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ENERGY AND SPECTRAL EFFICIENCY TRADEOFF IN WIRELESS COMMUNICATION

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ABSTRACT

SYED JOBAIRUL ALAM: ENERGY AND SPECTRAL EFFICIENCY TRADEOFF IN WIRELESS COMMUNICATION
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In the wireless communication world, a significant number of new user equipments is connecting to the network each and every day, and day after day this amount is increasing with no known bounds. Diverse quality of service (QoS) along with better system throughput are the crying needs at present. With the advancement in the field of massive multiple-input multiple-output (MMIMO) and Internet-of-things (IoT), the QoS is provided smoothly with the limited spectrum by the wireless operator. Hundreds of antenna elements in the digital arrays are set up at the base station in order to provide the smooth coverage and the best throughput within these spectra. However, implementing hundreds of antenna elements with associated a huge number of RF chains for digital beamforming consumes too much energy. Energy efficiency optimization has become a requirement at the present stage of wireless infrastructure. Due to the conflicting nature between the energy efficiency and the spectral efficiency, it is hard to make a balance. This thesis investigates how to achieve a good tradeoff between the energy and the spectral efficiency with maximum throughput outcomes from MMIMO, with the help of existing topologies and a futuristic perspective. Although the signal noise power is less in massive MIMO than the conventional cellular system, it still needs to be decreased and at the same time, the average channel gain per user equipment must be increased. Fixed power requirement for control signaling and load-independent power of backhaul infrastructure must be cut at least by a factor two as well as the power amplifier efficiency has to increase by 10% than LTE networks. The minimum mean square error (MMSE) estimator can be a possible solution in terms of the energy and the spectral efficiency despite having computational complexity which can be solved with the aid of Moore's law and it is proposed by the non-profit research organization IMEC, which has developed an online web tool for observing and predicting contemporary as well as futuristic cellular base station's power consumption. It supports various types of base stations with a wide range of operating conditions. The multicell minimum mean square error (M-MMSE) scheme can perform better than other existing schemes and showcase satisfactory tradeoff with frequency reuse factor higher than 2, where regularized zero-forcing (RZF) and maximum ratio (MR) combining fall down their capabilities for performing. With the precipitous rising of IoT, the Narrowband Internet-of-things (NB-IoT) may play an efficient supportive role if we can collaborate it with MMIMO. With its low power, wide area topologies combining with MMIMO technologies can show better tradeoffs. Due to its narrow bandwidth, the signal noise power would be less compared to the existent wideband topologies, and the average channel gain of active user equipment would be higher too. Hence it will give a great impact in terms of the tradeoff between energy and the spectral efficiency which is addressed in this thesis.

Keywords: Spectral efficiency, energy efficiency, throughput, massive MIMO, NB-IoT

The originality of this thesis has been checked using the Turnitin Originality Check service.

PREFACE

All praise goes to the supreme creator ALLAH, who has given me enough courage and patience to complete my master's thesis. The process wasn't easy, neither the roadmap. There were lots of ups and downs, enormous unsuccessful attempts, countless awakened nights, but finally, HE enlightened me with the right and successful approaches to come to an end.

I want to thank cordially to my thesis supervisor, Associate Professor, Dr. Elena Simona Lohan for mentoring me, motivating me and giving me this beautiful as well as updated topic. Her supervision and time asking for feedback help me to complete my thesis. Secondly, I want to thank my Co-supervisor, Dr. Jukka Talvitie for giving me his precious time and guiding me. Thank you so much from the core of my heart and thanks once again to keep faith in me and my capabilities.

Special thanks go to Tampere University for giving me the chance to peruse my higher education. Really thankful to the entire faculty, my friends and my family.

This is a milestone achievement in the journey of my life. Though it is not the end, it will always encourage me in every step in my life.

Tampere, 18 October 2019

Syed Jobairul Alam

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LIST OF SYMBOLS AND ABBREVIATIONS

ADC	Analog-to-Digital Converter
ASD	Angular Standard Deviation
ATP	Area Transmit Power
AWGN	Additive White Gaussian Noise
BS	Base Station
CDF	Cumulative distribution function
CP	Circuit Power
CSI	Channel State Information
D2D	Device-to-Device
D2I	Device-to-Infrastructure
DAC	Digital-to-Analog Converter
DL	Downlink
EC-GSM-IoT	Extended Coverage Global System for Mobile Internet-of-Things
EE	Energy Efficiency
eNB	eNode B
ETP	Effective Transmit Power
EW-MMSE	Element-Wise MMSE
FEC	Forward Error Control
FDD	Frequency-Division Duplex
GSM	Global System for Mobile Communications
HSPA+	Evolved High Speed Packet Access
I/Q	In-Phase/Quadrature
LoRA	Long-Range
LO	Local Oscillator
LoS	Line-of-Sight
LPWAN	Low Power Wide Area Network
LS	Least-Squares
LTE	Long Term Evolution
LTE-M	Long Term Evolution for Machine
MAC	Medium Access Control
MIMO	Multiple-Input Multiple-Output
MMIMO	Massive Multiple-Input Multiple-Output
M-MMSE	Multicell Minimum-Mean Square Error
MMSE	Minimum-Mean Square Error
MSE	Mean-Squared Error
MOO	Multi-objective Optimization
MR	Maximum Ratio
MRC	Maximum Ratio Combining
MRT	Maximum Ratio Transmission
NB-IoT	Narrowband Internet-of-Things
NLoS	Non-Line-of-Sight
OFDM	Orthogonal Frequency-Division Multiplexing
PA	Power Amplifier
PC	Power Consumption
RF	Radio Frequency
RMS	Root Mean Square
RZF	Regularized Zero-Forcing
SDMA	Space-Division Multiple Access
SE	Spectral Efficiency
SINR	Signal-to-Interference-and-Noise-Ratio
S-MMSE	Single-Cell Minimum Mean-Squared Error

SNR	Signal-to-Noise Ratio
TDD	Time Division Duplex
UE	User Equipment
UL	Uplink
Wi-FI	Wireless-Fidelity
WiMAX	Worldwide Interoperability for Microwave Access
WLAN	Wireless Local Area Network
ZF	Zero-Forcing
ZTE	Zhongxing Telecommunication Equipment
3GPP	3rd Generation Partnership Project

1. INTRODUCTION

With the enormous development in the field of wireless communication as well as fast reiterative modification of user equipment, the requirement for communication networks and better quality of service has become a matter of concern and technologies are eagerly working on it to fulfill their demand. In this 21st century, with the advancement in the multiple access technologies, the concept has changed from “being always connected” to “always best connected” [1]. It refers to the fact that “always connected” is not what people need, rather they need the best possible way to connect. To meet up people’s demand, the wireless throughput is increasing whereas our spectrum resource remains fixed [2], [3]. Hence, different technologies are emerging in this field to cope with the up situation and interestingly these technologies are increasing the throughput along with a limited spectrum. Multi-Access massive MIMO (MMIMO) technology has successfully overcome this crisis. Its linear precoders and decoders are asymptotically optimal to capacity by turning its base station’s number to infinity [4]. In MMIMO, hundreds of antennas are coupled in the base station which communicates with users smaller than by number [5], [6]. As a result, users are getting higher throughput and their demands are fulfilled. On the contrary, deploying hundreds of antenna elements in array at a base station (BS) consumption of energy is escalated. BS is now regarded as the number one consumer of the total energy used in the wireless network. In the European cellular market, 18% of the operating expenditure is the energy bill of BS [7]. From the statistics [8], [9], UE-wise power utilization is rapidly increasing and in wireless communication, electricity demands are increasing by 20% annually. Hence, the energy efficiency and spectral efficiency have become a matter of concern for both industries as well as government not only in sense of expense but also in a sense of global warming. Spectral efficiency was the concern issue for researchers so far, but recently they considered energy efficiency as an important performance metric. However, to design an efficient wireless network, these two metrics should consider together rather than separate. Besides, the spectral efficiency (SE), and the energy efficiency (EE) need to improve by the same amount of data rate, which is challenging [10]. As these two are contradictory, maximizing one is the reason for minimizing the other, making a balance between them (EE and SE) is an apple of discard in present and future wireless structure.

Works have been done for balancing the EE-SE tradeoff. A fundamental, EE-SE tradeoff was proposed for wireless networks in AWGN [11], but the proposal was without taking into account the fading channel effects. In [12], it explains that, MMIMO without considering the circuit power consumption can improve EE almost three orders of magnitude. This is achievable with simple precoding and combining schemes like zero-forcing (ZF) or a maximum ratio (MR) combining where the computational complexity is very low, and they don't need an inverted matrix. Moreover, SE in these schemes is also very low. In addition, in the single-cell MMIMO system, two linear precoders zero-forcing (ZF) and maximum ratio transmission (MRT) are compared with EE and SE [13]. EE-optimal architecture considering circuit power consumption in MMIMO is shown in [14]. All the above works are considered in single-cell circumstances. With MMIMO, EE of the multicell network has shown in [15], [16]. To improve EE, antenna selection for reducing radio frequency (RF) chains in MMIMO [17],[18].

1.1 Thesis Objectives

Keeping all the above in mind, the thesis goal is to try to make a balance between these two very conflicting metrics, namely SE and EE. The tradeoff is a multi-objective optimization (MOO) problem. In order to sort this problem out, the adopted methodology was to go through several simulations by changing the factors which work behind them.

1.2 Author's Contributions

First, the Author simulated simple statistic equations to see the nature of the response of the EE and SE metrics. Then with deeper insights, the Author checked the response of them individually and jointly when factors such as the number of transmitters, number of UEs, power amplifier's efficiency, signal power, and average channel gain factor's ratio were changed. Moreover, the Author tried to combine Low Power Wide Area Network (LPWAN) topologies, such as narrow band internet-of-things (NB-IoT) with MMIMO features to observe the impact and whether they are able to perform in MMIMO's platform or not, as researchers have already started to collaborate NB-IoT with MMIMO [19]. Moreover, MIMO antennas are also customized for narrowband as well as for ultra-wideband [20]. Finally, the Author came up with the conclusion about the ratio of antenna-user equipment for which we can keep out wireless network stable, i.e., maximum SE will be obtained with the minimum energy consumption. In addition, the Author tried to figure out in the future what challenges we will be going to face and what we should perform to cope with it.

1.3 Thesis Structure

The rest of the thesis is as follows: Chapter 2 introduce the basic Device-to-infrastructure (D2I), Device-to-device (D2D), Low-power wide area network (LPWAN), its categories and MMIMO. Chapter 3 introduce SE, EE, and throughput concepts. Methods to enhance SE and EE are described in chapter 4. All the simulations and results are discussed in chapter 5. Finally, chapter 6 gives conclusions about this research and the challenges to come along with further work needed to be done in the future.

2. CONCEPTS OF D2I AND D2D

Wireless communication is the most important medium to transport voice, data, video or information to other networks, or for private networks. In the advancement of the technological field, wireless communication has become an integral part of a variety of devices like mobile phones, tablets, laptops, wireless telephones, GPS, satellites, ZigBee and so on that allows this user equipment's or devices to communicate with each other from anywhere at any time. Moreover, to keep these communications uninterrupted and providing better Quality-of-Service (QoS), either new technologies are adding or constantly improving the existing infrastructure. With this advancement in wireless infrastructure, devices are now communicating among themselves (D2D) or communicating via cellular network (D2I).

In wireless cellular infrastructure, all communications must pass through a base station access point. All UEs or devices can access the wired network and other devices via this base station transceiver. Cellular radio frequency bands are used for communication from 700 MHz up to 4 GHz depending on the used technology. Base stations communicate point-to-point communication with themselves via microwave backhaul (wireless link) or fiber(wired) connections. Antennas that are needed for this microwave backhaul are configured as the line-of-sight setting.

On the other hand, in satellite infrastructure, satellites itself are considered as an access point or base station. It operates almost in a similar way, and the only difference is that there remains two-unit for satellite infrastructures: one is- indoor box also called set-top-box and the other one is the outdoor unit, called transceiver. The set-top-box is connected wirelessly with the transceiver and the dish (antenna). In satellite infrastructure, downlink communication uses 10.7-12.75 GHz Ku-band or 18.2-22.0 Ka-band and for uplink, it uses 13 GHz and/or 30 GHz frequency bands [21].

2.1 D2I (Device-to-Infrastructure) Concept

D2I is a traditional mobile concept. D2I has basic five things: UEs, cells, BSs, Mobile installation paths, and Radio link or leg. All the UE activity has represented by the Mobile Installation path toward base transceiver station cell. With the aid of this mobile installation path, and mobile services can be delivered to the end customers. The service resembles specific attributes and supplement features. A basic D2I inventory model is shown below in figure 1.

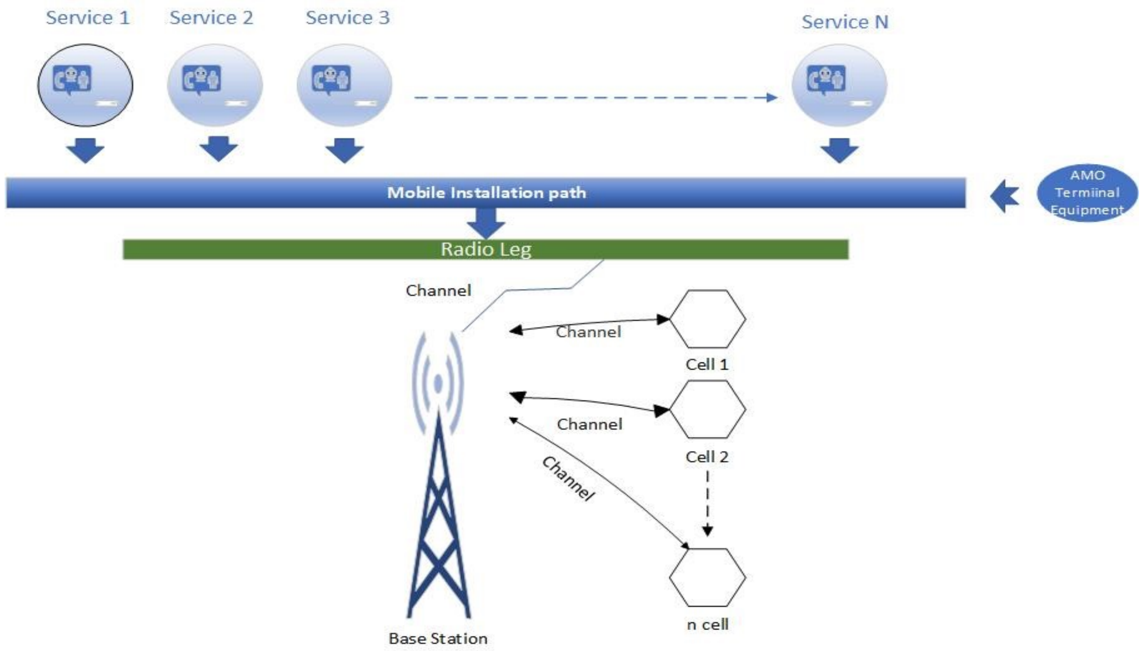


Figure 1. *Basic D2I (Device-to-Infrastructure) inventory model.*

The positive sides of D2I communication are that its functionality is simple. It has greater central control of the network. It can reach a long way [22]. On the contrary, with increasing UEs, BSs got overloaded. Devices need to involve in the BSs for local communication despite having under proximity. The spectral resource is not used in full range [22].

2.2 D2D (Device-to-Device) Concept

D2D concept relies on the technique in which devices can directly communicate with each other without the necessity of any infrastructure's access point or without BSs. In D2D, UEs or devices can transmit or receive data signals from each other via a direct connection or link in close proximity with the help of cellular resources but not using eNB. Underlying to cellular networks, D2D communication increases spectral efficiency (SE). It is an add-on component in 4G and expected to become a native feature in 5G networks.

Figure 2 illustrates a basic inventory model for D2D communication. The D2D model is updated on the basis of the D2I model that directs UEs' communication with each other. From the technical point of view, the wireless network access side remains unchanged compared to D2I while the main technical upgrades have been done on the device's side. The network takes care of signalization which is the same for both D2D as well as D2I while the hardware of the UEs should be upgraded enough to support D2D communication.

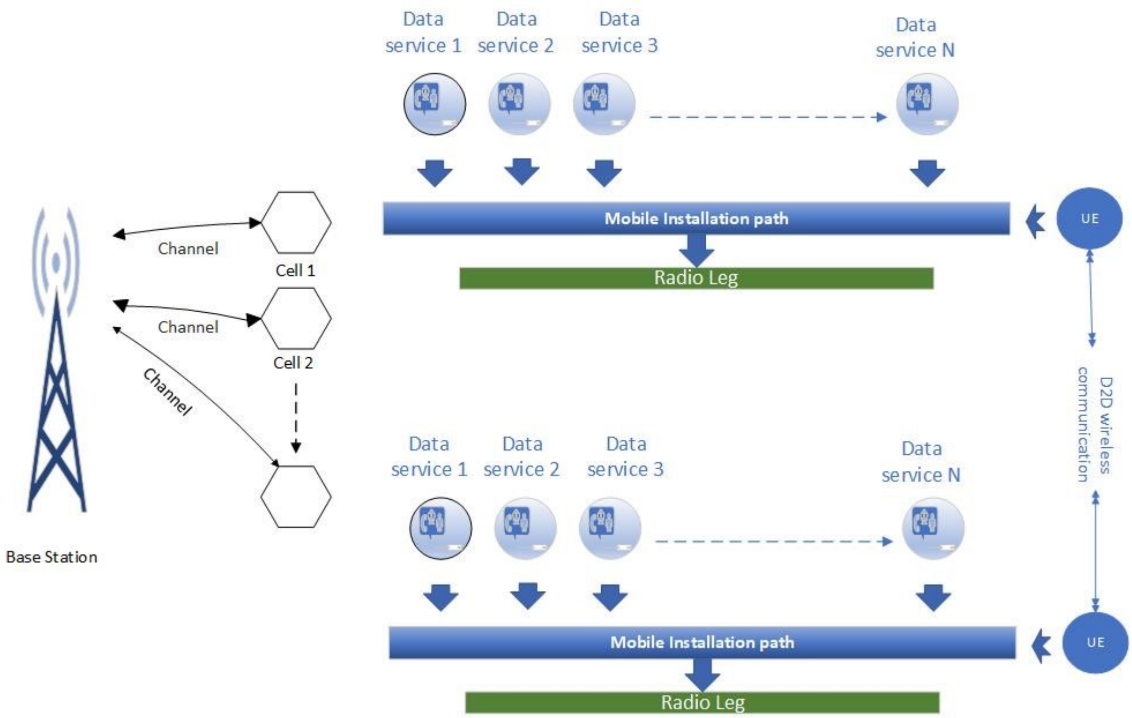


Figure 2. *Basic D2D (Device-to-Device) inventory model*

Basic D2D communication is nothing but an additional feature developed on the existent mobile service, also modeled as additional subscriber service.

One of the best benefits involves about D2D in high data rates with ultra-low latency communication. It is easier to allocate resources in D2D and it increases the spectral efficiency of the network. It offloads local communications from BSs which are overloaded. D2D communication supports local data service efficiently through broadcast, groupcast and unicast transmission [23]. Moreover, there remains no interference between D2I and D2D subscribers [24].

On the contrary, packets are needed to decoded and encoded for D2D communication. In addition, power management needs to be very efficient for this type of communication. Moreover, not every radio interface can be used for D2D communication, only a few (like, LTE, LTE-A, WiFi, 5G) can be used [24].

2.3 IoT (Internet-of-Things)

The IoT (Internet-of-things) has become a topic-of-interest in the wireless communication field nowadays. It has changed the dimension of the wireless network. The world is now going in the concept of, “Anything that can be connected, will be connected.” With the abrupt growth of the IoT technologies, a massive number of practical applications are imposing including smart metering, smart homes, security, agriculture, asset tracking and so on [28]. The specification of requirements of IoT applications includes low energy consumption, long-range, low data rate and cost-effectiveness. The short-range radio technologies (e.g., Bluetooth, Zigbee) are not adopted for it as they are unable for long-range transmission. Therefore, a low power wide area network (LPWAN) has driven as new wireless technology to meet up the requirements for IoT. It has characteristics of low power, low cost, and long-range communication. High energy efficiency [29], inexpensive radio chipset and long-range coverage (1-5 km in the urban zone and 10-40 km in the rural area) [30] have made it highly compatible with IoT. Different LPWAN technologies have been used for IoT both in the licensed and unlicensed frequency bandwidth. Among all of them, a few (i.e., NB-IoT, LoRa, LTE-M, Sigfox, and EC-GSM-IoT) are now rolling emergent technologies with a variety of technical aspects. The basic parameters of these LPWAN technologies are inscribed in table 1.

Table 1*. Comparison of different LPWAN technologies for IoT operation.*

Parameters	NB-IoT	LTE-M	LoRa	Sigfox	EC-GSM-IoT
Bandwidth	200 KHz	1.4 MHz	125 KHz	100 Hz	200 KHz
Coverage expressed as Maximum Coupling Loss	164 dB	156 dB	165 dB	165 dB	164 dB
Battery Life	10+ years	10+ years	15+ years	15+ years	10 years
Throughput	250 kbps	1 mbps	50 kbps	100-600 bps	140 kbps
Band	Licensed LTE	Licensed LTE	915 kHz	<1 GHz	Licensed GSM
Energy Efficiency	High	Medium	High	High	high
Power Class	23 dBm	23 dBm 20 dBm	14 dBm	14 dBm	33 dBm 23 dBm
Latency	1.6s- 10s	15 ms	Depends on class	1s-30s	700ms-2s

2.4 Massive MIMO

Massive MIMO (MMIMO) is an extension of MIMO which stands for Multiple-input multiple-output. Basically, MIMO is an antenna system method that uses multiple receiving and transmitting antennas for multiplying the capacity of the radio link for the sake of exploiting multipath propagation. The word, “massive” refers due to the number of base station antennas. It is a multi-user multiple-input multiple-output technology which provides better service in high-mobility environments of the wireless network. The main concept lies in equipping the BSs with arrays of multiple antennas for providing simultaneous service to multiple terminals using the time-frequency resource. It is basically grouping the antennas together at both transmitter and receiver for the sake of providing better spectrum efficiency and throughput. It has the capability to multiply the antenna links. This capability has made it an important element of wireless standards of HSPA+, 802.11n (Wi-Fi), 802.11ac (Wi-Fi), WiMAX, LTE, LTE-A and 5G [25]. Shifting towards MMIMO from MIMO, according to IEEE, involves making “a clean break with current practice through the use of a large excess of service antennas overactive terminals and time-division duplex operation. Extra antennas help by focusing energy into ever-smaller regions of space to bring huge improvements in throughput and radiated energy efficiency.” [26]. The group of antennas has several other benefits, including the Simplification of MAC layer, Very low latency, robustness against tensional jamming, cheaper parts and so on. It has improved significantly end-user experience increasing the network’s coverage and capacity at the same time reducing interference, as shown in figure 3.

Figure 3 illustrates a simplistic view of MMIMO increasing delivery capacity and coverage compared to a current metropolitan site with the aid of beamforming. It also reduces interference by transmission effectiveness. The antenna arrays of MMIMO [26] have interesting facts such as it has in 2 GHz band with a half-wavelength spaced rectangular array with 200 dual-polarized elements and size of 1.5 m*0.75 m. MMIMO operates in Time Division Duplex (TDD) mode. The downlink beamforming utilizes the uplink-downlink collaboration of radio propagation.

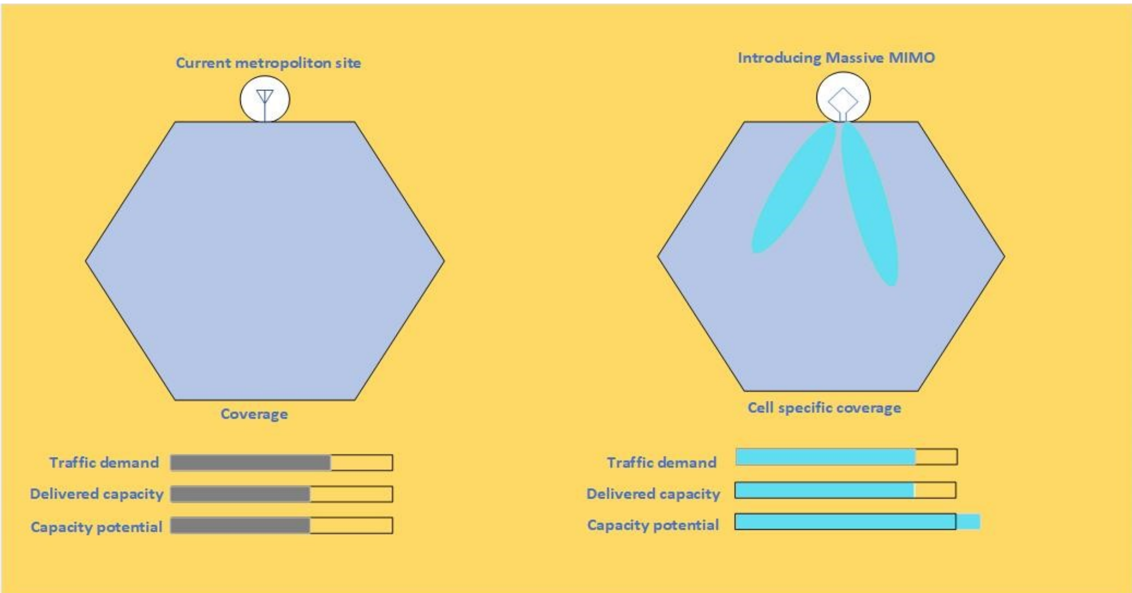


Figure 3. *Advantages of MMIMO over existent technology.*

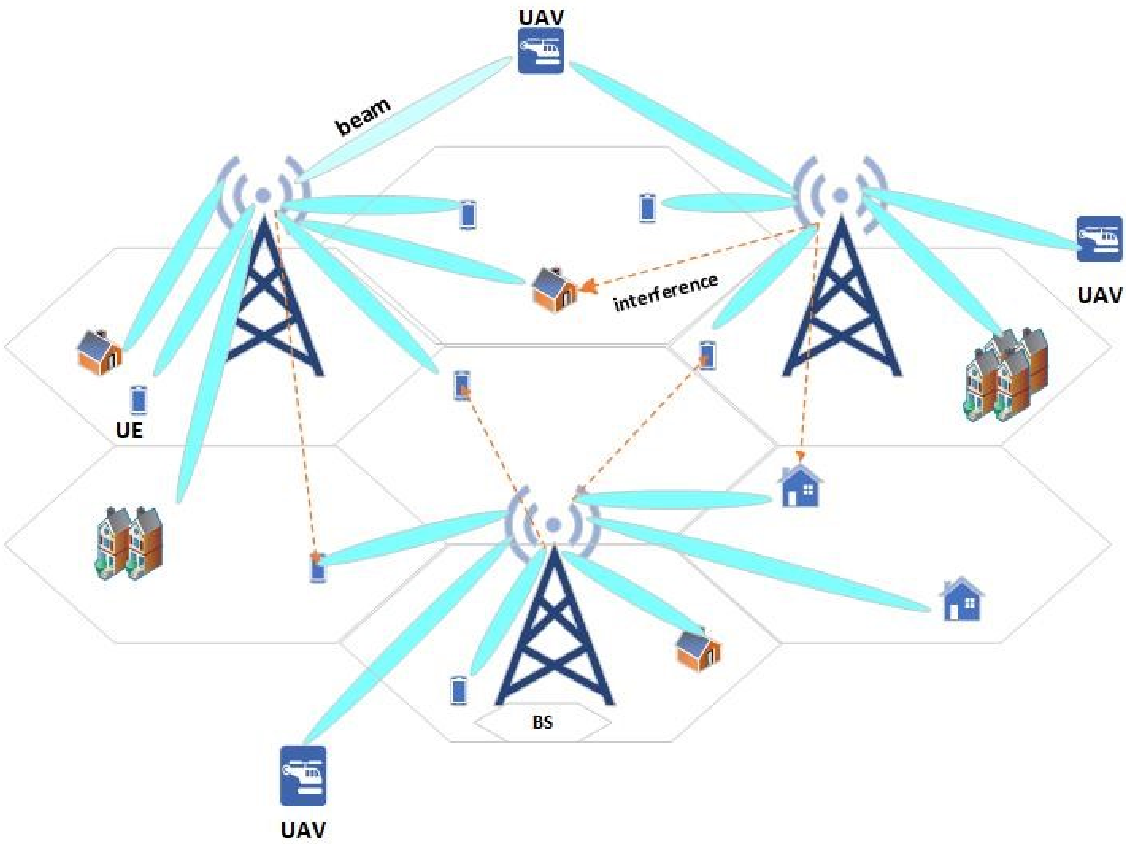


Figure 4. *Illustration of basic massive MIMO network setup*

In addition, the channel estimator is used by BS array to know the channel in both directions which makes MMIMO scalable regarding the number of BS antennas. It does not need to share its channel state information or payload data with other cells as its BSs operate autonomously.

Figure 4 illustrates the basic setup for MMIMO. It refers to a system with tens up to hundreds of antennas [65]. Facebook, ZTE, and Huawei described MMIMO systems with 96 to 128 antennas. In addition, Ericsson's AIR presented a 5G NR radio which uses 64 transmitting and 64 receiving antennas [27].

2.5 Pilot Contamination

Pilot contamination occurs while channel estimation at the base station in a cell is polluted due to the users from another cell. It basically happens using the same pilot sequence by two terminals. It is mostly described as one of the main limiting factors of MMIMO. Although Pilot contamination exists to most of the cellular networks due to the necessity of the time-frequency resource reuse across the cell, however, its impact is greater in MMIMO than conventional cellular networks as the number of channels is much higher than conventional MIMO or other cellular networks. All existing channels between receivers and transmitters need to be estimated in the MMIMO system. In that case, orthogonal pilots are being used to estimate that. The number of these orthogonal pilot sets is limited, hence in MMIMO, these pilots need to be more reused. In MMIMO, cell radius is smaller and hence the pilot reuse distance is also smaller which results in much more interference among the pilots than conventional cellular networks or conventional MIMO for a short coherence time [68]. However, due to the pilot contamination, the MMIMO system's capacity becomes limited by the inter-cell interference when the number of MMIMO's antennas approaches to infinity [67]. As a result, mitigating interference between user equipments while using the same pilot becomes particularly very tough for the base stations.

2.6 Channel Estimation

Channel estimation has an important phenomenon for securing better performance of the wireless communication system. It forms the heart of the MMIMO-OFDM based communication system. Due to multiple transmitters and receivers, channel estimation is a high dimensional problem and a major challenge for MMIMO [69]. The appropriate channel estimation in MMIMO improves spectral efficiency, system throughput as well as energy efficiency. With hundreds of antennas, it has low SNRs. In addition, array gain can not be fully realized and thus errors in channel estimators are devastating. There are several types of channel estimators presented in the literature, but in this thesis, there are basically three of them are experimenting,

2.6.1 Minimum Mean Square Error (MMSE)

According to signal processing, the MMSE is an estimation method by which mean square error (MSE) can be minimized. It is a common estimation quality measurement method. According to the Bayesian setting, It refers to estimation with the aid of quadrature loss function.

2.6.2 Element–Wise Minimum Mean Square Error (EW-MMSE)

In EW-MMSE method, only the diagonals of the covariance matrices are needed. In addition, the estimator ignores the correlation between the elements. Hence, full matrix inversion is not needed for his method, and the computational complexity is much less than the MMSE estimator. It can utilize as an alternative approach when the base station does not know the entire covariance matrices.

2.6.3 Least-Square (LS) Channel Estimator

The LS estimator is used when the partial statistics are not very reliable due to the abrupt change in the uplink scheduling in other cells or not known since it does not need prior statistical information. The LS estimator and estimation error are correlated random variables.

2.7 Precoding And Combining Schemes

MMIMO transmit precoding and receiving combining are different compared to the traditional approaches used in sub-6 GHz cellular networks. This is because the hardware constraints are different compared to traditional low frequencies cellular networks. In MMIMO, due to mmWave signals, a very large number of array of antennas are used as a small form factor. In addition, the high cost and the high power consumption of ADC, DAC, I/Q mixers, etc, have made it tough to allow a separate complete radio frequency (RF) chain for each antenna [70]. Moreover, due to a very large antenna array, complexity in signal processing functions like equalization, channel estimation and so on are different. However, mmWave propagation characteristics are also varying. For the thesis purpose, five types of schemes are used for simulations,

2.7.1 Multicell-Minimum Mean Square Error (M-MMSE)

M-MMSE scheme is proposed for MMIMO networks. It has an uplink MMSE detector as well as a downlink MMSE precoder [71]. Unlike conventional single-cell schemes where only channel estimator is used for suppressing interference for intra-cell users, M-MMSE scheme utilizes the available pilot resources to suppress both inter-cell and intra-cell interference. Remarkable spectral efficiency gains along with system throughput are achieved with M-MMSE compared to other schemes. In addition, large scale approximations for the uplink and downlink SINRs are derived from M-MMSE which are asymptotically tight in case of a large system limit.

2.7.2 Singlecell- Minimum Mean Square Error (S-MMSE)

M-MMSE combining is optimal although it is not frequently used due to the high computational complexity of computing matrix inversion. In addition, mathematical analyzation is also hard work to do. The most important one is, receiving combining schemes are mainly developed for single-cell scenarios, later it applies heuristically for multicell [72, chapter 4.1.1]. For these reasons, the S-MMSE scheme is the most common form in literature and suboptimal. S-MMSE reduces computational complexity along with the number of channel estimates and channel statistics in order to calculate the combining vector than M-MMSE. Its ability to suppress interference from other cells' user equipment is substantially weaker. It can only coincide with M-MMSE if there remains only one isolated cell.

2.7.3 Regularized Zero-Forcing (RZF)

RZF is enhanced processing in order to consider the impact of unknown user interference as well as background noise where the unknown user interference and background noise are emphasized in the result (known) interference signal nulling. RZF combining is a suitable scheme when the interfering signal from another cell is weak and the channel condition is good. It reduces complexity as it needs to invert UE metric, not antenna metric [72, equation 4.9] and performs better compared to S-MMSE, but the spectral efficiency is lower compared to M-MMSE as well as S-MMSE. The term "Regularized" is a signal processing technique that improves for improving the numerical stability of an inverse. It gives weighting between maximization of the desired signal and interference suppression.

2.7.4 Zero-Forcing (ZF)

ZF precoding is a spatial signal processing method through which a multi-antenna transmitter can nullify the multiuser interference signal and the desired signal remains non-zero [73]. It is a linear equalization algorithm that inverts the frequency response of the channel. It applies the inverse of the channel in order to receive and restore the signal before the channel. It is preferable when the inter-symbol-interference is significant compared to the noise. If the frequency response of a channel is $F(f)$, then the zero forcing equalizer $C(f)$ is constructed as, $C(f) = 1/F(f)$. Hence the channel and equalizer combination gives a flat response as well as linear phase as, $F(f)*C(f) = 1$. Its performance in the field of spectral efficiency and throughput is lower than the M-MMSE, S-MMSR, and RZF.

2.7.5 Maximum Ratio (MR) Combining

MR is a diversity combining method in which signals from each channel are summed together and the gain of each and every signal is made proportional to the root mean square (RMS) value of the signal, which is inversely proportional to the mean square noise level in that channel [73]. It is also known as pre-detection combining. For independent additive white gaussian noise channel, it performs at its optimal level. MR does not require any matrix inversion, hence its computational complexity is the lowest.

For this purpose, in many research works, MR combining is preferred. However, in reality, not every user equipment shows a low signal-to-noise ratio, hence it exhibits the lowest spectral efficiency than others.

2.8 Unimodal Function

A function f(x) is said to be an unimodal function if for some value m it is monotonically increasing for $x \leq m$ and monotonically decreasing for $x \geq m$. For unimodal function, the maximum obtainable value is f(m) and at the same time, there would be no other maximum value.

3. DEFINITIONS OF SPECTRAL AND ENERGY EFFICIENCY

3.1 Spectral Efficiency Definitions

Spectral efficiency (SE) (sometimes also called bandwidth efficiency or spectrum efficiency) is referred to the rate of the information which can be transmitted successfully over a given bandwidth for a specific time period in a communication system. The unit of SE is bits per second per hertz abbreviated as bits/s/Hz. It measures how efficiently physical layer protocol or channel protocol utilizes a frequency spectrum [31]. It provides a very important piece of information; that is the amount of data that is carried out in our networks [32]. Basically, spectral efficiency is the ability of the channels to carry information for a given bandwidth.

In wireless communication, the rate of the information is dependent on the transmission medium's bandwidth as well as the signal-to-noise ratio. From the Shannon-Hartley theorem [33] which sets the channel capacity, C as:

$$C = Blog_2\left(1 + \frac{S}{N}\right) \tag{3.1}$$

where B refers as channel bandwidth and $\frac{S}{N}$ refers to the signal-to-noise ratio.

As frequency spectrum is a scarce resource, hence it is a major concern of how well we can utilize this frequency spectrum. This channel ability carrying information for a fixed and limited bandwidth is specified as spectral efficiency. Therefore, we can express spectral efficiency's formula as:

$$\text{Spectral Efficiency}\left[\frac{\frac{\text{bits}}{\text{s}}}{\text{Hz}}\right] = \frac{Channel\ Throughput\left[\frac{bits}{s}\right]}{Channel\ Bandwidth\ [Hz]}. \tag{3.2}$$

If we want to know how much the channel utilizes the bandwidth, then this formula becomes,

$$\text{Spectral Efficiency}\left[\frac{\frac{\text{bits}}{\text{s}}}{\text{Hz}}\right] = \frac{Channel\ Throughput\left[\frac{bits}{s}\right]}{Channel\ Bandwidth\ [Hz] \times Channel\ Utilization[\%]}. \tag{3.3}$$

Spectral efficiency is expressed in several ways, from which a couple is discussed in the following subsections.

3.1.1 Link Spectral Efficiency

Link spectral efficiency is the net bitrate (without error-correcting codes) or maximum throughput over a given bandwidth in a digital communication system or data link. It is used in digital modulation or link code to analyze efficiency. It can also be used with the combination of forwarding error correction (FEC) code along with other physical layer overhead.

3.1.2 Area Spectral Efficiency or System Spectral Efficiency

Area spectral efficiency or system spectral efficiency is the measurement of the amount of the users or services which we need to provide simultaneous support with our limited frequency bandwidth within a fixed geographic area. It's measured in bits/s/Hz per unit area.

3.2 Energy Efficiency

Based on the circuit power consumption model, energy efficiency has been defined here. From all aspects of science and technology, the basic theory of energy efficiency refers to how much energy something consumes while doing a certain unit of work [34]. The unit of work is more or less the same in all fields though in wireless communication, expressing one unit of work is not easy at all. We have to explain a few different things before we can exactly give the definition of work. In general, the wireless network in a certain area provides wireless connectivity by transporting bits from BS to UEs and vice versa. For these bits, the user has to pay the bill. But the fact is, users are paying not only for the bits they are delivering but also for using the network. All above, classifying the performance of a cellular network is more challenging than it appears as the performance can be measured in a variety of ways and eventually it affects the energy efficiency in different ways [34]. Moreover, the most common and popular definitions of energy efficiency of a cellular network can be defined as, "The energy efficiency of a cellular network is the number of bits that can be reliably transmitted over per unit of energy" [37]. From the definition, energy efficiency can be derived as,

$$\text{Energy Efficiency (EE)} = \frac{Throughput\left[\frac{\frac{bit}{s}}{cell}\right]}{Power\ Consumption\left[\frac{W}{cell}\right]} \tag{3.4}$$

where throughput is the measure of the amount of data(bits) move successfully from one place to another in a given time period [35] (typically measured in bits per second(bps), as in megabits per second (Mbps) or gigabits per second (Gbps)). Moreover, power consumption from the perspective of electrical engineering refers to the electrical energy per unit time supplied to operate something [36]. It is usually measured in watts (W) or in bigger volume, kilowatts (kW).

The unit of energy efficiency is bit/Joule. And this definition is also known as the benefit-cost ratio, as the ratio is between the throughput and power consumption which means, the quality of service (throughput) is being calculated with associated costs (power consumption) [37].

Changes in the numerator and denominator affect the EE metric since both are variable, which ensure that caution is taken to prevent the incomplete and possibly fals e findings of the EE assessment. Especially, concentration should be emphasized more and more when we do modeling of the power consumption (PC) of the network. Sometimes, we assume that power consumption in a wireless network only comprises transmit power, but this is a completely wrong conception. In [47], it has shown that we can reduce transmit power towards zero as $1/\sqrt{M}$ when $M \rightarrow \infty$ while approaching a non-zero asymptotic downlink (DL) spectral efficiency limit, which is misleading. The real fact is that transmit power is a part of the overall power consumption.

Figure 5 shows the power consumption of the different parts of the coverage tier Base Station. Data has been collected from [38].

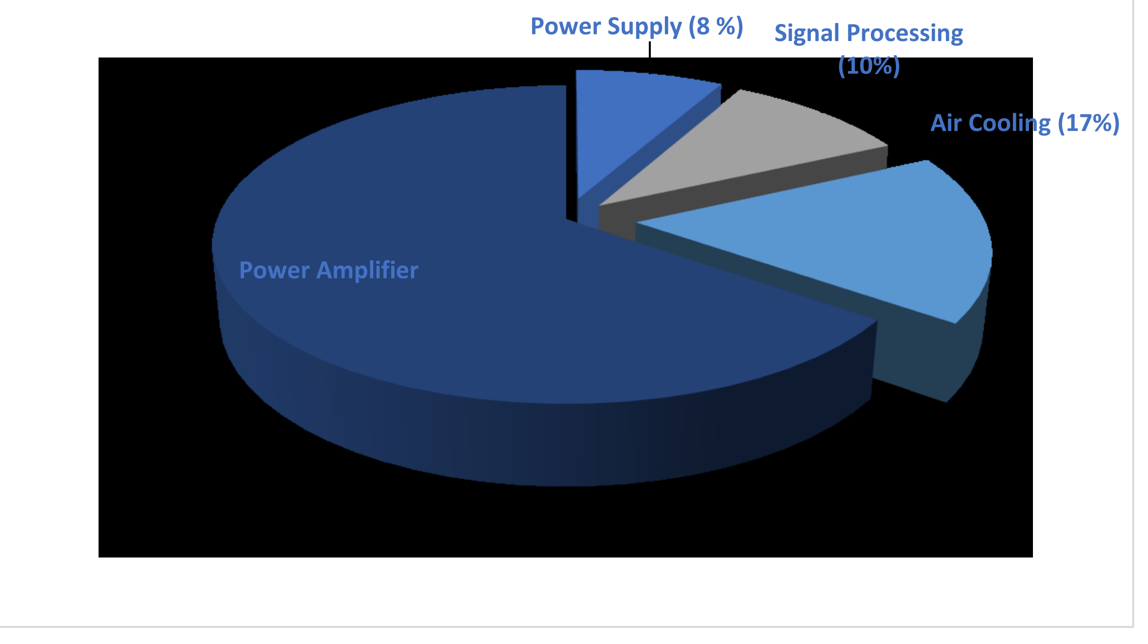


Figure 5. *Power consumed in percentage by different components of BS coverage tier*

To compute network power consumption, we have to calculate the effective transmit power (ETP) which is necessary, because it calculates the efficiency of the power amplifier (PA). The efficiency of the power amplifier is vital because when the efficiency of the power amplifier is low, that indicates a huge portion of the supply power is dissipated as heat. Hence, we can calculate the power consumption of the Network like,

$$Power\ Consumption\ (PC) = \text{Effective Transmit Power (ETP)} + \text{ Circuit Power (CP)} \quad (3.5)$$

where the effective transmit power (ETP) refers to the exact amount of energy needed to successfully transport a data package of a fixed number of bits from one palace. In addition, circuit power refers to the energy consumed but the base station for control signaling, backhaul infrastructure and load-independent power of the baseband processors. It is a constant quantity which consumes almost one-quarter of the total consumed power [figure 5]. Therefore, a common form of circuit power stands as,

$$\text{Circuit Power (CP)} = P_{FIX}. \quad (3.6)$$

This is not precise enough for comparing systems with various hardware configurations and variable network loads because the energy dissipation of the analog hardware and the digital signal processing is not accountable to it. Consequently, a too simplistic CP model may lead to incorrect findings in many respects. For the evaluation of energy consumption by a practical network and the identification of non-negligible parts, detailed CP models are required.

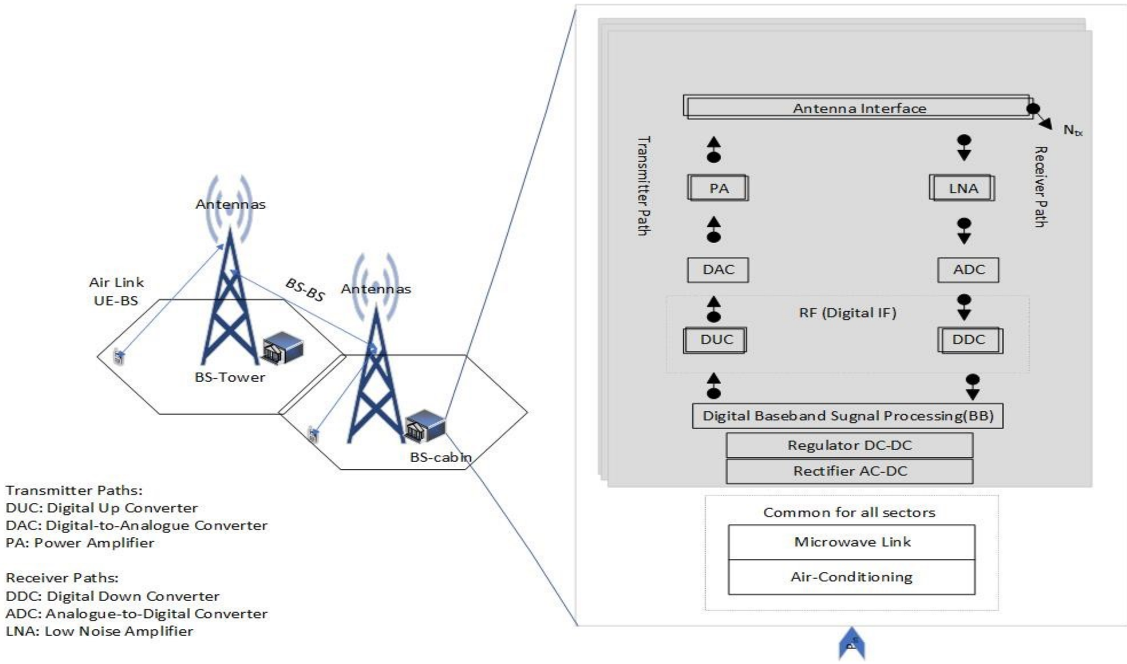


Figure 6. *Basic block diagram of coverage BS's power-consuming hardware element*

Figure 6 represents a basic CP model of an arbitrary BS [39]. Different power consuming parts are needed to calculate for the exact CP model. Because of the enhanced computational complexity of precoding / combining systems, encoding and decoding as well as channel estimation, for serving a bigger amount of UEs, we need more CP. These are not the only modifications to properly assess the Uplink and Downlink strength of MMIMO. It will be demonstrated that it is also needed to consider the energy consumed by digital signal processing, backhaul signaling, encoding, decoding, transceiver chains, and channel estimation [40]. Combining above all circumstance, a circuit power (CP) model for MMIMO networks stands like,

$$\text{Circuit Power, CP} = P_{FIX} + P_{TC} + P_{CE} + P_{\frac{C}{D}} + P_{BH} + P_{SP} \tag{3.7}$$

where P_{FIX} equals to the fixed power required for control signaling and load-independent power of backhaul infrastructure and baseband processors of a cell, P_{TC} equals Power consumed by transceiver chains in a cell. Consider a cell n, then this part can be quantified as [76], [77],

$$P_{TC,n} = M_n P_{BS,n} + P_{LO,n} + K_n P_{UE,n}\,. \tag{3.8}$$

Here, M_n refers to the number of the antenna in BS n, $P_{BS,n}$ is the power required to compute the circuit's components in cell n like I/Q mixers, ADCs, DACs, filters, and OFDM modulation and/or demodulation, M_n refers to the number of User equipment in cell n, and $P_{UE,n}$ accounts for power required for all circuit components like I/Q mixers, ADCs, DACs, filters, and OFDM modulation and/or demodulation of each single-antenna UE. P_{CE} equals Power required for the channel estimation process.

Estimating the UL channel plays a significant role in making effective use of the large number of antennas in MMIMO. In BS, UL channel estimation is processed by each coherence block which increases the computational cost that eventually transforms into Channel estimation computational power. The complexity of the DL channel estimation is lower compared to UL channel estimation as from the receiver data signal user equipment only needs to estimate the precoded scalar channel.

$P_{C/D}$ refers to the power required for channel coding and/or decoding units in a cell. Such as, for the DL, BS n sends to the user equipment a sequence of information symbols by applying channel coding and modulation. Each UE then uses a practical fixed complexity algorithm to decode its own data sequence. For the UL coding and decoding the opposite is performed. The qualified form of $P_{C/D}$ in cell n is,

$$P_{\frac{C}{D},n} = (P_{COD} + P_{DEC})TR_n \tag{3.9}$$

where P_{COD} and P_{DEC} are the respectively coding and decoding power(W/bit/s) and TR_n is the throughput(bit/s) of the cell n [41].

P_{BH} refers to the power required to calculate load-dependent backhaul signaling. Backhaul is the data transferring process. Depending on the network deployment it can be either wired or wireless. It basically transports DL or UL data from BS to the core network and vice versa. Backhaul can be classified into two parts. Load-independent and Load-dependent backhaul. Load-independent backhaul is included in the P_{FIX} part of a cell and it consumes the most power (around 80%). On the other hand, the Load-dependent backhaul of each BS is proportional to the sum throughput of its served UE. It can be computed for cell n as,

$$P_{BH,n} = P_{BT} * TR_n. \tag{3.10}$$

As we already know, TR_n is the throughput(bit/s) of the cell n and P_{BT} is the backhaul traffic power(W/bit/s) and for simplicity, it assumes to be the same in all cells.

P_{SP} refers to the power required to processing the signal (receive combining and transmit precoding) at the base station. To calculate P_{SP}, computational complexity analysis has been done in [42]. It can be shown for cell n as,

$$P_{SP,n} = P_{SP-\frac{R}{T},n} + P_{SP-C,n}^{UL} + P_{SP-C,n}^{DL}. \tag{3.11}$$

Here, $P_{SP\text{-}R/T,n}$ refers to the total power consumed for a given combining and precoding vector by DL transmission and UL reception. $P_{SP\text{-}C^{UL},n}$, and $P_{SP\text{-}C^{DL},n}$ are the power required in the cell n for calculating combining and precoding vectors respectively.

For small Multiuser MIMO, these transceiver chains, channel estimation, precoding, and decoding power consumption are neglected. For the limited number of UEs and antennas, these parts of the circuit power consumption are negligible compared to the power consumed by the fixed part power consumption. However, after introducing the MMIMO system, these parts of the circuit power consumption are considered both in single-cell systems [43],[44],[45] and multi-cell systems [46].

4. SIMULATIONS TO ENHANCE SPECTRAL & ENERGY EFFICIENCY

4.1 Achievable Uplink Spectral Efficiency

From the perspective of the wireless networks, by linear receiving combining scheme, any BS can detect their desire signal. Any BS can receive a signal from UE by selecting the combining vector as a function of channel estimator which is acquired from the pilot transmission. At the time of data transmission, any BS can correlate received signal and this combining vector by summing the desired signal over the estimated channel, desired signal over an unknown channel, intra-cell interference, inter-cell interference and noise [48].

For a random cell j, if MMSE channel estimator is considered for UL ergodic channel capacity of a random UE k, then lower bounded SE for UL would be like:

$$SE_{jk}^{UL} = \frac{\tau_u}{\tau_c} \mathbb{E}\left\{\log_2\left(1 + SINR_{jk}^{UL}\right)\right\} \tag{4.1}$$

where $\mathrm{SINR}_{\mathrm{jk}}^{\mathrm{UL}}$ is UL instantaneous SINR though it is not conventional sense,τ_u is the UL data samples per coherence block, τ_c is the number of samples per coherence block and together $\frac{\tau_u}{\tau_c}$ is a pre-log factor that a fraction of the samples per coherence block that are used for uplink data. From this SE equation, SE for UL can be achieved.

From this lower bounded SE for UL formula, UL data samples per coherence block, $\tau_u = \tau_c - \tau_p - \tau_d$. Where τ_p is the number of samples allocated for pilots per coherence block, and τ_d donates for DL data samples per coherence block. Hence, SE of cell j for the kth UE can be increased if the per-log factor is increased. This can be performed if the reduction is made in the τ_d and/or shorten the τ_p length [49].

In order to exemplify the SE and how to increase it in the simulation and results part, values have been taken from [50, table 4.2] for MMIMO. Considering 16 (4 * 4) cell wrap-around network layout is taken, and the coverage of each cell is considered 0.25km*0.25km. The reason for using wrap around the technology is so that interference from all surrounding can be received by all BSs. Taking a shorter distance from UE to BS, a large-scale fading model is used. For MMIMO, the communication bandwidth of 20 MHz is considered and for NB-IoT, 200 kHz is taken. For MMIMO, UL transmit power per UE is considered as 20 dBm and for NB-IoT it has taken 23 dBm. On the other hand, for DL transmission, MMIMO is considered 20 dBm while NB-IoT is considered 43 dBm per UE from BS [51]. For calculation, 2 sets of data are considered (for MMIMO and NB-IoT) from [48],[49],[52]. As the simulation has performed for UL, the receiver noise power is taken from the UL frequency of NB-IoT (15 kHz).

Table 2. *System parameters regarding MMIMO and NB-IoT.*

Parameter	Value of MMIMO	Value of NB-IoT
UL transmit Power	20 dBm	23 dBm
DL transmit Power	20 dBm	43 dBm
Bandwidth	20 MHz	200 kHz
Shadow fading (standard deviation)	10	10
Pathloss exponent	3.76	3.76
Receiver Noise Power	-94 dBm	-129 dBm (for 15 KHz)
Samples per coherence block	200	200
Pilot reuse factor	f = 1, 2, 4	f = 1, 2, 4
Number of pilot sequences	f*K	f*K

Coherence block, τ_c consist of 200 samples, considering M antennas in each BS and K UEs per cell. Changing the value of M and K and taking the ratio of M/K simulation has performed for results. Pilot sequence, τ_p is used in different ways among the UEs and calculated the multiplication of pilot reused factor, f and number of UEs, K. To simplify the calculation and simulation pilot reused factor has taken as, f = {1, 2, 4}. In every cell, these pilots are assigned randomly for the UEs.

With all of these values, in [50], the simulation has done for MMIMO average sum SE which is a function of a number of BS antennas for different combining schemes [48, figure 4.5]). The simulation has done here for calculations and coming to the conclusion (figure 7). From figure 7, information can be extracted that with the pilot reused factor, f equals 1, M-MMSE receiving combing schemes provides the highest SE followed by S-MMSE. SE is reduced with every other scheme after M-MMSE.

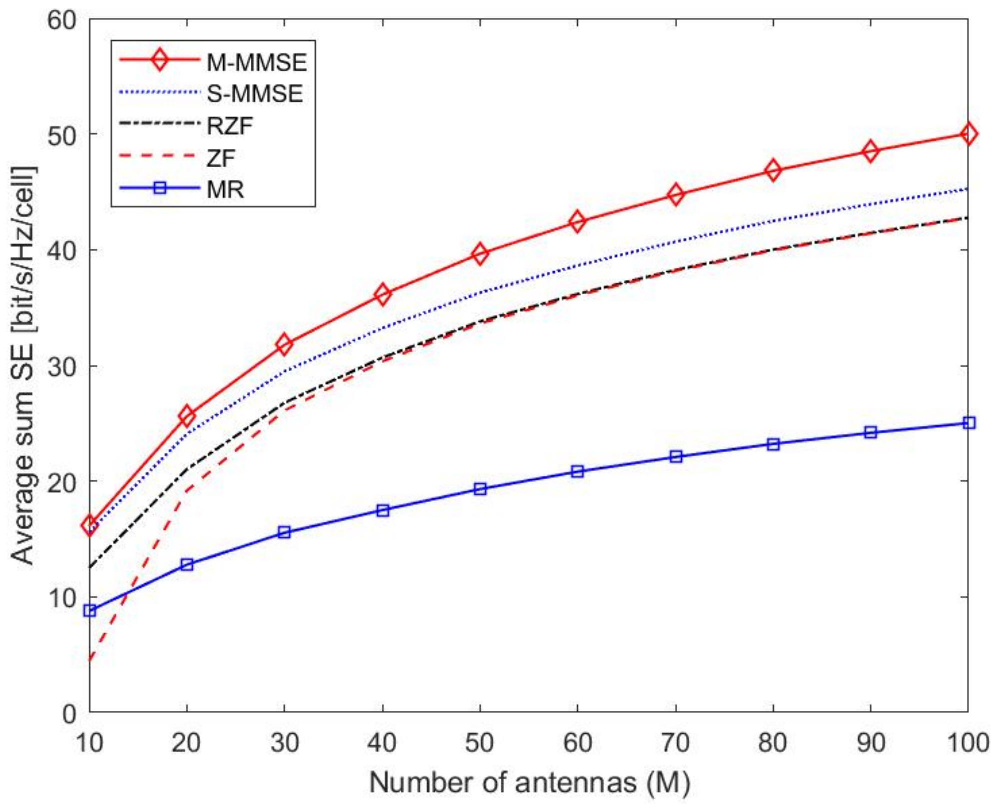


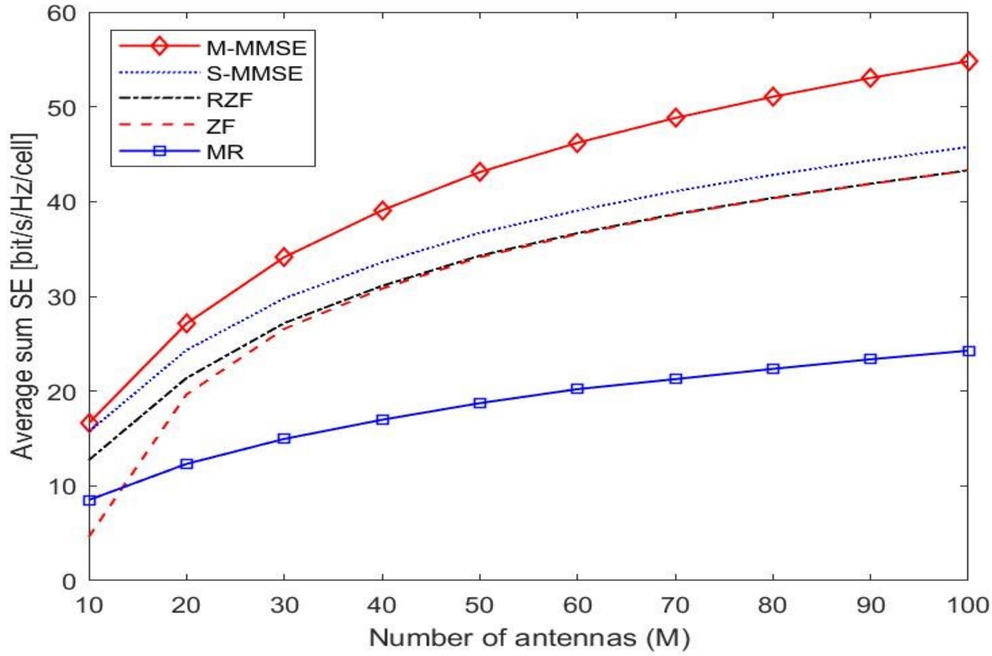
Figure 7. *Average UL sum SE for five different combining schemes as a function of the number of BS antennas, M. Considering the number of UEs, K = 10 and Pilot reuse factor, f = 1*

S-MMSE provides lower SE than M-MMSE but 5-10% higher than RZF and ZF. Basically, when the number of antennas, M is ≥30, RZF and ZF have the same SE across the same M which he points the main matter of concern in MMIMO. But, for robust implementation ZF should be avoided because it deteriorates (M<30) quickly and to cancel the interference, BS has to also cancel a large part of the signal which we desire. MR provided low SE (almost half) than other schemes. Since MR did not require an inversion matrix and it can reduce computational complexity near about 10-20%, it's been used in many experimental scenarios.

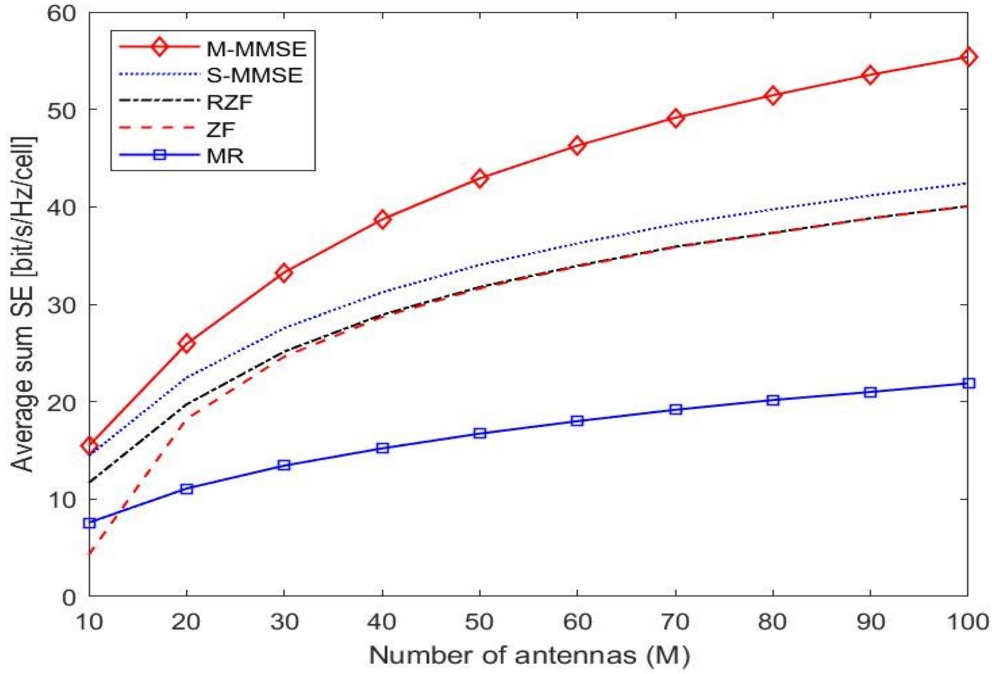
With the non-universal Pilot reuse factor f, later in figure 8 (a & b) simulation considering each pilot is being reused in every second and fourth cell. As we know,

$$\tau_u = \tau_c - f * K \tag{4.2}$$

Here, the pilot reused factor is increased. Increasing pilots caused a decreasing pre-log factor. Resultant, SE decreased. Also, from SINR equation [48, equation 4.3], it can state that, due to increasing f, instantaneous SINR is also increased.



(a) Taking Pilot Reuse Factor, f = 2



(b) Taking Pilot Reuse Factor, f = 4

Figure 8. *Average UL sum SE for five different combining schemes as a function of the number of BS antennas, M. Considering the number of UEs, K = 10 and Non-universal Pilot reuse factor, f = 2, 4*

The explanation can be given from figures 8a and 8b that, for M-MMSE increasing the pilot reuse factor has more benefits in SE since it can suppress the interference from UEs in the neighbor cells as other pilots have been used by these UEs. For comparison, the data table for different receiving combining schemes with different pilot reuse factor is given below in table 3.

***Table 3**. Average UL sum SE [bits/s/Hz/cell] for different pilot reuse factors.*

Combining Schemes	f = 1	f = 2	f = 4
M-MMSE	50.32	55.10	55.41
S-MMSE	45.39	45.83	42.41
RZF	42.83	43.37	39.99
ZF	42.80	43.34	39.97
MR	25.25	24.41	21.95

With increasing f, the M-MMSE scheme gives better SE than before. For S-MMSE, RZF, and ZF, SE increases up to f = 2, then it starts falling down with increasing f. The highest SE value among these three is obtained when f = 2. The scenario is different in the case of MR. It gives the highest sum SE at f = 1 and with increasing pilot reuse factor, MR reduces. The reason behind that is since the estimation is only related to coherently combine the desired signal and not used to cancel interference, hence improved quality of estimation can't outweigh the pre-log factor which is reduced. Also, from table 3, it can be seen that the highest sum SE is achieved at any f for M-MMSE compared to others. For S-MMSE, RZF, and ZF this value belongs to f = 2 and for MR it remains in f = 1.

The main reason behind these 5 different schemes description is to choose which schemes can be chosen for implementation. They are, M-MMSE, RZF, and MR. M-MMSE gives the highest SE in all values of the pilot reuse factor, f in spite of having computational complexity. MR has the lowest SE but has the lowest computational complexity as well. RZF has a well balanced between SE and complexity. Its computational complexity is only ten of a percentage higher than MR but has SE almost double to MR. Though ZF has almost the same SE as RZF RZF is a better choice than ZF when $M \approx K$ because at this stage ZF has serious robustness issues.

4.1.1 Impact of Spatial Channel Correlation

Spatial channel correlation has a significant impact on the quality of channel estimation, channel hardening as well as propagation. Under spatial channel correlation, channel estimation quality improves and more favorable propagation of the UEs has exhibited which have different spatial characteristics.

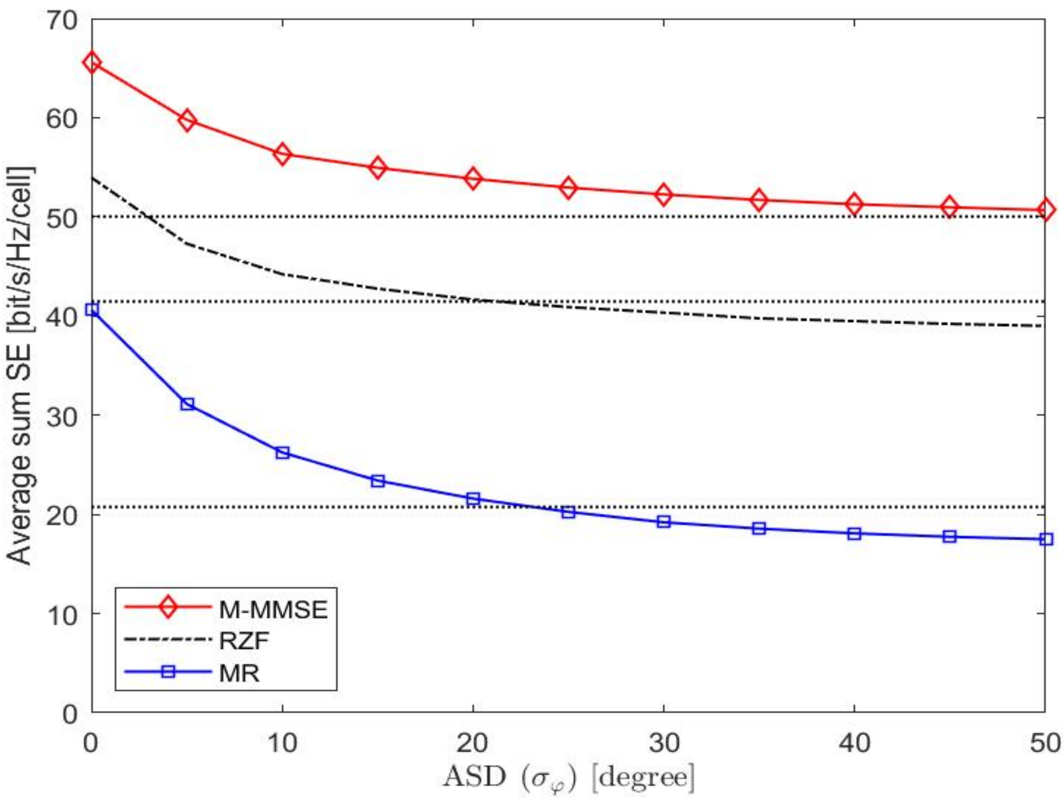


Figure 9. *Average UL sum SE using the Gaussian local scattering channel model as a function of varying ASD. Considering K =10 UEs, M = 100 antennas and the number of setups with random UE locations = 10. Three combining schemes are used, and the dotted lines represent achievable SE with the aid of uncorrelated Rayleigh fading channels*

Based on the SE-computational complexity tradeoff which has already done, the simulation has done again for average UL sum SE as a function of Angular Standard Deviation, σ_φ with M-MMSE, RZF and MR combining with the help of data and code from [48]. Considering the number of antennas, M = 100 in a BS equips with UEs, K = 10. Varying σ_φ from 0 to 50 to observe the impact in figure 9.

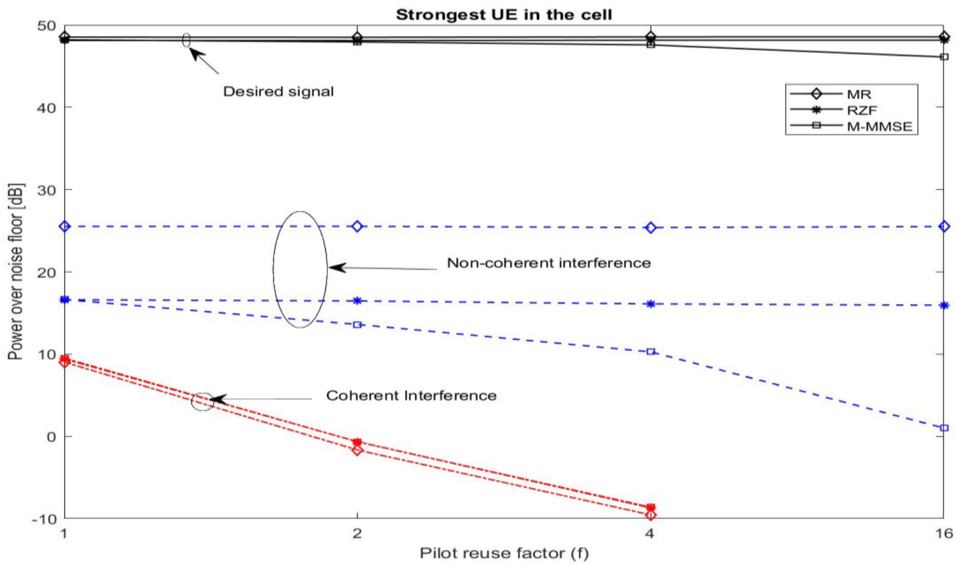
From the figure, it is observable that, M-MMSE has the highest SE for any value of ASD, followed by RZF and after that MR. But, all of them, the common thing is, SE decreases with increasing ASD. This is an indication of high spatial channel correlation's dominant effect which reduces interference between UEs that have different spatial correlation matrices. With small ASD (σ_φ≤10), the interference between UEs is low and LoS scenario resembles there unless UEs have the same ASD from BS. It can also observe that the SE performance order of both spatial channel correlation and combining schemes remain the same. For $\sigma_\varphi \leq 50$, M-MMSE benefited from spatial correlation. The performance of RZF and MR remain better if $\sigma_\varphi \leq 20$. Performance drops down increasing σ_φ afterward. If ASD is large enough then SE of these three schemes fall slightly compared to the uncorrelated Rayleigh fading channel because of the geometry of the uniformed linear array.

Therefore, a conclusion can be made that, ASD value should be kept smaller (within 10 to 20) for all three schemes in order to acquire the highest average UL sum SE.

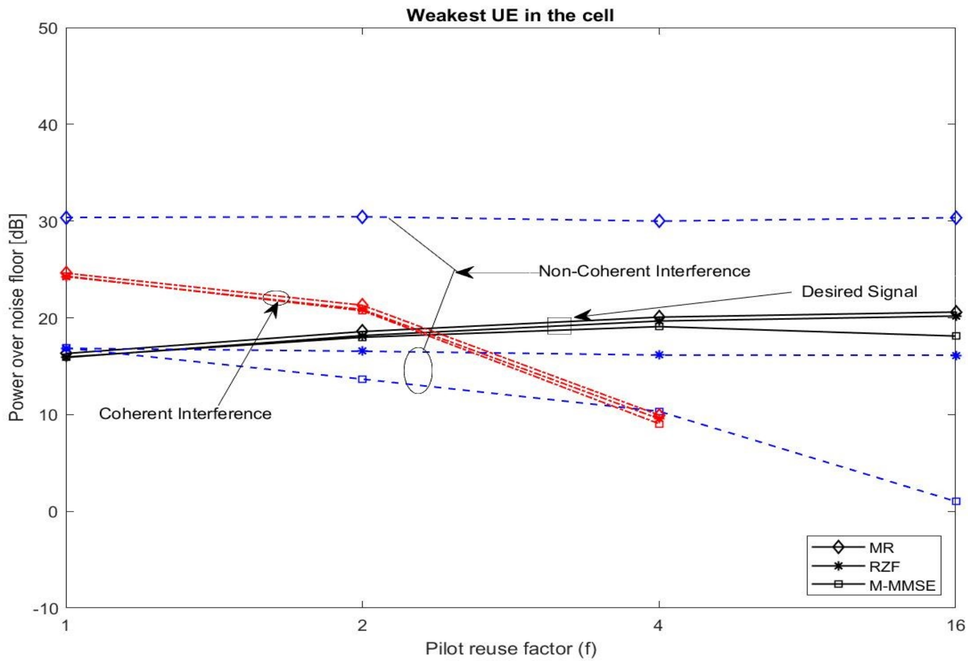
4.1.2 Impact of Pilot Contamination and Coherent Interference

In UL, pilot contamination has few adverse effects. Firstly, due to the contamination, the channel's Mean-Square error (MSE) increases. As a result, it reduces the ability to choose to combine vector which can provide strong array gains as well as can reject non-coherent interference. And secondly, it raises the coherent interference which array gain amplifies.

To examine the impact of pilot contamination, the simulation has performed in [50] considering uncorrelated fading channel with the number of antennas, M = 100, UEs K = 10, Gaussian local scattering channel model taking σ_φ = 10. Estimation of the average power of the signal, the coherent interference, and non-coherent interference have estimated from Monte Carlo simulations. The average power of the strongest and the weakest UEs are taken from a random cell just because of UEs locating various locations display different power levels. UEs are responsible for non-coherent interference while coherent interference is additional interference which is caused by the pilot contaminating UEs. With respect to the noise power, all powers are normalized. For examinations, simulations and results part, the simulation has performed taking into account the number of setups with random UE locations equals 10 (figure 10).



(a) Strongest UEs in the cell



(b) Weakest UEs in the cell

Figure 10. *Average UL power of the desired signal with coherent interference and non-coherent interference*

The simulation's figure 10a has shown the signal power with coherent and non-coherent interference for both the strongest and weakest (figure 10b) UEs of all the three combining schemes. From the curve, the strongest UE has almost the same signal power for any value of the pilot reuse factor. Hence, the impact on the MSC for the channel estimator is very minor. The received desire signal has 25 dB higher signal power than con-coherent interference and more than 40 dB higher power than coherent interference.

MR combining has provided the highest signal power, while to find combining vectors, M-MMSE and RZF lose a few signal powers in order to suppress 10 dB or more interference. Hence, the nutshell of the simulation is, as UEs, which causes interference far away from receiving BS, coherent interference's impact is negligible to the strongest UEs than non-coherent interference.

Figure 10b shows the UEs which is located at the cell edge. Compared to the strongest UE, additional path loss has decreased the signal's power many tens of dB lower. The quality of channel estimation is poor for that after receive combining the desired signal power can be increased with the aid of larger f. MR has the strongest signal power though it is almost 10 dB weaker than the non-coherent interference. As their present intra-cell interference which can't suppress. To find combining vector, RZF and M-MMSE sacrifice a few dB of signal power which suppresses non-coherent interference by more than or equals 10 dB. Hence, for calculating signal power for the weakest UEs, coherent interference holds the dominant interference. For uncorrelated fading coherent interference is almost the same for all schemes. But, increasing f, its dominant effect can be diminished. In that sense, and for strongest UE, M-MMSE has the most beneficial effect from increasing f as for suppressing inter-cell interference, it performs better.

To conclude, pilot contamination has an adverse impact on the cell edge UEs which exhibit uncorrelated fading. But, a very low impact on the channel estimation quality. Pilot contamination has given birth to Coherent interference. Coherent interference can be stronger than the non-coherent interference in some cases when UEs are at the cell edge and exhibit uncorrelated fading. However, it can be alleviated if the pilot reuse factor can increase. The remaining pilot contamination's impact lies in the pre-log factor of SE. This can also be decreased as the number of pilots grow.

4.1.3 SE with Other Channel Estimation Schemes than MMSE

To compensate for the computational complexity with the aid of estimation quality reduction, alternative EW-MMSE, as well as LS channel estimator, are proposed in [53]. To compare these different channel estimators, simulation has been executed. We have tried to figure out the average UL sum SE by using MMSE, EW-MMSE, and LS.

Considering the number of BS antennas, M = 100 and K = 10 UEs simulation has been done. The pilot reuse factor is used according to the combining schemes by which SE becomes maximized From the simulation output and curves in figure 11, it has observed a bar diagram of the average UL sum SE with M-MMSE, RZF, and MR combining schemes.

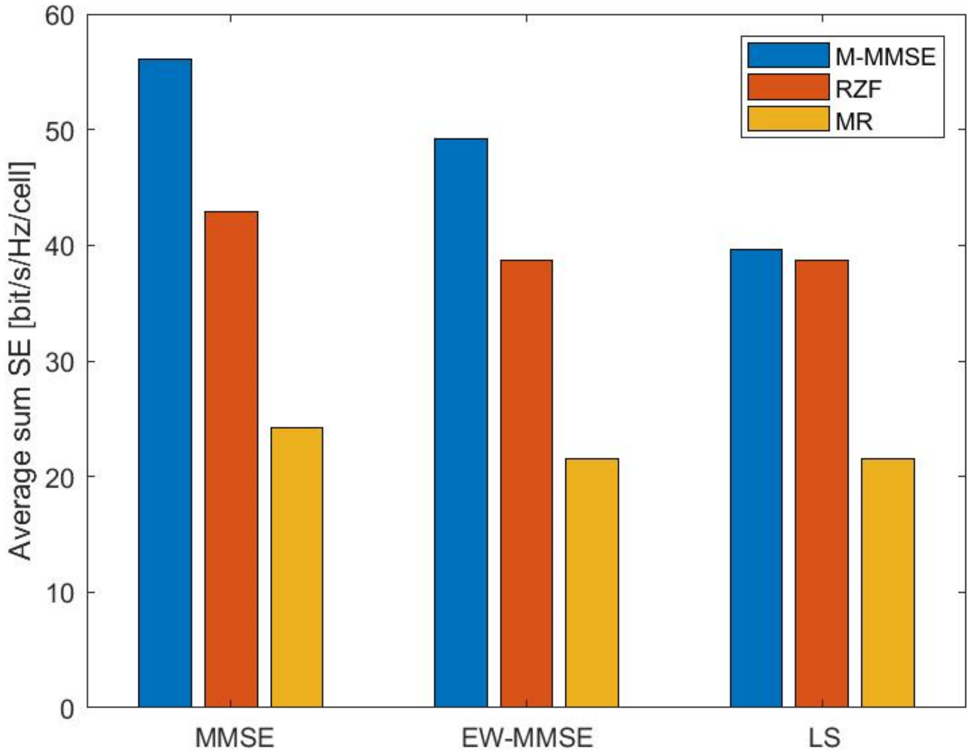


Figure 11. *Average UL sum SE of M-MMSE, RZF, and MR combining by using MMSE, EW-MMSE, and LS estimator*

From the figure, the highest SE is achieved by using the MMSE estimator followed by the EW-MMSE estimator which has on average 8%-12% less SE depending on combining schemes compared to MMSE. M-MMSE combining performance is very poor in LS estimators but compared to EW-MMSE, RZF and MR have the same SE in both cases. In the presence of pilot contamination, the LS estimator is unable to provide the right scaling of the channel estimates. On the contrary, it acts like an estimator that sum the interfering channel.

The main target is to obtain substantial SE gain irrespective of channel estimator. MMSE provides better SE in all three schemes but introduces high complexity. Since high complexity estimation schemes are tried to be avoided sometimes. In that case, EW-MMSE can be a better option as it shows the good tradeoff between SE and complexity. Hence, an alternative, EW-MMSE channel estimator can be a suitable preference if the highest SE is not the priority. However, LS estimation should be avoided.

4.2 Energy Efficiency

4.2.1 Hotspot Tier

Hotspot tier is a part of the heterogeneous network. It consists of mainly indoor base stations that provide high throughput within a small area. The mmWave bands are congenial for it to improve throughput.

Hotspot BS has played an important role to reduce transmit power at the same time increasing throughput. It basically provides additional capacity within the coverage tier BSs by narrowing the distance between serving BSs and UEs [54]. The mechanism behind hotspot BS is, deploying a wider range of network infrastructure and a large amount of transceiver hardwires [55]. But deploying such a large number of transceivers and network structure, it can increase the power consumption of the network, although there remain various possible solutions. Sensor technology can be a possible solution where hotspot BSs is equipped with a traffic load monitoring mechanism [56],[57], and an automatic turn-on, turn-off components according to the demands. These technologies are really efficient to reduce power consumption without losing area throughput. But there remains a huge leakage, that is, these technologies degrade the coverage the mobility support and coverage. Hence, it is not very suitable for the operation of the coverage tier. Researches have been going over how to make the consumed power equal to the network load so that the dynamic turn-on and turn-off can be avoided.

Before making any network Energy Efficient, we have to know Area Transmit Power (ATP), which is the network-average power uses for the sake of per area data transmission. It is basically a metric that measures the consumed transmit power by the wireless network. Therefore, it is described as,

$$ATP = P * D \tag{4.3}$$

where P is the transmit power (W/cell) and D is the average cell density in the unit area (cells/km^2). The unit of ATP is W/km^2.

Now, for ATP for UL in MMIMO, if a network is considered which is equipped with L cells, number of BS j, and K UEs, and if BS j wants to communicate with K_j UEs, p_{jK} is the signal variance, then, ATP of the BS_j for UL becomes,

$$ATP_J^{UL} = D \sum_{K=1}^{K_j} P_{jK} \, . \tag{4.4}$$

For the corresponding ATP for DL, ATP_J^{DL} can be achieved only by replacing P_{jK} by ρ_{jK}.

If we want to calculate ATP_J^{DL} or ATP_J^{UL} (both would be same as both needs transmit power to 20 dBm for MMIMO), considering K equals 10 UEs, pilot reuse factor, f equals 1, 4 by 4 cells, BS coverage area of (0.25*0.25) km^2, and number of antennas, M, then the total transmit power would be = 100 mW * 10 = 1000 mW = 1W = 30 dBm. Therefore, ATP_J^{DL} would be = (4*4) *1 = 16W/km^2.The same result would be achievable for ATP_J^{UL}.

Compared to the LTE network this UL or DL ATP is much smaller.

***Table 4**. Average DL throughput over 20 MHz channels per cell.*

Schemes	M = 10	M = 50	M = 100
M-MMSE	243 Mbit/s	795 Mbit/s	1053 Mbit/s
RZF	217 Mbit/s	648 Mbit/s	832 Mbit/s
MR	118 Mbit/s	345 Mbit/s	482 Mbit/s

Table 4 represents the average DL throughput for M-MMSE, RZF, and MR combining over 20 MHz channels per cell. Values are collected from [48]. From the table it can experience, M-MMSE, as expected, has the highest throughput for every number of BS antenna. For, M = 100, M-MMSE and MR have DL throughput of 1053 Mbit/s and 482 Mbit/s respectively which is almost 10 times higher than LTE [58]. Hence, total area throughput of M-MMSE become 3.88 Gbit/s/km^2, 12.72 Gbit/s/km^2 and 16.8 Gbit/s/km^2 for M = 10, 50 and 100 respectively.

Hence, with a large number of BS antennas, MMIMO can achieve much higher throughput and an-order-of magnitude ATP savings than LTE at the same time. Besides total transmit power divides among all the antennas M, resultant transmit power per antenna is very low. As it can be seen from here, if the total 1W transmit power is divided among 100 antennas, then only 10mW per antenna for transmission is consumed. As transmit power per antenna is low, we don’t need to use high power-consuming PAs which are being used in the traditional cellular networks. Operators can replace them with hundreds of low powers (~mW range) and low-cost PAs.

One and most important drawback of ATP metric is that it increases the circuit power of the network. Since, for this setup, we need to deploy multiple RF chains, precoding/combining schemes, in each BS. For that, the computational complexity becomes much higher depending on the number of UEs and BS antennas, M and resultant increases CP. As a result, to make the network energy efficient which is the main motto of this thesis remains under obstacle. For that EE metric can be a better choice than ATP metric.

4.2.2 Asymptotic Analysis of Transmit Power

Asymptotic analysis means calculating the operating time of an algorithm in mathematical units of computation. It basically mentions an algorithm's mathematical boundation or framing according to its run-time performance [66]. After performing asymptotic analysis, the algorithm's case scenario (the best case, average case or worst case) can be judged.

The explanation of asymptotic analysis of the transmit power has given about the impact in EE when the number of antennas grows higher. It will see the CP performance when $M_j \rightarrow \infty$ in the asymptotic regime while keeping the number of UEs, K fixed. MMIMO can be operated at really very small transmit power levels. In theoretical assumption, approaching toward a non-zero SE, transmit power can asymptotically become zero.

To reach the asymptotic non-zero limit, a calculation has performed in [50] with DL transmit power and considering MR schemes. As other precoding and combining schemes have better and larger SE value than MR, that's why he establishes with MR so that other schemes can hold the same result as well. With MR precoding, having K UEs in cell j has DL channel capacity which is lower bounded by,

$$SE_{jK}^{DL} = \frac{\tau_d}{\tau_c}\ log_2\left(1 + SINR_{jK}^{DL}\right) \tag{4.5}$$

where this term $\underline{SINR}_{jK}^{DL}$ has derived from [48, equation 5.4].

[48, lemma 5.1] has shown transmit power scaling low for MMIMO networks, where the conditions are,

$$M \rightarrow \infty \text{ if } \in_1 + \in_2 < 1$$

$$\text{while } \underline{SINR}_{jK}^{DL} \rightarrow 0 \text{ if } \in_1 + \in_2 > 1.$$

The condition $\in_1 + \in_2 < 1$ implies that, either both UL and DL transmit power p_{jK} and ρ_{jK} should decrease roughly as $1/\sqrt{M}$ or, or we can decrease one faster, one slower until the product $P_{jK}*\rho_{jK}$ doesn't decay faster than 1/M.

From the power scaling low, if transmit power can be reduced faster than these two conditions, then zero asymptotic SE is achievable.

To exemplify this asymptotic result, simulation has performed with the lemma 5.1 taking MR precoding. Assuming $\in = \in_1 = \in_2$, number of UEs, K = 10, UL/DL transmit power per UE, $\overline{P} = \underline{P}$ = 20 dBm, total DL transmit power, K$\underline{P}$ = 30 dBm, $\in$ = 1/2 , $\in$ = 1 and $\in = 0$. Considered Uncorrelated Rayleigh fading showed in figure 12.

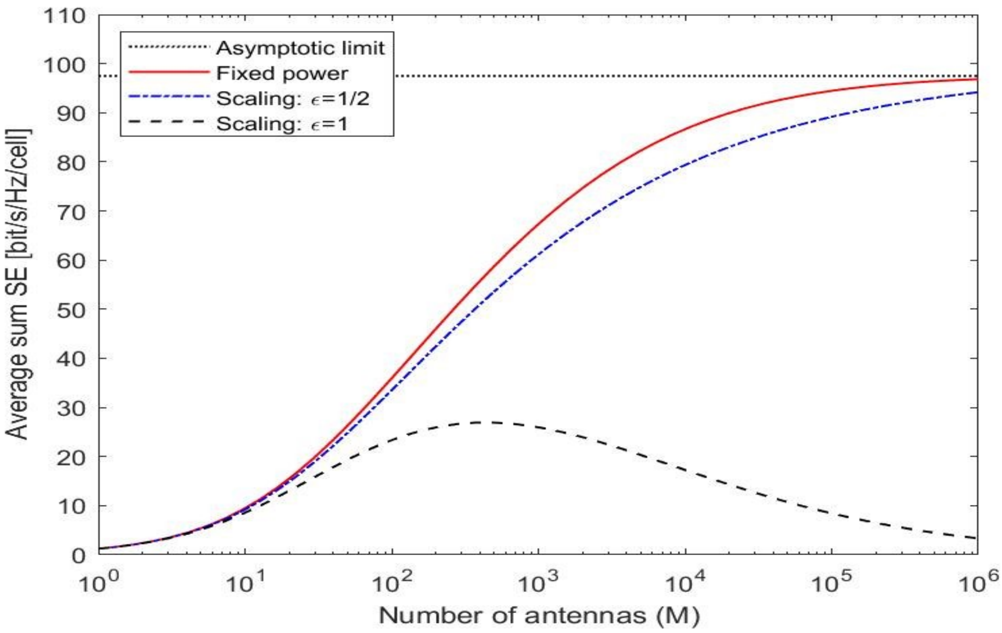


Figure 12. *Average DL sum SE with normalized MR precoding as a function of the number of antennas, M. Taking $\overline{P} = \underline{P} = 20$ dBm ; fixed power (i.e., ∈ = 0), ∈ = ½ and ∈ = 1; Considering Uncorrelated Rayleigh fading.*

From figure 12, it can be shown that, when ∈ = ½ i.e., P_{jK} and ρ_{jK} decrease as $1/\sqrt{M}$, DL sum SE approaches towards the non-zero asymptotic limit. The behavior is somewhat almost similar to fixed power (when ∈ = 0). 55% asymptotic value is obtained when the number of antennas, M =10^3 i.e., 1000. While almost 95% asymptotic value can be achieved with M = 10^6 i.e., 1,000,000. When ∈ = 1, the average DL sum SE vanishes.

In addition, when M = 100, the total transmit power of BS decreases from 1W to $K\underline{P}/\sqrt{M}$ = 0.1W.

Dividing this 0.1W among 100 transmitting antennas, 1 mW power is needed to operate each antenna. This clearly indicates that, theoretically, MMIMO can be operated at low transmit power, keeping the same SE values. Although this transmits power reduction comes for deploying more BSs antennas which increase circuit power eventually.

5. SIMULATIONS AND RESULTS

Massive MIMO and NB-IoT can certainly improve the network efficiency of the cellular network. Whereas, at the same time, increasing the performance of spectral efficiency substantially degrades the energy efficiency due to the huge number of RF chains and PAs. Experimenting the spectral and energy efficiencies along with RF chains, power amplifiers, base station's power consumption, precoding and combining schemes and so on, it has shown that there exists an optimal point, where it is possible to maintain the energy efficiency without decreasing the spectral efficiency as well as throughput. For the simulation purposes, a general form of 20 MHz band MMIMO network is considered which is mathematically more convenient to study and MATLAB simulations have performed by using data from [48]. From [59], the upper bound of the energy efficiency is derived as,

$$\hat{\eta}ZF = \frac{\mathrm{K}log_2\left[1+\left(\frac{P_{OUT}}{\mathrm{K}}\right)*\left(\frac{N_{TX}\pi^2-\pi+4}{4}\right)\right]}{\frac{1}{\alpha}P_{OUT}+K((P_{RF}+P_{BB})+P'C} \tag{5.1}$$

where K is the total number of Users Equipment, P_{OUT} is the BS downlink transmit power, P_{RF} is the power consumed by RF chains, P_{BB} is the power consumed for the baseband processing, P'_C is the fixed power consumption by BS not including the power consumed for downlink transmission, N_{TX} is the number of transmitting antennas in BS.

Implementing this algorithm in Matlab and then the result has illustrated in figure 13. The energy efficiency as a function of the number of transmitting antennas in a single BS, the first assumption is that, with increasing the number of transmitters energy efficiency increases. At first, when the number of transmitters rises from 1 to 20, energy efficiency increases rapidly. After that, the increment of EE is smoother and gradual. From 1 to 40 transmitters, EE increasing rate is high and after that, it becomes gradual and smooth.

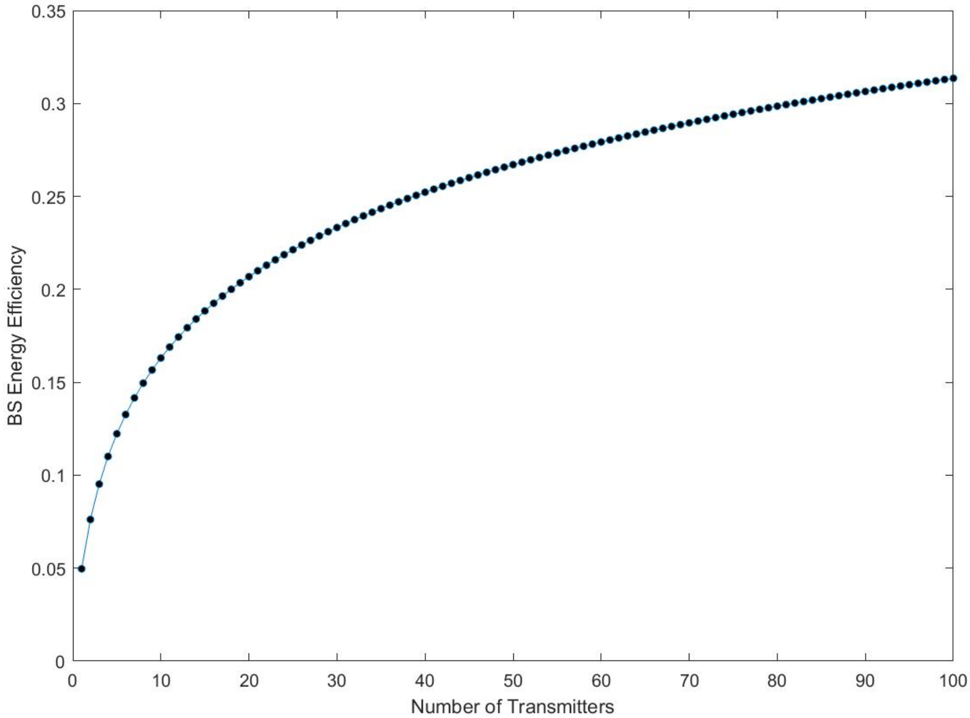


Figure 13. *Energy Efficiency curve with respect to the number of transmitters where K=1, P_{OUT}= 10^(-30/30) i.e.,-30dB; P_{RF}=P_{BB}= 10^(-10/30); P'_C= 20W and N_{TX} is a vector = [1:100]. EE is an uprising function against the transmitter number. Initially, the incensement is higher ($N_{TX} \leq 40$). As the transmitter number grows, it becomes gradual.*

In [59], a proposition has been made for energy efficiency optimization in MMIMO for 5G radio frequency chain systems where EE is expressed as a function of UEs and N_{tx}. In this thesis, Matlab simulation has performed over this proposition and result has shown in figure 14. It brought us to the point that, energy efficiency increases with the increasing number of antennas while keeping the UEs at the optimal number. When the number of UEs increases, energy efficiency monotonously decreases.

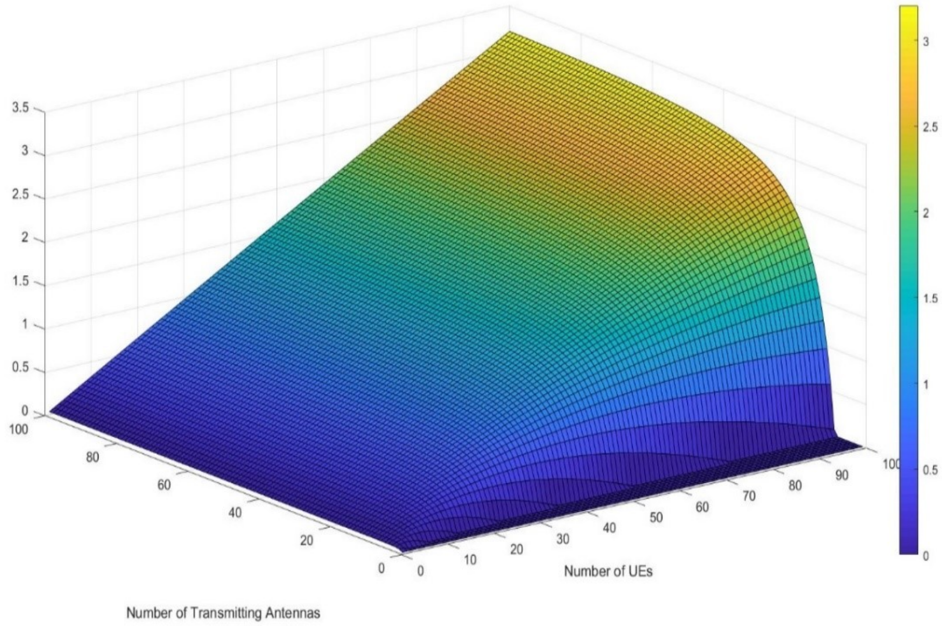


Figure 14. *G(K, N_{TX}) as a function of UEs with respect to the number of antennas. K is a vector = [1:100], P_{OUT}= 10^(-30/30) i.e.,-30dB; P_{RF}=P_{BB}= 10^(-10/30); P'$_C$= 20W and N_{TX} is a vector = [1:100]. The function is monotonically decreasing with relevant to the number of antennas, N_{TX}. Also, it decreases gradually while increasing the number of UEs.*

To explore into more detail calculations considering various network parameters under different operating conditions, first, it has examined the two-cell Wyner model for UL [60]. From [60], the number of UE in cell 1 is 1, assuming no Inter-cell Interference (ISI) from cell 2 and considering Rayleigh fading channels, SE and EE have calculated from cell 1 as,

$$SE = \left[1 + (M-1)\frac{p}{\sigma^2}\,\beta\right] \tag{5.2}$$

$$EE = \frac{B * SE}{(2^{SE}-1)\frac{\vartheta}{(M-1)} + P_{FIX}}\,. \tag{5.3}$$

Form the above expressions, calculating them and doing simulation the maximum tradeoff of EE and SE for cell 1 (Figure 15) has obtained. The maximum tradeoff has been achieved as it has only considered the basic model ignoring fading, non-line-of-sight (NLoS), ISI and RF chains power consumption in BS.

According to the [60], the Maximum EE(EE*) and maximum SE(SE*) in cell 1 satisfy the identity as,

$$log_2(EE^*) + SE^* = log_2\left[(M-1)\frac{B}{\vartheta log_2(2)}\right]. \tag{5.4}$$

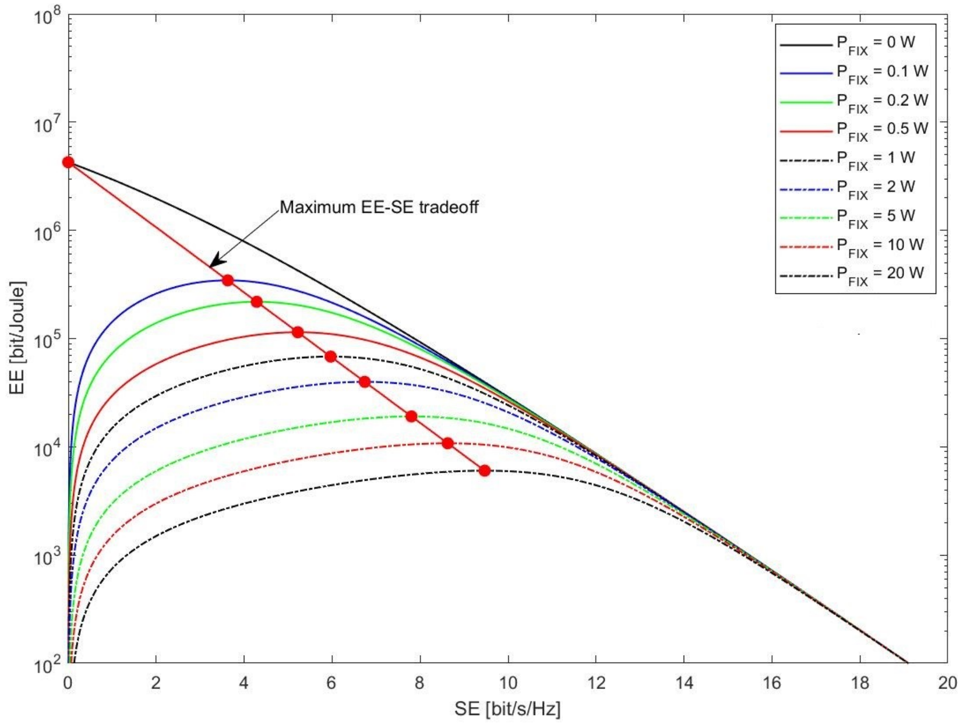


Figure 15. *Linear dependence between maximum EE and SE for different values of BS's fixed power, P_{FIX}. Taking, Bandwidth, B = 15KHz; Number of antennas, M = 10; PA's Efficiency, μ = 0.5; It shows exponential EE is acquired sacrificing linear SE.*

Figure 15 exemplifies the relation between EE and SE for different values of P_{FIX} = {0, 0.1, 0.2, 0.5, 1, 2, 5, 10, 20} in cell 1. The maximum energy efficiency is represented here by a red dot in every line. And the red line represents the tradeoff between EE and SE. From the curve, when circuit power, P_{FIX} is 0W, there is an abrupt decreasing tradeoff between EE and SE. This is due to the fact that when there is no CP, EE and SE behave just opposite to each other; i.e., SE increases at the cost of decreasing EE. However, when P_{FIX}> 0W, the EE curve becomes unimodal which means it increases up to the peak for increasing SE($(2^{SE}-1)\frac{\vartheta}{(M-1)}$ <P_{FIX}) and then starts to decrease towards 0. One more thing to be noticed that with increasing the value of P_{FIX}, the EE-SE curve becomes curvatured. This is due to the fact that with increasing circuit power if the EE is needed to be kept at the same level then more SE values are needed. Hence, the maximum EE-SE curves become flattered. In nutshell it can be explained as, transmit power is an obstacle for EE, otherwise, with higher BS' fixed power, higher SE can be achieved.

To observe the impacts of the Number of BS's antennas, Matlab simulation has performed with EE versus SE as a function of the number of antennas, where EE increases boundlessly. The EE and SE equations derived in the book [60] are given as,

$$SE = \frac{W\left((M-1)\frac{P_{FIX}}{\vartheta e} - \frac{1}{e}\right) + 1}{log_2(2)} \tag{5.5}$$

$$EE = \frac{(M-1)Be^{-W\left((M-1)\frac{P_{FIX}}{\vartheta e} - \frac{1}{e}\right)-1}}{\vartheta log_2(2)} \tag{5.6}$$

here, w(.) is the Lambert function [74] and e is the Euler's number [75].

Simulating these equations, the impacts of the number of antennas are shown in figure 16. This time the circuit power is kept in fixed value as, P_{FIX} = 10W. Whereas the other values are kept the same. From the simulation results, it is observed that with the increasing number of antennas both EE and SE increase. EE curve monotonically increases when M increases, but this is not feasible in practical scenarios. This is because simulation has been performed with a wide range of antennas (from 1 to 1000), but only considering the fixed power consume at the BS.

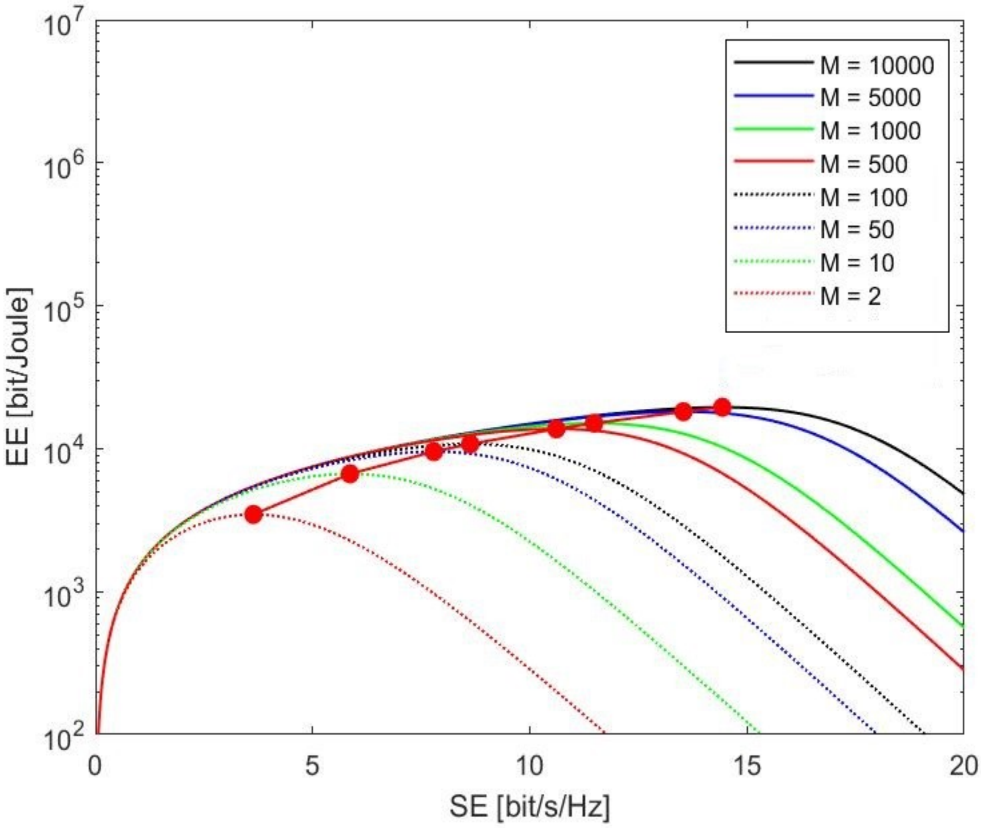


Figure 16. *EE and SE relationship for different values of BS's antennas, M. Taking, P_{Fix} = 10W, channel Bandwidth, B = 15KHz; PA's Efficiency, μ = 0.5; and M = [1000, 500, 100, 50, 10, 2, 1]. Here Both EE and SE are increasing as M grows higher.*

In MMIMO, each and every antenna is equipped with RF chains and PAs. These things consume power which can not be ignored when calculating the number of antennas like 50, 100, 500 or 1000. Hence for basic and simple understanding, increasing the BS transmitting antennas, both EE and SE increase unless the total power consumption is considered.

When the EE-SE tradeoff exemplifies, the impact of the noise power, σ^2 and the average channel gain of the active UEs, β should be considered. In all these simulations, the value of σ^2/β is defined as -6dBm as it is the most common case considering 20 MHz band cellular MMIMO. Here, simulation has been performed by taking into account different σ^2/β values which has shown in figure 17. The same equations of SE and EE, which have used to illustrate EE and SE relationship for different values of BS's antennas, have been used here. In this case, the number of antennas kept fixed as, M = 10,000.

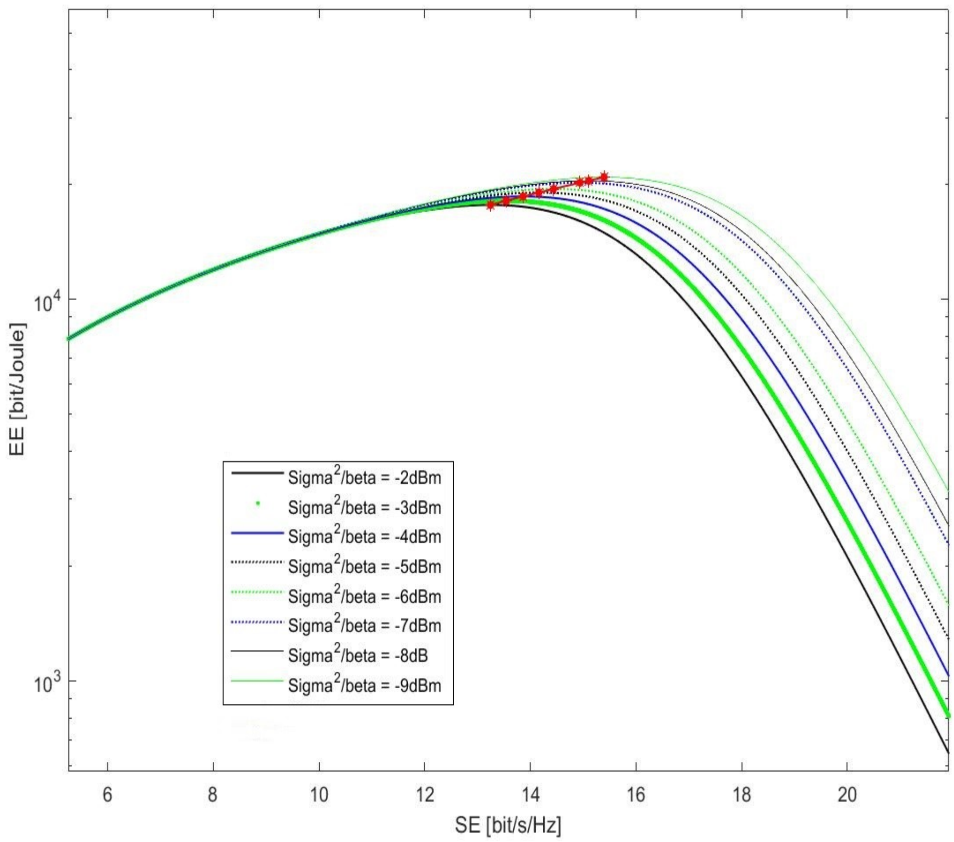


Figure 17. *EE versus SE relation for different σ^2/β values. Keeping P_{Fix} = 10W, channel Bandwidth, B = 15KHz; PA's Efficiency, μ = 0.5; and M = 10000. We have taken value as [-2, -3, -4, -5, -6, -7, -8, -9].*

Figure 17 illustrates, changing the ratio value between signal power and average channel gain per active UE, it is observed that EE increases when the value of σ^2/β decreases. This indicates that in order to glorify EE, the average channel gain fo the active UE's needs to increase and at the same time, the signal noise power needs to decrease. The MMIMO's assume UL bandwidth is 100 kHz, whereas in NB-IoT, for UL, the bandwidth is 15KHz bandwidth. As from equations,

$$\text{Noise Power} = K_b * \mathrm{T} * \mathrm{B} \tag{5.7}$$

where K_b is the Boltzmann constant of value $1.38*10^{-23}$ J/K, T is the absolute temperature of the device which is approximate ~ 273.15K and B is the channel bandwidth. Here, if K_b and T are considered as constant quantity, then the noise power is totally dependent on B. Hence if channel BW is smaller (such as NB-IoT), the system's noise power will be less. For example, if calculation is done for the noise power of MMIMO and NB-IoT, NB-IoT has smaller noise power values compared to the proposed MMIMO. In the same way, the average channel gain β is better in NB-IoT than other technologies. Therefore, the value of the σ^2/β is smaller and certainly better EE and SE value can be achievable.

So far, from [60, corollary 5.2], it can be observed that with increasing the number of antennas M, EE grows higher in the logarithmical scale and in the contrary it decreases more or less linearly with increasing P_{FIX}. Whereas SE goes higher with a logarithmic scale for both M and P_{FIX} [60, equation 5.22]. The reason behind that is, until now, only the simplistic model of power consumption is used of the P_{FIX} in CP. As the M increases in BS, the number of RF chains connecting with each antenna also increases. Hence, increasing M equally increasing the RF chains in BSs which contains the components like, Power Amplifiers (PAs), Digital-to-Analog Converters (DACs), Analog-to-Digital Converters (ADCs), In-phase or Quadrature-phase filters (I/Q), Local Oscillators (LOs), Mixers, Modulators, and Demodulators. All these components are consuming energy. Now If there are M antennas in a BS, then the power consumption for all these will be M times higher, like $M*P_{BS}$. Where P_{BS} is the power consumption of the RF components in each antenna. From here it can be calculated the CP model for cell 1 as,

$$CP = P_{FIX} + M * P_{BS}\,. \tag{5.8}$$

From here the EE equation can be derived for cell 1 as,

$$EE = \frac{B * SE}{(2^{SE} - 1)\dfrac{\vartheta}{(M-1)} + P_{FIX} + MP_{BS}}. \tag{5.9}$$

Assuming that each BS antenna's RF components consume the power of 1W (including all the RF chains, like PA, ADC, DAC, Mixer, and so on). Hence, P_{BS} equals to 1W.

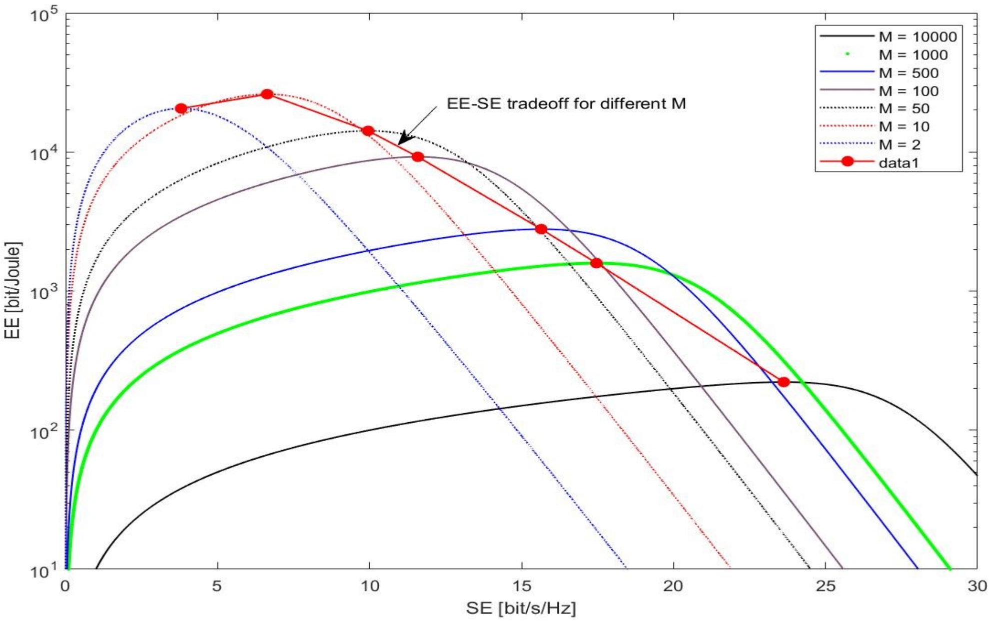


Figure 18. *EE versus SE relation for wide range of antennas, M. Considering P_{BS} = 1W, P_{FIX} = 10W, B = 100KHz; PA's Efficiency, μ = 0.5; and = -6dBm. The red dotted line represents the tradeoff of EE and SE for different values of M and the red dot shows the maximum EE on each value of M.*

Now taking into account this CP, if the simulation can be performed as EE versus SE under the same conditions, but keeping σ^2/β value fixed (-6dBm), then the achievable output is shown in figure 18. The contrast can be observed between the figure 17 and figure 18 due to the impact of the PBS.

In figure 18, the tradeoff curve of EE-SE increases with the number of antennas up to M ≤ 10. This part, increasing EE is a unimodal function of M. After M > 10, the EE-SE curve decreases monotonically and the highest EE is achieved when M = 10. In figure 17 it is observed that the EE-SE increases with the number of antennas and it grows unboundedly. Whereas taking into account the power consumption of the BS's RF chains, these number of antennas begins the limit the EE. Hence, the EE-SE curve here doesn't grow unboundedly. It illustrates that, while dealing with energy and spectral efficiency and calculating their cut-off values, CP modeling should be given one of the highest priorities and calculation should be accurate.

Getting into deeper calculations in this thesis, consideration has been made for a few existing things like inter-cell, intra-cell interference and CP consumption by active UEs in the system. As considering the two-cell Wyner model (cell 1 & 2), the calculation for inter-cell interference's relative strength would be,

$$\bar{\beta} = \frac{\beta_2^1}{\beta_1^1} = \frac{\beta_1^2}{\beta_2^2} .$$

Moreover, considering additional power used by the active UEs in cell 1 as,

$$CP = P_{FIX} + M * P_{BS} + K * P_{UE} \tag{5.10}$$

where P_{UE} denotes as power requires for each single cell-antenna UE.

Consedring all these things, calculation has done for EE with respect to SE for cell 1 as,

$$log_2(EE) + SE - 2log_2[1 - \left((2^{SE} - 1)\frac{1}{(M-1)}\right)\left(K\bar{\beta} - 1 + K\right) = log_2\left[(M-1)\frac{B}{\vartheta log_2(2)}\right]. \tag{5.11}$$

Which has simulated to observe the impact in EE-SE tradeoff in figure 19. Assuming inter-cell interference's relative strength -10dB and number of active UEs in cell 1 as 10 the simulation has performed.

In figure 19, EE-SE tradeoff is a unimodal function of the number of UEs, K where EE increases with the ratio of UEs and antennas up to M/K ≤ 3. When M/K > 3, EE starts decreasing slowly. Sum SE is an increasing function of K whereas, EE degrades with increasing sum SE. This is due to the fact that each UE is consuming the power of 0.5W and hence BS's PC increases. Intuitively, in the operating regime, there remains a maximal pair of BS antennas and UEs for which the maximum EE in cell 1 is achievable. With taken values and simulations, EE is maximum when M/K = 3.

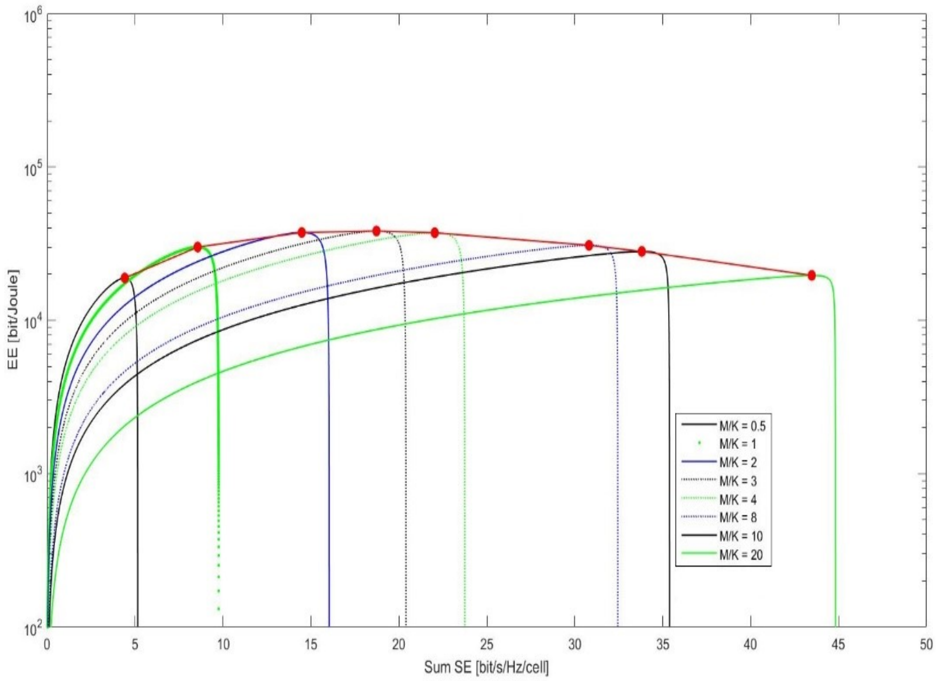


Figure 19. *EE as a function of SE for different M/K ratios. Considering, P_{FIX} = 10W, P_{BS} = 1W, P_{UE} = 0.5W, K = 10, $\bar{\beta}$ = -10dB, B = 100 KHz, μ = 0.5; and = -6dBm.*

Hence, serving multiple UEs need to increase the number of BS antennas to keep the network energy efficient at the same time we have to keep in mind that, RF chains and hardware are sufficiently energy efficient.

Working with the impact of the throughput in EE, a table has proposed in [60] containing different parameters of the BS and CP model with different precoding and combining schemes. For measurements and simulations, values are taken from this table.

***Table 5**. BS's CP model based on the combining and precoding schemes.*

Parameter	Value Set 1	Value Set 2
Fixed Power: P_{FIX}	10W	5W
Power for BS LO: P_{LO}	0.2W	0.1W
Power per BS antennas: P_{BS}	0.4W	0.2W
Power per UE: P_{UE}	0.2W	0.1W
Power for data encoding: P_{COD}	0.1W/(Gbit/s)	0.01W/(Gbit/s)
Power for data decoding: P_{DEC}	0.8 W/(Gbit/s)	0.08 W/(Gbit/s)
BS computational efficiency: L_{BS}	75 Gflops/W	750 Gflops/W
Power for backhaul traffic: P_{BT}	0.25 W/(Gbit/s)	0.025 W/(Gbit/s)

Two different value set has been given in this proposal. Data set 1 is collected from variety of works [61],[62],[63],[64]. In addition, the second set of values is the assumption CP model's [60] current work relating to this field and assuming what would be the value of these parameters in the future. Considering Moore's law in [60], it increased computational efficiencies by a factor of ten and with the advancement in RF fields, and from the IMEC online web tool model, where, to predict future cellular BS's power consumption, the PC of the transceiver's hardware has been decreased by a factor of two. However, caution has been taken as it stressed that, these parameters are very hardware-specific and can have different values.

Considering MMIMO, different precoding and combining schemes and the data table of two different value sets, simulation has performed of the EE as a function of average throughput in each cell. Here, simulation has been done for NB-IoT collaborating with MMIMO, taking the same values to form data table 5, (figure 20) and tested different numbers of BSs to see the impact in EE. Lately, it has tried to compare the different impacts in the proposed 20 MHz band cellular MMIMO and NB-IoT with MMIMO.

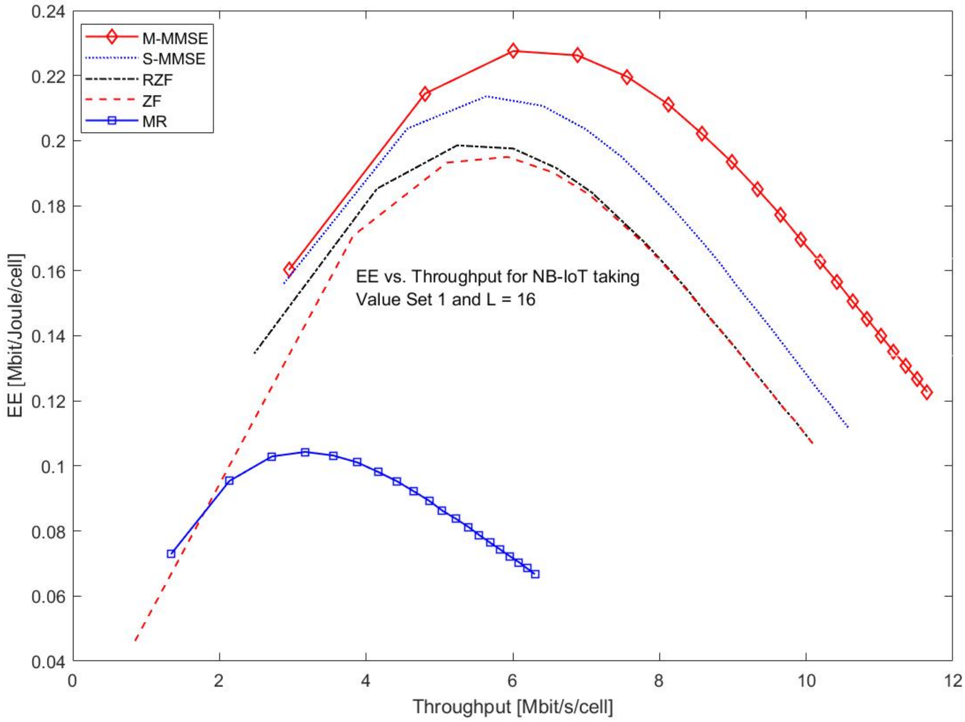


Figure 20. *EE as a function of average throughput per cell for L = 16. Taking into consideration of NB-IoT and the first set of the value-form table. M from 1o to 200 with a step size of 10 and K = 10. All combining and precoding schemes are increasing EE and throughput but M-MMSE has the highest EE values followed by S-MMSE.*

Figure 20 illustrates EE versus throughput for all schemes when the number of BSs is 16 and the number of BS antennas varies from 10 to 200 in step size of 10. EE becomes and unimodal function of throughput for the value set 1 of the table for all schemes. It means EE and throughput can jointly increase until the maximum edge of EE. After that, EE falls at the cost of increasing throughput. From different schemes, the highest EE at different throughput points is observed. M-MMSE has the highest EE for any value regarding throughput followed by S-MMSE. Maximum M-MMSE for this setup is 0.227 Mbit/Joule/cell corresponding throughput of 6 Mbit/s/cell. Moreover, this maximum EE is conquered at M = 30. Hence, the total area throughput stands for 96 Mbit/s/km^2.

With S-MMSE, the highest EE obtained is 0.2136 Mbit/joule/cell which reduced EE by 6.3% compared to M-MMSE and corresponding throughput of 5.638 Mbit/s/cell which is also lower than M-MMSE by 6.5%. Both achieved at M = 30.

RZF and ZF have almost similar performance except. RZF has maximal EE of 0.1985 Mbit/joule corresponding throughput of 5.24 Mbit/s/cell and it's achieved when M = 30. On the contrary, ZF has 0.195 Mbit/joule EE for throughput of 5.927 Mbit/s/cell and it comes at M = 40.

MR provides maximal EE of 0.1043 Mbit/joule corresponding to the throughput of 3.17 Mbit/s/cell. Therefore, the total throughput of the area stands for 1.6688 Mbit/s/km^2.

Now, if a comparison is made for the NB-IoT collaborating with MMIMO system with defined cellular MMIMO, at first glance it seems like EE and throughput has been fallen in NB-IoT compared to 20 MHz band MMIMO. But it doesn't happen actually. Compare taking the value of M-MMSE,

In [60], for M-MMSE scheme, 21.26 Mbit/joule/cell of EE is achieved considering the throughput of 600 Mbit/s/cell and total area throughput of 9.6 Gbit/s/km^2. In addition to NB-IoT, it is 0.227 Mbit/joule/cell EE at the cost of 6.008 Mbit/s/cell throughput and total area throughput of 96 Mbit/s/km^2. In both cases, the highest EE is obtained at M = 30. But, in 20 MHz band MMIMO, in [60] BW of 20 MHz is used and for NB-IoT BW is only 200 kHz, which is 100 times smaller. Now, if multiplication can be done with the EE and throughput by the factor of 100, it can be obtained EE of 22.7 Mbit/joule/cell and each cell throughput of 600 Mbit/s. Which stands total throughput of 9.6 Gbit/s/km^2. Comparing these two scenarios, a conclusion can be made like, with the same throughput and number of antennas NB-IoT with MMIMO has better EE (approximately 6.3%) than traditional 20 MHz Band MMIMO.

In the time following, to see the impact of increasing the number of BSs, the simulation has done considering the same scenario. BS numbers are taken as, L = 32, L = 64, and L = 128, 3 more different values to observe the changes in EE (figure 21, 22 and 23).

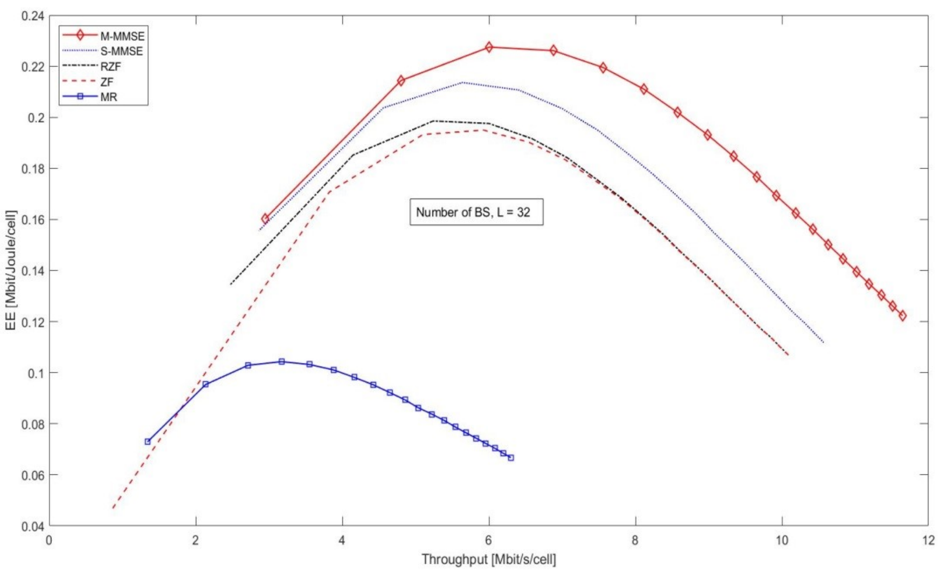


Figure 21. *EE as a function of average throughput per cell for L = 32*

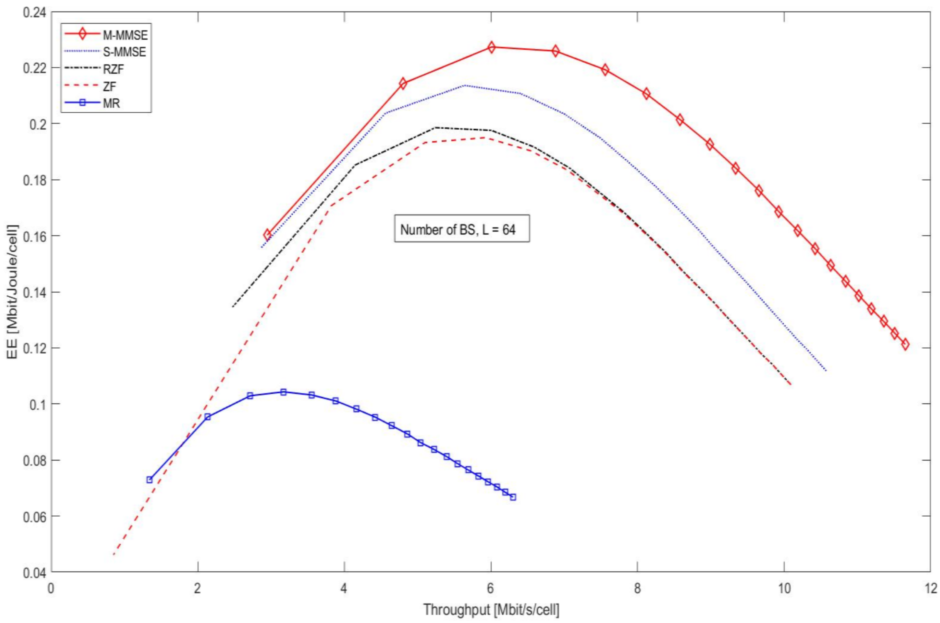


Figure 22. *EE as a function of average throughput per cell for L = 32*

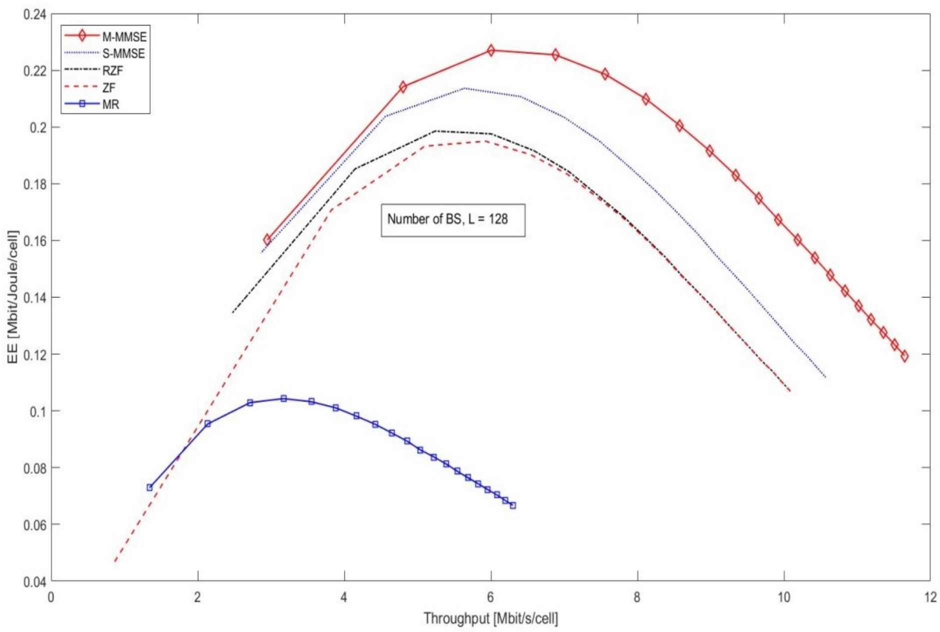


Figure 23. *EE as a function of average throughput per cell for L = 64*

From figures 21, 22, and 23, it can observe that increasing the BS number has no or very little impact on both EE and throughput. This is due to the fact that the system has calculated the EE versus throughput depending on the CP model, where consideration is only in the P_{FIX}, P_{BS}, P_{UE}, P_{LO}, P_{COD}, P_{DEC} & $P_{BT.}$ Now, in every case, the number of transmitting antennas, M remained fixed (from 10 to 200 in steps of 10). Hence, increasing L has either no or negligible impact on the EE versus throughput curve.

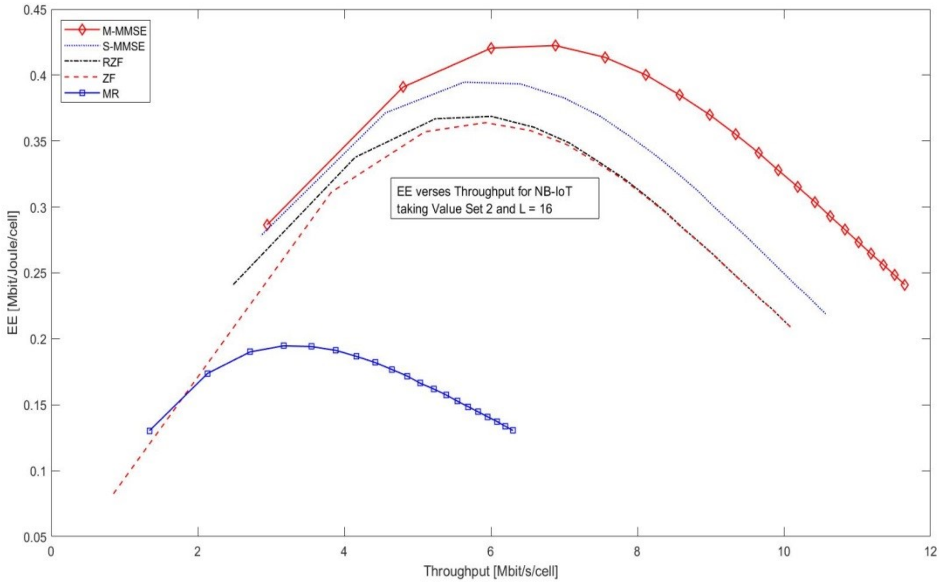


Figure 24. *EE as a function of average throughput per cell for the NB-IoT with MMIMO system. Considering hardware parameters from value set 2 and the number of BS, L = 16. Different throughputs are gained varying numbers to transmitter antenna, M from 20 to 200 with a step size of 10. Apart from the Hardware parameter's value set, rest are kept the same.*

Taking the value set 2 from the table (where computational efficiencies have been increased by a factor of ten and transceiver's hardware PC has been decreased by a factor of two) the simulation has done exactly the same as the value set 1 for NB-IoT with MMIMO (figure 24). It is observed that, for all considered combining and precoding schemes, the EE is almost double.

Comparing figure 20 (for the value set 1) with figure 24 (for the value set 2), EE has become almost double due to reducing most of the coefficient of CP. The maximum EE has achieved in the M-MMSE scheme among all the schemes followed by S-MMSE. In M-MMSE, EE is 0.4224 Mbit/joule/cell followed by S-MMSE of 0.3947 Mbit/joule/cell. Both are achieved for M = 40 and M = 30 respectively. Throughput per cell 6.88 Mbit/s for M-MMSE and 5.638 Mbit/s for S-MMSE. For RZF and ZF schemes, the highest EE is achieved at the cost of M = 40 and after M = 40, increasing throughput causes EE decreasing. The downslope is almost similar for both schemes. It achieved 0.1947 Mbit/joule/cell EE for MR along with 3.17 Mbit/s/cell throughput. However, in both value sets, the MR curve is smoother than with other schemes.

Again, comparing NB-IoT collaboration with MMIMO scheme and 20 MHz band defined MMIMO scheme, the same output is observed. For MMIMO (B = 20 MHz), where for the value Set 2, it has achieved EE 41.52 Mbit/Joule/cell corresponding throughput of 688 Mbit/s/cell. Whereas, for NB-IoT collaboration with MMIMO has obtained EE of 0.4224

Mbit/s/cell corresponding throughput of 6.88 Mbit/s/cell. The conclusion can be made that, with the same throughput, NB-IoT collaboration with MMIMO can be approximately 1.7% more energy efficient than the following defined 20 MHz band MMIMO. Moreover, gaining the same throughput, the NB-IoT with MMIMO system can impose 10 more antennas (as for NB-IoT with MMIMO, maximum EE is achieved for M = 40) than 20 MHz band MMIMO which increases the SE at the same time but without decreasing EE of the network.

Again, to see the impact of the BSs in the proposed system, the simulation has been performed by considering L = 32 as shown in figure 25, L = 64 as shown in figure 26, and L = 128 as shown in figure 27,

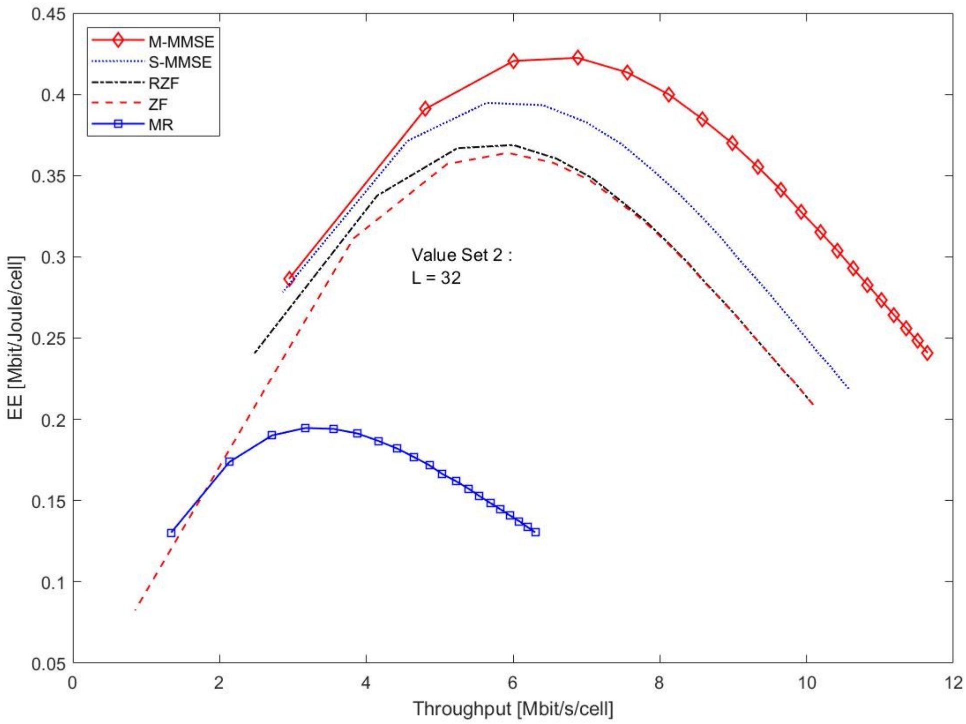


Figure 25. *EE as a function of throughput for value set 2 and number of BS, L = 32*

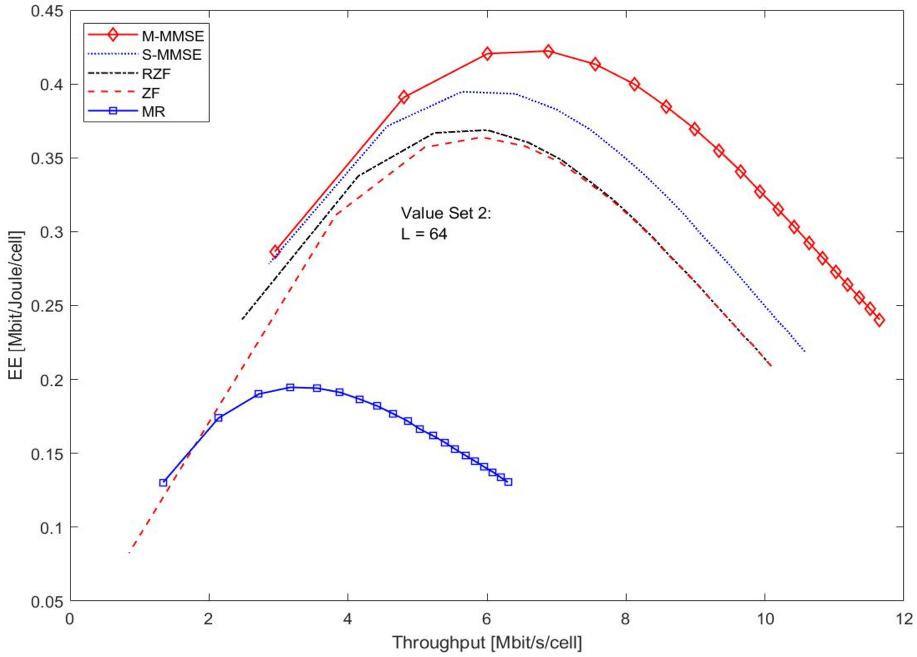


Figure 26. *EE as a function of throughput for value set 2 and number of BS, L = 64*

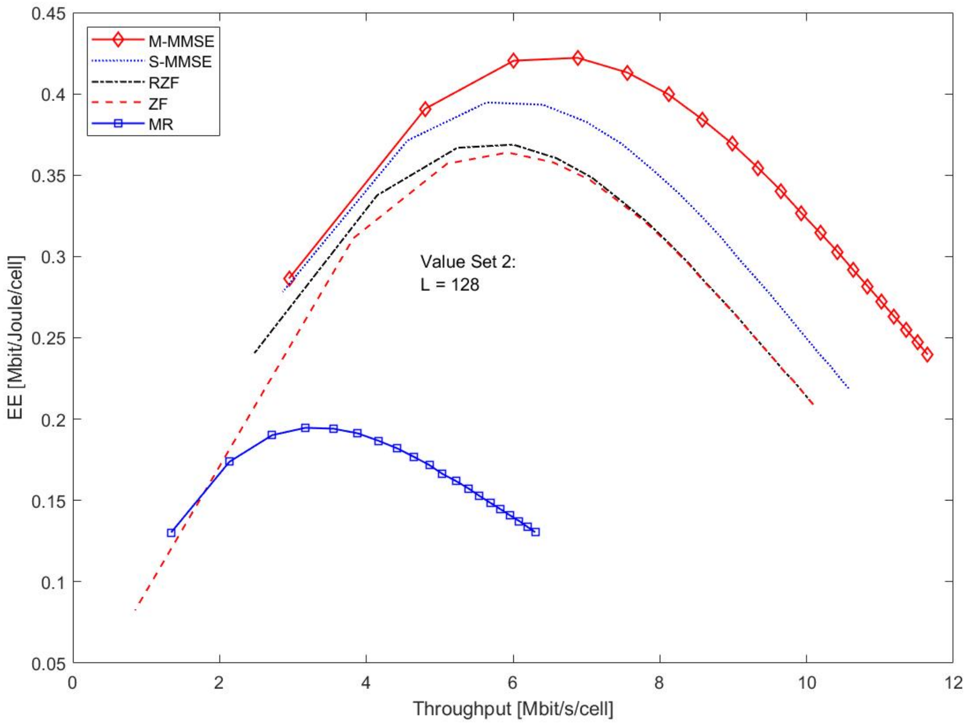


Figure 27. *EE as a function of throughput for value set 2 and number of BS, L = 128*

From figure 25, 26, and 27 as expected, there is no or very tiny (which can be negligible) effect of L over EE.

To put it in a nutshell, the M-MMSE scheme has the best EE against throughput from any other schemes. But the computational complexity is higher in this case, and for high throughput, high CP is needed. Hence, CP is higher in this scheme compared to others. A similar situation is observed in the case of S-MMSE. RZF and ZF have almost the same EE across the same throughput. But for small throughput value, ZR deteriorates abruptly.

To recapitulate, EE is a unimodal function of the throughput for both 20MHz band MMIMO and NB-IoT with MMIMO scenarios. Maximum EE has achieved when M = 30 or M = 40 for different schemes serving for 10 UEs. NB-IoT with MMIMO has a better EE scenario compared to 20 MHz band MMIMO for similar throughput. And EE reaches its maximum edge when the antenna-UE ratio, M/K becomes 3 or 4 as we have obtained.

Simulation results show in figures 25 and 26 that with a fixed number of UEs, increasing M up to 30 or 40 depending on schemes, EE has increased. However, if the number of UEs is also increase at the same time, then the scenario becomes different from what is obtained.

In this final step, a scratch network with modified parameters is observed to obtain the highest EE with varying both antenna and UE. The perspective is to achieve the optimum antenna-UE ratio without a priori assumptions so that our EE becomes highest.

In [60], achievable EE for MMIMO with different M/K values along with different combination schemes have shown. In this thesis, simulation has been performed for NB-IoT with MMIMO to observe the results and to come to the conclusion (figure 28).

To simulate this, the value set 1 has taken from table 5 except the number of UE which is considered here from 10 up to 200 with a step size of 10 and the number of antennas from 20 to 200 with the same step size.

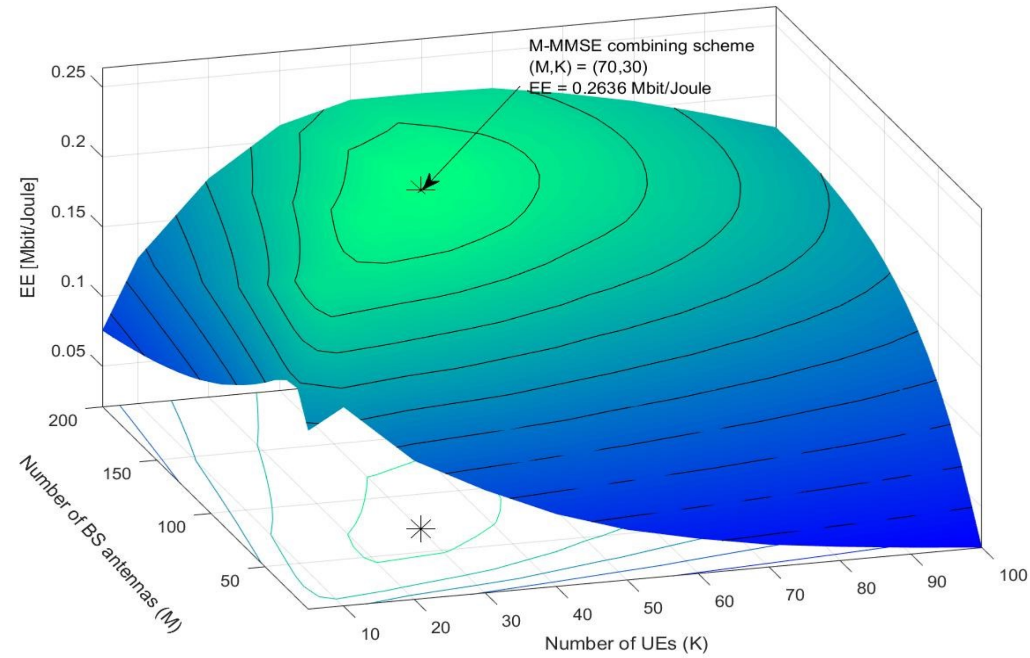


Figure 28. *Maximal EE as a function of M/K for the M-MMSE combining scheme. Considering value set 1 from table 5.1 and K ∈ {10, 20, 30, . . . 200}, M ∈ {20, 30, 40, . . . 200} with a step size of 10 for both.*

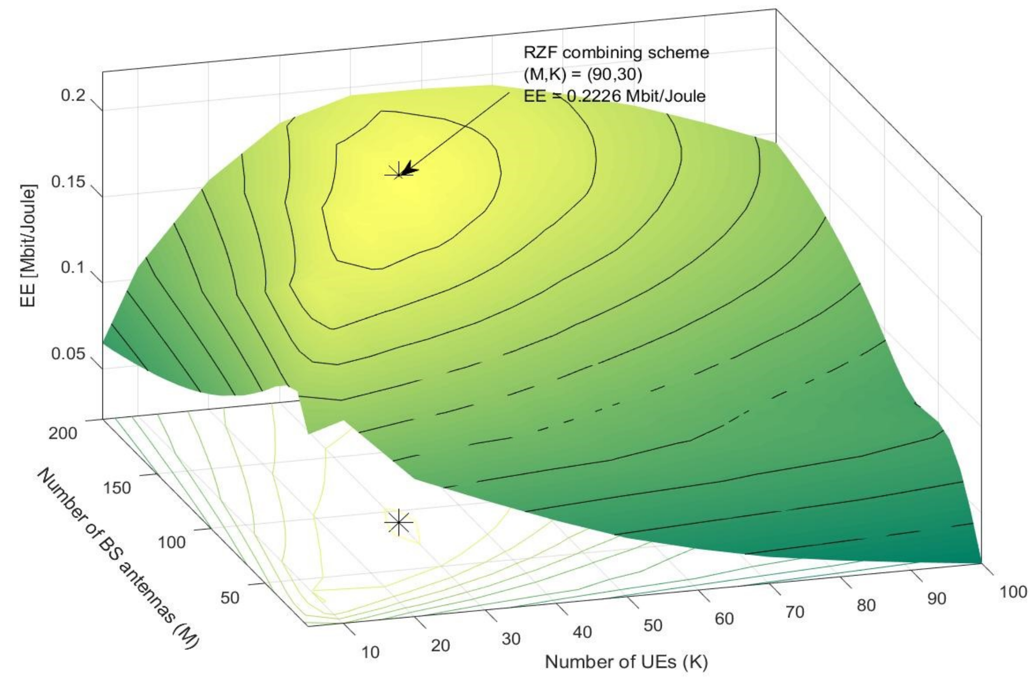


Figure 29. *Maximal EE as a function of M/K for the RZF combining scheme. Considering value set 1 from table 5.1 and K ∈ {10, 20, 30, . . . 200}, M ∈ {20, 30, 40, . . . 200} with a step size of 10 for both.*

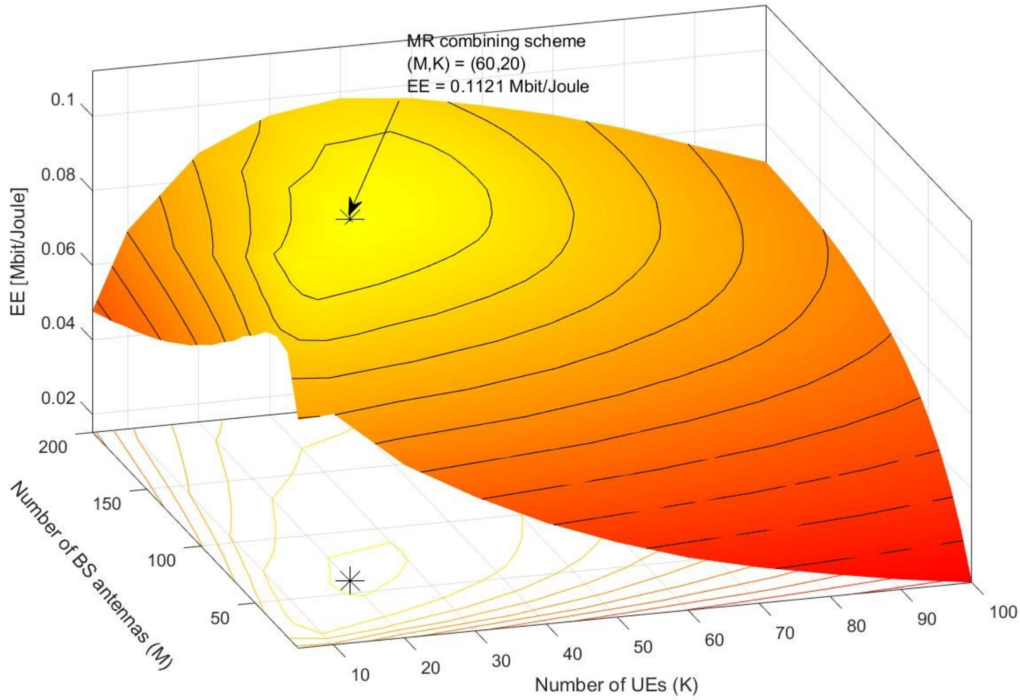


Figure 30. *Maximal EE as a function of M/K for MR combining scheme. Considering value set 1 from table 5.1 and K ∈ {10, 20, 30, . . . 200}, M ∈ {20, 30, 40, . . . 200} with step size of 10 for both.*

From figure 28, 29, 30 it is observed that, for NB-IoT with MMIMO in every combining scheme, there is a global optimum EE point and the surface of the EE curve is concave. It is obtained a different M/K ratio to achieve this global maximal EE. With M-MMSE scheme, it has obtained the maximal EE of 0.2636 Mbit/Joule corresponding (M,K) = (70,30) or M/K = 2.3~ 2.5. With RZF and MR schemes, we got EE of 0.2226 Mbit/Joule at the cost of (M, K) = (90,30) or the ratio, M/K = 3. In addition to MR combining 0.1121 Mbit/Joule EE has acquired at the cost of (M, K) = (60,20) or the ratio of M/K = 3. A piece of positive and important information can be acquired from here. That is, for M-MMSE, the ratio for M and K is decreased. For, cellular MMIMO, the M/K is 3 to 4 whereas for NB-IoT with MMIMO it is 2.3~2.5 which indicates that, to obtain the same SE NB-IoT with MMIMO may need fewer antennas compared to the considered reference MMIMO system. It means that energy can be saved more in NB-IoT with MMIMO than considered reference MMIMO system as less number of antenna needs fewer RF chains, DAC, ADC, I/Q mixers, PAs, and others part which consume power.

Here, experiments have performed under the consideration of M-MMSE, ZRF, and MR combining scenarios because S-MMSE and ZF have almost similar CP to that of RZF. From the simulation, it can be that EE is maximized when the antenna-UE ratio(M/K) is between 2.5 to 3, and M-MMSE has the best performance with this ratio from the perspective of EE and throughput. However, as it has already said that, due to larger M and K values, CP increases in this scheme more. Moreover, computational complexity is still present here. However, with more energy-efficient hardware and within our resultant M/K = 2.5~3 ratio, M-MMSE is the potential solution for EE from the throughput and SE perspective.

From all of these simulations and comparisons between NB-IoT with MMIMO and 20 MHz band cellular MMIMO technology to observe tradeoff EE and SE, the conclusion can be made as,

1. Noise Power, σ^2 should be minimized or average channel gain of the active UE should be increased at any cell so that the values of $\frac{\sigma^2}{\beta}$ can be kept smaller. For this circumstance, NB-IoT with MMIMO has better performance than that of 20 MHz band cellular MMIMO. However, if the value of $\frac{\sigma^2}{\beta}$ can be kept like -8 dBm or 9-dBm (usual case it is -6 dBm), 20MHz cellular MMIMO EE performance against SE will be better.
2. The power consumption of BS transceiver hardware should be minimized by a factor of 2 or at least 1.5 in order to get a better EE-SE tradeoff. With the advancement in the field of RF and electronics, BS's hardware technology already works on that [7] to make some extent energy-efficient transceiver's hardware.
3. For the best EE-SE tradeoff, the antenna-UE ratio or M/K should be in-between 3-4 and for NB-IoT with MMIMO it would be 2-3.
4. For this M/K ratio, M-MMSE can be better combining scheme for better EE-SE tradeoff as well as for throughput if energy-efficient transceiver hardware can be considered. Since M/K ratio is between 2 to 3 for NB-IoT with MMIMO and 3 to 4 for 20 MHz bands defined cellular MMIMO, computational complexity would be within a reasonable range. In turn as an alternative option, RZF can be used which provides moderate tradeoff.

6. CONCLUSION

In this thesis, a framework for EE-SE tradeoff is presented in the wireless communication network using a simple two-cell Wyner model considering 4*4 cells and 0.25km*0.25km per cell dimension. Improvisation has been done from [60] and attempts have been taken to modify it for better EE-SE tradeoff. Besides, an effort has given to observe whether the EE and SE will be upgraded or not if, in the future, NB-IoT will collaborate with MMIMO. The simulations and results have proven that, if the ratio of signal's noise power and the average channel gain of active user equipments can be decreased, the EE-SE tradeoff becomes better, as noise power-average channel gain ratio value decrease which improves the EE-SE tradeoff. Besides, increasing the power amplifier's efficiency has the same result as expected. The best possible way to increase that is, firstly, to use multiple PAs instead of a big powerful one, because the loss factor is higher in a bigger one than a few smaller ones. Secondly, decreasing the cell radius. If the cell radius is small, the signal need not be amplified more. Uses of power amplifiers will be limited and hence loss factor will be decreased as well. In that scenario, NB-IoT with MMIMO would show better performance compared to defined 20 MHz band cellular MMIMO. Choosing precoding and combining schemes have a great impact on EE-SE tradeoff. MMSE has the best performance in terms of EE-SE tradeoff. Though the computational complexity is high, other schemes can't transgress its barrier. Besides, with the consideration of Moore's law, the IMEC web tool model, and the advancement in the field of RF technologies, computational complexity is becoming diminished [61]. Finally, when the wireless network can be able to keep the antenna-user equipment ratio between 3-4, the best EE-SE tradeoff can be achieved. In addition, in the future, considering Moore's law, if the power consumption of the transceiver's hardware can decrease by a factor of two and increase computational efficiencies by a factor of 10, both EE and SE will be increased and resultant, better EE-SE tradeoff can be achieved than ever. Also, the antenna-user equipment ratio will be lower.

However, fulfilling Moore's law regarding BS's circuit power consumption model is the open challenge right now. Good thing is, researchers have already started working on that [62]. Besides, they have also started working on efficient digital signal processing and circuit architecture to minimize the CP consumption for MMIMO [63].

In the future, structure-based MMIMO alone with such a high increasing rate of the UEs in wireless networks will not be able to provide the best throughput as its proving right now. As the world is going through Internet-of-things, we must collaborate NB-IoT technology with MMIMO networks. Although researchers have been trying to customize MMIMO’s antennas to collaborate with both narrowband and ultrawide-band, emphasis should be given more to make it happen at the earliest possible time.

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