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BACHELOR OF SCIENCE IN ELECTRONIC AND TELECOMMUNICATION ENGINEERING

Performance Investigation of Three Precoding Methods for Maximal Energy Efficiency in Next Generation Wireless Communications System

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(THIS THESIS REPORT IS SUBMITTED FOR THE PARTIAL FULFILMENT OF THE BACHELOR OF SCIENCE IN ELECTRONIC AND TELECOMMUNICATION ENGINEERING)

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DECLARATION OF CANDIDATE

It is hereby declared that the work presented here in is genuine work done by me and has not concurrently submitted in candidature for any degree. The result of the thesis that ihave found totally depend on my own investigation/work.

This work was done under the guidance of **Engr. Syed Zahidur Rashid**, Assistant Professor of Electronic and Telecommunication Engineering, International Islamic University Chittagong.

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In the name of Allah, the most Beneficent and most Merciful

All praises and glory be to Allah (SWT) for blessing us with opportunities and showering upon us His mercy and guidance all through the life.

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ABSTRACT

Nowadays, Energy Efficiency (EE) has become a buzzword for future wireless communication systems. Consequently, Massive Multiple Input and Multiple Output (MMIMO) technology have attained a great attention for Multi-User Communication scenario. MMIMO systems are crucial to maximizing energy efficiency (EE) and battery-saving technology. Achieving EE without sacrificing the quality of service (QoS) is increasingly important for mobile devices. We first derive the data rate through three linear precoding: Maximum Ratio Transmission (MRT), Zero-Forcing (ZF), and Minimum Mean Square Error (MMSE). Performance EE can be achieved when all available antennas are used and when taking account of the consumption circuit power ignored because of high transmit power.The aim of this work is to demonstrate how to obtain maximum EE while minimizing power consumed, which achieves a high data rate by deriving the optimal number of antennas and number of users in the massive MIMO system. The consumed power of the system includes transmitting power, circuit power consumption, and idle power consumption. The circuit power consumption dominates the system power consumption when the transmitter is equipped with the massive number of antennas. Hence, to analyze this problem, we propose a power consumption model. Maximized EE depends on the optimal number of antennas and determines the number of active users that should be scheduled in each cell. The results show the optimization of Energy with respect to the number of functioning mobile users, number of assigned base stations and launch input power in the system respectively.

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List of Abbreviations

5G	Fifth Generations
EE	Energy E□ciency
MMIMO	Massive Multiple Input and Multiple Output
ZF	Zero Forcing
MRT	Maximum Ratio Transmission
MMSE	Minimum Mean Square Error
D2D	Device to Device
ICT	Information and Communication Technology
LTE	Long Term Evolution
IoT	Internet of Things
Gbps	Giga bits per second
Mbps	Megabits per second
CP	Circuit Power
MIMO	Multiple-Input Multiple-Output
MU-MIMO	Multiuser MIMO
UEs	User equipments
BS	Base station
SNRs	Signal to noise ratios
CSI	Channel State Information
ML	Maximum-likelihood
DPC	Dirty Paper Coding
RBF	Random Beamforming
SUS	Semi-orthogonal User Selection
CQI	Channel Quality Indicator

SINR	Signal to Interference plus Noise Ratio
SISO	Single-Input-to-Single-Output
PC	Power Consumption
SDMA	Space-Division Multiple Access
SE	Spectral E□ciency
TDD	Time-Division Duplex
PA	Power Amplifier
PAPR	Peak-to-average-power Ratio
OFDM	Orthogonal Frequency Division Multiplexing
FDD	Frequency-division Duplex
SIC	Successive Interference Cancellation
MSE	Mean Square Error
LO	Local Oscillator
ETP	E□ective Transmit Power

List of Meaning of Symbols

M	Number of Antenna
K	Number of Users
C_{UL}	Shannon capacities on the Uplink
C_{DL}	Shannon capacities on the Downlink
β_k	Large-scale Fading Coe□cient
p_u	Average Signal to Noise Ratio
I_M	The M × M Identity Matrix
det(X)	Determinant of a Square Matrix X
H	Channel Matrix
$\boldsymbol{g_k}$	The k^{th} Column of H
H*	The Complex Conjugate of H
H^T	The Transpose of H
H^H	The Conjugate Transpose of H
H^{-1}	The Inverse of a Square Matrix H
p_d	The Average Transmission SNR
$C^{M\times K}$	The set of Complex-valued M × K Matrix
z_k	Additive Noise at the k^{th} User
D_q	The Diagonal Matrix
A	Linear Detection Matrix
P_{BS}	Power per BS antennas for Transceiver Hardware
P_{BT}	Power per (bit/s) for Backhaul Tra□c
P_{COD}	Power per (bit/s) for data encoding
P_{DEC}	Power per (bit/s) for data decoding
P_{FIX}	Fixed power of a BS

P_{LO}	Power per LO
P_{UE}	Power per UE for Transceiver Hardware
P_{SYN}	Power Consumed by the Local Oscillator
P_{TC}	Power Consumption by Transceiver Chains
τ_c	Number of samples per Coherence Block
τ_d	DL data samples per Coherence Block
τ_p	Number of samples allocated for pilots per Coherence Block
τ_u	UL data samples per Coherence Block
B	Total bandwidth used for Communication
$\overline{R}$	The User Gross Rates
$P_{TX}^{(ul)}$	UL Transmit Power per BS
$P_{TX}^{(dl)}$	DL Transmit Power per BS

Chapter 01

Introduction

This chapter presents an introduction to the thesis. An overview of Fifth Generation (5G) wireless system an Energy E□ciency (EE) perspective is given before a more detailed breakdown of the key aspects of the thesis.

1.1 Background of 5G

The rapid development of wireless communication technology has resulted in the explosive increases of mobile users. It has reported that there are over 1,069 million mobile users in Americas [2], while over 5 billion mobile phone users are projected to have on a global scale, which is shown in Fig. 1.1. The prevalence of smart devices leads to the explosive growth of requirements for digital wireless communication. As a result, the issue related to shortage of frequency resources is revealed. Although new technologies such as small cell and high order modulation can improve frequency efficiency to certain extent, it still cannot satisfy the requirements.

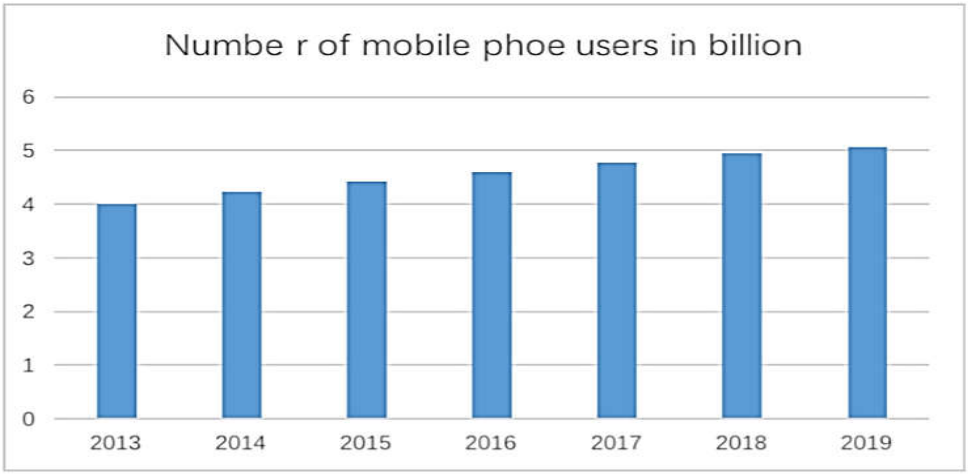

Figure 1.1: Total number of mobile phone users worldwide from 2013 to 2019 [1]

The fifth generation communication system (5G) is new emerging technology recent years since it enhances data speed, ultra reliable low latency, energy efficiency and massive machinetype communication [2]. Additionally, 5G wireless communication is not only for traditional mobile devices like smart phone and laptop, but also provides services for Device to Device (D2D) communications [2].

1.2 New technology in 5G

5G is expected to provide us with high capacity, low complexity, high data rate and ultra-

low latency communication system. The advancements in 5G are shown in Fig. 1.2 [2].

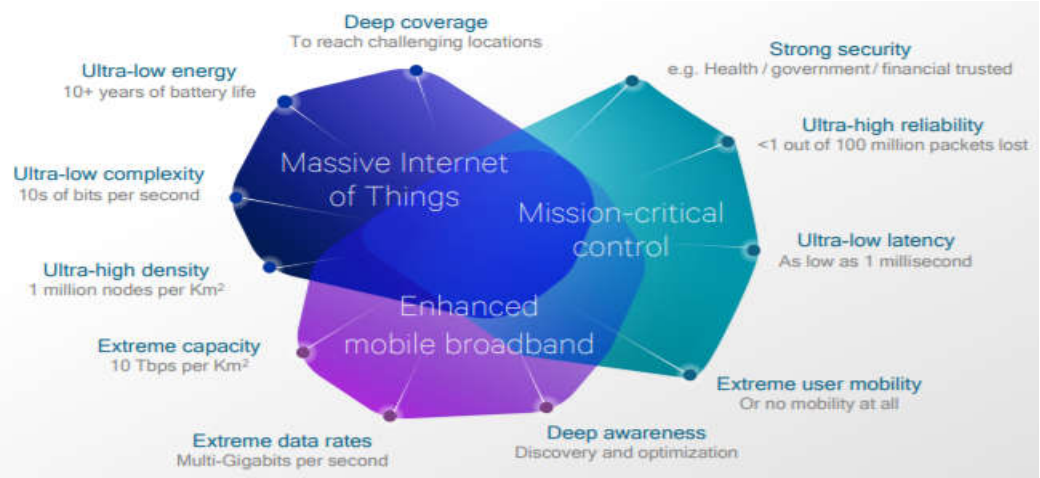

Figure 1.2: Advancement in 5G [2]

To achieve these goals, new technology including non-orthogonal multiple access, millimeter wave communication, massive MIMO, visible light communication, will be introduced. In this thesis, we will mainly focus on energy efficiency of massive MIMO systems [1, 2,and 3].

1.3 Expectations from 5G Cellular Networks

The information and communication technology (ICT) industry currently connects and manages billions of devices across the globe. Currently, we are in the era of 4G and 4.5G

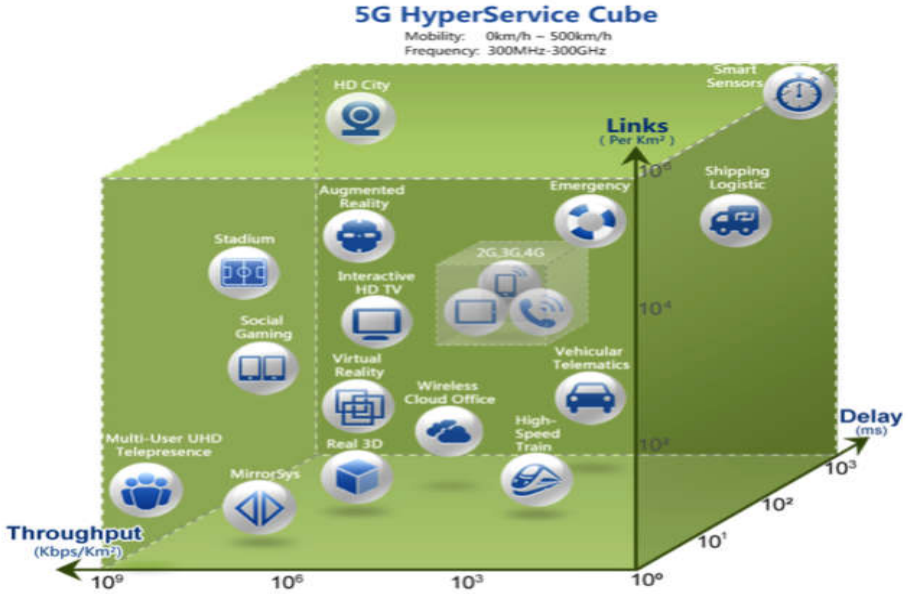

Figure 1.3: Overview of services expected in future 5G networks [2]

networks, which are referred to as Long Term Evolution (LTE) and LTE-Advanced networks respectively by standardization bodies. Global trends suggest that future 5G networks should handle up to a 1000-fold increase in the current tra□c demands. In addition, a wide spectrum of services should be supported. See Figure 1.3 for an overview of 5G services envisioned by Huawei Technologies Co. Ltd. [5]. As we can observe from Fig. 1.3, the Internet of Things (IoT), which promises to connect almost everything, is expected to be an integral part of 5G networks. A host of emerging networks, such as, smart cities, vehicular networks, and augmented reality hubs will co-exist and operate simultaneously within 5G. In terms of technology demands, 5G networks should support latencies ranging from 1 millisecond (ms) to a few seconds, peak data rates up to 20 Giga bits per second (Gbps), average data rates up to 100 Megabits per second (Mbps), seamless connectivity for millions of IoT devices per square kilometer, and signaling loads ranging from 1% to almost 100% [5].

1.4 Need for Energy-Efficient Systems

When 5G networks are designed to meet such huge service expectations, energy consumption becomes a critical concern because mobile communication networks contribute towards asignificant stake in the global carbon footprint.

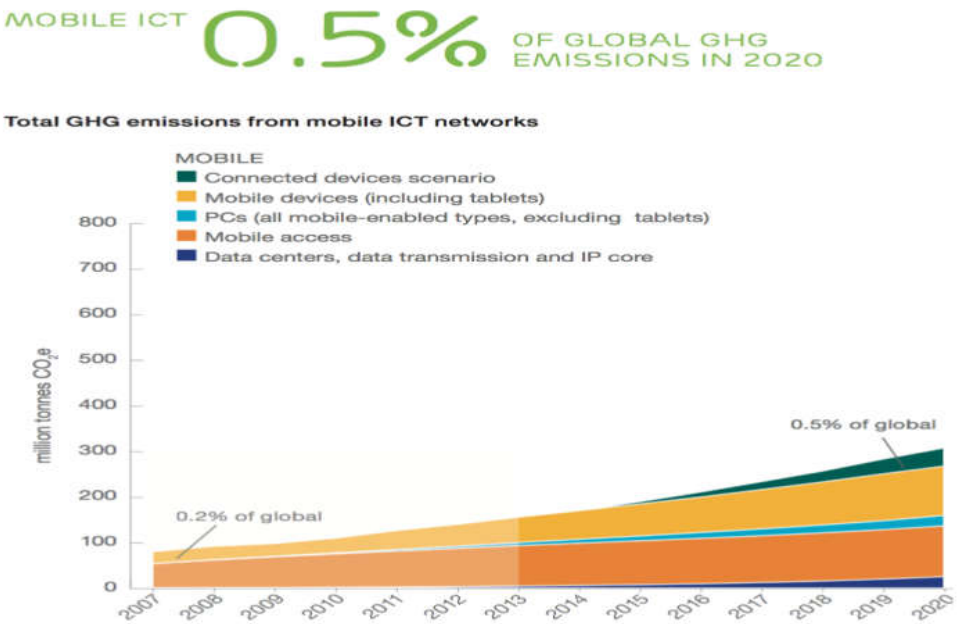

Figure 1.4: Trends and forecast for greenhouse gas emissions by the mobile ICT sector [2]

Trends [6] suggest that the mobile ICT sector would emit more than 300 million tonnes of greenhouse gases per annum by 2020. Observe from Figure 1.4 [4] that a majority of these emissions come from mobile access and mobile devices, i.e., from powering the wireless communications between the base stations (BSs) and the user equipment's

(UEs). Therefore, for a sustainable evolution into future 5G networks, it becomes critically important for future wireless technologies to not only address the multifold increase in service expectations, but also to operate at reduced power consumption levels. A key design parameter in this regard is the bit-per-joule energy e□ciency, defined as:

$$\text{Energy Efficiency (bits/joule)} = \frac{\text{Throughput (bits/s)}}{\text{Power Consumption (Joule/s)}} \text{---------- (1)}$$

In equation (1), the energy e□ciency (EE) of a wireless communication systemcan be increased by using methods which maximize the system throughput or minimize power consumption, or both. The focus of this thesis is on the massive multiple-input multiple-output (MIMO) technology, which o□ers higher EE levels current cellular communication networks.

1.5 Goal and Motivation

1.5.1 Goal

The goal of this thesis is to performance investigation of three precoding methods for maximal energy e□ciency (EE) in the next-generation wireless communication system. Precoding methods such as Maximal Ratio Combining (MRC), Minimum mean square error (MMSE), and Zero-forcing (ZF). Our main goal is to find out which precoding method performs better based on the parameters like the number of an antenna (M), the number of users (K), throughput and power consumption.

1.5.2 Motivation

Massive MIMO is an emerging technology, which scales up the number of TX and RX antennas by at least an order of magnitude relative to conventionalMU-MIMO systems. This approach leverages the spatial dimension providing significant increases in data rate, link reliability, energy e□ciency, and multiplexing gains while reducing inter-user interference. Above the discussion this thesis will study energy efficiency in massive MIMO based on three pre-coding algorithms including MRC, MMSE and ZF in mathematical and simulation approaches. A simplified massive MIMO system is built in this system which equips with adjustable number of transmitted antenna and users with signal received antenna. In particular, a computational efficient resource allocation will be designed for the maximization of energy efficiency of the massive MIMO system. Besides, the impact of the amount of transmitted antenna on capacity will be assessed under different pre-coding algorithms. Based on this, energy efficiency will be then discussed. Finally, optimal and suboptimal transmission scheme will be presented in order to maximize the usage of materials and resources.

Based on this motivation, this thesis studies how massive MIMO technology can be used

to design maximum energy-e□cient systems for future 5G deployments.

1.6 Objectives

The mainpurpose of the thesis is to provide insights on how M, K and the transmit power affect the total EE of a multi-user massive MIMO system for different linear processing schemes at the BS.The objectives of this thesis are:

a. To find the optimal number of base station antennas and users.
b. To analyze the energy e□ciency (EE) of Massive MIMO based on a Circuit Power (CP) consumption model.
c. To analyze and achieve the optimal performance of maximize energy e□ciency (EE) using different pre-coding algorithms.

1.7 Thesis Outline

This thesis is organized as follows:

Chapter 01: Introduction.

Chapter 02: Literature Review.

Chapter 03: Massive MIMO Cellular Systems Model.

Chapter 04: Simulation and Result Analysis.

Chapter 05: Conclusion and Future Work.

Chapter 02

Literature Review

To understand what massive MIMO is, as a new technology for wireless access, let us first overview the massive MIMO concept. This chapter describes the literature review of the thesis work, the theoretical advantages brought by scaling up MIMO, and the challenges we encounter in practice.

2.1 Background on MIMO and Massive MIMO

One standard technique to increase throughput in a wireless communication system is to deploy multiple transceiver antennas at the transmitters and the receivers. When multiple antennas are used at the transmitters and the receivers, throughput gains can be achieved because the transmitter can spatially multiplex parallel streams of data over the same time frequency resource. Such multiple-input multiple-output (MIMO) systems have been under active research investigation over the last decade and are currently being used in LTE and LTE-Advanced networks.

Multiuser MIMO (MU-MIMO) systems [7], where a BS with multiple antennas can use scheduling algorithms to simultaneously serve multiple spatially-separated UEs over the same time-frequency resource have gained prominence because (i) MU-MIMO systems o□er multiple access and broadcast capabilities and (ii) each UE in an MU-MIMO system can host a single antenna and still achieve similar throughput gains as achieved in point-to-point MIMO systems. In fact, the performance of point-to-point MIMO systems can be limited by the physical size and cost constraints at the UEs because the UEs are generally low-cost handheld devices and are therefore, unable to host several antennas.

Definition 2.1: Massive MIMO is a form of MU-MIMO systems where the number of BS antennas and the numbers of users are large. In Massive MIMO, hundreds or thousands of BS antennas simultaneously serve tens or hundreds of users in the same frequency resource.

2.2 Massive MIMO: A Multiuser MIMO Technology

Massive MIMO is a multi-user MIMO technology in which K single-antenna user equipments (UEs) are serviced simultaneously on the same time-frequency resource by a base station (BS) equipped with a relatively large number M of antennas, i.e., $M >> K$ (c.f. Fig. 2.1). In general, the UEs in a massive MIMO system can be equipped with more than one antenna. However, to simplify our analysis, discussions in this thesis are limited to systems with single-antenna UEs.

Deploying several antennas at the BS results in an interesting propagation scenario called favourablepropagation, where the channel becomes near-deterministic because the radio links between the BS and the UEs become nearly orthogonal to each other [8]. This is becausethe e□ects of small-scale fading tend to disappear asymptotically in the large M regime. Significant EE gains can be achieved under favourable propagation because multiple orders of multiplexing and array gains are realizable. For the purpose of illustration, let us consider the uplink and downlink transmissions in a massive MIMO cell.

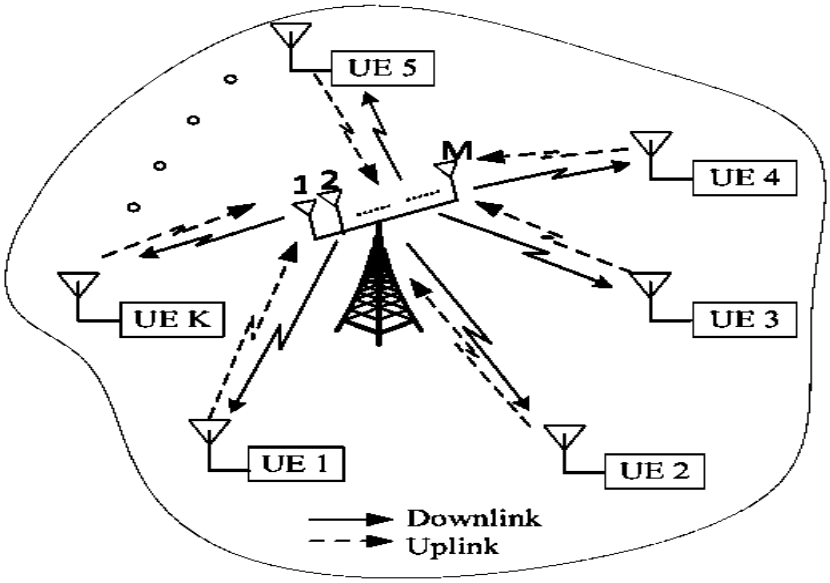

Figure 2.1: Massive MIMO: a multi-user MIMO technology where K single-antenna UEs are served by a BS with M >> K antennas [8].

The asymptotic Shannon capacities on the uplink (C_{UL}) and the downlink (C_{DL}) for a multiuser MIMO channel under favourable propagation are given by [9]

$$C_{UL} = \sum_{k=1}^{K} log_2(1 + p_{u,k} M \beta_k), \quad \text{---------- (2.1)}$$

$$C_{DL} = \max_{(a_k \geq 0, \sum a_k \leq 1)} \sum_{k=1}^{K} log_2(1 + p_{d,k} M a_k \beta_k)$$

Where $p_{u,k}$and $p_{d,k}$ are the uplink and downlink signal to noise ratios (SNRs) for the k^{th}UE, $\beta_k$represents the large-scale fading coe□cient for the k^{th} UE, and $\{a_k, k=$ 1,2,...,K$\}$, is an optimization vector to obtain C_{DL}. For simplicity, if we neglect the

e□ectof $\beta_k$and assume that each UE transmits with an average signal to noise ratiop_u, the uplink Shannon capacity simplifies to

$$C_{UL} = K\ log_2(1 + Mp_u) \qquad \text{---------- (2.2)}$$

A similar argument can be made about downlink transmissions as well. The simplification illustrated in (2.2) leads us to two important observations (i) the system throughput can be improved by increasing K, i.e., by multiplexing parallel streams of data to more number of UEs over the same time-frequency resource, and (ii) transmission power per UE can be decreased by increasing M, i.e., the number of BS antennas, while still maintaining the same throughput per UE. In other words, the simplification in (2.2) shows that we can achieve O (K) multiplexing gains and O (M) array gains under favourable propagation.

While the large array gains are a straightforward opportunity to reduce UE transmission powers, massive MIMO also facilitates a drastic reduction in the circuit power consumed in the system. As discussed next, this is because the BS can implement (i) linear signal processing techniques and (ii) low-complexity user scheduling algorithms, and still achieves near-optimal throughput performance.

The main benefits of Massive MIMO systems are:

1. **Huge spectral efficiency and high communication reliability:** Massive MIMO inherits all gains from conventional MU-MIMO, i.e., with M-antenna BS and K single-antenna users, we can achieve a diversity of order M and a multiplexing gain of min (M,K). By increasing both M and K, we can obtain a huge spectral efficiency and very high communication reliability.
2. **High energy efficiency:** In the uplink Massive MIMO, coherent combining can achieve a very high array gain which allows for substantial reduction in the transmit power of each user. In the downlink, the BS can focus the energy into the spatial directions where the terminals are located. As a result, with massive antenna arrays, the radiated power can be reduced by an order of magnitude, or more, and hence, we can obtain high energy efficiency. For a fixed number of users, by doubling the number of BS antennas, while reducing the transmit power by two, we can maintain the original the spectral efficiency, and hence, the radiated energy efficiency is doubled.
3. **Simple signal processing:** For most propagation environments, the use of an excessive number of BS antennas over the number of users yields favorable propagation where the channel vectors between the users and the BS arepair wisely (nearly) orthogonal. Under favorable propagation, the effect of interuser interference and noise can be eliminated with simple linear signal processing (liner precoding in the downlink and linear decoding in the uplink). As a result,

simple linear processing schemes are nearly optimal. Another key property of Massive MIMO is channel hardening. Under some conditions, when the number of BS antennas is large, the channel becomesdeterministic, and hence, the effect of small-scale fading is averaged out. The system scheduling, power control, etc., can be done over the large-scale fading time scale instead of over the small-scale fading time scale. This simplifies the signal processing significantly.

2.2.1 Comparison between traditional MIMO and Massive MIMO

Compared to traditional MIMO, the advantages of massive MIMO include [2-5]:

- Enhancement of SE
- Massive amount of degrees of freedom in spatial domain
- Good system performance with only linear precoding scheme, e.g. Zero forcing, Maximum Ratio Transmission, Minimum Mean Square Error
- Facilitate resource allocation

2.3 How Massive MIMO Works

In Massive MIMO, TDD operation is preferable. During a coherence interval, there are three operations: channel estimation (including the uplink training and the downlink training), uplink data transmission, and downlink data transmission. A TDD Massive MIMO protocol is shown in Figure 2.2.

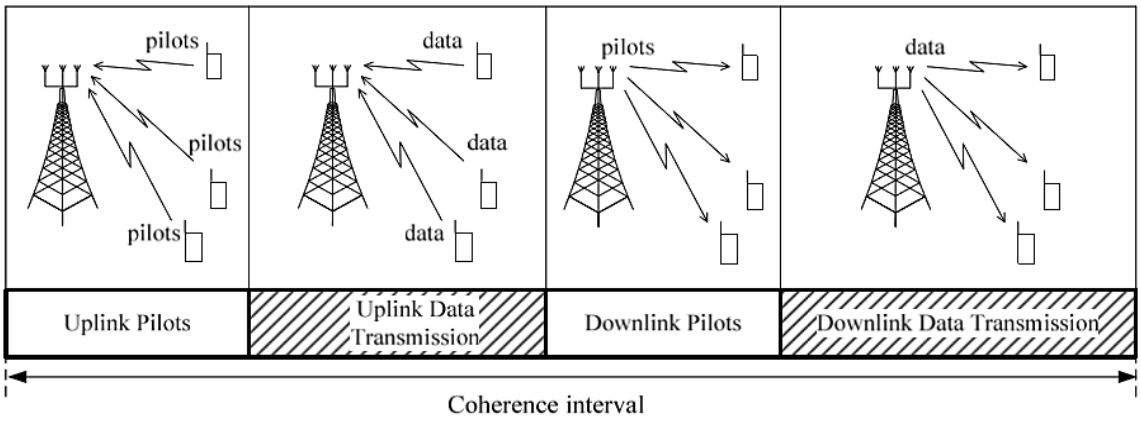

Figure 2.2: Transmission protocol of TDD Massive MIMO [10].

2.3.1 Channel Estimation

The BS needs CSI to detect the signals transmitted from the users in the uplink, and to precode the signals in the downlink. This CSI is obtained through the uplink training. Each user is assigned an orthogonal pilot sequence, and sends this pilot sequence to the BS. The BS knows the pilots sequences transmitted from all users, and then estimates the channels based the received pilot signals.

Furthermore, each user may need partial knowledge of CSI to coherently detect the signals transmitted from the BS. This information can be acquired through downlink training or some blind channel estimation algorithm. Since the BS uses linear precoding techniques to beamform the signals to the users, the user needs only the effective channel gain to detect its desired signals. Therefore, the BS can spend a short time to beamform pilots in the downlink for CSI acquisition at the users [10].

2.3.2 Uplink Data Transmission

A part of the coherence interval is used for the uplink data transmission. In the uplink, all K users transmit their data to the BS in the same time-frequency resource [11]. The BS then uses the channel estimates together with the linear combiningtechniques to detect signals transmitted from all users.The detailed uplink data transmission was discussedin detail in later Section.

2.3.3 Downlink Data Transmission

In the downlink, the BS transmits signals to all K users in the same time-frequency resource [12]. More specially, the BS uses its channel estimates in combination with the symbols intended for the K users to create M precoded signals which are then fed to M antennas. The downlink data transmission was discussed in detail in later Section.

2.4 Why Massive MIMO

The demand for wireless throughput and communication reliability as well as the user density will always increase. Future wireless commination requires new technologies in which many users can be simultaneously served with very high throughput. Massive MIMO can meet these demands. Consider the uplink transmission. The same argument can be used for the downlink transmission. From (2.2), the sum-capacity of the uplink transmission is [10]:

$$C_{sum} = log_2 \det(I_K + p_u M I_K) = K log_2(1 + p_u M) \quad \text{..... (2.3)}$$

In (2.3), K is the multiplexing gain, and M represents the array gain. We can see that, we can obtain a huge spectral efficiency and energy efficiency when M and K are large. Without any increase in transmitted power per terminal, by increasing K and M, we can simultaneously serve more users in the same frequency band. At the same time the throughput per user also increases. Furthermore, by doubling the number of BS antennas, we can reduce the transmit power by 3 dB, while maintaining the original quality-of-service.

The above gains are obtained under the conditions of favorable propagation and the use of optimal processing at the BS. In Massive MIMO, when the number of BS antennas is

large, due to the law of large numbers, the channels become favorable. As a result, linear processing is nearly optimal. The multiplexing gain and array gain can be obtained with simple linear processing. Also, by increasing the number of BS antennas and the number of users, we can always increase the throughput.

2.5 Linear Signal Processing

In conventional multiuser MIMO systems, optimal capacities can be achieved if the BS implements complex signal processing techniques, such as, maximum-likelihood (ML) multiuser detection on the uplink and dirty paper coding (DPC) [6] on the downlink. Unfortunately, such complex signal processing techniques incur large computational burdens which grow exponentially with the size of the system, for example with the number of BS antennas M. As a result, when M and K are large, such techniques consume large amounts of circuit power, thus becoming highly unsuitable for massive MIMO operations.

Fortunately, in the large M regime, linear signal processing techniques, such as maximum-ratio combining (MRC) on the uplink and maximum-ratio transmission (MRT) on the downlink, can achieve near-optimal throughput performance.

2.6 Low-complexity User Scheduling

In conventional multiuser MIMO systems, simple linear precoding techniques, such as maximum ratio transmission (MRT), do not achieve optimal capacities on the downlink. To reduce the performance gap, the BSs generally implement certain user scheduling methods which exploit multi-user diversity in the system. Basically, the BS selects few UEs during each transmission interval and schedules them for simultaneous transmissions. Two seminal works on user scheduling are the random beamforming (RBF) and the semi-orthogonal user selection (SUS) [8] methods. In the RBF method, the BS selects a group of UEs by matching them to a pre-determined set of orthogonal beams transmitted on the downlink. The matching is based on feedback provided by each UE, in terms of a channel quality indicator (CQI), such as the signal to interference plus noise ratio (SINR), and the best beam index. In SUS method, the BS acquires full channel state information (CSI) from the entire candidate UEs and selects a subset of UEs which have near-orthogonal channel vectors.

Conventional user scheduling methods, such as RBF or SUS, may not be appropriate for massive MIMO systems due to a variety of reasons: (i) performance gains based on multiuser diversity may not be significant in the large M regime because the e□ects of small scale fading are diminished (ii) such methods are computationally intensive and consume significant amounts of circuit power when M is large − SUS incurs O(M3K) computational complexity [8], and (iii) such methods often su□er from practical

limitations−RBF schemes do not perform well in systems with finite number of UEs [13] and SUS schemes are unsalable because significant overhead is incurred when acquiring full CSI from all the candidate UEs.

Fortunately, in the large M regime, very simple user scheduling schemes, such as, selecting a subset of UEs randomly [15], selecting a subset of UEs in the descending order of theirlarge-scale fading coe□cients [15], or selecting UEs in a round-robin fashion [16], are known to achieve near-optimal throughput performance. This is because the channel vectors become near-orthogonal to each other and the e□ects of small-scale fading are diminished in the large M regime.

Since low-complexity signal processing and user scheduling algorithms achieve near optimal throughput performance in massive MIMO systems, we observe that the circuit power consumption is drastically reduced when compared to conventional multiuser MIMO systems. Note that this reduction in circuit power consumption is in addition to the large array gains, which allow for a significant reduction in the UE transmission powers. Consequently, by achieving near-optimal throughput performance at reduced power consumption levels, massive MIMO networks deliver multiple orders of EE gains over current LTE networks.

In the next section, we present a discussion on three prominent linear multiuser detection techniques for massive MIMO, namely maximum-ratio combining (MRC), zero-forcing (ZF) detection, and minimum mean squared error (MMSE) detection. We explain how these linear detection techniques are derived and show that these techniques achieve near-optimal throughput performance in the large M regime.

2.7 Precoding

Precoding provides two fundamental advantages, including eliminate interference and performing beamforming to the desired users. In general, there are two types of precoding, non-linear precoding schemes and linear pre-coding schemes. Non-linear precoding can achieve both of these two functions, while the linear one can only reduce inter-users interference [18].

In wireless communication system, due to the geographic effect, received signalcannot be obtained simultaneously [19]. Inter-user interference cannot be eliminated by multi-user detection as well. Under this circumstance, precoding will play a significant role in improving system performance.

Compared to nonlinear precoding schemes, the complexity of linear precoding schemes the complexity is remarkably lower. Moreover, due to a massive amount of degrees of

freedom in massive MIMO, linear precoding schemes are enough to satisfy communication requirements [17, 19].

2.8 Linear Precoding Schemes

In massive MIMO systems, when the amount of transmitted antennas approaches infinity, the system can be simplified as Single-input-to-Single-output (SISO) systems [20]. Therefore, to optimize spectral resources in massive MIMO systems, pre-coding is used at the transmit side in order to reduce the complexity of system, diminish noise effect and optimize stream data transmission based on channel state information (CSI) [21,22,23]. There are three common linear pre-coding schemes, including MRC, ZF and MMSE.

2.8.1 Maximum-Ratio Combining (MRC)Detection

This scheme is to maximize SNR by seeking to maximize the power at the receiver combiner. MRC is considered as a viable linear reception scheme for massive MIMO systems since it can be applied in a distributed manner. The mathematical model for MRC is shown as below,

$$W = \frac{g_k}{\|g_k\|} = H \quad \text{..... (2.4)}$$

Moreover, MRC has a satisfactory performance in the low-power regime, even approaching to optimal performance as the amount of antennas grows infinitely. However, as the power increase, systems based on MRC scheme suffer from serious inter-user interference [16].

Advantage: The signal processing is very simple since the BS just multiplies the received vector with the conjugate-transpose of the channel matrix $\boldsymbol{H}$, and then detects each stream separately. More importantly, MRC can be implemented in a distributed manner.This implies that at low SNR, MRC can achieve the same array gain as in the case of a single-user system.

Disadvantage: As discussed above, since MRC neglects the effect of multiuser interference, it performs poorly in interference-limited scenarios.

2.8.2 Zero-forcing (ZF) Detection

The ZF scheme is to eliminate inter-user interference by projecting the received signals into the orthogonal elements. It can be written as

$$W = H\,(H^H H)^{-1} \quad \text{..... (2.5)}$$

Since ZF scheme does not take noise into consideration, system based on ZF precoding scheme has a poor performance in low power regime. The performance in high-power regime approaches to optimal [16].

Advantage: The signal processing is simple and ZF works well in interference-limited scenarios. The SINR can be made as high as desired by increasing the transmit power.

Disadvantage: Since ZF neglects the effect of noise, it works poorly under noise-limited scenarios. Furthermore, if the channel is not well conditioned then the pseudo-inverse amplifies the noise significantly, and hence, the performance is very poor. Compared with MRC, ZF has a higher implementation complexity due to the computation of the pseudoinverse of the channel gain matrix.

2.8.3 Minimum Mean Squared Error (MMSE) Detection

MMSE scheme seeks to eliminate inter-user interference as well as noise. Compared to MRC and ZF, system complexity of MMSE is relatively higher.

$$W = H\left(H^H H + \frac{1}{p_u} I_M\right)^{-1} \quad \text{..... (2.6)}$$

From mathematical perspective, MRC has the lowest complexity among these three precoding schemes. MMSE requires perfect channel state information [16].

2.9 Performance Comparison

Figure 2.3 plots the throughput performance of MRC, ZF, and MMSE detection methods when the number of BS antennas is increased up to 100. We assume K = 10, p_u = −10 dB, and calculate the uplink sum-rates,wherevalues are calculated for the three detectors by substituting the detection matrices in (2.4), (2.5) and (2.6). When M is large, we observe that all the linear detection methods achieve near-optimal throughput performance. The MRC detection method does not perform as well as the other two linear detection methods because it neglects the e□ects of inter-user interference in the system.

Nevertheless, the performance of MRC is comparable to the other two methods and is, in fact, the preferred choice for practical deployments because (i) MRC requires minimal number of computations and hence incurs low circuit power consumption and (ii) MRCdoes not su□er from noise amplification when the channels are ill-conditioned, as often experienced in practice.

On similar lines to our discussions for linear multiuser detection methods, linear precoders can also be derived for downlink transmissions in a massive MIMO system. Three prominent linear precoders in the current literature, namely maximum-ratio

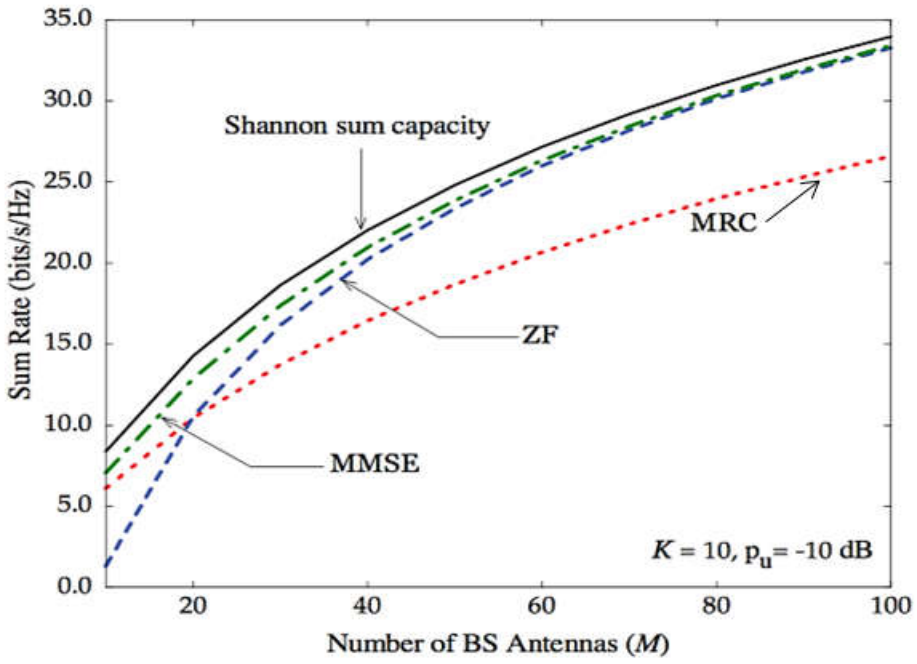

Figure 2.3: Throughput comparison for di□erent linear detection methods respect to number of antenna (M) [8].

transmission (MRT), zero-forcing (ZF), and minimum mean squared error (MMSE) precoders, have similar operational meanings and exhibit similar properties as MRC, ZF, and MMSE detection techniques respectively. Therefore, the precoding matrices W^{MRC}, W^{ZF} and W^{MMSE} for the three linear precoders mentioned above are given by

$$\begin{aligned} W^{MRC} &= H, \\ W^{ZF} &= H(H^H H)^{-1} \\ W^{MMSE} &= \left(H^H H + \frac{1}{p_d} I_M\right)^{-1} \end{aligned} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.7)$$

Where $p_d$is the average transmission SNR on the downlink. Similar to the case with lineardetection methods, these linear precoders achieve near-optimal throughput performance in the large M regime. This completes our discussion on how signal processing requirements are simplified in massive MIMO systems.

The next section presents a few guidelines on how realistic power consumption models can be developed for massive MIMO systems. This is important because the EE metric, relies on the accuracy of power consumption model used.

2.10Energy Efficiency in Massive MIMO

In massive MIMO system, when allocating transmitted power equally to antennas, the spatialefficiency will be improved by M and$\sqrt{M}$ for perfect CSI and imperfect CSI

system, respectively where M represents the number of transmitted antennas. Moreover, with the increase amount of antennas, noise and small scale fading will decrease correspondingly; correlation among channels will be reduced by expending distance among antennas. According to statistics, channels between antennas and users will approach to orthogonal when the number of antennas is overwhelmingly large than that of users [18]. Traditional MIMO systems pay more attention on transmitted power consumption instead of EE [20].

MassiveMIMOaimsatevolvingthecoveragetierBSsbyusingarrays with a hundred or more antennas, each transmitting with a relatively low power. This allows for coherent multiuser MIMO transmission with tens of UEs being spatially multiplexed in both UL and DL of each cell. The area throughput is improved by the multiplexing gain. However, the throughput gains provided by Massive MIMO come from deploying more hardware (i.e., multiple RF chains per BS) and digital signal processing (i.e., SDMA combining/precoding) which, in turn, increase the CP per BS [28].

EE refers to how much energy it takes to achieve a certain amount of work. This general definition applies to all fields of science, from physics to economics, and wireless communication is no exception [24]. Unlike many fields wherein the definition of "work" is straightforward, in a cellular network it is not easy to define what exactly one unit of "work" is. The network provides connectivity over a certain area and it transports bits to and from UEs. Users pay not only for the delivered number of bits but also for the possibility to use the network anywhere at any time. Moreover, grading the performance of a cellular network is more challenging than it first appears, because the performance can be measured in a variety of di□erent ways and each such performance measure a□ects the EE metric di□erently. Among the di□erent ways to define the EE of a cellular network, one of the most popular definitions takes inspiration from the definition of SE, that is, "the SEof a wireless communication system is the number of bits that can be reliably transmitted per complex-valued sample. By replacing "SE" with "EE" and "complex-valued sample" with "unit of energy", the following definition is obtained [24, 25, 28]:

Definition 5.1: The Energy e□ciency (EE) of a cellular network is the number of bits that can be reliably transmitted per unit of energy.

$$Energy\ Efficiency\ (EE) = \frac{Throughput\ (bit/s/cell)}{Power\ Consumption\ (W/cell)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.8)$$

which is measured in bit/Joule and can be seen as a benefit-cost ratio, where the service quality (throughput) is compared with the associated costs (power consumption).

2.11 Methods to Improve Energy E□ciency in Massive MIMO Systems

Observe, from (2.8), that the energy e□ciency of a massive MIMO network can be maximized by achieving optimal throughput performance while operating at minimum levels of power consumption. Based on this analogy, a number of research directions have been pursued for the design of energy-e□cient massive MIMO networks see Fig 3.1 for a broad overview. Few methods devise low-complexity algorithms for BS operations, such as, multi-user detection, precoding, and user scheduling, so as to achieve near-optimal throughput performance at low power expenditure. Few other methods, such as, transceiver re-design, antenna selection, and power amplifier dimensioning, focus on improving resource utilization in the system so as to relax hardware requirements and thereby, the power expenditure in the system. Available literature also includes methods which minimize power losses in the system, such as, antenna reservation and amplifier-aware design, and methods which relax hardware quality, i.e., by introducing hardware imperfections, to reduce power expenditure in the system. In this section, we study some of the techniques mentioned above and identify few open research challenges thereof.

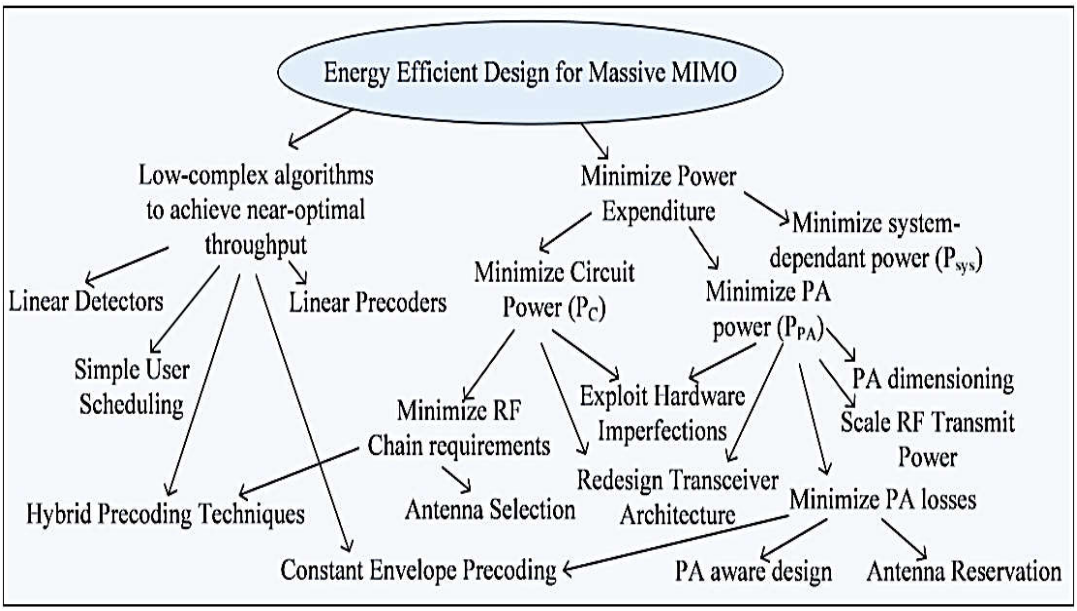

Figure 2.4: Overview of standard EE-maximization techniques for massive MIMO systems [8].

2.11.1 Low-complexity BS operations

Due to favourable propagation in the large M regime, simple linear processing techniques,such as Maximum-Ratio Combining (MRC) and Maximum-Ratio Transmission (MRT) precoding, and simple user scheduling algorithms, such as random and round robin scheduling,achieve near-optimal throughput performance. These simplifications yield significant EE gains because the circuit power PC is drastically

reduced when compared to conventional systems with computationally intensive signal processing schemes, such as ML detection and successive interference cancellation (SIC), and complex scheduling algorithms, such as random beamforming and semi-orthogonal user selection.

While channel reciprocity can be exploited in TDD systems to derive near-optimal low complexity linear precoding schemes, precoders for FDD systems cannot exploit channel reciprocity because the UL and DL communications occur on separate frequency bands. FDD precoders cannot also rely on pilot signalling and feedback from the UEs because this consumes at least M +K symbols per coherence interval, making them impractical for high mobility scenarios. Few low overhead FDD precoders, which assume channel sparsity for channel dimensionality reduction, have been proposed recently [26]. However, such precoders are limited to high frequency bands, such as mmWave, where channel sparsity assumptions are valid. Consequently, low-complexity and low-overhead FDD precoding continues to be a major research challenge for massive MIMO networks. Since there are many more licenses worldwide for FDD than for TDD, progress on low overhead FDD precoders will promotewider acceptance of massive MIMO as a future technology.

2.11.2 Minimize Power Amplifier (PA) Losses

Significant energy e□ciency gains can be achieved by minimizing power amplifier losses because ine□cient power amplifier operations in the current LTE networks discard as much as 60% to 95% of the power input to the amplifiers [27]. Prominent research directions to minimize power amplifier losses include (i) dimensioning the power amplifier, (ii) use of low peak-to-average-power-ratio (PAPR) techniques, and (iii) PA-aware design.

2.11.3 Power Amplifier Dimensioning

Losses at the power amplifiers can be minimized by operating the power amplifiers at points close to the maximum allowed output. Unfortunately, most power amplifiers in current LTE deployments are operated, on an average, at points much lower than the maximum allowed output because of the high linearity requirements imposed by high peak to average power (PAPR) waveforms such as OFDM. Power losses at linear power amplifiers can be reduced significantly by adaptively dimensioning, i.e., adjusting, the power amplifier's maximum output power based on temporal variations in the tra□c load in the system. Such load adaptive power amplifier dimensioning techniques are known to enhance the energy e□ciency of massive MIMO systems by up to 30 % [8]. A major drawback for power amplifier dimensioning methods is that their performance is sensitive to the accuracy of availableinformation on temporal tra□c variations in the system, which are generally very di□cult to predict.

2.11.4 Low PAPR Techniques

As an alternative to linear power amplifiers, the BS can deploy non-linear power amplifiers, which are known to be about 4-6 % more power e□cient [26]. However, non-linear PAs require low PAPR input signals to avoid signal distortions. To address this concern, researchers havebeen exploring di□erent PAPR reduction methods. For example, few antenna reservation methods have been recently proposed [24], wherein the signals sent to one set of antennas are deliberately clipped so as to achieve low PAPR, while correction signals are sent on the remaining set of reserved antennas so as to compensate for the clipping. In [8], the authors assume M = 100 and reserve 25 % of the antennas so as to achieve a PAPR reduction of 4 dB. A major drawback with antenna reservation methods is that they may not necessarily increase the system energy e□ciency because reserving antennas results in reduced throughput and the reservation process increases signaling overhead in the system.

Few low-PAPR non-orthogonal waveforms, such as single carrier modulation (SCM), have been proposed recently. However, designing appropriate non-orthogonal waveforms continues to be a major research challenge because most of the recently proposed non-orthogonal waveforms su□er from limitations, such as long filter lengths and complex receiver techniques. Linearity requirements of power amplifiers can also be relaxed using constant envelope input signals. When appropriate precoding schemes are employed, constant envelope signals can achieve similar throughputs as achieved by high-PAPR signals. A major unresolved challenge concerning constant envelope signal studies is the generation of perfectly constant envelope continuous-time signals.

2.11.5 PA-Aware Design

A di□erent approach to minimize power amplifier losses is the design of PA-aware massive MIMO systems. This can be beneficial because conventional massive MIMO systems, designed with sum-power constraints per BS, do not impose constraints on the maximum output power and the power loss per PA. Recent studies on simple MIMO systems [8]show that significant improvements in the throughput performance per UE can be achieved when PA-aware design is implemented with realistic constraints on both the PA output power and the power losses per PA. We observe that the design of PA-aware systems is a relatively new research field with no literature currently available for massive MIMO systems.

2.12 Summary

In this chapter, we discuss massive MIMO technology. By analyzing system capacity and power consumption, we obtain that the energy efficiency is closely associated to the transmitted power and the number of activated antennas.

Chapter 03

Massive MIMO Cellular Systems Model

In the previous chapter, the basic theory of massive MIMO system has been discussed. In massive MIMO systems, since a large amount of antennas arrays are implemented, we can achieve a desired capacity with lower power consumption. In this chapter, we will concentrate on the achievable capacity of massive MIMO systems. In theory, the base station will apply the maximum likelihood detector in order to achieve optimal capacity. Under this circumstance, however, the complexity in received side will be exponentially raised as increase of the number of users. As we discussed previously, in massive MIMO systems, linear coding schemes can also meet our requirements. Therefore, in this chapter, we will theoretically analyze the system performance of massive MIMO based on ZF, MRC and MMSE.

3.1 System Models and Assumptions

Massive MIMO is a MU-MIMO cellular system where the number of BS antennas and the number users are large.We consider a MU-MIMO system which consists of one BS and K active users. The BS is equipped with M antennas, while each user has a single-antenna. In general, each user can be equipped with multiple antennas. However, for simplicity of the analysis, we limit ourselves to systems with single-antenna users. See Figure 3.1. We assume that all K users share the same time-frequency resource. Furthermore, we assume that the BS and the users have perfect CSI. The channels are acquired at the BS and the users during the training phase. The specific training schemes depend on the system protocols frequency-division duplex (FDD) or time-division duplex (TDD), and will be discussed in detail in Section 2.5.

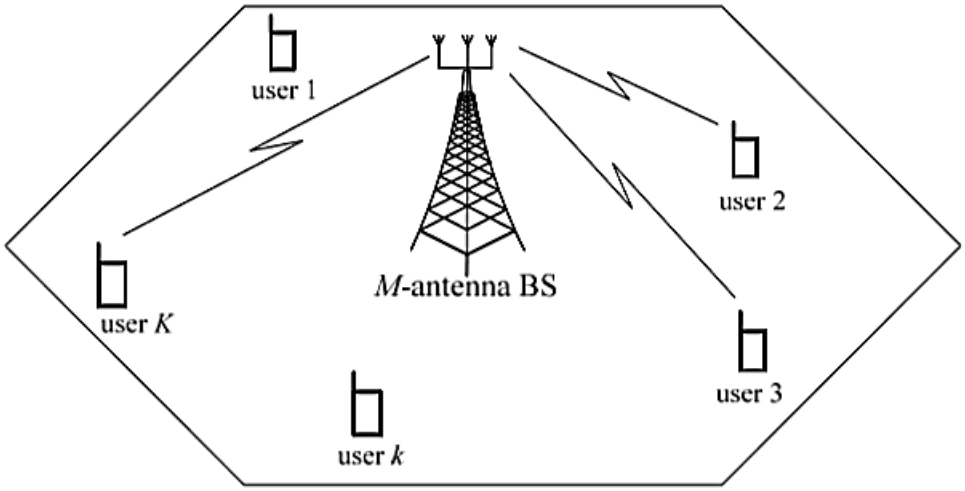

Figure 3.1: Multiuser MIMO Systems. Here, K single-antenna users are served by the M-antenna BS in the same time-frequency resource [12].

Let $H \in C^{M\times K}$ be the channel matrix between the K users and the BS antenna array, where the k^{th} column of *H*, denoted by h_k, represents the $M \times 1$channel vector between the k^{th} user and the BS. In general, the propagation channel is modeled via large-scale fading and small-scale fading. But in this chapter, we ignore large-scale fading, and further assume that the elements of *H* are i.i.d. Gaussian distributed with zero mean and unit variance.

3.2 Uplink Transmission

Uplink (or reverse link) transmission is the scenario where the *K* users transmit signals to the BS. Let s_k, where $\mathbb{E}\{\|s_k\|^2\} = 1$, be the signal transmitted from the k^{th} user. Since *K* users share the same time-frequency resource, the $M \times 1$ received signal vector at the BS is the combination of all signals transmitted from all *K* users [10]:

$$y_{ul} = \sqrt{p_u}\sum_{k=1}^{K} h_k s_k + n \quad \text{..... (3.1)}$$

$$= \sqrt{p_u}H_s + n \quad \text{..... (3.2)}$$

Where $p_u$is the average signal-to-noise ratio (SNR), $n \in C^{M\times 1}$is the additive noise vector, and$s \triangleq [s_1 \dots \dots \dots s_k]^T$. We assume that the elements of $n$are i.i.d. Gaussian random variables (RVs) with zero mean and unit variance, and independent of *H*.

From the received signal vector y_{ul}together with knowledge of the CSI, the BS will coherently detect the signals transmitted from the *K* users. The channel model (3.2) is the multiple-access channel which has the sum-capacity [29].

$$C_{ul,sum} = log_2\, det(I_K + p_u H^H H) \quad \text{..... (3.3)}$$

The aforementioned sum-capacity can be achieved by using the successive interference cancellation (SIC) technique [10]. With SIC, after one user is detected, its signal is subtracted from the received signal before the next user is detected.

3.3 Downlink Transmission

Downlink (or forward link) is the scenario where the BS transmits signals to all *K* users. Let $x \in C^{M\times 1}$, where $\mathbb{E}\{\|x\|^2\} = 1$, be the signal vector transmitted from the BS antenna array. Then, the received signal at the k^{th} user is given by [10]:

$$y_{dl,k} = \sqrt{p_d}h_k^T x + z_k \quad \text{..... (3.4)}$$

Where $p_d$the average SNR and z_k is the additive noise at the k^{th} user. We assume that z_k is Gaussian distributed with zero mean and unit variance. Collectively, the received signal vector of the *K* users can be written as

$$y_{dl} = \sqrt{p_d} H^T x + z \quad \text{..... (3.5)}$$

Where $y_{dl} \triangleq [y_{dl,1} y_{dl,2} \dots\dots y_{dl,K}]^T$ and $z \triangleq [z_1 z_2 \dots\dots z_K]^T$. The channel model (3.5) is the broadcast channel whose sum-capacity is known to be

$$C_{sum} = \max_{q_k \geq 0, \sum_{k=1}^{K} q_k \leq 1} log_2 \, det\left(I_M + p_u H^* D_q H^T\right) \quad \text{..... (3.6)}$$

Where D_q is the diagonal matrix whose k^{th} diagonal element is q_k. The sum-capacity (3.6) can be achieved by using the dirty-paper coding (DPC) technique.

3.4 Linear Processing

To obtain optimal performance, complex signal processing techniques must be implemented. For example, in the uplink, the maximum-likelihood (ML) multiuser detection can be used. With ML multiuser detection, the BS has to search all possible transmitted signal vectors $\boldsymbol{s}$, and choose the best one as follows:

$$\hat{s} = \arg\max_{s \in S^K} \left\| y_{ul} - \sqrt{p_u} H_s \right\|^2 \quad \text{..... (3.7)}$$

Where $\boldsymbol{S}$ is the finite alphabet of $\boldsymbol{s_k}, k = 1, 2, \dots\dots, K$. The problem (3.7) is a least squares (LS) problem with a finite-alphabet constraint. The BS has to search over $|S|^K$ vectors, where $|S|$ denotes the cardinality of the set *S*. Therefore, ML has a complexity which is exponential in the number of users.

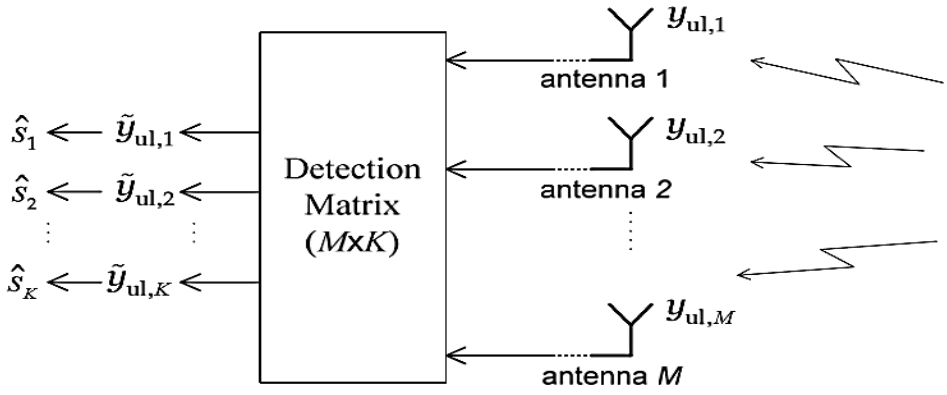

Figure 3.2: Block diagram of linear detection at the BS [12].

The BS can use linear processing schemes linear receivers in the uplink and linear precoders in the downlink to reduce the signal processing complexity. These schemes are not optimal. However, when the number of BS antennas is large, it is shown in [30,31] that linear processing is nearly-optimal. Therefore, in this thesis, we will consider linear processing. The details of linear processing techniques are presented in the following sections.

3.5 Linear Receivers (in the Uplink)

With linear detection schemes at the BS, the received signal $y_{ul}$is separated into *K*streams by multiplying it with an$M \times K$ linear detection matrix,*A*:

$$\widetilde{y_{ul}} = A^H y_{ul} = \sqrt{p_u} A^H H_s + A^H n \quad \text{..... (3.8)}$$

Each stream is then decoded independently. See Figure 3.2. The complexity is on the order of $K|S|$**.** From (3.8), the k^{th} stream (element) of$\widetilde{y_{ul}}$, which is used to decode s_k, is given by [10]:

$$\widetilde{y_{ul,k}} = \sqrt{p_u} a_k^H h_k s_k + \sqrt{p_u} \sum_{\acute{k} \neq k}^{K} a_k^H h_{\acute{k}} s_{\acute{k}} + a_k^H n \quad \text{..... (3.9)}$$

Wherea_k denotes the k^{th} column of *A*. The interference plus noise is treated as effective noise, and hence, the received signal-to-interference-plus-noise ratio (SINR) of the k^{th} stream is given by [10]:

$$SINR_k = \frac{p_u |a^H h_k|^2}{p_u \sum_{\acute{k} \neq k}^{K} |a_k^H h_{\acute{k}}|^2 + \|a_k\|^2} \quad \text{..... (3.10)}$$

We now review some conventional linear multiuser receivers.

3.5.1 Maximum-Ratio Combining (MRC) Receiver:

With MRC, the BS aims to maximize the received signal-to-noise ratio (SNR) of each stream, ignoring the effect of multiuser interference. From (3.9), thek^{th} column of the MRC receiver matrix *A* is [10]:

$$a_{mrc,k} = \underset{a_k \in C^{M \times 1}}{argmax} \frac{power\ (desired\ signal)}{power\ (noise)}$$

$$= \underset{a_k \in C^{M \times 1}}{argmax} \frac{p_u |a_k^H h_k|^2}{\|a_k\|^2} \quad \text{..... (3.11)}$$

Since,

$$\frac{p_u |a_k^H h_k|^2}{\|a_k\|^2} \leq \frac{p_u \|a_k\|^2 \|h_k\|^2}{\|a_k\|^2} = p_u \|h_k\|^2$$

And equality holds when a_k = constant·h_k, the MRC receiver is: $a_{mrc,k}$= constant·h_k. Plugging $a_{mrc,k}$ into (3.10), the received SINR of thek^{th} stream for MRC is given by [10]:

$$SINR_{mrc,k} = \frac{p_u \|h_k\|^4}{p_u \sum_{\acute{k} \neq k}^{K} |h_k^H h_{\acute{k}}|^2} \quad \text{..... (3.12)}$$

$$\rightarrow \frac{\|h_k\|^4}{\sum_{\acute{k}\neq k}^{K}|h_k^H h_{\acute{k}}|^2}, as\ p_u \rightarrow \infty \quad \text{..... (3.13)}$$

3.5.2 Zero-Forcing (ZF) Receiver:

By contrast to MRC, zero-forcing (ZF) receivers take the interuser interference into account, but neglect the effect of noise. With ZF, the multiuser interference is completely nulled out by projecting each stream onto the orthogonal complement of the interuser interference. More precisely, the k^{th} column of the ZF receiver matrix satisfies [10]:

$$\begin{cases} a_{zf,k}^H h_k \neq 0 \\ a_{zf,k}^H h_{\acute{k}} = 0, \forall k \neq \acute{k}. \end{cases} \quad \text{..... (3.14)}$$

The ZF receiver matrix, which satisfies (3.14) for all *k*, is the pseudo-inverse of the channel matrix *H*. With ZF, we have

$$\widetilde{y_{ul}} = (H^H H)^{-1} H^H y_{ul} = \sqrt{p_u}\, s + (H^H H)^{-1} H^H n \quad \text{..... (3.15)}$$

This scheme requires that M ≥ K (so that the matrix $H^H H$ is invertible). We can see that each stream (element) of $\widetilde{y_{ul}}$in (3.15) is free of multiuser interference. The k^{th} stream of $\widetilde{y_{ul}}$ is used to detects_k:

$$\widetilde{y_{ul,k}} = \sqrt{p_u} s_k + \widetilde{n_k}, \quad \text{..... (3.16)}$$

Where $\widetilde{n_k}$ denotes the kth element of$(H^H H)^{-1} H^H n$. Thus, the received SINR of the k^{th} stream is given by [10]:

$$SIRN_{zf,k} = \frac{p_u}{[(H^H H)^{-1}]_{kk}} \quad \text{..... (3.17)}$$

3.5.3 Minimum Mean-Square Error (MMSE) Receiver:

The linear minimum mean-square error (MMSE) receiver aims to minimize the mean-square error between the estimate $A^H y_{ul}$and the transmitted signal ***s***. More precisely [10],

$$A_{mmse} = \underset{A\in C^{M\times K}}{argmin} E\{\|A^H y_{ul} - s\|^2\} \quad \text{..... (3.18)}$$

$$= \underset{A\in C^{M\times K}}{argmin} \sum_{k=1}^{K} E\{|a_k^H y_{ul} - s_k|^2\} \quad \text{..... (3.19)}$$

Where a_k is the k^{th} column of *A*. Therefore, the k^{th} column of the MMSE receiver matrix is [10]

$$a_{mmse,k} = \underset{a_k\in C^{M\times 1}}{argmin} E\{|a_k^H y_{ul} - s_k|^2\} \quad \text{..... (3.20)}$$

$$= cov\,(y_{ul}, y_{ul})^{-1} cov(s_k, y_{ul})^H \quad \text{..... (3.21)}$$

$$= \sqrt{p_u}(p_u HH^H + I_M)^{-1} h_k \text{..... (3.22)}$$

Where $cov\,(v_1, v_2) \triangleq E\{v_1 v_2^H\}$, $v_1 and\ v_2$ are two random column vectors with zero-mean elements.

It is known that the MMSE receiver maximizes the received SINR. Therefore, among the MMSE, ZF, and MRC receivers, MMSE is the best. We can see from (3.22) that, at high SNR (high p_u), ZF approaches MMSE, while at low SNR, MRC performs as well as MMSE. Furthermore, substituting (3.22) into (3.10), the received SINR for the MMSE receiver is given by [10]:

$$SINR_{mmse,k} = p_u h_k^H \left(p_u \sum_{i \neq k}^{K} h_i h_i^H + I_M \right)^{-1} h_k \quad \text{... ... ... (3.23)}$$

3.6 Linear Precoders (in the Downlink)

In the downlink, with linear precoding techniques, the signal transmitted from M antennas x, is a linear combination of the symbols intended for the K users. Let q_k, $E\{|q_k|^2\} = 1$, be the symbol intended for the k^{th} user. Then, the linearly precoded signal vector x is [10]:

$$x = \sqrt{\alpha} W q, \quad \text{... ... ... (3.24)}$$

Where $q = \triangleq [q_1 q_2 \dots\dots q_k]^T, W \in C^{M \times K}$ is the precoding matrix and α is a normalization constant chosen to satisfy the power constant $E\{\|x\|^2\} = 1$. Thus,

$$\alpha = \frac{1}{E\{tr(WW^H)\}}, \quad \text{... ... ... (3.25)}$$

A block diagram of the linear precoder at the BS is shown in Figure 3.3.

Plugging (3.24) into (3.4), we obtain

$$y_{dl,k} = \sqrt{\alpha p_d} h_k^T W q + z_k \quad \text{... ... ... (3.26)}$$

$$= \sqrt{\alpha p_d} h_k^T w_k q_k + \sqrt{\alpha p_d} \sum_{\acute{k} \neq k}^{K} h_k^T w_{\acute{k}} q_{\acute{k}} + z_k \quad \text{... ... ... (3.27)}$$

Therefore, the SINR of the transmission from the BS to the k^{th} user is

$$SINR_k = \frac{\alpha p_d |h_k^T w_k|^2}{\alpha p_d \sum_{k \neq k}^{K} |h_k^T w_{\acute{k}}|^2 + 1}. \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.28)$$

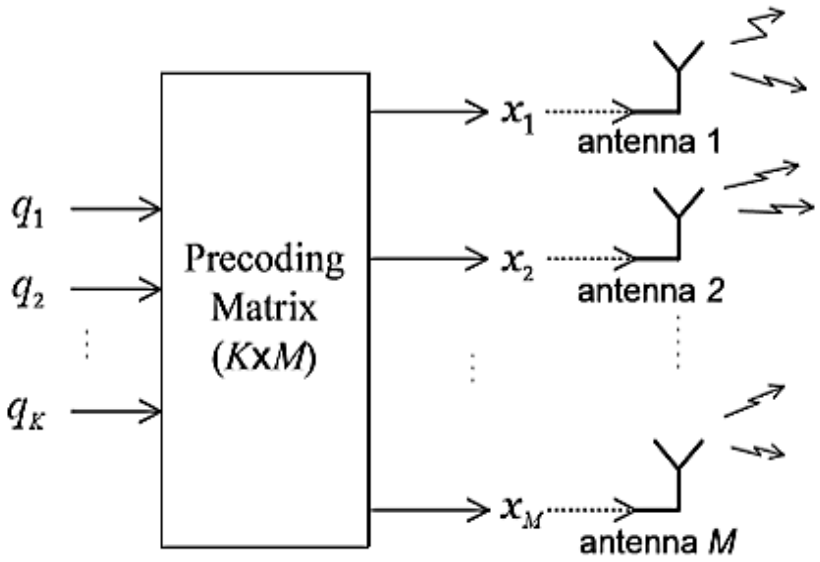

Figure 3.3: Block diagram of the linear precoders at the BS [12].

Three conventional linear precoders are maximum-ratio transmission (MRT), ZF, and MMSE precoders. These precoders have similar operational meanings and properties as MRC, ZF, MMSE receivers, respectively. Thus, here we just provide the final formulas for these precoders, i.e.,

$$W = \begin{cases} H^*, & for\ MRT \\ H^*(H^T H^*)^{-1}, & for\ ZF \\ H^*\left(H^T H^* + \dfrac{K}{p_d} I_K\right)^{-1}, & for\ MMSE \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.29)$$

3.7 Circuit Power Consumption Model

The Circuit power consumption$P_{CP}$is the sum of the power consumed by different analog components and digital signal processing [32]. The network model to show that a PC model accounting for the transmit power as well as for the CP consumed by the transceiver hardware at the BS and UEs is necessary to avoid misleading conclusions about the EE. These are not the only contributions that must be taken into account to appropriately evaluate the CP of the UL and DL of Massive MIMO. We will show that we must also consider the power consumed by digital signal processing,

backhaulsignaling, encoding, and decoding [33]. Building on [10, 32 - 36] a CP model for a generic BS in a Massive MIMO network is:

$$P_{CP} = P_{FIX} + P_{TC} + P_{CE} + P_{C/D} + P_{BH} + P_{LP} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.30)$$

Where P_{FIX}defined before as a constant quantity accounting for the fixed power was required for control signaling and load-independentpower of backhaul infrastructure and baseband processors. Furthermore, P_{TC}accounts for the power consumed by the transceiver chains, P_{CE} forthechannelestimationprocessperformedoncepercoherence block, $P_{C/D}$ for the channel encoding and decoding units, P_{BH} for the load dependent backhaul signaling, and P_{LP} for the linear signal processing at the BS. Note that neglecting the power consumed by transceiver chains, channel estimation, precoding, and combining was previously the norm in multiuser MIMO. More precisely, the small numbers of antennas and UEs, before Massive MIMO was introduced, were such that the CP for all those operations was negligible compared to the fixed power. The CP associated with those operations was modeled for single-cell systems in [10, 36], while multicellular systems were considered in [37]. Inspired by these works, we provide in what follows a tractable and realistic model for each term in (3.30), as a function of the main system parameters *M* and *K*. This is achieved by characterizing the hardware setup using a variety of fixed hardware coe□cients, which are kept generic in the analysis; typical values will be given later and strongly depend on the actual hardware equipment and the state-of-the-art in circuit implementation.

3.7.1 Transceiver Chains

As described in [10] and [40], the power consumption P_{TC} of a set of typical transmitters and receivers can be quantified as

$$P_{TC} = MP_{BS} + P_{SYN} + KP_{UE} \quad \ldots\ldots\ldots\ldots\ldots (3.31)$$

Where$P_{BS}$is the power required to run the circuit components such as converters, mixers, and filters attached to each antenna at the BS and P_{SYN} is the power consumed by the local oscillator. The last termP_{UE} accounts for the power required by all circuit components such as amplifiers, mixer, oscillator, and filters of each single-antenna UE. M and K denote by the number of antenna array at BS and number of user.

3.7.2 Channel Estimation

All processing is carried out locally at the BS and UEs, whose computational efficiency areL_{BS} and L_{UE} arithmetic complex-valued operations per Joule respectively. There are $\frac{B}{U}$coherence blocks per second and the pilot-based CSI estimation is performed onceper block. In the uplink, the BS receives the pilot signal as an $M \times \tau^{(ul)}$ K matrix and estimates

each UE's channel by multiplying with the corresponding pilot sequence of length $\tau^{(ul)}K$ [40]. This standard linear algebra operation [39] and requires $P_{CE}^{(ul)} = \frac{B}{U}\frac{2\pi^{(ul)}MK^2}{L_{BS}}$ Watt. In the downlink, each active UE receives a pilot sequence of length $\tau^{(dl)}K$ and processes it to acquire its effective precoded channel gain one inner product and the variance of interference plus noise one inner product. From [39], we obtain$P_{CE}^{(dl)} = \frac{B}{U}\frac{4\pi^{(dl)}K^2}{L_{UE}}$Watt. Therefore, the total power consumption of the channel estimation process becomes [10]:

$$P_{CE} = P_{CE}^{(ul)} + P_{CE}^{(dl)}$$

$$P_{CE} = P_{CE}^{(ul)} = \frac{B}{U}\frac{2\pi^{(ul)}MK^2}{L_{BS}} + P_{CE}^{(dl)} = \frac{B}{U}\frac{4\pi^{(dl)}K^2}{L_{UE}} \quad \ldots\ldots\ldots\ldots\ldots\ldots (3.32)$$

Where $P_{CE}^{(ul)}$ is the uplink channelestimationprocess, $P_{CE}^{(dl)}$ is the downlink channelestimationprocess.

3.7.3 Coding and Decoding

In the downlink, the BS applies channel coding and modulation to *K* sequences of information symbols and each UE applies some suboptimal fixed-complexity algorithm for decoding its own sequence. The opposite is done in the uplink. The power consumption $P_{C/D}$ accounting for these processes is proportional to the number of bits [10, 40] and can thus be quantified as:

$$P_{C/D} = \sum_{k=1}^{K}\left(E\left\{R_k^{(ul)} + R_k^{(dl)}\right\}\right)(P_{COD} + P_{DEC}) \quad \ldots\ldots\ldots\ldots\ldots\ldots (3.33)$$

whereP_{COD} and P_{DEC} are the coding and decoding powers in Watt per bit/s,$R_k^{(ul)}$ and$R_k^{(dl)}$ areuplink and downlink user gross raterespectively. For simplicity, we assume that P_{COD} and P_{DEC} are the same in the uplink and downlink, but it is straightforward to assign them different values.

3.7.4 Backhaul

The backhaul is used to transfer uplink/downlink data between the BS and the core network. The power consumption of the backhaul is commonly modeled as the sum of two parts [10]: one load-independent and one load-dependent. The first part was already included in P_{FIX}, while the load-dependent part is proportional to the average sum rate. Looking jointly at the downlink and uplink, the load-dependent term P_{BH} can be computed as [38]:

$$P_{BH} = \sum_{k=1}^{K} \left(E\left\{ R_k^{(ul)} + R_k^{(dl)} \right\} \right) P_{BT} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.34)$$

whereP_{BT} is the backhaul traffic power in Watt per bit/s, $R_k^{(ul)}$ and$R_k^{(dl)}$ are uplink and downlink user gross rate.

3.7.5 Linear Processing

The transmitted and received vectors of information symbols at the BS are generated by transmit precoding and processed by receive combining, respectively. This costs [39]

$$P_{LP} = B\left(1 - \frac{\left(\tau^{(ul)} + \tau^{(dl)}K\right)}{U}\right)\frac{2MK}{L_{BS}} + P_{LP-C} \qquad \ldots\ldots\ldots\ldots\ldots\ldots (3.35)$$

where the first term describes the power consumed by making one matrix-vector multiplication per data symbol and L_{BS} is computational efficiency at BSs. The second, term, P_{LP-C}, accounts for the power required for the computation of G and V. The precoding and combining matrices are computed once per coherence block and the complexity depends strongly on the choice of processing scheme. Since $G = V$ is a natural choice except when the uplink and downlink are designed very differently, we only need to compute one of them and thereby reduce the computational complexity. If MRT/MRC is used, we only need to normalize each column of H. This requires approximately [10]:

$$P_{LP-C}^{(MRT/MRC)} = \frac{B}{U}\frac{3MK}{L_{BS}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.36)$$

which was calculated using the arithmetic operations for standard linear algebra operations in [39]. On the other hand, if ZF processing is selected, then approximately [10]:

$$P_{LP-C}^{(ZF)} = \frac{B}{U}\left(\frac{K^3}{3L_{BS}} + \frac{3MK^2 + MK}{L_{BS}}\right) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.37)$$

is consumed, if the channel matrix inversion implementation is basedonstandardCholeskyfactorizationand back-substitution [39]. The computation of optimal MMSE processing is more complicated since the power allocation in is a fixed-point equation that needs to be iterated until convergence. Such fixed-point iterations usually converge very quickly, but for simplicity we fix the number of iterations to some predefined number Q. This requires $P_{LP-C}^{(MMSE)} = QP_{LP-C}^{(ZF)}$Watt since the operations in each iteration are approximately the same as in ZF.

3.8 Comparison of CP with Di□erent Processing Schemes

We will compare the CP consumed with di□erent combining/precoding schemes. There are M antennas at each BS and K user in each cell. The numberofsamplespercoherenceblock that is used for data is τ_c and τ_p, whereof 1/3 is used for UL and 2/3 forDL.WeconsiderULand DL transmit powers of 20 dBm per UE. The Gaussian local scattering with ASD σ_ϕ is used as channel model. The throughput of cell for computing the consumed power for backhaul, encoding, and decoding are obtained using the UL and DL.Computational complexity per***j*** coherence block of di□erent receives combining schemes [28]:

Table I: Computational Complexity for Di□erent Receives Combining Schemes.

Linear Precoding Methods	**Computing combining vectors Multiples**
MMSE	$\sum_{l=1}^{L} \frac{\left(3M_j^2 + M_j\right) K_l}{2} + \frac{M_j^3 - M_j}{3} + M_j\tau_p\left(\tau_p - K_j\right)$
ZF	$\frac{3K_j^2 M_j}{2} + \frac{K_j M_j}{2} + \frac{K_j^3 - K_j}{3}$
MRC / MRT	$\frac{K_j M_j}{2} + \frac{K_j^3 - K_j}{3}$

Power required by each BS for the signal processing with di□erent combining / precoding schemes over a bandwidth B, under the assumption that the precoding vectors are chosen as normalized versions of the receive combining vectors [28]:

Table II: PowerRequired for EachBSwithDi□erentCombiningPrecodingScheme.

Linear Precoding Methods	$\boldsymbol{P_{UL}}$	$\boldsymbol{P_{DL}}$
MMSE	$\frac{3B}{\tau_c L_{BS}}\left(\sum_{l=1}^{L} \frac{\left(3M_j^2 + M_j\right)K_l}{2} + \frac{M_j^3}{3} + 2M_j + M_j\tau_p\left(\tau_p + K_j\right)\right)$	$\frac{3B}{\tau_c L_{BS}} M_j K_j$

ZF	$\frac{3B}{\tau_c L_{BS}}\left(\sum_{l=1}^{L}\frac{3K_j^2M_j}{2}+\frac{K_jM_j}{2}+\frac{K_j^3-K_j}{3}+2M_j+\frac{7}{3}K_j\right)$	$\frac{3B}{\tau_c L_{BS}}M_jK_j$
MRC / MRT	$\frac{7B}{\tau_c L_{BS}}K_j$	$\frac{3B}{\tau_c L_{BS}}M_jK_j$

3.9 Tradeo between Power Consumption (PC) and Throughput

The tradeo between PC and throughput, using the CP model introduced in the previous section and the sets of CP values reported in Table 3. We focus on the PC and throughput of the Massive MIMO system to stress that one can't complete EE examination without determining the data transfer capacity. There are M antennas at each BS and K UEs in each cell. The values of M and K will be changed and specified in each figure. The quantity of samples consistent with coherence block used for UL and DL are$\tau_u = \frac{1}{3}(\tau_c - \tau_p)$and $\tau_d = \frac{2}{3}(\tau_c - \tau_p)$, respectively. We take into account UL and DL transmit powers of 20 dBm in step with UE. The throughput is acquired as in with the aid of using the UL and DLSE expressions.

The EE of cell is computed as:

$$EE = \frac{TR}{ETR+ CP} \quad \text{..... (3.38)}$$

WhereETP denotesthe E ective Transmit Power of cell, TR denotes throughputof cell and CP denotes consumed power of cell BSs.Thistermaccountsforthepower consumed by the transmission of the pilot sequences as well as of UL and DL signals:

$$ETR = \frac{\tau_p}{\tau_c}\sum_{k=1}^{K}\frac{1}{\mu UE,k}p_k + \frac{\tau_u}{\tau_c}\sum_{k=1}^{K}\frac{1}{\mu UE,k}p_k + \frac{1}{\mu BS}\frac{\tau_d}{\tau_c}\sum_{k=1}^{K}p_k \quad \text{..... (3.39)}$$

Where$\mu UE,\ k$ is the PA e ciency at UE k in cell and $\mu BS,\ j$isthatof BS.

The throughput of cell for computing the consumed power for backhaul, encoding, and interpreting is gotten utilizing the UL and DL SE articulations. For each plan and number of antennas, we utilize the limit destined for the UL and the one that gives the biggest SE between those of the DL:

$$TR = B\ \sum_{k=1}^{K}(SE_k^{UL} + max(SE_k^{DL}, SE_k^{DL})) \quad \text{..... (3.40)}$$

Where B is the Transmission Bandwidth, $SE_k^{UL}$and$SE_k^{DL}$are the Spectral Efficiency of uplink and downlink system per user.

3.10 Problem Statement

The EE of a communication system is measured in bit/Joule [16] and is computed as the ratio between the average sum rate (in bit/second) and the average total power consumption P_T (in Watt = Joule/second). In a multi-user setting, the total EE metric accounting for both uplink and downlink takes the following form.

The total EE of the uplink and downlink is

$$EE = \frac{\sum_{k=1}^{K}\left(E\left\{R_k^{(ul)}\right\} + E\left\{R_k^{(dl)}\right\}\right)}{P_{TX}^{(ul)} + P_{TX}^{(dl)} + P_{CP}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.41)$$

WhereP_{CP} accounts for the circuit power consumption, $R_k^{(ul)}$ and$R_k^{(dl)}$ are uplink and downlink user gross rate, $P_{TX}^{(ul)}$and $P_{TX}^{(dl)}$ are total power required for uplink and downlink system.

In most of the existing works, P_{CP} is modeled as $P_{CP} = P_{FIX}$ where the term P_{FIX} is a constant quantity accounting for the fixed power consumption required for site-cooling, control signaling, and load-independent power of backhaul infrastructure and baseband processors [16]. Hence, the simplified model $P_{CP} = P_{FIX}$gives the impression that we can achieve an unbounded EE by adding more and more antennas. This modeling artifact comes from ignoring that each antenna at the BS requires dedicated circuits with non-zero power consumption, and that the signal processing tasks also become increasingly complex.

In other words, an accurate modeling of P_{CP} is of paramount importance when dealing with the design of energy-efficient communication systems. The next section aims at providing an appropriate model for $P_{CP}(M,K, \bar{R})$ as a function of the three main design parameters: the number of BS antennas (M), number of active UEs (K), and the user gross rates ($\bar{R}$).

3.10.1 Problem Solutions:

An EE-optimal multi-user MIMO setup is achieved by solving the following optimization problem:

$$\underset{M \in Z_+, K \in Z_+, \bar{R} \geq 0}{maximize} \; EE = \frac{\sum_{k=1}^{K}\left(E\left\{R_k^{(ul)}\right\} + E\left\{R_k^{(dl)}\right\}\right)}{P_{TX}^{(ul)} + P_{TX}^{(dl)} + P_{CP}(M, K, \bar{R})} \quad \ldots\ldots\ldots\ldots\ldots\ldots (3.42)$$

This Problem is solved analytically for Linear Precoding Methods.

1. Observe that prior works on EE optimization have focused on either uplink or downlink.

2. Problem is an optimization in which the total EE is maximized for given fractions UL and DL of uplink and downlink Transmissions.
3. Maximizing the EE in does not mean decreasing the total power, but to pick a good power level and use it wisely.

Chapter 04

Simulation and Result Analysis

4.1 Why Simulation?

Simulation is defined as the process of creating a model of an existing or proposed system in order to identify and understand their functioning. We can predict the estimation and assumption of the real system by using simulation results.

4.2 Simulator

In this thesis, the theoretical analysis presented previously, we conducted a system level simulation using a MATLAB 2015a.

4.3 Implementation of the Model

The implementation consists of three main programs:

The Linear Precoding Method: In the linear precoding function, the inputs are: number of antenna (M), number of users (K), the channel matrix H and the output signal W. By implementing equation (3.29), we estimate the number of complex multiplication from channel matrix function. For linear precoding calculation, MATLAB simulator first calculates the response channel matrix and inverse channel matrix function according to formula and table 3.1 with respect to number of antenna and users. Finally, this function evaluates the number of complex multiplication response for different linear precoding methods.

The Total Circuit Power (CP) Consumption: In the Total Circuit Power Consumption function, the given inputs: the fixed power of BS (P_{FIX}), the power consumed by the transceiver chains (P_{TC}), thechannelestimationprocessperformedoncepercoherence block (P_{CH}), the loaddependent backhaul signaling (P_{BH}), the linear signal processing at the BS(P_{LP}) and the output signal (P_{CP}). By implementing equation (3.30), we calculate the total circuit power consumption. For calculate total circuit power consumption with different linear precoding methods, MATLAB simulator first calculates the circuit power consumption according to formula and table 3.2 with respect to number of antenna and users. Finally, this function evaluates the total circuit power consumption response for different linear precoding methods.

The Maximize Energy Efficiency (EE): In the maximize Energy Efficiency (EE) function, the given inputs: uplink and downlink gross rate, uplink and downlink transmit power, total circuit power consumption and the output signal EE. By implementing

equation (3.38 and 3.39), we calculate the maximize Energy Efficiency (EE) for different linear precoding methods.

4.4 Purpose of the Simulation:

The goal of the simulation is get maximum energy efficiency (EE) with the proposed method. The simulation scenarios enable analysis of different precoding estimator performance to find the optimal numbers of antenna (M) and numbers of users (K) with maximize energy efficiency. In our simulation, on EE optimizations have focused on uplink and downlink transmissions process. In this thesis is to compare the various linear precoding algorithms for maximum energy efficiency with respect to numbers of antenna (M), numbers of users (K) and total circuit power (P_{CP}). Thus, the accurate goal will be achieved.

4.5 Simulation Parameters

The corresponding simulation parameters are given Table 3.

Table III: Simulation Parameters

Parameter	**Value**
Number of Antenna	200
Number of Users	100
Transmission Bandwidth (B)	20 MHz
Coherence Bandwidth (B_C)	180 kHz
Coherence Time (T_C)	10 ms
Coherence Block (τ_c)	400
Computational Efficiency at BSs (L_{BS})	12.8 Gflops/W
UL Transmit Power (P_{UL})	20 dBm
DL Transmit Power (P_{DL})	20 dBm
Fixed Power Consumption (P_{FIX})	9 W
Power for BS LO: P_{LO}	0.1 W

Power of Circuit Components (such as converters, mixers, and filters) (P_{BS})	1 W
Power consumed by Local Oscillator at BSs (P_{SYN})	1 W
Power required of circuits components of each single-antenna UE. (P_{UE})	0.1 W
Power for data encoding (P_{COD})	0.01 W
Power for data decoding (P_{DEC})	0.08 W
Power for backhaul tra□c (P_{BT})	0.025 W

4.6 Analysis of Simulation Result: Complex Multiplications per Coherence Block with Different Precoding Schemes.

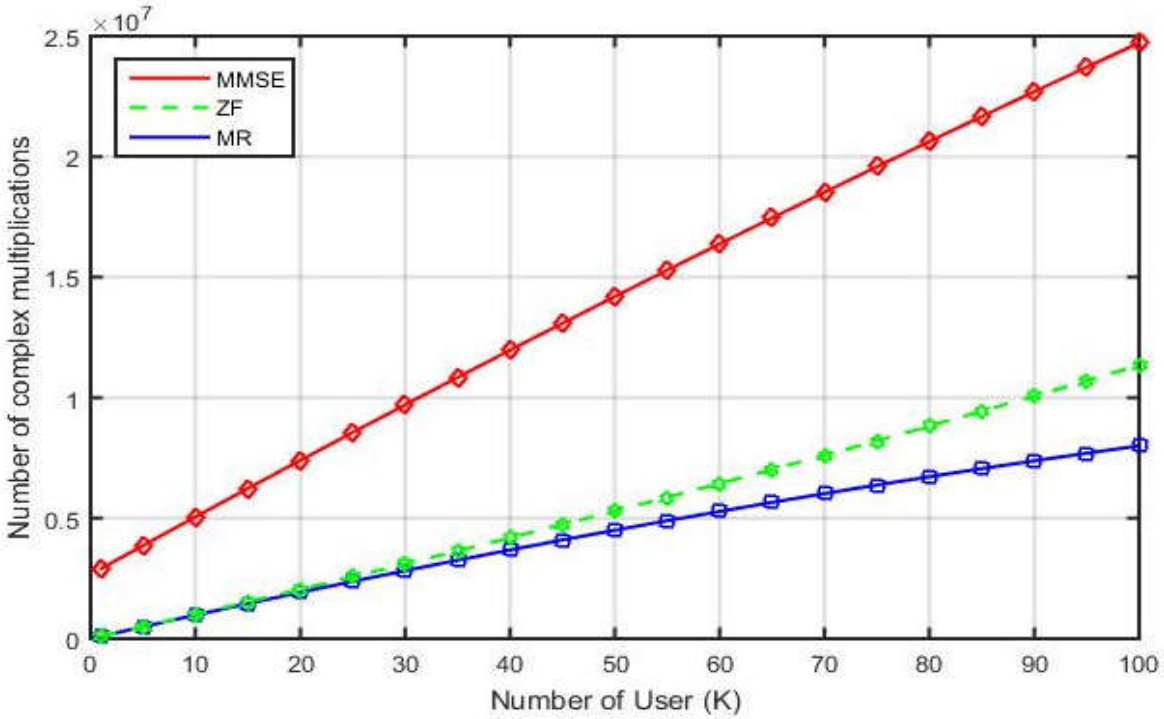

Figure 4.1: Number of complex multiplications per cell when using different combining methods with varies K and Fixed M

In Figure 4.1 and 4.2 illustrate the number of complex multiplications per coherence block as a function of either the number of UEs or the number of BS antennas. In Figure 4.1 we assume that $K \in [1,100]$ and $M = 200$ in every cell. On the other hand, in Figure

4.2 we consider K = 100 and let M vary from 0 to 200. The complexity increases with the number of UEs and BSs antennas for all combining schemes.

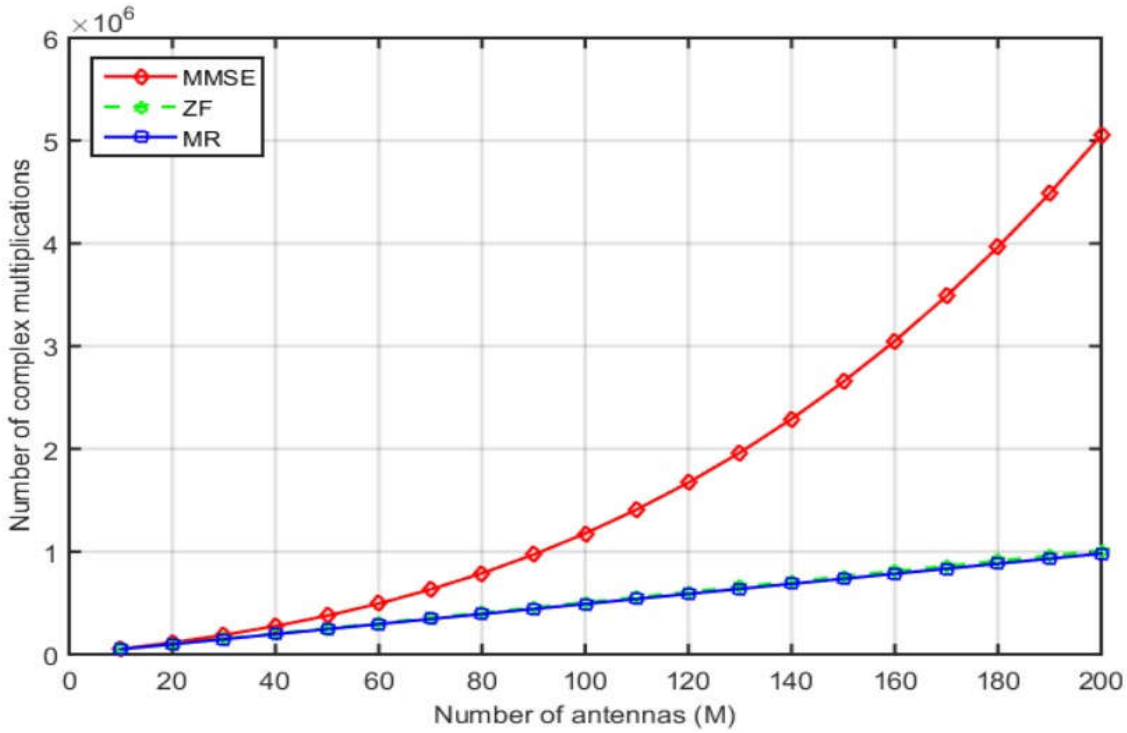

Figure 4.2: Number of complex multiplications per cell when using different combining methods with varies M and Fixed K

MMSE has clearly the highest complexity. ZF provide even lower complexity than MMSE since these schemes invert substantially smaller Kj × Kj matrices (compared to the Mj × Mj matrices that are inverted by MMSE). MR provides the lowest computational complexity since no matrix inverses are computed, which also means that all computations can be parallelized in the implementation a separate processing core can be used per antenna and UE.

Table IV: Number of Complex Multiplications per cell when using Different Combining Methods with Varies K and Fixed M

Linear Precoding Method	**Value**
MMSE	2.472e+07 = 13.72
ZF	1.134e+07 = 10.08
MRC	1.125e+06 = 9.06

Table V: Number of Complex Multiplications per cell when using Different Combining Methods with Varies M and Fixed K

Linear Precoding Method	Value
MMSE	5.052e+06 = 19.73
ZF	1.011e+06 = 8.75
MRC	0.98e+05 = 7.66

Table VI: Comparison of Complex Multiplications per cell with Reference Paper [28]:

Linear Precoding Methods		Data from Table IV (W)	Data from Table V (W)
This Work	MMSE	2.472e+07 = 13.72	5.052e+06 = 19.73
	ZF	1.134e+07 = 10.08	1.011e+06 = 8.75
	MRT/MRC	1.125e+06 = 9.06	0.98e+05 = 7.66
Reference Paper [28]	MMSE	3.393e+06 = 15.22	6.128e+06 = 22.65
	ZF	2.033e+05 = 10.53	2.058e+05 = 10.59
	MRT/MRC	1.84e+05 = 10.00	1.9e+05 = 10.16

4.7 Analysis of Simulation Result: The Total CP per cell for the Combined UL and DL Scenario with Different precoding schemes.

In Figures 4.3 & 4.4 illustrates the total CP per cell for the combined UL and DL scenario with di□erent combining/precoding schemes. In Figure 4.3: we consider M = 200 and let K vary from 0 to 100. The CP increases with the number of UEs. MMSE requires the highest CP and MR the lowest. In Figure 4.4: we consider K = 100 and let M vary from 0 to 200. The CP increases with M for all schemes. The highest CP is required by MMSE. This is mainly due to the increased computational e□ciency. ZF consume less CP, since invert matrices of dimensions K × K, rather than M × M. MR is characterized by the lowest CP since no matrix inversions are required. MR only provides a substantial complexity reduction when the number of UEs is very large.

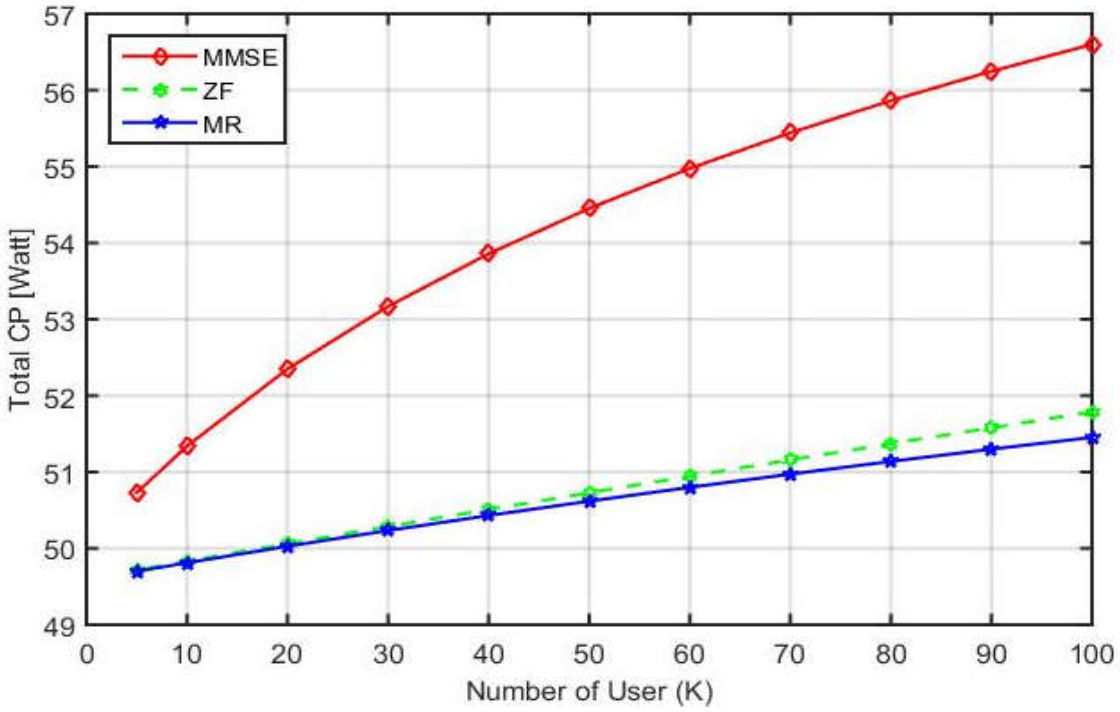

Figure 4.3: Total CP vs. Number of Users (K) when using different combining methods with fixed antenna (M).

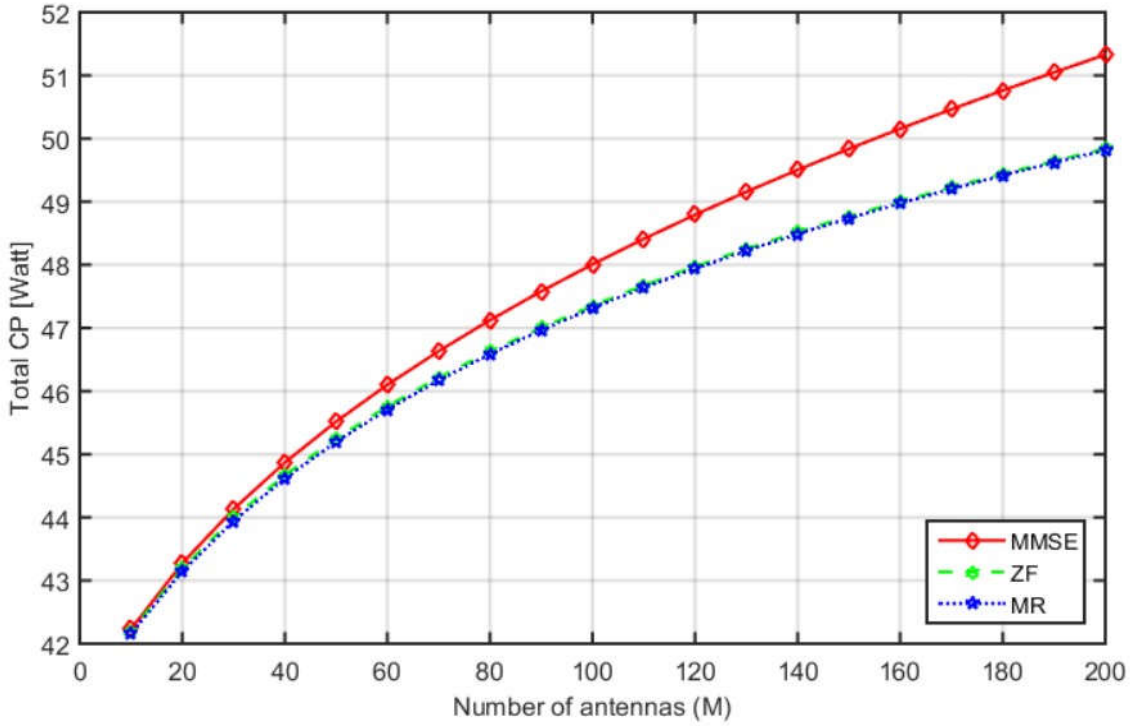

Figure 4.4: Total CP vs. Number of antenna (M) when using different combining methods with Fixed Users (K).

The CP of all schemes, for the two di□erent sets of parameter values, M =200, and K =100 are summarized in Table VII & VIII. As we can see, in this considered setup the CP required by the di□erent schemes is marginally di□erent. This happens because the CP of the transceiver hardware dominates over that of signal processing. The CP contributed by the fixed power, Transceiver chains, Signal processing for UL reception, DL transmission and Precoding computation are the same for all schemes.

Table VII: Total CP per cell of both UL and DL for fixed user (K) and varying number of antennas (M).

Methods	**Value [Watt]**
MMSE	51.33
ZF	49.84
MR	49.83

Table VIII: Total CP per cell of both UL and DL for fixed number of antennas (M) and varying user (K).

Methods	**Value [Watt]**
MMSE	49.53
ZF	47.72
MR	47.64

Table IX: Comparison of Total CP with Reference Paper [28]:

Linear Precoding Methods		**Average CP vale of UL and DL Data from Table VII & VIII**
This Work	MMSE	50.43
	ZF	48.78
	MRT/MRC	48.74
Reference Paper [28]	MMSE	56.35
	ZF	54.43
	MRT/MRC	53.96

4.8 Analyzed the Average SEper cell for the Combined UL and DL Scenariowith Different Precoding Schemes.

In MRC, the multiple antenna transmitters use the channel estimate of a terminal to maximize the strength of that terminal's signal by adding the signal components coherently. MRC precoding maximizes the SNR and works well in the massive MIMO system, since the base station radiates low signal power to the users on average.ZF precoding is a method of spatial signal processing by which the transmitter can null out multiuser interference signals. In general, ZF precoder performs well under high SNR conditions. The ZF precoder outperforms MRC, as shown in Figure 4.5 in performance as well as in computational complexity. It also suppresses inter-cell interference at the cost of reducing the array gain [6]. It is noted that spectral efficiency increases as the number of BS antennas grows. In addition, the figure shows the superiority of the performance of MMSE, especially in massive MIMO. MMSE precoding is the optimal linear precoding in a massive MIMO downlink and uplink system. This technique uses the mean square error (MSE). The Lagrangian technique is used to optimize this precoder, using the average power of each transmitting antenna as the constraint.

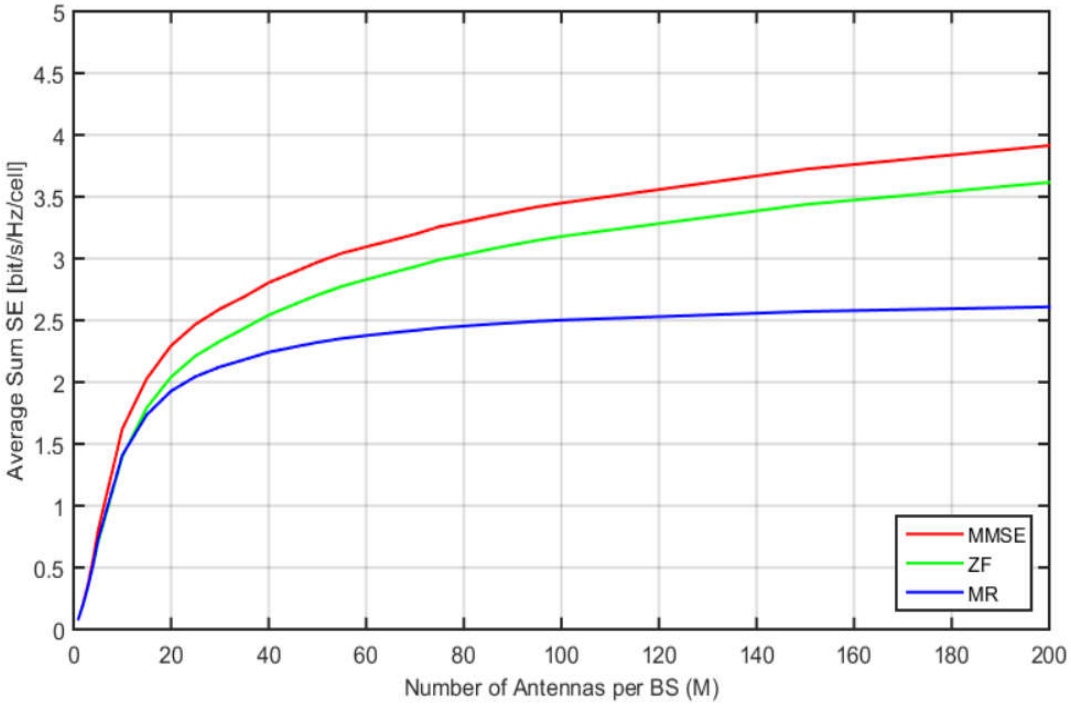

Figure 4.5: Average DL and UL sum SE as a function of the number of BS antennas for different precoding schemes.

Now we compare the average SE achieved with different precoding schemes. We consider K =10UEspercellandavaryingnumberofBSantennas.Equal DL and UL power

allocationof20dBmperUE. For each scheme and number of antennas, we use the DL and UL capacity bound and pilot reuse factor f ∈ 1, that gives the largest SE. Figure 4.5 shows the average DL and UL sum SE with f =1. We consider MMSE, ZF and MRC precoding. MMSE provides the highest SE (SE = 3.917) for any number of antennas. ZFprovide almost the same SE (SE = 3.605). Finally, MRC provides the lowest SE (SE = 2.617) among all schemes and it is also the only scheme that prefers the hardening bound over the estimation bound.

As in the average SE of DL and UL, the computational complexity is higher for the precoding/combining schemes that provide higher SEs, and we can appoint MMSE, ZF and MRC as three distinct tradeo□s between high SE and low complexity. These are the schemes to choose between in a practical implementation.

4.9 Analyzed the Power Consumption (PC) and Throughput with different precoding schemes.

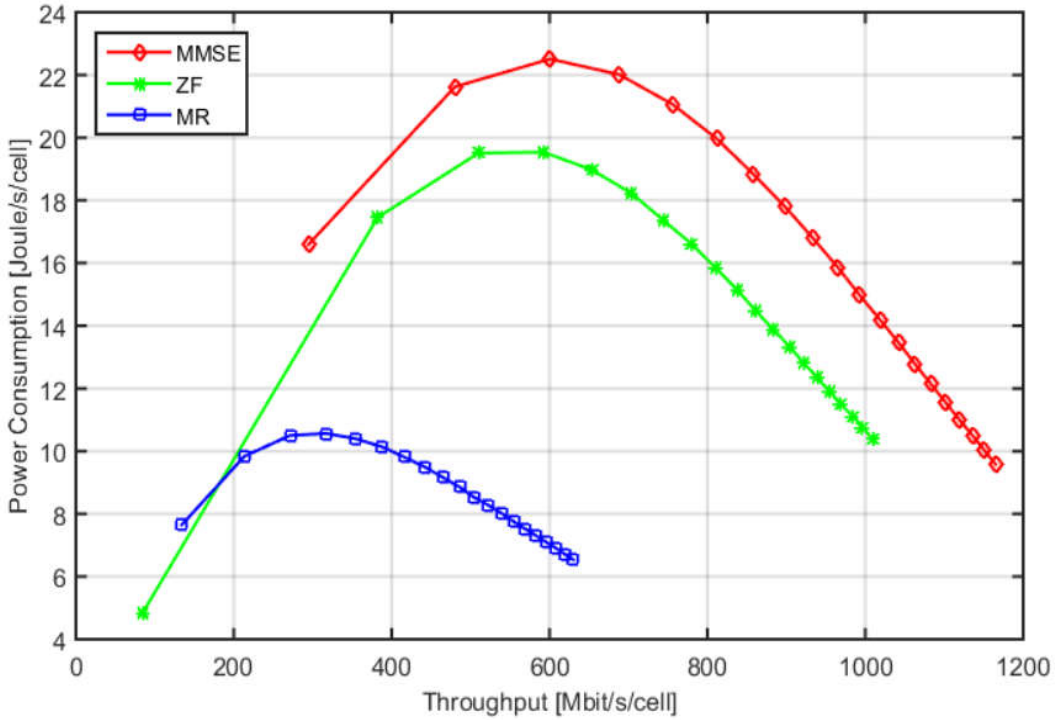

Figure 4.6: PC versus throughput forfunction of the different precoding schemes.

Figure4.6illustratesthe PC asafunctionoftheaveragethroughput per cell with all processing schemes. The different throughput values are achieved with K =10 UEs and by letting the number of BS antennas vary from M = 10 to M =200. We notice that the PC is a unimodal function of the throughput for all schemes and both sets of CP values. This implies that we can jointly increase the throughput and PC up to the maximum point, but

further increases in throughput can only come at a loss in PC. The curves are quite smooth around the maximum PC point; thus, there are a variety of throughput values or, equivalently, numbers of BS antennas that provide nearly maximum PC. MMSE provides the highest PC for any value of the throughput. MR has the lowest performance. This shows that, in the considered setup, the additional computational complexity of MMSE processing pays o□ both in terms of SE.

From Figure 4.6, we can see that the maximal PC value with MMSE is 22.51 Joule/s/cell is achieved at throughput of 600.8 Mbit/s/cell. MR has performance the lowest PC value is 10.57 Joule/s/cell is achieved at throughput of 317 Mbit/s/cell. ZF provides a maximum PC of 19.54 Joule/s/cell is achieved at throughput of 592.7 Mbit/s/cell. Interestingly, ZF and MR tend to perform as MMSE when the throughput increases. This happens since the higher the throughput, the higher is also the CP, duetothelargernumberofantennas.

4.10 Network Design for Maximal Energy E□ciency

Intheprevioussection,we discussed thecomplex multiplications, total circuit power (CP), average sum Spectral Efficiency (SE), Power Consumption (PC) and Throughput ofMassiveMIMOnetworks for a given number of UEs and varying number of BS antennas. In the following, we look at the EE from a di□erent perspective: we design the network from scratch to achieve maximal EE, without assumptions on the number of antennas or UEs. We focus the following questions:

a. What is the optimal number of BS antennas?
b. How many UEs should be served?
c. When di□erent processing schemes should be used?

Figure 4.7, 4.8 and 4.9 show that the set of achievable maximum energy efficiency (EE) values with different linear precoding methods. In figure 4.7, MMSE precoding method get the maximum energy efficiency values other precoding methods. With MMSE, a maximal EE of 24.16 Mbit/Joule is achieved by (M, K) = (50, 30). In figure 4.8, ZF precoding method gets the slightly less maximum energy efficiency value than MMSE. The corresponding set of achievable a maximal EE of 22.96 Mbit/Joule is achieved by (M, K) = (80, 30). Interestingly, MRT precoding method shows a very different behavior: the energy efficiency value is much smaller than with MMSE and ZF which is 11.77 Mbit/Joule achieved at (M, K) = (50, 20). The MMSE gives better performance because the MMSE is able to make the massive MIMO system less sensitive to SNR at an increased number of antennas for achievable data rates compared with ZF and MRT, where an MMSE and ZF are able to work at high SNR. Consequently, EE first increases and then decreases with an increased number of antennas, which maximizes the transmit power when taking into account the consumption circuit power and the transmit power.

In addition, increasing the number of antennas inside the cell will increase the transmit power and operating power consumption, which creates the tendency of a concave shape for EE.

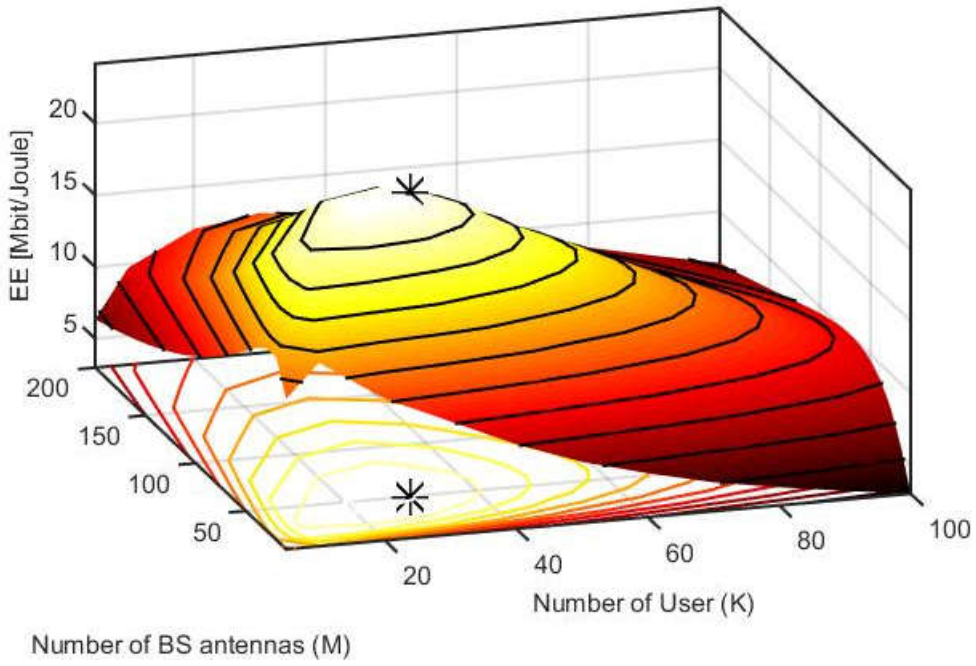

Figure 4.7: Maximum Energy Efficiency per cell as a function of number of BS (M) and number of Users (K) with MMSE Precoding Method.

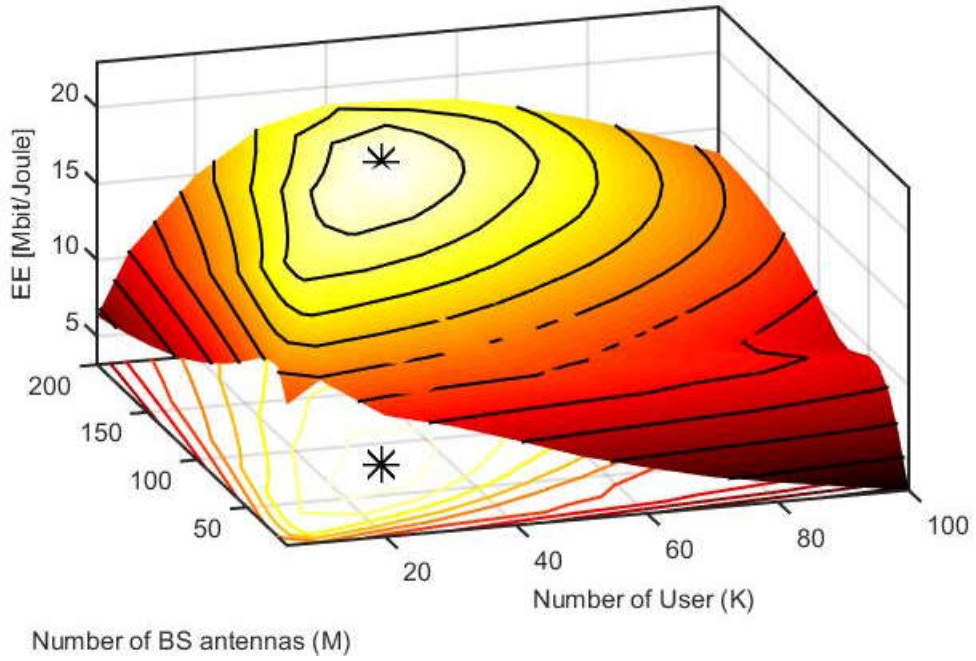

Figure 4.8: Maximum Energy Efficiency per cell as a function of number of BS (M) and number of Users (K) with ZF Precoding Method.

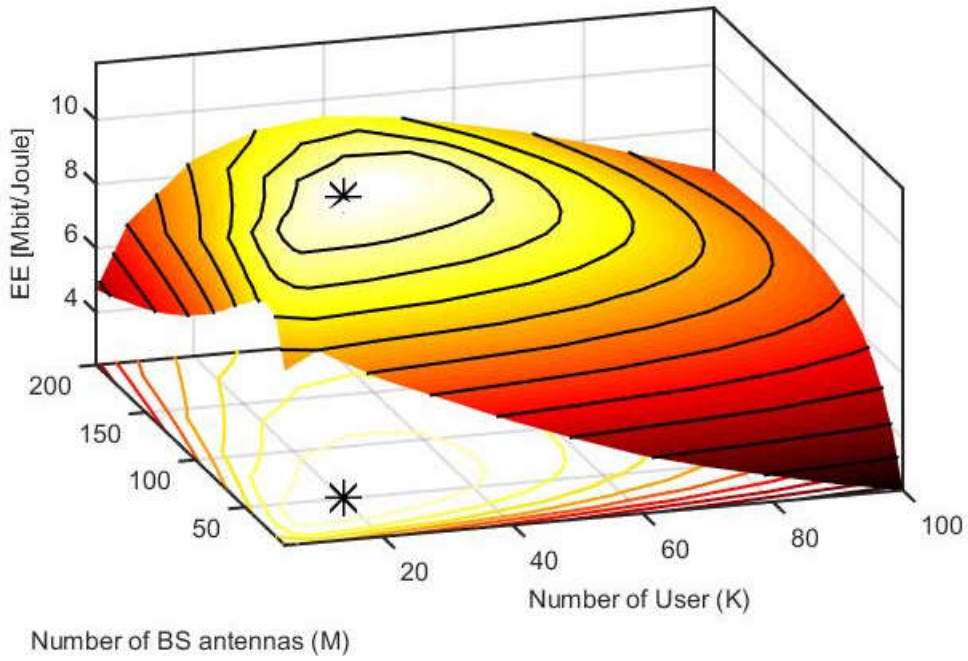

Figure 4.9: Maximum Energy Efficiency per cell as a function of number of BS (M) and number of Users (K) with MRT/MRC Precoding Method.

Table X: Comparison of Maximum EE with Reference Paper [28]:

Linear Precoding Methods		**Number of antenna (M)**	**Number of Users (K)**	**Maximum Energy Efficiency [Mbit/Joule]**
This Work	MMSE	50	30	24.16
	ZF	80	30	22.96
	MRT/MRC	50	20	11.77
Reference Paper [28]	MMSE	40	20	20.73
	ZF	90	30	20.25
	MRT/MRC	60	20	10.63

The explanation behind is that MRT/MRC works under strong inter-user interference, in this manner the rate per UE is small and it makes sense to plan whatever number UEs as could be allowed. The signal processing complexity is lower than with ZF for a similar M and K, but yet the power reserve funds are not sufficiently huge to adjust for the lower rates. To accomplish an indistinguishable rate from with ZF, MRT/MRC requires which would radically increase the computational/circuit power and not enhance the EE [10], [28].

Interestingly, we observe that all the EE-optimum configurations of (M,K) fall within the Massive MIMO networks, with a number of antennas in the range of tens and an antenna-UE ratio M/K. Numerical results were used in this section to find the numbers of BS antennas and UEsthat jointly achieve high EE. The EE maximization problem can potentially be solved analytically with respect to M and K.Other system parameters can also be optimized. Closed-form expressions for the optimal (M,K) and transmit power were derived, from which valuable insights into the interplay between the optimization variables, hardware characteristics, and propagation environment were provided. A further leap in EE can then be achieved by adding more BS antennas to spatially multiplex UEs in every cell. The corresponding EE gains come from suppressing intra-cell interference by the many antennas and by sharing the per-cell CP costs among multiple UEs.

Chapter 05

Conclusion and Future Work

5.1 Conclusion

Since the appearance of Massive MIMO, the system performance of wireless communication system has been improved significantly in terms of capacity, latency, reliability and etc. In this thesis,

1. We firstly analyze the background of next generation wireless communication system.
2. Introduce the massive MIMO system, power consumption model and energy efficiency.
3. And to make the system model of massive MIMO according to linear precoding methods, problem formulation solvable, we apply precodingmethod to address this optimization problem with number of antenna per BS and Users.
4. Finally, combining numerical results, we present that massive MIMO remarkably improves the energy efficiency.

We mainly focused on energy efficiency in massive MIMO systems. Although we have studied power allocation in uplink and downlink transmission, there are still some aspects that should be done in the future.Energy efficiency in a multiple cellular system is achieved by increasing the number of antennas at the BS. We have examined how to obtain maximum EE, which depends on selecting the optimal number of antennas and fixing the number of scheduled users inside cells. In addition, analyzing how to minimize total power consumption depends nonlinearly on M and K. Total power consumption consists of circuit power from analog devices and power amplifiers in massive MIMO systems. The techniques of linear precoding beamforming, MMSE, ZF and MRT/MRC enable minimum power transmission at the BS to select the best-performing active antenna. Consequently, linear precoding MMSE achieves maximum EE, more so than ZF and MRT, because the MMSE is able to suppressinterference actively and make a massive MIMO system less sensitive to SNR at an increased number of antennas.

5.2 Future Work

There are several scopes to work on energy efficiency of massive MIMO systems-

1. The energy efficiency model in these thesis only suits to single cell massive MIMO system. In the future, it can be developed to multi-cells Massive MIMO system.

2. Find other limitations of this precoding techniques and designing new precoding techniques with good overall performance in massive MIMO system.
3. Distances between users and BS are not being taken into account in this thesis. This should be considered in the future for more accurate simulation results.
4. Designing such precoding schemes can lead to promising results for FDD massive MIMO systems.

In future, we will develop a more massive MIMO system model from energy efficiency perspective, which will provide faster data transmission rate with reliable uplink and downlink wireless communication system.

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Appendix A

MATLAB Function and Code

In order to obtain the performance of the discussed maximize energy efficiency techniques, some of the functions and Code used in the Matlab15a.

01. Function of Compute DL and UL SE for different transmit precoding schemes

```
function [SE_MR,SE_RZF,SE_MMMSE] = functionComputeSE_DL_impairments(H,Hhat,C,tau_c,tau_p,nbrOfRealizations,M,K,L,p,rho,kappatBS,kapparUE)

%Store identity matrices of different sizes

eyeK = eye(K);

eyeM = eye(M);

%Compute sum of all estimation error correlation matrices at every BS

C_totM = reshape(p*sum(sum(C,3),4),[M M L]);

%Compute the pre-log factor assuming only downlink transmission

prelogFactor = (tau_c-tau_p)/(tau_c);

%Prepare to store simulation results for signal gains

signal_MR = zeros(K,L);

signal_ZF = zeros(K,L);

signal_MMSE = zeros(K,L);

%Prepare to store simulation results for norms of precoding vectors

precodingNorm_MR = zeros(K,L);

precodingNorm_ZF = zeros(K,L);

precodingNorm_MMSE = zeros(K,L);

%Prepare to store simulation results for sum interference powers

interf_MR = zeros(K,L);
```

```
interf_ZF = zeros(K,L);
interf_MMSE = zeros(K,L);
%Prepare to store simulation results for sum impairment-caused interference
impair_MR = zeros(K,L);
impair_ZF = zeros(K,L);
impair_MMSE = zeros(K,L);
%% Go through all channel realizations
for n = 1:nbrOfRealizations
   %Go through all cells
for j = 1:L
      %Extract channel realizations from all users to BS j
Hallj = reshape(H(:,n,:,:,j),[M K*L]);
      %Extract channel estimate realizations from all UEs to BS j
Hhatallj = reshape(Hhat(:,n,:,:,j),[M K*L]);
      %Compute MR combining in (4.11)
      V_MR = Hhatallj(:,K*(j-1)+1:K*j);
ifnargout> 1 %Compute ZF combining in (4.9)
         V_RZF = p*V_MR/(p*(V_MR'*V_MR)+eyeK);
end
ifnargout> 2 %Compute MMSE combining in (4.7)
         V_MMMSE = p*(p*(Hhatallj*Hhatallj')+C_totM(:,:,j)+eyeM)\V_MR;
end
      %Go through all users in cell j
for k = 1:K
%%MR precoding
```

```
        w = V_MR(:,k)/norm(V_MR(:,k)); %Extract precoding vector
wrep = repmat(w,[1 K*L]);
        %Compute realizations of the expectations in signal and interference
signal_MR(k,j) = signal_MR(k,j) + (w'*H(:,n,k,j,j))/nbrOfRealizations;
        precodingNorm_MR(k,j) = precodingNorm_MR(k,j) +
        norm(w).^2/nbrOfRealizations;
        interf_MR = interf_MR + rho*reshape(abs(w'*Hallj).^2,[K
        L])/nbrOfRealizations;
        impair_MR = impair_MR + rho*reshape(sum(abs(wrep.*Hallj).^2,1),[K
        L])/nbrOfRealizations;
        %%ZF precoding
ifnargout>=2
            w = V_RZF(:,k)/norm(V_RZF(:,k)); %Extract precoding vector
wrep = repmat(w,[1 K*L]);
            %Compute realizations of the expectations in signal and
            %interference terms in (6.46)
signal_ZF(k,j) = signal_ZF(k,j) + (w'*H(:,n,k,j,j))/nbrOfRealizations;
        precodingNorm_ZF(k,j) = precodingNorm_ZF(k,j) +
        norm(w).^2/nbrOfRealizations;
        interf_ZF = interf_ZF + rho*reshape(abs(w'*Hallj).^2,[K L])/nbrOfRealizations;
        impair_ZF = impair_ZF + rho*reshape(sum(abs(wrep.*Hallj).^2,1),[K
        L])/nbrOfRealizations;
end
        %%MMSE precoding
ifnargout>=3
            w = V_MMSE(:,k)/norm(V_MMSE(:,k)); %Extract precoding vector
wrep = repmat(w,[1 K*L]);
```

```
%Compute realizations of the expectations in signal and interference

signal_MMSE(k,j) = signal_MMSE(k,j) + (w'*H(:,n,k,j,j))/nbrOfRealizations;

precodingNorm_MMSE(k,j) = precodingNorm_MMSE(k,j) + norm(w).^2/nbrOfRealizations;

interf_MMSE = interf_MMSE + rho*reshape(abs(w'*Hallj).^2,[K L])/nbrOfRealizations;

impair_MMSE = impair_MMSE + rho*reshape(sum(abs(wrep.*Hallj).^2,1),[K L])/nbrOfRealizations;

end

end

end

end

%Precompute terms that appear multiple times

sigma2 = 1/(kapparUE*kappatBS);

factor1 = 1/kapparUE;

factor2 = (1-kappatBS)/(kapparUE*kappatBS);

%Compute SEs according to Theorem 6.5 and (6.46)

SE_MR = prelogFactor*real(log2(1+(rho*abs(signal_MR).^2) ./ (factor1*interf_MR + factor2*impair_MR - rho*abs(signal_MR).^2 + sigma2)));

ifnargout>=2

  SE_ZF = prelogFactor*real(log2(1+(rho*abs(signal_ZF).^2) ./ (factor1*interf_ZF + factor2*impair_ZF - rho*abs(signal_ZF).^2 + sigma2)))

;end

ifnargout>=3

  SE_MMSE = prelogFactor*real(log2(1+(rho*abs(signal_MMMSE).^2) ./ (factor1*interf_MMSE + factor2*impair_MMSE - rho*abs(signal_MMSE).^2 +sigma2)));

end
```

02.Function of Compute the UL and DL Power

```
function [channelGains_MR,channelGains_RZF,channelGains_MMMSE] = functionComputeULDLPowerLevels(H,Hhat,C,nbrOfRealizations,M,K,L,p)

%Store identity matrices of different sizes

eyeK = eye(K);

eyeM = eye(M);

%Compute sum of all estimation error correlation matrices at every BS

C_totM = reshape(p*sum(sum(C(:,:,:,:,:),3),4),[M M L]);

%Prepare to store simulation results

channelGains_MR = zeros(K,L,K,L);

channelGains_ZF = zeros(K,L,K,L);

channelGains_MMSE = zeros(K,L,K,L);

%% Go through all channel realizations

for n = 1:nbrOfRealizations

   %Go through all cells

for j = 1:L

      %Extract channel estimate realizations from all UEs to BS j

Hallj = reshape(H(:,n,:,:,j),[M K*L]);

      %Extract channel estimate realizations from UEs in cell j to BS j

Hhatallj = reshape(Hhat(:,n,:,:,j),[M K*L]);

      %Compute three different combining/precoding schemes

      V_MR = Hhatallj(:,K*(j-1)+1:K*j); %MR in Eq. (XX)

      V_ZF = p*V_MR/(p*(V_MR'*V_MR)+eyeK); %RZF in Eq. (XX)

      V_MMSE = p*(p*(Hhatallj*Hhatallj')+C_totM(:,:,j)+eyeM)\V_MR; %MMSE in Eq. (XX)

      %Go through all UEs in cell j
```

```
for k = 1:K

        %%MR combining/precoding

        v = V_MR(:,k); %Extract combining vector

        v = v/norm(v);

        %Compute UL powers for the interfering channels from all UEs to

%UE k in cell j. These are also the interfering DL gains

%from UE k in cell j to all other UEs.

channelGains_MR(k,j,:,:) = channelGains_MR(k,j,:,:) + reshape(abs(v'*Hallj).^2,[1 1 K L])/nbrOfRealizations;

        %%ZF combining/precoding

        v = V_ZF(:,k); %Extract combining vector

        v = v/norm(v);

        %Compute UL powers for the interfering channels from all UEs to

%UE k in cell j. These are also the interfering DL gains

%from UE k in cell j to all other UEs.

channelGains_ZF(k,j,:,:) = channelGains_RZF(k,j,:,:) + reshape(abs(v'*Hallj).^2,[1 1 K L])/nbrOfRealizations;

        %%M-MMSE combining/precoding

        v = V_MMSE(:,k); %Extract combining vector

        v = v/norm(v);

        %Compute UL powers for the interfering channels from all UEs to

%UE k in cell j. These are also the interfering DL gains

%from UE k in cell j to all other UEs.

channelGains_MMMSE(k,j,:,:) = channelGains_MMSE(k,j,:,:) + reshape(abs(v'*Hallj).^2,[1 1 K L])/nbrOfRealizations;

end
```

```
end

end
```

03.Function of the CP model Coefficients

```
function [P_FIX,P_LO,P_BS,P_UE,P_COD,P_DEC,L_BS,P_BT] = functionCPmodel(valueset)

%% Define parameter values for Value

if

   P_FIX = 10;

   P_LO = 0.2;

   P_BS = 0.4;

   P_UE = 0.2;

   P_COD = 0.1*10^(-9);

   P_DEC = 0.8*10^(-9);

   L_BS = 75*10^9;

   P_BT = 0.25*10^(-9);

end
```

04.Function of the total CP computation with different processing schemes

```
function [P_MR,P_RZF,P_MMMSE,P_ZF,P_SMMSE] = functionCPcomputation(Mrange,K,L,B,tau_c,tau_p,valueset,sumSE_MR,sumSE_RZF,sumSE_MMMSE,sumSE_ZF,sumSE_SMMSE)

%Obtain CP model

[P_FIX,P_LO,P_BS,P_UE,P_COD,P_DEC,L_BS,P_BT] = functionCPmodel(valueset);

%Prepare to store simulation results

P_MR = zeros(length(Mrange),1);

P_TC = zeros(length(Mrange),1);
```

```
P_CE = zeros(length(Mrange),1);
P_SP_RT = zeros(length(Mrange),1);
P_SP_DL = zeros(length(Mrange),1);
P_SP_UL_MR = zeros(length(Mrange),1);
%Compute CP for coding and decoding using (5.35)
P_CD_MR = (P_COD + P_DEC)*B*sumSE_MR;
%Compute CP for backhaul traffic using (5.36)
P_BH_MR = P_BT*B*sumSE_MR;
%Repeat computations for MMSE
ifnargin>9
   P_MMSE = zeros(length(Mrange),1);
   P_CD_MMSE = (P_COD + P_DEC)*B*sumSE_MMSE;
   P_BH_MMSE = P_BT*B*sumSE_MMSE;
   P_SP_UL_MMSE = zeros(length(Mrange),1);
end
%Repeat computations for ZF
ifnargin>10
   P_ZF = zeros(length(Mrange),1);
   P_CD_ZF = (P_COD + P_DEC)*B*sumSE_ZF;
   P_BH_ZF = P_BT*B*sumSE_ZF;
   P_SP_UL_ZF = zeros(length(Mrange),1);
end
%Go through all number of antennas
for index = 1:length(Mrange)
   %Extract current number of antennas
```

```
    M = Mrange(index);
    %Compute CP for transceiver chains
    P_TC(index) = M*P_BS + P_LO + K*P_UE;
    %Compute CP for channel estimation with all other schemes, where only
    %the channels to UEs in other cells are estimated
    P_CE(index) = 3*K*B/(tau_c*L_BS)*(M*tau_p + M^2);
    %Compute CP for UL reception and DL transmission
    P_SP_RT(index) = (tau_c - tau_p)*3*B/(tau_c*L_BS)*M*K;
    %Compute CP for computation of precoding vectors
    P_SP_DL(index) = 4*M*K*B/(tau_c*L_BS);
    %Sum up the power terms that are independent of the processing scheme
    P_SAME = P_FIX + P_TC(index) + P_SP_RT(index) + P_SP_DL(index);
    %Compute CP for computation of the combining vectors with different schemes
    P_SP_UL_MR(index) = 7*B*K/(tau_c*L_BS);
    %Compute the final CP values
    P_MR(index) = P_SAME + P_CE(index) + P_CD_MR(index) + P_BH_MR(index) +
P_SP_UL_MR(index);
    %Repeat same computations for MMSE
ifnargin>9
        P_SP_UL_MMSE(index) = 3*B*(L*(3*M^2 + M)*K/2 + M^3/3 + 2*M +
M*tau_p*(tau_p-K))/(tau_c*L_BS);
        P_MMSE(index) = P_SAME + P_CE(index) + P_CD_MMSE(index) +
P_BH_MMSE(index) + P_SP_UL_MMSE(index);
end
    %Repeat same computations for ZF
ifnargin>10
```

```
    P_SP_UL_ZF(index) = 3*B*(3*K^2*M/2 + M*K/2 + (K^3 - K)/3 +
(7/3)*K)/(tau_c*L_BS);

    P_ZF(index) = P_SAME + P_CE(index) + P_CD_ZF(index) + P_BH_ZF(index) +
P_SP_UL_ZF(index);

end

end
```

05. Function ofCompute Maximize Energy Efficiency

```
function [EE,rate,power] =
functionEnergyEfficiency(power,h,etaUE,etaBS,noise,R,kappaUE,kappaBS,omega,rho,z
eta,trafficPortion,ULDLratio)

%A typical pilot signal

d = sqrt(power);

%Extract number of antennas

N = size(h,1);

%Extract number of Monte Carlo simulations

nbrOfMonteCarloRealizations = size(h,2);

%Compute matrix A in the LMMSE estimator (see Eq. (9))

A_MMSE = conj(d) * R / (abs(d)^2*(1+kappaUE)*R +
abs(d)^2*kappaBS*diag(diag(R))+eye(N));

%Placeholders for storing Monte Carlo simulation results

firstMoment = zeros(nbrOfMonteCarloRealizations,1);

distortionTerm = zeros(nbrOfMonteCarloRealizations,1);

%Go through all Monte Carlo realizations

for k = 1:nbrOfMonteCarloRealizations

%Compute received signal

   z = h(:,k) * ( d + d*etaUE(k) ) + d*etaBS(:,k) + noise(:,k);

%Compute channel estimates
```

```
hhat = A_MMSE*z;

%Compute the beamforming vector (MRT/MRC)

beamforming = sqrt(power)*hhat/norm(hhat);

%Compute a realization of the first moment of the inner product between beamforming and channel

firstMoment(k) = h(:,k)'*beamforming;

distortionTerm(k) = sum( (abs(h(:,k)).^2) .* (abs(beamforming).^2));

end

%Finalize the Monte Carlo simulations by computing lower bounds on the capacity

rate = trafficPortion * log2(1+ abs(mean(firstMoment,1)).^2 ./ ( (1+kappaUE) * var(firstMoment) + kappaUE* abs(mean(firstMoment,1)).^2 + kappaBS*mean(distortionTerm,1) + 1) );

%Compute the energy efficiency according to Definition 1

EE = rate/((power/omega + N*rho + zeta)*ULDLratio);
```

06.Complexity of Computing Combining Matrix

```
close all;

clear;

tau_c = 400; %Select length of coherence block

Mrange = 10:10:200; %Define range of number of BS antenna

Krange = 1:100; %Define range of number of UEs

L = 5; %Set number of cells considered in the MMSE scheme

%% Consider M=100 and varying K

K = Krange;

M = max(Mrange);

tau_u = (tau_c-K); %Compute number of samples for uplink data

receiverProcessing = tau_u.*K*M; %Compute complexity of receive combining
```

```
%Add complexity of computing combining matrix

complexity_MMMSE = receiverProcessing + L*K*(M^2+M)/2 + M^2*K + (M^3-M)/3;
%M-MMSE

complexity_ZF = receiverProcessing + 3*K.^2*M/2 + M*K/2 + (K.^3-K)/3; %ZF

complexity_MR = receiverProcessing; %MR

%Plot the simulation results for M=100 and varying K

figure(1);

grid on;

hold on;

box on;

plot(K,complexity_MMSE,'r-','LineWidth',1);

plot(K,complexity_ZF,'g--','LineWidth',1);

plot(K,complexity_MR,'b-','LineWidth',1);

plot(K([1 5:5:100]),complexity_MMSE([1 5:5:100]),'rd-','LineWidth',1);

plot(K([1 5:5:100]),complexity_MR([1 5:5:100]),'bs-','LineWidth',1);

plot(K([1 5:5:100]),complexity_ZF([1 5:5:100]),'gh--','LineWidth',1);

xlabel('Number of UEs (K)');

ylabel('Number of complex multiplications');

legend('MMSE','ZF','MR','Location','NorthWest');

%% Consider K=10 and varying M

K = Krange(10);

M = Mrange;

tau_u = (tau_c-K); %Compute number of samples for uplink data

receiverProcessing = tau_u*K*M; %Compute complexity of receive combining

%Add complexity of computing combining matrix
```

```
complexity_MMMSE = receiverProcessing + L*K*(M.^2+M)/2 + M.^2*K + (M.^3-M)/3;

complexity_ZF = receiverProcessing + 3*K^2*M/2 + M*K/2 + (K^3-K)/3;

complexity_MR = receiverProcessing;

%Plot the simulation results for K=10 and varying M

figure(2);

grid on;

hold on;

box on;

plot(M,complexity_MMSE,'rd-','LineWidth',1);

plot(M,complexity_ZF,'gh--','LineWidth',1);

plot(M,complexity_MR,'bs-','LineWidth',1);

xlabel('Number of antennas (M)');

ylabel('Number of complex multiplications');

legend('MMSE','ZF','MR','Location','NorthWest');
```

07.Compute the total CP Power with number of Antenna

```
close all;

clear;

load section5_Mvarying_K10_20; %Load simulation data

%Number of UEs per BS

k_index = 1;

K = Krange(k_index);

%Fractions of data samples used for UL and DL

ULfraction = 1/3;

DLfraction = 2/3;
```

```
%Compute joint UL/DL sum SE using the fractions of UL/DL data

sumSE_MMSE = ULfraction*sumSE_MMMSE_UL(:,k_index) + DLfraction*sumSE_MMMSE_DL(:,k_index);

sumSE_ZF = ULfraction*sumSE_ZF_UL(:,k_index) + DLfraction*sumSE_ZF_DL(:,k_index);

sumSE_MR = ULfraction*sumSE_MR_UL(:,k_index) + DLfraction*sumSE_MR_DL(:,k_index);

L = 16; %Number of BSs

B = 20e6; %Communication bandwidth

tau_c = 450; %Select length of coherence block

tau_p = K; %Select length of pilot sequences

%Prepare to store simulation results

P_MMSE = zeros(length(Mrange),2);

P_ZF = zeros(length(Mrange),2);

P_MR = zeros(length(Mrange),2);

%% Compute CP values for different value sets

forvalueset = 1

[P_MR(:,valueset),P_ZF(:,valueset),P_MMSE(:,valueset)]=functionCPcomputation(Mrange,K,L,B,tau_c,tau_p,valueset,sumSE_MR,sumSE_ZF,sumSE_MMSE);

End

%% Plot the simulation results

grid on;

hold on;

box on;

forvalueset = 1

plot(Mrange,10*log10(P_MMSE(:,valueset)/0.001),'rd-','LineWidth',1);

plot(Mrange,10*log10(P_ZF(:,valueset)/0.001),'gh--','LineWidth',1);
```

```
plot(Mrange,10*log10(P_MR(:,valueset)/0.001),'bp:','LineWidth',1);
end
xlabel('Number of antennas (M)');
ylabel('Total CP [Watt]');
legend('MMSE','ZF','MR','Location','SouthEast');
```

08.Compute the total CP Power with number of Users

```
close all;
clear;
load section5_M100_Kvarying; %Load SE simulation data
%Fractions of data samples used for UL and DL
ULfraction = 1/3;
DLfraction = 2/3;
%Compute joint UL/DL sum SE using the fractions of UL/DL data
sumSE_MMSE = ULfraction*sumSE_MMSE_UL + DLfraction*sumSE_MMSE_DL;
sumSE_ZF = ULfraction*sumSE_ZF_UL + DLfraction*sumSE_ZF_DL;
sumSE_MR = ULfraction*sumSE_MR_UL + DLfraction*sumSE_MR_DL;
L = 16; %Number of BSs
M = 200; %Number of BS antennas
B = 20e6; %Communication bandwidth
tau_c = 400; %Select length of coherence block
tau_p = Krange; %Select length of pilot sequences
%Prepare to store simulation results
P_MMSE = zeros(length(Krange),2);
P_ZF = zeros(length(Krange),2);
P_MR = zeros(length(Krange),2);
```

```
%% Compute CP values for different value sets 1

forvalueset = 1 %1:2

for k = 1:length(Krange)

%Compute the total CP with different schemes
[P_MR(k,valueset),P_ZF(k,valueset),P_MMSE(k,valueset)]=functionCPcomputation(M,
Krange(k),L,B,tau_c,tau_p(k),valueset,sumSE_MR,sumSE_MMSE,sumSE_ZF);

        end

end

%% Plot the simulation results

grid on;

hold on;

box on;

forvalueset = 1

plot(Krange,10*log10(P_MMSE(:,valueset)/0.001),'rd-','LineWidth',1);hold on;

plot(Krange,10*log10(P_ZF(:,valueset)/0.001),'gh--','LineWidth',1);

plot(Krange,10*log10(P_MR(:,valueset)/0.001),'bp-','LineWidth',1);

end

xlabel('Number of UEs (K)');

ylabel('Total CP [Watt]');

legend('MMSE','ZF','MR','Location','NorthWest');
```

09.Power Consumption vs. Throughput

```
close all;

clear;

%Load SE simulation data, generated using the code from Section 4

load section5_Mvarying_K10_20;

k_index = 1; %Selecting K = 10 from the loaded SE results
```

```
K = Krange(k_index);

%Fractions of data samples used for UL and DL

ULfraction = 1/6; %1/3

DLfraction = 2/6; %2/3

%Compute joint UL/DL sum SE using the fractions of UL/DL data

sumSE_MMSE = ULfraction*sumSE_MMSE_UL(:,k_index) + DLfraction*sumSE_MMMSE_DL(:,k_index);

sumSE_ZF = ULfraction*sumSE_ZF_UL(:,k_index) + DLfraction*sumSE_ZF_DL(:,k_index);

sumSE_MR = ULfraction*sumSE_MR_UL(:,k_index) + DLfraction*sumSE_MR_DL(:,k_index);

%Number of BSs

L = 16; %16

%Communication bandwidth

B = 20e6;

%PA efficiency UEs and BSs

mu_UE = 0.4;

mu_BS = 0.5;

%Define the pilot reuse factor

f = 1;

%Select length of coherence block

tau_c = 200;

%Compute length of pilot sequences

tau_p = f*K;

%Transmit power per UE in W

p = 0.1;
```

```
%Compute total effective transmit power

ETP_total= K*p*(tau_p/mu_UE + (tau_c-tau_p)*(ULfraction/mu_UE + DLfraction/mu_BS))/tau_c;

%Compute the total CP with different schemes

[P_MR,P_MMSE,P_ZF] = functionCPcomputation(Mrange,K,L,B,tau_c,tau_p,valueset,sumSE_MR,sumSE_MMSE,sumSE_ZF);

 %Compute EE with M-MMSE

EE_MMMSE = (B*sumSE_MMMSE)./(ETP_total + P_MMMSE);

%Compute EE with ZF

EE_ZF = (B*sumSE_ZF)./(ETP_total + P_ZF);

%Compute EE with MR

EE_MR = (B*sumSE_MR)./(ETP_total + P_MR);

%Plot simulation results

figure;

hold on;

plot(B*sumSE_MMSE/10^6,EE_MMSE/10^6, 'rd-','LineWidth',1);

plot(B*sumSE_ZF/10^6,EE_ZF/10^6,'rs--','LineWidth',1);

plot(B*sumSE_MR/10^6,EE_MR/10^6,'bs-','LineWidth',1);

xlabel('Throughput [Mbit/s/cell]');

ylabel('Power Consumption [Joule/s/cell]');

legend('M-MMSE','RZF','MR','Location','NorthWest');
```

10.Average UL and DL sum SE

```
close all;

clear;

L = 16; %Number of BSs
```

```
K = 10; %Number of UEs per BS
Mrange = 10:10:210; %Define the range of BS antennas
%Mrange = 10:10:100;
Mmax = max(Mrange); %Extract maximum number of BS antennas
fRange = 1;
%Select the number of setups with random UE locations
nbrOfSetups = 1; %100
%Select the number of channel realizations per setup
nbrOfRealizations = 1; %100
B = 20e6;
%Total uplink transmit power per UE (mW)
p = 100;
noiseFigure = 7;
noiseVariancedBm = -174 + 10*log10(B) + noiseFigure;
tau_c = 400;
%Use the approximation of the Gaussian local scattering model
accuracy = 2;
%Angular standard deviation in the local scattering model (in degrees)
ASDdeg = 10;
%Prepare to save simulation results
sumSE_MR = zeros(length(Mrange),length(fRange),nbrOfSetups);
sumSE_ZF = zeros(length(Mrange),length(fRange),nbrOfSetups);
sumSE_MMMSE = zeros(length(Mrange),length(fRange),nbrOfSetups);
%% Go through all setups
for n = 1:nbrOfSetups
```

```
%Output simulation progress
disp([num2str(n) ' setups out of ' num2str(nbrOfSetups)]);
   %Compute channel statistics for one setup
   [R,channelGaindB] = functionExampleSetup(L,K,Mmax,accuracy,ASDdeg);
   %Compute the normalized average channel gain, where the normalization
   %is based on the noise power
channelGainOverNoise = channelGaindB - noiseVariancedBm;
   %Go through all number of antennas
for m = 1:length(Mrange)
      %Output simulation progress
disp([num2str(m) ' antennas out of ' num2str(length(Mrange))]);
      %Go through all pilot reuse factors
for s = 1:length(fRange)
         %Extract pilot reuse factor
         f = fRange(s);
%Generate channel realizations with estimates and estimation error correlation matrices
         [Hhat,C,tau_p,Rscaled] =
functionChannelEstimates(R(1:Mrange(m),1:Mrange(m),:,:,:),channelGainOverNoise,nbr
OfRealizations,Mrange(m),K,L,p,f);
         %Compute SEs
         [SE_MR,SE_ZF,SE_MMSE] =
functionComputeSE_UL(Hhat,C,Rscaled,tau_c,tau_p,nbrOfRealizations,Mrange(m),K,L,
p);
         %Save average sum SE per cell
sumSE_MR(m,s,n) = mean(sum(SE_MR,1));
sumSE_ZF(m,s,n) = mean(sum(SE_ZF,1));
sumSE_MMMSE(m,s,n) = mean(sum(SE_MMMSE,1));
```

```
clearHhat C Rscaled;
end
end
   %Delete large matrices
clear R;
end
%% Plot the simulation results
for s = 1:length(fRange)
figure;
grid on;
hold on;
box on;
plot(Mrange,mean(sumSE_MMMSE(:,s,:),3),'rd-','LineWidth',1);
plot(Mrange,mean(sumSE_ZF(:,s,:),3),'rh--','LineWidth',1);
plot(Mrange,mean(sumSE_MR(:,s,:),3),'bs-','LineWidth',1);
xlabel('Number of antennas (M)');
ylabel('Average sum SE [bit/s/Hz/cell]');
legend('M-MMSE','ZF','MR','Location','NorthWest');
ylim([0 80]);
end
```

11. Compute Maximum Energy Efficiency with Different Precoding Methods

```
close all;
clear;
valueset = 1;
```

```
%Load SE simulation data
load section5_Mvarying_Kvarying.mat;
L = 16; %Number of BSs
B = 20e6;
mu_UE = 0.6;
mu_BS = 0.75;
f= 1;
tau_c = 400;
%Fractions of data samples used for UL and DL
ULfraction = 1/3;
DLfraction = 2/3;
p = 0.01;;
%Compute joint UL/DL sum SE using the fractions of UL/DL data
sumSE_MMSE = ULfraction*sumSE_MMSE_UL + DLfraction*sumSE_MMSE_DL;
sumSE_ZF = ULfraction*sumSE_ZF_UL + DLfraction*sumSE_ZF_DL;
sumSE_MR = ULfraction*sumSE_MR_UL + DLfraction*sumSE_MR_DL;
%Prepare to save simulation results
EE_MR = zeros(length(Mrange),length(Krange));
EE_ZF = zeros(length(Mrange),length(Krange));
EE_MMMSE = zeros(length(Mrange),length(Krange));
%% Go through all number of BS antennas
for m = 1:length(Mrange)
   %Go through all number of UEs
for k = 1:length(Krange)
      %Compute length of pilot sequences
```

```
tau_p = f*Krange(k);

    %Compute the total CP with different schemes

    [P_MR,P_ZF,P_MMSE] = functionCPcomputation(Mrange(m),Krange(k),L,B,tau_c,tau_p,valueset,sumSE_MR,sumSE_ZF,sumSE_MMSE);

    %Compute total effective transmit power

ETP_total= Krange(k)*p*(tau_p/mu_UE + (tau_c-tau_p)*(ULfraction/mu_UE + DLfraction/mu_BS))/tau_c;

    %Compute EE with MR

    EE_MR(m,k) = (B*sumSE_MR(m,k))./(ETP_total + P_MR);

    %Compute EE with ZF

    EE_ZF(m,k) = (B*sumSE_ZF(m,k))./(ETP_total + P_ZF);

    %Compute EE with MMSE

    EE_MMMSE(m,k) = (B*sumSE_MMSE(m,k))./(ETP_total + P_MMSE);

end

end

%% Plot simulation results

figure;

hold on;

box on;

grid on;

surfc(Krange,Mrange,EE_MMSE/10^6,'EdgeColor','none');

colormap hot

shadinginterp

hold on

contour3(Krange,Mrange,EE_MMSE/1e6,10,'k')
```

```
[~,I] = max(EE_MMMSE(:));

[row,col] = ind2sub(size(EE_MMSE),I);

Kopt = Krange(col);  %Optimal number of UEs

Mopt = Mrange(row);  %Optimal number of BS antennas

hold on

plot3(Kopt,Mopt,EE_MMSE(row,col)/1e6,'k*','MarkerSize',16,'MarkerFaceColor','black'
);

hold on

plot3(Kopt,Mopt,min(min(EE_MMSE))/1e6,'k*','MarkerSize',16,'MarkerFaceColor','blac
k');

view([-17 32]);

xlabel('Number of UEs (K)')

ylabel('Number of BS antennas (M)');

zlabel('EE [Mbit/Joule]');

%Plot Figure MAX EE of ZF

figure;

hold on;

box on;

grid on;

surfc(Krange,Mrange,EE_ZF/10^6,'EdgeColor','none');

colormap hot

shadinginterp

hold on

contour3(Krange,Mrange,EE_ZF/1e6,10,'k')

[~,I] = max(EE_ZF(:));

[row,col] = ind2sub(size(EE_RZF),I);
```

```
Kopt = Krange(col);  %Optimal number of UEs
Mopt = Mrange(row);  %Optimal number of BS antennas
hold on
plot3(Kopt,Mopt,EE_ZF(row,col)/1e6,'k*','MarkerSize',16,'MarkerFaceColor','black');
hold on
plot3(Kopt,Mopt,min(min(EE_ZF))/1e6,'k*','MarkerSize',16,'MarkerFaceColor','black');
view([-17 32]);
xlabel('Number of UEs (K)')
ylabel('Number of BS antennas (M)');
zlabel('EE [Mbit/Joule]');
%Plot Figure MAX EE of MR
figure;
hold on;
box on;
grid on;
surfc(Krange,Mrange,EE_MR/10^6,'EdgeColor','none');
colormap hot
shadinginterp
hold on
contour3(Krange,Mrange,EE_MR/1e6,10,'k')
[EE_max,I] = max(EE_MR(:));
[row,col] = ind2sub(size(EE_MR),I); %2D maximizer
Kopt = Krange(col);  %Optimal number of UEs
Mopt = Mrange(row);  %Optimal number of BS antennas
hold on
```

```
plot3(Kopt,Mopt,EE_MR(row,col)/1e6,'k*','MarkerSize',16,'MarkerFaceColor','black');
hold on
plot3(Kopt,Mopt,min(min(EE_MR))/1e6,'k*','MarkerSize',16,'MarkerFaceColor','black');
view([-17 32]);
xlabel('Number of UEs (K)')
ylabel('Number of BS antennas (M)');
zlabel('EE [Mbit/Joule]');
```