Cooperative Resource Allocation in Cellular Networks with Multiple Antennas

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DOCTOR OF
PHILOSOPHY

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2010 (School Year)

March 2011

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by

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A dissertation submitted to the Faculty of Informatics, School of Multidisciplinary Sciences, Graduate University for Advanced Studies, in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

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March 2011

Abstract

Multi-antenna transmission and reception technique, also known as MIMO, has evolved as one of the key enabling techniques to meet the ever-increasing demand for high-speed wireless data access in current and emerging wireless cellular networks. This dissertation addresses some critical issues on the resource allocation for MIMO-enhanced cellular networks with centralized or distributed antenna architecture.

With the dramatic growth of mobile services provided by cellular networks, the first problem that we should confront is to support and differentiate diverse services, particularly the quality of services (QoS) guarantee for real-time services. However, traditional algorithms for resource allocation fail to provide a better solution that dynamically guarantees the QoS requirements while obtaining the throughput efficiency, since they have neglected competing and sharing characteristics between services from a systems perspective. In contrast, I consider this problem based on a cooperative game model, which gives great insights into the nature of competing and cooperative relations. Consequently, I successfully formulated this problem on resource allocation as a cooperative game and obtained the notion of QoS guaranteed fairness based on the well known Nash bargaining solution. The algorithm based on QoS guaranteed fairness, can satisfy the QoS requirements of all services and achieve the Pareto optimal system throughput, which is validated through

simulations and discussed at the end of Chapter 3. Moreover, this work also provides a theoretical framework that paves the way to solving resource allocation problems in other similar scenarios.

At the same time, the huge amount of traffic have highly saturated the bandwidth available by current cellular networks, which pushes us to utilize bandwidth more efficiently than ever so that universal frequency reuse is usually considered by future cellular networks. However, this raised the second problem, severe inter-cell interference(ICI), which has become the bottleneck of further enhancement of spectral efficiency. The spatial multiplexing transmissions in MIMO-enhanced cellular networks, whose main advantage is a dramatic improvement in spectral efficiency, lose much of their effectiveness due to this high levels of interference. Fortunately, the advances in MIMO technique such as cooperative transmission, especially that between base stations (BS) within a cellular context, have emerged as one of the most promising techniques to mitigate ICI and thus improves total system throughput. I proposed an algorithm in Chapter 4 for allocating wireless resources cooperatively, which is aimed at mitigating ICI and efficiently utilizing wireless resources. Based on game theoretic analysis, the proposed algorithm achieves Pareto optimal efficiency and considers proportional fairness. Due to the prohibitive complexity of computation, I also developed a heuristic algorithm and compared it with a benchmark that is regarded as a Nash equilibrium outcome in a non-cooperative scenario. The simulation and analysis results are also given at the end of Chapter 4.

I also investigated the distributed antenna scenarios in both Chapter 5 and 6 that have a topology of distributed antennas for the BS at each cell. The intuitive advantages of this architecture are better signal coverage and lower power consumption. However, We expect to further exploit other advantages since resource allocation with distributed antennas is more flexible in cooperation and optimization than that in traditional architectures. In Chapter 5, I proposed two energy-efficient resource allocation algorithms, based on beamforming transmission and selection transmission, respectively. the simulation results shows that both algorithms have a higher energy efficiency that conventional algorithms, and the selection transmission outperforms the beamforming transmission algorithm in terms of energy efficiency and complexity. The ICI problem in distributed antenna architecture is also investigated in Chaper 6. I proposed a cooperative beamforming algorithm that mitigates ICI and achieves a higher system capacity. A comparison and analysis of performance between a scenario with co-located antennas and that with distributed antennas are given, which clearly demonstrate the advantages of the architecture with distributed antennas.

In summary, the cooperative resource allocation problems is investigated in the MIMO-enhanced cellular networks. The game theoretic framework is proposed to provide QoS guarantee for diverse services, mitigate interference, and conserve transmission energy. All these algorithms can achieve the Pareto optimal in terms of system throughput. my investigations with both architectures of distributed antenna and traditional co-located antenna is also discussed in this dissertation.

Acknowledgments

First and foremost I offer my sincerest gratitude to my supervisor, Assoc. Prof. Yusheng Ji, not only for her excellent academic advice, but also for all kinds of understanding and support during the study life. I applied for internship program of National Institute of Informatics (NII) in 2007, and got enrolled in The Graduate University for Advanced Studies (SOKENDAI) as a Ph.D. student in 2008. Without Prof. Ji's trust and help, I would not have had the chance to pursue my Ph.D. in Japan. It was her insight that helped me to initiate this topic. And this dissertation has been significantly benefited from her valuable guidance and constant encouragement. I also greatly appreciate her care and concern for my life in Japan. Here, I would also like to thank my master-course supervisor, Prof. Fuqiang Liu at Tongji University in China, for shaping my interests in wireless networks. Their rigorous scholarship will greatly influence the rest of my life. I am blessed to have them as my supervisors.

I would like to thank my dissertation committee members, Prof. Shigeo Urushidani, Prof. Motonori Nakamura, Prof. Shigeki Yamada, Asst. Prof. Gene Cheung, and Asst. Prof. Hai Lin. Their broad perspective and suggestions have helped me in refining this dissertation. I'm honored to have them on my committee. I would like to show my special thanks to Prof. Urushidani, and Prof. Yamada, for the courses on network QoS and wireless communications. I also want to thank Prof. Cheung for his great discussion and comments in the seminars of our laboratory. I have learned so much from them.

I wish to thank Prof. Kun Yang at Essex University in UK, for his thoughtful guidance and insightful suggestions, and Min Gong, intern student coming from Tsinghua University in China, for some joint work during my Ph.D. study. These collaborations are also included in this dissertation.

I would like to thank all current and former members in my laboratory for the wonderful friendship, especially Liping Wang, Kien Nguyen, Tananun Orawiwattanakul, Yunlong Feng, Zhi Liu, Yu Gu, and Ruijian An, for all the joys we had together. I am so proud of being a part of the brilliant and fruitful group.

Last bu not least, I would like to express my gratitude to my parents Yongli Zhong and Jianfang Xin. Without their continuous support, years of hard work in this dissertation would not have been possible. I would also like to thank my wife Ting Jiang, who constantly encourage me throughout the ups and downs in my Ph.D. study. This dissertation is dedicated to them.

Contents

List of Figures

List of Tables

List of Publications

Journals:

[1] Lei Zhong, Yusheng Ji, Proportional Fair Resource Allocation in Coordinated MIMO Networks with Interference Suppression, in *IEICE Trans. Comm.*, E93-B, No. 12, Dec. 2010.

[2] Lei Zhong, Yusheng Ji, and Kun Yang, Energy-Efficient Resource Allocation in Mobile Networks with Distributed Antenna Transmission, in *ACM/Springer Journal Mobile Networks and Applications (MONET)* special issue on Advanced in Green Mobile Networks, 2011.

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[1] Lei Zhong, Yusheng Ji, Min Gong, and Fuqiang Liu, Interference Mitigation for Distributed MIMO Cellular Systems Using Cooperative Beamforming, in *ACM Proceedings of 6th International Wireless Communications and Mobile Computing Conference (IWCMC'10)*, pp.1060-1064, June 2010.

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Chapter 1

Introduction

1.1 Motivation

Wireless communications has undergone significant growth worldwide over the last few decades and has been one of the most vibrant research areas in communications. On the one hand, we have observed the evolution of different wireless communication systems that have gradually improved the throughput and supported even more services. As well as traditional mobile services such as voice calls, messages, and simple Web browsing, the upcoming cellular networks are expected to provide a wide variety of new services from high-quality video calls to online games, since numerous mobile users are being attracted by these kinds of real-time multimedia interactive services with the help of powerful mobile devices nowadays. On the other hand, we are still facing hostile wireless channels and scarce wireless spectrum with the increasing demand for higher throughput. Signals can be severely distorted by wireless channels whose parameters such as path delay, path amplitude, as well as carrier phase and frequency shifts may vary with time, frequency, and location. In addition, another negative characteristic of wireless networks is that the broadcast nature of channel behavior causing interference between channels. Excessive interference can significantly deteriorate the performance of networks and waste wireless resources. Strict limitations in wireless resources such as power, bandwidth, and spatial beams also are another major difficulty in the design of wireless networks. Due to these reasons, resource allocation could have significant effect on the performance of next-generation cellular networks to provide highly efficient and fair services.

As advanced technology in link level of wireless systems, multiple-antenna transmissions, also known as MIMO, has been widely adopted as one of the key enabling technologies by next-generation broadband wireless access and cellular system standards such as IEEE 802.16m [1] and 3GPP LTE-Advanced [2]. In MIMO-enhanced cellular networks, it offers the potentials to provide better quality-of-service (QoS), higher system throughput, and energy efficiency [3]. However, to fully explore the potentials of MIMO, efficient allocation of wireless resources to multiple users with the additional degree of freedom in spatial dimension has become more crucial and challenging. Therefore, it has been identified as the essential for the success of next-generation cellular networks when we aim to satisfy the three critical requirements as follows: efficiently supporting and differentiating heterogeneous services to different users, mitigating inter-cell interference (ICI) to obtain higher spectral efficiency, and improving the power efficiency in the wireless transmission.

Meanwhile, driven by the explosive demand for high data rates, researches from the early work on point-to-point MIMO transmissions [4,5] to the recent work on multi-user MIMO systems [6] that achieve aggregated capacity of all users, people have ceaselessly pursuit the potentials offered by techniques of multiple antennas. The research community as well as industrial actors has

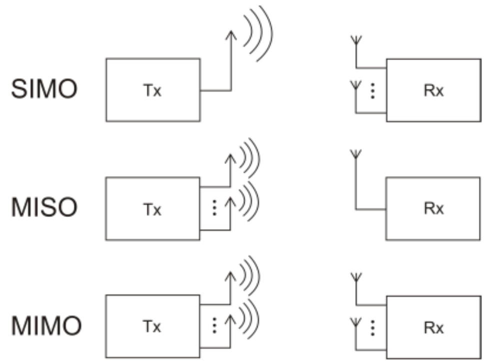

Figure 1.1: Basic Forms of MIMO

recently begun to focus on exploiting the utilization of wireless resources in a form of distributed but cooperative antennas [7–9]. Resource allocation optimized for this kind of cooperation has been identified to emerge as the next innovation toward the implementation of next-generation broadband cellular networks since it aims to overcome inefficient non-cooperation in traditional networks.

1.2 MIMO-Enhanced Cellular Networks

1.2.1 Basic of MIMO Techniques

Multiple-input and multiple-output (MIMO) is the use of multiple antennas at both the transmitter and receiver to improve communication performance. some basic forms are illustrated as Fig. 1.1. MIMO technique has attracted attention in wireless communications, because it offers significant increases in data throughput and link range without additional bandwidth or transmit power. It achieves this by higher spectral efficiency and link reliability or diversity (reduced fading). Because of these properties, MIMO is an important part of modern wireless communication standards such as IEEE 802.11n (WiFi), 802.16e (WiMAX), 3GPP LTE, and fundamental technology in fu-

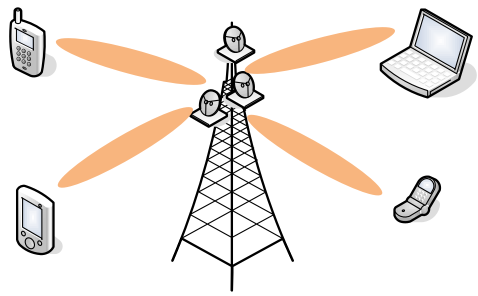

Figure 1.2: An Example of SDMA

ture wireless systems.

For a multi-user MIMO system, it do not necessarily require the user devices equipped with multiple antennas as well. A technology, so-called Space-Division Multiple Access (SDMA), is a channel access method based on the principles of MIMO techniques, which creating spatially parallel sub-channels to obtain higher system capacity through spatial multiplexing. Because of this, it is able to offer superior performance in multi-user wireless networks even when the user terminals are less antennas. In traditional cellular networks, the base station has no information on the position of the mobile units within the cell and radiates the signal in all directions within the cell in order to provide radio coverage. It results in wasting power on transmissions when there are no mobile units to reach, in addition to causing interference for adjacent cells using the same frequency, so called inter-cell interference. Likewise, in reception, the antenna receives signals coming from all directions including noise and interference signals. By using differing spatial locations of mobile units within the cell, SDMA techniques offer attractive performance enhancements. The radiation pattern of the base station, both in transmission and reception, is adapted to each user to obtain highest gain in the direction of that user, as illustrated in Fig 1.2. This is often done using beamforming techniques.

As aforementioned, SDMA technique obtains multiple spatial access channels by precoding to form multiple beams, which are known as beamforming. When using beamforming precoding, we can not only multiplex transmissions of multiple users, but also mitigate interference. One classical beamforming is maximum ratio (MR) transmission or matched beamforming. If the reference BS has knowledge of the channel of its own users, then it is possible to use MR transmission to maximize throughput for individual user without considering other users. This increases the interference between users. Conversely, another classical beamforming is zero-forcing (ZF) transmission or nulling beamforming. The ZF beam-former orthogonalizes all the correlated users, which sometime decreases the channel gain for each user.

1.2.2 Cooperative Transmission

Over the last decades, cooperative cellular systems have emerged as the next improvement toward the implementation of broadband wireless networks. However, the term ”cooperation” can mean diverse things within the context of wireless networks. Therefore, the purpose of this section is to explain which major cooperative forms and strategies can be identified in MIMO-enhanced cellular networks. As the demand for cost-efficient high-rate wireless services increases, wireless network operators have to employ new wireless architectures to achieve higher data-rates. However, despite the evolution of wireless cellular technologies, the increase in system complexity has become disproportional with respect to the provided gain in capacity. Therefore, the research community as well as industrial actors have begun a quest to find compatible or alternative cellular architectures that have the ability to provide high spectral efficiencies. Cooperative cellular architectures are gaining

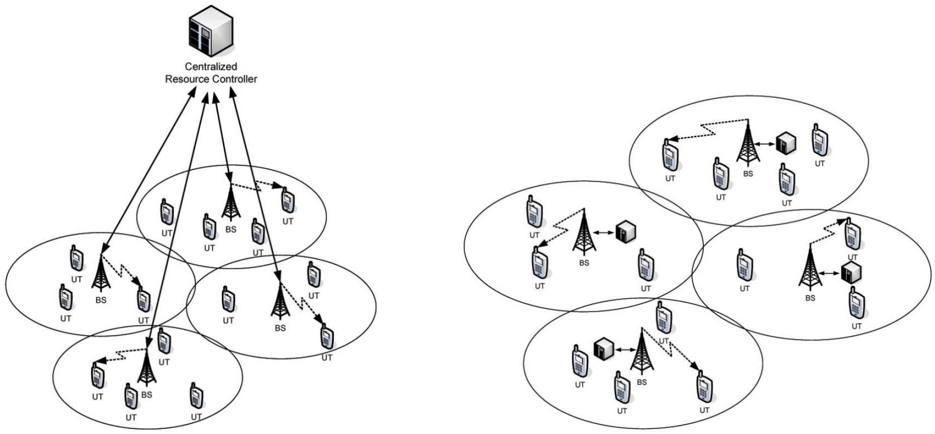

Figure 1.3: Centralized vs. Distributed Connection of BSs

momentum as dominant candidates for alternative approaches in wireless cellular networks. Cooperation in wireless networks can take many forms, such as user cooperation, BS cooperation and relaying. User cooperation is theoretically possible but is very complicated in practice, because they have to communicate either on a separate wireless frequency band or through the BS to exchange cooperative information. This fact results in a waste of spectrum and energy, which is very serious in terms of the battery life and complexity of mobile devices. Both BS cooperation and relaying have recently been the focus of extensive research. Relaying can be beneficial, but it either consumes the limited resources of relaying users or requires network operators to install additional transponders (i.e., relay stations). Therefore, we have only focused on BS cooperation in this dissertation.

Based on the previous discussion, the approach to BS cooperation is analyzed and compared to that of conventional cellular systems. As demonstrated in Fig. 1.3, BS cooperation generally assumes that all BSs are mutually connected or clusters of BSs are connected to a central processor through high-capacity error-free channels (e.g., optical fibers), which coordinates or jointly encodes/decodes user signals. This multi-cell coordination or joint processing has the ability to transform the cellular network to a wide-area MIMO network or distributed antenna system (DAS). The main benefit of BS cooperation is higher system capacity gain than that in conventional cellular network, because ICI is no longer harmful to the capacity of the cellular system. We discuss our investigation into BS coordination to mitigate interference in Chapter 4 of this dissertation, and BS joint processing with a topology of distributed antennas is explained in Chapter 6.

1.3 Review of Related Work

The state-of-the-art techniques for resource allocation are reviewed in this section, including cross-layer design and resource allocation for SDMA systems.

1.3.1 Cross-Layer Design for Resource Allocation

In conventionally layered network architecture, each layer is designed and operated independently to provide transparency between layers to enable simplicity in design. Of these layers, the physical (PHY) layer handles raw-bit transmission, and the medium access control (MAC) layer manages multiple users so that they can gain access to shared wireless resources, it also maintains traffic arriving from the upper layer. There are different components with respect to each kind of wireless resource for resource allocation in cellular networks. These components may reside in different layers, for instance, power is controlled in the PHY layer, while scheduling is done in the MAC layer. Each of these components in the overall network design can be targeted separately, thereby enabling important inter-dependencies to be ignored between them. Exploiting these inter-dependencies through the joint optimization of these components leads to significant gains in performance [10], but it may otherwise be computationally prohibitive to be of any use in practice. Theoretically, a heuristic algorithm may help to solve this problem by balancing performance and complexity.

Earlier generations of cellular networks that were based on a layered architecture adopted static resource allocations, in which the BS took turns to equally serve individual users with a fixed time slot series or frequency band, irrespective of specific conditions such as their channel and traffic-queuing states. Due to the time-varying characteristics of channels and traffic, unawareness in this architecture resulted in inefficient use of resources by cellular networks. Since some main functionality in the allocation of resources such as power control, time scheduling, and dynamics information such as channel state information (CSI) and queuing state information (QSI) are operated and collected in different layers, we need an integrated design that is adaptive across these layers. Therefore, the well known concept of cross-layer design and optimization across the PHY and MAC layers has been proposed in the recent literature [10–16], for the allocation of wireless resources. Many resource allocation algorithms, such as maximum carrier-to-interference (max C/I), max-min fairness [11], and proportional fairness (PF) [12] have been proposed by these researchers and different tradeoffs have been obtained between system throughput and fairness by exploiting the independent fading characteristics of users, i.e., multi-user diversity. However, these strategies have always assumed an infinite backlog, which did not take into account the QoS requirements of traffic and may also have caused instability [13] when implemented in the practical systems that had finite data buffers for queuing traffic. Because of this, we classified these strategies as a class of channel-aware resource allocation algorithms. However, another class of queue-aware strategies, which include Max Weight (MW) [14], Largest Weighted Delay First [15], and Exponential Rule schedulers [16], have been proposed for cases in which finite queues are fed by an arrival process, and they have aimed at not only balancing throughput and fairness but also maintaining system stability. However, although almost all the prior resource allocation algorithms that have been proposed, i.e., both channel- and queue-aware, have been suitable for best-effort services but failed to provide QoS guarantee to real-time services.

1.3.2 Resource Allocation for MIMO Systems

MIMO systems have drawn vast attentions for its significant improvement in channel capacity [4] and widely adopted by future wireless systems. In the downlink of Multi-User MIMO (MU-MIMO) systems, multiple users can be multiplexed in space and share the same resource in frequency and time to improve spectral efficiency. The multiplexing technique forms multiple spatial channels by using a MIMO beamforming precoder such as Zero-Forcing (ZF) transmit precoder [17], therefore, the performance of resource allocation in MU-MIMO systems largely depends on the spatial channel correlation between users. Since the number of transmitting antennas at Base Station (BS) is usually less than the total number of users, traditional resource allocation algorithms for MU-MIMO systems try to select a subgroup in each allocation interval with an appropriate number of users in which their spatial channels are close to orthogonal. However, the problem of finding the optimal group of users that maximizes the system capacity is a mixed integer combinatorial problem and proved to be an NP-complete problem [18]. Although we can find its optimal solution through an exhaustive search algorithm, due to its exponential complexity, the algorithm can reach prohibitive computational cost even for a moderate number of users and transmitting antennas. Therefore, sub-optimal algorithms able to solve this resource allocation problem with low complexity are more attractive and have been studied in some recent work [18–20]. All these studies took great effort on maximizing the system capacity with low-complexity algorithms. In [18, 19], the proposed algorithms reduce the computational complexity by separating the scheduling and power allocation and selecting users directly based on their spatial correlations. The algorithm in [20] takes emphasis on the limited feedback with an equal power allocation. However, the performance of these sub-optimal algorithms only investigated through simulations.

1.4 Contributions

Based on the seminal work discussed above, we aimed at solving three main problems in resource allocation research on MIMO-enhanced cellular networks by using a game theoretical approach.

The problems we are going to solve and primary contributions of this research below:

1. How could the QoS be guaranteed when we achieved some kind of trade-off between efficiency and fairness?

   We successfully modeled the resource allocation problem in a multi-user MIMO network as a cooperative game and obtained the notion of QoS guaranteed fairness based on the well known Nash bargaining solution. It provides a framework that paves the way to solving similar resource allocation problems with QoS guarantees in other scenarios.

2. How could ICI be mitigated to gain higher system throughput?

We developed cooperative resource allocation algorithms that were both optimal and heuristic to solve the interference problem and improve system throughput between cells in a cellular network where BS antennas cooperatively mitigated interference.

3. How could the signal distribution be fundamentally changed through an alternative infrastructure topology of MIMO techniques? And the consequence in energy consumption?

   The distributed antennas architecture was investigated and is discussed in Chapter 5 and 6. We investigate the energy efficiency issue and propose two algorithms in Chapter 5, and ICI mitigation is investigated in Chapter 6.

1.5 Organization of Dissertation

The remainder of this dissertation is structured as follows:

Chapter 2 describes the basic principles underlying cooperative resource allocation in MIMO-enhanced cellular networks. It also highlights the resource allocation problem under the system model.

Chapter 3 proposes a joint resource allocation algorithm for a downlink SDMA network in a single-cell scenario that offers QoS guaranteed fairness (QGF), i.e., the QoS requirements of all real-time services will be satisfied if this is feasible while providing proportional fairness with respect to both their channel and queuing conditions without loss of throughput efficiency. We derived the QGF from the Nash bargaining solution in a cooperative game model in which the well known proportional fairness could also be incorporated into our framework. We then formulated the resource allocation problem into a combinatorial optimization problem based on the QGF concept.

We compared our proposed strategy with PF and MW strategies through simulations, which indicated superior performance by QGF in providing services particularly for real-time users.

Chapter 4 explains our investigations into resource allocation with a multi-cell coordinated MIMO system incorporating proportional fairness and interference suppression. We formulated an optimal resource allocation problem in a multi-cell MIMO system coordinated to suppress ICI. Our aim was to achieve high throughput and proportional fairness. Although we divided the original problem into easily solvable sub-problems, the computational complexity was still high. Therefore, we propose a low-complexity algorithm to achieve better fairness and less computational complexity with only a slight loss in throughput. We also obtained a tradeoff between throughput and fairness by achieving proportional fairness. The simulation results revealed that our algorithm improved system throughput, particularly for cell-edge users in a multi-cell environment and achieved proportional fairness for all of them.

Chapter 5 proposes two energy-efficient algorithms in the distributed antenna architecture, one is beamforming based and the other is antenna selection based. The simulation results show that both algorithms are energy-efficient that traditional ones. In addiction, the antenna selection algorithm is with low complexity than beamforming algorithm.

Chapter 6 investigates a fundamental framework to mitigate ICI in distributed MIMO systems. We will focus on the partially sharing issues in the next step, including an optimal scheduling scheme to make our algorithms more practical. Therefore, distributed MIMO systems applying cooperative transmission should be able to provide higher network capacity at any location and better link reliability at any time.

Chapter 7 summarizes the dissertation and proposes several stimulating topics for future work.

Chapter 2

Background

This chapter briefly introduces the principles underlying all proposed algorithms, including technical details on MIMO-enhanced cellular networks, utility-based resource allocation, and the background to game theory. Before that, I first make some general assumptions that have been used for analysis and evaluation throughout the entire dissertation.

2.1 General Assumptions

1. Block-fading channels

   We assumed that multipath fading would be constant within the time duration of our interest. We specifically assumed that multipath fading would be constant within a frame, which is reasonable in practical scenarios where users move at moderate speeds.

2. Perfect channel state information feedback

   User CSI is crucial for exploiting multi-user diversity in cellular networks. In this dissertation, we assumed users would ideally estimate and feedback their CSI to the BS. The amount of feedback information increases the system overhead, and limited feedback techniques [21, 22] or channel prediction [23, 24] can be used to reduced the amount of overhead from feedback. The performance of cellular networks with imperfect CSI is still an intensive area for ongoing research [25].

3. Continuous Rate Model

   The Shannon capacity, which is a continuous function, is used as the user throughput in this dissertation. User data rates in practical system present discrete values due to different modulation and coding schemes. The continuous Shannon capacity formula, however, simplified the analysis of resource allocation and provides an upper bound on achievable throughput. A signal-to-noise ratio gap can be included in the Shannon capacity formula to model degradation in the signal-to-noise ratio [26].

4. User terminal is equipped with only one antenna and provided with only one service

   This assumption is mainly to simplify analysis in the following chapters without any loss of generality. Actually, all the studies mentioned in this dissertation can be easily extended to users attached by multi-antennas and multi-services.

2.2 Fundamentals of Resource Allocation

2.2.1 Frame-Based Resource Allocation

Almost all modern cellular networks, especially those based on multi-channel techniques, have adopted frame structures to facilitate the organization of resources. A general frame structure has been illustrated in Figure 2.1. The frame in the time division duplexing (TDD) mode is further divided into

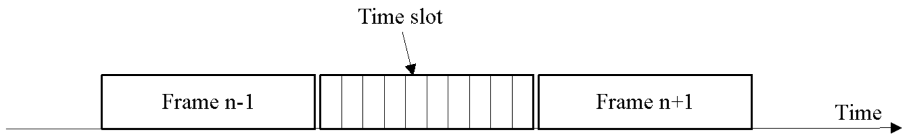

Figure 2.1: General Frame Structure

a downlink subframe and an uplink subframe. The downlink and uplink subframes in frequency division duplexing (FDD) mode are transmitted in two different frequency bands respectively. However, their basic frame structures are the same. The wireless resources that we have considered within a MIMO-enhanced cellular context in this dissertation include power, time slots, and spatial beams. These wireless resources are jointly allocated based on the frame-by-frame structure.

In fact, as the analysis is based on some general structures, the results in this dissertation can be easily applied to other cellular networks incorporating extra resource dimensions, since transmission by multiple antennas is always combined with other link techniques (e.g., MIMO-OFDM systems) in practical networks.

2.2.2 Performance Metrics

The allocation and management of wireless resources are crucial for cellular networks, in which scarce wireless resources are shared by multiple users with respect to the fundamental tradeoff between efficiency and fairness. The notions of both efficiency and fairness have different definition depending on the objective of resource allocation. More specifically, the notion of efficiency can be defined by throughput, the signal-to-interference-plus-noise ratio (SINR), power consumption, or any combination of these. While the notion of fairness also has many definitions in terms of data rate, users, and QoS, we have adopted widely used aggregate throughput as the efficiency metrics in this dissertation. Fairness is defined with respect to the QoS fairness we proposed.

2.2.3 Utility Functions

Utility functions are used for capturing all cross-layer information (i.e., CSI and QSI) and balancing efficiency and fairness. A utility function for each user maps all the information concerning wireless resources into a real number. As more efficiency and fairness are preferred, the utility function $U(x)$ should be a non-decreasing function in terms of these metrics. For instance, let denote the user's data rate, when $U(r) = r$, i.e., the utility is simply the data rate for this user. The aggregate utility for resource allocation will lead to maximum system throughput, which is the objective of some capacity-achieving systems. Therefore, this method can be regarded as a general extension to traditional network optimizations.

Utility functions instead of some explicit performance metrics serve as an optimization objective for cross-layer resource allocation. Consequently, they build a bridge between different layers.

2.3 Game Theoretic Approach

2.3.1 Introduction

Game Theory generally provides a formal modeling approach to situations in which decision makers interact with other players. It analyzes and represents such situations as games, where players choose different actions in an attempt to maximize their payoffs. Although some Game Theoretic analysis appears similar to Decision Theory, Game Theory studies the decisions made in environments where players interact. In other words, Game Theory studies the choice of optimal behavior when the costs and payoffs of each option depend upon the choices of other individuals.

Informally, a game is considered to be a collection of players who play different moves, and is aimed at maximizing their individual payoffs. The notion of a game is formally as follows:

Definition 2.1. *A game is defined by the tuple:* $Q = \langle \boldsymbol{K}, \mathbb{S}, \boldsymbol{v} \rangle$ *where*
$\boldsymbol{K} = \{k : k \in \{1, \ldots, K\}\}$ *is a set of* K *players,*
$\mathbb{S}$ *is the strategies space,*
$\boldsymbol{v} = (v_1, \ldots, v_K)$ *is a vector of payoff functions.*

2.3.2 Non-Cooperative Games and Nash Equilibrium

Non-cooperative games are able to model situations, in which players make decisions independently to maximize their own payoffs. There is one or more stable outcomes called the Nash Equilibrium in such games. For example, the power control at each BS in traditional cellular networks can be regarded as a non-cooperative game, since each BS will transmit the maximum power to achieve high throughput. The Nash Equilibrium is where all BSs transmit at their maximum power, which yields poor performance because of heavy interference.

2.3.3 Cooperative Games and Nash Bargaining Solution

A cooperative game is one in which players are able to make enforceable contracts. Hence, it is not defined as a game in which players actually do cooperate, but as games in which any cooperation can be enforced by an outside party. There are two major components of cooperative game theory: the bargaining solutions and coalition structures.

Chapter 3

Cooperative Resource Allocation with QoS Guarantee

3.1 Introduction

As discussed in previous chapters, resource allocation is one of the key mechanisms in cellular networks to support and differentiate heterogeneous services. Services provided by cellular networks can be generally classified into two categories: real-time and best-effort services. The data traffic produced by real-time services is highly sensitive to delay, while the one generated by best-effort services, also known as elastic traffic, seldom has specific QoS requirements. In such cases, the design of resource allocation algorithms that well handle these two kinds of services and gain good balance between efficiency and fairness, becomes more complicated.

Great difficulties have been encountered when modeling these kinds of traffic in conventional algorithms, since they have always been analyzed and

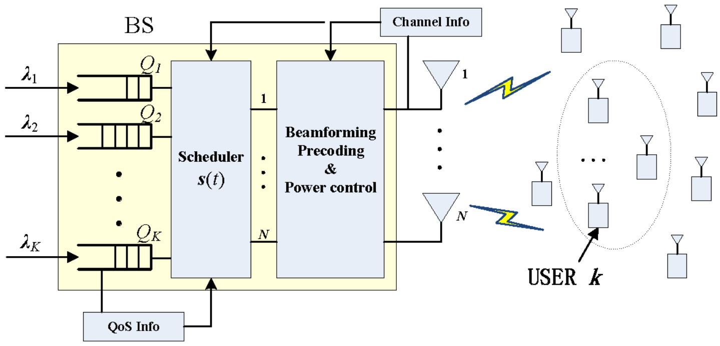

Figure 3.1: Downlink of Multi-User SDMA Systems

proposed in a resource-oriented way that took into account how the radio resources available to all traffic were to be allocated. One of most important area of research is in utility-based resource allocation algorithms, which capture QoS requirements with the help of utility functions. It is quite difficult to model diverse QoS requirements in this way for all active services from the perspective of resources by subjectively designing utility functions. We tried to derive utility functions from the perspective of services to deal with QoS requirements in an individual way, where we considered resource allocation to be a problem with many service instances competing and sharing radio resources. We can solve this problem based on this viewpoint using the game theoretic approach, which is a mathematical tool that promises to solve these kinds of problems.

3.2 System Model

This chapter presents our investigations into the downlink of multi-user SDMA networks with one BS serving users, which is illustrated in Figure 3.1. Let $\mathcal{K}$ denote the index set of all users and $k \in \mathcal{K} = \{1, \ldots, K\}$ represents the index of kth users in the set. Queue $\boldsymbol{Q}_k$ fed by an arrival rate λ_k buffers the data intended for user k. According to the assumption 4 have been proposed in Section 2.1, therefore, there are N antennas at the BS that can simultaneously transmit N data flows to N users (usually $N \leq K$) per time slot, which implies that the scheduler chooses N flows from K queues to serve at each time slot t. We adopted the zero-forcing (ZF) beamforming per-coding to separate the multi-user data streams into N independent spatial sub-channels, thereby multi-user diversity can be fully exploited through appropriate scheduling, and it asymptotically closes in on the optimal sum capacity as the number of users goes to infinity [27]. Users are chosen at time slot t according to scheduling policy $\boldsymbol{s}(t)$, which depends on both information from channels and QoS. We omit the notation of time t, and denote any possible scheduling policy as $\boldsymbol{s}_m \in \boldsymbol{\mathcal{S}} = \{\boldsymbol{s}_1, \ldots, \boldsymbol{s}_M\}(M = C_K^N)$. Define $\rho_k^m = \{0, 1\}$ as the entries of $\boldsymbol{s}_m = (\rho_1^m, \ldots, \rho_K^m)$ indicating that the user is scheduled under policy $\boldsymbol{s}_m$ when $\rho_k^m = 1$, otherwise, $\rho_k^m = 0$.

Consider a quasi-static fading MIMO channel, which holds when users are stationary or have low mobility. This means the channel state changes slowly and is almost constant within the period of one time slot. Due to the different scheduling policy $\boldsymbol{s}(t)$ generates different ZF pre-coding weight, and the receiving signal of user k will be different, which can be given by

$$y_{m,k} = \boldsymbol{h}_k \frac{\boldsymbol{w}_{m,k}}{\|\boldsymbol{w}_{m,k}\|} \sqrt{p_{m,k}} x_k + n_k. \tag{3.1}$$

The notations here are listed as:

$\boldsymbol{h}_k$	is the $1 \times N$ complex downlink channel gain vector of user k.
$\boldsymbol{w}_{m,k}$	is the column-normalized ZF beamforming weight for user k under policy $\boldsymbol{s}_m$.
$p_{m,k}$	is the transmitting power for user k under policy $\boldsymbol{s}_m$.
x_k	is the traffic bit flow for user k with $\mathbb{E}[x_k x_k^H] = 1$.
n_k	is the additive white Gaussian noise with $\mathbb{E}[n_k n_k^H] = \sigma^2$.
$\\|\cdot\\|$	is the Euclidean norm.
$\mathbb{E}[\cdot]$	is the expected value of the random variable.

Let $\boldsymbol{H}_m$ represent the channel matrix of all scheduled users in $\boldsymbol{s}_m$. Weight vector $\boldsymbol{w}_{m,k}$ is then the normalized corresponding column for user k of precoding weight matrix $\boldsymbol{W}_m$, which is the pseudo-inverse matrix of $\boldsymbol{H}_m$ given by

$$\boldsymbol{W}_m = \boldsymbol{H}_m^{\dagger}(\boldsymbol{H}_m \boldsymbol{H}_m^{\dagger})^{-1}.$$

M-ary quadrature amplitude modulation (MQAM) is a modulation scheme for high spectrum efficiency, which was also used in our system model. Therefore, adaptive modulation and coding (AMC) provides all users with the ability to match the spatial sub-channels achievable rate according to their channel conditions. As discussed in [26], a user k's bit error rate (BER) of MQAM as a function of rate $r_{m,k}$ and the signal-to-noise ratio (SNR) is approximated by

$$BER_k \approx c_1 e^{-c_2 \frac{SNR_{m,k}}{2^{r_{m,k}}-1}},$$

where $c_1 \approx 0.2$, $c_2 \approx 1.5$, and the effective SNR based on ZF beamforming can be expressed by [28]

$$SNR_{m,k} = \frac{p_{m,k}}{\|\boldsymbol{w}_{m,k}\|^2 \sigma^2}.$$

Therefore, the data rate for user k in policy $r_{m,k}$ is given by

$$r_{m,k} = log_2(1 + \eta \frac{p_{m,k}}{\|\boldsymbol{w}_{m,k}\|^2 \sigma^2}), \tag{3.2}$$

where $\eta = -c_2/\ln(BER_k/c_1)$.

3.3 QoS Guaranteed Resource Allocation

3.3.1 Game Theoretic Model

We explain our modeling of the resource allocation problem with real-time services as a cooperative game in this section. We then obtain the notion of QGF based on the Nash bargaining solution, which provides QoS-guaranteed fairness with Pareto optimal system throughput. Moreover, our notion of QGF can be taken as an extension to the well known concept of proportional fairness, which is widely accepted in wired and wireless networks.

The K-person bargaining model of a cooperative game can be described as follows. There are K users with real-time traffic sharing the channels. Each of them has delay cost $d_{m,k}$, which is defined as:

Definition 3.1. *Once a packet has arrived at queue $\boldsymbol{Q}_k$ at time t, for a given queue length $q_k(t)$, the expected queuing delay can be expressed by:*

$$d_{m,k}(t) = q_k(t)/r_{m,k}(t), \forall k, \tag{3.3}$$

where $r_{m,k}(t)$ is the instantaneous data rate of user k in time t.

In addition, let $D_k \in \boldsymbol{D} = (D_1, \ldots, D_K)$ represent the maximum cost that user k can afford and the baseline for bargaining, otherwise, the user will not cooperate. Define $\boldsymbol{R}$ as all feasible rate sets. Since the duality of the game, our objective here is to minimize the total cost to users. We gave the following Pareto optimal allocation point as a criterion to choose optimal $\boldsymbol{r}$ from feasible set $\boldsymbol{R}$.

Definition 3.2. *The allocation point* $\boldsymbol{r} = (r_{m,1}, \ldots, r_{m,K})$ *is said to be Pareto optimal, if and only if there is no other allocation* $\mathbf{r}'$ *and its corresponding delay* $\mathbf{d}'$*, such that* $d'_{m,k} \leq d_{m,k}, \forall m, k$*, and* $d'_{m,k} < d_{m,k}, \exists m, k$*, in other words, there exists no other allocation that leads to a lower delay for some users without increasing delays for other users.*

There might be many Pareto optimal points in a cooperative game, and there are different system throughputs and fairness at different points. We need to add some more criteria to obtain a unique point, at which the QoS for all users is fairly satisfied while achieving as high throughput as possible. One commonly used criterion for fairness is max-min [29], it tends to allocate radio resources to the worst users as long as all users achieve the same performance. This criterion penalizes users with good channels, and as a result, generates inferior system performance with no guarantees to ensure QoS to all users. Although proportional fairness achieves a tradeoff between fairness and system throughput, there are still no guarantees to ensure user QoS, and neither do the rest of the scheduling strategies we discussed in Section 3.1. Therefore, we propose a criterion of QGF, which is derived from the Nash bargaining solution. The intuitive idea behind this is that at least the QoS requirements of all users are met; we further provide fairness proportionally to users according to their channel and queuing conditions. We also discuss the proportional fairness criterion in detail, which is a special case of QGF, at the end of this section. Of the many Pareto optimal solutions, QGF provides a unique and QoS constrained fair Pareto optimal operation point under the following conditions, which is briefly explained as follows [30].

Definition 3.3. $\boldsymbol{r}^*$ *is said to be a Nash bargaining solution in feasible set* $\boldsymbol{R}$ *for constraints* $\boldsymbol{D}$*, i.e.,* $\boldsymbol{r}^* = \varphi(\boldsymbol{R}, \boldsymbol{D})$*, if the following axioms are satisfied:*

1) Individual Rationality.

2) Feasibility.

3) Pareto Optimality.

4) Independence of Irrelevant Alternatives.

5) Independence of Linear Transformations.

6) Symmetry.

We have omitted the mathematical expressions for these axioms here, which can be found in [30]. Axioms 1-2 assert that the baseline QoS requirement must be satisfied if it is feasible. Axiom 3 asserts the efficiency of this solution, Axiom 4-6 assert that fairness distributed among users proportionally to their channel and queuing conditions. As a result, the following theorem indicates that there is exactly one Nash bargaining solution that satisfies the six axioms.

Theorem 3.1. *Existence and Uniqueness of Nash bargaining solution: There is unique solution function* $\boldsymbol{r}^* = \varphi(\boldsymbol{R}, \boldsymbol{D})$ *that satisfies all six axioms in Definition 3.3, and it satisfies*

$$\boldsymbol{r}^* = \arg \max_{r_{m,k} \geq \frac{q_k}{D_k}} \prod_{k=1}^{K} (D_k - \frac{q_k}{r_{m,k}}). \tag{3.4}$$

Proof. Please refer to [30]. □

Recall that the well known proportional fairness is derived from the Nash bargaining solution as well; we demonstrate that PF is a special case of the fairness provided by QGF as follows.

Lemma 3.1. *When there is no requirement* $\boldsymbol{D}$*, the vector of allocation rates*

$\hat{\boldsymbol{r}}$ is proportionally fair, i.e., if it is feasible, and for any other feasible vector $\boldsymbol{r}$, the aggregate of proportional changes is non-positive, i.e.,

$$\sum_k \frac{r_{m,k} - \hat{r_k}}{\hat{r_k}} \leq 0. \tag{3.5}$$

Proof. when there is no specific QoS requirement $\boldsymbol{D}$, (3.4) can be simplified by

$$\min_{r_{m,k}} \prod_{k=1}^{K} \frac{q_k}{r_{m,k}}, \tag{3.6}$$

since the function of the natural logarithm is concave and monotonic and defines $\hat{U}_r = -\sum_{k=1}^{K} \ln(q_k/r_{m,k})$, i.e., (3.6) is equivalent to maximizing $\hat{U}_r$. As shown in [12], for convex utility function $\hat{U}_r$ and convex feasible set $\boldsymbol{R}$, the following optimality condition holds:

$$\sum_k \frac{\partial U_r}{\partial r_{m,k}}|_{\bar{r_k}}(r_{m,k} - \hat{r_k}) = \sum_k \frac{r_{m,k} - \hat{r_k}}{\hat{r_k}} \leq 0. \tag{3.7}$$

Equation (3.7) satisfies the proportional fairness criterion in (3.5). Consequently, proportional fairness is a special case of QGF when there are no specified QoS restrictions. □

To sum up, the cooperative game model for a multi-user system can be defined as follows: the system has rate vector $\boldsymbol{r}$ as its objective solution, where all entries of $\boldsymbol{r}$ are bounded and have a nonempty convex feasible set. The goal is to minimize all d_k simultaneously from an initial agreement point $\boldsymbol{D}$. Define $\boldsymbol{R}$ as the feasible set of rate allocation vector $\boldsymbol{r}$ that satisfies $q_k/r_{m,k} \leq D_k, \forall k$. The problem, in the next section, is to find a way of choosing the QGF operating point in $\boldsymbol{R}$ for all users.

We formulate the resource allocation problem in the following based on the gradient function of logarithmic equivalence in (3.4) derived from the last

Section, and solve it with the Lagrange Multiplier method.

3.3.2 Problem Formulation

As we described in section II, the SDMA system can support up to N users sharing resources at each time slot. Because of this, we form N-user coalitions to share the channels each time. Actually, since we aimed to devise an iterative algorithm for this repeated game, there is still a K-user cooperative game in the long term. Note that we omit all the constraints for some intermediate expression during the mathematical derivation, but we give them in detail in the final objective function in (3.10).

Definition 3.4. *a non-empty subset of the set of K players is called a coalition.*

According to the discussion above, the function in (3.4) needs to be slightly modified in case of any $\boldsymbol{s}_m$, given as

$$\arg \max_{\rho_k^m, r_{m,k}} \sum_{m=1}^{M} \prod_{k=1}^{K} (D_k - \frac{q_k}{r_{m,k}})^{\rho_k^m}, \tag{3.8}$$

where $r_{m,k}$ represents the instantaneous data rate for user k in scheduling policy $\boldsymbol{s}_m$. The problem in (3.8) is difficult to solve directly. Actually, the following expression is equivalent to (3.8) by

$$\arg \max_{\rho_k^m, r_{m,k}} \sum_{m=1}^{M} \sum_{k=1}^{K} \rho_k^m \ln (D_k - \frac{q_k}{r_{m,k}}), \tag{3.9}$$

Define $U_{\boldsymbol{r}} = \sum_{k=1}^{K} \rho_k^m \ln(D_k - q_k/r_{m,k})$. To find the maximum value of $U_{\boldsymbol{r}}(t)$ defined on variable $\boldsymbol{r}(t) = (r_{m,1}(t), \ldots, r_{m,K}(t))$, we can find the maximum value of $\nabla U_{\bar{\boldsymbol{r}}}(t-1) \cdot \boldsymbol{r}(t)$ for the repeated game, such that

$$\arg \max_{\rho_k^m, r_{m,k}} \sum_{m=1}^{M} \sum_{k=1}^{K} \rho_k^m \frac{\partial U_r}{\partial r_{m,k}} |_{\bar{r_k}} r_{m,k} \tag{3.10}$$

subject to

$$\begin{aligned}
&\text{C1:} \quad \textstyle\sum_{k=1}^{K} \rho_k^m p_{m,k} \leq P_{total}, \forall m \\
&\text{C2:} \quad r_{m,k} \leq q_k / T_s, \forall m, k \\
&\text{C3:} \quad \textstyle\sum_{k=1}^{K} \rho_k^m = N, \forall m \\
&\text{C4:} \quad \rho_{i,k} = \{0, 1\}
\end{aligned}$$

where q_k is the queue length of user k at this time slot. P_{total} and T_s correspond to the total transmitting power constraint and time slot duration. Constraints 1-2 define the feasible set of $\boldsymbol{r}(t)$, and Constraints 3-4 define the feasible set of $\boldsymbol{s}_m$. In each time slot, the iterative algorithm can be viewed as selecting rate vector $\boldsymbol{r}(t) = (r_{m,1}, \ldots, r_{m,K})$ that has maximum projection onto the gradient of the function at optimal point $\bar{\boldsymbol{r}}(t-1)$, where $\nabla U_{\boldsymbol{r}}(t-1)$ is a concave gradient function of user s average throughput $\bar{\boldsymbol{r}}(t-1)$ up to time $t-1$, which can be updated by using an exponentially weighted low-pass time window with filtering factor t_c, given as

$$\bar{r}_k(t) = (1 - \frac{1}{t_c})\bar{r}_k(t-1) + \frac{1}{t_c} r_{m,k}(t), \tag{3.11}$$

where t_c is the exponential moving average weight factor.

3.3.3 Algorithm

The problem in (3.10) is easier to solve with the Lagrange Multiplier. The KKT condition in [31] is utilized to reformulate the optimal scheduling policy. We have the following theorem.

Theorem 3.2. *Let scheduling policy $\boldsymbol{s}_m^*$ be the optimal user scheduling and $p_{m,k}$ be the power allocation both for user k. Then, they satisfy the conditions:*

$$\begin{cases} \boldsymbol{s}_m^* & = \arg\max_{\boldsymbol{s}_m \in \boldsymbol{S}} \sum_{m=1}^{M} \boldsymbol{s}_m \boldsymbol{r}_m \\ p_{m,k} & = [\frac{\nabla U_{\bar{\boldsymbol{r}}}(t-1)}{\mu} - \frac{\sigma^2 \left\|\boldsymbol{w}_{m,k}\right\|^2}{\eta}]^+ \end{cases} \tag{3.12}$$

Proof. The following Lagrangian is obtained with the Lagrange multiplier:

$$L = \sum_{m=1}^{M} \sum_{k=1}^{K} \rho_k^m \frac{\partial U_r}{\partial r_{m,k}} |_{\bar{r}_k} r_{m,k} - \mu(\sum_{k=1}^{K} \rho_k^m p_{m,k} - P_{total}) - \xi(\sum_{k=1}^{K} \rho_k^m - N) \tag{3.13}$$

where μ and ξ are non-negative Lagrange multipliers. Differentiate (3.13) with respect to ρ_k^m and $p_{m,k}$, by using the KKT optimality conditions,

$$\frac{\partial L}{\partial \rho_k^m} = \sum_{\boldsymbol{s}_m} \frac{\partial U_{\boldsymbol{r}}}{\partial r_{m,k}} |_{\bar{r}_k} r_{m,k} - \xi = \begin{cases} < 0 & \rho_k^m = 0 \\ = 0 & \rho_k^m = 1 \end{cases} \tag{3.14}$$

$$\frac{\partial L}{\partial p_{m,k}} = \rho_k^m \frac{\partial U_{\boldsymbol{r}}}{\partial r_{m,k}} |_{\bar{r}_k} \frac{\partial r_{m,k}}{\partial p_{m,k}} - \mu = \begin{cases} < 0 & p_{m,k} = 0 \\ = 0 & p_{m,k} > 0 \end{cases} \tag{3.15}$$

assuming that sub-channel

$$\sum_{k=1}^{K} \rho_k^{m^*} \frac{\partial U_r}{\partial r_{m^*,k}} |_{\bar{r_k}} r_{m^*,k} = \xi > \sum_{k=1}^{K} \rho_k^m \frac{\partial U_r}{\partial r_{m,k}} |_{\bar{r_k}} r_{m,k}, \forall m^* \neq m. \tag{3.16}$$

That is, we meet the KKT conditions by scheduling the user that has the largest $\sum_{k=1}^{K} \rho_k^m \frac{\partial U_r}{\partial r_{m,k}} |_{\bar{r_k}} r_{m,k}$ for each $\boldsymbol{s}_m$. The solution is the global maximum because the problem is convex.

From (3.15), if scheduling policy $\boldsymbol{s}_m$ is selected, then, $\rho_k^m = 1$, therefore, the power allocation to user k^* is

$$p_{m,k} = [\frac{\nabla U_{\bar{\boldsymbol{r}}}(t-1)}{\mu} - \frac{\sigma^2 \left\|\boldsymbol{w}_{m,k}\right\|^2}{\eta}]^+ \tag{3.17}$$

$\square$

Obviously, the optimal resource allocation must simultaneously satisfy the conditions in (3.12). This can be achieved through a combination of power allocation, and an update of the gradient function.

3.4 Evaluation

We compared the performance of QGF, PF, and MW strategies with respect to system throughput, packet loss ratio, and average delay.

3.4.1 Simulation Layout

In our simulation, a single BS with multiple antennas serves multiple users. We assumed all the users would be fed by Poisson arrival traffic as illustrated in Figure 3.1. Arrival rate λ_k with different mean values was used to simulate different system loads. The packet size was exponentially distributed around a mean of 128 bytes, and any packets larger than 576 bytes were set to a maximum of 576 bytes. The users were uniformly distributed within a cell and moved according to the random walk mobility model. All users in each time slot had a probability of $\frac{1}{2}$ of holding still, otherwise, they moved randomly at a uniformly chosen speed of up to 2 m/s.

Since the users were also randomly distributed, we modeled the multi-user MIMO channel including both large-scale and small-scale fading. l_k and θ_k are defined as the distance from BS to user k and shadow fading,

Table 3.1: Simulation Parameters

Parameters	Values
Cell radius	1000 m
System bandwidth	200kHz
Noise density	-174dBm/Hz
Path loss	128.1+37.6log10(d) (d in km)
No. of transmitting antennas (N_t)	4
No. of users	10
Exponential moving average weight factor (t_c)	100
BER	10^{-4}

respectively. Thus, the channel vector for user k is $h_k = \sqrt{\beta\theta_k / l_k^{\alpha}}\boldsymbol{h}_w$, where $\boldsymbol{h}_w$ is a classical frequency-flat Rayleigh fading channel vector in which the entries are independent and identically distributed complex Gaussian random variables with zero mean and unit variance. β is a constant and α is the path-loss exponent. Shadow fading was modeled as a normal distribution with a mean value of 0 and a variance of 8 dB. The correlation distance for shadow fading was set to 10 m. The other simulation parameters are listed in Table 3.1.

3.4.2 Simulation Results

We evaluated the performance of our proposed QGF strategies with MW and PF strategies. The utility functions for these strategies are listed as follows.

QGF: $U = \frac{\partial U_r}{\partial r_{m,k}}|_{\bar{r}_k} = \frac{q_k}{D_k \bar{r}_k^2 - q_k \bar{r}_k}$

PF: $U = \frac{1}{\bar{r}_k}$

MW: $U = q_k$

Figure 3.2 shows the variation in the utility function value of the QGF

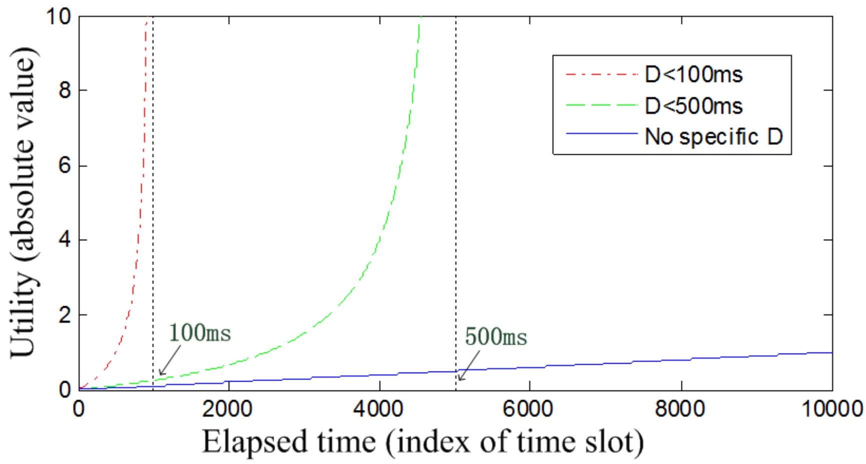

Figure 3.2: Utility Value vs. Elapsed Time

strategy as the time elapsed. Different delay requirements present different utility values. For example, VoIP traffic commonly requires a delay within 100 ms and video streaming requires a delay within 500 ms. Where their utility values vary as in Fig. 3.2, when the elapsed time is close to the delay bound, the utility value will become infinite. Users with this traffic will have a high probability of being scheduled. There are no specific delays for the best-effort traffic, therefore, utility increases much slowly than that for real-time traffic. Moreover, the utility function of the QGF strategy for best-effort traffic, as we discussed in Section 3.3, is equivalent to the PF utility function.

How the throughputs with these three strategies vary with increasing arrival rates are illustrated in Fig. 3.3. Both QGF and MW strategies outperform PF in the region of high system load, which is simply because QGF and MW strategies also adapt their rates to traffic characteristics, while our proposed QGF only has negligible throughput loss compared to MW. Figs. 3.4 and 3.5 demonstrate the performance of average delay and packet loss ratio, respectively. The MW strategy in Fig. 3.4 has the best delay since it tries to minimize the expected delay without other constraints. Our QGF

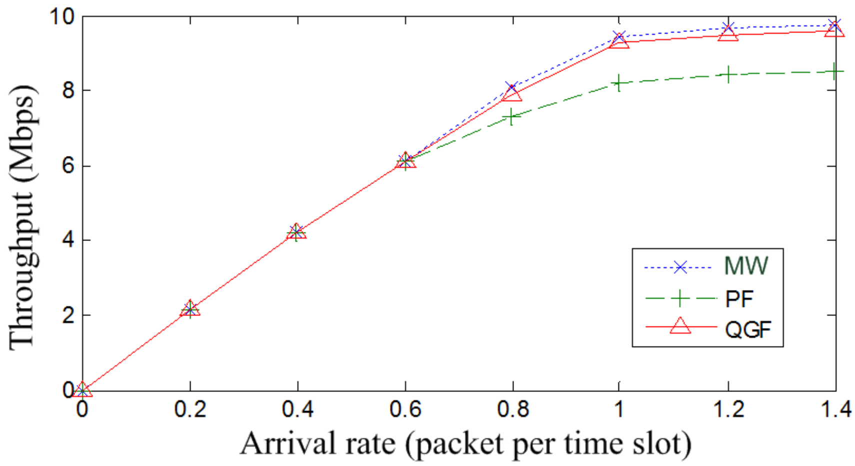

Figure 3.3: System Throughput vs. System Load

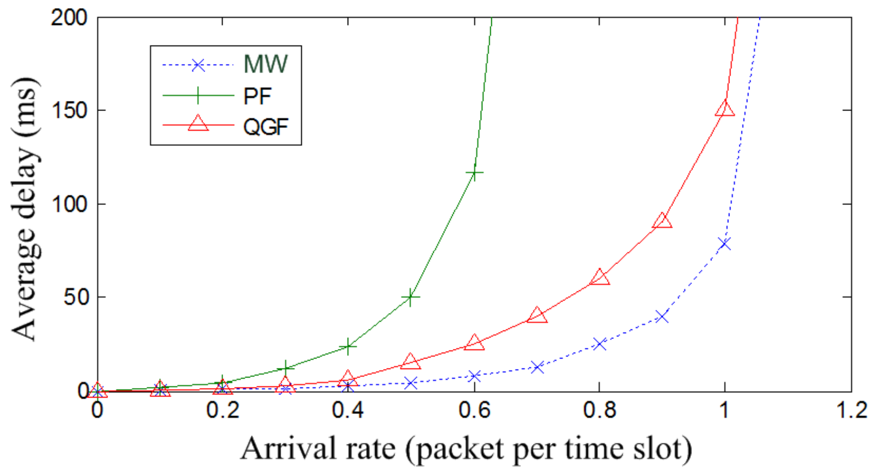

Figure 3.4: Average Delay vs. System Load

strategy serves some packets that are close to the delay bound so that it costs some decrease in performance of overall average delays. If we add some mechanism to drop the overdue packets, we can find the packet-loss-ratio for these strategies as shown in Fig. 3.5. Because our QGF strategy can guarantee QoS if this is feasible, packets have a higher probability of being successfully transmitted to their destinations than with any other strategies.

The overdue packets are meaningless to the users with real-time traffic.

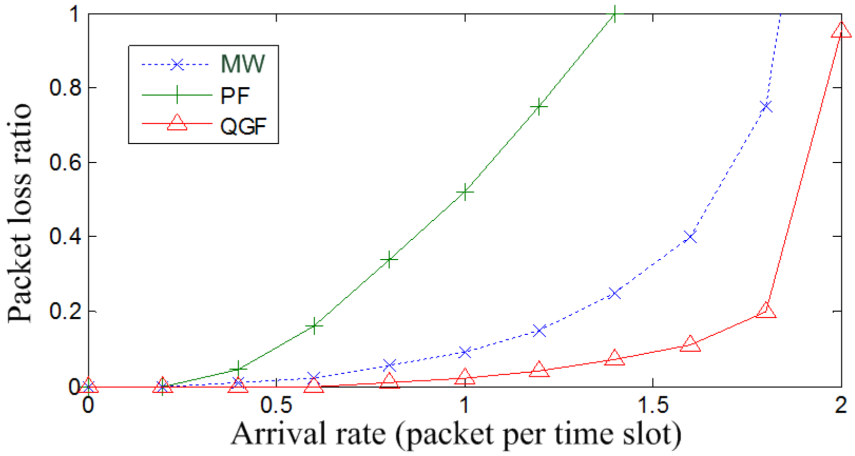

Figure 3.5: Packet Loss Ratio vs. System Load

Although MW achieves a little more gain in throughput than QGF, many packets transmitted by MW are actually useless since they might be overdue. Therefore, our proposed QGF algorithm achieves a tradeoff between traffic QoS requirements and time-varying wireless channel capacity in multi-user MIMO systems, which is much more meaningful to any traffic with QoS requirements. Furthermore, as QGF incorporates PF characteristics, this strategy is also suitable for best-effort traffic.

3.5 Summary

In conclusion, we proposed a joint resource allocation algorithm for downlink SDMA systems in this paper that offers QoS guaranteed fairness, i.e., all real-time users will be satisfied with their QoS requirements if they are feasible while providing proportional fairness with respect to both their channel and queuing conditions without loss of efficiency in throughput. We derived the QGF strategy from the Nash bargaining solution in a cooperative game model, in which the well known proportional fairness could also be incorporated into our framework. We then formulated the SRA problem into a combinatorial optimization problem based on the QGF concept. We compared our proposed strategy with PF and MW strategies in simulations, which demonstrated QGF had superior performance to provide services particularly to real-time users.

Chapter 4

Cooperative Resource Allocation with ICI Mitigation

4.1 Introduction

Next generation cellular networks currently involve plans to adopt some aggressive radio resource reuse patterns between cells such as smaller cells and universal frequency reuse that results in severe inter-cell interference to obtain higher system capacity. Although spatial multiplexing can be used to simultaneously transmit data to multiple users and to multiply the total throughput in single-cell scenarios, its performance sharply decreases when the received SINR gets low [32]. Therefore, applying a SDMA technique to interference-limited cellular networks is a huge challenge particularly because of the efficiency loss at edge users. In consequence, researchers in resource allocation have begun to shift to multi-cell scenarios [33, 34], and cooperative resource allocation has been identified as a promising way of dynamically mitigating inter-cell interference (ICI), which is the main difference from the previous single-cell scenario.

Many static and dynamic solutions have been proposed for SDMA system to solve this problem. However, one is immediately confronted with two issues to implement the idea of cooperation in real systems: delay and overhead. The mutual communications of channel state information (CSI) of concerned users between BSs is the main reason for long delays and large overhead. The simplified cooperation architecture, called coordinated MIMO, which we propose here, is one in which the BSs only broadcast their resource allocations and the CSI of their edge users to adjacent BSs. A given BS does not need to wait for feedback from its adjacent BSs and only broadcasts small amounts of information, which consequently saves time and reduces the system overhead. The details on the coordinating framework are explained in Section 4.3.

Under the condition of any pair of adjacent BSs being coordinated, we use the zero-forcing beamforming (ZFBF) interference suppression (IS) algorithm proposed in our previous study [28] to mitigate the ICI in a multi-cell MIMO system. This algorithm prevents interference from being generated to adjacent cells by orthogonalizing these mutually interfered channels and only allocating power to the sub-channels of local users. The simulations presented in [28] demonstrated that this resulted in dramatic improvements in performance at the cell edge. However, its system overhead needs to be reduced since each BS needs to share the CSI of all their users with its adjacent BSs. In this paper, we only discuss the ZFBF-IS algorithm for edge users, which reduced the system overhead. We integrated it into a joint resource allocation framework, which included pre-coding, power allocation, and user scheduling.

Since we have only focused on the mitigation of interference through resource allocation in this chapter, we have simply taken the proportional fairness into consideration, which has been largely ignored in resource allocation studies on SDMA systems. The majority of the previous researches focused on maximizing the throughput of the system [6, 18, 27]. Only a few studies have referred to fairness. The opportunistic beamforming algorithm with proportional fairness (PF) was proposed in [35]. PF maximizes the sum of the logarithmic function of users' throughput and involves a tradeoff between system throughput maximization and fairness. In this paper, we formulate resource allocation as an optimization problem that can achieve proportional fairness in the long term. This is an NP-hard non-linear combination optimization problem that cannot be easily solved. We further divided it into many sub-problems, which are convex and can be solved by using the Lagrange multiplier approach. However, it still needs to exhaustively search for all the sub-problems and this still creates enormous complexity with computation. To make it more practical, we further propose a low-complexity (LC) algorithm. We decouple the user scheduling and power allocation problems through pre-calculating equal power allocation utility to determine user scheduling first. The LC algorithm avoids having to do an exhaustive search of power allocation on all possible users, and therefore, greatly reduces the computation time.

4.2 System Model

Consider the multi-cell cooperative downlink architecture of SDMA/TDMA cellular network illustrated in Figure 4.1, which is described in what follows. For each cell, the BS with N antennas simultaneously transmits data to N best users chosen from a total number of K users per time slot. Here, "best" means it maximizes the aggregated value of the utility function of these N

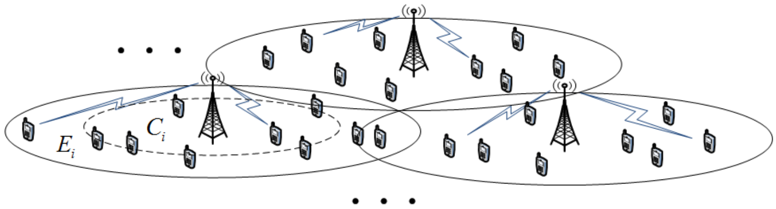

Figure 4.1: Multi-Cell System Model

users, which we define as fulfilling a certain resource allocation criterion. We also assume that the users only have one receiving antenna just like the majority of handheld terminals in the real world. We denote the instantaneous scheduled users as set $\boldsymbol{\mathcal{S}}_i$ and the total users as set $\boldsymbol{\mathcal{K}}$. Let $k \in \boldsymbol{\mathcal{K}} = \{1, \ldots, K\}$ represent the index of users. Obviously, set $\boldsymbol{\mathcal{S}}_i \subseteq \boldsymbol{\mathcal{K}}$ is an N-element-combinations of the given set $\boldsymbol{\mathcal{K}}$ with subscript $i \in \{1, \cdots, I\}(I = C_K^N)$ denoting the index of all possible $\boldsymbol{\mathcal{S}}_i$ sets. The BS separates multi-user data streams into N independent spatial sub-channels by using the ZFBF multiplexing approach thereby fully exploiting multi-user diversity, and this asymptotically closes in on the optimal sum capacity as the number of users reaches infinity [27].

Let us take into consideration a cell of interest surrounded by M adjacent cells for analysis from the perspective of the network. The users within it are therefore affected by any interference from the adjacent cells, and the interference coming from the cells that are farther away are treated as white noise. We classify all the users within a cell into two sets to simplify the following analysis: center users set $\boldsymbol{C}$ and edge users set $\boldsymbol{E}$. User $k \in \boldsymbol{C}$ receives little interference. Due to its short access distance, its BS is only required to allocate a small amount of power, which also results in this signal interfering very little with the other cells. Therefore, we will also take the interference to be white noise for any user in $\boldsymbol{C}$ and do not take into consideration this interference on users in adjacent cells. The situation is completely opposite for user $k \in \boldsymbol{E}$. The BS needs greater transmission power due to the long access distance, which also causes strong interference on the edge users of adjacent cells and the user itself also easily receives interference due to the transmission of adjacent cells. The resulting inference issue, which will only be evaluated for users in $\boldsymbol{E}$, is described in Section 4.2.2.

4.2.1 Signal Model

Let us consider a flat-fading MIMO channel, which means the channel status will not change within the period of one time slot. We first analyze the simple situation of a $k \in \boldsymbol{C}$ user, since we can omit weak interference. According to [28], the ZFBF multiplexing pre-coding weight for user k depends on all the other channels of the users in this $\boldsymbol{S}_i$. This implies that the independent sub-channel for user k is determined together with other $N-1$ users who are scheduled simultaneously if we let $\boldsymbol{S}_j^{-k}$ denote the sub-set of users who are scheduled together with user k, and with subscript $j \in \{1, \cdots, J\}(J = C_{K-1}^{N-1})$ denoting the index of all possible combinations of users of $\boldsymbol{S}_j^{-k}$. From another point of view, j also represents the index of all possible independent sub-channels for user k. Therefore, the signal received by user k can be expressed by

$$y_{k,j} = \boldsymbol{h}_k \frac{\boldsymbol{w}_{k,j}}{\|\boldsymbol{w}_{k,j}\|} \sqrt{p_{k,j}} x_k + n_k \tag{4.1}$$

The notations here are listed as:

$\boldsymbol{h}_k$	is the $1 \times N$ complex downlink channel gain vector of user k.
$\boldsymbol{w}_{m,k}$	is the column-normalized ZF beamforming weight for user k under policy $\boldsymbol{S}_i$.
$p_{m,k}$	is the transmitting power for user k under policy $\boldsymbol{S}_i$.

x_k is the traffic bit flow for user k with $\mathbb{E}[x_k x_k^H] = 1$.

n_k is the additive white Gaussian noise with $\mathbb{E}[n_k n_k^H] = \sigma^2$.

$\|\cdot\|$ is the Euclidean norm.

$\mathbb{E}[\cdot]$ is the expected value of the random variable.

Since users are randomly distributed, we will model the multi-user MIMO channel including both large-scale and small-scale fading. Thus, the channel vector is given by

$$\boldsymbol{h} = \sqrt{\beta/d^{\alpha}}\boldsymbol{h}_w,$$

where $\boldsymbol{h}_w$ is a classical frequency-flat Rayleigh fading channel in which the entries are independent and identically distributed complex Gaussian random variables with zero mean and unit variance. The β is a constant that embodies the antenna and near-field propagation characteristics, and β is the path-loss exponent.

Vector $\boldsymbol{w}_{k,j}$ is the first column of pre-coding weight matrix $\boldsymbol{W}_{k,j}$, which is the pseudo-inverse matrix of $\boldsymbol{H}_{k,j}$ given by

$$\boldsymbol{W}_{k,j} = \boldsymbol{H}_{k,j}^{*}(\boldsymbol{H}_{k,j}\boldsymbol{H}_{k,j}^{*})^{-1},$$

where $\boldsymbol{H}_{k,j} = [\boldsymbol{h}_k^T, \boldsymbol{H}_j^T]^T$ is the channel matrix of all scheduled users $k \cup \boldsymbol{S}_j^{-k}$. The superscripts T and $*$ correspond to transpose and conjugate transpose matrix operations, respectively. Therefore, the achievable throughput of user $k \in \boldsymbol{C}$ is given as that in [28] by

$$c_{k,j} = \log_2\left(1 + \frac{p_{k,j}}{\|\boldsymbol{w}_{k,j}\|^2, \sigma^2}\right) \tag{4.2}$$

where $p_{k,j}$ is the allocated transmitting power on user k under the condition that it is scheduled with users in set $\boldsymbol{S}_j^{-k}$.

4.2.2 Interference Model

We investigate the ICI problem in this section. Each user in traditional system operations is registered at and communicates with a single BS, which is called the serving BS. However, a user in many modern wireless systems may communicate with more than one BS at the cell edge since it may receive multiple signals of comparable power. In addition to the serving BS, other BSs within the transmission range of the user are called neighboring BSs and are denoted by $\boldsymbol{D}_k$. The transmission range of a user is usually a little more than the radius if a cell but less than its diameter. This implies that not all adjacent cells except $\boldsymbol{D}_k$ are considered to cause interference to a particular edge user. For example, the new wireless system of IEEE 802.16e, which has been implemented, defines a diversity set for users to keep track of the serving BS and neighboring BSs that are within the transmission range of a given user. In a classic hexagonal cellular layout, the diversity set may contain one serving BS and 0-2 neighboring BSs. Some advanced techniques (e.g., soft handover and fast cell selection) standardized in 3GPP 3/3.5G systems, incorporate similar operations. Edge user k will feedback its CSIs including both channels to serving BSs and channels to neighboring BSs. A serving BS will share the CSIs with neighboring BSs using back-haul connections when user k is scheduled. This reduces a large amount of the cooperation overhead, while conventional cooperative networks share all CSIs of users.

As the traditional ZFBF multiplexing technique only orthogonalizes the channels of the local scheduled users, the edge users of the adjacent cells, which are spatially correlated, will interfere with each other. For clarity and without any loss of generality, we index a cell of interest as 0, then we let $m \in \{1, \cdots, M\}$ denote the index of the adjacent cells and all the cell indexes are superscripted in the given notations when necessary. Regarding

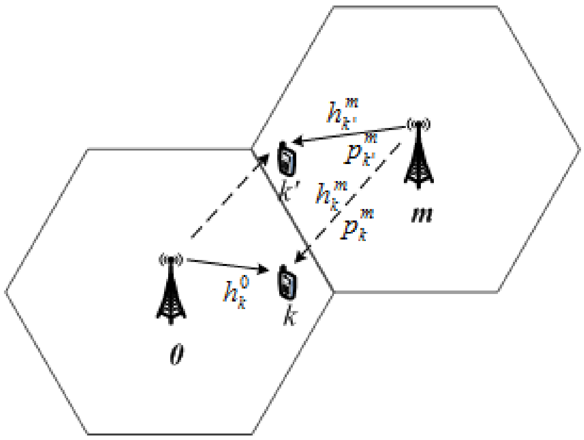

Figure 4.2: ICI Model

our above description and assumption, at each time slot, a user k in cell 0 will interfered by cell m when $k \in \boldsymbol{E}^0 \cap \boldsymbol{S}_i^0, m \in \boldsymbol{D}_k$ and $\boldsymbol{E}^m \cap \boldsymbol{S}_i'^m \neq \emptyset$. An ICI model of two spatial correlated users that we used in our analysis is illustrated in Fig. 4.2. The solid lines with arrows are the desired signals and the dashed lines represent the interference. To quantify the ICI, we define a correlation coefficient δ to measure this kind of interference. For the user k, the correlation coefficient with a user $k' \in \boldsymbol{E}^m \cap \boldsymbol{S}_{i'}^m$is expressed as

$$\delta_k^m = \frac{\left|h_k^0 (h_{k'}^m)^H\right|}{\left\|h_k^0\right\| \left\|h_{k'}^m\right\|} \tag{4.3}$$

thus, the received interference power from cell m to user k is given by

$$p_k^m = \delta_k^m \left\|\boldsymbol{h}_k^m\right\|^2 p_{k'}^m \tag{4.4}$$

where $P_{k'}^m$ is the transmitting power intended for user k' in cell m. The received signal of user k being scheduled is given as

$$y_{k,j}^0 = \boldsymbol{h}_k^0 \frac{\boldsymbol{w}_{k,j}^0}{\left\|\boldsymbol{w}_{k,j}^0\right\|} \sqrt{p_{k,j}^0} x_k^0 + \sum_{\boldsymbol{D}_k} \sum_{\boldsymbol{E}^m \cap \boldsymbol{S}_{i'}^m} \sqrt{p_k^m} \boldsymbol{x}_{k'}^m + n_k \tag{4.5}$$

therefore, the achievable throughput of the user $k \in \boldsymbol{E}^0$ is given as

$$c_{k,j}^0 = \log_2 \left(1 + \frac{p_{k,j}^0}{\left\| \boldsymbol{w}_{k,j}^0 \right\|^2 (\sigma^2 + \sum_{\boldsymbol{D}_k} \sum_{\boldsymbol{E}^m \cap \boldsymbol{S}_{i'}^m} p_k^m)} \right) \tag{4.6}$$

4.3 Resource Allocation with ICI Mitigation

We propose a joint resource allocation with inter-cell cooperation, incorporating not only the proportional fairness tradeoff but also the inter-cell IS algorithm. In general, there are two steps in the proposed joint resource allocation framework for multi-cell MIMO systems: 1) joint resource allocation with user scheduling, ZFBF pre-coding, and power allocation, followed by a broadcast of the scheduled edge users' information to adjacent cells. 2) A comparison of the utility function values of local edge users with those of the adjacent cells, and a decision being made as to whether to suppress interference or not.

4.3.1 First Step: Single-cell Resource Allocation

Similar to that of a single-cell resource allocation, in the first step, each BS schedules the users, calculates the pre-coding matrix, and allocates the transmitting power based solely on the local information. Let us define $\rho_{k,j} = \{0, 1\}$ as the users set $\boldsymbol{S}_j^{-k}$ selection indicator. $\rho_{k,j} = 1$ represents if and only if user k is scheduled together with the users $\boldsymbol{S}_j^{-k}$. $c_{k,j}$ represents the instantaneous throughput of user k. Thus, user k's achievable throughput at time slot t is $\sum_{j=1}^{J} \rho_{k,j}(t) c_{k,j}(t)$. To achieve a proportional fairness among the users over the long term, we further define the user's utility function at the tth time slot as

$$U_{k,j}(t) = \frac{1}{\bar{R}_k(t)} \sum_{j=1}^{J} \rho_{k,j}(t) c_{k,j}(t) \tag{4.7}$$

where $\bar{R}_k(t)$ is the average throughput for user k by the tth time slot, which can be updated each time slot by using

$$\bar{R}_k(t+1) = (1 - \frac{1}{t_c})\bar{R}_k(t) + \frac{1}{t_c} \sum_{j=1}^{J} \rho_{k,j}(t) c_{k,j}(t) \tag{4.8}$$

where t_c is the exponential moving average window factor. We omit the notation of time slot t in the following analysis of instantaneous resource allocation problem, and therefore the joint resource allocation problem can be mathematically formulated as follows:

$$\max_{\rho_{k,j}, p_{k,j}} \sum_{k=1}^{K} \frac{1}{\bar{R}_k} \sum_{j=1}^{J} \rho_{k,j} c_{k,j} \tag{4.9}$$

subject to

C1: $\sum_{k=1}^{K} \sum_{j=1}^{J} \rho_{k,j} p_{k,j} \leq P_{total}$

C2: $p_{k,j} \geq 0, \quad \forall j$

C3: $\rho_{k,j} = \{0, 1\}, \quad \forall k, j$

C4: $\sum_{k=1}^{K} \sum_{j=1}^{J} \rho_{k,j} = N$

C5: if $\rho_{k,j} = 1 \text{and} \{k\} \cup \boldsymbol{S}_j^{-k} = k' \cup \boldsymbol{S}_{j'}^{-k'}, \text{then} \rho_{k',j'} = 1, \forall k \neq k'$

where constraint C1 denotes that there is a total transmitting power constraint in each cell. C2 denotes the non-negative transmit power. C3 denotes that $\rho_{k,j}$ is a binary variable. C4 and C5 denotes that there is only on possible selection of user scheduling per time slot. The solution value of $\rho_{k,j}$ and $p_{k,j}$

are the optimal user scheduling and power allocation, respectively. However, problem in (4.9) involves both binary variables $\rho_{k,j}$ and continuous variables $p_{k,j}$, also with non-linear constraints. Such a non-linear combinational problem is generally very difficult to solve.

According to constraint C5 above, we noticed that if k and j are both determined, the set $\boldsymbol{S}_i = \{k\} \cup S_j^{-k}$ is determined and this means that $\boldsymbol{w}_{k,j}$ is also determined. From (4.2)and (4.6), we know that $c_{k,j}$ is a monotonic function of $p_{k,j}$. Provided a given set of scheduled users $\boldsymbol{S}_i$, let $n \in 1, \cdots, N$ denote the index of the users in $\boldsymbol{S}_i$, we can replace the indicator $\rho_{k,j}$ with i and the power allocation issue is constrained within a set $\boldsymbol{S}_i$, the user n's utility function simplified from (4.9) as

$$U_{n,i}(t) = \frac{c_{n,i}(t)}{\bar{R}_{n,i}(t)} \tag{4.10}$$

Then, a sub-problem is

$$\max_{p_{n,i}} \sum_{n=1}^{N} \frac{c_{n,i}}{\bar{R}_{n,i}} \tag{4.11}$$

subject to

$$\begin{aligned} &\text{C1:} \quad \textstyle\sum_{n=1}^{N} p_{n,i} \leq P_{total} \\ &\text{C2:} \quad p_{n,i} \geq 0, \quad \forall n \end{aligned}$$

where constraint C1 denotes that there is a total transmitting power constraint in a given $\boldsymbol{S}_i$. C2 denotes the non-negative transmit power for users.

We can see that the sub-problem is a simple convex optimization problem (the solution is known as water-filling power allocation) and can be easily solved using the Lagrange multiplier approach, we obtain

$$p_{n,i} = \left(\gamma - \|\boldsymbol{w}_{n,i}\|^2 \sigma^2\right)^+ \tag{4.12}$$

where $(x)^+ = \max(x,0)$ and constant γ are obtained by bisection search of the following expression:

$$\sum_{n=1}^{N} \frac{1}{\bar{R}_{n,i}} \log_2 \left(1 + \frac{(\gamma - \|\boldsymbol{w}_{n,i}\|^2 \sigma^2) + 1/\|\boldsymbol{w}_{n,i}\|^2}{\sigma^2}\right) = P_{total} \tag{4.13}$$

The algorithm finally exhaustively search all I optimal power allocation results, and select the optimal $\boldsymbol{S}_i$ with the highest$\sum_{n=1}^{N} U_{n,i}$.

As soon as the BS gets the optimal allocation results, it broadcast only the information of the edge users, including the allocated power, the value of the utility function of these users, and their CSI. When the BS receive the broadcast from the adjacent cells, it carry out the IS algorithm, which we describe in the next section.

4.3.2 Second Step: Interference Suppression

After the BS finishes step one, it evaluates the allocation results of the edge users, and if it finds that L adjacent cells' edge users are being scheduled with a higher utility value, it will delete L scheduled edge users of this cell, and redo the pre-coding by taking the L interfering users into account. Note that we define L as an integer number no more than the number of scheduled edge users in this cell. In other words, it will schedule $N - L$ local users, and only allocate the transmitting power to these users. Take a user n for example, in case that the transmission to user$n \in \boldsymbol{E}^0 \cap \boldsymbol{S}_i^0$ causes interference to user$n^* \in \boldsymbol{E}^m \cap \boldsymbol{S}_{i^*}^m$ and $U_{n,i} < U_{n^*,i^*}^m$, the BS will delete the user n from the set scheduled users, and redo the pre-coding to orthogonalize the users' channels including the user n^*. Then, the BS allocate the transmitting power only to its local users, and it ensures that there is no interference to user n^*.

The joint resource allocation with proportional fairness is briefly summarized as follows.

Algorithm 4.1 Optimal joint resource allocation

Step One:
  initialize temporary scheduling information.
  for each cell
    $\boldsymbol{S}_i = \emptyset$; update sets $\boldsymbol{E}, \boldsymbol{C}$.
    for each user set $\boldsymbol{S}_i \in \boldsymbol{\mathcal{K}}, i = \{1, \cdots, I\}$
      Calculate $p_{n,i}, n = \{1, \cdots, N\}$ which maximizes the value of $\sum U_{n,i}$ by
      using Eqs. (4.2), (4.6), (4.10) - (4.13).
    end
    Obtain the $\boldsymbol{S}_i$ with highest value of $\sum U_{n,i}$.
    Broadcast to adjacent cells the $p_{n,i}, U_{n,i}$and CSI of the users exist in $\boldsymbol{S}_i \cap \boldsymbol{E}$.
  end

Step Two:
  for each cell
    Compare the local $U_{n,i}$ of the users in $\boldsymbol{S}_i \cap \boldsymbol{E}$ with the received ones from
    adjacent cells.
    if not the highest$U_{n,i}$ (e.g.$U_{n,i} < U^m_{n^*,i^*}$)
      Delete user n ($\boldsymbol{S}_i = \boldsymbol{S}_i - \{n\}$).
      Perform pre-coding by adding the channel of user n^*.
      Recalculate $p_{n,i}$ which maximizes the value of $\sum U_{n,i}$ under the
      condition $p_{n'} = 0$ by using Eqs. (4.2), (4.6), (4.10) - (4.13).
    end
  end
  Scheduling the users in $\boldsymbol{S}_i$.
  Power allocation according to $p_{n,i}$.
  Update $\bar{R}_{n,i}$.

Although the sub-problem is easier to solve, we still need to carry out an extensive search of all the user sets, and solve the sub-problems for every given $\boldsymbol{S}_i$ to find a global optimal solution. For a cell of K-users N-transmit antenna L-interfered users, the complexity is approximately $\mathcal{O}(K^N + LNK)$ [35]. For these reasons, we propose a suboptimal LC algorithm in the following section.

4.3.3 Low-Complexity Suboptimal Solution

Due to the prohibitive computational burden at the BS to reach the optimal solution in (4.9) and for fast changing wireless channels, it's necessary to implement a low-complexity sub-optimal algorithm for cost-effective and delay-sensitive wireless systems. We noticed that most of the computational time is consumed at I times calculations of power allocation for every possible set of scheduled users. Therefore, an efficient way is to decouple the user scheduling from power allocation. Based on this idea, we define a new utility function of the users assuming an equal power allocation to approximately search for the optimal user set $\boldsymbol{S}_i$, which is given by

$$U_{n,i} = \frac{1}{\bar{R}_{n,i}} \sum_{n=1}^{N} \log_2 \left(1 + \frac{P_{total}/N}{\|\boldsymbol{w}_{n,i}\|^2 \sigma^2} \right) \tag{4.14}$$

BS calculates all the $U_{n,i}$ to find the highest one which is a sub-optimal $\boldsymbol{S}_i$, and then we need to allocate the transmitting power only once. In the second phase, we also reduce the reallocation processing time by deleting the users with lower utility values and skip the pre-coding if they have a higher spatial correlation coefficient. Therefore, we define a spatial correlation threshold δ_T to adjust the computation level. When a system has a heavy load, we can increase the threshold and only when the spatial correlation is more than δ_T, the ICI suppression algorithm will be used. In the worst case, the most computational consuming situation for an LC algorithm is the spatial correlation threshold set to 0, and the complexity is $\mathcal{O}(NK + LK)$. A brief summary of the low-complexity algorithm is as follows.

Algorithm 4.2 Low-complexity resource allocation

Step One:
  initialize temporary scheduling information.
  for each cell
    $\boldsymbol{S}_i = \emptyset$; update sets $\boldsymbol{E}, \boldsymbol{C}$.
    for each user set $\boldsymbol{S}_i \in \boldsymbol{\mathcal{K}}, i = \{1, \cdots, I\}$
      Calculate $\sum U_{n,i}$ by using Eq. (4.14).
    end
    Obtain the $\boldsymbol{S}_i$ with highest value of $\sum U_{n,i}$.
    In a given $\boldsymbol{S}_i$, calculate $p_{n,i}, n = \{1, \cdots, N\}$ which maximizes the value
    of $\sum U_{n,i}$.
    Broadcast to adjacent cells the $p_{n,i}, U_{n,i}$and CSI of the users exist in $\boldsymbol{S}_i \cap \boldsymbol{E}$.
  end

Step Two:
  for each cell
    Compare the local $U_{n,i}$ of the users in $\boldsymbol{S}_i \cap \boldsymbol{E}$ with the received ones from
    adjacent cells.
    if $U_{n,i} < U^m_{n^*,i^*}$ and $\delta^m_{n,i} > \delta_T$
      Delete user n ($\boldsymbol{S}_i = \boldsymbol{S}_i - \{n\}$)
      Recalculate $p_{n,i}$ which maximizes the value of $\sum U_{n,i}$ under the condition
      $p_{n'} = 0$ by using Eqs. (4.2), (4.6), (4.10) - (4.13).
    end
  end
  Scheduling the users in $\boldsymbol{S}_i$.
  Power allocation according to $p_{n,i}$.
  Update $\bar{R}_{n,i}$.

4.4 Simulation Results

4.4.1 Simulation Setup

Table 4.1: Simulation Parameters

Parameters	Values
Cell radius	1000 m
System bandwidth	1 MHz
Noise density	-174 dBm/Hz
Path loss	128.1+37.6log10(d)
t_c	100

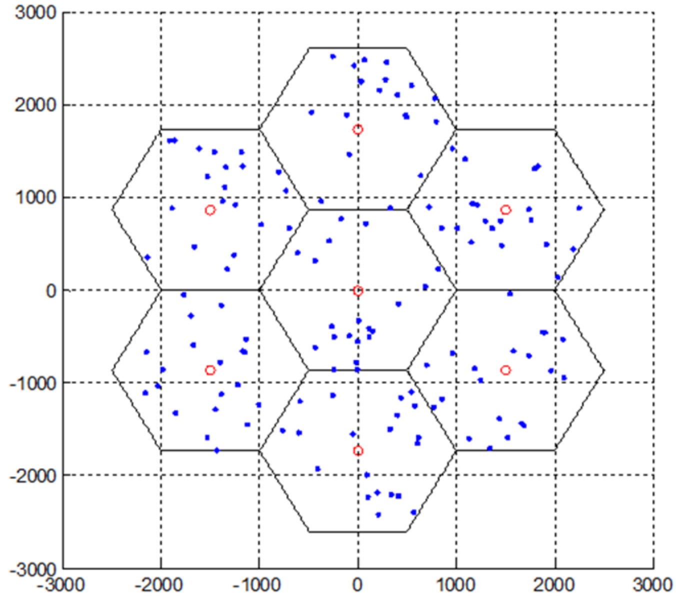

Figure 4.3: Example of Simulation Layout

In this section, we evaluated the performance of the proposed algorithms through simulations. An example of the simulation layout is shown in Fig. 4.3. We considered a wrap-around 7-cell hexagonal cellular MIMO system with K single antenna users (dots in Fig. 4.3) uniformly distributed within each cell. The center cell is the cell of interest and the 6 surrounding cells are the adjacent cells according to our previous definitions in Section 4.2. For simplicity reasons, we classified each user into either set $\boldsymbol{E}$ or $\boldsymbol{C}$ according to their distance from the serving BS in our simulation. The MIMO channel is assumed to be a flat-fading channel including large-scale path loss but without shadowing. There are always packets in the buffers of BSs waiting to be transmitted. Some of the simulation parameters are listed in Table 4.1. We compared three algorithms in our simulation. 'Optimal w/ IS' is the extensive search algorithm in (4.9) with ICI suppression, while 'Optimal w/o

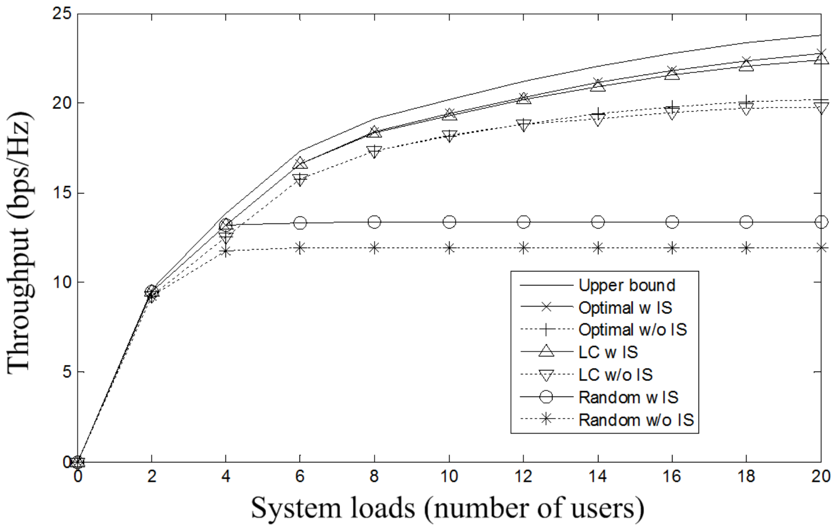

Figure 4.4: Throughput vs. No. of Users. ($P_{total} = 43dBm, N = 4, \delta_T = 0$)

IS' means there is no coordination between the BSs, every cell just performs the water-filling power allocation based on the local information. 'LC' is the proposed low-complexity algorithm in Section 4.3.3, and 'Random' means randomly selecting users to transmit.

4.4.2 Throughput Evaluation

Figure 4.4 illustrates the comparison of the average cell throughput among the three algorithms with and without IS for an increasing number of users. We ran the simulation 10000 times, each time the users were uniformly distributed in the cell. The solid line without marks on it is the single cell throughput based on the optimal user selection and water-filling power allocation. We can see that both the 'Optimal' and 'C' algorithms are close to the single cell upper bound and we found that our LC algorithm had a negligible throughput loss compared to that of the 'Optimal' algorithm. However, as the number of user increases, the interference increases, and the performance

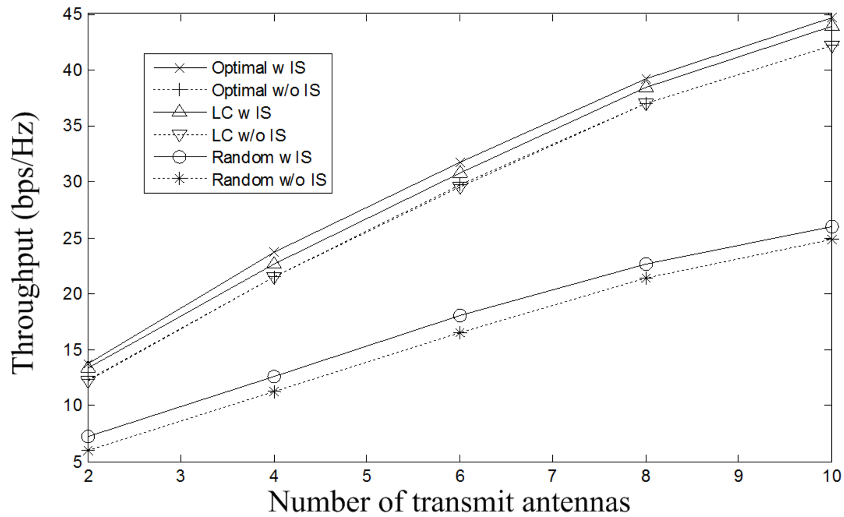

Figure 4.5: Throughput vs. No. of Transmit Antennas.
($P_{total} = 43dBm, K = 20, \delta_T = 0$)

loss is larger for the algorithms without IS. Note that when there are more users than transmit antennas, both the 'Optimal' and 'LC' algorithms can gain further at the system throughput due to the exploitation of the multi-user diversity. Whereas the performance of the 'Random' algorithm remains at the throughput at which the number of users equals the transmit antennas. This is because it only utilizes the space diversity, which is limited to the number of transmitting antennas.

The variation in system throughput based on the number of transmit antennas is illustrated in Fig. 4.5. In a multiplexing MIMO system, the throughput increases approximately proportional to the minimum number of transmit or receive antennas. As the total number of transmit antennas increases, the throughput based on the 'Optimal' and 'LC' algorithms increases faster than that based on the 'Random' algorithm. We also investigated the performance of the three algorithms on the edge users, which is illustrated in Fig. 4.6. The edge throughput of the three algorithms are compared as the to-

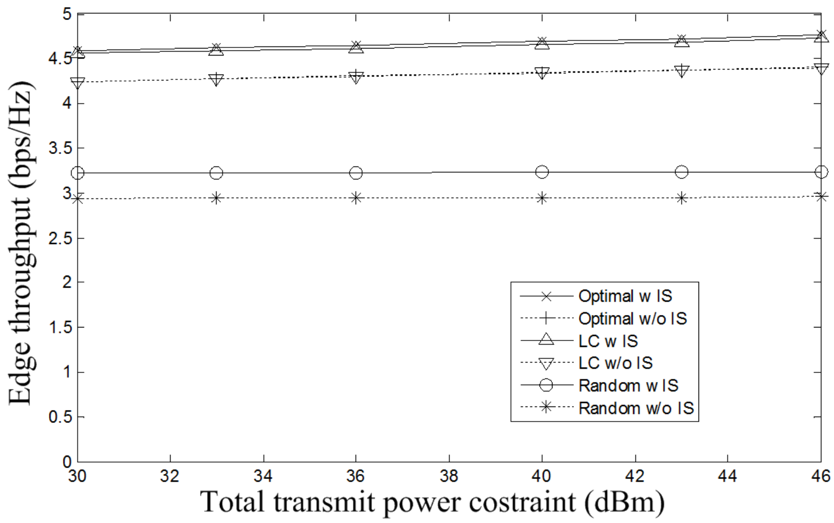

Figure 4.6: Edge throughput vs. Total Power Constraint.
$(K = 10, N = 4, \delta_T = 0)$

tal transmit power constraint increases. We found that there is a comparable edge throughput of the 'Optimal' and 'LC' algorithms. All three algorithms gain very little on the edge throughput as the total power constraint increases. This is easy to understand in an interference-limited network. Also, the 'Optimal' and 'LC' algorithms outperformed the 'Random' algorithm.

4.4.3 Effect of Spatial Correlation Coefficient Threshold

We use the same simulation configuration to evaluate the effect of the spatial correlation coefficient threshold on the system throughput. The spatial correlation coefficient varied between 0 and 1. The spatial correlation threshold in our algorithm can dynamically control the computational complexity. The appropriate spatial correlation threshold can be set as a fix number or dynamically adjusted by an algorithm according to the real system processing ability and interference level. But here, we want to know how the throughput varies. When the spatial correlation coefficient is less than this threshold, we

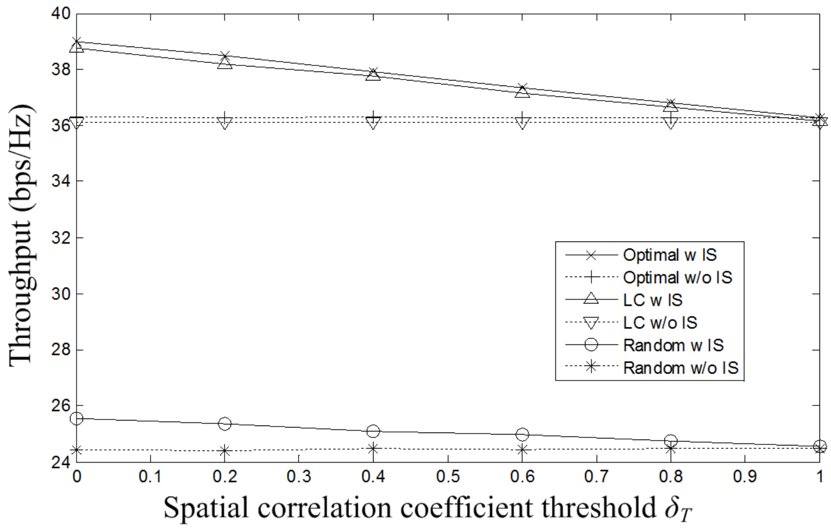

Figure 4.7: Throughput vs. Spatial Correlation Coefficient Threshold. ($P_{total} = 43dBm, K = 10, N = 4$)

assume the two users are comparatively orthogonal. This means that they will not interfere with each other too much. If the spatial correlation coefficient is more than the threshold, we have to perform interference suppression to decrease the interference between them. The system throughput varies with the spatial correlation coefficient threshold, as illustrated in Fig. 4.7. As the threshold δ_T increases, only the highly correlated users perform the interference suppression, which results in a decreased throughput for the algorithms with IS. When $\delta_T = 0$, each scheduled user at the cell edge will be suppressed the ICI by the BSs. Whereas, when $\delta_T = 1$, there is no IS operations. Therefore, the curves of the algorithm with IS and those without IS converge at this point.

4.4.4 Fairness Evaluation

We plotted the fairness index of the three algorithms with and without IS. To evaluate the fairness, we assumed that all the users' locations were fixed and

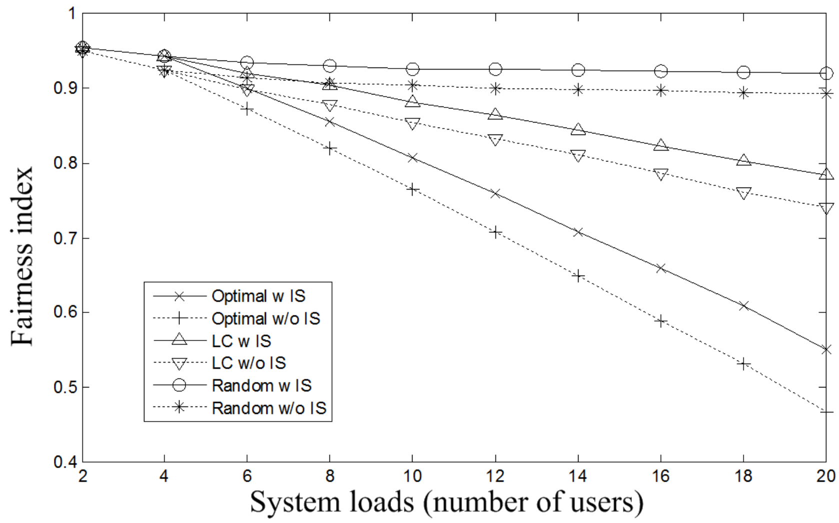

Figure 4.8: Fairness vs. No. of users ($P_{total} = 43dBm, N = 4, \delta_T = 0$)

ran the simulation for a 10000-time slot. As the number of users increased, we witnessed the index variation as shown in Fig. 4.8. The fairness index is based on the Jain's fairness index [36], which is defined as

$$\text{Fairness Index} = \frac{(\sum \bar{R}_k^m)^2}{K \sum (\bar{R}_k^m)^2}$$

where $\bar{R}_{n,i}$ denotes the average throughput of the kth user in cell m. Although the 'Random' algorithm exhibited a poor throughput, it achieved the highest fairness index. Since it treats every user equally and randomly selects them, it exhibits a good fairness. However, to our surprise, our 'LC' outperformed the 'Optimal' algorithm because it selects users according to the utility with equal power allocation. We can see that all the fairness indices go down as the number of users increases. The main reason for this is due to the heavier amount of inference between the cells and the users have less opportunity to be scheduled by the BS. The algorithms without IS deceased more rapidly than those with IS. The algorithms with IS are always better than those without IS in terms of fairness. This is because the IS most benefits the edge users, which usually have only a low throughput and have less chance to be scheduled compared to the centre users. Since the algorithms with IS can have a higher throughput for the cell edge users, it gives more fairness to the edge users.

4.5 Summary

We investigated a multi-cell coordinated MIMO system resource allocation incorporating proportional fairness and IS. We formulated the optimal resource allocation problem in a multi-cell MIMO system coordinated to suppress the ICI. Our aim was to achieve a high throughput and proportional fairness. Although we divided the original problem into easily solvable sub-problems, the computational complexity was still high. Therefore, we proposed a low-complexity algorithm to achieve a better fairness and less computational complexity with only a slight loss in throughput. We also obtained a tradeoff between the throughput and fairness by achieving proportional fairness. The simulation results showed that our algorithm improves the system throughput, particularly for cell edge users in a multi-cell environment and achieves proportional fairness for all users.

Chapter 5

Energy-Efficient Resource Allocation with Distributed Antennas

5.1 Introduction

Global warming has become one of the world's most serious environmental problems and there has raised concerns about greenhouse-gas emissions fueled by industrial progress that continues to consume huge amount of natural resources. High-energy consumption is not the only cause of the energy crisis, but it has also deteriorated the environment in which we live. Because of this, people are eagerly seeking methods of conserving energy in every walk of life for the sake of our future. Meanwhile, the unprecedented expansion of mobile networks has resulted in a tremendous increase in energy consumption and become a non-negligible contributor to global warming [37]. In addition, the electrical power consumed by the infrastructure of mobile networks already accounts for up to 50 percents of their operators' total operational costs [38].

In such cases, energy-efficient wireless transmissions that achieve both high spectral and energy efficiencies are the main objectives for the next generation mobile networks and these have triggered activities in standardization and regulatory bodies such as 3GPP and ITU, as well as research projects such as the European Commission's research project EARTH [39].

Generally speaking, there are many aspects in the mobile systems that can be investigated to conserve energy, and some of them are even beyond the scope of communication research area such as those on semiconductors and cooling technologies. However, as the consumed energy for the wireless transmission has been regarded as one of major sources of total energy consumption [38], in this study, we concentrated on energy-efficient techniques for wireless transmission, i.e., how to transmit the wireless signals and configure the systems that achieves high energy efficiency and fulfills specified capacity with limited output power. Early researches [40–45] were on energy efficiency issues for mobile nodes or sensors, which mainly focused on how to save total energy or prolong the network life time. Because these devices are powered by supplies of limited energy such as batteries. A recent survey on energy-efficient mobile networks [38] has presented a holistic approach and has clearly summarized the potentials for saving energy from the link to network levels as well as different components of mobile networks. The study in [46] has investigated energy efficiency based on MIMO techniques both in slow-fading and fast-fading channels, and [47] has focused on the impact on coverage and capacity when we limit transmitting power. However, aforementioned studies on the energy conservation methods for base stations (BS) in mobile networks are preliminary surveys or theoretical performance analysis on the effects of conserving transmitting power. Majority of these studies have involved in the energy management of the mobile networks. As far as we know, there are few work particularly on energy-efficient transmission that dedicated to the development of practical algorithms or solutions for mobile networks.

The approaches toward enhancing energy efficiency, roughly, can be explained as follows. Based on the fundamental information theory on MIMO channels [17], we can easily derive a basic expression for energy efficiency, which is defined as the number of bits transmitted per output Watt. Accordingly, considering the case that the channel state is known at the transmitter, the energy efficiency, denoted by η, can be given as

$$\eta = \frac{B}{P} \sum_{i=1}^{N} \log_2 \left(1 + \frac{p_i g_i^2}{\sigma^2} \right), \tag{5.1}$$

where B is the signal bandwidth, and N is the number of transmitting antennas. g_i^2, p_i and σ^2 correspond to the channel gain, effective power for transmission and interference-plus-noise power in the ith spatial channel, respectively. P is the sum of all the p_i and overhead power, which will be explained in section 5.3.1. It is worth noting that, the BS facilitated by some kind of feedback mechanisms can adaptively allocate wireless resources to users with different channel gains, this benefits achieving optimal energy efficiency through optimization. According to (5.1), we basically have three technical approaches to improve the energy efficiency while without being loss in capacity and consuming extra spectrum:

- Improve the channel gain g_i^2 such as reducing the access distance and number of obstacles between transmitter and receiver.
- Reduce the interference to decrease σ^2, specifically, reducing the co-channel interference in mobile networks.
- Increase the number of antennas N to achieve power gain promised by

MIMO techniques.

Because of the dramatic decrease in signal power during its propagation, large amount of energy that are emitted by BS antennas is wasted during the wireless transmission. The longer distance signals are traveled, the more energy is lost. Although large amount of work have been done on mitigating or utilizing negative effect of the small-scale fading, the major part of power loss, i.e. large-scale fading including path loss and shadowing, has not attracted much attention. The main reason for this is that large-scale fading depends on the distance and obstacles between the BS and users, which is difficult to overcome unless we fundamentally change the layout of the cell. The distributed antenna systems (DAS) is such kind of architecture to reduce the access distance and provide macro-diversity and recently shows great potential for increasing the system capacity in mobile networks [28, 48–55]. Earlier studies on DAS focused on the theoretic capacity comparison with conventional centralized antenna systems in a single-cell scenario [48–50], where the interference from outside are taken as Gaussian noise. Two studies [51], [52] considered a multi-cell scenario, in which the authors paid much attention on the inter-cell interference. However, all these studies, both signal cell and multi-cell, only analyzed either a broadcast transmission where all antennas transmit the same signal or a single-antenna selection transmission where only the nearest antenna transmit the signal to avoid excessive interference. As the study in [56] pointed out, the co-channel interference plays an important role in system performance. Recent studies [28, 53–55, 57] have identified that DAS can be generalized as a distributed MIMO system and focused on the MIMO capacity, which seems natural, therefore, to apply MIMO technologies such as beamforming to DAS in order to mitigate interference and enhance the performance.

Based on the above analysis of prior work, in our study, we focused on the energy efficient algorithms with the promising DAS configuration. More specifically, we investigated the resource allocation problems that aim at achieving high energy efficiency with satisfied capacity and identified the effect on them with different system configuration. Thus, there are mainly three contributions in our study.

- proposed a beamforming based resource allocation (BF) to optimize energy efficiency by jointly allocate power and control interference.
- further proposed an antenna-selection (AS) algorithm, which combined the advantage of high energy efficiency in BF algorithm and low complexity in single-antenna selection case.
- identified the influences on energy efficiency with different configuration of DAS.

The remainder of this paper is organized as follows. We present in Section 5.2, the assumptions and system model of DAS that considered in this study as well as the model for resource allocation. Section 5.3 is devoted to the resource allocation algorithm based on BF, and our demonstration of AS algorithm is described in Section 5.4. Section 5.5 compares energy efficiencies between conventional centralized antennas and different configurations of DAS as well as performance evaluation between BF and AS algorithms with extensive simulations. Section 5.6 concludes the whole work.

5.2 System Model

In order to clearly describe the following models, we begin with some definitions of notations. Matrices are denoted by bold capital letters and vectors

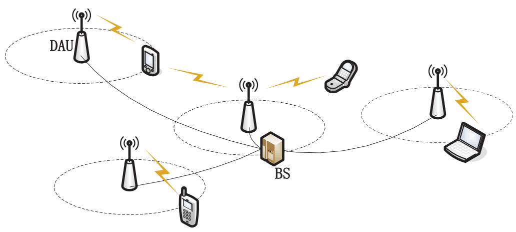

Figure 5.1: Distributed Antennas Architecture

by bold lower-case letters. $|x|$ means the absolute value of scalar number x, and $\|\boldsymbol{x}\|$ means the Euclidean norm of vector $\boldsymbol{x}$. Notations $\boldsymbol{H}^H$ and $\boldsymbol{H}^\dagger$ correspond to the conjugate transpose and pseudo inverse of matrix $\boldsymbol{H}$. The set of complex numbers is denoted by $\mathbb{C}$.

5.2.1 System Architecture

We consider the downlink of DAS where a BS serves K-mobile users, which is outlined in Figure 5.1. In DAS, randomly distributed antenna units (DAUs) are equipped with only a simple RF transceiver module. There are M DAUs evenly deployed within the cell and all of them are connected to the BS central processing unit where all the signal processing is done, via optical fiber or other high-bandwidth wired connections that can be assumed to be an ideal back-haul. As each DAU is equipped with L antennas, we denote these kinds of system configurations as (M, L) distributed antenna networks with total $N = ML$ transmitting antennas, which is similar to the notation in [48]. Note that $(1, N)$ means conventional centralized MIMO systems that are equipped with N antennas at a center location.

Our scenario is assumed to be a single cell where all outside interference is taken as Gaussian noise, and we only deal with the interference between DAUs. Without loss of generality, we only considered simple TDMA technique as the multiple access method. However, the system still allows time

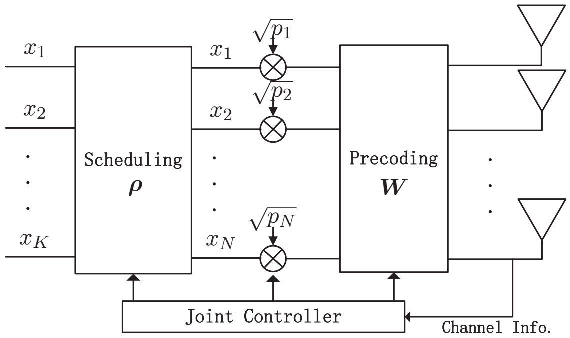

Figure 5.2: Resource Allocation Diagram

sharing by multiple users with beamforming. Our algorithms can also be applied to a more complicated scenario to incorporate the frequency domain. For example, a combination known as MIMO-OFDM that incorporates all three dimensions of wireless resources has already been extensively studied. In each time slot for allocating resources, we assumed a block fading channel in which the channel gains could be taken as a constant during the time interval and ideally feedback to the BS. The user devices were assumed to be only equipped with one antenna, which is very common in practical networks, particularly for mobile devices.

Regarding the traffic pattern, we assume an infinite backlog where there are always sufficient data waiting to be transmitted to users. Here, we do not consider the unbalanced traffic that may result in inefficient energy use. In fact, we may consider to adaptively adjust the number of active antennas for transmission to tackle with this problem, which is beyond the scope of this study.

5.2.2 Resource Allocation Model

Our goal was to develop a resource allocation algorithm that can use the energy more efficiently in the downlink transmission of DAS without loss in throughput by optimal power allocating, precoding, and scheduling. Figure 5.2 shows the diagram for basic operation in resource allocation for mobile networks with multiple antennas. The BS first schedules N users chosen from total K-users, it then allocates the power to their information bits, and precodes them onto N antennas, where the signals are transformed into RF and emitted. Let $\boldsymbol{p} = \{p_1, \ldots, p_K\}$ denote the power allocation vector, $\boldsymbol{W} = \{\boldsymbol{w}_1, \ldots, \boldsymbol{w}_K\}$ denote the precoding matrix, and $k \in \mathcal{K} = \{1, \ldots, K\}$ denote the index of all users. Scheduling vector $\boldsymbol{\rho}$ represents users who are being scheduled, and its entry $\rho_k = 1$ indicates the kth user is being scheduled by the BS, otherwise, $\rho_k = 0$. Unless noted, all variables representing the allocation of wireless resources, such as $\boldsymbol{p}$, $\boldsymbol{W}$, $\boldsymbol{\rho}$, are time-varying. We omit subscript t for them to represent the time slot in the following analysis, since we mostly discuss the problem for instantaneous resource allocation within one time slot of interest. Therefore, the received signal by user k is given by

$$y_k = \underbrace{\boldsymbol{h}_k \boldsymbol{w}_k \rho_k \sqrt{p_k} x_k}_{desired\ signal} + \underbrace{\sum_{j=1, j \neq k}^{K} \boldsymbol{h}_j \boldsymbol{w}_j \rho_j \sqrt{p_j} x_j}_{interference} + n, \tag{5.2}$$

where vectors $\boldsymbol{h}_k \in \mathbb{C}^{1 \times N}, \boldsymbol{w}_k \in \mathbb{C}^{N \times 1}$ are channel gains and corresponding precoding weights, x_k is the original information bit for user k. The p_k is the allocated effective power on the signal intended for user k and n is the Gaussian noise with variance $\mathbb{E}[nn^H] = \sigma_N^2$. The second term is the interference from the other scheduled users at the same time slot t. Therefore, the signal-to-interference-plus-noise ratio (SINR) for user k is given by

$$SINR_k(\boldsymbol{p}, \boldsymbol{\rho}, \boldsymbol{W}) = \frac{\rho_k \cdot p_k \left|\boldsymbol{h}_k \boldsymbol{w}_k\right|^2}{\sum_{j=1, j \neq k}^{K} \rho_j \cdot p_j \left|\boldsymbol{h}_j \boldsymbol{w}_j\right|^2 + \sigma_N^2}. \tag{5.3}$$

Assuming adaptive modulation and coding scheme is adopted, users have the ability to match the rate they can achieve according to their channel conditions. As discussed in [26], rate r_k of user k that can be approximated as a function of bit error ratio (BER) and SINR by

$$r_k(\boldsymbol{p}, \boldsymbol{\rho}, \boldsymbol{W}) \approx \log_2(1 + \delta \cdot SINR_k), \tag{5.4}$$

where $\delta = -1.5/\ln(5 \cdot BER_k)$ is a parameter to bridge the gap between Shannon capacity and the practical modulation and coding scheme.

5.3 Beamforming based Energy-Efficient Resource Allocation

5.3.1 Energy Efficiency Metrics

To evaluate the energy efficiency of resource allocation algorithms for practical systems, we first need a reasonable metric to appropriately reflect the key parameters in the problem. Some studies [46, 47] have proposed their own metrics for mobile networks scenario. Since energy consumption in the infrastructure is a systematic problem that depends on many factors and has only recently been investigated, there are not any widely accepted metrics for energy efficiency in this field yet. Because of this, we used a metric model similar to that in [47], which only captured the key components that affect the energy efficiency during the transmission. In real scenario, the reference signals and common control signaling in downlink transmissions of mobile networks account for nearly a constant part of the actual transmitting power. Therefore, we defined α denoting the overhead percentage of the maximum output power by BS, and the metric for transmission power efficiency of user

k can be expressed by

$$\eta_k = \frac{r_k}{\alpha P_{max}/N + p_k}, \quad 0 \leq \sum_{k \in \mathcal{K}} p_k \leq (1-\alpha) P_{max} \tag{5.5}$$

where P_{max} is the maximum total output power of the BS. Maximizing (5.5) leads to an optimal energy efficiency for user k.

5.3.2 Beamforming Transmission

Beamforming can obtain multiple spatial channels by precoding user singals into multiple beams. When using beamforming precoding, we can control the power concentration to particular users or interference power leaked to other users. linear precoding technique can directly calculates the precoding weight with the channel matrix, or derive it from a linear combination of two extreme beamforming weights, which is described in what follows.

One strategy is maximum ratio (MR) transmission. If the base station has knowledge of channel $\boldsymbol{h}_k$ of user k, then it is possible to use the technique to maximize desired signal power. MR weight vector $\boldsymbol{w}_{MR}$ for user k is given by

$$\boldsymbol{w}_k^{MR} = \boldsymbol{h}_k^H / \left\| \boldsymbol{h}_k \right\|. \tag{5.6}$$

This strategy clearly achieves the greatest power weight for user k as no attempt is made to reduce interference to other users. Another strategy is zero-forcing (ZF) transmission, which places nulls in the direction of users with interference thereby ensuring no interference is applied to these users. ZF weight vector $\boldsymbol{w}_{ZF}$ for user k is given by

$$\boldsymbol{w}_k^{ZF} = \boldsymbol{h}_k^{\dagger} / \left\| \boldsymbol{h}_k^{\dagger} \right\|, \tag{5.7}$$

where $\boldsymbol{h}^\dagger$ is the corresponding column of weight matrix $\boldsymbol{H}^\dagger$, and $\boldsymbol{H}$ is composed of all scheduled users' channel vectors. The linear combination of MR and ZF weights may simplify computational complexity [58] for the iterative solution to resource-allocation problems. Thus, the precoding vectors can be just parameterized by a real number $\lambda_k \in [0, 1]$ by

$$\boldsymbol{w}_k(\lambda_k) = \frac{\lambda_k \boldsymbol{w}_k^{MR} + (1-\lambda_k)\boldsymbol{w}_k^{ZF}}{\left\|\lambda_k \boldsymbol{w}_k^{MR} + (1-\lambda_k)\boldsymbol{w}_k^{ZF}\right\|}. \tag{5.8}$$

Thus, (5.4) can be simplified as $r_k(\boldsymbol{p}, \boldsymbol{\rho}, \boldsymbol{\lambda})$.

5.3.3 Problem Formulation

We formulated the energy-efficient resource allocation as an optimization problem based on above resource-allocation model discussed in Section 5.2.2. Note that if we only consider maximizing the efficiency of system energy, the obvious outcome is that the BS will always transmit to users who have superior channel conditions, however, this is unfair to the other users with inferior channel conditions. To solve this problem, the aggregated utilities of all users incorporate proportional fairness [29] in terms of throughput and this can be given by

$$\sum_{k \in \mathcal{K}} U_k = \sum_{k=1}^{K} \frac{r_k}{(\alpha P_{max}/N + p_k)\bar{r}_k}, \tag{5.9}$$

where $\bar{r}_k$ is the average throughput for user k by the tth time slot, which can be updated each time slot by using

$$\bar{r}_k(t+1) = (1 - \frac{1}{t_c})\bar{r}_k(t) + \frac{1}{t_c} r_k(t). \tag{5.10}$$

Thus, to optimize resource allocation in terms of energy efficiency in each time slot with proportional fairness we solve

$$
\begin{aligned}
&\max_{p_k,\boldsymbol{\rho},\lambda_k} \sum_{k\in\mathcal{K}} U_k \\
\text{s. t.} \quad & \text{C1: } 0 \le p_k \le P_{max}, \forall k \\
& \text{C2: } \rho_k \in \{0,1\}, \forall k, and\, \|\boldsymbol{\rho}\| = N \\
& \text{C3: } \lambda_k \in [0,1], \quad \forall k
\end{aligned} \tag{5.11}
$$

The interpretation of the above optimization is as follows. The three constraints are limitations for power control, scheduling, and beamforming. When the BS carries out resource allocation, the controller jointly computes the maximal value of the aggregate utility to find the best point for operation. This solution with the optimal scheduling vector, power control, and beamforming maximize the energy efficiency of the network. However, the objective function is discrete, and the problem in (5.11) is not easy to solve in a real-time processing environment. Algorithm 5.1 to solve this problem is briefly summarized as follows.

Algorithm 5.1 Beamforming based Resource Allocation

```
for each time slot t
   create all possible ρ based on set 𝒦
   for each ρ
       create corresponding H based on ρ;
       calculate W based on (5.6), (5.7), (5.8) with parameters λ;
       calculate max∑_ρ U(p, λ) using Lagrange multiplier;
       store the sub-optimal values;
   end
   search all sub-optimal values;
   obtain the optimal p, λ together with corresponding ρ;
   update r̄_k(t + 1), ∀k;
end
```

5.4 Antenna Selection based Energy-Efficient Resource Allocation

Due to the computational complexity of the BF based energy-efficient resource allocation, we proposed a low-complexity algorithm that selects part of the total antennas to transmit. Note that in DAS, users usually have different distances from different DAUs. In some cases, any of them may have one or several (less than the total number of antennas) dominant channels where the gain of these channels are much greater than that of others, e.g., users are geographically close to one or several DAUs. This inspired us to simply restrict the transmission of signals only through one or several closest DAUs instead of joint transmitting them from all antennas. Intuitively, although this subset antenna-selective beamforming may avoid power wastage on distant antennas, it increases interference to some extent since we lose fully coordinating in BF transmission. We hereby defined $\gamma_{k,n}$ as the dominance degree to quantify the nth antenna comparative channel gain for user k, which can be given as

$$\gamma_{k,n} = \frac{|h_{k,n}|^2}{\sum_{i \neq n} |h_{k,i}|^2}, \quad i \in \{1, \cdots, N\}. \tag{5.12}$$

Higher value of $\gamma_{k,n}$ represents the user k getting close to the corresponding antenna n. Consequently, (5.12) can be used to determine antenna selection, if we defined a appropriate threshold γ_0 for selection criterion. The criterion is defined as

$$\rho_{k,n} = \begin{cases} 1 & \gamma_{k,n} > \gamma_0 \\ 0 & \gamma_{k,n} \leq \gamma_0 \end{cases}. \tag{5.13}$$

Let the set of selected DAUs by user k be $\mathcal{A}_k$, comparing to (5.4), the date rate for user k in AS based resource allocation should be updated as

$$r_k(\boldsymbol{p}, \boldsymbol{\rho}, \boldsymbol{\lambda}) = \log_2\left(1 + \delta \cdot \frac{\rho_{k,n} \cdot p_k \left|\sum_{n \in \mathcal{A}_k} h_{k,n} w_{k,n}\right|^2}{\sum_{j \neq k} \cdot p_j \left|\sum_{n' \in \mathcal{A}_j} h_{j,n'} w_{j,n'}\right|^2 + \sigma_N^2}\right), \tag{5.14}$$

where $\sum_{j \neq k} \cdot p_j \left|\sum_{n' \in \mathcal{A}_j} h_{j,n'} w_{j,n'}\right|^2$ is the interference coming from other unselected antennas. In addition, the antennas is restricted to be selected only once considering the exceed interferences. Thus, the constraint C2 in the optimization problem in (5.11) is also updated as

$$\rho_{k,n} \in \{0, 1\}, \sum_{k=1}^{K} \sum_{n=1}^{N} \rho_{k,n} = N, \sum_{k=1}^{K} \rho_{k,n} = 1, \forall k, n, \tag{5.15}$$

which shows a loose correlation in the scheduling feasible set. Algorithm 5.2 to solve this problem is briefly summarized as follows.

Algorithm 5.2 Antenna Selection based Resource Allocation

for each time slot t
    create all possible $\boldsymbol{\rho}$ based on set $\mathcal{K}$
    for each $\boldsymbol{\rho}$
        create corresponding $\boldsymbol{H}$ based on $\boldsymbol{\rho}$;
        select the serving antenna based on (5.12), (5.13);
        calculate $r_k(\boldsymbol{p}, \boldsymbol{\rho}, \boldsymbol{\lambda})$ based on (5.6), (5.7), (5.8), (5.14);
        calculate $\max \sum_{\boldsymbol{\rho}} U(\boldsymbol{p}, \boldsymbol{\lambda})$ using Lagrange multiplier;
        store the sub-optimal values;
    end
    search all sub-optimal values;
    obtain the optimal $\boldsymbol{p}, \boldsymbol{\lambda}$ together with corresponding ρ;
    update $\bar{r}_k(t+1), \forall k$;
end

5.5 Simulation Results

To validate the effectiveness of the proposed algorithms, we compared the above two algorithms with conventional centralized architecture, and also gave a comprehensive evaluation results on the energy efficiency with different numbers of antennas, network configurations, networks loads, and power overheads. The abbreviations BF and AS are short for beamforming and antenna selection. We evenly generated the DAUs and users locations for all simulation instances, and run for 10000 time slots to obtain the averaged value. Some simulation parameters are listed in Table 5.1.

Table 5.1: Simulation Parameters

Parameters	**Values**
Cell radius	1000 m
System bandwidth	1 MHz
Background noise density	-174 dBm/Hz
Path loss	128.1+37.6log10(d) (d in km)
Minimum BS and user distance	30 m
Maximum transmission power	43 dBm
Exponential moving average weight factor (t_c)	100
BER	10^{-4}

The power efficiencies with different antenna configurations and resource allocation algorithms have been given in Fig. 5.3 with increasing numbers of antennas. The green curve with stars plotted the efficiency of distributed antennas with full beamforming that outperforms the other two configurations. We can see that the energy efficiency of all these algorithms increases as the

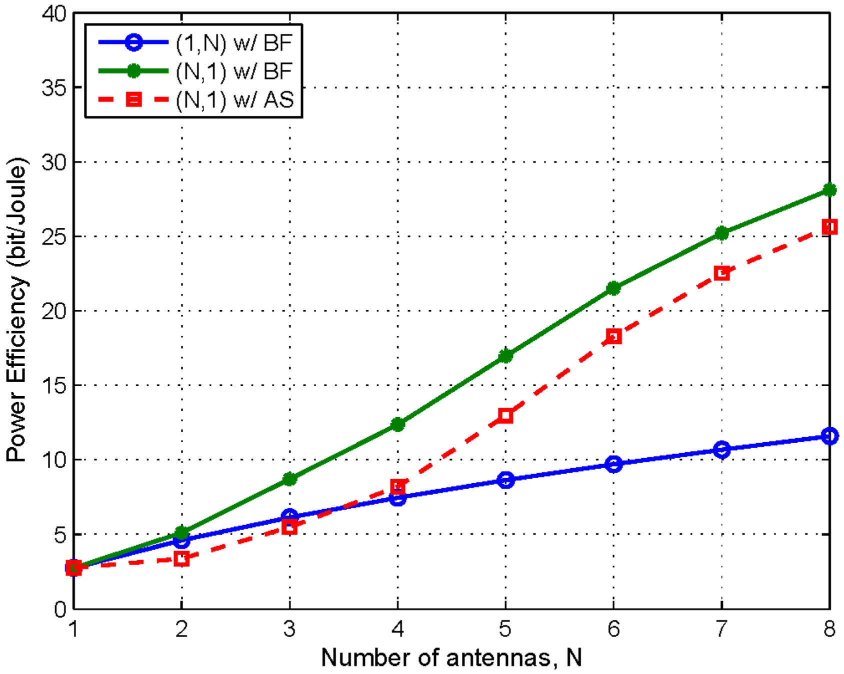

Figure 5.3: Power Efficiency vs. Number of Antennas
(total transmitting power =1 W)

number of antennas increases. However, the configuration with distributed antennas $(N, 1)$ increases faster than that with centralized ones, mainly because it reduces the access distance that achieves a huge macro-diversity gain in the MIMO channel. Note that the AS algorithm performs poorly when there are two or three antennas, since mutual interference is quite strong with a small number of distributed antennas, and this results in poor performance for an AS algorithm. However, as the number of antennas in-creases, the performance of AS approaches that of BF in the distributed configuration.

Figure 5.4 plotted the power efficiency with different configurations and resource allocation algorithms, which varies with spectral efficiency, i.e., throughput. As can be seen in the figure, the power efficiency curves are always plotted as concave functions among different antenna configurations and re-

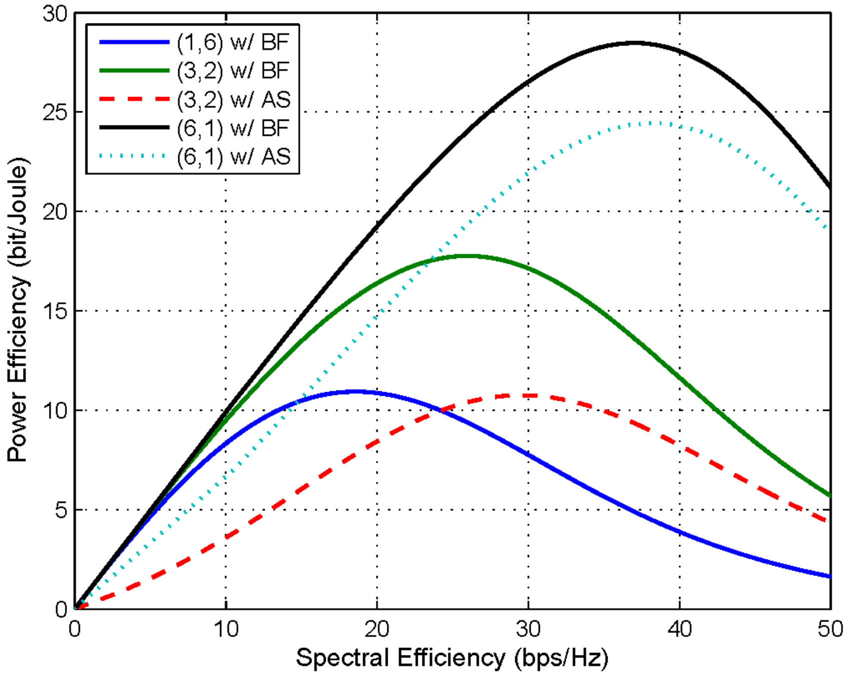

Figure 5.4: Power Efficiency vs. Spectral Efficiency

source allocation algorithms. It is obvious that a particular antenna configuration and resource allocation has a unique point of throughput that provides optimal power efficiency. It is better for operators to set up the BS operational throughput around the point of peak power efficiency. Regardless of this, distributed antenna configurations always achieve better energy use than centralized ones. We can also see that the performance of AS algorithms approach those of BF algorithms with the same antenna configuration when we distribute all available antennas as much as possible.

We can see from Fig. 5.5 that as the number of users increases in the network, the energy efficiency also slowly increases. As our resource allocation algorithms were optimized for energy efficiency, all user diversity gain was mainly to reduce transmission powers and improve throughput, both of these

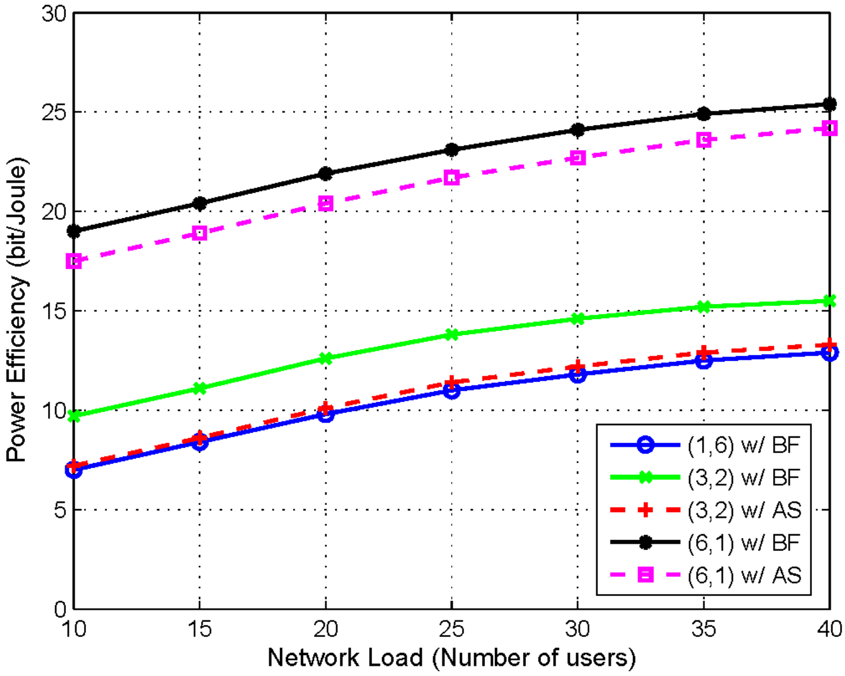

Figure 5.5: Power Efficiency vs. Network Load

effects enhanced energy efficiency. Regarding Fig. 5.4, another similar situation can be found in Fig. 5.5 where the distributed antenna configuration outperforms the centralized one and energy efficiency with AS approaches that of the BF algorithm as the number of antennas increases.

We have also investigated what effect the power overhead had on energy efficiency as seen in Fig. 5.6. It is clear that the lower power overhead leads to higher energy efficiency. All simulation results indicated that the algorithm of BF resource allocation for distributed antenna configurations not only dramatically increased energy efficiency at every point of throughput, but also improved the throughput region with high energy efficiency. While the AS algorithm is mainly used in distributed antenna networks, it can approach the performance of the BF algorithm when there are many antennas (usually one

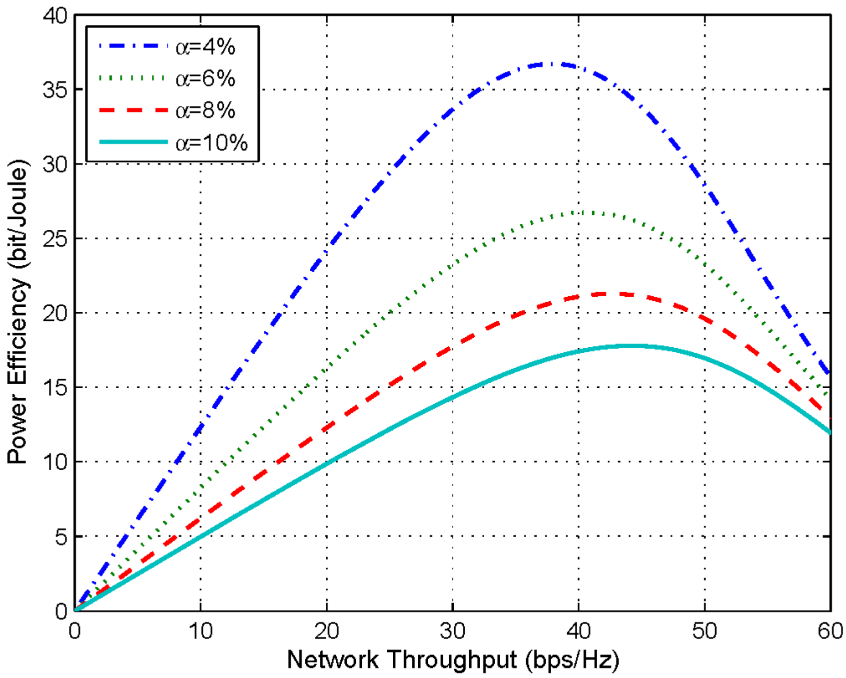

Figure 5.6: Power Efficiency vs. Throughput with Various Power Overheads

with more than three antennas outperforms traditional centralized networks).

5.6 Conclusions

In this paper, we considered a multi-user MIMO networks with distributed antenna transmission where two energy-efficient resource allocation algorithms are proposed and validated. We first proposed a beamforming based algorithm to achieve the optimal energy efficiency in this scenario. Due to computational complexity and real-time processing requirements, we further proposed an algorithm with low-complexity based on antenna selection to make the energy-efficient algorithm tractable for practical use with negligible loss in performance. Finally, we compared these algorithms as well as different network configurations through extensive simulations and the simulation results demonstrated that the proposed resource allocation algorithms in the configuration of distributed antenna networks can achieve higher energy efficiency in regions with high operational throughput. Based on all these analyses, we have gained some insights into energy efficiency in the downlink of mobile networks where there are many factors that we should jointly take into consideration. Enhancing every aspects in mobile networks is intrinsically difficult in practical scenario as wireless resources are limited and there are many system constraints. This requires joint optimization of these metrics of concern and sometime tradeoff is achieved.

Chapter 6

Cooperative Resource Allocation with Multi-cell Distributed Antennas

6.1 Introduction

The increasing demand for ubiquitous access to higher data rates and better quality of service (QoS) calls for innovative techniques that provide higher network capacity anywhere and better link reliability anytime. The biggest challenge to achieving this goal is how to enhance the wireless channel capacity and reliability for users at the cell edge. The distributed antenna system (DAS), which has traditionally been used to cover dead spots in indoor environments [59], shows great potential for increasing the system capacity in outdoor settings especially the cell edge because it reduces the access distance and provides macro-diversity [48], [49], [54]. In DAS, randomly distributed antenna elements (AEs) in a cell are equipped with only a simple RF transceiver module. They are connected to a central processing unit where all the signal

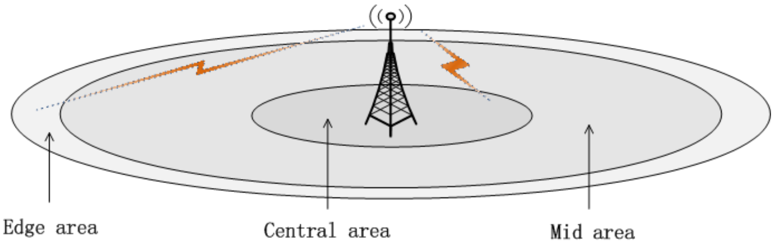

Figure 6.1: Areas with Different Interference Levels

processing is done, via fiber optic or exclusive RF link.

Most current cellular systems are interference-limited, which means the quality of signals depending on not only the received power but also the interference. According to the signal-to-interference-and-noise ratio (SINR), we may classify the whole coverage of a cell into three kinds of area, where users experience different interference level, shown in Fig. 6.1. The center area is very close to the base station (BS), where users are hardly affected by the other cells' interference. The second area, called the mid area, is a large area between center and edge of a cell; users within it suffer moderate levels of interference. The cell edge area is where users are severely affected by interference from other cells. DAS provides higher received power to enhance the SINR of users in the mid-area, but it still suffers from strong interference in the edge area: this severely limits further improvements to the SINR. Most research on DAS has focused on performance comparisons with conventional co-located antenna systems in single-cell noise-limited scenario [50], [53], [54]. Two studies [51], [52] considered a multi-cell interference-limited scenario with frequency reuse factors of 1 and 7, respectively. However, these studies only analyzed a simple antenna selection transmission (AST) strategy with interference reduction, which still performs poorly at the cell edge. Recent studies [53], [54] have shown that DAS can be generalized as a distributed multiple-input multiple-output (D-MIMO) system when the user device is equipped with more than one antenna, even though the original intent of these studies was to solve problems inherent in the conventional co-located MIMO (C-MIMO) systems. It seems natural, therefore, to apply advanced MIMO interference mitigation technology to D-MIMO systems in order to enhance cell-edge performance.

Beamforming is a simple but effective precoding strategy to reduce interference among users by projecting a multiuser channel into multiple independent single-user channels. Extensive research on beamforming has been conducted, and the majority of these studies, e.g., [27], [29], focus on improving capacity in a single-cell multi-user environment. The study in [34] considers eliminating interference among multi-cells; unfortunately, it is impractical to implement a multi-cell processing scheme in current co-located antenna systems because of severe path loss among cells. Owing to no such problems existing in D-MIMO systems, we were inspired to devise a cooperative beamforming transmission (CBT) algorithm for multi-cell D-MIMO systems as an attempt to resolve these co-channel-interference (CCI) issues. While antenna selection can clearly reduce the interference from the transmit power perspective, we seek a more aggressive method, one which can fully utilize the degrees of freedom of the transmit antennas to achieve better performance in universal frequency reuse environments.

The rest of this paper is organized as follows. Section 6.2 describes the system architecture and channel model. CBT is mathematically analyzed in comparison with other transmission methods in Section 6.3. Section 6.4 gives some numerical results on performance evaluation, and Section 6.5 gives our conclusions.

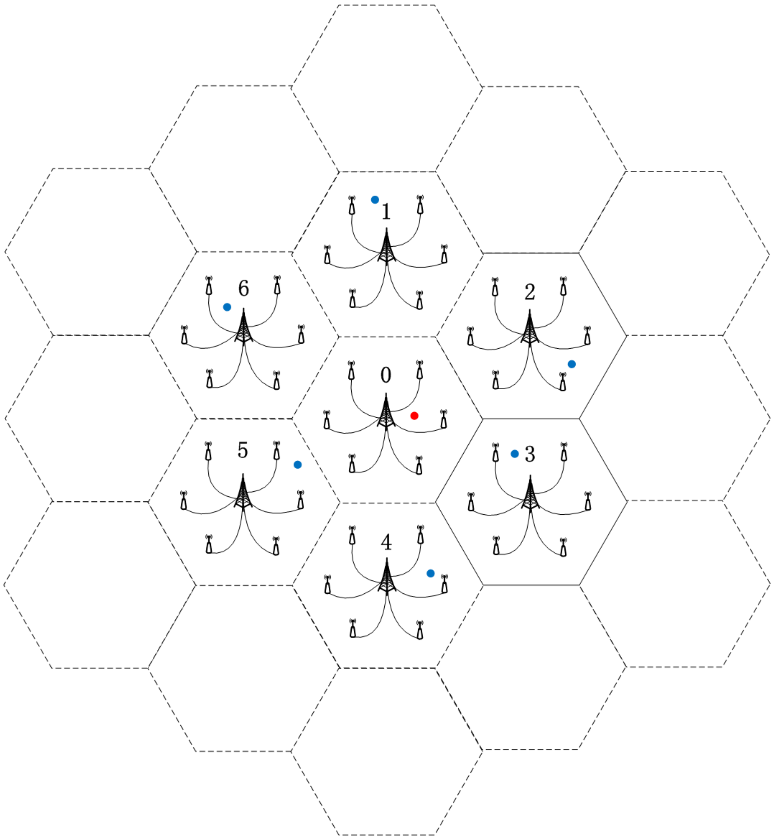

Figure 6.2: Configuration (7, 1, 6) of Distributed-MIMO Systems
(• Target user ; • Co-channel user)

6.2 System Model

6.2.1 Distributed MIMO System

Following the similar notation used in [48], (M, N, K) is used to briefly describe the network configuration, whereby a generalized distributed MIMO cellular system employs M randomly distributed AEs within each cell and there are N receive antennas on a user device. Each cell has K adjacent cells. For simplicity, we consider a practical $(M, 1, K), MK+1$ scenario in which the user has only one antenna, as in a conventional DAS, and it's easy to extend the study to the case of $N \geq 2$ by simply implementing receiver shaping functions or adopting . Since the users' devices are limited in their energy and processing capabilities, and it is hardly for them to cooperate with each other, we would like to concentrate on exploring the degrees of freedom at the transmit end to do processing. Unless noted, we will consider this kind of configuration (7,1,6), an example of which is shown in Fig. 6.2 with the central cell numbered 0.

Moreover, we assume that the users' channels are orthogonal within the cell and there is only one co-channel interfered user in each of the other cells during the transmission, which holds for most orthogonal multiple access systems such as TDMA, FDMA, Orthogonal-CDMA, and OFDMA, in a universal frequency reuse scenario.

6.2.2 Channel Model

An interference-limited distributed MIMO channel is considered. Without loss of accuracy, we will take the CCI coming from the adjacent cells to be the major sources of interference. The rest of the interference from farther cells can be treated as Gaussian noise. We shall focus on a user located at cell 0, called the target user (red dot in Fig. 6.2), whose receiving signal can be expressed as

$$y = \sqrt{P}\boldsymbol{h}_0^0\boldsymbol{x}_0 + \sum_{k=1}^{K}\sqrt{P}\boldsymbol{h}_k^0\boldsymbol{x}_k + n \tag{6.1}$$

Where P is the total transmission power in each cell. Notation$n$ is the noise including insignificant interference and additive white Gaussian noise with variance $\mathbb{E}[nn^*] = \sigma^2 = \sigma_i^2 + \sigma_n^2$. Vector $\boldsymbol{x}_k = [x_{k,1}, x_{k,2}, , x_{k,M}]^T$, $(k = 0, 1, \cdots, K)$ is the transmitting signal from the kth cell. Vector $\boldsymbol{h}_k^0 = [h_{k,1}^0, h_{k,2}^0, \cdots, h_{k,M}^0]$ is the channel gain from the kth cell to the target user. Since AEs are geographically separated, we will model the distributed MIMO channel including both large-scale and small-scale fading. We assume a rich scattering Non-line-of-sight (NLOS) environment, therefore, the channel vector is given by

$$\boldsymbol{h} = \boldsymbol{l} \odot \boldsymbol{h}_w \tag{6.2}$$

where $\odot$ is the element-wise product, and h_w is a classical frequency-flat Rayleigh fading channel in which the entries are independent and identically distributed complex Gaussian random variables with zero mean and unit variance. The large-scale fading vector l, which reflects path loss and shadowing, parameterized by the distance vector $\boldsymbol{d} = [d_1, \cdots, d_M]^T$ and shadow fading ψ_n is given by

$$l = \left[\sqrt{\frac{\beta\psi_1}{d_1^\alpha}}, \sqrt{\frac{\beta\psi_2}{d_2^\alpha}}, ..., \sqrt{\frac{\beta\psi_M}{d_M^\alpha}}\right] \tag{6.3}$$

where β is a constant that embodies the antenna and near-field propagation characteristics, and α is the path-loss exponent.

Under different transmission algorithms, vector $\boldsymbol{x}_k$ is a weighted transmitting signal with a constraint $\mathbb{E}[x_k x_k^*] = 1$. Let $\boldsymbol{w}_k$ be the normalized weight vector and s be the original information signal; thus, transmitting $\boldsymbol{x}_k$ can be expressed as $\boldsymbol{w}_k$ s. For maximum ratio transmission (MRT) algorithm, the weight vector is [27]

$$\boldsymbol{w}_k = \boldsymbol{h}_k^* / \|\boldsymbol{h}_k\| \tag{6.4}$$

where $\|\cdot\|$ represents the Euclidean norm, and * represents conjugate transpose. In particular, the weight vector for AST is all zero but only one entry equal to 1 [52]. Note that the weight vectors $\boldsymbol{w}_k$ are intended for the kth user (without loss of generality, we refer to the kth user as co-channel user in the kth cell, blue dot in Fig. 6.2).

6.3 Resource Allocation in Distributed Antennas Networks

In a multi-user MIMO system, M transmitting antennas and $K+1$ receiving antennas can generate up to $\min(M, K+1)$ independent channels. In other words, by beamforming, if we expect to eliminate signals to the K users and transmit signals only to the target user, we should have $M \geq K+1$. This is exactly why we consider the $(M, 1, K) M \geq K+1$ scenario mentioned in Section 6.2. Obviously, an $(M, 1, K)$ distributed antenna system with only one user interfered in each adjacent cell can basically be regarded as a generalized M by $K+1$ distributed MIMO multi-user system. The case of $M < K+1$, implies that we cannot eliminate all the interference goes to adjacent cells. If we virtually take all the co-channel interfered users together with target user, consequently, the receiving signal in (6.1) can be extended in vector form as

$$\boldsymbol{y} = \sqrt{P}\boldsymbol{H}_0\boldsymbol{x}_0 + \sum_{k=1}^{K}\sqrt{P}\boldsymbol{H}_k\boldsymbol{x}_k + \boldsymbol{n} \tag{6.5}$$

where $\boldsymbol{y} = [y_0, y_1, \cdots, y_K]^T$ is a vector formed from all receiving signals of the K+1 users. The vector $\boldsymbol{x}_0 = [x_1, x_2, \cdots, x_M]^T$ is the transmit signal of cell 0. The row vectors $\boldsymbol{h}_0^k$ of channel matrix $\boldsymbol{H}_0 = [\boldsymbol{h}_0^0, \boldsymbol{h}_0^1, \cdots, \boldsymbol{h}_0^K]^T$represent the channel gain vectors from cell 0 to the corresponding kth user.

We assume that every two adjacent cells cooperate perfectly and share their users' channel state information (CSI). Take cell 0 for instance, with a target user and Kco-channel users' CSI, CBT performs, which places nulls in the direction of the adjacent interfered users thereby ensuring no CCI is delivered to these users. The signal $\boldsymbol{x}_0$ is weighted by the normalized weight vector $\boldsymbol{w}_0$ which is given by

$$\boldsymbol{w}_0 = \frac{\boldsymbol{h}_0^{\dagger}}{\left\|\boldsymbol{h}_0^{\dagger}\right\|} \tag{6.6}$$

where $\boldsymbol{h}_0^{\dagger}$ is the first column vector of the pseudo-inverse matrix $\boldsymbol{H}_0^{\dagger}$ given by

$$\boldsymbol{H}_0^{\dagger} = \boldsymbol{H}_0^{*}(\boldsymbol{H}_0\boldsymbol{H}_0^{*})^{-1} \tag{6.7}$$

Effective SINR

Assuming that all the cells perform CBT, the second term in (6.5), which is expressed to be adjacent cell interference for the target user, will be canceled. Accordingly, (6.5) becomes

$$\boldsymbol{y} = \sqrt{P}\boldsymbol{H}_0\boldsymbol{w}_0 s + \boldsymbol{n} \tag{6.8}$$

As is done above, substituting $\boldsymbol{w}_0$ into (6.8), we can get $y_0 = \frac{\sqrt{P}s}{\left\|h_0^{\dagger}\right\|} + n$, while $y_1 = \cdots = y_K = n$, which implies the transmission is only delivered to the target user so that there is only white noise received. Consequently, the effective SINR of the CBT is given by

$$\gamma_{CBT} = \frac{P}{\left\|\boldsymbol{h}_0^{\dagger}\right\|^2 \sigma^2} = \frac{P}{\sigma^2}\delta_{CBT} \tag{6.9}$$

where we have defined $\delta_{CBT} = 1/\left\|\boldsymbol{h}_0^{\dagger}\right\|^2$, which can be interpreted as the effective channel gain of the target user, and it is directly proportional to the effective SINR.

Similarly, the effective SINR of the MRT and AST are

$$\gamma_{MRT} = \frac{P\left\|\boldsymbol{h}_0^{0}\right\|^2}{\sigma^2 + \sigma_{MRT}^2} = \frac{P}{\sigma^2}\delta_{MRT} \tag{6.10}$$

$$\gamma_{AST} = \frac{P \max\left(\left|\boldsymbol{h}_0^0\right|\right)^2}{\sigma^2 + \sigma_{AST}^2} = \frac{P}{\sigma^2}\delta_{AST} \tag{6.11}$$

where $\max\left|h_0^0\right|$ represents the largest absolute value of entries in the vector $\boldsymbol{h}_0^0$, and where we have defined

$$\delta_{MRT} = \frac{\left\|\boldsymbol{h}_0^0\right\|^2}{1 + \sigma_{MRT}^2/\sigma^2}, \quad \sigma_{MRT}^2 = \mathbb{E}[P\sum_{k=1}^{K}\left|\boldsymbol{h}_k^0\boldsymbol{w}_k\right|^2] \tag{6.12}$$

$$\delta_{AST} = \frac{\max\left(\left|\boldsymbol{h}_0^0\right|\right)^2}{1 + \sigma_{AST}^2/\sigma^2}, \quad \sigma_{AST}^2 = \mathbb{E}[P\sum_{k=1}^{K}\left|\boldsymbol{h}_{k,i}^0\right|^2] \tag{6.13}$$

from (6.12) and (6.13), we know that the effective channel gain δ_{MRT} and δ_{AST} is decreased by incorporating interference in the denominator.

Ergodic Capacity

The ergodic capacity of an interference-limited frequency flat-fading MIMO channel at a given location in cell 0 can be written as [60]

$$C = \mathbb{E}\left[\log_2 \frac{\det(\sigma^2\boldsymbol{I}_M + \boldsymbol{H}_0\boldsymbol{R}_0\boldsymbol{H}_0^* + \boldsymbol{H}_I\boldsymbol{R}_I\boldsymbol{H}_I^*)}{\det(\sigma^2\boldsymbol{I}_M + \boldsymbol{H}_I\boldsymbol{R}_I\boldsymbol{H}_I^*)}\right] \tag{6.14}$$

where the covariance of the transmitting signal in cell k is $\boldsymbol{R}_k = \mathbb{E}[x_k x_k^*]$. $\boldsymbol{H}_I$ is the channel gain matrix from the adjacent K cells to the target user. Substituting (6.5) and (6.6) into (6.14), we find that the ergodic capacity of the CBT is reduces to

$$C_{CBT} = \mathbb{E}\left[\log_2(1 + \frac{P}{\sigma^2\left\|\boldsymbol{h}_0^\dagger\right\|^2})\right] \tag{6.15}$$

In the case of only one receiving antenna, we can see the equivalent form of (6.15) is simply $C_{CBT} = \mathbb{E}[\log_2(1+\gamma_{CBT})]$. Therefore, the derivation for this matrix channel is a generalization of the channel denoted in (6.1), and the ergodic capacities of the MRT and AST are respectively given by

$$C_{MRT} = \mathbb{E}\left[\log_2(1 + \gamma_{MRT})\right] \tag{6.16}$$

$$C_{AST} = \mathbb{E}\left[\log_2(1 + \gamma_{AST})\right] \tag{6.17}$$

Approximate Comparison

Some coarse results based on the analysis above represent here. So far, having the close-form solution of our algorithm, we intuitively would like to do some qualitative assessment.

Firstly, assuming in C-MIMO systems, we can have $\mathbb{E}[\delta_{MRT}] > \mathbb{E}[\delta_{AST}]$, which means the MRT outperforms AST algorithm in C-MIMO systems, whereas $\delta_{MRT} < \delta_{AST}$in D-MIMO systems, showing that AST performs better than MRT in distributed scenario. Meanwhile, our above analysis confirms the results presented in [52], which were gotten by another approach and simulation.

Secondly, according to (6.12) (6.13), the effective channel gain $\delta_{MRT}\delta_{AST}$ is more likely smaller than δ_{CBT} . It obviously knows that CBT is superior to MRT and AST at certain locations in the D-MIMO systems. To have a better understanding of the performance comparison among the three algorithms, in next section, we describe the results of numerical simulations investigating how much gain can be obtained.

Practical Issues

In the above, we analyzed only the target user in the center cell; actually, every cell shares all of the users' CSI with adjacent cells. This implies that the cell of interest can perform CBT for any of its users and suppress interference to the co-channel users in adjacent cells.

For the sake of simplicity of analysis, we assume BS perform CBT algorithm to all the users, which cause the adjacent BSs exchange large amount of users CSI. Even the CBT require only the channel gain $\boldsymbol{h}$ information, the cell of interest should collect all the users CSI from adjacent cells. So much amount of information will be a heavy burden for the network. We may notice that the edge users are much more sensitive to the interference than the users close to the AEs. Considering this, as a more practical scenario, therefore, the neighboring cells only share the edge users CSI with each other, and perform CBT to the chosen users according to a scheduling approach, in order to save much of network and processing resources while incurring only a negligible performance loss in the inner cell. The scheduling scheme is out of the scope of this paper, though, we shall assume that CBT is performed for all users.

6.4 Numerical Results

The previous section gives analytical performance results and makes approximate comparisons. In this section, we seek a more complete understanding by analyzing the results of extensive Monte-Carlo simulations of a 7-cell model with universal frequency reuse. At present, we have not taken the location of AEs into consideration; however, the study in [28] shows that uniformly deployed AEs provide nearly the same performance as regularly spaced AEs, in the aspect of the whole network. Without loss of generality, we can consider a (7, 1, 6) configuration, with 6 AEs evenly space on a circle with a radius of 2/3 cell and one AE located at central of the cell, which is illustrated in Fig. 6.2. Each cell transmitted at a total power of 43 dBm over a Rayleigh flat-fading channel with a path-loss exponent $\alpha = 3.76$ and lognormal shadow fading standard deviation σ_s=8 dB, as suggested in [61].

Firstly, we try to evaluate the receiving signal qualities based on the three

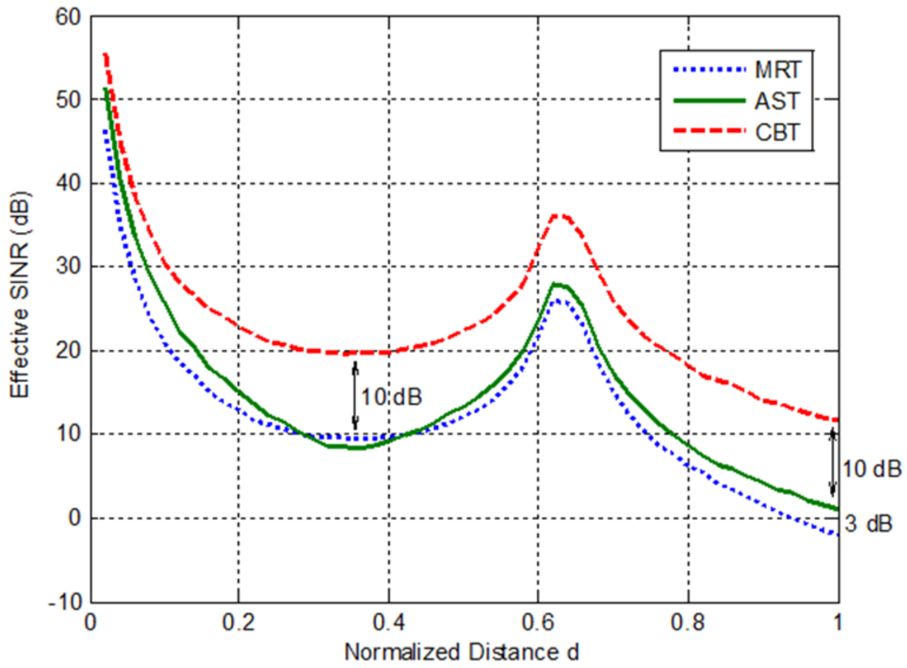

Figure 6.3: Effective SINR versus normalized distance

algorithms. We uniformly distribute target user based on the distance from cell 0's center (referred to as normalized distance d=0) to its edge (referred to as normalized distance d=1) with co-channel user randomly located in adjacent cells. The simulator generated complex random variables with zero mean and unit variance for the Rayleigh fading and calculated the path loss for the given location of the user to simulate the channel in (6.1) and (6.5). We calculate the mean value of effective SINR from 10000 realizations of the channel. Figure 6.3 shows that the target user effective SINR varies with the distance from the cell center. Clearly, AST algorithm achieves a small gain over the MRT algorithm at most locations and obtains the largest gain (about 3 dB) at the cell edge; while proposed CBT algorithm outperforms both of them and obtains a higher SINR gain, at most about 10 dB, at the cell

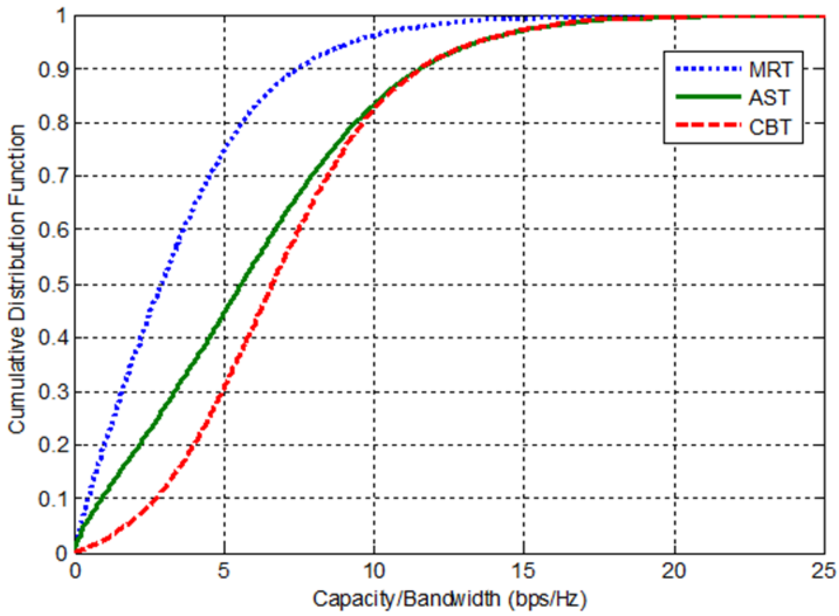

Figure 6.4: Cumulative distribution function of capacity

edge and the spots in the middle of the two AEs. Moreover, CBT algorithm confers a high SINR over the entire cell. Most locations are more than 20 dB, and the edge area, where MRT performance drops below 0 dB and AST is less than 3 dB, is more than 10 dB. The edge users can sustain more high date rate through CBT algorithm performing.

To demonstrate the overall performance, users were uniformly distributed at every location one by one within cell 0, and the ergodic capacity was calculated from 1000 sample averages at each location. As in the previous simulation setup, the co-channel users in adjacent cells were randomly chosen. Figure 6.4 shows the cumulative distribution function of ergodic capacities of uniformly distributed users in cell 0. Note that the CBT algorithm performs better than AST especially in the lower capacity region because of interference mitigation. The curve at the higher capacity region (greater than 10bps/Hz in Figure 6.4) implies that CBT and AST perform well when the user is close to the AEs, where the receiving signal is much greater than the interference. This result verifies the approximation described in the preceding section. We see that the CBT algorithm sacrifice some overhead on network to enhance a large performance gain especially for the edge users.

6.5 Summary

By regarding an $(M, 1, K)$ distributed antenna system with only one user interfered in each adjacent cell as a generalized M by $K + 1$ distributed MIMO multi-user system, our cooperative beamforming transmission scheme can provide higher capacity near the cell edge. The results of our mathematical analysis and Monte-Carlo simulation, verify that CBT achieves at most a 10 dB gain in SINR compared with other schemes, has a desirable effective SINR at the cell edge (more than 10 dB) and maintains a relatively high SINR over the whole cell (around 20 dB). In this paper, we proposed a fundamental framework to mitigate inter-cell interference in distributed MIMO systems; the next step, we will focus on the partly sharing issues including an optimal scheduling scheme to make our algorithms more practical. Therefore, distributed MIMO systems applying CBT should be able to provide a higher network capacity anywhere and better link reliability anytime.

Chapter 7

Conclusions and Future Work

This final chapter summarizes the major contributions of the dissertation and highlights numerous topics for future research.

7.1 Summary of Contributions

In this dissertation, we tried to solve three critical problems on resource allocation in MIMO-enhanced cellular network. The first problem that we solved is to support and differentiate diverse services, particularly on the quality of services (QoS) guarantee for real-time services. Traditional resource allocation algorithms in cellular networks either not considered the QoS requirements, or subjectively design utility functions for individual services. However, both of these methods are failed to incorporate the QoS into the fairness, since they neglect the completing and sharing relations between services from a system perspective. In contrast, we consider this problem based on game theory, which gives great insight into the nature of completing and cooperation relations. In consequence, we successfully formulate this resource allocation problem as a cooperative game and obtain the notion of QoS guaranteed fairness based on the well known Nash bargaining solution. The algorithm based on the QoS guaranteed fairness, can satisfied the QoS requirements for each service and still achieve the tradeoff between efficiency and fairness, which has been validated by simulations in the end of Chapter 3. Moreover, this work also provides a theoretical framework that paves the way to solve resource allocation problem in other similar scenarios.

Based on the demand for high spectral efficiency and cost-effectiveness in cellular networks, universal frequency reuse is usually required for future cellular networks, which means a high inter-cell interference (ICI) level. However, SDMA and other spatial multiplexing transmissions, whose principle merit on dramatic improvement in spectral efficiency, lose much of their effectiveness in high levels of interference. Fortunately, the advancement of MIMO techniques such as cooperative transmission, especially between the base stations (BS) in cellular context, has emerged as one of the most promising techniques to mitigate inter-cell interference (ICI) and thus improve the total system throughput. In order to exploit the extra wireless resource provided by inter-cell cooperation, we proposed a cooperative resource allocation algorithm in Chapter 4, aiming to ICI mitigation and efficient utilization of the wireless resources. Based on the game theoretic analysis, the proposed algorithm achieves the Pareto optimal and fulfills the fundamental tradeoff of efficiency and fairness. Due to the prohibitive computational complexity, we also developed a heuristic algorithm and compared with the benchmark that regarded as a Nash equilibrium outcome in a non-cooperative scenario. The simulation results and analysis are given in the end of Chapter 4 as well.

I also investigated the distributed antenna scenarios in both Chapter 5 and 6 that have a topology of distributed antennas for the BS at each cell. The intuitive advantages of this architecture are better signal coverage and lower power consumption. However, We expect to further exploit other advantages since resource allocation with distributed antennas is more flexible in cooperation and optimization than that in traditional architectures. In Chapter 5, I proposed two energy-efficient resource allocation algorithms, based on beamforming transmission and selection transmission, respectively. the simulation results shows that both algorithms have a higher energy efficiency that conventional algorithms, and the selection transmission outperforms the beamforming transmission algorithm in terms of energy efficiency and complexity. The ICI problem in distributed antenna architecture is also investigated in Chaper 6. I proposed a cooperative beamforming algorithm that mitigates ICI and achieves a higher system capacity. A comparison and analysis of performance between a scenario with co-located antennas and that with distributed antennas are given, which clearly demonstrate the advantages of the architecture with distributed antennas.

In summary, we investigated some cooperation problems on resource allocation in the multiple antennas cellular networks. We proposed a game theoretic framework to guarantee QoS for diverse services, developed cooperative resource allocation both optimal and heuristic to solve interference problem and improve system throughput among cells, and finally investigate a promising architecture with distributed antennas at BS that achieves better performance than traditional cellular architecture.

7.2 Future Work

Although resource allocation is a concept with a long history, it always has new form and new requirements along with the advance of other techniques for cellular networks, particularly, the link techniques. As the first chapter described, this dissertation has studied a part of problem in the resource allocation in MIMO-enhanced cellular networks, however, as far as we know, there are several issues remained for further investigation.

First of all, Chapter 3 introduced a cooperative resource allocation with QoS guarantee is mainly focused on the real-time services. Although it can also incorporate the best-effort traffic, but in practical, cellular operators prefer to use some kind of priority mechanism to distinguish users, since there might be different subscription plan for the users. Furthermore, in this study, we only investigate the most important delay parameter for real-time services. However, there are other important QoS parameters such as minimum data rate should be considered. This needs to further explore the characteristic of traffic.

Second, in the multi-cell BS cooperative resource allocation, every interfered user needs the interfering BS one nulling beams. Some recent work pointed out that if we align all the interfered users in adjacent cells, the interfering BS will only need one nulling beam to mitigate all the interference to adjacent cells, which will save a lot of antenna resources to allocate to its own users. The resource allocation for interference alignment has great potential to fully use all the freedom degree of multi-cell cooperation.

Last but not least, since the new architecture of distributed antennas totally changed the signal distribution of the traditional cellular cell. this emerging topology provides great potential to be further investigated.

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