Thesis for the degree of Doctor of Philosophy

Downlink Resource Allocation in Cooperative Wireless Networks

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To my parents and Gongpei

Abstract

Wireless cooperative networks, which are based on exploiting coordination among multiple access nodes, has been considered as a promising approach to improve the spectral efficiency, reduce the energy consumption, and extend the network coverage of future wireless communication systems. In practice, the actual benefit of multi-node cooperation is affected by a variety of factors, including the quality of channel state information (CSI), the constraints on the feedback and backhaul links, hardware impairments, resource allocation and data processing schemes. This thesis investigates the design of resource allocation algorithms and the performance of different coordinated transmission schemes for downlink wireless cooperative systems under practical constraints.

First, we consider multi-node cooperation in homogeneous cooperative networks. In [Paper A], a power allocation scheme is proposed for a worst case scenario, where the carrier phases between base stations (BSs) are un-synchronized so that joint transmission must be performed without precoding. We show that in this scenario, joint transmission happens with higher probability when the maximum transmit power is high, or the users are in the overlapped cell-edge area. In practice, the network is divided into clusters of coordinated BSs, and the cooperation gain is limited by the inter-cluster interference. In [Paper B], different fractional frequency reuse schemes are proposed to coordinate inter-cluster interference. Simulation results show that the proposed schemes can efficiently reduce the inter-cluster interference and provide considerable performance improvement in terms of both the cell-edge and cell-average user data rate. [Paper C] compares different coordinated transmission schemes, considering the effects of the feedback and backhaul latency. Compared to zero-forcing coherent joint transmission, we show that non-coherent joint transmission and coordinated scheduling are more robust to channel uncertainty.

The second part of the thesis focuses on heterogeneous cooperative networks. In [Paper D], we analyze the performance of amplify-and-forward two-way relaying with in-phase and quadrature-phase imbalance (IQI) at the relay node. Different design guidelines and power allocation schemes are proposed to improve the system reliability under a total transmit power constraint. [Paper E] investigates adaptive power allocation for hybrid automatic repeat request based relay networks. Our results demonstrate that depending on the relay positions and the total power budget, the system should switch between the single-node transmission mode and the joint transmission mode, in order to minimize the outage probability. Finally, [Paper F] studies the joint design of precoding and load balancing for energy-efficient small cell networks with imperfect CSI. An optimal BS association condition is parameterized, which reveals how it is impacted by different system parameters. Our results also show that putting BSs into sleep mode by proper load balancing is an important solution for energy savings in heterogeneous networks.

Keywords: Coordinated multi-point transmission, fractional frequency reuse, imperfect channel state information, imperfect synchronization, I/Q imbalance, load balancing, precoding design, relaying, resource allocation.

List of Included Publications

This thesis is based on the following appended papers:

[A] J. Li, T. Eriksson, T. Svensson, and C. Botella, "Power Allocation for Two-cell Two-user Joint Transmission," *IEEE Commun. Letters*, vol. 16, no. 9, pp. 1474-1477, 2012.

[B] J. Li, C. Botella, and T. Svensson, "Resource Allocation for Clustered Network MIMO OFDMA Systems," *EURASIP J. Wireless Comm. and Netw.*, vol. 2012, 2012.

[C] J. Li, A. Papadogiannis, R. Apelfröjd, T. Svensson, and M. Sternad, "Performance Evaluation of Coordinated Multi-Point Transmission Schemes with Predicted CSI," in *Proc. IEEE PIMRC'12*, Sydney, Australia, Sept. 2012.

[D] J. Li, M. Matthaiou, and T. Svensson, "I/Q Imbalance in Two-Way AF Relaying," *IEEE Trans. Commun.*, vol. 62, no. 7, pp. 2271-2285, Jul. 2014.

[E] J. Li, B. Makki, and T. Svensson, "Performance Analysis and Cooperation Mode Switch in HARQ-based Relaying," in *Proc. IEEE GLOBECOM workshop*, Austin, Texas, USA, Dec. 2014.

[F] J. Li, Emil Björnson, Tommy Svensson, Thomas Eriksson, and Mérouane Debbah, "Joint Precoding and Load Balancing Optimization for Energy-Efficient Heterogeneous Networks," submitted to *IEEE Trans. Wireless Commun.*, Sep. 2014.

List of Additional Related Publications

Publications by the author not included in this thesis:

[J1] **J. Li**, M. Matthaiou, and T. Svensson, "I/Q imbalance in AF dual-hop relaying: Performance analysis in Nakagami-m fading," *IEEE Trans. Commun.*, vol. 62, no. 3, pp. 836-847, Mar. 2014.

[J2] **J. Li**, X. Xu, X. Chen, X. Tao, T. Svensson, and C. Botella, "Downlink radio resource allocation for coordinated cellular OFDMA networks," *IEICE Transactions on Communications*, vol. E93.B, no. 12, pp. 3480-3488, 2010.

[J3] Z. Mayer, **J. Li**, A. Papadogiannis, and T. Svensson, "On the impact of control channel reliability on coordinated multi-point systems," *EURASIP Journal on Wireless Communications and Networking 2014,* 2014:28.

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[C1] **J. Li**, Emil Björnson, Tommy Svensson, Thomas Eriksson, and Mérouane Debbah, "Optimal design of energy-efficient HetNets: Joint precoding and load balancing," in *Proc. IEEE ICC'15*, London, UK, June 2015.

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[C4] **J. Li**, M. Matthaiou, and T. Svensson, "I/Q imbalance in two-way AF relaying: Power allocation and performance analysis," in *Proc. IEEE ICC'14*, Sydney, Australia, June 2014.

[C5] **J. Li**, B. Makki, T. Svensson, and T. Eriksson, "Power allocation for multi-point joint transmission with different node activeness," in *Proc. IEEE WCNC'13*, Shanghai, China, April 2013.

[C6] **J. Li**, X. Chen, C. Botella, T. Svensson and T. Eriksson, "Resource allocation for OFDMA systems with multi-cell joint transmission," in *Proc. IEEE SPAWC'12*, éme, Turkey, June 2012.

[C7] **J. Li**, T. Svensson, C. Botella, T. Eriksson, X. Xu, and X. Chen, "Joint scheduling and power control in coordinated multi-point clusters," in *Proc. IEEE VTC'11*, San Francisco, USA, Sept. 2011.

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[C9] Y. Hong, X. Xu, M. Tao, **J. Li**, and Tommy Svensson, "Cross-tier handover analyses in small cell networks: A stochastic geometry approach," in *Proc. IEEE ICC'15*, London, UK, June 2015.

[C10] Z. Mayer, **J. Li**, A. Papadogiannis, and T. Svensson,"On the Impact of Backhaul Channel Reliability on Cooperative Wireless Networks," in *Proc. IEEE ICC'13*, Budapest, Hungary, June 2013.

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Contents

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Acronyms

ABS:	Almost blank subframe
3GPP:	3rd Generation Partnership Project
BBU:	Baseband unit
bps:	bit per second
BS:	Base station
CoMP:	Coordinated multi-point
CRS:	common reference signals
CSI:	Channel state information
CSIT:	Channel state information at the transmitter
CU:	Control unit
eICIC:	Enhanced inter-cell interference coordination
FDD:	Frequency division duplex
FeICIC:	Further enhanced inter-cell interference coordination
HARQ:	Hybrid automatic repeat request
ICI:	Inter-cell interference
ICIC:	Inter-cell interference coordination
IQI:	In-phase and quadrature-phase imbalance
KKT:	Karush-Kuhn-Tucker
LTE:	Long term evolution
LoS:	Line-of-sight
MIMO:	Multiple input multiple output
OFDMA:	Orthogonal frequency division multiple access
PDCCH:	Physical downlink control channel
PDSCH:	Physical downlink shared channel
PSS:	primary synchronization signals

QoS:	Quality of service
RF:	Radio frequency
RRH:	Remote radio head
SFR:	Soft frequency reuse
SINR:	Signal to interference plus noise ratio
SSS:	Secondary synchronization signals
TDD:	Time division duplex
ZF:	Zero-forcing

Part I

Overview

Chapter 1

Introduction

Over the past few decades, wireless communication has played an important role as a way to let people get and share information with each other anywhere and anytime. Studies have shown that the data traffic in wireless communication networks continues to grow at an impressive rate, mainly driven by the uptake of smart devices and applications. Based on extrapolations from Ericsson [1] and Cisco [2], it is possible to conclude that beyond 2020, wireless communication systems will have to support more than 1,000 times todays traffic volume.

The raised user expectations of quality of service (QoS) as well as the rapid growth of the data traffic impose very different requirements on future wireless communication networks, such as higher system throughput and spectral efficiency, sufficient data rate and speed to run apps with an affordable price. At the same time, the network also needs to provide a homogeneous QoS distribution over the communication area in order to guarantee fairness among the users independent of their locations [3, 4]. Moreover, energy efficiency also becomes one of the important key performance indicators for the design of future wireless communication systems, in order to achieve a low cost and green networked society.

In traditional multi-cell communication networks, system spectral efficiency is mainly limited by inter-cell interference (ICI), which is caused by the transmission from other cells on the same time-frequency resource block [5]. The presence of ICI especially degrades the performance and affects the experience of the users located in the cell-edge areas. This is because that the cell-edge users typically receive weak desired signals from their connected cell, while suffering strong interference from neighboring cells.

Under current macro-cell network deployment, one of the promising approaches for combating ICI is to introduce coordination between base stations (BSs). In the 3rd generation partnership project (3GPP) long term evolution (LTE) systems, inter-BS signaling can be accomplished over the X2 interface between BSs. Hence, inter-cell interference coordination or avoidance was proposed as a key technique to deal with the ICI issue [3, 6]. The common theme of inter-cell interference coordination or avoidance in LTE is to apply restrictions to the time or frequency or power resources available in a cell in a coordinated way. Such restrictions provide improvement in the ratio of the desired received signal power over interference and noise power on the corresponding resource blocks in the neighboring cells. Consequently, the cell-edge data rates and the cell coverage can be improved. However, it should be pointed out that the ICI is reduced at the expense of the available resources that can be scheduled in each cell, leading to a degradation in the system peak or sum throughput. Instead of coordinating ICI by restricting how radio resources are used in each cell, multi-cell advanced coordination and joint transmission can be used as a more proactive way to handle the ICI issue with much tighter multi-BS cooperations [7, 8]. The technology component "Coordinated multi-point (CoMP) transmission/reception", which has the same basic principles, is considered in 3GPP LTE-Advanced [9]. Based on the channel state information (CSI) and/or the user data shared via backhaul links between multiple transmission nodes, CoMP operation performs dynamic coordination among multiple BSs. Depending on the levels of multi-BS cooperation, CoMP techniques can either coordinate or exploit the interference in order to improve the coverage of high data rates, the cell-edge throughput, as well as the system throughput.

Besides further enhancing the performance of existing homogeneous macro-cell networks, new heterogeneous deployment scenarios, such as relay-assisted networks and dense small-cell networks, have also been considered for future wireless communication networks to address the challenge of being able to provide very high data rate in specific scenarios, e.g., in shopping malls, in dense urban environments, or big events in stadiums [10–12]. Future heterogeneous dense networks will consist of low-cost and low-power access nodes, being densely deployed and coexisting with the traditional macro BSs. By creating a large number of small cells, these low-power access nodes have the potential to offload traffic from macro BSs, reduce the average distance between users and transmitters, and thereby improving the data rates and/or reducing the transmit power. In order to fully exploit the benefits offered by all these low-power nodes, a mechanism to efficiently coordinate their transmissions will be needed. Different from traditional homogeneous macro-cell networks, the densely deployed access nodes will be heterogeneous in the number of antennas, transmit power, backhaul capacity and reliability, and coverage area, etc. Moreover, the CSI at each BS is highly likely to be different and imperfect. All these heterogeneous properties make the multi-node coordination and ICI mitigation more challenging.

In an ideal and global cooperative system, where the CSI and the data of all users are perfectly shared between all transmission nodes, all the communication links can be exploited to provide joint data transmission to all users. The ICI can be completely eliminated, and hence the system throughput as well as cell-edge data rates can be significantly improved [7]. However, implementing multi-node cooperation in practical wireless communication systems faces some major challenges. Firstly, multi-node cooperation may require large amount of CSI and control signaling overhead placed on the over-the-air feedback links and the backhaul links between transmission nodes. Secondly, the quality of feedback and backhaul links in terms of capacity, latency and reliability cannot be granted. Therefore, information sharing between multiple transmission nodes can introduce errors and delays, and thereby affecting the transmission decisions made at the network side. Thirdly, in practice, most communication systems suffer from hardware impairments, e.g., phase noise, power amplifier nonlinearities, and in-phase and quadrature-phase imbalance (IQI), etc. Moreover, synchronization errors between multiple BSs can significantly impair the effectiveness of the most advanced coordinated transmission techniques. Heterogeneous wireless networks can be more prone to hardware impairments, since the hardware of the low-cost access nodes is most likely to be of low quality compared to the macro BSs. Without careful compensation, these hardware impairments can result in significant performance degradation. Finally, the involved large number of transmission nodes and users, as well as the increased spatial degrees of freedom, make the radio resource management that performs scheduling, power control and precoding design more difficult in a cooperative system to achieve the promising cooperation gain.

Motivated by the above discussion, in this thesis, we investigate different multi-node cooperative techniques in the downlink of realistic wireless communication networks. The aim is to study the performance of different multi-node coordinated transmission schemes under the real-world impairments, and to develop efficient radio resource allocation algorithms for overcoming these limitations. In particular, the consequences of imperfect BS synchronization on multi-node joint transmission, the impact of IQI on relaying-assisted transmission, and the impact of imperfect CSI on the design of energy-efficient heterogeneous networks are studied. In addition, practical and efficient resource allocation algorithms are proposed to overcome the impact of these impairments, and to reduce the network overhead and the complexity for different cooperation schemes.

The thesis is organized as follows. Chapter 2 gives a brief introduction of cooperative wireless networks, where different cooperative scenarios, different multi-node coordination strategies, and the associated challenges for practical implementations are discussed. Chapter 3 presents the system model considered for the downlink multi-node joint transmission, and illustrates a general way to formulate and solve different radio resource optimization problems. Finally, in Chapter 4, we summarize the contributions of the thesis. The future work are also presented in this chapter.

Chapter 2

Cooperative Wireless Networks

In traditional wireless communication systems as shown in Fig. 2.1, each macro BS transmits desired signals only to users within its coverage area, namely a cell. For each user, the signals received from other cells on the same time-frequency resource will be treated as interference. The presence of ICI limits the system throughput, and it especially degrades the performance and affects the experience of the users located in the cell-edge areas, e.g., UE1 in Fig. 2.1.

In cooperative wireless systems, a user's communication link is enhanced in a cooperative way or in a supportive way by other transmission nodes, e.g., neighbouring macro BSs, relay nodes, small cell BSs, and nearby users. These cooperative nodes either contribute to making decisions on scheduling/beamforming/power control in the time-frequency resource, or directly participate in data transmission. Compared to the traditional wireless communication systems, a properly designed cooperative communication system has the potential to improve the system capacity and reliability, reduce the energy consumption, and expand the network coverage.

This chapter gives a brief introduction of cooperative wireless networks. In particular, different cooperative scenarios, cooperative transmission schemes, and the associated challenges posed by practical constraints are discussed.

2.1 Cooperative Scenarios

Depending on what and how the transmission nodes are deployed, cooperative wireless networks can be divided into two categories, i.e., homogeneous cooperative networks and heterogeneous cooperative networks.

2.1.1 Homogeneous Cooperative Networks

In homogeneous cooperative networks, the multiple geographically separated transmission nodes are typically within the same type; that is all transmission nodes have the similar transmit power levels, antenna patterns, receiver noise floors and backhaul connectivity, etc. Fig. 2.2 illustrates an example of the downlink of a multi-cell cooperative system, where all macro BSs are inter-connected via wired backhaul links for information sharing. If infinite cooperation between the BSs is enabled (i.e., with ideal feedback, backhaul and synchronization), the system is effectively a network multiple-input-multiple-output (MIMO) broadcast channel, where all communication links, including the interfering ones,

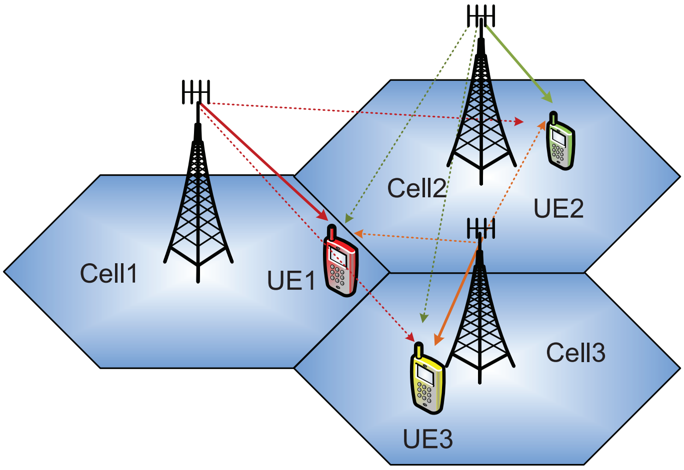

Figure 2.1: Illustrations of a traditional cellular system. The solid lines represent the useful signals, while the dashed lines denote the interference signals.

can be exploited to coherently transmit user data via joint processing of information. Therefore, the ICI can be completely eliminated, and the system throughput as well as cell-edge data rates can be significantly improved [7, 8, 13].

2.1.2 Heterogeneous Cooperative Networks

A heterogeneous cooperative network may include a number of low-cost low-power access nodes which are deployed to coexist with the traditional macro BSs. A low-power node refers to a node whose transmit power is lower than macro BS classes. There are various types of low-power nodes including relay nodes, micro BSs, Pico BSs or femto BSs (also called home eNBs). These access nodes create multiple tiers of the network and differ in terms of the number of antennas, transmit power, backhaul reliability and coverage area, etc. The low-power nodes have the potential to offload traffic from macro BSs, bring the transmitter closer to the users, and thereby improving spectral efficiency per unit area and providing a uniform QoS experience to users anywhere in the network. Two most commonly considered heterogeneous cooperative networks are relay-assisted networks and small-cell networks.

A Relay-assisted network can be considered as a two-tier heterogeneous network, consisting of two types of transmission nodes, i.e., source nodes (e.g., macro BSs) and relay nodes. In such a heterogeneous network, if a communication cannot be established between a source and a destination due to severe fading, a third party device (i.e., the relay node) that receives the information from the transmitter can help forward the information via a relaying channel that is independent from the source-to-destination link. Moreover, by processing and retransmitting the received signals from the source to the destination, relay nodes have the potential to extend the coverage area, improve system reliability and the link-level performance. Relay-assisted networks do not need wired connection between the transmission nodes, and thereby reducing operators' backhaul cost. However, relaying techniques do little to increase the performance of the users placed in severe ICI-dominated areas, such as the cell-edge areas of current cellular networks [8].

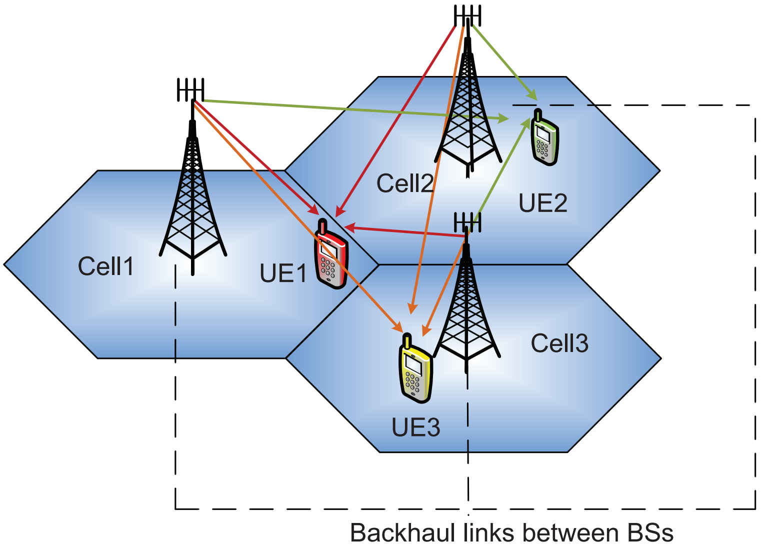

Figure 2.2: Illustrations of a homogeneous cooperative system with multi-cell joint transmission.

Small-cell networks can be referred to as multi-tier heterogeneous networks, with different low-cost low-power access nodes deployed in the presence of an overlaid macro cellular network. The macro cells provide wide coverage, while the low-power nodes are deployed in a more targeted manner to offload traffic from macro BSs, or to alleviate coverage dead zones, or to improve the data rate in hot spot areas [15, 16]. The macro cells and the small cells may share the same spectrum (a co-channel deployment), or different frequency bands could be assigned for the macro layer and small cell layers. The backhaul links between macro and small cells, as well as between small cells can be different. For example, the macro and small cells can be connected via very high throughput and low latency backhaul such as dedicated point-to-point optical fiber, while the small cell nodes are inter-connected via xDSL, microwave or wireless self-backhauling. The small cell nodes can be deployed indoors or outdoors, and in either case they could provide service to indoor or outdoor users. Depending on the scenarios, the deployment of small cell nodes can be either sparse or dense. For the indoor or outdoor hot spots, a few low-power nodes could be sparsely deployed to cover the areas. On the other hand, for the dense urban area or large shopping malls, a large number of small cell nodes needs to be densely deployed to boost the capacity and support large traffic over a relatively wide area. Fig. 2.3 illustrates an example of the downlink of a small cell network, where all BSs are deployed outdoors and sharing the same spectrum.

2.2 Cooperative techniques

In order to achieve the promising cooperation gain in terms of the spectral efficiency, cell-edge data rate, system reliability and potentially the energy efficiency, cooperative schemes need to be properly designed and selected for different scenarios. This section introduces some key technical components that have been widely considered in cooperative

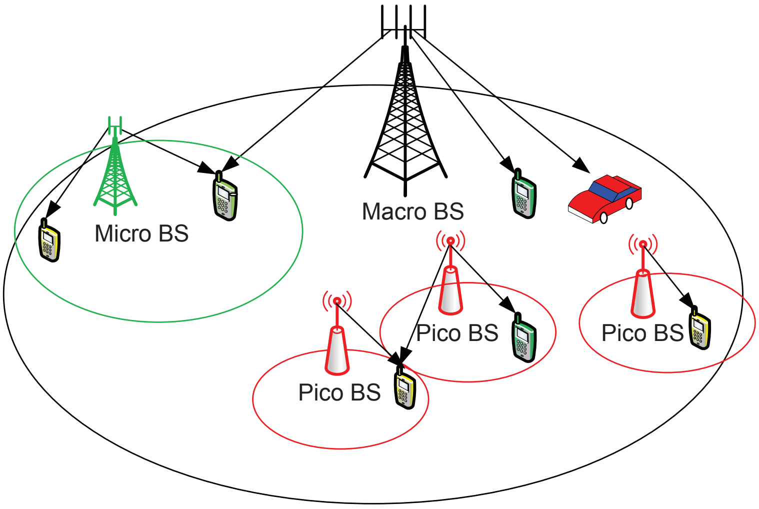

Figure 2.3: Illustration of a downlink small cell network consisting of macro, micro and pico BSs.

wireless networks.

2.2.1 Inter-Cell Interference Coordination

Traditional techniques for combating ICI have focused on either allocating orthogonal radio resources to different transmit signals, for example, frequency reuse, cell sectoring, or canceling interference via signal processing [5, 6]. These interference mitigation approaches can be characterized as passive. In the 3rd generation partnership project (3GPP) long term evolution (LTE) systems, inter-BS signaling can be accomplished over the X2 interface between BSs. Hence, inter-cell interference coordination (ICIC) was proposed in LTE Release 8 as a key technique to deal with the ICI issue between neighboring macro BSs in a proactive way [3]. ICIC is a power and frequency domain interference coordination scheme. In particular, it restricts the available frequency resources of different cells through a predefined frequency reuse rule or through appropriate power control. Fig. 2.4 shows a classic ICIC approach, named as soft frequency reuse (SFR) [17]. In the SFR scheme, the spectrum in each cell are divided into two sets, i.e., major sub-band and minor sub-band. Normally, the maximum allowed transmit power for major sub-band is higher than that of the minor sub-band. The major sub-band (high-power sub-band) can be used to cover the whole cell area, while the minor sub-band (low-power sub-band) is used only in cell-center area. Major sub-bands in the neighboring cells are non-overlapping. Therefore, for a user located at the cell-edge area, the received ICI comes only from the low-power sub-band in the neighboring cells. This provides improvement in the ratio of the desired received signal power over interference and noise power (SINR). Consequently, the cell-edge data rates and the cell coverage can be improved. However, it should be pointed out that the SINR for the cell-edge users is improved at the expense of degrading SINR for the cell-center users, which will result in a degradation in the system peak or sum throughput.

In heterogeneous networks, different types of cells are randomly deployed and over-

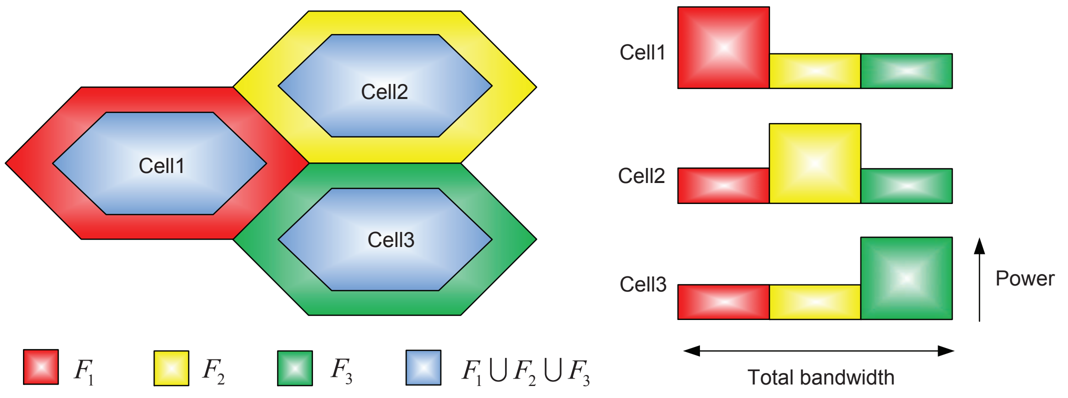

Figure 2.4: An example of soft frequency reuse (SFR).

lapping in many scenarios. Having a highly heterogeneous network topology makes it more difficult to control and coordinate the ICI in co-channel deployed scenarios. The power and frequency domain based ICIC strategy can effectively reduce the ICI on data channels between macro BSs, however, it cannot mitigate the ICI on control channels. This is because for downlink data transmission, each subframe consists of two parts: one is used for control channel (physical downlink control channel (PDCCH)) and the other is for data channel (physical downlink shared channel(PDSCH)). The data channels are used for transmitting user data, while the control channels are used for delivering the resource allocation information and other signalling information. ICIC can assign different frequency sub-bands to cell-edge users only for data channels. The control channels have to be distributed over the entire frequency bandwidth. This causes ICI on the control channels of neighboring cells. ICI on control channels is not a big issue in homogeneous networks, since all BSs's transmit power are at the same level. However, in heterogeneous networks, there is a large difference in transmission power between macro BSs and low-power nodes. Therefore, control channels of small cells can be significantly interfered by the macro cells, resulting in ineffective ICIC on the data channels.

To cope with the above problem, enhanced inter-cell interference coordination (eICIC) was introduced in Release 10 to reduce ICI on both data and control channels in co-channel deployed heterogeneous networks [11, 16, 18, 19]. Compared to ICIC, in addition to coordinate the ICI in power and frequency domain, eICIC introduces a new concept of almost blank subframe (ABS) to coordinate ICI in the time domain. ABS subframes do not transmit any power on the data channels and carry only some necessary control signals, including common reference signals (CRS), primary and secondary synchronization signals (PSS and SSS), paging information, etc.) with low power. eICIC configures ABS subframes in the interfering macro BS. By sharing this ABS pattern information between the macro BSs and small cell access nodes over X2 interface, the interfered small cells can perform data transmission to their users during these ABS subframes. In this way, the ICI is effectively coordinated by assigning different subframes to different types of cells. To further reduce the ICI, enhanced receivers can perform interference cancellation of the residual control signals transmitted by macro cells in ABS subframes. This technique is named as further enhanced ICIC (FeICIC) in LTE Release 11 [20, 21].

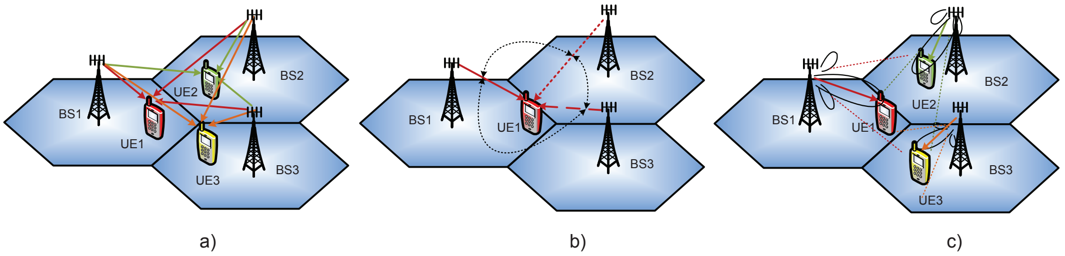

Figure 2.5: Illustrations of different downlink CoMP transmission schemes: a) joint transmission, b) dynamic point selection/muting, c) coordinated scheduling/beamforming.

2.2.2 Multi-Node Cooperative Transmission

Instead of coordinating ICI by restricting how radio resources are used in each cell, multi-cell advanced coordination and joint transmission can be used as a more proactive way to handle the ICI issue with much tighter multi-node cooperation. In the literature, a family of cooperative communication techniques have emerged and gained significant interest, such as "network MIMO " [6], "network coordination" [7], "multi-cell processing" [8], "multicell multiuser MIMO" [13, 22, 23], "distributed antenna systems" [24] and "group cells" [25]. In the 3GPP standard development organization, this concept is referred to as "Coordinated multi-point (CoMP) transmission/reception", which is considered as a dedicated study item in LTE-Advanced Release 11 [26] and Release 12 [27].

In 3GPP LTE-Advanced, a *CoMP cooperating set* is defined as a set of nodes that directly participate in data transmission or contribute to making decisions on scheduling/beamforming in the time-frequency resource [26]. A CoMP cooperating set typically consists of multiple geographically separated transmission nodes from either a homogeneous or a heterogeneous network. In the literature, cooperating sets are usually labeled as "CoMP cluster".

Depending on whether the user data is shared among all the transmission points within a CoMP cluster, downlink CoMP schemes can be divided into two main categories: *joint processing* and *coordinated scheduling/beamforming*.

Joint Processing

In the CoMP joint processing approach, user data is available simultaneously at all transmission points within the CoMP cluster. By sharing both the CSI and the data of all users in the cluster, coordinated multiple points can act as a single and distributed antenna array. Simultaneous joint data transmission can then be performed coherently or non-coherently to a single user or multiple users from multiple transmission points in a time-frequency resource. In this way, the ICI is mitigated as signals transmitted from other points assist the transmission rather than acting as interference. This network MIMO technique falls into one subset of joint processing, labeled as *joint transmission*, see Fig. 2.5 a).

Another subset of joint processing, which is shown in Fig. 2.5 b), is *dynamic point selection/muting*, where the data of a user is only transmitted from one of the points within the CoMP cluster in a certain time-frequency resource. However, user data is available at multiple points and the transmission/muting point may change from one subframe to another via dynamic scheduling by exploiting changes in the channel fading conditions.

Note that dynamic point selection may be combined with joint transmission, that is, multiple points can be selected for data transmission in a time-frequency resource. In this case, data to a single user can be transmitted non-coherently from the selected multiple points without phase adjustment. Even with perfect CSI available at the transmitter side, this non-coherent joint transmission scheme can not completely mitigate ICI unless the unselected points are muted. However, it might be more robust to channel uncertainty than coherent joint transmission [28].

Coordinated Scheduling/Beamforming

In the *coordinated scheduling/beamforming* approach, as shown in Fig. 2.5 c), the data symbols to a user is only available at and transmitted from one point from the CoMP cluster on a time-frequency resource. However, by sharing the CSI of all users among multiple transmission points, user scheduling and beamforming can be coordinated in order to control ICI. Note that this CoMP approach can only mitigate ICI rather than exploiting it.

2.2.3 Load Balancing

In many relevant wireless communication scenarios, e.g., in shopping malls, in dense urban environments, or during the occurrence of traffic jams, users are typically non-uniformly distributed over the network, yielding load imbalance between cells. Even with a uniform user distribution, in heterogeneous networks, large disparity in transmit power between macro BS and low-power nodes, as well as different BS capabilities can still lead to a major load imbalance problem. In particular, if the traditional user association metric is applied, i.e., each user selects the cell associated with the highest downlink received power, most of the users may connect to the macro BSs even when some small cells have no user to serve [10, 29]. As a result, some users in overloaded macro cells could be unable to get services due to lack of resources, and the advantages of deploying low-power nodes cannot be fully utilized.

Load balancing is referred to as an approach to balance the load (e.g., users, data traffic) across different cells in order to optimize the system metrics such as sum throughput, user fairness, resource utilization, energy efficiency, etc. This is usually achieved by adjusting the network control parameters in such a way that overloaded cells can offload the excess load to low-loaded adjacent cells, whenever it is available. In the following, we discuss two key techniques used for load balancing: cell range expansion and centralized optimization.

Centralized Optimization

Depending on the objectives and the practical constraints, the design of wireless communication networks can be formulated into different system-level optimization problems, where load balancing, transmission scheme and power control are coupled with each other. By solving these large optimization problems, different load balancing strategies can be obtained for optimizing different system metrics [30–38]. In general, these system-level optimization problems are combinatorial optimization problems, which are non-convex and difficult to solve. The computational complexity can grow exponentially with the number of users or the number of cells in the network. This makes it difficult to implement the designed algorithms in large-scale networks. Moreover, these proposed algorithms are typically sensitive to the changes in the networks, e.g., the deployment of access nodes, the user locations, the channel conditions, etc. Therefore, the algorithms need to rerun every time slot in order to keep track of these changes. Nevertheless, for a given system optimization problem, the obtained optimal solution can be used to serve as the upper bound for any other suboptimal load balancing solutions.

Cell Range Expansion

Biasing-based cell selection is a suboptimal but simple technique to balancing the load among high and low power BSs. Traditionally, in practical systems, cell selection is determined by the strongest received signal power. Based on this user association metric, the coverage of low-power nodes (e.g., micro or pico BSs) can be very small such that most of the users get connected to high-power nodes (e.g., macro BSs). In order to offload users from high-power nodes to low-power nodes and hence make better use of the network resources, different biasing-based cell selection schemes have been proposed, e.g., biased-received-power-based, biased-SINR-based, biased-rate-based schemes [10, 39–42]. These schemes allows users to connect to a low-power node by adding a multiplicative bias to each tier of BSs. For example, consider a network consisting of M macro BS and N pico BSs. The N pico BSs are deployed as an overlay to the macro cell layer. Let $P^{\mathrm{rx}}_{k,\mathrm{M}_i}$ be the received power from macro BS i to user k for $i = 1, \ldots M$, and $P^{\mathrm{rx}}_{k,\mathrm{P}_j}$ denotes the received power from pico BS j to user k for $j = 1, \ldots N$. Then, utilizing a biased-received-power-based load balancing strategy, the selected BS for user k will be the one that provides the maximum biased received signal power, i.e., $\arg\max_{\mathrm{M}_i,\mathrm{P}_j} \left\{ B_{\mathrm{M}} P^{\mathrm{rx}}_{k,\mathrm{M}_i}, B_{\mathrm{P}} P^{\mathrm{rx}}_{k,\mathrm{P}_j} \right\}$, where B_{M} and B_{P} are the bias for macro BSs and pico BSs, respectively. If $B_{\mathrm{M}} = 1$ and $B_{\mathrm{P}} = 10$, then a user would connect to a pico BS until its received power from a macro BS was 10dB higher than the pico BS. Biasing-based load balancing can effectively expand the coverage of low-power nodes, therefore, it is referred to as cell range expansion in 3GPP standardization work.

2.2.4 Cell On/Off

Except from the spectral efficiency and user experience, energy efficiency is also an important performance metric for the design of future green wireless networks. The global energy consumption of a network can be roughly divided into two parts: a circuit part that depends on the transceiver hardware and a dynamic part which is a function of the transmission power [43–46]. Cooperative communication networks have the potential to achieve substantial energy savings for the dynamic part. In particular, multi-node transmission can provide better energy-focusing to the desired users. Moreover, adding more low-power nodes reduces propagation losses between the users and the transmitters. Therefore, the total transmit power in cooperative networks can be effectively reduced. However, multi-node cooperation also requires extra power on feedback and backhaul information exchange. Furthermore, since more access nodes means that more hardware is required, increasing the number of small cells will thus increase the circuit power consumption, and therefore it may increase the global energy consumption.

The circuit power consumption depends on the operation mode of each access node. In general, there are three different operation modes considered for a cell, i.e., the *on*, *sleep* and *off* modes [47]. When a cell is turned *on*, it can transmit the data signals and also the control signals necessary for data transmission, such as reference signals used for measurements and demodulation. Users may be connected to and receive data transmission from the cell. In the *sleep* mode, a cell cannot send or receive any signals, and users cannot access the cell and will not receive data transmission from the cell, but the cell can be woken up by a control unit (CU) (e.g., a macro BS) though backhaul links. In the *sleep* mode, the power amplifier and the radio frequency (RF) components are deactivated. This provides significant energy savings compared to the *on* mode. For example, the circuit power consumption of a macro BS in the *sleep* mode is only 57% of the power consumption in the *on* mode [43, 44]. Note that, in the *sleep* mode, in order for enabling fast transition to the *on* mode, some hardware elements, such as the power supply and the baseband processing components, are not switched off. In order to further reduce the energy consumption, a cell can be put into the *off* mode, in which the cell is completely deactivated. However, with current technology, the transition time from the *off* to the *on* mode is non-negligible.

Since the circuit power consumption under the *sleep* or *off* mode is much lower compared to the one under the *on* mode, the increase in the circuit part from the extra power consumed by activating BSs clearly outweighs the decrease in the dynamic part. Therefore, putting a BS into the *sleep* or *off* mode by proper coordination strategies is an important solution for energy savings, especially for dense cooperative network scenarios or when the network traffic is low. Note that cell on/off may also provide benefits for interference avoidance and coordination [48–50]. In particular, a network may turn off certain cells to reduce ICI, especially the interference caused by common channel transmissions such as CRS in heterogeneous networks.

2.2.5 Cell Clustering

In practice, the cooperation area is limited by the feedback, backhaul, synchronization, and complexity constraints in a real system deployment. Thus, the network is typically divided into clusters of coordinated access point so that cooperative transmission can be independently implemented within each cluster. The cluster formation becomes an important issue that affects the cooperation performance.

There are various ways to divide the network into different cooperation clusters. Based on the cluster reconfiguration time scale, the cluster formation can be characterized into two categories:

- Static clustering, which specifies a predefined set of disjoint clusters of cells that does not change in time or changes over a very long time scale (e.g., based on traffic statistics) [51–53]. The static cluster formation is easily implementable, and it requires very limited inter-cluster information exchange.

- Dynamic clustering, where the clusters are formed based on the varying channel conditions of the users [54, 55] or uneven traffic load of the system [56]. With

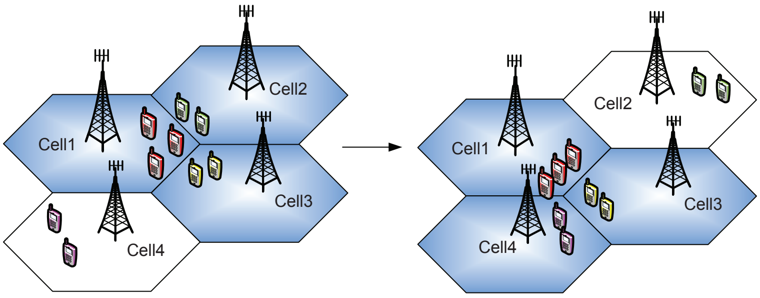

Figure 2.6: An example of dynamic network-specific clustering.

higher flexibility, theoretically, the dynamic cluster formation can provide more cooperation gains compared to the static clustering approach. However, large amount of signaling information exchange between different BSs is needed for cluster reconfiguration decisions, which is infeasible in large networks. Examples of exchanged information can be traffic distribution within different cells, downlink interference contribution from cell A to cell B, user channel conditions, etc.

Depending on where the cluster formation decision is made, cell clustering can also be classified as network-specific, user-specific or hybrid.

- Network-specific clustering: disjoint clusters of cells are formed by the network based on e.g., the dominating interference cells and/or the traffic-distribution within different cells, regardless of the channel condition of each individual user. Users belonging to the same cell are assigned to the same cluster. The cluster construction can be performed either in a static or a dynamic fashion. Static network-specific clustering can only mitigate the interference within the cluster. The performance is mainly limited by the inter-cluster interference, especially for the users located at the cluster-edge area, referred to as cluster-edge effect. An example of network-specific dynamic clustering is shown in Fig. 2.6 where, in a certain time frame, cell 1 is grouped with cell 2 and cell 3 as a cluster; In the next time frame, according to the network traffic distribution cell 2 will be replaced by cell 4 to form a new cluster.

- User-specific clustering: each user selects a set of BSs that are suitable to form a cluster. The clusters of different users may overlap. The construction of the cluster for each user can be semi-static or changed dynamically based on the channel conditions between the user and the BSs. This way, users are guaranteed to be always located at the cluster center to avoid the cluster-edge effect. However, user-specific clustering requires joint scheduling across BSs, which increases the inter-BS information exchange as well as the resource allocation complexity. Fig. 2.7 illustrates a user-specific clustering method, named as slide Group Cell, proposed in [57]. In the current time slot, cells 1, 3 and 4 are selected by UE 1 as a CoMP cluster, while the cluster for UE 2 is formed by cells 1, 2 and 3. In the next time slot, with the possible move of UE 1 and UE 2, UE 1 will select cells 1, 2 and 3 as its cluster and UE 2 will choose cells 1, 3 and 4 to form a new cluster.

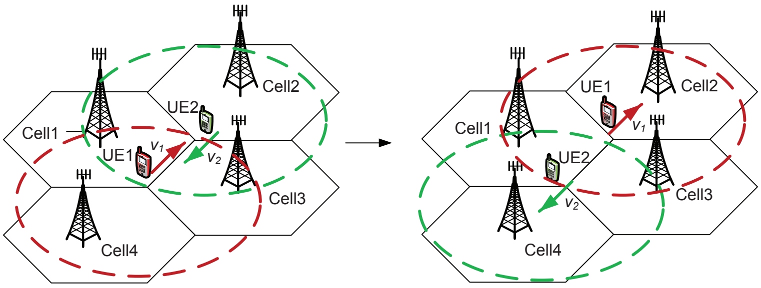

Figure 2.7: An example of user-specific clustering based on the slide Group Cell method.

- Hybrid clustering: the network pre-divides the whole system into several clusters. Within each pre-defined cluster, each user selects a subset of cells from the cluster for CoMP transmission [58–60].

2.3 Challenges and Difficulties

Theoretically, global network cooperation can provide significant performance gains both in terms of system spectrum efficiency and the cell-edge throughput. However, the realistic gains can be limited by many practical constraints for a cooperative network deployment. In this section, we discuss some of the most important challenges that need to be considered in the design of cooperative wireless networks.

2.3.1 Non-Ideal Feedback

In order to enable multi-node cooperative transmission, the CSI of all users in the network (named as *full CSI*) is required at the transmitter side. In a time division duplex (TDD) system, each transmission node can obtain the CSI from the users belonging to its coverage (named as *local CSI*) by exploiting channel reciprocity. Then, the local CSI can be exchanged via backhaul links with other coordinated nodes or be forwarded to a CU, where the resource allocation and/or data processing take place. In frequency division duplex (FDD) systems, each point acquires local CSI through feedback from its users instead. In contrast to the traditional non-cooperative networks, each user within the FDD-mode CoMP cluster needs to not only estimate and feedback the CSI related to the strongest transmission node, but also related to the other coordinated nodes. Therefore, the feedback load grows proportional to the number of transmission nodes in the network, which poses tight capacity requirements on the feedback channels [61, 62].

In practice, the fed back CSI acquired at the serving BS can never be perfect due to hardware deficiencies, channel estimation errors, quantization errors, and the feedback latency [16, 27, 63–65]. It should be pointed out that different levels of channel knowledge may be required by different categories of cooperation techniques. For example, for inter-cell interference coordination, coordinated scheduling/beamforming, and dynamic point selection schemes, no inter-point phase information is needed. However, for coherent joint transmission schemes, inter-point phase information is required, inter-point amplitude information may also be needed. Therefore, the feedback overhead might be different when considering different cooperation techniques.

2.3.2 Non-Ideal Backhaul

All cooperation techniques rely on information exchange between cooperative nodes through the backhaul network, i.e., a network interconnecting the transmission nodes. For multi-node cooperative transmission, the fed back local CSI needs to be shared over backhaul links among multiple access nodes in order to gather CSI at the transmitter side. For the case of joint processing, user data also needs to be available simultaneously at the cooperative nodes. The control signaling information may need to be exchanged between different nodes in order to support (e)ICIC. In addition, resource utilization information exchange may be needed to assist load balancing decision making. All those inter-node information exchange places a large amount of overhead on the backhaul links [61, 66]. Therefore, in order to achieve the potential cooperation gain, high capacity backhaul links are required, especially for the joint processing schemes.

Depending on the backhaul network deployment of a realistic system, e.g., the transport technology and the network topology, the overall latency introduced by only one hop backhaul link can range from hundreds of microseconds to 20 ms, and the capacity requirement ranges from a few Mbps to 10 Gbps [16, 67]. It is also pointed out in [67] that, even with point-to-point fiber technology, inter-BS information exchange may require the X2 logical link to go through several aggregation routers, hence, the normal latency between two BSs (eNBs) would be 10-20 ms. In 3GPP LTE-Advanced, the latency values of 2, 10, and 50 ms are recommended for evaluation of both homogeneous and heterogeneous cooperative networks [27, 48].

Besides capacity and latency constraints, the reliability of the backhaul links also plays an important role when performing different cooperation techniques. In heterogeneous cooperative networks, the backhaul links interconnecting multiple nodes are highly likely to be wireless and unreliable. This is because the high number of access nodes cannot be accompanied by a proportionally high financial investment in order to build high quality wireline backhaul. Furthermore, the flexible deployment of heterogeneous access points, i.e., some will be mounted on high towers (macro BSs), some will be deployed on the street level below roof tops (pico BSs and relays) and others will be indoors (femto BSs), requires that backhaul links interconnecting access nodes are wireless and without guaranteed line-of-sight (LoS) [68–71]. In other words, the backhaul links of future dense heterogeneous networks will be unreliable to some degree and the system designers should optimize the system by taking this constraint into account.

2.3.3 Hardware Impairments

In practice, most communication systems suffer from hardware impairments, e.g., phase noise, power amplifier nonlinearities, and in-phase and quadrature-phase imbalance (IQI) [72, 73]. Here, we discuss two main hardware impairments that have been considered in this thesis.

Synchronization

Multi-node cooperative transmission requires tight time and frequency synchronization between different transmission points. The synchronization constraint is most challenging for the joint transmission approach, since the carrier phases between coordinated nodes also need to be synchronized, which can be extremely difficult mainly due to the effect of carrier frequency offset, or/and phase noise from local oscillators in each BS [74–76]. An example in [76] shows that for a small relative velocity (5 km/h), the phase noise process can be assumed to vary much faster than the channel. This is because the bandwidth of the phase noise (arising from the local oscillators) is much higher than the Doppler spread. Note that the user velocity of interest in 3GPP LTE-A CoMP scenarios is 3 km/h [26], which makes the difference even larger. In a worst case scenario, where the phase shift of each link (arising from the oscillator) has a random uniform distribution and varies much faster than the channel fading, the effect of phase adjustment by joint precoding will be averaged out. In this case, if phase uncertainty is not handled, joint precoding cannot contribute to the performance improvement when performing joint processing.

I/Q Imbalance

In general, I/Q imbalance (IQI) refers to the phase and/or amplitude mismatch between the in-phase (I) and quadrature (Q) signals at the transmitter and receiver sides. With perfect I/Q matching, the I and Q branches of the transceiver will have exactly the same amplitude and a 90° phase shift. However, in practice, due to the limited accuracy of the used analog components at the transceivers, IQI is always present in the up- and down-converters. The sources of IQI include: errors in the nominal 90° phase shift between the local oscillator signals during up- and down-conversion, and the difference in amplitude transfer of the I and Q arms [73, 77]. Such imbalance results in an additional image signal, which appears as interference on top of the desired signal.

The mixture of the image and the desired signals can lead to significant performance loss, especially in high-rate wireless communications systems. In heterogeneous networks, the good channel connection experienced by the users from their nearby access nodes provides the possibility for using higher order modulation scheme (i.e., 256QAM) for the downlink data transmission, and thereby improving system spectrum efficiency [48]. However, it has been shown in [26] that the real gains of 256 QAM are dependent on the transceiver IQI, especially the IQI at the receiver. When modelling of receiver IQI with -25dB image rejection ratio, no gains from 256QAM were observed.

Note that compared to the traditional macro-cell cellular networks, heterogeneous wireless networks are more prone to hardware impairments, since the hardware of the low-cost access nodes is most likely to be of low quality compared to the macro BSs.

2.3.4 Resource Optimization

In order to achieve a certain network design objective, the available resources need to be efficiently utilized. Resource allocation may include user scheduling, subchannel allocation, node selection, power control, as well as precoding/beamforming design. In general, the optimization problems in a multi-cell multi-user system are non-convex and difficult to solve. The computational complexity for a centralized resource allocation increases with the number of subchannels, users and transmission nodes in the system. Moreover, resource allocation algorithms are designed based on the CSI available at the transmitter side, which is never perfect due to the non-ideal feedback and backhaul. Therefore, the algorithms relying on perfect CSI may lose significant cooperation gains under practical scenarios, especially for the heterogeneous cooperative networks. Developing practical resource allocation solutions for cooperative wireless systems, taking different practical constraints into account, is a difficult task. This is the main focus of this thesis.

2.3.5 Cluster-Edge Effect

The CoMP performance gains highly rely on the accuracy of CSI at the transmitter side. How to acquire the full CSI and design CoMP transmission parameters is an important issue for the system level design. Regarding this aspect, different centralized and decentralized CoMP architectures are proposed [78, 79]. As the size of cluster increases, i.e., the number of transmission nodes and the number of users increase, the inter-point information exchange via backhaul links, as well as the amount of CSI fed back from users over the feedback links will increase. In addition, the complexity for channel estimation and resource allocation will become prohibitively high. Therefore, the cluster size is limited by the feedback, backhaul, synchronization, and complexity constraints in a real system. Thus, a cooperative network is typically divided into clusters of coordinated nodes so that cooperation techniques can be independently implemented within each cluster.

A coordinated cluster may also cause inter-cluster interference to the users in the neighboring clusters, especially to users in the cluster-edge area, named as *cluster-edge effect*. It has been shown in [80] that for large networks relying on clustered cooperation, the spectral efficiency hits a ceiling that is independent of the transmit powers. This fundamental limitation cannot be overcome through faster backhaul, more sophisticated signal processing, or any other technological advance.

Different schemes have been proposed for mitigating inter-cluster interference, and thereby reducing the cluster-edge effect. An interference-floor shaping technique was introduced in [58], where overlapping clusters, so-called cover-shifts, are pre-designed on different radio resources. As a user moves to the edge area of one cluster, it can then be scheduled into another cover-shift, where it becomes a cluster-center user again. The cover-shift concept can be supported by active antennas where a smaller tilt is applied for beams pointing towards cluster-center areas and a stronger tilt for beams pointing towards cluster-edge areas. With appropriate power allocation, it has been shown in [58] that the interference floor is significantly reduced. As we will show later in this thesis, for systems that cannot support frequency selective titling, fractional frequency reuse can be considered as another promising technique to coordinate the inter-cluster interference for static CoMP clusters.

Chapter 3

Radio Resource Allocation

Resource allocation plays an important role in wireless communication networks as a way of optimizing the assignment of available resources to achieve a network design objective and at the same time guarantee the QoS for all users. All cooperative transmission techniques require the network to jointly design the user scheduling, subchannel allocation, power control, and/or the precoding/beamforming matrices for all transmission nodes within the cooperative network. In general, the optimization problems are non-convex and difficult to solve. In a cooperative system, where large number of transmission nodes and users are involved, the resource allocation and data processing problems can be more complex and challenging, especially for the case of multi-node joint processing. In addition, the design of resource allocation algorithms highly relies on the CSI at the transmitter side, which can be corrupted by various practical constraints as mentioned in Chapter 2. Developing practical resource allocation solutions for cooperative wireless systems, taking different practical constraints into account, is a difficult task. This is the main focus of this thesis.

In this chapter, by assuming ideal global cooperation between all transmission nodes, a system model for the multi-node coherent joint transmission is presented in Section 3.1. Then, a general way of formulating resource allocation problems is illustrated in Section 3.2. In Section 3.3, we introduce basic concepts of convex optimization. Then, different resource optimization problems that can be formulated in convex forms are discussed. Finally, the effect of different practical constraints on the design of resource allocation algorithms for multi-node coordinated transmission is discussed in Section 3.4.

3.1 System Model

We consider the downlink of a cooperative network, which consists of M BSs and K single-antenna users. The system spectrum is universally reused by each BS. The K users don't belong to any particular cell and are randomly deployed in the network. BS v is assumed to have N_v antennas. The total number of transmit antennas is $N = \sum_{v=1}^{M} N_v$.

At each time slot, the channels from all BSs to user k is denoted by $\mathbf{h}_k^H = \left[\mathbf{h}_{k,1}^H, \ldots, \mathbf{h}_{k,M}^H\right] \in \mathbb{C}^{1\times N}$, where $\mathbf{h}_{k,v}^H \in \mathbb{C}^{1\times N_v}$ is the channel from BS v to user k for $v = 1, \ldots, M$ and $k = 1, \ldots, K$. Similarly, let $\mathbf{x} = \left[\mathbf{x}_1^H, \ldots, \mathbf{x}_K^H\right]^H \in \mathbb{C}^{N\times 1}$ denote the signal vector transmitted from all M BSs, where $\mathbf{x}_v \in \mathbb{C}^{N_v\times 1}$ is the transmitted signal from BS v. Then, the received signal at user k is

$$y_k = \mathbf{h}_k^H \mathbf{x} + n_k, \tag{3.1}$$

where $n_k \backsim \mathcal{CN}(0, \sigma_k^2)$ is the independent additive receiver noise at user k.

Assume that the CSI and data symbols of the K users are perfectly known at each BS. In addition, the BSs are connected via backhaul links, and all BSs are able to coherently transmit to all users at the same time-frequency resource. By using linear precoding, the transmitted signal vector $\mathbf{x}$ can be expressed as

$$\mathbf{x} = \mathbf{W}\mathbf{b}, \tag{3.2}$$

where $\mathbf{b} \in \mathbb{C}^{K\times 1}$ denotes the normalized complex data symbols for the K users, with $b_k \backsim \mathcal{CN}(0,1)$. Here, $\mathbf{W} \in \mathbb{C}^{N\times K}$ is the precoding matrix used to map the data symbol vector to the transmit signal vector. The k-th column of $\mathbf{W}$ corresponds to the aggregated precoding vector for user k from all BSs, and is denoted by $\mathbf{w}_k$ with $\mathbf{w}_k \triangleq \left[\mathbf{w}_{k,1}^T, \ldots, \mathbf{w}_{k,M}^T\right]^T \in \mathbb{C}^{N\times 1}$, where $\mathbf{w}_{k,v} \in \mathbb{C}^{N_v\times 1}$ is referred to as the precoding vector for user k from BS v.

Substituting (3.2) into (3.1), the received signal of user k is

$$y_k = \mathbf{h}_k^H \mathbf{w}_k b_k + \sum_{i\neq k} \mathbf{h}_k \mathbf{w}_i b_i + n_k, \tag{3.3}$$

We assume that data symbols for different users are independent. Then, the signal to interference plus noise ratio (SINR) of user k is

$$\gamma_k = \frac{\left\|\mathbf{h}_k^H \mathbf{w}_k\right\|^2}{\sum_{i\neq k}\left\|\mathbf{h}_k^H \mathbf{w}_i\right\|^2 + \sigma^2} \tag{3.4}$$

$$= \frac{\left\|\mathbf{h}_k^H \mathbf{u}_k\right\|^2 p_k}{\sum_{i\neq k}\left\|\mathbf{h}_k^H \mathbf{u}_i\right\|^2 p_i + \sigma^2}. \tag{3.5}$$

Here, $\mathbf{w}_k = p_k \boldsymbol{u}_k$ with the normalized precoding vector $\|\boldsymbol{u}_k\| = 1$ for $k = 1, \ldots, K$. By treating interference as noise, the achievable data rate of user k is

$$R_k = \log_2(1 + \gamma_k). \tag{3.6}$$

According to (3.2), the transmit power of BS v can be derived as

$$P_{\text{trans},v} = \sum_{k=1}^{K} \left\|\mathbf{w}_{k,v}\right\|^2 \mathbb{E}\left\{|b_k|^2\right\} = \sum_{k=1}^{K} \left\|\mathbf{w}_{k,v}\right\|^2. \tag{3.7}$$

From (3.5) we see that the beamforming vectors $\mathbf{u}_k$ and the power control solution p_k can be immediately obtained from the precoding vectors $\mathbf{w}_k$. Moreover, based on (3.2), if $\mathbf{w}_{k,v} = \mathbf{0}$, then, the transmitted signals from BS v (i.e., $\mathbf{x}_v$) will not contain the data symbols of user k, i.e., BS v will not provide data transmission to user k. Hence, by finding the precoding solution, we can also obtain the load balancing and cell selection solution; that is, the set of users assigned to BS v is $\mathcal{U}_v \triangleq \{k|\mathbf{w}_{k,v} \neq \mathbf{0}, k \in \{1, \ldots, K\}\}$, and the set of BSs that provide data transmission to user k is $\mathcal{V}_k \triangleq \{v|\mathbf{w}_{k,v} \neq \mathbf{0}, v \in \{1, \ldots, M\}\}$. Therefore, the joint design of beamforming, power control and user scheduling can be done by solving a global precoding optimization problem: for any given time slot, the coordinated M BSs jointly determine the precoding vector $\mathbf{w}_k$ for each user k, so as to achieve a certain system-level criterion subject to some practical constraints. In the next subsection, we introduce a general way of formulating resource allocation problems in wireless communication systems.

3.2 Problem Formulation

A generic optimization problem has the standard form

$$\begin{aligned} \underset{\mathbf{x}}{\text{minimize}}\ & f_0(\mathbf{x}) \\ \text{subject to}\ & f_i(\mathbf{x}) \leq 0,\ i = 1, \ldots, m, \\ & h_i(\mathbf{x}) = 0,\ i = 1, \cdots, p, \end{aligned} \tag{3.8}$$

where $\mathbf{x} \in \mathbb{R}^n$ is the optimization variable, the function f_0 is the objective function, $f_1, \ldots, f_m$ are the m inequality constraint functions and $h_1, \ldots, h_p$ are the p equality constraint functions.

Depending on the targets and the requirements for the design of the networks, different resource optimization problems can be formulated. In this section, based on the system model in Section 3.2, we present a number of different objectives and constraints that have been widely considered in radio resource allocation problems.

3.2.1 Objectives

In general, the optimization objectives can be divided into the following three categories:

- Transmit power minimization: minimize $f_0\left(P_{\text{trans},1}, \ldots, P_{\text{trans},v}, \ldots, P_{\text{trans},M}\right)$.
  Typical examples for the utility functions of $f_0\left(\right)$ for transmit power minimization are weighted sum and max. The corresponding objective functions are

  $$\sum_{v=1}^{M} \alpha_v P_{\text{trans},v} \tag{3.9}$$

  and

  $$\max_{v} P_{\text{trans},v} \tag{3.10}$$

  respectively. Here, $\alpha_v \geq 0$ denotes the weight assigned to BS v, which can be used to balance the power consumptions of different BSs.

- Rate maximization: maximize $f_0\left(R_1, \ldots, R_k, \ldots, R_K\right)$.
  For this category, the most common utility functions of $f_0\left(\right)$ are weighted sum and min. The corresponding objective functions are

  $$\sum_{k=1}^{K} \beta_k R_k \tag{3.11}$$

  and

  $$\min_{k} R_k \tag{3.12}$$

respectively. Similarly, $\beta_k \geq 0$ is the weight assigned to user k, which is introduced to compensate for the heterogeneous QoS requirements at the users.

- Energy efficiency maximization: maximize $f_0(P_{\text{trans},1}, \ldots, P_{\text{trans},M}, R_1, \ldots, R_K)$. If the energy efficiency of a network is measured by bit/Joule delivered to the users, the objective function can then be expressed as

  $$\frac{\sum_{k=1}^{K} R_k}{P_{\text{tot}}} \tag{3.13}$$

  where $P_{\text{tot}} = g(P_{\text{trans},1}, \ldots, P_{\text{trans},M})$ is the total power consumption of the network, which is a function of the transmit powers $P_{\text{trans},v}$ for $v = 1, \ldots, M$.

3.2.2 Constraints

The constraints of downlink radio resource optimization problems include:

- Power constraints, for example, the total transmit power constraint

  $$\sum_{v=1}^{M} P_{\text{trans},v} \leq P_{\text{trans,tot}} \tag{3.14}$$

  and the per-BS power constraints

  $$P_{\text{trans},v} \leq P_{v,\max}, \ \forall v, \tag{3.15}$$

  where $P_{\text{trans,tot}}$ and $P_{v,\max}$ denote the maximum total transmit power and the maximum transmit power for BS v, respectively.

- The QoS expectations of the users, which is usually modeled as a function of the SINR

  $$\gamma_k \geq \Gamma_k, \ \forall k, \tag{3.16}$$

  or a function of the user data rate as

  $$R_k \geq r_k, \ \forall k, \tag{3.17}$$

  where Γ_k and r_k denote the target SINR and the target data rate for user k.

Depending on the network architectures and traffic models, some resource optimization problems may also include backhaul capacity constraints [81–84], CSI feedback constraints [85, 86] and transmission latency constraints [87], etc. Finding the optimal resource allocation solution for a multi-cell multi-user cooperative system is generally NP hard. However, as will be shown in Section 3.3, some resource optimization problems have hidden convexity structures, and therefore can be formulated or transformed into convex problems. Thus, these problems can be efficiently solved by using standard optimization techniques.

3.3 Radio Resource Optimization

An optimization problem in (3.8) is a convex problem, if the equality constraint functions $(h_1, \ldots, h_p)$ are affine, and the objective function (f_o) and the inequality constraint functions $(f_1, \ldots, f_m)$ are convex, i.e.,

$$f_i(\alpha_1 \mathbf{x}_1 + \alpha_2 \mathbf{x}_2) \leq \alpha_1 f_i(\mathbf{x}_1) + \alpha_2 f_i(\mathbf{x}_2),\ i = 0, 1, \ldots, m, \tag{3.18}$$

for all $\mathbf{x}_1, \mathbf{x}_2 \in \mathbb{R}^n$ and all $\alpha_1, \alpha_2 \in \mathbb{R}$ with $\alpha_1 + \alpha_2 = 1$, $\alpha_1, \alpha_2 \geq 0$. A fundamental property of convex problems is that the local optimal point is also globally optimal. Another attractive property is that the optimal solution of the primary convex problem (3.8) can be obtained by solving its Lagrange dual problem, leading to decomposable structures and distributed algorithm design [88, 89]. In general, a convex optimization problem can be solved efficiently and reliably by using interior-point methods or other methods. There are many standard convex optimization software, such as CVX [90], YALMIP [91], developed for solving different classes of convex problems.

The benefits of convex optimization only come when the problem is a convex problem. In many cases, the original optimization problem does not have a standard convex from. Recognizing a convex problem or transforming an original problem into a convex problem is a big challenge. In the following, we will introduce three widely considered resource allocation problems in wireless cooperative systems. Some of them can be reformulated to a convex problem, thus, efficiently solved via convex optimization approaches.

3.3.1 Power Minimization

The first category of the optimization problems is to minimize some functions of transmit power of M BSs subject to SINR constraints for the selected users. We assume that the target SINR values are feasible. The *weighted sum transmit power minimization* problem can be formulated as

$$\begin{aligned} \underset{\{\mathbf{w}_{k,v}\}}{\text{minimize}} \ & \sum_{v=1}^{M} \alpha_v P_{\text{trans},v} \\ \text{subject to } & 1)\ P_{\text{trans},v} \leq P_{v,\max}, \forall v \\ & 2)\ \gamma_k \geq \Gamma_k, \forall k. \end{aligned} \tag{3.19}$$

Plugging (3.4) and (3.7) into (3.19), problem (3.19) becomes

$$\begin{aligned} \underset{\{\mathbf{w}_{k,v}\}}{\text{minimize}} \ & \sum_{v=1}^{M} \alpha_v \sum_{k=1}^{K} \left\|\mathbf{w}_{k,v}\right\|^2 \\ \text{subject to } & 1)\ \sum_{k=1}^{K} \left\|\mathbf{w}_{k,v}\right\|^2 \leq P_{v,\max}, \forall v \\ & 2)\ \frac{\left\|\mathbf{h}_k^H \mathbf{w}_k\right\|^2}{\sum_{i \neq k} \left\|\mathbf{h}_k^H \mathbf{w}_i\right\|^2 + \sigma^2} \geq \Gamma_k, \forall k. \end{aligned} \tag{3.20}$$

The SINR constraints in (3.20) are complicated functions of the precoding vectors, making the problem non-convex in its original formulation. However, we can prove that problem (3.20) can be reformulated as a convex problem by using semi-definite relaxation from [92].

Recall that $\mathbf{w}_k \triangleq \left[\mathbf{w}_{k,1}^T, \ldots, \mathbf{w}_{k,M}^T\right]^T \in \mathbb{C}^{N\times 1}$. We define $\mathbf{W}_k \triangleq \mathbf{w}_k\mathbf{w}_k^H \succeq 0$, $\mathbf{R}_k \triangleq \mathbf{h}_k\mathbf{h}_k^H$, and

$$\boldsymbol{Q}_v \triangleq \operatorname{diag}\left(\mathbf{Q}_{1,v}, \mathbf{Q}_{2,v}, \ldots, \mathbf{Q}_{M,v}\right) \tag{3.21}$$

where

$$\mathbf{Q}_{i,v} = \begin{cases} \mathbf{I}_{N_v}, & \text{if } i = v \\ \mathbf{0}_{N_v \times N_v}, & \text{otherwise.} \end{cases} \tag{3.22}$$

By gathering the power weights in a diagonal matrix form as

$$\mathbf{A} \triangleq \operatorname{diag}\left(\alpha_1\Delta_1\mathbf{I}_{N_1}, \alpha_2\Delta_2\mathbf{I}_{N_2}, \ldots, \alpha_M\Delta_M\mathbf{I}_{N_M}\right) \tag{3.23}$$

and noting that $\mathbf{w}_k^H\mathbf{Q}\mathbf{w}_k = \operatorname{Tr}\left(\mathbf{Q}\mathbf{W}_k\right)$ for any matrix $\mathbf{Q}$, problem (3.20) can be reformulated as

$$\begin{aligned} &\underset{\{\mathbf{W}_k\succeq 0\}}{\text{minimize}} \quad \sum_{k=1}^{K} \operatorname{Tr}\left(\mathbf{A}\mathbf{W}_k\right) \\ &\text{subject to } 1) \sum_{k=1}^{K} \operatorname{Tr}\left(\boldsymbol{Q}_v\mathbf{W}_k\right) \le P_{v,\max}, \forall v \\ &\qquad\qquad 2) \left(1 + \frac{1}{\Gamma_k}\right) \operatorname{Tr}\left(\mathbf{R}_k\mathbf{W}_k\right) - \sum_{i=1}^{K} \operatorname{Tr}\left(\mathbf{R}_k\mathbf{W}_i\right) \ge \sigma_k^2, \forall k \end{aligned} \tag{3.24}$$

with the additional constraints $\operatorname{rank}\left(\mathbf{W}_k\right) = 1, \forall k$. The problem (3.24) is convex except for the rank constraints, but based on [93, Theorem 1], it can be shown that (3.24) always has a rank one solution, if the problem is feasible. Therefore, the rank-one constraints can be dropped without loss of optimality. Thus, the optimization problem (3.19) can be transformed into a convex form, which can be efficiently solved via standard convex optimization techniques [94].

In case it is difficult to choose the weights for all BSs, an alternative is to *minimize the maximum transmit power* over all the N coordinated BSs as [95]

$$\begin{aligned} &\underset{\left\{\mathbf{w}_{k,v}\right\}}{\text{minimize}} \ \max_{v} P_{\text{trans},v} \\ &\text{subject to } 1) \, P_{\text{trans},v} \le P_{v,\max}, \forall v \\ &\qquad\qquad 2) \, \gamma_k \ge \Gamma_k, \forall k. \end{aligned} \tag{3.25}$$

which is equivalent to

$$\begin{aligned} &\underset{\left\{\mathbf{w}_{k,v}\right\},\rho}{\text{minimize}} \ \rho \\ &\text{subject to } 1) \, P_{\text{trans},v} \le P_{v,\max}, \forall v \\ &\qquad\qquad 2) \, \gamma_k \ge \Gamma_k, \forall k \\ &\qquad\qquad 3) \, P_{\text{trans},v} \le \rho, \forall v. \end{aligned} \tag{3.26}$$

Similar to (3.19), problem (3.25) can be transformed into a convex form, thus solved via convex optimization.

When our target is to improve the energy efficiency of networks, the objective can be changed to *minimize the total power consumption of the network* instead of the total transmit power. The total power consumption can be modeled with a circuit part that depends on the transceiver hardware and a dynamic part which is a function of the transmitted signal power. The circuit power consumption also depends on the operational mode of each BS, i.e., whether the BS is active or in the sleep mode. This objective function is typically non-convex, and it can lead to a hard combinatorial problem. One way to solve this problem is to perform iterative convex approximations of the non-convex power consumption functions, and thereby find a local optimum to the original problem. In Paper F, by considering a linear approximated, non-continuous power consumption model proposed in [44], we illustrate how to design an iterative heuristic algorithm to efficiently obtain a local optimal solution for the design of downlink precoding and load balancing.

3.3.2 Worst SINR Maximization

Another category of joint precoding problems is to maximize the worst data rate or SINR subject to per-BS power constraints in order to guarantee the user fairness [96–98]. The optimization problem can be written as

$$\begin{aligned} &\underset{\{\mathbf{w}_k\}}{\text{maximize}} \ \min_k \gamma_k \\ &\text{subject to} \ P_{\text{trans},v} \leq P_{v,\max}, \forall v. \end{aligned} \tag{3.27}$$

Using the fact that for any give target SINR value Γ, similar to (3.24), $\gamma_k \geq \Gamma$ can be reformulated as a second order cone constraint, which is convex. Therefore, the objective function $\min(\gamma_k)$ is quasi-concave in $\mathbf{w}_{k,v}$. Hence, (3.27) can be efficiently solved by using the bisection method, which is illustrated in Algorithm 1 [94].

Algorithm 1 Bisection method for maximization of the worst SINR

```
given $l \leq \gamma^*$ and $u \geq \gamma^*$, tolerance $\epsilon > 0$.
repeat
  $\Gamma = (l + u)/2$.
  Solve the convex feasibility problem:
      $$\begin{aligned} &\text{find } \mathbf{w}_k, \ \forall k, \\ &\text{subject to } 1) \sum_{k=1}^{K} P_n^k \leq \rho, \ \forall n, \\ &\qquad 2) \gamma_k \geq \Gamma, \forall k, \end{aligned} \tag{3.28}$$
  if (3.28) is feasible then
      $l := \Gamma$;
  else
      $u := \Gamma$.
  end if
until $u - l < \epsilon$.
```

In a system where some users have different QoS requirements, the design objective can be modified by replacing the γ_k with $\gamma_k \beta_k$ in (3.27). Here, β_k is the weight for user k used to prioritize different users. In this case, the solution of (3.27) ensures a weighted user fairness among users.

3.3.3 Sum Rate Maximization

In general, the weighted sum rate maximization problem subject to per-BS power constraints can be formulated as

$$\begin{aligned} &\underset{\{\mathbf{w}_k\}}{\text{maximize}} \ \sum_{k=1}^{K} \beta_k R_k \\ &\text{subject to } P_{\text{trans},v} \le P_{v,\max}, \forall v. \end{aligned} \tag{3.29}$$

This problem is not convex. Finding the optimal solution of (3.29) is typically non-tractable. However, some iterative algorithms can be designed to obtain the local optimal solutions, for example, by iteratively solving a set of Karush-Kuhn-Tucker (KKT) conditions of the non-convex problem [99], or by iteratively solving the problem in each step with respect to one variable keeping the other variables fixed [97].

Note that the precoding matrix specifies both the beamforming vectors and the allocated power to each data symbol. Thus, $\mathbf{w}_k$ can be further divided into two parts, i.e., the normalized beamforming vector $\boldsymbol{u}_k$ and the symbol power p_k allocated for the kth user, with $\mathbf{w}_k = p_k \boldsymbol{u}_k$ and $\|\boldsymbol{u}_k\| = 1$. A simple linear beamforming scheme for joint transmission is known as zero-forcing (ZF) beamforming, where the beamforming matrix $\mathbf{U}$ is firstly calculated as the pseudo-inverse of the channel matrix $\mathbf{H}^H$, then the columns of $\mathbf{U}$ are normalized to have a unit norm. With ZF beamforming, the inter-user interference within the cooperation cluster can be eliminated, that is

$$\mathbf{h}_k^H \mathbf{u}_i = 0, \ i \neq k. \tag{3.30}$$

The problem of maximizing the weighted sum rate in (3.29) is reduced to a joint power allocation problem given by

$$\begin{aligned} &\underset{\{p_k\}}{\text{maximize}} \ \sum_{k=1}^{K} \beta_k \log_2\Big(1 + \frac{\left\|\mathbf{h}_k^H \mathbf{u}_k\right\|^2 p_k}{\sigma^2}\Big) \\ &\text{subject to } \sum_{k=1}^{K} \left\|\mathbf{u}_{k,v}\right\|^2 p_k \le P_{v,\max}, \ \forall v. \end{aligned} \tag{3.31}$$

where the beamforming vector $\mathbf{u}_k$ are fixed. The problem (3.31) is convex since the objective function is concave in p_k and the constraints are linear. Therefore, it can be effectively solved by standard convex optimization techniques [100, 101].

3.4 Remarks on Practical Constraints

The resource allocation problems discussed above are based on the assumption that the data symbols of all M users are perfectly synchronized at each BS. However, as mentioned in Chapter 2, the phase synchronization between coordinated BSs can be extremely difficult in practice. Imperfect phase synchronization can significantly reduce the joint transmission gain. In the worst case, as shown in Paper A, the random phase shift arising from the oscillators of different BSs can average out the effect of phase adjustment provided by joint precoding, thus, resulting in a different power allocation solution. Moreover, in practice, the channel vectors $\mathbf{h}_{k,v}$ are imperfectly known to the user k and the BSs. This can be modeled as $\mathbf{h}_{k,v} = \hat{\mathbf{h}}_{k,v} + \mathbf{e}_{k,v}$ with $v = 1, \ldots, M$, where $\hat{\mathbf{h}}_{k,v}$ is the known channel estimate (at both the corresponding transmitter and receiver). The error vectors $\mathbf{e}_{k,v} \backsim \mathcal{CN}(\mathbf{0}, \mathbf{E}_{k,v})$ are assumed to be zero-mean with covariance matrix $\mathbf{E}_{k,v} \in \mathbb{C}^{N_v \times N_v}$. The errors can, for example, originate from channel estimation/prediction errors [102]. Based on this channel model, in Paper F, we illustrate how to design the precoding vectors under imperfect CSI.

Chapter 4

Conclusions and Future Work

4.1 Contributions

The purpose of this thesis is to investigate the design and the performance of downlink cooperative wireless communication systems. To achieve this, a number of contributions (see the list of included papers and the list of additional related publications) are introduced considering different cooperative techniques in different network scenarios. This section summarizes the contributions of this thesis, which are divided into two parts: resource allocation in homogeneous cooperative networks, and resource allocation in heterogeneous cooperative networks.

4.1.1 Resource Allocation in Homogeneous Cooperative Networks

The first part of the contributions focus on the design of resource allocation algorithms for homogeneous cooperative networks. In particular, we consider the scenarios where different cooperative transmission schemes are performed between multiple macro BSs.

Paper A: "Power Allocation for Two-Cell Two-User Joint Transmission"

This paper considers the downlink of a two-cell two-user joint transmission system. We study a worst case scenario where the carrier phases between the BSs are un-synchronized so that multi-cell joint transmission must be performed without precoding. An optimal power allocation scheme is proposed to maximize the sum rate under per-BS power constraints. The derived power allocation scheme is remarkably simple, i.e., each cell transmits with full power to only one user. Note that joint transmission is still possible, when two cells select the same user for data transmission. In addition, we show that, in this scenario, the joint transmission case happens with higher probability when the maximum transmit power is high, or the two users are in the overlapped cell-edge area.

Paper B: "Resource Allocation for Clustered Network MIMO OFDMA Systems"

In this paper, we address the resource allocation problem for the downlink of a large network MIMO orthogonal frequency division multiple access (OFDMA) system with

3-sector BSs. The system is statically divided into a number of disjoint clusters of sectors. A two-step resource allocation scheme is proposed involving the inter-cluster and the intra-cluster levels. As a first step or inter-cluster level, the inter-cluster interference is mitigated by two fractional frequency reuse approaches, which restrict the available frequency resources for cluster-edge users in a cooperative way. Then, as a second step or intra-cluster level, a utility-based joint scheduling and power allocation algorithm is proposed for each cluster, to maximize the sum utility of all users in the cluster under per-sector power constraints. Zero-forcing based coherent joint transmission is used across multiple sectors within the same cluster. Our simulation results show that the proposed scheme can efficiently reduce the inter-cluster interference and provide considerable performance improvement in terms of both the cell-edge and cell-average user data rate. The proposed two-step resource allocation scheme can be implemented independently in each cluster without inter-cluster information exchange, which is an attractive property for practical systems, since it reduces both the network signaling overhead and the computational complexity.

Paper C: "Performance Evaluation of Coordinated Multi-Point Transmission Schemes with Predicted CSI"

In this paper, we consider the downlink of a CoMP cluster and compare three different CoMP transmission schemes: zero-forcing coherent joint transmission, non-coherent joint transmission and coordinated scheduling. For each of the analyzed schemes, the performance in terms of average sum rate of the CoMP cluster is studied with predicted CSI, considering the effects of the feedback and backhaul latency, as well as the user mobility. Compared to zero-forcing coherent joint transmission, we show that non-coherent joint transmission and coordinated scheduling are more robust to channel uncertainty. In addition, depending on the latency, user mobility and user locations, different schemes would achieve the highest average sum rate performance. Hence, a system could switch between the transmission schemes to improve the sum rate.

Related contributions

In [C6], we investigate multi-cell resource allocation with zero-forcing coherent joint transmission for a downlink OFDMA system with universal frequency reuse. Joint optimization of the user selection and power allocation is studied with the objective of maximizing the weighted sum rate under per-BS power constraints. Our results in [C6] show that joint user set selection across multiple subchannels significantly improves the system performance in terms of the weighted sum rate.

Coherent joint transmission requires tight phase synchronization between coordinated BSs and the knowledge of network CSI at the transmitters with sufficiently high quality. When those constraints are not satisfied, non-coherent joint transmission together with coordinated scheduling can be used as a fallback transmit mode to harvest the macro-diversity gains. Considering non-coherent joint transmission, in [C7], we propose two joint user scheduling and power allocation algorithms for the downlink of a CoMP cluster with 3 neighboring base station sectors. We prove that, in this scenario, binary power control is the optimal strategy for maximizing the cell-edge sum rate under per-sector transmit power constraints. Moreover, the simulation results in [C7] demonstrate that the proposed algorithms achieve a good trade-off between joint transmission and interference coordination, which helps to improve the cell-edge performance. The results in [C7] are limited to the flat-fading channel case. In [C12, J2], we investigate non-coherent joint transmission in downlink multi-cell OFDMA systems. In particular, an efficient optimal power allocation algorithm is derived for maximizing the sum rate of a two-cell system under per-cell transmit power constraints in [C12]. In [J2], utility based coordinated scheduling schemes are proposed to maximize the users sum utility. The utility function is based on the user average throughput, which provides a good balance between the system spectrum efficiency and fairness between the users.

Apart from the backhaul latency, backhaul capacity can also become a constraint restricting multi-cell coordination. This issue is partly addressed in [C11] and [C12], where different backhaul load reduction schemes are proposed for zero-forcing joint transmission. In particular, a decentralized network architecture is considered in [C11] for backhaul load reduction. In this setting, users broadcast the quantized CSI such that the coordinating BSs could simultaneously receive the CSI. The advantage of this decentralized architecture is that it does not require a CU, and each BS can design its own precoding matrix and perform data transmission locally with minimum amount of information sharing over the backhaul links. [C12] considers the feedback and backhaul load reduction problem in a centralized CoMP architecture. In this work, a feedback load reduction technique is employed via partial joint processing to alleviate the CSI feedback overhead. Similarly, to reduce the backhaul load due to precoding weights forwarded from the CU to the coordinated BSs, different scheduling approaches are proposed, which choose the best subset of the BSs and UEs at the CU that yields the best sum rate under different constraints of efficient backhaul use. Simulation results in [C12] show that scheduling a smaller subset of BSs and users can potentially achieve a better trade-off in terms of the sum rate per backhaul use.

All the above contributions adopt the assumption of full buffer traffic model for all users, however, in practical communication systems, different users may have different traffic patterns, resulting in diverse QoS requirements. Taking this into account, different utility based joint resource allocation algorithms are proposed in [J4, C14, C15], considering mixed real-time voice over IP and best-effort services. System level simulation results show that, by exploiting multi-cell joint transmission and utility diversities, the proposed algorithms can provide a great improvement in the average throughput of best-effort users, and meanwhile substantially reduce the average packet drop ratio and call outage ratio of voice over IP users.

4.1.2 Resource Allocation in Heterogeneous Cooperative Networks

The second part of the contributions considers the design of resource allocation algorithms and performance analysis for heterogeneous cooperative networks. The studies mainly focus on two scenarios, i.e., relay-assisted networks and multi-tier small cell networks, where different challenges, e.g., the hardware impairments in low-power low-cost relay nodes, unreliable backhaul links between different types of BSs, random node activities, and load balancing, have been addressed.

Paper D: "I/Q Imbalance in Two-Way AF Relaying"

This work analyzes the performance of dual-hop, two-way amplify-and-forward relaying in the presence of IQI at the relay node. In particular, two power allocation schemes, namely, fixed power allocation (FPA) and instantaneous power allocation (IPA), are proposed to improve the system reliability and robustness against IQI under a total transmit power constraint. For each proposed scheme, the outage probability is investigated over independent, non-identically distributed Nakagami-m fading channels, and exact closed-form expressions and bounds are derived. Our theoretical analysis indicates that without IQI compensation, IQI can create fundamental performance limits on two-way relaying. However, these limits can be avoided by performing IQI compensation at source nodes. Compared to the equal power allocation scheme, our numerical results show that the two proposed power allocation schemes can significantly improve the outage performance, thus reducing the IQI effects, especially when the total power budget is large. We also observe that IPA is particularly effective for the symmetric channel case. On the other hand, for the asymmetric channel case, it is better to select the FPA scheme to mitigate I/Q imbalance and keep the signaling overhead as low as possible.

Paper E: "Performance Analysis and Cooperation Mode Switch in HARQ-based Relaying"

In this paper, adaptive power allocation is investigated for hybrid automatic repeat request (HARQ) based relay networks, where the helping relay node becomes active only if it successfully decodes the data transmitted from the source node. For HARQ-based relaying techniques, relay-assisted cooperative transmission can be divided into two categories, namely, Single-Node Transmission (SNT) and multi-node Joint Transmission (JT). In the SNT mode, only one node (either the source or the relay) is active in each retransmission round. In the JT mode, once the relay decodes the data correctly, the source and the relay use, e.g., distributed space-time coding, to provide joint retransmission to the destination. Here, we study a cooperation mode switch in HARQ-based relaying by using adaptive power allocation. The outage probability is minimized under a total power constraint. Our results demonstrate that adaptive power allocation reduces the outage probability significantly. Moreover, depending on the channel conditions and the total power budget, switching between the SNT mode and the JT mode is the optimal way for minimizing the outage probability. Another important observation is that, in order for minimizing the power-limited outage probability, the optimal relay position with equal power allocation is closer to the source. On the contrary, when performing adaptive power allocation, the optimal relay position is closer to the destination.

Paper F: "Joint Precoding and Load Balancing Optimization for Energy-Efficient Heterogeneous Networks"

This paper considers the downlink of a heterogeneous network, where multiple BSs can serve the users by non-coherent multiflow beamforming. We assume imperfect channel state information at both BSs and users. The objective is to jointly optimize the precoding, load balancing, and BS operation mode (active or sleep) for improving the energy efficiency of the network. The considered problem is to minimize the weighted total power consumption (both circuit power and dynamic transmit power), while satisfying per-user quality of service constraints and per-BS transmit power constraints. This problem is non-convex, but we prove that for each combination of BS modes, the considered problem has a hidden convexity structure. Thus, the global optimal solution is obtained by an exhaustive search over all possible BS mode combinations. Furthermore, by iterative convex approximations of the non-convex power consumption functions, a heuristic algorithm is proposed to obtain a local optimal solution with low complexity. We show that although multi-cell joint transmission is allowed, in most cases, it is optimal for each user to be served by a single BS. An optimal BS association condition is parametrized, which reveals how it is impacted by different system parameters. Simulation results illustrate that our proposed algorithms significantly reduce the total power consumption, compared to the scheme where all BSs are continuously active. This implies that putting BSs into sleep mode by proper load balancing is an important solution for energy savings in heterogeneous networks. Moreover, the BS activation probability depends on the target QoS requirements, as well as the ratio between the circuit power consumed in the active mode and that consumed in the sleep mode.

Related contributions

In heterogeneous dense networks, the access points will be heterogeneous in transmit power, coverage area, and activation probability. In this complex scenario, high-capacity and reliable feedback links are unlikely to be available due to the limited bandwidth and high inter-cell interference. Furthermore, the backhaul links interconnecting multiple nodes are highly likely to be wireless and unreliable. In [C10], we propose a backhauling model by assigning a link failure probability to each backhaul link. The performance of various multi-node coordinated transmission schemes is investigated under unreliable backhaul. We show that the performance gains offered by multi-node coordination quickly diminish, as the unreliability of the backhaul links grows. This work is extended in [J4], where the impact of both the feedback and the backhaul channel reliability on multi-node coordination is studied under three different network architectures. In particular, two transmission schemes, coherent joint transmission and coordinated scheduling, are evaluated under the centralized, semi-distributed, and fully-distributed CoMP architectures. Numerical results show that cooperative transmission techniques have the potential to improve the performance of the cellular system, in terms of sum rate. However, the performance of the system highly depends on the reliability of the control channels and, more importantly, on the probability of successful channel state information exchange. Moreover, we show that the semi- and fully distributed architectures are more robust to LFP, and the performance of the considered cooperative transmission schemes under these architectures will converge to traditional single cell transmission, as the link failure probability grows.

Due to some practical constraints, e.g., energy saving, bad channel quality, and time constraint, the coordinated nodes may not always be available for helping data transmission. Also, the receiving nodes may not request data all the time. In [C5], we study the power allocation problem for the downlink of a cooperative system with different node activeness; that is, each receiving node requests for data transmission according to a certain probability. Data symbols of the active nodes are jointly transmitted from cooperative transmission points using zero-forcing precoding. The problem is cast in form of maximizing the achievable sum rate subject to per-transmit-point average total power constraints. The optimal power allocation solution is proved to fall into two categories: 1) Greedy power allocation, when two receiving nodes are located close to one transmission node and the per-transmit-point power budget is below a threshold; 2) Power sharing solution, i.e., both receiving nodes receive the data from the transmission nodes, when different receiving nodes are close to different transmission nodes or the per-transmit-point total power budget is above a threshold. Moreover, we show that depending on the channel condition and the RNs' activation probability, a system should switch between cooperative joint transmission and non-cooperative transmission to improve the sum rate.

4.2 Future Work

In this thesis, we have investigated different multi-node cooperative techniques in the downlink of realistic wireless communication networks. We showed that, by proper design of radio resource allocation algorithms, multi-node cooperation can provide promising performance gains in terms of system throughput, user fairness, system reliability, and/or energy efficiency.

Throughout the thesis, we have made a simplifying assumption that each user has only a single receiving antenna. As future users are high likely to be equipped with multiple antennas, interference cancellation can be performed at the user side to further improve the received SINR, and thereby improving the overall system performance. Future work should look into the joint design of the cooperative transmission schemes at the transmitters and the interference cancellation schemes at the receivers.

As shown in Paper F, putting BSs into sleep mode by proper load balancing is an important solution for energy savings in heterogeneous networks. The joint precoding and load balancing algorithms designed in Paper F are based on the assumption of a full buffer traffic model for all users. However, in order to provide a realistic analysis of the network energy efficiency, it is essential to know what kind of traffic demands are supported by the network. The traffic load situation of a network may vary radically over the time. Therefore, in order to always operate in an energy efficient mode, network resource optimization solutions should be derived by taking realistic traffic models into account.

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