

PERFORMANCE ANALYSIS OF PRECODING TECHNIQUES FOR EXTREMELY LARGE MIMO SYSTEM



Bereketeab Zinabu Tadesse

A Thesis Submitted to

the 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

**PERFORMANCE ANALYSIS OF PRECODING TECHNIQUES
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DECLARATION

I declare that this Master Thesis entitled “**Performance Analysis of Precoding Techniques for Extremely Large MIMO System**” is my own 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 dully acknowledged through citations.

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We, the advisors of this thesis, hereby certify that we have read the revised version of the thesis entitled “**Performance Analysis of Precoding Techniques for Extremely Large MIMO System**” prepared under our guidance by Bereketiab Zinabu Tadesse. submitted in partial fulfillment of the requirement 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

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We, the advisors of the thesis entitled “**Performance Analysis of Precoding Techniques for Extremely Large MIMO System**” and developed by Bereketeab Zinabu Tadesse, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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ACKNOWLEDGMENT

First of all, I am thankful to our creator God for having guided me throughout this thesis at each stage and for each new idea that he setup in my minds. I express my gratitude to my advisor, Dr. Rajaveerappa Devadas, for his guidance, kind attitude, and generous sharing of numerous insightful concepts. I am particularly appreciative of Dr. Demissie Jobir, my co-advisor, for his ongoing assistance and insightful advice. Furthermore, I would like to thank to every member of the School of Electrical and Computing Engineering members and staff of the department of Electronics and Communication Engineering coordinator, for creating such a good environment for research and instruction. Finally, I would want to thank my friends and family for their continuous support and for always being there for me.

ABSTRACT

Currently, beyond the 5G mobile network, is a promising technology in wireless communication. This requires a very large number of antennas to increase the performance. Extremely Large Multiple Input Multiple Output (XL-MIMO) is a technique that allows the use of numerous antennas to improve spectral efficiency and is one of the most important technologies for 5G and beyond 5G (B5G) wireless communication systems. Despite its advantages, the proliferation of antennas introduces challenges such as interference and heightened complexity. To address interference and optimize the transmission of multiple independent data streams, spatial multiplexing and beamforming play pivotal roles. In this thesis, five distinct precoding schemes have been examined such as SwoR-rKA, rKA, TPE, RZF, and MRT, in terms of their complexity and performance. XL-MIMO systems take advantage of spatial variety to provide high capacity and spectrum efficiency. Because of the large number of antennas, this performance comes at the expense of significant computational complexity. Low-complexity precoding techniques can be used to solve this problem by lowering computational complexity without sacrificing performance. SwoR-rKA has high performance in terms of SE. The rKA method chooses the column to be updated randomly, on the other hand, the SwoR-rKA approach tends to choose a column that corresponds to a channel in better condition. This method is ineffective because the channel in good condition can be selected more frequently for small iteration. To address this issue, the PCP-SwoR-rKA method chooses a column that corresponds to a channel in bad condition in order to reduce the error term. When SwoR-rKA is compared with RZF, it has a 0.9% improvement in SE. Based on the simulation result, it can be observed that the PCP-SwoR-rKA method lowers the bit error by 12.5% compared to the existing method with the same performance and complexity.

Keywords: Precoding; randomized Kaczmarz; maximum ratio transmission; complexity; regularized zero-forcing; XL-MIMO

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LIST OF SYMBOLS

$\ \cdot\ ^2$	2-norm
$\ \cdot\ _F$	Frobenius norm.
ρ	Average transmit power at the BS
B	Normalized power factor
σ^2	Noise variance
C	Interference term
λ	Regularization factor which is the inverse of SNR
D_j	Precoding matrix in j^{th} subarrays
D_s	Precoding matrix in s^{th} subarrays
H	Channel matrix
H_j^H	Conjugate transpose for j^{th} subarrays
I_M	Identity matrix
J	TPE order
K	User equipment
$K^{(j)}$	The number of UEs in the j^{th} subarray
M	Base station antenna
$M^{(j)}$	The number of subarray antennas
P_{tr}	Downlink transmitted power
S_j	Data symbols for all UEs in the j^{th} subarrays
S_s	Data symbols for all UEs in the s^{th} subarrays

LIST OF ACRONYMS

6G	Sixth Generation
B5G	Beyond Fifth Generation
BER	Bit Error Ratio
BS	Base Station
CG	Conjugate Gradient
CPU	Central Processing Unit
CSI	Channel State Information
DPC	Dirty Paper Coding
EE	Energy Efficiency
ISI	Inter Symbol Interference
MIMO	Multiple Input Multiple Output
mMIMO	massive Multiple Input Multiple Output
MMSE	Minimum Mean Square Error
MRT	Maximum Ratio Transmission
NTP	Normalized Transmit Power
PCP-SwoR-rKA	Poor Condition Prioritization Sampling without Replacement randomized Kaczmarz
rKA	randomized Kaczmarz
RZF	Regularized Zero Forcing
SE	Spectral Efficiency
SLE	Set of Linear Equations
SINR	Signal Interference Noise Ratio
SNR	Signal-to-Noise Ratio
SwoR-rKA	Sampling without Replacement randomized Kaczmarz
TPE	Truncated Polynomial Expansion
UEs	User Equipment's
WT	Wiener Transmit
XL-MIMO	Extremely Large Multiple Input Multiple Output
ZF	Zero Forcing

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Due to the rise in connected devices and the demand for data-intensive applications, there has been an exponential increase in requiring of high data rates and reliable wireless connections in recent years. Large-scale antenna arrays are essential for various candidate technologies for B5G or 6G to achieve their expected performance (Cui et al., 2023). The extremely large multiple input multiple output (XL-MIMO) approach is one of the many 6G technologies that stands out because of its capacity to offer dependable huge access, high spectral efficiency (SE), and high energy efficiency (EE). This technology has the potential to alleviate the throughput and reliability issues in contemporary wireless networks. Unlike traditional massive MIMO (mMIMO), the main objective of XL-MIMO is to install an extremely large number of antennas in a small space. In addition to having a different hardware architecture, XL-MIMO also adds many new features that are absent in mMIMO. By changing electromagnetic characteristics fundamentally and adding more antennas, XL-MIMO technology increases spectral efficiency (Z. Wang et al., 2023). The concept behind XL-MIMO is to expand the antenna array at the access point in order to capture additional spatial degrees of freedom (Amiri & Manch, 2019). When users cannot reach some areas of the array because of its large aperture and when propagation circumstances in different viewable zones are completely uncorrelated, a phenomenon known as spatial non-stationarity may arise (Mar, 2021). The area of the array that a certain user sees, or can receive signals from the user, is known as the visibility zone. It is linked to a specific user (Amiri et al., 2018). Moreover, the XL-MIMO should take into consideration the channel's spatial non-stationarity, mutual coupling, and polarization, whereas the mMIMO ignores these factors.

Effective precoding algorithms are essential to provide reliable and high-performance downlink transmission in XL-MIMO systems due to the presence of multiple users as well as the difficulties caused by interference and channel conditions. It is one of the ways to improve transmission using channel state information at the transmitter. The information describes the path that a signal takes

from the sender to the recipient and includes details like the impacts of fading, power decay, and distance scattering (Thurpati et al., 2021a).

By using the expanded spatial degrees of freedom, downlink precoding for XL-MIMO systems, which effectively eliminates obstruction, gives a significant sum rate gain. Precoding techniques in XL-MIMO systems aim to optimize the transmission of signals from the base station to the UEs by pre-processing the transmitted signals at the base station using spatial filtering and beamforming algorithms. These techniques are responsible for shaping the transmitted signal in such a way that it maximizes the received signal quality at the UEs while mitigating the impact of interference and inter-user interference. Another challenge is the practical implementation of XL-MIMO systems, the physical size and power consumption of the antenna array can be significant, requiring careful design and optimization (Amiri & Manch, 2019). Additionally, the deployment of XL-MIMO systems may require new infrastructure and modifications to existing networks. There are several precoding algorithms proposed for XL-MIMO systems, including Zero Forcing (ZF) precoding, Regularized Zero Forcing (RZF) precoding, Truncated Polynomial Expansion (TPE) precoding, randomized Kaczmarz Algorithm (rKA), and Sampling without Replacement rKA (SwoR-rKA).

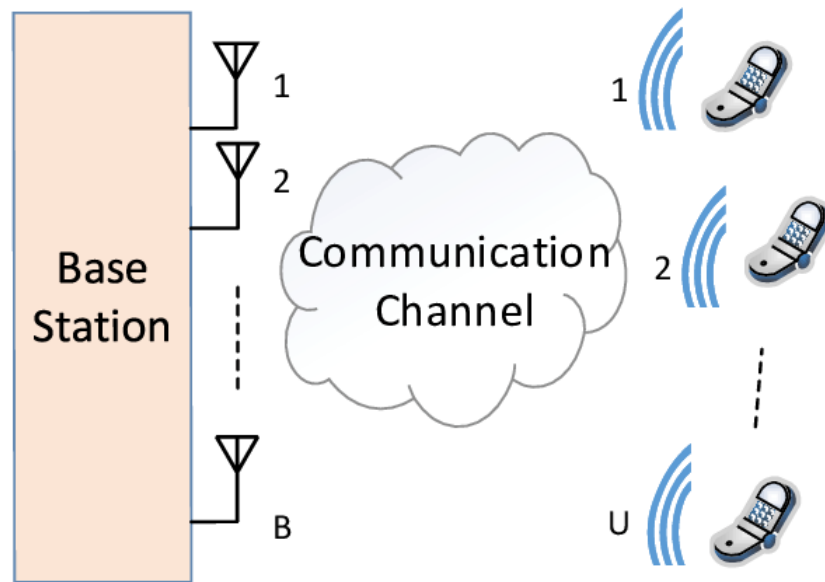


Figure 1.1: Wireless system (Shahabuddin et al., 2020).

1.2 Statement of the Problem

Interference can be a significant issue with the downlink of XL-MIMO systems, where several users are supplied simultaneously and multipath propagation exists between the transmitter and receiver. The simultaneous broadcast from several antennas, as well as reflections and multipath effects in the wireless channel, all cause interference. The interference might deteriorate signal quality and lower the users' possible data speeds. Therefore, it is essential to create and use efficient precoding algorithms that can reduce interference in XL-MIMO downlink system. These precoding methods seek to maximize the quality of the received signal at each user's receiver while minimizing the interference in the transmitted signals.

In addition to reducing interference in the downlink of XL-MIMO system, keeping low computational complexity is essential for precoding approaches. The computational complexity of precoding techniques can have a considerable impact on system performance and the viability of implementation given the huge number of antennas and users in XL-MIMO configurations. Signal processing approaches for XL-MIMO systems would require very high computational complexity because of the extremely large array aperture. Therefore, it is important to create precoding methods that balance performance and computational complexity in addition to interference prevention.

The majority of downlink beamforming techniques now in use operate under the assumption that the channel is spatially stationary, or statistical characteristics of the channel. As a result, the channel coefficients differ from antenna to antenna in real life since the channel is frequently spatially non-stationary. Two existing techniques for downlink beamforming in spatially non-stationary channels have been proposed like the sampling without replacement rKA (SwoR-rKA) approach and the randomized Kaczmarz algorithm (rKA). The rKA method chooses the column to be updated randomly, on the other hand, the SwoR-rKA approach tends to choose a column that corresponds to a channel in better condition. This method is ineffective because the channel in good condition can be selected more frequently for small iteration. To address this issue the Poor Condition Prioritization SwoR-rKA (PCP-SwoR-rKA), choose a column that corresponds to a channel in bad condition in order to reducing error term.

1.3 Objective of the Study

1.3.1 General Objective

The general objective of this thesis is to analyze and compare the performance of precoding techniques on an extremely large downlink MIMO system.

1.3.2 Specific Objectives

The specific objectives are:

- To analyze the performance of spectral efficiency and energy efficiency of XL-MIMO systems.
- To compare the performance of precoding for perfect and imperfect non-stationary channels.
- To compare the BER of precoding under 16PSK and 64QAM for imperfect non-stationary channels.
- To analyze and compare the computational complexities of SwoR-rKA, rKA, RZF, TPE, and MRT
- To compare the performance metrics of SwoR-rKA, rKA, RZF, TPE, and MRT

1.4 Significance of the Study

The importance of this thesis is in its capacity to offer insightful advice and useful recommendations for the development and deployment of downlink XL-MIMO systems. The study attempts to enhance system performance, reduce interference to increase energy and spectral efficiency, and solve computational complexity by analyzing and comparing various precoding techniques. This information can aid in the creation of wireless communication networks that are more capable, more spectrally efficient, and offer better user experiences. The findings of the study could ultimately influence the direction of XL-MIMO technology and its use in numerous industries.

1.5 Motivation

The motivation behind developing low-complexity precoding techniques for extremely downlink XL-MIMO systems with channel state information lies in the need to meet the increasing demand for high-speed wireless communication while addressing the computational complexity challenges of traditional precoding methods. As the number of antennas increases, conventional precoding methods, such as RZF, may not fully exploit the potential gains of the system. Therefore, there is a growing interest in more advanced precoding schemes to improve the performance of large-scale MIMO systems. However, the computational complexity of these precoding methods poses a significant challenge, particularly in downlink transmission where the precoding matrix needs to be computed within strict time constraints. Low-complexity precoding techniques, such as the randomized Kaczmarz method, bridge the gap between the performance of conventional and advanced precoding schemes while meeting the stringent computational latency requirements of extremely large MIMO systems.

1.6 Scope of the Study

The study will focus on assessing the effectiveness of various precoding methods in mitigating interference, improving spectral efficiency, and enhancing overall system performance. The performance analysis of these strategies is the main emphasis of this paper, which considers parameters like feasible sum rate, energy efficiency, and spectral efficiency. The study includes an analysis of the computational complexities and overheads associated with implementing these techniques. Additionally, it considers the influence of channel conditions. However, it is important to note that the study is limited to analyzing and comparing precoding techniques in the downlink of XL-MIMO systems and does not cover other aspects or system-wide optimization of XL-MIMO technology.

1.7 Thesis Contribution

This thesis investigates the performance of precoding techniques in extremely downlink XL-MIMO systems, considering the non-stationarity of the channel and proposing a method to reduce the BER. In this thesis, various precoding schemes, including SwoR-rKA, rKA, RZF, TPE, and MRT schemes, are thoroughly analysed under various scenarios by comparing important

performance metrics including spectral efficiency, energy efficiency, and computing complexity. The CA-SwoR-rKA improves the BER performance of the entire system by reducing the error of the SwoR-rKA technique.

1.8 Thesis Organization

There are five chapters in this thesis. An overview of XL-MIMO and precoding approaches, as well as a problem description, objectives, significance, scope, and motivation for the research are provided in Chapter 1. Chapter 2 reviews the existing literature on XL-MIMO and precoding techniques, identifying the gaps that the thesis aims to address. The research methodology and analytic methods are covered in Chapter 3. Chapter 4 presents the results and discusses their implications, comparing the proposed methods with existing methods. Chapter 5 summarizes the main findings of the thesis, draws conclusions based on the results, and makes recommendations for future research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Overview

The performance of large MIMO system technologies which are closely relevant to the goal of this study is reviewed in this chapter along with some related literature. There is a discussion of the benefits and drawbacks of the examined literature based on spectral efficiency, energy efficiency, BER and complexity utilizing various precoding algorithms.

2.2 Massive MIMO

New developments in wireless communication technology include massive MIMO (Multiple-Input Multiple-Output), which significantly enhances wireless network performance and capacity by using a large number of antennas at the Base Station (BS). A base station in a traditional MIMO system might have two or four antennas, but in a mMIMO system, there could be tens or even hundreds of antennas. By combining numerous antennas to broadcast and receive signals simultaneously, mMIMO makes use of the spatial dimension of wireless communication. A separate communication channel is created by each antenna, resulting in higher capacity and better spectral efficiency. A base station (BS) can serve multiple users simultaneously by sharing time and frequency resources, which is the fundamental idea behind mMIMO.

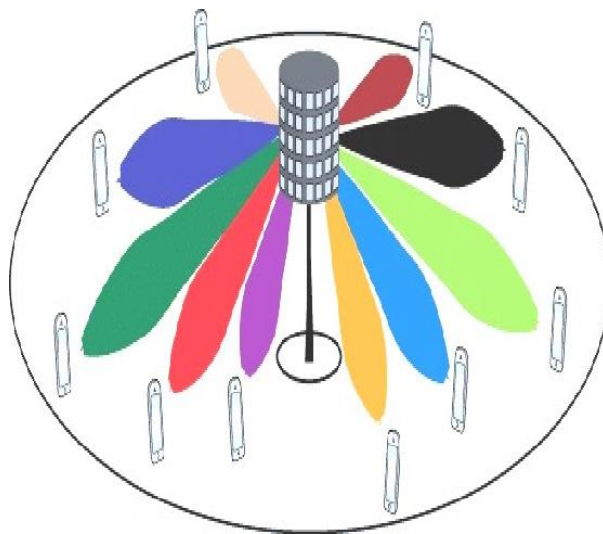


Figure 2.1: Structure for uplink and downlink mMIMO (Salah et al., 2023).

2.3 Extremely Large MIMO

XL-MIMO involves deploying an extremely large number of antennas in a compact space. This concept aims to significantly improve spectral efficiency and spatial degrees of freedom. In comparison to traditional mMIMO, XL-MIMO offers some unique features, such as a larger number of antennas and new channel characteristics, leading to fundamental changes in electromagnetic characteristics to improve spectral efficiency and spatial degrees of freedom. Because of the high dimensions of the array, XL-MIMO is characterized by spatial non-stationary field qualities along the array. This requires the design of a multi-antenna transceiver that is both suited to the dimensions of the array and has no stationary properties (Amiri et al., 2018).

2.4 Precoding

In the context of MIMO, precoding refers to a transmitter-side signal processing method that improves the efficiency of wireless communication networks. It delivers input signals to the various antenna elements in the proper ratio after combining them in a predetermined manner. Massive MIMO systems and developing 5G technologies both depend on precoding to provide satisfactory performance and eliminate interference from several data streams. Linear precoding and non-linear precoding are two techniques used in MIMO systems. Beamforming, also known as linear precoding, is a transmission technology that uses each transmit antenna to send out the same signal with the appropriate weighting, serving many users at once. It aims to increase the signal level of the targeted user or users. Linear precoding methods include Maximum Ratio Transmission (MRT), Zero Forcing (ZF), and Wiener Transmit (WT) precoding. The core concept of nonlinear precoding is the idea of DPC, which enables the subtraction of known interference at the transmitter sender without the need for additional radio resources. While nonlinear precoding can increase capacity and reduce errors in the receiver output, it is more difficult than linear precoding techniques.

There are various precoding techniques used in XL-MIMO systems, including linear precoding algorithms such as regularized zero-forcing precoding, maximum ratio transmission, truncated polynomial expansion precoding, and different algorithms such as randomized Kaczmarz (rKA), Sampling without Replacement of randomized Kaczmarz (SwoR-rKA).

- i. Regularized zero forcing: The Zero Forcing (ZF) precoding technique is improved upon by RZF, which also addresses some of its drawbacks and improves its functionality in real-world MIMO communication systems. It uses a matrix inversion.
- ii. Truncated polynomial expansion: Using a truncated polynomial expansion, the matrix inversion is rewritten to implement the precoding.
- iii. Maximum ratio transmission: A precoding method called MRT is applied in wireless communication systems, particularly in the context of MIMO systems. Used to maximize signal gain and SNR at the user.
- iv. randomized Kaczmarz algorithm: The rKA Algorithm uses iterative projections to try and recreate the unknown signal (C. Wang et al., 2015). This method selects each column at random.
- i. Sampling without randomized Kaczmarz Algorithm: an updated version of rKA. The SwoR-rKA approach selects a column that corresponds to the channel in better condition

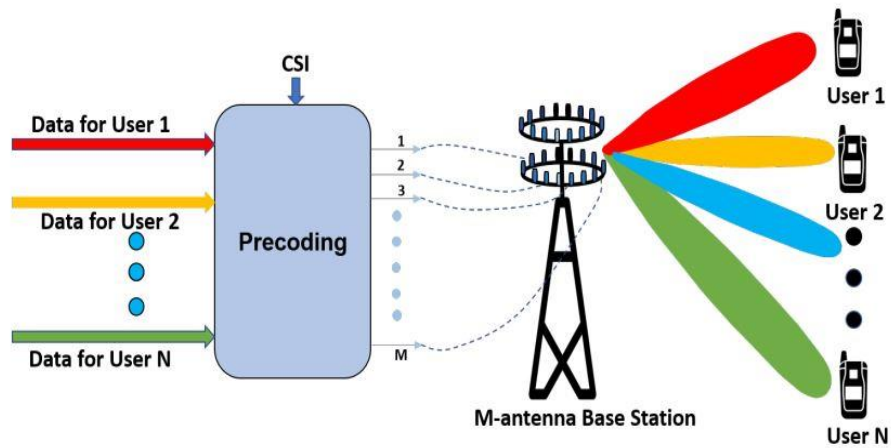


Figure 2.2: Precoding techniques (Chataut & Akl, 2020).

Precoding in XL-MIMO (Extremely Large MIMO) systems offers several advantages:

Improved Spectral Efficiency: Precoding increases spectral efficiency by maximizing the received signal towards particular receivers while optimizing the broadcast signal.

Enhanced Spatial Multiplexing: Precoding enhances data transmission capabilities by allowing the superposition of numerous beams and different data streams for spatial multiplexing.

Better Focus of Energy: Precoding improves signal quality and coverage by directing energy toward the target receiver when used with beamforming.

Increased System Performance: By exploiting transmit diversity and optimizing information streams, precoding can significantly enhance system performance, especially in 5G networks.

QoS Optimization: Different Quality of Service (QoS) levels can be concurrently provided to many users based on their unique requirements and channel conditions using scheduling and precoding.

2.5 Related Work

The paper (Xu et al., 2023) proposed a novel low-complexity precoding algorithm, rKA, and its improved version, SwoR-rKA, for XL-MIMO systems over non-stationary channels. It addressed the spatial non-stationary features of downlink XL-MIMO systems and provided a closed-form formulation of spectral efficiency taking subarray interference into account. The paper provides comprehensive simulation results that demonstrate the significantly reduced complexity of the proposed algorithms compared to traditional precoding algorithms while achieving high spectral efficiency performance. Additionally, the algorithms effectively reduce the bit error rate in the presence of imperfect channel estimation. The paper contributed valuable insights and practical solutions for addressing the challenges of large-scale MIMO systems over non-stationary channels. SwoR-rKA is updating the column corresponding to good conditions. Since a small number of iterations can be used to estimate the columns corresponding to good channels, so this approach is ineffective.

The proposed approach (Mar, 2021) begins by establishing the motivation for low-complexity precoding techniques in XL-MIMO systems. It emphasizes the advantages of XL-MIMO technology, such as increased spectral efficiency and improved coverage, while acknowledging the computational complexity associated with handling a massive number of antennas. The authors emphasize the need for precoding schemes that strike a balance between performance and complexity. The author offers two novel precoding techniques, tensor zero-forcing and mean-angle-based zero-forcing, that are intended to reduce complexity in XL-MIMO transmissions while maintaining a high level of performance. The suggested methods obtain a low complexity of the ZF precoder by grouping users and using a plane-wave approximation. The paper presents

the proposed low-complexity zero-forcing precoding scheme. The authors outline the key principles and algorithms employed in their approach, focusing on reducing the computational complexity while maintaining the performance of ZF. However, this paper focuses only on zero-forcing do not consider other types of precoding that have high performance when compared with ZF and does not consider CSI.

(Rodrigues et al., 2020) The efficiency of the suggested precoding techniques in terms of BER and computational complexity is illustrated numerically in the article. Two power normalization methods for non-stationary channels have been considered, and non-stationary qualities have been implemented using the visibility region concept. The proposed schemes achieve a significant reduction in computational complexity while maintaining a low BER. The results presented in the paper demonstrate that the proposed distributed XL-MIMO technique achieves significant improvements in terms of both performance and complexity compared to conventional detection methods which are ZF and RZF. The authors discussed the advantages and limitations of their approach and provided insights into the applicability of distributed XL-MIMO in practical wireless networks. The imperfect channel state information cannot be considered.

The paper (Rodrigues, 2019) proposed a modified version of the randomized Kaczmarz algorithm (rKA) to enhance its trade-off between performance and complexity for mMIMO systems. The purpose of their research was explained in the paper's opening section, which also emphasizes the value of precise channel estimation and the significance of spatial correlation in huge MIMO settings. The authors highlight the significance of spatial correlation and channel estimation in mMIMO systems as well as the unaffordable complexity of conventional precoding algorithms like zero-forcing in mMIMO transmissions. The updated rKA method that has been suggested tries to keep the ZF precoder's performance while reducing complexity. They discuss the computational complexity of the algorithm and provide insights into its convergence behavior and robustness.

(Thurpati et al., 2021)The performance study of linear precoding techniques in MIMO systems is covered in this paper, with a special emphasis on massive MIMO systems. It evaluates and contrasts alternative precoding techniques, including Truncated Polynomial Expansion, Regularized Zero-Forcing, Maximum Ratio Transmission, and Zero Forcing, to the influence of channel state information, feasible sum rates, and efficiency at various power levels. The work

presents TPE as a viable low-complexity linear precoding technique and emphasizes the benefits of RZF precoding, particularly in situations with high power values and numerous base station antennas. About spectrum efficiency, interference management, and overall system performance in Massive MIMO setups, the work sheds important data on the efficiency of Polynomial Expansion-based precoding techniques. The authors show how Polynomial Expansion techniques can improve the quality of downlink communication in Massive MIMO systems using extensive performance analysis and simulation research. It does not consider the computational complexity and effect of BER.

(Ibrahim et al., 2022) In huge MIMO systems for 5G networks, the article assesses the performance of precoding schemes, particularly ZF and MRT. According to the study, ZF with turbo coding performs better than MRT in both downlink and uplink scenarios concerning throughput, bit error rate, number of supported users, and error rate. The significance of channel coding in improving system performance is highlighted, and it is concluded that in large MIMO systems, ZF with turbo coding is the best option for obtaining high throughput and low BER. The lack of explicit consideration of the complexity of the precoding system for mMIMO can be considered a gap in the paper.

(Asif et al., 2020) The goal of the study is to maximize area capacity and energy efficiency in huge MIMO systems by utilizing various power consumption models and precoding strategies. It goes over the computations needed to increase energy efficiency while taking typical data rates, power distribution, and power consumption at base stations and user equipment into account. The suggested approach improves area throughput and energy efficiency. The EE system model that they suggest is practical and realistic. It does not consider BER.

Under the article (Pramono & Triyono, 2018), Comparative analysis of the effectiveness of linear precoding systems has been conducted in detail., including block diagonalization, ZF, and MRT. The authors compare the bit error rate and achievable sum rate of those three methods using simulations. The paper concludes MRT precoding scheme excels in low SNR scenarios with a larger number of active users, while the ZF precoding scheme is dominant in scenarios with a smaller number of active users. Additionally, the MRT precoding scheme yields a better BER, while the ZF precoding scheme provides a better achievable sum rate, especially when there are

lots of active users. The SNR, number of users, and antennas all have an impact on how well precoding techniques perform, according to the authors. Furthermore, the MRT precoding scheme includes decreasing performance with a larger number of active users, suboptimal achievable sum rate in scenarios with a large number of active users, challenges in wave propagation in the millimeter wave spectrum, and potential limitations in addressing interference and link reliability in multi-user MIMO scenarios. It only considers perfect CSI.

In the (Subitha & Vani, 2021) paper the author analyzes the performance of linear precoding techniques for mMIMO-OFDM systems under different condition such as rural, sub-urban, and urban. In terms of achievable sum rate and BER, the methods zero forcing, minimum mean square error, and conjugate gradient (CG) are studied. The channel model is stochastic channels. The CG precoding shows better performance in rural areas. If the number of users is increased, the performance will decrease. It is effective only in rural environments.

Table 2.1: Summary of some related work.

Authors	Year	Title	Techniques	Gap
Xu et al.	2023	Low-Complexity Precoding for Extremely Large-Scale MIMO Over Non-Stationary Channels.	proposed low computational complex algorithm and high spectral efficient algorithms.	SwoR-rKA is updating the column corresponding to good conditions.
Mar et al.	2021	Low-Complexity Zero-Forcing Precoding for XL-MIMO Transmissions	emphasize the need for precoding schemes that strike a balance between complexity and performance.	focuses only on zero forcing and does not consider CSI.

Rodrigues et al.,	2020	Low-Complexity Distributed XL-MIMO for Multiuser Detection	non-stationary channels have been considered, and non-stationary qualities have been implemented using the visibility region concept	Imperfect channel state information cannot be considered
Thurpati et al.	2021	Performance analysis of linear precoding in downlink based on polynomial expansion on massive MIMO system.	It evaluates and contrasts alternative TPE, RZF, MRT, and ZF.	It does not consider computational complexity and effect of BER.
Ibrahim et al.,	2022	Performance evaluation of precoding system for massive multiple-input multiple-output	assesses the performance of precoding schemes, particularly ZF and MRT both in uplink and downlink transmission	The lack of explicit consideration of the complexity of the precoding system for mMIMO can be considered
Asif et al.,	2020	Energy Efficiency Augmentation in Massive MIMO Systems through Linear Precoding Schemes and	The EE system model that they suggest is practical and realistic.	It does not consider BER

		Power Consumption Modeling		
Pramono & Triyono	2018	Comparative performance analysis of linear precoding in downlink multiuser MIMO	compare the BER and achievable sum rate of ZF, MRT, and BD.	SE and EE are not considered
Subitha & Vani	2021	Analysis of a linear precoding techniques for massive MIMO-OFDM systems under various scenarios	The algorithms ZF, MMSE, and CG are analyzed in terms of BER and achievable sum rate under various scenarios such as rural, sub urban and urban.	If the number of users is increased, the performance will decrease. It is effective only in rural environments.

CHAPTER THREE

METHODOLOGY

3.1 Overview

In this thesis, different articles and secondary data sources are reviewed from various journals such as IEEE, Springer, and Elsevier, past study trials by scholars, and also books that are related to XL-MIMO precoding techniques are highlighted. Based on literature review, the statement of the problem, and the limitation of existing precoding, the methodology of this study is designed and simulated as follows.

3.2 Material Used

The simulation is carried out in MATLAB/R2022b for the performance analysis of precoding techniques for an extremely large downlink MIMO system. Generally, to write, simulate, test, and view results from codes, MATLAB software tools are applied.

3.3 Methodology

System Model: Establish a comprehensive system model for downlink XL-MIMO, considering the number of antennas at the base station, the number of users, channel conditions, and interference sources. Define the performance metrics, such as sum rate, SE, EE and BER, to evaluate the effectiveness of precoding techniques.

Simulation: simulate the channel models with computer software using MATLAB. We calculate the Achievable rate and the energy efficiency to analyze the effect of an XL-MIMO downlink system over different channel models. includes mathematical modeling of the system.

Performance Analysis and Evaluation: Conduct a comprehensive performance evaluation of the precoding techniques. Analyze the SE, EE and BER for each technique under various scenarios.

Result and discussion: depending on the results from the simulation, discussion is performed on the results.

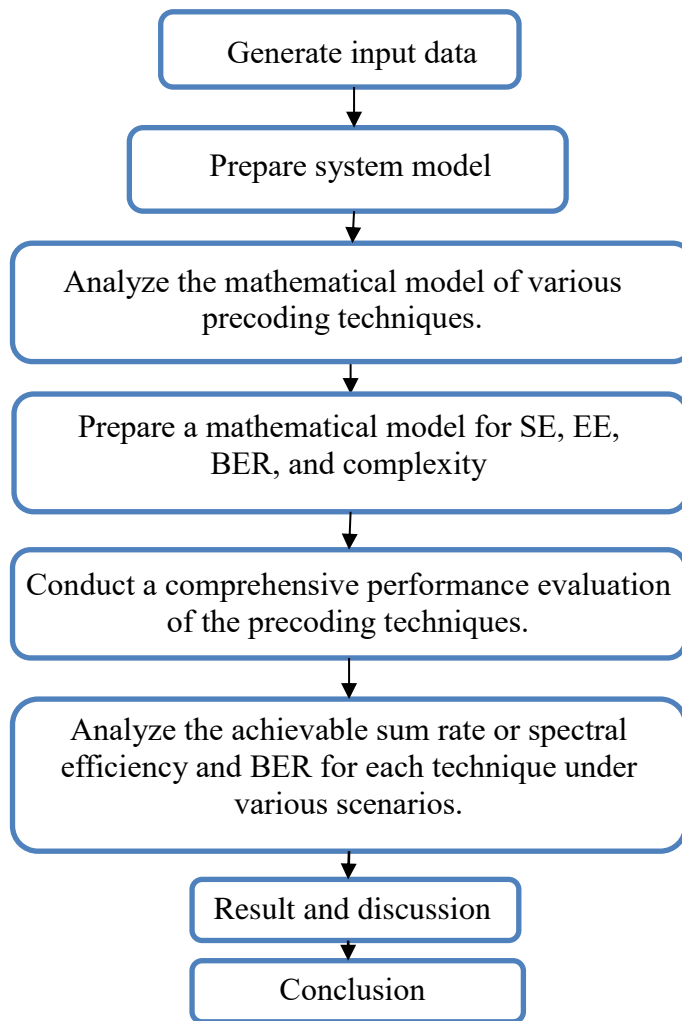


Figure 3.1: Methodology of the thesis.

3.4 System Model

One way to utilize the spatial non-stationary properties of the channels is to divide the BS antenna array into multiple subarrays. Figure 3.2 below illustrates the XL-MIMO system, where K single antenna user equipment is served by a base station (BS) having M antennas. Each subarray has a local processing unit (LPU) connected to a central processing unit (CPU) to do the required processing.

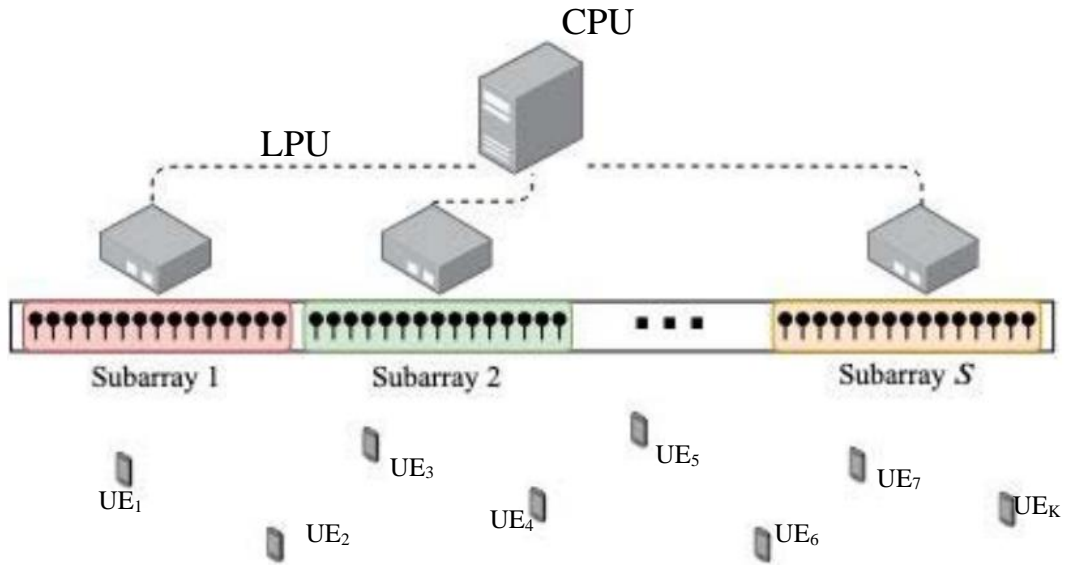


Figure 3.2: XL-MIMO architecture (Rodrigues et al., 2020).

The BS with M antennas serves K UEs simultaneously using linear precoding techniques. The BS antenna array can be split up into S subarrays. The BS multiplies the data symbols to be transmitted by using the linear precoding matrix D_s before transmitting them through the antenna array. This is important to increase signal quality at the UEs by minimizing interference. This block diagram in Figure 3.3 shows the different precoding techniques which is connected to the CPU which makes the signal processing of the system easier. In addition to providing details about the communication channel between the transmitter and receiver, CSI also shows how signals propagate. However, in order to estimate the channel from the transmitting antenna, the transmission can be simultaneously received by an antenna and compared with the pilot signal that is known (Albreem et al., 2021). Where individual channels were estimated to transmit, the reception antennas can simultaneously listen to the pilot (Björnson et al., 2017). Multiple user equipment's are connected to the XL-MIMO system's base station, which is equipped with numerous antennas at once.

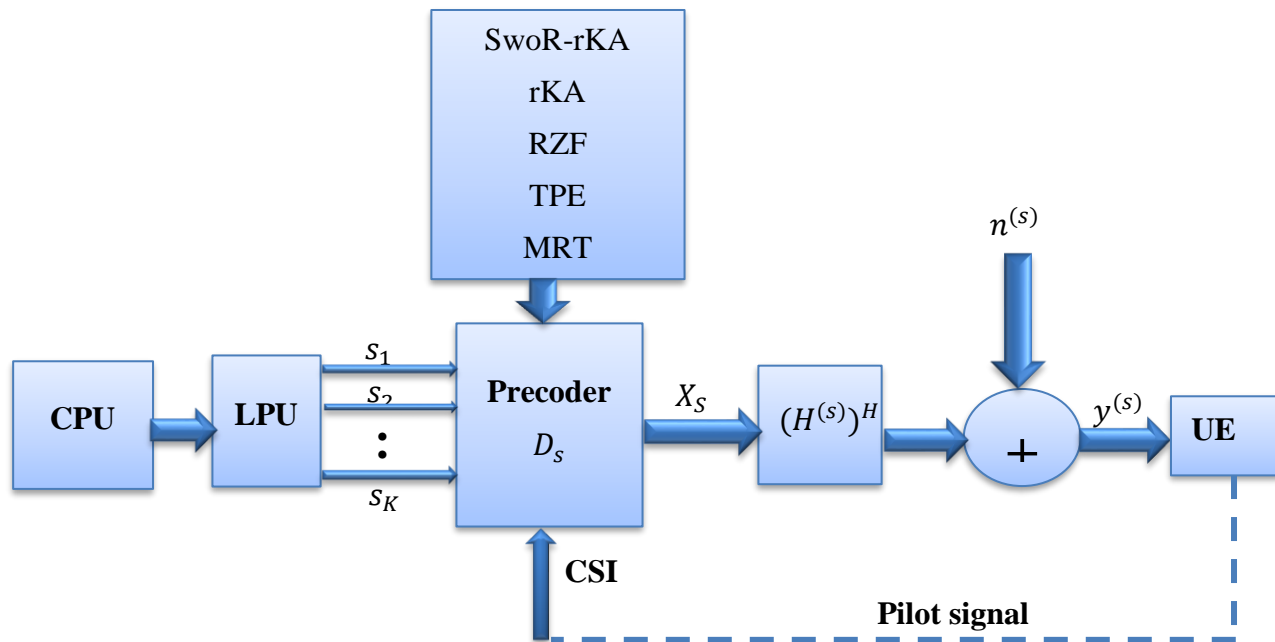


Figure 3.3: General block diagram of precoding techniques.

Note that M antennas for the BS are divided into S subarrays such that part is with $M^{(s)} = M/S$ antennas where $\sum_{s=1}^S M^{(s)} = M$ and M UEs are evenly distributed in the S subarrays, $\sum_{s=1}^S K^{(s)} = K$. It is assumed that $M^{(s)} \geq M$. The received complex signal at the k^{th} UE in the k^{th} subarray is given by (Xu et al., 2023).

$$y_{jk} = \sum_{s=1}^S (h_{jk}^s)^H X_s + n_{jk} \quad (3.1)$$

$$X_s = \sum_{i=1}^{K^{(s)}} d_{si} s_{si} = D_s S_s \quad (3.2)$$

Where $X_s \in \mathbb{C}^{M^{(s)} \times 1}$ is the transmit signal in the s^{th} subarray and $h_{jk} \in \mathbb{C}^{M^{(s)} \times 1}$ represents the channel vector between the BS in the s^{th} subarray and the k^{th} UE in the j^{th} subarray, respectively. Complex Gaussian noise at the k^{th} UE in the j^{th} subarray is denoted by $n_{jk} \sim CN(0, \sigma^2)$, where σ^2 is the noise variance at the receiver. $D_s = [d_{s1}, d_{s2} \dots \dots d_{sk^{(s)}}] \in \mathbb{C}^{M^{(s)} \times K^{(s)}}$ is precoding matrix for $M^{(s)}$ UEs in the s^{th} subarrays, $d_{si} \in \mathbb{C}^{M^{(s)} \times 1}$ denotes the precoding vector for the i^{th} UE the s^{th} subarray and $S_s = [s_{s1}, s_{s2} \dots \dots s_{sk^{(s)}}]^T$ is complex vector contain the data symbols for all UEs in the s^{th} subarrays.

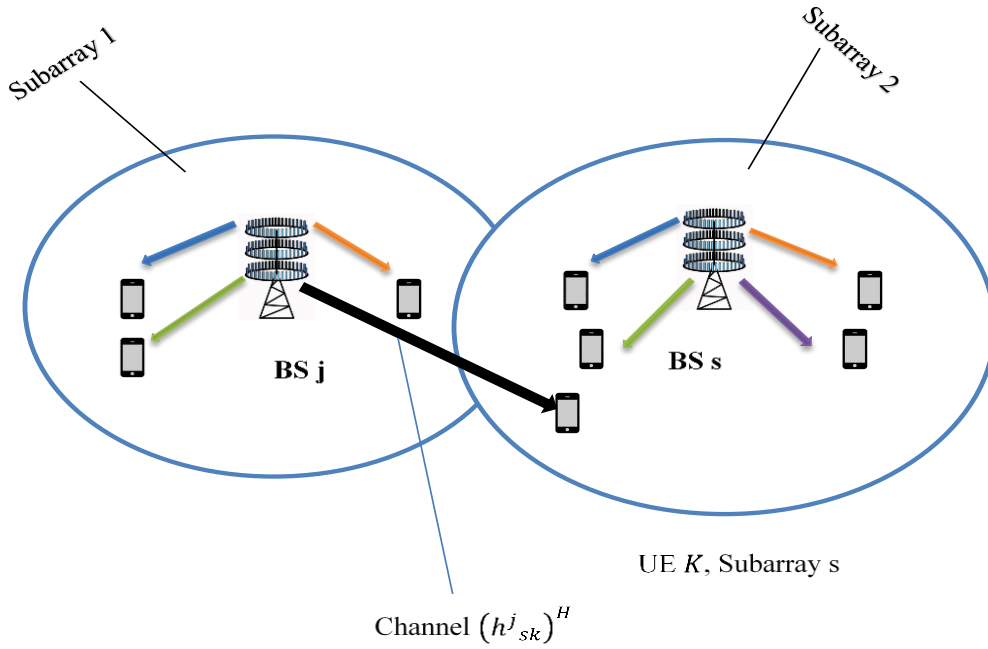


Figure 3.4: Illustration of the DL XL- MIMO transmission in subarray j and subarray s .

The vector transmitted signal for the K users during the downlink transmission where $M^{(s)} \geq K$ can be expressed as follows:

$$\begin{aligned}
 y_{jk} = & \underbrace{(h^j_{jk})^H d_{jk} s_{jk}}_{\text{Desired signal}} + \underbrace{\sum_{\substack{i=1 \\ i \neq k}}^{K^{(j)}} (h^j_{jk})^H d_{ji} s_{ji}}_{\text{Intra-subarray Interference}} + \underbrace{\sum_{\substack{s=1 \\ s \neq j}}^S \sum_{i=1}^{K^{(s)}} h^s_{jk}{}^H d_{si} s_{si}}_{\text{Inter-subarray Interference}} + \underbrace{n_{jk}}_{\text{Noise}}
 \end{aligned} \tag{3.3}$$

where; $s_{jk} \sim \mathcal{CN}(0, p_{jk})$ and d_{jk} satisfies the power constraints $\mathbb{E}\{\|g_{jk}\|^2\} = 1$.

Less interference channel for discrete memory, output $y \in \mathbb{C}$ is

$$y = hx + \gamma + n \tag{3.4}$$

Where; $n \sim \mathcal{CN}(0, \sigma^2)$ and γ is interference term.

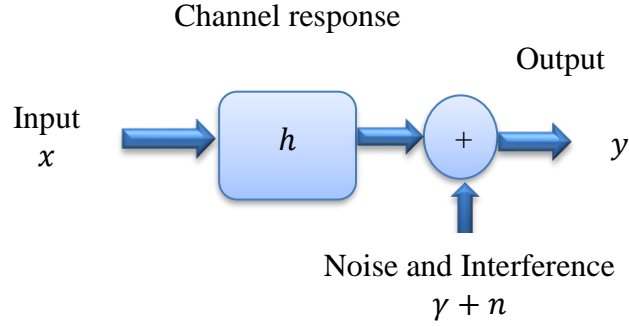


Figure 3.5: A memory less discrete channel with input x and output y .

If h is deterministic, then the channel capacity is

$$C = \log_2 \left(1 + \frac{p|h|^2}{p_\gamma + \sigma^2} \right) \quad (3.5)$$

3.4.1 Maximum Ratio Transmission (MRT)

In a multi-antenna system, MRT is a wireless communication technology that enhances data transmission performance and reliability. The fundamental idea behind MRT is to send the signal in a way that maximizes the power that reaches the receiver. This is accomplished by modifying each antenna's broadcast weights by the channel state information. Details regarding the channel's fading, interference, and noise levels are provided by the CSI. Situations where there are several antennas at the transmitter and receiver can be accommodated using the MRT approach. Under these circumstances, the transmit weights are determined using the channel status data, and the receiver applies the proper combining technique to merge the signals coming from various antennas.

$$X_j = \sum_{i=1}^{K(j)} \sqrt{\rho} d_{ji} s_{ji} = \sqrt{\rho} D_j S_j \quad (3.6)$$

$$D_j^{mrt} = \beta H_j^H \quad (3.7)$$

Where; $\beta = \sqrt{\frac{P_{tr}}{\text{tr}(F_j^H F_j)}}$, $F_j = H_j^H$

$$X_j = \sqrt{\rho}\beta H_j^H S_j \quad (3.8)$$

$$y_j^{mrt} = \sqrt{\rho}\beta H_j^H H_j^H S_j + n_j \quad (3.9)$$

Where; ρ is average transmit power at the BS,

β is normalized power factor

P_{tr} is downlink transmitted power

D_j is precoding matrix in j^{th} subarrays

S_j is data symbol in j^{th} subarrays

n_j is noise in j^{th} subarrays

The k^{th} user's related SNR can be found as follows for large values of M and K :

$$SINR = \frac{\text{Received signal power}}{\text{Interference power} + \text{Noise power}} \quad (3.10)$$

$$SINR_{jk}^{mrt} = \frac{P_{tr}M}{K(P_{tr} + 1)} \quad (3.11)$$

3.4.2 Regularized Zero Force (RZF)

A linear precoding approach called Regularized Zero Forcing in XL-MIMO is intended to alleviate the problem of noise enhancement that arises from applying Zero Forcing to mMIMO systems. RZF reduces noise amplification without significantly sacrificing performance by adding a regularization factor to the ZF method. However, if the number of antennas increases the complexity of the system also increases (Kebede et al., 2022).

$$D_j^{zf} = \beta H_j (H_j H_j^H)^{-1} \quad (3.12)$$

$$D_j^{rzf} = \beta H_j (H_j H_j^H + \lambda I_M)^{-1} \quad (3.13)$$

Where; $\lambda = \frac{1}{SNR} = \frac{\sigma^2}{P}$; $\beta = \sqrt{\frac{P_{tr}}{\text{tr}(F_j^H F_j)}}$; $F_j = H_j (H_j H_j^H + \lambda I_M)^{-1}$

$$X_j = \sqrt{\rho}\beta H_j (H_j H_j^H + \lambda I_M)^{-1} S_j \quad (3.14)$$

$$y_j^{rzf} = \sqrt{\rho}\beta H_j^H H_j (H_j H_j^H + \lambda I_M)^{-1} S_j + n_j \quad (3.15)$$

Let $D_{jk} \in \mathbb{C}^{M(s) \times M(s)}$ be the matrix D with column d_{jk} removed. Then, the SINR at the k^{th} UE becomes

$$SINR_{jk}^{rzf} = \frac{(h_{jk})^H d_{jk} d_{jk}^H h_{jk}}{(h_{jk})^H D_{jk} D_{jk}^H h_{jk} + \sigma^2} \quad (3.16)$$

Where; λ is regularization factor which is the inverse of SNR and I_M is identity matrix

3.4.3 Truncated Polynomial Function (TPE)

Truncated Polynomial Expansion is a technique used to simplify the calculation of certain mathematical operations, especially in the context of mMIMO. Instead of working with infinite or extremely high-order polynomials, TPE focuses on calculating their truncated versions up to a specified order, known as the truncation parameter or degree. In the context of mMIMO, TPE helps reduce the computational burden associated with evaluating the inverse of Hermitian matrices, which is necessary for constructing optimal precoding matrices like RZF. By employing TPE, one can approximate the inverse of a matrix using a lower-degree polynomial, making calculations feasible even when dealing with a large number of antennas (Benzin et al., 2019). Additionally, TPE enables the application of classical optimization techniques like minimum sum power and maximum minimum rate (Benzin et al., 2017). TPE provides a means to calculate the inverse of Hermitian matrices in massive MIMO systems, allowing for faster and less memory-intensive algorithms, which is critical for real-time applications. Now it is better to apply this technique to approximate the precoding of RZF by a matrix polynomial.

$$X_j = K(I - (I - KX)) = K \sum_{l=0}^{\infty} (I - KX)^l \quad (3.17)$$

$$D_j^{rzf} = \beta H_j (H_j H_j^H + \lambda I_M)^{-1} \quad (3.18)$$

$$= \beta k \sum_{l=0}^{\infty} I_M - K (H_j H_j^H + \lambda I_M)^l H_j^H$$

$$D_j^{tpe} = \sum_{l=0}^{J-1} u_l (H_j H_j^H)^l H_j^H \quad (3.19)$$

Where; u_0, u_1, \dots, u_{j-1} is a scalar coefficient. It is designed as a parameter that should be selected to increase the performance. For $J = 1$, $D_j^{mrt} = H_j^H$, Which equals MRT. Furthermore,

RZF precoding can be obtained by choosing $J = \text{Min}(M, K)$ and coefficients based on the polynomial characteristics of $D_j^{rzf} = H_j(H_j H_j^H + \lambda I_M)^{-1}$. Refer to J as the TPE order and note that corresponding polynomial degree is $J = 1$. It is obvious that choosing J correctly allows for a smooth transition from the conventional low-complexity MRT to the high-complexity RZF precoding (Mueller et al., 2016b).

$$SINR_{jk} d^{tpe} = \frac{D_{jk}^H A_{jk} D_{jk}}{D_{jk}^H B_{jk} D_{jk} + \sigma^2} = \frac{D_{jk}^H [A_{jk}]_{l,m} D_{jk}}{D_{jk}^H [A_{jk}]_{l,m} D_{jk} + \sigma^2} \quad (3.20)$$

Where; $D_{jk} = [d_0 \dots \dots d_{j-1}]^T$ and the (l, m) the element of the matrices $A_{jk}, B_{jk} \in \mathbb{C}^{J \times J}$ are

$$[A_{jk}]_{l,m} = h_{jk}^H (H_j H_j^H)^l h_{jk} h_{jk}^H (H_j H_j^H)^m h_{jk} \quad (3.21)$$

$$[B_{jk}]_{l,m} = h_{jk}^H (H_j H_j^H)^l H_j H_j^H (H_j H_j^H)^m h_{jk} - [A_{jk}]_{l,m} \quad (3.22)$$

For $l = 0, \dots, J - 1$ and $m = 0, \dots, J - 1$.

3.4.4 Randomized Kaczmarz Algorithm (rKA)

The linear system of equations can be solved using the rKA method, $Ax = b$ has been widely used (Strohmer & Vershynin, 2006). Equation 3.13 is applicable when the antenna size and subarrays are small. However, the computational cost of the inversion can be very large for XL-MIMO systems. Using the rKA technique, which is based on iterative matrix factorization, is essential for solving this problem. Using the received signal and the calculated channel information, this approach updates the precoding coefficients iteratively using randomization. By using this technique, interference is reduced and system performance is enhanced. To get D_j , is required to be solved for z_j (Xu et al., 2023).

$$(A_j)^H z_j = s_j \quad (3.23)$$

Where; $A_j = [H^j; \sqrt{\lambda} I_{K(j)}]$ and $z_j = A_j q_j$.

$K^{(j)}$ rKA program is run, $s_j = e_k \in \mathbb{C}^{K(j)}$, where e_k denotes k^{th} canonical basis (Boroujerdi & Haghghatshoar, 2018). The process of rKA is shown below in the following steps.

Table 3.1: rKA algorithm.

Inputs: $K^{(j)}$: The number of UEs in the j^{th} subarray,

$M^{(j)}$: The number of subarray antennas,

λ : the inverse of SNR,

$\mathbf{H}^j \in \mathbb{C}^{M^{(j)} \times K^{(j)}}$: the subarray channel matrix,

T : number of the algorithm iterations;

Step 0: Define the state vector $\mathbf{m}^t_j \in \mathbb{C}^{M^{(j)}}$ and $\mathbf{n}^t_j \in \mathbb{C}^{K^{(j)}}$ with $\mathbf{m}^0_j = \mathbf{0}$ and $\mathbf{n}^0_j = \mathbf{0}$.

Initialize the output matrix $\mathbf{Q}_j \in \mathbb{C}^{K^{(j)} \times K^{(j)}}$ with zeros. Define user canonical basis, where $[\mathbf{e}_k]_j = \mathbf{0}$ and $[\mathbf{e}_k]_k = \mathbf{1}$, $j \neq k$.

Step 1: Repeat steps 1a to 1e for t times, where $t = 0, 1, \dots, T - 1$. After that go to step 2.

Step 1a: Select $r(t)^{\text{th}}$ row of $(\mathbf{H}^j)^H$ and denotes it $\mathbf{h}^j_{jr(t)}$ with $r(t) \in [1, 2, \dots, K^{(j)}]$, where the selecting probability of $r(t)$ is given by $\mathbf{p}^j_{r(t)} = \frac{1}{K^{(j)}}$

Step 1b: Compute the error term $\eta_t = \frac{[\mathbf{e}_k]_{r(t)} - \langle \mathbf{h}^j_{jr(t)}, \mathbf{m}_j^t \rangle - \lambda \mathbf{n}^t_{jr(t)}}{\|\mathbf{h}^j_{jr(t)}\|^2 + \lambda}$ (3.24)

Where $[\mathbf{e}_k]_{r(t)}$ denotes the $r(t)^{\text{th}}$ factors of \mathbf{e}_k , $\langle \mathbf{h}^j_{jr(t)}, \mathbf{m}_j^t \rangle$: denotes the inner product of $\mathbf{h}^j_{jr(t)}$ and \mathbf{m}_j^t and $\|\cdot\|$ denotes the \mathbf{l}_2 norm.

Step 1c: Update $\mathbf{m}_j^{t+1} = \mathbf{m}_j^t + \eta_t \mathbf{h}^j_{jr(t)}$

Step 1d: Update $[\mathbf{n}^{t+1}_j]_{r(t)} = [\mathbf{n}^t_j]_{r(t)} + \eta_t$

Step 1e: Repeat $[\mathbf{n}^{t+1}_j]_{r(t)} = [\mathbf{n}^t_j]_{r(t)}$, $j \neq k$

Step 2: Update the k^{th} column of \mathbf{Q}_j with \mathbf{n}^T_j

$$\mathbf{Output} \ D_j^{r_z f} = \beta H_j Q_j \quad (3.25)$$

$$Q_j = (H_j H_j^H + \lambda I_M)^{-1} S_j \quad (3.26)$$

$$D_j^{r_z f} = \beta H_j Q_j \quad (3.27)$$

Where; $\beta = \sqrt{\frac{P_{tr}}{\text{tr}(F_j^H F_j)}} > 0$

$$X_j = D_j^{r_z f} S_j = \beta H_j Q_j S_j \quad (3.28)$$

The algorithm presented is a low-complexity precoding scheme designed using the rKA. It operates based on several inputs: the number of UEs in each subarray, the number of antennas in each subarray, the inverse of the SNR, the subarray channel matrices, and the total number of algorithm iterations. Initially, the algorithm initializes a matrix Q_j to zero. It then iterates through each UE in the subarray, defining state vectors and a user canonical basis. The algorithm proceeds by selecting specific rows of the subarray channel matrix, computing residuals, and updating state vectors iteratively until reaching the specified number of iterations. Finally, it calculates the output.

3.4.5 Sampling Without Replacement rKA (SwoR-rKA)

Sampling without replacement rKA is an essential technique for addressing the computational issues associated with huge antenna arrays in the context of extra-large systems. Large-scale multi-antenna and multi-user systems can effectively manage processing complexity by integrating sampling without replacement rKA techniques into the rKA architecture. To ensure a fair and impartial selection of equations for precoding calculations in XL-MIMO installations, the sampling without replacement rKA algorithm intentionally chooses random equations to update iteratively. With this method, XL-MIMO systems can effectively manage computational loads and optimize precoding performance, which is a useful way to improve spectral efficiency and overall system stability in large-scale MIMO deployments.

This is a technique that greatly improves the efficiency of solving linear equation problems in huge MIMO setups when used with XL-MIMO systems. This approach enables a more efficient and rapid convergence towards the solution by randomly selecting rows of the matrix with a probability proportional to the 2-norm of the rows. This method surpasses classic Kaczmarz methods by selecting projections randomly and depending on their relevance, highlighting the significance of unbiased sampling in enhancing computing performance and accuracy in XL-MIMO systems.

If P is poorly scaled, two bad phenomena can occur

- A) weak users might be chosen less frequently, which would result in poor performance.
- B) When users see similar channel gains, convergence performance naturally degrades, which implies $p_{r(t)}^j = \frac{1}{K(j)}$.

Both problems can be partly eliminated using sampling without replacement rKA techniques. In step 1a of the algorithm of rKA replace Equation 3.29 with the selection probability of,

$$p_{r(t)}^j = \frac{(\|h_{jr(t)}^j\|^2 + \lambda)}{\|H_j^j\|_F^2 + K^{(j)}\lambda} \quad (3.29)$$

Where $\|\cdot\|_F$ denotes Frobenius norm.

This sampling without replacement rKA can pick different $h_{jr(t)}^j$ and $n_{jr(t)}^t$ values each time the selection is made. This method enhances the likelihood of selecting users with better channel conditions compared to the equal probability selection in the rKA algorithm. SwoR-rKA prioritizes users with good communication channels by varying the selection probability according on the channel quality. In comparison to more conventional methods like rKA, this strategy seeks to increase system performance by giving users with better channel conditions more resources. This results in improved SE and a faster rate of convergence.

3.4.5.1 Convergence Analysis

In this section, the canonical and generic set of linear equations (SLE) are considered as $Ax = b$, where $A \in \mathbb{C}^{m \times n}$ is a constant coefficient matrix, $x \in \mathbb{C}^n$ is the unknown vector, and $b \in \mathbb{C}^m$ is known offset coefficient vector. Using a relevance metric as a basis, the rKA selects the rows of A at random and independently in its updated schedule. In particular, each $r(t)$ possesses a sample probability specified as $p_{r(t)} \in [0, 1]$, which includes a vector whose distribution of samples across all rows is as defined equal to $p = (p_1, \dots, p_m) \in \mathbb{R}_m^+$; wherein it is reasonable to note that $\sum_{r(t)=1}^m p_{r(t)} = 1$.

$$X^{t+1} = X^t + \frac{b_{r(t)} - \langle a_{r(t)}, X^t \rangle}{\|a_{r(t)}\|^2} a_{r(t)} \quad (3.30)$$

Where $r(t)$ is chosen from the set $1, 2, \dots, m$ with probability distribution p .

$$\mathbb{E}\{\|X^t - X^*\|^2\} \leq (1 - k_x(A))^t \|X^0 - X^*\|^2 \quad (3.31)$$

Where; X^t is the solution of the t^{th} iteration of the SLE $Ax = b$ and X^* being the optimal solution and X^0 an arbitrary initial guess. From Equation (3.30), it is seen that the convergence speed of SwoR-rKA algorithms depends on the parameter $k_x(A)$. Moreover, a larger $k_x(A)$ guarantees a

faster convergence (Xu et al., 2023). It should be noted that in order to reduce the initial error $\|X^0 - X^*\|^2$ towards the intended boundary, more rKA iterations are required higher the $1 - k_x(A)$. So, to reduce the number of rKA iterations required to appropriately reach the predicted error limit, it is preferable to have a high value of $k_x(A)$. This indicates that the $k_x(A)$ and the rKA's convergence is inextricably linked (Rodrigues, 2019).

Then the SINR is calculated using the formula of:

$$SINR = \frac{p|h|^2}{p_\gamma + \sigma^2} \quad (3.32)$$

Where; $h = \mathbb{E}\{d_{jk}^H h_{jk}^j\}$.

Then, we consider the interference term γ according to Equation (3.3) for the BS in the j^{th} subarray and UEs in the s^{th} subarray

$$\begin{aligned} \gamma &= \left((h_{jk}^j)^H d_{jk} - \mathbb{E}\{(h_{jk}^j)^H d_{jk}\} s_{jk} \right) + \sum_{\substack{i=1 \\ i \neq k}}^{K(j)} (h_{jk}^s)^H d_{ji} s_{ji} \sum_{\substack{s=1 \\ s \neq j}}^S \sum_{i=1}^{K(s)} (h_{jk}^s)^H d_{si} s_{si} \quad (3.33) \\ &= \sum_{\substack{s=1 \\ s \neq j}}^S \sum_{i=1}^{K(j)} (h_{jk}^s)^H d_{si} s_{si} - \mathbb{E}\{(h_{jk}^j)^H d_{jk}\} s_{jk} \end{aligned}$$

The variance of the interference term is

$$p_\gamma = \mathbb{E}\{|\gamma|^2\} \quad (3.34)$$

$$\begin{aligned} p_\gamma &= \sum_{\substack{s=1 \\ s \neq j}}^S \sum_{i=1}^{K(j)} \mathbb{E}\left\{ \left| (h_{jk}^s)^H d_{si} \right|^2 \right\} \mathbb{E}\{|s_{si}|^2\} - \left| \mathbb{E}\{(h_{jk}^j)^H d_{jk}\} s_{jk} \right|^2 \mathbb{E}\{|s_{jk}|^2\} \\ p_\gamma &= \sum_{\substack{s=1 \\ s \neq j}}^S \sum_{i=1}^{K(j)} p_{si} \mathbb{E}\{|d_{si}^H h_{jk}^s|^2\} - p_{jk} \left| \mathbb{E}\{d_{jk}^H h_{jk}^j\} \right|^2 \end{aligned}$$

So, the SINR in the in the j^{th} subarray

$$SINR_{jk}^{rKA} = \frac{p_{jk} \left| \mathbb{E}\{d_{jk}^H h_{jk}^j\} \right|^2}{\sum_{\substack{s=1 \\ s \neq j}}^S \sum_{i=1}^{K(j)} p_{si} \mathbb{E}\{|d_{si}^H h_{jk}^s|^2\} - p_{jk} \left| \mathbb{E}\{d_{jk}^H h_{jk}^j\} \right|^2 + \sigma^2} \quad (3.35)$$

3.4.6 Poor Condition Prioritization SwoR-rKA (PCP-SwoR-rKA)

Using iterative techniques, SwoR-rKA actively selects users based on communication channel information to improve accuracy. However, this method frequently chooses users with better

channel conditions, which causes changes in the signal estimation accuracy. Therefore, there's a chance that the bit error rate will typically reduce. A solution to this issue in which every column that corresponds to a channel is considered to estimate to a certain extent. There is low SNR in poor channel conditions. It's important to implement column probability selection policy that guarantees columns with poorer conditions are chosen more frequently in order to mitigate interference. This will help to lower overall BER.

$$p_{r(t)}^j = 1 - \frac{(\|h_{jr(t)}^j\|^2 + \lambda)}{\|H_j\|_F^2 + K^{(j)}\lambda} \quad (3.36)$$

3.5 Performance Parameter Analysis

The Shannon channel capacity Theorem is the most fundamental form that measures the highest rate at which data can be sent across a noisy channel and maintains a desired level of reliability. Defining a theoretical maximum data rate enables engineers to create communication systems that work best as they approach this limit. The formula provides a theoretical framework for evaluating the trade-off between bandwidth, signal power, and noise in communication channels. It demonstrates the essence of how the Shannon theorem enables the quantification of possible data rates in communication systems. Communication system designers can maximize data rates within the limitations given by the channel characteristics by following the theorem's guidelines, which will maximize the effectiveness and reliability of information delivery. It describes the lowest spectral efficiency that a MIMO system can achieve over a fading channel.

Channel capacity per user in a single cell a downlink XL-MIMO networks expressed as

$$C = \log_2(1 + SINR) \text{ (bps/Hz)} \quad (3.37)$$

For K users, the channel capacity is given as follows

$$C_{jk} = \sum_{k=1}^{K^{(j)}} \log_2(1 + SINR_{jk}) \quad (3.38)$$

3.5.1 Spectral Efficiency

One important metric in wireless communications is the SINR, which measures how well a signal is received about the noise and interference in the communication channel. A measurement of how

well the desired signal can be separated from unwanted elements in the channel is provided by the SINR, which measures the desired signal power to the overall power of noise and interference. In wireless communication systems, a greater SINR number denotes a higher degree of signal reception quality to the channel's levels of noise and interference. Achieving a high signal-to-interference noise ratio is necessary for dependable and effective communication since it indicates a strong signal in comparison to undesired elements that could affect the quality of the conversation. To improve overall system capacity, optimize communication performance, and improve signal clarity, wireless system designers frequently strive to maximize the SINR. Through the management of interference, reduction of noise, and enhancement of signal strength, operators can improve the signal-to-noise ratio and hence the efficiency and dependability of wireless communication connections.

A key parameter in wireless communications, spectral efficiency measures the data rate that can be regularly transmitted over a specific communication channel bandwidth. It emphasizes the data quantity that can be carried per unit of bandwidth and shows how well the available spectrum is used to carry information (Liu et al., 2022).

Spectral efficiency of MRT

$$SE_{jk}^{mrt} = \sum_{k=1}^{K(j)} \log_2(1 + SINR_{jk}^{mrt}) \quad (3.39)$$

$$SE_{jk}^{mrt} = \sum_{k=1}^{K(j)} \log_2 \left(1 + \frac{P_{tr} M}{K(P_{tr} + 1)} \right)$$

Spectral efficiency of RZF

$$SE_{jk}^{rzf} = \sum_{k=1}^{K(j)} \log_2(1 + SINR_{jk}^{rzf}) \quad (3.40)$$

$$SE_{jk}^{rzf} = \sum_{k=1}^{K(j)} \log_2 \left(1 + \frac{(h_{jk})^H d_{jk} d_{jk}^H h_{jk}}{(h_{jk})^H D_{jk} D_{jk}^H h_{jk} + \sigma^2} \right)$$

Spectral efficiency of TPE

$$SE_{jk}^{tpe} = \sum_{k=1}^{K(j)} \log_2(1 + SINR_{jk}^{tpe}) \quad (3.41)$$

$$SE_{jk}^{tpe} = \sum_{k=1}^{K(j)} \log_2 \left(1 + \frac{D_{jk}^H [A_{jk}]_{l,m} D_{jk}}{D_{jk}^H [A_{jk}]_{l,m} D_{jk} + \sigma^2} \right)$$

Spectral efficiency of rKA

$$SE^{rKA} = \sum_{k=1}^{K(j)} \log_2(1 + SINR_{jk}^{rKA}) \quad (3.42)$$

$$SE_{jk}^{rKA} = \sum_{k=1}^{K(j)} \log_2 \left(1 + \frac{p_{jk} |\mathbb{E}\{d_{jk}^H h^j_{jk}\}|^2}{\sum_{\substack{s=1 \\ s \neq j}}^S \sum_{i=1}^{K(j)} p_{si} \mathbb{E}\{|d_{si}^H h^s_{jk}|^2\}} - p_{jk} |\mathbb{E}\{d_{jk}^H h^j_{jk}\}|^2 + \sigma^2} \right)$$

Where; SE_j is the spectral efficiency in subarray and achievable in the communication system.

Essentially, spectral efficiency measures the speed at which data can be sent over a specific bandwidth while achieving a desired level of performance in terms of signal-to-noise ratio, bit error rate, or other quality metrics. When the available spectrum is efficiently utilized, a higher rate of data can be achieved with a smaller amount of bandwidth. This is known as high spectral efficiency. In wireless communication system design, increasing spectral efficiency is a key objective since it all operators to increase the capacity of networks, maximize data flow, and optimize resource utilization. Communication systems can increase their spectral efficiency and make better use of the radio spectrum by implementing sophisticated modulation methods, effective coding techniques, and adaptive transmission strategies. The SE expression presented for rKA here is more inclusive than the one in (Rodrigues et al., 2020) which ignores the interference between subarrays. Suppressing interference is essential for designing algorithms that yield improved SE performance.

3.5.2 Energy Efficiency

Energy efficiency is the ratio of transmission and the transmit power (Belmega et al., 2011). Energy efficiency aims to maximize the trade-off between fast data transfer speeds and low energy usage. This statistic assesses how well a system uses energy resources for other tasks, such as data reception and transmission. An energy-efficient system works to lower total energy usage while maintaining or improving performance measures like data rates. Managing power usage, optimizing data transmission rates via effective modulation and coding methods, and resource allocation methods are important factors to consider for energy efficiency.

$$EE = \frac{SE_j}{P_t} (\text{bits/J/HZ}) \quad (3.43)$$

$$P_t = \mu \sum_{k=1}^{K(j)} p_{jk} + P_c + P_{fix} \quad (3.44)$$

Where μ is the inverse of the power amplifier efficiency at the BS, p_{jk} is downlink transmitter power allocation for K user in the j^{th} subarray, P_c is the constant circuit power consumption per antenna which contains power dissipation in the transmit filter, mixer, frequency synthesizer, and digital-to-analog converter, P_{fix} is the fixed power consumption at the BS which is independent of the number of the transmit antennas.

3.5.3 Bit Error Ratio (BER)

Bit error rate is considered as an essential metric for determining the performance of data channels. When sending a signal via a wireless link, a key factor to be aware of is the amount of errors that will appear in the signal that is received. Therefore, the rate at which an error occurs in a wireless communication system while data or a signal is being transmitted from transmitter to receiver is known as BER (Salah et al., 2023).

$$BER = \frac{N_e}{\sum N_b} \quad (3.45)$$

Where; N_e number of errors and N_b number of transmitted bit.

3.6 Non-Stationary Channel Model

The channel becomes spatially non-stationary in an XL-MIMO system with large arrays. The channel vector between UE k in the j^{th} subarray and $M^{(s)}$ antennas in the s^{th} subarray is denoted by:

$$h^s_{jk} = \sqrt{M^{(s)}} \left(\phi^s_{jk} \right)^{\frac{1}{2}} z^s_{jk} \quad (3.46)$$

$$\phi^s_{jk} = \left(V^s_{jk} \right)^{\frac{1}{2}} R^s_{jk} \left(V^s_{jk} \right)^{\frac{1}{2}} \in \mathbb{C}^{M^{(s)} \times M^{(s)}} \quad (3.47)$$

Where $h^s_{jk} \in \mathbb{C}^{M^{(s)} \times 1}$, $z^s_{jk} \in \mathbb{C}^{M^{(s)} \times 1}$ follows a Gaussian distribution with mean 0 and covariance $\frac{1}{M^{(s)}} I_{M^{(s)}}$, $I_{M^{(s)}}$ denotes identity matrix of order $M^{(s)}$, $R^s_{jk} \in \mathbb{C}^{M^{(s)} \times M^{(s)}}$ denotes the spatial correlation matrix between UE k in the j^{th} subarray and BS in the s^{th} subarray, and $V^s_{jk} \in \mathbb{C}^{M^{(s)} \times M^{(s)}}$ denotes a diagonal matrix and has V^s_{jk} non-zero diagonal elements between UE k in the j^{th} subarray and BS in the s^{th} subarray.

3.6.1 Perfect and Imperfect Channel

A perfect channel, as used in communication systems, is one in which all parameters of the channel, such as noise and interference levels, are fully and accurately known to the receiver. This is frequently used as a standard by which to compare how well communication technologies operate in world scenarios. Conversely, an imperfect channel estimate admits the existence of noise, interference, or insufficient understanding of the channel properties. It is a frequent problem in wireless communication systems, and different methods have been developed to mitigate its impacts, including interference alignment and iterative decoding.

3.6.2 CSI Assumption

Since we typically have $M > K$ in practice, we assume that the BS has an imperfect estimate of the channel for UE k in the s^{th} subarray as

$$\hat{h}_{jk}^s = \left(\phi_{jk}^s\right)^{\frac{1}{2}} \left(\sqrt{1-\tau^2} z_{jk}^s + \tau U_{jk}^s\right) = \sqrt{1-\tau^2} h_{jk}^s + \tau n_{jk}^s \quad (3.48)$$

Where; h_{jk}^s is the actual channel $U_{jk}^s \sim \mathcal{CN}(0_{M^{(s)} \times 1}, I_{M^{(s)}})$, and $n_{jk}^s = \left(\phi_{jk}^s\right)^{\frac{1}{2}} U_{jk}^s \sim \mathcal{CN}(0_{M^{(s)} \times 1}, \phi_{jk}^s)$ Where is the actual channel $U_{jk}^s \sim \mathcal{CN}(0_{M^{(s)} \times 1}, I_{M^{(s)}})$, and is independent error. The scalar parameter $\tau \in [0,1]$ indicates the equality of the instantaneous CSI, where $\tau = 0$ corresponds to perfect instantaneous CSI and $\tau = 1$ corresponds to having only statistical channel knowledge. The channel matrix between the BS in the s subarray and $K^{(j)}$ users in the j subarray are $\hat{H}_{jk}^s = [\hat{h}_{j1}^s \dots \hat{h}_{jK^{(j)}}^s] \in \mathbb{C}^{M^{(s)} \times K^{(j)}}$ denotes the joint imperfect knowledge of all user channels.

3.7 Number of Complex Multiplication

Efficiently solving linear systems is a key task in computational mathematics with applications in a variety of fields. The rKA and Truncated Polynomial Expansion are two well-known techniques for solving linear problems. These approaches and approaches vary in complexity and offer unique benefits and drawbacks when it comes to solving linear equations. By truncating a polynomial expansion of the system matrix, a method known as truncated polynomial expansion, or TPE, approximates the solution of a linear system. TPE seeks to deliver an accurate, computationally efficient solution by keeping only a subset of the terms in the expansion. TPE is known for its efficiency in lowering computing complexity and for its capacity to manage large-scale systems. On the other hand, the rKA is an iterative technique for solving linear systems that uses random projections of the system equations to update the solution vector over time. Because of its ease of use and scalability, rKA is preferred for problems involving large sparse systems, which are frequently seen in signal processing and image reconstruction. Table 3.1 shows the computational complexity of different precoding techniques for MRT, RZF, rKA, and SwoR-rKA (Xu et al., 2023) and the other precoding method is TPE (Mueller et al., 2016a) are listed.

Table 3.2: Computational complexity of precoding.

Scheme	Computational Complexity
MRT	$SM^{(s)}K^{(s)}$
RZF	$S \left[\frac{3(K^{(s)})^2 M^{(s)}}{2} + \frac{3K^{(s)}M^{(s)}}{2} + \frac{(K^{(s)})^3 - K^{(s)}}{3} \right]$
TPE	$S[(4J - 2)M^{(s)}K^{(s)} + (J - 1)M^{(s)} + K^{(s)}(2 - J)]$
rKA	$S[M^{(s)}T^{(s)} + M^{(s)}]$
SwoR-rKA	$S[M^{(s)}T^{(s)} + 2M^{(s)}K^{(s)}]$

3.8 Flow Chart

The PCP-SwoR-rKA, considering the probability of column selection tending toward bad conditions, aims to lower the BER in a wireless communication system. In Figure 3.6 first, the simulation settings are initialized. Next, random data bits are generated and modulated using either 64QAM or 16PSK to produce complex symbols. After generating a channel matrix, an appropriate precoding matrix is calculated using methods such as rKA, SwoR-rKA, RZF, TPE, or MRT. Then add noise, which then transmits the signal through the channel. At the receiver side, detect the received message using a hard output detector, and then BER is calculated for the given NTP.

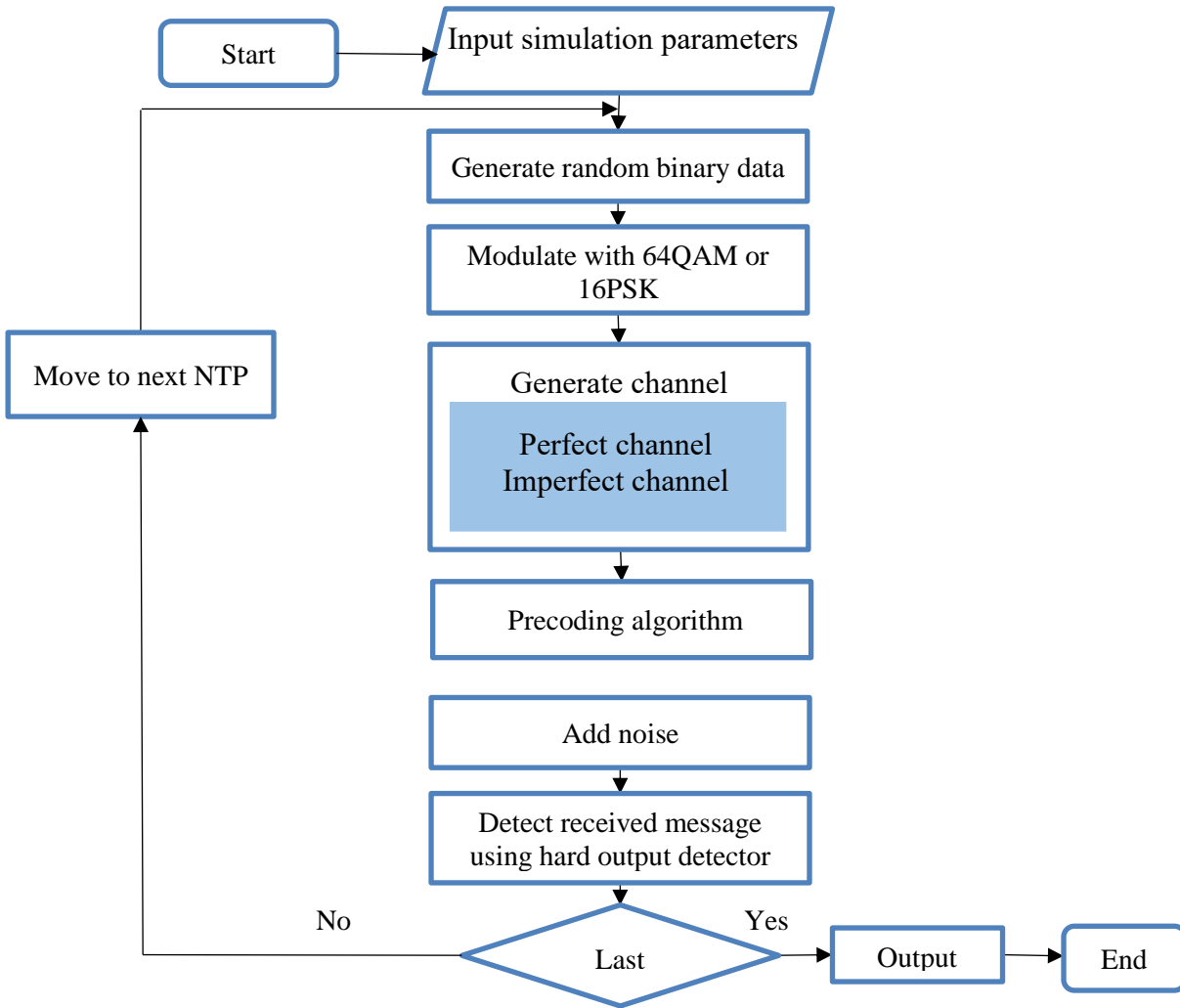


Figure 3.6: Flow chart for BER.

Figure 3.7 shows how the EE and SE of precoding techniques are analysed. First, initialize the values by Assign variables required inside the program, such as the number of antennas, the number of users, iteration, etc. Next channel generations are required; for this work, the channel has an imperfect CSI. Define matrices of precoding using power constraints. Calculate the sum rate, and after that, calculate spectral efficiency and energy efficiency. By repeating this process by changing variables, Lastly, compare and analyse the results.

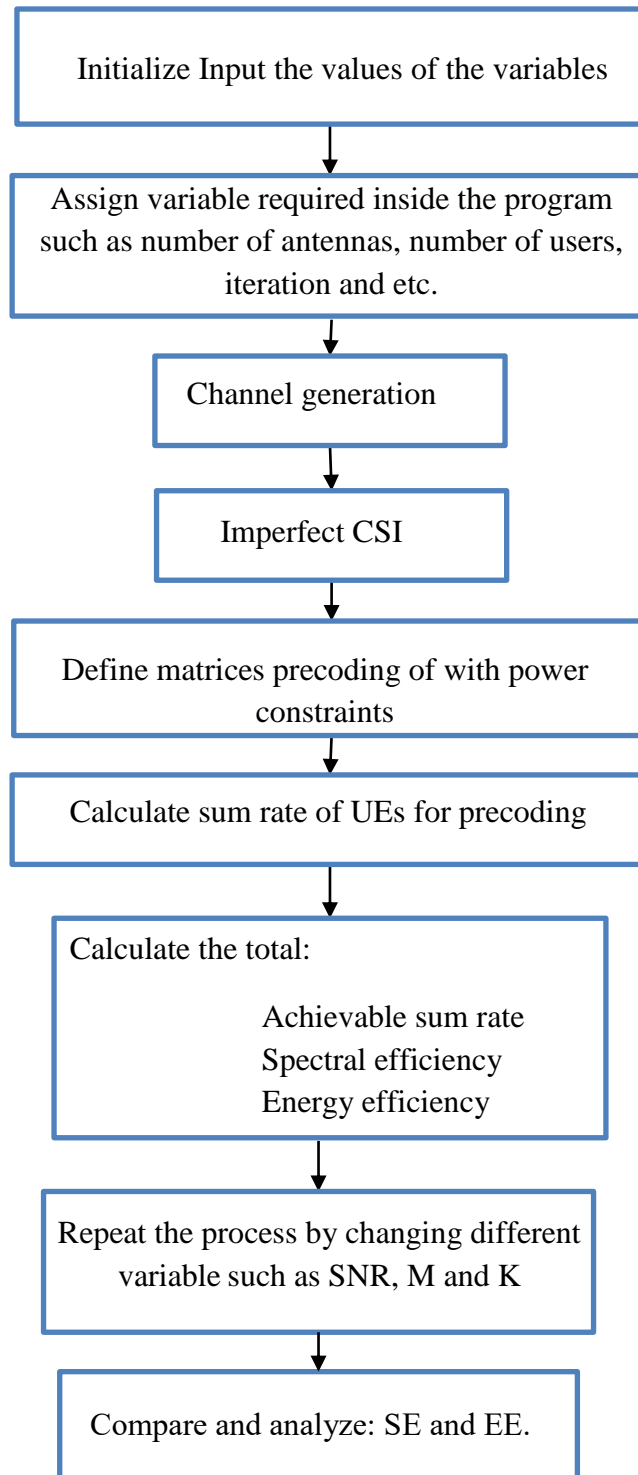


Figure 3.7: Flow chart for comparison of performance matrix.

CHAPTER FOUR

RESULT AND DISCUSSION

4.1 Overview

The system setup includes antennas at BS, the number of UEs, and channel conditions, which determine how well these precoders work. Therefore, choosing the best linear precoding techniques for a specific system through simulation analysis is important. Linear precoding techniques including TPE, RZF, ZF, and MRT are widely used in mMIMO systems. However, these conventional precoding techniques tend to perform less as the array's number of antennas increases. Iterative algorithms like the randomized Kaczmarz Algorithm and Sampling without Replacement randomized Kaczmarz Algorithm must be incorporated to alleviate this drawback. It is possible to improve precoding performance even in situations with a large number of antennas in massive MIMO systems by utilizing iterative techniques, such as rKA. This eventually improves system efficiency and communication reliability. The downlink XL-MIMO system's simulation results are shown in this chapter. A performance analysis simulation for several scenarios, such as has been observed.

Case 1: Performance analysis of spectral and energy efficiency.

Case 2: Complexity changes as base station antennas and number of user's increase

Case 3: Effect of channel condition (perfect and imperfect channel model) on precoding based on BER.

Case 4: Comparison of PCP- and SwoR-rKA based on BER under different modulation techniques.

All results are shown in terms of,

- ❖ Achievable sum rate versus SNR.
- ❖ Spectral efficiency versus SNR.
- ❖ Energy efficiency versus SNR.
- ❖ Complexity versus the number of antenna arrays.
- ❖ Complexity versus the number of UEs.
- ❖ Bit error rate versus Normalized transmit power in dB.

- ❖ Spectral Efficiency versus number of antenna arrays.
- ❖ Energy Efficiency versus number of UEs.

4.2 Simulation Parameter

This table provides a summary of the simulation parameters that were used in the thesis paper. These parameters include the values that were used for key variables, such as the number of antennas in BS, UEs, subarrays, downlink transmitted power, CSI, and Covariance and Correlation between antennas and the values of other input parameters are listed (Xu et al., 2023).

Table 4.1: Simulation parameter values.

Parameters	Description	Value	Remark
P_{tr}	Downlink transmitted power	1W	
S	Number of subarrays	4	
M	Number of base station antennas (when fixed)	256	
M_{range}	Number of base station antennas (when varied)	10 to 512	Assumption
K	Number of user equipment (when fixed)	16 and 32	
K_{range}	Number of user equipment (when varied)	10 to 150	
J	TPE order	2,3,4	Assumption
B	Bandwidth	2.6 GHz	Standard
τ	Channel state information quality	0.1 and 0.3	
α	Covariance/Correlation between antennas	0.1	
λ	Regularization factor	0.05	Assumption
T	Number algorithm Iteration	100 and 150	Assumption
σ^2	Power noise	1 dBm	
SNR	Signal-to-Noise Ratio	-10 to 50	Assumption

4.3 Performance of Spectral Efficiency and Energy Efficiency

In this section, the spectral and energy efficiency of different precoding techniques are analyzed and compared. Here, different parameters are considered, such as the number of BS antennas, the number of UEs, and subarrays. This comparison gives insights about the efficiency and effectiveness of the of the precoding method in downlink XL-MIMO.

4.3.1 Comparison of XL-MIMO and mMIMO

Figure 4.1 compare the achievable rate of XL-MIMO and mMIMO systems shows major differences in performance between the two architectures. When it comes to possible data rates, the investigation shows that XL-MIMO performs noticeably better than mMIMO. XL-MIMO systems are very effective in maximizing data throughput and spectrum efficiency because of their much higher number of antennas and improved spatial multiplexing capabilities. XL-MIMO systems outperform conventional mMIMO configurations in terms of data transmission rates and overall spectrum efficiency by utilizing a larger number of antennas and sophisticated precoding algorithms. These results illustrate the significant performance benefits provided by XL-MIMO systems, emphasizing their potential to transform wireless communication systems and meet the increasing need for high-speed data transfer in contemporary communication networks.

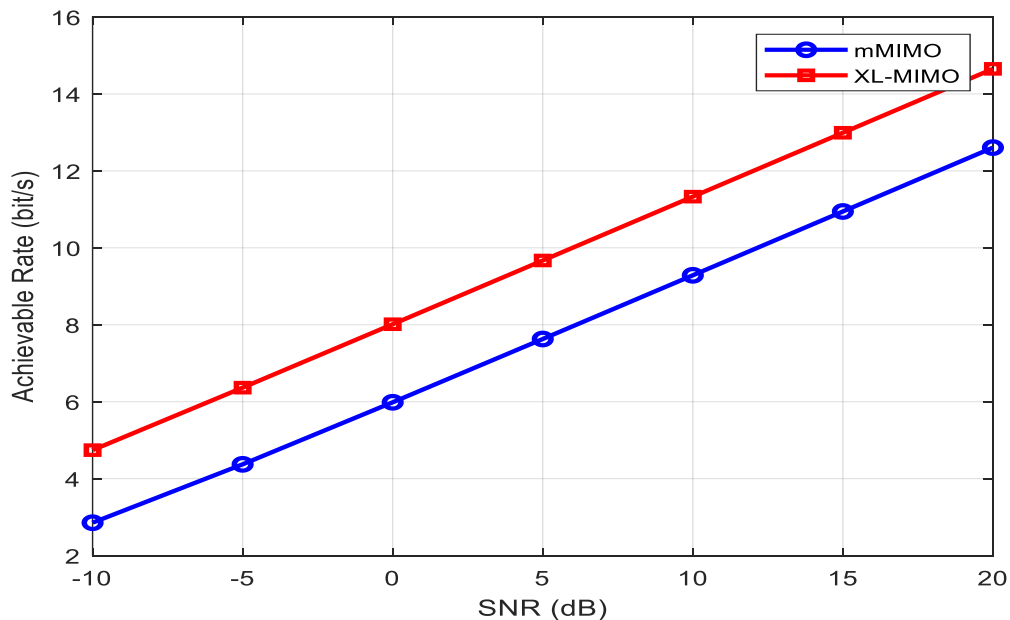


Figure 4.1: Comparison of mMIMO and XL-MIMO.

4.3.2 Performance Analysis of Spectral Efficiency

Figure 4.2 illustrates the achievable sum rate performance for different precoding techniques with the number of user equipment of $K= 32$, and the number of antennas of base stations $M= 256$ subarray $S = 4$. All of the precoding algorithms namely MRT, TPE, RZF, rKA, and SwoR-rKA perform better as SNR rises. This is because a higher SNR indicates that the received signal is less distorted by noise, which facilitates data decoding by the receiver. The precoding methods get better at reducing interference and enhancing signal quality as the SNR rises. Table 4.2 describes the spectral efficiency of various precoding techniques at various SNR levels (5 dB, 10 dB, and 15 dB). Both the figure and table show that SwoR-rKA has high spectral efficiency when it is compared with other precoding methods. MRT precoding has the lowest spectral efficiency as the SNR increases. All precoding techniques indicate an increase in spectral efficiency as the SNR values increase.

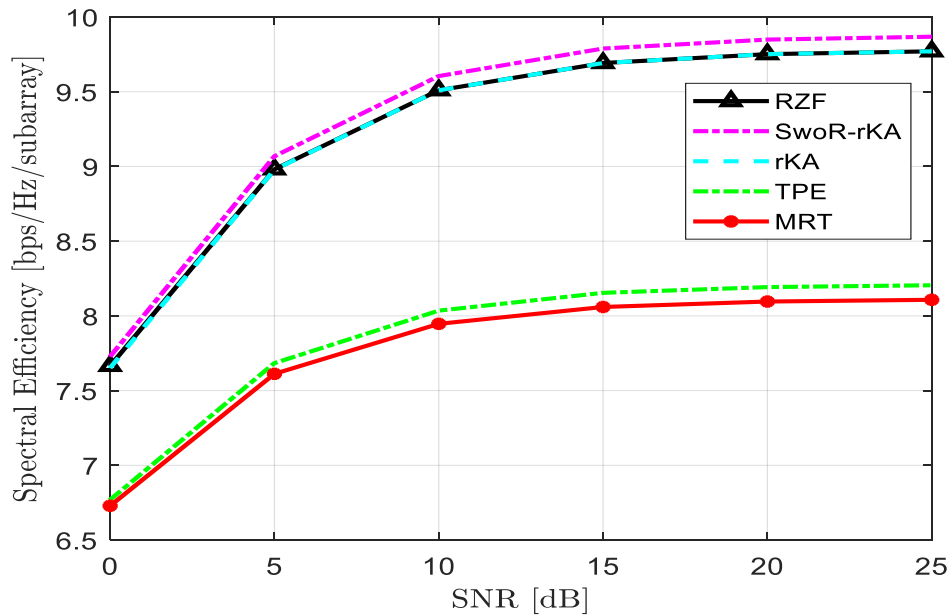


Figure 4.2: Performance comparison of Spectral efficiency of different precoding techniques at $K=32$, $M= 256$, and $S = 4$.

Table 4.2: Spectral efficiency versus SNR at $K=32$, $M= 256$, and $S = 4$.

Precoding Techniques	Spectral Efficiency (bps/Hz/subarray)		
	SNR=5	SNR=10	SNR=15
MRT	7.61	7.95	8.06
TPE	7.68	8.04	8.15
RZF	8.98	9.52	9.69
rKA	8.98	9.52	9.69
SwoR-rKA	9.07	9.61	9.79

Figure 4.3 shows more relationship between the spectral efficiency of UEs and the TPE order J . By considering $\tau = 0.1$, $M = 256$ and $K = 32$ but in terms of spectral efficiency, RZF performs better than TPE $J = 3$ and TPE $J = 4$. Among the TPE variations, TPE $J=2$ has the lowest spectrum efficiency since it has the poorest equalization capabilities. The spectral efficiency of TPE increases as J rises to 3 and 4, indicating that the equalization is becoming more successful in minimizing inter-symbol interference. In conclusion, TPE $J = 2$ has the lowest spectral efficiency compared to RZF, which offers the maximum. At higher values of J , TPE $J = 4$ starts to resemble RZF performance, whereas TPE $J = 3$ and TPE $J = 4$ offers intermediate spectrum efficiency. The TPE order J should be chosen to achieve a certain limited rate loss about RZF precoding. Notably, TPE precoding never outperforms RZF performance since it has J degrees of freedom for optimization but RZF has just one design parameter.

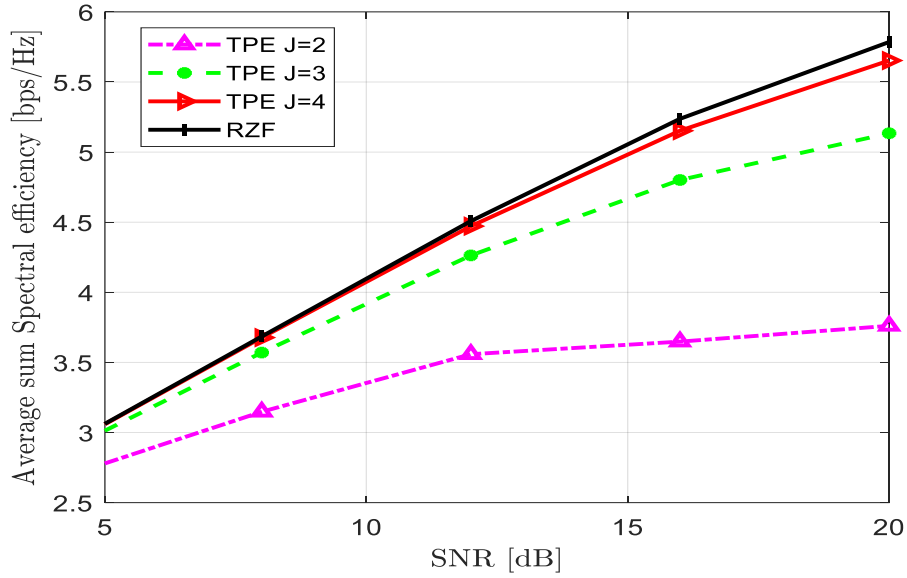


Figure 4.3: Comparison of Spectral efficiency of TPE and RZF.

Figure 4.4 illustrates the spectral efficiency of two different precoding schemes: rKA with $K=20$, SwoR-rKA with $K=20$ and SwoR-rKA with $K=40$. SwoR-rKA outperforms rKA in terms of spectral efficiency, especially at the high number of base station values. In terms of spectral efficiency, SwoR-rKA performs better than rKA, particularly at high base station values. This is a result of the more advanced equalization method that SwoR-rKA uses, which can more successfully reduce inter-symbol interference (ISI). The type of SwoR-rKA that achieves the maximum spectral efficiency is SwoR-rKA with $K=40$, followed by rKA with $K=20$ and SwoR-rKA with $K=20$. A comparatively straightforward precoding scheme that offers an adequate level of spectral efficiency is rKA with $K=20$. However, it is outperformed by SwoR-rKA with $K=20$.

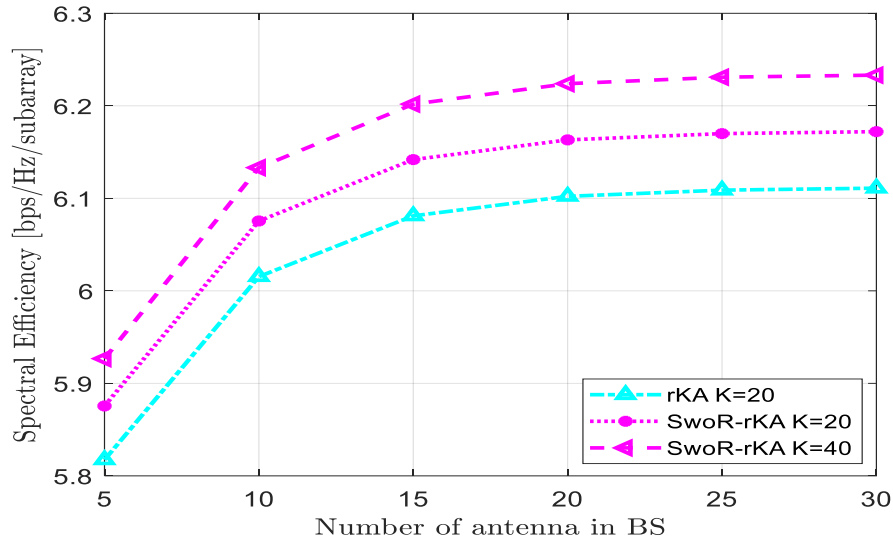


Figure 4.4: Comparison of Spectral efficiency of SwoR-rKA and rKA at different values of UE.

Table 4.3: Comparison of Spectral efficiency of SwoR-rKA and rKA.

Precoding Techniques	Spectral Efficiency (bps/Hz/subarray)		
	$M=10$	$M=20$	$M=25$
rKA ($K=20$)	6.02	6.1	6.11
SwoR-rKA ($K=20$)	6.08	6.16	6.17
SwoR-rKA ($K=40$)	6.13	6.22	6.23

4.3.3 Performance Analysis of Energy Efficiency

Figure 4.5 shows the EE versus SNR at $K=16$. The data rate achieved by the precoding techniques or spectral efficiency is divided by the system's overall power consumption. The energy efficiency of five precoding methods MRT, TPE, RZF, rKA, and SwoR-rKA has been compared in this work. The findings we obtained indicate that SwoR-rKA has the maximum energy efficiency, followed by rKA, RZF, TPE, and MRT. With SNR, each precoding method becomes more energy-efficient when SNR. SwoR-rKA is a more efficient precoding method that can make use of the channel's spatial diversity and more effectively reduce inter-user interference. Both data rates and energy

efficiency increase as a result of this. Comparing this to SwoR-rKA, reduced data rates and energy efficiency are the outcomes. Compared RZF to SwoR-rKA and rKA, RZF has a larger computational complexity but can eliminate inter-user interference. So, this leads to lower energy efficiency. While TPE can reduce inter-user interference to some degree, it is not as successful as rKA, SwoR-rKA, and RZF. When compared to all other precoding approaches, MRT has poorer data speeds and lower energy efficiency since it makes no effort to reduce inter-user interference.

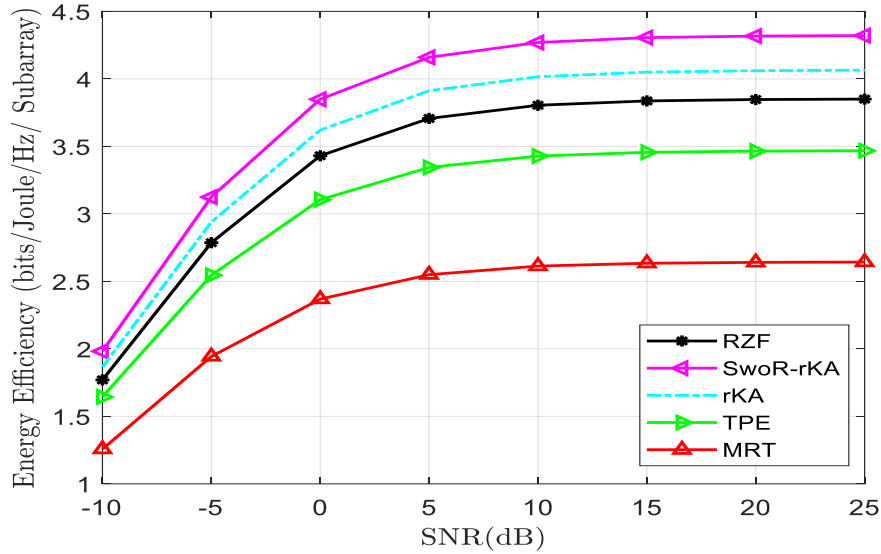


Figure 4.5: Performance comparison of Energy efficiency of different precoding techniques.

Table 4.4: Energy efficiency comparison of precoding at $K=16$.

Precoding Techniques	Energy Efficiency (bit/J/Hz/subarray)		
	SNR=5	SNR=10	SNR=15
MRT	2.55	2.61	2.63
TPE	3.34	3.43	3.46
RZF	3.71	3.80	3.84
rKA	3.91	4.02	4.05
SwoR-rKA	4.16	4.27	4.31

Figure 4.6 illustrates all results showing that the system performance is improved. The energy efficiency of MRT, TPE, RZF, rKA, and SwoR-rKA is increased by increasing the number of user equipment. SwoR-rKA is the most EE precoding technique, followed by rKA, RZF, TPE, and MRT. The energy efficiency of each precoding technique increases with SNR. The same works with Figure 4.5 but $K=32$.

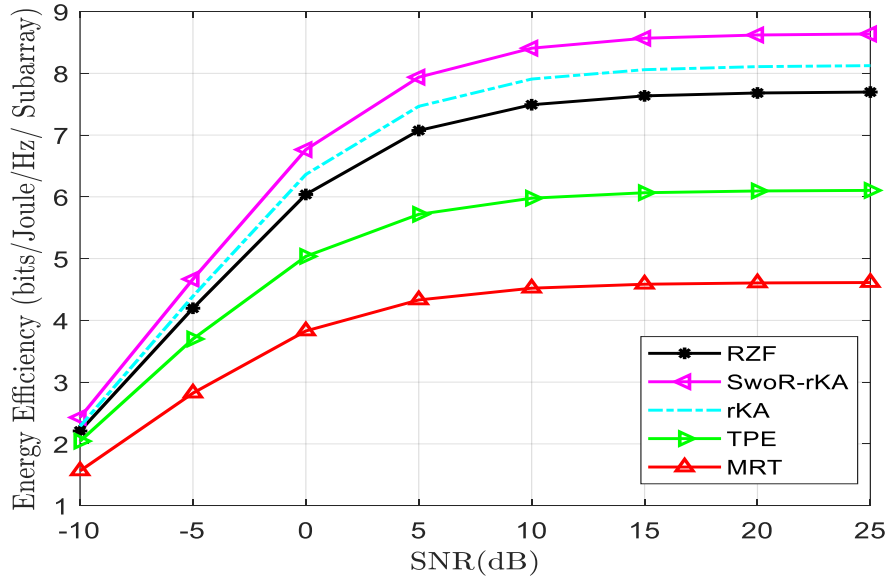


Figure 4.6: Performance comparison of Energy efficiency of different precoding techniques.

Table 4.5: Energy efficiency comparison of precoding at $K=32$.

Precoding Techniques	Energy Efficiency (bit/J/Hz/subarray)		
	SNR=5	SNR=10	SNR=15
MRT	4.33	4.52	4.59
TPE	5.72	5.98	6.07
RZF	7.07	7.49	7.63
rKA	7.47	7.91	8.06
SwoR-rKA	7.94	8.41	8.57

4.4 Performance Analysis of Bit Error Rate

Performance analyses of BER under perfect and imperfect CSI are analysed and compared. The PCP- SwoR-rKA method and the existing method are compared and evaluated.

4.4.1 Comparison of BER of Precoding Techniques Under Perfect CSI

In Figure 4.7 $M = 256$, $K = 16$, and the scalar parameter $\tau = 0.3$ signify the instantaneous CSI's quality. A thorough analysis provides important insights into the efficiency of the TPE, MRT, RZF, rKA, and SwoR-rKA precoding techniques in optimizing data transmission when comparing their performance in terms of bit error rate versus normalized transmit power under perfect non-stationary channels. This comparison shows how the precoding algorithm adapt to various signal strengths and noise levels by analyzing how BER changes with changing NTP levels. It also highlights how well both algorithms preserve signal integrity and reduce error in optimal channel settings. Analyzing the BER-NTP curves for TPE, MRT, RZF, rKA, and SwoR-rKA allows for a thorough evaluation of their error performance in a range of normalized transmit power scenarios, providing insight into their capacities for dependable and strong communication in wireless systems with perfect non-stationary channels circumstances. rKA has low BER when it is compared with SwoR-rKA.

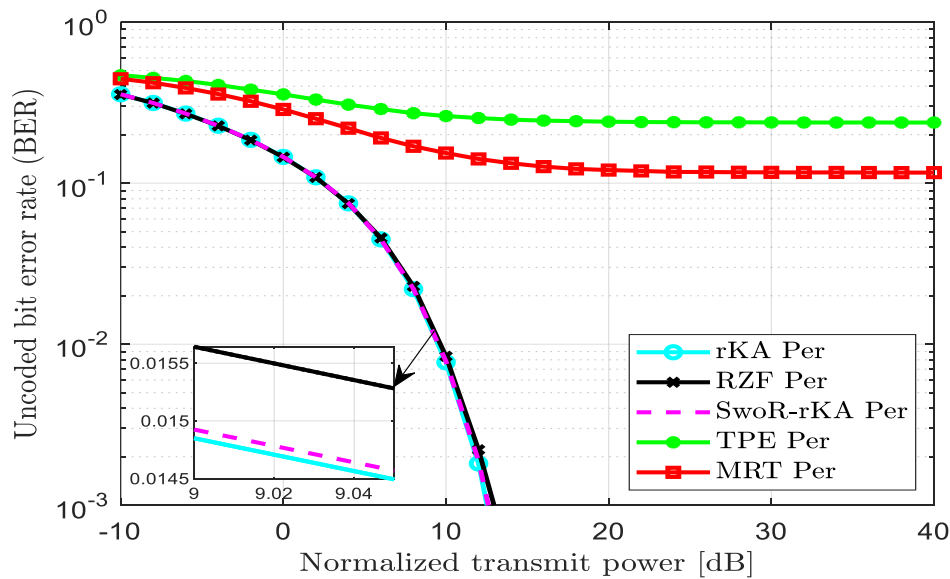


Figure 4.7: BER performances of TPE, MRT, RZF, rKA, and the SwoR-rKA against the normalized transmit power over perfect non-stationary channels.

4.4.2 Comparison of BER of Precoding Techniques Under Imperfect CSI

Figure 4.8 illustrates the bit error against the NTP plot is an important indicator to compare the performance of TPE, MRT, RZF, rKA, and the SwoR-rKA with defects in a digital communication system. The graph provides insights into the robustness and efficiency of the precoding approaches in noisy communication contexts by demonstrating how they manage errors under different NTP levels. A thorough assessment of the error-correcting capabilities of RZF, rKA, and SwoR-rKA with flaws can be obtained by analyzing their BER curves. This analysis can help determine the best precoding technique for a given communication system based on its performance and reliability requirements. When the transmitter has an imperfect channel estimate, the figure shows the SwoR-rKA algorithm can lower the BER when compared to rKA, but RZF has the lowest BER.

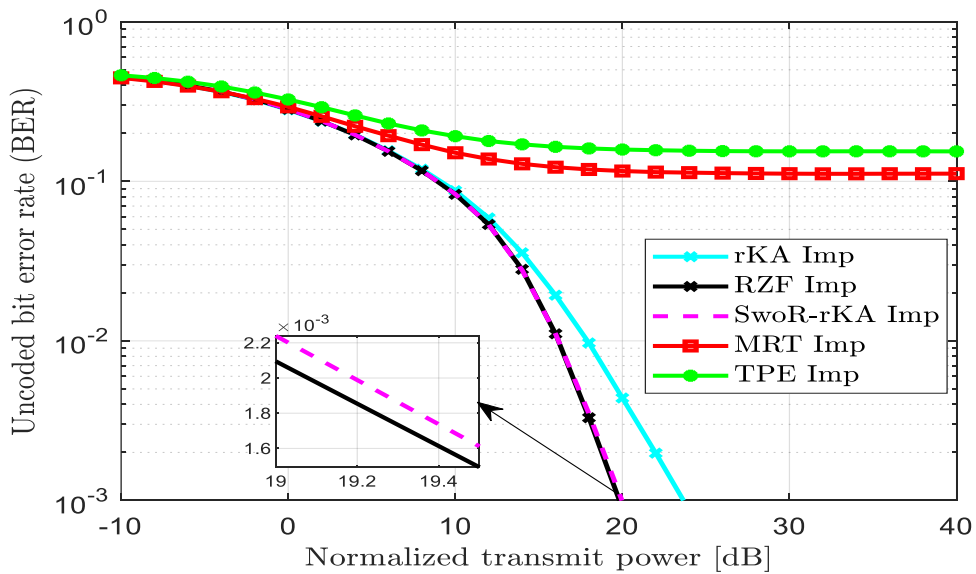


Figure 4.8: BER performances of TPE, MRT, RZF, rKA, and the SwoR-rKA against the normalized transmit power over imperfect non-stationary channels.

Table 4.6: BER performances of TPE, MRT, RZF, rKA, and the SwoR-rKA imperfect non-stationary channels.

Precoding Techniques	BER		
	NTP=14	NTP=16	NTP=18
MRT Per	0.1287	0.1226	0.1186
TPE Imp	0.1705	0.1645	0.1607
rKA Imp	0.035	0.0193	0.0097
RZF Imp	0.028	0.011	0.0032
SwoR-rKA Imp	0.0278	0.011	0.0034

As seen in Figure 4.9, the PCP- SwoR-rKA method outperforms the SwoR-rKA method in terms of BER. This gain is mainly because to the unique column selection strategy used in the PCP- SwoR-rKA method, which selectively chooses column matrices with low SNR to reflect poor channel conditions. By focusing on these suboptimal channels, the method effectively reduces interference within the system, as the selected columns are less likely to contribute significantly to overall signal interference. The robustness of the system is increased and the BER is decreased by taking use of the characteristics of low SNR channels, where interference potential is reduced. As a result, the system is able to sustain increased data integrity and communication reliability, demonstrating the effectiveness of the PCP- SwoR-rKA strategy under difficult channel circumstances.

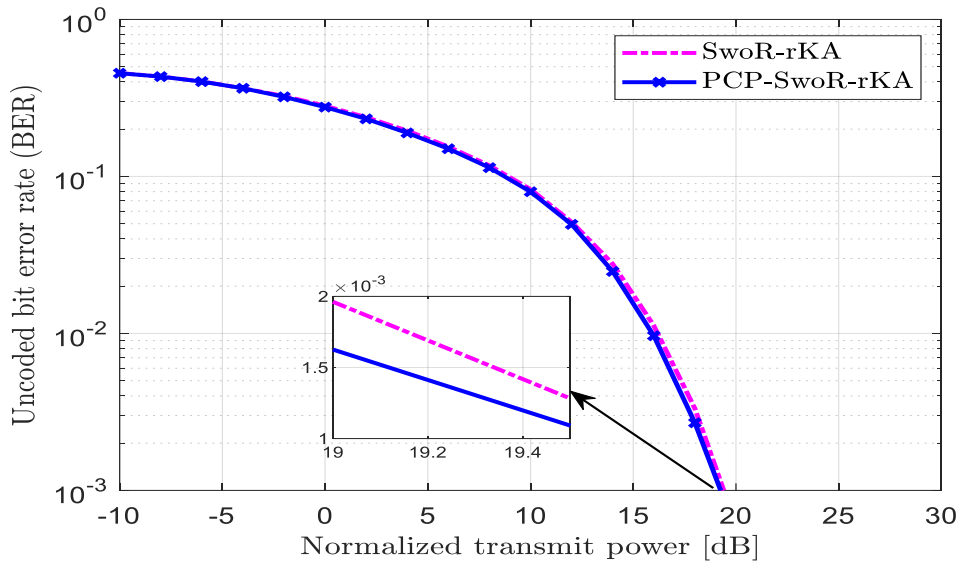


Figure 4.9: BER performances of PCP- SwoR-rKA and SwoR-rKA against the normalized transmit power over imperfect non-stationary channels.

Figure 4.10 shows the comparison of existing precoding with the PCP- SwoR-rKA. As explained above, this PCP- SwoR-rKA method has a lower BER when compared with the existing method. When considering that the channel is imperfect, the rKA has a high BER. Comparing the PCP- SwoR-rKA method to the existing SwoR-rKA method, the BER is 12.5% lower.

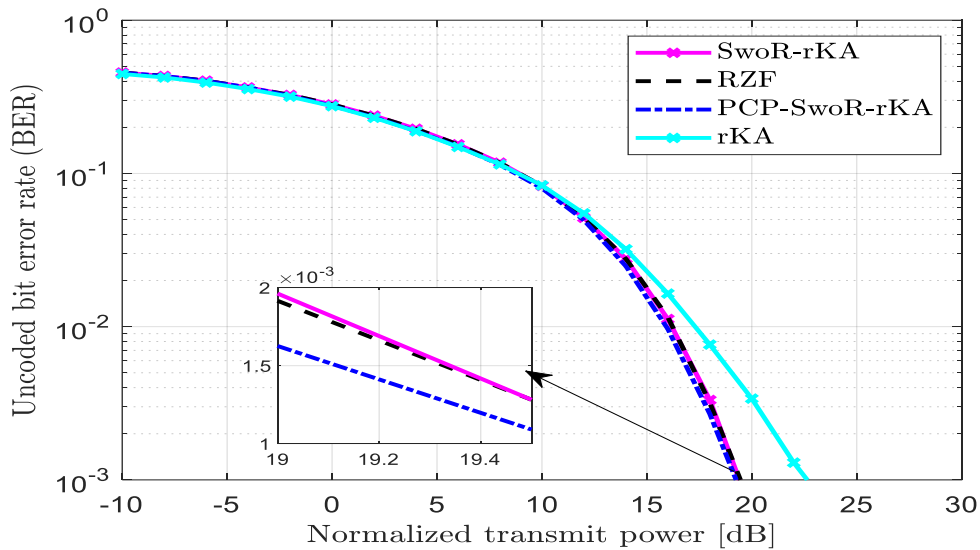


Figure 4.10: BER performances of RZF, rKA, SwoR-rKA, and PCP- SwoR-rKA against the normalized transmit power over imperfect non-stationary channels.

Table 4.7: BER performances of RZF, rKA, SwoR-rKA, and PCP- SwoR-rKA under imperfect non-stationary channels.

Precoding Techniques	BER		
	NTP=14	NTP=16	NTP=18
rKA	0.032	0.0164	0.0076
RZF	0.0277	0.0115	0.0032
SwoR-rKA	0.0277	0.0112	0.0033
PCP- SwoR-rKA	0.02482	0.0096	0.0027

For various modulation schemes (64QAM and 16PSK) and transmission power levels, the various precoding methods show different BER performance. This performance is compared in Figure 4.11. rKA 64QAM achieves better performance at high power levels, especially after 13 dB, while rKA 16PSK has lower BER at low NTP. Additionally, at low NTP values up to 18dB, RZF 16PSK and SwoR-rKA 16PSK have lower BER than RZF 64QAM and SwoR-rKA 64QAM. The PCP-SwoR-rKA method performs well at 16 PSK, which has a lower bit error rate than 64QAM. Across both modulation schemes, MRT and TPE consistently have higher BERs, indicating a poorer level of effectiveness in error mitigation.

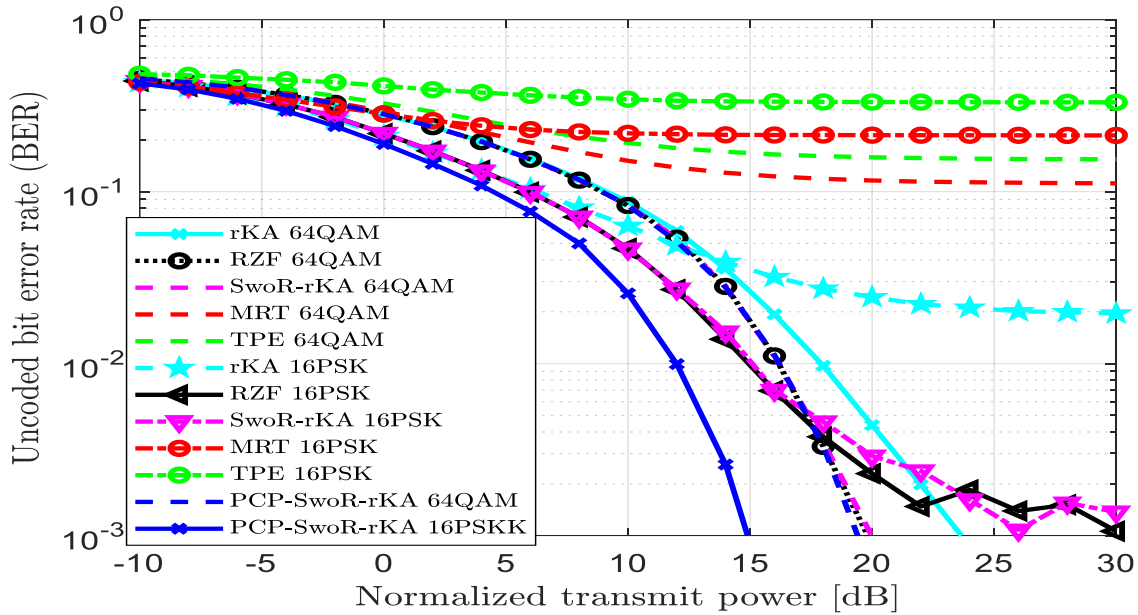


Figure 4.11: BER performances of precoding method against the normalized transmit power over imperfect non-stationary channels under 64QAM and 16PSK.

4.5 Comparison of Computational Complexity

Here the computational complexity is evaluated and analyzed under different parameters. All the simulation shows what happened if the number of antenna or number of user equipment increases.

4.5.1 The Computational Complexity Comparison of RZF and TPE

The computational complexity of the RZF and TPE precoding algorithms has been shown through the analysis of their computational complexity in two ways the at $K=50$ by taking different values of the number of antennas are compared in Figure 4.12. RZF has more computational complexity than TPE. This is because RZF requires matrix multiplication and inversion, which can be computationally expensive, especially for large matrices. As opposed to matrices operation, TPE uses polynomial expansion and multiplication, which often requires less computer power. Moreover, focusing on TPE and change the J values between 2 and 4, the complexity grows as J increases. According to this analysis, the computational burden in TPE is highly influenced by the choice of J value, with a higher J values resulting in greater complexity.

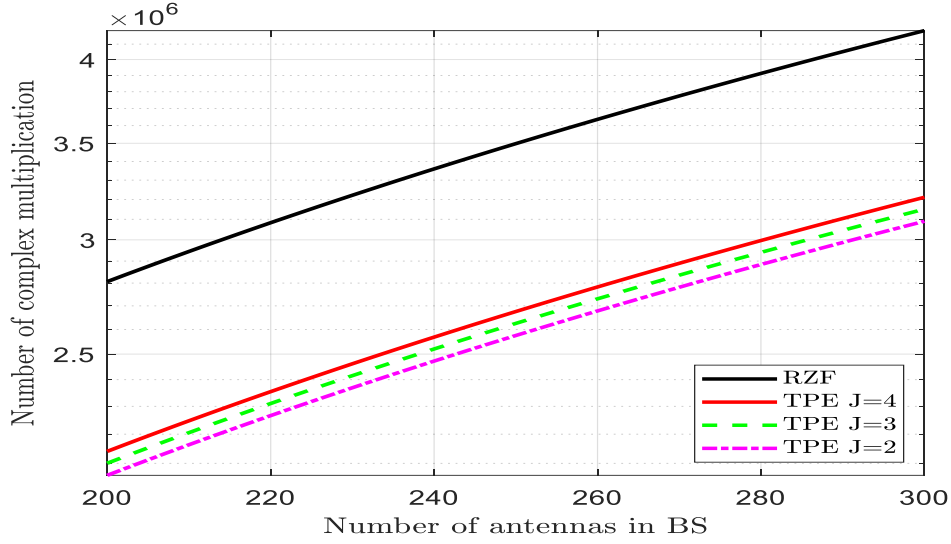


Figure 4.12: Comparison of the computational complexity of RZF and TPE at $K = 50$ and varying M .

Table 4.8: Comparison of computational complexity of RZF and TPE.

Precoding Techniques	Computational Complexity		
	$M=220$	$M=240$	$M=280$
RZF	3,083,150	3,359,650	3,912,5650
TPE J=4	2,354,560	2,568,620	2,996,740
TPE J=3	2,320,890	2,520,430	2,940,510
TPE J=2	2,276,520	2,482,540	2,884,280

Figure 4.13 illustrates the complexity at $M=250$ by taking different values of the number of UEs in particular, the computational demands are comparatively reduced for $J = 2$, but the computational complexity of TPE noticeably increases as J increases to 3 and then to 4. The truncated polynomial expansion has lower complexity when the number of user equipment and base stations becomes larger and has good performance for large MIMO systems.

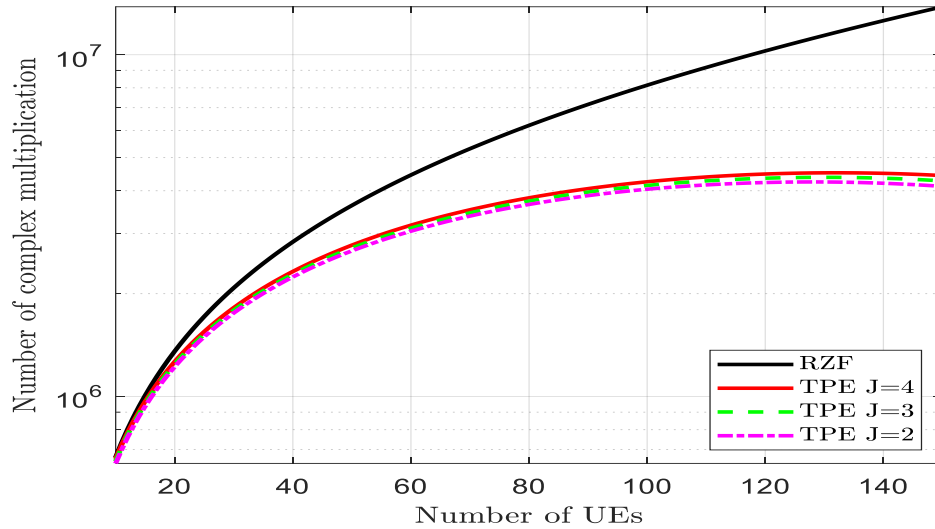


Figure 4.13: Comparison of the computational complexity of RZF and TPE at $M=250$ and varying K .

Table 4.9: Comparison of computational complexity of RZF and TPE.

Precoding Techniques	Computational complexity		
	$K=40$	$K=80$	$K=120$
RZF	2,834,060	6,210,520	10,257,400
TPE $J=4$	2,321,340	3,813,100	4,476,060
TPE $J=3$	2,279,680	3,730,040	4,551,600
TPE $J=5$	2,238,020	3,646,980	4,227,140

4.5.2 The Computational Complexity Comparison of Different Precoding

In this work, distinct patterns in computational demands and performance levels are revealed by analyzing the computational complexity of various precoding techniques, such as RZF, TPE, SwoR-rKA, rKA, and MRT at $K=100$ in an XL-MIMO scenario. The result in Figure 4.14 shows that RZF has a higher computational complexity than TPE. Afterward, rKA exhibits a very low computational complexity, proving its effectiveness in solving linear equation systems repeatedly.

Lastly, while MRT displays low computational complexity, its performance lags behind other techniques in the XL-MIMO setting, pointing to potential trade-offs between computational efficiency and performance.

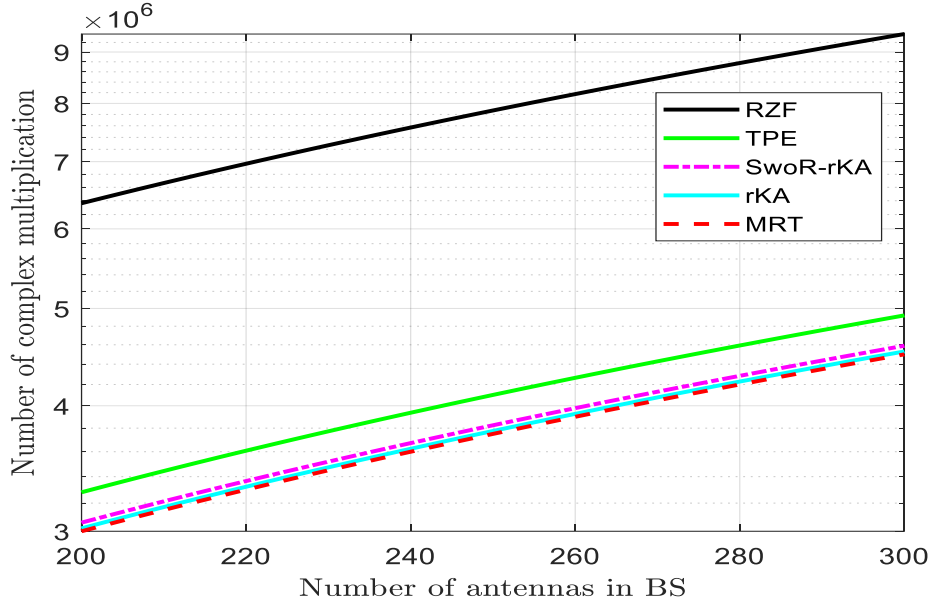


Figure 4.14: Comparison of the computational complexity of RZF, TPE, rKA, MRT, and SwoR-rKA at $K = 100$ and varying M .

Table 4.10: Comparison of computational complexity of precoding varying M .

Precoding Techniques	Computational complexity		
	$M=220$	$M=240$	$M=280$
MRT	3,300,000	3,600,000	4,200,000
rKA	3,322,220	3,624,240	4,228,280
SwoR-rKA	3,366,000	3,672,000	4,284,000
TPE	3,608,460	3,936,520	4,592,640
RZF	6,966,300	7,569,300	8,775,300

Figure 4.15 the complexity of RZF, TPE, rKA, MRT, and SwoR-rKA at $M=250$ is compared and analyzed. rKA, MRT, and SwoR-rKA show almost identical numbers of complex multiplication,

which has a low computational complexity when compared with RZF. The analysis which highlight the trade-offs between computational complexity and performance precision in various precoding systems, offer helpful guidance for maximizing computational efficiency when choosing precoding techniques in XL-MIMO settings.

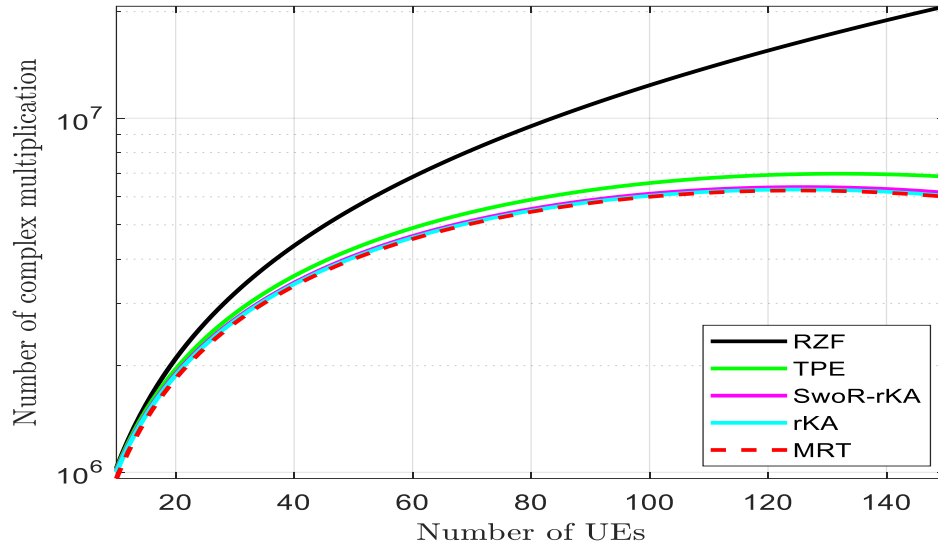


Figure 4.15: Comparison of the computational complexity of RZF, TPE, rKA, MRT, and SwoR-rKA at $M = 400$ and varying K .

Table 4.11: Comparison of computational complexity of precoding varying K .

Precoding Techniques	Computational complexity		
	$K=40$	$K=80$	$K=120$
MRT	3,360,000	4,440,000	6,240,000
rKA	3,400,400	5,480,400	6,280,400
SwoR-rKA	3,432,000	5,544,000	6,376,00
TPE	3,585,120	5,889,040	6,912,960
RZF	4,365,320	9,498,040	15,528,000

4.5.3 The computational complexity versus coherence block

The computational complexity of precoding techniques in huge MIMO systems is highly dependent on the size of the coherence blocks. Computational complexity increases with increasing coherence block size. This is so that the precoding technique can handle a larger matrix that is produced by a greater coherence block size. The computation of a big matrix's pseudo-inverse is the primary source of computational complexity in RZF precoding, as illustrated in Figure 4.16. As a result, the computational complexity of RZF precoding increases with increasing coherence block size. SwoR-rKA and RZF have higher computational complexity than rKA precoding. TPE lies between RZF and SwoR-rKA. The least computationally demanding precoding scheme of the ones that were taken into consideration was MRT precoding. Thus, the computational complexity of precoding techniques in huge MIMO systems is significantly affected by the size of the coherence block. This increases computing complexity with increasing coherence block size.

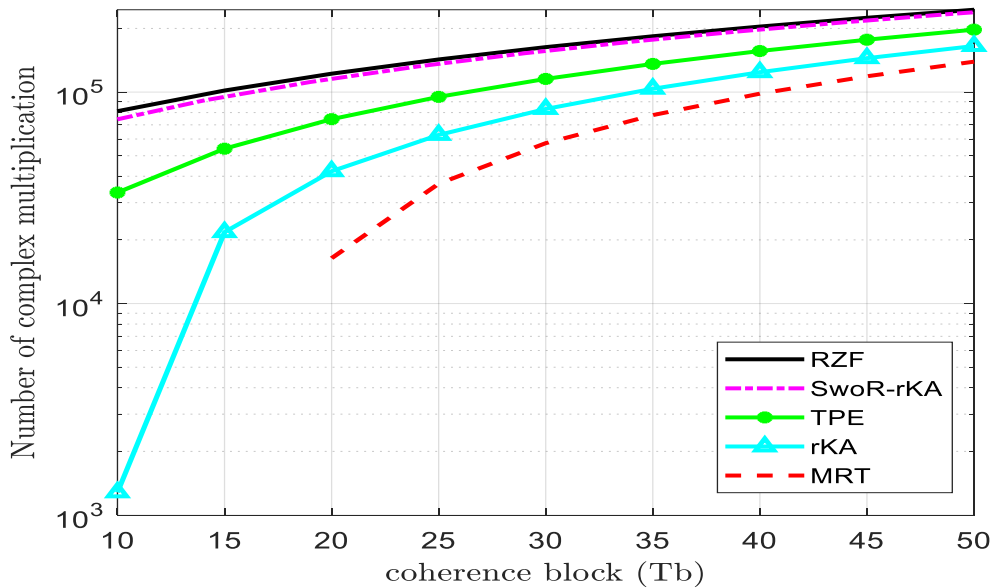


Figure 4.16: Comparison of computational complexity versus coherence block.

Table 4.12: Comparison of computational complexity versus coherence block.

Precoding Techniques	Computational complexity		
	$T_b=25$	$T_b=35$	$T_b=45$
MRT	36,864	77,824	11,8784
rKA	62,720	103,680	144,640
TPE	94,944	135,904	176,884
SwoR-rKA	139,805	180,202	222,031
RZF	142,672	183,632	224,592

4.5.4 Comparison of Complexity between mMIMO and XL-MIMO.

Figure 4.19 shows the complexity of all the considered schemes, in two typical scenarios: mMIMO and XL-MIMO. For mMIMO taking $M = 5$ to 64 range, $K = 5$, and for XL-MIMO $M = 5$ to 256, $K = 16$, and $S = 4$. Table 4.13 summarizes the computational complexity between mMIMO and XL-MIMO at $M=20$ for both values in both cases MRT has low complexity but it has low performance. In mMIMO RZF has low computational complexity which has a 4.9% reduction of SwoR-rKA algorithm but in XL-MIMO case RZF has high computational complexity. The algorithm complexity of the rKA and SwoR-rKA is lower than that of the RZF algorithm, especially when there are extremely large numbers of antennas. Both the rKA and SwoR-rKA algorithms have a 9.31% lower complexity than the conventional RZF at $M=20$. Additionally, even though the SwoR-rKA algorithm is more complex than the rKA algorithm, it can yield higher SE.

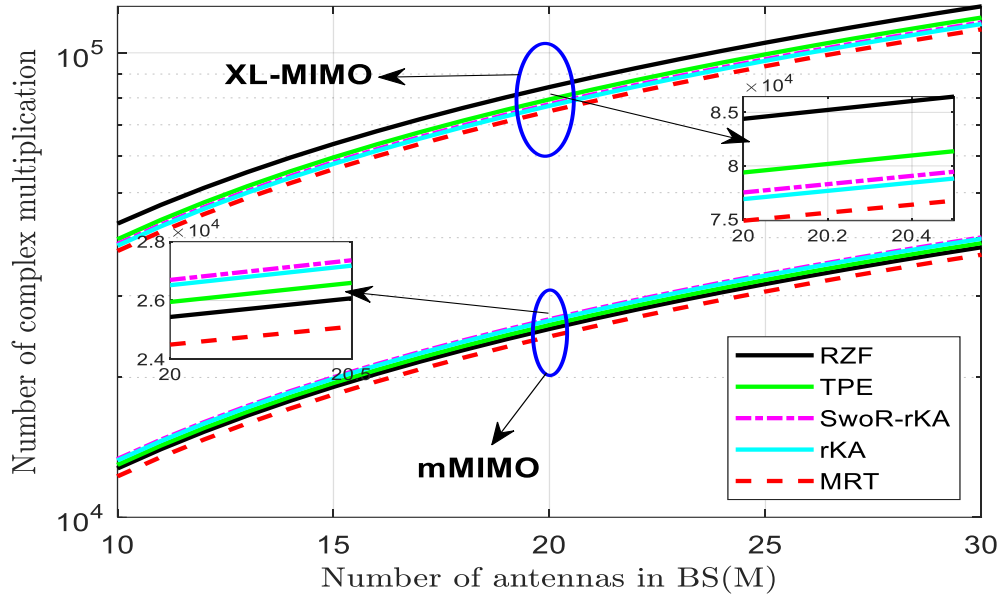


Figure 4.17: Computational complexity comparison between mMIMO and XL-MIMO at $K=5$ and $K=16$ respectively.

Table 4.13: Computational complexity comparison mMIMO and XL-MIMO.

Precoding Techniques	Computational complexity	
	mMIMO	XL-MIMO
	$M=20$	$M=20$
MRT	24,500	74,880
TPE	25,950	79,388
RZF	25,440	84,400
rKA	26,520	76,900
SwoR-rKA	26,700	77,520

4.6 Performance Metrics Analysis Under Different Number of UEs

For a particular case where $M = 240$, the relationship between energy efficiency and the number of transmit power is illustrated in Figure 4.18. Energy efficiency values for different numbers of UEs are provided in the associated Table 4.14. After some value the energy efficiency of all precoding techniques becomes constant. Increasing transmitted power simply will not improve the system due to the interference limited region and transmission power domination.

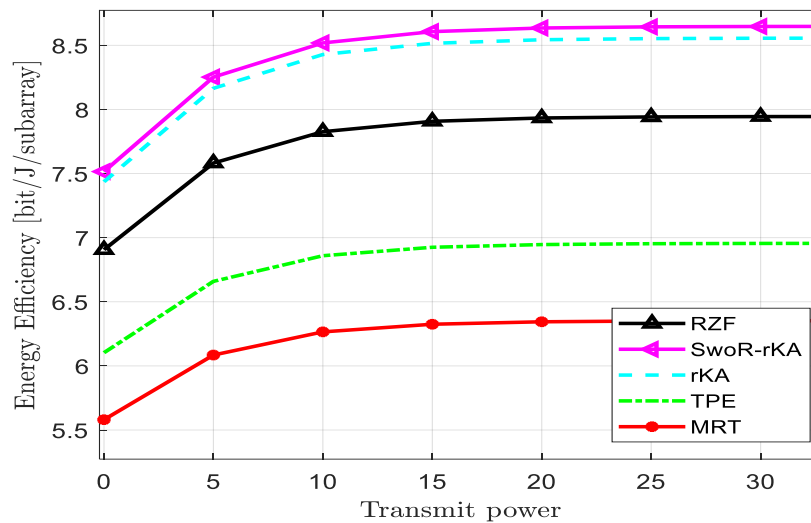


Figure 4.18: Energy efficiency versus transmit power at $M = 240$ and $K = 20$.

Table 4.14: Energy efficiency versus transmit power at $M = 240$ and $K = 20$.

Precoding Techniques	Computational complexity		
	$P_t=5$	$P_t=15$	$P_t=20$
MRT	6.084	6.325	6.344
TPE	6.659	6.925	6.946
RZF	7.582	7.907	7.933
rKA	8.165	8.428	8.543
SwoR-rKA	8.252	8.47	8.635

Comparative analysis shown in Figure 4.19, analyses spectral efficiency of RZF, TPE, SwoR-rKA, rKA, and MRT at $K= 20$ by considering different number of antennas. Here, when number of antennas increases the spectral efficiency also increase. This finding emphasizes how the performance of the precoding methods perform when increasing antennas.

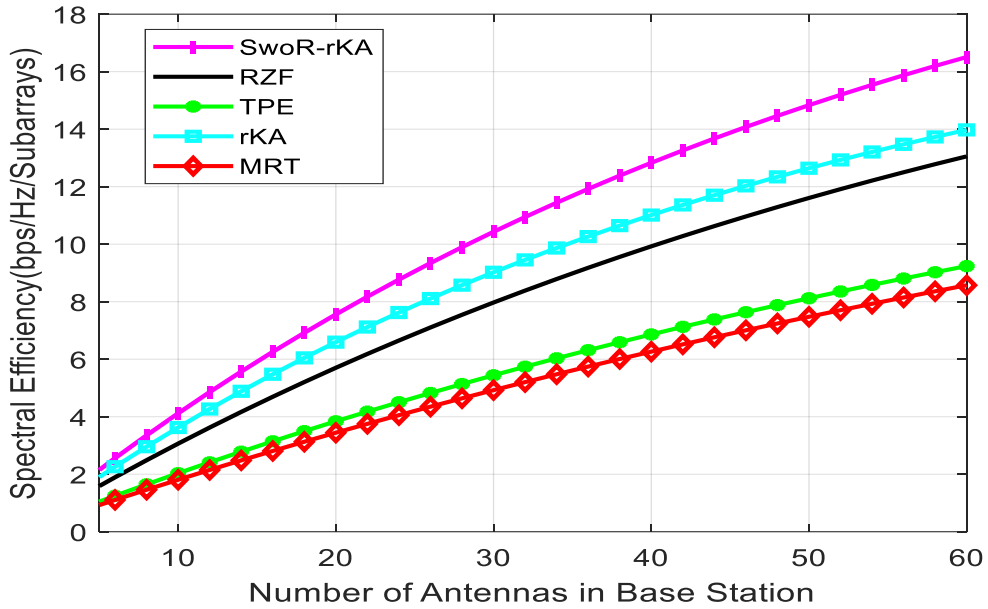


Figure 4.19: Spectral efficiency versus number of antennas in BS at $K = 20$.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The complexity and performance of five distinct precoding schemes are analyzed and compared in this thesis such as SwoR- rKA, rKA, RZF, TPE, and MRT. The outcomes demonstrate that a promising precoding method for XL-MIMO systems is SwoR-rKA. When compared to rKA, it has the largest computational cost but also provides the best spectral efficiency of all the precoding methods. Applications, where performance is not as important but computational complexity is a key concern, are a suitable fit for rKA. With the same performance as rKA, RZF has the most complexity among all methods. MRT is a low-complexity and low-performance system. The performance and complexity of the suggested precoding techniques are examined to the number of antennas and users. The outcome demonstrates that as more antennas are added, all of the precoding techniques under investigation perform well. But as the number of antennas rises, so does the computational complexity of all the precoding systems. Thus, the future generation of wireless systems needs an XL-MIMO architecture. It offers benefits in terms of energy efficiency, spectral efficiency, and achievable rate. The PCP- SwoR-rKA method lowers the BER when it is compared with existing method by reducing interference in bad channel condition.

5.2 Recommendation for Future Work

After comparing different precoding which are linear precoding. Power consumption in XL-MIMO systems may rise when more antennas are in operation. Therefore, it is important to create a precoding technique that preserves system performance while maintaining a balance between energy efficiency. The PCP-SwoR-rKA selects columns which are in bad condition, so further research to investigate column selection based on machine learning and deep learning algorithm. Further research will also focus on developing precoding methods based on deep learning machine learning that improve the spectral efficiency and performance of XL-MIMOS.

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