Power Control for Multi-Cell Massive MIMO

Amin Ghazanfari

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Power Control for Multi-Cell Massive MIMO

Amin Ghazanfari

Division of Communication Systems
Department of Electrical Engineering (ISY)
Linköping University, 581 83 Linköping, Sweden
www.commsys.isy.liu.se

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Abstract

The cellular network operators have witnessed significant growth in data traffic in the past few decades. This growth occurs due to the increases in the number of connected mobile devices, and further, the emerging mobile applications developed for rendering video-based on-demand services. As the frequency bandwidth for cellular communication is limited, significant effort was dedicated to improve the utilization of the available spectrum and increase the system performance via new technologies. For example, 3G and 4G networks were designed to facilitate high data traffic in cellular networks in past decades. Nevertheless, there is a necessity for new cellular network technologies to accommodate the ever-growing data traffic demand. 5G is behind the corner to deal with the tremendous data traffic requirements that will appear in cellular networks in the next decade.

Massive MIMO (multiple-input-multi-output) is one of the backbone technologies in 5G networks. Massive MIMO originated from the concept of multi-user MIMO. It consists of base stations (BSs) implemented with a large number of antennas to increase the signal strengths via adaptive beamforming and concurrently serving many users on the same time-frequency blocks. As an outcome of using Massive MIMO technology, there is a notable enhancement of both sum spectral efficiency (SE) and energy efficiency (EE) in comparison with conventional MIMO based cellular networks. Resource allocation is an imperative factor to exploit the specified gains of Massive MIMO. It corresponds to properly allocating resources in the time, frequency, space, and power domains for cellular communication. Power control is one of the resource allocation methods to deliver high spectral and energy efficiency of Massive MIMO networks. Power control refers to a scheme that allocates transmit powers to the data transmitters such that the system maximizes some desirable performance metric.

In the first part of this thesis, we investigate reusing the resources of a Massive MIMO system, for direct communication of some specific user pairs known as device-to-device (D2D) underlay communication. D2D underlay can

conceivably increase the SE of traditional Massive MIMO systems by enabling more simultaneous transmissions on the same frequencies. Nevertheless, it adds additional mutual interference to the network. Consequently, power control is even more essential in this scenario in comparison with conventional Massive MIMO systems to limit the interference that is caused between the cellular network and the D2D communication, thereby enabling their coexistence. In this part, we propose a novel pilot transmission scheme for D2D users to limit the interference to the channel estimation phase of cellular users in comparison with the case of sharing pilot sequences for cellular and D2D users. We also introduce a novel pilot and data power control scheme for D2D underlaid Massive MIMO systems. This method aims at assuring that D2D communication enhances the SE of the network in comparison with conventional Massive MIMO systems.

In the second part of this thesis, we propose a novel power control approach for multi-cell Massive MIMO systems. The new power control approach solves the scalability issue of two well-known power control schemes frequently used in the Massive MIMO literature, which are based on the network-wide max-min and proportional fairness performance metrics. We first explain the scalability issue of these existing approaches. Additionally, we provide mathematical proof for the scalability of our proposed method. Our scheme aims at maximizing the geometric mean of the per-cell max-min SE. To solve this optimization problem, we prove that it can be rewritten in a convex form and then be solved using standard optimization solvers.

Populärvetenskaplig sammanfattning

Under de senaste årtiondena har mobilnätoperatörerna bevitnat en snabb ökning i datatrafik. Denna tillväxt har skapats av ett ökat antal anslutna mobiler och nya mobilapplikationer såsom videobaserade on-demand-tjänster. Då frekvensbandbredden för mobil kommunikation är begränsad, har forskare gjort stora insatser för att förbättra användandet av det tillgängliga spektrumet och för att öka systemprestanda via nya teknologier. Under de senaste årtiondena designades 3G- och 4G-nät för att hantera den ökande trafiken i mobilnäten. Icke desto mindre finns ett behov av nya mobilnätsteknologier för att tillmötesgå den ständigt växande datatrafiksefterfrågan. 5G väntar runt hörnet för att hantera de enorma datatrafikskraven under nästa årtionde.

Massiv MIMO (eng. multiple-input-multi-output) är en av nyckelteknologierna i 5G. Massiv MIMO härstammar från konceptet av fleranvändar-MIMO. Massiv MIMO-teknologin består av basstationer, utrustade med ett stort antal antenner, som ökar signalstyrkan via adaptiv lobformning och samtidigt betjänar många användare på samma tids- och frekvensblock. Genom att använda massiv MIMO-teknologi kan man uppnå en stor förbättring av både den summerade spektraleffektiviteten och energieffektiviteten i nätet, i jämförelse med konventionella mobilnät. Resurstilldelning är en nödvändig faktor för att kunna utnyttja vinsterna av massiv MIMO. För cellulär kommunikation innebär det att resurser noggrant måste tilldelas i tids-, frekvens-, rums- och effektdomänerna. Effektregering är en av resurstilldelningsmetoderna för att kunna leverera hög spektraleffektivitet och energieffektivitet i massiv MIMO-nätverk. Effektregering syftar på ett system som tilldelar sändeffekter till datasändarna så att systemet uppnår den högsta möjliga prestandan baserat på ett givet sätt att mäta prestanda.

I den första delen av avhandlingen undersöker vi återanvändning av cellulära resurser för direkt kommunikation av vissa specifika användarpar, känt som underlagd enhet-till-enhet (D2D, eng. device-to-device) kommu-

nikation i ett massiv MIMO-system. Underlagd D2D kommunikation kan öka spektraleffektiviteten genom att återanvända cellulära resurser, om den ömsesidiga interferensen i nätverket kan hanteras. Effektereglering är därför ännu mer väsentligt i underlagd D2D massiv MIMO jämfört med konventionell massiv MIMO. I den här delen av avhandlingen föreslår vi ett nytt pilotsändningssystem för D2D-användare för att undvika interferens i kanalskattningsfasen för de cellulära användarna. Vi introducerar även ett nytt pilot- och dataeffektereglerssystem för massiv MIMO-system med underlagd D2D-kommunikation.

I den andra delen av den här avhandlingen föreslår vi ett nytt tillvägagångssätt för effektereglering i flercells massiv MIMO-system. Effekteregleringsmetoden löser skalbarhetsproblemen hos två välkända effekteregleringssystem som ofta används i massiv MIMO-litteraturen: nätvärksvid max-min och proportionell rättvisa. Vi förklarar först skalbarhetsproblemen av dessa tidigare tillvägagångssätt. Dessutom ger vi matematiska bevis för skalbarheten av vår föreslagna metod. Vår metod maximerar det geometriska medelvärdet av spektraleffektiviteten per cell med max-min effektereglering inom varje cell. För att lösa detta optimeringsproblem bevisar vi att vi kan skriva om det som ett konvext optimeringsproblem och sedan lösa det med existerande optimeringslösare.

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Chapter 1

Introduction

1.1 Motivation

The idea of using cellular network technology dates back to at least 1947 [1,2] and was supported by the first practical implementation later in 1979 by Nippon Telegraph and Telephone (NTT). Before the cellular technology, the wireless transmitter usually communicated directly with the receiver, even if they were located very far apart. The core intention of using cellular network technology is to overcome two main limitations of early wireless communications:

1. High attenuation of signals when transmitted over a considerable distance. This severely limits the performance of wireless communication over a wide coverage area and requires very high transmit power.
2. Large interference would occur if other transmissions take place (on the same time and frequency) in the area between the transmitter and receiver. To avoid that, only one transmission was permitted, which lead to few transmissions taking place at the same time in a country [3].

Cellular communication is a fundamental technology where the transmitter and receiver communicate with nearby base stations (BSs) instead of directly with each other. This leads to wireless networks where transmissions take place over shorter distances and thereby more efficient utilization of the limited available frequency band for wireless communication. Figure 1 shows a cellular network in which the coverage area is divided into cells, where each cell has a fixed BS that the devices in the cell are connected to and provides service for them. In addition, the frequency band can be divided into the frequency sub-bands, and each cell uses some of the sub-bands. The

Figure 1: A basic cellular network. Note that the same pattern corresponds to utilization of the same frequency sub-bands.

system also considers reusing the frequency sub-bands between the cells if sufficient distances separate them, which is called frequency reuse. Therefore, the frequency reuse is selected to balance between inter-cell interference and frequent reuse of the frequency bands. Note that in Figure 1, the cells with same pattern use the same frequency sub-bands. Hence, cellular technology helped wireless network designers to provide service for larger number of users in a given area and thereby accommodated the widespread usage of wireless communication. Ultimately, the idea of cellular technology resulted in the commercial implementation of wireless communication systems [3] across the world.

Since 1979, cellular communication systems have developed significantly and became a revolutionary technology that is well utilized for the daily life of

humans worldwide. Cellular networks were initially developed for providing voice communication services to mobile users. However, the advancement of mobile devices and wireless technologies enabled mobile users to also benefit from data transmission for various kinds. This facilitates the usage of data hungry applications and services such as online gaming and video calls by mobile users.

In the past few decades, there has been an ever-increasing demand for higher data rates and more data traffic [4]. This trend is due to the developments of wireless devices and the increase of data demanding services such as on-demand video-based applications as well as an increase in the number of simultaneously active users in the networks. Cisco has predicted that a similar growth will occur in the next decade [5], and Ericsson has reported an annual growth of 30 percent between 2018 and 2024 [6]. Considering the recent trends, most of this traffic growth should come from video traffic. There has been a notable joint effort by industrial and research parties to deal with the ever-increasing inclination for higher data traffic resulting in gradual improvements of the wireless networks technologies. Different generations of wireless communication systems, from 1G to 5G, were released approximately every 10 years. Each new generation is based on a standard that continues to be evolved even when a new generation is released [4].

The following three ways are the leading solutions proposed to handle the higher demand for data traffic in the wireless networks [7, 8]:

1. Allocating more frequency bands and higher bandwidths.
2. Densification of networks by deploying more BSs in the coverage areas.
3. Improving the SE per cell.

Note that the SE is defined as the amount of information transferred per second over one Hz of bandwidth. This thesis is primarily concerned with improving the SE.

1.1.1 Massive MIMO

This subsection introduces one of the influential technologies which offers significant enhancement of the SE of future cellular networks: Massive MIMO. It was first introduced in [9] and it is considered as a backbone technology of 5G networks [4, 10]. In Massive MIMO systems, each BS is implemented with hundreds of antenna elements and each BS is assisting tens of single-antenna users. The Massive MIMO BSs are serving these users over the same time-frequency block [11]. These stand in contrast to conventional

BSs that use one or a few antennas and normally only serve one user per time-frequency block. Here, we list some of the main benefits of having large number of antennas at the BSs in Massive MIMO systems. Note that the detailed explanation of the benefits of Massive MIMO are provided in later sections.

1. It enhances the SE per cell as it provides simultaneous data transmission to more users. The interference between users are dealt with using directional transmissions.
2. By providing narrow directional transmission and reception of signals, it increases the received signal power, and consequently, for a given data rate, it requires lower transmit power. Hence, it increases also the EE of the network.

1.1.2 D2D Communication

D2D communication was introduced as a smart paradigm to enhance the utilization of the limited bandwidth in cellular networks [12]. In D2D communication, instead of sending the data through an intermediate point, i.e., the BS in the cellular system, D2D offers direct communication. Different from pre-cellular wireless communication, this feature is only utilized when it is beneficial as compared to cellular communication. To be more precise, D2D communication is practical in the case of short distances between transmitter and receiver [13]. D2D communication can either get its own dedicated resources for communication or share the same resources as cellular users. The case of sharing the same resource as cellular users is known as D2D underlay communication and this is the case considered in this thesis. It can potentially improve the SE of cellular networks as we can serve more users in a given area for a given resource in comparison with conventional cellular networks. It also enables low power data transmission (higher EE and longer battery life of cellular devices) [14, 15].

1.1.3 Topic and Motivation of the Thesis

The primary motivation of this thesis is to investigate some possible approaches to increase the SE of cellular systems. To be more specific, we mainly focus on Massive MIMO systems and D2D underlay communication as two possible technologies to enhance the SE of cellular networks. For example, in the first part, the motivation is to couple the benefits mentioned above for D2D underlay communication within Massive MIMO frameworks

to intensify the increase in SE of cellular networks. Note that a more detailed explanation of both technologies is given in later parts of the thesis.

1.2 Background

Massive MIMO originated as an extension of a multi-user MIMO system operating in time-division duplexing. A multi-user MIMO is a system that is serving multiple users simultaneously by a multi-antenna BS. Multiple antennas at the BS provides an array gain if properly used. That means the BS performs directional beamforming towards the desired receiver that amplifies the received signal power. Moreover, the multiple antennas can be used for spatial multiplexing, which is simultaneous transmission of multiple signals with different directional beamforming for serving multiple users at the same time and frequency. This can increase the SE per cell proportionally to the number of multiplexed users [16]. However, due to the limited number of antennas at the BSs in conventional multi-user MIMO, the system is only capable of simultaneous multiplexing of a small number of users. Massive MIMO refers to a system that consists of BSs with hundreds of antennas that can serve tens of users simultaneously. The BSs serve all users over the same time-frequency block by spatial multiplexing [11]. Here, we highlight two offered benefits of Massive MIMO systems.

First, it enhances the SE per cell in comparison with the conventional MIMO systems as a result of spatial multiplexing more users with Massive MIMO BSs [17]. In addition, a large number of antennas at the Massive MIMO BSs increases the array gain and the increased directivity reduces the inter-user interference, which results in higher SE per user. Therefore, Massive MIMO offers a significant boost in the per-cell SE of the cellular network.

Second, a large number of antennas at the Massive MIMO BSs makes the users' channels become almost spatially orthogonal. This is one of the key properties of Massive MIMO, which is also known as favorable propagation. As a result of favorable propagation, relatively simple processing schemes that treat interference as noise can be used efficiently. Due to the large number of antennas at the Massive MIMO BSs, the effect of small-scale fading of wireless propagation channels are averaged out. This phenomenon is known as channel hardening. One can say that under channel hardening, the channels are more deterministic. Hence, we can perform resource allocation, power control, etc., over the large-scale fading only without having small-scale fading involved in the allocation or control process. This reduces the complexity of signal processing in the system. Favorable propagation and channel hardening are

further considered in the next section.

1.3 Key Properties of Massive MIMO

In this section, we discuss some essential aspects of Massive MIMO in further detail. In particular, we explain and define favorable propagation and channel hardening in a mathematical way. In addition, we present a brief discussion on the possible duplexing protocols for Massive MIMO systems and explain why one is preferred.

1.3.1 Favorable Propagation

Favorable propagation is a phenomenon that appear when the propagation channels of two cellular users are mutually orthogonal. Favorable propagation helps the BS to cancel co-channel interference between users without having to design advanced algorithms for interference suppression. Consequently, it enhances the SE of both users. Let us assume that we have a single cell consisting of a BS that has M antennas and two single-antenna users. The vectors $\mathbf{g}_1 \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_M)$ and $\mathbf{g}_2 \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_M)$ denote the channel responses of the two users over a narrowband channel. These vectors are circularly symmetric complex Gaussian distributed with zero mean and correlation matrix $\mathbf{I}_M$ and this channel model is known as independent and identically distributed Rayleigh fading. In case the channel vectors are orthogonal, the inner product satisfies [18]

$$\mathbf{g}_1^H \mathbf{g}_2 = 0. \quad (1)$$

The BS is then capable of separating the received signal from these two users without any loss in the desired signals. Let us assume x_1 and x_2 denote the data signals transmitted by these two users. The received signal at the BS is given by

$$\mathbf{y} = \mathbf{g}_1 x_1 + \mathbf{g}_2 x_2. \quad (2)$$

Assuming the BS has perfect knowledge of both channel vectors, it can cancel the interference between the users by taking the inner product of the received signal $\mathbf{y}$ with the channel of the desired user. In addition, the noise effect is neglected for simplicity. For example, when considering user 1, the inner product is

$$\mathbf{g}_1^H \mathbf{y} = \|\mathbf{g}_1\|^2 x_1 + \mathbf{g}_1^H \mathbf{g}_2 x_2 = \|\mathbf{g}_1\|^2 x_1, \quad (3)$$

that gives the desired signal of user one, since the part $\mathbf{g}_1^H \mathbf{g}_2 x_2$ is zero thanks to orthogonality of the vectors in (1). This is an ideal situation for the BS, which is why it is called favorable propagation; however, this is not very likely to occur in practice or if the channel vectors are drawn from random distributions. However, in the case of Massive MIMO BSs, we can show that an approximate favorable propagation can happen asymptotically in the case of Rayleigh fading channels. It is defined as the inner product of the two normalized vectors satisfying [18]:

$$\frac{\mathbf{g}_1^H \mathbf{g}_2}{M} \rightarrow 0, \quad (4)$$

with almost sure convergence when $M \rightarrow \infty$, therefore as the number of antenna M grows large, these two channel vectors are asymptotically orthogonal. We denote that the above property holds for Rayleigh fading channels.

1.3.2 Channel Hardening

In this part, we define and explain the concept of channel hardening. Channel hardening refers to the case that channel is less susceptible to the small-scale fading effects and behaves more like a deterministic channel when we are using all the antennas [19]. Let us assume $\mathbf{g} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_M)$ is the channel vector of an arbitrary user towards a Massive MIMO BS, asymptotic channel hardening is defined as [7]

$$\frac{\|\mathbf{g}\|^2}{\mathbb{E}\{\|\mathbf{g}\|^2\}} \rightarrow 1, \quad (5)$$

when $M \rightarrow \infty$ the convergence holds almost surely. Note that a squared norm of the kind (5) appeared in (3) when the BS processed the received signal, which is why its value is important for the communication performance. Asymptotic channel hardening implies that the value of $\|\mathbf{g}\|^2$ is close to its mean value, so the variations are small. This phenomenon is an extension of the spatial diversity concept from small-scale MIMO systems to the case of having a large number of antennas at the BSs. Channel hardening implies that the channel quality $\|\mathbf{g}\|^2$ for a given channel realization is well approximated by the average channel quality $\mathbb{E}\{\|\mathbf{g}\|^2\}$. Hence, if we want to select power coefficients based on the channel quality, we don't need to adapt them to the small-scale fading variations, but the same power can be used for a long time period. We consider channel hardening as one of the essential benefits

of Massive MIMO systems which help us to propose practical power control schemes in the included papers in this thesis.

1.3.3 Duplexing Protocol

This subsection briefly explains the possible duplexing protocols for Massive MIMO systems, i.e., time-division duplexing (TDD) and frequency-division duplexing (FDD). Each BS needs to estimate the channel vectors of its users in each channel coherence block. A coherence block is defined as the time-frequency block in which the fading channel is static. In Massive MIMO, we assume that full statistical channel state information is available at the BSs. However, one should perform channel estimation at each BS, to obtain the instantaneous channel state information. Channel estimation is performed via pilot transmission [7, 17].

In the pilot transmission phase, each transmitter (e.g. cellular user in uplink pilot transmission) sends a set of predefined pilot signal sequences, which is known by both the transmitter and receiver (e.g. the BS in the uplink pilot transmission). The receiver compares the received pilot sequence signal with its available pilot sequence signals to estimate the channel from the transmitter. To support the pilot transmission of multiple transmitters in Massive MIMO systems, we require to have the same number of orthogonal pilot sequences signals as the number of transmitters. It is desirable to keep the pilot signals as short as possible to use most of the resources in a coherence block for data transmission. Pilot transmission for channel estimation in downlink and uplink of a Massive MIMO system requires a different number of pilot symbols. In the uplink, assuming that we have K single-antenna users, the system requires K pilot signal sequences to estimate the uplink channels. However, if the BS has M antennas, pilot transmission in the downlink requires M pilot signals, where $M \gg K$ is normal in Massive MIMO systems.

TDD refers to separating the uplink and downlink transmissions in the time-domain while using the whole bandwidth; assuming that both happen in the same coherence time, channel reciprocity holds. It means that the channel is the same in both directions. Hence, by doing channel estimation in one direction (i.e., uplink here), the estimated channel is valid for the other direction (i.e., downlink) as well. Therefore, in TDD Massive MIMO systems, we require K pilot sequences only. Hence, channel estimation does not depend on M .

In FDD, the uplink and downlink transmission occur at the same time but in different frequency bands. Hence, due to the different frequency bands

for uplink and downlink, the channel reciprocity does not hold. Consequently, we need to estimate the channels separately for each direction. Therefore, we require both uplink and downlink pilots for channel estimation in FDD. In downlink, we need M pilot signal sequences and an additional M signals for reporting back the estimated channel to the BS in the uplink. Besides, we need K pilots for uplink channel estimation. In total, assuming the resources are equally divided between uplink and downlink, FDD needs $(2M + K)/2$ pilots signal. The time-frequency separation of these two protocols is illustrated in Fig. 2.

Figure 2: Time-frequency separation of coherence block for TDD and FDD protocol [7].

One can see that channel estimation overhead in TDD Massive MIMO is substantially smaller than in FDD Massive MIMO, and it is not scaled with M . Therefore, TDD is a preferable duplexing mode for Massive MIMO systems, and we assume TDD for the included papers in this thesis.

1.4 Research Problems on Power Control

Academic researchers and companies have analyzed and studied Massive MIMO from many different perspectives [20–24]. Here, we focus on describing research into power control for Massive MIMO systems. In general, power control is an important design parameter in the cellular networks to mitigate mutual interference among users and enhance the desired part of the received signal at the receivers [25]. When many users are sharing the same time-frequency resources, it is necessary to make tradeoffs between their performance, which can be measured using different metrics. Power control is still an open problem for cellular networks, and as a matter of fact, it has a long research history from single-antenna communication to

Massive MIMO systems. Wireless channel fading and the conflicting nature due to co-user interference make power control a challenging design task. Power control algorithms provided in conventional MIMO papers are based on instantaneous channel state information, and they therefore depend on the small-scale fading coefficients. Hence, one should solve and update the transmit powers frequently to track the changes in the small-scale fading. Optimizing the power control based on small-scale fading brings high overhead due to the fact that frequent control signaling is needed.

The authors in [26] proved that finding a globally optimal power control solution that maximizes sum SE in a multi-user communication system with communication pairs re-using a common frequency band is an NP-hard problem for both uplink and downlink directions which means we can not solve it in polynomial time. Therefore, several research papers have developed power control schemes that achieve a locally optimal solution with a computational complexity that grows polynomially with the number of users [27].

One significant advantage of the channel hardening in Massive MIMO is that the SE expressions depend only on the large-scale channel coefficients representing the average channel quality. Hence, when applying power control to Massive MIMO systems we only need a long-term power control algorithm as the large-scale fading coefficients change less frequent than small-scale fading. This reduces the computational complexity of power allocation at the BSs and also reduces the signaling overhead of the system. As a result, there is a significant computation complexity reduction for solving power control problems in cellular networks equipped with Massive MIMO BSs.

Several researchers have investigated the coexistence of Massive MIMO technology with other existing cellular paradigms [28–30]. D2D communication underlaying cellular networks is one of these paradigms. Massive MIMO can overcome one major problem of D2D underlay communication. The concern is how to control the interference that the D2D underlay communication causes to the cellular network due to the sharing of the same channel between D2D pairs and cellular users. The massive number of antennas at each BS in Massive MIMO systems handles this thanks to the favorable propagation property.

This motivates us to investigate D2D underlaid multi-cell Massive MIMO systems. The idea is to design a framework which supports D2D pairs coexisting with cellular users in a conventional Massive MIMO setup. Channel estimation plays an essential role in the beamforming design of the Massive MIMO system. It is important in the D2D underlaid Massive MIMO setup as well. We propose a new pilot transmission scheme and do channel estimation

at both the D2D receiver and the BSs for a D2D underlaid multi-cell Massive MIMO system. Using this channel estimation, we try to find closed-form approximate capacity lower bounds for both D2D and cellular communication, which only depend on the large-scale fading coefficients. Finally, using these SE expressions, we develop power control schemes in D2D underlaid Massive MIMO systems.

In this thesis, we also develop a new power control framework for multi-cell Massive MIMO systems. The target of the framework is to overcome a hidden scalability issue of two well-known power control schemes in the Massive MIMO literature, i.e., network-wide max-min fairness and network-wide proportional fairness which will be discussed in details in later chapters.

1.5 Optimization Approaches

The main objective of this section is to briefly introduce some of the primary optimization approaches. Optimization theory is a mathematical tool which is widely used in the wireless communication literature. It is utilized to deal with different resource allocation problems and especially power control problems. In the included papers of this thesis, we formulate different optimization problems with respect to predefined constraints and solve these problems with different optimization methods.

An optimization problem on the standard form is written as [31, Ch. 4]

$$\begin{aligned} & \underset{\mathbf{x}}{\text{minimize}} && f_0(\mathbf{x}) \\ & \text{subject to} && f_i(\mathbf{x}) \leq 0, \quad i = 1, \dots, m, \\ & && f_j(\mathbf{x}) = 0, \quad j = 1, \dots, q. \end{aligned} \tag{6}$$

In this problem formulation, the vector $\mathbf{x} \in \mathbb{R}^n$ denotes the optimization variable (note that $\mathbb{R}^n$ is the set of real n -length vectors). The cost (or objective) function of this problem is denoted by $f_0 : \mathbb{R}^n \rightarrow \mathbb{R}$ and the m inequality constraints are $f_i(\mathbf{x}) \leq 0$, $i = 1, \dots, m$, in which $f_i : \mathbb{R}^n \rightarrow \mathbb{R}$ are the inequality constraint functions. In addition, $f_j(\mathbf{x}) = 0$, $j = 1, \dots, q$, denotes the q equality constraints with the constraint functions $f_j : \mathbb{R}^n \rightarrow \mathbb{R}$ [31, Ch. 4]. The domain of this optimization problem is defined as

$$\mathcal{D} = \bigcap_{i=0}^m \text{dom} f_i \quad \cap \quad \bigcap_{j=1}^q \text{dom} f_j,$$

which is the set of point in which the objective, equality and inequality functions are defined and we write it as the intersection of the domains of

the objective and all constraints. Note that the **dom** f notation is used to denote the domain of each function f , i.e., the subset of $\mathbb{R}^n$ containing points $\mathbf{x}$ for which $f(\mathbf{x})$ is defined.

The feasible set of this optimization problem is defined as the set of all vectors that belong to $\mathcal{D}$ and satisfies the inequality and equality constraints. A vector $\mathbf{x}^{\text{opt}}$ is a globally optimal solution of this problem if it provides the minimum objective function value among all the points in the feasible set. However, if a vector $\mathbf{x}^*$ provides the minimum objective function in the vicinity of itself, this vector is known as the locally minimum solution.

In general, solving an optimization problem to find the globally optimal solution (in case it exists) is a challenging task which depends on many different factors such as the type of cost functions or constraint functions. However, one can efficiently find the globally optimal solution for some specific sorts of optimization problems that will be described below.

1.5.1 Convex Optimization

Convex optimization problems is the fundamental type of problem formulation that we use in the included papers in this thesis. One excellent property of a convex problem is that any locally optimal point is also globally optimal. Hence, it is sufficient to design algorithms capable of finding a locally optimal solution. The standard form of a convex optimization problem follows the same formulation as (6) with the additional requirements that the objective function f_0 and inequality constraint functions $f_i, i = 1, \dots, m$ are convex. In addition, to satisfy convexity requirements, the equality constraint functions $g_j, j = 1, \dots, q$ have to be affine. A convex function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is defined such that the domain of f is a convex set (defined as the set such that the line segment of any two points of the set are also included in the set) and for all points $\mathbf{x}_1, \mathbf{x}_2 \in \text{dom } f$, and $0 \leq \alpha \leq 1$ the following holds [31]

$$f(\alpha \mathbf{x}_1 + (1 - \alpha) \mathbf{x}_2) \leq \alpha f(\mathbf{x}_1) + (1 - \alpha) f(\mathbf{x}_2). \quad (7)$$

For example $f(x) = x^2$ is a convex function. Note that if this equation always holds with equality, the function f is called an affine function and can be drawn as a straight line. The globally optimal solution to a convex optimization problem can be obtained by using, for example interior-point methods which requires computing the first and second derivative of the objective and constraint functions to update the optimization variable along iterations [31]. In the next part, we introduce linear programming as a special case of convex optimization problems.

1.5.2 Linear Programming

Linear programming is a fundamental optimization class defined as [31]

$$\begin{aligned} & \underset{\mathbf{x}}{\text{minimize}} && \mathbf{c}^T \mathbf{x} \\ & \text{subject to} && \mathbf{a}_i^T \mathbf{x} \leq b_i, \quad i = 1, \dots, m, \end{aligned} \quad (8)$$

where $\mathbf{c} \in \mathbb{R}^n$ and $\mathbf{a}_i \in \mathbb{R}^n$ are the corresponding coefficients for the objective and constraint functions, respectively. One can map this optimization problem to the standard form in (6) as $f_0(\mathbf{x}) = \mathbf{c}^T \mathbf{x}$ for the objective function and $f_i(\mathbf{x}) = \mathbf{a}_i^T \mathbf{x} - b_i, \forall i$ for the inequality constraint functions. Note that f_0 and f_i 's are linear functions of $\mathbf{x}$. In linear programming, we are minimizing a linear objective function with respect to linear constraints which is the reason for calling this type of problems linear programming.

The linear programming problem generally does not have simple analytical formula which provides a solution for it [31]. However, it is a convex problem, and there exist several effective methods that solve it in polynomial time. The computation complexity of solving linear programming is relatively low (i.e., in order of n^2m assuming $m \geq n$) because we do not need to compute the second derivative. In general, we can use general-purpose optimization solving toolbox such as CVX which applies interior-point methods for solving linear programming [32].

1.5.3 Epigraph Form

One can introduce an equivalent epigraph form for the original problem (6):

$$\begin{aligned} & \underset{\mathbf{x}, \lambda}{\text{minimize}} && \lambda \\ & \text{subject to} && f_0(\mathbf{x}) - \lambda \leq 0, \\ & && f_i(\mathbf{x}) \leq 0, \quad i = 1, \dots, m, \\ & && g_j(\mathbf{x}) = 0, \quad j = 1, \dots, q. \end{aligned} \quad (9)$$

This new problem is equivalent to the original problem, and besides, it has a more tractable structure as it has a linear objective function, therefore easier to be solved efficiently. We can solve the equivalent epigraph problem instead of the original problem, and the optimal solution is the solution for the original problem [31].

We applied this type of problem reformulation for solving max-min fairness power control problems in the included papers in this thesis. Note that a detailed explanation of max-min fairness is provided in the next chapter.

1.5.4 Geometric Programming

Another type of optimization problem that we used for developing our power control algorithm in this thesis is called geometric programming. A standard geometric program has the following form [33–35]

$$\begin{aligned}
 & \underset{\mathbf{x}}{\text{minimize}} && \sum_{k=1}^{K_0} a_{0k} \prod_{l=1}^n x_l^{c_{0k}^l} \\
 & \text{subject to} && \sum_{k=1}^{K_i} a_{ik} \prod_{l=1}^n x_l^{c_{ik}^l} \leq 1, \quad i = 1, \dots, m, \\
 & && a_j \prod_{l=1}^n x_l^{c_j^l} = 1, \quad j = 1, \dots, q,
 \end{aligned} \tag{10}$$

where a_{0k}, a_{ik}, a_j are positive coefficients and the exponents $c_{0k}^l, c_{ik}^l, c_j^l \in \mathbb{R}$. In this problem formulation, $x_l \in \mathbb{R}_+$ is one of the elements of the vector $\mathbf{x} = [x_1, \dots, x_n]^T \in \mathbb{R}_+^n$. To map this problem to the standard form provided in (6), we have $f_0(\mathbf{x}) = \sum_{k=1}^{K_0} a_{0k} \prod_{l=1}^n x_l^{c_{0k}^l}$, $f_i(\mathbf{x}) = \sum_{k=1}^{K_i} a_{ik} \prod_{l=1}^n x_l^{c_{ik}^l} - 1, \forall i$ and $f_j(\mathbf{x}) = a_j \prod_{l=1}^n x_l^{c_j^l} - 1, \forall j$.

The type of function used in the objective function and inequality constraints is known as a posynomial. The type of function provided in the equality constraint is called a monomial function. Geometric programming in the standard form provided in (10) is a non-convex problem, but can be rewritten as a convex problem. One can apply changes of variables as $x_l = e^{y_l}$ for all the variables x_l . In addition, by replacing the objective and inequality constraint functions with their corresponding logarithms, they become logarithms of the sums of the exponential function, which is convex. Besides, taking the logarithm of monomial constraints convert them to linear constraints. The reformulated problem by applying the mentioned changes is given by

$$\begin{aligned}
 & \underset{\mathbf{y}}{\text{minimize}} && \log \left(\sum_{k=1}^{K_0} a_{0k} e^{\sum_{l=1}^n y_l c_{0k}^l} \right) \\
 & \text{subject to} && \log \left(\sum_{k=1}^{K_i} a_{ik} e^{\sum_{l=1}^n y_l c_{ik}^l} \right) \leq 0, \quad i = 1, \dots, m, \\
 & && \log \left(a_j e^{\sum_{l=1}^n y_l c_j^l} \right) = 0, \quad j = 1, \dots, q.
 \end{aligned} \tag{11}$$

Since the new reformulated problem is convex, the globally optimal solution can be found efficiently by using a general-purpose optimization solving toolbox such as CVX [32, 33]. This type of optimization problem is useful for developing proportional fairness power control schemes and such schemes are proposed in the included papers in this thesis. In Paper A, we develop a power control framework for a D2D underlaid Massive MIMO system. In the first part on the paper, geometric programming is utilized to model the proportional fairness power control framework that deals with optimizing data transmission power of D2D and cellular communications at the same time. In addition, in Paper B, we investigate the scalability issue of available power control frameworks for conventional multi-cell Massive MIMO system. In this paper, geometric programming is used to model proportional fairness power control as well.

1.5.5 Signomial Programming

Signomial programming is an optimization problem that has a similar form as the geometric program provided in (10) but it has the following form

$$\begin{aligned}
& \underset{\mathbf{x}}{\text{minimize}} && \sum_{k=1}^{K_0} a_{0k} \prod_{l=1}^n x_l^{c_{0k}^l} \\
& \text{subject to} && \sum_{k=1}^{K_i} a_{ik} \prod_{l=1}^n x_l^{c_{ik}^l} \leq 1, \quad i = 1, \dots, m, \\
& && a_j \prod_{l=1}^n x_l^{c_j^l} = 1, \quad j = 1, \dots, q,
\end{aligned} \tag{12}$$

where unlike the geometric programming a_{0k}, a_{ik}, a_j can have negative values as well. Consequently, in this type of optimization problems, the objective and constraint functions can be signomial functions. This problem is non-convex if at least one of the coefficients is negative, and the non-convex problem does not have the hidden convex structure as a geometric program has. Solving this non-convex optimization problem has high computational complexity [35]. Therefore, it is more practical to find a locally optimal solution instead. We develop a successive approximation approach in Paper A that provides the local optimal solution for signomial problem efficiently [27]. This type of optimization problem is utilized to model proportional fairness power control when optimizing both pilot and data power coefficients.

Chapter 2

Power Control Schemes For Massive MIMO

In single-input-single-output (SISO) communication or in a MIMO system with perfect channel state information (CSI) available, one can claim that the transmitter can transmit data with full power to maximize its performance. This is due to the fact that there is no interference in the SISO case and for the case of MIMO with perfect CSI, applying beamforming techniques such as zero-forcing can offer orthogonal transmission without interference. However, in practical implementations, only imperfect CSI is available which leads to mutual interference in the system. Interference is known as one of the limiting factors in wireless communications and occurs due to the broadcast nature associated with wireless propagation channels.

Power control is a fundamental design part of the wireless cellular networks. Power control accommodates cellular networks to control the interference level of wireless links effectively. Consequently, power control directly influences the SE that each user achieves both in the uplink and downlink data transmissions [25].

Power control is likewise a crucial management part to improve the EE of cellular networks as it helps to minimize the energy consumption of both cellular devices and BSs while guaranteeing the required quality of service of each communication link. Power control has a long history in wireless cellular networks [36,37]. In this chapter, we discuss and explain some of the known power control schemes for Massive MIMO systems.

To explain the basic behaviors of power control, we first investigate two power control schemes. Figure 3 plots the cumulative distribution function (CDF) of the SE achieved by randomly located users in the uplink data transmission in a multi-cell Massive MIMO setup for two power control

schemes. In the first case, all users transmit with full power, and in the second case, we apply the power control scheme that we call A. We neglect the details of the simulation setup and schemes here to focus on the behaviors. Comparing the two plots, one can see that around 75 percent of the users get higher SE when we apply the scheme A in comparison with full power transmission. However, there is approximately 25 percent of users in the upper parts of the curves who get higher SE when using full power transmission. This highlights the fact that power control aims at increasing the overall performance of the whole network by balancing the transmit power and controlling the mutual interference. Note that the users with the lowest SEs benefit the most from power control, while the users with the highest SEs are getting a reduced performance. Hence, there is a nontrivial tradeoff between the performance of different users, and different power control schemes are managing the tradeoff differently.

Figure 3: Per user SE for uplink data transmission.

In this thesis, we investigate both uplink and downlink power control schemes with objective functions such as max-min fairness and proportional fairness. These schemes seek to control the mutual interference in the Massive MIMO networks to achieve the optimization objectives. In this chapter, we first introduce a typical multi-cell Massive MIMO system model. Then, we discuss the general form of the max-min and proportional fairness power control schemes that have previously appeared in the literature. Then, we provide the main use cases of these power control approaches that are

further discussed in the included papers. In Paper A, we extend these power control schemes for D2D underlaid Massive MIMO systems to optimize both data and pilot power of cellular and D2D users. We also show that these power control schemes can successfully control additional interference of D2D communication to the conventional Massive MIMO networks. Therefore, applying power control to D2D underlaid Massive MIMO networks eventually increases the sum SE of the whole network.

In the second use case, we introduce the scalability issue of max-min and proportional fairness for large multi-cell Massive MIMO systems and describe a new power control scheme to solve this issue which will be further discussed in details in Paper B.

2.1 System Model

In this section, we consider a multi-cell Massive MIMO setup. We use this system model to explain and discuss the original form of the network-wide max-min and proportional fairness power control schemes. The main goal is to give some required information, e.g., SE expressions that we use in the later sections. In this setup, we assume that the network consists of L cells, and each cell has one BS. The number of antennas at the BSs are equal, and each BS has M antennas. Besides, each cell serves K single antenna users in the coverage area.

In this system model, we assume that the system operates in TDD mode. We use a block fading assumption to model wireless propagation channels that are varying over time and frequency. This is a time-frequency block of τ_c samples in which the channel is constant and frequency-flat, which is defined as the coherence block of the channel. A stationary ergodic random process is used to model that the channel is changing independently over different blocks. The size of $\tau_c = T_c B_c$ which depends on the coherence time and bandwidth denoted by T_c and B_c , respectively [17, Ch. 2], [7, Ch. 2]. We denote the channel response between user k located in cell l' towards the BS in cell l by the vector $\mathbf{g}_{l'k}^l \sim \mathcal{CN}(\mathbf{0}, \beta_{l'k}^l \mathbf{I}_M)$. The channels take one independent realization in each coherence block. The nonnegative $\beta_{l'k}^l$ is the large-scale fading coefficient for this channel response. Fig. 4 illustrates the multi-cell model. The received signal during data transmission at BS l is

$$\mathbf{y}_l = \sum_{k=1}^K \sqrt{\rho_{ul} \eta_{lk}} \mathbf{g}_{l,k}^l s_{lk} + \sum_{\substack{l'=1, \\ l' \neq l}}^L \sum_{k=1}^K \sqrt{\rho_{ul} \eta_{l'k}} \mathbf{g}_{l'k}^l s_{l'k} + \mathbf{w}_l, \quad (13)$$

Figure 4: Illustration of multi-cell setup.

where s_{lk} is the zero mean and unit variance data symbol transmitted from user k in cell l and $\eta_{lk} \in [0, 1]$ denotes the power control coefficient of user k located in cell l . It is the power control coefficients that will be optimized in this thesis. In addition, ρ_{ul} is the maximum uplink transmit power. $\mathbf{w}_l \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_M)$ indicates the normalized additive white Gaussian noise at BS l . The actual noise variance can be included in either the large-scale fading coefficients or the maximum transmit powers, without loss of generality.

In this setup, we assume that the BSs do not have CSI a priori. Since the channels are changing over each coherence block, the system requires to carry out channel estimation in each coherence block. Therefore, $\tau_p \geq K$ symbols are dedicated to uplink pilot transmission from the users to BSs, which gives room for transmitting deterministic pilot sequences of length τ_p . Furthermore, we use the remaining $\tau_c - \tau_p$ symbols for uplink and downlink data transmission. Fig. 5 illustrates one coherence block of TDD Massive MIMO.

Figure 5: One coherence block in a TDD Massive MIMO system.

As we discussed in Subsection 1.3.3, due to channel reciprocity, the estimated channel for the uplink can be used for the downlink direction as well. The K users in a cell are assumed to be using orthogonal pilot sequences from the τ_p samples. However, as we have a limited number of pilot sequences in the network (LK is generally larger than τ_p), we need to reuse each pilot sequence in multiple cells according to some pilot reuse policy.

This will cause mutual interference in the pilot transmission of the users that are using the same pilot sequence. This mutual interference is called pilot contamination in the literature. Consequently, pilot contamination affects the channel estimation quality and is one of the limiting factors of Massive MIMO systems.

During the pilot transmission in the considered system model, the received pilot signal at BS l is denoted as $\mathbf{Y}_l^p \in \mathbb{C}^{M \times \tau_p}$

$$\mathbf{Y}_l^p = \sum_{k=1}^K \sum_{l'=1}^L \sqrt{\tau_p \rho_{ul}} \mathbf{g}_{l'k}^l (\phi_{l'k})^H + \mathbf{W}_l, \quad (14)$$

where $\phi_{lk} \in \mathbb{C}^{\tau_p}$ indicates the orthonormal pilot sequence assigned for user k in cell l and $\mathbf{W}_l \in \mathbb{C}^{M \times \tau_p}$ is the normalized additive white Gaussian noise at the BS l that consists of independent entries which are having the distribution $\mathcal{CN}(0, 1)$. Note that for simplicity, all users use full transmit power for pilot transmission, therefore there are no power control coefficients in (14). We denote the pilot matrix used by the users in cell l as $\Phi_l = [\phi_{l1}, \dots, \phi_{lK}]$. Each BS multiplies the received signal matrix during pilot transmission with its pilot matrix to despread the signals. Therefore, the received pilot signal at BS l is after despreading by the pilot matrix Φ_l is given by

$$\mathbf{Y}_l^p \Phi_l = \sum_{k=1}^K \sum_{l'=1}^L \sqrt{\tau_p \rho_{ul}} \mathbf{g}_{l'k}^l (\phi_{l'k})^H \Phi_l + \mathbf{W}_l \Phi_l. \quad (15)$$

The minimum mean square error (MMSE) estimates of $\mathbf{g}_{l'k}^l$ is denoted as $\hat{\mathbf{g}}_{l'k}^l \sim \mathcal{CN}(\mathbf{0}, \gamma_{l'k}^l \mathbf{I}_M)$ that follows the standard MMSE estimation approach in the literature, e.g., [7, 17, 38] given by

$$\hat{\mathbf{g}}_{l'k}^l = \frac{\sqrt{\tau_p \rho_{ul}} \beta_{l'k}^l}{1 + \tau_p \rho_{ul} \sum_{l'' \in \mathcal{P}_l} \beta_{l''k}^l} \mathbf{Y}_l^p \phi_{lk}, \quad l' \in \mathcal{P}_l, \quad (16)$$

and the mean-square of the channel estimate $\hat{\mathbf{g}}_{l'k}^l$ is

$$\gamma_{l'k}^l = \frac{\tau_p \rho_{ul} (\beta_{l'k}^l)^2}{1 + \tau_p \rho_{ul} \sum_{l'' \in \mathcal{P}_l} \beta_{l''k}^l}, \quad l' \in \mathcal{P}_l, \quad (17)$$

where $\mathcal{P}_l$ is the set of the BSs that are using the same K pilot sequences as BS l . We also assume that for the BSs that are sharing the same set

of pilot sequences, users with index k utilize an identical pilot sequence for $k = 1, \dots, K$.

In the discussion here, we apply maximum ratio (MR) combining at each BS during the uplink data transmission phase. BS l uses the channel estimates to detect the signal of its own user based on the received signal in (13). The resulting estimate of the data signal of user k in cell l can be expressed as

$$\begin{aligned} \left(\hat{\mathbf{g}}_{lk}^l\right)^H \mathbf{y}_l &= \sqrt{\rho_{ul}\eta_{lk}} \left(\hat{\mathbf{g}}_{lk}^l\right)^H \mathbf{g}_{lk}^l s_{lk} + \sum_{\substack{k'=1, \\ k' \neq k}}^K \sqrt{\rho_{ul}\eta_{lk'}} \left(\hat{\mathbf{g}}_{lk}^l\right)^H \mathbf{g}_{lk'}^l s_{lk'} + \\ &\sum_{\substack{l'=1, \\ l' \neq l}}^B \sum_{k'=1}^K \sqrt{\rho_{ul}\eta_{l'k'}} \left(\hat{\mathbf{g}}_{lk}^l\right)^H \mathbf{g}_{l',k'}^l s_{l'k'} + \left(\hat{\mathbf{g}}_{lk}^l\right)^H \mathbf{w}_l, \end{aligned} \quad (18)$$

where the first term is the desired part of the received signal, the second term is the intracell interference from other users in cell l , the third term is intercell interference coming from other users in the other cells. We rewrite the received data signal of the user k in the cell l by adding and subtracting $\sqrt{\rho_{ul}\eta_{lk}} \mathbb{E} \left[\left(\hat{\mathbf{g}}_{lk}^l\right)^H \mathbf{g}_{lk}^l \right] s_{lk}$ term as

$$\begin{aligned} \left(\hat{\mathbf{g}}_{lk}^l\right)^H \mathbf{y}_l &= \sqrt{\rho_{ul}\eta_{lk}} \mathbb{E} \left[\left(\hat{\mathbf{g}}_{lk}^l\right)^H \mathbf{g}_{lk}^l \right] s_{lk} + \sqrt{\rho_{ul}\eta_{lk}} \left(\left(\hat{\mathbf{g}}_{lk}^l\right)^H \mathbf{g}_{lk}^l - \mathbb{E} \left[\left(\hat{\mathbf{g}}_{lk}^l\right)^H \mathbf{g}_{lk}^l \right] \right) s_{lk} \\ &+ \sum_{\substack{k'=1, \\ k' \neq k}}^K \sqrt{\rho_{ul}\eta_{lk'}} \left(\hat{\mathbf{g}}_{lk}^l\right)^H \mathbf{g}_{lk'}^l s_{lk'} + \sum_{\substack{l'=1, \\ l' \neq l}}^L \sum_{k'=1}^K \sqrt{\rho_{ul}\eta_{l'k'}} \left(\hat{\mathbf{g}}_{lk}^l\right)^H \mathbf{g}_{l',k'}^l s_{l'k'} + \left(\hat{\mathbf{g}}_{lk}^l\right)^H \mathbf{w}_l, \end{aligned} \quad (19)$$

where the first term is treated as the desired part of the received signal and the rest of the terms are treated as noise in the signal detection. We can then use the use-and-then-forget technique [17, Ch. 3] to lower bound the capacity of each of the users, using the capacity bound for a deterministic channel with additive non-Gaussian noise provided in [17, Sec. 2.3]. We get the lower bound on the capacity of user k in cell l as

$$\text{SE}_{lk} = \left(1 - \frac{\tau_p}{\tau_c}\right) \log_2 (1 + \text{SINR}_{lk}), \quad (20)$$

where SINR_{lk} is the effective SINR of user k in cell l for uplink data trans-

mission

$$\text{SINR}_{lk} = \frac{M\rho_{\text{ul}}\gamma_{lk}^l\eta_{lk}}{1 + \rho_{\text{ul}} \sum_{l'=1}^L \sum_{k'=1}^K \beta_{l'k'}^l \eta_{l'k'} + M\rho_{\text{ul}} \sum_{l' \in \mathcal{P}_l \setminus \{l\}} \gamma_{l'k}^l \eta_{l'k}}. \quad (21)$$

We denote the lower bound in (20) as the SE of user k in cell l . Note that even though we only provide the results for the case of MR for the uplink data transmission in this chapter, the power control approaches can be taken also for downlink data transmission with MR as well as other processing schemes. We will use the effective SINR expression provided in this section for explanation and discussion of network-wide max-min and proportional fairness power control schemes in multi-cell Massive MIMO systems.

2.2 Max-min Fairness

This section introduces the general form of the max-min fairness power control scheme for the multi-cell Massive MIMO setup defined in Section 2.1. Max-min fairness is one of the well-known power control schemes that are suitable for a network that is serving users with identical data demand. Applying network-wide max-min fairness in the multi-cell Massive MIMO setup provides a uniform SE for all $K \times L$ users. We optimize data power coefficients here to satisfy network-wide max-min fairness criteria. We formulate the optimization problem as

$$\begin{aligned} & \underset{\{\eta_{lk}\}}{\text{maximize}} && \min_{l,k} \text{SINR}_{lk} \\ & \text{subject to} && 0 \leq \eta_{lk} \leq 1, \forall l, k. \end{aligned} \quad (22)$$

Note that we are maximizing the minimum SINR of the weakest user in the whole network. In the objective function, we replace SINR_{lk} by the corresponding effective SINR expression provided in (21), which is a function of all the power-control coefficients. To solve this problem, we can rewrite it in the epigraph form

$$\begin{aligned} & \underset{\{\eta_{lk}\}, t}{\text{maximize}} && t \\ & \text{subject to} && 0 \leq \eta_{lk} \leq 1, \forall l, k, \\ & && \text{SINR}_{lk} \geq t, \forall l, k. \end{aligned} \quad (23)$$

Now, we are maximizing an auxiliary variable t that indicates the SINR requirement of all the users in the network. We have new constraints over SINRs, which correspond to the original objective function. These new constraint are linear constraints for a fixed value of t . Hence, to solve this problem, we can fix t and solve the corresponding linear optimization problem which can be solved efficiently using standard solvers, as described in Subsection 1.5.2. We can then use the bisection algorithm to perform a line search over the interval $t \in [0, t^u]$ to find the optimal SINR solution. t^u is an upper bound on the SINRs for which the problem is known to be infeasible. Note that the detailed bisection algorithm for solving the max-min fairness problem is provided in [7, 31].

This section provided a brief description of the network-wide max-min fairness power control for a multi-cell Massive MIMO system. We offer a more detailed discussion of this scheme in the included papers. In Paper A, as a practical use case of one of the proposed power control schemes, we extend the network-wide max-min fairness scheme to the case when D2D communication is underlaying a Massive MIMO system. In the proposed scheme, we optimize both data and pilot power coefficients, which is more general than what we described here. In Paper B, we investigate a hidden scalability issue of network-wide max-min fairness power control in multi-cell Massive MIMO systems and propose a novel scalable solution. Hence, a more detailed study of the max-min fairness power control scheme is available in both of the included papers in this thesis.

2.3 Proportional Fairness

This section concentrates on explanation and discussion on network-wide proportional fairness power control approach for uplink data transmission of a multi-cell Massive MIMO system. Network-wide max-min fairness offers a uniform service for all the users in the network, but it has to sacrifice a lot in SE for an average user to bring up the SE for the weakest user. Therefore, network-wide max-min fairness limits the overall network service performance according to the weakest user. In addition, it cannot satisfies the users with higher service requirement and good channel condition.

Proportional fairness is a power control scheme that can potentially tackle the limitation mentioned above for network-wide max-min fairness [39]. We write the optimization problem as maximizing the product of the individual SINRs of all users in the network with respect to the power-control coefficient [7]. This objective function is a lower bound on the sum SE of the network. It offers fairness up to some level without sacrificing a lot in SE for an

average user. The optimization problem for uplink data transmission of the considered system model is given by

$$\begin{aligned} & \underset{\{\eta_{lk}\}}{\text{maximize}} && \prod_{l=1}^L \prod_{k=1}^K \text{SINR}_{lk} \\ & \text{subject to} && 0 \leq \eta_{lk} \leq 1, \forall l, k. \end{aligned} \quad (24)$$

This problem can be rewritten by using auxiliary variables λ_{lk} in the objective and adding corresponding SINR constraints as [7]

$$\begin{aligned} & \underset{\{\eta_{lk}\}, \{\lambda_{lk} \geq 0\}}{\text{maximize}} && \prod_{l=1}^L \prod_{k=1}^K \lambda_{lk} \\ & \text{subject to} && 0 \leq \eta_{lk} \leq 1, \forall l, k, \\ & && \text{SINR}_{lk} \geq \lambda_{lk}, \forall l, k. \end{aligned} \quad (25)$$

This is an optimization problem with monomial objective function and posynomial constraint. Therefore, it is a geometric programming optimization problem in which it can be solved efficiently by CVX [32].

Here, we provide a numerical comparison of network-wide max-min and proportional fairness algorithms (denoted by NW-MMF and NW-PF in the figures, respectively) to highlight their respective behavior. As a baseline, we provide the result for full power transmission denoted as full power in the figures. We consider uplink data transmission in a multi-cell Massive MIMO setup with nine BSs deployed on a square grid layout with wrap-around to avoid edge effects. Each BS is equipped with $M = 100$ antennas and applies MR combining. Furthermore, each BS serves five users that are randomly distributed with uniform distribution in the coverage area of the BS. We assume $\tau_p = K$ and each coherence block contains 200 symbols. The large-scale fading coefficients are given by [7]

$$\beta_{l',k}^l [\text{dB}] = -35 - 36.7 \log_{10} \left(d_{l',k}^l / 1 \text{ m} \right) + F_{l',k}^l, \quad (26)$$

where $d_{l',k}^l$ is the distance between user k located in cell l' to BS l . In addition, $F_{l',k}^l$ is the shadow fading generated from a log-normal distribution with standard deviation 7 dB. The noise variance is set to -94 dBm, and the maximum transmit power of the users is 200 mW for uplink data transmission [40]. Figure 6 plots the CDF of the SE of all the users for uplink data transmission, for different random user locations with uniform distribution.

Figure 6: Per user SE for uplink data transmission for different random user locations.

It can be seen from the figures that network-wide proportional fairness gives higher SE than max-min fairness for the majority of users. By comparing network-wide max-min and proportional fairness with no power control, we can see that 30% and 75% of users get higher SE, respectively. However, by making a one-to-one comparison for all the users, we notice that 12% of the users get better SE with network-wide max-min fairness than with network-wide proportional fairness. It is the users with the lowest SEs that benefit from the max-min fairness objective function.

In Fig. 7, we show the CDF of the sum SE in the network with respect to different random user locations. We can see that network-wide proportional fairness performs the best in terms of sum SE, as we mentioned previously. The conclusion is that different power control methods are maximizing different objective functions and it is up to the network designer to select an appropriate objective function.

2.4 Use Cases

This section describes some practical use cases of the power control schemes that are also considered in the papers included in this thesis.

Figure 7: Sum SE for uplink data transmission for different random user locations.

2.4.1 D2D Underlay Communications

In this subsection, we provide some basic definitions of D2D communications. We mainly focus on D2D underlay Massive MIMO communication and give a brief explanation of data and pilot power control for D2D underlaid Massive MIMO setups. D2D communications is an alternative communication paradigm in wireless cellular systems in which the transmitting and receiving users are offered direct communication instead of sending traffic through the BSs. For D2D communication to be effective, the transmitter and receiver must be located in the vicinity of each other. Bypassing the BS results in offloading a portion of the BS's traffic load which potentially improves the sum SE of the network. There are other gains that D2D offers, due to the short-range of communication between D2D users. These are higher SE for the D2D users and lower power resulting in longer battery life [15, 41–44].

Different D2D communication policies are available in the literature, e.g., [13]. There are two main classes of D2D communication. The first one is called inband communication in which D2D users reuse the cellular resources and the second one is outband that uses unlicensed spectrum. Outband D2D does not use cellular resources and make no overhead for the cellular network. However, the service providers do not have any control of the connection and quality of service as it uses the license-free band. Therefore, it has received less attention in the literature. In inband communication, the D2D users can either use the same resources as the cellular users, which is called

D2D underlay communication or the D2D users get dedicated resources for D2D communication that are not used by cellular users. Dedicating cellular resource for D2D communication can decrease the SE of the network; hence, underlay D2D communication is preferable. It can notably enhance the SE and EE of the cellular system, since it increases the usage of cellular resources by sharing them for D2D communication as well. However, sharing cellular resources for D2D underlay communication generates additional interference that need to be properly dealt with. There is a number of ways to mitigate the extra interference from D2D to cellular communication and vice versa. For example, mode selection, scheduling techniques, power allocation, and beamforming schemes [42, 44, 45].

In Paper A, we focus on D2D underlay communication cellular networks underlaying Massive MIMO systems. We investigate how Massive MIMO BSs helps us to mitigate the extra interference to the network from D2D underlay communication. We use power control as one of the main tools for interference management for D2D underlay communication. This paper utilizes both the network-wide max-min and proportional fairness power control schemes discussed in Section 2.2 and 2.3, respectively. To be more specific, we derive closed-form SE expressions for the cellular and D2D communications. Then, we use these SE expressions to formulate and solve the proposed power control schemes. However, instead of optimizing only the data power coefficients as in this chapter, we propose to optimize both the pilot and data power coefficients. Besides, we propose a new pilot allocation strategy to limit the interference of D2D communication to the cellular system during the channel estimation phase. We show that our new framework enhances the SE of conventional Massive MIMO systems without drastically affecting the performance of cellular users. Consequently, the cellular network serves more users and offers higher aggregate SE for the network.

2.4.2 Scalability Issue for Power Control in Multi-cell Massive MIMO

In this subsection, we highlight the scalability issues of network-wide max-min and proportional fairness power control schemes for the multi-cell Massive MIMO setup.

These two power control approaches seem to be beneficial for multi-cell Massive MIMO systems. However, applying network-wide max-min and proportional fairness as the utility function for multi-cell Massive MIMO systems has a significant limitation. Both of these approaches profoundly suffer from scalability issue in large networks. To be more specific, increasing

the network size, increases the risk of having a user in the network, with a very bad channel condition. This situation will penalize the whole system and result in zero overall SE for the system as the large-scale fading coefficient of the weakest user goes to zero. Paper B provides a detailed mathematical proof for the scalability issue of these two power control schemes. To overcome the scalability issue, we propose a novel approach, which builds on the use of a new objective function: maximization of the geometric mean of per cell max-min fairness. We prove that this problem is scalable and can be solved efficiently.

Chapter 3

Contributions of the Thesis

As explained in the previous chapters, this thesis focuses on the practical use cases of power control in multi-cell Massive MIMO systems, with and without D2D communications. The thesis consists of two journal articles, whereof one has been published and the other one is currently under review (but the conference version of the paper has been published). This chapter contains the publication information and abstracts of these papers.

3.1 Papers Included in the Thesis

Paper A: Optimized Power Control for Massive MIMO with Underlaid D2D Communications

Authored by: Amin Ghazanfari, Emil Björnson, and Erik G. Larsson

Published in: IEEE Transactions on Communications, volume 67, issue 4, pp. 2763-2778, December 2018

Abstract: In this work, we consider device-to-device (D2D) communication that is underlaid in a multi-cell massive multiple-input multiple-output (MIMO) system and propose a new framework for power control and pilot allocation. In this scheme, the cellular users (CUs) in each cell get orthogonal pilots which are reused with reuse factor one across cells, while all the D2D pairs share another set of orthogonal pilots. We derive a closed-form capacity lower bound for the CUs with different receive processing schemes. In addition, we derive a capacity lower bound for the D2D receivers and a closed-form approximation of it. We provide power control algorithms to maximize the minimum spectral efficiency (SE) and maximize the product of

the SINRs in the network. Different from prior works, in our proposed power control schemes, we consider joint pilot and data transmission optimization. Finally, we provide a numerical evaluation where we compare our proposed power control schemes with the maximum transmit power case and the case of conventional multi-cell massive MIMO without D2D communication. Based on the provided results, we conclude that our proposed scheme increases the sum SE of multi-cell massive MIMO networks.

Paper B: Enhanced Fairness and Scalability of Power Control Schemes in Multi-cell Massive MIMO

Authored by: Amin Ghazanfari, Hei Victor Cheng, Emil Björnson, and Erik G. Larsson

Submitted to IEEE Transactions on Communications, July 2019.

Abstract: This paper studies the transmit power optimization in multi-cell massive multiple-input multiple-output (MIMO) systems. Network-wide max-min fairness (NW-MMF) and network-wide proportional fairness (NW-PF) are two well-known power control schemes in the literature. The NW-MMF focus on maximizing the fairness among users at the cost of penalizing users with good channel conditions. On the other hand, the NW-PF focuses on maximizing the sum SE, thereby ignoring fairness, but gives some extra attention to the weakest users. However, both of these schemes suffer from a scalability issue which means that for large networks, it is highly probable that one user has a very poor channel condition, pushing the spectral efficiency (SE) of all users towards zero. To overcome the scalability issue of NW-MMF and NW-PF, we propose a novel power control scheme that is provably scalable. This scheme maximizes the geometric mean (GM) of the per-cell max-min SE. To solve this new optimization problem, we prove that it can be rewritten in a convex optimization form and then solved using standard tools. The simulation results highlight the benefits of our model which is balancing between NW-PF and NW-MMF.

3.2 Papers Not Included in the Thesis

The thesis also builds on two conference papers that are not included since their content is fully included in Paper A and Paper B.

Power Control for D2D Underlay in Multi-cell Massive MIMO Networks

Authored by Amin Ghazanfari, Emil Björnson, and Erik G. Larsson

Published in Proceedings of: 22nd International ITG Workshop on Smart Antennas (WSA), pp. 1-8, March 2018.

This paper contains preliminary results of Paper A.

Abstract: This paper proposes a new power control and pilot allocation scheme for device-to-device (D2D) communication underlaying a multi-cell massive MIMO system. In this scheme, the cellular users in each cell get orthogonal pilots which are reused with reuse factor one across cells, while the D2D pairs share another set of orthogonal pilots. We derive a closed-form capacity lower bound for the cellular users with different receive processing schemes. In addition, we derive a capacity lower bound for the D2D receivers and a closed-form approximation of it. Then we provide a power control algorithm that maximizes the minimum spectral efficiency (SE) of the users in the network. Finally, we provide a numerical evaluation where we compare our proposed power control algorithm with the maximum transmit power case and the case of conventional multi-cell massive MIMO without D2D communication. Based on the provided results, we conclude that our proposed scheme increases the sum spectral efficiency of multi-cell massive MIMO networks.

A Fair and Scalable Power Control Scheme in Multi-cell Massive MIMO

Authored by Amin Ghazanfari, Hei Victor Cheng, Emil Björnson, and Erik G. Larsson

Published in Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp.4499-4503, May 2019.

This paper contains preliminary results of Paper B.

Abstract: This paper studies the transmit power optimization in a multi-cell massive multiple-input multiple-output (MIMO) system. To overcome the scalability issue of network-wide max-min fairness (NW-MMF), we propose a novel power control (PC) scheme. This scheme maximizes the geometric mean (GM) of the per-cell max-min spectral efficiency (SE). To solve this new optimization problem, we prove that it can be rewritten in a convex

form and then solved using standard tools. To provide a fair comparison with the available utility functions in the literature, we solve the network-wide proportional fairness (NW-PF) PC as well. The NW-PF focuses on maximizing the sum SE, thereby ignoring fairness, but gives some extra attention to the weakest users. The simulation results highlight the benefits of our model which is balancing between NW-PF and NW-MMF.

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Included Papers

Papers

The papers associated with this thesis have been removed for copyright reasons. For more details about these see:

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Division of Communication Systems
of Electrical Engineering

Linköping University
SE-581 83 Linköping, Sweden

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