and MUs.

Figure 5.5 shows how ϵ affects the pay-offs of small cells and MUs. The pay-off sum of small cells decreases with ϵ while the pay-off sum of MUs increases with ϵ. Hence, apart from compensating the energy consumption for cooperation due to signaling and communicating, the ϵ can also act as a parameter which controls the trade-off between the small cells and the MUs.

5.6 Conclusion

In this chapter, the choice of access strategy in small cells is investigated. Based on the Stackelberg game formulation, both the small cells and MUs can improve their performances by making smart choices to the access strategies. Our simple distributed algorithm requires no inter-cell coordination. The proposed approach guarantees the capacity gain of the user-deployed small cell in open access mode. Furthermore, the overall benefits can be flexibly balanced between the capacity gain of small cells and the energy efficiency gain of the MU devices by adjusting the objective functions. It is also worth considering in the future that if there is information available to determine the probability of MU to join the small cell with respect to the amount of spectrum the small cell is willing to grant, which will result in a different algorithm design.

The analysis of proposed schemes is based on the assumption that, all the small cell BSs update the bandwidth offer in a synchronized manner. However, if no coordinator presents to synchronize the bandwidth offer, i.e., each of the small cell BSs update their bandwidth offer asynchronously, the sequential joining algorithm are invalid due to the fact that the MUs may will to wait for better offer. In this case only the two-side matching algorithm can be used.

Chapter 6

Coalition Formation Game for D2D Carrier Aggregation

6.1 Introduction

The device-to-device communications which enable the nearby mobile devices communicate directly without relaying by the BS, is a promising technique for improving the capacity of the mobile networks [21]. Nowadays the demand for proximity communications, for example, the media sharing or social network based applications [1], grows fast. The driving force behind this phenomenon is the rapidly growing density of mobile devices , which increases the chances of local communications within a cell range. The short range D2D communications reduce the signal attenuation due to propagation loss, which subsequently improves the quality of service, such as the transmission latency, the network spectral/energy efficiency, and traffic load of the BS. However, some fundamental problems occur when the D2D communications are enabled in the cellular networks.

- The D2D devices discovering problem. [20]
- The accessing mode selection problem. [49]
- The resource allocation problem. [21]

In [21][49], the authors proposed a spectrum sharing model between the D2D network and the cellular network. These approaches incorporated the cross-layer coordination between the D2D network and the cellular network, which required centralized control at a significant cost when the network size becomes large. The authors in [21] considered that the D2D devices transmitted in the cellular uplink slot only to avoid the interference to nearby cellular devices. However, their approach limited the chances of D2D transmission since the spectrum reuse among D2D links is missing. In [79], spectrum sharing in both uplink and downlink was taken into consideration, wherein the transmit powers of cellular and D2D links are jointly optimized. However, precise synchronization is required in their considered Time-Division Duplex (TDD) based cellular network, and the D2D device should jointly perform the optimization with BS and cellular devices, which introduces considerable communication overhead for information exchange. Most of the previous work [21] [49] [79] considered the spectrum sharing between the cellular and D2D networks. An alternative way is to separate the spectrum of the cellular and D2D network to avoid the cross-tier interference, but seek for the spectrum reuse between the D2D links. Since the D2D communications are occurred randomly, static spectrum assignment may not be efficient. Therefore, dynamic model using game theoretical tools to deal with D2D communication problems has been proposed in [63]. They expand the D2D communication concept to two categories: from direct link (D2D-direct) to D2D local area network (D2D-LAN), and analyze the two categories using Stackelberg/Auction game and coalitional game respectively.

The spectrum allocation scheme should catch the dynamic of D2D communications to avoid the inefficient allocation. The study of D2D communication can also be applied for content distribution between end users. In [83], the authors proposed a social-aware D2D network for multiple media content distribution. They establish the physical layer model based on exploring the social behavior of individual users and make the highly active users be the agent to help to distribute the content, which achieves the goal of off-loading the burden of the cellular network.

There are some similarities between the D2D networks and the ad-hoc wireless networks, which have been well studied in literature [24][75]. However, the devices in the ad-hoc networks are totally isolated with each other, therefore they behave non-cooperatively. In contrast, the D2D devices are also cellular subscribers of the BS, it is natural for them to be coordinated via the cellular infrastructure. The D2D devices are cellular subscribers when they transmit via the BS, or they are the D2D users when they communicate directly.

Essentially, the demand for D2D communication is to further improve the spectrum efficiency. Hence the spectrum usage becomes a key issue in this topic. The D2D communications can occur in a dedicated spectrum, which is subtracted from the cellular spectrum to avoid cross-tier interference to cellular users; or it will use a shared spectrum together with the cellular user. In the first case, the devices paired for D2D communications compete for limited spectrum resources, hence it can be modeled as a multiple accessing problem. In the second case, to address the interference towards the cellular user is an significant problem. For both cases, we can get some light from the previous literature which consider the multiple accessing and interference management in mobile ad-hoc networks and cognitive radio.

The concept of mobile ad-hoc networks has been developed for a couple of years and has been applied in various techniques, such as the Bluetooth, NFC and WiFi. There are many similarities between the mobile ad-hoc network and the D2D communications. (1) The links between devices are both established on demand. (2) The link between devices are established autonomously. (3) The devices communicate with each other directly without central stations. However, they are also different in many aspects. (1) The existing technique requires manually triggering to start communication, such as the pairing in Bluetooth. The

D2D communications are aided by the base station under certain network protocols, which is usually transparent to users. (2) The mobile ad-hoc network usually operates on the unlicensed spectrum while the D2D communications operates on the cellular spectrum. (3) The D2D communications can provide services with much more distances (in-cell communication up to 1km comparing with less than 100m of mobile ad-hoc services).

In current cellular networks, the communications between mobile devices are fully controlled by the BSs. Enabling the D2D communications sacrifices the centralized coordination in exchanging better performance. However, it may cause unpredictable interference and collision between the cellular users and the D2D users. Further more, it is more interesting to investigate that the nearby D2D devices can coordinate their radio resources to achieve better performance.

In this chapter, we focus on improving the spectral efficiency in D2D communications. In fact, it is worth to consider that the D2D links would further extend their transmit rate by performing the carrier aggregation (CA). The CA is a technique which enables two or more sub-bands to be aggregated for high data transmission, which already has been used in LTE-Advanced between the cellular subscribers. In the proposed scenario here we assume that the D2D links can also benefit from the performance improvement by carrier aggregation. After carrier aggregation, the spectrum bandwidths of D2D links are widening and the cooperation can be further achieved by cooperatively sending and receiving signals. We shall utilized the coalitional game to study the cooperative interaction between the D2D links. In a coalitional game, the D2D links are players who seek to improve their performance by forming coalitions. The coalition formation process contains a series of decision making and negotiation steps based on the channel information and the interactive actions among D2D links.

However, whether a coalition can be successfully formed relies on whether the D2D links satisfy with the pay-offs they obtain from this coalition. The pay-off depends not only on channel information but also the action of other players. Some times the behavior of another D2D link is not well known or predictable. For example, the request for cooperation may be rejected by other D2D links or other D2D links in the same coalition behaves maliciously. In other words, the D2D links only have limited knowledge about other D2D links, which is referred as *imperfect information*. The imperfect information will cause uncertainties when D2D links make their decisions. Generally speaking, there are two kinds of uncertainties, 1) the internal uncertainty means the D2D links is uncertain about its own action, 2) the external uncertainty means the D2D link is uncertain about other one's action [15]. It is tricky for the D2D links to predict their pay-offs under these uncertainties. In [12] [13], the authors introduce the coalition formation game built on the imperfect information. In the Bayesian coalition formation, each of the player maintains a belief about other players, based on this belief they take optimal actions to maximize the expected pay-off. To the best of the authors' knowledge, this is the first work considering the carrier aggregation between D2D links via the Bayesian coalition formation game approach.

6.2 System Setup

We consider a cellular network where the D2D communication is enabled, as illustrated in figure 6.1. The mobile devices are enabled with the D2D communication abilities, which means they can shift between the cellular and D2D modes. In cellular mode, the source and destination nodes of a transmission pair transmit and receive signal through the BS. In D2D mode, they communicate directly with each other. In this chapter, we assume the D2D link has already been established, i.e., the source node has already selected the D2D mode and handshake with the destination node. Then we only consider the transmission control problems, i.e., we consider the resource allocation and performance improvement problems.

We denote the set of D2D links as $\mathcal{D} = \{D_1, D_2, ..., D_K\}$ and its cardinality is

Table 6.1: The Notations

$\mathcal{C}$	a coalition
$\boldsymbol{b}_k$	the belief vector of D2D link D_k
τ_k	the probability of D_k requesting help form others
ς_k	the probability of D_k refusing to help others
$R_{k,k\prime}$	the sum rate of carrier aggregation members D_k and $D_{k\prime}$
$\overline{r}_k$	the target rate of D_k when performing high-data rate task
$\underline{r}_k$	the lower bound of the average data rate
$\mathbb{E}[r_{k,k'}]$	the expected rate of D_k when aggregating carriers with $D_{k\prime}$
δ_k	the degree of dissatisfaction of D_k with current coalition
η_k	probability of D_k to experimentally leave current coalition
α_k	the memory parameter
$\tilde{b}(t)_{k,k\prime}$	the estimated belief in time slot t
$\tilde{g}_{k,k\prime}$	the channel gain of source node of D_k to the destination node of $D_{k\prime}$
λ_{S_k}	the pay-off division factor for ULS S_k in sub-band m
$\pi_{k,k\prime}$	the pay-off obtained by D_k when aggregating carriers with $D_{k\prime}$

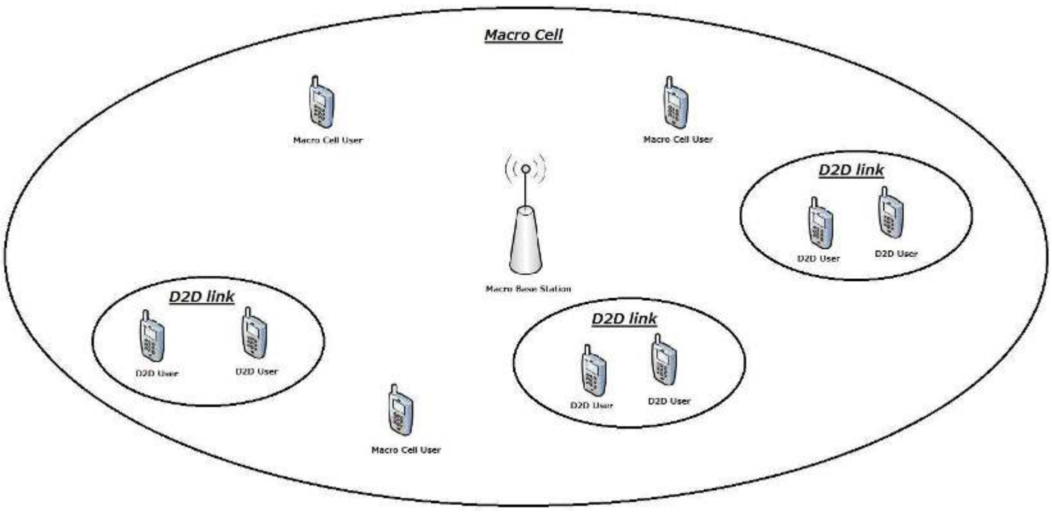

Figure 6.1: A cellular network with the D2D communication enabled.

$|\mathcal{D}| = K$. One D2D link contains two mobile devices who communicate directly with each other. We assume that the radio resource has been orthogonally divided between the cellular and the D2D network, hence the interference issues are omitted. The problem falls into how to efficiently coordinate the radio resources among the D2D links. Each of the D2D links is assigned by the BS an exclusive spectrum for transmission. The radio resource could be in the form of frequency bands or resource blocks, depending on the multiplex mode. We disregard the frequency selective fading so the D2D links have the uniform preference towards different frequency bands. The duplex mode of this D2D link is assumed to be TDD. Thus in one time slot, there is only single direction transmission within a D2D link.

We consider the cooperation between the D2D links is performed pair-wisely and without the help of the BS, which means the D2D links autonomously identify and negotiate with the potential collaborator to form the coalition. The improvement in performance using coalition formation is promising. With the help of carrier aggregation, the available bandwidth for each cooperative D2D link is increased. Furthermore, by forming virtual MIMO channel, the sum rate is further improved to the theoretical limit [64]. To achieve effective cooperation, the basic information such as the mutual channel gain should be measured by the D2D link via signaling. However, for the non-predictable and measurable parameter, such as the transmitting behavior, each of the D2D links maintains a belief - which can be considered as a private measure of the statistical distribution of the transmitting behavior - about the other D2D links. The belief of D_k towards other D2D links is defined as:

$$\boldsymbol{b}_k = [b_{k,1}, b_{k,2}, ..., b_{k,K}], \tag{6.1}$$

where $b_{k,j}$ is the probability that the D2D links D_k 'believes' D_j will refuse to cooperation with him.

6.3 Problem Formulation and Analysis

Each D2D link D_k is assigned an exclusively occupied sub-band ρ_k and we allow the D2D links to aggregate their spectrum for better performance. We define the D2D links who aggregate their carriers as a coalition, and hence the carrier aggregation problem becomes a coalitional game. We first give the definition about the coalitional game.

Definition 6.1 ([51], chapter 9). *A coalition $\mathcal{C}$ is a non-empty sub-set of the set of all players $\mathcal{K}$, i.e., $\mathcal{C} \subseteq \mathcal{K}$. A coalition of all players is referred as the grand coalition $\mathcal{K}$ A coalitional game is defined by $(\mathcal{C}, v)$ where v is the value function mapping a coalition structure $\mathcal{C}$ to a real value $v(\mathcal{C})$. A coalitional game is said to be super-additive if for any two disjoint coalitions $\mathcal{C}_1$ and $\mathcal{C}_2$, $\mathcal{C}_1 \cap \mathcal{C}_2 = \emptyset$ and $\mathcal{C}_1, \mathcal{C}_2 \subset \mathcal{K}$, we have,*

$$v(\mathcal{C}_1 \cup \mathcal{C}_2) \geq v(\mathcal{C}_1) + v(\mathcal{C}_2). \tag{6.2}$$

Given two coalitions $\mathcal{C}_1$ and $\mathcal{C}_2$, we say $\mathcal{C}_1$ and $\mathcal{C}_2$ overlaps if $\mathcal{C}_1 \cap \mathcal{C}_2 \neq \emptyset$.

Obviously, the supper additive condition is not always feasible in the proposed problem. For example, as discussed in [58] and [71], the cost for coalition would increase when the distance between mobile devices increased, therefore the grand coalition formed by all D2D links are naturally not stable. Hence, in this chapter, we focus on a special coalitional game which is the coalition formation game. In such a game we focus on finding the stable partition of the grand coalition, i.e., a stable coalition formation structure. More specifically, we assume that the D2D links perform simple pair-wise cooperation because lack of central coordinator, which means each of the coalitions contains at most two member players. The disjoint coalition is denoted as $\mathcal{C}_l$ with cardinality $|\mathcal{C}_l| \leq 2$, which satisfies $C_l \cap C_n = \emptyset, \forall l \neq n$ and $\bigcup_{l=1}^{L} C_l = \mathcal{D}$. The number of coalitions L depends on the coalition structure. Given the total number K of D2D links, there are in total

B_N possible divisions of the grand coalition, where:

$$B_N = \sum_{k=0}^{2} \binom{N-1}{k} B_k. \tag{6.3}$$

6.3.1 Coalition Formation Game

In practical system, the data rate requirement of the D2D links D_k is not constant, which may change from time to time. More specifically, we assume that the D2D links are occasionally transmit in high data rate, in this case it will request the help from the peer in same coalition for the transmission.

1) Low data rate. In this case, both D2D links transmit at low data rates. The sum rate achieved by carrier aggregation is equally divided between the two D2D links.

2) High data rate. In this case, one or two D2D links transmit at high data rate. The D2D link who demands high rate will request for help from the peer player in the same coalition. We denote the demanded high data rate of D_k as $\overline{r}_k$.

However, the high data rate request may not always be approved by the peer player due to miss-behavior (i.e., refused to help) or conflict request (i.e., the peer player also request high data rate). We denote the probabilities that $D_k$requests for help as τ_k and refuses to help the other player as ς_k. We assume that D_k and $D_{k'}$ are in the same coalition. Hence the sum rate achieved by virtual MIMO is given by,

$$R_{k,k'} = (\rho_k + \rho_{k'}) \sum_{i=k,k'} \log(1 + \lambda_i p_i). \tag{6.4}$$

Considering the pay-off of D_k, there are the following cases.

1) D_k and $D_{k'}$ both run low data rate task. The achieved data rate of D_k is,

$$\pi_k^1 = \frac{1}{2} R_{k,k'}. \tag{6.5}$$

2) $D_{k'}$ runs high data rate task and requests the help from D_k.

$$\pi_k^2 = \frac{\varsigma_k}{2} R_{k,k'} + (1 - \varsigma_k)(R_{k,k'} - \overline{r}_{k'}). \tag{6.6}$$

3) D_k runs high data rate task and requests the help from $D_{k'}$.

$$\pi_k^3 = \frac{\varsigma_{k'}}{2} R_{k,k'} + (1 - \varsigma_{k'})\overline{r}_k. \tag{6.7}$$

4) Both D_k and $D_{k'}$ request help from each other, and collision occurs.

$$\pi_k^4 = \frac{1}{2} R_{k,k'}. \tag{6.8}$$

Note that in the above cases $\overline{r}_k > \frac{1}{2} R_{k,k'}$, otherwise D_k or $D_{k'}$ does not need to request any help since simply equally divide the achieved data rate can fulfill their rate demand.

Then the expected data rate of D_k cooperate with $D_{k'}$ is given by,

$$\mathbb{E}[r_{k,k'}] = (1 - \tau_k)(1 - \tau_{k'})\pi_k^1 + (1 - \tau_k)\tau_{k'}\pi_k^2 + \tau_k(1 - \tau_{k'})\pi_k^3 + \tau_k\tau_{k'}\pi_k^4. \tag{6.9}$$

To calculate the expected pay-off in (6.9), the D2D link D_k must know the probability of being refused $\varsigma_{k'}$. However, this is a private parameter which can only be estimated by others. We formally define the proposed Bayesian coalition formation game as follows:

Definition 6.2. *A Bayesian coalition formation game is denoted by* $G = (\mathcal{K}, \mathcal{T}, \mathcal{B}, \boldsymbol{v})$,

- *Players:* $\mathcal{D} = \{D_1, D_2, ..., D_K\}$ *is the set of players which are the D2D links.*

- *Types: The type set* $\mathcal{T} = \{T_1, T_2, ..., T_K\}$ *specifies the transmission behavior of the D2D links.* T_k *corresponds to real value* $\{\tau_k : 0 \leq \tau_k < 1\}$, *which is the probability that* D_k *refuses to help with others for their transmission.*

- *Belief: The set* $\mathcal{B} = \{\boldsymbol{b}_1, \boldsymbol{b}_2, ..., \boldsymbol{b}_K\}$. $\boldsymbol{b}_k = [b_{k,1}, b_{k,2}, ..., b_{k,3}]$ *is the belief of* D_k *about the types of other players.*

- *Value: The real valued function $v(\mathcal{C})$ defines the worth of a coalition $\mathcal{C}$, and the pay-off of the member players is a division of the value.*

We assume that the D2D links are rational players, i.e., they try to choose the optimal coalition to maximize their pay-offs. The cooperation between the D2D links is achieved by the virtual MIMO technique, as it is shown to be the upper bound of the capacity of the multiple access channel [64]. Note that the virtual-MIMO requests the mutual information between the sources or between the destinations is much higher than that between the sources and destinations [71], i.e., the channel gains between the sources should be higher than the channel gains between the sources and destinations. Furthermore, for distant nodes, the high coalition cost tends to prevent them from forming coalitions [56].

We consider an equivalent 2-input 2-output channel which is constructed following the same line as [64]. We denote the channel gain of source node of D2D link D_k to the destination node of D2D link $D_{k'}$ as $\widetilde{g}_{k,k'}$, and the received interference power variance at $D_{k'}$ as $\sigma 2$. We define $g_{k,k'}$ as:

$$g_{k,k'} = \frac{\widetilde{g}_{k,D_{k'}}}{\sigma^2}. \tag{6.10}$$

The channel gain matrix of this 2×2 virtual-MIMO channel is given by:

$$\boldsymbol{G}_{\{C_k \in \mathcal{L}_m\}} = \begin{bmatrix} g_{k,k} & g_{k,k'} \\ g_{k',k} & g_{k',k'} \end{bmatrix}. \tag{6.11}$$

We denote the two non-zero eigenvalues of matrix defined in equation (6.11) as $\overline{\lambda} k$ and $\underline{\lambda}_k$ and $\overline{\lambda} k \geq \underline{\lambda}_k$.

The value of the coalition formed by two cooperative D2D links equals to the sum rate in (6.4). It is proved in [71] that the pay-off division among coalition members satisfies the proportional fairness [39], if the benefit allocated to each member equals to its contribution to the overall rate, i.e.,

$$r_k = (\rho_k + \rho_{k'}) \log(1 + \lambda_k p_k). \tag{6.12}$$

In this chapter, we focus on the analysis of the coalition formation and assume that the transmit power of D2D links is constant. Hence the maximizing of the sum rate relies on choosing the optimal $\boldsymbol{\lambda}_{S_k}^m$, i.e., choosing the optimal coalition structure. Note that the transmit power can also be optimized based on some criteria, for example the energy efficiency [48] [34] or interference constraint [37] [82]. The Bayesian coalition formation game proposed in this chapter can be easily extended to a hierarchical game to cover the power optimization problem, which could be the future work.

6.3.2 Problem Analysis

The D2D links form coalitions to achieve high data rate transmission, hence they has an expectation about the achieved data rate. This expectation can be considered as a lower bound of the average data rate, which is denoted as $\underline{r}_k$. In the other words, if a D2D link D_k requests for carrier aggregation, the rate after forming the coalition should satisfy,

$$\mathbb{E}(r_k) \geq \underline{r}_k. \tag{6.13}$$

There may be multiple coalitions which satisfy (6.13). Hence D_k will choose the most preferred to join, i.e., D_k evaluates its interest toward the potential coalitions based on its preference order.

Definition 6.3. *A preference $\succ_{D_k}$ specifies a preference order of D_k towards two coalitions, i.e., if $\mathcal{C}_1 \succ_{D_k} \mathcal{C}_2$, we say $\mathcal{C}_1$ is preferred to $\mathcal{C}_2$ by D_k.*

The D2D link will choose the coalition following the *best reply* rule, which means the preference order over different coalitions is evaluated by the expected pay-offs obtained from these coalitions.

$$\mathcal{C} = \arg \max_{mathcalC} \pi_{D_k}(\mathcal{C}). \tag{6.14}$$

Furthermore, we assume that the D2D links can do experiment to leave current coalition and join a new one, even if the predicted expected pay-off after joining the new coalition is smaller. Enabling the experiment during the coalition formation gives each D2D link more chances to contact others, hence it helps them to build more reliable beliefs. We call this modified best reply rule as *best reply with experiment*. However, introducing the experiment will increase the convergence time of the belief updating process. In one time slot D_k can leave and join only one coalition, hence it only updates the belief about only one D2D link. When the number of D2D links increases, the convergence time of the Bayesian updating algorithm grows exponentially.To accelerate the convergence of coalition formation, we define the degree of dissatisfaction (DoD) δ_k which characterizes the possibility that D_k leaves the current coalition. The degree of dissatisfaction is constructed as,

$$\delta_k = e^{\underline{r}^H - \mathbb{E}(r_k)}. \tag{6.15}$$

We define the probability of doing experiment η_k as a function of δ_k,

$$\eta_k = \begin{cases} \delta_k, \text{if } \delta_k \geq \epsilon \\ 0, \text{otherwise.} \end{cases} \tag{6.16}$$

The ϵ is a small constant. The above equation implies that if the DoD is less than ϵ, then the D2D links is considered as 'fully' satisfied and will not perform any experiment. Furthermore, the possibility of doing experiments if the achieved data rate is high.

Each D2D link maintains a belief vector of other D2D links about the probability of requesting high data rate. We denote an indicator $x_{k\prime,k}(t) \in \{0, 1\}$, where $x_{k\prime,k}(t) = 0$ means $D_{k\prime}$ agrees to help D_k at time t, while $x_{k\prime,k}(t) = 1$ stands for refuse. We assume that the D2D links are myopic so they just consider the current state and the belief is obtained using the following equation,

$$\tilde{b}_{k,k\prime} = \frac{\sum_{u \in 1,\ldots,t} x_{k\prime,k}(u)}{t}, \tag{6.17}$$

where $\sum_{u \in 1,\ldots,t} x_{k\prime,k}(u)$ is the number of times $D_{k\prime}$ refused to help D_k in the previous t time slots. Then the belief is updated as follows,

$$b_k(t) = \alpha_k b_{k,k\prime}(t-1) + (1 - \alpha_k)\tilde{b}_{k,k\prime}. \tag{6.18}$$

The estimation of individual pay-off requires the knowledge of the existing coalition structure. The D2D device communicates with the D2D coordinator to obtain the current coalition structure $\mathcal{S}$. The D2D links need to know the utilities in every possible coalition to make a decision to join or not. Furthermore , we assume the D2D links are individual rational, therefore they will only join a coalition to improve their own pay-offs.

By considering the power consumption on the sensing and negotiation during the coalition formation, we define the pay-off function of a D2D link as follows,

$$\pi_{k,k'} = \mathbb{E}[r_{k,k'}] - \vartheta p_T d_{k,k'}^n, \tag{6.19}$$

where ϑ is the cost factor, p_{td} is the receiving power threshold for decoding the information exchange data package, and $d_{k,k'}$ is the distance between the source nodes of D_k and $D_{k'}$. The cost function reflects the fact that, the extra power consumption for cooperation increases with the distance between two member players. Since p_{td} is fixed, then the transmit power p_s for interference exchange depends on channel condition. In most of the cases, the channel gain is a decreasing function of distance $d_{k,k'}$. If taking the simplest path-loss model, say $p_{td} = \frac{p_s}{d_{k,k'}}$, where n is the path-loss component, we get the cost term in (6.19). Obviously, bad channel condition of the signaling channel will prohibit signaling or make it consume much power. Under the path-loss model, the power consumption cost can be mapped to the distance between the D2D pairs, and the geolocation information can be obtained with the assistance of base station.

Here the cost for coalition depends on the distance $\vartheta d_{k,k'}$. This kind of linear cost functions are also adopted in [6] [58]. The establishment of (6.19) reflects an interesting trade-off of joining in a coalition for D2D links. The cost function directly reflects the extra power consumption for coalition. Suppose there is a threshold p_T of receiving power to decode the information exchange data package, then the transmit power p_s of the signal varies with channel conditions. If taking the simplest path-loss model, say $p_T = \frac{p_s}{d^n}$, where d is the distance between the transmission nodes of D2D pairs and n the path-loss component, then the transmit power is a decreasing function of the distance. Obviously, bad channel condition of the signaling channel will prohibit signaling or make it consume much power. Under the simple path-loss model, the power consumption cost can be mapped to the distance between the D2D pairs, and the geolocation information can be obtained with the assistance of base station.

6.4 The Coalition Formation Algorithm

6.4.1 Coalition Formation Rule

In previous section, we have utilized the Virtual-MIMO technique to achieve the cooperation between D2D pairs. Moreover, the parameter λ_k specifies how the pay-off is divided between players in the coalition. Note that we seek to improve both the sum pay-off of the coalition and the individual pay-off of the coalition members. Hence, we say that if a player D_j prefers coalition C_1 to C_2, then its pay-off will be strictly improved when joining C_1 comparing to C_2; and any other players D_i in C_2 will at least maintain a pay-off better than the value before D_j joining C_2. Follow this rule, the preference order of D_j will follow the Pareto efficient which is defined in[26]; i.e., there is no agreement that is better for player D_i and at least as good as any other player D_j. Mathematically, we define the preference order based on Parato efficiency as follows:

$$C_k \succ_i C_k^{'} \Leftrightarrow \begin{cases} u_i(C_k) > u_i(C_k^{'}), \forall D_i \in C_k, \\ u_{k'}(C_k) \geq u_{k'}(C_k^{'}), \forall D_{k'} \in C_k, i \neq j. \end{cases} \tag{6.20}$$

Following such order, whenever a player chooses to switch, it improves its individual pay-off without hurting other players in the target coalition. This assumption is practical in wireless network, since a larger spectrum may benefit to all the D2D links. The switch rule is defined as:

Switch: Given a disjoint partition $\mathcal{S} = \{S_1, S_2, ..., S_L\}$ of the set $\mathcal{N}$, any D2D link $i \in \mathcal{N}$ leaves his current coalition S_m and join another coalition S_n if and only if $S_n \succ_i S_m$, $\forall n, m \in \{1, 2, ..., l\}, n \neq m$. Hence, $\{S_m, S_n\} \rightarrow \{S_m \backslash \{i\}, S_n \cup \{i\}\}$. Our goal is to find a self-organizing approach wherein the D2D links form the coalitions distributively. The framework of such a coalition formation game includes three key ingredients: (1) the preference orders for comparing between coalitions, (2) rules for either joining or leaving coalitions, (3) notions for accessing the stability of a partition [5].

6.4.2 Coalition Formation Algorithm

The coalition forming coalition algorithm is presented and the convergence of proposed algorithm is shown as follows.

Firstly, if given an infinitive number of iterations, obviously the belief will converge to the true behavior. However, it is inefficient and unnecessary to make the beliefs reach the exact value. Because the belief updating itself consumes time, energy and bandwidth; too much belief updating overhead will dramatically degrade the overall performance. Hence, in this chapter, we design the belief updating algorithm allows the D2D pairs to build a big picture about the true behaviors of others in a limited number of iterations, and how precise of their estimations can be controlled by varying the value of DoD. More specifically, the D2D pairs are more likely to settle down after a few iterations when DoD is set high; and more likely to experiment more when DoD is set low.

Suppose there are K D2D pairs, and we consider the kth D2D pair D_k on its belief updating. Initially the D_k keeps a uniform belief about the type of other ones. After a few iterations, say iteration t, D_k will have a rough belief vector $b_1(t), ..., b_K(t)$. Now it chooses the one giving him the best pay-off, say D'_k, and fortunately it is also preferred by D_k. Furthermore, the DoD is satisfied, then D_k does not seek any opportunity to cooperate with anyone else. Hence, at last D_k only obtains accurate belief about D'_k (and vice versa.), but avoids the burden to obtain the accurate belief about all other D2D pairs.

Moreover, we have the following theorem.

Algorithm 6.1: D2D Carrier Aggregation Algorithm

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1) *Sensing:*

   a) The D2D link D_k randomly choose a nearby $D_{k'}$. Then it will sense the necessary parameters (i.e., $g_{k,j}$) to estimate the coefficients of Virtual-MIMO channel.

   b) After obtaining the parameters, D_k use (6.13) to validate if $D_{k'}$ worth to pair. If (6.13) is true, go to Step 1-a), if false, go to Step 2-a).

2) *Trial:*

   a) At time t, both the D2D links update the belief $b_{k,j}(t)$ using (6.18) based on the knowledge that whether $D_{k'}$ helps to do transmission.

   b) Then algorithm go to Step 1) in the following cases: a) If the result gives that the expected pay-off $\overline{\pi} \leq \underline{r}^H$, then the corresponding D2D pair will leave the coalition and make new trials. b) If the result gives that the expected pay-off $\overline{\pi} \geq \underline{r}^H$, the D2D pair still has small chance η to do experiment to leave the current coalition.

   c) Step 2-b) is repeated until the $|b(t) - b(t-1)| \leq \epsilon$ and the coalition formation structure is stable.

Theorem 6.1. *Suppose the belief of the D2D link converges, then the proposed algorithm will converge to a final state containing a number of disjoint coalitions, using the algorithm proposed in the previous subsection.*

Proof : Given a fixed belief vector, the expected pay-off of any coalition is readily to be obtained. Based on the switch rule, for any D2D link D_k, each switch operation will strictly improve its pay-off by the definition of the switch order, therefore, it has no incentive to revisit any of the coalition it has experienced before. However, since each D2D link makes the choice independently, other players' switch operation may result in that D_i revisiting an old coalition. In this case, even D_i leaves this coalition again, it still has the risk to be brought back, i.e. a risk to be trapped in a loop. Therefore we let the D2D link to keep the history set of the visited coalitions for revisit prevention. Therefore it is guaranteed that every switch operation of any player will lead to a new coalition status. Since the number of partitions is finite and given by the Bell number, the proposed algorithm will always reach a final partition after a number of turns. □

The stability of a partition can be accessed by the concept of *Nash-stable* [11]: Given a set of disjoint coalitions $\{\mathcal{C}_l, \cup_l \mathcal{C}_l = \mathcal{D}.\}$, which is a partition of the set of all D2D links. If $\forall D_k \in \mathcal{D}$, $C_i \succeq_{D_k} C_j$, then this partition is Nash-stable. This definition implies that, in a Nash-stable partition, none of the D2D links has the incentive to leave current coalition.

Proposition 6.1. *The final partition result from the coalition formation algorithm is Nash-stable.*

Proof : Suppose that the final partition $\mathcal{S}_f$ is not Nash-stable, therefore there exists a D2D link $D_i \in \mathcal{N}$ and a coalition $C_k \in \mathcal{S}$ that satisfies $C_k \cup \{i\} \succ S_{\mathcal{S}}(i)$. Hence, a switch operation is available for D_i, which contradicts to Theorem 6.1. Consequently, any final partition resulted from the proposed coalition formation algorithm is Nash-stable. □

The implementation of the D2D carrier aggregation does not require a central coordinator, since it is carried out based on pair-wise negotiation. If considering

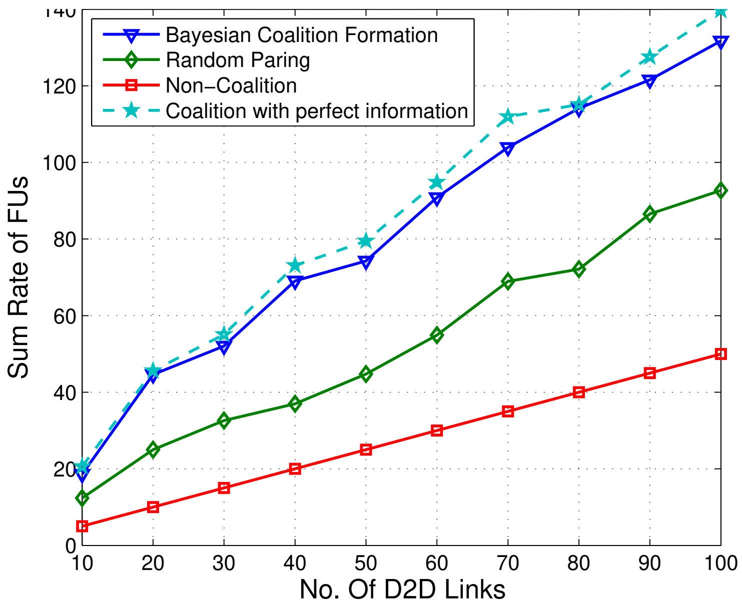

Figure 6.2: The capacity of the D2D network against the coalition cost δ.

there are no effective transmission during coalition formation, then the overhead is contributed by the power consumption of information exchange when D2D pairs negotiate with each other. However, because the exact time for belief convergence can not be specified, we provide the complexity of the algorithm to illustrate the possible overhead brought by the belief updating and coalition formation. In each iteration of algorithm 6.1, each of the D2D pair will at most contact $K1$ others for possible cooperation. There are hence the complexity of each iteration will be $\mathcal{O}(K(K-1))$.

6.5 Numerical results

In this section, we present some experimental results to better illustrate the proposed idea. In the setup, we assume that the D2D links are uniformly distributed. Each of the D2D link constitutes a source node and a destination node. Since D2D communications can be only performed between nearby nodes, we assume the destination node locates randomly in a circle with a fixed radius (e.g., 100m) around the source node. The channel gain between two D2D direct links is assumed to be $\widetilde{g}_{k,j} = \frac{g^0_{k,j}}{\sqrt{d^n_{k,j}}}$ where $g^0_{k,j}$ is the channel fading coefficient and n is the path-loss exponent. We investigate the following three scenarios to illustrate the performance of the proposed algorithm:

- Random pairing. The D2D links randomly chooses the peer to form the coalitions.

- Bayesian coalition formation. The D2D links know imperfect informatioand use the proposed algorithm for coalition formation.

- Non-cooperating. The D2D links do not perform carrier aggregation.

In figure 6.2, the curves show the pay-off sum of the D2D network in a fixed area against the number of D2D links. The benchmark is the coalition formation with perfect information. We observe that the trends of all three curves are increasing, since the more D2D users the more chances they form the virtual MIMO channels. The red line corresponds to the non-coalition case, here for simplification we assume the transmit power and bandwidth are uniform for all D2D links, so increasing the number of D2D links result in an linear growing of sum rate. However, since the random paring scheme does not achieve the optimal coalition formation structure, the resulting pay-off is relatively low compared with the other two schemes. In contrast, we see that both the optimal and Bayesian coalition formation schemes have achieved a high data-rate.

In figure 6.3, we investigate the impact of the coalition cost coefficient in the proposed algorithm. We consider a D2D link acts alone as a singleton coalition (i.e., a coalition which has only on member player). Therefore in figure 6.2, a constant green line corresponds to the non-cooperative scenario, which can be considered as a special case where all the D2D links form singleton coalitions. Obviously ϑ has no effort on this scenario. In contrast, we observe a significant increasing trend of the number of coalitions in the cooperative case when ϑ goes large - which reflects the fact that, when the cost for cooperation ϑ goes high,

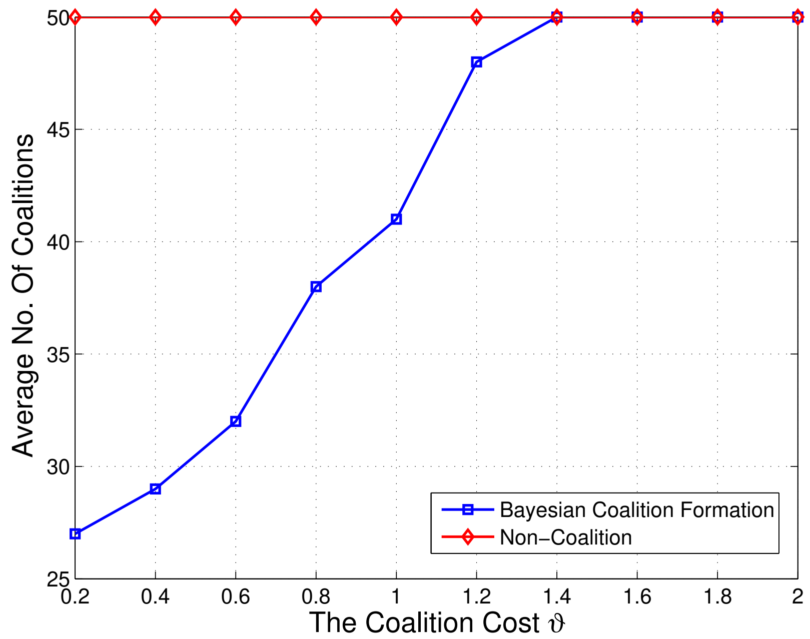

Figure 6.3: No. of coalitions versus coalition cost δ.

the D2D links tend to not form coalitions. At the end we see that an extreme high cost ϑ will prevent any coalitions other than the singleton coalitions to be formed.

In figure 6.4 we compare the convergence performances of the proposed algorithm with respect to different numbers of D2D links in a fixed area. It is shown that the convergence time grows with the density of the D2D links. When the density of D2D links grows, each D2D link may has more neighbors. Therefore, it needs to spend more time to negotiate with others and learning their types.

6.6 Conclusion

In this chapter, we have proposed a Bayesian coalition formation game for D2D carrier aggregation. We have developed distributed algorithm for the D2D links to

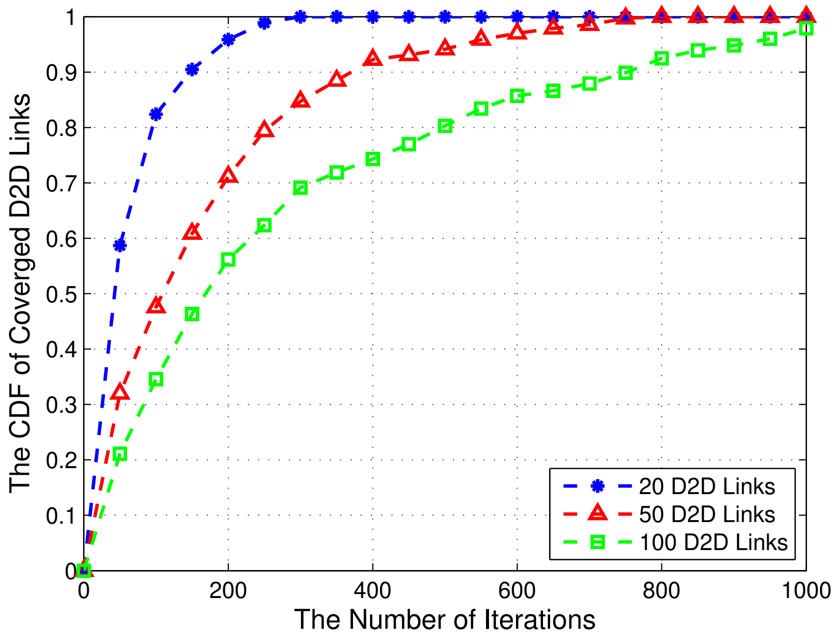

Figure 6.4: The convergence performance versus the densities of the D2D links.

optimally form pair-wise coalitions. The proposed algorithm requires no centralized control since the negotiation only happens between D2D links. Furthermore, we investigate impact of the density of D2D links and the coalition cost to the coalition formation process. The convergence and stability of the proposed algorithm were proved. Furthermore, a significant performance improvement was shown in the numerical result, especially when the D2D links were sparsely distributed. One of the limitations of this work is that the transmission power of the D2D link is assumed to be constant, and in future work a joint framework for both coalition formation and transmit power optimization will be presented. It is also interesting to investigate more details about the connection between the coalition cost δ and the physical parameters(e.g. power, spatial distribution) of the D2D links. Furthermore, enabling the coalition to be overlapped is a more challenging work.

The limitation of this work is that it only considers an isolated D2D network which avoids to deal with the interference management issue when considering the spectrum sharing with cellular network. Furthermore, the proposed D2D carrier aggregation scheme is suitable for the scenario that the status of D2D network does change rapidly. For example, the multimedia content sharing among D2D nodes in which the duration for data transmission are considerably longer than the belief updating. In cased that the network status changes fast, especially when the duration of mobile nodes staying in D2D mode is short, the belief updating based algorithm will bringing unbearable overhead.

Chapter 7

Conclusion and Future Works

7.1 Conclusion

In this thesis, we have studied the applications of game theoretical tools to the resource allocation and mobility management problems in heterogeneous wireless networks. We have reviewed several game models, such as the Stackelberg game, the coalitional game, and Bayesian dynamic game. We introduced the properties of these game models and highlighted their useful features in solving various problems in HetNets.

Firstly, we started from using non-cooperative game to investigate the competition for limited spectrum resources among the ULSs in a spectrum-sharing based two-tier network. Compared to most of the previous work for the scenario in which each ULS could only access one single frequency band, we proposed a new system setup in Chapter 3, in which multiple ULSs can access multiple subbands at the same time. The proposed scenario could be equivalently considered as a multiple-access channel with the presence of the spectrum owner. We have used Stackelberg game to model the interactions between the MCO and the ULSs. To solve the proposed resource allocation problem under the power constraints, we defined the pay-off of the ULSs as a revenue-cost function and introduced the interference price to regulate the transmission behavior of the ULSs. We proved that the existence of the SE that can be achieved by the proposed algorithm. A fully distributed algorithm which requires no information acquisition of the MCO is proposed, and is proved to be optimal under certain condition. The proposed multiple access model shows great improvements towards the conventional model which only allows the ULS to access a single sub-band.

Secondly, we have explored using cooperative game to model and analyze the cooperative behavior in resource allocation problem in HetNets. More specifically, we have proposed a novel hierarchical game framework which constitutes a Stackelberg game between the MCO and the ULSs, and an OCF-game among the ULSs. To the best of the author's knowledge, this is the first OCF-embedded hierarchical game model applied to study the cooperatively resource utilizing in HetNets. We use the virtual-MIMO as the policy of cooperation among the ULSs. We have proved that the proposed OCF-game is 2^n-finite, which subsequently lead to the existence of the core. Then we have proved that the SE of the hierarchical game exists and proposed a distributed algorithm which converges to the SE. We have showed that enabling the overlapping in the proposed coalition formation game achieves a great capacity gain of the whole network.

Then we apply the Stackelberg game to study the access mode selection problem in a user-deployed small cell network. We have focused on the interactively decision making of small cells about whether to admit the nearby MUs to help improving their performance. More specifically, we have investigated the open/closed model selection game from a demand-driven perspective. We assume a spectrum-sharing based two-tier network in which the spectrum utilized by the small cells and the MUs may partially overlap, which gives the motivation of the small cell BS to admit the nearby MU for eliminating the interfering source. We have found that sometimes choosing the open access mode would improve the performance of both small cells and MUs. We have establish a Stackelberg game in which the small cell BSs are leaders and the MUs are followers. The pay-off of the small cells is defined as the improvement on capacity, and the pay-off of the

MUs is defined as the improvement on energy efficiency. We start from the single small cell single MU case to illustrate how they interact with each other in the proposed game. Then we extend the single small cell single MU case to the more general case to consider multiple small cells and multiple MUs. Two algorithms are proposed to respectively maximize the pay-off of small cells and the MUs. Furthermore, the proposed algorithms could flexibly balance in performances of the small cells and the MUs by adjusting the embedded trade-off parameter in the pay-off functions. The simulation results provided solid supports to our conclusions that the small cells and MUs can obtain a win-win result by properly selecting the accessing strategies.

The four techniques discussed focus on different aspects in HetNets. It is possible to be jointly applied to benefit the performance of HetNets from different aspects. However, more policies should be applied when these techniques are used together to avoid collision on either power control or resource usage.

Firstly, the techniques proposed in chapters 3 and 4 are intended to solve the power control problem. Generally speaking, the technique in chapter 3 focuses on spectrum reuse between 'far-away' mobile devices, while the technique in chapter 4 focuses on in-band cooperation between 'near-by' mobile devices. Hence, it is possible to utilize both techniques in a HetNet. However, it should be noted that, these two techniques are both built on iterative algorithms to achieve the dynamically power control. Hence, it could not be applied to one mobile device in the mean time. For example, supposing there are three mobile nodes m_1, m_2 and m_3, m_1 and m_2 qualify to perform the spectrum-sharing while m_2 and m_3 qualify to perform in-band cooperation, then m_2 should either choose m_1 or m_3. A possible way to deal with this scenario is as follows: suppose m_2 chooses m_3, then these two nodes can be virtually considered as one node m'_4. Hence, we can apply the spectrum sharing algorithm between m'_4 and m_1. However, jointly applying these techniques does not guaranteed much gain as the performance depends on scenarios.

Secondly, the technique proposed in Chapter 5 is based on a assumption that the transmission power and sub-band allocation of the femto-cell networks are fixed. However, in previous chapters the transmission power of the femto-cell subscribers is dynamically adjusted by the MCO. Hence, if applied them together, the amount of spectrum provided by the SBS should also be calculated dynamically as it is affected by the transmit power of the small cell subscribers. This would make the proposed algorithms invalid.

At last, the technique of the proposed D2D carrier aggregation scheme in the chapter 6 can be directly applied upon the techniques proposed in previous chapters. Since in this chapter, we assume that the nodes perform D2D communication have been already decided and a dedicated spectrum has been already assigned to them for communication. Hence the analysis of the performance gain is based on a isolated D2D network. However, in practice, how to optimally trade-off the spectrum assignment between D2D network and the cellular network is also an important issue.

7.2 Future Works

There still remain many new frontiers to be explored in HetNets. Here we list several problems arising in our previous study which to be further studied in the future.

- Hybrid mode small cell networks

  As an emerging technique which has been standardized into the LTE-Advanced network. The HetNets show a bright way towards high data rate transmission. In our previous work, we focused on the spectrum-sharing model which operates on the frequency bands of the mobile networks (i.e., 400MHz to 3GHz). However, the purely spectrum-sharing based model may not meet the rapidly growing demands for the deployment of small cells. Hence higher frequency bands which are suitable for short range communications have been considered. Recently, in the 3GPP Release 12, the 3.5GHz band is considered as the dedicated spectrum for small cells to enable large-scale commercial implementation. However, to further expand the capacity of the future generation wireless networks, it is worth to discuss about the small cells operating in hybrid mode. The hybrid mode small cells can shift between both the licensed/unlicensed band dynamically. The basic idea is, the small cell can monitor the transmit behavior of nearby macro cell subscribers. Based on the observation, the small cell can help to improve the network capacity by the following two means: 1) The small cell and the macro-cell can mutually help each other by a spectrum leasing mechanism: if the macro-cell has a high traffic load the small cell may lease its spectrum to the macro-cell, and if the small cell is idle, it can help with the macro-cell subscribers to improve the performance, 2) The spectrum reuse and carrier aggregation can be performed in the dedicated frequency bands of small cells, hence the spectrum efficiency can be further improved. The hybrid small cell suggests a flexible way to keep a balance between the spectrum efficiency and the quality of service.

- D2D carrier aggregation with shared spectrum

  In this thesis we have considered the carrier aggregation problem in the D2D communications with exclusive spectrum occupancy. However, it is more challenging to investigate the D2D communications operating in the spectrum-sharing mode (i.e., the spectrum is shared with the cellular user) or hybrid mode (i.e., share or exclusively occupy the spectrum opportunistically). Furthermore, in previous work we have assumed the D2D carrier aggregation is performed pair-wisely. However, considering the carrier aggregation among more than two D2D links with imperfect information is a more challenging problem. In this case, we still need to consider the belief-based Bayesian dynamic game model, but the impacts of member players' actions to each other are more difficult to analyze. How the D2D link evaluates the expected pay-off efficiently for decision-making depends on the learning speed about the beliefs, which will be dramatically decreased when the size of the coalition is large.

- Long term pay-off evaluation in coalition formation game

  Our previous works about the applications of coalition formation game in HetNets were based on the acquisition and analysis of instantaneous information. We assumed the parameters remained unchanged in each time slot and the transmission behaviors of the mobile nodes were consistent. In a practical time-varying system, those assumptions may not always hold. Hence it may require frequently changing of the coalition structure. In the future, we will study the coalition formation game from the perspective of long term pay-off. More specifically, we consider the time varying transmit behavior of the mobile nodes in a coalition. Considering as a whole, a coalition will be in different states when the actions of the member players change. The state transition of the coalition can be modeled as a continuous-time Markov process, and by exploring the properties of the corresponding discrete-time Markov chain (DTMC), the long term performance of a coalition can be obtained. Hence, instead of considering the instantaneous pay-off in the coalition formation game, we evaluate the long term performance of coalition, which can be applied to the scenario in which the real-time information updating is not available.

List of Publications

1. Pu Yuan, Ying-chang Liang, Guoan Bi. ”‘Price-based distributed resource allocation for femtocell networks”’, IEEE International Conference on Communication Systems (ICCS), 418-422, 2012 , Singapore.

2. Pu Yuan, Ying-chang Liang, Guoan Bi. ”‘Dynamic access strategy selection in user deployed small cell networks”’, IEEE Wireless Communications and Networking Conference (WCNC), 3649-3653, 2013, China.

3. Pu Yuan, Guoan Bi. ”‘Resource Allocation in D2D-Enabled Cellular Networks Using Hierarchical Game”’, International Conference on Future Generation Communication Technologies (FGCT), 61-65, 2014, United Kingdom.

4. Pu Yuan, Yong Xiao, Guoan Bi. ”‘Towards Cooperation by Carrier Aggregation in Heterogeneous Networks: A Hierarchical Game Approach”’, IEEE Transactions on Vehicular Technology Communication Systems, under 2nd round review.

5. Pu Yuan, Yong Xiao, Guoan Bi. ’Spectrum Sharing Games(book chapter)’, Spectrum Sharing in Wireless Networks: Fairness, Efficiency, and Security. Taylor and Francis LLC, CRC Press. In press.

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