HAWASSA UNIVERSISTY

INSTITUTE OF TECHNOLOGY

FACULTY OF ELECTRICAL ENGINEERING

DEPATMENT OF ELECTRICAL AND COMPUTER

ENGINEERING

Comparative Performance Analysis of Channel Estimation Techniques for Massive MIMO System

By: Ashenafi Gebre

Advisor: Shaikh Javed Rasheed (PhD)

Co-Advisor: Tewelgn Kebede (PhD Candidate)

A Thesis Submitted to the Department of Electrical and Computer Engineering, in Partial Fulfillment of the Requirements for the Degree of Masters of Science in Communication Engineering and Networking

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Approved by Board of Examiners

Fitsum Zerfu (MSc)	________________
Chair Person	Signature
Javed Sheikh (PhD)	________________
Advisor	Signature
Tewelgn Kebede (PhD Candidate)	________________
Co-Advisor	Signature
Shanko Chura (PhD Candidate)	________________
Internal Examiner	Signature
Amare Kassaw (PhD)	________________
External Examiner	Signature

Acknowledgment

I praise you LORD, for who you are and for everything. Let everything that hath breath praise the LORD.

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Declaration

I hereby declare that this MSc. Thesis is my original work and has not yet been submitted for a degree in Hawassa University and another institution, and all source of materials used for this Thesis have been duly acknowledged.

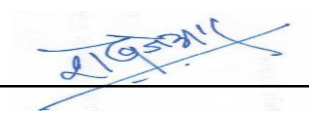
Ashenafi Gebre ________________________

Name Signature

Date of Submission: 20 / 09 / 2021

Place: Hawassa, Ethiopia

This Thesis has been submitted for examination with my approval as an advisor.

Dr. Javed Sheikh 

Advisor Signature

Tewelgn K.(PhD Candidate) ______________________

Co-Advisor Signature

Abstract

The need for an internet connection is growing universally, so people need much higher data rate connection to meet their need but every physical resource in communication like frequency band, transmit signal strength are finite. Within the given limited resource, higher data speed is accomplished by a new technology called massive Multiple Input Multiple Output (massive MIMO) system. Massive MIMO fulfills the high data rate requirement through antenna diversity gain. It is one of 5G wireless network technology with array antennas at both transmitter and receiver sides to providing high spectral and energy efficiencies.

In massive MIMO, the signal obtained by the receiver is in different phase and amplitude from the transmission signal. Therefore, the system quality is highly depending on the accuracy of the channel estimation. Channel estimation plays a significant role in the performances of massive MIMO system because the dimension of the channels matrix is large, phase changes and noises are added when the signals pass through channel, these reduces the efficiencies of the whole system. To solve these problems, this Thesis focuses on the comparative analysis of pilot-based channel estimation schemes for massive MIMO system, which includes: Minimum Mean square Error (MMSE), Element Wise Minimum Mean Square Error (EW-MMSE), Maximum Likelihood (ML) and Least Square (LS) estimator with respect to Normalized Mean square Error (NMSE), Signal to Noise Ratio (SNR), Spectral Efficiency (SE), number of BS antennas, and number of computational complexities.

Based on the simulation results, MMSE channel estimator has the best performance, followed by EW-MMSE, ML and LS channel estimators in terms of NMSE and SNR. And depending on the number of computational complexities of each coherent block as a function of BS antennas M with constant UE, the complexity of LS is less than that of MMSE, and it has almost the same complexity as ML and EW-MMSE. And also, according to SE with respect to BS antenna M, the MMSE provides the highest SE using the highest complexity, EW-MMSE and ML achieves a good balance between SE and complexity, and LS has the lowest complexity, but also provides the lowest SE. Finally, the result confirms that MMSE channel estimation technique has the best performance compared to EW-MMSE, ML and LS channel estimators with the cost of high complexity.

Keywords:*5G, Channel estimation, Pilot-based channel estimation, Massive MIMO, SE*

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List of Abbreviations

3GPP	3rd Generation Partnership Thesis
5G	Fifth Generation
AoA	Angles of Arrival
AoD	Angle of Departure
AP	Access Point
ASD	Angular Standard Deviation
BER	Bit Error Rate
Block-ISD	Block Iterative Support Detection
BS	Base Station
CAGR	Compound Annual Growth Rate
CE	Channel Estimation
CIR	Channel Impulse Response
CS	Compressed Sensing
CSI	Channel State Information
EE	Energy Efficiency
EW-MMSE	Element Wise-Minimum Mean Square Error
FDD	Frequency Division Duplex
FEC	Forward Error Correction
IoT	Internet of Things
LoS	Line-of-Sight
LS	Least Square
LTE	Long-Term Evolution
MIDE	Modified Iterative Discrete Estimation
MIMO	Multiple-Input Multiple-Output
ML	Maximum Likelihood
MMSE	Minimum Mean Square Error
MR	Maximum Ratio Combination
MRT	Maximum Ratio Transmission
NLoS	Non-Line-of-Sight
NMSE	Normalized Mean Square Error
OFDM	Orthogonal Frequency Division Multiplexing
OSTBC	Orthogonal Space Time Block Coding
PDF	Probability Density Function
PE	Polynomial Expansion
SE	Spectral Efficiency
SIR	Signal-to-Interference Ratio
STBC	Space-Time Block Coded
TCO	Total Cost of Ownership
TDD	Time Division Duplex
ULA	Uniform Linear Array

CHAPTER ONE

Introduction

Wireless communication has become more necessary and therefore the demand for wireless connections is increasing specially in recent years. At all network user needs a fast wireless connection to meet their demand whether at work place, at home or everywhere. Furthermore, device to device communication has growing rapidly, leading to increased pressure for wireless performance. In order to reach the requirements, the 5G wireless communication system appeared. It is the upcoming cellular networks and it brings new technologies such as massive MIMO systems and mmWave communication [1].

Massive MIMO technology is an essential and timely topic, it uses a large number of antennas at both transmitter and receiver to provide high spectral and energy efficiencies and also system reliability. And its main motivation is the demand of the 5G and future wireless communication. In a massive MIMO system, the signal received by the receiver is different from the transmitted signal. So, the system is depended accurateness of the estimated channel. [1,2]. The massive MIMO can use beamforming technology, whereby the transmitter concentrates the transmitted energy to the receivers instead of omnidirectional. The receiver often detects interfering signals mixed with the desired signals, which can impact systems performance. By spatial multiplexing to provide services for much user on the same time-frequency resources, higher SE can be obtained, and the EE improvement is mainly due to the matrix gain providing by a huge number of antennas [2].

In mobile communications system the behavior of mobile radio channel leads to multipath propagations that results in rapid variations of the phase and amplitude of transmitted signal. This leads to the degradation in the quality of the system unless good receiver is implemented that estimate the instantaneous channel variation and take mitigation actions. So channel estimation is an integral part of recent mobile communication systems [3]. To get the performance gains of the massive MIMO systems the BSs needs to knows the CSI. CSI in wireless communication system provides information on properties of the wireless channel taking into account the effect of signal propagation mechanism such as scattering and fading [3]. For reliable communication knowledge of the CSI is very critical in determining the channel property. Because of several number of BS antennas in massive MIMO system, the channel estimation overhead consumes a lot of system resources. To mitigate the problems of excess channels estimation pilot overhead many Thesis are focused on TDD mode [4] to use channels reciprocity and to minimize the overhead of the channels.

Various channels estimation schemes are introduced in the literature review and are broadly categorized as: pilot-based, blind and semi blind channel estimations. This Thesis uses pilot-based channel estimation techniques, namely MMSE, EW-MMSE, ML and LS [5]. It works by sending training sequences which are a series of bits along with the information to be sent. This training sequence is a set of pilot symbols, that are recognized by the receivers which are united to the transmitted data sequences to performs the channels estimation on the next data symbol. Assuming the channel has not changed (coherent time interval) in a massive MIMO system, multiple channels can be estimated at the same time [6].

1.1 Problem Statement

Wireless communication system has become a necessity and the demand for wireless connections is increasing, especially in recent years. All network user needs a fast wireless connection to meet their demand. furthermore, device to device communication has growing rapidly, leading to increased pressure for wireless performance. Massive MIMO is one of the important technology, and its main motivation is the demand of the 5G and future wireless communication.

Massive MIMO is a form of MU-MIMO systems where the number of BS antennas and the numbers of users are large. In Massive MIMO, hundreds or thousands of BS antennas simultaneously serve tens or hundreds of users in the same frequency resource. But due to signal distortion, interference, noises, and others obstacle the signal received by the receiver is different from the transmitted signal in amplitude and phase in a massive MIMO system. So, to overcome these issues, the performance quality of the massive MIMO systems highly depends on the accuracy of the channel estimation. Therefore, these issues motivated us to work on the comparative performance analysis of pilot-based channel estimation techniques and evaluate their performance for a massive MIMO system with respect to MSE, SNR, SE, number of BS antennas and number of computational complexities.

1.2 Objectives of the Thesis

1.2.1 General Objective

- To compare the performance analysis of pilot-based channels estimation techniques for massive MIMO system.

1.2.2 Specific Objectives

The specific objectives are:

- ✓ To analysis the mathematical model of MMSE, EW-MMSE, ML and LS channel estimation techniques
- ✓ To analysis the performance of MMSE, EW-MMSE, ML and LS channel estimation schemes in terms of NMSE and SNR.
- ✓ To analysis the performance of MMSE, EW-MMSE, ML and LS channel estimation schemes in terms of SE and number of BS antennas.
- ✓ To identify the complexity of the MMSE, EW-MMSE, ML and LS channel estimation schemes in terms of number of BS antennas and number of computational complexities.

1.3 Scope of Thesis

The general scope of the Thesis will be observing the comparative performance analysis of pilot-based channel estimation schemes for massive MIMO system using specific performance parameters namely, NMSE, SNR, SE, number of BS antennas and number of computational complexities.

1.4 Methodology

Here is the methodology of Thesis:

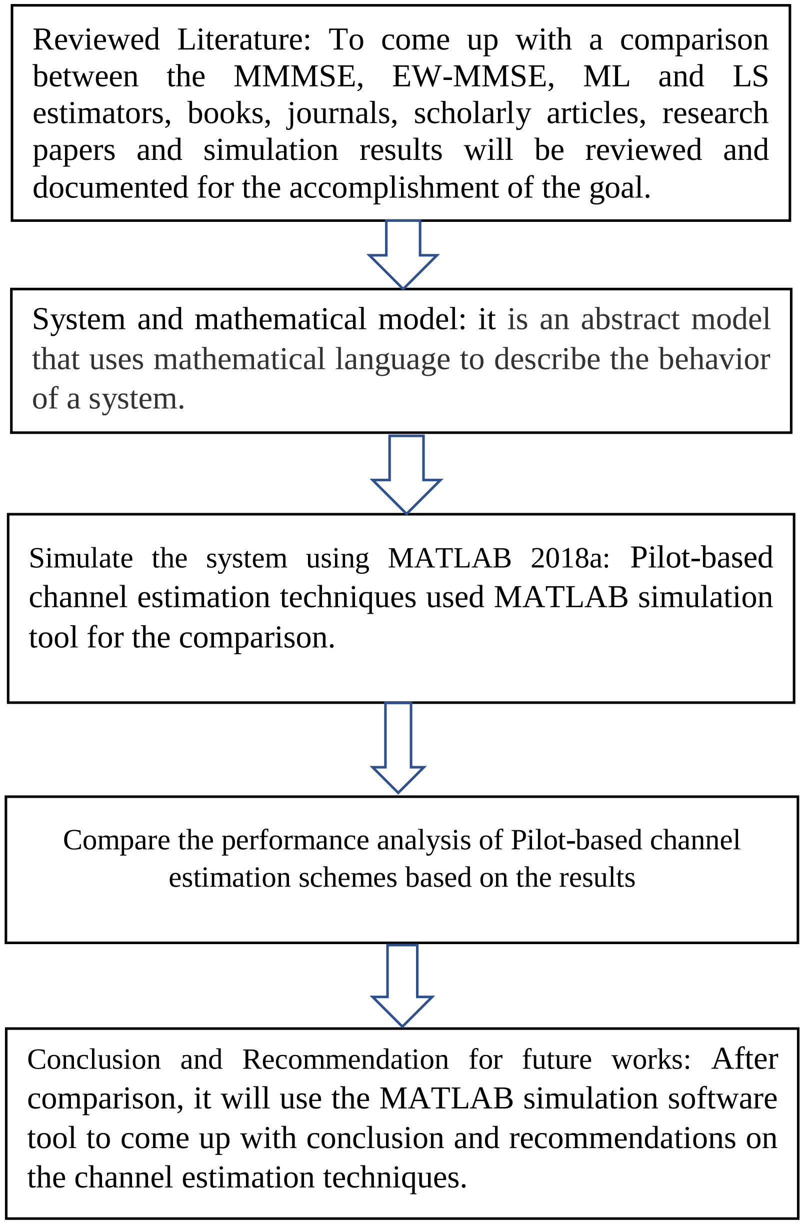

Figure 1.1: Methodology

1.5 Thesis Contribution

The key contribution of this Thesis is comparison of MMSE, EW-MMSE, ML, and LS channel estimation schemes for massive MIMO system in terms of SNR, MSE, SE, number of BS antennas, and number of computational complexities with spatial correlation of Rayleigh fading.

1.6 Thesis Organization

The first chapter presents the concepts of Massive MMO and channel estimation, including problem statements, Thesis objectives, Scopes of Thesis and Thesis contributions and methodology. And in chapter 2 to introduces review of related works.

In chapter 3 introduces the latest technology and describes the basic principles of massive MIMO, such as requirements, advantages and disadvantages, and the main ideas behind it. And also focuses on the uplink pilot signals in channel estimation and the main ideas behind it. And various training-based channel estimation techniques, namely LS, MMSE, EW-MMSE, and ML Channel estimator. And also, blind and semi-blind channel estimation are discussed.

In Chapter 4, a four-channel estimation technique model with inter-cell interference (called pilot contamination) is described.

In chapter 5, discussed about simulation results of comparative performance analysis of channel estimation techniques in massive MIMO system with spatial correlation are presented. MATLAB software simulation tool are used to simulate the system.

In the last section, the work is concluded and future tasks will be discussed.

CHAPTER TWO

Review of Related Work

There are several Thesis conducted on the channel estimation for performance analysis and evaluation of massive MIMO system. Since the focus of this thesis is on channel estimation methods in massive MIMO systems, in this section it will review few important papers that are written in the topic related to channel estimation in Massive MIMO systems. Many papers have been written on different channel estimation techniques. For this thesis I have reviewed many papers, some of the Thesis are reviewed here:

The author in [7] confirms that, the channel estimation of UL and DL channels in massive MIMO system is a complicated subject because of the increasing dimension of channel matrices. The aim is to minimizes the overhead of channel estimation and optimizes the spectral and energy efficiency of the massive MIMO by using the sparse attributes. To address this issue, they proposed a new technique to minimizes the channel estimations overhead by using Compressed Censing (CS), Angle of Departure (AoD) and Block Iterative Support Detection (Block-ISD) algorithms. Their simulation indicates that, the proposed CS-based algorithm significantly reduces feedbacks and pilots overheads, and improves system capacity. In addition, the energy efficiency level increases with the increase in BS antenna, and by decreasing UE density in hardware implementation level. The limitation of this Thesis is that the number computational complexities are not clearly addressed.

The author in [8] a TDD cellular system is proposed, which uses a BS array with a huge number of antennas that simultaneously communicates with a small number of inexpensive single antenna terminal through MU-MIMO systems. The author uses LS channel estimator to analyze the problem created by pilot contamination to this system. Their conclusion is that even if different set of orthogonal pilots are used in different cell, there is almost no effect on the resulting signal-to-Interference Ratio (SIR). This article emphasizes to raise the concept of massive MIMO system and determine its inherent problems, but it did not propose a method to eliminate the issue of pilot contamination and also not addressing the effect of computational complexity on the performance of the systems.

The author in [9] introduced the training-based MMSE channel estimation technique and CS has been proposed for uplink channel estimation of the massive MIMO. To test the efficiency of the proposed technology performance comparisons were made in terms of NMSE and Bit Error Rate (BER), but computational complexity is a still big problem and the number of antennas is not addressed as a performance parameter.

The author in [10] considered the channel estimation for a massive MIMO system with spatially correlated Rician fading channel. A channels model consists of a deterministic LoS path and a NLoS random components that describes the spatially correlated multipath environments. They derived the statistical characteristics of the estimates of MMSE and the LS channel estimation models. Their simulation indicates that, when MMSE estimator is used, the SE estimator is higher than the LS estimator and their performance differences are also increases as the number of BS antenna increases. Furthermore, the Rician fading gives a better SE than that of Rayleigh fading because of LoS paths increases the sum of SE, but the number of computational complexities of each technique are not mentioned.

The author in [11] pilot-based channels estimation technique is applied to massive MIMO systems. The objective of the Thesis is on how to reduce pilot contamination. The Thesis concluded that covariance-aided channel estimation methods are good methods in order to decrease the pilot contamination. It also stated that blind and semi-blind channel estimation have a good estimate but are complex. This Thesis compares between the estimators based on SE and MSE. It does not consider other comparison merits. And also, its limitation is do not compare the performance of different estimators.

The author in [12] estimation of channel for massive MIMO system based on the spatially correlated fading. They designed a covariance-assisted channel estimations technique, which uses covariance information of the interfering user and desired channel. And they used MMSE estimator. The simulation results express that under ideal conditions, the interference matrix and the expected covariance matrix span different subspaces. In the occasion of a large antenna array, the pilot contamination effect on the pilot tends to disappear. Therefore, users with AoA that do not contaminate each other. According to these results, the author proposed coordinate pilot allocation method, that allocates correctly selected user group to the same pilot sequence, but does not mention the influence the computational complexities via number of antennas on the system.

The Thesis in [13], channel estimation for massive MIMO system was studied and they derived the Cramer Rao Bounds (CRB), which are used to estimate AoA, AoD, and associated path gain, and compared them to their counterpart by using zero and time-varying threshold. They, used the ML techniques for channel estimation of massive MIMO system, they also considering a relaxation-based cyclical algorithms called one-bit RELAX for channels estimation of massive MIMO system. numerically result is used to compared the performance of signed measurements by using different threshold technique and to verifies the efficiency of the one-bit RELAX algorithms for channels estimation. The authors did not suggest any method to reduce the problem of pilot contamination.

The author in [14], studied the Spectral Efficiency (SE) of the Downlink (DL) of massive MIMO systems with Rician fading channel. the form of LoS path is model as a uniformly distributed random variables to account for phase changes due to phase noise and mobilities. Consider that the presence of previous data in the Access Point (AP), the MMSE and LS estimates of the phase are derived. MMSE estimation gets knowledge phase for perfect estimation, while LS does not. In addition, two transmission mode are analyzed (coherent and incoherent). For both estimators, a DL SE expression for coherent and noncoherent transmissions with Maximum Ratio precoding (MR) is derive. the numerically outcome expressed which the performance losses due to shortage of phase information is low, and the performance of the coherent transmission mode is greater than that of the non-coherent transmission, however computational complexity is not considered when the performance comparison between MMSE and LS is done.

The author in [15], studied the performance analyzing of the estimation of channel for the LTE downlink systems using the MIMO system in a time-varying mobile environment. The MMSE, LS, and ML estimation schemes have become key domain systems with different bandwidths when changing the number of resource blocks used in the LTE OFDM structure of LTE system. The Thesis concludes, the number of pilots increasing as the bandwidth increasing and the estimator performance improves. The simulation results in the Thesis show that MMSE performs well at a low SNR. LS and ML work well with a high SNR because they use knowledge of the number of channel taps. However, impact of pilot contamination and computational complexity of the estimators are not mentioned.

In the review of literatures mentioned above some Thesis works have already been done on channel estimation. However, to the best of my knowledge, the Thesis work on channel estimation has some parameter limitation and some of them are not address the impact of pilot contamination. Thus, this Thesis work address clearly the Pilot based channel estimation techniques for massive MIMO system in terms of the metrices NMSE**,** SNR, number of Antenna, and number of computational complexities.

CHAPTER THREE

Background of Massive MIMO System

3.1 Introduction to massive MIMOM system

All network user needs a fast wireless connection to meet their demand whether at work place, at home or everywhere. Furthermore, device to device communication has growing rapidly, leading to increased pressure for wireless performance. In order to reach the requirements, the 5G wireless communication system appeared. it is the upcoming cellular networks and it brings new technologies such as massive MIMO systems and mmWave communication. The massive MIMO use a huge number of antennas to attain high improvements of energy and spectral efficiency [16].

In a massive MIMO scheme, the signals received by the receiver is different from the transmitted signal. So, the system is depended accurateness of the estimated channel. When the channel estimation scheme is based on acknowledged pilot signal, this signal is unique to each user and preferable orthogonally to each other. so, the receivers can perfectly estimate the channels response. The time intervals at which the channels are assume to be constant is called the coherent, where the channels estimation operation could happen. Therefore, the training sequences are integrated with data sequences and sent on each considered coherent intervals [17]. Which mean that there is a trade-off among the span of the training sequence and the data rates of the payloads. In addition, the number of parallel training sequence is also restricted by the channel coherent intervals. Consequently, by increasing the number of BS antenna and serving users as massive MIMO proposes, the number of channels to be estimate and the number of orthogonally training sequences required become equally large. So, the training sequence should be reused in another cell, which will lead to pilot contamination. Therefore, pilot contamination and estimation of channels are the main challenges in massive MIMO technology.

3.2 Single Input Single Output

A Single Input Single Output (SISO) is a part of wireless communication technology in that one antenna is used at transmitter and receiver as shown in the Figure 3.1. SISO is the easiest antenna system. at some conditions, SISO technology are susceptible to issues caused by multipath effects. When the EM field encounters obstacles such as canyons, hills, buildings, and public power lines, the wavefront will scatter, so they will have to cross many paths to reaches their destination. The late arrivals of the scatter part of the signals might reason for problem like fading, interruption, and near pilings. In digital communication systems, it will cause a decrease in data speed and the number of errors increase [18].

It doesn't require diversities and no more process is needed, but the performance of the SISO is restricted. The impact of interference and fading on the system is greater than that of the MIMO system.

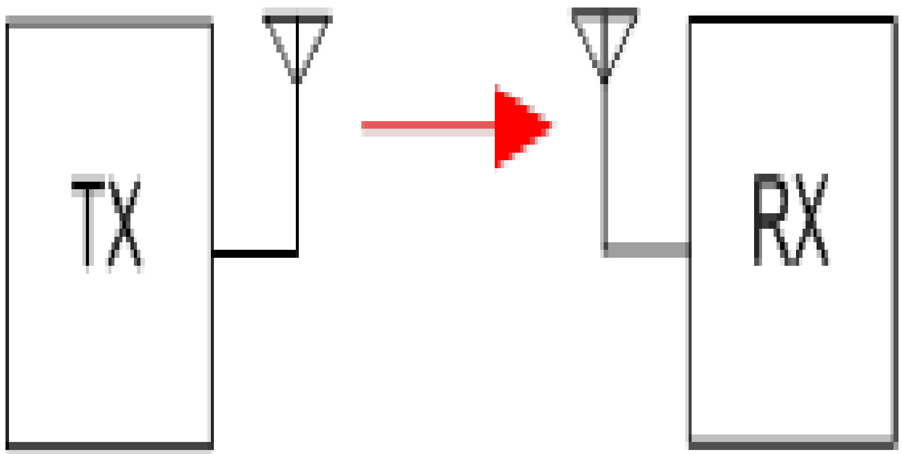

Figure 3.1: SISO system model with one transmit and receive antenna [18]

3.3 Multiple Input and Multiple Output

The Multiple Input and Multiple Output (MIMO) is a wireless system which needs many transmitter antennas and receiver antennas to transmitting more data at the same time. To execute MIMO, the UEs or access point (AP) should support MIMO. MIMO systems needs a radio wave event called multipath. For multipath, the transmitted data will bounce off ceilings, walls, and others object. so, hold out the receiving antenna many times at various angles and at somewhat different times. The delay multipath reason for interference and slowed down the wireless signal. Through multipath, MIMO system needs multiple smart transmitters and receiver antennas with additional spatial dimensions to improve performance and range. MIMO system allows the antenna to combine data streams from different routes and at different times, thus improving the receiver's signal capture capacity. Smart antennas need spatial diversity technique to make full use of the remaining antennas. That the number of antennas exceed the spatial stream, the antennas can increase the receiver diversity and expand the range.

The different MIMO technique formats are MISO, SIMO, MIMO and MU-MIMO, they require unlike numbers of antennas and have different levels of complexity based on the types of techniques and processing. MIMO system uses multiple transmitted and received antennas for wireless signals transmission, as shown in the Figure 3.2.

The number of antennas according to their type is proportional to the data transmission speed (multiplexing), quality of the signal (diversity) and transmission capacity [19].

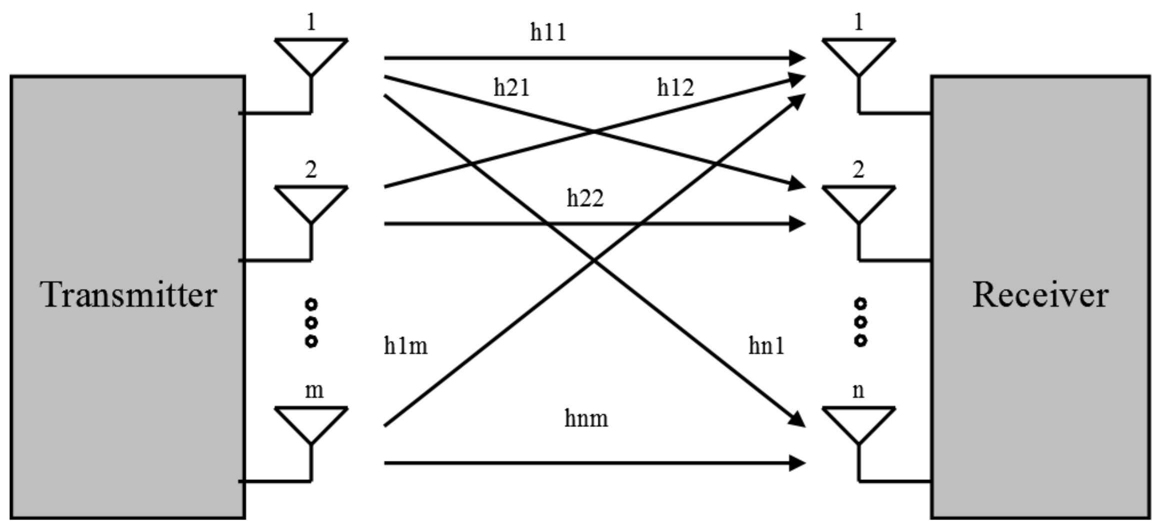

Figure 3.2: MIMO system model with M transmit antennas and N receive antennas [19]

3.4 Multi-user MIMO

Multi-user MIMO (MU-MIMO) system has essential part in the growth of current wireless communication technology, one of which is MU-MIMO. When a single stream is allocated to multiple users, this is called MU-MIMO. This way is specifically necessary on the UL, because of much complexities on the UEs sides could be reserved to a minimum by means of one transmit antenna.

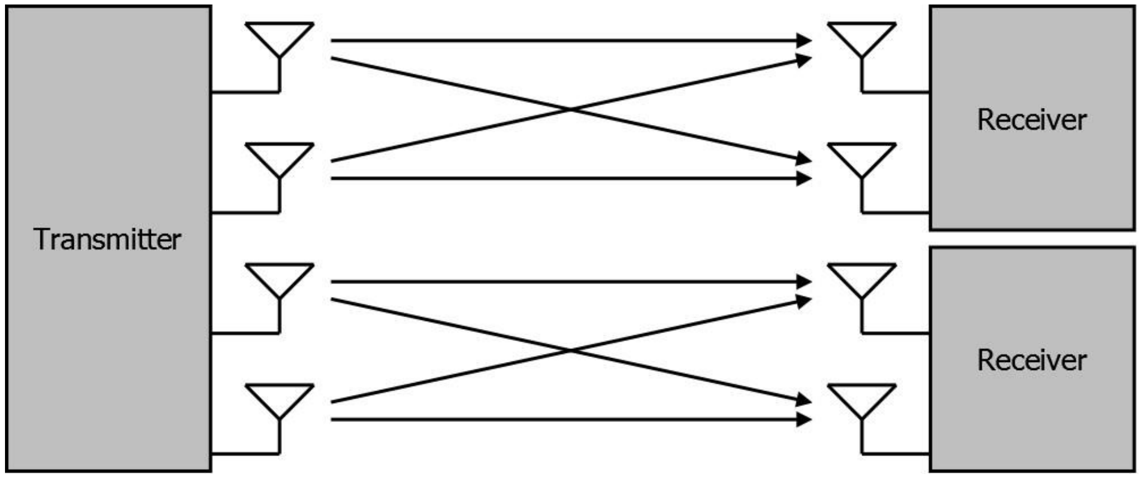

Figure 3.3: MU-MIMO model with two users [20]

Compared to SU-MIMO, MU-MIMO technology have several advantages, some of which are [20]:

- ✓ Through the multi-user multiplexing scheme, the gain of channel capacity is proportional to the minimum between the number of BS antennas and the number of antennas in the MS.
- ✓ Since multiple users can communicate on the same frequency spectrum, system performance can be improved.
- ✓ Communication is less impacted by the LoS propagation or antenna correlation. Although the above-mentioned aspects are increased to the diversity of each user, it can be avoided if the programmer extracts the multi-user diversity.

3.5 Massive Multiple-Input and Multiple-Output

Massive Multiple-Input and Multiple-Output (MIMO) system is an essential and appropriate topic, and its main motivation is the demand of the 5G and future wireless communication. 5G can serve many users simultaneously with high gains, this boosting spectral and energy efficiency and also system reliability. Massive MIMO antenna systems can allow BSs to use relatively low complexity linear processing to achieve vast improvements in spectral and energy efficiency. By spatial multiplexing to provide services for much user on the same time-frequency resource, higher SE can be obtained, and the EE improvement is mainly due to the matrix gain providing by a huge number of antennas [21].

The main concept behind the massive MIMO system is to massively expand the multi-user MIMO system by implementing a large number of antennas at the receiver or transmitter side to provides a high level of spectral and energy efficiency. SDMA is used to attain multiplexing gain and serve many UE on the same time-frequency resources; each cell has a lot base station antennas than UEs to attain effective interferences suppress. When the expected number of UE increases by one cell, the BS must be updated and the number of antennas increases parallelly. As shown in Figure 3.4, in massive MIMO the BS use a large number of antennas to provide services for dozens of users or mobile users (MS) on the same time-frequency network.

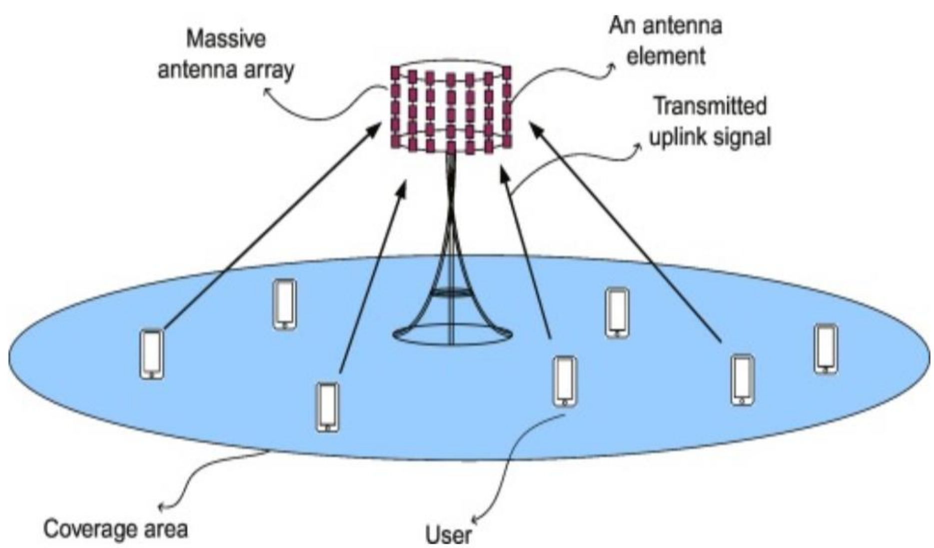

Figure 3.4: Massive MIMO system in the uplink transmission with k users [21]

In the technology flow PCs, mobile phones and tablets are not the only device that needs wireless connections, countless users are require wireless capabilities every day to change to the uses and habits of the population in the world. Home equipment's, computers, machines, and multiple other devices that were once unable to connect to the Internet are making a comeback with many advanced systems, and in most cases need wireless data transmission. This has led to a future generation of better cellular networks [22]. To keep up with this demand, it need to implement new requirements for mobile traffic, such as:

➢ Traffic: From the first quarter of 2017 to 2018, data traffic increased by 60.547%. The large amount of traffic data is due to the increase in smartphone subscription and the high needs for video content. The total mobile data traffics is grown at a compound annual growth rate (CAGR) of about 46%. By 2022, the total traffic of all devices will increase tenfold, approximating 77.49 ExaBytes per month [23] as shown in Figure 3.5.

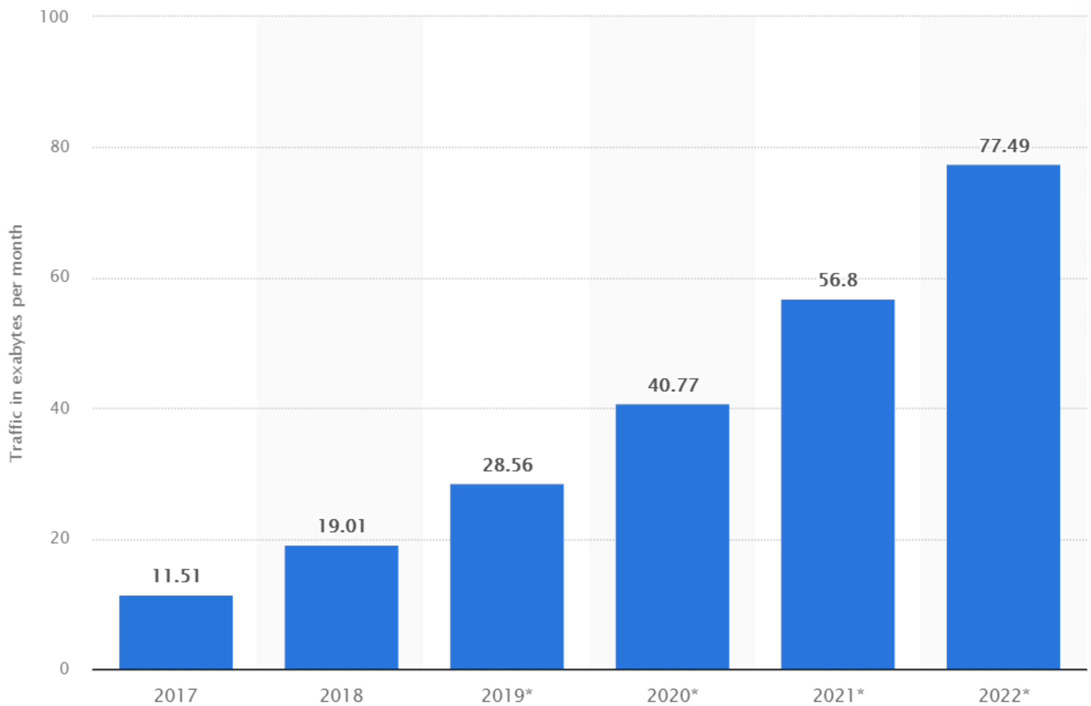

Figure 3.5: Global mobile data traffic from 2017 to 2022 (Exabytes per month) [23]

✓ Indoor or access point traffic: Now, mobile traffic is usual indoors, with 70% voice traffic and 80% traffic. It is expected to be close to about 95% in the future. Depends on the condition, qualities and types of communication services, picocell or femtocell are better candidate for achieving higher capacities, although it has been shown that the arrangement of femtocells in indoor environments is more effective than picocells because it enables larger Build capacity [24].

✓ Number of connected devices: IoT machines or devices are expecting to raises at a compound annual growth rate (CAGR) of 26.9% between 2017 and 2022. It is estimated that by 2022, the total number of connected devices will reach around 29 billion, of which around 8.9 billion will be mobile users [24].

✓ Energy consumptions: A basic requirements are to provide high networks power performance to track needed expected traffics, reduce total cost of ownership (TCO), and simplify network connection access in distance area. In a long-term evolution (LTE) network, regardless of the traffic load, more than 90% of the power consumptions in the total traffics used to make the network discoverable and accessible, as shown in the Figure 3.6.

Even without data transmission or processing, energy efficiency is as important as high traffics capacities and data transmission speed [25].

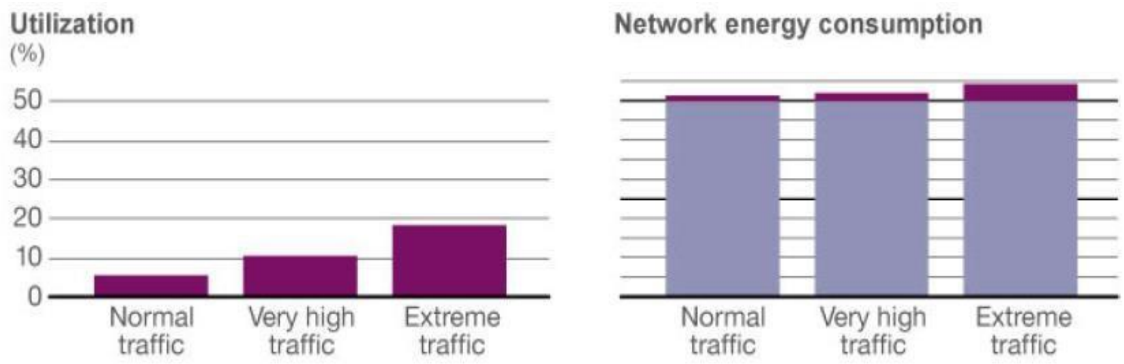

Figure 3.6: Utilization rate with different traffic loads and corresponding grid energy consumption [25]

Table 3. 1: Comparison between MU-MIMO and Massive MIMO [26]

Requirements	**MU-MIMO**	**Massive MIMO**
M_j and K_j	M ~ K and both are small (example: <10)	M >> K and typically large (example: M=100, K=10)
Duplexing	Designed to operate in TDD and FDD	Designed for TDD
CSI acquisition	Mostly based on code books with set of predefined angular beam	Based on sending UL pilot and exploiting channel reciprocity
Link quality	Various rapidly due to frequency selective and small-scale fading	Small variations over time and frequency
Resource allocation	Changes rapidly due to link quality variations	Can be planned since the link quality varies slowly

3.5.1 Advantage and Disadvantage of massive MIMO

The followings are the advantage of Massive MIMO technology [26]:

- ✓ Due to large multiplexing and antenna array gain, the spectrum efficiency is high.
- ✓ Because the radiated energy is concentrated in the UE, the energy efficiency is high.
- ✓ Due to great diversity gain its reliability is high.
- ✓ Due to orthogonally UE channels and extremely narrow beams, weak inter-user interference and improved physical security.
- ✓ It can greatly reduce the delay of the air interface.

The followings are the disadvantage of Massive MIMO technology:

- ✓ Due to the limited orthogonal pilot subcarriers, pilot contamination occurs in the bounded coherent interval and bandwidth.
- ✓ Due to the use of a large number of antennas and multiplexing UEs (or mobile users), the complexity of signal processing is high.
- ✓ Sensitive to beam alignment, use extremely narrow beams that are sensitive to UE movement or antenna array swing.
- ✓ In massive MIMO it used TDD mode, because channel reciprocity.

3.6 Fundamental Technologies that Used in Massive MIMO

3.6.1 Diversity

In the wireless transmissions, the signals use multiple divergent paths because of obstacles across the paths, especially in urban and indoor environment. Hence, the receiver detects multiple time-delayed and distorted signal, resulting in the worsening of efficiencies and data rate of the communications. Adding much antennas at receiver, it is possible to combine each received type of the signal and collectively improve those defects [27].

The wireless system supports three receiver diversity methods:

- ✓ Selection Combining: choose signal from receive antenna with strongest SNR
- ✓ Equal Gain Combining: sum magnitudes of voltage from each receive antenna
- ✓ Maximum Ratio Combining: apply weights to each channel to align the phase for voltage from each antenna, while also adjusting magnitude (normalizing by SNR to increase weaker channels)

Diversity also useful at the transmitter (known as transmit diversity) when numerous antennas send the same signal. The same attitude applies, where the probability of the signal attainment the receiver in better condition is higher than with less antennas. In its place of using numerous antennas to transmit the identical signals, each antenna can be used to send various information in parallel. This system is known as spatial multiplexing and increases the whole capacity of the systems [27].

3.6.2 Multiplexing

Spatial multiplexing consists sending different data streams independently to provide higher peak performance. Spatial multiplexing uses the channel difference between the transmit and the receive antennas pair to deliver many independent streams, and increases performance by sending data in parallel. Instead using many antennas to transmitting the same signals, it can use every antenna to transmit various data in parallel, this system is known as spatial multiplexing and it can increase the entire performance of the systems.

3.6.3 Massive MIMO Beamforming

Massive MIMO system is use beamforming technology, beam forming massive MIMO technique is the shaping of overall antenna beam in the direction of the intended receiver terminal and this is done by using the available knowledge of the downlink channels (the relative channel phases) of the different transmit antennas at the transmitter side. Which means it involves the transmitter concentrating transmitted signal to the receiver rather than being omnidirectional as shown in figure 3.7. The receiver often detects interfering signal mixed with original signals that can impact system capacity, so beamforming uses spatial separation to remove interfering signal from the desired signa [28].

The goal of beamforming is to uses many antennas to be form a beam, thereby increasing the SINR and improving the performance of the receiver. currently, the wireless system support two beamforming method:

- ✓ Maximum Ratio Transmission (MRT): maximize the beams between Tx and Rx point (adaptively).
- ✓ Precoding Table: permits users to define table beam, that support multiple methods (codebooks, etc.) these methods allow to select from predefined beam.

The Maximum Ratio Transmission needs information regarding channel in the middle of transmitting and receiving antenna to form the best beams towards the receiver. In practically, this technology is usually used in TDD system, where the UL and DL shares the same frequency bands, attaining the receiver to sends a pilot signal, and the BS can use the signal to adaptively form the maximum beams. Users can mention many sets of predefined beamforming weights and it measure different weights and select the best beam for each receiver point. The MIMO at the BS has a predefined beam and needs one of several method to determines the utmost appropriate method for a given channels [28].

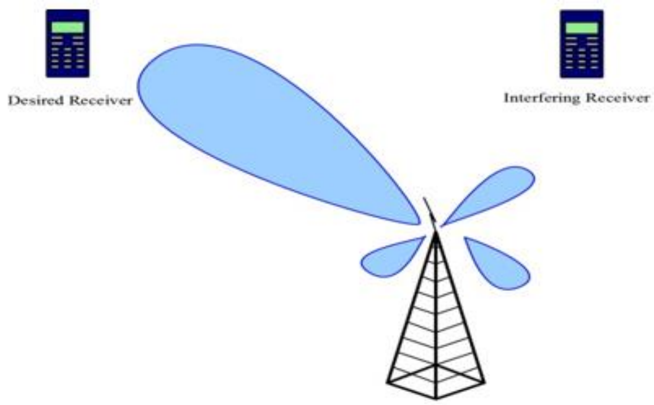

Figure 3.7: System with beamforming technique [28]

One of the most necessary system optimization tasks is based on exact adjustment of the tilt, or tilt of the antenna relative to the axis. With the tilt, it adjusts the radiation further downward or upward, focusing the signal in the new desired direction [29]. The tilt indicates inclination angle of the antenna to its axis. When the given antenna is tilted downward, it called downward tilt, this is the more common one. If it tilts upwards, it called upward tilt. It is very rare.

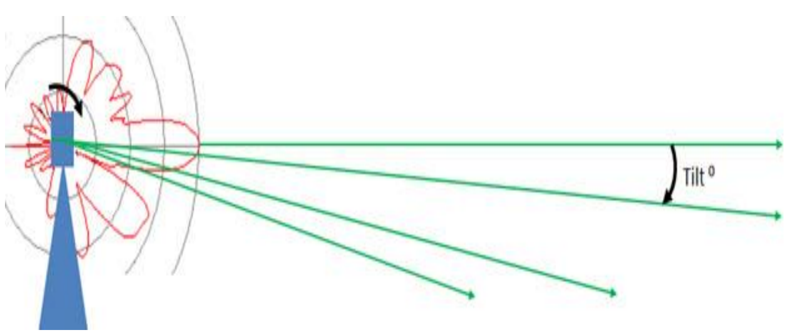

Figure 3.8: Tilt – Inclination angle of the antenna to its axis [29]

3.7 Massive MIMO system Duplexing Methods

3.7.1 Time Division Duplex Protocol

In Time Division Duplex (TDD) protocol, the UL and DL transmission use similar frequency spectrum, but various time slots. And their channels are reciprocal [30]. It means that the channel response is the same in both direction and can be estimate at the base station by using only K uplink pilot. For example, the Base station in cell *j* need to know the full response of channels h_{jk}^{j} for its *k*th user equipment. In figure 3.9, every box denotes a time-frequency blocks and the channels responses are constant [30].

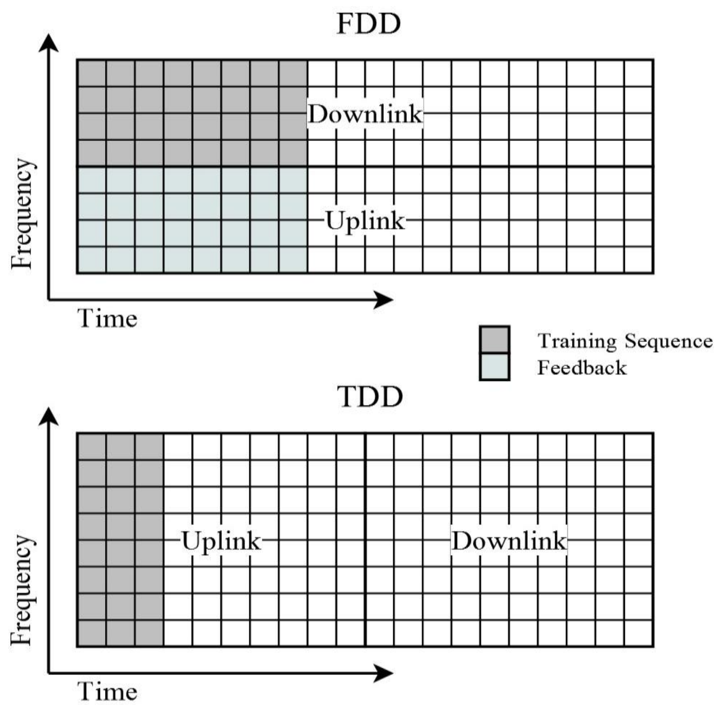

Figure 3.9: Time slot in channel estimation for FDD and TDD protocol [30]

3.7.2 Frequency Division Duplex protocol

In Frequency Division Duplex (FDD) method, the UL and DL transmission uses different frequency spectrum and their channels are not reciprocal [30], so it needs to send pilot in uplink and downlink. Furthermore, the downlink channel response estimate must be feedback to the BS for DL precoding computation. The feedback overhead is almost similar as that of the uplink pilot signal [30]. Therefore, using the TDD protocol that uses channel reciprocity can estimate the channel more efficiently because only UL pilots signal is needed and no feedback is required.

3.8 Acquisition of Channel State Information

The BS *j* uses channel response h_{jk}^{j} to process uplink and downlink signals. It is supposed that the channels response is perfectly known, but practically the vector must be estimated periodically. The current adjust of channel responses implementations is known as channel states, and the BS's need to knows the knowledge of channel state is called Channel State Information (CSI).

The system acquiring channels state information is pilot signal, which sends a predefined pilot signals from an antenna. As shown in Figure 3.10, when antenna transmits a pilot signal, any numbers of receiving antenna can parallelly received the pilot signals and it used to estimates their channels to the transmitter [30].

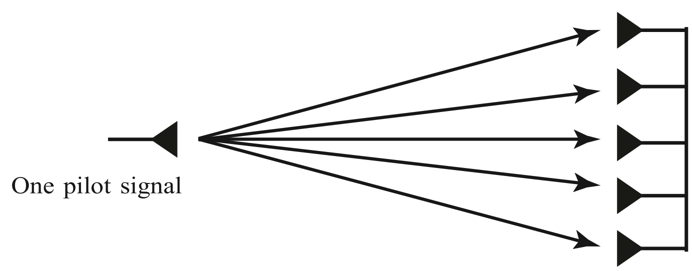

Figure 3.10: Pilot signal from UE antenna to any number of receive BS antennas [30]

3.9 Channel Models for Massive MIMO system

In these sections, let's take a closer look at the massive MIMO channel model. Generally, the channel is the medium between the UE and the BS. There are different channel models present that are already studied. To be able to design and build a wireless communication system it is essential to have some understanding of different kinds of channel models and their properties. Channel models are used when modeling networks in order to see how the system design works in different situations and under certain circumstances.

- **Line-of-Sight Channels**

To facilitate the argument, assume that there are no reflectors or scatterer in the propagation environments. The transmitted wave propagates in straight paths between the source and destination. The BS is array with M antenna, and the users only has one antenna. Antennas should be organized according to various arrangement geometric. The main one is Uniform Linear Array (ULA), in which that the antennas are consistently distributed on a straight line. The antennas space (in wavelength) among antenna is represented by d_H. Then, the distance among two near to antenna is $d_H\lambda$, where λ is the wavelength [31].

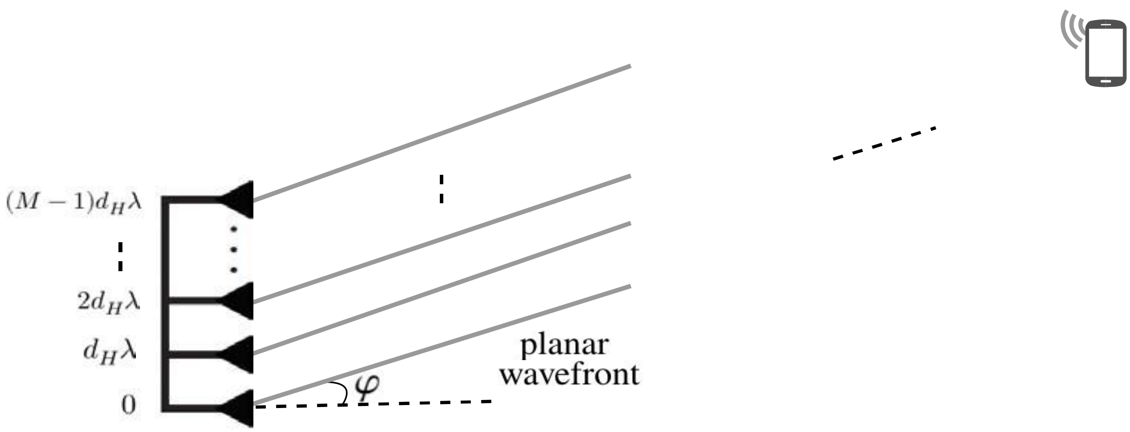

Figure 3.11: LoS between UE antenna and BS arranged with a ULA [31]

3.9.1 Channel Fading

In wireless communication, EM wave are developed to transmit data from transmitter to receiver. One of the main issues of wireless communication system is because of obstacle in the propagation environments, the transmitted waves generally cannot arrive at the receiving antenna directly. Because of reflections, refraction, scattering, and diffraction because of trees, building, and other objects [32]. Some of these models are: -

When the waves arrive at the receivers through two or more paths, this action is known as multipaths. When the number of paths is less, the deterministic ray tracing method is useful. Generally, the complexities and variability of radio channels make it challenging to get perfect models by using deterministic method. In reality, the numbers of path are huge, and statistical model is used to identify the constructive and destructive inclusion of various multipaths component. Variability behavior of the propagation channel is due to the fact that the mobility of the transmitter and receiver or object in the environments will change the multipath characteristic. So, the amplitude and delay of the transmitted wave fluctuating unpredictable over time.

The aforementioned change in received power is called fading. The propagations impact that causes fading is divided into small-scale impacts and large-scale impacts. Path loss caused by dissipations of radiated powers over distances and fading of shadows caused by power-absorbing obstacle is called the large-scale fading effect. Variation caused by multipath will produce small-scale fading impacts. These changes are called small-scale fading due to they happen when users move small distant on the orders of the signal wavelength, and large-scale fading impacts happen where users move greater distances [33].

The different multipath components of the channels can be in the form of a single scatter or a group of scatters. In a multipaths channel, when the transmitter sends out a single pulse, these scatterers reflect it. due to the scattered natures of the wireless channels, pulse sequences with different time delays are received at the destination. The times delay between the first receiving pulse and the final received is called channel delay spreads. When the reciprocal of the delay spread with respect to the signal's bandwidth is large, the signals will spread from various multipath component and interfere with following transmitted signal. This impact is known as inter-symbol interferences and can cause a lot of signals distortion. Thie channel is called broadband channel. If the delay spreads are less than the reciprocal of the signal's bandwidth, the received signals are small distorted, and these channels referred as narrowband channel [38]. The best method to the problems of inter-symbol interference is to classified the bandwidth into many sub-carriers, and each sub-carrier has an enough narrow bandwidth. The frequency range Bc over which the channels are nearly constant is called the coherent bandwidth. so, all frequency component of the signals experiences the same amount of fading. Comparably, the coherent time Tc indicates the almost constant time interval of the channel's response. Every resource block is composed of several subcarrier and time sample. The channels response can be approximate as a flat and constant fading, which is known as a coherence block. A coherence block gives τc = $BcTc$ complex value samples [34].

Therefore, channel models are used when modeling networks in order to see how the system design works in different situations and under certain circumstances. Some of these models are: -

- **Additive White Gaussian Noise**

The Additive White Gaussian Noise (AWGN) is often used as a channel model in which the only impairment to communication is a linear addition of wideband or white noise with a constant spectral density (expressed as watts per hertz of bandwidth) and a Gaussian distribution of amplitude. The model does not account for fading, frequency selectivity, interference, nonlinearity or dispersion. However, it produces simple and tractable mathematical models which are useful for gaining insight into the underlying behavior of a system before these other phenomena are considered [35]. AWGN is a statistical model which gives the distribution of noise, which naturally occurs in a communication system.

- **Rayleigh Fading**

The Rayleigh fading models assume that the magnitude of a signal that has passed through such a transmission medium (also called a communication channel) will vary randomly, or fade, according to a Rayleigh distribution, The radial component of the sum of two uncorrelated Gaussian random variables. Rayleigh fading is a statistical model for a small-scale fading channel when there is no line of sight (LOS) component, which is typical in urban areas. A Rayleigh distribution describes the amplitude variations of two uncorrelated orthogonal Gaussian random variables [35].

- **Rician Fading**

The Rician fading channel block implements a baseband simulation of a Rician fading propagation channel. This block is useful for modeling mobile wireless communication systems when the transmitted signal can travel to the receiver along a dominant line-of sight or direct path. If the signal can travel along a line-of-sight path and also along other fading paths, then you can use this block in parallel with the Multipath Rayleigh Fading Channel block. The Rician fading channel is a statistical model for a small-scale fading channel when there is line of sight (LOS) component in addition to the non-LOS [35].

3.9.2 Spatially Correlated Fading

The channels response among UEs k in cell l and the BS in cell j is represented by $h_{lk}^{j} \epsilon\, c^{M_j}$, since every of the element communicate to the channel response from the user equipment to one of the BSs M_j Antenna. Note that the superscription of h_{lk}^{j} is Base station indices, and the subscript indicates the cell and user equipment index [36]. The channel response in the uplink and downlink of the coherent block is the same. For the convenience of notational, let us use h_{lk}^{j} to denote the uplink channel and $(h_{lk}^{j})^{H}$ for the downlink channels, even though there is actually only one transpose instead of a complex conjugate. The extra conjugation will not change the spectral efficiency or any other performance indicators, nonetheless it does simplify the representation. Meanwhile the response of channel is a vector, it is described by its norm and directions in the vector space. They are random variable in the fading channel.

Practical channels are often spatially correlated, also called spatially selective fading [36], because antenna has a non-uniform radiation pattern and the physical propagations condition make certain spatial directions much likely than others to transmit strong signal from the transmit to receivers. Spatial channel correlation is especially necessary for huge arrays because they have good spatial resolution related to the number of scattered groups.

One of the main characteristics of spatial channel correlation is that the BS array receives different average signal powers from many spatial directions. Therefore, in the correlated Rayleigh fading channels such that: $h_{lk}^{j} \sim \mathcal{N}c(0_{M_j}, R_{lk}^{j})$, where $R_{lk}^{j} \,\epsilon\, c^{M_j x M_j}$ is an optimistic semi-defined spatial correlation matrix it is known as covariance matrices because of the zero means). It is assuming that the matrix is known in BS, and the estimate of such matrix is analyzed in the following section 3.9.3 On the other hand, the spatial correlation matrix characterizes the macroscopic propagation impacts, includes the antenna and the radiation pattern of the transmitter and receiver. i.e., $\beta_{lk}^{j} = \frac{1}{M_j} tr(R_{lk}^{j})$. The normalized trace denotes the average gain of the channel from one of the antennas at BS j to UE k in cell l.

3.9.3 Local Scattering Spatial Correlation Model

The subgroup of the correlation matrix parameterizing by the azimuth angle of the user equipment's (UE). The main objective is to provide a spatial correlation matrix Rϵ $\mathbb{C}^{MxM}$

model for the NLoS channel between the UE and the BS array with a ULA. For simplicity, the UE and BS indexes are removed. The signal received at the BS is the superposition of N_{path} multipaths component, since N_{path} is a great number. It is assumed that the scattering is located near the UE and the BS is raised, so there is no scattering in its near field [37].

The standard deviation $\sigma_{\varphi} \geq 0$ is measured in radian and is known as the Angle Standard Deviation (ASD), it represents how much deviation from nominal angle. The fair values of σ_{φ} in urban cellular network is 10^0, while a less value is expected in rural area and a higher value in mountainous area [38]. Figure 3.12 shows a schematic diagram of the NLoS propagation in the local scattered models, since the scattering is around the use equipment. Since in this diagram Two of the many multipath component are looking. The ASD (σ_{φ}) and the nominal angle (φ) of the multipath component are the key parameter for modeling the spatial correlation matrices. The spatial channel correlation reduces as σ_{φ} increases.

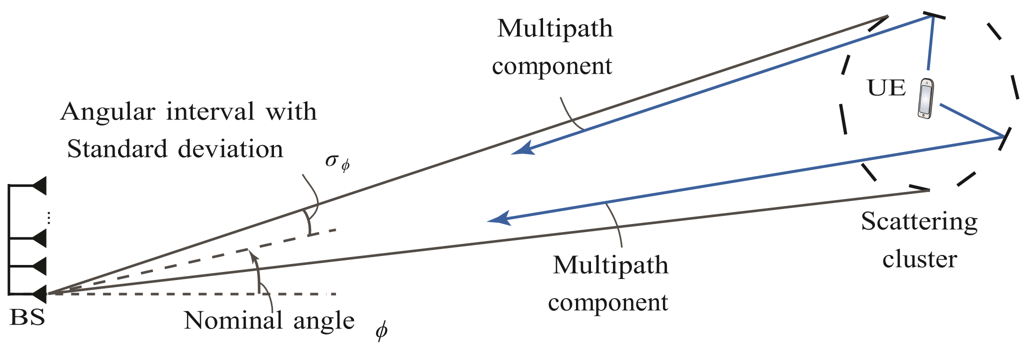

Figure 3.12: NLoS propagation under the local scattering model [38]

Each multipath component will cause the plane wave to reach the array from a specific angle $\overline{\varphi}_n$ and give an array response $a_n \epsilon \, C^M$ alike to the LoS occasion.

$$a_n = g_n[1 \; e^{2\pi j d_H \sin(\overline{\varphi}_n)} \dots e^{2\pi j d_H (M-1) \sin(\overline{\varphi}_n)}]^T \tag{3.1}$$

where $g_n \epsilon \, C^M$ is the gain and rotation of the phase of the path, and d_H is space of the antenna (measured by number of wavelengths) in the array. The response of channel h, $h = \sum_{n=1}^{N_{path}} a_n$ is the superposition of the responses of the N_{path} component array.

It is assumed that angles $\overline{\varphi}_n$ are i.i.d. random variable with the angular PDF $f(\overline{\varphi}_n)$ and g_n are random variable with zero means and variance $E\{|g_n|^2\}$. The variance represents the average gains of the *nth* paths, and the total average gain of the multipath component is presented by $\beta = \sum_{n=1}^{N_{path}} E\{|g_n|^2\}$. The multidimensionals central limit theorem implies, $h \rightarrow \mathcal{N}_C(0_M, R)$, $N_{path} \rightarrow \infty$. If the convergence is distributed and the correlation matrix is $R = [\sum_n a_n a_n{}^H]$, this is the common motive behind the correlation Rayleigh fading models [39].

Note that in a specific formation, the element (l, m) *th* of R is

$$[R]_{l,m} = \sum_{n=1}^{N_{path}} E\{|g_n|^2\} E\{1\, e^{2\pi j d_H (l-1)\sin(\overline{\varphi}_n)} e^{-2\pi j d_H (m-1)\sin(\overline{\varphi}_n)}\}$$

$$[R]_{l,m} = \beta \int e^{2\pi j d_H (l-m)\sin(\overline{\varphi}_n)} f(\overline{\varphi}_n)\, d\overline{\varphi}\,,\ \ 1 \le l, m \le M, \tag{3.2}$$

Since, use the description of β and let $\bar{\varphi}$ express the angle of an arbitrary multipath components. The integrals declaration in (3.2) can be used for numerical calculation of any angular distributions. $[R]_{l,m}$ is dependent on the difference between *l – m*, not on individuals value of *l* and *m*, R is Toeplitz matrices. Since it is supposed that there is no scattering near the BSs, it is the case to other assumption that all the multipath component originates from the scattering cluster around the UEs, that is, $\bar{\varphi} = \varphi + \delta$, where φ is the deterministic nominal angle and δ is a random deviation from the nominal angle with standard deviation σ_φ. It calls it is a local scattering model [40].

3.10 Channel Estimation in Massive MIMO

The massive MIMO system has confirmed that one of the technology in 5G cellular network. The increase in the number of BS antenna integrated with MU-MIMO transmissions technology creates a massive MIMO technology, which has most energy efficient and can achieve higher spectral efficiency. The main limiting factors of massive MIMO system is the accessibility of accurate CSI, because spatial multiplexing can only perform when the channel response is accurately known. Therefore, channel estimation is the major topic discussed in wireless communication systems. Channel estimation is performed by computing an error using mathematical correlation algorithms. The fundamental algorithm for most of the channel estimation system comes from the theory of the channel estimation technique [41].

Channel estimation is need to get channel status information by using channel estimation technique to understand channel characteristics [42]. This information indicates how the signal propagate from the transmitter to the receiver and represent the merged effects of fading, dispersion, scattering etc., and power delay with distance. CSI allows it to adapts the transmission to recent channel phenomena, that is essential for reliable communications.

Massive MIMO systems is based on spatial multiplexing, for which the BS requires accurate channel knowledge. On the UL, UE transmit training sequences, and the BS estimates each UEs channel response. For DL, it may be more complicated to accurately obtain the respective channel response of each terminal, because the BS requires to understand the forward channels in advance. In the TDD mode, it is supposed that there is channels reciprocity, so that the forward and reverse channels are the same in certain coherent interval, so the estimated response of the reverse channel is used for the next direct transmissions. Therefore, channels reciprocity is one of the key advantages of the TDD system [42]. In a M- MIMO technology, as $M \to \infty$, users reuse a single pilot sequence in multiple cells. This creates interference commonly referred to as pilot contaminations and TDD transmission will not zero these contaminations.

3.10.1 Uplink Pilot in Channel Estimation

Studying the channel at the BS is a key operation. Subsequently, a wideband channel can be divided into a coherent interval of duration Tc seconds and bandwidth Bc Hz. Each such interval provides independent use of τc = BcTc of the flat frequency channel, as shown in Figure 4.2. Which shows that three activities involve each coherent time slot: UL data transmission, UL pilot transmission and DL data transmission. In each coherent interval, the terminal uses τp in the τc samples to transmit the known pilots at both end of the link, from which the channel estimates at BS [43].

- **Orthogonal Pilots**

Every coherent interval must contain K pilot waveforms, and to avoid interference, they must be orthogonal to each other. From now on, let assumed that the terminal is allocated a mutually orthogonal pilot sequence of length τ_p, Since $\tau_c \geq \tau_p \geq$ K. every set of orthogonal pilots with the identical energy produces the same capacity or performance. The importance of τ_p is to measure how much energy of all terminals pass on pilots in each coherent interval. In concept, any τ_p samples in the UL part of the coherent interval can be used for pilots. In practice, the maximum transmitter power is often limited, so a constant modulus signal (such as a quadrature sine wave) is an ideal pilot signal [43].

- **Pilot Assignment and Contamination**

Pilot Contamination may be a major obstacle in a multi-cell system, which can be eliminated by adopting a pilot reuse factor is more than one. However, the higher overhead of the high reuse factor limits the numbers of mobile terminal that can be served at the same time. Is pilot contamination an unavoidable fundamental limitation in a multi-cell system, or is it an artifact of suboptimal signal processing, in particular MMSE channel estimation and linear processing [44].

In MMSE channel estimation and linear processing, the consequence of pilot contamination is that all known capacity lower bounds approach a finite limit when $M \rightarrow \infty$, This is true even under more specific model assumptions. for example, if the channel is finite-dimensional. It is also known that contamination by payload data has similar effects as contamination by pilots in other cells. In contrast, that do not know of any relevant, non-trivial upper bounds on capacity that account for the effects of imperfect channel knowledge. It is known, however, for the related cases of Point-to-Point MIMO and cellular systems with base station cooperation that capacity is ultimately limited by the availability of sufficiently accurate CSI, which in turn is limited by the length of the channel coherence interval. Hence, its speculation that pilot contamination in Massive MIMO is an inevitable limitation that cannot be entirely overcome. Nevertheless, sophisticated pilot assignment and signal processing may significantly reduce the problem [45]. Adaptation and optimization of the pilot allocation between cells can further reduce the effects of pilot contamination. Difference in spatial correlation may be exploited to reuse pilots without incurring appreciable contamination effects.

3.10.2 Impact of Pilot Contamination on Channel Estimation

For channel estimation system, each terminals have a corresponding training sequence to avoid intracell interferences. In addition, channel estimation should be performed in every coherent interval. Therefore, the numbers of mutual orthogonal training sequence should be less than the number of elements in every coherent interval. Therefore, according to the number of time-frequency coherent element, the training sequence should be reused in another cell. because of this restriction, pilot contaminations might occur. When the receiver gets the similar pilot sequences from various source in various cell, the signal will be affected by pilot contamination, and resulting in incorrect channel estimation.

Now let us explain the main concept of pilot contamination. Consider a scenario since two User equipment's (UEs) use the same pilot sequence, as shown in Figure 3.13. BS1 want to estimates the channel of the desired UE needed in its own cell, and the interfering UE is in cell 2 transmitting the similar pilots. The mutual interferences caused by this UE through the pilot transmissions has two basic results: the channels estimation is correlated and the estimation quality is degraded. Therefore, the contamination limits the performance of the system [46].

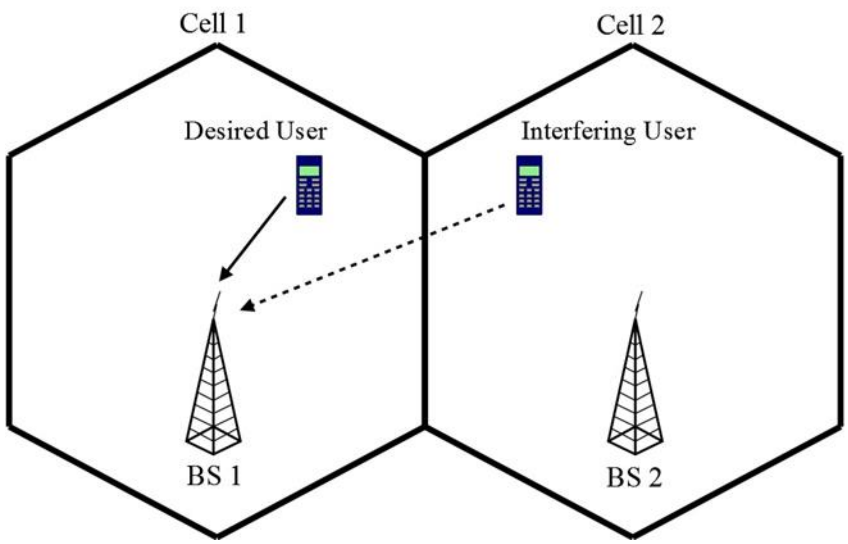

Figure 3.13: Example of pilot contamination when two users transmit non-orthogonal training sequences to each other [46]

- **SINR for Uplink Data Transmission**

Every user sends UL training sequences, so that users serving the BS can estimating the channel of each antenna, then detects the transmit user information. let assuming that user in other cell transmit data to the same time-frequency resources (typically in massive MIMO situation), and the pilot reuse factor is one, the bad probable se case situation. Since all base stations reuse the similar set of pilots and transmit the same time-frequency resources, the pilot contaminations issues occur, Therefore, others base stations will also be receiving pilot sent by user being served by others base stations, which restricting the qualities of the channel estimations [47].

Since the base station's estimate of the required channel response is not accurate, the precoding achieved on the transmit signals is also wrong. Incorrect precoding knowingly reduces the SINR of the entire transmissions. Since the BS executes beamforming in the MRT precoding technique, the signals power is misaligned because of the channel estimation value, that is, the signal with the lowest power received by the desired user, and the power lost it redirects to the unwanted user Interference, by using the similar training sequences.

The number of transmit antenna and user increase, the coherent intervals might not be sufficient to generate the vital number of training sequence to serves all active users. In practically, in order to also permit data transmissions with better SE, the number of end terminals must be crucially lesser than the number of symbols in the coherent intervals. Therefore, pilot contaminations become the main issues in massive MIMO systems. As summarized in [48], the number of BS antennas move to infinity, it will cause SINR saturation. As shown in Figure 3.14, as the path loss gains (the ratio of the path loss coefficient between the desired user and the interfering user channel) increase, the saturation value of the SINR increase.

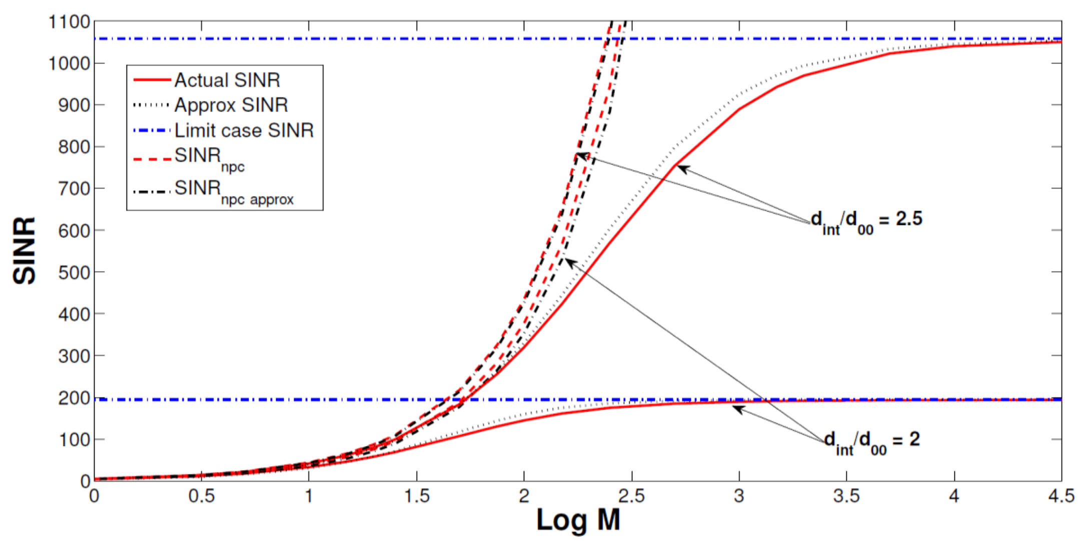

Figure 3.14: The change in SINR with an interference-free SNR of 10 dB and its approximate for different path loss gains (2 and 2.5) [48]

3.11 Channel Estimation Techniques

Channel estimation is a system use in transmissions, its objective is to predicts or estimates the channel impulse response of the transmitted signals. The impact of the transmitted signal produced by the channel estimation should be changed, so that the detected signal become more precise information. There are various types of channel estimation technique [49] and the basic channel estimation techniques are shown in Figure 3.15.

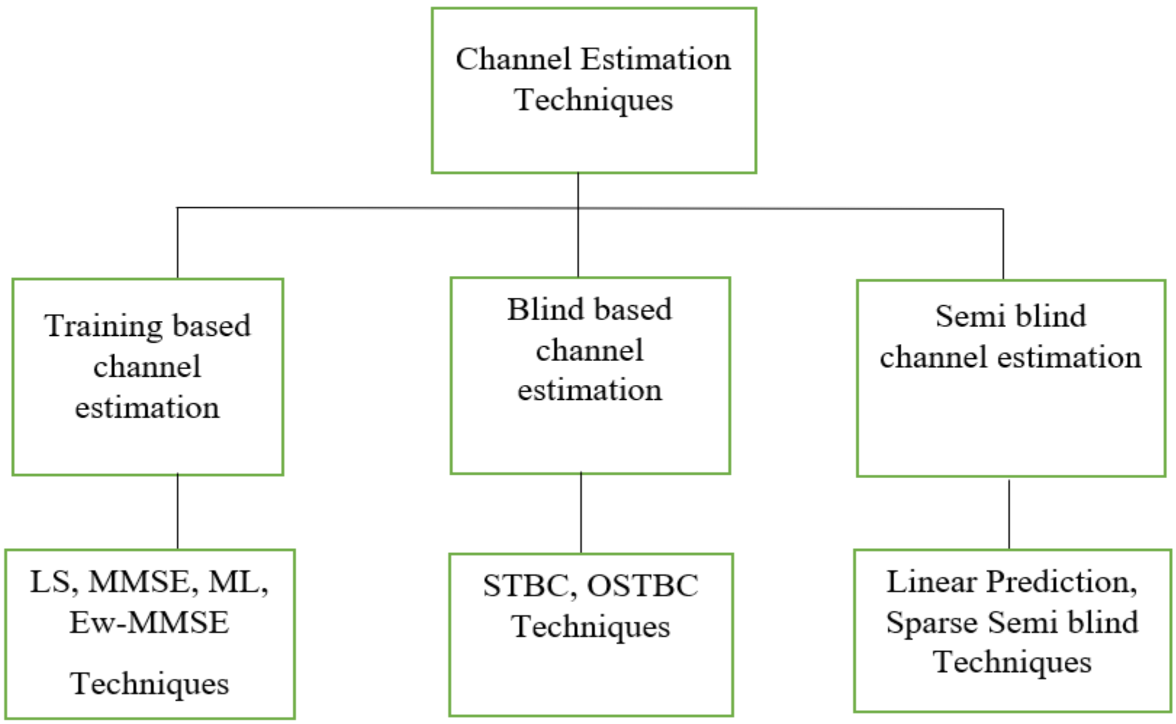

Figure 3.15: Classification of channel estimation techniques [49]

3.11.1 Pilot or Training-based channel estimation techniques

This Thesis used pilot or training-based channel estimation techniques, the Pilot-based channels estimation operate by sending pilot symbols, which are a series of bits as shown in Figure 3.16, laterally with the information to be sent. The pilot symbols are needed to check the patterns change. In addition, through these changing patterns used to know the impulse responses of the channels. Then using the estimation method, the information signal can expect before passing through the channel, so the occurrence of errors can be minimized [49, 50].

The training sequence is a set of pilot symbol, that knowns by the receivers, which is joined to the data sequences to be transmitted to performs the channel estimation on the next data symbol assuming that the channel has not changed, also known as coherent time interval. In a massive MIMO system, since there are multiple antennas on the transmitter and receiver, multiple channels must also be estimated at the same time. So, a huge set of pilot symbol should be combined into the transmissions frame to reduce the payloads [49].

Figure 3.16: Time interval structure in pilot-based channel estimation systems [50]

The sequence unique to each user and they are orthogonally, so the receiver can accurately estimate the channel response. Where the channel estimation process should occur, the time intervals at which the channel is assume to be constant is called the coherent interval. Therefore, the training sequences are integrated with the information sequences and sent in every coherent interval considered, means that there is a trade-off between the length of the training sequences (which is proportional to the accuracy of the estimation) and the payload data rate [50]. Some of pilot-based channel estimation techniques that used in this Thesis are:

- **Least-Squares Channel Estimator**

The Least-Square (LS) channel estimator minimizes the squared error quantity between the estimated signal and received signal [51]. This estimation technique is easy to implement and has very low complexity but it performs less. The Least Square channel estimation is suitable for systems that can have high BER, where high BER is negotiable. The Least Square channel estimation technique provides only small improvement in error calculation. Generally, there are many techniques for estimating the channel. The number of techniques is based on reducing errors that occur when compare the pilot symbol initially sent and received. However, the least squares channel estimator was chosen because of its easier and very easy to apply.

The basic principle of least squares channel estimation is to minimize errors using the least squares approach [52]. For example, if x [n] is the transmitted signals and y [n] is the received signal after passing through the channel, then the error ε[n] occurred and can be expressed in the equation ε[n] = y[n] - x[n] and least square error that is the square values of ε[n] is $\sum_{n=0}^{N-1} (x[n]-y[n])^2$.

- **Minimum Mean-Square Error Channel Estimator**

The Minimum Mean-Square Error (MMSE) channel estimator provides much accurate channel estimation approximation when compared to the Least Square channel estimation technique. This technique employs calculation of channel effects along with the Least Square channel estimation. This technique shows very good performance but at the cost of too high complexities [53].

For example, let consider the diagram illustrated in the Figure 3.17, The minimum mean square error channel estimator minimizes the MSE between the received signal (channel H), and the MMSE estimated channel $\hat{h}^{MMSE}$ by finding a better linear estimates with respect to M and the values of LS estimation $\hat{h}^{LS}$. Since, M is the weight matrices and $\hat{h}^{MMSE}$ correspond to the MMSE estimation [53].

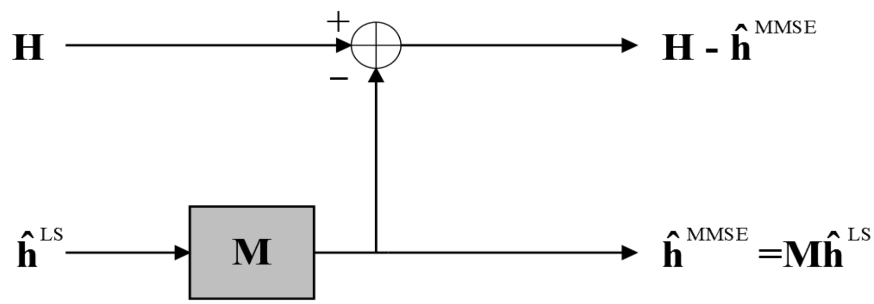

Figure 3.17 Diagram of the MMSE channel estimation [53]

- **Element-wise Minimum Mean Square Error Channel Estimator**

The Element-Wise Minimum Mean Square Error (EW-MMSE) channel estimator minimize the squared error quantities between the estimated signals and received signal by using diagonal matrix, if the Base station does not know the complete knowledge of covariance matrix, the EW-MMSE estimator can be used [54]. In this system, only the diagonal of the covariance matrix is required and the estimator ignores the correlation between element.

- **Maximum Likelihood channel Estimator**

The Maximum Likelihood (ML) process consists of determining the squared distance between the estimated received signal sequence and all possible received sequences. ML is the best receiver when ISI is present. ML is the good channel estimation scheme, but the complexities of the receiver increase exponentially with the length of the channel's impulse response [55].

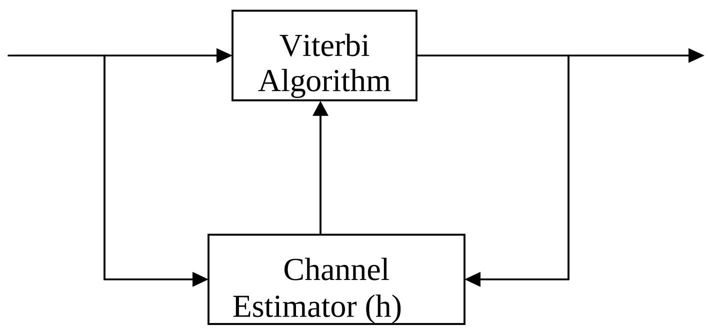

Figure 3.18: ML block diagram [55]

In the adaptive ML as shown in Figure 3.18, the sampled impulse response channel is measured with an adaptive channel estimator. ML technique mostly requires the Viterbi algorithm, which is computationally optimal and efficient. As user demand for more content and the consequent increase and requires more data bandwidth continue to drive communication systems, error controls coding has become extremely important. One method to improves the BER, hence maintain high data reliabilities is to use errors correction techniques such as the Viterbi algorithm. The Viterbi algorithm was originally conceived by Andrew Viterbi as an errors correction schemes for noise digital communications, providing an efficient system for Forward Error Correction (FEC), which can improve channel reliability [55].

3.11.2 Blind Channel Estimation

It is unlike the pilot-based channel estimation technique, means that it does not have to allocates a specific bandwidth to send pilot symbol. Compared to pilot-assisted channel estimation system, the efficiency of bandwidth usage is higher. The blind estimation channel is executed by evaluate the statistical information of the channel and the specific property of the transmit signal. It has no overheads lose and is preferable for slow time varying channel. This system is used to minimizes the pilot overheads of channels acquiring [56]. However, this method is an iterative solution, each iteration must calculate the single value decompositions of the covariance matrices of the received signals, which is a computationally complicated process.

The blind channels estimation technology can be divided into deterministic and statistical. In the statistical methods category, the cyclical statistical characteristics of the received signal is explored when the channel estimates. In the deterministic method, the statistical characteristics of the received signal is not used, rather the received signal and the channels coefficient is assumed deterministic quantity at the same time [57]. when comparing statistical and deterministic blind channel estimation system, deterministic methods converge faster than statistical methods. but, the computational complexities of the deterministic system are high and increases as the constellations order of the modulators used by the transmitter increase. When it comes to extremely short sample sequences, statistical methods are also affected by limited data.

Because blind systems do not require training symbol for estimation of the channel, this technique is attractive because they effectively use bandwidth. However, blind channel estimation techniques have other disadvantages. One of them is the need for a large amount of data records, which leads to slow convergence of methods, and their calculations are often more complicated [58].

3.11.3 Semi-blind channel estimation

The semi-blind channel estimation technique is a combinations pilot-based and blind channel estimation schemes. The blind and semi blind channel estimation techniques are alternative methods of pilot-based channels estimation technique. They do not use pilot signals sequence and small pilot signals sequence for channel estimation correspondingly.

The semi-blind channel estimation is decision-oriented channel estimation system. The aim of this system is use to estimations of the channel got from preceding symbols channel estimates. In addition, a new estimated value is got and uses to estimate the next one [59]. This method is the best one for estimates bandwidth, but compared to pilot-assisted channel estimation, this estimation is not good.

CHAPTER FOUR

System Model

Let consider a massive MIMO technology with L cell, since each cell is consisting of one base station which has M_j antenna and serving K single-antenna UE. The systems work in TDD protocol, where the response of channel remains constant over a coherent block of τ_c sample. The channel response between base station j and user equipment k in cell l is known as h_{lk}^{j} [60].

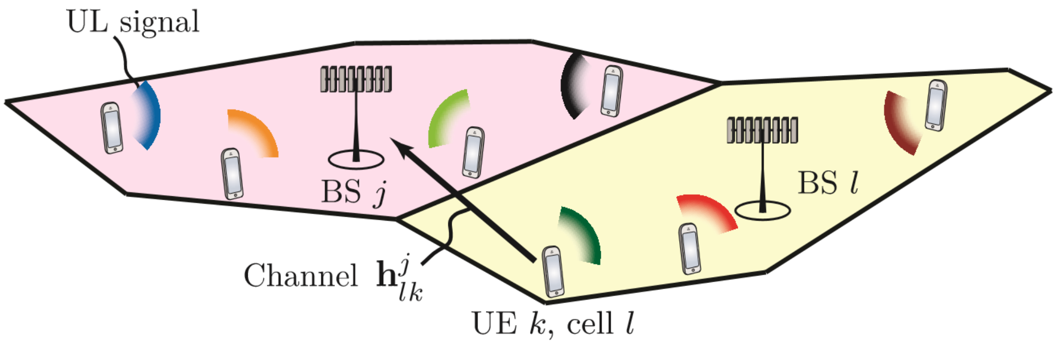

Figure 4.1: UL Massive MIMO transmission between BS j and UE k in cell l [60]

4.1 System Model for Received Pilot Signal

In this section discuss about system model and how channel estimations are operating at the base station based on the UL pilot transmissions. To use the large number of antennas efficiently, every BS requires to estimates the channel response from the user equipment's, that are available in the recent coherent block. It is specifically important for BS j to has the channel estimate from the UEs in cell j. The estimation of channels from interference user equipment's in another cell also useful to do interferences elimination during data transmissions.

Let assume, the channel achievement is independent between in any pair of coherent blocks. A Time-frequency space of duration Tc seconds and Bandwidth Bc Hz is referred as coherence interval [60]. This means that BcTc (complex-valued) samples are required to define a waveform that fits into one coherence interval. Therefore, a coherence interval has the length τ_c = BcTc samples as shown figure 4.2.

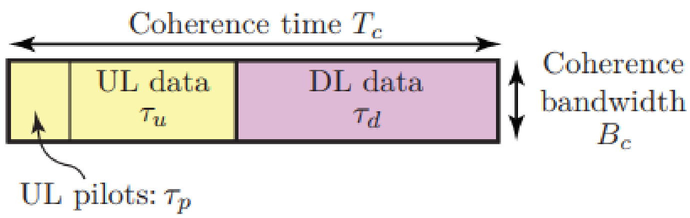

Figure 4.2: Assigning of the samples in the coherence interval [60]

The size of τc depends on the carrier frequency and externals factor, like propagation environment and the mobilities of the UE [61]. Thise sample is need for three various assignments: τp sample used for UL pilot signal, τd sample used for DL data transmissions, and τu sample for uplink data transmissions, where τc = τp + τu + τd. When using channel reciprocity in the TDD protocol, UL and DL channel are estimates by the UL pilot signal.

Every base station needs CSI to receive processing. So, the τp sample are prearranged for achieving uplink pilot-based channel estimations on every coherent block, providing room for τp mutual orthogonally pilot sequence. Thise pilot sequence is assigned to various user equipment's, and similar sequence is reused by user equipment's in many cells. The deterministic pilot sequences of user equipment (UE) *k* in cell *j* are represented by $Ø_{jk}$ ϵ $C^{\tau p}$ and assuming there is a unit amplitude element to get a constant power level, this means that $||Ø_{jk}||^2$ = τp [62].,

Let defines the set

p_{jk} = {(*l*, *i*): $Ø_{li}$ = $Ø_{jk}$, *l* = 1, . . ., *L*, *i* = 1, . . ., K_l, that the index of all user equipment's using similar pilot sequences as UE *k* in cell *j*. hence, (*l*, *i*) ϵ p_{jk} means that UE *i* in cell *l* use the same pilots as UE *k* in cell *j*. note that (*j*, *k*) ϵ p_{jk} by definition.

The element of $Ø_{jk}$ is scaled by the UL transmission power as $\sqrt{p_{jk}}$ and then transmit as s_{jk} the signals over τp uplink samples, resulting to the received pilot signals Y_j^p ϵ $C^{Mj\ x\ \tau p}$ at BS $_j$ [63] is given by

$$Y_j^p = \underbrace{\sum_{k=1}^{K_j} \sqrt{p_{jk}} h_{jk}^j Ø_{jk}^T}_{\text{Desired pilots}} + \underbrace{\sum_{\substack{l=1 \\ l\neq j}}^{L} \sum_{i=1}^{K_l} \sqrt{p_{li}} h_{li}^j Ø_{li}^T}_{\text{Inter-cell pilots}} + \underbrace{N_j^p}_{\text{Noise}} \tag{4.1}$$

Since, $N_j^p \in C^{Mj \times \tau p}$ is the additional noise of receiver and identically distribute as $\mathcal{N}_C(0, \sigma_{UL}^2)$ and Y_j^p is the examination that base station *j* can use to estimates the channels response.

In order to estimates the channels of a specific UEs, the BS require to know which pilot sequences the UE has sent. This is why the pilot is deterministic sequence and the pilot allocation is usually done when the UEs link to the BS. Suppose that the BS *j* needs to estimates the channels h_{li}^j of any UE *i* in cell *l*. Then the BS can correlate or multiply Y_j^p with the UE's pilot sequences ϕ_{li} to get the processed received pilot signals y_{jli}^p [64]

$$y_{jli}^p = Y_j^p \phi_{li}^* = \sum_{l'=1}^{L} \sum_{i'=1}^{K_{l'}} \sqrt{p_{l'i'}} h_{l'i'}^j \phi_{l'i'}^T \phi_{li}^* + N_j^p \phi_{li}^* \tag{4.2}$$

The processed received pilot signals $y_{jli}^p \in C^{Mj}$ is an enough statistic for estimates h_{li}^j [67]. now consider four various channel estimators, which depend on various amount of statistical channels knowledge. The statistical distribution (the mean vector and covariance matrices) can be estimated using the samples mean and samples covariance matrices in practice. Note that a small change in the UE location may result in a significant phase-shift of the LoS component. This phase shift will be identical for all BS antenna, and may therefore be accurately tracked in practice [63, 64].

4.2 System Model for Pilot Based Channel Estimation Techniques

4.2.1 MMSE Estimator

Base on a pilot book that has an orthogonal sequence and also on received pilot signal Y_j^p in equation (4.1), lets determine the estimator of the channel response h_{li}^j. Keep in mind that the estimator requires that the statistical distributions are known. i.e., in this case $h_{li}^j \sim \mathcal{N}_C(0_{Mj}, R_{li}^j)$.

The MMSE channel estimates h_{li}^j is the vector $\hat{h}_{li}^j$ that minimizes the MSE $E\{\|h_{li}^j - \hat{h}_{li}^j\|^2\}$ [64]. And using pilot books with orthogonal sequence [65], the MMSE estimation of the channel h_{li}^j based on the processed Y_j^p at BS *j* in (3.1) is

$$\hat{h}_{li}^{j} = \sqrt{p_{li}} R_{li}^{j} \psi_{li}^{j} y_{jli}^{p} \tag{4.3}$$

$$\text{Where, } \psi_{li}^{j} = \tau_p \mathrm{Cov}\{y_{jli}^{p}\}^{-1} = \left(\sum_{(l',i') \epsilon p_{li}} p_{l'i'} \tau_p R_{l'i'}^{j} + \sigma_{UL}^{2} I_{Mj}\right)^{-1} \tag{4.4}$$

The channel estimation error $\tilde{h}_{li}^{j} = h_{li}^{j} - \hat{h}_{li}^{j}$ has a correlation matrices $C_{li}^{j} = E\{(\tilde{h}_{li}^{j}(\tilde{h}_{li}^{j})^{H})\}$, that's given by

$$C_{li}^{j} = R_{li}^{j} - p_{li}\tau_p R_{li}^{j} \psi_{li}^{j} R_{li}^{j} \tag{4.5}$$

This assumption allows a system to calculate the MMSE estimation of the channel from UE in the networks to BS *j*. The qualities of channel estimation is determine by the MSE, which is $E\{||h_{li}^{j} - \hat{h}_{li}^{j}||^2\} = tr(C_{li}^{j})$ for the MMSE channel estimates. The better channel estimations quality is determined by a minor MSE.

In order to estimates the channel h_{li}^{j} according to (4.3) the BS must correlate the received pilot signals with the pilot sequences use by UE *i* in cell l, as $y_{jli}^{p} = Y_j^{p} \emptyset_{li}^{*}$ and then this observation value multiply with the two matrixes ψ_{li}^{j} and R_{li}^{j}. The matrices ψ_{li}^{j} is the inverse of the normalized correlations matrices $E\{y_{jli}^{p}(y_{jli}^{p})^{H}\} / \tau_p$ of the processed received signals [66], and R_{li}^{j} is the spatial correlations matrices of the channels to be estimate that defined in (3.2). mind that the transmitted power emerges in the estimating errors correlation matrix in (4.5) only as the product with the pilot lengths: $p_{li}\tau_p$.

Now defining the effectives SNR during the pilot signaling period from UE i in cell l to its serving BS j as

$$SNR_{li}^{j} = \frac{p_{li}\tau_p \beta_{li}^{j}}{\sigma_{UL}^{2}} \tag{4.6}$$

Where $\beta_{li}^{j} = \frac{1}{M_j} tr(R_{li}^{j})$ was defined as the average gain of the channel to the antenna in the base station array.

The term effectives SNR means that the pilot processing gains τ_p is merged in the SNR. The processing gain is got from the facts that the pilot sequences span τ_p sample. Assume that the length of the pilot sequence is 10 sample, the effective SNR is 10 dB greater than the nominal SNR of a single samples [67]. For user equipment's with low transmit power and / or bad channel conditions, this gain is also very useful to perform good estimation.

Note that MMSE minimize the MSE of the channels estimation, as it defined: $E\{||h_{li}^{j} - \hat{h}_{li}^{j}||^2\}$ $= E\{||\tilde{h}_{li}^{j}\}||^2 = E\{tr(\tilde{h}_{li}^{j}(\tilde{h}_{li}^{j})^H)\} = tr(C_{li}^{j})$. so, to comparing the quality of estimation got by various estimation techniques in various conditions, the normalized MSE [67] is define as

$$NMSE_{li}^{j} = \frac{tr(C_{li}^{j})}{tr(R_{li}^{j})} \tag{4.7}$$

It is a good parameter, because it measures the relative errors of each antenna estimate. Its value is between 0 (perfect estimate) and 1 (not good), and it delivered by using the mean values of the variables, $E\{ h_{li}^{j}\}$ as the estimates.

$$NMSE_{MMSE} = \frac{real(tr(R1 - SNR1*R1*((SNR1*R1+SNR2*R2+I_M)R1)))}{tr(R1)} \tag{4.8}$$

Where: R1 is the spatial correlation matrix of the desired UE

R2 is the spatial correlation matrix of the interfering UE

SNR1 is the range of the effective SNR for the desired UE

SNR2 the range of the effective SNR for the interfering UE

In this Thesis consider that uplink spectral efficiency with MMSE estimator, the SE of a channel between a UE and a BS, which for simplicity it refers to as the SE of the UE. A related metric is the information rate [bit/s], which is defined as the product of the SE and the bandwidth *B*. In addition, it commonly considers the sum SE of the channels from all UEs in a cell to the respective BS, which is measured in bit/s/Hz/cell.

Since, the MMSE estimator is used, it obtains a closed form expression for the SE in (4.9). If MR combining with $v_{jk} = h_{li}^{j}$ is used based on the MMSE estimator, then The Uplink spectral efficiency expression for the MMSE estimator was derived by the Paper [67, 68] and by using equation (4.6):

$$SE_{MMSE} = \beta(1 - \frac{\tau_p}{\tau_c} log_2(1 + \frac{p_{li}{}^2 \tau_p tr\left(R_{li}^{j} \psi_{li}^{j} y_{jli}^{p}\right) + p_{li} ||\hat{h}_{li}^{j}||^2}{\sum_{i=1}^{k} p_{li} + \sum_{i=1}^{k} \sqrt{p_{li}} \hat{h}_{li}^{j} ||^2 + \sigma_{UL}^2 \left(\frac{tr(\psi^{-1}}{p_{li}\,\tau_p} + \frac{||y_{jli}^{p}||^2}{p_{li}\tau_p{}^2}\right)}) \tag{4.9}$$

Where: τ_p is the number of UL pilot sequences/length, τ_c is the samples per coherence block, $\hat{h}^j_{li}$ is the estimate of the channel h^j_{li} between BS j and UE i in cell l, ψ^j_{li} is the inverse of the correlation matrix in the estimation of the channel between BS j and UE i in cell l, R^j_{li} is the spatial correlation matrix of the channel between BS j and UE i in cell l, σ^2_{UL} is the noise variance in the UL, p_{li} is the UL transmit power, β is the channel gain. This mathematical expressions for the SE of the MMSE estimator that will enable us to compare between the different channel estimators.

4.2.2 EW-MMSE Estimator

The EW-MMSE channel estimator is more necessary, when the BS does not have the knowledges of the complete covariance matrices [67]. In this technique, only the diagonal of the covariance matrix is used and the estimator ignores the correlations among the element. Because of this, there is no matrix inversion, so the computationally complexity is much reducing compare to the MMSE estimation system. More precisely, looking at the processed received signals in (4.2) and considering only one of the M *j* elements at a times.

Based on the statement $[y^p_{jli}]_m$, BS *j* can calculate the MMSE estimation of the *m*th elements $[h^j_{li}]_m$ of UE *i* channels in cell *l. i.e.*, the EW-MMSE channel estimation from BS *j* to UE *i* in cell *l* is [69] is

$$[\hat{h}^j_{li}]_m = \frac{\sqrt{p_{li}}[R^j_{li}]_{mm}}{\sum_{(l',i')\epsilon p_{li}} p_{l'i'} \quad \tau_p [R^j_{l'i'}]_{mm} + \sigma^2_{UL}} [y^{p\ \ j}_{jli_{li}}]_m \tag{4.10}$$

The EW-MMSE estimation correspond to let A^j_{li} be diagonals with

$$[A^j_{li}]_{mm} = \frac{\sqrt{p_{li}}[R^j_{li}]_{mm}}{\sum_{(l',i')\epsilon p_{li}} p_{l'i'} \quad \tau_p [R^j_{l'i'}]_{mm} + \sigma^2_{UL}} \quad m = 1, \dots M, \tag{4.11}$$

The MSE accomplished by the EW-MMSE channel estimator is get from (4.6, 4.7 & 4.11), which can be expressed as

$$\text{NMSE}_{\text{EW-MMSE}} = \frac{(\text{tr(R1)} + \text{tr(A\_EWMMSE}*(\text{SNR1}*\text{R1}+\text{SNR2}*\text{R2}+\text{I}_\text{M})*\text{A\_EWMMSE}') - 2*\text{real(tr(A\_EWMMSE}'*\text{R1}))*\sqrt{\text{SNR1}})}{\text{tr(R1)}} \tag{4.12}$$

Where: R1 is the spatial correlation matrix of the desired UE

R2 is the spatial correlation matrix of the interfering UE

SNR1 is the range of the effective SNR for the desired UE

SNR2 the range of the effective SNR for the interfering UE

It can easily obtain the desired output using the identical method has worked to derives the MMSE estimation, however it estimates every element separately using only the signals got at antennas and then calculating the result statistic.

Uplink spectral efficiency with EW-MMSE Estimator, if MR combining with $v_{jk}= \mathrm{h}_{\mathrm{li}}^{\mathrm{j}}$ is used based on the EW-MMSE estimator, then the uplink spectral efficiency expression for the EW-MMSE estimator was derived by the Paper [67, 68] and by using equation (4.6):

$$\mathrm{SE}_{\mathrm{EW-MMSE}} = \beta(1 - \frac{\tau_p}{\tau_c} log_2(1 + \frac{{\tau_p}^2 \mathrm{p_{li}}\ \mathrm{p_{jk}} \| tr\left(\mathrm{R}_{\mathrm{li}}^{\mathrm{j}} \psi_{\mathrm{li}}^{\mathrm{j}} \mathrm{R}_{\mathrm{jk}}^{\mathrm{j}}\right)\|^2 + 2\sqrt{\mathrm{p_{li}} \mathrm{p}_{jk}\tau_p}}{\mathrm{p_{jk}}\ \tau_p\ tr\left(\mathrm{R}_{\mathrm{li}}^{\mathrm{j}} \psi_{\mathrm{li}}^{\mathrm{j}} \mathrm{R}_{\mathrm{jk}}^{\mathrm{j}}\right) + \|\bar{h}_{li}^{j}\|^2}) \tag{4.13}$$

Where: τ_p is the number of UL pilot sequences/length, τ_c is the samples per coherence block, $\hat{\mathrm{h}}_{\mathrm{li}}^{\mathrm{j}}$ is the estimate of the channel $\mathrm{h}_{\mathrm{li}}^{\mathrm{j}}$ between BS j and UE i in cell l, $\psi_{\mathrm{li}}^{\mathrm{j}}$ is the inverse of the correlation matrix in the estimation of the channel between BS j and UE i in cell l, $\mathrm{R}_{\mathrm{li}}^{\mathrm{j}}$ is the spatial correlation matrix of the channel between BS j and UE i in cell l, σ_{UL}^2 is the noise variance in the UL, $\mathrm{p_{li}}$ is the UL transmit power and β is the channel gain.

4.2.3 LS Estimator

The EW-MMSE estimator does not use the complete spatial correlation matrixes ($\mathrm{R}_{\mathrm{li}}^{\mathrm{j}}$), however it uses only the element of the main diagonal [67]. In case when these partial statistics are unknown or unreliable (for example, because of rapid change in the UEs scheduling in another cells), it may be important to considers an estimator that does not requires prior statistical information.

In the system, it has the statement y_{jli}^{p} in (4.2), that hold the desired channel in the form of $\sqrt{p_{li}}\tau_p \mathrm{h}_{\mathrm{li}}^{\mathrm{j}}$. If the BSs has no prior information's regarding $\mathrm{R}_{\mathrm{li}}^{\mathrm{j}}$, the LS estimator can use to obtain an estimation of the propagation channels $\mathrm{h}_{\mathrm{li}}^{\mathrm{j}}$ by using the transmitted power [69].

The LS estimating of h_{li}^{j} is described as the vectors $\hat{h}_{li}^{j}$ that minimize the squared deviation $\|y_{jli}^{p} - \sqrt{p_{li}}\tau_p \hat{h}_{li}^{j}\|^2$. And its estimation is given by

$$\hat{h}_{li}^{j} = \frac{1}{\sqrt{p_{li}\tau_p}} y_{jli}^{p} \tag{4.14}$$

And this is a linear LS estimation, where:

$$A_{li}^{j} = \frac{1}{\sqrt{p_{li}\tau_p}} I_{Mj} \tag{4.15}$$

And meanwhile the matrices are a diagonals matrix, the computational complexity of each coherent blocks is proportional to M j. the matrices A_{li}^{j} does not directly dependent on the channel's statistic, but it depends on the transmission power, that the UE may changes when the statistic changes [70].

The MSE accomplished by the LS estimation in (4.12) can't be calculate, unless the statistic of the channel are knowns, but it can be got from (4.6, 4.7 & 4.15) and which can be expressed as

$$\text{NMSE}_{\text{LS}} = \frac{(\text{tr(R1)} + \text{tr(A\_LS}*(\text{SNR1}*\text{R1}+\text{SNR2}*\text{R2}+\text{I}_\text{M})*\text{A\_LS}') - 2*\text{real(tr(A\_LS}'*\text{R1}))*\sqrt{\text{SNR1}})}{\text{tr(R1)}} \tag{4.16}$$

Where: R1 is spatial correlation matrix of the desired UE

R2 is spatial correlation matrix of the interfering UE

SNR1 is the range of the effective SNR for the desired UE

SNR2 the range of the effective SNR for the interfering UE

Uplink Spectral Efficiency with LS Estimator, if MR combining with $v_{jk} = \frac{1}{\sqrt{p_{li}\tau_p}} y_{jli}^{p}$ is used based on the LS estimator, then the Uplink spectral efficiency expression for the LS estimator was derived by the Paper [67, 68] and also by using equation (4.6):

$$\text{SE}_{\text{LS}} = \beta(1 - \frac{\tau_p}{\tau_c} log_2(1 + \frac{p_{li}\|tr\left(R_{li}^{j}\right)+\sum_{i=1}^{k}\sqrt{p_{li}}\hat{h}_{li}^{j}\|^2}{\sum_{i=1}^{k} p_{li}-\|tr\left(R_{li}^{j}\right)+\sum_{i=1}^{k}\sqrt{p_{li}}\hat{h}_{li}^{j}\|^2 + \sigma_{UL}^2\left(\frac{tr(\psi_{li}^{j})^{-1}}{p_{li}\,\tau_p}+\frac{\|y_{jli}^{p}\|^2}{p_{li}\tau_p{}^2}\right)}) \tag{4.17}$$

Where: τ_p is the number of UL pilot sequences/length, τ_c is the samples per coherence block, $\hat{h}_{li}^{j}$ is the estimate of the channel h_{li}^{j} between BS j and UE i in cell l, ψ_{li}^{j} is the inverse of the correlation matrix in the estimation of the channel between BS j and UE i in cell l, R_{li}^{j} is the spatial correlation matrix of the channel between BS j and UE i in cell l, σ_{UL}^{2} is the noise variance in the UL, p_{li} is the UL transmit power and β is the channel gain.

4.2.4 ML Estimator

The ML process is use to determining the squared distance between the sampled received signal sequence and all possible received sequences, and to determining the transmission symbol sequence with a smallest distance [71]. it is a better estimation technique, but the complexities of the receiver increase exponentially with the length of the channel's impulse response. It operates by allocating two times slots for training sequences, those time slots are divided equally in to two phase, and trainings signal are only sent out during the first phase [72]. The ML estimating of the channel h_{li}^{j} is described as the vector $\hat{h}_{li}^{j}$ which minimizes the squared deviation is

$$\hat{h}_{li}^{j} = \frac{2}{\sqrt{p_{li}}\,\tau_p} y_{jli}^{p} \tag{4.18}$$

Generally, for a complexed parameters the ML Channel Estimation can be expressed as

$$A_{li}^{j} = \frac{\sigma^2{}_{UL} I_{Mj}}{p_{li}\tau_p} + \frac{2}{\sqrt{p_{li}}\,\tau_p} y_{jli}^{p} \tag{4.19}$$

Where $\frac{\sigma^2{}_{UL}}{p_{li}\tau_p}$ is variance and $\frac{2}{\sqrt{p_{li}}\,\tau_p} y_{jli}^{p}$ is the square bias relationships of the estimation. The MSE achieved by the ML estimator can be obtained from (4.6, 4.7 & 4.19) and simplifying to:

$$\text{NMSE}_{\text{ML}} = \frac{(\text{tr}(R1) + \text{tr}(A_{ML} * (SNR1 * R1 + SNR2 * R2 + I_M) * A_{ML}') - 2 * \text{real}(\text{tr}(A_{ML}' * R1)) * \sqrt{SNR1})}{\text{tr}(R1)} \tag{4.20}$$

Where: R1 is the spatial correlation matrix of the desired UE

R2 is the spatial correlation matrix of the interfering UE

SNR1 is the range of the effective SNR for the desired UE

SNR2 is the range of the effective SNR for the interfering UE

Uplink spectral efficiency with ML Estimator, if MR combining with $v_{jk} = \frac{2}{\sqrt{\mathrm{p_{li}}\tau_p}} \mathrm{y}_{\mathrm{jli}}^{\mathrm{p}}$ is used based on the ML estimator, then the Uplink spectral efficiency expression for the ML estimator was derived by the Peper [67, 68] and also by using equation (4.6):

$$\mathrm{SE_{ML}} = \beta(1 - \frac{\tau_p}{\tau_c} log_2(1 + \frac{\mathrm{p_{li}}||tr\left(\mathrm{R}_{\mathrm{li}}^{\mathrm{j}}\right)+2\sum_{i=1}^{k}\sqrt{\mathrm{p_{li}}}\hat{\mathrm{h}}_{\mathrm{li}}^{\mathrm{j}}||^2}{\sum_{i=1}^{k}\mathrm{p_{li}}-||tr\left(\mathrm{R}_{\mathrm{li}}^{\mathrm{j}}\right)+\sum_{i=1}^{k}\sqrt{\mathrm{p_{li}}}\hat{\mathrm{h}}_{\mathrm{li}}^{\mathrm{j}}||^2 + \sigma_{UL}^2\left(\frac{tr(\psi_{\mathrm{li}}^{\mathrm{j}})^{-1}}{\mathrm{p_{li}}\,\tau_p}+\frac{||\mathrm{y}_{\mathrm{jli}}^{\mathrm{p}}||^2}{\mathrm{p_{li}}\tau_p{}^2}\right)}) \qquad (4.21)$$

Where: τ_p is the number of UL pilot sequences/length, τ_c is the samples per coherence block, $\hat{\mathrm{h}}_{\mathrm{li}}^{\mathrm{j}}$ is the estimate of the channel $\mathrm{h}_{\mathrm{li}}^{\mathrm{j}}$ between BS j and UE i in cell l, $\psi_{\mathrm{li}}^{\mathrm{j}}$ is the inverse of the correlation matrix in the estimation of the channel between BS j and UE i in cell l, $\mathrm{R}_{\mathrm{li}}^{\mathrm{j}}$ is the spatial correlation matrix of the channel between BS j and UE i in cell l, σ_{UL}^2 is the noise variance in the UL, $\mathrm{p_{li}}$ is the UL transmit power and β is the channel gain.

4.3 Mathematical analysis of the length of coherence block

The concept of the coherence block associated with a certain mobile radio channel is of great practical importance in future systems based on massive MIMO technology. In fact, it is one of the factors that determines the achievable spectral efficiency (SE) [73]. The size of the ChB answers the fundamental question: for how long and in what frequency range can we consider the radio channel to be approximately constant? Answering this question is crucial since it determines the overhead incurred by periodically dedicating a certain number of carriers to transmit pilots that update the knowledge of the channel. Moreover, in massive MIMO systems, based on the use of a large number of antennas at the base station, the number of pilots dedicated to channel estimation is a limiting factor on the maximum number of users that the system can serve simultaneously.

A coherence block consists of a number of subcarriers and time samples over which the channel response can be approximated as constant and flat-fading. If the coherence bandwidth is Bc and the coherence time is Tc, then each coherence block contains τc = BcTc complex-valued samples [73]. For this Thesis, it will assume normal walking speed of humans with no vehicular speed considered. The distribution of the users with in the cell is assumed to be random with in the cell. The BTS is located at the center of the cell. Since planning 5G system, it reasonable to assume urban environment because high data rate is usually for required urban duelers.

There are different types of cells based on their size. it will assume this cell to be UMa (Urban Macro-cell) because the UMa have a coverage of less than 2000*m* as mentioned in [74] and this Thesis system have a coverage of 300*m*. So, it is reasonable to seslect UMa cell for this system. So, based on this environment, it will calculate the length of coherence block for this system based on choice of environment. If the coherence bandwidth is Bc and the coherence time is Tc, then each coherence block contains τc complex-valued samples. Which means:

$$\text{Length of the Coherence Block } (\tau c) = \text{BcTc} \tag{4.22}$$

And now select the operating frequency for massive MIMO system, based on the recommendation [75] it will choose 45 *GHz* for operation. So, based on this frequency it can find the coherence time (Tc) and coherence bandwidth (Bc), now first calculate λ, by using the equation $C = \lambda * f$,$=6.6mm$. And now calculate the value of coherence time (Tc) by using equation (4.23).

$$\text{Coherence time (Tc)} = \frac{\lambda}{8 * v} \tag{4.23}$$

For this Thesis, it will assume normal walking speed (v) of humans with no vehicular speed, it considered as UE speed and as recommendation [76, 77] on average it usually assumed to be 1.4 *m/s*. so, by using this numerical value, the value of Tc is approximate to 0.589 ms. And now determine the values of coherence bandwidth (Bc), So, now based on Thesis [78], the coherence bandwidth can be designed as;

$$\text{coherence bandwidth (Bc)} = \frac{1}{2\pi * Ds} \tag{4.24}$$

Since, the Ds is the delay spread and using the parameters as defined above (UMa cell and operating frequency of 45 GHz) it will select Ds for this system from Table 4.1. it will choose the Ds for this system to be 240 *ns* according to the Thesis [79]. By using this value in (4.24), the value of the *Bc* is 663.481 *KHz*. This result is logical because the value of the *Bc* can range up to 1000 *KHz* values. So, using the value of both *Bc* and *Tc* in to (4.22), the length of the coherence block to be approximately 391 *samples*. So, each coherence block consists of

τc = 391 samples and also, consider that communication over a 20*MHz* channel and assume the total receiver sensitivity to be -94*dB*.

Table 4.1: How to calculate absolute delay values [79].

Proposed Scaling Factor Delay Spread desired [ns])		Frequency [GHz]						
		2	6	15	28	39	60	70
Indoor office	Short-delay profile	20	16	16	16	16	16	16
	Normal-delay profile	39	30	24	20	18	16	16
	Long-delay profile	59	53	47	43	41	38	37
UMi Street-canyon	Short-delay profile	65	45	37	32	30	27	26
	Normal-delay profile	129	93	76	66	61	55	53
	Long-delay profile	634	316	307	301	297	293	291
UMa	Short-delay profile	93	93	85	80	78	75	74
	Normal-delay profile	363	363	302	266	249	228	221
	Long-delay profile	1148	1148	955	841	786	720	698
RMa & RMa O2I	Short-delay profile	32	32	N/A	N/A	N/A	N/A	N/A
	Normal-delay profile	37	37	N/A	N/A	N/A	N/A	N/A
	Long-delay profile	153	153	N/A	N/A	N/A	N/A	N/A
UMi / UMa O2I	Normal-delay profile	240						
	Long-delay profile	616						

4.4 Computational Complexity of Matrix Operations

In the linear algebra operation, like matrices multiplication and matrices inversion has a well-determined structure, so they can be effectively performed in hardware. However, thus huge arrays required to be manipulated each milli-second, computational complexities can be a bottleneck. The exact complexity of matrix operations is highly dependent on the hardware implementations, include the bit length (that is, the numbers of binary digit need to denote numbers) and types of data (for example, fixed or floating point). In this Thesis, discussing the complexity of divisions and multiplications, while ignoring the complexity of addition and subtraction, since these operations are easier to implement in hardware [80].

4.4.1 Computational Complexity of different Estimators

Let compute the computational complexity of MMSE, Ew-MMSE, LS and ML estimator based on Appendix 3 computational complexity of matrix operations.

Let now evaluate the computational complexity of MMSE estimator based on Appendix 3. the MMSE channel estimation in (4.3) is calculated once for each coherent block of each UEs (K_j) in BS j. the inter-cell channel is optional to estimates, but if used for combining or precoding, they must also be calculated once for each coherent block. The processed received pilot signals at BS j is multiplied in (4.3) with two $M_j \times M_j$ matrixes [81].

Thus, this matrix depends only on the spatial correlation matrix. the matrices products can be precalculated and updated only, when the channel statistic has changes significantly (for example, because of UEs mobility or a new UEs timetable decision). notice that the channel statistic is usually similar over all subcarrier, so only one matrix is precomputed per UEs. If estimates the channels of multiple UEs using the similar pilot sequences, it only needs to computing the matrices-ψ, so it only needs to spend M_j^2 multiplications to get the extra.

The estimation in each coherent block only needs to correlate the received signal matrices with the pilot sequences as $\mathrm{y}_{\mathrm{jli}}^{\mathrm{p}} = \mathrm{Y}_{\mathrm{j}}^{\mathrm{p}} \varnothing^*{}_{\mathrm{li}}$ in (4.2) and then multiplying it with the precomputed statistical matrices $\sqrt{p_{li}}\mathrm{R}_{li}^{j}\Psi_{li}^{j}$. This operation requires $M_j\tau_p + M_j^2$ complex multiplication per UEs. So, to estimates the channel of another UEs using the same pilot, since $\mathrm{y}_{\mathrm{jli}}^{\mathrm{p}}$ is already known, the extra cost is only M_j^2 multiplication.

According to Appendix 3, the computational complexity of Ew-MMSE Channel Estimator per UE is proportional to M_j in (4.11), both when precomputes the fractional expressions in (4.10) and multiply it with the processed received pilot signal. This is much less than the complexities of the MMSE estimation, excepts in the special cases where all spatial correlation matrixes are diagonals so that each channel element can be estimated separately without loss of performance. Note that the key complexities from that A_{li}^{j} is diagonals [82].

The computational complexity of LS Channel Estimator with A_{li}^{j} in (4.15) and since the matrix is diagonal, then according to appendix 3, The computational complexity of each coherent block is proportional to M_j. The matrices A_{li}^{j} is does not directly dependent on the channel statistic, however it depends on the transmitting power.

And the computational complexity of ML channel estimator per coherence block in (4.19) is proportional to M_j [83]. Suppose that two time slots are allocated to trainings, those time slots are equaly divided into two phases, and trainings signal are only sent out during the first phases. So, to estimates the channel of another UEs using the same pilot, since y_{jli}^{p} is already known, the extra cost is only $2M_j$ multiplication.

The MMSE, EW-MMSE, LS and ML channel estimations are reviewed in table 3.1, with respect to computational complexity. The complexities are divided in to two parts: the complexities of the received signals Y_j^p in (4.1) correlated to the pilot sequences and complexities of estimate the UEs channel (after correlating with its pilots). The complexities of these operations are calculated in section 4.4.1 of the MMSE, EW-MMSE, LS and ML estimator, based on Appendix 3. The MMSE estimation has the greatest complexity, both in the computation an estimate and in precomputing the statistical coefficient. And also, ML has more complexity than EW-MMSE and LS, but has small difference when compared the sum of the first two columns.

So, all above discussion about computational complexity per coherence block for MMSE, Ew-MMSE, LS and ML channel estimator can be summarized in short form in the following table 4.2. the 1st column is the complexity of received signal correlating with pilot, the 2nd column is the complexity needed for estimate the channel of a UEs using that pilot sequences. And the 3rd columns are the summation of column1 and column2.

Table 4.2: The computational complexity of each coherent block of the channel estimation

Channel estimation scheme	The complexity of received signal Correlating with pilot in (4.1)	Per UE (after correlation with its pilot)	Over all computational complexity (summation of column 1 & 2)
MMSE	$M_j \tau_p$	M_J^2	$M_j \tau_p + M_J^2$
EW-MMSE	$M_j \tau_p$	M_j	$M_j \tau_p + M_j$
LS	$M_j \tau_p$	-	$M_j \tau_p$
ML	$M_j \tau_p$	$2M_j$	$M_j \tau_p + 2M_j$

CHAPTER FIVE

Simulation Result and Discussion

The comparison between the MMSE, EW-MMSE, ML and LS channel estimation schemes are presented in this section. Table 5.1 lists the general simulation parameters in this work and the performance evaluation is done using MATLAB platform.

Table 5.1 Simulation Parameters

Parameters	**Values**	**Remark**
Range of BS antennas (M range)	1 to 100	M >> K [26]
Number of UEs per cell (K)	10	[26]
Number of Pilot length ($\tau_p = K$)	10	[47]
Range of the effective SNR for the desired UE (in dB)	0 to 20	
Range of the effective SNR for the interfering UE (in dB)	10 dB weaker than SNR of desired signal	[71]
Antenna Spacing	λ/2	
Range of nominal angles of the desired and interfering UE	Between 0^0 and 360^0	[41, 42]
Samples per coherence block (length of the coherence block)	391	(4.22)
Communication BW	20MHz	[68]
Angular standard deviation in the local scattering model (ASD deg σ_φ)	10^0 (Assuming urban cellular networks)	[42]
Channel	Rayleigh channel	

5.1 Comparison of the estimating quality of MMSE, ML, LS and EW-MMSE estimator in terms of NMSE and SNR

In this analysis consider that a base station (BS *j*) estimates the channels of its user equipment (UE *k*), and a UEs in other cells transmit identical pilot sequences. And considering that scattering model is around UEs with Gaussian angular distribution, and also the fair value of the angular standard deviation that deviates from the nominal angle (φ) in urban cellular networks is approximate to 10^0 in [42]. And the average difference of the nominal angle (φ) of the multipath component is between 0^0 and 360^0 and the spatial correlation matrix that from (3.2) is also considered.

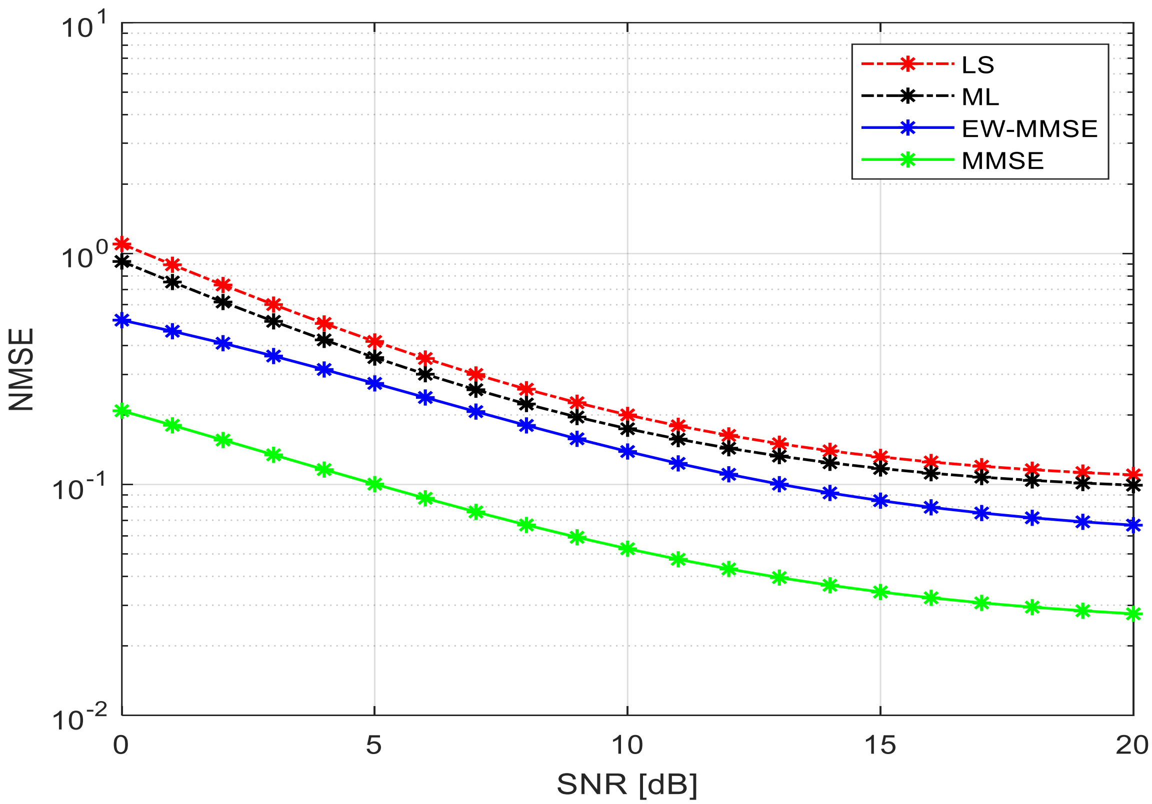

Figure 5.1: Compared the estimating quality of MMSE, LS, EW-MMSE, and ML in terms of NMSE and SNR.

As shown from figure 5.1, the MMSE estimator provides best estimation performance between the given SNR of the desired UEs are differing from 0 dB to 20dB and always interfering UEs signals are assuming that 10 dB weaker than the desired one, And the EW-MMSE estimator provides good estimation performance and ML provides decent estimation performance, while the LS estimation performance is much poor at lower SNR.

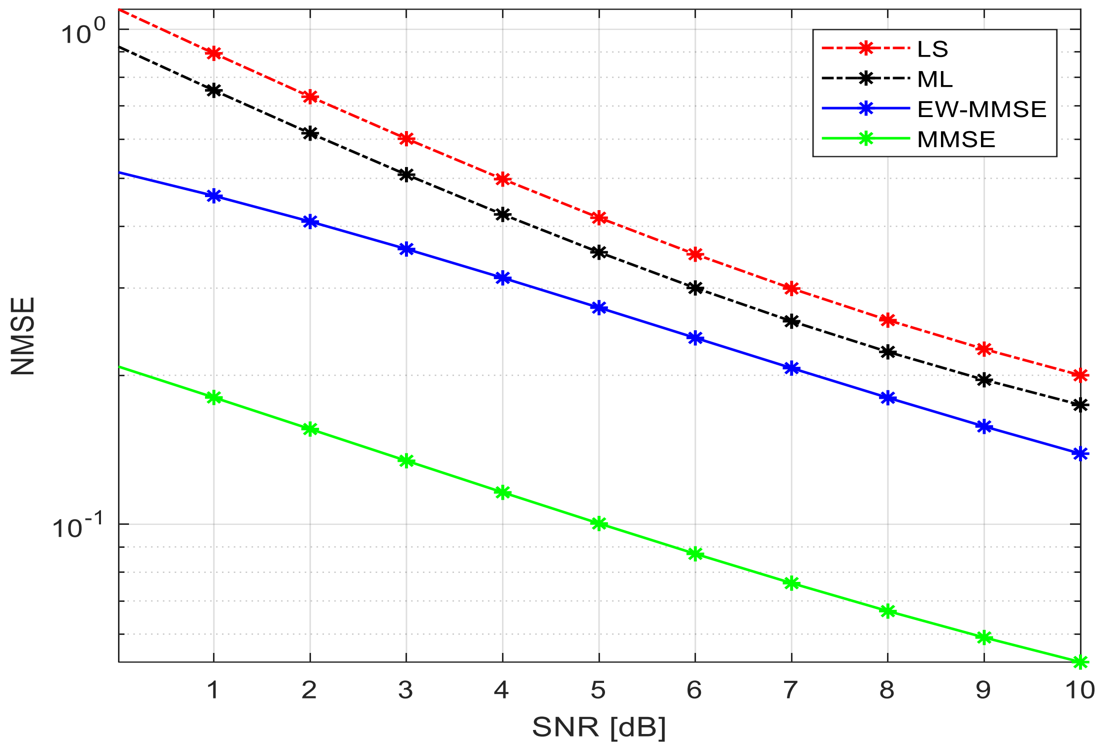

Figure 5.2: Compared the estimating quality of MMSE, LS, EW-MMSE, and ML in terms of NMSE and SNR with varying ASD.

In this case also consider that the same thing as discussed in figure 5.1, but the difference is the ASD, that reduced to 5^0. So, as shown from figure 5.2, the MMSE estimator provides best estimation performance and the EW-MMSE estimator provides good estimation performance and ML provides decent estimation performance, while the LS estimation performance is much poor at lower SNR. Therefore, it concludes that at low and high SNRs, the estimation quality of the MMSE estimator is the best one and EW-MMSE is better than both ML and LS estimators.

5.2 Comparison of the complexities and qualities of the MMSE, ML, LS and EW-MMSE estimators with respect to M

In this analysis consider that, base station antennas (M) are varied from 1 to 100 and with a constant UEs means that K = τ_p = 10 UEs in each cell based on table 4.2. The computational complexity of each coherent block is considered as a function of M and τ_p, And it does not consider the complexity of the pre-computation matrix and only depends on the channel statistic, as it is usually constants for a great number of coherent blocks.

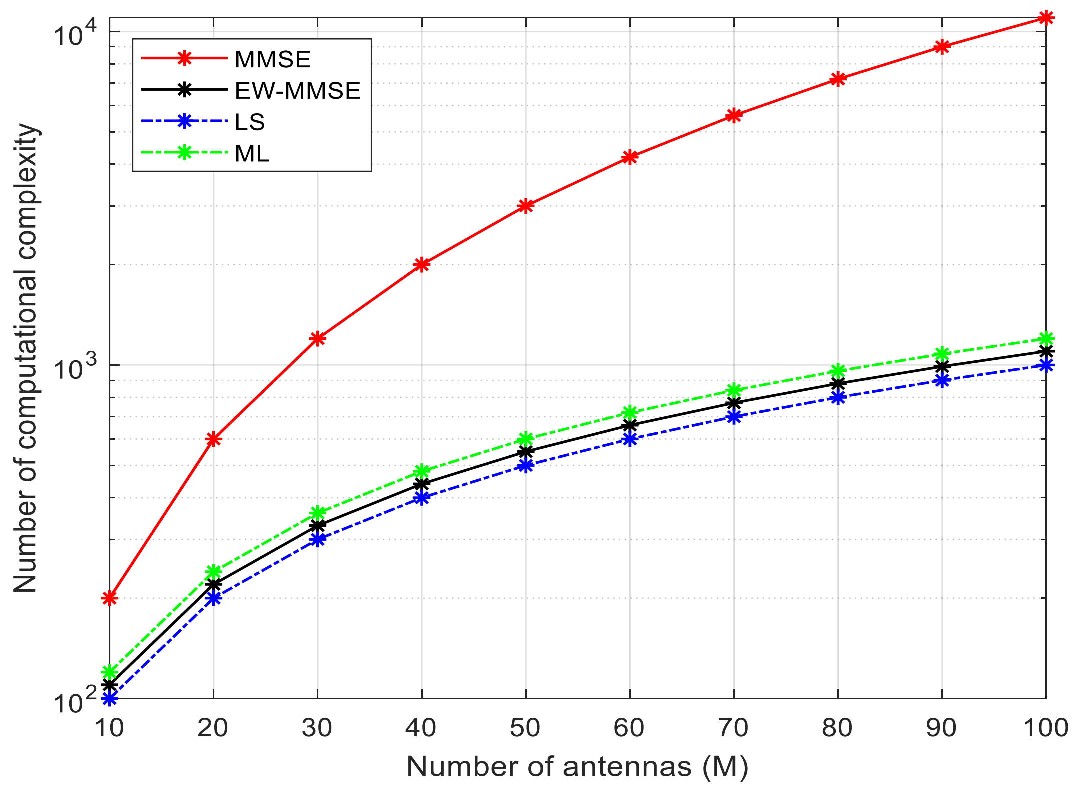

Figure 5.3: Computational complexity of coherent block of MMSE, LS, EW-MMSE, and ML channel estimator in terms of M varied from 1 to 100 with constant UE

As shown in figure 5.3, that describes the number of computational complexities in each coherent blocks as functions of BS antennas M with a constant τ_p which equivalent to user equipment's (K) = 10 UEs in every cell. And in this case the range of BS antennas are varied from 1 to 100. Based on this consideration figure 5.3 shows that, when number of BS antenna

M increase, MMSE have the higher computational complexity, and ML has also high complexity and that follow by EW-MMSE estimator. The computational complexity of LS estimator is very low relative to MMSE and also the complexity reduced by using LS rather ML and EW-MMSE at M varied from 1 to 100, can reduce by 2% and 1% respectively.

Therefore, it concludes that based on the number of computational complexities of each coherent blocks as functions of BS antennas M with constant UEs, LS have less complexity than MMSE and also nearly have the same complexity with ML and EW-MMSE, but there is a 1% to 2% difference with them.

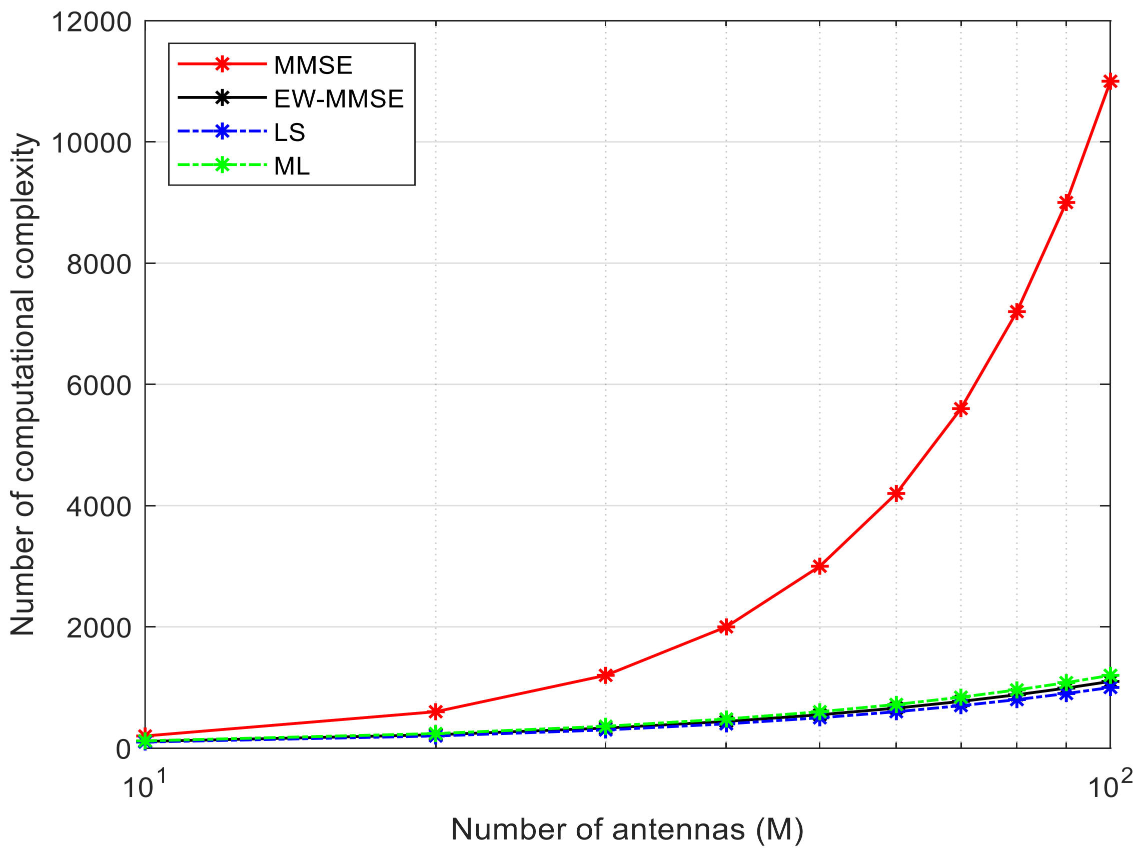

Figure 5.4: Computational complexity of coherent block of MMSE, LS, EW-MMSE, and ML channel estimator in terms of M

As shown from figure 5.4, when the numbers of BS antenna increasing and the numbers of UEs are constant, the overall complexities of each estimator are increased. And it concludes that, the complexity of MMSE is still higher and followed by ML and EW-MMSE consequently. While LS estimation technique has less complexity than other techniques.

5.3 Uplink Spectral Efficiency with MMSE, ML, LS and EW-MMSE Estimators

In this analysis consider that a BS *j* estimates the channels of UE *k* with *K* = 10 UEs per cell, $\tau_c = 391\ samples, \tau_p = 10$ and a varying number of BS antennas from 1 to 100. There are τ_p pilots in each coherence block and the remaining $\tau_c - \tau_p = 391 - 10 = 381$ samples are used for UL data transmission. And it uses gaussian local scattering with ASD is 10^0 as channel model (assuming urban cellular networks).

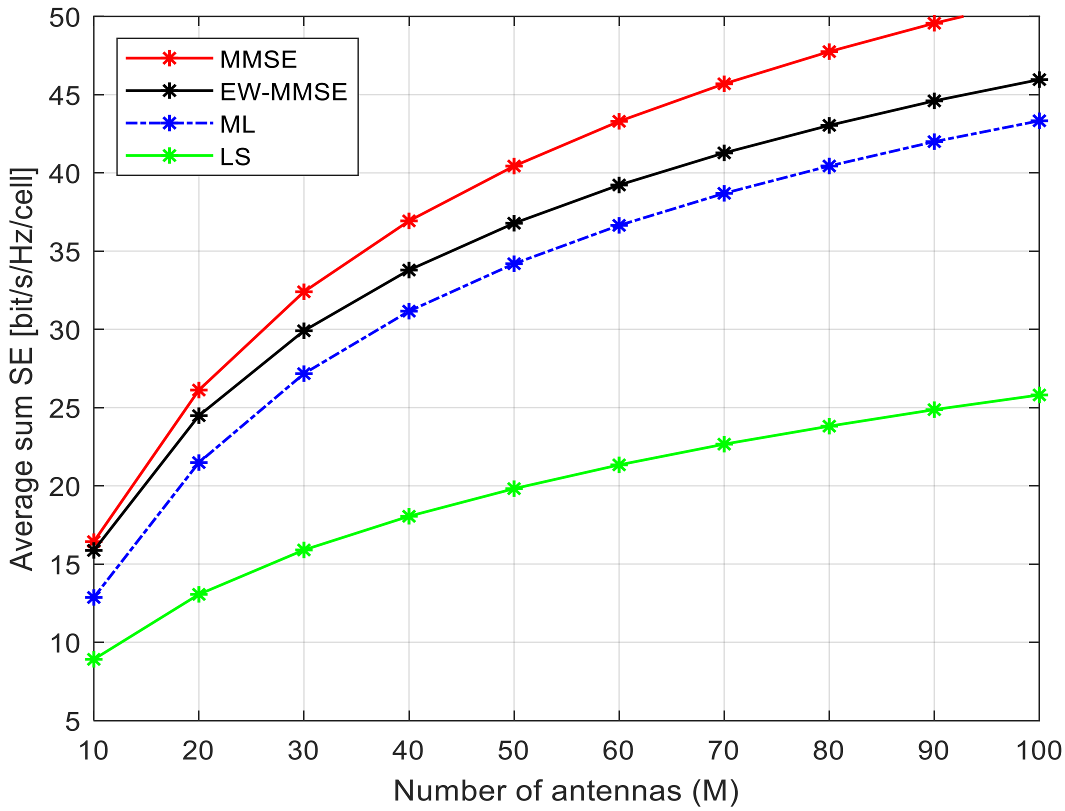

Figure 5.5: Average UL sum SE for K = 10 as a function of the number of BS antennas for different channel estimators

Figure 5.5 shows that the UL averaged sum SE using MR detection based on either the MMSE, EW-MMSE, ML or LS estimators. The SE of the MMSE estimator at *M* = 90 is about 49.5 *bits/s/Hz/cell*, the SE of the EW-MMSE estimator at *M* = 90 is about 45.5 *bits/s/Hz/cell*, the SE of the ML estimator at *M* = 90 is about 42.5 *bits/s/Hz/cell* and the SE of the LS estimator at *M* = 90 is about 25 *bits/s/Hz/cell*. So, based on this information the value of SE of MMSE estimator was larger than the value of SE of EW-MMSE estimator by 3 *to* 4 *bits/s/Hz/cell* and the value of SE of EW-MMSE estimator was larger than the value of SE of ML and LS estimators by 3 and 20.5 *bits/s/Hz/cell* respectively. Therefore, MMSE gives the largest SE and the EW-MMSE scheme provides well SE, ML has provided good SE, and LS has lowest SE.

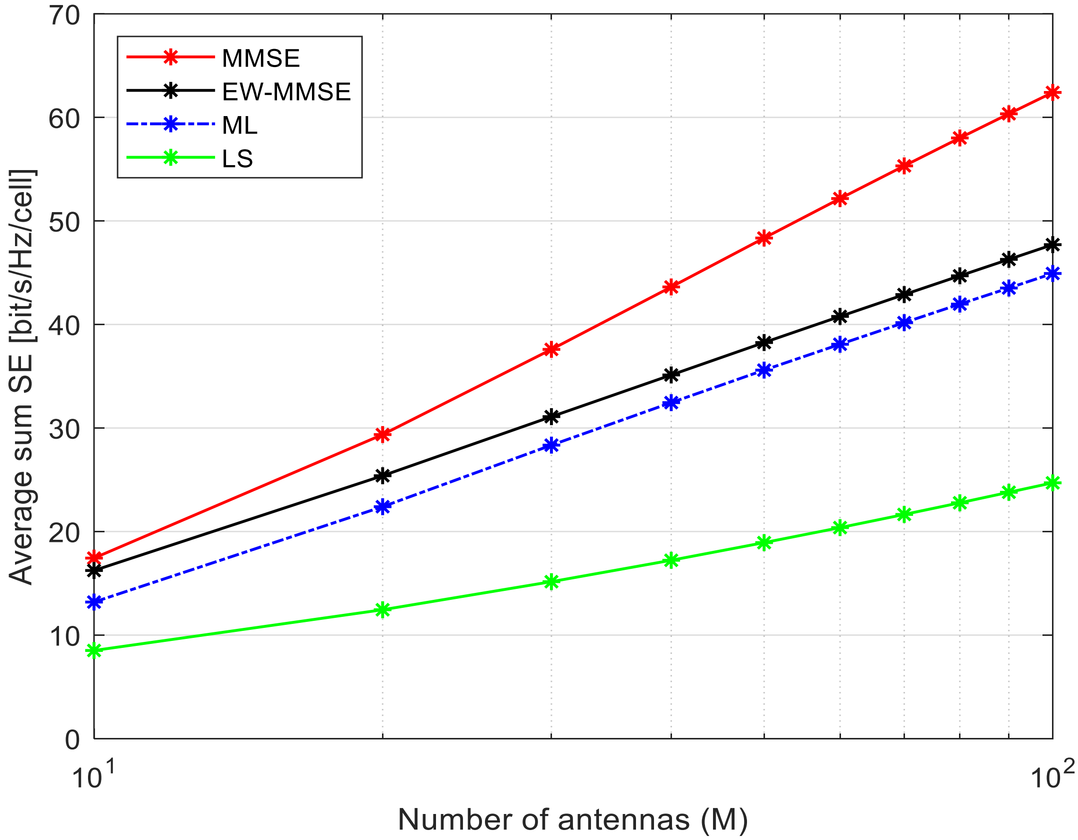

Figure 5.6: Average UL sum SE for K = 10 as a function of the number of BS antennas for different channel estimators with varying ASD.

As shown figure 5.5 and 5.6 it concludes that the MMSE provides the highest SE with highest complexity and EW-MMSE and ML accomplishes a good between SE and complexity. while, LS provides the lowest SE with low complexity.

CHAPTER SIX

Conclusion and Recommendation

6.1 Conclusion

This Thesis evaluates the performance comparison and analysis of UL pilot-based channels estimating techniques for massive MIMO technology with respect to NMSE, SNR, SE, number of BS antenna and computational complexities with spatially correlated Rayleigh fading channel. In all communication the signals pass through channels and the signals are distorted because of different obstacles. Therefore, in order to correctly interpret the received signals without many errors, the first thing is to find out the characteristics of the signal in the channel using a channel estimator. This Thesis uses pilot-based channel estimation schemes namely: MMSE, EW-MMSE, ML, and LS estimator to estimate the channel.

According to the result of simulation, the performance of the MMSE estimator with respect to NMSE and SNR is the highest, and followed by EW-MMSE and ML, while LS has the lower performance with considering impacts of pilot contamination. However, based on the number of computational complexities of each coherent blocks as a functions of BS antennas M, with a constant UE, the complexity of LS is less than that of MMSE, and it has almost the same complexity as ML and EW-MMSE, but there are some differences with them. And according to SE with respect to Base station antenna M, the MMSE provides the highest SE using the highest complexity, and EW-MMSE and ML achieves a good balance between SE and complexity. Finally, LS has the lowest complexity, but also provides the lowest SE. Therefore, this Thesis conclude that in Massive MIMO systems, MMSE channel estimation technique has the best performance compared to EW-MMSE, ML and LS channel estimators, but at the cost of high complexity.

6.2 Recommendation for future works

The result described for this task can used for futures effort to speed the Fifth-Generation-5G and beyond the revolution. The main goal of this Thesis is very important for the development of massive MIMO system and impose important limitations for the performance of the expected system. There are a lot of possible Thesis areas related to this topic:

- ✓ One possible Thesis idea is when no pilot signals are needed, pilot contamination will not happen. Therefore, the more optimistic method is to the develop blind channel estimating schemes. Because, the blind channels estimation is executed by evaluates the statistical information of the channel and the specific property of the transmitted signal instead of the pilot signal. It should be widely study.
- ✓ Additional probable future Thesis related to this Thesis is to realize the effect of increasing the number of users on the difference between the MMSE, EW-MMSE, ML and LS estimation schemes in the existence of pilot contamination.
- ✓ Wholly the work in this Thesis is done assuming TDD operation of the massive MIMO systems. From this, it can see that doing all these simulations done on this thesis for FDD massive MIMO systems might be additional possible field of Thesis.

Appendices

Appendix 1: Mathematical Notation

$\mathbb{C}^{N\mathrm{x}M}$ The set of complex-valued $N \times M$ matrices

$x \in S$ x is a member of the set S

X^{*} The complex conjugate of X

X^{T} The transpose of X

X^{H} The conjugate transpose of X

X^{-1} The inverse of a square matrix X

tr(X) Trace of a square matrix X

I_M The M ×M identity matrix

0_M The M × 1 matrix (i.e., vector) with only zeros

Appendix 2: System Model Notation

A_{li}^{j} Matrix used as $A_{li}^{j} y_{jli}^{p}$ in an arbitrary linear estimator of h_{li}^{j}

B_c Channel coherence bandwidth [Hz]

C_{li}^{j} Estimation error correlation matrix for channel between BS j and UE i in cell l

h_{li}^{j} Channel response between BS j and UE i in cell l

$\hat{h}_{li}^{j}$ Estimate of the channel h_{li}^{j} between BS j and UE i in cell l

$\tilde{h}_{li}^{j}$ Estimation error defined as $\tilde{h}_{li}^{j} = h_{li}^{j} - \hat{h}_{li}^{j}$

j, l, l' Used as cell indices

j, i, i' Used as UE indices

K Number of UEs per cell (if it is the same in all cells)

K_j Number of UEs in cell j

L Number of cells

M Number of BS antennas (if it is the same in all cells)

M_j Number of BS antennas in cell j

p_{jk} UL transmit power used by UE k in cell j

φ Azimuth angle

$\emptyset_{jk}$ Pilot sequence associated with UE k in cell j

ϕ Pilot book with τ_p mutually orthogonal sequences

ψ_{li}^{j} Inverse of the correlation matrix in the estimation of the channel between BS j and UE i in cell l

R_{li}^{j} Correlation matrix of the channel between BS j and UE i in cell l

σ_{UL}^{2} Noise variance in the UL

T_c Channel coherence time [s]

T_d Delay spread [s]

τ_c Number of samples per coherence block (equals $B_c T_c$)

τ_d DL data samples per coherence block

τ_p Number of samples allocated for pilots per coherence block

τ_u UL data samples per coherence block

y_{jli}^{p} Processed received pilot signal

Appendix 3: Matrix Analysis

Let consider the matrices $\mathbf{A} \in \mathrm{C}^{N_1 \mathrm{X}\ N_2}$ and $\mathrm{B} \in \mathrm{C}^{N_2 \mathrm{X}\ N_3}$; The matrix-matrix multiplication AB requires $N_1 N_2 N_3$ complex multiplications. The multiplication AA^H only requires $\frac{{N_1}^2 + N_1}{2}\ N_2$ complex multiplications, by utilizing the Hermitian symmetry.

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