JIMMA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

JIMMA INSTITUTE OF TECHNOLOGY

FACULTY OF ELECTRICAL AND COMPUTER ENGINEERING

Power Optimization of Massive MIMO in Heterogeneous Network for 5G System

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A Thesis submitted to Jimma University in partial fulfillment of the requirements for the degree of Masters of Science in Communication Engineering

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Declaration

I, the undersigned, declare that this thesis work is my original work, has not been presented for a degree in this or any other universities, and all sources of materials used for the thesis work have been fully acknowledged..
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Abstract

In future wireless networks, there is an increasing demand of high quality of service, high data rates, network coverage and low latency. However, the existing network is limited in capacity to address the requirements of the data rate in the order of gigabits.

Massive MIMO and small cells are the foremost technologies to address such challenges for the next generation (5G) wireless systems. Massive MIMO is a technique that deploying a large number of antennas at the base station, and thus, improving energy efficiency and spectral efficiency of wireless networks. Small cell provides high data rate and good coverage with reduced transmit power by reducing the distance between base station and user. Since, the number of users are increasing, which give a rise to a lot of problems like increased interference, complexity and power consumption in the processing and transmission.

This can be analyzed to enhance the data rate and EE by combining massive MIMO base station and small cell base stations with higher spatial reuse. To provide resource aware energy saving technique with a low complexity algorithm based on classical regularized zero force (RZF) beamforming is used and compared with optimal solution cases.

The simulation result is conducted to prove that, the total power consumption can be greatly improved more than 1.2 % by combining massive MIMO and small cells, this is possible with both optimal beamforming and low-complexity beamforming.

Based on the result obtained, it is better to use the heterogeneous system of massive MIMO macro cell with low power complementary small cells can achieve a greater EE (EE) than massive MIMO macro cell alone.

KEY WORDS: ***5G, Beamforming, HetNet, Massive MIMO, RZF, Small cell***

Dedication

Dedicated to all my family

my mother, Wessene Alie, brothers Fikadu Endale and Habtamu Endale , sister Zuriash Endale , and Seble Argaw.......

With gratitude for your inspiration, love, and support.

Acknowledgment

In the name of God, the most gracious and the most merciful. All praise is for God, for his blessings to complete this thesis. Without his guidance, my accomplishments would never have been possible.

First and foremost, I would like to express my deepest gratitude and appreciation to my adviser Dr.-Ing. Towfik Jemal for his insightful technical advice and guidance throughout my research studies.

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I would like to offer my heartfelt thanks to my family Specially, my mother. Your love, patience, understanding and supports are worth far more to me than I could ever express.

A very special thanks to Seble Argaw, whose daily encouragement and unconditional support have made this journey a wonderful experience.

Last but not the least, I would like to extend my sincere thanks to all my friends for their continuous support and friendship.

Abinet Endale

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Abbreviations and List of Symbols

1G	Frist Generation
2G	Second Generation
3G	Third Generation
3GPP	Third Generation Partnership Project
4G	Fourth Generation
5G	Five Generation
AP	Access Points
ASE	Area Spectral Efficiency
AWGN	Additive white Gaussian noise
BS	Base Station
CSI	Channel State Information
CSG	Closed Subscribed Group
CSMA	Carrier Sense Multiple Access
CVX	Convex
DL	Downlink
EE	Energy Efficiency
HetNet	Heterogeneous network
IEEE	Institute of Electrical and Electronics Engineers
iid	independent and identically distributed
IoT	Internet of Things
LTE-A	Long Term Evolution Advanced
LTE	Long Term Evolution
MU MIMO	Multi User Multiple Input Multiple Output
MBS	Macro Base Stations
MUE	Macrocell user equipment
MMSE	Minimum mean square error
MRT	Maximum ratio transmission
NLoS	Non-line of Sight
OFDM	Orthogonal Frequency Division Multiplexing
OPT	Optimization
PDF	Probability Density Function

PPP	Poisson Point Process
PSD	Positive semidefinite
QCQP	quadratic constrained quadratic programs
QoS	Quality of Service
QP	Quadratic Program
RB	Resource Block
RRH	Remote Radio Head
RZF	Regularized Zero Forcing
SBS	Small cell Base Station
SE	Spectrum Efficiency
SDP	Semidefinite Programing
SDR	Semidefinite Relaxation
SINR	Signal to Noise Plus Interference Ratio
SNR	Signal to Noise Ratio
SU MIMO	Single User Multiple Input Multiple Output
SUE	Small-cell user equipment
TDD	Time Division Duplexing
WiFi	Wireless Fidelity
ZFBF	Zero Force Beamfoarming
ZF	Zero Force
$\succeq$	Component-wise inequalities
$(\cdot)^*$	Complex conjugate
λ_{SBS}	Density of SBS
λ_{UEs}	Density of UEs
$\|\cdot\|$	Euclidean norm
ω	Fixed propagation loss
Γ	Gamma function
δ	Level of hardware impairments
$(\cdot)^{-1}$	Matrix inverse
σ^2	Standard Deviation
Φ	Poisson Point Process
α	Path loss exponent
$Tr(\cdot)$	Trace operator
$(\cdot)^H$	Vector/matrix Hermitian transpose
$(\cdot)^T$	Vector/matrix transpose

Chapter 1

Introduction

1.1 Motivation

In today's globalized world, wireless communication systems play a key role in fields such as education centers, economics, science, company, healthcare, transportation and our social and cultural lives. Some techniques have been developed to assist us interact with each other and make it easier at anytime and anywhere to access data.

Accordingly, global mobile data traffic will grow at a compound annual growth rate (CAGR) of 63 % from 2017 to 2022, nearly 12-fold from 22 petabytes per month in 2017, to 254 petabytes per month in 2022 as shown bellow in the Figure 1.1.

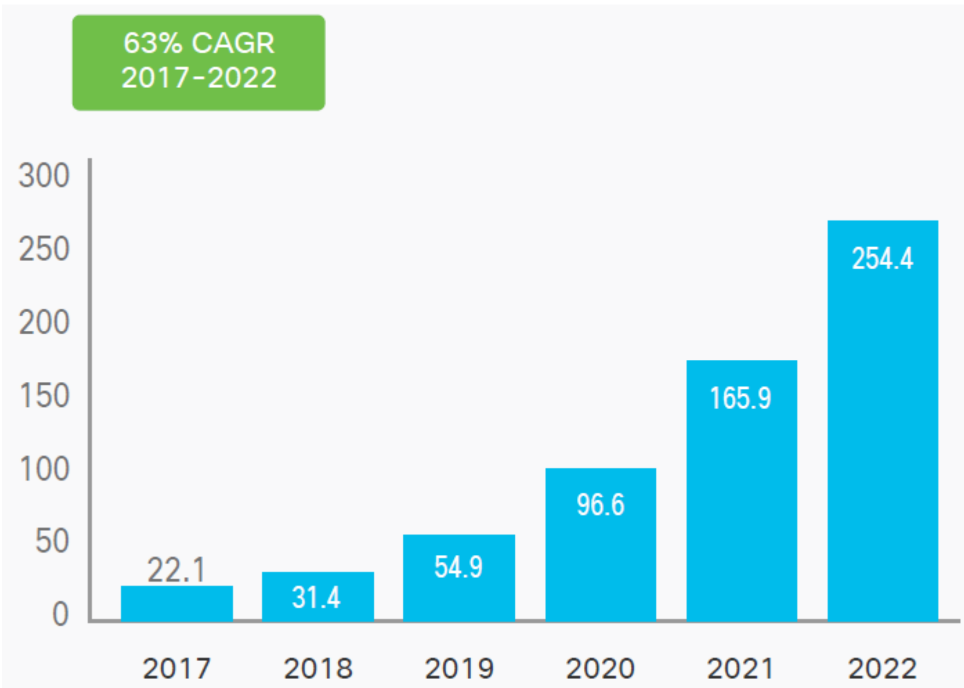

Figure 1.1: Source: Cisco VNI mobile, February 2019 [1]

1.2 Capacity scaling dimension of future cellular networks

It is essential to know, the different aspects of how capacity can be enhanced when targeting order of magnitude improvements in network capacity. In a simplified form, the Shannon-Hartley theorem [2].

$$\mathrm{C} = \mathrm{B}_w \mathrm{Log}_2(1 + \mathrm{S}/\mathrm{N}) \tag{1.1}$$

provides an insight into what are the variables that influence the amount of information capacity (C) one can transmit over a communication channel of a specified bandwidth B_w with a signal received with power S in the presence of white Gaussian noise with power N.

The capacity can be scaled by increasing the bandwidth B_w per user and increasing the SNR, or the SINR in a multi-user network [3]. Addressing the bandwidth is a more promising approach since this result in a linear scaling compared to the logarithmic scaling when increasing spectral efficiency by improving the SINR. In a network with multiple users, the bandwidth per user can be scaled by either increasing the frequency resources, or by network densification based on the reduction of cell size.

The efficiency of a wireless network may be improve in three basic ways wireless channel capacity densification, bandwidth and spectral efficiency contributed to capacity gains as mentioned by Mallinson [4],

- 56× from densifying to smaller cells
- 6× by improving spectral efficiency such as coding, medium access control and modulation techniques.
- 3× by using more spectrum bandwidth,

From this, it is clear that the majority of the gain was achieved by increasing the spatial frequency reuse though densifying the network to small cells.

1.2.1 Densification

In a multiuser network, users in the coverage of a cell share the available bandwidth. Through this methode, the bandwidth per user can be increased until each cell serves only a few user [2, 3]. When further densifying, only the SINR is improved by reducing the range between the base station and the user.

The other aspect of densification is that the required transmit power reduces to an extent where its contribution to the total energy consumption becomes insignificant, and the processing power becomes the dominant factor.

1.2.2 Bandwidth

A second dimension to increase capacity is increasing the bandwidth, where it can achieve linear scaling from the Shannon Hartley theorem, Eq.1.1. However, there are several challenges with this approach as well. First, the available bandwidth at lower frequencies is limited. Second, the required transmit power increases significantly when increasing bandwidth due to the higher path loss at higher frequency bands and the fact that more carriers need to be allocated [2]. Although increasing spectrum availability can provide high capacity gains, bandwidth is already used up at lower carrier frequencies. More bandwidth is available at higher carrier frequencies, but is mainly applicable to smaller cells due to the increasing transmit power requirements [3].

1.2.3 Spectral efficiency

The third dimension for increasing capacity is increasing the spectral efficiency, for example, by signal processing through error correction coding, increasing the SINR using interference mitigation, or with multiple antennas. The progress in signal processing have already led to near-saturation of gains in this dimension. Current coding schemes already operate close to the Shannon Hartley capacity limit, and further signal processing gains require significant overhead like MIMO [2]. Multiple antennas can be used to increase SINR through beamforming or for spatial multiplexing, but the low number of antennas at the user equipment (UE) at cellular bands and issues with channel state information acquisition limit the gain for traditional MIMO systems [3]. As mentioned in Mallinson [2], an increase capacity of 1000$\times$ is required to support this increasing demand. High capacity can be achieve by improving spectral efficiency, employing more spectrum and increasing network density.

Improving spectral efficiency and employing more spectrum are related to enhancements of the link level, radical gains cannot be expected above the current networks that are already functioning at near optimal.

In the next Figure 1.2 shows, the major gains are expect through increasing network density by installing an overlay network of small cells over the macrocell coverage area.

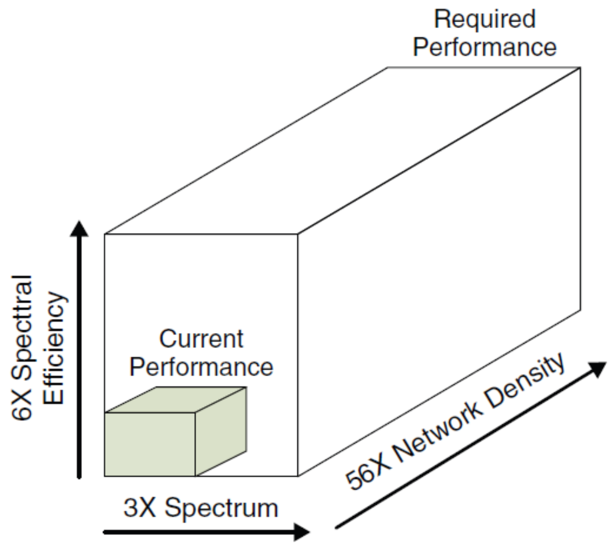

Figure 1.2: Quantitative prediction about capacity enhancement for future wireless networks [3]

The cellular networks are developed into heterogeneous networks by deploying small cells over the entire macrocells to support the increasing traffic demands. Heterogeneous networks are an encouraging result having met the ever-increasing demand for higher data rates. For network operators however, it is scheduled to face much better challenges in the future. Mobile broadband data is highly localized as the majority of current traffic is generate indoors and in hotspot such as universities, shopping malls and convention centers. Therefore, it makes sense to enhance the capacity where it is needed by using an overlay of small cell in those domain of the macro cell coverage area, which generates higher data request.

Any wireless network's quality restriction will always be on the physical layer because, basically spectrum availability, electromagnetic propagation rules restrict the amount of data that can be transferred between two locations. Mobile broadband data is highly localized as the majority of current traffic is generated indoors and in hotspots such as malls and convention centers. Therefore, it makes sense to add capacity where it is needed by deploying an overlay of small cells in those regions of the macro coverage area which generates high data demand [3].

One of the most challenging problems for future broadband wireless systems is providing a comprehensive range of service areas with different quality of service (QoS) and taking priority given limited resource availability [2]. Implementing mathematical instruments such as convex optimization and stochastic optimization in resource allocation design increases the network's performance. However, it is a major challenge to improve performance and practical use of resources.

Massive MIMO and small cell networks are both analyzed as critical technologies in future 5G wireless systems due to the capacity to realize the impacted network coverage and restricted system resources throughput trends. Besides improving network capacity, small cells also address the second concern of operators, cost reduction. A small cell-based heterogeneous network is much more energy efficient than a macrocell network [2, 3].

Generations of cellular technology

The 1G uses analog technology for voice communication only and 2G provides digital modulation for voice, encrypted text (including SMS, and low rate data GSM, CDMA) and low data rate . The 3G offers minimum data rate of 384 Kbps for highly mobile and 2 Mbps for stationary users; Enables wireless internet access, video conferencing, mobile TV and location-based services. 4G provides data rate up to 100 Mbps for high mobility and 1 Gbps for low mobility users; Cellular network is an all IP network; Supports IP telephony and high definition mobile TV. Finally, the 5G wireless network addresses the evolution beyond mobile internet to massive IoT (Internet of Things) from 2019/2020 forwards as shown in the Figure 1.3, bellow. The main evolution compared with today's 4G and LTE advanced is that beyond data speed improvements, new IoT and critical communication use cases will require new types of improved performance.

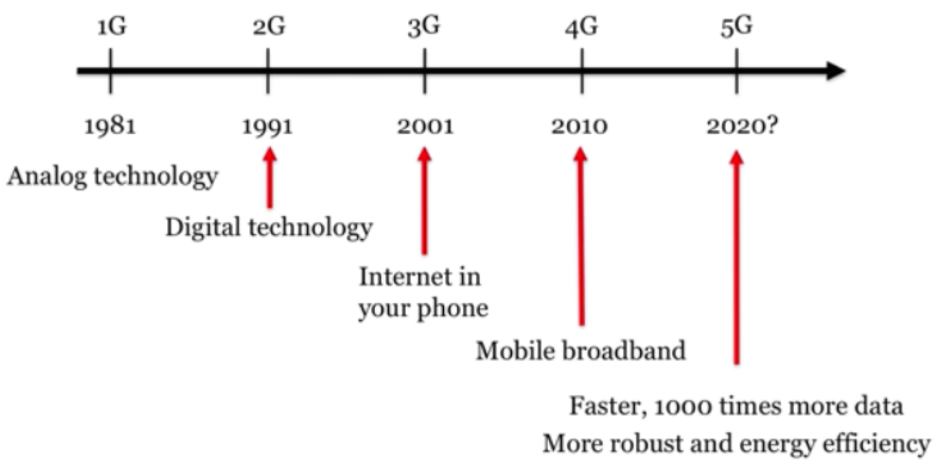

Figure 1.3: Generations of cellular technology [5]

The expectation of 5G wireless technologies

In order to support the exponential growth of existing mobile traffic and the emergence of new wireless applications and services, researchers and standardization bodies worldwide have set out to develop a 5G of wireless networks. Some of the stringent requirements for this next generation of wireless networks are listed in Table 1.1. To meet these challenging requirements, a mere evolution of the current networks is not sufficient.

Table 1.1: Requirements for 5G wireless communication systems [6].

Figure of merit	5G requirement	Comparison with 4G
Peak data rate	10 Gb/s	100 times higher
Guaranteed data rate	50 Mb/s	–
Mobile data volume	10 Tb/s/km^2 1000	times higher
End-to-end latency	Less than 1 ms	25 times lower
Number of devices	1 M/km^2	1000 times higher
Total number of human-oriented terminals	$\geq$ 20 billion	–
Total number of IoT terminals	$\geq$1 trillion	–
Reliability	99.999%	99.99%
Energy consumption	–	90% less
Peak mobility support	$\geq$ 500 km/h	–
Outdoor terminal location accuracy	$\leq$ 1 m	–

1.2.4 Massive MIMO systems

MIMO systems have established significant consideration due to the rising number of served users and increasing demand for large amount of data. Multi-user MIMO systems can provide an innovation technique to enhance wireless communications spectral efficiency. Massive MIMO systems are described as an operation of MIMO scheme in which large amounts of antenna elements are installed at BSs and large amounts of antennas at terminals. In massive MIMO systems, large quantities of antennas associated to BS at the same time work for significantly fewer terminals using similar time and carrier frequency resources [7].

Massive MIMO systems can increase the capacity of 10× or more wireless communication systems due to their characteristics and about 100× in EE. The capacity increase supported by massive MIMO systems is due to the large number of antennas that are applied. However, using a large number of antennas causes interference problems, which can be mitigated by design beamforming antennas rather than conventional antennas [7, 8].

Beamforming is a signal processing system used on the transmitter side and the receiver side with multiple antenna arrays to independently transmit or identify signals from different required terminals to increase the system's capacity and efficiency.

1.2.5 Massive MIMO and small cell networks

Massive MIMO and small cell network have been recognized an encouraging technologies for satisfying the objectives of future high data rate wireless networks. Small cell networks corresponds to a high-density cellular network where the cell radius is small [8]. Traditional WLAN APs typically have a coverage radius of tens of meters. However, large cell sizes may result in a high possibility of poor coverage and low data rates, mostly at the cell boundaries. Particularly for indoor environments, the walls and other large obstacles may strongly attenuate the radio signals, deteriorating the user experience of the WLAN service. By reducing the cell size, a number of benefits can be obtained.

1.3 Statement of problem

Energy efficiency in wireless communication networks appears to be one of the most significant and important issues in 5G systems. Currently, there is an increasing demand of high quality of service, high data rates, network coverage and lesser processing time. Since, the number of users are increasing, which give arise to a lot of problems like increased interference, complexity and significant amount of power consumption in the processing and transmission. Any wireless network's performance limitation will always be on the physical layer because, basically the availability of spectrum, the laws of electromagnetic propagation and the principles of information theory limit the amount of information that can be transferred between the transmitter and the receiver.

Some of the problems are verified to be with the arrival of massive MIMO in the wireless field however, adding small cell networks to making low cost and low precision components for successful cooperation, effective exploitation extra degrees of freedom which have resulted in an excess of service antennas, resource allocation and reducing internal power consumption for achieving total EE reductions.

Among these issues, this thesis is given a strong attention to compute the required power to be transmitted by both MBS and SBS, that is finding the power allocated by the system in order to satisfy the peak power constraints considering total power consumption. The level of interference at the SBS depends upon its transmission power. Thus, the optimal power allocation to meet the system requirement is desirable criteria to enhance the system performance.

1.4 Objectives

1.4.1 General objective

The main objective of this, thesis work is to optimize the power of massive MIMO in heterogeneous network by reducing the total power consumption in the downlink system.

1.4.2 Specific objectives

The specific objectives are:

- To analyze mathematical model that resolves the non-convexity of the original optimization problem by convex approximations for power consumption in order to improve system performance.
- To analyze the system performance, using low complexity algorithm and multiflow regularized ZF beamforming techniques.
- To analyze the required backhaul and received power in terms of antenna number.
- To evaluate energy efficiency in the single cell downlink system.
- To compare the power consumption of homogeneous and heterogeneous networks in a single cell environment.
- To show the effect of number antenna for both MBS and SBS in the system .
- To evaluate the radiated power of MBS and SBS in the downlink system.

1.5 Methodology

In this thesis work, it has been investigated the potential improvements in power optimization by modifying the classical macro-cell with massive MIMO at the BS, which is overlaid with small cell BS. This can be achieved certainly, assigning each user to the optimal transmitter of BS or small cell BS. To combine these small cell BSs to massive MIMO have been proved as one of an efficient way to achieve the maximum EE. The methods used to achieve the desired objectives of this thesis were as follows. First, related literature about massive MIMO BS offers higher data rates due to spatial multiplexing and robustness against fading due to spatial diversity with the same time and frequency resources and small cell BS an efficient way to provide local capacity enhancements, which reduces the average distance among users and transmitters, correspondingly results in lower propagation losses and higher EE. Second, spatial coordination of MBS and SBSs this comes at the cost of highly HetNet topology, it is possible to improve the capacity of the network, with the features like EE and high coverage. Finally, provide using MATLAB simulation results shows the total power consumption can be greatly improved by combining massive MIMO and small cell BSs, this is possible with both optimal and low complexity beamforming.

1.6 Scope of this thesis

This thesis paper contains two basic tasks which, have been accomplished, the first task is to focus massive MIMO and small cell BS, due to the overall performance and coordination issue in the total power consumption, which is the dynamic and static power consumption to analyze the EE, information rate and minimize the transmitted power. Based on that concept using this combination compare different number of antennas in the MBS and SBSs, control the interference between them, non coherent multi flow regularized ZF as beamforming direction and adding low complexity beamforming algorithm to minimize the total power consumption to validate all these by simulation.

The second task is, to analyze static part of power consumption from the total power, which have small and constant value. To maximize the EE optimize the number of SBSs (λ_{SBSs}), number of antennas(N) per SBS, the number of users (K) per cell and optimized the transmitted power (P_{tx}) as the required parameters, perfect channel knowledge and zero forcing precoding. Here in this part analyze only SBSs using Lambert function for mathematical problem which have shown using MATLAB simulation.

1.7 Significance of the study

The significance of this paper comprises of the use of massive MIMO and small SBSs scheme for power optimization.

- In this thesis work, analyzing the potential of massive MIMO and small site BS from an EE perspective.
- Adding small cells to the network and large number of antennas at the macro site BSs to satisfy the user's in future 5G networks.

- This thesis explores future improvements in power optimization by modifying the existing macro site BS with massive MIMO and overlaying it with small site BSs while maintaining a low complexity.
- The other significance is using a geometric approach that analyzes the feasible region governed by the constraints, which gives rise to the optimal radiated power control solution.

1.8 Thesis organization

This thesis work contains six different chapters. These are, chapter one, which includes introduction, capacity scaling dimension of future cellular networks, technological overview of the topic, the statement of problems and objective, methodology, scope and significance of the study. Chapter two is the literature review. Chapter three about massive MIMO and heterogeneous network which contains point to point MIMO , MU MIMO , massive MIMO ,massive MIMO precoding techniques, HetNet components, HetNet deployment. Chapter four is about the proposed system model which includes the analysis and downlink description, channel model, EE, power optimization, Optimal beamforming, SDP, low complexity, stochastic model and performance metrics of SBSs. Chapter five contains simulation results and discussion. And finally, the conclusion of this thesis work and recommendations for the future work are given in Chapter six.

Chapter 2

Litreture Review and Related Work

2.1 Introduction

Massive MIMO is advanced MIMO system used for EE, SE has been expected that multiple users are using single base station or multiple base stations with multiple antenna arrays spatial multiplexing.

Recently, attempts have been made in co-channel deployment techniques, where the available spectrum is fully used during both macro and small cells phase. To explain the underlying ideas, the co-channel TDD and the co-channel reverse TDD modes [25]. However, quality of interference estimation and rejection varies significantly between the co-channel TDD and the co-channel reverse TDD, also it requires tight timing synchronization of all devices.

In addition, spatial blanking techniques are more resource-efficient than interference mitigation techniques, such as almost blank subframes and fractional frequency reuse, which are proposed under the enhanced Inter Cell Interference Coordination (eICIC) in the current LTE standards [27]. This is because spatial blanking techniques avoid the need for orthogonalizing time-frequency resources by spatially blanking out the dominating interference subspace during each time-frequency slot. However, covariance-based blanking relies on quasi-static channels and very sensitive to pilot contamination.

2.2 Related works

Massive MIMO is advanced MIMO system used for EE, spectral efficiency and throughput optimizations. Since, multiple antennas exists at the base station and at the UE side, it has been expected that multiple users are using single base station or multiple base stations with multiple antenna arrays spatial multiplexing.

Recently, attempts have been made in co-channel deployment techniques, where the available spectrum is fully used during both macro and small cells phase. To explain the underlying ideas, the co-channel TDD and the co-channel reverse TDD modes [25]. However, quality of interference estimation and rejection varies significantly between the co-channel TDD and the co-channel reverse TDD, also it requires tight timing synchronization of all devices.

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Lastly, EE-maximization in massive MIMO HetNets has also been attempted through the use of appropriate user association techniques. Conventional user association techniques based on reference signal received power or reference signal received quality may not be suitable for massive MIMO HetNets because these techniques do not perform well for cells with asymmetric transmission powers, number of antennas, and load distributions [25].

Additionally, biasing techniques, which artificially scale the by a bias term to offload traffic from macro-cells to small cells, may not be effective because these methods do not balance traffic within each network tier and are generally based on average performance metrics. Generally, the joint optimization problem of user association, precoding design, and power allocation is known to be non-deterministic polynomial-time hard. Fortunately, in the massive MIMO regime, this problem is decoupled because the asymptotic UE rates are independent of each others cell association. Thanks to this simpliffication, studies such as propose optimal user association algorithms which achieve efficient load balancing, both within and across network tiers [27].

Chapter 3

Massive MIMO based Heterogeneous Networks

3.1 Introduction

MIMO technology has extensively studied during the last two decades and applied to many wireless standards because of its ability to significantly improve the capacity and reliability of wireless systems. It is the multiple antenna technology that develops and provides a significant stay in wireless broadband requirements such as LTE and Wi-Fi for wireless communications.

The primary aspect of MIMO is the use of multiple antennas on the transmitter and receiver sides to provide numerous acceptable signal routes, which will enhance efficiency in terms of data rate and reliability of connections, but at the expense of increased hardware complexity and energy consumption of both ends of signal processing.

Due to the popularity of smart phones, cellular network operators have faced challenges in recent years to meet the exponential traffic growth. This exponential growth in data traffic and the continuous growth of various services and applications started the investigation of the 5G for future cellular systems [9]. In the future, 5G wireless network users will require more data traffic and additional services compared to the current. Massive MIMO and HetNets are both deliberate as critical technologies in the future 5G wireless system due to the ability to achieve massive improvements in network coverage and throughput within restricted system resources. Small cells can be used in combination with macro cells to develop multi tier or HetNets capable of delivering higher capacity and quality than conventional homogeneous networks[10].

To meet future high traffic demands, 5G networks need to be built to enhance network performance in terms of ability, EE, latency, network security and overall robustness [9, 11]. However, a mere evolution of the legacy network architecture could not achieve the dramatic network performance enhancement targeted by 5G. Therefore, the future architecture of the cellular network is requested to incorporate various technologies for radio access. Thus, 5G is not only envision as an evolution of LTE, but it should also consider new potential technologies that were not included in the previous networks.

To address this challenge, a factor of 1000 over the next ten years requires an increase in network capacity. Since spectral resources are scarce, there is universal agreement that can be achieved by densifying the network which, is deploying more antennas per unit area into the network.

3.2 MIMO downlink transmission

Spatial multiplexing, a spatial diversity allows a MIMO BS to transmit different data streams on the same resource block at the same time [15, 23]. If technique, all the transmitted data streams belong to one user, the system is known to operate in the singleuser MIMO (SU-MIMO) mode, where as if the data streams are intended for different users, the system is known to operate in the multiuser MIMO (MU-MIMO) mode. SU-MIMO makes it possible to achieve substantial peak data rates for a single user and MU-MIMO offers good performance trade-off.

As one of the most effective means to improve the system spectrum efficiency, transmission reliability and data rate. As the MIMO implementations, the most modern standard, LTE-Advanced, allows for up to eight antenna ports at the base station and the corresponding improvement is relatively modest. MIMO technology is classify into three categories, whose development occurred during roughly disjoint epochs: Point-to-point MIMO, multiuser MIMO and massive MIMO [7, 8].

3.3 Point-to-point MIMO

Point-to-point MIMO emerged in the late 1990s and represents the simplest form of MIMO. In Point-to-point MIMO, a BS equipped with an antenna array serves a terminal equipped with an antenna array, with both arrays connected by a channel such that every receive antenna is subject to the combined action of all transmit antennas [7].

Consider a narrowband point-to-point MIMO communication system equipped with N_t antennas at the transmitter and N_r antennas at the receiver, as shown in Figure 3.1. Different terminals are orthogonally multiplexed, for example via a combination of time and frequency division multiplexing. In each channel use, a vector is transmitted and a vector is received. In the presence of additive white Gaussian noise at the receiver, Shannon theory yields the following formula for the link SE (in b/s/Hz):

$$C^{DL} = \log_2 \left| \mathbf{I}_K + \frac{\rho_{DL}}{N} \mathbf{G}\mathbf{G}^H \right| \tag{3.1}$$

where, G is an $N \times K$ matrix that represents the frequency response of the channel between the BS array and the terminal array and ρ_{DL} is downlink SNR, which is proportional to the corresponding total radiated powers, N is the number of BS antennas and K is the number of terminal antennas.

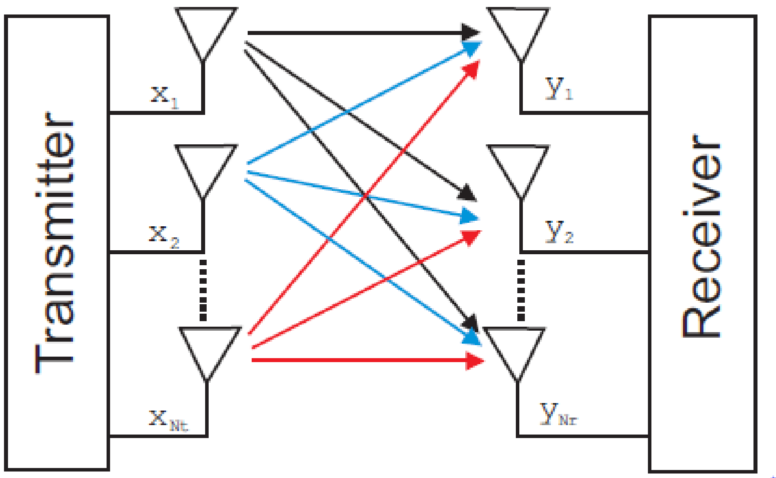


Figure 3.1: point to point MIMO [8]

3.4 Multiuser MIMO

A multiuser MIMO concept is for a BS to serve a multiplicity of terminals using the same time-frequency resources, which illustrated in the Figure 3.1. Effectively, the multiuser MIMO scenario is obtained from the point-to-point MIMO setup by breaking up the K antenna terminal into multiple autonomous terminals. MIMO, technology relies on multiple antennas to simultaneously transmit multiple streams of data in wireless communication systems.

MU-MIMO in cellular systems brings improvements on, increased data rate, because the more antennas, the more independent data streams can be sent out and the more terminals can be served simultaneously, improved EE and reduced interference. Hence, in the setup in Figure 1.3 the BS serves K terminals. Let G be an $N \times K$ matrix corresponding to the frequency response between the BS array and the Kterminals. The

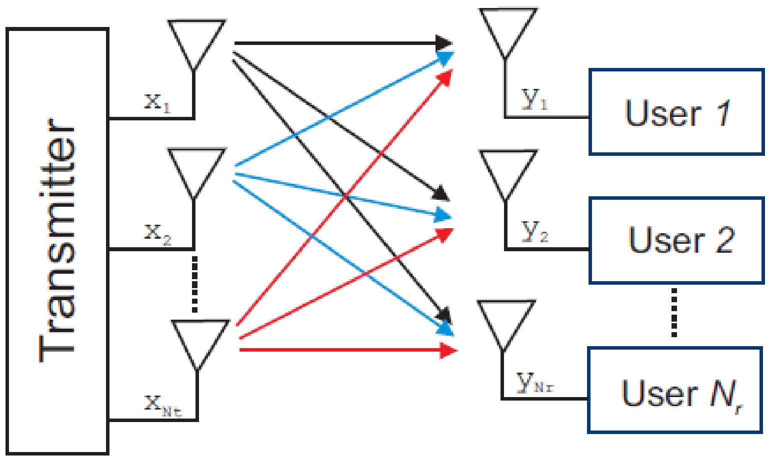


Figure 3.2: Multi User MIMO [8]

downlink spectral efficiency of MU MIMO is given as

$$C^{DL} = \max_{(v_k \geq 0, \sum_{k=1}^{K} v_k \leq 1)} \log_2 \left| \mathbf{I}_N + \rho_{DL} \mathbf{G} \mathbf{D}_{\mathbf{v}} \mathbf{G}^H \right| \tag{3.2}$$

$\mathbf{v} = [\boldsymbol{v}_1, , , , , , , , \boldsymbol{v}_{\boldsymbol{K}}]^T$, ρ_{DL} is the downlink SNR. The computation of downlink capacity according to Eq.3.2 requires the solution of a convex optimization problem.

Note that the terminal antennas in the point-to-point case can cooperate, whereas the terminals in the multiuser case cannot. Multiuser MIMO has two fundamental advantages over Point-to-Point MIMO. First, it is much less sensitive to assumptions about the propagation environment. For example, LoS conditions are stressing for Point-to-Point MIMO, but not for Multiuser MIMO. Second, Multiuser MIMO requires only single-antenna terminals. Notwithstanding these virtues, two factors seriously limit the practicality of multiuser MIMO in its originally conceived form.

3.5 Massive MIMO

The next generation mobile networks alliance believes that 5G should be brought out by 2020 to satisfy the continuously increasing demand for higher data rates, higher EE, larger network capacity and higher mobility required by new wireless applications. The industry generally believe that compared to 4G, the 5G network should increase the system capacity by 1000 times, enhance the SE, EE and data rates by 10 times and increase the average cell throughput by 25 times [9].

Massive MIMO is an emerging technology, which scales up MIMO by possibly orders of magnitude compared to current state-of-the-art. Massive MIMO relies on spatial multiplexing that in turn relies on the base station having good enough channel knowledge, on both the uplink and the downlink.

Massive MIMO have many advantages, which comprises of the use of inexpensive low power components and reduced latency. First, only the base station gets CSI. Thanks to channel hardening, no channel estimation is required at the terminals. By operating in TDD mode and exploiting reciprocity of the propagation channel, the amount of resources needed for pilots only depends on the number of simultaneously served terminals, K. This renders massive MIMO entirely scalable with respect to the number of base station antennas, N. When N is large, linear processing at the base station is nearly optimal[7, 8].

The asymptotic Shannon capacities on the downlink (C^{DL}) for a multiuser MIMO channel under favourable propagation are given by [8]

$$C^{DL} = \max_{(a_k \geq 0, \sum a_k \leq 1)} \log_2(1 + p_{d,k} N a_k \beta_k) \tag{3.3}$$

where $p_{d,k}$ is the downlink signal to noise ratios (SNRs) for the k^{th} UE, β_k represents the large-scale fading coefficient for the k^{th} UE, and $a_k, k = 1, 2, ...K$ is an optimization vector to obtain (C^{DL}).

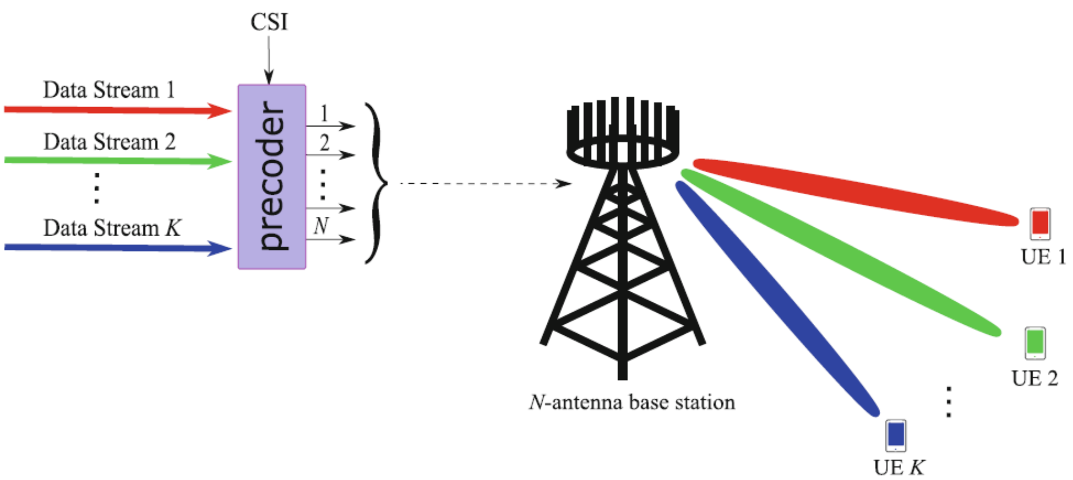


Figure 3.3: Example of a downlink massive MIMO system where the base station antenna number N is larger than the number of UEs K. Data streams are simultaneously transmitted to all UEs in the cell [12]

It is a form of multi-user MIMO where BS deploys an antenna array with hundreds of active elements to serve tens of active UEs in the same time frequency resource block [12, 13]. Figure 3.3, illustrates the concept of a typical downlink massive MIMO system, where multiple data streams for different intended UEs are precoded using CSI estimated from training phase, and sent out simultaneously from the BS. It has been shown that as the BS antenna array scales up, beams steered at different UEs will eventually be almost orthogonal to each other. In this regard, massive MIMO enables each of its UEs to enjoy a wireless channel which, have high power gain and small crosstalk.

3.5.1 Massive MIMO challenges

Massive MIMO technology depends on phase-coherent but computationally very simple processing of transmissions from all the base station antennas. Large amounts of data are generated in typical massive MIMO systems with large antenna arrays. The data needs to be processed in an efficient manner and simple processing methods are therefore required. The simple methods can preferably be linear, but performance of linear processing may not be accurate enough in some cases [14]. This presents a need for fast converging non-linear precoding or beamforming algorithms.

Since massive MIMO relies on the law of large numbers, the large number of RF chains required presents increased costs and energy consumption. Thus the equipment is likely to be low cost and hence relatively inaccurate. This means that massive MIMO systems are more prone to errors in CSI acquisition due to hardware impairments. In addition, operation with the TDD scheme requires reciprocity calibration, which has to be performed regularly. In order to address these challenges, the concept of hybrid beamforming has been proposed for massive MIMO systems. Hybrid transceivers use analog beamformers in the RF chains, coupled with digital beamforming in the baseband through up/down converters [15].

In a multi-cell massive MIMO system the number of available orthogonal pilot sequences used for channel estimation can easily be exhausted. The negative effects that result from the reuse of pilot sequences in adjacent cells in a multi-cell network are termed pilot contamination [16]. Using contaminated channel estimate results for downlink beamforming results in users using the same pilots experiencing interference. Some pilot contamination coordination techniques for large-scale antenna systems are based on BS coordination and applying pilot contamination precoding [17–20].

3.5.2 Massive MIMO for interference elimination techniques

There are some linear precoding techniques for downlink transmission in massive MIMO system.

ZF precoding

The ZF precoding method eliminates inter-user interference by transferring the signal to the expected user and forcing zeros into the direction of other users. By assuming perfect CSI at the transmitter, the ZF precoding scheme ensures zero interference, although this comes at a cost of reduced power received by each user [17]. This results in the users having low QoS in terms of data transmission rate. The ZF precoding scheme makes use of a pseudo-inverse of the channel matrix to determine the precoding matrix, W^{ZF}, which is given by [14],

$$\mathbf{W}^{ZF} = \mathbf{H}^{H}(\mathbf{H}\mathbf{H}^{H})^{-\mathbf{1}} \tag{3.4}$$

Where $\mathbf{H}^{H}$is the is the Hermitian inverse of the channel matrix $\mathbf{H}$.

MMSE precoding

MMSE precoding is an optimal precoding technique that obtains the precoding matrix by minimizing the MSE subject to power constraint [18]. By applying the Lagrangian method with the average power constraint at each transmit antenna, the optimal MMSE precoding matrix is

$$\mathbf{W}^{MMSE} = \mathbf{H}^{H}(\mathbf{H}\mathbf{H}^{H} + \alpha\mathbf{I}_{K})^{-1} \tag{3.5}$$

$\alpha = \dfrac{K}{pb}$ with K being the number of users served by the BS with power limit pb and $\mathbf{I}_K$ being a $K \times K$ identity matrix. It is concluded that the precoding technique of MMSE provides optimal precoding through a trade-off between suppression of interference and EE.

MRT precoding

MRT is a linear precoding technique that maximizes SNR for the users, and it is best suited to application in massive MIMO with low signal power transmission [19]. MRT has an additional advantage over ZF in that it can be implemented in a distributed massive antenna system. It was shown that by increasing the number of antennas at the BS while keeping the number of users fixed.

$$\mathbf{W}^{MRT} = \alpha I_{MRT}\mathbf{H}^{H} \tag{3.6}$$

Where αI_{MRT} is a normalization constant, which ensures that the BS transmit power constraint, is satisfied.

Regularized zero forcing

RZF was developed with the aim of achieving the near optimal performance of ZF in practical applications [20]. It is a precoding technique that is applicable to distributed massive MIMO systems, where the overall beamforming calculations are broken down into smaller, less complex calculations carried out in groups [20]. RZF is different from ZF which introduces a regularizing parameter and a set of linear precoders can achieve an RZF framework by choosing this parameter correctly. The precoding matrix for the RZF method is provided by

$$\mathbf{W}^{RZF} = (\mathbf{H}\mathbf{H}^{H} + \mathbf{F}_{dh} + \beta\mathbf{I}_{M})^{-1}\mathbf{H} \tag{3.7}$$

Where F_{dh} is a deterministic Hermitian non negative matrix and for the considered setups, to derive the effective SINR at a given UE for the RZF precoder as N, K $\longrightarrow \infty$, while the ratio $\frac{N}{K} = \beta$ is fixed regularizing parameter value 2, $\mathbf{I}_M$ being a $M \times M$ identity matrix. It has been shown that by reducing the multiuser interference, RZF significantly outperforms MRT and they both achieve the same performance when RZF have an order of magnitude fewer antennas per user terminal.

3.5.3 Backhauling

Backhauling is the transmission of data back to the basic core network from the base station, either through a direct link to the core network or via online connection [21]. It is possible to provide point-to-multipoint wireless backhaul from the MBS to a fraction of the SBSs with massive MIMO infrastructure in place.

Support the backhaul traffic from radio switch to cell site wirelessly becomes popular due to the viability and cost-efficiency. Wireless backhaul allows operators to control their network an end-to-end principle instead of leasing wired backhaul connections from third parties [22]. However, the optimal selection among wireless backhaul solution depends on several factors that includes cell site location, propagation environment, desired traffic volume, interference conditions, cost efficiency, EE, hardware requirements and the availability of spectrum [23].

Massive MIMO BS ensure coverage and serve highly mobile UEs while the SBSs provide high capacity for indoor and outdoor hotspots. The unrestrained small cell deployment "where needed" rather than "where possible" requires a high-capacity and easily accessible backhaul network [22].

Massive MIMO for wireless backhaul

Massive MIMO plays a key role in HetNets to ensure coverage over large areas and to serve fast-moving UEs. A two tier network consisting of massive MIMO BS and SBSs together with a synchronized TDD protocol allows the BSs to use their excess antennas to reduce intratier interference. Massive MIMO is also a promising solution for wireless backhaul provisioning to a large number of SBSs, without the need for LoS links [23]. Massive MIMO for wireless backhaul have the following additional advantages:

- No standardization or backward compatibility required for backhauling, manufacturers can use proprietary solutions and rapidly integrate technological innovations.
- The MBS - SBS channels vary very slowly with time, due to the fixed deployment.
- In wireless backhaul links, SBSs only require a power connection to be operational.
- Line of sight not necessary if operated at low frequencies.

Consider the massive MIMO cellular network with a single cell BS having N antennas, that operate according to a synchronous TDD protocol. Additionally, simplifying assumption that a BS have N antennas and serve S SBSs each and that perfect CSI is available.

A power minimization algorithm from [24], which allows to fix a desired SINR target γ_{ts} for each backhaul link in each cell and to find the precoding vectors $\mathbf{w}_{ts}$ and transmit powers η_{ts} that achieve the minimum necessary total transmit power.
In other words, to solve the optimization problem, $\mathbf{w}_{ts}$ is the beamforming vector of BS $\boldsymbol{t}$ towards SBS $\boldsymbol{s}$ in its cell, γ_{ts} is the target SINR of the backhaul link to SBS $\mathbf{s}$ in cell $\mathbf{t}$, SINR_{ts}^{DL} is the donlink SINR of the backhaul link to SBS $\boldsymbol{s}$ in cell $\boldsymbol{t}$: where $h_{mts} \in C^{N\times 1}$ is the channel from BS to SBS $\boldsymbol{s}$ in cell $\boldsymbol{t}$ and $\boldsymbol{L}$ is the number of of BSs.

$$\begin{aligned} \underset{\{\eta_{ts}, w_{ts}\}}{\text{minimize}} \quad & \sum_{t=1}^{L}\sum_{s=1}^{S} \\ \text{subject to} \quad & \text{SINR}_{ts}^{DL} \geq \gamma_{ts} \quad t=1,...,L, s=1,...,S \\ & \|\mathbf{w}_{ts}\| = 1 \quad t=1,...,L, s=1,...,S \end{aligned} \tag{3.8}$$

Where $\eta_{ts}, \mathbf{w}_{ts}$ denotes the set of transmit powers and precoding vectors respectively , and

$$\mathrm{SINR}_{ts}^{DL} = \frac{\eta_{ts}|\mathbf{w}_{ts}^{H}\mathbf{h}_{ts}^{t}|^2}{\sum_{l=1}^{L}\left(\sum_{i=1(l,i)\neq(t,s)}^{S}\eta_{li}|\mathbf{w}_{li}^{H}\mathbf{h}_{ts}^{t}|^2\right)+\sigma_{DL}^2} \tag{3.9}$$

is the instantaneous SINR of SBS s in cell t. The solution to 3.8 is provided by the following proposition.

Proposition 3.1([24]). The solution to 3.8, if it exists, is given by η_{ts} and $\mathbf{w}_{ts}^{*} = \frac{\mathbf{u}_{ts}^{*}}{\|\mathbf{u}_{ts}^{*}\|}$ for t = 1, . . . ,L, s = 1, . . . , S, where

$$\mathbf{u}_{ts}^{*} = \left(\sum_{l=1}^{L}\sum_{i=1}^{S}\zeta_{li}^{*}\mathbf{h}_{li}^{t}(\mathbf{h}_{li}^{t})^{H}+\mathbf{I}_M\right)^{-1}\mathbf{h}_{ts}^{t} \tag{3.10}$$

This solution can be computed by a standard fixed-point algorithm which iteratively updates ζ_{ts}^{*} starting from some random initial values.

$$\zeta_{ts}^{*} = \frac{\left(1+\frac{1}{\gamma_{ts}}\right)^{-1}}{\left(\mathbf{h}_{ts}^{t}\right)^{H}\left(\sum_{l=1}^{L}\sum_{i=1}^{S}\zeta_{li}^{*}\mathbf{h}_{li}^{t}(\mathbf{h}_{li}^{t})^{H}+\mathbf{I}_M\right)^{-1}\mathbf{h}_{ts}^{t}} \tag{3.11}$$

for t = 1,...,L and s = 1,...,S, where η_{ts}^{*} s are the unique solutions to the set of equations

$$\frac{\eta_{ts}^{*}}{\gamma_{ts}}\left|\left(\mathbf{w}_{ts}^{*}\right)^{H}\mathbf{h}_{ts}^{t}\right|^2-\sum_{i=1,i\neq s}^{S}\eta_{ti}^{*}\left|\left(\mathbf{w}_{ti}^{*}\right)^{H}\mathbf{h}_{ts}^{t}\right|^2-\sum_{l=1,l\neq t}^{L}\sum_{i=1}^{S}\eta_{li}^{*}\left|\left(\mathbf{w}_{li}^{*}\right)^{H}\mathbf{h}_{ts}^{t}\right|^2=\sigma_{DL}^2 \tag{3.12}$$

Eq. 3.12, can be written in a matrix form and solved through matrix inversion. Note, that if 3.8 is infeasible, no solution to 3.11 is found or the fixed-point algorithm does not converge.

3.6 Heterogeneous network

In modern wireless system devices, such as smartphones, tablets and laptops, are generating more indoor traffic than outdoor, leading to an inhomogeneous data demand across the entire network. However, the conventional cellular networks are designed to cover large areas and optimized under homogeneous traffic profile, thus facing the challenge to meet such unbalanced traffic profile from different geographical areas [25].

HetNets comprise of macro cell coverage overlaid with the small cell having different transmit power, coverage and capabilities. A promising solution for the future generation wireless networks to manage with the demands for better coverage and higher data rates is the deployment of heterogeneous network, which consists of smaller, cheaper and less energy consuming base stations. The use of HetNets have the potential to provide both the required coverage and increase the data rates of the end users [26].

3.6.1 Heterogeneous network deployment

There are two different approaches to heterogeneous deployment both of which provide support for excessive range expansion [27].

- Resource partitioning and
- Shared cells (Soft-cell) schemes

Resource partitioning

To enable resource coordination among base stations, two different sets of resources may be allocated for the two classes of nodes; namely high power (MBS) and low power base stations (SBSs) [27]. By limiting the transmission of macro cells from using the same time-frequency resources as the low power node, can be protected from the low power node to the terminal [28]. .

Resource partitioning can be implemented also, into two ways

- Frequency domain partitioning.

The resources can be frequency domain (groups of sub-carriers) in a synchronous system. By installing control signaling from the macro and low power nodes on separate carriers, this technique protects downlink control signaling from the low power node in the range expansion region. Assuming low-power node transmissions are synchronized with the overlying macro, there is no major interference from the macro node to the control signaling on the carrier in the range-expansion area. At the same time, data transmissions can still benefit from the complete bandwidth of both carriers by using carrier aggregation [27, 28].

- Time domain partitioning.

The resources can be time domain (slots or sub-frames) in a synchronous system. By reducing macro transmission activity in certain subframes, this technique prevents downlink control-signaling from the low-power node [28].

In both, frequency and time domain partitioning schemes, low power nodes create new cells, with individual cells identities that differ from the macro cell identity. As a consequence, each low power node transmits unique system information and synchronization signals; that is to say, each of these cells has separate broadcast channel, cell-specific reference signal, primary synchronization signal and secondary synchronization signal [27].

The soft cell approach

In the shared cells approach, low power nodes and the macro station do not create new cells; therefore, they are all part of the same cell. This fact leads to a cell with a unique cell identity and synchronization signals but with more than one transmission points. As a result, different types of information can come from different sites, or in other words, different transmission point, which are transparent to the UE [27].

So coordination between low power nodes and the macro station is one of the most important issues in this approach. A terminal can derive the cell-specific reference signal structure from the cell with the cell identity information and get the system information it needs to access the network. On the other side, a transmission point is also just one or more collocated antennas from which a terminal can receive transmissions of data [28].

This technique has some important benefits compared to the previous resource partitioning technique. Since there is only one cell formed by low power nodes and the macro site, the deployment is easier because careful cell planning is not needed. Specified that low power nodes can turn off their transmissions when they are not necessary, it is possible to say that this technique is energetically efficient.

The soft cell scheme also allows an efficient use of the spectrum as there is no problem with cell-specific reference signal interference. In addition, to these advantages, due to the fact that transmission nodes are transparent to UE, soft cells can provide greater mobility robustness than deployments with separate cells [27]. Traditional, handover procedure is not required when moving between macro and low power nodes, so the probability of dropped connections is lower, which further enhance the performance of the soft-cell system.

In practice, this link should use high-speed microwave or optical fiber as it needs low latency and a relatively high-capacity connection for tight coupling between macro and low power nodes, where control and data signaling originate from different transmission points [28]. With the exception of avoiding much of interfering with cell-specific reference signal transmissions, heterogeneous deployments using soft cells can provide greater robustness of mobility than separate cell deployments [27, 28].

3.6.2 Classification of heterogeneous network

Classical macro cell topology is inadequate to handle exponential growth of users and their demand for data. Hence, need to gratify such a large number of users brings the concept of heterogeneity in a cellular network. HetNets consist of macro cell coverage overlaid with the small cell having different transmit power, coverage and capabilities [21]. Therefore, this subsection briefly discuss about different types of small cell. Table 3. 1 summarizes the classification and various features of small cells.

Table 3.1: Specification of different nodes in HetNet[21].

Type	**Range**	**Tx.Power**	**Backhaul**	**Applications**	**Capacity**
Macrocell BS	Few km	46 dBm	Dedicated wired	outdoor	$<$ 1000 users
Pico cell BS	100m	33 dBm	Wired	indoor/outdoor	$10 - 50$ users
Femto cell BS	10 - 30m	20dBm	Wired/wireless	Indoor	<5 users
Relay	100m	33dBm	wireless	indoor/outdoor	$10 - 50$ users
RRH	Few km	46 dBm	Optical fiber	outdoor	$<$ 1000 users

Pico cell

Picocell BS is a low power, operator-deployed wireless access point using the same backhaul and access features compliant with classical macroce. It has small physical dimensions, in which an antenna radiating a transmit power ranging from 23 to 30 dBm is usually integrated [29]. It should be noted that omnidirectional antenna is typically installed, different from the directional antenna used for macrocell BSs. By covering a radio range of 300 m and serving a few tens of mobile users, picocell can be deployed to fill the macrocell coverage hole, or provide extra data service in the wireless hot spot areas. Furthermore, through the capacity data offloading effect, more frequency-time resources of the macrocell networks can be released, which is beneficial to macrocell terminals as well [26].

Femto cell

Being an important part of HetNet, femtocell BS in the 3GPP standard, is usually defined as a low power device operating in the licensed spectrum. Backhauled onto the operator's network via the wired internet connection, such as digital subscriber line, cable broadband access, or fiber, femtocells are designed to provide voice and high data-rate sustained services for indoor environments, where a majority of user traffic comes from [30].

Because of offloading indoor traffic from the macrocells to femtocells and employing smaller cell sizes, femtocells bring a multitude of benefits, including more efficient spatial reuse of spectrum, enhanced coverage and capacity for indoor applications, reduced capital costs and operational costs, better user experiences, and lower churn of subscribers. Aiming to cover a range less 30 m, the femtocell BS is operated with a transmit power less than 23 dBm [30].

Relay

Relay nodes have almost same transmission power and range as those of pico cells, but connected to the core network through wireless backhauling. The major purpose of its deployment is to improve edge performance and provide coverage to a dead zone users in the macro cell. Relay nodes are armed with directional antennas to establish backhaul links and with omni-directional antennas for access link establishment.

Remote radio head

RRH are high power, compact, low weight units mounted outside the macro BSs and connected through a fiber optic cable. The central macro BS takes charge of the control and signal processing. RRHs reduces power consumption and eliminate power losses in antenna cable as some radio circuitry are moved to the remote antennas [16]. It provides flexibility to the operators in deploying networks especially for those facing physical limitations or site acquisition problems.

Chapter 4

Proposed System Model

4.1 Introduction

The traditional radio coverage network is a macrocell topology, this network is used to provide the large area coverage for mobile network. However, it could not manage the extremely surging mobile users and quality of service which includes EE, capacity of the network. Now, mobile users want faster data rate and more reliable service. In order to deal with the explosive increase in mobile data traffic, the 5G communication system have been at the head of theoretical research in wireless communications [8].

According to the expectations of 5G networks, it can be anticipated that energy consumption is one important concern. Among these problems, this section focus on optimizing the power consumption. Massive MIMO and HetNets are currently the two known promising and efficient solutions for achieving high data rates, coverage gain and addressing the continuous demand for ubiquitous mobile broadband services. The most important need of massive MIMO is channel acquirement which uses time-division duplexing for the exploitation of channel reciprocity. Time division duplexing limits the accuracy of channel estimation by the number of users and not with the number of BS antennas [8]. HetNet deployments are an other promising alternatives that improve network capacity, to expand coverage and improve spectrum and EE at low cost of deployment.

4.1.1 Combination of massive MIMO and small cell base stations

Complementing high-power massive MIMO macro cell BS with lower-power SBSs is an interesting way to meet the expected demands for higher data rates and additional capacity [28]. Here, the two network combination of multiple antenna system motivated from massive MIMO and small cell at the BSs by minimizing the total power consumption (static and dynamic) and satisfying QoS constraints , simultaneously [31].

The first and the primary method is to develop a massive MIMO network by deploying large number of antennas in the form of antenna arrays at existing macro base stations which helps in precise focusing of emitted energy on the specific users [31]. The second technique in this chapter's mainly stay, which helps in optimizing power. An overlaid layer of small cell BS is deployed in this method that helps to offload traffic from BS.

Small cells are an efficient means of improving local capacity such as urban hotspots ,campus, super market and other public areas. Therefore, most data traffic is sited and demanded by users with low mobility, which reduces the average distance between users and transmitters, leading to lower propagation losses and higher EE [32]. But, this comes at the cost of highly heterogeneous network topology, which is difficult to control and coordinate and thus give rise to inter-user interference. To meet this challenge, researchers around the globe are now flowing their interest from small cells deployed by the user and emphasizing small cell access points deployed by the operator. The key objective behind the emphasis is that small cell access points depends on reliable backhaul connectivity and coordination of base station and small cell access points.

In HetNets, gains in spatial reuse are utilized through the deployment of small cells through extreme network densification [33]. Small cell base stations are relatively low-power nodes with one or very few antennas and higher performance and expanded coverage is obtained by substantially reducing the distance between small cell users (SUEs) and SBSs. By exploiting the channel vectors spatial directionality in massive MIMO, very effective inter tier interference management with comparatively low complexity can be obtained [32].

Small cell deployment improves coverage and SE, as mobile devices are closer to base stations. In addition, high SE and EE are achieved by base station equipped with a large number of antennas [34]. Heterogeneous networks with massive MIMO are therefore viewed as a powerful 5G architecture. While both small cell network and massive MIMO are considered as important techniques for achieving high SE and EE. The two key challenges are backhauling and interference management while deploying small cells in the real world. Massive MIMO systems have remarkable properties to reduce or almost eliminate interference in the heterogeneous network as they are more targeted and nullify interference from the use of beamforming by small cell users. As it provides wireless backhaul to small cell and can serve the active users simultaneously and thus improves the backhaul capacity and overall performance of the cellular network.

4.1.2 Single cell downlink system model

In today's wireless networks, due to several factors and limits like restricted resource, bandwidth and energy is an important technical problem. Also due to coexisting and sharing of same spectrum by several wireless networks leads to interference between different networks. These problems can be tackled by using various techniques of optimization

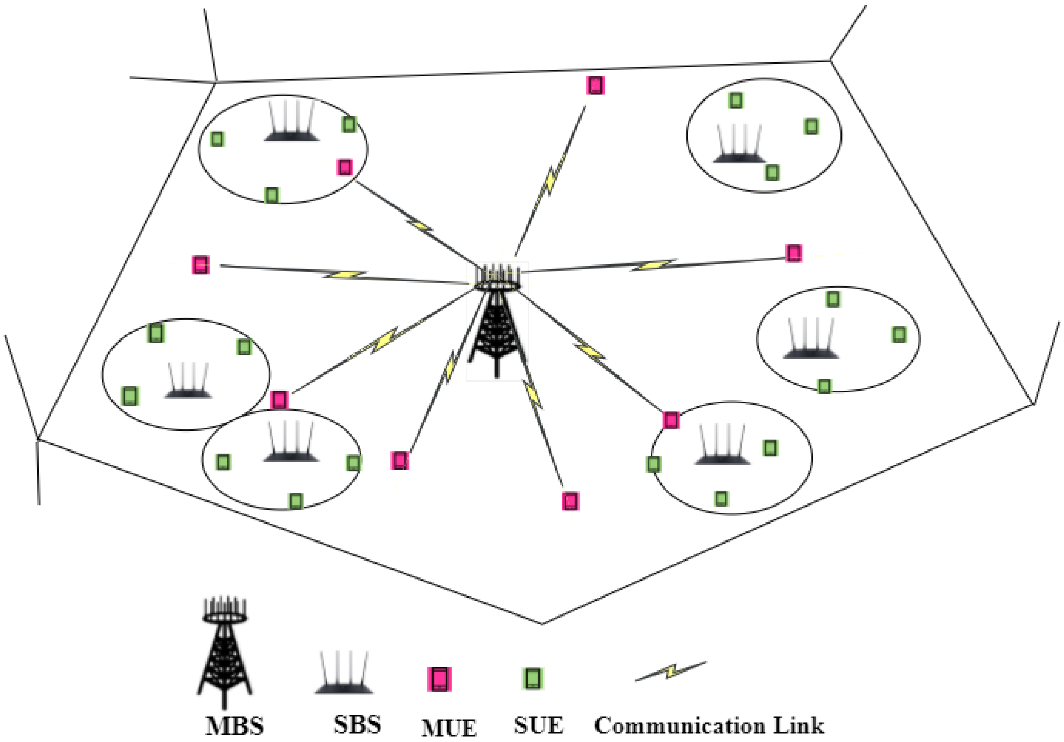


Figure 4.1: System model of massive MIMO macro cell base station combined with spatial distribution of SBSs having $N_{SBS} = 4$ antennas per SBS and K = 3 UEs uniformly distributed within each cell.

such as linear, convex, semi-definite approximations.

Convex optimization has appeared in recent history as the most suitable methods for algorithm design and study of wireless communication systems. Convex optimization techniques are a great achievement due to some unique features. It has established to be the most suitable methods for designing algorithms and studying wireless communication systems in the past. Because of some distinctive features, convex optimization methodologies is a tremendous success. The first and most important reason that makes it easy to use in wireless communication systems implemented is its fast and efficient algorithms that solve convex problems. The second reason helps to achieve sight in the ideal buildings of the solution, which exposes the nature of the wireless communication problems. The last reason for its achievement is that it is already relatively well known and makes it interesting for engineering applications [35].

Power optimization can be obtained from both the static and the dynamic part where the static part depends on the transceiver hardware and a dynamic part is connected to the emitted signal power [36]. In the dynamic part, massive MIMO and small cell network promise potential progress, but at the cost of extra hardware. So it's a better alternative to intensify the static part. In addition, it is essential that the dense network topologies should be properly deployed and optimized for real improvement in the overall EE.

At the BS, massive MIMO uses hundreds of antenna elements to serve tens of users simultaneously at the same time as the time-frequency resource block (RB)[32]. Not only does the large size of the transmit antenna array considerably increase the capacity with excessive spatial dimensions, it also averages the impact of fast channel fading and offers extremely sharp beamforming focused in small areas [36]. Besides from these, the high degrees-of-freedom offered by massive MIMO can also reduce the transmit power.

On the other side, densely deploying low power access points into traditional high power macrocells, a small cell improves the system capacity [42]. In this way, the distance between the transmitter and receiver can be significantly reduced, which results in remarkably enhanced rate gains. Since small cells do not always have direct links to the macro BS, they can be wisely deployed in accordance with the demand for traffic without much cost on the fiber usage.

Massive MIMO is implemented in macro cells, where each MBS have N antennas and communicates with K users simultaneously over the same time and frequency band, $N \gg \mathrm{K} \geq 1$, whereas each SBS and user is a single antenna node [43]. To transmit K data streams with equal power assignment, each MBS uses linear zero force beamforming. Consider the perfect downlink CSI and reuse of universal frequency so that all levels share the same bandwidth. All the channels undergo independent and identically distributed (i.i.d.) quasi-static rayleigh fading.

4.1.3 System model analysis and downlink description

The system model consists of the combination of both massive MIMO and small cell base stations such that the power constraints at the SBS and macro base station (MBS) are fulfilled without compromising on QoS constraints. This work analyzes the power optimization by employing massive MIMO at the base station and overlaying with small cell base stations [44].

Consider a two-tier massive MIMO, HetNet downlink system model where macro BS is overlaid with small BSs. There are S number of SBSs, where $S \geq 0$, which are deployed in a macro cell's coverage area as shown in above Figure 4.1. The MBS and SBSs use non-coherent joint transmission coordinated multipoint beamforming to deliver information for K single antenna users.

In this way, the MBS and SBSs cooperate in transferring data to the users, but every BS sends a separate stream of data. The MBS is equipped with N antennas and SBSs are equipped with N_{SBS} antennas each, typically $1 \leq N_{SBS} \leq 4$, characterized by strict power constraints that limit their coverage area. In comparison, the MBS has large power constraints that can support high QoS targets in a large coverage area. The number of antennas, N_{MBS} in the macro site BS which $N \gg K$ and the number of antennas in the one of small cell BS or j^{th} SBS is defined as N_j. The TDD protocol is considered to be a primary enabler for estimating channel reciprocity without additional overhead [44].

4.1.4 Channel model

Channel models are the most important and desirable part of communication system. Its importance in wide range of applications like in modulation, coding and multi antenna system design. It is also useful in the selection of channel estimation method and channel equalization. Since radio, propagation has a substantial impact on the performance of future broadband systems so channel models have to be accurate. This point is suitable for massive MIMO radio communication systems in which degrees of radio channel freedom in space, time, frequency, and polarization can be used to satisfy the user's requirements in terms of bit rate, spectrum efficiency, and cost [44].

For the structure model, assuming that the channel conditions are known at both sides of the channel. The channels between users and access points are consider as block at fading, while for base station and small cell access points, the access points and users are perfectly synchronized and coordinated with the TDD protocol, which perfect CSI is available at the BSs. Each channel is equivalent to the combination of small scale fading and large scale fading.

Consider the fading distribution of rayleigh as small scale fading. The large scale fading include path loss, shadowing, penetration loss and the antenna correlation loss in massive MIMO BS [44].

There are some parts of channel parameters in the macro site BS and small cell BSs [45].

Path and penetration loss within 40 m from SBS point PL_{SBS-40},

$$\mathrm{PL}_{SBS-40} = 127 + 30\log_{10}\mathbf{d}(\mathrm{km}) \tag{4.1}$$

Path and penetration loss at distance **d** (km) PL_{MBS}

$$\mathrm{PL}_{MBS} = 148.1 + 37.6\log_{10}\mathbf{d}(\mathrm{km}) \tag{4.2}$$

Noise floor (NF) in dBm,

$$\mathrm{NF}(dBm) = -174 + 10\log_{10}(\mathbf{B}_s) + \mathbf{N}_f \tag{4.3}$$

where **d** is the distance(km), $\mathbf{B}_s$, is subcarrier bandwidth, $\mathbf{N}_f$ = -127dBm, is noise figure and the pass loss (**PL**) = 20dB and Standard deviation (**SD**) = 7dB respective order.

4.2 Power consumption model

The main objectives of this section are to maximize EE by minimizing total power consumption while supporting each user's QoS constraints.

Considering that the channel matrix $h_{k,j}$ presented, before it is perfectly known at transmitters and receivers by channel estimation [45]. The channel between the k^{th} user and the MBS and between the k^{th} user and the j^{th} SBS is denoted by $h_{k,0} \in C^{N_{MBS \times 1}}$ and $h_{k,j} \in C^{N_{SBS \times 1}}$, respectively.

So the total received signal at k^{th}user is model as

$$y_k = h_{k,0}^H \mathbf{w}_{k,j} x_{k,j} + \sum_{k=1, j\neq k}^{K} \left(\sum_{j=0}^{S} h_{k,j}^H x_{k,j} \mathbf{w}_{k,j} \right) + b_k \tag{4.4}$$

where $x_{k,j}$ is the data transmitted from antenna j to user k, and **W** indicates the beamforming matrix. The last term in Eq.4.4 where $b_k \sim CN(0, \sigma_k^2)$ is refers to the symmetric complex Gaussian receiver noise received unwanted signal with zero-mean and variance σ_k^2 which is expressed in milliwatts(mW).

In this paper, multiflow regularized zero-forcing (MRZF) beamforming is adopted for MBS downlink. Here the MBS and SBSs are linked by a backhaul network which have a soft cell type allocation of resource, but for non-coherent linear communication which infers to be, information symbols would be emitted immediately but each user are served by multiple transmitters which is termed to be something like spatial multi-flow transmission. This would enable users covered by one SBS to receive additional signal from the other SBSs or MBS [46].

4.2.1 Quality of service

The QoS constraints is the information rate that each user must achieve in parallel.

$$\mathrm{R}_k = \log_2(1 + \mathrm{SINR}_k) \tag{4.5}$$

These are defined as $\log_2(1 + \mathrm{SINR}_k) \geq \gamma_k$ Here, γ_k is the QoS target and SINR_k is given in Eq.4.5 of the k^{th} user as follows [47].

$$\mathrm{SINR}_k = \frac{|h_{k,0}^H \mathbf{w}_{k,0}|^2 + \sum_{j=1}^{S} |h_{k,j}^H \mathbf{w}_{k,j}|^2}{\sum_{i=1, i\neq k}^{K} \left(|h_{k,0}^H \mathbf{w}_{i,0}|^2 + \sum_{j=1}^{S} |h_{k,j}^H \mathbf{w}_{i,j}|^2 \right) + \sigma_k^2} \tag{4.6}$$

where $\mathbf{w}_{k,0}^H \in C^{N_{MBS} \times 1}$ and $\mathbf{w}_{k,j}^H \in C^{N_{SBS} \times 1}$ represents the beamforming vectors. Equation 4.6 provides the k^{th} user's signal to interference plus noise ratio.

The information rate $(\log_2(1 + \mathrm{SINR}_k))$ can be achieved by applying MRZF, cancelling interference successively on symbols. Note that $\mathbf{w}_{k,j} \neq 0$ only for the $\mathbf{j}^{th}$ transmitter that serves the $\mathbf{k}^{th}$ user. The MBS and $\mathbf{j}^{th}$ SBS to user k are denoted $x_{k,0}$ and $x_{k,j}$ respectively, which originates from independent Gaussian codebooks as $x_{k,j} \sim CN(0, 1)$ for $j = 0, ..., S$ having unit power [45]. These beamforming vectors are the variables that will serve as the source for solving the optimization problem.

4.2.2 Energy efficiency

Energy consumption have become a major concern in the design and operation of wireless communication systems of the next generation. In fact, while communication networks have been intended primarily to optimize performance metrics such as data rate, throughput, latency for more than a century, in the last decade EE has emerged as a new prominent figure of merit, due to economic, operational, and environmental concerns [44]. Therefore, the design of the next wireless network generation will necessarily have to consider EE as one of its pillars. Indeed, 5G systems will serve an extraordinary number of devices, providing ubiquitous connectivity as well as state-of-the-art and rate demanding services. For cellular network EE is defined as the ratio of network throughput and total power consumed per unit area [48]. More generally, it can be defined as a measure of cost benefit ratio.

$$\text{Energy Efficinecy (bit/joule)} = \frac{\text{Data throughput (bit/s)}}{\text{Energy consumpption(joule/s)}} \tag{4.7}$$

4.2.3 Performance evaluation metrics

The performance evaluation of massive MIMO and SBS is done by calculating the total power consumption which can be defined as follows:

$$P_r = \frac{\sum_{i=1}^{K} P_r^i}{K} \tag{4.8}$$

where P_r is the average received power at users, P_r^i is the power received at user i and K denotes the total number of users. However, this total power consumption $\sum_{i=1}^{K} P_r^i$ and EE have inversely proportional.

4.3 Power optimizations

Optimization theory deals with the minimization of an objective function subject to a set of constraints [50]. Wireless network design and optimization depends heavily on mathematical modeling tools. Convex optimization is commonly used as a mathematical method to solve a specific class of optimization problems, such as minimum squares and linear programming problems [46, 48]. It can find the optimal solution for nonlinear problems over convex constraint sets.

Convex optimization has been studied about complex problems, that can be solved as easily as linear programs, such as semi-definite programs and second-order cone programs.

The power resources available for transmission need to be limited somehow to model the inherent restrictions of practical systems. The total power consumption of each per sub carrier can be demonstrated as $P_{dynamic} + P_{static}$ [41] where

$$\mathbf{P_{total}} = \mathbf{P_{dynamic}} + \mathbf{P_{static}} \tag{4.9}$$

$$\mathbf{P_{dynamic}} = \mu_0 \sum_{k=1}^{K} ||\mathbf{w}_{k,0}||^2 + \sum_{j=1}^{S} \mu_j \left(\sum_{k=1}^{K} ||\mathbf{w}_{k,0}||^2 \right) \tag{4.10}$$

$$\mathbf{P_{static}} = \frac{\theta_0}{C} N_{MBS} + \sum_{j=1}^{S} \frac{\theta_j}{C} N_{SBS} \tag{4.11}$$

with the dynamic and static terms respectively. The dynamic term is the collection of the emitted powers, $\sum_{k=1}^{K} ||\mathbf{w}_{k,0}||^2$ each multiplied with a constant $\mu_j \geq 1$ which would represent the inefficiency of particular transmitter's power amplifier having the values $\mu_0 = 2.577$ and $\mu_j = 19.25$ for MBS and SBSs. While the static power consumption is proportional to the number of antennas and $\theta_0 \geq 0$ which is the power dissipation of filters, converters, mixers, baseband processing and number of antennas as well with the constant values $\theta_0 = 189mW$ for MBS and $\theta_j = 5.6mW$ for SBS respectively [45]. The total number of subcarriers is $C \geq 1$ where, C = 600 and also have an impact on the equation each MBS and SBS is prone to T_j, which the power constraints.

In this thesis, to consider per-antenna power constraints for all BSs, which are more practical than total power constraints when each antenna has its own radio frequency chain [46].

The per antenna power constraints $T_{\mathbf{0}}$ for each MBS and $T_{\mathbf{j}}$ for the $\mathbf{j}^{th}$ SBS can also be expressed, respectively, as

$$\sum_{k=1}^{K} \mathbf{w}_{k,0}^{H} D_{0,t} \mathbf{w}_{k,0} \leq \mathbf{d}_{0,t}, t = 1, ...T_0 = N_{MBS} \tag{4.12}$$

$$\sum_{k=1}^{K} \mathbf{w}_{k,j}^{H} D_{j,t} \mathbf{w}_{k,j} \leq \mathbf{d}_{j,t}, \mathbf{j} = 1, .., N_{SBS}, t = 1, ..N_j \tag{4.13}$$

where $D_{0,t} \in C^{N_{MBS} \times N_{MBS}}$ and $D_{j,t} \in C^{N_{SBS} \times N_{SBS}}$, for $\mathbf{j}$ = 1........,S with order $N \times N \times T$, where N and T stands for total number of antennas and total number of power constraints, respectively. The positive semidefinite zero weighting matrices with only "**1**" at the $\mathbf{t}_{th}$ diagonal element and the corresponding limits are $\mathbf{d}_{j,t} \geq 0$.
However, these constraints are given in advance and based on [42],

- Physical limitations, to protect the dynamic range of power amplifiers;
- Regulatory constraints, to limit radiated power in certain directions;
- Interference constraints, to control interference caused to certain users;
- Economic decisions, to manage the long-term cost and revenue of running a base station.

The parameters $D_{j,t}$, $\mathbf{d}_{j,t}$ are fixed and describe any combination of per-antenna, per-array and soft shaping constraints [43]. Typically the value of $\mathbf{d}_{0,t} \gg \mathbf{d}_{j,t}$ for $1 \leq j \leq S$, represent the maximum transmitted powers from the $\mathbf{t}^{th}$ antenna of the MBS and the j^{th} SBS, respectively [44].
The numerical evaluation considers per-antenna constraints of $\mathbf{d}_j$ power in (mW) at the j^{th} transmitter, given by $T_0 = N_{MBS}$, $T_j = N_{SBS}$, $\mathbf{d}_{j,t} = \mathbf{d}_j \quad \forall_t$ and

$$\tilde{D_{j,t}} = \mathbf{diag}(D_{j,t}, ..., D_{M,t}) \tag{4.14}$$

where

$$\tilde{\mathrm{D}_{j,t}} = \begin{cases} \mathbf{1}, & \text{if } \mathbf{j} = \mathbf{t}; \\ \mathbf{0}, & \text{otherwise.} \end{cases}$$

So for optimizing the power, the total power consumption $P_{dynamic} + P_{static}$ from Eq.4.9 have been reduced, while satisfying the QoS constraints in Eq. 4.5 and Eq. 4.6 and the power constraints in Eq. 4.12 and Eq.4.13 thus in [45]

$$
\begin{aligned}
\underset{\mathbf{w}_{k,j} \quad \forall_{kj}}{\textbf{minimize}} \quad & \mathbf{P}_{\textbf{dynamic}} + \mathbf{P}_{\textbf{static}} \\
\text{subject to} \quad & \log_2(1 + \text{SINR}_k) \geq \gamma_k, \quad \forall_k \\
& \sum_{k=1}^{K} \mathbf{w}_{k,0}^H D_{0,t} \mathbf{w}_{k,0} \leq \mathbf{d}_{0,t}, \quad \forall_{j,t} \\
& \sum_{k=1}^{K} \mathbf{w}_{k,j}^H D_{j,t} \mathbf{w}_{k,j} \leq \mathbf{d}_{j,t}, \quad \forall_{j,t}
\end{aligned} \tag{4.15}
$$

In the single cell downlink system model shown that there are three possibilities of case 2 as described in the next section 4.4 for optimizing the power.

4.4 Optimization based on beamforming and algorithmic solution

To increase the EE of a wireless communication system is use low-complexity algorithms to allocate the system radio resources to maximize EE rather than through Eq.4.15 QoS have complicated functions with the beam vectors. It creates a non-convex problem in the formulation of original vectors [45].

So the above Eq.4.15 can be redesigned as a convex optimization problem which can be solvable in polynomial time with the help of standard algorithms. In addition, the optimal power minimizing solution is self-organizing in the sense that each user will be served by only one or few transmitters. It has a low convex structure and is extracted by means of the semi definite relaxation [51].

4.4.1 Convex and self dual minimization software

Convex (CVX) and self dual minimization software (SeDuMi) is an add on for MATLAB which, solve optimization problems with linear quadratic and semidefiniteness constraints. It is possible to have complex valued data and variables in SeDuMi [50, 51]. SeDuMi implements the self-dual embedding techniques for self-dual homogeneous optimization cones. Additionally, large scale optimization problems are solved efficiently by exploiting sparsity.

4.4.2 Semidefinite programming

Semidefinite programming (SDP) has now become an important algorithm designing tool for a wide variety of optimization problems [48]. This part make known to SDP relaxation procedure for quadratic optimization problems that can generate a provably approximately optimal solution with a randomized polynomial time complexity [50].

SDP relaxation

In the semidefinite programming (SDP) relaxation approach for the quadratic constrained quadratic program (QCQP) problems, which has not only a polynomial time computational complexity, but also guarantees a worst case approximation performance. Mathematically, a QCQP can be written as

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & (\mathbf{X}^T\mathbf{P}_0\mathbf{X}) + (\mathbf{q}_0^T\mathbf{X}) + r_0 \\ \text{subject to} \quad & (\mathbf{X}^T\mathbf{P}_i\mathbf{X}) + (\mathbf{q}_i^T\mathbf{X}) + r_i \leq 0; i = 1, \ldots, m. \end{aligned} \tag{4.16}$$

where $\mathbf{x}$, $\mathbf{q}_i \in R^K$, $\mathbf{r}_i \in R$ and $\mathbf{P}_i \in R^{K \times K}$ are symmetric. If all the $\mathbf{P}_i$ are positive SDP, where $\mathbf{P}_i \succeq 0$. The QCQP in Eq 4.16 is convex and can be efficiently solved to the global optimum. However, if at least one of the $\mathbf{P}_i$ is not SDP, the QCQP is nonconvex and, in general, computationally difficult to solve.

Since the nonconvex QCQPs is NP-hard in general, a polynomial time approximation method is desired. To put the SDP relaxation into context, let us consider the following homogeneous QCQP:

$$\nu_{qp} = \begin{aligned} \underset{x}{\text{minimize}} \quad & Tr(\mathbf{P}_0\mathbf{X}) + r_0 \\ \text{subject to} \quad & Tr(\mathbf{P}_i\mathbf{X}) + r_i \leq 0, \ i = 1, \ldots, m. \end{aligned} \tag{4.17}$$

The SDP relaxation makes use of the following fundamental observation:

$\mathbf{X} = \mathbf{x}\mathbf{x}^T \Longleftrightarrow \mathbf{X} \succeq \mathbf{0}$, which is componentwise inequality,
$rank(\mathbf{X}) = 1$ and $\mathbf{x}^T\mathbf{P}_i x = Tr(\mathbf{P}_i\mathbf{X})$

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & Tr(\mathbf{P}_0\mathbf{X}) + r_0 \\ \text{subject to} \quad & Tr(\mathbf{P}_i\mathbf{X})) + r_i \leq 0, \ i = 1, \ldots, m. \end{aligned} \tag{4.18}$$

Using this observation, it can be linearize the QCQP problem in Eq 4.16 by representing it in terms of the matrix variable $\mathbf{X}$. Specifically, note that $x^T P_i x = Tr(P_i\mathbf{X})$, so Eq.4.19

can be rewritten as

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & Tr(\mathbf{P}_0\mathbf{X}) + r_0 \\ \text{subject to} \quad & Tr(\mathbf{P}_i\mathbf{X})) + r_i \leq 0, \; i = 1, \ldots, m. \\ & \mathbf{X} \succeq \mathbf{0} \\ & rank(\mathbf{X}) = 1 \end{aligned} \tag{4.19}$$

From the above expression the only nonconvex constraintis rank($\mathbf{X}$) $=$ 1, one can directly relax the last constraint, in other words, dropping the nonconvex rank($\mathbf{X}$) $= 1$ and keeping only $\mathbf{X} \succeq \mathbf{0}$, to obtain the following SDP:

$$\nu_{sdp} = \begin{aligned} \underset{x}{\text{minimize}} \quad & Tr(\mathbf{P}_0\mathbf{X}) + r_0 \\ \text{subject to} \quad & Tr(\mathbf{P}_i\mathbf{X})) + r_i \leq 0, \; i = 1, \ldots, m. \\ & \mathbf{X} \succeq \mathbf{0} \end{aligned} \tag{4.20}$$

The relaxed problem ($\nu_{sdp)}$ gives a lower bound on the optimal objective value, that is, $\nu_{sdp} \leq \nu_{qp}$. In fact, this gives the same lower bound as the Lagrangian dual of ν_{qp} because it can be shown that the SDP relaxation problem ν_{sdp} is, the bi-dual of ν_{qp} [50].

Now, based on the above expression Eq. 4.18 - 4.20 the constraints can be convert to convex constraints by using some positive semidefinite relaxation matrices as

$$\mathbf{W}_{k,j} = \mathbf{w}_{k,j}\mathbf{w}_{k,j}^H, \quad \forall_{k,j} \tag{4.21}$$

This matrix should be positive semidefinite, denoted as $\mathbf{W}_{k,j} \succeq 0$. The rank of the matrix is $rank(\mathbf{W}_{k,j}) \leq \mathbf{1}$ and the rank of the matrix can be zero, which implies that $\mathbf{W}_{k,j} = \mathbf{0}$. However, this one is dropped as a relaxation without loss of optimality. This becomes a convex semidefinite optimization problem. Additionally, it will always have an optimal solution $\mathbf{W}_{k,j}^{*}\forall_{k,j}$ where all matrices satisfy $rank(\mathbf{W}_{k,j}^{*}) \leq \mathbf{1}$.

By incorporating the MBS and SBSs in sum expressions, can rewrite as follow

$$
\begin{aligned}
\underset{\mathbf{W}_{k,j}\succeq 0 \quad \forall_{k,j}}{\text{minimize}} \quad & \sum_{j=0}^{S} \mu_j \left(\sum_{k=0}^{K} Tr(\mathbf{W}_{k,j}) \right) + P_{static} \\
\text{subject to} \quad & (\mathbf{W}_{k,j}) \leq 1, \quad \forall_{k,j} \\
& \sum_{k=1}^{K} \mathbf{w}_{k,0}^{H} D_{0,t} \mathbf{w}_{k,0} \leq \mathbf{d}_{0,t}, t = 1, ...T_0 = N_{MBS} \\
& \sum_{k=1}^{K} \mathbf{w}_{k,j}^{H} D_{j,t} \mathbf{w}_{k,j} \leq \mathbf{d}_{j,t}, j = 1, ...N_{SBS} \\
& \sum_{j=0}^{S} h_{kj}^{H} \left(\left(1 + \frac{1}{2^{\gamma_k} - 1} \right) \mathbf{W}_{kj} - \sum_{i=k}^{K} \mathbf{W}_{ij} \right) h_{kj} \geq \sigma_k^2, \quad \forall, k \\
& \sum_{j=0}^{S} h_{kj}^{H} \left(\left(1 + \frac{1}{\tilde{\gamma}_k} \right) \mathbf{W}_{kj} - \sum_{i=k}^{K} \mathbf{W}_{ij} \right) h_{kj} \geq \sigma_k^2, \quad \forall k \\
& \sum_{k=1}^{K} Tr \left(D_{0,t} \mathbf{W}_{k,j} \right) \leq \mathbf{d}_{j,t} \quad , \forall j, t
\end{aligned}
\tag{4.22}
$$

where the target QoS have been transformed into SINR targets of $\tilde{\gamma}_k = 2^{\gamma_k} - 1$ and σ_k^2 variance [**see: Appendix - B**] as

$$
\tilde{\gamma}_k = \frac{P_k V_k^H A_k V_k}{\sum_{i \neq k} P_i V_i^H A_k V_i + 1} = \frac{\Omega_{a,k} V_k^H A_k V_k}{V_k^H B_k V_k} \tag{4.23}
$$

Except for the constraints of ranks, the expression in Eq.4.22 is convex optimization. But by relaxing these constraints, optimality can be achieved without losing its optimality.

There are two special cases required to accomplish this:

The first reason is to provide the complete analysis of the problem of complexity and the second reason is provided to analyze the problem of power optimization [48].

Case 1. For achieving a convex semidefinite optimization problem, consider a semi-definite relaxation of Eq.4.22 in which the limitation of position rank$(\mathbf{W}_{k,j}) \leq 1$ are extracted. Additionally, it will always have an optimal solution $\{\mathbf{W}_{k,j}^* \quad \forall k, j\}$ where all matrices satisfy rank $(\mathbf{W}_{k,j}^*) \leq 1$.

Case 2. For achieving the optimality, consider $\{\mathbf{W}_{k,j}^*, \quad \forall k, j\}$ as the optimal solution to Eq. 4.22 and for each user **k** there are three options:

- $\mathbf{W}_{k,j}^* = \mathbf{0}$, $1 \leq j \leq S$. It is only assisted by the macrocell base station.
- $\mathbf{W}_{k,0}^* = \mathbf{0}$, and $\mathbf{W}_{k,i}^* = \mathbf{0}$ for $i \neq j$. It is only assisted by one of the small cell base stations and finally

- $\sum_{k=1}^{K} Tr(D_{0,t}\mathbf{W}^{*}_{k,j}) = \mathbf{d_{0,\ t}}$, Same as $\sum_{k=1}^{K} Tr(D_{0,t}\mathbf{W}^{*}_{k,j}) = \mathbf{d_{j,\ t}}$

It is assisted by a combination of macrocell base station and small cell base stations, where at least one transmitter $\boldsymbol{j}$ has an active power constraint $\boldsymbol{t}$ [45].

This statement now, illustrates the above three possibilities indicated in the 2^{nd} part as a special case. This result demonstrates that users can be served by multi-flow transmission, but at least one transmitter is selected for each UE to achieve optimality [45]. Users close to an SBS are served by it alone, while most other users are served by the MBS. Around each SBS there are transition regions where multi-flow transmission is operated.

Since the SBS is not able to fully support the QoS targets, the coverage area around each SBS in which multi-flow transmission is applied will be started to change. The other advantage of this consequence is a favorable outcome as a reduced complexity of transmission or reception is often optimal [48]. The power transition areas will vanish if the power limitations are removed.

4.4.3 Low complexity algorithm for resource allocation

This algorithm defines the spatial soft cell coordination. The level of complexity related to optimal beamforming is relatively modest, but when N_{MBS} and number of smal cell bases grow larger, i.e. for real-time implementation, the algorithm becomes infeasible [44].

Additionally, Case 1 provides a centralized algorithm requiring the MBS to gather all channel information. Distributed algorithms can definitely be achieved using primary or dual decomposition methods, but these require iterative backhaul signaling of coupling variables, so they are not suitable for real-time implementation as they require iterative coupling variables backhaul signals [42]. Therefore, when calculating less complex codes for non-coherent coordination, Case 1 is considered the standard.

Use non-iterative multiflow regularized zero-forcing beamforming with low complexity, Therefore to validate this, a less complex non-iterative multiflow RZF beamforming vector $\mathbf{V} \in \mathbf{C}^{K \times Kt}$ is computed by :

$$\mathbf{V}_{k,j} = \frac{\tilde{\mathbf{V}}_{k,j}}{\|\tilde{\mathbf{V}}_{k,j}\|} \quad \forall_k \in \{1, 2..., K\}, n \in \{1, 2..., K_t\} \tag{4.24}$$

where K is the number of users, K_t number of transmitters and $\tilde{\mathbf{V}}_{k,j}$ is given by

$$\tilde{\mathbf{V}}_{k,j} = \left(\sum_{i=1}^{K} \frac{1}{\sigma_i^2} \mathbf{h}_{i,j}^{H} \mathbf{h}_{i,j} + \frac{K}{\tilde{\gamma}_k d_j} \mathbf{I} \right)^{-1} \mathbf{h}_{k,j} \tag{4.25}$$

- Each transmitter compute j = 1,.............,**S**

$$V_{k,j} = \frac{\left(\sum_{i=1}^{K} \frac{1}{\sigma_i^2}\mathbf{h}_{i,j}^H\mathbf{h}_{i,j} + \frac{K}{\tilde{\gamma}_k d_j}\mathbf{I}\right)^{-1}\mathbf{h}_{k,j}}{\left\|\left(\sum_{i=1}^{K} \frac{1}{\sigma_i^2}\mathbf{h}_{i,j}^H\mathbf{h}_{i,j} + \frac{K}{\tilde{\gamma}_k d_j}\mathbf{I}\right)^{-1}\mathbf{h}_{k,j}\right\|} \quad \forall_k \tag{4.26}$$

The magnitude of the channel have become

$$\mathrm{g}_{i,k,j} = \left|\mathbf{h}_{i,j}^H \mathbf{V}_{k,j}\right|^2 \quad \forall_{i,k} \tag{4.27}$$

where $\mathrm{g}_{i,k,j}$ be a scalar which denotes the equivalent channel status of each access point, given by Eq.4.27.

$$D_{j,t,k} = \mathbf{V}_{k,j}^H \mathbf{D}_{j,t} \mathbf{V}_{k,j} \quad \forall t, k \tag{4.28}$$

where, $D_{j,t}$ is the block diagonal matrix [**see: Appendix - B**].

- The j^{th} SBS sends the scalars of $\mathrm{g}_{i,k,j}$, $D_{j,t,k}$ $\forall k, i, t$ to the MBS. The MBS solves the convex optimization problem $\mathrm{g}_{i,k,j}$ and $D_{j,t,k}$ $\forall_{k,i,t}$

$$\begin{aligned}
\underset{P_{k,j}\geq 0 \quad \forall kj}{\text{minimize}} \quad & \sum_{j=0}^{S} \mu_j \left(\sum_{k=1}^{K} P_{k,j}\right) + P_{ststic} \\
\text{subject to} \quad & \sum_{k=0}^{K} D_{j,t,k} P_{k,j} \leq d_{j,t} \quad \forall j, t \\
& \sum_{j=0}^{S} P_{k,j} \mathrm{g}_{k,k,j} \left(1 + \frac{1}{2^{\gamma_k} - 1}\right) - \sum_{i=1}^{K} P_{i,j} \mathrm{g}_{k,i,j} \geq \sigma_k^2 \quad \forall k
\end{aligned} \tag{4.29}$$

- The power allocation $p_{k,j}^* \forall k$ that can solve Eq.4.29 is sent to the j^{th} SBS, which computes

Each AP obtain the final beamforming vector through

$$\mathbf{w}_{k,j}^2 = p_{k,j}^* V_k^2 \quad \forall k \tag{4.30}$$

this imply that $\mathbf{w}_{k,j} = \sqrt{p_{a,k,j}^*} V_k \quad \forall k$

This algorithm is applied to the heuristic RZF beam forming in which transforms the problem given in Eq.4.15 into the problem of power allocation provided in Eq. 4.27, while maintaining it less complex regardless of the antenna number [50]. In this case, the code does not give iteration, but some scalar variables are interchanged between the MBS and

SBS points to maintain coordination [45]. This change between MBS and SBS points will only affect those users near a SBS point. Therefore, for each SBS point only few variables are interchanged, while all other variables are set to zero.

The traditional zero forcing method, based on an observation, attempts to nullify the inter-cell interference of mobile users at the edges of the cell. But to complete this, the system's complexity is increased. If the inter-cell interference vanishes, however, there is even thermal noise [47]. Therefore, there is no need to remove inter-cell interference, but it is comparable to that of thermal noise at a certain level. Thus the amount of complexity is reduced by relaxing the ZF interference limitations and now the number of antennas is increased to give a higher rate than that of the ZF system [48]. But along with low complexity, power optimization is also an important concern. So for optimizing or minimizing the power while maintaining the low complexity.

4.4.4 Average achievable sum information rate

Consider a downlink scenario which, have checked the performance of prescribed factors by assuming a systematic design with respect to following constraints. Suppose that the transmitter $K_t = 4$ with four number of antennas and there exist $K_r = 4$ users. The channel link existing between transmitter **j** and user **k** is generated as an uncorrelated rayleigh fading. So the average channel gain $E = \{||h_{j,k}||_2^2\}$ equals four for serving transmitters and two for the transmitters which are interfering. To illustrate the behavior of different heuristic beamforming directions, a 4 - user interference channel with $N_j = 4$ antennas per base station and global interference coordination [52]. The channel vectors $h_{j,k}$ are generated as uncorrelated Rayleigh fading and the average channel gains $E = \frac{\{||h_{j,k}||_2^2\}}{\sigma_K^2}$ equal N_j for the serving base station and $\frac{N_j}{2}$ for all interfering base stations.

By looking into the simple power minimization problem as given below it is not a complicated task to use this to derive optimal beamforming structure.

$$\begin{aligned} \underset{w_1,.......,w_k}{\text{maximize}} = \quad & f(SINR_1, ..., SINR_K) \sum_{k=1}^{K} ||w_k||^2 \leq p \\ \text{subject to} \quad & SINR_K \geq \gamma_k \end{aligned} \tag{4.31}$$

Here in this expression the parameters such as $\gamma_1.........\gamma_k$ are the SINR parameters that will be achieved by all users as per depending on number users for optimum of the equation above. These γ-parameters elaborate the SINRs which is needed to obtain some certain value of data rates. The values of the γ-parameters are not variable in the equation above and this gave clear impact to optimal beamforming solution, but there is no variation in the solution structure [52].

Here the cost function $\sum_{k=1}^{K} ||w_k||^2$ is clear depiction of convex function of beamforming vector. The basic purpose and main goal is to determine the noise impact. By transmit beamforming the maximization of metric of performance utility can be achieved where as it is the general function of SINR [14,15]. The task is to maximize the arbitrary utility function $f(SINR_1, ..., SINR_K)$ which is increasing in the value of SINR of every user and there exist a limitation in the total transmit power i.e. limited by Power. Mathematically it can be stated as:

$$\begin{aligned} \underset{w_1,.......,w_k}{\text{maximize}} = \quad & f(SINR_1, ..., SINR_K) \\ \text{subject to} \quad & ||w_k||^2 \leq p \end{aligned} \tag{4.32}$$

It is a quite complicated task to solve the problem Eq. 4.32 however, suppose that if the values of SINR, i.e. $SINR_1^*, ..., SINR_k^*$ that have obtained by an optimal solution to the problem 4.32. Than what would be the outcome result in case of $\gamma_k = SINR_k^*$, for the values k = 1,....,K. with it if solve Eq. 4.31 for the parameter specifically with particularity of γ-parameter. With respect to this simple scenario it is very clear that the particular constraints that will solve 4.31 will also be same for providing the solution to Eq. 4.32 and will solve it definitely [42]. It can be specifically described as follow that Eq.4.31 finds the beamforming vectors that are solving it achieves the SNR values; $SINR_1^*, ..., SINR_k^*$. The solution for the problem 4.31 must satisfy the total values of power constraints in the problem 4.32. The basic reason is that the problem 4.31 gives the beam-forming which further achieve the given SINRs by using the minimal value of the power [52]. So it can be depicted clearly that the beam-forming vectors from 4.31 are feasible for 4.32 and got optimal SINRs values and these are the optimal solution for the problem 4.32 also [53].

To find out the values of $SINR_1^*, ..., SINR_k^*$ it need to solve 4.32, and it is a quite complicated task because the values of SINR are predefined in 4.31 and are to be calculated in 4.32. However an optimal beamforming value of 4.32 as follow

$$\mathbf{w}^* = \sqrt{p_k}\frac{\left[I_N + \sum_{i=1}^{k} \frac{\lambda_i}{\sigma^2} h_i h_i^H\right]^{-1} h_k}{\left\|[I_N + \sum_{i=1}^{k} \frac{\lambda_i}{\sigma^2} h_i h_i^H]^{-1} h_k\right\|} \quad for \quad k = 1, ...K \tag{4.33}$$

However, the importance of is that it provides a simple structure for the optimal beamforming [53]. Although the matrix above in Eq. 4.33 is same for all of the users, the matrix with respect to the optimal beamforming vectors and these can be written in the very compact form. The optimal beamforming direction in the above Eq. 4.33 consist of two main parts. The channel vector h_k which between the BS and the intended users k and 2 is the matrix;

$$\left[I_N + \sum_{i=1}^{k} \frac{\lambda_i}{\sigma^2} h_i h_i^H \right]^{-1} h_k \tag{4.34}$$

As with respect to the beam-forming in the same direction from the expression of the channel as

$$\tilde{W}_k^{MRT} = \frac{h_k}{||h_k||}$$

Is the matched filtering or MRT. The maximization of the received signal power, $|p_k h_k^H \tilde{W}_k|^2$ and due to this selection at the respective intended user. As arg max

$$\tilde{W}_k : ||\tilde{W}_k||^2 = 1$$

$$|h_k^H \tilde{W_k}|^2 = \frac{h_k}{||h_k||}$$

The expression shows with respect to above mentioned fact for MRT is due to the Cauchy-schwarz-inequality. The optimality in beamforming directions for the values as K = 1.

As the value before normalization $\left[I_N + \sum_{i=1}^{k} \frac{\lambda_i}{\sigma^2} h_i h_i^H \right]^{-1}$ when multiplied with h_k, take care of the respective values and it rotates the MRT for reducing the value of interference which is due to the co - user directions, as $h_1, ...h_{k-1}, ..h_{k+1}, ..h_k$[54].

4.5 Stochastic models for SBS locations

The performance of wireless systems depends strongly on the locations of the users or nodes. In modern networks, these locations are subject to considerable uncertainty and thus need to be modeled as a stochastic process of points in the two or three dimensional space [55]. The field of mathematics that offers such models and techniques to evaluate their features is stochastic geometry, especially the theory of point processes.

The central idea for applying stochastic geometry to wireless cellular network analysis is to model base station and user terminal locations as realizations of a random mathematical subject class called point process [56].

Stochastic geometry is concerned with random patterns of space. The most fundamental and important such objects are random point patterns or point procedures, so point process theory is often considered as the primary sub-field of stochastic geometry [57].

4.5.1 Point processes as wireless network spatial models

Spatial point processes are mathematical models that describe the arrangement of objects distributed in the plane or space irregularly or randomly. The development of classes of large wireless networks such as ad hoc network, femto cell, picocell, sensor network and cellular networks with coverage extensions such as relays or micro-base stations has been intensively investigated over the past decade [55, 56]. For the following reasons, classical communication theory methods are adequate to analyze these new types of networks [55].

- Signal-to-interference-plus-noise ratio (SINR) is the performance-limiting metric rather than the signal-to-noise ratio (SNR).
- The interference depends on the features of path loss and fading, which in turn are functions of the geometry of the network.
- The amount of uncertainty present in large wireless networks far exceeds the amount present in point-to-point systems: the locations and channels of all but perhaps a few other nodes can not be known or predicted by each node.

There are two primary tools that have recently proven to be extremely most helpful in avoiding the above problems: stochastic geometry and random geometric graphs. Stochastic geometry allows one to investigate the average behaviour over many spatial network realizations whose nodes are arranged according to some distribution of probability [55]. Random geometric graphs capture the node connectivity's distance influence and randomness.

4.5.2 Poisson point process

The most important and widely used point process is the Poisson point process, often abbreviated to PPP or called just the Poisson process. Lacking any information on the dependence of the points, it is the model of choice due to its super analytical tractability [57].

- The number of points of the process in any finite region $\boldsymbol{A} \subset R^2$, denoted $N(\boldsymbol{A})$, is a random variable with the Poisson distribution

  $P\{N(\boldsymbol{A}) = n\} = exp^{[-\mu(\mathbf{A})]} \frac{[\mu(\mathbf{A})]^n}{n!}, n = 0, 1, 2........., , , , , ,$

with mean, if $\mu(\mathbf{A})$ admits a density λ, the Poisson distribution can be expressed as

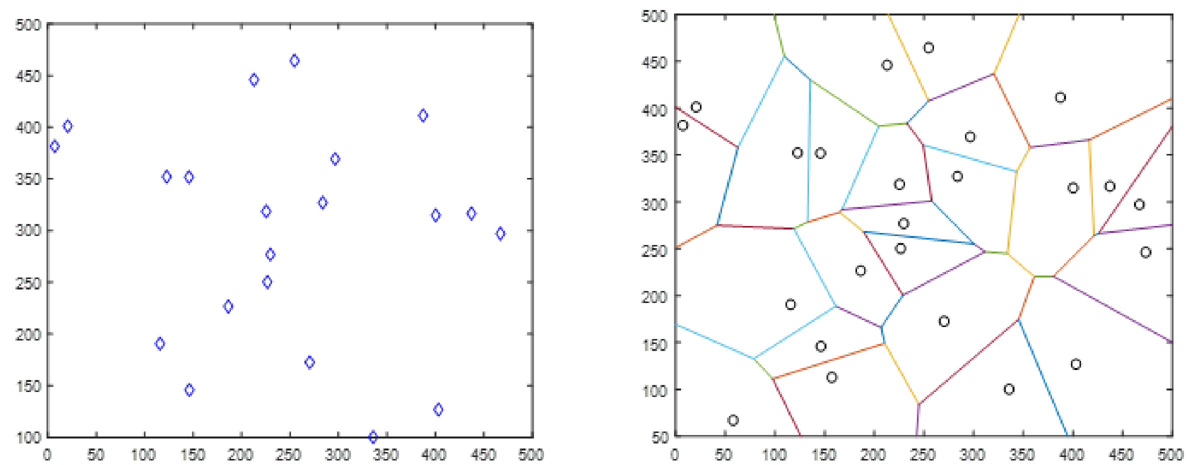
$$\mu(\boldsymbol{A}) = \int\int_{\boldsymbol{A}} \lambda(x, y) d_x d_y, \mathbf{A} \subseteq R^2 \tag{4.35}$$

where $\lambda(.,.)$ is a non-negative-valued function of two variables called the intensity function of the PPP Φ.

- Given the number of points of Φ in any finite region $A \subset R^2$, i.e. conditioned on $N(\boldsymbol{A}) = n$, say, the locations of these n points are i.i.d. with Probability Density Function (PDF) of $\lambda(x, y)/\mu(\mathbf{A})$ over $\mathbf{A}$.

- For two disjoint finite regions $\mathbf{A} \subset R^2$ and $\mathbf{B} \subset R^2$, the corresponding numbers of points of Φ in these regions,$N(\mathbf{A})$ and $N(\mathbf{B})$, are independent. These three properties are not independent [58].

It is possible to derive SE and EE. On the basis of the particular point process analytical experiment of coverage probability. Many literature results have been evaluated using stochastic geometry of the heterogeneous network [55–58].



λ = 20

Figure 4.2: A realization of a homogeneous Poisson point process with different intensity value in a finite window [56].

The static part of the power consumption, P_{static}, focuses on the number of antennas and SBSs. Therefore, from the perspective of EE, placing inactive SBSs and antenna elements in sleep mode makes sense [44].

Consider the downlink of a network running over a B_w bandwidth in which all SBSs are active and distributed randomly according to a homogeneous PPP Φ with $\lambda_{(SBSs/km^2)}$ intensity. Each SBS is equipped with N antennas and serves randomly distributed K $\leq$ N single antenna UEs within the Voronoi cells. It is assumed that the UEs are static and equipped with hardware-impaired transceivers [56]. UE's stationarity implies that the time of validity is sufficiently large to neglect the overhead introduced by channel estimation.

Furthermore, the impacts of hardware impairments in the UEs are regarded dominant over the channel estimation errors and in turn is also neglected [59]. It is connected to $SBS_0 \in \Phi$ and has an arbitrary UE index k.

The received baseband signal $Z_k \in C$ at the typical UE is modeled as

$$Z_k = \sqrt{1 - \delta^2}\left(\sqrt{\frac{P_{tx}}{B_w}} h_{0,k}^H W_0 S_0 + \sum_{i \in \Phi \backslash \{SBS_0\}} \sqrt{\frac{P_{tx}}{B_w}} h_{i,k}^H W_i S_i\right) + b_k \tag{4.36}$$

where $h_{j,k} \sim CN(0, \omega^{-1} d_{i,k}^{-\alpha}\, \mathbf{I}_N)$ is the rayleigh flat-fading channel from $SBS_i \in \Phi$ to the typical $UE_k, d_{i,k}$ is the distance between them $\alpha > 2$ is the path loss exponent, and ω models fixed propagation losses such as wall penetration at a reference distance of 1 km [60].

Take $s_i \sim CN(0, \mathbf{I}_K)$ contains the normalized information symbols sent by SBS_i,to its associated K UEs and $P_{tx} > 0$ the average transmission power per UE over the complete bandwidth B_w and $W_i \in C^{N \times K}$as the corresponding beamforming matrix with normalized columns [60]. The additive receiver noise is modeled by $b_k \sim CN(0, \frac{\sigma^2}{B_w})$ with σ^2 being the noise energy per symbol, while δ model the distortions from hardware impairments. The impact of hardware impairments is modeled based on as a reduction of the received signal energy of $1 - \delta^2$ and an additive distortion noise given by

$$e_k \sim CN\left(0, \delta^2 \frac{P_{tx}}{B_w} \sum_{i \in \Phi} ||h_{i,k}^H W_i||^2\right) \tag{4.37}$$

By assuming zero force precoding and denote $W_i = [w_{i,1}, ..., w_{i,K}] \in C^{N \times K}$ as the precoding matrix of SBS_i with $w_{i,k}$ being the normalized precoding vector associated to

UE k and given by

$$w_{i,k} = \frac{H_i\left(H_i^H H_i\right)^{-1} e_k}{\left\|H_i\left(H_i^H H_i\right)^{-1} e_k\right\|} \tag{4.38}$$

where $H_i = [h_{i,1}, ..., h_{i,K}] \in C^{N\times K}$ is the channel gain matrix between SBS_i and its associated K UEs, and the notation $\|.\|$ stands for the Euclidean norm. Notice that for W_i to exist the matrix $H_i^H H_i$ needs to be invertible [59, 60]. This is why need to enforce the condition $N \geq K$.

4.5.3 Average achievable spectral efficiency

The wireless communication link's spectral efficiency is strictly bounded by the channel capacity [59]. In comparison, the EE metric of a communication link shows that it can achieve unbounded EE in massive MIMO if the power of the circuit is neglected and only time will show how small circuit energy in future hardware becomes [61]. In other words, on a network's EE, it can only define achievable lower bounds. Try to obtain a lower bound in this thesis, which is tractable for analytical optimization, and need a closed-form SE expression for that. ZFBF is the typical ergodic achievable SE

$$E\left\{\log_2\left(1+\frac{1-\delta^2|h_{0,k}^H W_0|^2}{\sum_{i\in\Phi_{\backslash\{SBS_0\}}}||h_{i,k}^H W_i||^2+\delta^2|h_{0,k}^H W_0|^2+\frac{\sigma^2}{P_{tx}}}\right)\right\} \tag{4.39}$$

Where the channel fading expectation for the given Φ_λ is. Now take the PPP average of Eq. 4.39. This is difficult to do in a closed form, but a lower bound can be obtained. An achievable lower bound on the average SE of the network with ZFBF where $N \geq K+1$ [60].

$$\tilde{\text{SE}} = \log_2\left(1+\frac{(1-\delta^2)(N-K)}{\frac{2K}{\alpha-2}+\delta^2(N-K)+\frac{\Gamma(\frac{\alpha}{2}+1)}{(\lambda\pi)^{\frac{\alpha}{2}}}+\frac{\omega\sigma^2}{P_{tx}}}\right) \tag{4.40}$$

The SE in Eq. 4.39 is achieved by canceling intra-cell interference using zero force beamforming, treating inter-cell interference as the worst-case decoding Gaussian noise, and using the distortion noise variance in Eq. 4.36 [61].

In other words, the average lower bound can be written as follows:

$$\tilde{\text{R}} = \text{B}_w\log_2\left(1+\frac{(1-\delta^2)(N-K)}{\frac{2K}{\alpha-2}+\delta^2(N-K)+\frac{N}{(\lambda\pi)^{\frac{\alpha}{2}}}+\frac{\omega\sigma^2}{P_{tx}}}\right) \tag{4.41}$$

According to Jensen's inequality in solving the average take Eq. 4.39 in terms of channel realizations and PPP Φ computing a achievable reduced boundary in the form of

$$E\left\{\log_2\left(1+\frac{1}{r}\right)\right\} \geq \log_2\left(1+\frac{1}{E\{r\}}\right) where, r = SINR_{0,k}^{-1} \tag{4.42}$$

Using complex Wishart and complex inverse Wishart distributed random matrices to calculate the expectations for channel realizations [60].

$$E\left\{\frac{1}{|h_{0,k}^H W_0|^2}|d_{0,k}\right\} = \frac{\omega d_{0,k}^{\alpha}}{N-K} \tag{4.43}$$

$$E\left\{||h_{i,k}^H W_i||^2 |d_{i,k}\right\} = \frac{K}{\omega d_{i,k}^{\alpha}} for, i \neq 0 \tag{4.44}$$

model the statistical properties of complex sample covariance matrices and complex inverse sample covariance matrices as relevant [55]. Beamforming at SBS_0 is independent of channel reliability in other cells since zero force [61]. Assume that the transmitting nodes form a stationary PPP Φ of intensity λ is in the two dimensional plane. The distance to the serving MBS is $d_{0,k} \sim$ rayleigh $(\frac{1}{\sqrt{2\pi\lambda}})$. All nodes transmit at unit power and the $\mathbf{g}(r) = r^{-\alpha}$ path loss calculate the expectation with respect to the interfering SBSs, which are further away as

$$E\left\{\sum_{i\in\Phi_{\lambda\backslash\{SBS_0\}}} |d_{i,k}^{-\alpha}|d_{0,k}\right\} = \int_{d_{0,k}}^{\infty} r^{-\alpha} 2\pi\lambda r dr \tag{4.45}$$

which gives $\frac{2\pi\lambda}{2-\alpha} r^{2-\alpha}|_{d_{0,k}}^{\infty}$ $\alpha \neq 2 = \frac{2\pi\lambda}{\alpha-2}$ $r^{2-\alpha}$. If $\alpha < 2$, the upper integration bound is incorrect [60]. There is too much interference from all the far nodes. If $\alpha > 2$, the lower integration bound is the culprit. The nodes near the origin make $E\left\{\sum_{i\in\Phi_{\backslash\{SBS_0\}}} |d_{i,k}^{-\alpha}|d_{0,k}\right\}$ diverge, since $r^{-\alpha}$ grows too quickly as r tends to zero if $\alpha > 2$ [60].

A bounded path loss model would solve the problem for $\alpha > 2$. Similarly, if it can be ensure that no node is close to the origin, $E\left\{\sum_{i\in\Phi_{\backslash\{SBS_0\}}} |d_{i,k}^{-\alpha}|d_{0,k}\right\}$ remains finite for $\alpha > 2$. Replace the lower integration bound by $P_{tx} > 0$, to obtain $E\{I\} = E\left\{\sum_{i\in\Phi_{\backslash\{SBS_0\}}} |d_{i,k}^{-\alpha}|d_{0,k}\right\}$, $E\{I\} = \frac{2\pi}{\alpha-2}$ $P_{tx}^{(2-\alpha)}$. This can be used to model CSMA. Applied to Laplace transform into this interference $E\{d_{0,k}^{v}\} = \frac{\Gamma(\frac{v}{2}+1)}{(\lambda\pi)^{\frac{v}{2}}}$. where , $v > -2$, and, $\alpha = v$ which gives Eq.4.40 [60].

4.6 Performance metric of SBSs

In a wireless network the spatial distribution of APs is highly irregular and the cell geometry plays a key role when determining the performance.

The key performance metric in this paper is the achievable downlink EE. The ratio between the area spectral efficiency (ASE) and the energy consumption area is described [56] ,[60]. The ASE is defined for a given SE

$$\mathrm{ASE} = \lambda \mathrm{KSE} \tag{4.46}$$

The overall energy consumption area accounts for radiated signal energy, circuit dissipation, digital signal processing, signaling backhaul, and overhead such as cooling. These are all non-negligible parts of practical power consumption [56].

$$\tilde{\mathrm{EE}} = \frac{\lambda \mathrm{K}\tilde{\mathrm{SE}}}{\lambda\left(\frac{KP_{tx}}{\mu} + P_{stat} + P_{ue}K + P_{bs}N + P_{sign}NK + P_{decob}\tilde{SE}\right)} \tag{4.47}$$

where $\mu \in (0, 1]$ is the efficiency of the radio frequency amplifiers at the SBS and we recall that P_{tx} is the average RF transmission energy per symbol per active UE. The term P_{stat} is an SBS's static energy consumption, whereas $P_{ue}K$ and $P_{bs}N$ are the terms that linearly scale with the number of active UEs and the number of antennas in the SBS [60]. The $P_{sign}NK$ higher-order term accounts for signal processing expenses, in specific computing the W_iSi product for each si information vector and other matrix operations. The energy consumed by the mechanism of coding and decoding and signaling backhaul is proportional to the ASE with a coefficient of proportionality of P_{decob} [60].

4.6.1 Optimizing the energy efficiency of SBSs

The following EE optimization problem is considered to guarantee reasonable user performance:

$$\begin{aligned} &\underset{P_{tx}\geq 0, 0\leq\lambda\leq\lambda_{max}}{\text{maximize}} && \tilde{EE}(N, K, P_{tx}, \lambda) \\ &\text{subject to} && \tilde{SE} = \Upsilon, N \geq K+1 \end{aligned} \tag{4.48}$$

where Υ is an SE level that is guarantee on average to UEs in the network [60]. Note that the P_{tx} can be any positive number, while λ is a positive number upper bounded by λ_{max}, this is the highest average SBSs density that can be physically deployed. N and K belong to the set Z^+ of strictly positive integers.

Now, in the above-mentioned expression Eq.4.48, to fix this EE optimization problem, derive expressions must show the basic relationship between the parameters required.

4.6.2 Optimizing the SBS density

Consider problem of Eq.4.48 with N, K, and P_{tx} allocated values. If the problem is feasible, the EE metric increases in $\lambda_{(SBSs/m^2)}$ monotonically and is therefore maximized in $\lambda^* = \lambda_{max}$ while the other parameters are fixed. Observe that even if λ goes to infinity and consequently P_{tx} becomes zero, the EE has the finite upper limit because the transmission power term goes away in the EE expression, while the circuit power consumption remains [60]. Hence, smaller cells will only bring EE improvements till the point where the transmission power becomes negligible and then higher cell density only brings marginal improvements [61].

4.6.3 Optimizing the transmission power

To find the optimal transmission power per UE, P^*_{tx} which, is used Lambert W function repeatedly . For any values on λ, N, and K, the SE constraint in Eq.4.43 is satisfied by

$$P^*_{tx} = \frac{\left(\frac{2^{\Upsilon}-1}{1-2^{\Upsilon}\delta^2}\frac{\omega\sigma^2\Gamma(\frac{\alpha}{2}+1)}{(\lambda\pi)^{\frac{\alpha}{2}}}\right)}{\left(N-K-\frac{2^{\Upsilon}-1}{(1-2^{\Upsilon}\delta^2)}\frac{2K}{\alpha-2}\right)} \tag{4.49}$$

Use the Lambert W function is denoted by W(x) and defined by the equation $x = W(x)e^{W(x)}$ for any x $\in$ C [62].

if problem Eq.4.47 is feasible. The problem is infeasible whenever P^*_{tx} is negative .

This expression offers the connection between P^*_{tx} and other parameters of the system. Due to shorter path losses when λ increases, the optimal transmission power is inversely proportional to the SBS density as $\lambda^{\alpha/2}$.

It is decreasing function of the number of antennas, N, due to the array gain from coherent beamforming, the relationship is as $\dfrac{1}{N}$ when N is large [62].

Finally, P^*_{tx} increases with K since K makes the denominator of Eq. 4.49 smaller, this is explained by the will to operate at higher SNRs when the inter-cell interference grows stronger. By substituting P^*_{tx} into Eq.4.48 and taking λ as a constant, the EE optimization problem is reduced to

$$\begin{aligned} &\underset{N,K\in Z_+}{\text{maximize}} \quad \frac{K\Upsilon}{(\frac{KP^*_{tx}}{\mu}+P_{stat}+P_{ue}K+P_{bs}N+P_{sign}NK+P_{decob}K\Upsilon)} \\ &\text{subject to} \quad (N-K)-\frac{(2^{\Upsilon}-1)}{(1-2^{\Upsilon}\delta^2)}\frac{2K}{\alpha-2} \end{aligned} \tag{4.50}$$

By removing interference and noise, it can be shown that Eq.4.48 is only feasible for $0 \leq \Upsilon < 2\log_2(\delta)$ thus Υ assume that lies in this interval [60].

4.6.4 Optimizing SBS antenna number

Now, if P_{tx}^{*} is given and the other system parameters are fixed, find the optimal number of SBS antennas, N [59, 60]. The EE metric in Eq. 4.48 is maximized for any specified values on λ and K

$$N^{*} = K + \frac{2K(2^{\Upsilon} - 1)}{(\alpha - 2)(1 - 2^{\Upsilon}\delta^2)} + \sqrt{\frac{2^{\Upsilon} - 1}{(1 - 2^{\Upsilon}\delta^2)} \frac{K\mu^{-1}\omega\sigma^2\Gamma(\frac{\alpha}{2} + 1)}{(\pi\lambda)^{\frac{\alpha}{2}}(P_{bs} + P_{sign}K)}} \tag{4.51}$$

If N^{*} is not an integer, then either the nearest smaller or greater integer will produce the optimum.

4.6.5 Optimization of the number of UEs

Finally, the optimum number of active UEs per SBS should always be found. Because the constraint has $N \geq K + 1$ in Eq. 4.48, K's tractable optimization requires N to be changed too. Therefore, the value of $\beta = N/K$ should be fixed and N and K should be optimized together [59–61].

For any given values on λ and $\beta = N/K > 1$, the EE metric in Eq. 4.49 is maximized by

$$K^{*} = \sqrt{\frac{\frac{2^{\Upsilon}-1}{(1-2^{\Upsilon}\delta^2)} \frac{\omega\sigma^2\Gamma(\frac{\alpha}{2}+1)}{(\pi\lambda)^{\frac{\alpha}{2}}}}{\beta P_{sign}\left(\beta - 1 - \frac{(2^{\Upsilon} - 1)}{(1 - 2^{\Upsilon}\delta^2)} \frac{2}{(\alpha-2)}\right)} + \frac{P_{stat}}{\beta P_{sign}}} \tag{4.52}$$

If K^{*} is not an integer, then either the nearest smaller or greater integer can achieve the optimum. Using this operation Lambert W denotes W(x) and describes the equation $x = W(x)e^{W(x)}$ for any x $\in$C [62].

Chapter 5

Results and Discussion

5.1 Introduction

Chapter two covers literature review, chapter three deal some theoretical and analytical part which helps to understand this thesis work and in chapter four, proposed system model and analysis was discussed. Channel model, EE, HetNet, massive MIMO, power optimization and consumption model and small cell BS, stochastic geometry was discussed. Simulation results will be discussed in chapter five using MATLAB and SeDuMi modeling software depending on the concepts of chapters three and four respectively.

5.1.1 Simulation setup and its parameters

The downlink system of a HetNet consisting one macro cell with radius 500m and there are four small cell base stations each SBSs with radius 40m which are deployed at the same area. Suppose there are six active users in the macro cell and one user in each small cell. The users are uniformly distributed in the coverage area between the radiuses of 35m and 500m for MUEs and the radiuses between 3m and 40m for SUEs. Assume that all the SBSs have equal number of antennas, i.e. $T_j = N$, for j = 1, ...,N_{SBS} where N = 1, 2, 3 and N_{MBS} = { 20, 30,.......,100}

This thesis shows a clear performance on the user locations and channel information. There are some variables such as carrier frequency $f_c = 2GHz$ with $B_w = 10MHz$ and number of subcarrier is 600 with, 15 kHz bandwidth used in numerical calculation and the channel model is 3GPP channel model LTE standard. Taking the hardware parameters for numerical analysis macro cell power amplifiers efficiency $\mu_0 = 2.577$ for MBS and $\mu_j = 19.25$ for SBS respectively, constraints per- antenna in miliwatt, also $\mathbf{d_{o,t}}$ = 66 mW foe MBS and $\mathbf{d_{j,t}}$ = 0.08 mW for SBSs ∀ **j, t** and finally, the circuit power per antenna of θ_0 = 189mW and θ_j = 5.6mW $\forall_{\mathbf{j}}$ of MBS and SBSs respective orders.

Consider the small-scale fading of rayleigh: $h_{k,j} \sim CN(0, R_{k,j})$. The correlation matrix is spatially uncorrelated, $R_{k,j} \propto I$, between the j^{th} SBS and each user k [32]. The matrix of correlation between the MBS and each user is based on the model of the physical channel.

5.1.2 Backhual power

Massive MIMO is a promising solution for wireless backhaul provisioning to a large number of SBSs, without the need for LoS links. A co-channel deployment of massive MIMO BSs and small cell base stations can achieve a very attractive rate region. The minimum number of MBS antennas necessary to provide a desired DL backhaul rate to either { 21, 10 or 5} randomly selected SBSs in each cell with a maximum power budget of 46 dBm for MBS and 30dBm for SBS transmit power.

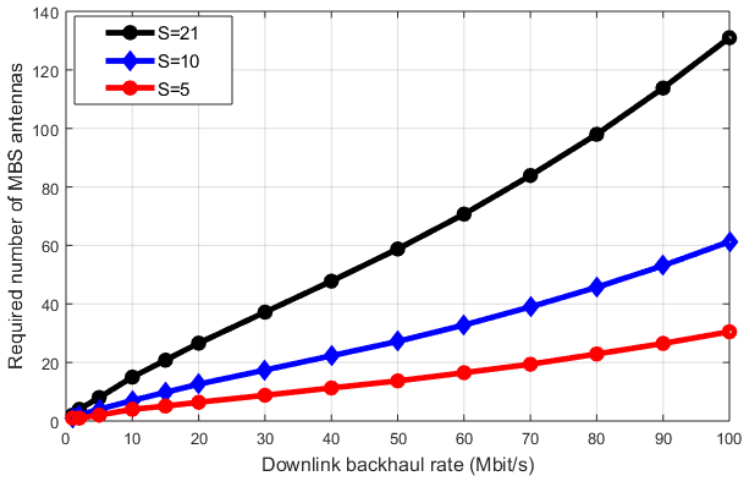


Figure 5.1: Required number of MBS antennas N_{MBS} Vs the DL backhaul rates

Figure 5.1, shows the average transmit power in MBS that is needed to achieve a certain backhaul rate for different numbers of randomly selected SBSs $S \in \{5, 10, 21\}$ using the smallest possible number of antennas and a maximum average transmit power of 46 dBm MBS, in Figure 5.2, for large target rates, the entire power budget is needed, independently of the number of SBSs.

In this Figure 5.2, shown the minimum required transmit power per BS in competition with the DL backhaul rates for different numbers of randomly selected SBSs $S \in \{5, 10, 21\}$. The curves are not entirely smooth since each point on the curves uses a different number of antennas.

Generally, Figures 5.1 and 5.2 provide some evidence that high speed backhaul provisioning via massive MIMO BSs is possible up to a very large number of SBSs per cell.

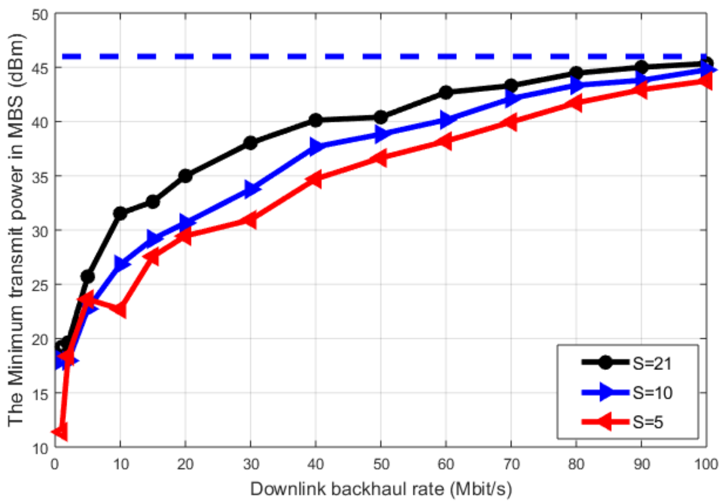


Figure 5.2: Minimum required transmit power per BS Vs the DL backhaul rates

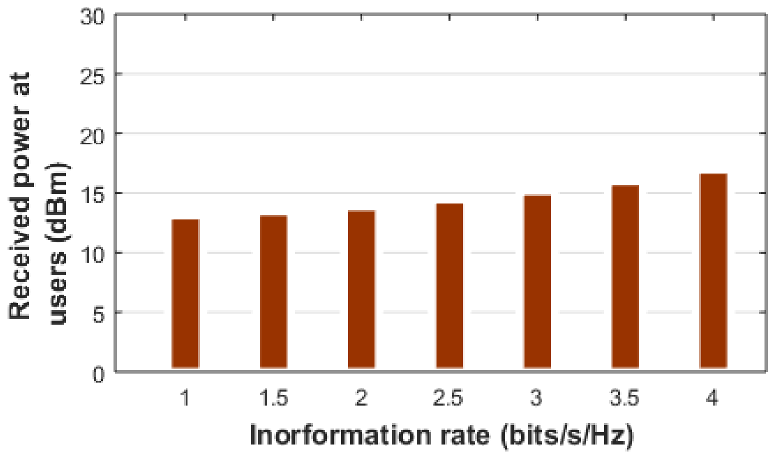


Figure 5.3: Received power at users Vs QoS target

Figure 5.3, shows the average received power at users (dBm) with respect to QoS target per user (bits/sec/Hz). It is clear that the higher the information rate is, the higher the average received power becomes. However, the average received power becomes saturated when the information rate is high enough higher than 2.5 (bits/sec/Hz).

First analyze the effects both the homogeneous and heterogeneous network having different number of antennas:
Figure 5.4, show the total power consumption per subcarriers with different N_{MBS} and SBSs where, users are uniformly distributed with massive MIMO and SBSs, having 2 (bits/sec/Hz) for each user in the single-cell downlink system.

Figures 5.4 and 5.5, illustrate the average total power consumption per subcarrier(dBm)

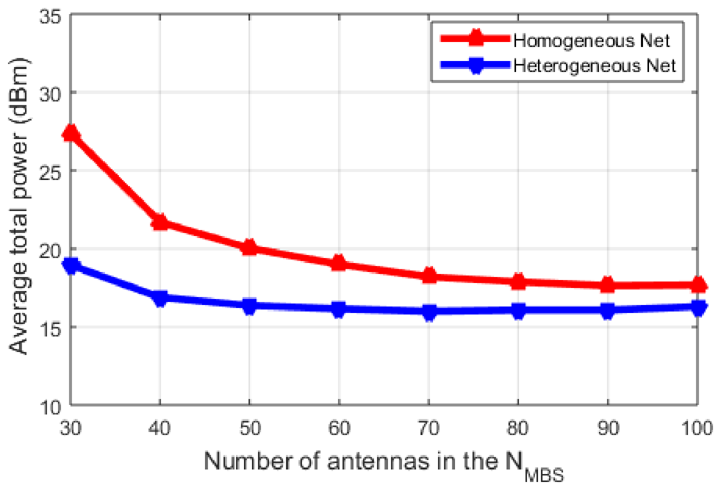


Figure 5.4: Average power Vs Number of antennas

at MBS and SBSs, versus the number of antennas at MBS required. The information rate considered here is (2 bits/sec/Hz). According to Figure 5.4, it is obvious that the higher the number of antennas or increasing extra hardware at { $N_{SBS} = 1, 2, 3$} is, reducing the total power consumption. In other words, addition of extra hardware is decreasing the total power consumption, because if there is a decrease in the dynamic part, then an increase in the static part, from the additional electric circuit systems will equate it for maintaining the EE and decreasing the propagation losses. Massive MIMO brings large EE improvements by itself, but the same power consumption can be achieved with half the number of MBS antennas by deploying a few SBSs in the areas with active users. This will reduce the power consumption and maintain the EE. The EE is further improved by HetNet topology.

When the number of MBS antennas is large, after the saturation points (bending), the total power consumption per subcarrier is not relevant to the number of MBS antennas.

Next, Figure 5.6, shows the average total power consumption, considering without MRZF and different QoS constraints and beamforming users are randomly distributed, take the value of $N_{MBS} = 50$ and $N_{SBS} = 2$ with 15 users.

Figure 5.7, demonstrates that adding more hardware can significantly reduce $P_{dynamic}+P_{static}$ total power consumption.

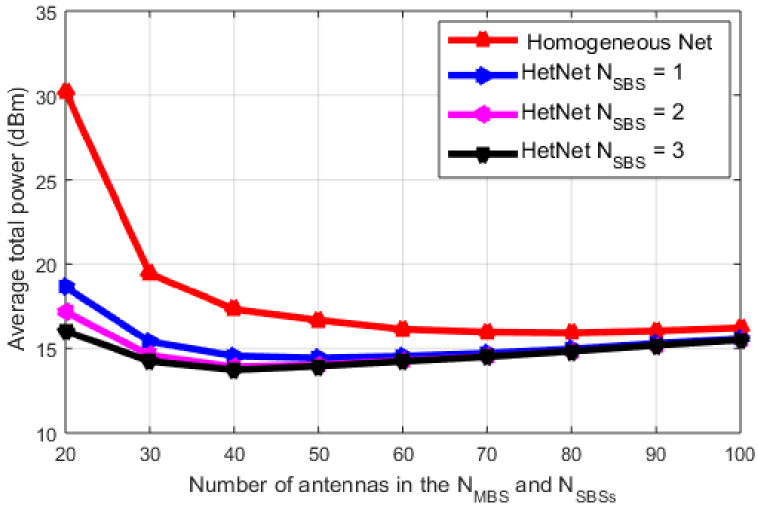


Figure 5.5: Average total power Vs Number of antennas

In this case, the 50 MBS antennas and 2 antennas per SBS are adopted for different QoS constraints,

The three cases of performance are compared;

1. It is only assisted by the MBS (Homogeneous Network);

2. low complexity MRZF algorithm;

3. It is assisted by mixture of SBSs and MBS, where at least one transmitter has an active power constraint (Heterogeneous Network)

It is obvious that combination of massive MIMO to SBS has the lowest total power consumption among all methods. For Figure 5.7, the total power consumption if different QoS constraints with MRZF and beamforming users are distributed randomly, take the value of N_{MBS} =50 and N_{SBS} = 2 for 15 users

In the previse Figure 5.6, it can be shown that by offloading users to the SBSs, there are major improvements in E. The implemented multiflow-RZF beamforming provides appropriate results for practical applications, as functional low complexity beamforming techniques can achieve a majority of EE improvements.

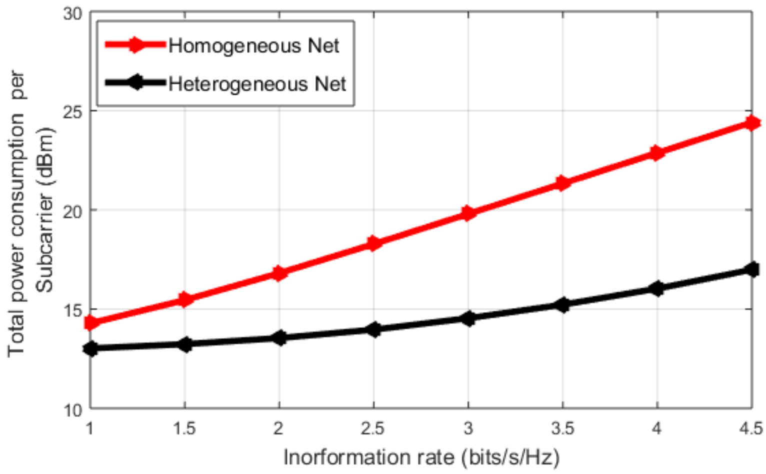


Figure 5.6: Total power consumption Vs Information rate

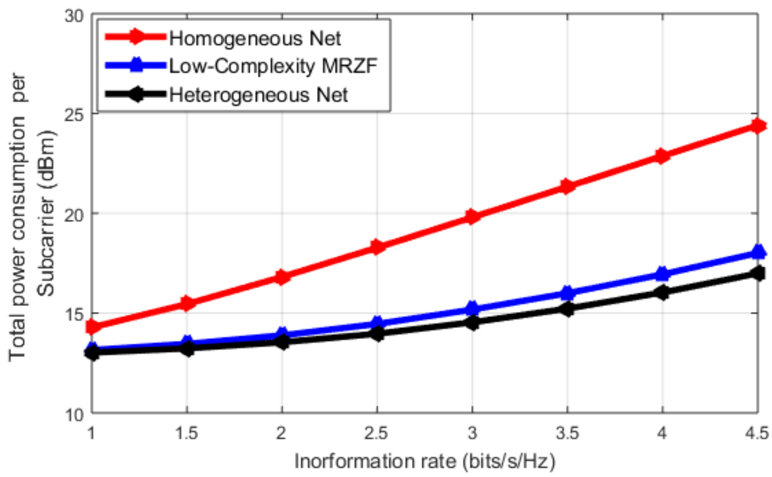


Figure 5.7: Total power consumption Vs Information rate

The average achievable sum information rate is shown in Figure 5.8, as a function of the total transmit power (per base station). The optimal transmit strategy is computed using the branch-reduce-and-bound algorithm. The diagrams illustrate scenarios separately and collective comparative results are also elaborated with multiple numbers of antennas. As the number N increases MRT become optimal at the rate at which SNR range is low. For ZFBF it asymptotically seems optimal at high SNR range. In the area of spectral efficiency and energy consumption models, a number of hardware and propagation parameters

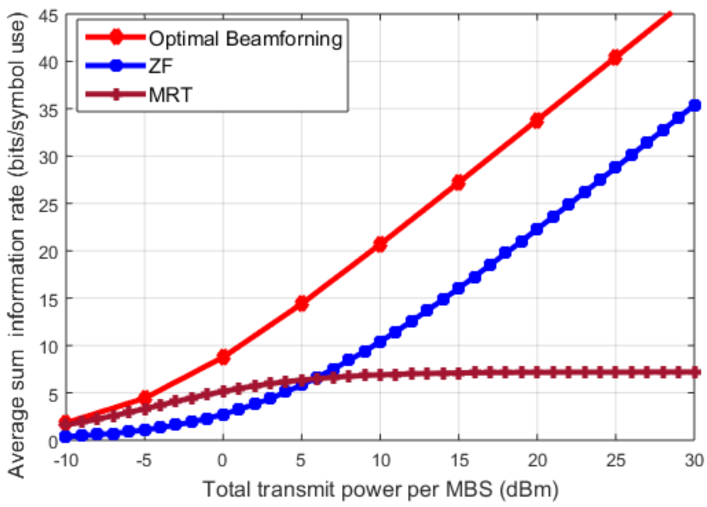


Figure 5.8: Total transmit power Vs Average sum information rate

5.1.3 Optimizing energy efficiency of SBSs

The number of antennas, number of UEs, and transmission power are optimized to produce maximum EE. There are four factors in the EE optimization problem of Eq. 4.48, but stated that the λ_{SBS} density should be large.

The procedure for both SE constraints is the same, but the highest EE values are given by (3 bit/symbol). Also considered is the alternative optimization algorithm. It began at (N, K) = (10, 1) and translated to (N, K) = (91, 10) with an EE of (5.71 Mb/j) in three iterations. This value is obtained by mathematically calculated in Eq.4.47 and take $\Upsilon = 3$. The 0.2 % deviation from the global optimum is due to rounding impacts, as only real-valued N and K are expected to efficiently converge. The EE is optimized with respect to (N, K, λ_{SBS}, P_{tx}), or only with respect to (λ_{SBS}, P_{tx}) for given N and K.

Figure 5.9, the EE has an UE density function for SE = (3 bit/symbol) and figure 5.10, the corresponding SBS density is expressed.

5.1.4 Optimization under fixed UE density

Assume that the SBSs would be incorporated to satisfy a certain UE density. Now to study how this UE density determines the SBS density. In the hotspot areas, future densities from 10^2 UEs per km^2 to 10^5 UEs per km^2 are used as reference points.

Table 5.1: Simulation Parameters

Parameter	Symbol	Value
Path loss exponent	α	3.77
Fixed propagation loss	ω	35dB
Power amplifier efficiency	μ	0.39
Level of hardware impairments	δ	0.05
Symbol time	S	$\frac{1}{2\cdot 10^7}(s/symbol)$
Coding, decoding and backhaul	P_{decob}	1.15 (J/Gbit)
Static energy consumption	P_{stst}	$10W \cdot S(J/symbol)$
Circuit energy per active UE	P_{ue}	$0.1W \cdot S(J/symbol)$
Circuit energy per SBS antenna	P_{bs}	$1W \cdot S(J/symbol)$
Signal processing coefficient	P_{sign}	$1.56 \cdot 10^{-20}(J/symbol)$
Noise variance	σ^2	$10^{-20}(J/symbol)$

The design parameters N, K, λ and P_{tx} are optimized as in Eq.4.48 but with the extra constraint. Single-user transmission (N, K)=(10,1) and large multi-user MIMO transmission (N, K)=(91,10). In the two reference cases, only the SBS density and transmission power have been optimized for EE. It is possible to produce several significant observations. First, it is possible to keep almost the same EE regardless of the UE density. This is achieved mainly by linear scaling of the SBS density

5.1.5 EE maximization for a given UE density

Next, study the tradeoff between massive MIMO and small cells when a cellular network is deployed to cover a heterogeneous UE density of (UE/km2). Mathematically, this amounts to solving 4.47 with the additional constraint $\Theta = K\lambda_{UE}$, which can be easily solved numerically. Consider the range $\Theta \in [10^2; 10^5]$ predicted in [60, 61] is fully covered in these saturation regimes. Figure 5.9, shows the EE as a function of the UE density Υ for the average SINR level = 3, while Figure 5. 10 shows the corresponding BS density. Apart from the optimal solution, by considering the two reference cases: transmission with (N, K) = (10, 1) and with (N, K) = (91, 10).

In contrast, single-user SIMO transmission performs reasonably well at low UE densities, but saturates earlier and at an EE level that is 3× lower than the maximal EE in

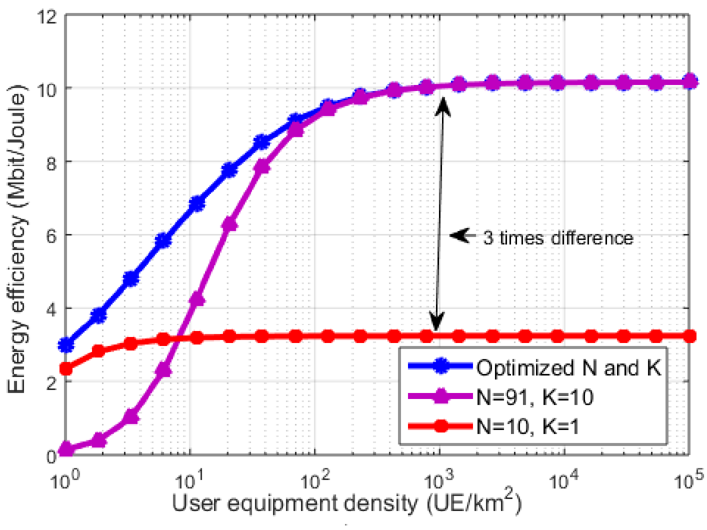


Figure 5.9: Energy efficiency Vs UE density

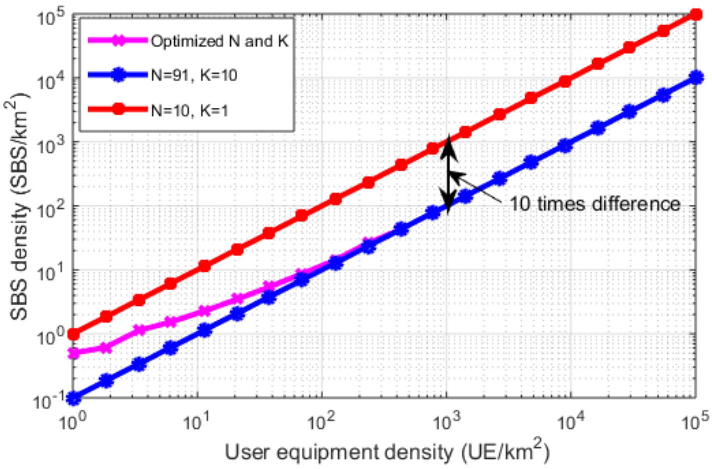


Figure 5.10: Optimized SBSs density Vs UE density

Figure 5.9. More importantly, Figure 5.10, shows that the single-user case requires a 10× higher BS density in the saturation regime, which might greatly reduce the deployment cost.

Chapter 6

Conclusion and Recommendation

6.1 Conclusion

To conclude this thesis work, investigate further the power optimization technique between the MBS and SBS in 3GPP, under the performance of massive MIMO in the HetNet using power optimization technique. To achieve the maximum EE, the typical approaches are to increase the throughput or to reduce the power consumption.

Heterogeneous networks of the small BSs to massive MIMO has been proved as one efficient way to achieve the maximum EE. It also achieves the spectral efficiency by employing overlaid SBS's with current infrastructure. This can be analyzed a combination of these concepts based on shared cell (soft-cell) coordination, where each user can be served by non-coherent beamforming from multiple transmitters. The performance is measured and compared with the existing work in terms of total power consumption per subcarrier of both the massive MIMO BS and small cell BSs.

Further improvements in EE are achieved by having multi-antenna SBSs a network topology that combines massive MIMO and small cell BSs is desirable to achieve high EE with little additional hardware. Note that the power is shown in dBm using MATLAB simulation, thus there is 10-fold improvement from the highest to the lowest point. The results illustrate that increasing the number of antennas at the BSs and also increasing the number of small cells antennas in the network leads to a higher user satisfaction.

To provide promising results showing that the total power consumption can be greatly improved by combining massive MIMO and small cells. Most of the benefits are also achievable by low-complexity beamforming, such as the proposed multiflow-RZF beamforming. The analysis considered both the dynamic emitted power and static hardware consumption. Based on anlysis the relationship among the number of antennas in macro base station, the number of small cells. It can be concluded that the power consumption decreases when the number of antennas per SBS increases.

The other variables were SBSs density, number of antennas and UEs per SBS, and the transmission power. Its result show that the EE increases with the SBSs density, but the positive effect saturates when the circuit power dominates over the transmission power.

6.2 Recommendation for future work

There are some promising future works were proposed.

- This thesis was done by assuming perfect channel acquisition and a backhaul network that supports interference coordination, while the future work will consider fast fading channels where the channel estimation overhead and account errors.
- Multiow beamforming techniques are based on sharing information on controls between network tiers. Furthermore, optimal beamforming can receive significant computational complexity, although beneficial in terms of reducing circuit power and hardware requirements. To address this concern, future studies should investigate designing suboptimal multiow beamforming techniques for energy maximization.
- The analysis of this thesis focused on the downlink and single cell, while future work will consider uplink and multi cell environment of an other interesting area to investigate.
- This thesis work is limited to mobility management, which comes as another technical challenge with heterogeneous networks, thus some advanced mobility management schemes are proposed adaptive sleep mode techniques make the sensing of user mobility and user grouping based on their velocities, where stationary users are served by small BSs while mobile users are allocated to the macro BSs

Bibliography

[1] Index, Cisco Visual Networking. ”global mobile data traffic forecast update, 2017 - 2022.” Cisco White paper (2019).

[2] Claussen, Holger, David Lopez-Perez, Lester Ho, Rouzbeh Razavi, and Stepan Kucera. Small Cell Networks: Deployment, Management, and Optimization. Vol. 16. John Wiley and Sons, 2017.

[3] Acharya, Joydeep, Long Gao, and Sudhanshu Gaur. Heterogeneous Networks in LTE-advanced. John Wiley , Sons, 2014.

[4] Mallinson, K. (2012) The 2020 vision for LTE, Available at
$http://www.3gpp.org/2020-vision-for-LTE$.

[5] Bjornson, E. (2017), How will wireless 5G technology handle 1 000 times more data? Available at $https://www.youtube.com/watch?v=zN7_npagPHY$ *[online]*.

[6] Panwar, Nisha, Shantanu Sharma, and Awadhesh Kumar Singh. ”A survey on 5G: The next generation of mobile communication.” Physical Communication 18 (2016): 64-84.

[7] Erik G. Larsson, Ove Edfors, Fredrik Tufvesson, Thomas L. Marzetta, Massive MIMO for Next Generation Wireless System January 23, 2014.

[8] Rusek, F., Persson, D., Lau, B.K., 2013. Scaling up MIMO: opportunities and challenges with very large arrays. IEEE Signal Process. Mag., 30(1):40-60.

[9] Liand, L., Wei, Y.: Massive device connectivity with massive MIMO. In: IEEE International Symposium on Information Theory (ISIT) (2017)

[10] Ericsson, 5G Radio Access Capabilities and technologies. Ericsson White Paper, 1 - 10 (2016).

[11] Chen, Y., Zhang, S.,Xu, S.,Li, G.Y.: Fundamental trade-offs on green wireless networks. IEEE Commun. Mag. 49, 3037 (2011)

[12] S. K. Mohammed and E. G. Larsson, ”Per-antenna constant envelope precoding for large multi user MIMO systems,” IEEE Trans. Commun., vol. 61, pp. 1059 - 1071, Mar. 2013

[13] J. Nam, J.-Y. Ahn, A. Adhikary, and G. Caire, ”Joint spatial division and multiplexing: Realizing massive MIMO gains with limited channel state information,” in 46^{th} Annual Conference on Information Sciences and Systems (CISS), 2012.

[14] X. Gao, O. Edfords, F. Rusek, and F. Tufvesson, ”Linear Pre-coding Performance in Measured Very Large MIMO Channels,” in IEEE Vehicular Technology Conference (VTC Fall), 2011, pp. 1-5.

[15] A. F. Molisch, Hybrid beamforming for massive MIMO: A survey , IEEE Communications Magazine, vol. 55, no. 9, pp. 134-141, Sept. 2017.

[16] D. Lopez-Perez, I. Guvenc, G. d. l. Roche, M. Kountouris, T. Q. S. Quek, and J. Zhang, Enhanced intercell interference coordination challenges in heterogeneous networks, IEEE Wireless Commun., vol. 18, no. 3, pp. 22 - 30, 2011.

[17] R. Milind, A. Kazerouni, and O. Aryan. ”Precoding Schemes for MIMO Downlink Transmission.” Stanford University, Stanford, CA, EE360 Paper Summary (2007).

[18] E. Pakdeejit, ”Linear Precoding Performance of massive MU-MIMO Downlink System,” M.S. thesis, Linkoping University, Linkoping, Sweden, May 2013.

[19] H.Q. Ngo, E.G. Larsson, and T.L. Marzetta, ”Massive MU-MIMO Downlink TDD Systems with Linear Precoding and Downlink Pilots,” in 51^{st} Annual Allerton Conference on communication, Control and Computing, 2013, pp. 293-299.

[20] C.K. Wen, J.C. Chen, K.K. Wong, and P. Ting, ”Message Pasing Algorithm for Distributed Downlink Regularised Zero Forcing Beamforming with Cooperative Base Stations,” IEEE Transactions on Wireless communications, vol. 13, no. 5, pp. 2920-2930, May. 2014.

[21] Rajoria, Shweta, Aditya Trivedi, and W. Wilfred Godfrey. ”A comprehensive survey: Small cell meets massive MIMO.” Physical communication 26 (2018): 40-49.

[22] Siddique, U., Tabassum, H., Hossain, E. and Kim, D.I., 2015. Wireless backhauling of 5G small cells: Challenges and solution approaches. IEEE Wireless Communications, 22(5), pp.22-31.

[23] Hoydis, Jakob. Massive MIMO and HetNets: Benefits and challenges. Newcom Summer School on Interference Management for Tomorrow’s Wireless Networks (2013)

[24] Dahrouj, H. and Yu, W., 2010. Coordinated beamforming for the multicell multi-antenna wireless system. IEEE transactions on wireless communications, 9(5), pp.1748 - 1759

[25] Hosseini, K., Hoydis, J., Brink, S.T., and Debbah, M. (2013) massive MIMO and small cells: How to densify heterogeneous networks. In Proceedings of IEEE International Conference on Communications (ICC), June 2013.

[26] Ghosh, Amitabha, Nitin Mangalvedhe, Rapeepat Ratasuk, Bishwarup Mondal, Mark Cudak, Eugene Visotsky, Timothy A. Thomas "Heterogeneous cellular networks: From theory to practice." IEEE communications magazine 50, no. 6 (2012): 54-64

[27] Martinez, Elena Rodriguez. "Inter Cell Interference Coordination techniques in HETNETS-Almost Blank Sub - Frames approach." Universitat Politechnica de Catalunya (2013).

[28] Parkvall, Stefan, Erik Dahlman, George Jongren, Sara Landstrm, and Lars Lindbom. "Heterogeneous network deployments in LTE." Ericsson review 2 (2011): 34-38.

[29] Rong, B., Qiu, X., Kadoch, M., Sun, S. and Li, W., 2016. 5G heterogeneous networks: self-organizing and optimization. Berlin, Germany: Springer.

[30] F. Vaz, P. Sebastiao, L. Goncalves, and A. Correia, Economic and environmental comparative analysis on macro-femtocell deployments in LTE-A," in Proc. Int. Conf. on Wireless Commun., Veh. Technol., Inform. Theory and Aerospace Electron. Syst.(VITAE), June 2013,pp.15.

[31] Hu, R.Q. and Qian, Y., 2014. An energy efficient and spectrum efficient wireless heterogeneous network framework for 5G systems. IEEE Communications Magazine, 52(5), pp.94 - 101

[32] Hoydis, J., ten Brink, S., Debbah, M. (2013). Massive MIMO in the UL and DL of cellular networks: How many antennas do we need? IEEE Journal of Selected Areas in Communications, 31(2), 160 - 171.

[33] A. Aijaz, H. Aghvami, and M. Amani, A survey on mobile data offloading: technical and business perspectives, IEEE Wireless Commun., vol. 20, no. 2, pp. 104 112, Apr. 2013.

[34] A. Gupta, R. K. Jha, A survey of 5G network: Architecture and emerging technologies, IEEE access (2015)1206 - 1232.

[35] Vorobyov, S. A., Cui, S., Eldar, Y. C., KinMa, W., and Utschick, W. (2009). Optimization techniques in wireless communications. EURASIP Journal on Wireless Communications and Networking, 2009, 567416

[36] I. Hwang, B. Song, and S.S. Soliman, A holistic view on hyper - dense heterogeneous and small cell networks, IEEE Commun. Mag., vol. 51, no. 6, pp. 2027, June 2013.

[37] Hu, R.Q. and Qian, Y., 2014. An energy efficient and spectrum efficient wireless heterogeneous network framework for 5G systems. IEEE Communications Magazine, 52(5), pp.94 - 101

[38] Rajoria, Shweta, Aditya Trivedi, and W. Wilfred Godfrey. "A comprehensive survey: Small cell meets massive MIMO." Physical communication 26 (2018): 40-49.

[39] X. Hou, X. Wang, H. Jiang, H. Kayama, Investigation of massive MIMO in dense small cell deployment for 5G, in: 2016 IEEE 84^{th} Vehicular Technology Conference (VTC - Fall), 2016, pp. 1 - 6.

[40] Vorobyov, S. A., Cui, S., Eldar, Y. C., KinMa, W., and Utschick, W. (2009). Optimization techniques in wireless communications. EURASIP Journal on Wireless Communications and Networking, 2009, 567416

[41] Cui, S., Goldsmith, A., and Bahai, A. (2005). Energy constrained modulation optimization. IEEE Transactions on Wireless Communications,4(5), 2349 - 2360.

[42] Bjornson, E., Jorswieck, E. (2013). Optimal resource allocation in coordinated multi cell systems. Foundations and Trends in Communications and Information Theory, 9(2 - 3), 113 - 381.

[43] E. Bjrnson, N. Jalden, M. Bengtsson, and B. Ottersten, Optimality properties, distributed strategies, and measurement-based evaluation of coordinated multicell OFDMA transmission, IEEE Trans. Signal Process., vol. 59, no. 12, pp. 60866101, 2011.

[44] K. Vinoth, S. Purushothaman, R. Baskar, C. Gomathi Optimal Energy Efficiency for 5G Wireless Communications,IJRESM , Issue - 12, December (2018).

[45] Bjornson, E., Kountouris, M. and Debbah, M., 2013. Massive MIMO and small cells: Improving energy efficiency by optimal soft cell coordination.

[46] H. Holma and A. Toskala, LTE Advanced 3GPP Solution for IMT Advanced. New York, NY John Wiley and Sons Ltd., 2012.

[47] Gupta, Akhil, and Rakesh Kumar Jha. ”Power optimization using massive MIMO and small cells approach in different deployment scenarios.” Wireless Networks 23, no. 3 (2017): 959-973.

[48] Ng, D., Lo, E., Schober, R. (2012). Energy efficient resource allocation in OFDMA systems with large numbers of base station antennas. IEEE Transaction on Wireless Communication, 11(9), 3292 - 3304.

[49] Abarghouyi, Hadis, S. Mohammad Razavizadeh, and Emil Bjrnson. "QoE-Aware Beamforming Design for massive MIMO Heterogeneous Networks." IEEE Transactions on Vehicular Technology 67, no. 9 (2018): 8315-8323.

[50] Daniel P. Palomar, Yonina C. Eldar Convex Optimization in Signal Processing and Communications Cambridge University Press 2010

[51] Chong-Yung - Chi . Wei - Chiang Li . Chia - Hsiang Lin Convex Optimization for Signal Processing and Communications (2017) by Taylor and Francis Group, LLC

[52] Rizwan M, Gong T, Janjua K (2018) Analysis of Efficient Beamforming and Power Optimization in Wireless Communication. J Telecommun Syst Manage 7: 162.

[53] Boyd, S. and Vandenberghe, L., 2004. Convex optimization. Cambridge university press.

[54] Bengtsson, M., Ottersten, B. (2001). Optimal and suboptimal transmit beamforming. In L. C. Godara (Ed.), Handbook of antennas in wireless communications. Boca Raton: CRC Press.

[55] Haenggi, M., 2012. Stochastic geometry for wireless networks. Cambridge University Press.

[56] M. Haenggi, J. G. Andrews, F. Baccelli, O. Dousse, and M. Franceschetti, ”Stochastic geometry and random graphs for the analysis and design of wireless networks,” IEEE J. Select. Areas Commun., vol. 27, no. 7, pp. 1029 - 1046, Sep. 2009.

[57] D. Stoyan, W. S. Kendall, and J. Mecke, Stochastic Geometry and its Applications, 2nd ed. New York, NY: John Wiley and Sons Ltd., 1995.

[58] Mukherjee, Sayandev. Analytical modeling of heterogeneous cellular networks. Cambridge University Press, 2014.

[59] Bjornson, E., Hoydis, J., Kountouris, M. and Debbah, M., 2014. Massive MIMO systems with non ideal hardware: Energy efficiency, estimation, and capacity limits. IEEE Transactions on Information Theory, 60(11), pp.7112-7139. pp. 136-141, 2015.

[60] E. Bjornson, L. Sanguinetti and M. Kountouris, "Designing Wireless Broadband Access for Energy Efficiency: Are Small Cells the Only Answer?," in Proc. IEEE Int. Conf. on Commun. Workshop (ICCW), pp. 136-141, 2015.

[61] Daniel Verenzuela, Emil Bjornson, and Luca Sanguinetti, Optimal Design of Wireless Networks for Broadband Access with Minimum Power Consumption, 2016, IEEE International Conference on Communications (ICC)

[62] E. Bjornson, L. Sanguinetti, J. Hoydis and M. Debbah, "Optimal Design of Energy-Efficient Multi-User MIMO Systems: Is Massive MIMO the Answer?," IEEE Trans. Wireless Commun., vol.14, no.6, pp. 3059-3075, 2015.

Appendix

Appendix - A

According to the standard in [50, 53], the relaxed problem is Eq. 4.15 in a semidefinite optimization problem. So far, there always exist a solution with rank $(\mathbf{W}_{k,j}) \leq 1, \forall k, j$. To verify this consider there exist an optimal solution $\{\mathbf{W}_{k,j}^{**}, \quad \forall k, j\}$ with rank$(\mathbf{W}_{k,j}^{**}) > 1$. So $\mathbf{W}_{k,j}^{**}$ can be replaced by any $F \geq 0$ such that it

$$\begin{aligned} &\text{maximizes} \quad h_{k,j}^H F h_{k,j} \\ &\text{subject to} \quad Tr(F) \leq Tr\Big(\mathbf{W}_{k,j}^{**}\Big), Tr(D_{j,t}F) \leq Tr\Big(D_{j,t}\mathbf{W}_{k,j}^{**}\Big), \quad \forall t \end{aligned} \tag{6.1}$$

which means that, it is not using more power than $\mathbf{W}_{k,j}^{**}$ and for not causing more interference than $\mathbf{W}_{k,j}^{**}$

$$h_{i,j}^H F h_{i,j} \leq h_{i,j}^H \mathbf{W}_{k,j}^{**} h_{i,j} \quad \forall i \neq k \tag{6.2}$$

So one solution will be $F = \mathbf{W}_{k,j}^{**}$, but according to [54] in Lemma 3 these types of problems always have rank-one solutions.

Appendix - B

To analysis of these can be $A_k = \frac{1}{\sigma_k^2}\boldsymbol{diag}\Big(\frac{1}{\mu_0}h_{k,0}h_{k,0}^H, , , , , , , \frac{1}{\mu_s}h_{k,s}h_{k,s}^H\Big)$ can be block-diagonal matrix and $\mathbf{w}_k = \Big[\sqrt{\mu_0}\mathbf{w}_{k,0}^T, , , , , , , \sqrt{\mu_s}\mathbf{w}_{k,s}^T\Big]^T$ be the aggregate beamforming vectors. where, $\tilde{D}_{j,t}$ is the block diagonal matrix that makes $\mathbf{w}_k^H\tilde{D}_{j,t}\mathbf{w}_k = \mathbf{w}_{k,j}^H D_{j,t}\mathbf{w}_{k,j}$ and $\mathbf{w}^* = \sqrt{P_k}V_k$ is the optimal solution to 4.21), where V_k is unit-norm.

According to the uplink-downlink duality as given in[54], Lemma 4, is given as

$$\tilde{\gamma_k} = \frac{P_k V_k^H A_k V_k}{\sum_{i\neq k} P_i V_i^H A_k V_i + 1} = \frac{\Omega_{a,k} V_k^H A_k V_k}{V_k^H B_k V_k} \tag{6.3}$$

Where $B_k = \Big(\sum_{i\neq k}\Omega_i A_i + \sum_{j,t}\xi_{j,t}\tilde{D}_{j,t} + I\Big)$ and $\Omega_i, \xi_{j,t}$ ideal Lagrange multipliers for the QoS and power constraints, respectively.

From the expression provided in Eq.6.3, therefore it is evident that the uplink SINR targets or QoS targets will take the greatest value when V_k will be the dominating eigenvector of $B_k^{-1/2}A_k B_k^{-1/2}$. Since B_k and A_k are block diagonal with each block belongs to either the MBS or one of the SBS points.

Appendix - C

The lambert function is denoted W(x) and written the equation $x = W(x)e^{W(x)}$ for any x $\in$ C. By considering the optimization problem in Eq.4.49, Eq.4.51 and Eq.4.52 to maximizing the EE in the Eq.4.48, where taking λ_{SBS} as a constant, the EE optimization problem is reduced to Eq. 4.50.

$$\underset{z>\frac{-a}{b}}{\text{maximize}} \frac{g\log(a+bz)}{c+dz+h\log(a+bz)} \tag{6.4}$$

with constant coefficients a $\in \mathbf{R}$, c, h ≥ 0, and b, d, $g > 0$.

$\varphi(z) = \frac{g\log(a+bz)}{c+dz+h\log(a+bz)}$ denote the objective function.

To prove this function is quasiconcave, the level sets $S_k = \{z : \varphi z \geq \kappa\}$ need to be convex for any $\kappa \in \mathbf{R}$.

Since $\frac{\partial^2\varphi(z)}{\partial z^2} = \frac{(h\kappa-g)}{\ln(2)}\frac{b^2}{(a+bz)^2} \leq 0$ for $\kappa \leq \frac{g}{h}$. If there exists a point $z^* > \frac{-a}{b}$ such that $\varphi^{'}(z^*) = 0$. Then the quasi-concavity implies that z^* is the global maximizer and that $\varphi(z)$ is increasing for $z < z^*$ and decreasing for $z > z^*$. To prove the existence of z^* thus, note that $\varphi^{'}(z) = 0$, if and only if $\frac{1}{\ln(2)}\frac{b(c+dz)}{a+bz} - d\log(a+bz) = 0$.

$$\frac{bc-ad}{a+bz} = d(\ln(a+bz)-1) \tag{6.5}$$

Plugging $x = \ln(a+bz)-1$ into Eq.6.5 yields $\frac{bc}{de} - \frac{a}{e} = xe^x$ whose solution is eventually found to be $x^* = W(\frac{bc}{de} - \frac{a}{e})$, W is Lambert function.