Performance Evaluation of Antenna Beam-forming in Millimeter -Wave Massive MIMO Systems

Ayalew Tsehay Tilahun

A Thesis Submitted to the Department of Electronics and Communication Engineering

School of Electrical Engineering & Computing

Presented in Partial Fulfillment of the Requirements of the Degree of Masters of Science in Communication Engineering

Office of Graduate Studies

Adama Science and Technology University

June, 2024

Adama, Ethiopia

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DECLARATION

I hereby declare that this Master Thesis entitled "**Performance Evaluation of Antenna Beam-forming in Millimeter Wave Massive MIMO Systems**" is my original work. That is, it has not been submitted for the award of any academic degree, diploma, or certificate at any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

Ayalew Tsehay	____________	20/06/2024
Name of student	Signature	Date

RECOMMENDATION

We, the advisors of this thesis, hereby certify that we have read the revised version of the thesis entitled "**Performance Evaluation of Antenna Beamforming in Millimeter Wave Massive MIMO Systems**" prepared under our guidance by **Ayalew Tsehay Tilahun** submitted in partial fulfillment of the requirements for the degree of Masters of Science in Electronics and Communication Engineering. Therefore, we recommend the submission of a revised version of the thesis to the department, following the applicable procedures.

Dr. Demissie Jobir	________________	________________
Major Advisor	Signature	Date
Dr. Rajaveerappa Devadoss	__________________	__________________
Co-advisor	Signature	Date

APPROVAL PAGE OF M.SC. THESIS

We, the advisors of the thesis entitled "Performance Evaluation of Antenna Beam-forming in Millimeter Wave Massive MIMO Systems, "developed by Ayalew Tsehay Tilahun, hereby certify that the recommendations and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Dr. Demissie Jobir	______________	______________
Major Advisor	Signature	Date
Dr. Rajaveerappa Devadoss	______________________	______________
Co-advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by **Ayalew Tsehay Tilahun,** have read and evaluated the thesis entitled "**Performance Evaluation of Antenna Beam-forming in Millimeter Wave Massive MIMO Systems**" and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement for the degree of Master of Science in Electronics and Communication Engineering.

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

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ACKNOWLEDGMENT

Primarily, I would like to thank the almighty God for providing me with strength, wisdom, and perseverance throughout this journey. Your unwavering presence has been a source of inspiration and motivation. I am extremely grateful to my family for their unconditional love, understanding, and continuous support. Your belief in me has been a constant source of encouragement, and I am blessed to have you by my side. I would like to extend my heartfelt thanks to my main advisor, Dr. Demissie Jobir. Your expertise, guidance, and mentorship have been invaluable. Your dedication to excellence and commitment to my academic growth have shaped me into a better researcher. I am truly grateful for the opportunity to work under your supervision. I would also like to express my appreciation to my co-advisor, Dr. Rajevarappa. Your insightful feedback, constructive criticism, and collaborative spirit have significantly contributed to the development and refinement of my work. Your guidance has been instrumental in shaping my research direction. Furthermore, I would like to thank Dr. Ram Sewak Singh for his guidance and continuous support, motivation and immense knowledge. I would like to thank the department head for their support and encouragement throughout my academic journey. Your leadership and commitment to fostering an environment of intellectual growth and innovation have been instrumental in shaping my research experience. Lastly, I would like to acknowledge all the doctors, colleagues, and friends who have provided assistance, insightful discussions, and encouragement along the way. Your contributions, whether big or small, have made a significant impact on my personal and professional growth. To everyone who has contributed to my success, thank you sincerely. Your support and encouragement have been invaluable, and I am truly grateful for your presence in my life.

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LIST OF ABBREVIATIONS

AoA	Angle of Arrival
AoD	Angle of Departure
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BS	Base Station
CSI	Channel State Information
DSP	Digital Signal Processing
EVM	Error Vector Magnitude
FSPL	Free Space Path Loss
GHz	Giga Hertz
IoT	Internet of Things
LCMV	Linearly Constrained Minimum Variance
LMS	Least Mean Squares
LOS	Line of Sight
LPI	Low Probability-of-Intercept
Mm-Wave	Millimeter-Wave
MIMO	Multiple Input Multiple Output
ML	Maximum Likelihood
MMSE	Minimum Mean-Squared Error
MRT	Maximum Ratio Transmission
MSNR	Maximum Signal-to-Noise Ratio
MU-MIMO	Multi-user Multiple input and Multiple output
MVDR	Minimum Variance Distortionless Response

NLOS	None Line of Sight
NMS	Normalized Mean Square
NS	Number of Spatial Streams
OFDM	Orthogonal Frequency Division
PDF	Probability Density Function
PER	Packet Error Rate
QAM	Quadrature Amplitude Modulation
QPSK	Quadrature Phase Shift Key
RF	Radio Frequency
RLS	Recursive Least Squares
RMS	Root Mean Square
RX	Receiver
RZF	Regularized Zero Forcing
SINR	Signal-to-Interference-plus-Noise Ratio
SMI	Sample Matrix Inversion
SNR	Signal-to-Noise Ratio
TX	Transmitter
UE	User Equipment
UPA	Uniform Planar Array
ZF	Zero Forcing
ZFBF	Zero Forcing Beam-forming

ABSTRACT

Massive Multiple Input Multiple Output (MIMO) utilizes a substantial number of antennas positioned at the base station and offers a promising solution for achieving high spectral efficiency and enhancing wireless communication capacity. However, challenges arise within the millimeter wave (mm-wave) spectrum, attributed to path loss and blockage. This thesis have been addressed these challenges by implementing a beamforming technique to focus transmitted energy in specific directions, thereby enhancing signal strength and mitigating the impacts of path loss and blockage. The thesis comprehensively aims to evaluate massive MIMO systems in mm-wave bands, considering factors such as the number of antennas, beamforming algorithms, and channel conditions. Performance metrics, including spectral efficiency, coverage, and interference management, have been rigorously assessed through extensive simulations. The findings of this thesis have been contribute to an enhanced understanding of massive MIMO performance in mm-wave environments, offering valuable insights for the design and optimization of wireless communication systems. Consequently, network operators, researchers, and system designers have better equipped to make informed decisions regarding the deployment and configuration of massive MIMO systems in mm-wave environments. This thesis have been deepen the understanding of the advantages, challenges, and trade-offs associated with massive MIMO systems utilizing antenna beamforming techniques in mm-wave bands. Finally, from the simulation result, RMS EVM can outperform and shows the importance of considering the number of users and the choice of modulation scheme in mm-wave massive MIMO channels to ensure optimal performance and reliable communication in dense user environments. The result shows that the importance of maintaining performance in dense user environments, the limitations of higher-order modulation schemes, the use of massive MIMO and hybrid beamforming techniques to address mm-wave communication challenges, with improved performance at higher SNRs.

Keywords: *Millimeter wave band, massive MIMO, hybrid beamforming, signal-to-noise ratio, root mean square error vector magnitude (RMS EVM).*

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

The exponential growth in wireless communication services, coupled with the increasing demand for high data rates and seamless connectivity, has necessitated the exploration of new technologies to support the ever-increasing user requirements (Mo et al., 2014)(Das & Kolangiammal, 2017). One such technology that has gained significant attention is systems utilizing a large number of antennas and multiple inputs and outputs (MIMO) operating at millimeter-wave (mm-wave) frequencies. Massive MIMO is a promising solution for achieving high spectral efficiency and enhancing the capacity of wireless communication systems (Singh & Joshi, 2021)(Cheng et al., 2017). Massive MIMO systems can serve multiple users simultaneously by employing a substantial number of antennas at the base station and spatially multiplexing signals. By utilizing the spatial dimension, this technique optimizes the system's performance, facilitating increased data transmission speeds and improved quality of service. In recent years, the utilization of mm-wave frequencies for wireless communication has developed into a key enabler for meeting the growing demand for bandwidth-intensive applications (Albreem et al., 2019). Mm-wave bands offer abundant spectrum resources, enabling the transmission of extensive quantities of data over short distances. However, mm-wave signals are highly susceptible to path loss and blockage due to their limited penetration and high sensitivity to challenges like buildings and vegetation. To overcome the challenges posed by mm-wave propagation, beamforming techniques have been widely employed in massive MIMO systems. Beamforming enables the concentration of transmitted energy in a specific direction, improving the signal strength and mitigating the adverse effects of path loss and blockage (Gong et al., 2023)(Busari et al., 2018). By adapting the directional characteristics of the antenna’s radiation, beamforming maximizes the received power for the intended user while minimizing interference from other users. This thesis aims to investigate the efficiency of massive MIMO systems in mm-wave bands through the utilization of antenna beamforming techniques. We assess the effects of various factors, including the number of antennas, beamforming algorithms, and channel conditions, on system performance metrics such as spectral efficiency, coverage, and interference management (Xiao et al., 2022)(Alouzi & Chan, 2018a). The assessment is conducted by conducting extensive simulations and comparing the results with conventional MIMO systems operating at lower frequency bands. The findings of this thesis are expected to contribute to the understanding of massive MIMO performance in mm-wave bands and provide valuable insights for the design and optimization of upcoming wireless communication systems. The results will help network operators, researchers, and system designers make informed decisions about the deployment and configuration of massive MIMO systems in mm-wave environments, ultimately enhancing the capacity and efficiency of wireless networks.

1.1.1 Massive MIMO Systems

Massive MIMO refers to the utilization of a significant quantity of antennas located at the base station in wireless communication systems. Unlike traditional MIMO systems that typically employ a few antennas, massive MIMO systems have the ability to serve multiple users simultaneously by spatially multiplexing signals (Qi et al., 2021)(Shim et al., 2020). This capacity for spatial multiplexing facilitates enhanced data rates, increased system capability, and enhanced spectral efficiency.

1.1.2 Millimeter Wave (mm-wave) Bands

Millimeter waves are electromagnetic waves with frequencies typically ranging from 30 to 300 gigahertz (GHz). These high-frequency bands offer vast amounts of underutilized spectrum, allowing for the transmission of significant quantities of data. However, mm-wave signals experience significant propagation challenges, including severe path loss and sensitivity to blockage (Shim et al., 2020)(Qi et al., 2021). These characteristics necessitate the development of advanced techniques to overcome these challenges and harness the potential of mm-wave bands.

1.1.3 Antenna Beam-forming Techniques

Beam forming is a signal processing method employed to focus transmitted energy in a specific direction, thereby improving the signal strength and quality at the intended receiver. Regarding massive MIMO systems in mm-wave bands, beamforming plays a crucial role in mitigating path loss and blockage effects. By adapting the radiation pattern of the antennas, beamforming maximizes the received power at the desired user, enhances coverage, and minimizes interference from other users (Alouzi & Chan, 2018a)(Xiao et al., 2022).

1.1.4 Performance Evaluation

The primary objective of this thesis is to evaluate the performance of massive MIMO systems operating in mm-wave bands with the application of antenna beamforming techniques. Metrics related to system performance, such as spectral efficiency, coverage, and interference management, are analyzed to assess the effectiveness of the proposed system (Busari et al., 2018)(Singh & Joshi, 2021). By investigating these aspects in greater detail, researchers can gain a deeper understanding of the potential benefits, challenges, and trade-offs associated with the implementation of massive MIMO systems in mm-wave bands with antenna beamforming techniques. This knowledge acts as a basis for future developments in wireless communication technologies and facilitates the development of future-generation networks capable of meeting the ever-growing demands for high-speed, reliable, and ubiquitous connectivity.

1.2 Statement of the Problem

The increasing demand for high data rates in wireless communication services has driven the exploration of advanced technologies, including massive MIMO systems operating in millimeter wave (mm-wave) bands, combined with antenna beamforming techniques. However, several research gaps need to be-addressed to ensure accurate and reliable evaluation of massive MIMO systems in mm-wave bands with antenna beamforming techniques. Firstly, the effects of interference on the channel estimate during the channel-training phase have not been adequately addressed in the existing literature. Interference can significantly affect the accuracy of channel estimation, leading to sub-optimal beamforming performance. Understanding and mitigating the effects of interference during the channel-training phase is essential for reliable performance evaluation. Secondly, the limitations and challenges associated with the proposed hybrid approach for addressing multiple interference in mm-wave systems have not been explicitly discussed. The hybrid approach may introduce complexities and trade-offs that affect system performance. Identifying and addressing these limitations is crucial for reliable and efficient mm-wave system designs. Lastly, the proposed recovery technique for mm-wave system designs lacks consideration of the limitations and effects of interference on the channel estimate. Interference in mm-wave systems can degrade the quality of the channel estimate, leading to sub-optimal beamforming performance. Evaluating and accounting for these limitations is necessary to ensure the effectiveness of the proposed technique. By addressing these research gaps, this study aims to conduct a comprehensive performance evaluation of massive MIMO systems in mm-wave bands with antenna beamforming techniques. The evaluation have been analyzed the effects of different parameters and operating conditions on performance metrics, providing insights into the capabilities and limitations of massive MIMO in mm-wave environment. Therefore, the key problems for the existing method are the high complexity of orthogonal matching pursuit (OMP) for large antenna arrays, and the limited spectral efficiency compared to the hybrid beamforming technique specifically root mean square error vector magnitude (RMS EVM) method. This thesis aims to address these challenges by proposing root mean square error vector magnitude (RMS EVM) method to enhance the spectral efficiency, mitigate interference and reduce bit error rate.

1.3 Objectives of the Study

1.3.1 General Objective

The primary goal of the study is to comprehensively evaluate the performance of massive MIMO systems operating in mm-wave bands, specifically focusing on antenna beamforming techniques.

1.3.2 Specific Objectives

The specific objective of the performance evaluation of antenna beamforming in millimeter wave massive MIMO systems is to provide a comprehensive understanding of the performance characteristics and capabilities of massive MIMO systems at mm-wave bands with antenna beamforming technique. i.e.

- To develop an efficient antenna beamforming technique for massive MIMO in millimeter wave bands.
- To measure the parameters like spectral efficiency for numbers of BS antennas.
- To evaluate how RMS EVM varies with the number of users for scattered and massive MIMO channels in millimeter wavebands.
- To measure the bite error rate in relation to the number of users for scattered and massive MIMO channels in millimeter wavebands.

1.4 Scope of the Study

The performance evaluation of antenna beamforming in millimeter-wave massive MIMO systems has a scope that includes assessing performance metrics, investigating beamforming techniques, conducting simulations and comparisons, and providing insights for system design. However, there are limitations to consider, such as hardware limitations, the scalability and complexity of massive MIMO systems. Despite these limitations, the evaluation provides valuable insights for the planning and enhancement of wireless communication systems.

1.5 Significance of the Study

The study of performance evaluation of antenna beamforming in millimeter-wave massive MIMO system hold significant importance in the field of wireless communication and have several key implications:

Advancement of wireless technology: The study contributes to the advancement of wireless communication technology by exploring the performance of massive MIMO systems in millimeter wave (mm-wave) bands. It provides insights into the effectiveness of antenna beamforming techniques in mitigating propagation challenges and maximizing system performance in mm-wave environments. This knowledge can drive the development of future-generation wireless networks that can support high data rates, accommodate increasing user demands, and exploit the underutilized mm-wave spectrum.

Enhanced spectrum utilization: The research investigates the performance of massive MIMO systems at mm-wave bands, which offer vast amounts of underutilized spectrum. By evaluating the system's capacity, coverage, and interference management capabilities, the study guides network operators and system designers in effectively utilizing the mm-wave spectrum. This efficient spectrum utilization enables the provision of high-speed, bandwidth-intensive services and improves the overall spectral efficiency of wireless networks.

Improved system design and optimization: The findings of the study provide valuable insights for the design and optimization of massive MIMO systems at mm-wave bands. The thesis identifies the impact of various parameters, such as the number of antennas, beamforming algorithms, and channel conditions, on system performance. These insights facilitate informed decision-making regarding system configuration, resource allocation, and beamforming technique selection, leading to optimized system designs that maximize performance, coverage, and capacity.

Realistic performance evaluation: The study conducts comprehensive simulations and comparisons to evaluate the performance of massive MIMO systems at mm-wave bands. By considering realistic channel conditions, system configurations, and performance metrics, the thesis provides a thorough assessment of the system's capabilities and limitations. This realistic performance evaluation helps researchers and practitioners understand the practical implications of deploying massive MIMO systems in mm-wave environments, enabling them to make informed decisions regarding system deployment and operation.

Enabling bandwidth-intensive applications: The study's insights and recommendations support the development of wireless networks capable of accommodating bandwidth-intensive applications. By evaluating the system's spectral efficiency and capacity, the thesis helps ensure that future networks can handle the increasing demand for high-quality video streaming, virtual reality, internet of things (IoT) applications, and other data-intensive services. This enables the realization of innovative applications and services that rely on high-speed, reliable, and low-latency connections.

Contribution to standardization and industry guidelines: The study's findings and guidelines can contribute to the development of industry standards and guidelines for massive MIMO systems at mm-wave bands. The thesis outcomes can inform standardization bodies, network operators, and equipment manufacturers in defining best practices, system requirements, and deployment guidelines. This promotes interoperability, facilitates the adoption of massive MIMO technology, and accelerates the deployment of mm-wave-based wireless communication systems.

In general, the study of Performance Evaluation of Massive MIMO Systems in Millimeter Wave Bands with Antenna Beam-forming Technique has significant significance by advancing wireless technology, enhancing spectrum utilization, guiding system design and optimization, enabling bandwidth-intensive applications, facilitating realistic performance evaluation, and contributing to standardization efforts.

1.6 Thesis Contribution

The main contribution of performance evaluation of antenna beamforming in millimeter wave massive MIMO systems is to evaluate the performance of antenna beamforming techniques in millimeter wave (mm-wave) massive multiple-input multiple-output (MIMO) systems. The thesis focuses on the utilization of mm-wave frequencies for wireless communication, which enables high data rates due to the availability of large bandwidths. However, mm-wave signals are susceptible to severe path loss and atmospheric absorption, which can significantly degrade the system’s performance. To overcome these challenges, beamforming techniques are employed to concentrate the transmitted power in the user defined direction and mitigate the effects of channel interference. The thesis investigates the performance of different beamforming schemes in mm-wave massive MIMO systems. It analyzes the impact of the number of antennas at the base station, the number of users, and the beamforming algorithm on system-level performance metrics such as spectral efficiency, coverage, and energy efficiency. The findings of this thesis provide valuable insights into the performance trade-offs and limitations of different beamforming techniques in mm-wave massive MIMO systems. The results can guide the design and optimization of future wireless communication systems operating in the mm-wave frequency range, with the aim of maximizing spectral efficiency and system capacity while minimizing interference.

1.7 Limitations of the Study

There are limitations to studying this thesis, such as hardware limitations, the scalability and complexity of massive MIMO systems. Despite these limitations, the evaluation provides valuable insights for the planning and enhancement of wireless communication systems.

1.8 Organization of the Thesis

The thesis has been divided into five chapters. Chapter one presents the introduction, statement of the problem, objectives of the study, scope, significance, and main contribution of the thesis. Chapter two includes a review of different literature on massive multiple input multiple output, millimeter-wave, analog, digital, and hybrid beamforming and the existing works related to the performance evaluation of antenna beamforming in millimeter-wave massive MIMO systems. Chapter three describes the system model and mathematical formulation for millimeter-wave massive MIMO, considering the performance evaluation of antenna beamforming in millimeter-wave massive MIMO systems. Chapter four presents the simulation results obtained using MATLAB 2023b and discussions those results. Finally, Chapter five is describes the conclusion and recommendations for future works. In this thesis, root mean square error vector magnitude (RMS EVM) provide a framework to compute the beamforming vectors based on the channel characteristics and desired signal. By applying these beamforming techniques at the transmitter, the system can optimize the received signal quality, mitigate interference, and enhance the overall performance of the wireless communication system.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The theoretical background of the study on performance evaluation of antenna beamforming in millimeter-wave massive MIMO systems involves several key concepts and principles. Here are some important theoretical aspects that form the foundation of this study:

2.2 Channel Modeling

Precise channel modeling is essential in evaluating the operational effectiveness of massive MIMO systems at mm-wave bands. Researchers have developed various channel models to capture the distinct properties of mm-wave propagation, including path loss, shadowing, and small-scale fading effects. These models consider factors such as propagation in direct view (LOS) and indirect view (NLOS) scenarios, blockage effects, and spatial correlation between antenna elements (Cheng et al., 2017)(Gong et al., 2023).

2.3 Hybrid Beamforming

Hybrid beamforming, which combines digital and analog beamforming techniques, has gained significant attention within massive MIMO systems operating at mm-wave frequencies. It allows for a balance between performance and intricacy, as it reduces the number of radio frequency (RF) chains while maintaining beamforming capabilities. Several studies have investigated the effectiveness of hybrid beamforming algorithms, considering factors such as beamforming gain, beam alignment, and power consumption (Das & Kolangiammal, 2017).

2.4 Mobility and Handover

Assessing the effectiveness of massive MIMO systems at mm-wave bands in mobile scenarios is an ongoing research area. Mobility introduces challenges such as beam misalignment, handover, and Doppler effects, which can affect system performance. Researchers are exploring techniques to address these challenges, including adaptive beamforming, beam tracking, and handover algorithms, to maintain seamless connectivity and maximize system performance in mobile environments (Doctorale & Fadel, 2021).

2.5 Interference Management

Interference is a key consideration in massive multiple-input multiple-output (MIMO) systems operating in the millimeter wave (mm-wave) spectrum due to the high density of users and the narrow beam widths of mm-wave signals. Researchers are investigating interference management techniques, such as beamforming nulling, interference alignment, and advanced scheduling algorithms, to reduce interference and enhance system performance (Ali et al., 2017)(Albreem et al., 2019). These techniques strive to optimize the spatial reuse of the mm-wave spectrum and enhance overall system capacity.

2.6 Challenges of propagation characteristics for mm wave bands

Directionality: The signal needs to be transmitted and received using directional antennas to overcome the path loss and attenuation. This requires accurate beam alignment and tracking, as well as beam-forming techniques (Mo et al., 2014).

Blockage: The signal is vulnerable to shadowing and obstruction by obstacles and mobility. This requires robust link adaptation and handover mechanisms, as well as diversity techniques.

Channel modeling: The signal exhibits complex and dynamic channel behavior that depends on the environment and the antenna configuration. This requires accurate and efficient channel measurements and models, as well as channel estimation and feedback techniques.

2.7 Advantages of propagation characteristics for mm wave bands

Abundant bandwidth: The signal can exploit a large amount of spectrum that is underutilized or unlicensed, enabling multi-Gbps data rates and low latency (Albreem et al., 2019).

Spatial reuse: The signal can support high-density and interference-free transmissions due to the narrow beams and short ranges.

New applications: The signal can enable new use cases and scenarios that require high performance and reliability, such as 5G cellular networks, wireless LANs, vehicular communications, and backhaul/front haul.

2.8 Beam-forming in MIMO Systems

Beam forming is a technique used in multiple-input, multiple-output (MIMO) systems to enhance the performance of wireless communication. MIMO systems utilize multiple antennas at both the transmitter and the receiver to improve data throughput, increase link reliability, and enable spatial multiplexing. In a MIMO system, beam forming is employed to focus the transmitted signal power in a specific direction, thereby increasing the received signal strength at the desired receivers and reducing interference from other directions. This is accomplished by adjusting the phase and amplitude of the signals transmitted from each antenna element (Gong et al., 2023). There are two main types of beam forming in MIMO systems:

Analog Beam-forming: In analog beam forming, the beam-forming weights are applied at the radio frequency (RF) level. Each antenna element has a dedicated RF chain that adjusts the phase and amplitude of the signal before it is transmitted. Analog beam forming is relatively simple to implement and requires lower hardware complexity. However, it provides limited beam-forming capabilities and is mainly effective in scenarios with a small number of antenna elements (Singh & Joshi, 2021).

Digital Beam-forming: Digital beam forming operates at the base band level and involves processing the signals from each antenna element using digital signal processing (DSP) techniques. The received signals are combined with specific weights, which are determined based on channel state information (CSI). Digital beam forming allows for more advanced beam-forming capabilities, such as adaptive beam-forming and nulling interference from specific directions. However, it requires more complex hardware and higher computational resources. The beam-forming technique used in a MIMO system depends on the specific requirements of the application, such as system complexity, desired performance, and available resources. Analog beam forming is often used in applications with a limited number of antenna elements, such as small-scale MIMO systems or millimeter-wave (mm-wave) communications. On the other hand, digital beam-forming is commonly employed in larger-scale MIMO systems, such as massive MIMO or multi-user MIMO (MU-MIMO) systems (Xiao et al., 2022). Generally, beam forming plays a crucial role in MIMO systems by improving signal quality, increasing system capacity, and mitigating interference. It is an essential technique for achieving high-performance wireless communications in modern networks.

2.9 General Beam-forming Classification

Here are the main classifications of beam-forming techniques, along with their sub-classifications. In this thesis work, i have applied hybrid beamforming techniques to improve spectral efficiency and to mitigate interference.

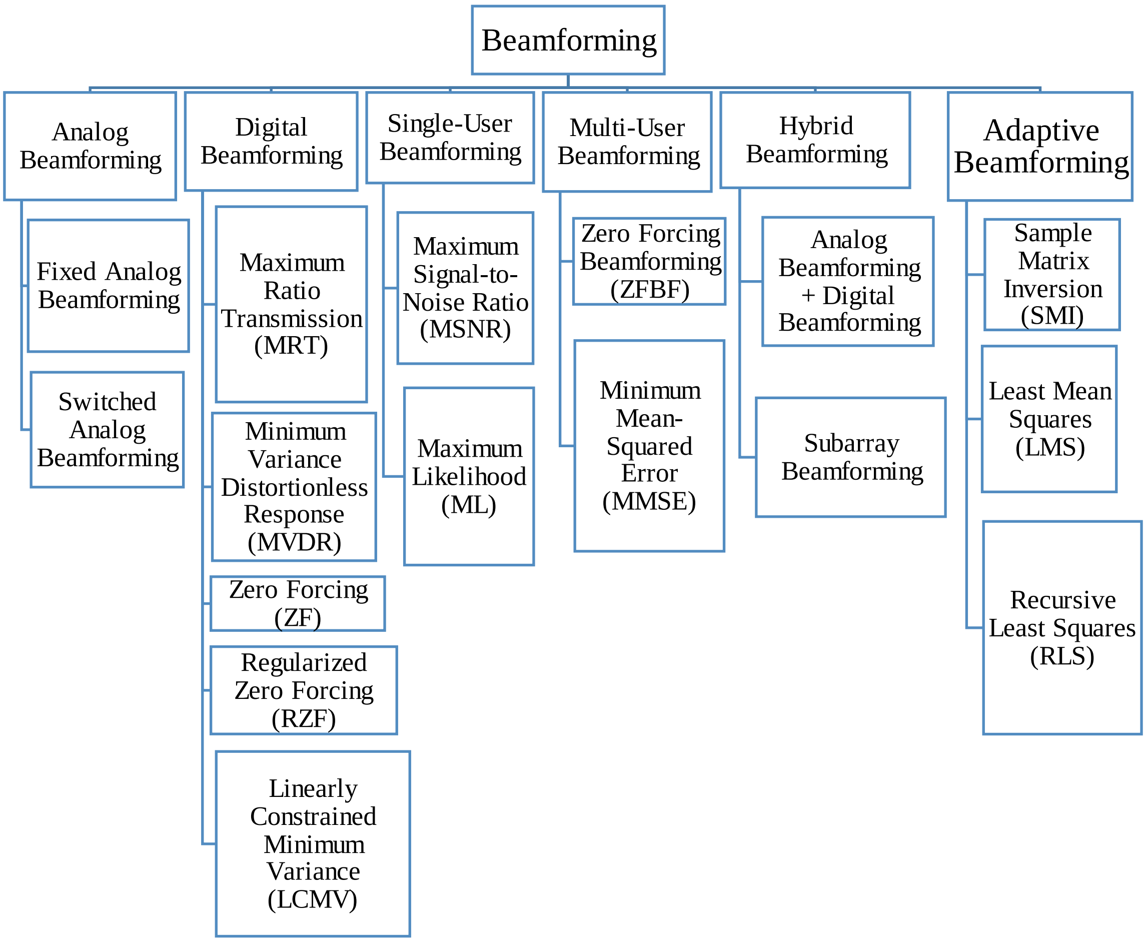

Figure 2.1 Classification of beam forming (Zhang, Yu, and Letaief 2020)

2.9.1 Analog Beam-forming

Fixed Analog Beam-forming: This involves using fixed phase shifters or time delays to steer the beam in a specific direction. The phase shifters, or time delays, are set based on the desired beam direction and are not dynamically adjusted (Mohammed, 2022).

Switched Analog Beam-forming: This technique uses a set of fixed beam-forming patterns, and the system switches between these patterns based on the desired beam direction. Each pattern corresponds to a specific combination of phase shifters or time delays.

2.9.2 Digital Beam-forming

Maximum Ratio Transmission (MRT): MRT beam forming maximizes the received signal power at the receiver by adjusting the complex weights of the antenna elements. It does not consider interference or noise.

Minimum Variance Distortionless Response (MVDR): MVDR beam forming minimizes the output power subject to a constraint on the desired signal. It suppresses interference and noise by adjusting the complex weights to create nulls in the directions of interference.

Zero Forcing (ZF): ZF beam forming completely cancels the interference by adjusting the complex weights to make the received interference signals zero at the output. It sacrifices some signal power to achieve interference cancellation.

Regularized Zero Forcing (RZF): RZF beam forming is similar to ZF but adds regularization to mitigate the noise amplification that occurs with ZF beam forming.

Linearly Constrained Minimum Variance (LCMV): LCMV beam forming applies constraints on both the desired response and interference, providing a trade-off between interference suppression and desired signal enhancement.

2.9.3 Single-User Beam-forming

Maximum Signal-to-Noise Ratio (MSNR): MSNR beam forming maximizes the signal power at the receiver while minimizing the noise power.

Maximum Likelihood (ML): ML beam forming maximizes the likelihood of receiving the desired signal based on statistical models and assumptions.

2.9.4 Multi-user Beam-forming

Zero Forcing Beam-forming (ZFBF): ZFBF beam forming cancels the interference from other users by creating nulls in their directions, while maximizing the signal power for the desired user.

Minimum Mean-Squared Error (MMSE): MMSE beam forming minimizes the mean-squared error between the desired signal and the received signal, providing a trade-off between interference suppression and desired signal enhancement.

2.9.5 Hybrid Beam-forming

Analog Beam-forming + Digital Beam-forming: This hybrid approach combines analog beam forming at the RF front-end and digital beam forming at the baseband processing stage. It reduces the complexity of digital beam forming while maintaining adaptability.

Sub-array Beam forming: In hybrid beam forming, the antenna array is divided into sub-arrays, and analog beam forming is performed at the sub-array level, while digital beam forming is applied at the sub-array outputs.

2.9.6 Adaptive Beam-forming

Sample Matrix Inversion (SMI): SMI beam forming uses the sample co-variance matrix to estimate the beam-forming weights. It is computationally efficient but may suffer from performance degradation in certain scenarios.

Least Mean Squares (LMS): LMS beam forming uses a gradient-based optimization algorithm to iteratively update the beam-forming weights based on the received signals and desired signal characteristics.

Recursive Least Squares (RLS): RLS beam forming is a more computationally intensive algorithm that provides better performance than LMS by recursively updating the beam-forming weights.

2.10 Spatial Diversity

Spatial diversity is a technique used in wireless communication systems to improve the reliability and robustness of the transmitted signals in the presence of fading and interference. It leverages multiple antennas to exploit the spatial characteristics of the wireless channel and enhance the quality of the received signal. In spatial diversity, the transmitter sends the same data stream over multiple transmit antennas simultaneously. The signals transmitted through different antennas experience independent fading and interference due to the varying characteristics of the wireless channel. At the receiver, which is equipped with multiple receive antennas, the received signals from the different antennas are combined to improve the overall signal quality. The main idea behind spatial diversity is that the fading and interference affecting the signals at one antenna may not affect the signals at other antennas in the same way. By combining the signals from multiple antennas, the receiver can mitigate the effects of fading and interference, resulting in improved signal quality and increased reliability (Qi et al., 2021)(Biradar et al., 2022).

2.11 Hybrid Precoding Design

Hybrid precoding is a technique used in millimeter-wave (mm-wave) MIMO (multiple-input, multiple-output) systems to reduce the complexity of digital precoding by combining analog and digital precoding stages. The hybrid precoding design aims to optimize the precoding matrices at both the analog and digital stages to achieve efficient beam forming and maximize system performance. The mathematical model for hybrid precoding design enables the analysis, design, and optimization of system performance in terms of beam-forming gain, interference mitigation, and capacity improvement in mm-wave MIMO systems. It helps in understanding how the analog and digital precoding stages can be jointly optimized to achieve efficient beam-forming with reduced complexity (Shim et al., 2020).

2.12 Millimeter-wave hybrid beam-forming

Millimeter-wave (mm-wave) hybrid beam forming is a technique used in wireless communication systems operating in the mm-wave frequency range to overcome the challenges posed by the high path loss and narrow beam widths at these frequencies. Hybrid beam-forming combines analog and digital beam-forming to achieve efficient beam-forming with reduced complexity (Alouzi & Chan, 2018a).

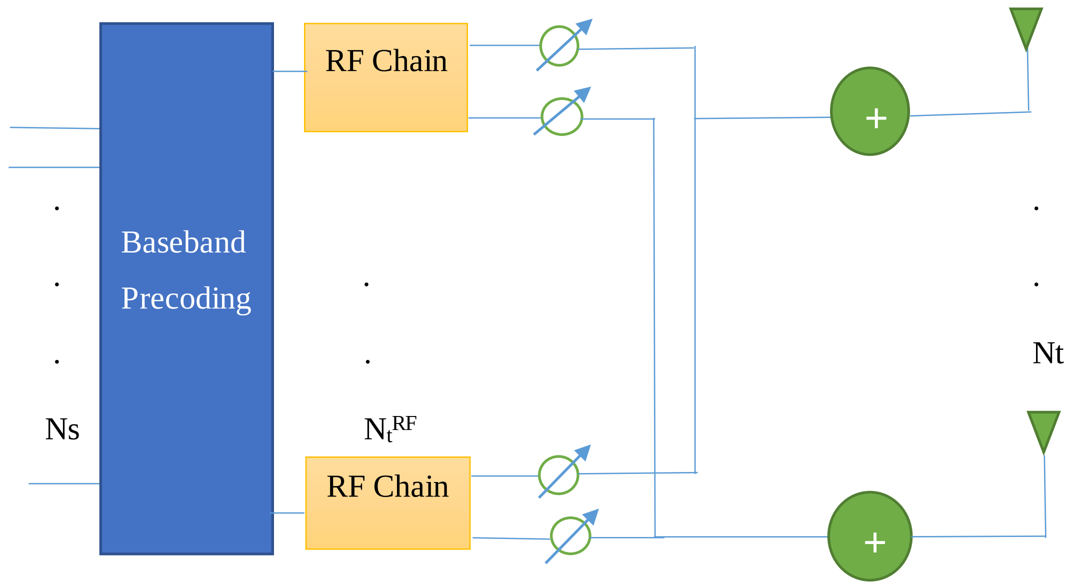

Figure 2.2 mm-wave MIMO architecture based on hybrid precoding and combining (Mohammed 2022)

2.13 Frequency Selective fading in mm-wave Wireless Channels

Frequency-selective fading refers to the phenomenon where the wireless channel's characteristics vary with frequency, resulting in different fading characteristics for different frequency components of the transmitted signal. In mm-wave wireless channels, frequency-selective fading becomes more pronounced due to the large bandwidths and the presence of multiple propagation paths (Busari et al., 2018). The mathematical model for frequency selective fading in mm-wave wireless channels involves understanding the channel response, multipath propagation, and the effect of frequency selectivity.

Channel Response: The channel response in frequency-selective fading represents the relationship between the transmitted and received signals for different frequency components. It captures the frequency-dependent attenuation, phase shifts, and delay spread caused by the wireless propagation environment. The mathematical model for the channel response involves representing it as a complex-valued frequency response function or an impulse response function that varies with frequency.

Multipath Propagation: Multipath propagation refers to the phenomenon where the transmitted signal reaches the receiver through multiple propagation paths due to reflections, diffractions, and scattering in the environment. Each propagation path contributes differently to the overall channel response, resulting in frequency selectivity. The mathematical model for multipath propagation involves representing the channel response as a sum of complex-valued contributions from different propagation paths. This can be achieved using techniques like the Saleh-Valenzuela model or the geometric channel model.

Frequency Selectivity: Frequency selectivity in mm-wave wireless channels arises due to the different delays and phases associated with the multipath components, resulting in constructive and destructive interference at different frequencies. The mathematical model for frequency selectivity involves characterizing the channel's frequency response using parameters such as the delay spread, Doppler spread, coherence bandwidth, or coherence time. These parameters provide insights into the variation of the channel response over the frequency range.

Channel Estimation and Equalization: In practical communication systems, frequency selective fading poses challenges for signal detection and decoding. Channel estimation and equalization techniques are employed to mitigate the effects of frequency selectivity and recover the transmitted signal accurately. The mathematical model for channel estimation and equalization involves formulating algorithms based on techniques like least squares estimation, maximum likelihood estimation, or adaptive algorithms such as recursive least squares (RLS) or minimum mean square error (MMSE) equalization (Doctorale & Fadel, 2021). The mathematical model for frequency selective fading in mm-wave wireless channels enables the analysis, design, and optimization of system performance in terms of signal quality, capacity, and error rates. It helps in understanding the impact of frequency selectivity on the wireless communication system and aids in the development of appropriate equalization and estimation techniques (Cheng et al., 2017). The received signal model in a communication system can be described by the equation in (2.1), which includes the effects of inter-symbol interference and additive noise.

$$y(t)=\int_{-\infty}^{\infty} h(t-\tau)x(\tau)d\tau+v(t) \quad (2.1)$$

In this equation, y(t) represents the received signal, x(t) is the transmitted signal, h(t) is the channel response, and v(t) is the additive noise. This continuous-time equation can be discretized and sampled, resulting in the discrete-time equation (2.2)

$$y[n] = \sum_{k=-\infty}^{\infty} s[k]h[n-k]+v[n] \quad (2.2)$$

To show the desired signal, inter-symbol interference, and additive noise parts, the above equation can be-written

$$y[n] = s[0]h[0]+ \sum_{k=-\infty,k\neq 0}^{\infty} s[k]h[n-k]+v[n] \quad (2.3)$$

Practically, the received signal can be-modeled as

$$y[n] = \sum_{l=0}^{L} h[l]s[n-l]+v[n] \quad (2.4)$$

Where L is the number of multipath. It is worth to mention that the channel estimation in millimeter-wave systems is to estimate h[l].

2.14 Channel Model

The channel model describes the characteristics of the wireless communication channel, including the effects of propagation, interference, and noise. It provides a mathematical representation of how the transmitted signal propagates from the transmitter to the receiver, and it depends on the type of channel being considered, such as a wireless fading channel or a multipath channel (Das & Kolangiammal, 2017).

Channel Gain: The channel gain represents the attenuation or amplification of the transmitted signal as it propagates through the wireless medium. It accounts for factors such as path loss, shadowing, and fading. The channel gain can be-modeled as a complex-valued random variable, denoted by h, which captures both the magnitude and phase of the channel response. The mathematical model for the channel gain involves statistical distributions, such as Rayleigh, Rician, or Nakagami, to characterize the fading behavior.

Multipath Propagation: Wireless channels often exhibit multipath propagation, where the transmitted signal reaches the receiver through multiple paths due to reflections, diffraction, and scattering. Each path can have different delays, attenuation, and phases. The mathematical model for multipath propagation involves representing the channel as a sum of multiple delayed and attenuated copies of the transmitted signal, where each path is characterized by its delay, attenuation, and phase shift.

Path Loss: Path loss refers to the attenuation of the signal power as it propagates through the wireless medium. It is primarily determined by the distance between the transmitter and receiver and the frequency of the transmitted signal. Path loss can be modeled using empirical or theoretical models, such as the Friis free space model or the Okumura-Hata model. The mathematical model for path loss involves incorporating the distance, carrier frequency, and path loss exponent to estimate the signal power attenuation.

Small-Scale Fading: Small-scale fading refers to the rapid fluctuations in the received signal strength due to constructive and destructive interference caused by multipath propagation. Small-scale fading can be-modeled as a random process, such as a Rayleigh or Rician fading process. The mathematical model for small-scale fading involves incorporating statistical distributions to describe the variations in the channel gain over time or frequency.

Channel Coherence: The channel coherence time and frequency represent the duration or bandwidth over which the channel remains relatively constant. The coherence time is related to the mobility of the user or objects in the environment, while the coherence bandwidth is determined by the multipath delay spread. The mathematical model for channel coherence involves characterizing the time and frequency correlation properties of the channel gain, which affect the design of communication techniques such as equalization or channel estimation. The mathematical model for the channel provides a means to analyze and design communication systems by understanding the behavior of the wireless propagation medium. It enables the evaluation of system performance metrics such as signal-to-noise ratio, bit error rate, or capacity. The mm-wave channel model can be-represented using different approaches, including deterministic, stochastic, or hybrid models. Deterministic models are based on physical principles and require detailed knowledge of the environment, while stochastic models use statistical methods to capture the channel variations. Hybrid models combine deterministic and stochastic elements to strike a balance between accuracy and complexity. These models provide guidelines for designing and evaluating mm-wave systems and are often used in system simulations and performance analysis.

Mathematically the channel matrix can be-written as equation (2.5)

$$H=\sqrt{N_t N_r / N_{cl} N_{ray}} \sum_{i,l=1}^{N_{cl} N_{ray}} \alpha_{il}\, a_r(\phi_{il}^{r}, \theta_{il}^{r})\, a_t(\phi_{il}^{t}, \theta_{il}^{t})^{H} \quad (2.5)$$

The channel model considers a clustered multipath propagation environment, where each cluster contains multiple paths. The complex gain αi,l for the l^{th} path in the i^{th} cluster is a complex random variable following a circular complex Gaussian distribution with zero mean and variance σ^2. Each path has associated azimuth and elevation angles of arrival (ϕ^ril, θ^ril) and departure (ϕ^til, θ^til). These angles are modeled as having uniform random means and constant standard deviations. The antenna array response vectors at the transmitter and receiver are denoted as a_t(ϕ^til, θ^til) and ar(ϕ^ril, θ^ril), respectively. These vectors describe how the antenna elements respond to signals arriving from different directions. The overall channel matrix H is normalized to satisfy the condition that the expected squared Frobenius norm of H is equal to the product of the number of receive and transmit antennas, N_rN_t. It is assumed that both the transmitter knows the channel and receiver, meaning the channel state information (CSI) is available. If the channel were not known, it would need to be estimated instantaneously in order to adapt the precoding and combining vectors according to the channel state. The specific antenna array considered is a uniform planar array (UPA) with dimensions N = W x H, where W and H represent the width and height of the array, respectively.

2.15 Channel Estimation in Millimeter-Wave Systems with Inter-Cell Interference

The mathematical model for channel estimation in millimeter-wave (mm-wave) systems with inter-cell interference involves estimating the channel characteristics between the transmitter and receiver in the presence of interference from neighboring cells. This model considers the specific challenges posed by mm-wave frequencies, such as high path loss and susceptibility to blockage, as well as the interference from adjacent cells.

Channel Model: The mm-wave system employs a massive multiple-input, multiple-output (MIMO) architecture, where a large number of antennas are used at both the base station (BS) and the user equipment (UE). The channel between the BS and UE is modeled as a frequency-selective fading channel, which takes into account the large number of propagation paths in the mm-wave spectrum.

Inter-Cell Interference: In a multi-cell environment, interference from neighboring cells can significantly degrade the performance of mm-wave systems. Inter-cell interference arises due to the high spatial resolution of mm-wave beams, where the beams from neighboring BSs can overlap with the intended beam, leading to interference.

Antenna Beam-forming: Beam-forming techniques are-employed to enhance the signal strength at the intended UE and mitigate interference from other directions. Beam forming weights are-applied at the BS antennas to focus the transmitted energy towards the desired UE and nullify interference from other directions.

Channel Estimation: Accurate channel estimation is crucial for effective beam forming in mm-wave systems. To estimate the channel between the BS and UE, pilot signals are-transmitted from the BS to the UE. The UE measures the received pilot signals and sends the measurements back to the BS for channel estimation. The mathematical formulation of the channel estimation process in mm-wave systems with inter-cell interference involves estimating the channel matrix H, which represents the channel between the BS and each UE. Let H be an MxN matrix, where M represents the number of BS antennas and N represents the number of UEs. The channel estimation can be-formulated as:

$$Y = H * X + N \quad (2.6)$$

Where Y is the received pilot signal matrix at the UE, X is the transmitted pilot signal matrix from the BS, N is the noise matrix, and * denotes matrix multiplication. Based on the received pilot signals, the UE performs channel estimation to estimate the channel matrix H. The estimated channel matrix is used for beam-forming design to mitigate interference and enhance the signal quality at the intended UE. It helps in understanding the impact of interference on channel estimation accuracy and supports the design and evaluation of interference mitigation techniques. Channel estimation in millimeter-wave (mm-wave) systems with inter-cell interference is a challenging task due to the unique characteristics of mm-wave channels and the presence of interference from neighboring cells. Channel estimation is essential for accurate beamforming, spatial multiplexing, and interference management in mm-wave systems. We consider a mm-wave cellular system with K BSs. Each base station communicates with one or more MSs in their respective cell only. The system consists of base stations (BSs) and mobile stations (MSs), where each BS is equipped with N_{BS} antennas and N_{RF} radio frequency (RF) chains. Each MS is equipped with N_{MS} antennas and N_{RF} RF chains. On the downlink transmission from the BS to the MS. The BS applies a digital precoder matrix P_{BB} of size $N_{RF} \times NS$ to the symbol vector s of size NRF × 1. The BS then applies an analog precoder matrix P_{RF} of size $N_{BS} \times N_{RF}$ to the precoded symbol vector. This allows the BS to transmit the N_S symbols using the N_{RF} RF chains and N_{BS} antennas. At the MS side, the MS applies an RF combining matrix Q_{RF} of size $N_{MS} \times N_{RF}$. The MS then applies a digital combining matrix Q_{BB} of size $N_{RF} \times N_{RF}$ to obtain the final received signal. The received signal at the mobile station (MS) can be-expressed as equation (2.7)

$$r_j = \sqrt{\rho_j}\, Q^*_{BB}, jQ^*_{RF,j} H_{j,j} x_j + \sum_{k,k\neq j}^{k-1} \sqrt{\rho_k}\, Q^*_{BB}, kQ^*_{RF,} kH_j, kX_k + Q^*_{BB,}\, jQ^*_{RF,}\, jn_j \qquad (2.7)$$

Where $x_j = P_{RF}, jP_{BB}, js_j$ is the j^{th} BS downlink precoding vector, ρ_j is the average transmitted power per symbol from the j^{th} BS and $n \sim N(0, \sigma^2 I)$ is the additive noise. The second term in this expression represents the interference from the neighboring K-1 BSs. H_j, k is the $N_{MS} \times N_{BS}$ channel matrix between the k^{th} BS and the j^{th} MS. Under this system model, the millimeter-wave (mm-wave) channel H_j, k can be-expressed in (2.8). The key points are that the received signal at the MS consists of the desired signal from the serving BS, interference from neighboring BSs, and additive noise. The channel matrices H_j, k capture the mm-wave propagation characteristics between the BSs and MS.

$$H_{j,k} = \sqrt{\frac{N_{BS} N_{MS}}{L_j}} \sum_{l=1}^{L_j} \alpha l,\ j a_{MS,}\ j(\theta_{l,}\ j) a^*_{BS,}\ k(\phi l, j) \qquad (2.8)$$

Where $\alpha\ell$, j ~ CN(0, 1) is the complex gain of the ℓ^{th} propagation path towards the j^{th} user. $\phi\ell, j \in [0, 2\pi]$ is the angle of departure (AoD) of the ℓ^{th} path from the k^{th} BS. $\theta\ell, j \in [0, 2\pi]$ is the angle of arrival (AoA) of the ℓ^{th} path at the j^{th} MS. aBS,k($\phi\ell$,j) is the array response vector of the kth BS antenna array for the AoD $\phi\ell$,j. aMS, j($\theta\ell$,j) is the array response vector of the j^{th} MS antenna array for the AoA $\theta_{\ell,j}$. It is assumed that both the k^{th} BS and the j^{th} MS know the geometry of their respective antenna arrays. While the formulation can be generalized to arbitrary antenna architectures, the specific case considered in this thesis assumes the use of uniform linear arrays (ULAs) at both the BSs and MSs. The key points are the expression for the mm-wave channel matrix H_j, k in terms of the path gains, AoDs, AoAs, and antenna array response vectors, under the assumption of known antenna geometry.

2.16 Related Works

A brief survey of literature in the area relevant to this work is as follows:

(Albreem et al., 2019) review the detection techniques employed in systems utilizing extensive multiple-input, multiple-output (MIMO) technology. Massive MIMO is a technology that makes use of a substantial quantity of antennas and radio frequency chains to meet the performance and quality of service demands of next-generation communication systems. The complexity of symbol detectors in the receiver of large-scale MIMO technology for uplink transmission increases significantly due to the significant quantity of antennas and the associated RF components. Therefore, the research focuses on finding the optimal detection algorithm with both high performance and low complexity. The paper provides insights into the various detection algorithms.

(Engda, Wondie, and Steinbrunn 2020) reviews about the 5G wireless network technologies and the key enabling technologies of ultra-dense networks (UDNs), millimeter-wave (mm-wave) communications, and massive MIMO. The aim of the reviewer is to provide a comprehensive overview and performance assessment of the three key 5G technologies massive MIMO, mm-wave, and their integration as mm-wave massive MIMO and the role of beamforming in enabling mm-wave massive MIMO systems. The authors also reviews the overview of mm-wave communications, including the challenges of path loss at mm-wave frequencies. The reviewer identify explanation of the mm-wave massive MIMO technology, which combines mm-wave and massive MIMO to achieve high data rates, spectral and energy efficiency, and reduced path loss. The author also reviews about the beamforming techniques (analog, digital and hybrid) in mm-wave massive MIMO systems.

(Singh and Joshi 2021) reviews the massive MIMO technology that uses a large number of antennas at the base station to serve multiple users simultaneously, providing improved spectral efficiency. The authors compare the spectral efficiency of different precoding techniques using various antenna array sizes at the base station. The author reviews the advantages and challenges of mm-wave communication, such as the larger unused bandwidth and higher signal attenuation at mm-wave frequencies. The reviewer also discusses the advantages of hybrid beamforming techniques, precoding techniques, and their performance in different channel environments for mm-wave massive MIMO systems.

(Mohammed 2022) reviews the concept of millimeter-wave massive MIMO systems with hybrid precoding techniques to overcome the high path loss at mm-wave frequency. The author proposes new algorithms to enhance the efficiency of the OMP reconstruction algorithm for mm-wave precoding design. The goal of the reviewer is to reduce the complexity of the precoding design while maintaining performance close to the optimal digital precoder. The author emphasizes large antenna arrays are required, which poses challenges for low-cost hardware and power consumption. The paper presents a comprehensive summary for improving the efficiency of hybrid precoding design for mm-wave MIMO systems, and addressing the challenge of mm-wave channel estimation in the presence of inter-cell interference.

(Samir, Nafea, and Zaki 2023) reviews the performance analysis for both single path and multi path channel conditions to evaluate the effectiveness of hybrid approach. The key goals are to improve spectral efficiency and reduce complexity compared to digital precoding, by utilizing the hybrid beamforming. The authors investigate the use of MMSE precoding as part of the hybrid beamforming technique, and compare its performance to analog only beamforming and zero-forcing (ZF) precoding. Generally, the reviewer focuses on developing and analyzing a hybrid-precoding scheme for millimeter-wave MIMO systems, with the aim of achieving high spectral efficiency.

Authors	Year	Title	Contribution/Concept covered	Gaps
Albreem et al.	2019	Massive MIMO Detection Techniques	Reviews detection techniques for massive MIMO systems. It emphasizes the complexity of symbol detectors in large-scale MIMO systems	The System is operated below 6 GHz carrier frequency
Engda, Wondie, and Steinbrunn	2020	Massive MIMO, mm-wave and mm-wave massive MIMO Communications	Reviews on mm-wave communications, including the challenges of path loss at mm-wave frequencies and how large antenna arrays can help address this Reviews about mm-wave massive MIMO technology, which combines mm-wave and massive MIMO to achieve high data rates, spectral and energy efficiency	Performance evaluation of beamforming techniques is limited to analytical and simulation results
Singh and Joshi	2021	A survey on hybrid beamforming in mm-wave massive MIMO system	compares the spectral efficiency of different precoding techniques using various antenna array sizes at the base station	Performance comparisons of different precoding techniques are limited to spectral efficiency
Mohammed	2022	Millimeter-wave and MIMO antenna Beamforming for next generation Wireless Communications	Millimeter wave systems use hybrid analog-digital precoding to overcome the high path loss	Performance evaluation is mostly focused on the specific precoding, channel estimation algorithms

Samir, Nafea, and Zaki	2023	Performance evaluation of spectral efficiency hybrid precoding and combining algorithm for millimeter-wave MIMO systems	The authors reviews a low-complexity hybrid precoding and combining algorithm for millimeter-wave MIMO systems, based on the concept of orthogonal matching pursuit (OMP)	Performance limitations of pure analog-only beamforming solutions

Table 2. 1 Some summary of related work

- Based on the literature review, the thesis work aims to assess the performance of massive MIMO systems in mm-wave bands with antenna beamforming techniques.
- It intends to evaluate the performance and feasibility of these techniques under various scenarios and conditions, considering factors such as channel estimation accuracy, interference levels, and mobility management.
- The work also acknowledges the need to address the impact of interference in performance evaluation techniques.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Introduction

This chapter is mostly concerned with the methods used in this thesis. The materials, data gathering, analysis methods, system mathematical modeling, and performance evaluation of antenna beam forming in millimeter-wave massive MIMO systems are all explained. Moreover, millimeter-wave, with an emphasis on millimeter-wave, massive MIMO, beam-forming techniques, and radio-frequency chain components, particularly those based on antenna beam-forming techniques, were reviewed in various journals, IEEE papers, and books.

3.2 Materials

Microsoft Office 2016 and Math Type 6.0 equation editor is utilized. MATLAB is a computer programming language that includes technical toolboxes and Simulink. The thesis documentation is written in Microsoft Office 2016. Math Type 6.0 is a Microsoft Office Word and PowerPoint presentation tool for composing mathematical formulas and equations.

3.3 Methods

The following techniques are-developed to achieve the desired objectives based on this literature and an explanation of the problem:

1) Different mathematical formulations and system modeling

- Using millimeter-wave hybrid beam-forming techniques, a mathematical model for calculating BER, SNR, and SINR has been-developed.
- A mathematical model for high data rates and system capacity according to hybrid beam forming.

2) Determine the simulation's input parameters.

3) Use MATLAB R2023b to run the simulation.

- Simulation for spectral efficiency analysis related to SNR, base station antenna, and BER.
- Simulation for spectral efficiency analysis using different parameter values.

- Simulation for RMS EVM analysis with relation to the number of users using different parameter values.

The procedure used throughout this thesis study can be-summarized in figure 3.1, which shows the workflow.

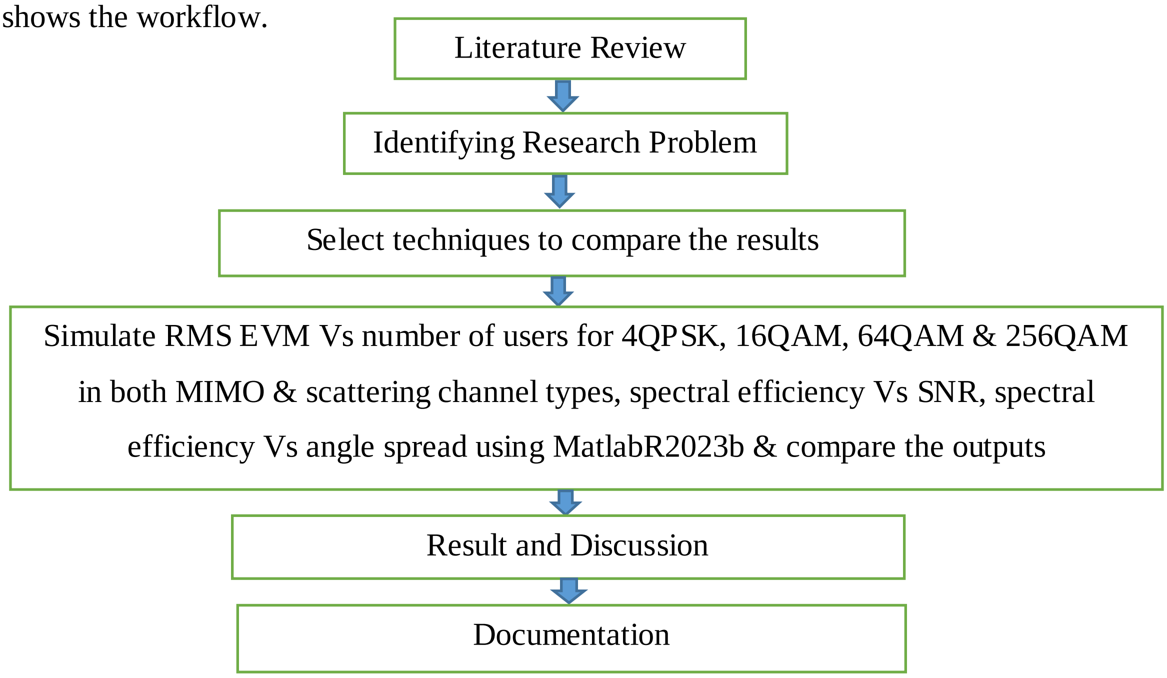

Figure 3.1 Methodology of the Study

3.4 Propagation Characteristics of mm Wave Bands

- High free space path loss: The signal power decreases rapidly with distance due to the inverse square law. The inverse square law describes how the intensity or power of a physical quantity decreases as the distance from the source. It states that the power decreases in proportion to the inverse square of the distance. Mathematically, the inverse square law can be-expressed as in equation (3.1).

$$I = \frac{P}{(4\pi r^2)} \tag{3.1}$$

Where

I represents the intensity of the quantity (i.e., signal power), P is the power of the source (i.e., transmitted power), r is the distance between the source and the point of measurement, and π is a mathematical constant representing pi. In high-free-space path loss, this formula can be-used to calculate the received signal power at a particular distance from the transmitter. Keep in mind that in practice, there are other factors that can affect the signal propagation, such as antenna characteristics, environmental conditions, and obstacles, which may require additional considerations in the calculation. Free space path loss (FSPL) is the attenuation of radio energy between two antennas that results from the distance and wavelength of the signal. A factor affects the signal strength and quality of wireless communication systems. Mathematically we can represent in equation (3.2)

$$FSPL = \frac{(4\pi \times d \times f)}{c} \tag{3.2}$$

Where

FSPL represents the free space path loss in decibels (dB), d is the distance between the antennas in meters, f is the frequency of the signal in hertz, and c is the speed of light in meters per second. In this formula, the numerator (4π x d x f) represents the total phase change that occurs as the signal propagates through space, while the denominator (c) represents the speed at which the signal travels. The FSPL formula assumes ideal conditions, such as a direct line-of-sight path between the antennas and no obstacles or interference. It also assumes that the antennas have isotropic radiation patterns (i.e., they radiate energy equally in all directions). The free space path loss increases with the square of the distance and the frequency, meaning that the signal power decreases rapidly as the distance and frequency increase. To overcome the free space path loss, directional antennas, high transmit power, or signal amplification can be-used.

- Significant atmospheric attenuation: oxygen and water vapor molecules in the air, especially at certain resonance frequencies, absorb the signal. The mathematical formula for atmospheric attenuation due to absorption by oxygen and water vapor molecules can be expressed using the Beer-Lambert Law. This law describes the attenuation of electromagnetic waves as they pass through a medium with absorbing particles. Mathematically we can represent for atmospheric attenuation due to absorption in equation(3.3)

$$A = \alpha \times d \tag{3.3}$$

Where

A represents the attenuation in decibels (dB), α is the absorption coefficient of the medium in nippers per meter (Np/m), and d is the distance traveled through the medium in meters. The absorption coefficient, α, depends on the frequency of the electromagnetic wave and the properties of the absorbing molecules. In the case of oxygen and water vapor, the absorption varies with frequency and is usually provided in tabular or graphical form for different frequency ranges. To calculate the total atmospheric attenuation, we need to sum up the attenuation caused by absorption at different frequencies. This can be-done by integrating the absorption coefficient over the frequency range of interest and summing the attenuation at each frequency. Mathematically we can represent the total atmospheric attenuation in equation (3.4).

$$A_{Total} = \int_{f_1}^{f_n} \alpha(f) \times d \text{ x } df \tag{3.4}$$

Where

A_{Total} represents the total atmospheric attenuation in decibels (dB), α(f) is the absorption coefficient as a function of frequency (in nippers per meter, Np/m), d is the distance traveled through the medium in meters, and df represents the differential frequency element. The integral is-performed over the frequency range of interest. By multiplying the absorption coefficient at each frequency by the distance traveled and summing this attenuation, we obtain the total atmospheric attenuation. The absorption coefficient, α(f), varies with frequency and is usually provided in tabular or graphical form for different frequency ranges. The specific form of the absorption coefficient function will depend on the molecular properties of the absorbing species, such as oxygen and water vapor, and the frequency range being-considered. This formula assumes there are no other factors affecting attenuation, such as scattering or diffraction. In practical situations, these additional factors may need to be-considered to accurately calculate the total attenuation.

- Diffuse reflections: The signal is scattered by rough surfaces that are comparable to the wavelength, creating multipath fading and angular spread. The mathematical formulation for diffuse reflections depends on the specific scattering model used. One commonly used model is the Rayleigh-fading model. In the Rayleigh fading model, the received signal power is characterized by a Rayleigh distribution due to the contributions of multiple scattered paths. The probability density function (PDF) of the received signal power, denoted as f(x), can be expressed as:

$$f(x)=\frac{x}{\sigma^2} \times \exp(\frac{-x^2}{2\sigma^2}) \qquad (3.5)$$

Where

x represents the received signal power and σ is the standard deviation of the signal power. The Rayleigh fading model assumes that the amplitude of each individual path undergoes Rayleigh fading, while the phases are random and uniformly distributed. To calculate the statistics of the signal, such as the average received power or the outage probability, additional mathematical operations may be required, such as taking the integral of the PDF over a specified range or integrating it with respect to the signal power.

- Limited penetration depth: The signal is blocked or attenuated by most solid materials, such as walls, windows, and human bodies. The mathematical formula for the limited penetration depth, or attenuation, of a signal through solid materials depends on various factors, including the properties of the material and the frequency of the signal. One commonly used model to describe this phenomenon is the exponential decay model. The exponential decay model describes the attenuation of a signal as it propagates through a material and can be expressed as:

$$P(d)= P(0)\times e^{-\alpha \times d} \qquad (3.6)$$

Where

P(d) represents the signal power at a distance d within the material, P(0) is the initial signal power at the material's surface, α is the attenuation coefficient of the material (units of reciprocal length, such as 1/m), and d is the distance traveled within the material. The exponential decay model assumes that the attenuation follows an exponential decay pattern, with the attenuation coefficient determining the rate of decay. The higher the value of α, the faster the signal power decreases with distance. It is important to note that the attenuation coefficient, α, is specific to the material and the frequency of the signal. It depends on the material's electrical properties, such as conductivity and permittivity, and the absorption characteristics at the signal frequency. The attenuation coefficient can be-obtained experimentally, measured, or estimated based on material properties. Additionally, this model assumes a homogeneous and isotropic material without considering other factors such as reflections, diffraction, or multiple scattering, which may influence signal propagation through solid materials.

3.5 System model for beam-forming in MIMO systems

System Setup: Consider a MIMO system with N_t transmit antennas and N_r receive antennas. Let H be the MIMO channel matrix of size N_r x N_t, where each element H (i, j) represents the channel gain between the i^{th} receive antenna and the j^{th} transmit antenna. The input signal vector at the transmitter is-denoted by x, which is a column vector of size N_T x 1. The received signal vector at the receiver is denoted by y, which is a column vector of size N_rx1.

Transmit Beam forming: The goal of transmit beam forming is to design the transmit signal vector x such that the received signal y at the receiver is maximized. This can be achieved by multiplying the transmit signal vector x with a beam-forming matrix W, where W is of size N_t x N_t. The beam forming matrix W is designed to align the transmit signal with the desired receive antennas. Mathematically, the transmit signal vector x can be expressed in equation (3.7)

$$x = W \times s \tag{3.7}$$

Where s is the symbol vector representing the data symbols to be transmitted. The beam-forming matrix W is-designed based on the channel matrix H and the desired beam-forming strategy.

Receive Beam forming: The goal of receive beam forming is to extract the transmitted signal from the received signal vector y. This can be achieved by multiplying the received signal vector y with a receive beam forming matrix V, where V is of size N_r x N_r. The receive beam forming matrix V is designed to align the received signal towards the desired receive antennas. Mathematically, the received signal vector y can be-expressed in equation (3.8)

$$y = V \times r \tag{3.8}$$

Where r is the symbol vector representing the received symbols. The receive beam forming matrix V is designed based on the channel matrix H and the desired beam forming strategy.

Beam forming Optimization: The beam forming matrices W and V can be-optimized to achieve different objectives, such as maximizing the received signal power, minimizing the interference from other users, or maximizing the capacity of the MIMO system. The optimization can be formulated as an optimization problem, typically involving constraints and an objective function.

The system model for performance evaluation of antenna beam forming in millimeter-wave (mm-wave) massive multiple-input, multiple-output (MIMO) systems encompasses several key components.

System Model: The system under consideration involves mm-wave massive MIMO, where a base station equipped with a large number of antennas communicates with multiple user equipment (UE) devices simultaneously. The mm-wave frequency band offers large bandwidth but is susceptible to severe path loss and high channel variability. Beam forming is-employed to exploit the spatial domain by focusing the transmitted signals towards the intended UE devices.

Channel Model: The mm-wave channel exhibits unique characteristics such as large path loss, directional propagation, and significant spatial channel variations. To capture these properties, the model incorporates a stochastic channel model based on the mm-wave channel measurement campaigns. This model characterizes the channel state information (CSI), including path loss, small-scale fading, and spatial correlation.

Antenna Array and Beam-forming: The base station employs a uniform linear antenna array with a large number of antennas, typically in the range of several tens to hundreds. Beam forming is-achieved by applying complex weights to each antenna element, forming a spatially focused beam towards the intended UE devices. The mathematical model incorporates the antenna array geometry, element spacing, and beam-forming vector design.

Signal Model: The transmitted signal from the base station experiences propagation through the mm-wave channel, including path loss, shadowing, and small-scale fading. The received signal at each UE device is a linear combination of the signals from all the antennas at the base station, corrupted by additive white Gaussian noise (AWGN). The mathematical model represents these effects in the signal model, taking into account the channel characteristics and noise statistics.

Performance Metrics: The performance of beam forming in mm-wave massive MIMO systems is-evaluated using various metrics. These metrics include signal-to-interference-plus-noise ratio (SINR), spectral efficiency, and bit error rate (BER), and outage probability.

The mathematical model incorporates these performance metrics to assess the effectiveness of beam-forming techniques under different scenarios.

Analytical Techniques: To evaluate the performance metrics, various analytical techniques are-employed in the mathematical model. These techniques include statistical analysis, stochastic geometry, channel capacity analysis, and optimization theory. These mathematical tools enable the derivation of closed-form expressions or numerical solutions for the performance metrics, providing insights into the behavior of beam forming in mm-wave massive MIMO systems.

Simulation and Validation: simulations and validation using real-world measurements or system-level simulations often complement the mathematical model. These simulations help verify the accuracy and reliability of the model and provide a practical understanding of the system's performance under different scenarios, such as varying user densities, mobility patterns, and antenna configurations.

By integrating these components, the system model for the performance evaluation of antenna beam forming in mm-wave massive MIMO systems provides a comprehensive framework to analyze and optimize the performance of beam forming techniques in next-generation wireless communication systems. It enables researchers and engineers to gain insights into the impact of various system parameters and devise strategies to enhance the overall system performance.

3.6 The system model of mm-wave system

The mm-wave system model describes the key components and parameters of a wireless communication system operating in the millimeter-wave (mm-wave) frequency range. The mathematical model for an mm-wave system encompasses various aspects such as channel characteristics, path loss, antenna arrays, and modulation schemes.

3.7 Hybrid Precoding Design

Figure 2.2 presents a millimeter-wave single-user system that employs a hybrid precoding architecture at both the transmitter and receiver sides. From transmitter side N_t antennas, N^t_{RF} radio frequency (RF) chains, N_s data streams, where $N_s \leq N^t_{RF} \leq N_t$. From receiver side N_r antennas, N^r_{RF} RF chains, N_s data streams, where $N_s \leq N^r_{RF} \leq N_r$. For simplicity, it is assumed that the transmitter and receiver have the same number of RF chains i.e. $N^t_{RF} = N^r_{RF} = N_{RF}$. At the transmitter side, RF chains are used to apply a baseband precoder F_{BB}

with $N_{RF} \times N_s$, followed by a F_{RF} constrained radio frequency precoder with $N_t \times N_{RF}$. The $N_s \times 1$ symbol vector s, such that the co-variance of the transmitted symbol $E[ss^H] = \frac{1}{Ns} INs$, is multiplied by the $N_t \times N_s$ precoding matrix F_T which is chosen as a function of multiplication F_{BB} and F_{RF} to yield the $N_t \times 1$ transmitted vector x as shown:

$$x = F_T s \tag{3.9}$$

Since RF precoding F_{RF} is implemented using RF phase shifters, its entries are constant modulus and normalized to satisfy $F_{RF}F^H_{RF} = I_{Nt}$. Another constraint related to design F precoding matrix is that the total transmitted power is enforced by normalizing F_{BB}, such that $\|F_{RF}F_{BB}\|^2_F = N_s$. At the receiver side, an $N_r \times 1$ received vector r is determined by adapting a memoryless and a narrowband fading channel.

$$r = \sqrt{\rho} HF_T S + n \tag{3.10}$$

Where the average received power is denoted by ρ, H is the $N_r \times N_t$ normalized channel matrix, such that $E[\|H\|^2_F] = N_rN_t$, and the vector n is the complex Gaussian noise, such that $N(0, \sigma^2 I)$, corrupting the received signal r. Similarly, to the process of transmitted signal by the precoding matrix F, the received signal y is-obtained after multiplying r by $W^H = W^H_{BB} W^H_{RF}$.

$$y = \sqrt{\rho} W^{H_{BB}} W^{H_{RF}} HF_{RF}F_{BB} S + W^{H_{BB}} W^{H_{RF}} n \tag{3.11}$$

Where W_{RF} is the $N_r \times N_{RF}$ RF combining matrix, such that $W_{RF}W^H_{RF} = I_{Nr}$, and W_{BB} is the $N_{RF} \times N_s$ baseband combining matrix.

3.8 Analog Matrix Design

In the case where the mobile station (MS) has a single RF chain, the antenna architecture simplifies to a conventional analog architecture. In this case, with knowledge of the angle of arrival (AoA) θ_K of the interfering base station (or the AoA of maximum interference if there are multiple interferers), the analog combining matrix Q is designed to perform destructive combining at θ_K. This effectively creates a null in the beam pattern towards the interfering source. To enable channel sensing while maintaining the interference null, the system uses a random subset of the MS antennas at each time instant m. This randomization of the antenna subset ensures the beam pattern is perturbed at angles $\theta \neq \theta K$, while still maintaining the null at θ_K. Specifically, let I_m be the subset of indices corresponding to $\frac{N_{MS}}{2}$ randomly selected antennas at the mth time instant. One simple way to design the m^{th}-combining vector is as follows:

$q_m = b_m \circ a_{Ms}(\theta_k)$ (3.12)

Where the ◦ operator represents the Hadamard (element-wise) product of q_m with the vector, $[b_m]n \in I_m = e^{j\pi} = -1$, for the antennas n that are selected in the subset I_m. This creates a phase shift of π, resulting in destructive combining at the angle θ_K and for the antennas n that are not in the subset I_m, the corresponding elements of the vector $[b_m]n$ is not $\in I_m = 1$. The weighting vector q_m results in destructive combining at θ_K. Grouping all M_{MS} combining vectors we obtain $Q = [q_1, \ldots, qM_{MS}]$. This formulation assumes that the mobile station (MS) has an even number of antennas. In the case of an odd number of antennas, one antenna is switched off during the channel estimation phase.

3.9 Hybrid Analog/Digital Matrix Design

The previous design of the analog combining matrix Q enables joint channel estimation and nulling of a single interference source. In the presence of multiple interfering sources, the combining matrix Q needs to be-designed to null the multiple interference sources while also perturbing the beam pattern at non-interfering angles to enable effective channel sensing. To design the combining matrix Q, the approach is:

First, create a digital codebook of size $N_{MS} \times N_{MS}$, where the column vectors in the codebook satisfy the orthogonality constraint, i.e., they are in the null space of the steering vectors corresponding to the interfering base stations (BSs). Then, randomly select $M_{MS} << N_{MS}$ columns from this codebook to form the hybrid digital/analog measurement matrix Q, which is used to sense the millimeter-wave channel. This hybrid design relaxes the requirement for a large number of RF chains at the mobile station (MS), overcoming the hardware limitations of implementing pure digital beamforming in millimeter-wave systems. To achieve the orthogonality constraint and null the interference from multiple sources, the key step is to find all possible column vectors that are orthogonal to the steering vectors of the (K-1) interfering BSs. These columns are then used to populate the codebook matrix Q. Using the householder transformation, Q can be-obtained as follows

$$Q = I\, N_{MS} - A(\,\text{inverse}(A^* A))A^* \quad (3.13)$$

The array response matrix $A \in C^{N_{MS} \times K-1}$ contains the array response vectors corresponding to the (K-1) interfering base stations (BSs). These array response vectors are denoted as BSs (a_{MS}, j, 1 a_{MS}, j, 2... a_{MS}, j, K−1). Due to the large antenna size at the receiver, the codebook matrix $Q \in C^{N_{MS} \times N_{MS}}$ contains $N_{MS} - K + 1$ normalized combining vectors that are orthogonal to the K-1 interfering sources. Since $M_{MS} << N_{MS}$, we select M_{MS} random columns from the codebook Q to form the M_{MS} digital combining vectors that satisfy the orthogonality constraint. Let the vectors q_d and m represent the m^{th} digital combing vector selected from the codebook matrix Q. To obtain the equivalent hybrid combing vector, we set, $q_{h,m} = Q^*_{RF,\ m} q^*_{BB,\ m}$,where $q^*_{BB,m} \in C^{N_{RF} \times N_{RF}}$ is a digital combing vector and $Q^*_{RF,m} \in C^{N_{MS} \times N_{RF}}$ is an analog combining matrix. Consequently, the design of the hybrid combiner is-accomplished by solving equation (3.14) as follows

$$Q^*_{RF,\ m} q^*_{BB,\ m} = \arg\min \left\| q_{d,m} - Q_{RF} q_{BB} \right\| F \qquad (3.14)$$

Using $Q^*_{RF,\ m}$ and $q^*_{BB,\ m}$, the m^{th} entry of the hybrid combiner matrix becomes $[Q]_{:,\ m} = Q^*_{RF,\ m}$ and $q^*_{BB,\ m}$

3.10 Proposed Block Diagram of Performance Evaluation of Antenna Beamforming in Millimeter Wave Massive MIMO Systems

The root mean square error vector magnitude (RMS EVM) is a measure of the error between an ideal or reference signal and a received signal in wireless communication systems. It quantifies the quality of the received signal by calculating the deviation of the received constellation points from the ideal points.

The mathematical equation for calculating RMS EVM can be-expressed as follows:

$$\text{RMS EVM} = \text{sqrt}\ ((1/N)\ x\ \text{sum}\ (|E|^2)) \qquad (3.15)$$

Where

N is the total number of samples or symbols in the signal, E represents the error vector, which is the difference between the received signal and the ideal reference signal for each sample or symbol, |E| denotes the magnitude of the error vector. To calculate the RMS EVM, we need to compute the error vector for each sample or symbol, calculate the magnitude of each error vector; square the magnitudes, sum them up, divide by the total number of samples or symbols, and then take the square root of the result. It is worth noting that the calculation of RMS EVM can vary depending on the specific modulation scheme and signal processing techniques used in the wireless communication system. Different systems may have different definitions and formulas for calculating EVM. Let us assume we have a set of N complex symbols representing the ideal reference signal, denoted as S_i, and a corresponding set of N complex symbols representing the received signal, denoted as R_i.

The error vector for each symbol can be-defined as:

$$E\_i = S\_i - R\_i \quad (3.16)$$

The magnitude-squared of the error vector can be-calculated as:

$$|E\_i|^2 = (Re (E\_i))^2 + (Im (E\_i))^2 \quad (3.17)$$

Where Re (E_i) and Im (E_i) represent the real and imaginary components of the error vector E_i, respectively.

To calculate the RMS EVM, we need to compute the average of the magnitude-squared error vectors over all N symbols, and then take the square root of the result:

$$RMS\ EVM = sqrt((1/N) \times sum(|E\_i|^2)) \quad (3.18)$$

Where the sum is-taken over all N symbols.

$$\%EVM = \frac{\sqrt{\frac{1}{N}\sum_{n=0}^{N-1} Ierr[n]^2 + Qerr[n]^2}}{\text{EVM Normalization Reference}} \times 100\% \quad (3.19)$$

Where n = symbol index, N = number of symbols, Ierr = I Ref – I Measure, Qerr = Q ref – Q Measure. This equation provides a mathematical model for computing the RMS EVM, which is a commonly used metric for evaluating the performance of wireless communication systems.

3.11 Number of spatial streams (N_S)

N_S (number of spatial streams) refers to the parallel data transmission paths enabled by the MIMO antenna configuration, which is a critical factor for maximizing throughput in wireless MIMO systems. Each spatial stream represents a distinct data path that can carry independent information. The number of spatial streams is limited by the minimum of the number of transmit antennas and the number of receive antennas. More spatial streams allows for higher data throughput, but requires more complex signal processing. The number of spatial streams is a key parameter that determines the maximum achievable data rate in a MIMO system. Common numbers of spatial streams are 1, 2, 3, 4, and sometimes up to 8 in very high-end systems. The mathematical model for N_S involves understanding the relationship between N_S and various system parameters, such as channel capacity, data rate, and signal quality.

Channel Capacity: The channel capacity represents the maximum achievable data rate in a given channel. The mathematical model for channel capacity considers factors like channel bandwidth, signal-to-noise ratio (SNR), and N_S. The capacity C can be-expressed as:

$$C = N_S \times B \times \log_2 (1+SNR) \qquad (3.20)$$

Where

N_S is the number of spatial streams.

B is the channel bandwidth.

SNR is the signal-to-noise ratio.

Data Rate: The data rate is the rate at which information can be-transmitted over the wireless channel. It depends on the modulation scheme, coding rate, and channel conditions. The mathematical model for data rate incorporates N_S as a parameter. The data rate R can be-calculated as:

$$R = N_S \times B \times \log_2 (1+SNR) \times \eta \qquad (3.21)$$

Where

N_S is the number of spatial streams.

B is the channel bandwidth.

SNR is the signal-to-noise ratio.

η is the spectral efficiency, which represents the amount of information that can be transmitted per unit bandwidth.

Signal Quality: The signal quality is often measured using metrics like signal-to-interference-plus-noise ratio (SINR) or signal-to-noise ratio (SNR). The mathematical model for signal quality takes into account N_S as it affects the received signal power and interference. The SINR or SNR can be-expressed as:

SINR = (P_signal x N_S) / (P_interference + P_noise) (3.22)

Where

P_signal is the received signal power.

N_S is the number of spatial streams.

P_interference is the power of interfering signals.

P_noise is the power of background noise.

By incorporating N_S into the mathematical models for channel capacity, data rate, and signal quality, we can analyze and optimize the system performance based on the number of spatial streams. This enables us to understand the impact of N_S on the system's ability to transmit data, the achievable data rate, and the overall signal quality in a wireless communication system.

Mathematically signal to noise ratio (SNR) is expressed as:

SNR = Signal Power / Noise Power

$$\text{SNR(dB)} = 10\log_{10}(\text{Signal Power/Noise Power}) \quad (3.23)$$

3.12 Digital Precoder

A digital precoder is a signal processing technique used in wireless communication systems to optimize the transmitted signal based on the channel conditions. It involves manipulating the data symbols at the transmitter to enhance the received signal quality at the receiver. The mathematical model for a digital precoder incorporates the following components:

Channel Model: The channel model represents the wireless communication channel's characteristics, including path loss, fading, and interference. The mathematical model for the channel can vary depending on the specific scenario, such as flat fading or frequency-selective fading. The channel model is typically represented by a complex-valued matrix H, where each element represents the channel gain between the transmitter and receiver antennas.

Data Symbols: The data symbols represent the information to be-transmitted over the wireless channel. In the mathematical model, a complex vector d typically represents the data symbols, where each element corresponds to a symbol intended for a specific receiver antenna.

Precoding Matrix: The precoding matrix is a key component of the digital precoder. A complex-valued matrix represents the linear transformation applied to the data symbols before transmission. The precoding matrix optimizes the transmitted signal based on the channel conditions to enhance the signal quality at the receiver. The precoding matrix is denoted by W.

The transmitted signal x can be-expressed as:

$$x = W \times d \quad (3.24)$$

Where

x is the transmitted signal vector.

W is the precoding matrix.

d is the data symbol vector.

The precoding matrix W is designed based on various optimization criteria, such as maximizing the signal-to-noise ratio (SNR), minimizing the bit error rate (BER), or maximizing the channel capacity. The digital precoder aims to minimize the effects of channel impairments, such as fading and interference, and maximize the received signal quality at the receiver. The design of the precoding matrix involves considering the channel state information (CSI), which can be-estimated through pilot symbols or feedback from the receiver. By adapting the precoding matrix based on the channel conditions, the digital precoder optimizes the transmitted signal to improve the overall system performance in terms of data rate, error performance, and spectral efficiency. It is important to note that the mathematical model for a digital precoder can vary depending on specific precoding schemes and system configurations. Different precoding techniques, such as maximum ratio transmission (MRT), zero-forcing (ZF), or minimum mean square error (MMSE) precoding, have their own mathematical models and design criteria. The specific mathematical formulation for the digital precoder would depend on the chosen precoding scheme and the optimization objective.

3.13 RF Chain

RF Chain refers to the radio frequency (RF) components in a wireless communication system that are responsible for transmitting and receiving signals at RF frequencies. The mathematical model for an RF chain involves understanding the various components and operations involved in RF signal processing.

Transmitter Model: The transmitter model represents the signal processing operations performed in the RF chain for signal transmission. This includes processes such as modulation, up conversion, filtering, and amplification. The transmitter model can be-described using equations that capture the specific operations and transformations applied to the baseband signal to generate the RF signal.

Receiver Model: The receiver model represents the signal processing operations performed in the RF chain for signal reception. This includes processes such as down conversion, filtering, demodulation, and amplification. The receiver model can be-described using equations that capture the specific operations and transformations applied to the received RF signal to recover the baseband signal.

RF Components: The RF chain consists of various components, such as mixers, filters, amplifiers, and oscillators, which perform specific functions in signal processing. The mathematical model for an RF chain involves understanding the characteristics and behaviors of these components, which can be-represented using equations or transfer functions.

Gain and Noise: The RF chain introduces gain and noise to the signal during transmission and reception. The gain represents the amplification or attenuation applied to the signal, while the noise represents the unwanted random components added to the signal. The mathematical model for the RF chain incorporates the gain and noise parameters, which can be-expressed using appropriate equations or statistical models.

Signal Quality Metrics: The performance of an RF chain can be evaluated using various metrics, such as signal-to-noise ratio (SNR), bit error rate (BER), or error vector magnitude (EVM). The mathematical model for the RF chain may include equations or expressions to calculate these metrics based on the signal characteristics, gain, noise, and other relevant parameters.

3.14 Analog Precoder

An analog precoder is a signal processing technique used in wireless communication systems to optimize the transmitted signal based on the channel conditions. It involves manipulating the analog signal at the transmitter to enhance the received signal quality at the receiver. The mathematical model for an analog precoder incorporates the following components:

Channel Model: The channel model represents the wireless communication channel's characteristics, including path loss, fading, and interference. The mathematical model for the channel can vary depending on the specific scenario, such as flat fading or frequency-selective fading. The channel model is typically represented by a complex-valued matrix H, where each element represents the channel gain between the transmitter and receiver antennas.

Data Symbols: The data symbols represent the information to be-transmitted over the wireless channel. In the mathematical model, a complex vector d typically represents the data symbols, where each element corresponds to a symbol intended for a specific receiver antenna.

Precoding Matrix: The analog precoding matrix is a key component of the analog precoder. A complex-valued matrix represents the linear transformation applied to the analog signal before transmission. The precoding matrix optimizes the transmitted signal based on the channel conditions to enhance the signal quality at the receiver. F denotes the precoding matrix

The transmitted signal x can be-expressed as:

$$x = F \times s \qquad (3.25)$$

Where

x is the transmitted signal vector.

F is the analog precoding matrix.

s is the analog signal vector.

The analog precoding matrix F is designed based on various optimization criteria, such as maximizing the signal-to-noise ratio (SNR), minimizing the bit error rate (BER), or maximizing the channel capacity. The specific optimization criterion determines the mathematical formulation and design algorithm for the analog precoding matrix. The analog precoder aims to minimize the effects of channel impairments, such as fading and interference, and maximize the received signal quality at the receiver. The design of the analog precoding matrix involves considering the channel state information (CSI), which can be-estimated through pilot symbols or feedback from the receiver. By adapting the analog precoding matrix based on the channel conditions, the analog precoder optimizes the transmitted signal to improve the overall system performance in terms of data rate, error performance, and spectral efficiency.

3.15 Antenna

An antenna is a device used for transmitting and receiving electromagnetic waves in wireless communication systems. The mathematical model for an antenna involves understanding its radiation pattern, gain, polarization, and impedance characteristics. Radiation Pattern: The radiation pattern of an antenna describes how the antenna radiates or receives electromagnetic waves in different directions. It can be-represented using mathematical functions or plots. The radiation pattern is typically characterized by the antenna's directivity, which measures the concentration of power radiated in a particular direction. The mathematical model for the radiation pattern can include equations or mathematical expressions that describe the antenna's radiation characteristics in terms of azimuth and elevation angles.

Gain: The gain of an antenna represents its ability to radiate or receive electromagnetic waves in a particular direction compared to an isotropic radiator. It is typically expressed in decibels (dB) and can be calculated using the antenna's radiation pattern. The gain G can be-mathematically represented as:

$$G = 10\times \log_{10}(D) \quad (3.26)$$

Where

G is the antenna gain in decibels.

D is the directivity of the antenna.

Polarization: The polarization of an antenna refers to the orientation of the electric field in the radiated or received electromagnetic waves. It can be linear, circular, or elliptical. The mathematical model for polarization can involve representing the electric field vector in terms of its amplitude and phase, or using mathematical equations that describe the polarization state of the antenna.

Impedance: The impedance of an antenna represents the opposition to the flow of electrical current in the antenna. It affects the matching between the antenna and the transmission line or receiver. The mathematical model for antenna impedance can include complex numbers or equations that describe the real and imaginary components of the impedance.

Antenna Arrays: In some cases, multiple antennas are used in an array configuration to enhance the overall performance of the system. The mathematical model for antenna arrays involves understanding the relationship between the individual antenna elements, their positions, and the resulting combined radiation pattern. This can be-represented using mathematical equations or matrix operations. The mathematical model for an antenna enables the analysis, design, and optimization of its performance in terms of radiation pattern, gain, polarization, and impedance. It helps in understanding how the antenna radiates or receives electromagnetic waves and how it interacts with the wireless communication system.

3.16 Channel

The channel in a wireless communication system represents the medium through which signals propagate from the transmitter to the receiver. The mathematical model for a channel involves understanding the characteristics of signal propagation, such as path loss, fading, and interference.

Path Loss Model: The path loss model represents the attenuation of the signal as it propagates through space. It takes into account factors such as distance, frequency, and environmental conditions. The mathematical model for path loss can be-represented using equations or empirical models, such as the Friis transmission equation or the log-distance path loss model.

Fading Model: Fading refers to the variations in the received signal strength due to multipath propagation, where multiple copies of the signal arrive at the receiver with different delays and phases. Fading models are used to characterize the statistical properties of fading, such as Rayleigh fading, Rician fading, or Nakagami fading. These models can be-mathematically represented using probability density functions.

Interference Model: Interference represents the unwanted signals or noise that can degrade the quality of the received signal. The interference model takes into account factors such as co-channel interference from other users or adjacent channel interference. The interference model can be mathematically represented using power spectral density functions.

Channel Gain: The channel gain represents the power or amplitude of the received signal compared to the transmitted signal. It takes into account the path loss, fading, and interference effects. The channel gain can be-represented as a complex-valued quantity that includes both the magnitude and phase of the received signal compared to the transmitted signal.

Channel Matrix: In multiple-input, multiple-output (MIMO) systems, where multiple antennas are used at the transmitter and receiver, the channel can be-represented by a complex-valued matrix. Each element of the matrix represents the channel gain between a specific transmitter-receiver antenna pair. The channel matrix can be-used for precoding or decoding techniques in MIMO systems. The mathematical model for a wireless communication channel enables the analysis, design, and optimization of system performance in terms of signal quality, capacity, and error performance. It helps in understanding the signal propagation characteristics and the impact of various factors such as path loss, fading, and interference. The specific mathematical formulations and models used for channel modeling depend on the specific wireless communication scenario, frequency band, environment, and system configuration.

3.17 Users

Users in a wireless communication system refers to the individuals or devices that transmit and receive signals over the wireless channel. The mathematical model for users involves understanding their behavior, data transmission characteristics, and interaction with the communication system.

User Behavior: The behavior of users can be-modeled based on various parameters, such as data arrival patterns, traffic patterns, and user mobility. The mathematical model for user behavior can include statistical models, probability distributions, or queuing models to capture the arrival and departure of data, the duration of user sessions, or the user's movement patterns.

Data Transmission: Users transmit data over the wireless channel, and the mathematical model for data transmission involves understanding the data rate, modulation scheme, coding scheme, and transmission parameters. The data transmission model can incorporate equations or models that describe the data rate, bit error rate, or signal-to-noise ratio based on the user's transmission parameters and channel conditions.

Traffic Models: Traffic models describe the characteristics of the data traffic generated by users. This includes the arrival rate of data packets, packet size distribution, and burstiness of the traffic. The mathematical model for traffic can involve statistical models, such as Poisson processes, Markov models, or self-similar models, to capture the statistical properties of the data traffic generated by users.

User Interactions: In a wireless communication system, users can interact with each other, leading to interference and resource sharing. The mathematical model for user interactions can include interference models, such as interference power calculations or interference probability models, to analyze the impact of user interactions on system performance.

User Capacity: The capacity of a wireless communication system represents the maximum number of users that can be-supported while maintaining a certain level of performance. The mathematical model for user capacity can involve analyzing system parameters, such as bandwidth, signal-to-noise ratio, and interference levels, to determine the maximum number of users that can be-accommodated. The mathematical model for users in a wireless communication system enables the analysis, design, and optimization of system performance in terms of throughput, delay, capacity, and resource allocation. It helps in understanding user behavior, data transmission characteristics, and the impact of user interactions on system performance. The specific mathematical formulations and models used for user modeling depend on the specific wireless communication scenario, user characteristics, and system configuration.

3.18 Feedback Information

Feedback information in wireless communication systems refers to the information sent from the receiver back to the transmitter to provide channel state or quality information. This information helps the transmitter adapt its transmission parameters or strategies to optimize system performance. The mathematical model for feedback information involves understanding the types of feedback, the channel state information (CSI), and the transmission parameters being fed back. Here is an overview of the mathematical model for feedback information:

Types of Feedback: There are different types of feedback information depending on the specific system and requirements. Some common types of feedback include:

a. Channel State Information (CSI): CSI refers to the information about the channel conditions between the transmitter and receiver. It can include parameters such as channel gains, fading coefficients, or channel matrices for multiple antennas. The mathematical model for CSI can involve complex-valued matrices or vectors that represent the channel state for each user or antenna.

b. Quality of Service (QoS): QoS feedback provides information about the quality of the received signal, such as the signal-to-noise ratio (SNR), bit error rate (BER), or packet error rate (PER). The mathematical model for QoS feedback can include equations or probability distributions that describe the performance metrics of the received signal.

c. Resource Allocation Feedback: This type of feedback provides information about the allocation of system resources, such as bandwidth, power, or time slots. The mathematical model for resource allocation feedback can involve parameters or indicators that represent the allocated resources for each user or transmission.

Feedback Channel: The feedback information is typically sent over a feedback channel, which can be a separate channel or piggybacked on the uplink channel. The mathematical model for the feedback channel involves understanding its capacity, latency, and error characteristics. The feedback channel can be-represented using mathematical models for transmission channels, such as capacity calculations or error probability models.

Transmission Parameters: The feedback information provides feedback on specific transmission parameters that can be adapted at the transmitter. These parameters depend on the system design and may include modulation and coding schemes, power control, beamforming weights, or resource allocation decisions. The mathematical model for transmission parameter feedback can involve equations or indicators that represent the specific parameters being fed back. The mathematical model for feedback information enables the analysis, design, and optimization of system performance in terms of channel adaptation, resource allocation, and quality of service. It helps in understanding the information flow between the transmitter and receiver and how the feedback information can be utilized to improve system performance. The specific mathematical formulations and models used for feedback information depend on the specific wireless communication system, feedback type, and system requirements.

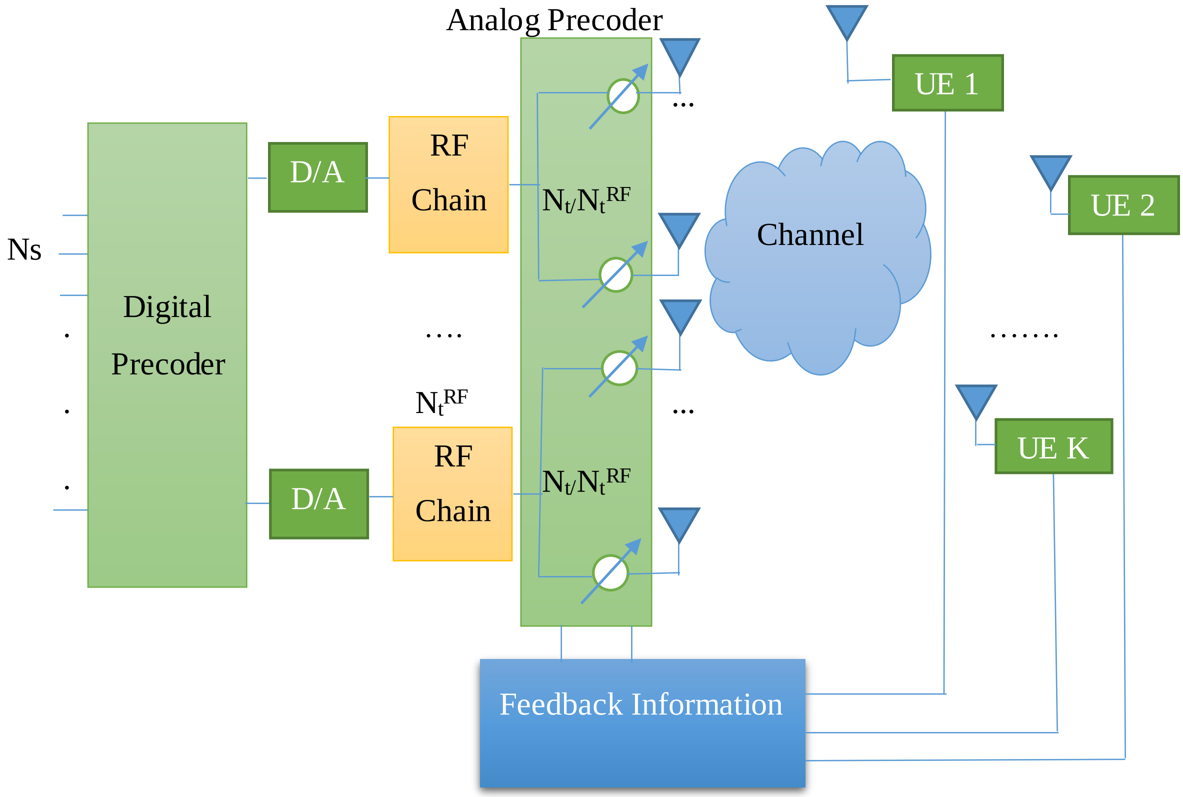

Figure 3.2 Proposed Block Diagram of Performance Evaluation of Antenna Beamforming in Millimeter Wave Massive MIMO Systems

3.19 Adaptive Antenna Arrays

Adaptive antenna arrays, also known as adaptive arrays or smart antennas, are advanced antenna systems that can adapt their radiation patterns in real-time to optimize the reception or transmission of signals in wireless communication systems. These arrays consist of multiple antenna elements that work together to form a spatially selective beam, which can be dynamically adjusted to track and communicate with desired signals while minimizing interference. The main goal of adaptive antenna arrays is to enhance the signal quality by improving the signal-to-interference-plus-noise ratio (SINR) at the receiver. They achieve this by exploiting the spatial diversity of the received signals and applying adaptive processing techniques based on the information about the channel.

Mathematically, the received signal vector y can be-expressed as:

$$y = H \times X \qquad (3.27)$$

Where H is the antenna array response matrix of size N x N, and each element H(i,j) represents the complex-valued response between the i-th receive antenna and the j-th transmit antenna. The antenna array response matrix H is determined by the physical arrangement of the antennas in the array and the propagation environment.

The array-weighting vector w can be-expressed as:

$$w = W \times X \qquad (3.28)$$

Where W is the weight matrix of size N x N, and each element W(i,j) represents the weight between the i-th antenna and the j-th antenna. The weight matrix W is the main parameter that is adjusted to optimize the array performance.

3.20 Adaptive Beamforming

Adaptive beamforming is a technique used in wireless communication systems to improve the signal reception or transmission in a specific direction by dynamically adjusting the antenna array's radiation pattern. It aims to optimize the spatial characteristics of the transmitted or received signals to enhance the signal quality, increase the system capacity, and mitigate interference. In adaptive beamforming, an array of antennas is used at the transmitter or receiver. The weights or coefficients applied to each antenna's signal are adaptively adjusted based on the channel conditions and system requirements. By adjusting the weights, the antenna array can steer the main beam towards the desired direction, enhancing the signal power in that direction and suppressing interference or noise from other directions. Adaptive beamforming has several benefits in wireless communication systems. It can improve the signal-to-interference-plus-noise ratio (SINR), increase the coverage range, and enhance the system capacity by focusing the transmitted or received energy in the desired direction. Adaptive beamforming is particularly useful in scenarios with interference, multipath propagation, or in environments with dynamic channel conditions. Overall, adaptive beamforming is a powerful technique that allows wireless communication systems to optimize the spatial characteristics of the transmitted or received signals, leading to improved performance and better utilization of the available spectrum.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

In this section, the simulation results of the proposed system on the MATLAB2023b software when compared to the prior works on the literature to verify the general objective as well as specific objectives of the thesis, and different millimeter-wave hybrid beamforming techniques are also compared. The simulation results shown in this chapter are all for the same given value with the number of BS transmit antennas = 256, a number of users K= 16, number of bits per sub carrier = 2, 4, 6, 8 for the system parameters. I have select these input parameters based on modulation scheme i.e. 2^4 = 16, 2^8 = 256, mm-wave Bandwidth is operated in the range of 30 GHz to 300GHz.

Input parameters	**Values**
Number of users	16
Number of BS transmit antennas	256
Number of receive antennas per user	16
Number of independent data streams per user	16
Number of bits per sub carrier	2, 4, 6, 8
Bandwidth	30 GHz
Channel Type	MIMO, Scattering
Modulation order	4QPSK, 16QAM, 64QAM, 256QAM

Table 4.1 Simulation input parameters

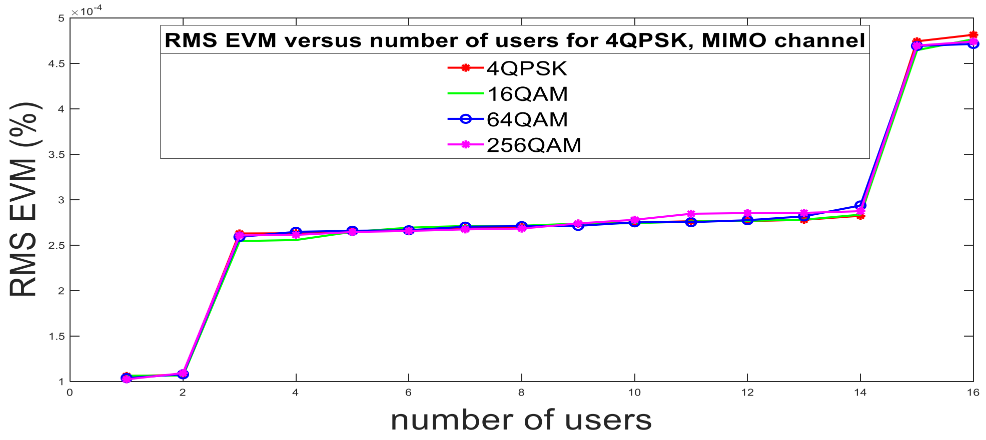

Figure 4.1 Simulation result for RMS EVM values versus number of users for mm-wave massive MIMO channel type and 4QPSK modulation

Figure 4.1 illustrates the RMS EVM values versus the number of users for a mm-wave massive MIMO channel type with 4QPSK modulation. The graph shows that RMS EVM values remain relatively stable for a low number of users across all modulation schemes. A significant increase in RMS EVM values is observed at around 10 users, particularly for the 256QAM scheme, indicating a threshold where performance begins to degrade. The graph includes 4QPSK, 16QAM, 64QAM, and 256QAM, with 256QAM being the most affected by the increase in the number of users. Generally, the simulation suggests that careful consideration must be-given to the number of users and the choice of modulation scheme to ensure optimal performance in mm-wave massive MIMO channels. This analysis is essential for network planning and maintaining high-quality communication in dense user environments. When we use massive MIMO channel type and 4QPSK modulation, we gate the values in table 4.2 as shown below

Modulation	Channel type	Number of users	BER values	RMS EVM values (%)
4QPSK	MIMO	1	0.00008	0.00010594
		2	0.00012	0.00026274
		3	0.00213	0.00026977
		4	0.03010	0.00048134

Table 4.2 RMS EVM values and BER values for mm wave massive MIMO channel and 4QPSK modulation

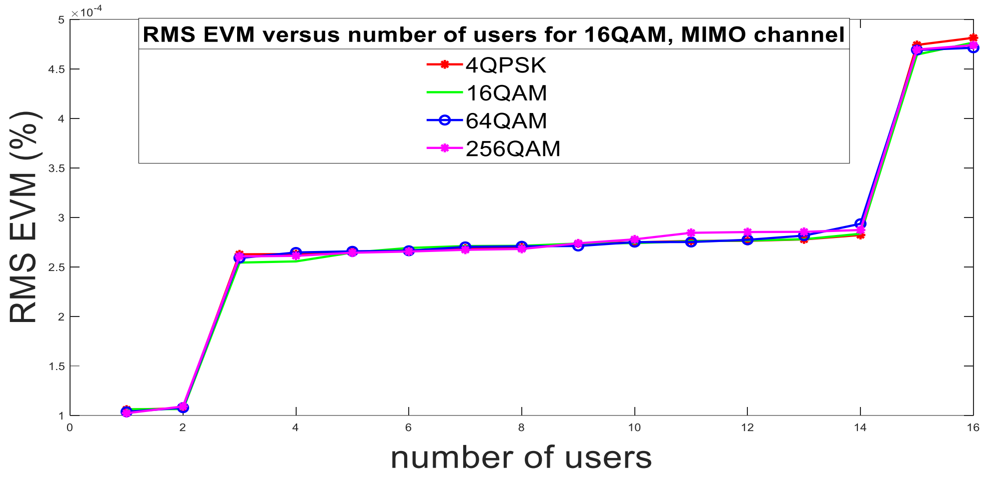

Figure 4.2 Simulation result for RMS EVM values versus number of users for mm wave massive MIMO channel type and 16QAM modulation

Figure 4.2 shows the RMS EVM values versus the number of users for a mm-wave massive MIMO channel with 16QAM Modulation. Up to around 12 users, the RMS EVM values remain stable across all modulation schemes. Beyond 12 users, there is a significant increase in RMS EVM, especially for 256QAM, indicating a decline in performance. This suggests that higher user counts can adversely affect the signal quality, particularly for higher-order modulations like 256QAM. Generally, the simulation highlights the need for careful consideration of user density and modulation choice in system design to maintain communication quality. This result is critical for optimizing network performance and ensuring robust communication in mm-wave massive MIMO channels. When we use massive MIMO channel type and 16QAM modulation, we gate the values in table 4.3 as shown below

Modulation	Channel type	Number of users	BER values	RMS EVM values (%)
16QAM	MIMO	1	0.00009	0.00010647
		2	0.00020	0.00025437
		3	0.00215	0.00028346
		4	0.03500	0.00046445

Table 4.3 RMS EVM values and BER values for the mm wave massive MIMO channel type and 16QAM modulation

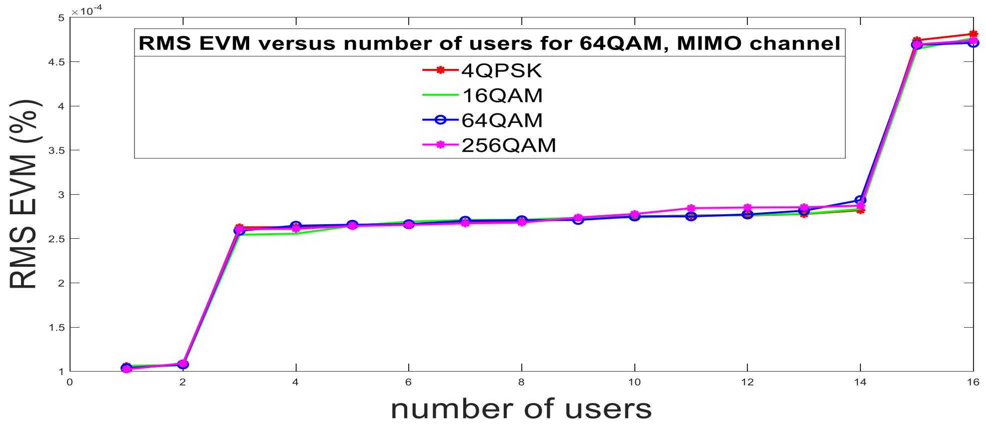

Figure 4.3 Simulation result for RMS EVM values versus number of users for mm-wave massive MIMO channel type and 64QAM modulation

Figure 4.3 demonstrates the relationship between RMS EVM values and the number of users for various modulation schemes in a mm-wave Massive MIMO channel. Initially, the RMS EVM values for 4QPSK, 16QAM, and 64QAM remain stable as the number of users increases. A sharp increase in RMS EVM values is observed for 256QAM at around 14 users, indicating a potential performance degradation with higher user counts. The results suggest that higher order modulation schemes like 256QAM are more susceptible to degradation in quality as the number of users increases in a mm-wave massive MIMO channel. For system designers, this graph highlights the importance of considering user count and modulation scheme when designing communication systems to ensure signal quality. This analysis is crucial for optimizing the performance of communication systems and ensuring reliable data transmission in various channel conditions. When we use massive MIMO channel type and 64QAM modulation, we gate the values in table 4.4 as shown

Modulation	Channel type	Number of users	BER values	RMS EVM values (%)
64QAM	MIMO	1	0.00010	0.00010782
		2	0.00400	0.00025895
		3	0.01910	0.00027112
		4	0.04200	0.00047128

Table 4.4 RMS EVM values and BER values for the mm wave massive MIMO channel type and 64QAM modulation

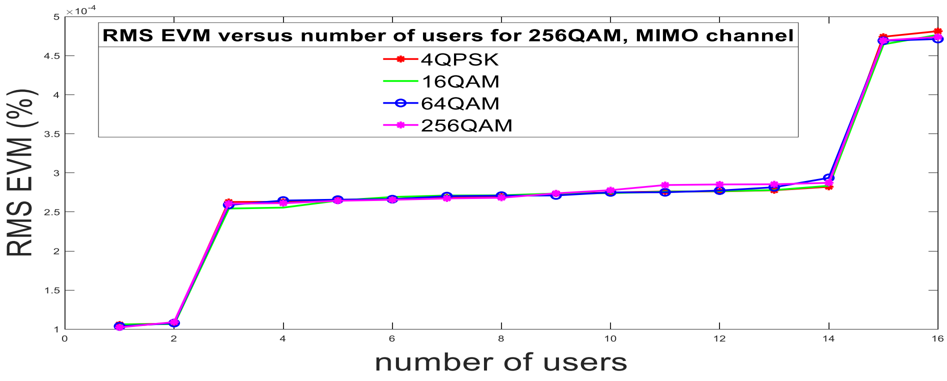

Figure 4.4 Simulation result for RMS EVM values versus number of users for mm wave massive MIMO channel type and 256QAM modulation

Figure 4.4 is a line plot that illustrates the simulation results for RMS EVM values versus the number of users for mm-wave massive MIMO channel type and 256QAM modulation. The graph includes four schemes: 4QPSK, 16QAM, 64QAM, and 256QAM, each represented by a different marker and color. Initially, the RMS EVM values increase gradually as the number of users goes from 0 to around 12. This trend is consistent across all modulation schemes. After reaching around 12 users, there is a noticeable spike in RMS EVM values for all schemes, with 256QAM showing the most significant rise. The x-axis, labeled number of users, ranges from 0 to about 16, while the y-axis, labeled RMS EVM, ranges from 0 to approximately 5 times 10^-4. This graph is significant as it demonstrates the impact of user count on the quality of communication for different modulation schemes in a specific channel type. The sharp increase in RMS EVM values after a certain number of users suggests a threshold for maintaining signal quality. When we use massive MIMO channel Type and 256QAM modulation we gate the values in table 4.5 as shown below

Modulation	Channel type	Number of users	BER values	RMS EVM values (%)
256QAM	MIMO	1	0.00012	0.00010227
		2	0.00500	0.00026118
		3	0.02023	0.0002852
		4	0.05012	0.00047393

Table 4.5 RMS EVM values and BER values for the mm-wave massive MIMO channel type and 256QAM modulation

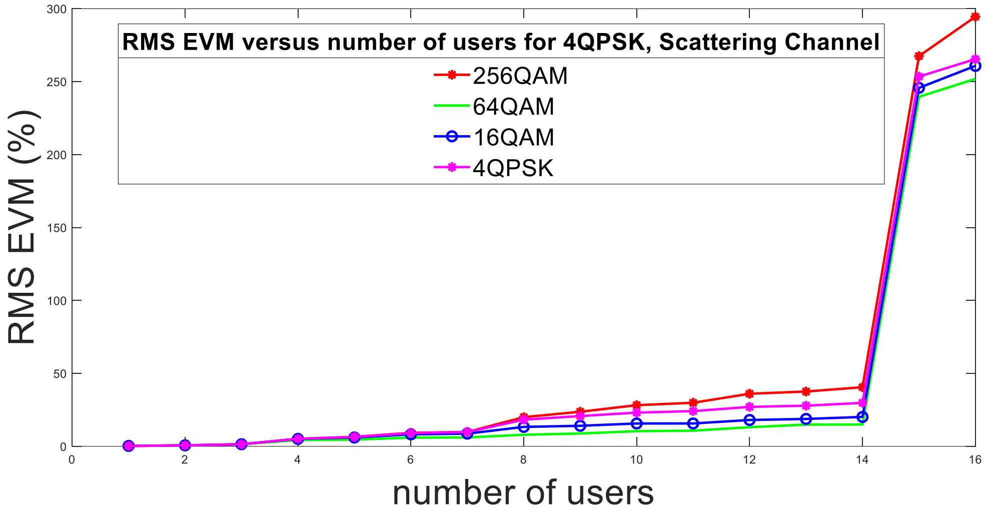

Figure 4.5 Simulation result for RMS EVM values versus number of users for scattering channel type and 4QPSK modulation

Figure 4.5 presents a simulation of RMS EVM values against the number of users for various modulation schemes in a scattering channel type with 4QPSK modulation. The graph includes 256QAM, 64QAM, 16QAM, and 4QPSK. Initially, all modulation schemes maintain stable RMS EVM values up to about 14 users. For 256QAM, there is a noticeable spike in RMS EVM values after 14 users, indicating a decline in performance. The x-axis represents the number of users (0-16), and the y-axis shows RMS EVM values (0-300). This graph is useful for understanding how the number of users affects the quality of different modulation schemes in a given channel type. When we use scattering channel type and 4QPSK, modulation we gate the values in table 4.6 as shown below

Modulation	Channel type	Number of users	BER values	RMS EVM values (%)
4QPSK	Scattering	1	0.00193	0.20581
		2	0.00771	6.9704
		3	0.22340	18.8261
		4	0.33719	108.9505

Table 4.6 RMS EVM values and BER values for scattering channel type and 4QPSK modulation

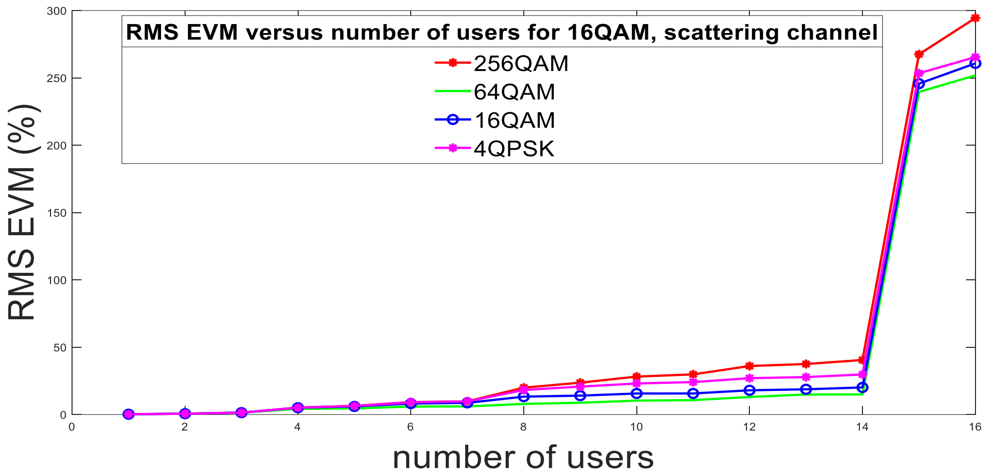

Figure 4.6 Simulation result for RMS EVM values versus number of users for scattering channel type and 16QAM modulation

Figure 4.6 is a line plot that compares the RMS EVM values for different modulation schemes as the number of users' increases. It includes 256QAM, 64QAM, 16QAM, and 4QPSK. The RMS EVM values are low for up to 14 users, after which there is a sharp increase, particularly for 256QAM. The x-axis shows the number of users (0 to 16), and the y-axis shows the RMS EVM values (0 to ~300). This plot is useful for analyzing the performance of different modulation schemes in a scattering channel environment. The significant rise in RMS EVM for 256QAM beyond 14 users suggests a limit to the number of users for maintaining quality with this scheme. When we use scattering channel type and 16QAM, modulation we gate the values in table 4.7 as shown below

Modulation	Channel type	Number of users	BER values	RMS EVM values (%)
16QAM	Scattering	1	0.01396	0.20559
		2	0.01428	7.0773
		3	0.13763	18.0067
		4	0.47431	89.5211

Table 4.7 RMS EVM values and BER values for scattering channel type and 16QAM modulation

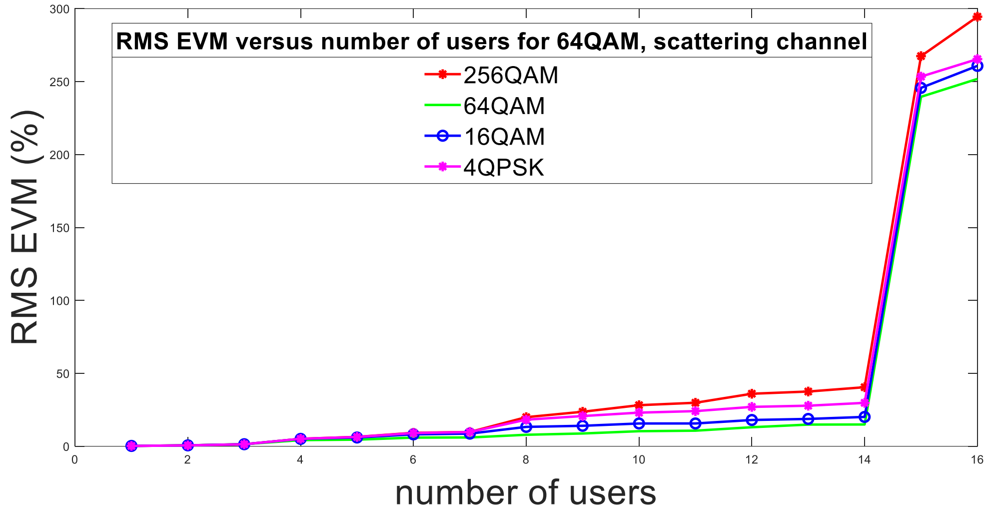

Figure 4.7 Simulation result for RMS EVM values versus number of users for scattering channel type and 64QAM modulation

In figure 4.7, the simulation analyzes the RMS EVM (root mean square error vector magnitude) values as a function of the number of users for various modulation schemes. It is a measure of the modulation quality and error performance. The graph compares the performance of different schemes like 256QAM, 64QAM, 16QAM, and 4QPSK. The simulation shows that as the number of users increases, the RMS EVM values also increase, particularly after 12 users, indicating a degradation in signal quality with more users. This simulation is crucial for assessing the scalability of communication systems and their ability to maintain signal integrity with an increasing number of users. When we use scattering channel type and 64QAM modulation, we gate the values in table 4.8

Modulation	Channel type	Number of users	BER values	RMS EVM values (%)
64QAM	Scattering	1	0.00374	0.20553
		2	0.12658	6.8869
		3	0.18922	12.9788
		4	0.49636	76.3448

Table 4.8 RMS EVM values and BER values for scattering channel type and 64QAM modulation

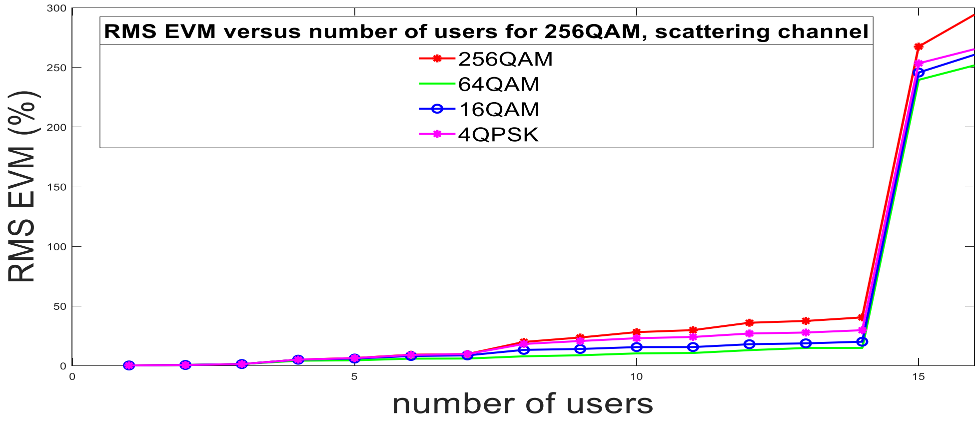

Figure 4.8 Simulation result for RMS EVM values versus number of users for scattering channel type and 256QAM modulation

Figure 4.8 represents the simulation results for RMS EVM values versus the number of users for a scattering channel type with 256QAM modulation. A measure of the difference between the expected and actual signal vectors in a communication system, indicating the quality of the signal. The graph compares four modulation schemes 256QAM, 64QAM, 16QAM, and 4QPSK with 256QAM being the most complex and 4QPSK the simplest. For a low number of users, all modulation schemes maintain a low RMS EVM value, signifying good signal quality. However, as the number of users increases beyond 12, there is a notable increase in RMS EVM for all schemes except 4QPSK, which suggests a degradation in signal quality due to the higher number of users. This simulation is crucial for understanding how different modulation schemes perform in a multi-user environment and for optimizing communication systems accordingly. When we use scattering channel type and 256QAM modulation, we gate the values in table 4.9

Modulation	Channel type	Number of users	BER values	RMS EVM values (%)
256QAM	Scattering	1	0.00064	0.2059
		2	0.00080	5.5586
		3	0.27882	7.6549
		4	0.50674	71.9772

Table 4.9 RMS EVM values and BER values for scattering channel type and 256QAM modulation

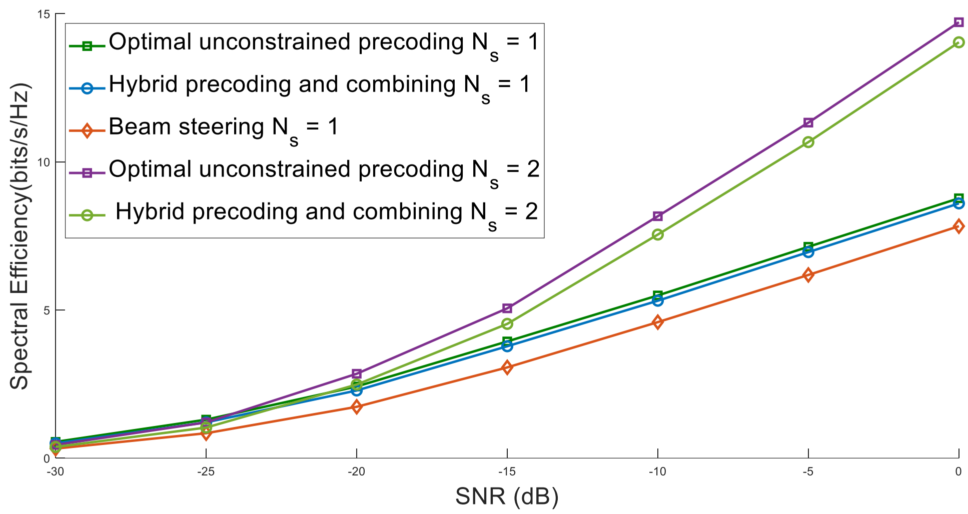

Figure 4.9 Simulation Result for Spectral Efficiency versus Signal to Noise Ratio

Optimal unconstrained precoding is a technique used in multi-antenna wireless communication systems, such as MIMO (Multiple-Input Multiple-Output) systems, to improve the overall system performance. The goal of optimal unconstrained precoding is to maximize the spectral efficiency of the communication link, which is the measure of how efficiently the available frequency spectrum is utilized.

Beam steering can significantly improve the spectral efficiency of a wireless communication system by focusing the transmitted energy in the direction of the intended receivers. By concentrating the signal power in the desired direction, beam steering can increase the signal-to-interference-plus-noise ratio (SINR) at the receiver, which in turn allows for higher-order modulation schemes, ultimately leading to higher spectral efficiency. Beam steering also helps to reduce the interference, further improving the overall spectral efficiency of the system.

Hybrid precoding and combining is a technique used in large-scale multiple-input multiple-output (MIMO) systems, particularly in millimeter-wave communication systems. Hybrid precoding and combining can achieve near-optimal spectral efficiency compared to a digital system, especially at high SNRs.

Figure 4.9 presents a comparison of spectral efficiency as a function of the signal-to-noise ratio (SNR) for different precoding and combining methods, with a focus on the number of streams (Ns = 1 and Ns = 2). An increase in spectral efficiency with higher SNR values. Optimal unconstrained precoding is consistently shows superior performance over others, especially with number of streams (Ns = 2). The figure compares optimal unconstrained precoding, hybrid precoding and combining, and beam steering methods. Spectral efficiency is a crucial metric in communication systems, reflecting the bandwidth efficiency of a transmission system.

No	Parameters	Assigned Values
1	Number of transmit antennas	64
2	Number of receive antennas	16
3	Number of data streams	1
4	Number of RF chains for precoding and combining	4

Table 4.10 Assigned values and used parameters to simulate spectral efficiency versus signal to noise ratio for transmit antenna value = 64 and receive antenna value = 16

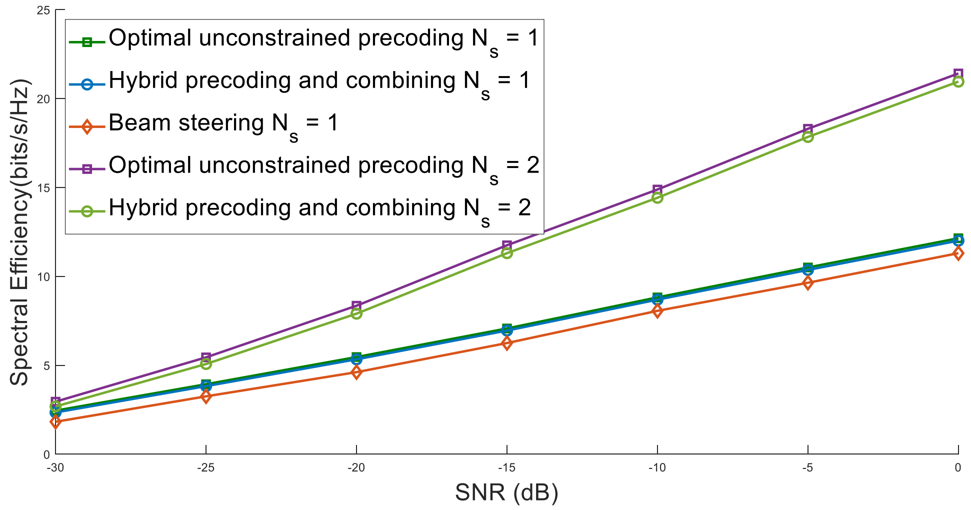

Figure 4.10 Simulation result for spectral efficiency versus signal to noise ratio using the transmit antenna value = 256 and receive antenna value = 64

Optimal unconstrained precoding is a technique used in multi-antenna wireless communication systems, such as MIMO (Multiple-Input Multiple-Output) systems, to improve the overall system performance. The goal of optimal unconstrained precoding is to maximize the spectral efficiency of the communication link, which is the measure of how efficiently the available frequency spectrum is utilized.

Beam steering can significantly improve the spectral efficiency of a wireless communication system by focusing the transmitted energy in the direction of the intended receivers. By concentrating the signal power in the desired direction, beam steering can increase the signal-to-interference-plus-noise ratio (SINR) at the receiver, which in turn allows for higher-order modulation schemes, ultimately leading to higher spectral efficiency. Beam steering also helps to reduce the interference, further improving the overall spectral efficiency of the system.

Hybrid precoding and combining is a technique used in large-scale multiple-input multiple-output (MIMO) systems, particularly in millimeter-wave communication systems. Hybrid precoding and combining can achieve near-optimal spectral efficiency compared to a digital system, especially at high SNRs.

Figure 4.10 depicts a graph of spectral efficiency versus signal to noise ratio (SNR), comparing various precoding and combining techniques with a transmit antenna value of 256 and a receive antenna value of 64. As SNR increases, all methods show improved spectral efficiency, indicating better performance at higher SNRs. This simulation result provides insights into the effectiveness of different techniques in enhancing communication system performance under varying SNR conditions.

No	Parameters	Assigned values
1	Number of transmit antennas	256
2	Number of receive antennas	64
3	Number of data streams	1
4	Number of RF chains for precoding and combining	6

Table 4.11 Assigned values and used parameters to simulate spectral efficiency versus signal to noise ratio for transmit antenna value = 256 and receive antenna value = 64.

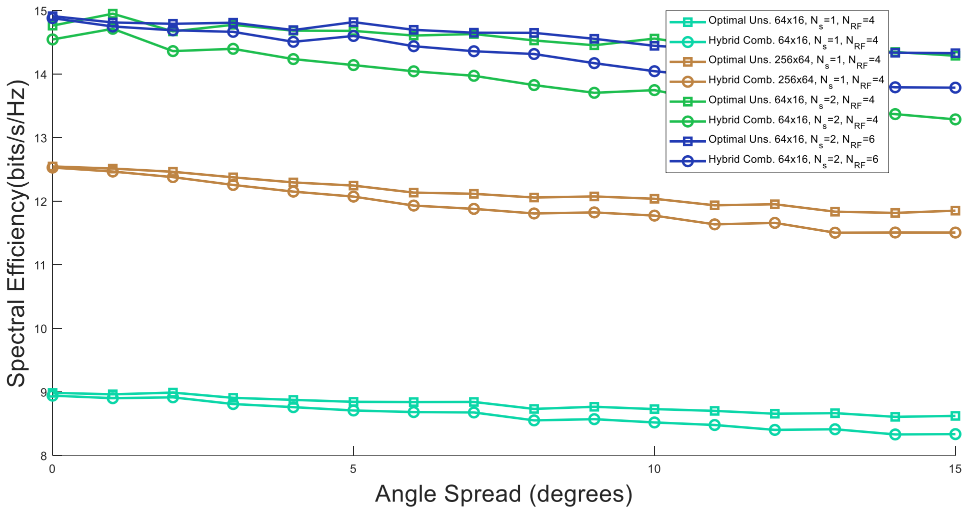

Figure 4.11 Simulation result for spectral efficiency versus angle of spread using the transmit antenna values = 256, 64 and receive antenna values = 64, 16

Angle of spread using the transmit antenna values = 256, 64 and receive antenna values = 64, 16 refers to a measure of the angular distribution of the signal radiation pattern from a wireless communication system. In this case, the transmit antenna has two different settings: 256 and 64. The receive antenna also has two different settings: 64 and 16. The angle of spread is a calculation that determines the angular range over which the signal is distributed from the transmit antenna, taking into account the different antenna settings. The angle of spread is an important parameter in wireless communications as it provides information about the directionality and coverage area of the transmitted signal. A smaller angle of spread indicates a more focused and directional signal, while a larger angle of spread suggests a more dispersed signal pattern. However, the general concept is that the angle of spread can be determined based on the transmit and receive antenna settings provided. The simulation explores the impact of angle spread on spectral efficiency in a communication system, considering different configurations of transmit (Tx) and receive (Rx) antennas.

The simulation tests various combinations of Tx and Rx antennas to observe how they affect spectral efficiency. The graph shows that spectral efficiency remains relatively stable across different angle spreads, suggesting that the system can maintain performance even with variations in signal directionality. This is valuable for designing robust communication systems that can handle diverse propagation environments.

No	Parameters	Assigned values
1	Number of transmit antennas	256, 64
2	Number of receive antennas	64, 16
3	Number of data streams	1, 2
4	Number of RF chains for precoding and combining	4, 6

Table 4.12 Assigned values and used parameters to simulate spectral efficiency versus angle of spread using transmit antenna values = 256, 64 and receive antenna values = 64, 16

Features	Existing Technique	Proposed Technique
Spectral Efficiency	Good spectral efficiency for single-user scenarios	Better spectral efficiency in multi-user scenarios
Number of users	Limited to single-user	effectively support a larger number of users
High data rate	Achieves high data rates for a single user	Enables high aggregate data rates in multi-user scenarios
Bit error rate reduction	Can achieve low bit error rate (BER)	optimize the beamforming weights to minimize the overall system BER

Table 4.13 Comparison of existing and proposed Techniques

Generally, Existing Technique is well suited for high spectral efficiency and data rates in single-user scenarios, while hybrid beamforming with root mean square error vector magnitude (RMS EVM) can provide better performance in terms of supporting a larger number of users, mitigating interference, and reducing the overall system's bit error rate.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

Performance evaluation of antenna beamforming in millimeter-wave massive MIMO systems are presented. The simulation was performed on MATLAB2023b software. However, mm-wave communications face challenges due to path loss and blockage. The simulation aims to address these challenges by implementing hybrid beamforming techniques to focus the transmitted energy in specific directions. This is intended to enhance signal strength and mitigate the impacts of path loss and blockage. The simulation comprehensively evaluates massive MIMO systems in mm-wave bands, considering factors such as the number of antennas, beamforming algorithms, and channel conditions. The findings of this thesis will contribute to a better understanding of massive MIMO performance in mm-wave environments. This provides valuable insights for the design and optimization of wireless communication systems. The simulation results show that the root mean square error vector magnitude (RMS EVM) can outperform, highlighting the importance of considering the number of users and the choice of modulation scheme in mm-wave massive MIMO channels. This is crucial for ensuring optimal performance and reliable communication in dense user environments. Root mean square error vector magnitude (RMS EVM) remains stable for a low number of users across different modulation schemes, but increases significantly around 10 users, especially for higher-order modulations like 256QAM. Bit error rate (BER) is occurred during scattering modulation type in all modulation scheme. Similarly for 16QAM, with root mean square error vector magnitude (RMS EVM) remaining stable up to around 12 users, but increasing significantly, especially for higher-order modulations. This indicates that the need for careful consideration of user density and modulation scheme to maintain communication quality in mm-wave massive MIMO systems. From the above analysis, root mean square error value magnitude (RMS EVM) values for 4QPSK, 16QAM, and 64QAM remain stable as the number of users increases. A sharp increase in root mean square error vector magnitude (RMS EVM) is observed for 256QAM at around 14 users. This indicates that higher-order modulation schemes like 256QAM are more susceptible to performance degradation with higher user counts. When we analyze the result of root mean square error vector magnitude

(RMS EVM) values, number of users for mm-wave massive MIMO channel type and 256QAM modulation shows that root mean square error vector magnitude (RMS EVM) values increase gradually up to around 12 users, then show a noticeable spike, with 256QAM having the most significant rise. This shows the impact of user count on communication quality for different modulation schemes in mm-wave massive MIMO. When we analyze the result of root mean square error vector magnitude (RMS EVM) values, number of users for scattering channel type and 4QPSK modulation shows that up to about 14 users, modulation schemes maintain stable root mean square error vector magnitude (RMS EVM) values, but 256QAM shows a spike after 14 users. Figure 4.6 shows root mean square error vector magnitude (RMS EVM) values are low for up to 14 users, after which there is a sharp increase, particularly for 256QAM. Suggests a limit to the number of users for maintaining quality with higher-order modulation schemes in a scattering channel environment. Figure 4.7 Analyzes the RMS EVM values as a function of the number of users for various modulation schemes. As the number of users' increases, the root mean square error vector magnitude (RMS EVM) values also increase, particularly after 12 users, indicating a degradation in signal quality. Figure 4.8 shows the simulation results for root mean square error vector magnitude (RMS EVM) values versus the number of users for a scattering channel type with 256QAM modulation. As the number of users increases beyond 12, there is a notable increase in root mean square error vector magnitude (RMS EVM) for all schemes except 4QPSK, suggesting a degradation in signal quality. Figure 4.9 shows a comparison of spectral efficiency as a function of the signal-to-noise ratio (SNR) for different precoding and combining methods. Optimal unconstrained precoding consistently shows superior performance over others. Figure 4.10 shows a graph of spectral efficiency versus signal to noise ratio (SNR), comparing various precoding and combining techniques. As signal to noise ratio (SNR) increases, all methods show improved spectral efficiency. Figure 4.11 shows the impact of angle spread on spectral efficiency in a communication system. Spectral efficiency remains relatively stable across different angle spreads, suggesting the system can maintain performance with variations in signal directionality. Overall, the simulation focuses on addressing the challenges of mm-wave communications through massive MIMO and hybrid beamforming techniques, providing valuable insights for system design and deployment. The results highlight the importance of considering user density, modulation scheme, and channel conditions to ensure reliable communication in mm-wave massive MIMO systems.

5.2 Recommendation

In this thesis, the performance of antenna beamforming in millimeter-wave massive MIMO systems was evaluated. Finally, I improve the spectral efficiency by minimizing the bit error rate using the RMS EVM method and the spectral efficiency versus number of users in different modulations.

In the future, if any researchers will want to do with hybrid beamforming method, apply:-

- Maximum ratio transmission (MRT) hybrid beamforming technique, zero-forcing (ZF) hybrid beamforming technique, or minimum mean square error (MMSE) hybrid beamforming technique.
- Finally using other algorithms to improve the performance of millimeter-wave massive MIMO systems, data rate, capacity of the system, by minimizing interference and bit error rate.

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