ADDIS ABABA UNIVERSITY

ADDIS ABABA INSTITUTE OF TECHNOLOGY

SCHOOL OF ELECTRICAL AND COMPUTER ENGINEERING

COMMUNICATION ENGINEERING STREAM

ANALYSIS OF ENERGY EFFICIENT TECHNIQUES FOR 5G ULTRA DENSE WIRELESS COMMUNICATION NETWORKS USING MASSIVE MIMO

By: Halefom Tswaslassie Gebrekidan

A research Thesis submitted to Addis Ababa University Institute of Technology in Partial Fulfillments of the Requirements for the Degree of Master of Science in Electrical and Computer Engineering (Communication Engineering Stream)

Advisor: Dr-Eng Yihenew W

Oct. 2021

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Approval by Board of Examiners

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Chairman Department of Graduate Committee	Signature	Date
Dr. -Eng. Yihenew Wondimu	____________	____________
Advisor	Signature	Date
____________________	____________	____________
Internal Examiner	Signature	Date
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External Examiner	Signature	Date

Declaration

I declare that this thesis, which I submit to Addis Ababa Institute of Technology for examination in partial fulfillments of the award of a master degree in Electrical and computer engineering, is my own original effort. It has not been presented for fulfillment of a degree in this or any other University and all sources and materials used for the thesis are duly acknowledged.

Halefom TSwaslassie Gebrekidan ______________________

Name Signature

Addis Ababa ______________________

Place Date of Submission

This thesis work has been submitted for examination with my approval as a University Advisor.

Dr. -Eng. Yihenew Wondimu ___________________________

Advisor's Name Signature

Acknowledgments

First, I would like to thank God Almighty for giving me the strength and encouragement especially during all the challenging moments in completing this research thesis. Next, I would like to express my deepest gratitude and special thanks to my advisor, Dr. Eng. Yihenew Wondie for his continuous support, patience, motivation and immense knowledge. His valuable idea, guidance and freedom the He give me helps me on the right way to my research thesis and without his help, it would not possible to accomplish and present this thesis work. I am also very grateful to my family, colleagues, friends , to all AAiT academic staffs of SECE and those who supported me in many ways for successful accomplishment of my thesis.

Abstract

In the modern wireless communication energy consumption becomes critical issue for wireless network operators. With the emergence of 5G wireless communication , the importance of energy efficiency (EE) has been appreciated since it is one of the significant performance analysis metrics of wireless networks. Energy can be saved in the design of wirless network if a proper analysis and design optimization is done. Massive MIMO and cell densfications are the latest encouraging technologies to maximize energy efficiency of 5G wireless communications.

This thesis work mainly aims on the analysis of energy efficiency techniques of 5G wireless communication using Massive MIMO technology.The techniques to be analysis are in the precoding , in channel state information and massive MIMOtechnology. The analysis begins from circuit power consumption model using zero forcing precoding schemes with TDD communication protocol. The main design parameters are the number of massive antennas at the base station (M), the number of active user equipment terminals (K) , the system throughput (R) and cell density . Then EE is defined as the number of bits transferred per Joule of energy consumed.

MATLAB tool is used to prove the impact of the main design parameters on energy efficiency. The impact of massive number of antenna , user equipments and system throughput on energy efficiency with perfect channel state information and imperfect channel state information is analyze . The simulation result shows that we can design optimal values of (M, K and R) that maximize energy efficiency of the system with perfect channel state information than imperfect channel state at the base station. The final results sows that zerforcing precoding and perfect channel state information at the base station saves more energy as compared to iperfect channel state information.

Key Words: 5G, Massive MIMO, Ultra Dense, Linear Precoding, CSI, Energy Efficiency

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List of Abbrevations and notations

Abbrevations	Definitions
1G	First Generation
2G	Second Generation
3D	Three Dimension
3G	Third Generation
3GPP	Third Generation Partnership Project
4G	Fourth Generation
5G	Fifth Generation
AoA	Angle of Arrival
ADC	Analog to Digital Converter
AP	Access Point
AWGN	Additive White Gaussian Noise
ASIC	An energy-efficient application Specific Integrated Circuit
BBU	BaseBand Unit
BS	Base Station
CBS	Cellular Base station
CDMA	Code Division Multiple Access
CIR	Constructive Interference Beamforming
CLT	Central Limit Theory
COD	Cutoff on Disconnect
CP	Circuit Power
CSI	Channel State Information

DAC	Digital to Analog Converter
DC	Digital Covrter
DECT	Digital European Cordless Telecommunications
DL	Down Link
DPA	Downlink Packet Access
DPC	Dedicated Physical Communication
EE	Energy Efficiency
FD	Frequency Division
FDD	Frequency Division Duplexing
FFT	Fast Fourier Transfer
FIX	Fixed
GBSM	Global Business System Management
GH	Giga Hertz
GLOBECOM	Global Communication System
GPP	Generation Partnership Project
GW	GateWay
HSDPA	High Speed Downlink Packet Access
HSPA	High Speed Packet Access
i.i.d	Independent and identically distributed
ICC	Independent Call Control
ICT	Internet Communication Technology
IEEE	Institute of Electrical and Electronic Engineers
IMT	International Mobile Telephony
ISCAS	International Symposium on Circuits And Systems
ISI	InterSymbol Interference
ITU	International Telecommunication Union
LMMSE	Least Mean Minimal Square Error
LO	Local Oscillator
LP	Location Protocol

LS	Label Switching
LTE	Long Term Evolution
MH	Mega Hertz
MIMO	Multiple Input Multiple Output
ML	Mobile Location
MMIMO	Massive Multiple Input Multiple Output
MMSE	Mean Minimum Square Error
MP	Mobile Phone
MPBS	Mobile Power at the Base Station
MR	Maximum Ration
MRC	Maximum Ration Combination
MRT	Maximum Ration Transmit
MT	Mobile Telephony
MU	Multi User
NB	Node Based
NL	Non Line
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiple Access
P2P	Point to Point
PA	Power Amplifier
PAPR	Peak-to-Average power Ratio
PBS	Base Station Power
PDF	Probability Density Function
PFIX	Fixed Power
PIMRC	Personal Indoor and Mobile Radio Communications
PSM	Power Save Mode
RAT	Radio Access Technology
REC	Radio Equipment Control
RF	Radio Frequency
SCN	System Analysis and Program

SDMA	Space Division Multiple Access
SE	Spectral Efficiency
SIC	Successive Interference Cancellation
SINR	Signal to Interference Noise Ration
SISO	Single Input Single Output
SNR	Signal to Noise Ration
SYN	SyNchrozation
TDD	Time Division Duplex
UDN	Ultra Dense Network
UE	User Eqipment
UL	Upper Link
UM	Universal Mobile
USA	United State of America
UTRA	Universal Terrestrial Radio Access
VLSI	Very Larg Signal Input
VTC	Vehicular Technology Conference
WCNC	Wireless Communication Networks Conference
ZF	Zero Forcing

Notations and Symbols

fc	Carrier Frequency
ul	Uplink
dl	Downlink
(ul)	Uplink pilot
(dl)	Downlink pilot
(ul)	The fraction of uplink plink transmission
(dl)	The fraction of downlink transmission

(ul)	Power Amplifier efficiency at the Base Station
(dl)	Power Amplifier efficiency at the User Equipments
(x)	Large-scale fading
(xk)	Average channel attenuation
f (x)	User Distribution
$\bar{R}$	uniform gross rate
ζul$\bar{R}$	uplink rate
ζdl$\bar{R}$	downlink rate
Sx	Propagation environment
$dmin$	minimum distance
$dmax$	maximum distance
ρ	optimization variable
B	Bandwidth
BC	Coherence Bandwidth
TC	Channel Coherence
U	Channel Block
M	Base station antenna
K	User equipment
H	User channel
G	Uplink linear receive combine matrix
V	Linear precoding matrix
$\mathbf{I}_N$	Identity matrix with size N
E[·]	Mean of the random variable

$|\cdot|$ Absolute value

$CN(0,\sigma^2)$ Circularly symmetric complex Gaussian random variable with zero mean and variance σ^2

$N(0,\sigma^2)$ Gaussian random variable with zero mean and variance σ^2

Chapter 1

1.1 Introduction

With the development of smart terminals and their application, the need for multimedia services has rapidly increase recently . The increment of the capacity of wireless networks assured the quality of service (QoS) requirements of mobile applications . In the meantime, telecommunication manufacturers and operators have also predicted that a load of wireless communication networks is growing exponentially [3]. It is expected that there would be 1billion 5G mobile subscriptions in 2020, from this smartphones accounting more digit [37]. Moreover, the traffic growth is also following an exponential growth. In 2020, it expected that the total mobile traffic would increase by a factor of 10 from the current growth rate, with video traffic making most of it [36].

Hence, it is necessary to introduce new technologies to meet the demands of explosive traffic for next generation wireless communications networks. The most vital metrics to choose candidate technologies for next generation wireless communication systems is usually Bandwidth Efficiency (BE). In the interim, with extreme power consumption in wireless communications networks, both carbon emission and operator expenses surge yearly [3], [4]. Thus, Energy Efficiency (EE) has become another important metric for evaluating the performances of wireless communications systems with some given BE limitations [5].

Multiple-Input and Multiple-Output (MIMO) technology have attracted much attention in wireless communication, as it offers significant rises in data throughput and link range without an additional increase in bandwidth or transmits power.

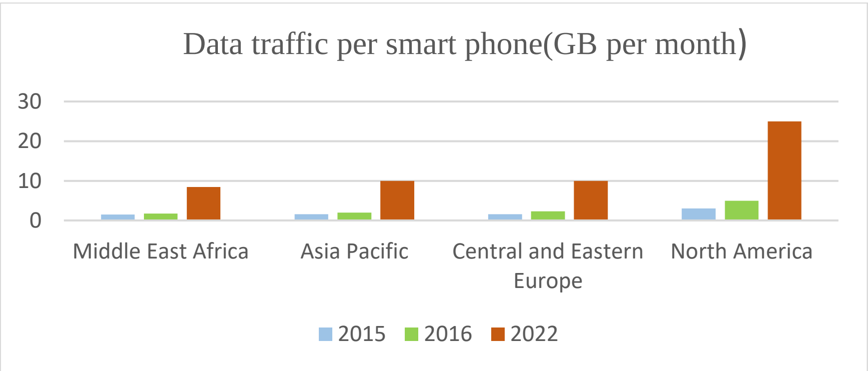

Figure 1.1 Mobile data traffic growth [15]

A MIMO approach and the corresponding patent proposed and issued in 1993 and 1994, where numerous transmit antennas jointly located at one transmitter with the objective of improving possible link throughput [5]. Currently, MIMO have recognized as one of the leading technologies in the Fourth Generation (4G) wireless communications systems. When an advanced Node B (eNB) equipped with several antennas communicates with several user terminals (UEs) over the same time frequency resources is called Multi-User MIMO (MU-MIMO) technology. MU-MIMO is capable of improving either the BE or the reliability by improving either the multiplexing gains or diversity gains [5].

The technology , Massive MIMO that was proposed by *Marzetta* to scale up these requirements is now the key promising technique in designing wireless communication [5]. Both theoretical and measurement results indicate that Massive MIMO is capable of significantly improving the BE, which simultaneously reduce the transmit power [5]. Therefore, it is the new candidate technique for next generation wireless communications systems to improve both their BE and EE. Traditional MIMO technology can merely adjust the signal transmission in a horizontal dimension when the down gradient of an Antennas Array (AA) is fixed. In order to exploit the vertical dimension of signal propagation, AAs such as rectangular, spherical, and cylindrical, were studied by the 3rd Generation Partnership Project (3GPP) [13]. MIMO with these arrays can adjust both azimuth and elevation angles, and propagate signals in Three-Dimensional (3D) space, thus termed 3D MIMO. To further increase capacity, 3D MIMO deploys more antennas to achieve larger multiplexing gains. Meanwhile, Massive MIMO adopts rectangular, spherical and cylindrical AAs in practical systems by considering the space of AAs. Thus, 3D MIMO with large-scale antennas can be as a practical deployment means of Massive MIMO.

Massive MIMO improves BE since it can achieve significant multiplexing gain when serving tens of UEs simultaneously [5]. The considerable increase in EE is due to the use of more antennas where it helps to focus energy to located UEs with a highly narrow beam on small regions [5]. Due to the excessive Degrees of Freedom , Massive MIMO can enhance transmission reliability [5]. It have mitigation of Inter-User Interference (IUI) because of the extremely narrow beam [5]. Similarly, approximating the performance achieved by optimal methods, such as Zero forcing (ZF), Maximum-Likelihood (ML) multiuser detection and Dirty Paper Coding (DPC) is capable of simple low-complexity signal processing algorithms [18].

Massive MIMO aims at evolving the coverage tier BSs by using arrays with a hundred or more antennas, each transmitting with a relatively low power. This allows for coherent multiuser MIMO transmission with tens of UEs spatially multiplexed in both UL and DL of each cell. Hence, Massive MIMO improves area throughput by multiplexing gain [19].

1.1. Research motivations

Mobile broadband for wireless cellular networks continuously progressed to meet the future demands for higher data rates, improved coverage and capacity. One candidate feature for the evolution of 5G-radio standard that expected to satisfy demands is Massive MIMO technology. Massive Multiple-input-multiple-output (MIMO) techniques provide the possibility of serving multiple users simultaneously with the same resources by proper precoding of the spatially separated streams.

In Massive MIMO, the base station is equipped with hundreds of antennas, new possibilities to do beamforming and spatial multiplexing arises, extending coverage and capacity in the system serving more users with higher bitrates. With this new functionality new cellular network deployment, become possible to reduce the networks' energy consumption and lower the deployment costs. This research focus in Massive MIMO Systems dense network environments to find the optimal number of base station antennas, and active user to accommodate the ever-increasing number of users who require universal access to high volumes of wireless data without increasing the power consumption. Hence, it is possible to get an optimal point of (M, K and R) with high-energy efficiency with compromising the quality of service.

1.2. Statement of the Problem

Energy consumption is becoming more and more a problem for network operators. In 2011, base stations alone were representing 5 GW of power and 20 Mt of carbon dioxide per year [5][20]. Since that, the figures have been constantly increasing. In terms of operational expenses and environmental impact energy efficiency has been targeted at the international level as one of the key capabilities of 5G [3]. So there is wastage of energy which affects both econimic and green environmental in wireless networks which needs optimization study.

1.4. Objectives

This thesis focused to achieve the following general and specific objectives.

1.4.1. General objective

The general objective of this research thesis is to simulate and evaluate zero forcing (ZF) linear pre-coding schemes on energy efficiency for massive MIMO dense networks under perfect and imperfect channel state information at the base stations.

1.4.2. Specific objectives

The research specific objectives, are briefly summarized as below:

- To understand Massive MIMO and ultra dense technology
- To analysis the total energy consumption model for Massive MIMO from circuit power consumption model to define energy efficiency
- To analysis and simulate the impact of of massive number of antennas on energy efficiency of the system
- To analysis and simulate the impact of multiple number of users on energy efficnecy of the system
- To analysis and simulate the relation of sum rate and energy efficiency
- To understand and analysis circuit power consumption of Massive MIMO system

1.5. Main contribution of the research

This research thesis has contributed to the following main contributions.

- The circuit power consumption is the sum of the power consumed by different analogue components and digital signal processing. Therefore, the total power clearly described how the total power consumption depends on some number of the BS antennas M, and the number of active users K
- In the final study EE under the theory of ZF processing scheme with perfect CSI, results shows that we can have an optimal point (M, K, R) that maximum energy efficiency. Which means we can design Massive MIMO technology with maximum EE if we chose the number of antennas and number of users properly with high data rate. This can contribute to balance the cost and benefit on the EE design as well as the tradeoff between EE and the main design parameters.

1.6. Thesis methodology

In the first phase of the research, a **literature review** of past and current works on the area of 5G, MIMO and Massive MIMO ultra dense networks have been carefully conducted to extend the perception on such areas of study. Following this review, the execution starts in focusing energy efficient literatures and journals for energy efficiency maximization and parameters compromising techniques of wireless networks

System modeling and simulation: included system modeling of massive MIMO , specifiying design parameters , analysis of mathematical circuit power consumption model, defining total energy efficiency and simulation of the main parameters to understand their effect on energy efficiency of the system using MATLAB.

Result and recommendation : the result obtained and analyzed from the simulation is studied and finally recommendation is given.

1.7. Literature Reviews

In modern wireless communication newtworks , energy effiiiency is an attractive metrices of performance analysis of the new generation of ICT industry. a lot of researches have been conducted in the analysis of energy consumptions in 5G wireless comuncations. Most of the researches focused on the base station of the wirelesscommunications which accounts more than 60% energy consumption using different methods to analys the total energy efficiency.

Valentin Poirot [*2017*], worked on the analaysis of energy efficiency techniques in ultra dense 5G wireless communication using low load by sleeping and cell brathing methods.

This work has a drawback that the users'delays can be impacted, if a user requests a service when the base station is in sleep mode, as the wake up process of the deactivated components needs some time. A compromise between the energy consumption reduction target and the preservation of an acceptable delay is thus needed. This compromise has to take into consideration the policy of the network operator regarding both metrics and the different requirements of 5G networks. So it degrades network coverage areas.

Hong Yang and Thomas L. Marzetta [2015], together worked on energy efficiency of 5G by optimal number of antennas per base station to maximize the cell total energy efficiency of a power-controlled multi-cell Massive MIMO. Moreover, they showed that equipping the same number of antennas in each base station results in virtually no loss in energy efficiency due to the flatness of energy efficiency function. How ever they considered only the optimal number of antennas at the base sation to evaluate the total energy efficiency of the system.

Emil Bjornson and Luca Sanguinetti [2017], worked and modelled cellular networks using stochastic geometry and optimize the energy efficiency with respect to the density of base stations, the number of antennas and users per cell, the transmit power levels, and the pilot reuse. This paper related the total energy efficiency of the system with number of antennas and user equpiments regardless of the datarate of the whole system which will leads to low quality of service.

Claude Desset, Bjorn Debaillie [2018], worked focusing the extend power consumption models for MIMO systems by evaluating different options such as precoder types, revisiting digital complexity estimates of different components. This work mainly focused at the precoding techniques and hardware components of the base station to define energy efficiency. Also worked on the role of the different components in the total system power for different MIMO scenarios. however, this research don't investigate the impact of multiples base station antennas and user equipments to analysis the total energy effieciency of the system.

Fakhar Abbas , Saifullah Adnan [2018], worked a case study of energy efficiency analysis in 5G MIMO to find the optimumal values of number of antennas and active users to achieve maximum energy efficiency without scarfing spectral efficiency. This paper worked only on the transmitted energy to relate the spectral efficiency and energy efficiency in which circuit power consumption needed to define the overall energy efficiency.

Joseph Isabona1 ,**Viranjay M. Srivastava [2018],** worked on the tradeoff the achievable sum rates and energy efficiency of a downlink MMIMO systems using linear and nonlinear precoding schemes. This paper tries to relate the increasing signal-to-noise ratio and base station antennas on the impact of the sum rates. Finally the paper concluded that energy efficiency improvements can be achieved in micro and pico cellular environments of downlink MIMO systems when non-linear successive interference cancellation precoding is applied compared to linear precoding schemes. But this work compares only the data rate and massive number of antennas with SNR to decided the total energy efficiency achievement in which the number of active users have impact on the total energy efficiency of the sysem.

In summary most of the lieteratures mentioned above have worked in the maximization of enegery efficiency techniques in wireless communications. Moreover , the are a lot of limitations which the authors don’t considered during their analysis and designing a wireless network with enery saving techniques. The circuit power consumption model and the main design parameters considered are difierent for most of the authors. The circuit power consumption model should be precisely modeled and the basic parameters must be clearly identified.

In this research thesis , the main parameters which some authors don’t considerd have been identified and considered since energy efficnecy is defiend with these variable parameters.

1.8. Thesis structure

There are five Chapters, and the Chapters are inter-related to each other in this thesis. Thus, to understand the contributions presented in this thesis, readers are suggested to read the entire Chapters.

Chapter 1 Introduction: This Chapter starts with introduction and then followed by literature reviews , motivations , research objective, main contribution and methodology of the thesis..

Chapter 2 Theoretical background of energy efficiency in 5G wireless communication: This Chapter presents energy efficiency techniques in wireless networks and the role of massive MIMO and dense technology in the analysis of energy efficiency

Chapter 3 System model: Energy Efficiency Maximization Techniques in 5G: This Chapter gives the outline of the considered topic, provides a context for the analysis, mathematical models and formulas and an understanding of existing theories and techniques used to maximize EE , which have been carried out in this thesis research with details of justification.

Chapter 4 Simulation Setup and Numerical Results: This Chapter describes description and evaluation for this investigation. The simulation procedures are explained in this Chapter. Also, presents the data, the graph generated from the simulation during testing and analysis of the result.

Chapter 5 Conclusion & Further Work: This Chapter involves analysis of the results and comparing the results, discussing the implications and concludes the results of the implementations, and recommendation of energy efficient power consumption model for Massive MIMO technology systems.

Chapter 2

Theoretical background of energy efficiency in 5G wireless communications

2.1. Introduction

Nowadays internet services such as web browsing, email, video streaming, have become urgent needs for the people's daily life, not only on the traditional wired networks but also on the wireless networks, particularly cellular systems [20][26]. Wireless communication uses electromagnetic spectrum to carry the modulated information data to the receiver. First generations of cellular systems are mainly designed for only voice and text services. With the advancement of smartphone technology, the devices are nowadays equipped with sophisticated capabilities, thus, new demands for multimedia and high data rate applications are generated [21]. While high data rates services can be reliably provided on wired networks, providing such services on the wireless networks, however, is not a minor matter to accomplish due to the limited resources and the unpredictable nature of the wireless channel. Besides, the number of subscribers all around the world is still increasing, making provisioning of high data rate services over the cellular systems very challenging problem for both manufacturers and operators. Consequently, the main issue becomes the problem of how to provide high data rate services over limited wireless resources such that the quality of service (QoS) is satisfied. Thus, wireless communication requires very different approaches than that of wired networks.

The first generations of wireless mobile networks were voice-oriented, providing low data rate services such as voice. With the dramatic evolution of wireless mobile systems over the last decades, wireless systems have become multimedia oriented mobile networks, and hence raising the expectations for higher data rates. The first generation (1G) was based on analogue technology, deployed in the USA and Europe in the early 1980's, followed by the digital technology-based second generation (2G) deployed in 1991 in Europe. In 2001, third generation (3G) system based on the code division multiple access (CDMA) technology was first operated. The dramatic enhancement of the mobile systems occurred in high-speed downlink packet access (HSDPA) supporting a speed of up to 21 Mbps. Then, it is evolved to HSPA+ with speed reaching up to 42 Mbps [26].

Later, long-term evolution (LTE) is introduced by the third-generation partnership (3GPP) to provide high data rate up to 160 Mbps within 20 MHz channel bandwidth. LTE is based on orthogonal frequency division multiple access (OFDMA technique for resources sharing among users, and incorporates advanced technologies such as MIMO, adaptive modulation, and
link adaptation [23]. In 2008, the technical requirement of the fourth generation (4G) has been identified in the international mobile Telecommunication-Advanced (IMT-A) [23]. In this direction, 3GPP targeted the candidate for cellular technologies that are meeting the IMT-A requirements and proposed LTE advanced (LTE-A) [23]. The key technologies that make LTE-A superior over LTE and 3G are carrier aggregation, OFDMA, CoMP technique for interference
management, and deploying the heterogeneous networks to improve spectral efficiency and provide uniform coverage [24].

Nowadays, researchers all over the world have been targeting 5G cellular, which is expected to be a brand-new technology, overcoming the limitation faced by the previous cellular generations. 5G is envisioned to include massive bandwidth with high frequencies, dense BSs deployment, a massive number of antennas, heterogeneous network deployment, cognitive radio, highly adaptive multi cell coordination strategies, and energy efficient technology, not to mention others [25].

2.2 Wireless channel

Wireless channel is the air medium which wireless transmission is performed via electromagnetic waves. Since the wave is not restricted to take the single path, it suffers from reflection, diffraction, scattering by buildings, hills, bodies, and other objects when travelling from the transmitter to receiver, hence multiple copies of the signal arrive at the receiver as shown in Figure 2.1 below.

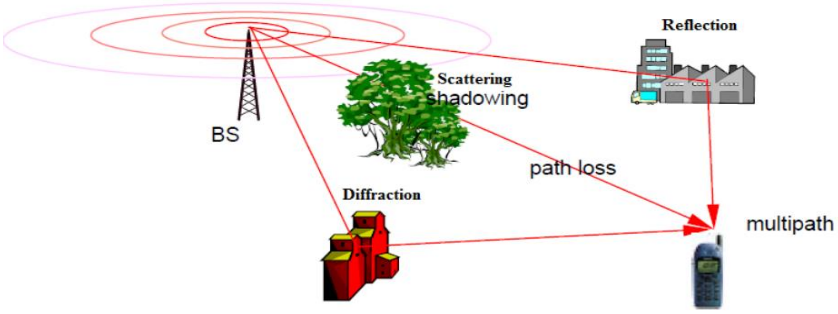

Figure 2.1 Radio signal propagation [26]

Each replica of the signal has a different delay, phase, and gain, and thus they interfere constructively or destructively. This is referred as a multipath phenomenon. In general, the wireless channel is affected by three main factors; path-loss, shadowing, and small-scale fading [28]. To characterize fully, the random time-varying properties of the multipath channel, statistical models have been developed [28]. In general, the wireless channel is affected by three main factors; path-loss, shadowing, and small-scale fading [28]. Path-loss refers to signal power dissipation in proportion to the distance between transmitter and receiver. In the free space, path-loss is given be

$$L = \frac{(4\pi d)^2}{\mathrm{GtGr}\ \varepsilon^2} \qquad 2.1$$

Where ε is the wavelength, G_t is the transmitter antenna gain, G_r is the receive antenna gain, d is the distance between the transmitter and receiver. This model valid only if there one single path between two points, i.e. line-of-sight (LoS), or few multipath component. In cellular communication, the signal propagates through different paths between transmitter and receiver, for which the path-loss is commonly modelled as

$$\mathrm{L} = \varsigma\, \mathrm{d} - \alpha \qquad 2.2$$

Where ς represents a constant that captures the antenna characteristics and channel attenuation, and α is the path-loss exponent that varies from 2 to 6 depending on the communication environment [26].

Shadowing is a random variation experienced by signal power due to obstacles between transmitter and receiver that attenuate the signal through scattering, reflection, and diffraction [24], [26]. Statistical methods are usually used to model shadowing where log normal shadowing model is the most accurately validated model [26].

The probability density function (PDF) of a log-normal random variable y is given as

$$\mathrm{f(y)} = \frac{1}{\mathrm{y}\sigma\sqrt{2\pi}}\mathrm{e}^{\frac{\ln \mathrm{y}-\mu}{(2\sigma)^2}} \qquad 2.3$$

Where μ and σ represent the mean and the standard deviation of y given in dB.

Small-scale fading refers to the microscopic channel variations due to the constructive and destructive addition of multipath signal replicas. Since each replica experiences different attenuation, delay, and phase, the superposition of all components results in a destructive and constructive addition, thus attenuating and amplifying the received signal, respectively [24], . When the drop of the signal is severe, it is referred to as deep fade or worst fading, and usually results in temporary outage in communication.

Fading variations and its impact on frequency domain can be characterized by the concept of coherence bandwidth W_c. This parameter measures the range of frequencies over which the channel is highly correlated, in other word the channel does not change over the entire signal bandwidth (or flat). Coherence bandwidth is connected to the delay spread arising from multipath phenomenon as

$$Wc = \frac{1}{Td} \qquad 2.4$$

where T_d is defined as the difference between delays spread associated with the most significant multipath component and the latest component.

If the signal bandwidth w is smaller than the coherence bandwidth, the exhibits a constant gain transfer function over the entire signal bandwidth. However, when the coherence bandwidth is larger than the signal bandwidth, the channel response exhibits frequency-selective fading behavior, in other words, different parts of signal bandwidth experience uncorrelated fading, rising the signal distortion or so-called inter-symbol interference (ISI).

To overcome this problem, sophisticated equalization needs to be utilized at the detection side, which is costly in implementation. The other widely adopted solution is recent advanced wireless technologies using low rate multi-carrier transmission such as orthogonal frequency division multiplexing (OFDM), whereby each subcarrier has the smaller bandwidth to ensure that the channel is flat over each subcarrier bandwidth [24]

On the other hand, fading variations in the time domain are characterized by the notion of coherence time T_c, which refers to time duration at which the channel remains correlated. Coherence time is related to the Doppler spread parameter f_d as

$$\mathrm{Tc} = \frac{1}{\mathrm{fd}} \qquad 2.5$$

which is the broadening in the signal bandwidth caused by relative the mobility of the transmitter and receiver. Channel with larger Doppler spread changes faster, thereby having shorter coherence time [33]. The rate at which the variation in the signal takes place determines how fast the fading is; fast fading occurs with multipath phenomenon as it takes place over very smalltime scale (in the order of milliseconds), while slow fading occurs with path-loss and shadowing as it happens over relatively larger time scale (in the order of tens of seconds).

To model small-scale fading, several statistical models have been proposed and utilized. One of the most common model is the Rayleigh fading model.

2.3 Rayleigh Channel Fading

This channel fading assumes that there is no line-of-site component between transmitter and receiver, and there are many independent signal paths. Per Central Limit Theorem (CLT), when there are many random variables, the limiting distribution will approximate Gaussian distribution. Thus, the fading channel modelled as a zero-mean complex-valued Gaussian random variable, $x \sim \mathcal{CN}(0, \sigma 2)$ with channel envelope $y = |x|$ and PDF given by

$$(y) = \frac{y}{\sigma 2}\, e^{\frac{y^2}{2}} \sigma 2 \qquad 2.6$$

Where $\sigma 2$ is, the average received power.

2.4 Channel Model

Actual wireless channels are complex and challenging to represent accurately. For simulation studies, empirical models have been developed based on extensive measurements that approximate the most common communication scenarios. As described previously, a complex random variable that models path loss, shadowing and small-scale fading effects modelled the channel coefficient between transmit and the receive antenna. The instantaneous magnitude and phase of the channel coefficient represent the amplitude and phase of channel’s frequency response respectively.

The international telecommunication union (ITU) and the 3rd generation partnership project (3GPP) developed spatial channels models (SCM) that model various urban and rural propagation scenarios for simulation studies. The ITU-R IMT-Advanced channel model is a stochastic model based on the scenario geometry. The model includes information about the angle of arrival (AoA) as well as the angle of departure (AoD), the so-called double-directional channel model. It specifies the directions, amplitudes and phases for several rays (plane-waves) instead of the spatial location of the scatters.

The instantaneous parameters are determined stochastically based on statistical distributions extracted from actual channel measurements for several well-known scenarios. A specific scenario of the simulation study decides the location, geometry and pattern of antennas. The effects of delay, power, and angular parameters are evaluated to obtain the channel coefficients at several instants in time while the rays superimposed at the location of antennas in the simulation setup. Moreover, the superposition of rays produces the effects of correlation between antenna elements, temporal fading and Doppler spectrum at the transmitter as well as at the receiver.

The urban macro model (UMa) targets coverage for pedestrian and vehicular users, with non-line of sight (NLoS) as the dominant mode of propagation. The dominant scatters such as buildings, which are usually assumed, placed in a Manhattan grid layout. While the BS elevated to a height greater than the buildings in the vicinity, the mobile terminal is located outdoors at ground level.

2.5 Multi-user MIMO

In the first three generation of cellular technology, the BS served multiple terminals by separating them in time, frequency or code. Each terminal was assigned a different fraction of spectrum resources for communication over the forward-and-reverse links, to minimize intra-cell interference. A multi-antenna BS opens the spatial dimension that allows it to discriminate the signal to/from each terminal based on its location, known as MU-MIMO. The spatial dimension

enables each terminal to use all available spectrum resources, improving the throughput without the need for additional (expensive) resources. The hardware cost involved with MU-MIMO is the need to place additional BS antennas at the locations that to transmit/receive the signal. Thus, the available spatial degrees of freedom at the BS is limited by the number of antennas.

A multi-antenna transmitter can precode the signal with a complex weight vector such that the radiated energy from each antenna adds constructively or destructively in desired directions. This approach, called transmit beamforming, can be used to maximize the signal power at the receiver or place nulls in the direction of interferers. The optimal beamforming weights depend on the instantaneous amplitude and phase of the channel. Analogously, a multi-antenna receiver may exploit channel knowledge for receive beamforming to maximize signal power and minimize the interference power.

The MU-MIMO setup of interest consists of a BS with M antennas serving K single antenna terminals ($K \leq M$), over the same time-frequency resources. The BS exploits channel knowledge for transmitting and receive beamforming to create a spatially separate data stream for each terminal. The data streams function as independent Single-Input Single-Output (SISO) links as under favourable channel conditions are shown in Figure 2.2, and can linearly increase the spectral efficiency with the number of terminals served. However, the benefits of this spatial multiplexing regarding spectral efficiency critically depend on the array size and the accuracy of channel estimates at the BS.

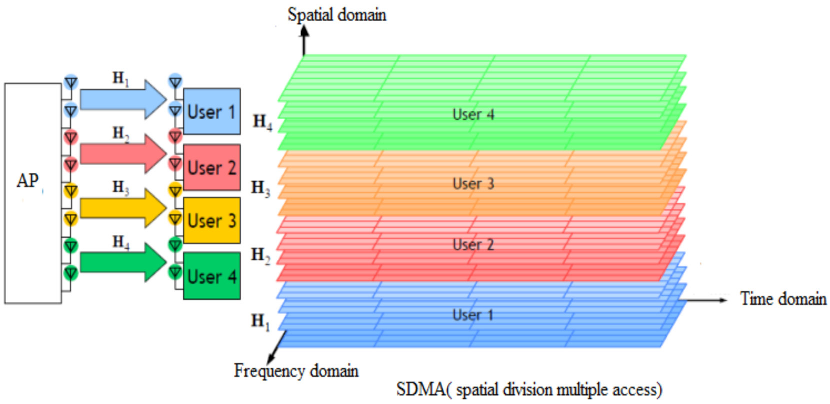

Figure 2.2 MU-MIMO [26]

2.6 Spatial multiplexing

Spatial multiplexing aims at increasing achievable data rate. The data stream is divided into multiple independent sub streams to increase data rates; the sub-streams are transmitted simultaneously through spatial channels. At the receiver, appropriate techniques can be used to separate these sub-streams. The spatial multiplexing gain defined as

$$d_{mul} = \lim_{y\to\infty}\left(\frac{R}{\log y}\right) \qquad 2.7$$

where R denotes the rate measured in (bits/s/Hz) and is a function of the SNR. The maximum spatial multiplexing gain achieved by MIMO channel (H) is

$$(d_{Mul})\ \max = \min(N_T, N_R) \qquad 2.8$$

which means, the minimum of N_T and N_R .so d_{Mul} is also known as the number of degrees of freedom that can be available by MIMO system with channel H. this shows that one of the standard techniques to increase throughput in wireless communication network is to deploy multiple transceiver antennas at the transmitter and the receiver.

2.7 Massive Multiple input multiple output system (Massive MIMO)

In the future wireless communication one of the main 5G requirements is to support 1000 times larger capacity per area compared with current Long Term Evolution (LTE) technology,
but with a similar cost and energy dissipation per area as in today's cellular systems[32]. In addition, an increase in capacity will be possible if all three factors that jointly contribute to system capacity are increased: More spectrum, a larger number of base
stations per area, and an increased spectral efficiency per cell.

Massive MIMO is a Multi-user MIMO technology where an array of an array of M active antenna elements is deployed at each base station (BS) and utilizes these to communicate with K single- antenna terminal-over the same time and frequency band. In a communication the path deploy is base stations with large numbers of antennas that simultaneously communicate with multiple spatially separated user terminals over the same frequency resource and exploit multipath propagation. This technology is also described as beamforming with a large number of antennas. For the future wireless communication, Massive MIMO technology and 5G communications are often mentioned in the same sentence.

Massive or large Multiple-Input Multiple-Output (MIMO) systems are considered essential in contributing to the last stated factor, as they promise to provide a substantially increased spectral efficiency per cell and energy efficiency. A massive MIMO system is typically defined as a system that utilizes a large number, i.e. 100 or more, of individually controllable antenna elements at least at one side of a wireless communications link, typically at the Base Station (BS) side [32][33]. An example of such usage of massive MIMO at the BS side is shown in Figure 2.3. A massive MIMO network exploits the many spatial Degrees of Freedom (DoF) provided by the many antennas to multiplex messages for several users on the same time-frequency resource (referred to as spatial multiplexing), and/or to focus the radiated signal toward the intended receivers and inherently minimize intra-cell and inter-cell interference [34]–[37]. Such focusing of radiated signals in a particular direction is possible

by transmitting the same signal from multiple antenna points, but with a different phase shift applied to each of the
antennas (and possibly a different phase shift for different parts of the system bandwidth), such that the signals overlap coherently at the intended target location. Note that in the remainder of the research thesis, beamforming is used when applying the same phase shift at individual transmit antennas over the entire system bandwidth and precoding is used when applying different phase shifts for different parts of the system bandwidth. With this definition, beamforming can be seen as a subclass of precoding algorithms.

By coherent processing of the signals over the array, transmit precoding can be used in the downlink to focus each signal at its desired terminal and receive combining can be used in the uplink to discriminate between signals sent from different terminals. The more antennas that are used, the finer the spatial focusing can be [36].

The predictable Massive MIMO system operates in a time-division duplex (TDD) mode, where the uplink and downlink transmissions occur in the same frequency resource but different in time. The physical propagation channels are reciprocal, meaning that the channel responses are the same in both directions, which utilized in TDD operation. In particular, Massive MIMO systems achievement the reciprocity to estimate the channel responses on the uplink and at that point utilize the acquired channel state information (CSI) for uplink the receive combining and downlink transmit precoding of payload data. Since the transceiver hardware is not reciprocal, calibration is needed to exploit the channel reciprocity; calibration is required to operate the channel reciprocity in practice [37]. Fortunately, the uplink-downlink hardware discrepancies only change by a few degrees over a one-hour period and can be mitigated by simple relative calibration methods, even without additional reference transceiver and by only relying on the mutual coupling between antennas in the array [38]. There are several good reasons to operate in TDD mode. Firstly, only the BS needs to know the channels to process the antennas coherently. Secondly, the uplink estimation overhead is proportional to the number of terminals but independent of M thus making the protocol fully scalable on some service antennas. Moreover, basic estimation theory tells that the estimation quality recovers with M if there is a known correlation structure between the channel responses over the array the estimation quality (per antenna) but not reduced by adding more antennas at the BS in fact [39].
Since fading makes the channel responses vary over time and frequency, the estimation and

payload transmission must fit into a time/frequency block where the channels are approximately static. The coherence bandwidth Bc Hz and the coherence time Tc, which fit

$$\tau = Bc\,Tc \qquad 2.9$$

transmission symbols essentially give the dimensions of this block. Massive MIMO can be implemented either using single carrier or multi-carrier modulation. The channel coherency depends on the propagation environment, user mobility, and the carrier frequency.

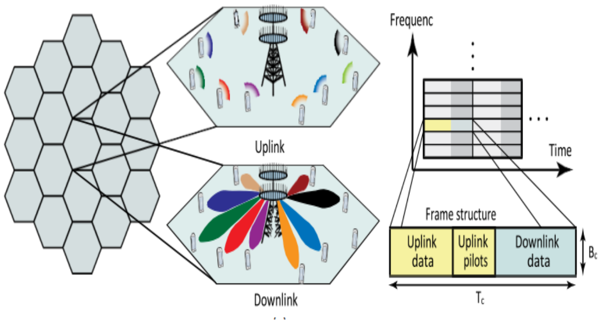

Figure 2.3 Concepts of MIMO technology [5]

2.7.1 Features of Massive MIMO

Compared to long term evolution (LTE, also known as 4G) the most important feature is to allow users to enjoy much higher data speed with peak data rate of 10 Gbps. To achieve this goal, millimeter wave communication is applied. However, path loss and fading is increasingly serious as the frequency increases. Moreover, inter-user interference creates a performance block in MIMO systems. To address this issue, massive MIMO (Multiple input and Multiple output) technology is applied. Due to application of millimeter wave communication, antennas can be designed smaller than before, while the distance among two of them will be shortened [20]. As a result, antennas array is possibly integrated in a small area [21]. When the amount of antennas increases infinitely, we can assume transmitter antennas and receiver antennas are pairwise. In this case, massive MIMO systems can be simplified as a series of SISO system, which means low interference among inter users. The gain obtained from massive number of antennas will enhance quality of service (QoS) of system, supplemented by beamforming and beam tracking. With these advantages, 5G communication systems are able to achieve high speed downlink and uplink, support 3D video .

In massive MIMO systems, the large number of antennas can provide with a large amount of degrees of freedom to facilitate efficient wireless communication signals, thus increasing spectral efficiency (SE) and capacity [24]. According to current research, the capacity of a point-to-point (P2P) MIMO systems based on fading channel increases linearly with the minimum number of transmitter and receiver antennas, while that of reliability improves in the order of $(SNR)NtNr$ where (Nt, Nr number of transmitters and receivers antennas, respectively).

MIMO has been applied in 3GPP (third generation partnership project) and LTE (long-term evolution, also known as 4G. To satisfy users' requirements in the future, it is important for researchers to combine massive MIMO with 5G communication criteria. Apart from capacity and spatial efficiency, energy efficiency is another essential feature for wireless communication system [5]. Massive MIMO technology not only increases capacity but improve energy efficiency (EE). For multi-user MIMO systems, EE can be optimized by algorithms such as Maximal Ratio Combining (MRC), Minimum mean square error (MMSE), and Zero-forcing (ZF) [26]. However, in massive MIMO systems, as the number of transmitted antennas increases over a threshold, the capacity will increase slightly. Hence, it is important for researchers to find a tradeoff between number of antennas versus energy efficiency as well as spatial efficiency.

In general comparing to traditional MIMO, the advantages of massive MIMO include [5,20,24]:

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

2.7.2 Energy efficiency of Massive MIMO in wireless communication

Energy efficiency has attracted significant attention nowadays since increasing spectral efficiency typically results in more energy consumption. The energy consumption increase in wireless communication systems results in an increase of CO_2 emission, which represents a significant threat to the environment. Thus, there is a consensus on the necessity of protecting the environment from the dangers of modern

technology. Moreover, the radio
access part of cellular systems consumes about 70% of the electric power bills as reported by mobile systems operators, which means high operational cost from an economic point of view. Additionally, for uplink radio access it is very reasonable to reduce energy consumption for mobile devices to save the battery power. For these reasons, reducing energy consumption motivates research circles to investigate new energy efficient techniques in wireless networks technology.

There is an inherent conflict in enhancing spectral efficiency and decreasing energy consumption at the same time; reducing energy consumption leads to a decrease in spectral efficiency and vice versa. Consequently, there always exists a trade-off between spectral and energy efficiencies. Thus, the spectral-energy efficiency trade-off can be set off as a milestone for the research to investigate the problem of how much energy consumption for a given spectral efficiency, or how much spectral efficiency can be obtained for a given energy consumption. In many research papers, two different definitions are used to define the energy efficiency. The first definition is to take the ratio of transmission bit rate (or spectral efficiency) to the transmitted power, measured in bit/Joule. This definition has used in literature. The other definition of energy efficiency (Joule/bit) is to take the ratio of consumed power over bit rate or spectral efficiency[5,24,26]. In this thesis,
the first definition of energy efficiency used as it implies the energy consumption.

2.7.3 Channel estimation of Massive MIMO

Although MU-MIMO is a promising technique to enhance spectral efficiency, nevertheless it is quite challenging in practical implementation. To achieve full multiplexing gain of MU-MIMO, the system requires an acquisition of instantaneous perfect CSI. The BS and the UEs are assumed to have perfect CSI. However, in practice, this CSI must be estimated. The system can acquire the CSI through two different ways depending on the duplex scheme adopted. Depending on the system duplexing mode, the channel estimation schemes are very different. In time division duplex (TDD), both transmitter and receiver utilize the same frequency band and reception, spacing them apart by multiplexing the downlink and uplink signals on different time slots. A user transmits specific pilot training signal and the BS can learn the CSI through channel reciprocity. This necessitates that the time coherence should be long enough to span the interval of both uplink signaling and downlink transmission [14]. On the other hand, in frequency division duplex (FDD), where the downlink and uplink use different frequency bands, the user can feedback the necessary information to the BS through dedicated low rate uplink channel [22].

The BS needs CSI to detect signals transmitted from the users in the uplink, and to pre code the signals in the downlink. This CSI is obtained through the uplink training. Each user is assigned an orthogonal pilot, sequences transmitted from all users, and then estimates the channels based on 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 beam form the signals to the users, the user needs only the effective channel gain, which is a scalar constant 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.

2.7.4 Channel Model in Massive MIMO

In modeling wireless channel, the Correlation-Based Stochastic Model (CBSM), the Parametric Stochastic Model (PSM) and the Geometry- Based Stochastic Model (GBSM) are three types of channel models developed for evaluating the performance of wireless

communications systems, in [4], [11]. The difficulty of the CBSM is low hence primarily used for assessing the theoretical performance of MIMO systems. However, it is somewhat simplistic and hereafter inaccurate for a practical MIMO system. Therefore, it is not directly applicable to the modelling of wireless channels, when encountering a spherical wave front. By comparison, the GBSM model is capable of accurately describing the realistic channel properties, and hence it is more suitable for Massive MIMO channels, although with an increased computational complexity.

The complex nature of the PSM is higher than the CBSM, while the accuracy of the PSM is lower than the GBSM, which results in a lack of studies on the PSM in Massive MIMO systems. The non-dispersive correlated channel model, the non-dispersive

independent identically distributed (i.i.d.) Rayleigh fading model and the dispersive multipath channel model are three kinds of simplified CBSMs, where each tap modelled as either a correlated or an uncorrelated fading process. Non-dispersive i.i.d. Rayleigh

channel model is when an i.i.d. Rayleigh fading channel supposed for Maaive MIMO systems; no correlation occurs between the transmit and receive antennas. Thus, the elements of the fast fading matrix are i.i.d. Gaussian variables. Non-dispersive correlated Rayleigh channel model is to characterize the Doppler-induced received signal correlation, the correlated
channel model considered for characterizing the possible implementation of LS MIMO systems [12]. The fast fading matrix of the correlated channel model developed by the product of the standard complex-valued Gaussian matrix and the correlation matrix. At the transmitter and receiver of the AEs, the correlation matrix quantifies the long-term correlation, attained through measurements. By comparison, the complex-valued Gaussian matrix describes the i.i.d. Rayleigh fading channel.

The dispersive multipath channel model is different distributions of the Angle of Arrivals (AoAs) from different UEs comprised in the dispersive multipath channel model of Massive MIMO systems [23]. Each UE's CIR constituted by multiple independent paths arriving from different directions, in this model. The steering vector of an AoA multiplies a path attenuation to characterize each independent path. The UEs can be separated according to their AoAs when they located at different angular positions. Therefore, this model is useful in analyzing the performances of the IUI or Inter-Cell Interference (ICI) schemes.

Currently, the CBSMs primarily devised for analysing the theoretical performance of Massive MIMO systems attributed to its simplicity. In conclusion, how to model accurately the channel of Massive MIMOs remains an open problem.

2.7.5 Data Transmission Protocol in Massive MIMO

In Massive MIMO technology, TDD operation is the desired data transmission protocol. In a coherence interval, there are three operations: channel estimation (with the uplink training and the downlink training), uplink data transmission, and downlink data transmission.

2.7.5.1 Uplink Data Transmission

In the coherence interval, a part of it 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. The BS then uses the channel estimates together with
linear combining techniques to detect a signal transmitted from all users.

2.7.5.2 Downlink Data Transmission

In the downlink, the BS transmits signals to all K users in the same time frequency resource. More specifically, the BS uses its channels estimates in combination with the symbols intended for the K users to create M precoded signals which are then feed to M antennas.

2.7.6 Precoding techniques in massive MIMO

Linear processing at the BS is fundamental for the payload transmission in Massive MIMO. 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 function, while the linear one can only reduce inter-users interference [13].

In wireless communication system, due to the geographic effect, received signal can not be obtained simultaneously [23]. Inter-user interference can not 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 degree of freedom in massive MIMO, linear precoding schemes are enough to satisfy communication requirements [5,14].

2.7.6.1 Linear precoding schemes in MIMO and detection techniques to estimate channel

Linear processing at the BS is fundamental for the payload transmission in Massive MIMO. In the uplink, the BS has a M number of antenna observation of the multiple access channels from the K terminal users. The BS applies linear receive combining to discriminate the signal transmitted by each terminal from the interfering signals. The simplest choice is the maximum ratio (MR) combining that uses the channel estimate of a terminal to maximize the strength of that terminal's signal, by adding the signal components coherently. This result signal amplification proportional to which is known as an array gain. The second choice of linear precoding is zero-forcing (ZF) combining, which suppresses inter-cell interference at the cost of reducing the array gain to $M - K + 1$, and the third is the minimum mean squared error (MMSE) combining that balances between amplifying signals and suppressing interference.

The receive combining creates one effective scalar channel per terminal where the intended signal is amplified and/or the interference suppressed. Any judicious receive combining will improve by adding more BS antennas since there are more channel observations to utilize. The remaining interference usually treated as extra additive noise; thus conventional single-user detection algorithm applied. Another benefit from the combining is that small-scale fading averages out over the array, in the sense that its variance decreases with M. This is known as channel hardening and is consequences of the law of large numbers.

There is a strong connection between receive combining in the uplink and the transmit precoding in downlink [16]. This is known as uplink-downlink duality since the uplink and downlink channels are reciprocal in TDD systems. Linear precoding based on MR, ZF, or MMSE principles can be applied to focus each signal at its desired terminal (and possibly mitigate interference towards other terminals).

In Multi-user MIMO systems, it is known that a multi-user detection technique called successive interference cancellation (SIC) can achieve maximum rate in the uplink channel [11]. However, the SIC is difficult to be implemented in practice due to its high computational complexity. Thus, other detection methods that are based on linear detectors, including ZF, MRC, MMSE have been developed [5], [20], . Among them, [11] derived the asymptotic analysis for the signal-to-interference-pulse-noise ratio (SINR) for the uplink by using MRC and the SINR for the downlink by using MRT. An exact performance analysis for the uplink was provided in [24] with arbitrary antennas at the BS. All these results have shown that a linear receiver can exploit the advantages of LS MIMO arrays at the BS with low implementation complexity. A ZF receiver can cancel intracell interference, and therefore it generally outperforms an MRC receiver. This implies that a ZF receiver can reduce the number of BS antennas necessarily, relative to the number needed for MRC, whilst obtain the same system performance.

In general, the performance of the ZF receiver is worse than the MMSE receiver. However, if the SINR is high enough, the performance of the ZF receiver and MMSE are equivalent [13], [21]. Furthermore, an MMSE receiver requires additional knowledge on the SINR and yields higher complexity than ZF receiver. In addition, exact performance analysis is not tractable even in the case of perfect CSI [12]. It was shown in [18] that ZF processing scheme can provide a good trade-off between complexity and system. Especially when the number of BS antennas is very large. Therefore, ZF processing scheme is used in this thesis.

In [24], the study considered MIMO configuration with a ZF receiver, where the CSI is assumed to be perfectly known to both transmitter and the receiver. Under such assumptions for the CSI, the expression of the exact performance of the system might be tractable. In practice, however, CSI is not perfect at the transmitter and the receiver. For the BS to acquire the CSI, a simple scheme can be employed where users send pilot signals to the BS, so that the BS can estimate the channel by analysing the received pilot signals in an uplink training phase [17] ,[22] . The Leastsquares (LS) methods is a conventional method that is generally used to estimate the CSI. Unfortunately, this method causes significant degradation in the system performance due to strong inter-cell interference. In contrast, the MMSE estimation method can results in more accurate channel estimation [4]. In the uplink transmission phase, the signals transmitted from the users to BS can be detected by using a linear detector using the estimated CSI.

2.7.7 Challenges of Massive MIMO

Although the, enormous advantages on Massive MIMO, many issues need to be undertook. The main challenges of Massive MIMO are explained below;

2.7.7.1 Pilot Contamination

In the previous sections, merely single-cell with perfect CSI situations are considered. However, in practice, the cellular network consists of many cells. Due to the limited availability of frequency spectrum, many cells have to share the same time-frequency resources. Thus, single -cell with imperfect CSI scenario and multi-cell systems scenarios are considered. In multi-cell systems, the orthogonal pilot can’t be assigned to all the users in all the cells, due to the limitation of channel coherence interval [7]. The orthogonal pilot sequences have to be reused from cell to cell. Therefore, the channel estimate obtained in a given cell will be contaminated by pilots transmitted by users in other cells. This effect, called “pilot contamination”, reduces the system performance [6]. The effect of pilot contamination is a major inherent limitation of LS MIMO. Pilot Contamination does not vanish even when the number of BS antennas grows without bound.Thus, considerable efforts have been made to reduce this effect. The eigen value decomposition based channel estimation, pilot decontamination, as well as pilot contamination precoding schemes are proposed in [5].

2.7.7.2 Unfavorable Propagation

Massive MIMO deployed under favourable propagation environments. However, in practice, there may be propagation environments where the channels are not favourable. For example, in propagation environments where the numbers of scatterers are small compared to the numbers of users, or the channels from different users to the BS share some common scatterers, the channel is not favourable [22]. Distributing BS antennas over a large area is one possibility to tackle the problem

Most earlier worked researches on Massive MIMO system either ignores the circuit power consumption at the nodes or the models it as fixed component [20], [21]. This model could be misrepresentative because the total power consumption caries with different system parameters such as the number of antennas, the numbers of users, and the choice of the transmit/receive filters. The tradeoff energy efficiency and spectral efficiency with the basic design parameters is scanned first. With this inspiration, EE of Massive MIMO with a scalable power consumption model is studied. The relationship between EE and the key parameters are examined.

2.8 Energy efficiency techniques in 5G wireless communications

To make the upcoming 5G networks energy efficient, various techniques can be adopted. These techniques can be classified under three categories which are using energy efficient architectures or energy efficient resource allocation or using radio technologies which are energy efficient [14]. The following techniques are available:-

- Energy-Efficient Architectures: Optimization of cell size, large vs small cell deployment, Overlay source , microcell, picocell or femtocell, Relay and cooperative communications.
- Energy-Efficient Resource Management: Joint power and resource allocation, SISO vs. MIMO with packet scheduling.

- Energy-Efficient Radio Technologies: Heterogeneous network deployment (Multi-RAT)

Many research approaches have been taken to increase EE in wireless networks. The Massive MIMO technology and the network densification has shown promise in this regard in the modern wireless communication. The building block of a Massive MIMO is a multi-antenna base station (BS) concurrently serving many single-antenna users, which the number of BS antennas is typically much larger than a number of users. With imperfect CSI at the transmitter, it has been shown that for a fixed rate, a single-cell Massive MIMO transmitter can reduce its radiated power by a factor proportional to the square root of the number of deployed BS antennas [18]. The work in [29] extends this result to account for the aggregate impact of various hardware impairments on Massive MIMO systems, concluding that high EE can still be obtained under realistic hardware configurations. This work suggest that Massive MIMO systems may
not only be attractive from an EE promising likewise can yield more cost effective implementations because conventional arrays with only a few antennas fed by expensive high-power amplifiers can be replaced by hundreds of antennas fed by low-cost low-power amplifiers and circuitry [27].

Power consumption has a direct impact on energy consumption. Power reductions, as well as energy efficiency are critical factors when operating using green energy sources (such as solar or wind power), which are power and not energy constrained.

5G wireless communication systems will be deployed in about 2020. It is expected that it has the capability to handle about 1000 times higher than in present cellular systems. It will also become the backbone of the Internet of Things (IoT). In the design of 5G wireless communication systems, the energy consumption has become a primary concern and critical challenges owing to economic, operational, and environmental considerations. The need for energy-efficient system design and operation will be even more critical requirement of 5G systems. Thus, the energy efficiency has to be improved in order to reduce the 5G network energy consumption. Several technologies have been designed to improve the energy efficiency of 5G systems such as radio resource allocation, Massive MIMO, on-Off switching algorithms, energy harvesting and transfer, and dense networks.

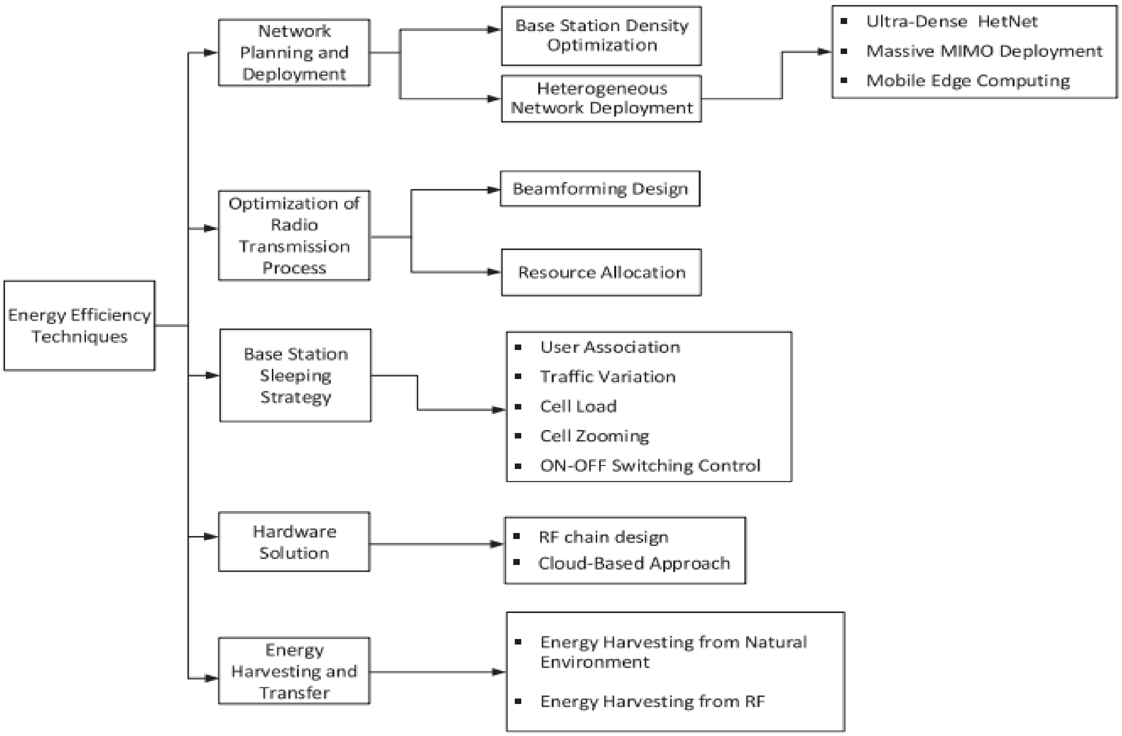

Figure 2.4 Summary of energy efficiency techniques in wireless communications [12]

This thesis provides an analysis of energy-efficient techniques in 5G ultra dense wireless communication systems from power consumption model in Massive MIMO.

2.8.1 Power consumption in Massive MIMO

The ICT industry recently have expressed significant interest in implementing Massive MIMO in both single and multi-cell environments [1], [5], [10]. The use of additional antennas at the BS has been shown to improve power efficiency both uplink [13] and for the downlink [8],[20]. Massive MIMO is a system where a BS equipped with a hundred or more antennas simultaneously serves several users in the same frequency band by exploiting the degrees of freedom in the spatial domain [11], [10]. Providentially, when the number of antennas at the BS is large enough, from the law of large numbers, the random and mutually independent channel vectors between the BS and the users become pairwise orthogonal [24]. Spatial-division multiplexing for Massive MIMO can enhance the reliability and throughput of the system because more distinct paths are established between the BS and the users [24], [25]. Notably, the additional DoF provided a massive number of antennas at the BS can reduce the

transmit power for the users on the uplink. This is very efficient when multimedia services are increasing and the design of battery with long time use is a major challenge for manufacturers [26]. Undoubtedly, the electrical power supply to the BS will be higher which is consumed by the rectifier, baseband digital signal processing circuit, power amplifier, feeder, and cooling system on the downlink. Henceforth, solutions to reduce the emission of RF power would help in reducing the power consumption of the BS [27].

An accurate modelling of the total power consumption is the fundamental importance to obtain a reliable guideline for EE maximization of a base station with M antennas and a number of active (UEs) K for Massive MIMO systems [27]. A common assumption in related literature that the total power consumption is computed as the sums of the radiated transmit power and a constant quantity accounting for the circuit power consumption [28]. This model might be very misleading although widely used and can lead to an unbounded EE if utilized to design systems wherein M can be very large because the user rates grow unboundedly as $M \to \infty$ [29]. Attaining infinite EE is evidently impossible as the model does not consider the power consumed by digital signal processing and analogue circuits (for radiofrequency (RF) and baseband processing) grows with M and K. Meaning to say, its contributions can be taken as a constant only in multi-user MIMO systems where M and K take relatively small values. Instead, its variability plays a key role in Massive MIMO systems in which , $K \gg 1$ and all the BS antennas are processed coherently as the original Massive MIMO defined in [15].

2.8.2 System Parameters in Massive MIMO

The impact on the EE by the number of antennas M has been recently investigated in [12] [19]. Power allocation problem focused in the uplink of multiuser MIMO systems and showed that the EE is maximized when specific UEs are switched off [14]. Likewise, in [15] the uplink was studied, where the EE was shown To be a concave function of M and the UE rates. In [13] the downlink was studied, whereby [5] and [19] showed that EE is a concave function of M while a similar result was shown for K in [11]. However, the system parameters were optimized by useful simulations, which do not provide a complete picture of how the EE is affected by the context of the different system. The coexisting work [26] derives the optimal M and K for a given uplink sum rate, nevertheless the ,necessary overhead signaling for channel acquisition is ignored thus leading to unrealistic results where it is beneficial to let K grow very large, or even go to infinity.

Another parameter is power amplifier (PA which is discussed in [11], the base station is divided into three parts. These are pre-transceiver block, transceiver block, and power amplifier (PA) part. The power consumption of these blocks are influenced by traffic load and required transmit power. As the power consumption due to PA is very large, it had been taken as a separate entity. The power of the PA is proportionated to the transmit power of the base station.

One of the reasons for power losses power losses in the BS is PA linearity. Linearity is an important aspect in PAs since the system performance and efficiency are highly dependent on it. The power consumption of PA depends on the peak to average power ratio (PAPR) and PA efficiency.

The non-constant envelope modulation schemes like OFDM exhibit a high PAPR, resulting in a need for a linear Radio Frequency PA. However, this can be mitigated by proper choice of PAPR reduction schemes and PA efficiency can be improved by the advanced PA technologies like Doherty PAs which exhibits high input back off.

Doherty PA (DPA) is designed using the combination of a carrier PA and a peak PA. The Peak amplifier will be active only the carrier amplifier saturates. Otherwise only the carrier amplifier will be in the active region. The DPA will provide high efficiency even at a large Back of Point (BOP) [14]. The BOP with peak efficiency can be achieved by the conventional 2-stage DPA is around 6dB and it can be further increased with the increased in a number of peak PAs [25].

The operation of an Massive MIMO systems uplink and downlink considered over a bandwidth of B Hz. The BS uses a co-located array with M antennas to communicate with K single-antennas UEs that are selected in round-robin fashion from a large set of UEs within the coverage area. A block flat-fading channels is considered where, B_C (in Hz) is the coherence bandwidth and T_C (in seconds) is the coherence time. Hence, the channels are static within time-frequency coherence block of symbols.

$$U = B_C T_C \qquad 2.10$$

The BS and UEs are assumed perfectly synchronised and operate per the time-division duplex (TDD) protocol shown in Figure 3.1. The fixed ratios of uplink and downlink transmission are denoted by $^{(ul)}$ and $^{(dl)}$, respectively, with $^{(ul)}$ + $^{(dl)}$ = 1 [5,26]. As seen from Figure 2.4, uplink transmission takes place first and consists of $^{(ul)}$ symbols. The subsequent downlink transmission consists of $^{(dl)}$ symbols. The pilot signalling occupies $^{(ul)}$ symbols in the uplink and $^{(dl)}$ in the downlink, where $^{(ul)}$ and $^{(dl)} \geq 1$ to enable orthogonal pilot sequences among the UEs [5],[6],[11]. The uplink pilots enable the BS to estimate the UE channels. Since the TDD protocol is matched to the coherence blocks, the uplink and downlink channels are considered reciprocal and the BS can make use of uplink estimates for both reception and downlink transmission. TDD protocols basically require M and K to be the same in the uplink and downlink. The downlink pilots let each UE estimate its effective channel and interference variance with the current precoding.

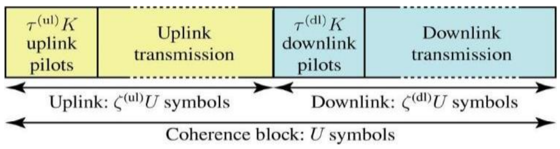

Figure 2.5 Illustration of TDD protocol [23]

The physical location of UE k is denoted by $x_k \in \mathbb{R}^2$ (in suare meters) and computed on the BS (assumed to be in origin). First, non-line-of-sight propagation considered for analytic tractability. The function (.): $\mathbb{R}^2 \rightarrow \mathbb{R}$ describes the largescale channel fading at different user locations; that is, $l(x_k)$ is the average channel attenuation due to path-loss, scattering, and shadowing at location x_k. Since the UEs are selected in a round-robin fashion, the user's location can be treated as random variables from user distribution f (x). Thus, user's location implicitly defining the shape and density of the coverage area; as illustrated in Figure 2.5. The large-scale fading between a UE and BS is assumed to be the same for all BS antennas. This is reasonable since the distances between UEs and the BS are much larger than the distance between the antennas. Since the forthcoming analysis does not depend on a choice of (.) and user distribution, it is kept generic. The following symmetric example is used for simulations.

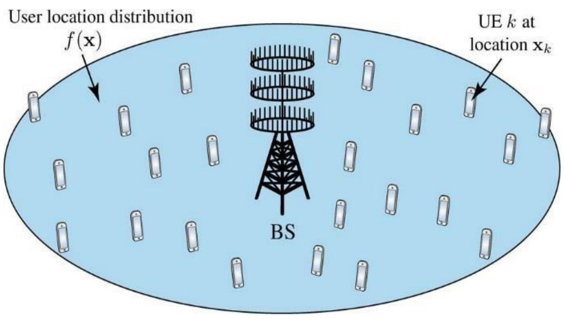

Figure 2.6 Illustration of generic multiuser MIMO [23]

The UEs are supposed uniformly distributed in a round cell radius d_{max} ,Moreover, the minimum distance d_{min}. The density function described this user distribution

$$f(x) = \begin{cases} \dfrac{1}{\pi({d^2}_{max} - {d^2}_{min}} & d_{min \leq ||x|| \leq d_{max}} \\ 0 & otherwise \end{cases} \quad 2.11$$

Considering path loss taken over large scale fading

$$\mathrm{l(x)} = \frac{\bar{\mathrm{d}}}{||\mathrm{x}||^{\mathrm{k}}} \qquad \text{for all } \big||\mathrm{x}|\big| \geq \mathrm{d_{min}} \quad 2.12$$

where $\kappa \geq 2$ is the path-loss exponent and the constant $\bar{d} > 0$ regulates the channel attenuation at a distance dmin [36].

There exist many valuable works analyzing the EE of Massive MIMO and SCN recently. The EE of SCN was analyzed in [19], which shows that increasing the base station (BS) density will improve the EE only when the circuit power consumption is less than a certain threshold. The analytical results are concise and explicit, but the BS was assumed always transmitting with its maximum power [19], which is not necessarily optimal in terms of EE. The EE-SE relationship of Massive MIMO was analyzed in [5,11], where the impact of circuit power on the EE-SE relationship was shown with closed-form expressions, but only single-cell scenarios without inter-cell interference (ICI) were considered.

2.8.3 Channel Model and Linear Processing Massive MIMO Systems

In Massive MIMO , all M antennas at the BS sufficiently are set apart so that the channel components are uncorrelated among the BS antennas and the single-antenna UEs.

The channel vector

$$\boldsymbol{h}k = [hk,1,hk,2,\ldots,hk,M]T \in \mathbb{C}M\ x \qquad 2.13$$

has entries $\{h_{k,}\}$ that describe the instantaneous propagation channel between the *n*th antenna at the BS and the *k*th UE. A Rayleigh small scale fading assumed distribution such that $hk \sim C\ N\ (OM, \imath\ (xk)\ IM)$, which is a valid model for both small and large arrays.

Linear processing is used for uplink data detection and downlink data precoding. For analytic tractability, the BS can acquire perfect CSI from the uplink pilots. The uplink linear receive combining matrix denote by

$$\boldsymbol{G} = [g1,g2,\ldots,gK] \in \mathbb{C}M\ x\ K \qquad 2.14$$

with the column $\boldsymbol{g}k$ being assigned to the *k*th UE. The MRC, ZF, and MMSE processing are considered for uplink detection, which gives [20]

$$\mathrm{G} = \begin{cases} \mathrm{H} & \text{for MRC,} \\ \mathrm{H}(\mathrm{H}^{\mathrm{H}}\mathrm{H})^{-1} & \text{for ZF,} \\ (\mathrm{H}\mathrm{P}^{\mathrm{ul}}\mathrm{H}^{\mathrm{H}} + \sigma^2 \mathrm{I}_{\mathrm{M}})^{-1}\mathrm{H} & \text{for MMSE,} \end{cases} \qquad 2.15$$

Where

$$H = [h1,h2,\ldots,hK] \qquad 2.16$$

contains all the user channels, $\sigma 2$ denotes the noise variance (in Joule/symbol),

$$P(ul) = diag\big(p1(ul),p2(ul),\ldots,pK(ul)\big) \qquad 2.17$$

and the design parameter $p_i^{(ul)} \geq 0$ is the transmitted uplink power of UE i (in Joule/symbol) for $i = 1, 2, \ldots, K$. Similarly, MRT, ZF, and MMSE as precoding schemes considered for downlink transmission [10]. The precoding schemes matrix denoted by

$$V = [v1, v2, \dots, vK] \in \mathbb{C}M \; x \; K \qquad 2.18$$

Where

$$V = \begin{cases} H & for\ MRC, \\ H(H^H H)^{-1} & for\ ZF, \\ (HP^{ul}H^H + \sigma^2 I_M)^{-1}H & for\ MMSE, \end{cases} \qquad 2.19$$

setting $V = G$ is normal since it reduces the computational complexity, but it is optional. The aim is to design the system assuring a uniform gross rate $\bar{R}$ (in bit/second) for any active UE, where $\zeta ul\bar{R}$ is the uplink rate and $\zeta dl\bar{R}$ is the downlink rate, while conventional systems have a significant difference between peak and average rates. As detailed below, this is achieved by combining the linear processing with proper power allocation.

2.8.3.1 Uplink in Massive MIMO System

Under the assumption of Gaussian codebooks, linear processing, and the perfect CSI [32], the achievable uplink rate in (bit/second) of the kth UE is

$$R^{ul}{}_K = \zeta^{(ul)}\left(1 - \frac{\tau^{ul}K}{U\zeta^{(ul)}}\right)R^{ul}{}_K \qquad 2.20$$

where $(1 - \frac{\tau^{ul}K}{U\zeta^{(ul)}})$ accounts for pilot overhead and $\zeta^{(ul)}$ is the fraction of uplink transmission. Likewise,

$$\bar{R}_K^{(ul)} = B\,log\left(1 + \frac{p_k^{ul}\left|g_{Kh_k}^H\right|^2}{\sum_{l=1;\neq k}^{k} p_l^{ul}\left|g_{Kh_l}^H\right|^2 + \sigma^2\left|\left|g_k\right|\right|^2}\right) \qquad 2.21$$

is the uplink gross rate (in bit/second) of the transmission from the kth UE, where “gross” refers to overhead factors which are excluded. As mentioned above, the aim is to provide the same gross rate[20,26]

$$\bar{R}_K^{(ul)} = \bar{R} \; for \; K = 1,2, \dots, K \qquad 2.22$$

By utilizing a technique from [38], this equal-rate condition is met if and only if the uplink power allocation vector

$$P^{(ul)} = \left[p_1^{(ul)}, p_2^{(ul)}, \dots, p_k^{(ul)}\right]^T \qquad 2.23$$

$$P^{(ul)} = \sigma^2 \left(D^{(ul)}\right)^{-1} 1_k \qquad 2.24$$

Where the (k, l)th element of $D^{(ul)} \in \mathbb{C}^{K \times K}$ is given by

$$[\boldsymbol{D}^{(ul)}]_{kl} = \begin{cases} \dfrac{|g_k^H h_k|^2}{(2^{\bar{R}/B} - 1)||g_k||^2} & for\ MRC \\ \dfrac{-|g_k^H h_l|^2}{||g_k||^2} & fior\ ZF \end{cases} \qquad 2.25$$

The average uplink PA power (in Watt) expressed as the power consumed by the power amplifiers (PAs), which comprises radiated transmit power and PA dissipation.

$$P_{Tx}^{(ul)} = \frac{B\zeta^{(ul)}}{\eta^{(ul)}} \mathbb{E}\{1_k^T P^{(ul)}\} = \sigma^2 \frac{B\zeta^{(ul)}}{\eta^{(ul)}} \mathbb{E}\{1_k^T (D^{(ul)})^{-1}\} 1_k \qquad 2.26$$

where $0 < \eta^{(ul)} \leq 1$ is the PA efficiency at the UEs.

Observe that it might happen that $\bar{\mathrm{R}}$ cannot be supported for any transmit powers. In such a case, computing $\boldsymbol{P}^{(ul)}$ from the above would lead to some negative powers. However, this can easily be detected and avoided by computing the spectral radius of $D^{(ul)}$[18]. Moreover, it only happens in interference-limited cases; thus, it is not an issue when ZF is employed (under perfect CSI). In these circumstances, $P_{Tx}^{(ul)}$ be computed is closed form as stated in the following [20,26].

If a ZF detector engaged with $M \geq K + 1$, with loss of generality the gross rate is parameterize as,

$$\bar{R} = B\ log\ 1 + \rho(M - K) \qquad 2.27$$

where ρ is a design parameter that is proportional to the received signal-to interference and-noise ratio (SINR). Using this parameterization, the RF power $P_{Tx}^{(ul-ZF)}$ required to guarantee each UE a gross rate is given by account for user distribution and propagation environment.

$$P_{Tx}^{(ul-ZF)} = \frac{B\zeta^{(ul)}}{\eta^{(ul)}} \sigma^2 \alpha \mathrm{S}_x K \qquad 2.28$$

$$\mathrm{S}_x = \mathbb{E}_x\{(1(x))^{-1}\} \qquad 2.29$$

2.8.3.2 Downlink in Massive MIMO System

A normalized precoding vector $vk/\|vk\|$ and the downlink signal to the kth

is assigned a transmit power of $p_k^{(dl)}$ (in Joule/symbol). In [10], assuming Gaussian codebooks and perfect CSI the achievable downlink rate (in bit/second) of the kth UE with linear processing is

$$R_k^{(dl)} = \zeta^{(dl)} \left(1 - \frac{\tau^{(dl)} K}{U\zeta^{(dl)}}\right) \bar{R}_K^{(dl)} \qquad 2.30$$

Where the $\left(1 - \frac{\tau^{(dl)} K}{U\zeta^{(dl)}}\right)$ accounts for downlink pilot overhead and $\bar{\mathrm{R}}_K^{(dl)}$ is the gross rate (in bit/second) given by [26]

$$\bar{R}_K^{(dl)} = B\, log\left(1 + \frac{P_k^{dl} \frac{|h_k^H v^k|^2}{||v_k||^2}}{\sum_{l=1, l\neq k}^{k} p_l^{dl} \frac{|g_k^H h_l|^2}{||v_l||^2} + \sigma^2}\right) \qquad 2.31$$

The average PA power defined as

$$P_{TX}^{(dl)} = \frac{B\zeta^{(dl)}}{\eta^{(dl)}} \sum_{k=1}^{k} \mathbb{E}\left\{P_l^{(dl)}\right\} \qquad 2.32$$

where $0 < \eta^{(dl)} \leq 1$ is the PA efficiency at the base station. Imposing the equal-rate condition where $\bar{\mathrm{R}}_K^{(dl)} = \bar{\mathrm{R}}$ for all k, it follows that the power allocation vector

$$P^{(dl)} = \left[p_1^{(dl)}, p_2^{(dl)}, \ldots, p_k^{(dl)}\right]^T \qquad 2.33$$

must be computed as

$$P^{(dl)} = \sigma^2 \left(D^{(dl)}\right)^{-1} 1_k \qquad 2.34$$

Where the (k, l)th element of $D^{(dl)} \in \mathbb{C}^{K \times K}$ is given by

$$[\boldsymbol{D}^{(dl)}]_{kl} = \begin{cases} \dfrac{|h_k^H v_k|^2}{(2^{\bar{R}/B} - 1)||v_k||^2} & for \;\; k = l \\ \dfrac{-|h_k^H v_l|^2}{||v_k||^2} & fior \; k \; \neq l \end{cases} \qquad 2.35$$

Putting

$$P^{(dl)} = \sigma^2 \left(D^{(dl)}\right)^{-1} 1_k \qquad 2.36$$

in to the equation the average downlink PA power (in Watt) is

$$P_{TX}^{(dl)} = \sigma^2 \frac{B\zeta^{(dl)}}{\eta^{(dl)}} \mathbb{E}\{1_k^T (D^{(dl)})^{-1} 1^k\} \qquad 2.37$$

Observe that $\boldsymbol{D}^{(\boldsymbol{dl})} = \left(D^{(ul)}\right)^T$ if the same processing scheme is used for transmit precoding and receive combining that is if $G = V$. in this case, the user specific uplink/downlink transmit powers are different, but the total uplink and downlink PA powers, are the same (except for the factors ζ^{ul}/η^{ul} and ζ^{dl}/η^{dl} This is a consequence of the well-known uplink downlink duality [31]. Like the uplink, the following result can be proved for ZF in the downlink.

If a ZF precoding devised with $M \geq K + 1$ then the average downlink PA power

$$P_{Tx}^{(dl-ZF)} = \frac{B\zeta^{(dl)}}{\eta^{(dl)}} \sigma^2 p S_x K \qquad 2.38$$

where S_x is the propagation environment parameter.

From the above, that the average uplink and downlink PA powers sum up to

$$P_{TX}^{ZF} = P_{Tx}^{(ul-ZF)} + P_{Tx}^{(dl-ZF)} = \frac{B\sigma^2 p S_X}{\eta} K \qquad 2.39$$

, under ZF processing, where

$$\eta = (\frac{\zeta^{ul}}{\eta^{ul}} + \frac{\zeta^{dl}}{\eta^{dl}})^{-1} \quad 2.40$$

A key assumption in this research thesis is that a uniform gross rate $\bar{R}$ is a guarantee to all UEs by means of power allocation. However, the main results are also applicable in cases with in cases with fixed power allocation. Suppose for example that the transmit power is allocated equally under ZF processing.

2.8.4 Existing Power Consumption Model in 5G Massive MIMO system

The EE of a wireless communication system measured in $bit/Joule$ is the measure of the benefit to cost ration. Likewise, the EE calculated as per the ratio between the average sum rate in $(bit/second)$ and the average total power consumption $P_T(\ in\ watt = joule/second)$.where the benefit is consider to the average rate and the cost is the power consumption [5,6,7, 26].

The total EE metric accounting for both uplink and downlink takes the following form, in a multi-user setting, where P_{CP} accounts for the circuit power consumption.

Therefore, the uplink and downlink total EE is

$$EE = \frac{\sum_{k=1}^{k}\left(\mathbb{E}\left\{R_k^{(ul)}\right\} + \mathbb{E}\left\{R_k^{(dl)}\right\}\right)}{P_T^{(ul)} + P_T^{(dl)} + P_{CP}} \quad 2.41$$

In most of the existing work of EE, $P_{CP} = P_{FIX}$ is a constant quantity accounting for fixed power consumption required for site-cooling, control signaling, and load independent power of backhaul infrastructure and baseband processors [28]. Moreover, this is not an accurate model to design a good system by optimizing a number of antennas (M) and number of UEs (K).

In fact, this shows that the achievable rates with ZF grow logarithmically with M (for a fixed PA power). Hence, the simplified model , $P_{CP} = P_{FIX}$ gives the impression that achieved an unbounded EE by adding more and more antennas. This modelling artefact comes from ignoring that each antenna at the BS requires dedicated circuits with non-zero power consumption, and that the signal processing tasks become increasingly complex. In other words, an accurate modelling of P_{CP} is of paramount importance when

dealing with the
design of energy-efficient communication systems.

Based on the the circuit power consumption model EE is defined as [5][6][26]

$$EE = \frac{\sum_{k=1}^{k}\left(\mathbb{E}\left\{R_k^{(ul)}\right\} + \mathbb{E}\left\{R_k^{(dl)}\right\}\right)}{P_T^{(ul)} + P_T^{(dl)} + P_{CP}(M,K,R)} \qquad 2.42$$

This model is used in this thesis to design an appropriate model $P_{CP(M,K,R)}$ as a function of the three main design parameters: the number of base station antennas (M), the number of active user equipment's (K)and the average user rate of (R). This problem is solved using ZF precoding schemes in Chapter 4 of the thesis. Maximizing EE in (2.41) doesn't decrease the total power, but choosing a right power level and use it wisely.

2.9 Ultra dense wireless communication

Since the beginning of mobile industry, cell splitting and densification has been one of the most effective means to deliver ever-increasing capacity and improving user experience. In recent years, UDN has emerged as a prominent solution to meet the challenges of fulfilling IMT-2020 (5G) extremely high capacity density requirements of up to 10 Mbps/m^2. Qualitatively, UDN is a network with much higher density of radio resources than that in current networks, i.e., much denser small cell network in terms of either relative density or absolute density of the BSs. Quantitatively, the definition of UDN varies among the literature. In [24], UDN is defined as a network where the BS (or AP) density potentially reaches or even exceeds the user density, which is appropriate to characterize the scenario when the traffic per user increases while the number of users does not. In [35], an UDN is characterized as a network where the inter-site distance is only a few meters. In [46], UDN is identified as a network reaching the point where its capacity grows sub-linearly, due to the growing impact of interference, as the BS density increases.

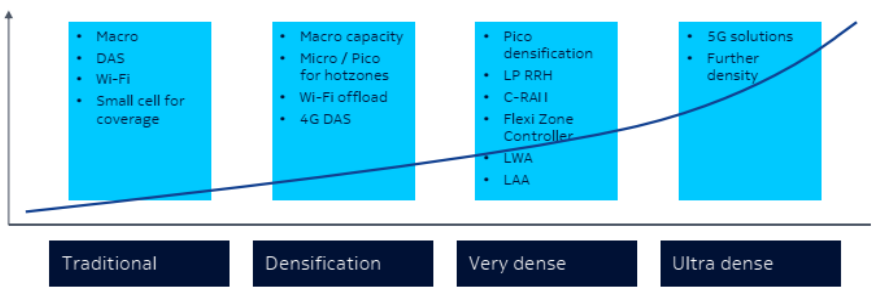

Figure 2.7 Evoluation to ultra dense networks [Nokia white paper ultra dense networks [2017]

Interference in an UDN becomes more severe, with higher volatility, and there may be a large number of strong interferers but none dominant. This leads to interference statistics different from those of an existing network with one (or a small number of) dominant interferers [36]. Under the assumption of heavy and uniform traffic load, all the BSs are always active in conventional cellular networks. In these networks with sparsely deployed BSs, the density of users often exceeds the density of BSs, at least during peak time. For such sparse networks, universal frequency reuse has long been believed as optimal to maximize the capacity [20], and the assumption that every BS has at least one user to serve (and hence all BSs should be activated) is reasonable. In a universal frequency reuse sparse network with time division multiple access, the average SE of the network increase with BS density linearly. When the network becomes dense where some BSs have no user to serve but are still activated, the SE first increases slowly and then decreases with BS density [8], and hence the density of BSs can be optimized [16]. The assumption of a constant path loss exponent in these papers might mask the UDN effect [26], nonetheless they showed that interference should be handled differently in an UDN. More interesting behaviors of the network can be found , where networks with variable path loss exponents are studied.

Due to the traffic load fluctuation, turning off the BSs in the cells with low or no traffic load is an essential way for UDNs in improving EE as well as reducing interference. In practice, the network traffic fluctuates over different times and locations due to user behavior and mobility, which is especially true for UDNs and naturally calls for BS sleeping. In a universal frequency reuse sparse network with BS sleeping where BS density is less than user density, the average SE still increases linearly with BS density [10] as in the network without BS sleeping. In a universal frequency reuse UDN with BS sleeping where BS density is larger than user density, the SE only logarithmically increases with BS density [11].

Utilizing the massive amount of radio resources optimally in an UDN becomes increasingly complex. Misallocation of increased radio resources can cause higher interference, unbalanced load distributions, and higher power consumption. Furthermore, due to interference, local radio resource allocation may have a global impact to a UDN. In other words, “locality” does not really exist in the UDN, and radio resource allocation has to be done based on a bigger picture of the UDN by taking into account of the tight coupling across the network [13].

Sufficient bandwidth over wired connectivity to directly backhaul each and every BS in an UDN may be practically infeasible. Wireless self-backhauling has been proposed, which consumes valuable radio resources, generates additional interference, and leads to extra latency.

The 5^{th} generation wirless communicaton industry uses ultra dense technology for energy efficiency. This is enabled by tracking energy efficiency (EE) maximization problem and solve it analytically with respect to the density of base stations (BSs), the transmit power levels, the number of BS antennas and users per cell, and the pilot reuse factor. The closed-form expressions obtained from this general EE maximization framework provide valuable insights on the interplay between the optimization variables, hardware characteristics, and propagation environment. Small cells are proved to give high EE, but the EE improvement saturates quickly with the BS density. Interestingly, the maximal EE is achieved by also equipping the BSs with multiple antennas and operate in a "massive MIMO" fashion, where the array gain from coherent detection mitigates interference and the multiplexing of many users reduces the energy cost per user[18].

Chapter 3

Analytical study of Energy efficiency in 5G using Massive MIMO system

3.1 System model

In this research thesis energy efficiency techniques in 5G dense wireless communication is analyzed using Massive MIMO technology. To do this, a literature review of past and current works on the area of 5G Massive MIMO and ultra dense technologies on energy efficiency performance have been carefully conducted.

The system considers a massive MIMO network consists of cellular cells and each cells are equipped with base station antennas of M and active users K. the network cells and active users are assumed uniformly distributed.

The work starts from the definition of energy efficiency in wireless communication , which is defined as the ration of average data rate to total energy consumption. In mathematics, it is defined as [5,6,11,20, 26]

$$EE = \frac{Throughput\ [bit/s/cell]}{Power\ consumption\ [W/cell]} = \frac{\sum_{k=1}^{k}\left(\mathbb{E}\left\{R_k^{(ul)}\right\}+\mathbb{E}\left\{R_k^{(dl)}\right\}\right)}{P_T^{(ul)}+P_T^{(dl)}+P_{CP}(M,K,R)} \qquad 3.1$$

Which is measured in $^{bit}/_{Joule}$ which can be considered as benefit to cost ratio in which the quality of service (throughput) is compared with the charge of the power. The total power consumption of the 5G wireless communication is analyzed and defined from circuit power consumption and transmit power. The energy efficiency equation above depends on many factors. Modelling precisely of total power consumption is one of the main factor that affects the energy efficiency.

The main design parameters are the number of massive antennas on the base station (M), then number of active users (K) and the system's throughput (R).

Next, we analyzed tradeoff between energy efficiency with the main design parameters mentioned above. A detailed circuit power and total power consumption of the uplink and downlink is analyzed. Then the data rate will be derived using zero forcing linear precoding for both uplink and downlink. The network system is assumed to be circular and uniformly identical user distribution uncorrelated Rayleigh flat fading.

The testing stage starts with simulation of MATLAB software using setup values and standards. The analytical ZF processing scheme is executed mathematical for perfect CSI and imperfect CSI at the base station in single-cell system. The overall workflow diagram is as follows.

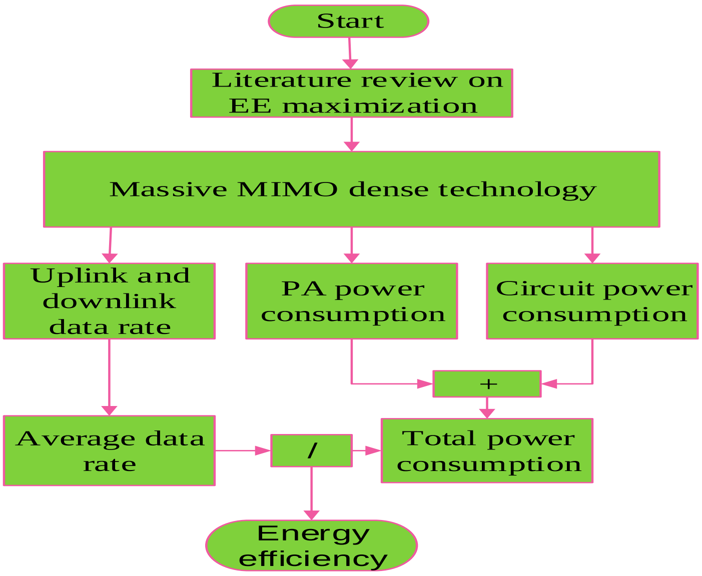

Figure 3.1 Workd flow diagram of Energy efficiency in wireless communication

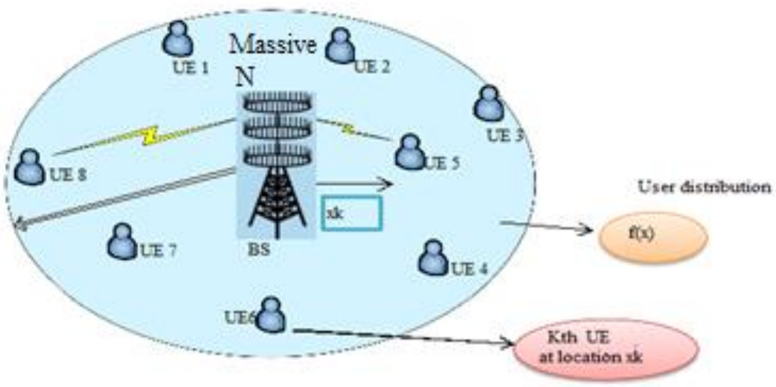

Figure 3.2 System model of Massive MIMO uplink and downlink communications[7]

From the definition of energy efficiency it depends on both the numerator and denumerator since both are variables. The total power consumption is analyzed based on the circuit power consumption model.

From equation (3.1) to increase energy efficiency we can have three different options.

- Increasing the throughput and decreasing the total power consumption
- Decrease both the throughput and the total power consumption

- Increase both the throughput and the total power consumption

In practical , the most likely option is the last option which is to increase both the data throughput and energy consumption which will leads to higher energy consumption but more energy efficiency.

The technology , Massive MIMO , can provid a potential improvement on throuput while giving a considerable power saving.

So we have to analyze the total power consumption of the Massive MIMO networks from the basic circuit power consumption mode carefully since it affects the whole energy efficiency of the system networks.

3.2 Analysis of total power consumption in Massive MIMO

The EARTH project has promoted energy efficiency optimization for wireless access networks and proposes a framework for the power consumption at BS's [31]. This is because most of the power consumption in modern wireless communication come from base station. Based on this energy efficiency framework, the BS is divided into several parts such as the antenna interface, the power amplifier, the RF chains, the BBU, the mains supply, and cooling and DC-DC. So each of these componenet's power consumption model is analyzed to define the total circuit power consumption.

The total power consumed by the base stations is composed of fixed power consumption (which is traffic independent) which accounts for control signaling and power supply and variable (traffic dependent) which is the most significant power consumed in the power amplification process. Mostly the fixed power is inefficient especially in rural areas this is completely wastage when active users are not in the coverage area. This indicates that we need to define the power consumption model precisely in order to analyzed the system EE.

Based on the energy efficiency definition of the model in Equation (3.1) , the total power consumption, P_T is defined as the sum of transmit power and circuit power[28].

$$P_T = P_{TX} + P_{CP} \qquad 3.2$$

Where P_{TX} represents the average transmit power consumption in watts and P_{CP} denotes the total circuit power consumption in watts . While connecting more antennas at the BS waders the data rate, but this additional antennas circuitry leads to increased power consumption. As stated by [33], the circuit power consumption allowed scaling with the key parameters such as M and K.

In specific, P_{TX} defines the total RF power, as in Equation (2.39) where η is the effective power amplifier efficiency, averaged over uplink and downlink. Based on works from [11] on advanced power amplifier technologies, the uplink power amplifier efficiency,$\eta^{(ul)}$ set to be 30% and the downlink power amplifier efficiency, $\eta^{(dl)}$ set to be 39% [18].

3.3 Analysis of circuit power consumption model in Massive MIMO system

The total power utilized by different analogue components and digital signal processing is the circuit consumption denoted as P_{CP} . Based on prior works of [28],[27] a new developed circuit power consumption model for Massive MIMO systems is proposed:

$$P_C = P_{FIX} + P_{TC} + P_{CE} + P_{C/D} + P_{BH} + P_{LP} \qquad 3.3$$

Where the fixed power P_{FIX} was defined in Chapter 2 of the paper in which a constant quantity accounting for fixed power consumption required for site-cooling, control signaling, and load independent power of backhaul infrastructure and baseband processors [28], P_{TC} represents the power consumed by transceiver chains, P_{CE} of the channel estimation process (performed once per coherence block), $P_{C/D}$ of the channel coding and decoding units , P_{BH} of the load-dependent backhaul ,and P_{LP} of the linear processing at the BS. And each of the power consumption components are defined and analyzed below.

3.3.1 Transceiver Circuit Power (P_{TC})

For standard wireless communications, transmitters and receivers, power consumption P_{TC} can be computed as[34,45]

$$P_{TC} = MP_{BS} + P_{SYN} + KP_{UE} \qquad 3.4$$

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. Where the last term P_{UE} accounts for the power required by all circuit components (such as amplifiers, mixer, oscillator, and filters) of each single-antenna UE.

3.3.2 Channel Estimation Circuit Power (P_{CE})

All channel estimation process is carried out at the BS and UEs, whose computational efficiency are L_{BS} and L_{UE}. In addition, computational efficiency is measured as arithmetic complex-valued operations per Joule also known as flops/Watt. There are $\frac{B}{U}$ coherence blocks per second where B and U are bandwidth and coherent unit , and, the pilot-based CSI estimation is performed once per block. In the uplink, the BS receives the pilot signal as a M×$\tau^{(ul)}K$ matrix and estimates each UE's channel by multiplying with the corresponding pilot sequence of length $\tau^{(ul)}K$ [17]. This standard linear algebra operation [15] requires a power consumption in watts of

$$P_{CE}^{(ul)} = \frac{B}{U}\frac{2\tau^{(ul)}MK^2}{L_{BS}} \qquad 3.5$$

In the downlink, each active UE receives a pilot sequence of length $\tau^{(ul)}K$ and processes it to acquire its effective precoded channel gain (one inner product). From [15], the downlink power in Watt is obtained as

$$P_{CE}^{(dl)} = \frac{B}{U}\frac{2\tau^{(dl)}K^2}{L_{UE}} \qquad 3.6$$

Therefore, the total power consumption is given as the sum of both the uplink and the downlink

$$P_{CE} = P_{CE}{}^{(ul)} + P_{CE}{}^{(dl)} \qquad 3.7$$

From this expression the total power in watt for the channel estimation process becomes.

$$P_{CE} = \frac{B}{U}\frac{2\tau^{(ul)}MK^2}{L_{BS}} + \frac{B}{U}\frac{2\tau^{(dl)}K^2}{L_{UE}} \qquad 3.8$$

3.3.3 Coding and Decoding Circuit Power ($P_{C/D}$)

In the downlink, the BS applies channel coding and modulation to K sequences of information symbols. Similarly, 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 [14] and thus be quantized as[11,17,15]

$$P_{C/D} = \sum_{K=1}^{K} (\mathbb{E}\{R_K{}^{(ul)} + R_K{}^{(dl)}\})(P_{COD} + P_{DEC}) \quad 3.9$$

Where P_{COD} and P_{DEC} are the coding and decoding powers (in Watt per bit/sec), respectively, and $R_K{}^{(ul)}$ and $R_K{}^{(dl)}$ are the uplink and downlink data rate , and the operator $\mathbb{E}$ denotes the expectation value.

For simplicity P_{COD} and P_{DEC} are assumed the same in the uplink and downlink, but it is straightforward to assign them different values.

3.3.4 Backhaul Circuit Power (P_{BH})

The backhaul circuit power is used to transfer uplink/downlink data between the BS and the core network. The power consumption of the backhaul is modelled as the sum of two parts [14]: one load-independent and one load-dependent. The first part is comprised 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 [14].

$$P_{BH} = \sum_{K=1}^{K} \left(\mathbb{E}\{R_K{}^{(ul)} + R_K{}^{(dl)}\}\right) P_{BT} \quad 3.10$$

Where P_{BT} is the backhaul traffic power (in Watt per bit/s).

3.3.5 Linear Processing Circuit Power (P_{LP})

The transmitted and received vectors of information symbols at the BS are generated by transmit precoding and processed by receive combining, respectively. From [26];

$$P_{LP} = B\left(1 - \frac{(\tau^{ul} + \tau^{dl})K}{U}\right)\frac{2MK}{L_{BS}} + P_{LP-C}\, Watt \quad 3.11$$

where the power consumed describes the first term by making one matrix-vector multiplication per data symbol. The second term P_{LP-C} , accounts for the power required for the uplink linear receive combining matrix **G**; and the linear precoding schemes matrix **V**, as described in Chapter 2.

The precoding and linear receive 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, only one need to be computed and thereby reduce the computational complexity.

When ZF processing is selected, then approximately , the following power is consumed

$$P_{LP-C}{}^{(ZF)} = \frac{B}{U}\left(\frac{K^3}{3L_{BS}} + \frac{3MK^2 + MK}{LBS}\right) \quad 3.12$$

3.4 Achievable Sum Rate

It's one of the methods to quantify the system performance. The achievable sum rate follows the Shannon theorem. Shannon theorem gives the maximum rate at which the transmitter can transmit via the channel. This section describes the achievable sum rate with ZF , with the assumption that the total downlink power is fixed and equally divided between all the users. From Shannon theorem, the channel capacity is given by equation [22].

$$R = log_2(1 + SNR)(bits/s/\,Hz) \quad 3.13$$

where , SNR : is the signal to noise ratio.

Channel state information (CSI) is a very important issue in multiuser communication systems. Typically, the transmitter sends multiple data streams for each user simultaneously

and selectively with CSI . The all receivers send feedback to the transmitter on the reverse link, so the transmitter obtains CSI. Hence, the transmitter communicate with all the receivers with perfect CSI. Then, the achievable sum rate per user in downlink massive MIMO system in a single cell, is given by

$$R_K = log_2(1 + SINR_K) \quad 3.14$$

And for K number of users, the achievable sum rate is given in equation

$$R_{SUM} = K\,log_2(1 + SINR_K) \quad 3.15$$

If a ZF detector engaged with $M \geq K + 1$, the gross rate is parameterize as,

$$\bar{R} = B\,log\,(1 + \rho(M - K)) \quad 3.16$$

ZF detection/precoding is applied under imperfect CSI, the average gross rate

$$\bar{R} = B\log\left(1 + \frac{\rho(M-K)}{1+\frac{1}{\tau^{ul}}+\frac{1}{\mathcal{P}K\tau^{ul}}}\right) \quad 3.17$$

with B stands for bandwidth.

3.5 Energy Efficiency Maximization with ZF Processing in Massive MIMO

A theoretical solution for the Energy Efficiency problem is explained here under the assumption of employing ZF linear processing in Massive MIMO system. The Energy Efficiency problem is solved analytically by utilizing ZF processing scheme in the uplink and downlink. The solution is motivated by analytic convenience and likewise the numerical results, which are close to optimal. So the total energy efficiency defined in equation (3.1) can be solved using zero forcing precoding as follow[5,6,11,26].

For ZF processing, Energy Efficiency is defined as

$$EE^{(ZF)} = \frac{K\left(1-\frac{\tau_{Total}K}{U}\right)R}{\frac{B\sigma^2 pS_X}{\eta}K + P_{CP}^{(ZF)}} \quad 3.18$$

where τ_{Total} is represented the sum of uplink and the downlink ($\tau_{Total} = \tau^{(ul)} + \tau^{(dl)}$).

Using the expression in (2.28), and the fact that

$$\mathbb{E}\left\{R_K^{(ul)}\right\} + \mathbb{E}\left\{R_K^{(dl)}\right\} = R_K^{(ul)} + R_K^{(dl)} = \left(1 - \frac{\tau_{Total}K}{U}\right) \quad 3.19$$

In addition

$$P_{CP}^{(ZF)} = P_{FIX} + P_{TC} + P_{CE} + P_{C/D} + P_{BH} + P_{LP}^{(ZF)} \quad 3.20$$

after replacing P_{LP-C} with $P_{LP-C}^{(ZF)}$. For notational convenience, the constant coefficient $\mathcal{A}$, $\{\mathcal{C}_i\}$, and $\{\mathcal{D}_i\}$ are introduced in Table 1 below. These, coefficients helps us to rewrite $P_{LP}^{(ZF)}$ in the more compact form as below.

$$P_{CP}^{(ZF)} = \sum_{i=0}^{3} \mathcal{C}iK^i + M\sum_{i=0}^{2} \mathcal{D}i\,K^i + \mathcal{A}K\left(1-\frac{\tau_{Total}K}{U}\right)\bar{R} \quad 3.21$$

Where remembering that $\bar{R}$ is given by (3.12) and, thus, is also a function of (M, K, R). Putting

$$\mathrm{EE}^{(\mathrm{ZF})} = \frac{\mathrm{K}\left(1 - \frac{\tau_{\mathrm{Total}}\mathrm{K}}{\mathrm{U}}\right)\bar{\mathrm{R}}}{\frac{\mathrm{B}\sigma^2 \mathrm{pS_X}}{\eta}\mathrm{K} + \sum_{i=0}^{3}\mathcal{C}i\mathrm{K}^i + \mathrm{M}\sum_{i=0}^{2}\mathcal{D}i\,\mathrm{K}^i + \mathcal{A}\mathrm{K}\left(1 - \frac{\tau_{\mathrm{Total}}\mathrm{K}}{\mathrm{U}}\right)\bar{\mathrm{R}}} \qquad 3.22$$

The next aim is to solve this equation with the main design parameters to optimize the energy efficnecy using zeroforcing precoding. In the first analysis, the impact of each design parameters is done separately. And then, the maximal energy efficiency numbers are taken to design optimal energy efficiency network.

Table 3-1 Circuits Power Coefficients for ZF Processing

Coefficients $\{\mathcal{C}_i\}$		Coefficients $\{\mathcal{A}_i\}$ and $\{\mathcal{D}_i\}$	
$\boldsymbol{\mathcal{C}_1 = \mathrm{P_{UE}}}$	$\boldsymbol{\mathcal{C}_0 = \mathrm{P_{FIX}} + \mathrm{P_{SYN}}}$	$\mathcal{A} = \mathrm{P_{COD}} + \mathrm{P_{DEC}} + \mathrm{P_{BT}}$	
$\boldsymbol{\mathcal{C}_2 = \frac{4\mathrm{B}_\tau^{(\mathrm{dl})}}{\mathrm{UL_{UE}}}}$	$\boldsymbol{\mathcal{C}_3 = \frac{\mathrm{B}}{3\mathrm{L_{BS}}}}$	$\mathcal{D}_1 = \frac{\mathrm{B}}{\mathrm{L_{BS}}}\left(2 + \frac{1}{\mathrm{U}}\right)$ $\mathcal{D}_2 = \frac{\mathrm{B}}{\mathrm{BL_{BS}}}\left(3 - 2\tau^{(\mathrm{dl})}\right)$	$\mathcal{D}_0 = \mathrm{P_{BS}}$

3.5.1 The impact of multiple active users on energy efficiency

In Massiev MIMO when the number of antennas M and the transmit power p are given, then the EE desired value of active users K is considered. In this case for simplicity , the sum $SINR$ $p\mathrm{K}$ (thereby the PA power) assumed and the number of BS antennas per UE,$\frac{M}{K}$ are kept constant and equal to $p\mathrm{K}$=$\bar{p}$ and,$\frac{M}{K} = \bar{\beta}$ with $\bar{p} > 0$ and $\bar{\beta} > 1$. The gross rate of the system is then fixed at[15]

$$\bar{C} = B\,log(1 + \bar{p}(\bar{\beta} - 1)) \qquad 3.23$$

Following this we can assume $\mathcal{A}$, $\{\mathcal{C}i\}$ and $\{\mathcal{D}i\}$ are non-negative and constant which are given above. For given values of $\bar{p}$ and $\bar{\beta}$, with the gross rate fixed the number of desired UEs that maximize the EE metric is[6,11,20,26]

$$K^* = \max_{l}\left[K_l^{(0)}\right] \qquad 3.24$$

Where the quantities $\{K_l^{(0)}\}$ represent the real positive roots of the quadratic equation of

$$K^4 - \frac{U}{\tau_{Total}}K^3 - \mu_1 K^2 - 2\mu_o K \frac{U\mu_o}{\tau_{Total}} = 0 \qquad 3.25$$

$$\mu_o = \frac{\frac{U}{\tau_{Total}}(\mathcal{C}_1 + \bar{\beta}\mathcal{D}_1) + (\mathcal{C}_1 + \bar{\beta}\mathcal{D}_1)}{\mathcal{C}_2 + \bar{\beta}\mathcal{D}_2} \; and \qquad 3.26$$

$$\mu_1 = \frac{\frac{U}{\tau_{Total}}(\mathcal{C}_1 + \bar{\beta}\mathcal{D}_1) + (\mathcal{C}_1 + \bar{\beta}\mathcal{D}_1)}{\mathcal{C}_2 + \bar{\beta}\mathcal{D}_2}$$

The optimal K is root to the quartic polynomial given in (3.24) shown . The euation in (3.18) states that the optimal value K^* is either the closest smaller or closest larger integer to $K_l^{(0)}$, which is simply assumed by analyzing the corresponding EE. A basic property in linear algebra is that quartic polynomials have exactly 4 roots (some can be complex-valued) and there are generic closed-form root expressions .

However, these expressions are very lengthy and not given here for a brevity in fact, the closed-form expressions are seldom used because there are simple algorithms to find the roots with higher numerical accuracy [14].

To gain insights K^* is affected by the different parameters, assume that the power consumption required for linear processing and channel estimation are both negligible (that is when $P_{CE} = P_{LP}^{(ZF)} \cong 0$). In this case is particularly relevant as P_{CE} and $P_{LP}^{(ZF)}$essentially decrease with the computational efficiencies L_{BS} and L_{UE} which are expected to increase rapidly in the future.

If P_{CE} and $P_{LP}^{(ZF)}$are both essentially negligible, then K^* can be approximated as

$$K^* = \left\lfloor \mu\left(\sqrt{1 + \frac{U}{\tau_{Total}\mu}} - 1\right)\right\rceil \qquad 3.27$$

With

$$\mu = \frac{\mathcal{C}0 + \frac{B\sigma^2 pS_X\bar{p}}{\eta}}{\mathcal{C}_1 + \bar{\beta}\mathcal{D}_0} = \frac{P_{FIX+}P_{SYS} + \frac{B\sigma^2 pS_X\bar{p}}{\eta}}{P_{UE} + \bar{\beta}P_{BS}} \qquad 3.28$$

From (3.26) and (3.27), it is seen that K^* is a decreasing function of the terms that are independent of K and M. This amounts to saying that the number of UEs increases with P_{FIX}, P_{SYS} and S_X , as well as with the PA power (proportional to p) and the noise power

σ^2. S_X increases proportionally to d_{max}^K which means that a larger number of UEs must be served as the cell radius d_{max} increases. Moreover, K^* is unaffected by the terms

$\{P_{COD}, P_{DEC}, P_{BT}\}$, which are the ones that are multiplied with the average sum rate. The above results are summarized on the following .

If the power consumptions for linear processing and channel estimation are both negligible, then the optimal K^* decreases UE and BS antenna $\{P_{UE}, P_{BS}\}$, is unaffected by the rate-dependent power$\{P_{COD}, P_{DEC}, P_{BT}\}$, and increase with the fixed power $\{P_{FIX}, P_{SYS}\}$. And A larger number of UEs must be served when the coverage area increases.

3.5.2 The impact of multiple active antennas on energy efficiency

In this when $M \geq K+1$ that increases the EE in (3.7) is anayzed and generated the following result. For given values of K and p, where the number of active users and transmit power held fixed the number of BS antennas maximizing

the EE metric can be computed as [9]

$$M^{(*)} = \frac{e^{\left(\frac{p\left(\frac{B\sigma^2 p S_X p}{\eta} + \mathcal{C}'\right)}{\mathcal{D}' e} + p\frac{K-1}{e}\right)+1} + pK - 1}{p} \qquad 3.29$$

where the constants $\mathcal{C}' > 0$ and $\mathcal{D}' > 0$ are defined as

$$\mathcal{C}' = \frac{\sum_{i=0}^{3} \mathcal{C}_i K^i}{K} \qquad and\ \mathcal{D}' = \frac{\sum_{i=0}^{3} \mathcal{D}_i K^i}{K} \qquad 3.30$$

This expression provides clear strategies on how to select M in a Massive MIMO system to maximize EE. So it gives us the following important sights on the impact of the antennas on the energy efficiency analysis.

The optimal $M^{(*)}$ does not depend on the rate-dependent power$\{P_{COD}, P_{DEC}, P_{BT}\}$, whereas it decreases with the power per BS antenna P_{BS} and increases with the fixed power and UE-dependent power$\{P_{FIX}, P_{SYS}, P_{UE}\}$. And a larger number of antennas are needed as the size of the coverage area increases. From he above observation $M^{(*)}$ increases almost linearly with S_X , which is a parameter that increases with the cell radius d_{max}^K [20,26].

3.5.3 The impact of transmit power on energy efficiency

The transmit power is proportional to$SINR$, which is directly related to the PA/transmit power. Under ZF processing , to maximize EE , the solution is , to find M and K, for EE optimal $p \geq 0$ can be computed as

$$p^* = \frac{e^{\left(\frac{\eta}{\beta\sigma^2 p S_X}\frac{(M-K)(\mathcal{C}\prime+M\mathcal{D}\prime}{e}-\frac{1}{e}\right)}}{M-K} - 1 \qquad 3.31$$

where $\mathcal{C}\,' > 0$ and $\mathcal{D}\,' > 0$ are give in the above in table 1 and equation (3.29)

The optimal desired p^* increases with $\mathcal{C}\,'$ and $\mathcal{D}\,'$, which were defined in (3.29), and thus with the coefficients in the circuit power model. Since the maximizing total PA power with ZF processing is

$$P_{TX}^{(ZF)} = \frac{\beta\sigma^2 p S_X}{\eta} K\, p^* \qquad 3.32$$

then, the optimal transmit power does not depend on the rate-dependent power $\{P_{COD}, P_{DEC}, P_{BT}\}$ whereas it increases with fixed power and the power per UE and BS antenna $\{P_{BS}, P_{FIX}, P_{SYS}, P_{UE}\}$. The fact that the optimal PA/transmit power increases with $\{P_{BS}, P_{FIX}, P_{SYS}, P_{UE}\}$ might seem a bit counter spontaneous at first, but it makes much sense and if the fixed circuit powers are large, then higher PA power $P_{TX}^{(ZF)}$(and thus higher average rates) can be afforded in the system since $P_{TX}^{(ZF)}$ has a small impact on the total power consumption.

It has recently been shown in [26], [17], and [18] that TDD systems permit a power reduction proportional to $\frac{1}{M}$ with perfect channel state information or $\frac{1}{\sqrt{M}}$ with imperfect channel state information while maintaining nonzero rates as $M \to \infty$.

Even though being a remarkable result and a key motivation for massive MIMO systems, this proves that this is not the most energy efficient strategy. In fact, the EE metric is maximized by the opposite strategy of increasing the power with M.

3.5.4 The impact of throughput on energy efficiency

Massive MIMO can potentially improve the area throughput while providing substantial power savings. Massive MIMO aims at evolving the coverage tier BSs by using arrays 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. Hence, the overall EE of the network,which was defined ealier is "how much energy it takes to achieve a certain amount of work", can be optimized only if these benefits and costs are properly balanced.

To obtain a closed-form expression of EE for optimization, we derive the asymptotic data rate for large system, where M and K grow infinitely while M/K is finite. According to the random-matrix theory [19], the asymptotic rate converges in mean square to the average rate. Hence, we can use the asymptotic data rate as the average rate.

Chapter 4

Simulation and numerical results

4.1 Introduction

MATLAB based simulations is implemented to confirm the numerical anaylsis given in the system is provided in this Chapter. In this, Chapter simulations of main design parameters on the impact of energy efficiency under perfect and imperfect channel state information is analyzed separately.

The optimal and desired design parameters for maximizing energy efficiency is simulated using ZF schemes at the end of the simulation.

The simulation uses a sample of Massive MIMO scenario ; number of antennas M (200) , number of active users K (120) and transmission bandwidth 20MHZ. and more simulation parameters are listed below in the table.

4.2 Simulation parameters

In the MATLAB demonstration , the following list of parameters are used. The parameters are taken from the telecommunication uninon standard reports and standard values mainly[5,6, 20,26,36,37]

Table 4-1 Simulation parameters

Parameters	Values
Carrier frequency: f_c	2 GHz
Cell radius (single-cell): d_{max}	250 m
Channel coherence bandwidth: B_C	180 kHz
Channel coherence time: T_C	10ms
Coherence block (symbols): U	1800
Computational efficiency at BSs: L_{BS}	12.8 GW
Computational efficiency at UEs: L_{UE}	5 GW

Fixed power consumption (control signals, backhaul): P_{FIX}	18 W
Fraction of downlink transmission: $\zeta^{(\text{dl})}$, $\zeta^{(\text{ul})}$	0.4/0.6
Minimum distance: d_{min}	35 m
Network Deployment for single-cell	Circular
Power Amplifier efficiency at the UEs: $\eta^{(\text{ul})}$ Power Amplifier efficiency at the BSs: $\eta^{(\text{dl})}$	0.3 0.39
Power consumed by local oscillator at BSs: P_{SYN}	2 W
Power required for backhaul traffic: P_{BT}	0.25 W/(Gbit/s)
Power required for coding of data signals: P_{COD}	0.1 W/(Gbit/s)
Power required for decoding of data signals: P_{DEC}	0.8 W/(Gbit/s)
Power required to run the circuit components at a BS: P_{BS}	1 W
Power required to run the circuit components at a UE: P_{UE}	0.1 W
Relative pilot lengths: $\tau^{(\text{ul})}$, $\tau^{(\text{dl})}$	1(ratio , no ut)
Total noise power: $B\sigma^2$	96 dBm
Transmission bandwidth: B	20 MHz

4.3 Simulation and result discussion

4.3.1 Energy efficiency and number of massive base station antennas

Here ,the impact of massive number of antennas on the total energy efficiency of the system is analyzed and evaluated. In this simulation the energy efficiency of the system decreases as the power consumption increases but increases without bound with the number of antennas as shown in Figure 4.1 below.

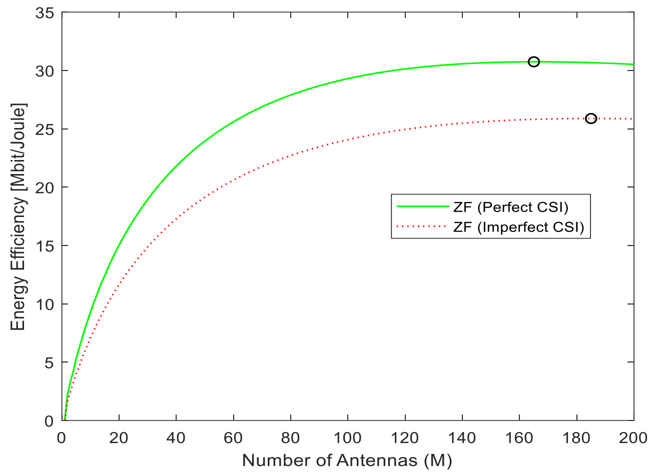

Figure 4.1 Simulation result of energy efficiency and number of antennas

Therefore, it seems that higher EE can be achieved by adding more and more massive antennas. This result is in the case when we don't considered the fact that the circuit power consumption increases with M in practice. In other words, there is a cost-performance tradeoff in practical systems. This tradeoff is particularly important when implementing a multiantenna system because a BS equipped with M antennas needs M RF chain components such as PAs, analog-to-digital converters (ADCs), digital-to-analog converters (DACs), local oscillators (LOs), filters, in-phase/quadrature (I/Q) mixers, and OFDM modulation/demodulation. The CP of such an implementation will be, roughly, M times higher than the CP of a single-antenna transceiver. So we need to design an optimal number of antennas in which the energy efficiency is maximum with minimal circuit component to decrease the power consumption. This is because each additional antenna increases the CP by PBS in practice.

$$C_P = P_{FIX} + M * P_{BS} \qquad 4.1$$

PFIX was defined before as a constant quantity accounting for the fixed power required for control signaling and load-independent power of backhaul infrastructure and baseband processors and PBS is the power consumed by the base station as the number of antenna increases.

In perfect channel state information at the base station performs higher energy efficiency as compared to imperfect channel state information at the base stations under same precoding. This is because ; in imperfect channel state the data rate affects by $\frac{1}{\sqrt{M}}$ of the number of base station antennas. So for fixed rate, a single cell transmitter can reduce its radiated power by a factor proportional to the square root of the number of deployed BS antennas [18],which directly affectes on EE.

4.3.2. Impact of active users and cell densities on energy efficiency

The number of user equipments has an impact on the total energy efficiency of the system unless an optimal design is considered. The power consumption of the users increases the total power consumption directly as it is stated below. So the total power consumtion should be correctly modeled to analysze its impact on the energy efficiency with number of antennas and users.

$$CP = P_{FIX} + M * P_{BS} + K * P_{UE} \qquad 4.2$$

where PUE accounts for the power required by all circuit components (e.g., DAC, I/Q mixer, filter, and so forth) of each single-antenna UE.

As it is stated circuit power consumption increases with number antennas and number of users. The optimal design of the ratio of antennas and users is needed to increase energy efficiency of the system as whole.

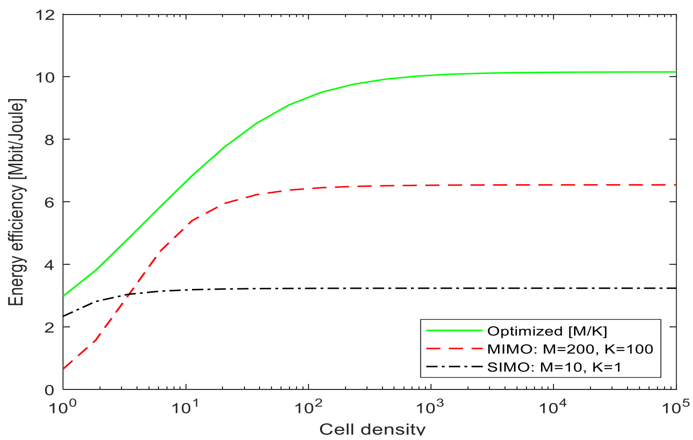

Figure 4.2 Analysis of impact of multiple users and cell density on EE

The technology densing cells have positive impact of energy efficiency as it decreases distance between the base station and users. Densifying network cell increases system throughput with proper interference mitigation techniques employed. In general serving a larger number of UEs requires more CP due to the increased computational complexity of precoding/combining schemes, encoding and decoding as well as channel estimation.

Increasing the densities of base station in the network area increases the system throughput while interference will be the challeange of designing. So by increasing cell densities we can save energy efficiently but this increment should be optimal.

In summary, serving multiple UEs while simultaneously increasing the number of BS antennas (to compensate for the higher interference) may improve the EE of the network only when the benefits and costs of deploying more RF hardware are properly balanced. then we need to define power circuit model precisely. So power consumed by digital signal processing and analog circuits (for radio-frequency (RF) and baseband processing) grows with M and K.

4.3.3 The impact of system throughput on energy efficiency

The analysis of system throughput and energy efficiency is very important design factor which affects the bandwidth of the network. This should be carefully specified with the circuit power consumption model.

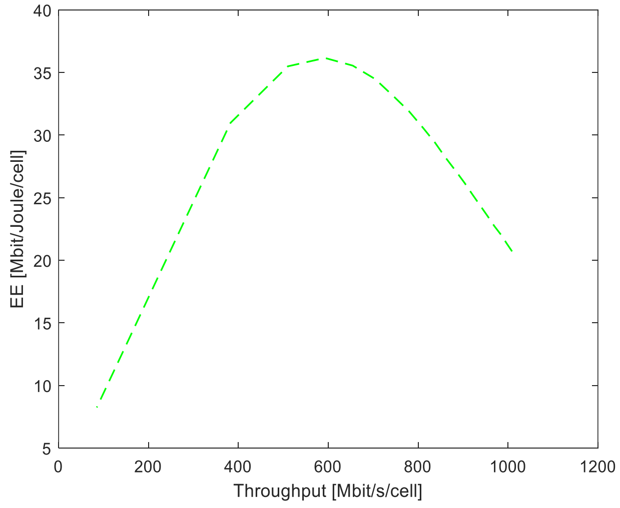

Figure 4.3 EE vs system throughput analysis using ZF

EE is a unimodal function of the throughput for the selected schemes. This implies that we can jointly increase the throughput and maximize EE up to some point, but further increases in throughput may loss in EE. The curves are quite smooth around the maximum

EE point. This happens since the higher the throughput, the higher is also the CP, due to the larger number of antennas. But , there is a variety of throughput values or, equivalently, numbers of BS antennas that provide nearly maximum EE.

4.3.4 Analysis of throughput and number of massive antennas on EE

Here the impact of system throughput and the number of antennas on the whole energy efficiency is analyzed using ZF precoding for perfect and imperfect channel state information at the base station. From the simulation, as the system throughput and number of antennas increases the EE maximizes. In perfect CSI, the line of the simulation is higher than the imperfect CSI since the number of antennas affects differently for both. That is the transmit power reduces as $\frac{1}{M}$ per user for perfect CSI and $\frac{1}{\sqrt{M}}$ for imperfect CSI.

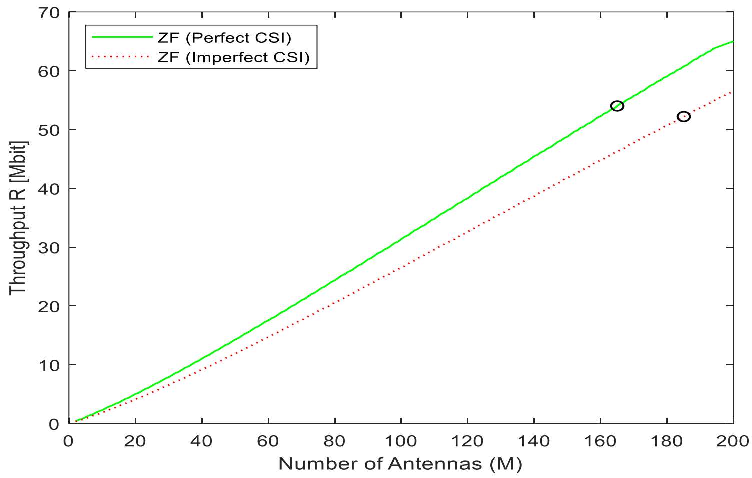

Figure 4.4 Data rate vs number of antennas with EE

In the simulation above , the circules represents the optimal number of antennas that maximize energy efficiency in perfect and imperfect channel state information.

4.3.5 Massive MIMO design for maximizing energy efficiency

In the above simulation , we have analyzed the performance of energy efficiency with number of antennas, users and system throughput separately. Here the design considers all the main parameters considered above so as to design a network model that maximizes EE using ZF under perfect CSI. The simulation is a 3D plot which analysis the optimam number of number of antennas, number of users and system rate that maximizes EE.

Serving multiple UEs while simultaneously increasing the number of BS antennas (to compensate for the higher interference) may improve the EE of the network only when the benefits and costs of deploying more RF hardware are properly balanced. The EE-optimum configuration of BS antennas and number of UEs will be evaluated.

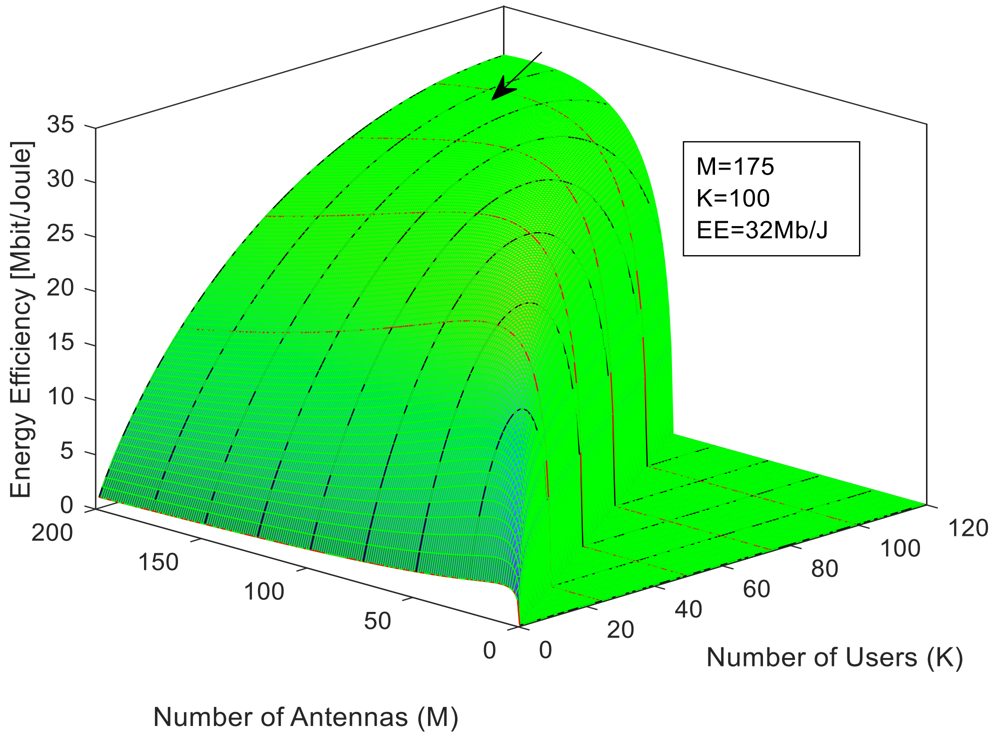

Figure 4.5Analysis of optimum points of number of antennas and users to maximize EE

This means that the EE attains its maximum at a finite value of the antenna-UE ratio M/K.

This analysis is the main goal of the thesis to show how a cellular network should be designed for maximal EE. This result show that a Massive MIMO setup, with in a range of number of antennas 100-200 to serve upto 100 users , is the EE-optimal solution. So from the overall simulation result the following main summary points are observed.

- Massive MIMO system with 100-200 BS antennas is the best way to design for better energy efficiency
- We should use these antennas to serve a number of UEs
- The transmit power should increase with the number of BS antennas since the circuit power increases
- ZF processing provides better EE because of active interference mitigation in ultra dense networks .

These are highly significant results that prove that Massive MIMO is the way to achieve high EE (tens of Mbit/Joule) in 5G wireless cellular networks.

Chapter 5

Conculsion and recommendations

5.1 Conculsion

This thesis focuses on the energy efficiency maximisation using Massive MIMO systems. In the simultions energy efficiency is higher in perfect channel state information than in the imperfect channel state. This is because imperfect channel undermines efficiency as general and the dependency on the number of antennas also affects the EE. Network desfication plays a significance role in energy efficiency. At the second this work analyzed how to select the number of BS antennas M, number of active UEs K, and system throughput to maximise the EE in Massive MIMO systems. From the total power consumption model , this thesis investigated how it depends non-linearly on M, K, and R using ZF shcemes for perfect and imperfect CSI. The EE (in bit/Joule) is a quasi-concave function of , K and R thus it has a finite global optimum. The numerical results show that deploying 100-200 antennas to serve a relatively large number of UEs is the EE-optimal solution using circuit model technology. This is Massive MIMO setups, but stress that M and K are at the same order of magnitude in contrast to the $M/K \gg 1$ assumption [11]. The radiated power per antenna is, however, decreasing with M. This indicates that massive MIMO can be built using low power consuming transceiver equipment at the BSs . Therefor higher energy efficiency is not a means of using low power consumption rather using precisely usage of energy and introducing super interference mitigations (like ZF schemes) in the Massive MIMO technology.

5.2. Recommendations

This research thesis analysis single cell in Massive MIMO but several limitations and technologies may miss for multicell technology to analysis energy efficiency. So I recommeneded to future researchers on this area to extend their studies for multicell and another precoding schems for futher investigations in energy efficiency analysis techniques.

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Appendix

Appendix A. Research Manuscript

Analysis of Energy Efficient Techniques for 5G ultra dense wireless communication networks using Massive MIMO

*Halefom Tswaslassie Gebrekidan **Dr-Eng Yihenew Wendie (Advisor)

*AAiT School of Electrical and Computer Engineering ** Communication Engineering

Abstract

In the modern wireless communication energy, consumption becomes critical issue. Therefore, energy efficiency has been appreciated performance analysis metrics. Massive MIMO and cell densifications are the latest encouraging technologies to maximize energy efficiency in 5G wireless communications.

This thesis work mainly on the analysis of energy efficiency from circuit power consumption using zero forcing precoding schemes. The main design parameters are the number of massive antennas at the base station (M), the number of active user equipment terminals (K), the system throughput (R) and cell density. Then EE is defined as the number of bits transferred per Joule of energy consumed.

MATLAB tool is used to demonstrate the impact of the main design parameters on energy efficiency. The results shows that we can design optimal number of (K, M, R) to maximize energy efficiency using zero forcing precoding. Perfect channel state information at the base station saves more energy as compared to imperfect channel state information.

***Key Words**: 5G, Massive MIMO, Ultra Dense, Linear Precoding, CSI, Energy Efficiency*

1. Introduction

With the development of smart terminals and their application, the need for multimedia services has rapidly increased recently. The increment of the capacity of wireless networks assured the quality of service (QoS) requirements of mobile applications. In the meantime, telecommunication manufacturers and operators have also predicted that a load of wireless communication networks is growing exponentially [3]. It is expected that there would be 1billion 5G mobile subscriptions in 2020, from this smartphones accounting more digit [37]. Moreover, the traffic growth is also following an exponential growth. In 2020, it expected that the total mobile traffic would increase by a factor of 10 from the current growth rate, with video traffic making most of it [36].

Hence, it is necessary to introduce new technologies to meet the demands of explosive traffic for next generation wireless communications networks. In the interim, with extreme power consumption in wireless communications networks, both carbon emission and operator expenses surge yearly [3], [4]. Thus, Energy Efficiency (EE) has become another important metric for evaluating the performances of wireless communications systems with some given BE limitations [5].

Multiple-Input and Multiple-Output (MIMO) technology have attracted much attention in wireless communication, as it offers significant rises in data throughput and link range without an additional increase in bandwidth or transmits power.

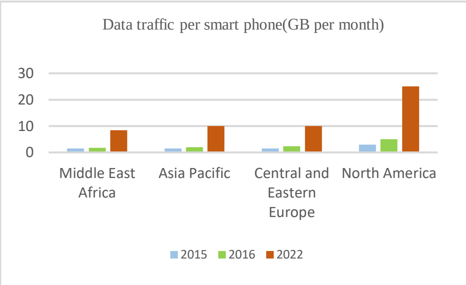

Figure 1-1 Mobile data traffic growth [15]

2. Analytical study of Energy efficiency in 5G using Massive MIMO system

2.1 System model and work flowchart

The system considers a massive MIMO network consists of cellular cells and each cells are equipped with the base station antennas of M and active users K. The network cells and active users are assumed uniformly distributed. The work starts from the definition of energy efficiency in wireless communication, which is defined as the ration of average data rate to total energy consumption. In mathematics, it is defined as [5, 6, 11]

$$EE = \frac{Throughput\ [bit/s/cell]}{Power\ consumption\ [W/cell]} = \frac{\sum_{k=1}^{k}\left(\mathbb{E}\left\{R_k^{(ul)}\right\} + \mathbb{E}\left\{R_k^{(dl)}\right\}\right)}{P_T^{(ul)} + P_T^{(dl)} + P_{CP}(M,K,R)} \qquad 0\text{-}1$$

Which is measured in $^{bit}/_{Joule}$ which can be considered as benefit to cost ratio in which the quality of service (throughput) is compared with the charge of the power. The overall workflow graph is as follow.

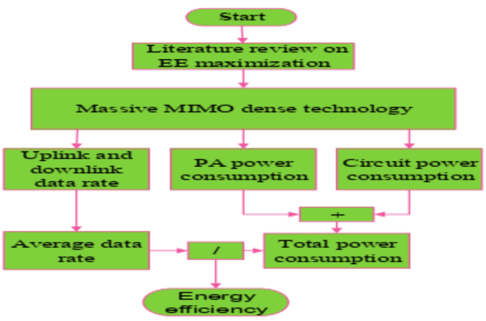

Figure 0-1Overall work flow graph

From equation (2.1) to increase energy efficiency we can have three different options.

- Increasing the throughput and decreasing the total power consumption
- Decrease both the throughput and the total power consumption
- Increase both the throughput and the total power consumption.

2.2. Analysis of total power consumption in Massive MIMO

Based on the energy efficiency definition of the model in Equation (2.1), the total power consumption, P_T is defined as the sum of transmit power and circuit power [28].

$$P_T = P_{TX} + P_{CP} \qquad 0\text{-}2$$

Where P_{TX} represents the average transmit power consumption in watts and P_{CP} denotes the total circuit power consumption in watts . While connecting more antennas at the BS waders the data rate, but this additional antennas circuitry leads to increased power consumption. As stated by [33], the circuit power consumption allowed scaling with the key parameters such as **M** and **K**.

Based on prior works of [28], [27] a new developed circuit power consumption model for Massive MIMO systems is proposed:

$$P_C = P_{FIX} + P_{TC} + P_{CE} + P_{\frac{C}{D}} + P_{BH} + P_{LP} \qquad 0\text{-}3$$

2.2.1 Transceiver Circuit Power (P_{TC})

For standard wireless communications, transmitters and receivers, power consumption P_{TC} can be computed as [34, 45]

$$P_{TC} = MP_{BS} + P_{SYN} + KP_{UE} \qquad 0\text{-}4$$

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. Where the last term P_{UE} , accounts for the power required by all circuit components of each single-antenna UE.

2.2.2 Channel Estimation Circuit Power (P_{CE})

All channel estimation process is carried out at the BS and UEs, whose computational efficiency are L_{BS} and L_{UE}. In addition, computational efficiency is measured as arithmetic complex-valued operations per Joule also known as flops/Watt. There are $\frac{B}{U}$ coherence blocks per second where B and U are bandwidth and coherent unit , and, the pilot-based CSI estimation is performed once per block. In the uplink, the BS receives the pilot signal as a M×$\tau^{(ul)}K$ matrix and estimates each UE's channel by multiplying with the corresponding pilot sequence of length $\tau^{(ul)}K$ [17]. This standard linear algebra operation [15] requires a power consumption in watts of

$$P_{CE}^{(ul)} = \frac{B}{U}\frac{2\tau^{(ul)}MK^2}{L_{BS}} \quad \text{0-5}$$

In the downlink, each active UE receives a pilot sequence of length $\tau^{(ul)}K$ and processes it to acquire its effective precoded channel gain (one inner product). From [15], the downlink power in Watt is obtained as

$$P_{CE}^{(dl)} = \frac{B}{U}\frac{2\tau^{(dl)}K^2}{L_{UE}} \quad \text{0-6}$$

Therefore, the total power consumption is given as the sum of both the uplink and the downlink

$$P_{CE} = P_{CE}{}^{(ul)} + P_{CE}{}^{(dl)} \quad \text{0-7}$$

From this expression the total power in watt for the channel estimation process becomes

$$P_{CE} = \frac{B}{U}\frac{2\tau^{(ul)}MK^2}{L_{BS}} + \frac{B}{U}\frac{2\tau^{(dl)}K^2}{L_{UE}} \quad \text{0-8}$$

2.2.3 Coding and Decoding Circuit Power ($P_{C/D}$)

In the downlink, the BS applies channel coding and modulation to K sequences of information symbols. Similarly, 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 [14] and thus be quantized as [11,17,15]

$$P_{C/D} = \sum_{K=1}^{K}(\mathbb{E}\{R_K{}^{(ul)} + R_K{}^{(dl)}\})(P_{COD} + P_{DEC}) \quad \text{0-9}$$

Where P_{COD} and P_{DEC} are the coding and decoding powers (in Watt per bit/sec), respectively, and $R_K{}^{(ul)}$ and $R_K{}^{(dl)}$ are the uplink and downlink data rate , and the operator $\mathbb{E}$ denotes the expectation value.

2.2.4 Backhaul Circuit Power (P_{BH})

The backhaul circuit power is used to transfer uplink/downlink data between the BS and the core network. The power consumption of the backhaul is modeled as the sum of two parts [14]: one load-independent and one load-dependent. The first part is comprised 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 [14].

$$P_{BH} = \sum_{K=1}^{K}\left(\mathbb{E}\{R_K{}^{(ul)} + R_K{}^{(dl)}\}\right)P_{BT} \quad \text{0-10}$$

Where P_{BT} is the backhaul traffic power (in Watt per bit/s).

2.2.5 Linear Processing Circuit Power (P_{LP})

The transmitted and received vectors of information symbols at the BS are generated by transmit precoding and processed by receive combining, respectively. From [26];

$$P_{LP} = B\left(1 - \frac{(\tau^{ul} + \tau^{dl})K}{U}\right)\frac{2MK}{L_{BS}} + P_{LP-C}\,Watt \quad \text{0-11}$$

When ZF processing is selected, then approximately , the following power is consumed

$$P_{LP-C}{}^{(ZF)} = \frac{B}{U}\left(\frac{K^3}{3L_{BS}} + \frac{3MK^2 + MK}{LBS}\right) \quad \text{0-12}$$

2.3 Achievable Sum Rate

The achievable sum rate follows the Shannon theorem. Shannon theorem gives the maximum rate at which the transmitter can transmit via the channel. This section describes the achievable sum rate with ZF , with the assumption that the total downlink power is fixed and equally divided between all the users. From Shannon theorem, the channel capacity is given by equation [22].

$$R = log_2(1 + SNR)(bits/s/Hz) \quad \text{0-13}$$

Where, SNR: is the signal to noise ratio. Channel state information (CSI) is a very important issue in multiuser communication systems.

If a ZF detector engaged with $M \geq K+1$, the gross rate is parameterize as,

$$\bar{R} = B\,log\,(1 + \rho(M - K)) \quad \text{0-14}$$

ZF detection/precoding is applied under imperfect CSI, the average gross rate

$$\bar{R} = B\log(1 + \frac{\rho(M - K)}{1 + \frac{1}{\tau^{ul}} + \frac{1}{\mathcal{P}K\tau^{ul}}}) \quad \text{0-15}$$

.

2.4 Energy Efficiency Maximization with ZF Processing in Massive MIMO

A theoretical solution for the Energy Efficiency problem is explained here under the assumption of employing ZF linear processing in Massive MIMO system. The Energy Efficiency problem is solved analytically by utilizing ZF processing scheme in the uplink and downlink. So it can be solved using zero forcing precoding as follow[5,6,11,26].

For ZF processing, Energy Efficiency is defined as

$$EE^{(ZF)} = \frac{K\left(1 - \frac{\tau_{Total}K}{U}\right)R}{\frac{B\sigma^2 pS_X}{\eta}K + P_{CP}^{(ZF)}} \quad \text{0-16}$$

Where τ_{Total} is represented the sum of uplink and the downlink ($\tau_{Total} = \tau^{(ul)} + \tau^{(dl)}$).

$$\mathbb{E}\left\{\mathrm{R}_\mathrm{K}^{(\mathrm{ul})}\right\} + \mathbb{E}\left\{\mathrm{R}_\mathrm{K}^{(\mathrm{dl})}\right\} = \mathrm{R}_\mathrm{K}^{(\mathrm{ul})} + \mathrm{R}_\mathrm{K}^{(\mathrm{dl})} \quad \text{0-17}$$
$$= \left(1 - \frac{\tau_{\mathrm{Total}}\mathrm{K}}{\mathrm{U}}\right)$$

In addition

$$P_{CP}^{(ZF)} = P_{FIX} + P_{TC} + P_{CE} + P_{C/D} + P_{BH} + P_{LP}^{(ZF)} \quad \text{0-18}$$

3. Simulation and numerical results

3.1 Introduction

MATLAB based simulations is implemented to confirm the numerical analysis given in the system is provided in this Chapter. In this, Chapter simulations of main design parameters on the impact of energy efficiency under perfect and imperfect channel state information is analyzed separately. The simulation uses a sample of Massive MIMO scenario ; number of antennas M (200) , number of active users K (120) and transmission bandwidth 20MHZ. and more simulation parameters are listed below in the table.

3.2 Simulation parameters

The parameters are taken from the telecommunication union standard reports and standard values mainly [5,6, 20,26,36,37]

Table 3-1 Simulation parameters

Parameters	Values
Carrier frequency: f_c	2 GHz
Cell radius (single-cell): d_{max}	250 m
Channel coherence bandwidth: B_C	180 kHz
Channel coherence time: T_C	10ms
Coherence block (symbols): U	1800
Computational efficiency at BSs: L_{BS}	12.8 GW
Computational efficiency at UEs: L_{UE}	5 GW
Fixed power (control signals, backhaul) P_{FIX}	18 W

Fraction of downlink transmission: $\zeta^{(dl)}$ $\zeta^{(ul)}$	0.4/0.6
Minimum distance: d_{min}	35 m
Network Deployment for single-cell	Circular
Power Amplifier efficiency at the UEs: $\eta^{(ul)}$ Power Amplifier efficiency at the BSs: $\eta^{(dl)}$	0.3 0.39
Power consumed by local oscillator at BSs: P_{SYN}	2 W
Power required for backhaul traffic: P_{BT}	0.25W/(Gbit/s)
Power required for coding of data signals: P_{COD}	0.1 W/(Gbit/s)
Power required for decoding of data signals: P_{DEC}	0.8 W/(Gbit/s)
Power required to run the circuit components at a BS: P_{BS}	1 W
Power required to run the circuit components at a UE: P_{UE}	0.1 W
Relative pilot lengths: $\tau^{(ul)}$, $\tau^{(dl)}$	1(ratio , no ut)
Total noise power: $B\sigma^2$	96 dBm
Transmission bandwidth: B	20 MHz

3.3. Energy efficiency and number of massive base station antennas

Here, the impact of massive number of antennas on the total energy efficiency of the system is analyzed and evaluated. In this simulation the energy efficiency of the system decreases as the power consumption increases but increases without bound with the number of antennas as shown in Figure 3.1 below

Perfect channel state information at the base station performs higher energy efficiency as compared to imperfect channel state information under same precoding. This is because; in imperfect channel state the data rate affects by $\frac{1}{\sqrt{M}}$ of the number of base station antennas. So for fixed rate, a single cell transmitter can reduce its radiated power by a factor proportional to the square root of the number of deployed BS antennas [18],which directly affected on EE.

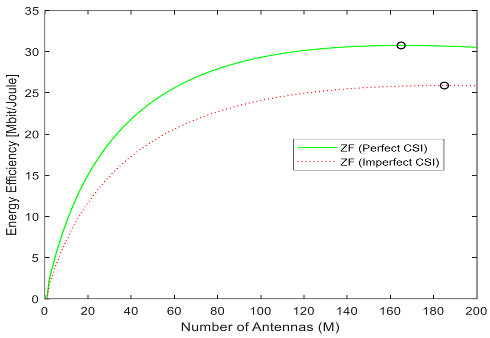

Figure 1-1 Simulation result of energy efficiency and number of antennas

This tradeoff is particularly important when implementing a multi antenna system because a BS equipped with M antennas needs M RF chain components. The CP of such an implementation will be, roughly, M times higher than the CP of a single-antenna transceiver.

$$C_P = P_{FIX} + M * P_{BS} \qquad 1\text{-}1$$

3.4 Impact of active users and cell densities on energy efficiency

The number of user equipment has an impact on the total energy efficiency of the system unless an optimal design is considered. The power consumption of the user's increases the total power consumption directly as it is stated below.

$$CP = P_{FIX} + M * P_{BS} + K * P_{UE} \qquad 1\text{-}2$$

Where, P_{UE} accounts for the power required by all circuit components (e.g., DAC, I/Q mixer, filter, and so forth) of each single-antenna UE.

The technology densing cells have positive impact of energy efficiency as it decreases distance between the base station and users. Densifying network cell increases system throughput with proper interference mitigation techniques employed.

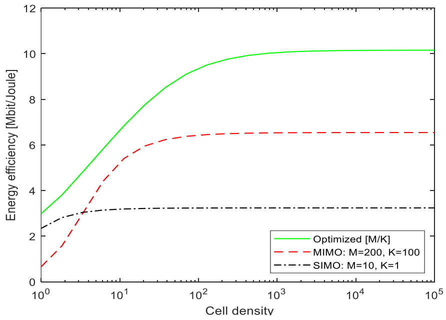

Figure 1-2 Analysis of impact of multiple users and cell density on EE

In summary, serving multiple UEs while simultaneously increasing the number of BS antennas (to compensate for the higher interference) may improve the EE of the network only when the benefits and costs of deploying more RF hardware are properly balanced. then we need to define power circuit model precisely. So power consumed by digital signal processing and analog circuits (for radio-frequency (RF) and baseband processing) grows with M and K.

3.5 The impact of system throughput on energy efficiency

The analysis of system throughput and energy efficiency is very important design factor which affects the bandwidth of the network. EE is a unimodal function of the throughput for the selected schemes. This implies that we can jointly increase the throughput and maximize EE up to some point, but further increases in throughput may loss in EE.

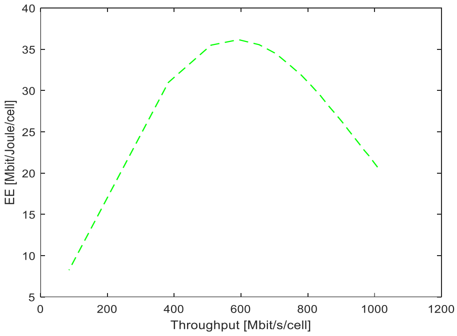

Figure 1-3 EE vs system throughput analysis using ZF

3.6 Analysis of throughput and number of massive antennas on EE

From the simulation, as the system throughput and number of antennas increases the EE maximizes. In perfect CSI, the line of the simulation is higher than the imperfect CSI since the number of antennas affects differently for both. That is the transmit power reduces as $\frac{1}{M}$ per user for perfect CSI and $\frac{1}{\sqrt{M}}$ for imperfect CSI.

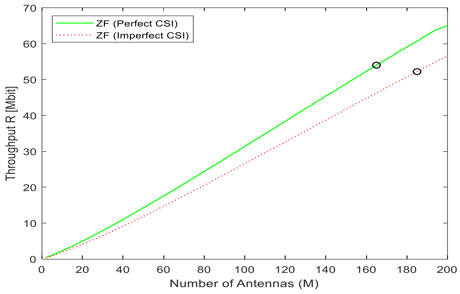

Figure 1-4 Data rate vs number of antennas with EE

In the simulation above, the circles represents the optimal number of antennas that maximize energy efficiency in perfect and imperfect channel state information.

3.7 Massive MIMO design for maximizing energy efficiency

In the above simulation, we have analyzed the performance of energy efficiency with number of antennas, users and system throughput separately. Here

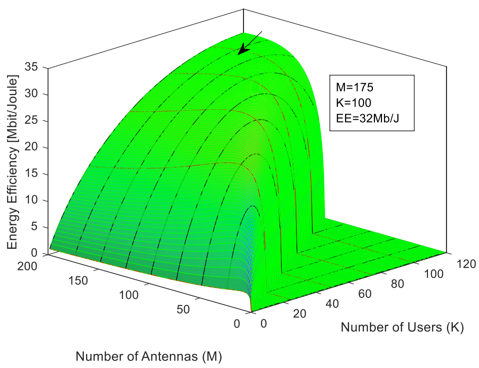

Figure 1-5 Optimal design of basic parameters

the design considers all the main parameters considered above so as to design a network model that maximizes EE using ZF under perfect CSI.

- Massive MIMO system with 100-200 BS antennas is the best way to design for better energy efficiency
- We should use these antennas to serve a number of UEs
- The transmit power should increase with the number of BS antennas since the circuit power increases
- ZF processing provides better EE because of active interference mitigation in ultra dense networks .

4. Conclusion and recommendations

4.1 Conclusion

This thesis focuses on the energy efficiency maximization using Massive MIMO systems. In the simulations, energy efficiency is higher in perfect channel state information than in the imperfect channel state. This is because imperfect channel undermines efficiency as general and the dependency on the number of antennas affects the EE. Network desfication plays a significance role in energy efficiency. At the second, this work analyzed how to select the number of BS antennas M, number of active UEs K, and system throughput to maximise the EE in Massive MIMO systems. The numerical results show that deploying 100-200 antennas to serve a relatively large number of UEs is the EE-optimal solution using circuit model technology. This is Massive MIMO setups, but stress that M and K are at the same order of magnitude in contrast to the $M/K \gg 1$ assumption [11]. The radiated power per antenna is, however, decreasing with M. This indicates that massive MIMO can be built using low power consuming transceiver equipment at the BSs . Therefor higher energy efficiency is not a means of using low power consumption rather using precisely usage of energy and introducing super interference mitigations (like ZF schemes) in the Massive MIMO technology.

4.2. Recommendations

This research thesis analysis single cell in Massive MIMO but several limitations and technologies may miss for multicellular technology to analysis energy efficiency. So I recommended to future researchers on this area to extend their studies for multicellular and another precoding schemes for further investigations in energy efficiency analysis techniques.

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