Investigation and mitigation of Spatially Correlated Fading in Massive MIMO

Habtamu Lema Adera

A Thesis Submitted to

Department of Electronics and Communication Engineering

School of Electrical Engineering and Computing

Presented in Partial Fulfillment of the Requirement for the Degree of Master’s in Electronics and Communication Engineering

Office of Graduate Studies

Adama Science and Technology University

June, 2024

Adama, Ethiopia

Investigation and mitigation of Spatially correlated fading in massive MIMO

Habtamu Lema Adera

Main Advisor Dr. Demissie Jobir Gelmecha

Co-Advisor Dr. Rajeev Kumar Shakya

A Thesis Submitted to

Department of Electronics and Communication Engineering

School of Electrical Engineering and Computing

Office of Graduate Studies

Adama Science and Technology University

June, 2024

Adama, Ethiopia

DECLARATION

I hereby declare that this Master Thesis entitled "**Investigation and mitigation of Spatially correlated fading in massive MIMO**" is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

Habtamu Lema Adera	________________	____________
Name of student	Signature	Date

RECOMMENDATION OF ADVISORS

We, the advisors of this thesis, hereby certify that we have read the revised version of the thesis entitled "**Investigation and mitigation of Spatially correlated fading in massive MIMO**" prepared under our guidance by Habtamu Lema Adera submitted in partial fulfillment of the requirements for the degree of Masters of Science in Electronics and Communication Engineering. Therefore, we recommend the submission of revised version of the thesis to the department following the applicable procedures.

Dr. Demissie Jobir Gelmecha	_______________	________________
Major Advisor	**Signature**	**Date**
Dr. Rajeev Kumar Shakya	_______________	________________
Co-advisor	**Signature**	**Date**

APPROVAL PAGE OF M.SC. THESIS

We, the advisors of the thesis entitled "**Investigation and mitigation of Spatially correlated fading in massive MIMO**" and developed by Habtamu Lema Adera, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Dr. Demissie Jobir Gelmecha	______________	__________
Advisor	**Signature**	**Date**
Dr. Rajeev Kumar Shakya	______________	__________
Co-Advisor	**Signature**	**Date**

APPROVAL OF BOARD OF REVIEWERS

We, the undersigned, members of the Board of Examiners of the thesis by Habtamu Lema Adera have read and evaluated the thesis entitled **“Investigation and mitigation of Spatially correlated fading in massive MIMO”** and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Electronics and Communication Engineering.

________________	______________	__________
Chairperson	**Signature**	**Date**
________________	______________	__________
Internal Examiner	**Signature**	**Date**
________________	______________	__________
External Examiner	**Signature**	**Date**

Finally, approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

________________	______________	__________
Department Chair	**Signature**	**Date**
________________	______________	__________
School Dean	**Signature**	**Date**
________________	______________	__________
Postgraduate Dean	**Signature**	**Date**

ACKNOWLEDGMENT

First of all, I would want to thank the Almighty God who provided me the strength and ability to complete the thesis successfully. After the almighty God, I would like to convey my ardent gratitude and compliments to my advisor **Dr. Demissie Jobir Gelmecha** for being the corner-stone of this endeavor. He provided constant motivation and direction during the period of questions and uncertainties, which helped me to continue with my thesis. I'm also grateful to my co-advisor, **Dr. Rajeev Kumar Shakya**, for his helpful recommendations and ongoing support. Also I would like to offer my special appreciation to **Dr. Ram Sewak Singh** for their advice while I faced challenges on my thesis. I would also like to thank the Electronics and Communication Engineering (ECE) program for providing me with the opportunity to complete this wonderful thesis on the topic " Investigation and mitigation of Spatially correlated fading in massive MIMO System," which will also help me in the future in doing a lot of research and learning about so many things. I am very thankful to them.

Finally, I would want to thank my parents for their endless counsel, as well as others who helped me directly or indirectly while working on my thesis.

Table of Contents

LIST OF TABLES

LIST OF FIGURE

LIST OF ACRONMYS AND ABBREVIATIONS

AP	Access Point
BS	Base Station
CDF	Cumulative distribution function
CE	Channel estimation
CSI	Channel state information
DL	Downlink
EW-MMSE	Element-Wise minimum mean square error
FDD	Frequency division duplex
i.i.d	independent and identical distributed random variable
L-MMSE	Local minimum mean square error
LOS	Line-of-sight
LS	Least square
MIMO	Multi-Input-Multi-output
MMSE	Minimum mean square error
M_MMSE	Multicell Minimum Mean-Squared Error
MRC	Maximum ratio combining
NLOS	Non-line-of-sight
UE	User Equipment
ULA	Uniform linear array
UL	Uplink
UPA	Uniform planar array
RZF	Regular –zero-forcing
RIS	Reconfigurable intelligent surface
SE	Spectral efficiency
SINR	Signal –to-interference-plus-noise ratio
TDD	Time-division Duplex

ABSTRACT

Massive MIMO (Multiple Input Multiple Output) systems, characterized by the use of a large number of antennas at the base station, offer significant improvements in capacity and spectral efficiency. However, the benefits of massive MIMO can be hindered by spatial correlation fading. Spatial correlation fading refers to the phenomenon where the fading characteristics of multiple antenna channels in a MIMO system are correlated. This correlation arises due to insufficient spatial separation between antennas, limited scattering environments, or specific propagation conditions. In order to mitigate these issues, this thesis explores channel estimator for accurate estimation of the fading channel to improve spectrum efficiency of massive MIMO. The study begin with provides statistical properties for the minimum mean squared error (MMSE), element-wise (EW-MMSE), and least-squares (LS) channel estimations in this model. Additionally, analyze rigorous closed-form uplink (UL) and downlink (DL) spectral efficiency (SE) expressions. Comprehensive simulations on MATLAB and an analysis comparing the LS, MMSE and EW-MMSE under different precoder in order to estimate accurate channel state information, the MMSE demonstrate its better performance. The simulation results show that the SE is higher with different values of SNR, NMSE, coherence block length, number of BS antennas and number of Ues when using MMSE channel estimator and lower when using LS channel estimator.

Key words: Massive-MIMO, Rician Fading, Spatial Correlation, Spectrum Efficiency, Channel Estimation

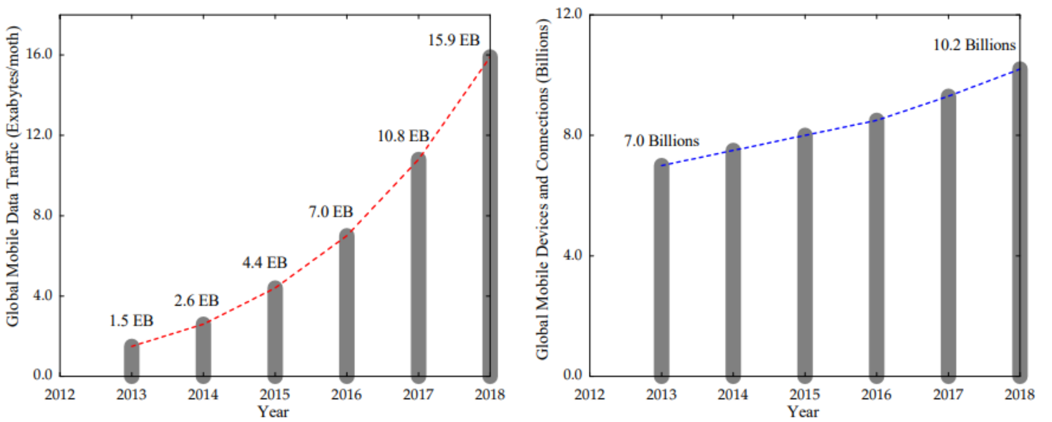
CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

In the recent past, there has been a tremendous increase in data traffics within both mobile and fixed networks. This increase can be largely attributed to the rising proliferation of smartphones, tablets, laptops, amongst many other wireless devices that heavily rely on the consumption of data. Figure 1.1 provides a visual representation of the increasing demand for mobile data traffic and the growing number of connected devices. Estimations indicate that global mobile data traffic is to grow six fold from the 2014 levels, reaching 15.9 Exabyte's per month in 2018. Secondly, by 2018, it is projected that mobile devices and connections will be 10.2 billion. In light of this shifting demand, there is need for the establishment of other technologies. In the case of wireless data traffic, one needs to note that wireless throughput purely refers to the rate at which data is transmitted wireless basically measured in bits per second)(Ngo, 2015):

Throughput = Bandwidth (Hz) × Spectral efficiency (bits/s/Hz)(Ngo, 2015).



(a) Global mobile data traffic.

(b) Global mobile devices and connections growth.

Figure 1. 1 (Ngo, 2015) Demand for mobile data traffic and number of connected devices.

The future generation of wireless networks is expected to support a significant number of devices and connections. The objective is to foster a connected society where various entities such as sensors, automobiles, drones, medical devices, and wearable technology can utilize mobile networks to establish connections with each other and engage in interactions with humans(Engineering, 2021). Massive multiple-input multiple-output (MIMO) is an emerging technology that significantly improves MIMO capabilities, outperforming the existing state-of-the-art by several orders of magnitude. Massive MIMO's performance is dependent on spatial multiplexing, which requires the base station to have correct channel knowledge for both uplink and downlink communications. Obtaining exact channel information for the up-link is quite simple because the terminals transmit pilot signals(Björnson et al., 2020). The base station uses these pilot signals to calculate the channel replies for each terminal. Downlinking is more difficult. Massive MIMO can boost capacity by tenfold or more while also improving radiated energy efficiency by 100 times. Massive MIMO capacity gains are due to the effective use of spatial multiplexing. While it is widely assumed that spatial channel correlation is detrimental to MIMO communications, this is not the case when multiuser communications are carried out using single-antenna user equipment (UE). The overall network performance is defined by the combination of spatial correlation matrices of the UE(Zhi et al., 2023). Typically, the UEs are physically separated by a large distance, producing statistically uncorrelated channels. Furthermore, while each UE's channel may exhibit strong spatial correlation at the base station (BS), the spatial correlation matrices can differ substantially amongst UEs. These features differentiate multiuser massive MIMO channels from point-to-point MIMO channels, where spatial channel correlation is observed from both the transmitter and the receiver, and the channel between transmit and receive antennas displays comparable spatial correlation patterns(Li et al., 2022).

The time-division duplex (TDD) mode is a typical configuration for massive MIMO systems, in which uplink and downlink transmissions occur at various time intervals yet within the same frequency resource. Several benefits encourage the use of TDD method. To begin, coherent antenna processing requires only the base station (BS) to have channel information. Second, the overhead for uplink estimation is proportional to the number of terminals, not the number of antennae (M), allowing for scalability with regard to the number of service antennas. Furthermore, fundamental estimation theory shows that adding more antennas to the BS does not reduce the quality of estimate per antenna. In fact, the estimation quality improves with M if a known correlation structure exists between the channel responses across the antenna array(Björnson et al., 2016).

1.1.1 Massive MIMO Techniques

Spatial diversity, spatial multiplexing, and beamforming are the three key ideas that form the foundation of massive MIMO. The principle behind multiple-input multiple-output (MIMO) is that a radio signal traveling between a transmitter and a receiver is filtered by its environment, creating several signal paths due to reflections from obstacles like buildings. The time delays, degrees of attenuation, and travel directions of the reflected signals will change when they reach the receiving antenna. The placement of many receiving antennas results in the somewhat different versions of the signal that each antenna receives, these versions can be added numerically to improve the transmission signals quality. Because the reception antennas are spatially separated, this strategy is known as spatial diversity. Spatial diversity is also achieved by distributing the radio signal across multiple antenna, with each antenna sending changed versions of the signal in some cases. While spatial diversity improves radio link reliability, spatial multiplexing boosts radio link capacity by utilizing numerous transition paths as additional data transmission channels. Spatial Multiplexing sends numerous data streams between the transmitter and receiver, considerably improving performance and allowing a single transmitter to accommodate multiple network users. Instead of broadcasting to a wide area, beamforming uses contemporary antenna technology to focus a wireless signal in a specific direction. Beamforming is an important wireless method that supports Massive MIMO in increasing network capacity and throughput. It directs the wireless signal in a certain direction, decreasing interference and allowing for larger antenna arrays(Wang et al., 2020)

1.1.2 Channel Estimation in Massive MIMO

Massive multiple-input multiple-output (MIMO) is a scaled version of multiuser MIMO (MU-MIMO) that uses a large number of base station (BS) antennas to improve spectral efficiency through spatial multiplexing and basic linear processing at the BS. Pilot contamination can occur when pilots are reused in various cells and the BS obtains channel state information (CSI). Pilot contamination can have a significant impact on the asymptotically achievable rate in large MIMO systems in independent and identically distributed (i.i.d) Rayleigh fading channels, and various pilot decontamination approaches have recently been proposed in the literature. Wireless channels are complex, and fading can cause frequency and time selective behavior. Signature phenomena include reflection, diffraction, scattering, and Doppler Shift. Doppler Shift refers to the frequency difference between emitted and received waves when the distance between the receiver and source changes.

As a result, channel estimation is a critical approach in wireless communication systems, especially mobile networks. In order to conduct signal equalization and retrieve the broadcast data, the receiver must have a correct understanding of the channel state information(Thomas et al., n.d.).

Determining the precise CSI can be a complex task in wireless channels. The wireless channel is prone to various impairments such as multipath fading, shadowing, and interference, which can significantly distort the transmitted signal. Without accurate CSI, the receiver will be unable to properly equalize the received signal and mitigate the effects of the wireless channel. This can lead to degraded signal quality, reduced data rates, and unreliable communication. So, effective channel estimation is vital to enable coherent detection and decoding at the receiver in mobile wireless networks. The complexity of this task underscores the importance of developing robust and efficient channel estimation algorithms to support high-performance wireless communication. Therefore, In MIMO, several antennas are used on both the sending and receiving sides, as illustrated in Figure 1.2(Sofi et al., 2018).

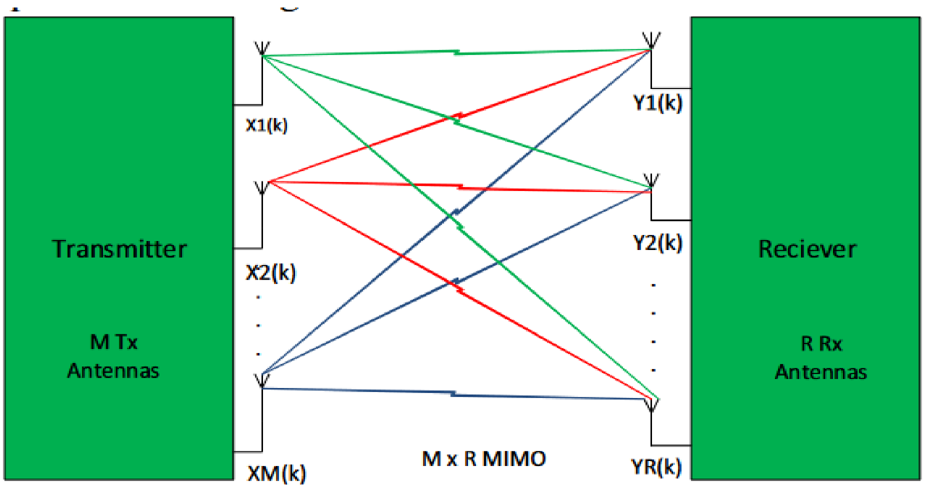


Figure 1. 2 (Sofi et al., 2018) Channel Estimation in Massive MIMO.

Most channel estimation techniques in wireless systems rely on the use of training sequences on transmission. These training sequences consist of pilot symbols that are known to the receiver. The pilot symbols are transmitted along with the actual data sequence. The receiver uses these known pilot symbols to estimate the current channel state information (CSI). This estimated CSI is then used to equalize and detect the data symbols that immediately follow the training sequence. The underlying assumption is that the channel remains unchanged during the coherence time interval, which is the duration over which the channel characteristics can be considered static.

Figure 1.3 illustrates a typical time slot structure in systems that perform channel estimation based on these training sequences. The time slot is divided into a training sequence segment followed by the actual data transmission. This approach allows the receiver to continuously update the CSI estimation by periodically inserting known training sequences within the data transmission. This is crucial for maintaining reliable communication in time-varying wireless channels(Nivethitha et al., 2015).

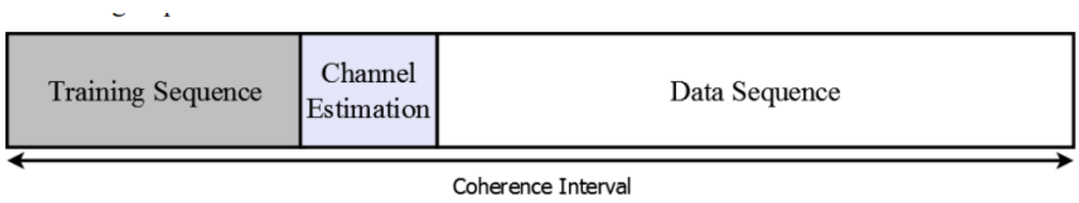


Figure 1. 3 (Nivethitha et al., 2015) Slot structure in systems with pilot –based channel estimation.

Massive MIMO systems rely largely on spatial multiplexing to obtain performance improvements. For this to work well, the base station must have an accurate understanding of the channel conditions. In the uplink, users send training sequences to the base station, which estimates the channel replies for each particular user. This channel state information (CSI) allows the base station to recognize signals from different users in a coherent manner. However, obtaining precise CSI for the downlink can be more difficult. Unlike the uplink, the base station must know the forward channel answers to each terminal ahead of time in order to execute precoding and beamforming to properly transmit to the users(Björnson & Demir, 2024).

Obtaining correct downlink CSI can be more difficult due to time-varying channels and the huge number of antennas at the base station. In Massive MIMO systems, efficient channel estimation techniques are critical to ensuring that the base station has the required CSI for both the uplink and the downlink. Massive MIMO operation relies largely on good channel estimates and data capture to enable continuous and reliable transmission. To estimate CSI, pilot data is transferred between the base station and the smart node to ensure optimal radio link connections. The technique is divided into two categories based on resource allocation (time and frequency). FDD is a time-continuous phenomenon, whereas TDD comprises discontinuous transmission slots as illustrate on figure 1.4 below(Siddiqui et al., 2023).

The system in TDD Massive MIMO topologies is designed to take advantage of channel reciprocity. This means that for a given coherence interval, the forward (downlink) and reverse (uplink) channel replies are expected to be the same. Using channel reciprocity, the base station can use the predicted channel responses from the uplink training sequences to describe the downlink channel as well. This enables the base station to obtain the necessary channel state information (CSI) for downlink transmission without requiring additional downlink pilots. Because the uplink and downlink channels are reciprocal, the base station can simply apply the uplink CSI estimates for subsequent downlink transmissions within the same coherence interval. This considerably minimizes the overhead requirements for downlink CSI acquisition. This method is a fundamental feature of TDD Massive MIMO systems since it simplifies channel estimation and allows for more efficient use of available resources. The assumption of channel reciprocity is crucial in realizing the full potential of massive MIMO in TDD designs(Rajani et al., 2018).

In contrast to TDD systems, FDD Massive MIMO topologies have non-reciprocal uplink and downlink channels. This means that the base station cannot simply use the uplink channel estimations for downlink broadcast. Instead, FDD systems require a closed-loop setup for channel estimation. In uplink channel estimation, the base station calculates the reverse (uplink) channel using training sequences given by users. This helps to lower the computational load and power consumption on mobile devices. To estimate the forward (downlink) channel, the base station must first send its own training sequences. The users then offer the base station with limited input on the predicted downlink channel state information (CSI). This feedback-based method is required in FDD systems since channel reciprocity cannot be assumed. The base station needs the downlink CSI to precoding and beamforming the downlink transmission(ScholarWorks et al., 2016).

Massive MIMO systems for TDD designs necessitate the same number of training sequences as the number of users since the base station can exploit channel reciprocity to reuse uplink channel estimates for downlink transmission. However, for FDD systems, the number of training sequences required is equal to the number of antennas deployed at the base. Because, the base station must transmit its own training sequences to all antennas in order to acquire the downlink channel state information (CSI) via feedback from the users(Siddiqui et al., 2023).

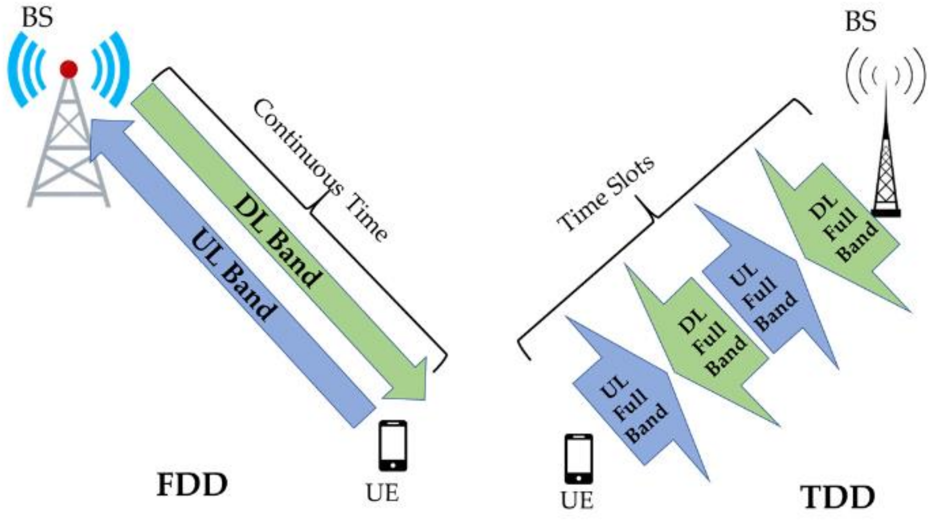


Figure 1. 4 (Siddiqui et al., 2023) FFD and TDD modes

1.2 Statement of the problem

The massive MIMO system is the technology lead to meet answer of the problem in high dense urban environment or areas with a high number of connected device as a promising solution to meet the growing need for faster data rates and enhance spectral efficiency in wireless communication systems. But, from an information-theoretical perspective, the spectral efficiency (SE) performance of a wireless communication system depends heavily not only on the signal-to-noise ratio (SNR), but also on the degree of spatial correlated fading. Since, in real-world circumstances, the SE of massive MIMO is influenced by spatial correlated fading, which is caused by LOS path along with scattered multipath components and dependencies among different antenna elements. So, in order to overcome the problem occurred due to spatial correlated fading, channel estimation techniques are introduced in this study. Furthermore, to improve the SE of Massive MIMO under spatial correlated fading MMSE, EW-MMSE and LS channel estimation techniques are developed.

1.3 Objective

1.3.1 General Objective

The main objective of this thesis is to investigate and Mitigation the impact of spatially correlated fading channels on massive MIMO system.

1.3.2 Specific Objectives.

- To investigate the impact of channel estimation errors on the spectral efficiency of uplink and downlink transmission in massive MIMO system.
- To evaluate the performance of various cumulative distribution function (CDF) curves for the UL SE per UE for different channels in Massive MIMO systems.
- To study and analyzes the performance of minimum mean squared error (MMSE) and Element-wise (EW-MMSE) for spatially correlated fading in Massive MIMO systems.
- To compare the average UL SE with uncorrelated fading as a function of the number of antennas.

1.4 Scope of the Study

This thesis is focus on optimizing spectral efficiency of massive MIMO performance in spatial correlated fading channels. Massive MIMO is an advanced wireless communication technology that leverages a large number of antennas at the base station to efficiently cater to multiple users concurrently. In wireless communication scenarios, Rician fading channels are frequently encountered, characterized by a combination of line-of-sight (LOS) and non-line-of-sight (NLOS) components that contribute to the overall signal propagation. The work offers a comprehensive analysis of channel estimation techniques and spectral efficiency in multi-cell Massive MIMO systems under spatially correlated Rician fading channels. Furthermore, the scope of the study may extend to investigate the impact of spatial correlation on the performance metrics of massive MIMO system such as spectral efficiency and system capacity. Overall, the scope of the study encompasses analysis an accurate mathematical model that captures the spatial correlation and Racian fading characteristics in massive MIMO system, with the aim of achieving better performance, optimizing the design and deployment of massive MIMO systems.

1.5 Significance of the Study

In telecommunications, the high data rate is essential for the smooth operation of wireless communications. Massive MIMO is a wireless communication technique that utilizes a substantial number of antennas at the base station to simultaneously serve multiple users. In a spatially correlated Rician fading channel, the fading characteristics are influenced by the correlation between different antennas and the presence of a dominant line-of-sight component. This study can assess the spectrum efficiency achieved by using massive MIMO in such channels, leading to improved wireless communication. Since in practical scenarios, the channels between different antennas are often correlated and understanding this correlation is crucial for designing efficient communication system. The significant of this thesis is that to enhance the understanding of the interaction between massive MIMO systems and realistic channel conditions, leading to improve design and performance of spectrum efficiency wireless communication networks. By incorporating the impact of spatially Rician fading the study seeks to enhance the quality of the received signals, energy efficiency, reliability, robustness of the communication system and overall system performance. Overall, a study on the investigation and mitigation correlated Rician fading channel in massive MIMO system can contribute to the advancement of based on performance by channel capacity, signal-to-noise ratio, and overall reliability of communication system.

1.6 Thesis Contribution

The major contributions of this thesis are as follows:

1. Applied different types of channel estimation techniques to alleviate the degradation of the spectrum efficiency in spatial correlation fading channel, which occurs due to physical proximity of antenna element and both line of sight and scattered components. Moreover, the performance comparisons of various type of channel estimation techniques performed in order to choose the best channel estimator to improve spectrum efficiency.
2. Depending upon the results found from the comparison, MMSE channel estimator demonstrated better performance to improve spectrum efficiency.

1.7 Limitation of the Study

This thesis is limited only to simulation based results. That means the performance of improving spectrum efficiency in spatial correlated fading channels are evaluated based on simulation results only.

1.8 Organization of the Thesis.

The thesis has been organized into five chapters.

Chapter 1 briefly discusses the background of the study. The problem statement, scope of the study, significance of the thesis and thesis objectives are also laid out here with its limitation.

Chapter 2 starts by discussing a brief introduction about Overview of massive MIMO and Massive MIMO techniques. Then functions of Massive MIMO are discussed in short. This chapter covers a related work of thesis.

Chapter 3 presents the research method that has been used in the thesis and the system models for spatial correlated fading in massive MIMO. Also, this chapter introduced materials that have been used for simulating the results.

Chapter 4 includes the results and discussion for the Uplink and Downlink Spectrum efficiency of multi-cell massive MIMO system are examined under spatial correlated Racian and Rayliegh fading channel.

Lastly, the Conclusion and Recommendation of the thesis are presented.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction.

Massive MIMO, also known as large-scale MIMO is a term used to describe MIMO systems with a significant number of antennas in which a base station equipped with M antennas communicates to K users concurrently. Concurrently refers to the transmission of signals to and from each user at the same time and frequency. Figure 2.1 represents the configuration, the transmission from the base station to the users is considered the downlink, while the transmission from the users to the base station is termed the uplink and it shows the base station with M antennas talking with multiple single-antenna users. MIMO (multiple-input multiple-output) is a radio antenna system that uses multiple antennas at both the transmitter and receiver to improve signal quality, throughput and capacity. It accomplishes this through two major strategies, spatial diversity and spatial multiplexing techniques. MIMO spatial diversity methods convey separate and independently encoded data signals called streams over the same time and frequency resource, resulting in increased data capacity. Spatial multiplexing techniques employ the same time and frequency resources to broadcast several data streams. In massive MIMO, the transmitter sends several streams to different users at the same time and frequency increasing network capacity. Adding more antennas to handle more streams can boost spectral efficiency and capacity, but power sharing and interference among users result in falling benefits and eventually, losses(Kansal et al., 2019).

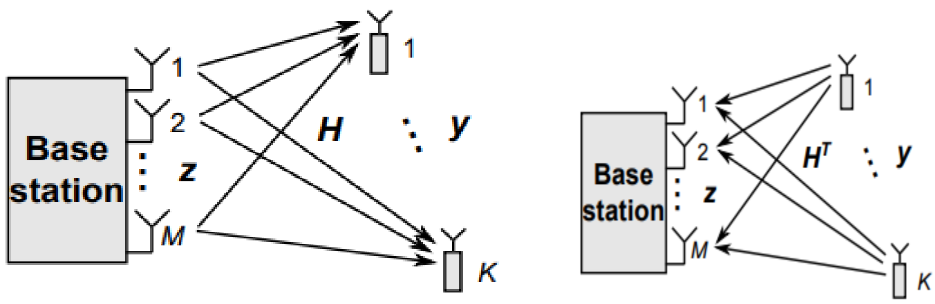


Figure 2. 1(a) (Kansal et al., 2019) Downlink (b) Uplink

Traditional MIMO systems use a small number (usually two) of antennas to broadcast and receive signals in several directions at the same time. Figure 2.2 depicts how the base station employs antennas to direct signals to the specified receiver in the downlink and divide them for uplink transmission. To reduce interference and enhance signal-to-noise ratio (SNR), consider using multiple antennas rather than delivering numerous data streams. As a result, in a Massive MIMO system the base station employs its huge number of antennas to downlink transmission and route the signal to the preferred receiver via techniques such as beamforming. This reduces interference and increases the signal-to-noise ratio (SNR) at the receiver. Additionally, uplink reception divides the numerous signals from different users, allowing for effective uplink transmission. This spatial segmentation of users aids in the management of interference and improves overall system performance.

The MIMO system provides enhanced wireless connectivity without the need for more spectrum, giving it a substantial advantage over traditional networks. Finally, massive MIMO can expand the capacity of a communication system by supporting more users with the same amount of resources(Ali et al., 2018)**.**

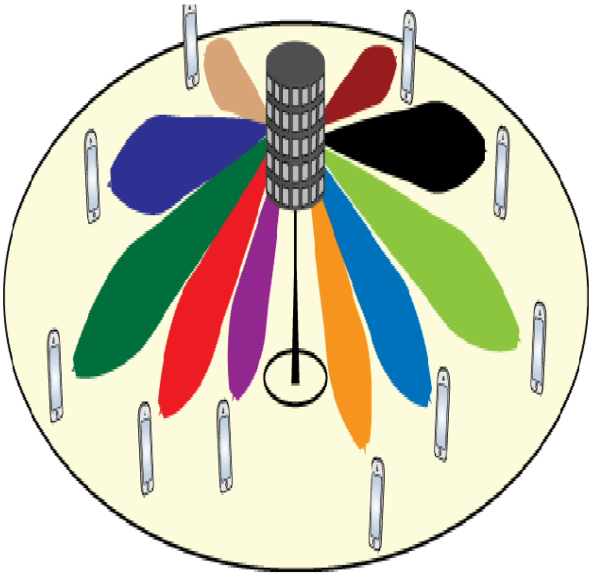


Figure 2. 2 (Ali et al., 2018) Uplink and Downlink transmission in a Massive MIMO system.

2.2 Related works.

In (Abebaw et al., 2023), analyze the spectral efficiency of an uplink multi-cell massive MIMO cellular communication system under fading channels. The paper proposes a model for evaluating area throughput using the linear zero forcing uplink combining scheme and considers the impact of different factors such as pilot reuse factor, number of users, number of base station antennas and propagation conditions on spectral efficiency. The paper also compares the performance of different channel estimators including LS, MMSE, and EW-MMSE and considers the impact of line-of-sight and non-line-of-sight communication over Rician fading channels. The paper may not extensively address the practical implementation challenges and considerations associated with deploying the proposed model and findings in real-world cellular communication systems.

In (Satya et al., 2023), a novel NOMA-Massive MIMO scheme are introduced to achieve higher spectral and power efficiency in 5G networks. In this paper where NOMA allows multiple users to share the same time-frequency resources by allocating different power levels and decoding orders, while massive MIMO utilizes a large number of antennas at the base station to exploit spatial diversity and multiplexing gain. By integrating NOMA and massive MIMO with successive interference cancellation(SIC) and zero forcing (ZF) techniques, the proposed scheme aims to mitigate multiuser interference and complexity challenges. While the paper mentions the use of successive interference cancellation(SIC) and zero forcing(ZF) techniques to mitigate multiuser interference. The effectiveness of these methods in dynamic and interference-laden environments not extensively discussed.

In (Abraham, 2022), the paper presents a comparative analysis of the performance of a massive MIMO base station using a correlated Rician fading model and an uncorrelated model. A statistical framework is employed, demonstrating that low-directivity antenna elements outperform high-directivity elements in angularly constrained Rician fading with off-axis incidence. Additionally, the paper introduces a method for handling correlated Rician fading in large-scale antenna systems, by providing accurate approximations. The paper facilitates effective analysis of the channel characteristics of a massive MIMO base station. Overall, the proposed model allows for a straightforward assessment of the performance of correlated Rician radio channels, considering factors such as antenna element pattern, array layout and Rician fading channels.

In (Shi et al., n.d.), the focus of this study is on the utilization of the minimum mean square error (MMSE) channel estimator for estimating the channels of aggregated reconfigurable intelligent surfaces (RIS). The paper presents an analysis of the uplink spectral efficiency in a cell-free massive MIMO system that incorporates spatially correlated RIS and multi-antenna access points (AP). Numerical results are provided to validate the analysis and assess the system's performance, considering the spatial correlation of RIS elements and AP antennas. The proposed techniques are compared with local minimum mean squared error (L-MMSE) and maximum ratio (MR) combining methods. The comparative results indicate that L-MMSE combining outperforms MR combining when there is a large number of RIS elements. Furthermore, the number of AP antennas has a more pronounced impact on system performance when there are fewer RIS elements, while the spatial correlation of RIS elements has a more significant negative effect on system performance compared to that of the AP antennas.

In (Zaheera, 2022), the paper examines the spectral efficiency of a cell-free massive multiple-input multiple-output (MIMO) system that operates in the presence of Rician fading channels. The analysis considers the impact of the random phase in the line-of-sight (LoS) path, which accounts for phase-shifts caused by mobility and phase noise. The study also takes into consideration the availability of prior information at the access points (APs) and compares the performance of different techniques including regularized zero-forcing (RZF), phase-aware minimum mean square error (MMSE), non-aware linear MMSE (LMMSE) and least-square (LS) estimators. The comparison reveals that the performance degradation resulting from the absence of phase information is influenced by the length of the pilot signal and remains minimal when pilot contamination is low.

In (Chaves et al., 2022), the purpose of this work is to investigate the computational complexity of various user selection algorithms and evaluate their performance in various system configurations while taking into account perfect and partial channel state information (CSI) under the LoS propagation channel. In addition, the research introduces and examines the computational complexity of ICIBS, a new user selection technique. Finally, the paper provides practical guidelines for massive MIMO system design, as well as a summary of the main findings of massive MIMO systems under LOS propagation. But, the research only addresses the LoS propagation model, which may not be representative of all practical cases and also does not give a comprehensive comparison of the proposed ICIBS algorithm with other state-of-the-art user selection algorithms.

In (Ueoka et al., 2022), analysis the performance of cell-free massive MIMO networks under different channel fading, specifically Rayleigh and Rician fading. In this paper it is used a simulation-based approach to investigate the performance of cell-free massive MIMO networks under different channel fading. Overall, the challenges of achieving reliable channel state information (CSI) in outdoor scenarios, where the low degrees of channel hardening can lead to poor spectral efficiency performance and the results indicate that Cell-Free systems achieve higher spectral efficiency when the channel behaves as a Rician fading and that statistical channel state information(CSI) is unreliable in outdoor scenarios. The study recommends alternative downlink (DL) channel estimation methods, such as blind estimation or DL pilot-based, to improve spectral efficiency in outdoor scenarios. But, the study only considers the downlink (DL) spectral efficiency (SE) and does not investigate other performance metrics, such as uplink (UL) SE or energy efficiency.

In (Amadid et al., 2022), the Channel Estimation (CE) process in a Massive MIMO system, particularly during the up-link (UL) phase is explained. This study compares the performance of various channel estimation strategies, such as the Minimum Mean Square Error (MMSE) estimator, the Least Squares (LS) estimator and the Modified MMSE (M-MMSE) estimator, for both uncorrelated and correlated channels. Also proposed was a Uniform Planar Array (UPA) configuration for correlated channels, which delivers greater performance than the typical Uniform Linear Array (ULA) arrangement. Overall, the research finds that the proposed methodologies can greatly improve channel estimation in Massive MIMO systems, emphasizing the relevance of spatial correlation in an urban network. However, the research does not address the effect of other forms of fading channels, such as Rayleigh or Rician fading on the performance of the suggested channel estimating algorithms. Furthermore, the research does not address the impact of the various types of pilot sequences on the performance of the channel estimation algorithms.

In (Naraiah et al., 2021), focuses on the issues of improving spectral efficiency in wireless communications to meet the needs of 5G technology. The research examined certain beam management approaches in millimeter-wave communications for 5G networks. This evaluation could entail determining the efficiency of beamforming technologies in enhancing spectral efficiency, capacity and coverage in wireless networks. The comparison of different methodologies for enhancing spectral efficiency in Massive MIMO systems has a limited scope, perhaps omitting alternative approaches or strategies that could be advantageous for 5G communications.

In (Fading et al., 2020), the analysis focuses on analyzing the performance of huge MIMO systems with users equipped with numerous antennas taking into account a generalized channel. The study considers a channel model that contains both line-of-sight propagation and spatially correlated multipath fading. To examine spectrum efficiency, the study employs the Weichselberger model, which allows for the inclusion of multiple representations such as Kronecker and virtual channel models as special cases. According to the study, in the case of jointly correlated fading, uplink spectrum efficiency does not increase forever as the number of base stations increases. This constraint can be solved by providing precoding at the user side, although this technique introduces additional overhead. In the scenario of omnidirectional uplink transmissions, the negative impact of the joint correlation structure of the channel can be mitigated by serving users with a single antenna.

In (Sadraei et al., 2020), it examines the instantaneous spectrum efficiency of multi-cell large MIMO systems using correlated Rician channels. The work suggests closed-form approximations for the ergodic spectrum efficiency of the Maximum Ratio Combining (MRC) detector in the presence of Least Squares (LS) and Minimum Mean Square Error (MMSE) estimators. The analysis focuses on the scenario of poor channel state information (CSI). A novel approach is presented for analyzing the spectrum efficiency of correlated Rician channels with poor CSI. In this method, each user's Signal-to-Interference-Plus-Noise Ratio (SINR) is determined using the equivalent channel, which is created by cascading the estimated channel and the detector. This technique uses all available CSI information. Overall, the paper presents a comprehensive analysis of the spectrum efficiency for correlated Rician channels in the presence of imperfect CSI, employing a novel methodology that incorporates the estimated channel and the detector to calculate the SINR of each user.

In (Wikiman & Idowu-bismark, 2019), it analyzes the performance of large MIMO systems in a Rician channel using a zero-forcing precoder to improve spectral efficiency and capacity. The study's goal is to validate large MIMO technology's ability to thrive over several fading channels while also exploiting spatial diversity to increase spectral efficiency. The research uses simulations and analysis to demonstrate that huge MIMO systems can achieve high throughput in a Rician channel. The adoption of a zero forcing precoder reduces interference and increases the system's spectral efficiency. The results confirm the hypothesis that massive MIMO technology may effectively leverage spatial diversity to increase performance in difficult and fading conditions. Overall, the study provides evidence that massive MIMO systems can deliver significant enhancements in throughput and spectral efficiency particularly in Rician fading channels, thus validating the potential and expectations associated with this technology.

In (Rajmane & Sudha, 2019), it looks into improving spectral efficiency in 5G wireless communication using huge Multiple Input Multiple Output (MIMO) devices. The work focuses on downlink spectral efficiency analysis in a single circular cell scenario, assuming that the base station has previous knowledge of channel state information (CSI) and applies linear precoding techniques. A comparison is provided between the spectral efficiency performance of Uniform Linear Array (ULA) and sub-ULA configurations, emphasizing the advantages of various array arrangements. The study focused on suppressing inter-user interference through the optimization of antenna array topologies and linear precoding techniques. By reducing interference, the system's spectral efficiency was improved. The paper has made simplifying assumptions in the modeling and analysis such as perfect Channel State Information (CSI) at the base station, which may not fully represent real-world scenarios where CSI estimation errors exist and while the paper compares ULA and sub-ULA configurations, it may not have explored a wide range of antenna array configurations, potentially overlooking other configurations that could offer improved spectral efficiency.

In (Shlezinger et al., 2019), focuses on the spectral efficiency (SE) of uplink massive MIMO systems that allow Base Stations (BSs) to collaboratively decode received signals. This research presented three decoding schemes, collaborative decoding of signals from related user terminals (UTs) at each BS, decoding signals from all (UTs) in the network at each BS and dividing the data transmission phase between cells to eliminate inter-cell interference. The research also discussed an optimized network that combines these approaches to increase SE by allowing BSs to decode some inter-cell interference while considering the rest as noise. Simulation tests show that allowing BSs to do joint decoding results in higher SE gains than separate linear decoding and that the usual strategy of separate linear decoding is inadequate especially when interference is prevalent. The paper primarily considers non-cooperative uplink massive MIMO systems without delving into the complexities of practical deployment challenges such as hardware constraints, synchronization issues, pilot contamination and feedback overhead. These real-world factors can significantly impact the performance of massive MIMO systems but are not extensively addressed in the paper. Additionally, its limitations lie in the lack of extensive empirical validation consideration of practical deployment challenges and the idealized assumptions made in the analysis. Addressing these limitations in future research could enhance the applicability and relevance of the findings in real-world wireless communication systems.

In (Abid et al., 2019), a low-complexity detector based on a two-layer linear receiver structure was proposed to prevent interference and improve uplink performance analysis for massive MIMO. The suggested two-layer processing techniques have much reduced computation complexity than the M-MMSE receiver, as demonstrated in this study. Analytical expressions for residual interference power at the output of the first-layer M-MMSE processing are studied, considering intra-cell and inter-cell interference, and the effects of small-scale fading, large-scale losses (e.g., path loss, shadow fading), and the number of antenna elements in each subset on residual interference power. But, the paper primarily considers the performance of the proposed schemes in the context of specific system parameters and scenarios, such as a limited number of interferers and a fixed antenna array size. The generalizability of the results to diverse network configurations and operating conditions may be limited, and further investigation under varying interference levels, antenna array sizes, and network topologies could provide a more comprehensive understanding of the proposed techniques effectiveness. Additionally, the paper focuses on uplink performance analysis, and the implications of the proposed linear processing schemes on downlink transmission and overall system efficiency are not extensively explored. Investigating the impact of the proposed schemes on downlink communication, resource allocation, and system-level performance optimization could offer a more holistic view of their benefits and limitations in practical massive MIMO deployments.

In (Wu et al., 2017), to increase channel estimation accuracy in the presence of pilot contamination, two algorithms are proposed, one based on LOS components and other based on data-aided iteration. This paper presents a novel channel estimation scheme that effectively addresses pilot contamination in massive MIMO systems operating in Rician fading channels. By leveraging the statistical information of channels and exploiting the property that the LOS component is not affected by pilot contamination with a large number of base station antennas, the proposed scheme accurately estimates the LOS components of users served by a base station. The suggested approach assumes that the Line-of-Sight (LOS) components are present between base stations and serviced users, but no LOS components exist between base stations and users from other cells. This assumption may not always hold in practice and also compares the proposed scheme to existing schemes in terms of spectral efficiency, a broader range of performance metrics such as latency, energy efficiency, or robustness to varying channel conditions could provide a more comprehensive evaluation.

Table 2. 1: A Summary of some related work.

Authors	Year	Title	Techniques and Concept Covered	Gaps or Concept not Covered
Abebaw et al	2023	Spectral Efficiency Analysis for Uplink Multi-cell Massive MIMO Cellular Communication System under Fading Channels	The paper uses a simulation-based approach to evaluate the spectral efficiency of an uplink multi-cell massive MIMO cellular communication system under fading channels	may not extensively address the practical implementation challenges and considerations associated with deploying the proposed model
Jens Abraham	2022	Statistics of the Effective Massive MIMO Channel in Correlated Rician Fading	The statistical framework are proposed for perform high-directivity elements in angular constricted Rician fading with off-axis incidence	This paper focuses only on angular constricted Rician fading. It doesn't include spherical wave model Rician fading
Shi et al., n.d	2022	Uplink Performance of RIS-aided Cell-Free Massive MIMO System Over Spatially Correlated Channels	Minimum mean square error (MMSE) channel estimator is Proposed to estimate the aggregated RIS channels.	Even though it improves the performance with a large number of RIS elements, the proposed technique is not robust to the beamforming design to enable the implementation of

				RIS-aided CF M-MIMO networks.
Fathima Zaheera	2022	Large-scale Fading Decoding based Massive MIMO System with Regularized Zero Forcing Precoder	In this paper A combined scheme of RZF equalizer-based inter cell interference mitigation approach is employed for enhancing the performance of Massive MIMO system	This paper focuses only on Rayleigh fading channel. It doesn’t include other types of Fading like Racian fading channel
Fading et a	2020	Massive MIMO with Multi-Antenna Users under Jointly Correlated Rician Fading	It proposed to analysis of spectrum efficiency utilizes the Weichselberger model and considers a channel model that incorporates line-of-sight propagation and spatially correlated multipath fading	It is only analyzed the performance of multi-cell massive MIMO with single-antenna users under correlated Rician fading and pilot contamination

CHAPTER THREE

MATERIAL AND METHODS

3.1 Overview

This thesis reviews several related papers and articles from publications such as IEEE, Springer, and Elsevier, as well as books on Massive MIMO systems. Based on the studied publications and with the problem statement in mind, the methodology and flow chart given in section 3.3 are followed to build and simulate the proposed methods/techniques.

3.2 Material

This study focused on the examination and mitigation of spatial correlated fading in massive MIMO systems. The MATLAB/R2023 software platform is used to investigate and mitigate spatial correlated fading in massive MIMO systems. MATLAB is a high-performance programming language for technical computing. It is also computing software, which includes technical boxes and Simulink. Developed algorithms using MATLAB, analyzed data and created models.

3.3 Methods of the study

To accomplish the above-mentioned general and specific objectives of the thesis, proceed through the following methodology and flow chart as shown in figure 3.1 and figure 3.2, respectively.

Literature Review: the thesis work is based on prior research on the subject by experts or scholars. So, by examining the works of these academics and acquiring relevant and important knowledge about the proposed thesis work. It is reviewed using a range of sources, such as books, journals, papers, the internet, and so on. As a result, the literature review includes reading articles, conference papers, books, journals, and exploring the internet for relevant topics (i.e. the impact of spatial correlated fading channels on a Massive MIMO system).

Problem Identification: based on examined papers from different publications, journals, and conferences, the research gaps identified for research inquiry.

System Designing: proceed to system designed after identification of research gap for thesis work**.**

Simulation of designed System using MATLAB: after modeled of proposed system designed, simulated using MATLAB tools.

Result and Discussion: based on simulation results, the performed discussions are done on the result and also performance analyzed are done on proposed techniques.

Documentation: After analyzed the results of the designed system, the whole work of the research study is concluded by suggesting an implied recommendation and future work to be done on the areas.

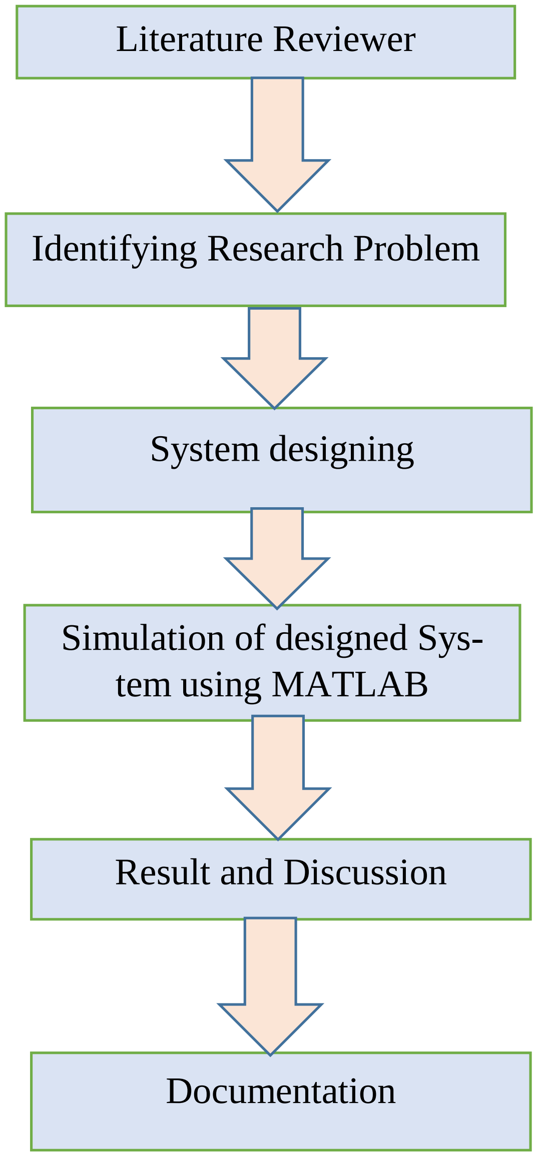


Figure 3. 1 Methodology.

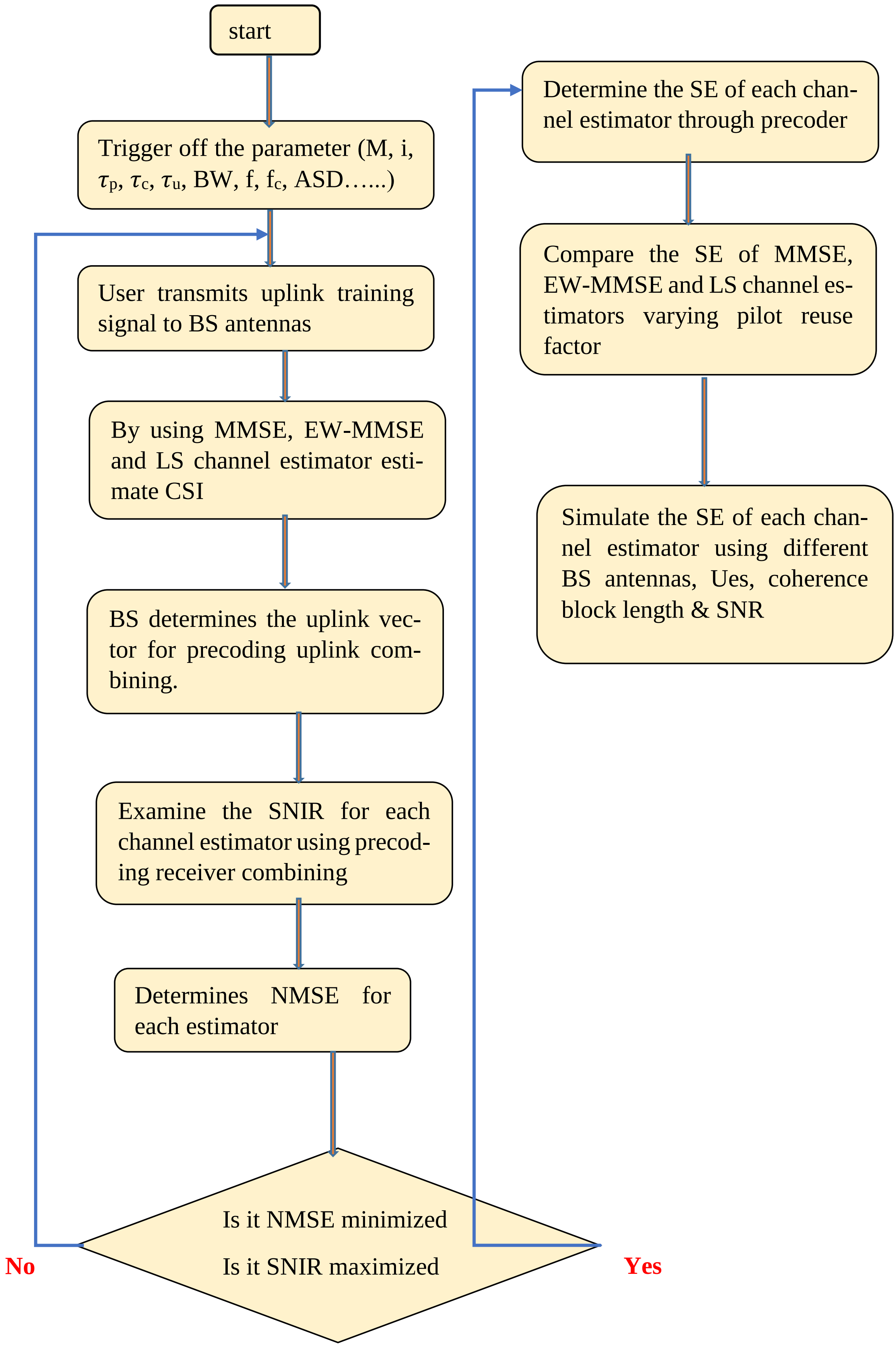


Figure 3. 2 Flow chart of Spectrum Efficiency analysis

3.4 System Model for spatially correlated fading in massive MIMO.

This section introduces a system model created specifically for a multicellular huge MIMO system running in Time Division Duplex (TDD). During the creation of the multicellular massive MIMO system model, relevant channel models are carefully selected and designed. The system model shown in Figure 3.2, accounts for the true characteristics of a multicellular massive MIMO system operating under Rician fading. This Time Division Duplex (TDD) technique allows several cells to share the same time-frequency resources. All user equipment concurrently uses the available frequency-time resources for both uplink pilot and data transmission functions. Taken into consideration a Massive MIMO system with M cells, where each cell is made up of one base station (BS) that supports i single-antenna user equipment (UEs) and has N_j antennas. When the system is in TDD mode, the channel responses throughout a coherence block of τ_c samples are constant. Furthermore, consider for granted that there is no correlation between the channel realizations of any two coherence blocks. The carrier frequency and extrinsic parameters like UE mobility and propagation environment dictate the size of τ_c. The samples have three distinct uses, τ_p samples for pilot signals in the uplink (UL) domain, τ_u samples for data transmission in the UL domain, and τ_d samples for data transmission in the downlink (DL) domain, where $\tau_c = \tau_p + \tau_u + \tau_d$. The channels UL and DL are estimated by the received pilot signals and sends back the channel state information (CSI) to the BS.

The channel response denoted as $h_{Mi}^{j} \in \mathbb{C}^{Nj}$, which represents the propagation from users i in cell M to the base station (BS) within the j^{th} cell, is modeled using Rician fading channels. Where the BS index is indicated by the superscript h_{Mi}^{j}, while the cell and UE indexes are identified by the subscript. In this context, examined spatial correlated fading channels, where $h_{Mi}^{j}, \forall j, m \in 1 \dots . M$ and $\forall i \in 1 \dots . I$ represents a specific instance of the circularly symmetric complex Gaussian distribution. So The channel coefficient h_{MI}^{j} between the j^{th} antenna at the base station and the N^{th} antenna of the i^{th} user can be modeled as a complex-valued random variable.

$$h_{Mi}^{j} \sim N_C(\check{h}_{Mi}^{j}, R_{Mi}^{j}) \qquad (3.1)$$

Where $\check{h}_{Mi}^{j} \in \mathbb{C}^{Nj}$ is corresponding to the LOS component with zero mean and unity variance assumed to be $N_C\,(0, I_m)$ and $R_{Mi}^{j} \in \mathbb{C}^{N_j \times N_j}$ is corresponding to the NLOS component of positive semi-define covariance matrix of spatial correlation. The small scale fading is characterized by a Gaussian distribution, while $\check{h}_{Mi}^{j}$ and R_{Mi}^{j} represent the macroscopic propagation effects, encompassing path loss, shadow fading, as well as the antenna gains and radiation patterns at the transmitter and receiver. This statistical model provides a compact way to describe the characteristics of the Massive MIMO channel, which is essential for analyzing and designing efficient communication systems that leverage the spatial degrees of freedom offered by Massive MIMO architectures. Since there is a lot of channel loss so the average channel gain from one of the antennas at BS j to UE i in cell M is try to determine by the normalized trace. Therefore, it is expressed as:

$$\beta_{Mi}^{j} = \frac{1}{N_j} tr\left(R_{Mi}^{j} \right) \qquad (3.2)$$

Where β_{Mi}^{j} represents the combined effect of path loss and shadowing on the wireless channel between the base station and the user which called large scale fading coefficient

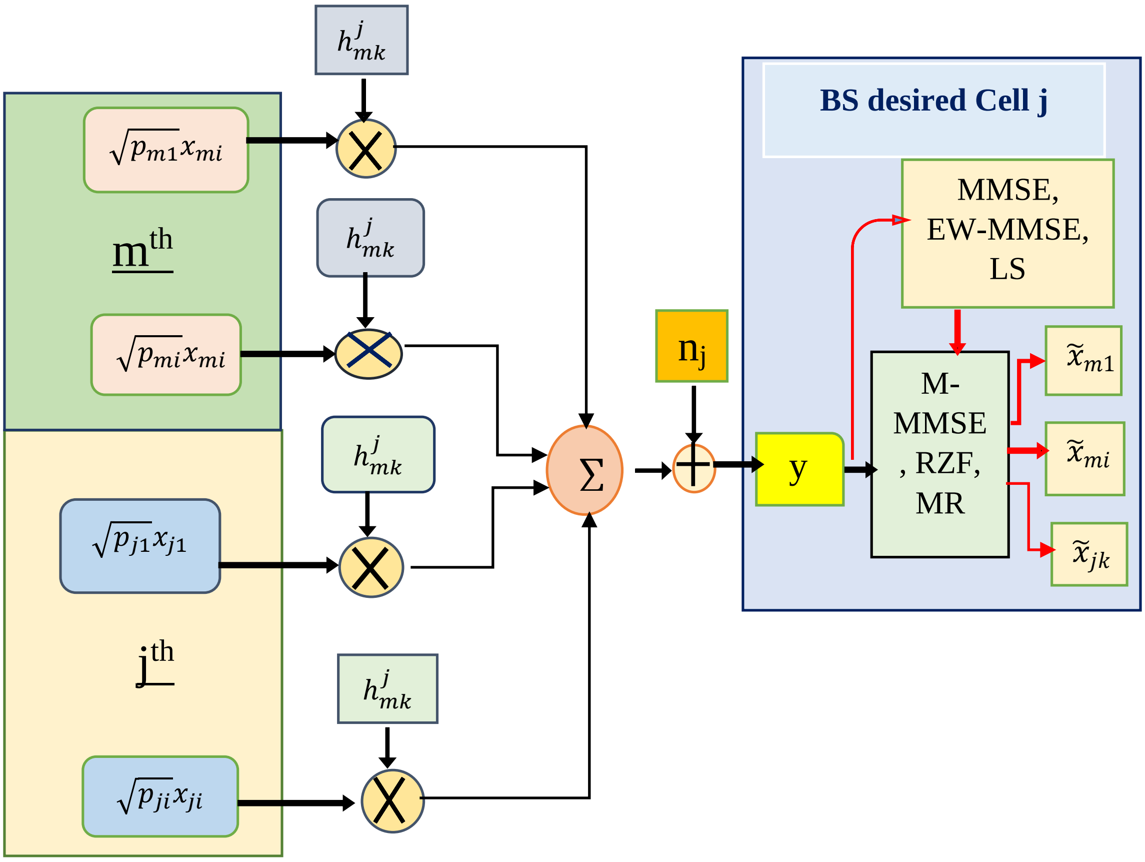


Figure 3. 3 System Block Diagram Model for Uplink Massive MIMO.

3.5 Channel Estimation for spatially correlated fading in massive MIMO

Channel estimation is critical in Massive MIMO (Multiple-Input Multiple-Output) systems, particularly where spatial correlation fading is a concern. Massive MIMO uses a base station with a high number of antennas to serve several users at the same time, resulting in better spectral efficiency and system capacity. However, due to the presence of spatial correlation, channel estimation becomes more complicated. Spatial correlation is a statistical link between the channel coefficients of different antennas. In Massive MIMO systems, the channels between the base station antennas and user equipment's (UEs) are often correlated due to the proximity of antennas and similar propagation environments. This correlation can affect the accuracy of channel estimation and subsequently degrade system performance if not properly considered. Therefore, it need to estimating the channel state information (CSI) between the base station and multiple users in a massive multiple-input multiple-output (MIMO) system, taking into account the spatial correlation of the fading channels. To address this issue, channel estimation algorithms for spatial correlation fading in Massive MIMO systems must take into account the spatial correlation structure of the channels. This can be accomplished by utilizing the known statistical properties of the spatial correlation, such as Toeplitz or circulant structures, to design efficient channel estimation. These techniques aim to accurately estimate the channel coefficients while taking into account the spatial correlation effects to improve system performance. Therefore, the channel estimation on this thesis considered under the uplink pilot based channel estimation τ_p sample in each coherence block are reserved, and allowing space for τ_p pilot sequences that are mutually orthogonal. A proper pilot assignment is a demanding task for minimizing interference in the transmission channel. While it is critical to dedicate more pilots for accurate channel estimation and to reduce pilot contamination, spectral efficiency suffers as more resources during the coherence interval are devoted to pilots for estimation rather than the actual data payload for transmission. These pilot sequences are assigned to different User Equipment (UEs), and the same sequences are used by UEs across many cells. The predetermined pilot sequence of UE i in cell j Consider Φ_{ji} as the pilot sequence for the i^{th} UE in the j^{th} cell. Each element of Φ_{ji} is multiplied by the uplink transmit power $\sqrt{p_{ji}}$ and transmitted as the signal x_{ji} over a duration of τ_p uplink samples. This results in the received uplink signal, denoted as $y_j^{pilot} \in \mathbb{C}^{N_j \times \tau_p}$ at BS j. Therefore, the expression for the received pilot signal is as follows:

$$y_j^{pilot} = \sum_{i=1}^{i_j} \sqrt{p_{ji}}\ h_{ji}^j + \sum_{\substack{m=1 \\ m\neq 1}}^{M} \sum_{k=1}^{i_M} \sqrt{p_{Mk}}\ h_{Mi}^j \Phi_{Mk}^j + n_j^{pilot} \tag{3.3}$$

Where $n_j^{pilot} \in \mathbb{C}^{N_j \times \tau_p}$ consists of independent and identically distributed complex Gaussian elements with zero mean and variance σ_{ul}^2. These element are used to estimate h_{Mi}^j, where BS j multiplies y_j^{pilot} by UE's pilot sequence Φ_{Mk}^* can be express as:

$$y_j^{pilot} \Phi_{mi}^* = \sqrt{p_{ji}}\, h_{ji}^j \Phi_{ji}^T\, \Phi_{mi}^* + \sum_{\substack{i=1 \\ i\neq k}}^{k_j} \sqrt{p_{ji}}\ h_{ji}^j\, \Phi_{ji}^j\, \Phi_{mi}^*$$
$$+ \sum_{\substack{m=1 \\ m\neq j}}^{M} \sum_{i=1}^{k} \sqrt{p_{Mi}}\ h_{Mi}^i\, \Phi_{Mi}^j \Phi_{Mi}^* + n_j^{pilot}\, \Phi_{mi}^* \tag{3.4}$$

In order to estimate the channel for the i^{th} user within the cell using the signal mentioned above, a projection of y_j^{pilot} onto Φ_{ji}^* is performed to obtain y_{jmi}^{pilot} . The procedure can be described as follows:

$$y_j^{pilot} = \sqrt{p_{ji}}\, h_{ji}^{\,j}\, \Phi_{ji}^T\, \Phi_{ji}^* + \sum_{\substack{k=1 \\ k\neq i}}^{i_j} \sqrt{p_{jk}}\ h_{jk}^j\, \Phi_{jk}^T \Phi_{ji}^* + \sum_{\substack{m=1 \\ m\neq j}}^{M} \sum_{k=1}^{i_m} \sqrt{p_{km}}\ h_{mk}\, \Phi_{ji}^*$$
$$+ n_j^{pilot} \Phi_{ji}^* \tag{3.5}$$

$$y_{jji}^{pilot} = \sqrt{p_{ik}}\, h_{mi}^j\, \tau_p + n_j\, \Phi_{ji}^* \tag{3.6}$$

Note that for all, $y_{jjk}^{pilot} = y_{jmi}^{pilot}$ where $(M, i) \in \vartheta_{jk}$, due to the utilization of the same pilot for all these UEs. When operating within its own cell, there is a potential for significant interference. Therefore, it is crucial to carefully assign pilots for the desired cellular network in order to effectively utilize the desired pilot sequence. The value of ϑ_{jk} is determined as follows:

$$\vartheta_{jk} = \{\, (m, i) \colon \Phi_{mi} = \Phi_{jk};\, m = 1, 2 \dots \dots M \ and\ i = 1, 2 \dots .\, K_m \}$$

The UL-DL duality drives a straightforward precoding design principle select DL precoding vectors depending on UL receive combining vectors as:

$$\mathtt{W}_{ji} = \frac{\vartheta_{ji}}{\|\vartheta_{ji}\|} \tag{3.7}$$

Where

$$\left[\vartheta_{ji} \dots \dots \dots \vartheta_{ji_j}\right] = \begin{cases} \vartheta_{ji}^{M-MMSE} \; with\ M - MMSE\ precoding. \\ \vartheta_j^{RZF} \qquad with\ RZF\ precoding. \\ \vartheta_j^{MR} \qquad with\ MR\ precoding. \end{cases}$$

Therefore, these precoding techniques depend on the UL transmit power utilized during pilot signaling, but none of them depends on the DL transmit power (which however appears in the DL effective SINR expression). One notable benefit of employing the receive combining vectors for transmit precoding is that the computational complexity of computing the precoding vectors reduced.

The prepared gotten pilot flag $y_{jmi}^{pilot} \in \mathbb{C}^{N_j}$ could be an adequate measurements for assessing h_{Mi}^{j}. presently consider channel estimation at the user end, each user receives the pilot signals and estimates the channel response by using techniques such as minimum mean square error estimation, element-wise minimum mean square error estimation, least squares estimation.

3.5.1 Least Square Channel Estimator(LS)

The Least Square channel estimator works on the premise of minimizing the sum of squared errors between the estimated channel response and the received signal. The Least Square channel estimator estimates the channel response by solving a series of linear equations that minimize the sum of squared errors between the received and estimated signals. This estimate procedure is commonly conducted using matrix operations, which describe the received signal and the channel response as matrices. In this channel estimator the transferred data rate and pilots are signified by x between user equipment and the base station.

$$y^{pilot} = h * x \qquad (3.8)$$

Where y^{pilot} is the received pilot signal, h is the unknown channel from UEs to BS antenna, and x represents both the data rate and pilot length.

The unknown channels between UEs and BS antennas can be estimated using the received pilot signal as:

$$h = y^{pilot} * \bar{x} \qquad (3.9)$$

If the BS has no prior knowledge of R_{mi}^{j} and $\bar{h}_{mi}^{j}$, the non-Bayesian LS estimator is utilized to estimate the propagation channel h_{mi}^{j}. The LS estimate is the vector of $\check{h}_{mi}^{j}$ that minimizes $\|y^{pilot} - \sqrt{p_{mi}}\,\tau_p\,\check{h}_{mi}^{j}\,||^2$. Which, in this case is:

$$\check{h}_{mi}^{j} = \frac{1}{\sqrt{p_{mi}}}\, y_{jmi}^{pilot} \tag{3.10}$$

The least square channel estimator and estimator error correlated random variable and distributed as:

$$\check{h}_{mi}^{j} \sim N_{\mathbb{C}}\,(\frac{1}{\sqrt{p_{mi}\tau_p}}\,\bar{y}_{jmi}^{pilot},\ \frac{1}{p_{mi}\tau_p}\,(\Phi_{mi})^{-1} \tag{3.11}$$

$$\tilde{h}_{mi}^{j} \sim N_{\mathbb{C}}\,(\bar{h}_{mi}^{j} - \frac{1}{\sqrt{p_{mi}}\tau_p} y_{jmi}^{pilot}, \frac{1}{p_{mi}\tau_p}\left(\Phi_{mi}^{j}\,)^{-1} - R_{mi}^{j}\right) \tag{3.12}$$

If reusing the chosen cellular system pilot increases capacity and reduces contamination, simplifying the expression as below.

$$\check{h}_{mi}^{j} = \frac{1}{\sqrt{p_{mi}\tau_p}}(\sqrt{p_{mi}}\,\tau_p\,h_{mi}^{j} + \sum_{(m,i)\setminus(j,m)}\sqrt{p_{mi}}\ \ \tau_p h_{mi}^{j} + n_j\Phi_j) \tag{3.13}$$

3.5.2 Minimum mean square error channel estimator (MMSE).

This channel estimator, estimate the channel response between the transmitter and receiver. The MMSE channel estimator in massive MIMO systems with spatial correlation fading seeks to reduce the mean square error between the estimated channel response and the true channel response. As a result, channel estimators employ observed pilot signals to estimate an unknown channel parameter (h). The estimated channel value is defined $\check{h}_{Mi}^{j}$. The MMSE channel estimator is designed to generate channel state information(CSI) at the receiver while minimizing interference errors. Using a pilot book that consists of mutually orthogonal sequences, the Minimum Mean Squared Error (MMSE) estimation of the channel h_{Mi}^{j} is performed based on the observation y_j^{pilot} in (3.3).

$$\check{h}_{Mi}^{j} = \sqrt{p_{Mi}}\,R_{Mi}^{j}\Phi_{Mi}^{j}y_{jmi}^{pilot} \tag{3.14}$$

An estimation error $\tilde{h}_{Mi}^{j} = h_{Mi}^{j} - \check{h}_{Mi}^{j}$ has the correlation matrix is represented by:

$$C_{Mi}^{j} = E\{\tilde{h}_{mi}^{j}\,(\tilde{h}_{mi}^{j}\,)^{H}\,\} \tag{3.15}$$

It is also represented by: $C_{Mi}^{j} = R_{Mi}^{j} - p_{Mi}\,R_{mi}^{j}\,\Phi_{mi}^{j}\,R_{mi}^{j}$ (3.16)

This equation calculates the MMSE from any user equipment(UE) in the network to the base station j. The MMSE estimator minimizes the MSE of the channel estimate, expressed as:

$$E\{ || h^{j}_{mi} - \check{h}^{j}_{mi} ||^{2} \} = E\{ || \tilde{h}^{j}_{mi} ||^{2} \} = E\{ tr(\tilde{h}^{j}_{mi} (\tilde{h}^{j}_{mi})^{H} \} = tr\left(C^{j}_{mi}\right) \quad (3.17)$$

The MMSE estimate $\check{h}^{j}_{mi}$ and estimated error $\tilde{h}^{j}_{mi}$ are independent random variables with the following distribution:

$$\check{h}^{j}_{mi} \sim N_{\mathbb{C}}\left(\tilde{h}^{j}_{mi}, R^{j}_{mi} - C^{j}_{mi}\right) \quad (3.18)$$

$$\tilde{h}^{j}_{mi} \sim N_{\mathbb{C}}\left(0_{M}, C^{j}_{mi}\right) \quad (3.19)$$

The estimation error covariance matrix C^{j}_{mi} is independent of mean values or the estimation error is unaffected by LoS components, as they may be removed from the received signals.

3.5.3 Element-Wise Minimum Mean Square Error Channel Estimator(EW-MMSE).

The EW-MMSE channel estimator divides the channel response into individual elements, which are estimated separately. This enables a more accurate estimation of the channel response, particularly in scenarios where the channel is time-varying or frequency selective. If the BS lacks information of the complete covariance matrix, the EW-MMSE estimation can be employed as an alternative. The EW-MMSE estimate for the channel from BS j to UE i in a specific cell M.

$$\check{h}^{j}_{mi} = \overline{h}^{j}_{mi} + \sqrt{p_{mi}}\, D^{j}_{mi}\, \Lambda^{j}_{mi} \left(y^{pilot}_{jmi} - \overline{y}^{pilot}_{jmi}\right) \quad (3.20)$$

Where $D^{j}_{mi} \in \mathbb{C}^{N_j \times N_j}$ and $\Lambda^{j}_{mi} \in \mathbb{C}^{N_j \times N_j}$ are diagonal matrices with $D^{j}_{mi} = diag([R^{j}_{mi}]_{nm} : n = 1 \ldots\ldots\ldots . N_j)$ and $\Lambda^{j}_{mi} = daig([\sum_{(m',\ i')} p_{m',i'}\, \tau_p\, R^{j}_{m',i'} + \sigma^2 I_{N_j}]_{nm} : n = 1 \ldots\ldots\ldots . N_j)$

3.5.4 Uplink Spectral Efficiency using the MMSE Estimator.

In a wireless system's uplink communication scenario, spectral efficiency refers to the rate at which data may be safely sent from user equipment (UE) to base station (BS) over a given bandwidth. When the MMSE channel estimator is used in uplink communication, the goal is to accurately predict the channel response between the UE and BS while accounting for channel statistical characteristics and noise. Minimizing the mean square error between the estimated and real channel responses. Generally when data transmitted, the received signal $y_j^{pilot} \in \mathbb{C}^{N_j}$ at BS j is

$$y_j^{pilot} = \sum_{i=1}^{i_j} h_{ji}^{j} S_{ji} + \sum_{\substack{m=1 \\ m\neq j}}^{M} \sum_{i=1}^{k_m} h_{mi} S_{mi} + n_j \qquad (3.21)$$

Where n_j represents additive noise expressed as $n_j \sim N_{\mathbb{C}}(0_m\ ;\ \sigma_{ul}^2\ I_{Mi})$ also the uplink signal from user i in cell M is expressed by $S_{Mi} \in \mathbb{C}$ and has power $p_{Mi} = E\{|S_{Mi}|^2\}$. From the above equation the first term represents desired signal, the second term represents interference and the last term represents noise. This section analyzes the possible SE of the UL using the MMSE estimator with various receive combining techniques. The total UL capacity of UE i in cell j can be calculated using the following formula

$$V_{ji}^{UL} = V_{ji}^{UL}\, \check{h}_{ji}^{j}\, S_i + V_{ji}^{H}\, \tilde{h}_{ji}^{j} S_{ji} + \sum_{\substack{i=1 \\ i\neq k}}^{i_j} V_{ji}^{H}\, h_{jk}^{j} S_{ji} \sum_{m=1}^{M} \sum_{k=1}^{i_m} V_{ji}^{UL} h_{Umi}^{j} S_{mi} + V_{ji}^{UL} n_j \qquad (3.22)$$

Therefore, the spectrum efficiency of the uplink for M cells and user equipment i expressed by:

$$SE_{ji}^{UL} = \frac{\tau_U}{\tau_C} E\{\log_2(1 + SINR_{ji}^{M})\}\ bitps/Hz \qquad (3.23)$$

Where the effective SNR becomes:

$$SINR_{ji}^{UL} = \frac{p_{ji}\, |V_{ji}^{H}\, \check{h}_{ji}^{j}|^2}{\sum_{m=1}^{M} \sum_{\substack{k=1 \\ (UL,k)\neq(j,i)}}^{i_m} p_{Umi} |V_{ji}^{H}\, \check{h}_{ji}^{j}|^2 + V_{ji}^{H}\,(\sum_{m=1}^{M} \sum_{UMi=1}^{i_m} p_{Umi}\, C_{Umi} + \delta_{UL}^2\, I_{Mj})V_{ji}} \qquad (3.24)$$

3.5.5 Uplink Spectral Efficiency using the EW-MMSE Estimator.

The EW-MMSE (Element- Wise Minimum Mean Square Error) estimator is a technique used for channel estimation and equalization in communication systems. The EW-MMSE estimator is an enhanced version of the MMSE estimator that incorporates exponential weighting to improve the estimation accuracy in time-varying channels. It assigns higher weights to recent channel observations and lower weights to older observations, which helps adapt the estimation to changing channel conditions. When it comes to uplink spectral efficiency using the EW-MMSE estimator, the basic idea remains the same as with the MMSE estimator. The goal is to estimate the channel characteristics accurately to optimize the equalization and decoding processes and maximize the spectral efficiency of the uplink communication. It takes into account the time-varying nature of the channel and assigns weights to different channel observations based on their recency. This helps in tracking and adapting to changing channel conditions, resulting in improved spectral efficiency. To calculate the uplink spectral efficiency using the EW-MMSE estimator from maximum Ratio receive combining vector $V_{ji} = \check{h}_{ji}^{j}$ then:

$$E\{ V_{ji}^{H} h_{ji}^{j}\} = p_{ji}\tau_{p} tr\left(D_{ji}^{j} \Lambda_{ji}^{j}\right) + \|\bar{h}_{ji}^{j}||^{2} \quad (3.25)$$

$$E\{ ||V_{ji}||^{2}\} = tr(\sum\nolimits_{ji}^{i}) + ||\bar{h}_{ji}^{j}||^{2} \quad (3.26)$$

$$E\{ |V_{ji}^{H}\, h_{mk}^{j}|^{2}\} = \chi_{mi}^{UL}$$

$$= tr(R_{mk}^{j} \sum\nolimits_{ji}^{j}) + (\bar{h}_{ji}^{j})^{H} R_{mk}^{j} \bar{h}_{ji}^{j} + (\bar{h}_{jk}^{j})^{2} \sum_{ji}^{j} \bar{h}_{mk}^{j} + |(\bar{h}_{ji}^{j})^{H} \bar{h}_{mk}^{j}|^{2}$$

$$+ \begin{cases} p_{ji}\, p_{mk}(tr\left(D_{mk}^{j}\, \Lambda_{ji}^{j}\, D_{ji}^{j}\right))^{2} + 2\sqrt{p_{ji}\, p_{mk}}\, \tau_{p}\, tr\left(D_{mk}^{j}\, \Lambda_{jk}^{j}\, D_{ji}^{j}\right) \\ \quad Re\{ (\bar{h}_{ji}^{j})^{H}\, \bar{h}_{mk}^{j} \qquad (m,k) \in p_{ji} \\ 0 \qquad (m, \quad k) \notin p_{ji} \end{cases} \quad (3.27)$$

So when plugged these expressions into effective SINR, spectrum efficiency in case of EW-MMSE is

$$y^{UL,EW-MMSE} = \frac{p_{ji}\,(p_{ji}\,\tau_{p}\, tr\left(D_{ji}^{j}\, \Lambda_{ji}^{j}\, D_{ji}^{j}\right) + ||\, \bar{h}_{ji}^{j}\, ||^{2})^{2}}{\sum_{m=1}^{M}\sum_{k=1}^{i_{m}} p_{mi}\, \chi_{mk}^{UL} - p_{ji}\,(p_{ji}\,\tau_{p}\, tr(D_{ji}^{j}\Lambda_{ji}^{j} D_{ji}^{j} + ||\bar{h}_{ji}^{j}||^{2})^{2} + \sigma_{Ul}^{2}\,(tr(\sum\nolimits_{jk}^{j}) + ||\bar{h}_{ji}^{j}\,||^{2}} \quad (3.28)$$

3.5.6 Uplink Spectral Efficiency using the LS Estimator

The LS estimator is a simple and computationally efficient method for estimating the channel response between the user equipment (UE) and base station (BS). By minimizing the sum of squared errors between the received signal and the estimated channel response. It is a straightforward method that involves solving a set of linear equations to estimate the channel response. This simplicity makes it computationally efficient and suitable for real-time channel estimation, enabling quick adaptation to changing channel conditions and enhancing spectral efficiency in uplink communication. The uplink spectral efficiency of a massive

MIMO system is derived using the least-squares (LS) estimator. Therefore the maximum ratio combining with $V_{ji} = \frac{1}{\sqrt{p_{ji}\tau_p}} y_{jji}^{pilot}$ are used based on least square estimator, then

$$E\{||V_{ji}^H||^2\} = tr(R_{ji}^j) + \sum_{(m,k)} \frac{\sqrt{p_{mk}}}{\sqrt{p_{ji}}} (\bar{h}_{mk}^j)^H \bar{h}_{ji}^j \qquad (3.29)$$

$$E\{||V_{ji}^H||^2\} = \frac{1}{p_{ji}\,\tau_p} tr((\Phi_{ji}^j)^{-1}) + \frac{1}{p_{ji}\tau_p^2} ||\bar{y}_{jji}^{pilot}||^2 \quad (3.30)$$

$$p_{ji}\tau_p^2 \{|V_{ji}^H h_{mk}^j|^2\} = p_{ji}\tau_p^2 \chi_{mk}^{UL,LS}$$
$$= \tau_p tr(R_{mk}^j (\Phi_{jk}^j)^{-1} + 2\sqrt{p_{mk}}\,\tau_p Re\{(\bar{y}_{jji}^{pilot})^H \bar{h}_{mk}^j tr\left(R_{mk}^j\right) + (\bar{y}_{jji}^{pilot})^H \bar{h}_{mk}^j tr\left(R_{mk}^j\right)$$
$$+ (\bar{y}_{jji}^{pilot})^H R_{mk}^j \bar{h}_{mk}^j$$
$$+ \begin{cases} p_{mk}\tau_p^2 |tr\left(R_{mk}^j\right)|^2 + \bar{\chi}_{ji}^H R_{mk}^j \bar{\chi}_{ji} + \tau_p(\bar{h}_{mk}^j)^H (\Omega_{ji}^j)^{-1} \bar{h}_{mk}^j + |\bar{\chi}_{ji}^H \bar{h}_{mk}^j|^2 \\ + p_{mk}\tau_p^2 ||\bar{h}_{mk}^j||^4 + 2\sqrt{p_{mk}}\,\tau_p\ Re\{\bar{\chi}_{ji}^H \bar{h}_{mk}^j ||\bar{h}_{mk}^j||^2\} & (m,\ k) \in p_{ji} \\ (\bar{y}_{jji}^{pilot})^H R_{mk}^j \bar{y}_{jji}^{pilot} + \tau_p(\bar{h}_{mk}^j)^H (\Phi_{ji}^j)^{-1} \bar{h}_{mk}^j + |(\bar{y}_{jji}^{pilot})^H \bar{h}_{mk}^j|^2 & (m,k) \notin p_{jk} \end{cases}$$
$$(3.31)$$

Where $\bar{\chi}_{ji} = \bar{y}_{jji}^{pilot} - \sqrt{p_{mk}}\,\tau_p \bar{h}_{mk}^j$ and $(\Omega_{ji}^j)^2 = (\Phi_{ji}^j)^{-1} - p_{mk}\tau_p R_{mk}^j$ Therefore, plugged these expression into effective $SINR$ got:

$$y_{ji}^{UL,LS}$$
$$= \frac{p_{ji}|tr\left(R_{ji}^j\right) + \sum_{(m,k)\in p_{ji}} \frac{\sqrt{p_{mk}}}{\sqrt{p_{ji}}} (\bar{h}_{mk}^j)^H\ \bar{h}_{ji}^j|^2}{\sum_{m=1}^{M}\sum_{k=1}^{i_m} p_{mk}\chi_{mk}^{UL,LS} - p_{ji}|tr\left(R_{ji}^j\right) + \sum_{(m,k)\in p_{ji}} \begin{matrix} \frac{\sqrt{p_{mk}}}{\sqrt{p_{ji}}}(\bar{h}_{mk}^j)\bar{h}_{ji}^j|^2 + \\ \sigma_{Ul}^2(\frac{tr((\Phi_{ji}^j}{p_{ji}\tau_p} + \frac{||\bar{y}_{ji}^p||^2}{p_{ji}\tau_p^2}) \end{matrix}} \qquad (3.32)$$

To derive the Rayleigh fading equivalent of above equation, the mean vectors set to be zero. The MMSE and LS/EW-MMSE estimators may have a minimal difference in spectral efficiency (SE). However, when employing the LS estimator with Rician fading, there can be a significant decrease in SE, which is influenced by the strength of line-of-sight (LoS) paths. Not incorporating mean values as prior knowledge results in higher interference terms in comparison to the MMSE estimator. The LS estimates of the UEs affected by pilot contamination are equivalent up to a scaling factor. In contrast to the MMSE estimator, the magnitude of the corresponding interference terms is determined by the inner product of $\bar{y}_{jji}^{pilot}$ and $\bar{h}_{mk}^{j}$, rather than the inner product of $\bar{h}_{ji}^{j}$ and $\bar{h}_{mk}^{j}$.

3.5.7 Downlink Spectral Efficiency using the MMSE Estimator

The downlink spectral efficiency in a wireless communication system is the rate at which data may be successfully sent from the base station (BS) to the user equipment (UE) over a given bandwidth. The downlink spectral efficiency (SE) can be calculated using the minimal mean square error (MMSE) estimation. The MMSE estimator is used to estimate the sent symbols at the receiving end while taking into consideration channel circumstances. To compute the SE, consider a wireless communication system with a fixed bandwidth and a set of users. The MMSE estimator uses the received signal, channel state information, and noise characteristics to estimate the broadcast symbols with the lowest mean square error. The SE can be expressed as the achievable data rate per unit bandwidth. Mathematically, it can be calculated from maximum ratio combining, through signal transmitting from Bastion(BS) M is :

$$\chi_M = \sum_{i=1}^{k_m} \mathrm{W}_{mi}\varsigma_{mi} \qquad (3.33)$$

Where in this equation, $\varsigma_{mi} \sim N_{\mathbb{C}}\,(0, p_{mi})$ represents the downlink data signal intended for UE i in the cell, with p_{mi} being the signal power allocated to that UE. The transmit precoding vector W_{mi} determines the spatial directivity of the transmission, and it satisfies the condition $E||\mathrm{W}_{mi}||^2 = 1$, ensuring that the expected power allocated to UE i is p_{mi}, which can be expressed as $E\{||\mathrm{W}_{mi}\varsigma_{mi}||^2\} = p_{mi}$. This constraint helps in managing the transmit power allocated to each UE efficiently. The received signal at UE i in cell j denoted as $y_{ji} \in \mathbb{C}$ can be expressed as:

$$y_{ji} = (h_{ji}^{m})^H \mathrm{W}_{ji}\varsigma_{ji} + \sum_{\substack{k=1 \\ k\neq i}}^{i_m} (h_{ji}^{j})^H \mathrm{W}_{jk}\varsigma_{jk} + \sum_{\substack{m=1 \\ m\neq j}}^{M} \sum_{k=1}^{i_m} (h_{ji}^{m})^H \mathrm{W}_{mk}\varsigma_{mk} + n_{ji} \qquad (3.34)$$

Where n_{ji} denotes the additive noise component which is assumed to be complex Gaussian with zero mean that is $n_{ji} \sim N_{\mathbb{C}}(0, \sigma_{dl}^2)$. In the equation mentioned (3.34), the terms have the following interpretations:

The first term represents the desired signal, which is the signal intended for UE i in the cell, the second term corresponds to the intra-cell interference. It is the combined effect of signals from other UEs within the same cell. This interference arises due to the simultaneous transmission of multiple UEs in the cell and is represented. the third term represents the inter-cell interference. It accounts for the interference caused by signals from neighboring cells. This interference arises due to the limited spatial separation between cells and the overlapping coverage areas. The ergodic downlink capacity of UE i in cell j has a lower bound, which can be expressed as follows:

$$SE_{ji}^{DL} = \frac{\tau_d}{\tau_c} \log_2(1 + y_{ji}^{DL}) \ (bit/s/Hz) \qquad (3.35)$$

Where the effective SINR becomes:

$$y_{ji}^{DL} = \frac{p_{ji}|E\{\mathrm{W}_{ji}^{H} h_{ji}^{j}\}|^2}{\sum_{m=1}^{M}\sum_{k=1}^{i_m} p_{mk}\, E\{|\mathrm{W}_{mk}^{H} h_{ji}^{m}|^2\} - p_{ji}|E\left\{\mathrm{W}_{ji}^{H} h_{ji}^{j}\right\}|^2 + \sigma_{DL}^2} \qquad (3.36)$$

By using the MMSE estimator, can obtained a mathematical expression for the downlink SE that does not require further calculations or approximations. This closed-form expression allows for a more straightforward evaluation of the SE in the downlink system. So a closed form expression presented in the above equation can derive according to the following theorem if maximum ratio(MR) precoding employed with $\mathrm{W}_{ji} = \frac{\check{h}_{ji}^{j}}{\sqrt{E\{||\check{h}_{ji}^{j}||^2\}}}$ is used based on the MMSE estimator then:

$$E\left\{\mathrm{W}_{ji}^{H} h_{ji}^{j}\right\} = \sqrt{p_{ji}\tau_d\, tr(R_{ji}^{j}\, \Phi_{ji}^{j} R_{ji}^{j})} + ||\bar{h}_{ji}^{j}||^2 \qquad (3.37)$$

$$\begin{aligned} & E\{||\check{h}_{mk}^{m}||^2\}\, E\{|\mathrm{W}_{mk}^{H} h_{ji}^{m}|^2\} \\ & = p_{mk}\tau_d tr(R_{jk}^{m}\, R_{mk}^{m}\, \Phi_{mk}^{m} R_{ji}^{j} + p_{mk}\,\tau_p (\bar{h}_{ji}^{m})^H\, R_{mk}^{m}\, \Phi_{mk}^{m}\, R_{mk}^{m}\, \bar{R}_{ji}^{m} + |(\bar{h}_{ji}^{m})^H\, \bar{h}_{mk}^{m}|^2 \\ & + (\bar{h}_{mk}^{m})^H\, R_{ji}^{m} \bar{h}_{mk}^{m} \\ & + \begin{cases} p_{ji}p_{mk}\tau_d^2\, |tr\left(R_{ji}^{m}\, \Phi_{mk}^{m}\, R_{mk}^{m}\right)|^2 + 2\sqrt{p_{ji}\, p_{mk}}\,\tau_d\, Re\{\, tr\left(\, R_{ji}^{m}\, \Phi_{mk}^{m}\, R_{mk}^{m}\,\right) \\ \quad (\,\bar{h}_{mk}^{m}\,)^H\, \bar{h}_{ji}^{m} & (m,k) \in p_{ji} \\ \quad 0 & (m,k) \notin p_{ji} \end{cases} \end{aligned} \qquad (3.38)$$

Where $E\{\,||\check{h}_{mk}^{m}||^2\} = p_{mk} tr(\, R_{mk}^{m}\, \Phi_{mk}^{m} R_{mk}^{m}) + ||\bar{h}_{mk}^{m}||^2$ when plugged this equation into effective SINR (3.36) give:

$$y^{DL,MMSE} \quad \frac{p_{ji}\, p_{ji}\, \tau_p\, tr\left(R_{ji}^{j} \Phi_{ji}^{j}\, R_{ji}^{j} \right) + \; p_{ji} || \, \bar{h}_{ji}^{j} \, ||^2}{\sum_{m=1}^{M} \sum_{k=1}^{i_m} p_{mk} \;\; \xi_{mk}^{DL} \; + \; \sum_{(m,k) \in p_{ji} \setminus (j,i)} \; p_{mk} \; \Gamma_{mk}^{DL} \; - \; p_{ji}\, V_{ji}^{DL} + \; \sigma_{DL}^2} \tag{3.39}$$

Where $V_{ji}^{DL} \; = \; \frac{|| \; \bar{h}_{ji}^{m} \; ||^4}{(\; p_{ji} \; tr \left(R_{ji}^{m} \; \Phi_{ji}^{m} \; R_{ji}^{m} \right) + \; || \; \bar{h}_{ji}^{m} \; ||^2}$ and

$$\xi_{mk}^{DL} = \frac{\begin{gathered} p_{mk}\tau_p \; tr\left(\; R_{ji}^{m} R_{mk}^{m} \; \Phi_{mk}^{m} \right) + \; p_{mk}\tau_p (\bar{h}_{ji}^{m})^H R_{mk}^{m} \Phi_{mk}^{m} R_{mk}^{m} \bar{h}_{ji}^{m} \\ +(\bar{h}_{mk}^{m} \;)^H R_{ji}^{m} \; \bar{h}_{mk}^{m} + (\bar{h}_{ji}^{m} \;)^H R_{ji}^{m} \bar{h}_{mk}^{m} \;\; + |(\bar{h}_{ji}^{m} \;)^H \; \bar{h}_{mk}^{m} \; |^2 \end{gathered}}{p_{mk}\tau_p tr(R_{mk}^{m} \Phi_{mk}^{m} R_{mk}^{m}) + ||\bar{h}_{mk}^{m}||^2} \tag{3.40}$$

Which this expression represents non-coherent interference and

$$\Gamma_{mk}^{DL} = \frac{\begin{gathered} p_{ji} p_{mk} \; \tau_p^2 \; |tr\left(R_{ji}^{m} \Phi_{mk}^{m} \; R_{mk}^{m} \right)|^2 + \; 2\sqrt{p_{ji} \, p_{mk}} \; \tau_p \\ Re\{tr(R_{ji}^{m} \Phi_{mk}^{m} R_{mk}^{m} (\bar{h}_{mk}^{m})^2 \; \bar{h}_{ji}^{m}\} \end{gathered}}{p_{mk}\tau_p \; tr(R_{mk}^{m} \Phi_{mk}^{m} R_{mk}^{m}) + ||\bar{h}_{mk}^{m}||^2} \tag{3.41}$$

This equation which represents coherent interference.

3.5.8 Downlink Spectral Efficiency using the EW-MMSE Estimator.

The EW-MMSE (Element-Wise Minimum Mean Square Error) estimator is a technique used in wireless communication systems to reduce interference and thereby enhance signal quality. The EW-MMSE estimator uses the MMSE estimating method to reduce interference. It takes into account the statistical aspects of the interference and noise, as well as the received signal, in order to minimize the mean square error between the estimated and actual signal. This decreases the influence of interference and improves the quality of the targeted signal. Therefore, in this section, the downlink spectral efficiency of a massive MIMO system with the EW-MMSE estimator is derived. So from downlink spectrum efficiency above when applying MR precoding based on the MMSE estimator got $\mathtt{W}_{ji} \; = \; \frac{\check{\mathrm{h}}_{ji}^{j}}{\sqrt{E\{|| \; \check{\mathrm{h}}_{ji}^{j} ||^2\}}}$ then:

$$E\left\{\mathtt{W}_{ji}^{H} \; h_{ji}^{j}\right\} = \; \sqrt{p_{ji}\tau_p \; tr\left(R_{ji}^{j} \Phi_{ji}^{j} R_{ji}^{j} \right) + ||\bar{h}_{ji}^{j} \; ||^2} \tag{3.42}$$

$E\{||\check{h}_{mk}^{m}||^2\}E\{|W_{jk}^{H}\, h_{ji}^{m}\ |^2\}$

$= p_{mk}\tau_p tr(\ R_{ji}^{m}R_{mk}^{m}R_{mk}^{j}) + \ p_{mk}\tau_p(\bar{h}_{ji}^{m}\ )^H R_{mk}^{m}\Phi_{mk}^{m}R_{mk}^{m}\bar{h}_{ji}^{m} + |(\bar{h}_{ji}^{m})^H\bar{h}_{mk}^{m}|^2$

$+ (\bar{h}_{mk}^{m})^H\ R_{ji}^{m}\bar{h}_{mk}^{m}$

$$+ \begin{cases} p_{ji}p_{mk}\tau_p^2\left|tr(R_{ji}^{m}\Phi_{mk}^{m}R_{mk}^{m})\right|^2 + \\ 2\sqrt{p_{ji}p_{mk}}\ \tau_p\ Re\{tr\left(R_{ji}^{m}\ \Phi_{mk}^{m}R_{mk}^{m}\right)\left(\bar{h}_{mk}^{m}\right)^H\ \bar{h}_{ji}^{m}\} & (m,k) \in\ p_{ji} \\ 0 & (m,k)\ \notin p_{ji} \end{cases} \quad (3.43)$$

Where $E\{||\ \check{h}_{mk}^{m}||^2\}\ =\ tr(\ \sum_{mk}^{m}) + ||\ \bar{h}_{mk}^{m}\ ||^2$, by inserting these expression into the DL effective SINR above, the resulting expression would give:

$$y_{ji}^{DL,EW\_MMSE} = \frac{p_{ji}(\ p_{ji}\ \tau_p\ tr\left(D_{ji}^{j}\Lambda_{ji}^{j}D_{ji}^{j}\right) + \ ||\bar{h}_{ji}^{j}||^2/(\ tr(\ \sum_{mk}^{m}) + ||\bar{h}_{ji}^{j}\ ||^2\ )}{\sum_{m=1}^{M}\sum_{k=}^{i_m} p_{mk}\ \frac{\chi_{mk}^{DL}}{tr(\ \sum_{mk}^{m}) + ||\bar{h}_{mk}^{m}||^2} - \ p_{jk}\frac{(\ p_{ji}\tau_p tr\left(\ D_{ji}^{j}\Lambda_{ji}^{j}D_{ji}^{j}\ \right) + ||\bar{h}_{ji}^{j}||^2\ )^2}{tr(\ \sum_{ji}^{j})\ + ||\bar{h}_{ji}^{j}\ ||^2} + \sigma_{DL}^2} \quad (3.44)$$

3.5.9 Downlink Spectral Efficiency using the LS Estimator

The least squares (LS) estimator is a statistical estimation approach that minimizes the sum of the squares of the discrepancies between observed and predicted values. In the context of downlink spectral efficiency, the LS estimator can be used to predict channel parameters such as channel gains or signal-to-noise ratio (SNR), which are critical for determining the feasible data rate. Therefore, the downlink spectral efficiency of a massive MIMO system with the LS estimator is derived. From above general Downlink spectrum efficiency, if MR (Maximum Ratio) precoding is used with the LS estimator, and the precoding weights are defined as $W_{ji} = \frac{\check{h}_{ji}^{j}}{\sqrt{E\{\ ||\check{h}_{ji}^{j}||^2\}}}$ then,

$$E\left\{\ W_{ji}^{H}h_{ji}^{j}\right\} = \frac{E\left\{\ V_{ji}^{H}h_{ji}^{j}\right\}}{\sqrt{E\{\ ||V_{ji}||^2\}}} = \frac{tr\ \left(R_{ji}^{j}\right) + \ \sum_{(m,k)\in p_{ji}}\frac{\sqrt{p_{mk}}}{\sqrt{p_{ji}}}(\bar{h}_{mk}^{j})^H\ \bar{h}_{j}^{j}}{\sqrt{\frac{1}{p_{ji}\tau_p^2}(\ \tau_p tr((\ \Phi_{ji}^{j}\ )^{-1}\ ) + ||\bar{y}_{jji}^{pilot}\ ||^2\ )}} \quad (3.45)$$

$$E\{\ ||\check{\text{h}}_{mk}^{m}||^2\}E\{\ |\text{W}_{mk}^{H}h_{ji}^{m}|^2\}\ =\ p_{mk}\tau_p^2\chi_{mk}^{DL,LS}$$

$$=\ \tau_p tr(\ R_{ji}^{m}(\Phi_{mk}^{m})^{-1})\ +\ 2\sqrt{p_{ji}}\,\tau_p Re\{\ (\ \bar{y}_{jmk}^{pilot})^H\bar{h}_{ji}^{m}tr(R_{ji}^{m})\ +(\ \bar{y}_{jmk}^{pilot})^H R_{ji}^{m}\bar{h}_{ji}^{m}\}$$

$$+\begin{cases} (\ \bar{y}_{jmk}^{pilot})^H R_{ji}^{m}\ \bar{y}_{jmk}^{pilot}\ +\ \tau_p(\bar{h}_{ji}^{m})^H(\Phi_{mk}^{m})^{-1}\bar{h}_{ji}^{m} \\ +|(\bar{y}_{jmk}^{pilot})^H\ \bar{h}_{ji}^{m}|^2 \quad (m,\ \ k)\notin\ p_{ji} \\ \\ p_{ji}\tau_p^2|tr\left(R_{ji}^{m}\right)|^2+\ \bar{\chi}_{mk}^{H}R_{ji}^{m}\bar{\chi}_{mk}\ +\ \tau_p(\bar{h}_{ji}^{m}\ )^H(\Omega_{mk}^{m})^{-1}\ \bar{h}_{jk}^{m} \\ +|\bar{\chi}_{mk}^{H}\bar{h}_{ji}^{m}\ |^2\ +\ p_{ji}\tau_p^2||\bar{h}_{ji}^{m}||^4+\ 2\sqrt{p_{ji}}\,\tau_p\ Re\{\bar{\chi}_{mk}^{H}\left(\bar{h}_{ji}^{m}\right)^H\bar{h}_{ji}^{m}\ \}\ (m,k)\ \in\ p_{ji} \end{cases} \tag{3.46}$$

To calculate the DL SINR by inserting the given expression for $E\{||\check{\text{h}}_{mk}^{m}||^2\}=\frac{1}{p_{mk}\tau_p^2}\ (\tau_p tr((\Phi_{mk}^{m})^{-1})\ +||\bar{y}_{mmk}^{pilot}||^2$into general equation of DL effective SINR (3.36) yield as below.

$$y_{ji}^{DL,LS}$$

$$=\frac{p_{ji}p_{ji}\tau_p^2|tr\left(R_{ji}^{j}\ \right)+\ \sum_{(m,k)\in p_{ji}}\frac{\sqrt{p_{mk}}}{\sqrt{p_{mi}}}\ (\bar{h}_{mk}^{j})^H\bar{h}_{ji}^{j}\ \ |^2\Big/(\tau_p tr(\ \Phi_{ji}^{j})^{-1}+||\bar{y}_{jji}^{pilot}||^2\ \ )}{p_{ji}p_{ji}\ \tau_p^2\ |tr\left(R_{ji}^{j}\ \right)+\ \sum_{(m,k)\in p_{ji}}\frac{\sqrt{p_{mk}}}{\sqrt{p_{ji}}} \quad \sum_{m=1}^{M}\sum_{k=1}^{i_m}p_{mk}\frac{p_{mk}\tau_p^2\chi_{mk}^{DL,LS}}{\tau_p tr((\Phi_{mk}^{m}\ )^{-1}+||\bar{y}_{jji}^{pilot}||^2}-\frac{(\bar{h}_{mk}^{j}\ )^H\ \bar{h}_{mk}^{j}\ |^2}{\tau_p\ tr((\Phi_{ji}^{j}\ )^{-1}+||\bar{y}_{jji}^{pilot}||^2}+\ \sigma_{DL}^2}$$

CHAPTER FOUR

4. RESULT AND DISCUSSION

In this section, the simulation result of spectrum efficiency of massive MIMO in uplink and downlink are obtained using MATLAB version 2023b. Furthermore, the simulation result Rician fading and Rayleigh fading spectrum efficiency under different estimator are obtained. Additionally, the obtained results are discussed and analyzed in these section. In this simulation to ensure a more realistic and representative evaluation of the system performance as the closed form spectral efficiency expressions in a typical cellular network has wrap-around topology used in simulation setup, to ensures that all base stations receive equal amount of interference from all direction, regardless of their position within the cellular layout. Generally, each UE is allocated to the BS with the highest channel gain, taking into account all potential combinations of UEs and BSs in the network. The position of each UE is used to compute large-scale fading and the nominal angle between the UE and BSs. The simulation result produced is consistent with 3GPP requirements. The simulation parameters utilized in the analysis are given in table 4.1.

The simulation results presented in this thesis are organized and discussed under three main topics.

- Performance of estimation quality of channel estimator in terms of NMSE.
- Results of Uplink spectrum efficiency under different channel estimator.
- Result of Downlink spectrum efficiency under different channel estimator.

Table 4. 1 Parameters used for Simulations.

Parameter Description	Parameter type and value	Remarks
Cell type	Micro cell	Based on (Zarai et al., 2011)
Cell coverage area	250m*250m	Based on (*25996-800*, n.d.)
Bandwidth	20MHz	Based on (*25996-800*, n.d.)
Number of UE per cell	$i \geq 10$	It can be vary
Pilot reuse factor	$f = 1$	It can be vary

Carrier Frequency	2GHz	Based on many paper
Pilot length	$\tau_p = fi$,since $f = 1$ pilot are allocated random in each cell	According to (3GPP TR 25.996, 2009)
Separation distance(UE to BS)	35m	Based on (*25996-800*, n.d.)
Shadow fading SD	$\delta_{sf} = 4$ for LOS,$\delta_{sf} = 10$ for NLOS	According to (3GPP TR 25.996, 2009)
Coherence Block	$\tau_c = 200$	Based on (*25996-800*, n.d.)
Path loss exponent	3.7 for urban	According to (*25996-800*, n.d.)
Number of BSs antenna	M = 16	It can be vary
ASD	5°	According to (3GPP TR 25.996, 2009)
Total received noise power	-94dBm	Based on (*25996-800*, n.d.)

4.1 Performance of estimation quality of channel estimator in terms of NMSE.

This section provides the Normalized Mean Squared Error (NMSE) in the estimation of a spatially correlated channel is analyzed based on the local scattering model with Gaussian angular distribution. The scenario considered involves a base station (BS) estimating the channel of its user equipment (UE) in the presence of interference from a UE in another cell transmitting the same pilot sequence. The simulation results underscore the significance of accurate channel estimation in Massive MIMO systems, the impact of different estimators on system. The simulation results present for estimation quality of channel estimator is:

- Comparison of estimation quality of channel estimator in terms of NMSE

4.1.1 Comparison of estimation quality of channel estimator in terms of NMSE.

The performance estimation quality comparison among various channel estimator can be analyzed in terms of the NMSE curves as shown in figure 4.1. The results are simulated at effective SNR of the desired UE is varied from $-10dB\ to\ 20dB$, $ASD = 10^{\circ}$ are used and results are averaged over different nominal angle between $0^{\circ}\ and\ 360^{\circ}$. As observed from the graph the three channel estimators produce varying NMSEs. The MMSE estimator is the most accurate because it takes into account spatial channel correlation when compared to other EW-MMSE and LS. Although, the EW-MMSE estimator performs similarly to the MMSE estimator for uncorrelated channels, it falls short of the MMSE estimate, even at high SNR due to pilot contamination. The LS estimator works badly at low SNR ($NMSE > 1$), while the trivial all-zero estimate yields an NMSE of 1. At higher SNRs, the LS estimator is comparable to the EW-MMSE estimator, but their error levels differ (assuming pilot contamination). The LS estimator can offer accurate channel direction estimates, but limited statistical information makes scaling the channel norm challenging.

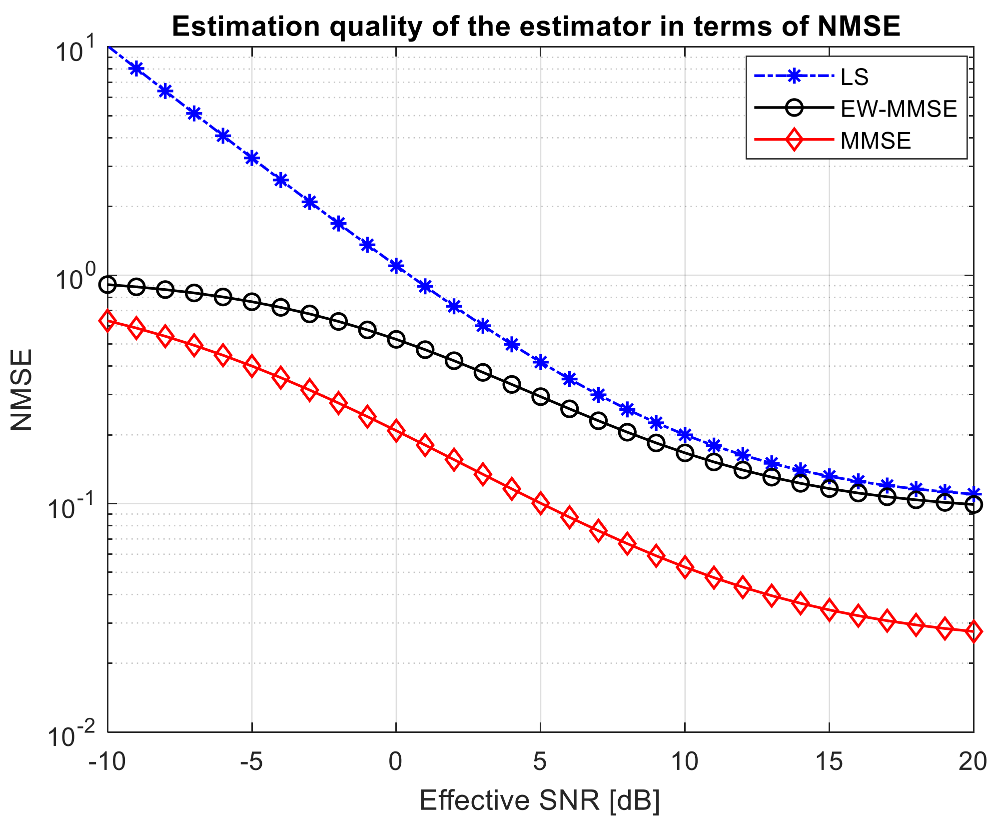


Figure 4. 1 NMSE in the estimation of a spatially correlated channel, based on the local scattering model with Gaussian angular distribution, for different estimators.

4.2 Result of Uplink Spectrum Efficiency Under Different Channel estimator.

This section provides further clarity on the simulations and analysis uplink spectrum efficiency under different channel estimator. The simulation results for spatially correlated and uncorrelated Racian, Rayleigh fading uplink spectrum efficiency under different channel estimator are discussed here. The key simulation results presented for the uplink spectrum under different channel estimator are:

- Average Uplink spectrum efficiency for different channel estimator.
- Cumulative distribution Uplink spectrum efficiency for different channel estimator.
- Average Uplink spectrum efficiency under different channel estimator where all have a LOS path
- Average Uplink spectrum efficiency under different pilot reuse factor and different channel estimator.
- Average Uplink spectrum efficiency with spatially uncorrelated Racian and Rayleigh fading under different channel estimator.

4.2.1 Average Uplink spectrum efficiency for different channel estimator.

Figure 4.2 depicts the average uplink (UL) sum spectral efficiency (SE) for a system with 10 users as a function of the number of base station (BS) antennas (N). The plot showcases the sum UL SE averaged across UE sites and shadow fading realizations utilizing maximum ratio combining with MMSE, LS, or EW-MMSE estimators. Also assume the Rayleigh fading curves with the same covariance matrices, reflecting the case when all LoS components are blocked but small-scale fading remains. The curves are generated using closed-form expressions from uplink spectrum efficiency. while the □ markers are generated through Monte Carlo simulations. The markers' overlap with the curves confirms the validity of the result analysis. The MMSE estimator turnout the highest uplink spectrum efficiency due to its ability to account for the LoS component and spatial correlation. For Rician fading, MMSE and EW-MMSE performance are very close to each other, but EW-MMSE outperforms LS due to its use the knowledge of channel mean values. For Rayleigh fading, MMSE is the preferred estimation method. However, the total SE with LS and EW-MMSE are same due to similar estimates up to a scaling factor. Generally, the result insights into how the UL sum SE changes with the varying number of antennas for each channel estimator. It demonstrates the impact of different estimation methods on the system's spectral efficiency in Massive MIMO scenarios.

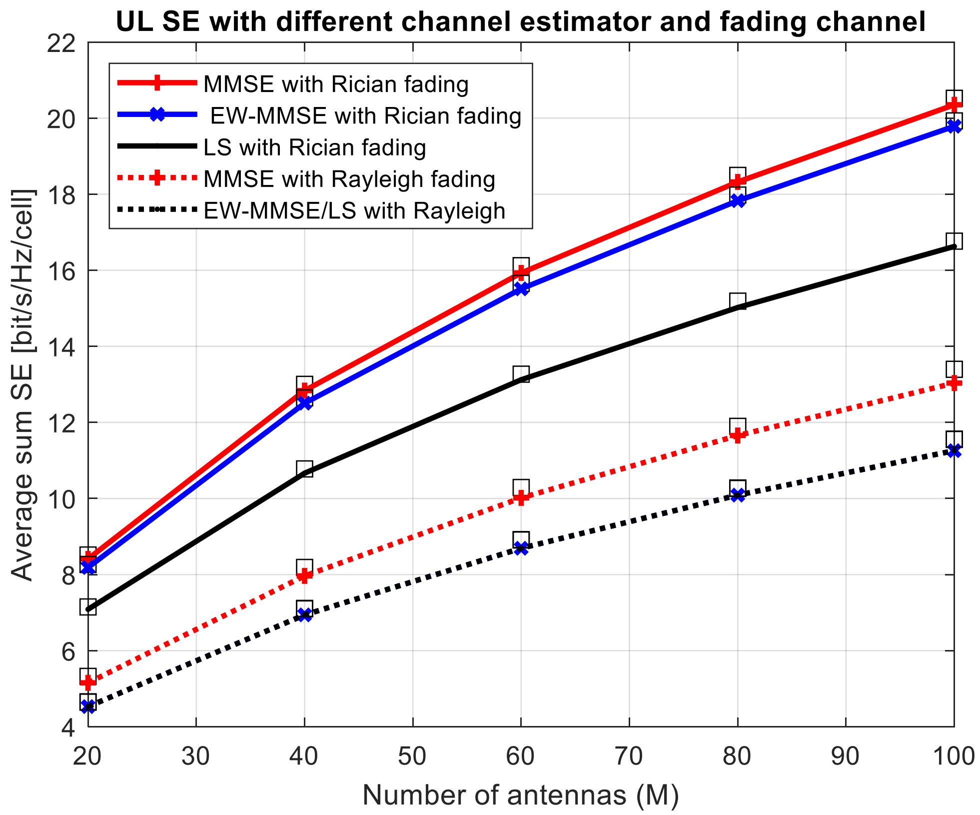


Figure 4. 2 Average Uplink Sum Spectrum efficiency for 10 user as function of number of antennas of BS under different Channel estimator and Fading channels.

4.2.2 Cumulative distribution Uplink spectrum efficiency for different channel estimator

In this result analyzed the distribution of spectrum efficiency value across different UEs in a multi-cell massive MIMO system. The CDF curve are show that how the spectrum efficiency value is distributed across UEs in the system, capturing the variability in channel condition and performance. So the result compares the CDF curves for different channel estimators of the spectrum distribution among UEs under varying channel condition and shadow fading realization. Therefore, which channel estimator performs better in terms of SE distribution among UEs compered. From the figure 4.3 the point where the CDF curves of different channel estimators intersect or touch each other signifies that SE value at which the performance of those estimators is comparable or similar spectrum efficiency. The graph indicates that for UEs with good channel conditions, the MMSE and EW-MMSE estimators provide similar spectral efficiency performance, as the estimation errors are small and However, there is a noticeable difference between the MMSE and EW-MMSE estimators for the UEs with the weakest channel conditions. In these cases, the MMSE estimator outperforms the EW-MMSE estimator. Generally, that the MMSE estimator is particularly beneficial for UEs experiencing poor channel conditions, as it is able to better utilize the knowledge of the channel statistics to improve the estimation accuracy and, consequently, the spectral efficiency performance.

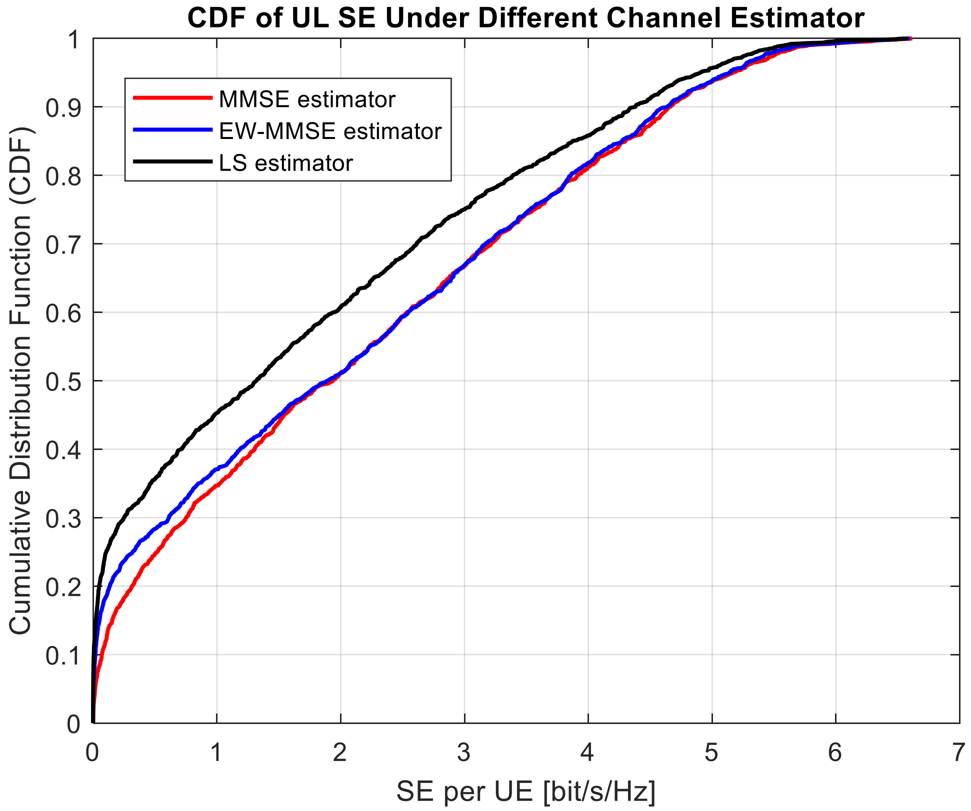


Figure 4. 3 CDF curve of the Uplink Spectrum Efficiency under different Channel estimator.

4.2.3 Average Uplink spectrum efficiency under different channel estimator where all have LOS path.

Figure 4.4 analyzed a situation with spatially correlated Rician fading channels between each pair of BSs and UEs, which may not be feasible in practice. In comparison to cases when only some UEs have LoS, the presence of a LoS component leads to greater average UL sum SEs, which improve the SE. As illustrate in graph the average UL SE as a function of the number of BS antennas for various channel estimators, including MMSE, EW-MMSE, and LS estimators. The plot underscores the critical role of channel estimation methods in maximizing spectral efficiency, especially in environments where all UE-BS pairs benefit from LoS propagation paths. So from comparison the MMSE estimator achieves the highest UL SE among the considered estimators when all UE-BS pairs have LoS paths, this superior performance is attributed to the MMSE estimator's capability to exploit the known LoS components and spatial correlation in the channel. The EW-MMSE estimator also demonstrates competitive performance in the scenario with all UE-BS pairs having LoS paths, its performance is very close to that of the MMSE estimator, indicating that leveraging the knowledge of channel mean values contributes to improved spectral efficiency. But he LS estimator shows comparatively lower UL SE performance in this scenario, The LS estimator lacks the ability to suppress pilot interference through spatial processing, which can limit its performance in environments with strong LoS components.

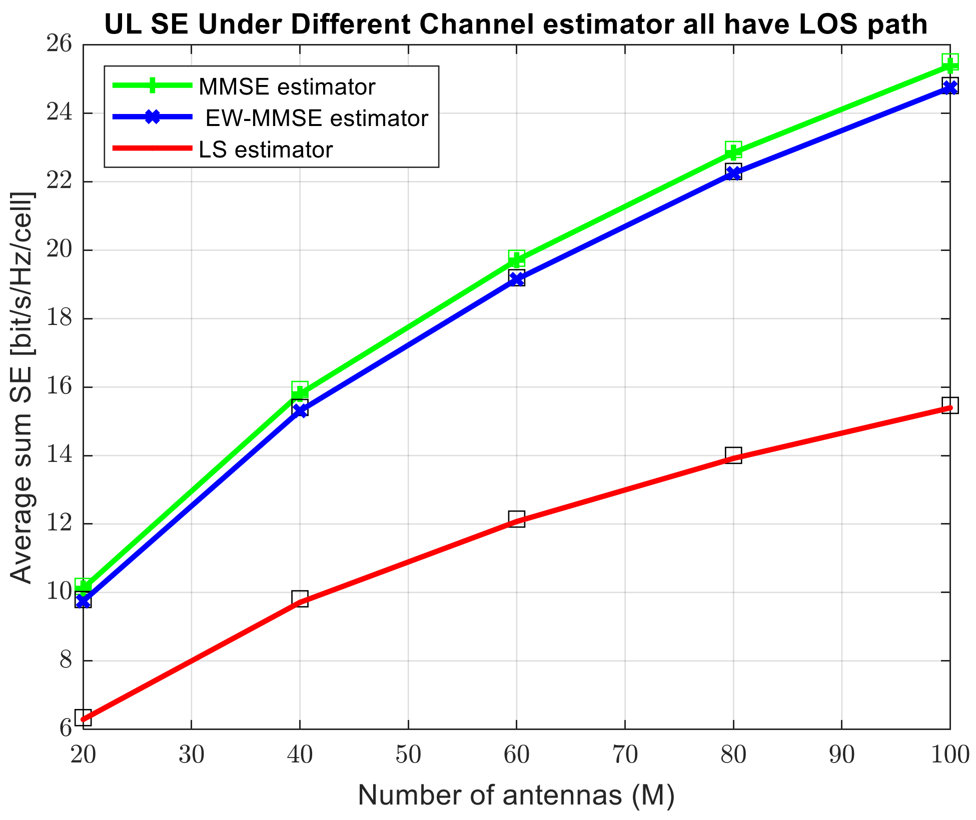


Figure 4. 4 Average Uplink sum of Spectrum efficiency for 10 user is shown as a function of BS antennas for various channel estimator where all UE-BS have a LOS Path.

4.2.4 Average Uplink spectrum efficiency under different pilot reuse factor and different channel estimator.

In this section the average uplink spectral efficiency (UL SE) for different pilot reuse factors and various channel estimators is analyzed. The figure 4.5 indicates that the average UL SE as a function of the number of BS antennas for different pilot reuse factors, denoted by the integer f, where $\tau_p = fi$. This setup indicates that there are f times more pilots than user equipment (UE) per cell, and the same subset of pilots is reused in a fraction $1/f$ of the cells. The figure demonstrates the impact of different pilot reuse factors on the average UL SE for various estimators. Increasing the pilot reuse factor affects the pre-log factor in the UL SE expression, where $\tau_u = \tau_c - \tau_p$, influencing the system's performance. Generally, a larger reuse factor reduces pilot contamination but increases the pre-log penalty and larger reuse factors lead to a decrease in the pre-log factor, affecting the overall system performance in terms of spectral efficiency. Additionally, from the plot the Least Squares (LS) estimator is shown to be more sensitive to pilot contamination due to its inability to suppress pilot interference through spatial processing. In contrast, the Minimum Mean Squared Error (MMSE) estimators can mitigate pilot interference, enabling them to function effectively even with tighter reuse factors. Overall, the figure 4.5 highlights that the optimal pilot reuse factor differs for the different estimators based on their sensitivity to pilot contamination and pre-log penalty considerations and selecting an appropriate reuse factor is crucial for balancing pilot interference suppression and pre-log factor optimization to maximize spectral efficiency.

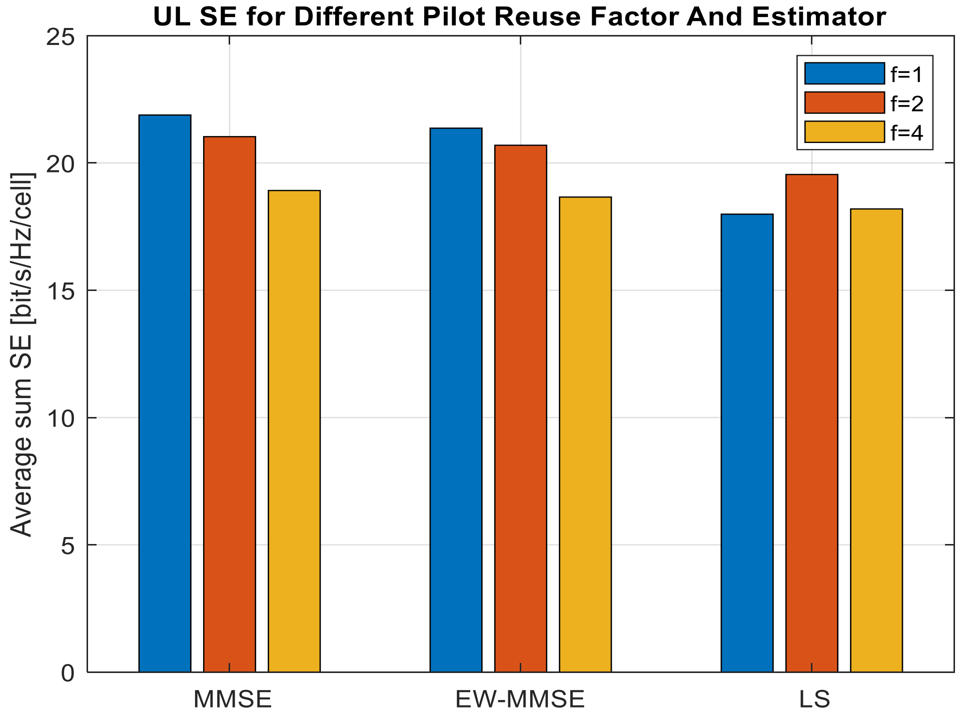


Figure 4. 5 Uplink Spectrum Efficiency for different Pilot reuse factor with Various channel estimator.

4.2.5 Average Uplink spectrum efficiency with spatially uncorrelated Rician and Rayleigh fading under different channel estimator.

This section considered the simulation result of the average uplink spectral efficiency (UL SE) in a scenario where spatially uncorrelated Rician and Rayleigh fading channels. The average UL SE analyzed as a function of the number of BS antennas under different channel estimators, including MMSE/EW-MMSE/LS with Rician fading, and MMSE/EW-MMSE/LS with Rayleigh fading. The figure 4.6 analyzed the differences in UL SE performance when utilizing different channel estimators under spatially uncorrelated Rician and Rayleigh fading. The simulation result indicates that the average UL SE with uncorrelated fading as a function of antenna count. EW-MMSE and MMSE coincide in this scenario because the spatial covariance matrices are diagonal. Rayleigh fading results in equal performance across all vectors due to a deterministic scaling factor that cancels out in SINR formulations. But the LS estimator shows lower UL SE performance in spatially uncorrelated Rician fading compared to MMSE and EW-MMSE estimators.

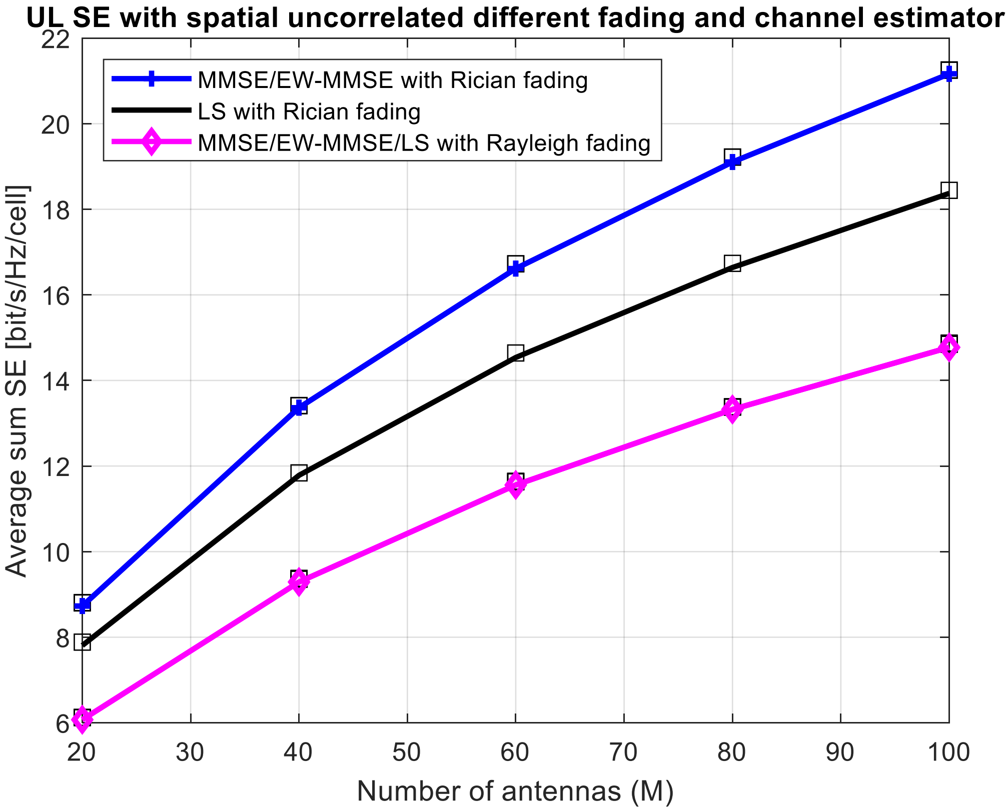


Figure 4. 6 Uplink Spectrum Efficiency for spatially uncorrelated Rician and Rayleigh fading under different channel estimation.

4.2.6 Average Uplink spectrum efficiency for different channel estimator and different Precoding schemes.

Figure 4.7 illustrates the simulation result of the average UL sum SE when M-MMSE, RZF, and MR combining schemes are considered. From the result MMSE estimator provides the largest SEs, as expected due to its accuracy in channel estimation and EW-MMSE instead results in some percent reduction in SE, depending on the combining strategy. But, in case of RZF or MR combining, the SE difference between EW-MMSE and LS estimators is minimal. However, M-MMSE combining performs poorly with LS. The LS estimator fails to scale channel estimates correctly in the presence of pilot contamination, instead estimating the sum of interfering channels. M-MMSE overestimates the norm of UE channels in other cells, emphasizing the importance of minimizing inter-cell interference. Using RZF or M-MMSE combining yields significant SE increases over low-complexity MR combining, regardless of the channel estimator utilized.

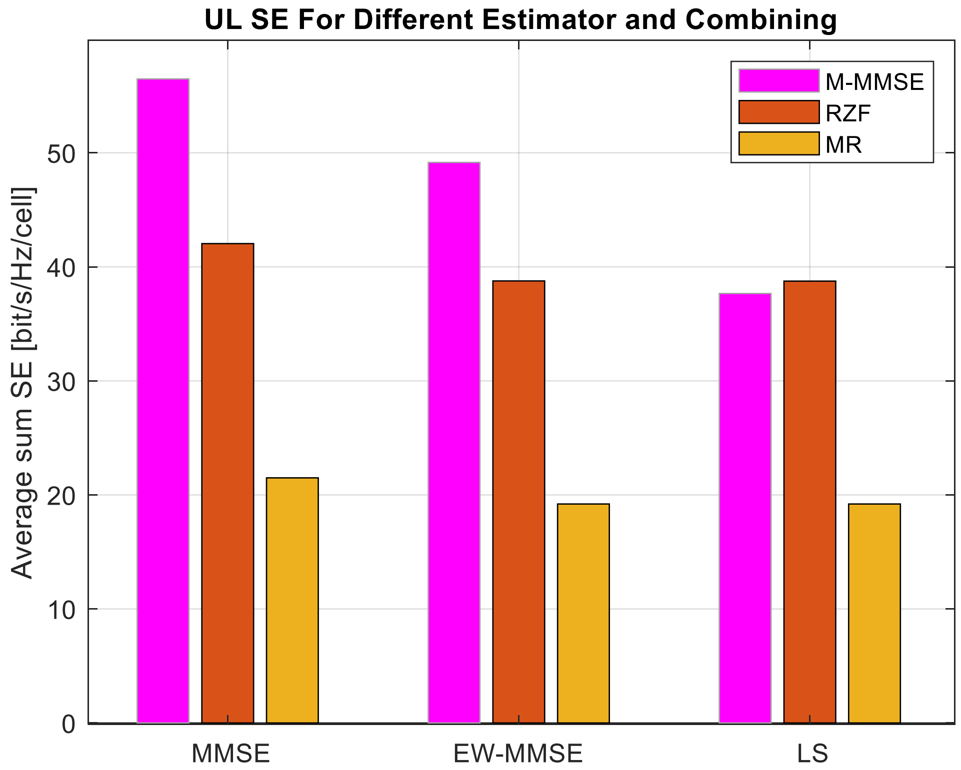


Figure 4. 7 Average UL sum SE when using MMSE, EW-MMSE, or LS channel estimators, for a setup with M = 100 BS antennas and K = 10 UEs per cell. Three different combining schemes are considered.

4.3 Result of Downlink spectrum efficiency under different channel estimator.

In this section the simulation result of downlink spectrum efficiency under different channel estimator analyzed. The simulation results for spatially correlated Racian, Rayleigh fading of downlink spectrum efficiency under different channel estimator are discussed here. The key simulation results presented for the downlink spectrum under different channel estimator are:

- Average Downlink spectrum efficiency for different channel estimator
- Average Downlink spectrum efficiency for different channel estimator and different Precoding schemes.

4.3.1 Average Downlink spectrum efficiency for different channel estimator.

In figure 4.8 the downlink spectral efficiency (DL SE) is examined as a function of the number of base station (BS) antennas for different channel estimators. The simulation result presents the downlink spectral efficiency (DL SE) as a function of the number of base station (BS) antennas for different channel estimators (MMSE, EW-MMSE, LS) in scenarios with Rician and Rayleigh fading channels. The graph analyzed that, the DL SE achieved with the MMSE estimator in Rician fading scenarios generally exhibits the highest values among the three estimators as the number of BS antennas increases. Because MMSE estimation optimally utilizes the knowledge of Rician fading characteristics and spatial diversity, leading to enhanced spectral efficiency in the downlink transmission scenario. The DL SE with the EW-MMSE estimator closely follows the MMSE estimator in Rician fading scenarios, showing competitive performance and relatively high spectral efficiency, due to EW-MMSE focuses on element-wise mean squared error optimization, contributing to improved spectral efficiency in Rician fading conditions. But the DL SE achieved with the LS estimator in Rician fading scenarios lags behind MMSE and EW-MMSE estimators, resulting in lower spectral efficiency values, because LS estimation may struggle to fully exploit the benefits of Rician fading and spatial diversity, leading to reduced spectral efficiency compared to MMSE and EW-MMSE. Also the simulation result analyzed DL SE in Rayleigh fading scenarios, from this result the DL SE achieved with the MMSE estimator generally exhibits the highest values among the three estimators as the number of BS antennas increases, reason MMSE estimation optimally utilizes the available channel information and spatial diversity, leading to enhanced spectral efficiency even in Rayleigh fading conditions. The DL SE with the EW-MMSE/LS estimator in Rayleigh fading scenarios coincide performance in improving spectrum efficiency.

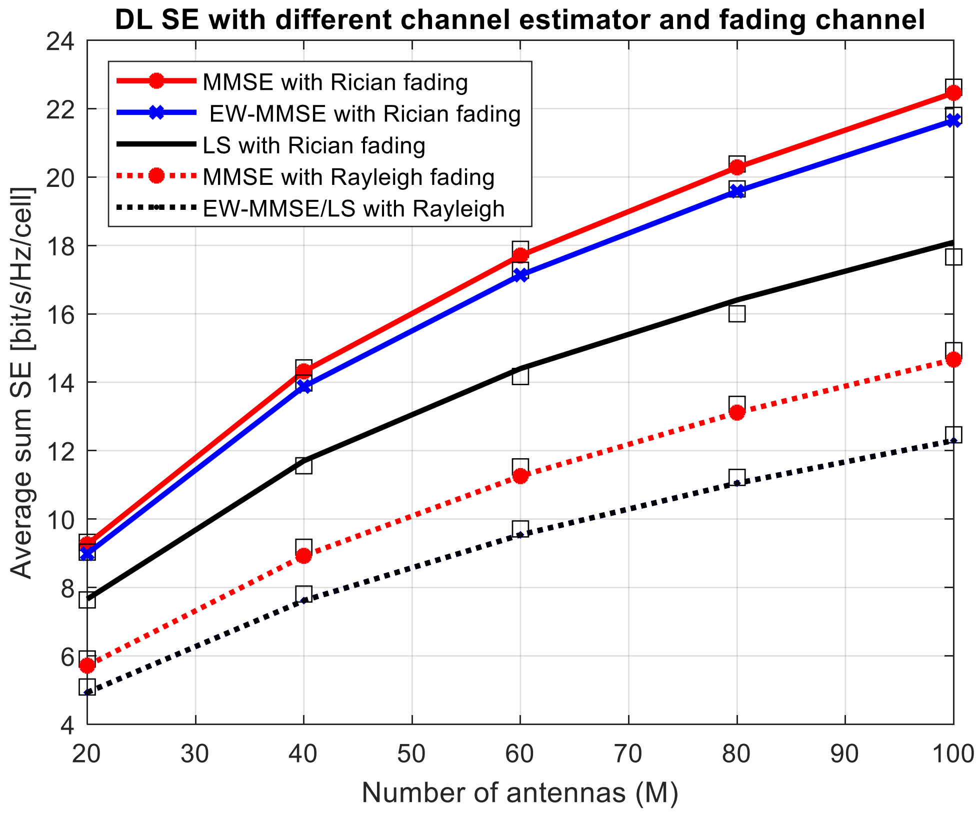


Figure 4. 8 Downlink Spectrum Efficiency for 10 user is shown as function of BS antenna for various channel estimation and fading channel..

4.3.2 Average Downlink spectrum efficiency for different channel estimator and different Precoding schemes.

Figure 4.9 shows the simulation results of a comparison of the spectrum efficiency performance of M-MMSE, RZF and MR combining schemes under difference channel estimator techniques. From the result MMSE channel estimator produces the greatest SEs and EW-MMSE instead results in some percent reduction in SE, depending on the combining strategy. Additionally, the difference in SE between the EW-MMSE and LS estimators is quite minor when employing RZF or MR precoding, but M-MMSE precoding performs badly with LS. The LS estimator incorrectly scales channels to UEs in other cells, leading to an overemphasis on mitigating inter-cell interference. To address this issue, reduce the norm of inter-cell channel estimates.

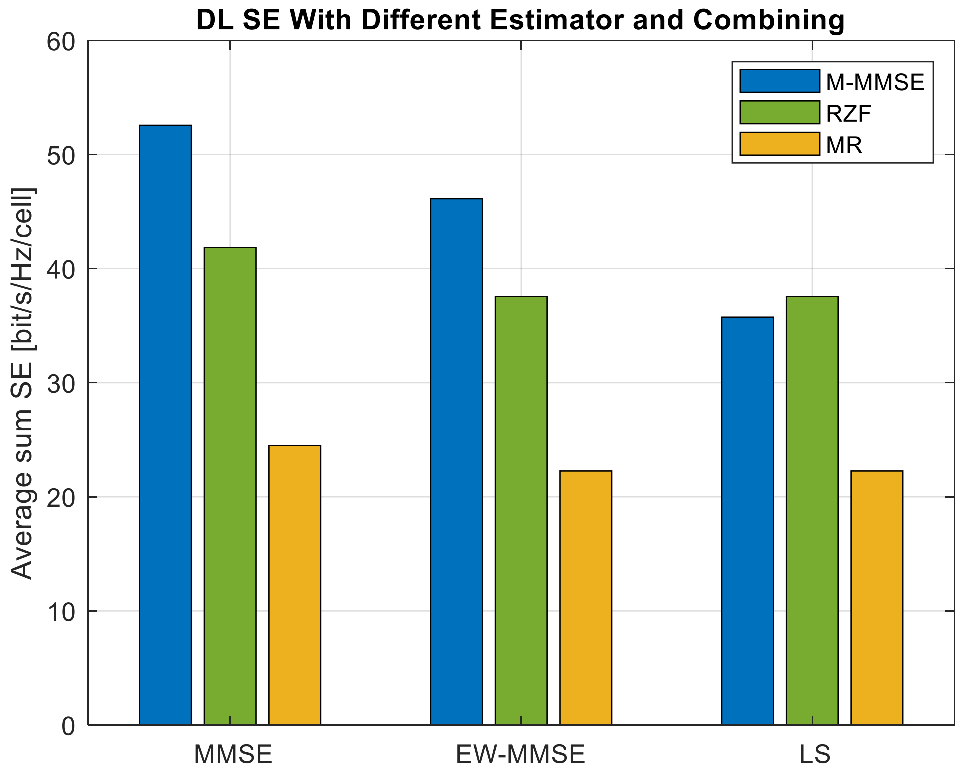


Figure 4. 9 Average DL sum SE when using the MMSE, EW-MMSE, or LS channel estimators, for a setup with M = 100 BS antennas and K = 10 UEs per cell. Three different precoding schemes.

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this thesis, the Uplink and Downlink Spectrum efficiency of multi-cell massive MIMO system are examined under spatially correlated Racian and Rayliegh fading channel. According to the simulation result channel estimation methods, such as MMSE, EW-MMSE, and LS estimators analyzed, in maximizing spectral efficiency, especially in environments with Line-of-Sight (LoS) and NLOS propagation paths. The comparison results reveal that the MMSE estimate outperforms other estimators for spatially coupled Rician and Rayleigh fading, while the LS estimator has the lowest SE. Furthermore, the results show that under Rician fading and Rayleigh circumstances, the MMSE estimator consistently obtains the highest Downlink (DL) spectral efficiency values among the estimators tested, demonstrating its optimal use of available channel information and spatial diversity. In contrast, the LS estimator falls behind the MMSE and EW-MMSE estimators in both Rician and Rayleigh fading scenarios, resulting in poorer spectral efficiency values due to constraints in fully exploiting fading benefits and spatial variety.

Overall, the simulation outcomes emphasize the significance of selecting appropriate channel estimation techniques to enhance spectral efficiency in massive MIMO systems, with MMSE estimation proving particularly beneficial in scenarios with challenging channel conditions. In practice, the covariance matrices and mean vectors may not be properly understood. The practical performance sits somewhere between the MMSE/EW-MMSE and LS estimators, because the mean is likely known up to a random phase shift and the covariance matrices are known with some error. These insights contribute to a deeper understanding of the impact of channel estimators on system performance, and can influence the design and optimization of massive MIMO installations.

5.2 Recommendation

In this thesis, the improvement of spectrum efficiency in Massive MIMO systems under different channel estimator are evaluated under simulation result only using the MATLAB tools. In the future exploring advanced channel estimation techniques beyond MMSE, EW-MMSE, and LS estimators. Investigating machine learning-based approaches or deep learning algorithms for channel estimation in massive MIMO systems could potentially improve spectral efficiency further. Another possibility for future research is effective interference management strategies for massive MIMO deployments. Developing interference mitigation techniques, such as advanced precoding algorithms or interference alignment methods, can improve spectral efficiency in interference-limited scenarios.

REFERENCES

25996-800. (n.d.).

3GPP TR 25.996. (2009). *Spacial channel model for Multiple Input Multiple Output (MIMO) simulations (3GPP TR 25.996 version 11.0.0 Release 11)*. *11.0.0*, 0–41.

Abebaw, Y., Shakya, R. K., Gelmecha, D. J., & Ware, E. T. (2023). Spectral Efficiency Analysis for Uplink Multicell Massive MIMO Cellular Communication System under Fading Channels. *Journal of Electrical and Computer Engineering*, *2023*. https://doi.org/10.1155/2023/6623938

Abid, W., Roy, S., & Ammari, M. L. (2019). Uplink Performance Analysis for Massive MIMO Linear Processing. *IEEE Access*, *7*, 180749–180760. https://doi.org/10.1109/ACCESS.2019.2959580

Abraham, J. (2022). *Statistics of the Effective Massive MIMO Channel in Correlated Rician Fading*. *3*(December 2021). https://doi.org/10.1109/OJAP.2022.3147015

Akgun, B., Krunz, M., & Koyluoglu, O. O. (2017). Pilot contamination attacks in massive MIMO systems. *2017 IEEE Conference on Communications and Network Security, CNS 2017*, *2017-Janua*, 1–9. https://doi.org/10.1109/CNS.2017.8228655

Ali, A., Qureshi, I. A., Memon, A. L., Memon, S. A., & Saba, E. (2018). Spectral efficiency of massive MIMO communication systems with zero forcing and maximum ratio beamforming. *International Journal of Advanced Computer Science and Applications*, *9*(12), 383–388. https://doi.org/10.14569/IJACSA.2018.091254

Amadid, J., Belhabib, A., Khabba, A., El Ouadi, Z., & Zeroual, A. (2022). Channel Estimation Evaluation For a Massive MIMO System Considering Spatially Correlated Channels in an Urban Network. *E3S Web of Conferences*, *351*, 1–6. https://doi.org/10.1051/e3sconf/202235101055

Björnson, E., & Demir, Ö. T. (2024). Introduction to Multiple Antenna Communications and Reconfigurable Surfaces. In *Introduction to Multiple Antenna Communications and Reconfigurable Surfaces*. https://doi.org/10.1561/9781638283157

Björnson, E., Hoydis, J., Labs, B., & Sanguinetti, L. (2020). * Massive MIMO Networks: Spectral, Energy, and Hardware Efficiency. *Foundations and Trends in Signal Processing*, *11*(3–4), 154–655. https://doi.org/10.1561/2000000093.Simulation

Björnson, E., Larsson, E. G., & Marzetta, T. L. (2016). Massive MIMO: Ten myths and one critical question. *IEEE Communications Magazine*, *54*(2), 114–123. https://doi.org/10.1109/MCOM.2016.7402270

Chaves, R. S., Lima, M. V. S., Cetin, E., & Martins, W. A. (2022). User Selection for Massive MIMO under Line-of-Sight Propagation. *IEEE Open Journal of the Communications Society*, *PP*(May), 1. https://doi.org/10.1109/OJCOMS.2022.3172621

Engineering, C. (2021). *Performance Analysis and Optimization in Massive MIMO Systems Approval Page*.

Fading, R., Mimo, B. M., & Users, M. (2020). *Massive MIMO with Multi-Antenna Users under Jointly Correlated Massive MIMO with Multi-Antenna Users under Jointly Correlated Ricean Fading*.

Kansal, L., Sharma, V., & Singh, J. (2019). Multiuser Massive MIMO-OFDM System Incorporated with Diverse Transformation for 5G Applications. *Wireless Personal Communications*, *109*(4), 2741–2756. https://doi.org/10.1007/s11277-019-06707-1

Li, F., Sun, Q., Ji, X., & Chen, X. (2022). Scalable Cell-Free Massive MIMO with Multiple CPUs. *Mathematics*, *10*(11). https://doi.org/10.3390/math10111900

Ngo, H. Q. (2015). Massive MIMO: Fundamentals and System Designs. In *Massive MIMO: Fundamentals and System Designs* (Issue 1642). https://doi.org/10.3384/lic.diva-112780

Nivethitha, R., Suresh, M. N., & Ananthi, G. (2015). Channel estimation in massive mimo systems. *International Journal of Applied Engineering Research*, *10*(20), 18807–18811. https://doi.org/10.22214/ijraset.2022.39775

Rajani, A., Teja, S. R., & Tech, M. (2018). *Energy Efficient Data Detection for Uplink Multiuser Massive Mimo Systems*. *8*(1169), 1169–1175.

Sadraei, M. H., Fazel, M. S., & Doost-hoseini, A. M. (2020). *Ergodic spectral efficiency of massive MIMO with correlated Rician channel and MRC detection based on LS and MMSE channel estimation*. https://doi.org/10.1049/iet-com.2019.0905

ScholarWorks, U., Graduate Theses, U., & Mayouche, A. (2016). *Channel Estimation Overhead Reduction for Downlink FDD Channel Estimation Overhead Reduction for*

Downlink FDD Massive MIMO Systems Massive MIMO Systems Part of the Electrical and Electronics Commons, and the Systems and Communications Commons Citation Cit. https://scholarworks.uark.edu/etd://scholarworks.uark.edu/etd/1688

Shi, E., Zhang, J., Wang, Z., Wing, D., Ng, K., & Ai, B. (n.d.). *Uplink Performance of RIS-aided Cell-Free Massive MIMO System Over Spatially Correlated Channels*.

Shlezinger, N., Eldar, Y. C., & Mimo, A. M. (2019). On the Spectral Efficiency of Noncooperative Uplink Massive MIMO Systems. *IEEE Transactions on Communications*, *67*(3), 1956–1971. https://doi.org/10.1109/TCOMM.2018.2884008

Siddiqui, M. U. A., Qamar, F., Kazmi, S. H. A., Hassan, R., Arfeen, A., & Nguyen, Q. N. (2023). A Study on Multi-Antenna and Pertinent Technologies with AI/ML Approaches for B5G/6G Networks. *Electronics (Switzerland)*, *12*(1). https://doi.org/10.3390/electronics12010189

Sofi, I. B., Gupta, A., & Kausar, R. (2018). Performance evaluation of different channel estimation techniques in MIMO system for hata channel model. *Proceedings - 2nd International Conference on Intelligent Circuits and Systems, ICICS 2018*, *April*, 126–132. https://doi.org/10.1109/ICICS.2018.00041

Thomas, L., Erik, G., Yang, H., & Ngo, H. Q. (n.d.). *Fundamentals of Massive MIMO*.

Ueoka, T. T. R., Souza, D. D., Freitas, M. M. de, Cavalcante, A. M., & Costa, J. W. (2022). *Performance of Cell-Free Massive MIMO Networks under Rayleigh and Rician fading*. 1–2. https://doi.org/10.14209/sbrt.2022.1570811228

Wang, S., Wen, M., Xia, M., Wang, R., Hao, Q., & Wu, Y. C. (2020). Angle Aware User Cooperation for Secure Massive MIMO in Rician Fading Channel. *IEEE Journal on Selected Areas in Communications*, *38*(9), 2182–2196. https://doi.org/10.1109/JSAC.2020.3000837

Wikiman, O. O., & Idowu-bismark, O. (2019). *Performance of Massive MIMO in a Rician Fading Channel Using a ZF Precoder*. *9*(1), 1–7. https://doi.org/10.5923/j.jwnc.20190901.01

Zaheera, F. (2022). *Large-scale Fading Decoding based Massive MIMO System with Regularized Zero Forcing Precoder*. *13*(03), 16–26.

Zarai, F., Boudriga, N., & Obaidat, M. S. (2011). Universal Mobile Telecommunications

System. *Handbook of Computer Networks*, *2*, 699–715. https://doi.org/10.1002/9781118256114.ch46

Zhi, K., Pan, C., Ren, H., Wang, K., Elkashlan, M., Renzo, M. Di, Schober, R., Poor, H. V., Wang, J., & Hanzo, L. (2023). Two-Timescale Design for Reconfigurable Intelligent Surface-Aided Massive MIMO Systems With Imperfect CSI. *IEEE Transactions on Information Theory*, *69*(5), 3001–3033. https://doi.org/10.1109/TIT.2022.3227538

Zuo, X., Zhang, J., Mu, X., & Yang, L. (n.d.). *Channel Correlation Relied Grouped Spatial Modulation for Massive MIMO Systems*. 1–11.