Recursive Least Squares based Kalman Hybrid Precoding for Multi-User Millimeter Wave Massive MIMO Systems

Muluken Desalegn Woldesenbet

A Thesis Submitted to the

Department of Electronics and CommunicationEngineering

School of Electrical Engineering and Computing

Presented in Partial Fulfillment of the Requirement for the Degree of

Master’s in Electronics and Communication Engineering

Office of Graduate Studies

Adama Science and Technology University

July 2023

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Major Advisor: Dr. Satyasis Mishra

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APPROVAL PAGE OF M.SC. THESIS

We, the advisors of the thesis entitled **"Recursive Least Squares based Kalman Hybrid Precoding for Multi-User Millimeter Wave Massive MIMO Systems"** and developed by **Muluken Desalegn Woldesenbet**, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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We, the undersigned members of the board of Examiners of the thesis by **Muluken Desalegn Woldesenbet** have read and evaluated the thesis entitled **"Recursive Least Squares based Kalman Hybrid Precoding for Multi-User 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 of the degree of Master of Science in Electronics and Communication engineering.

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

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DECLARATION

I hereby declare that this Master Thesis entitled "**Recursive Least Squares based Kalman Hybrid Precoding for Multi-User 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 in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

Muluken Desalegn Woldesenbet	____________________	__________________
Name	Signature	Date

RECOMMENDATION

We, the advisors of this thesis, hereby certify that we have read the revised version of the thesis entitled **"Recursive Least Squares based Kalman Hybrid Precoding for Multi-User Millimeter Wave Massive MIMO Systems"** prepared under our guidance by Muluken Desalegn Woldesenbet submitted in partial fulfillment of the requirements for the degree of Mater's of Science in Electronics and Communication Engineering. Therefore, we recommend the submission of revised version of the thesis to the department following the applicable procedures.

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LIST OF ABBREVIATIONS

ADC	Analog to Digital converter
AE	Auto Encoder
BS	Base Station
CSI	Channel State Information
DAC	Digital-to-Analog converter
DB	Digital Beamforming
DNN	Deep Neural Network
DSP	Digital Signal Processing
EE	Energy Efficiency
ELM	Extreme Learning Machine
FDD	Frequency Division Duplexing
FP-MM	Factional Programming and Majorization-Minimization
Gbps	Giga bits per second
HBF	Hybrid Beamforming
LOS	Line of Sight
MATLAB	Matrix Laboratory
MIMO	Multiple Input and Multiple Output
MMSE	Minimum Mean Square Error
MM-WAVE	Millimeter-Wave
MDDL	Model-Driven Deep Learning
MS	Mobile Station
NHB	Neural Hybrid Beamforming
NLMS	Normalized Least Mean Square
RF	Radio Frequency
RLS	Recursive Least Square

SE	Spectral Efficiency
SNR	Signal-to-Noise-Ratio
TDD	Time Division Duplexing
UE	User Equipment
UL	Uplink
ZF	Zero Forcing

ABSTRACT

Massive MIMO and mmWave are critical enabling technologies in the 5G cellular network. mmWave has a higher frequency range, which corresponds to a very short wavelength, resulting in high path loss and blockage in communication systems. To address these challenges, Integrating mmWave and massive MIMO can improve communication performance and RLS Kalman Filter-based Hybrid beamforming is the best technique for minimizing bit error rates, efficiently utilizing energy, and improve spectral efficiency. This thesis compares the performance of various precoding techniques, including Zero Forcing (ZF), Minimum Mean Square Error (MMSE), Kalman, Normalized Least Mean Squares (NLMS) Kalman, Minimum Square Error Fully digital (MSE Fully digital), and Proposed Recursive Least Squares (RLS) Kalman Hybrid Precoding, using performance metric parameters such as bit error rate, energy efficiency, and spectral efficiency. For the simulation purpose Matlab R2018a is used. Simulation outcomes demonstrate that the Proposed Recursive Least Squares (RLS) Kalman Hybrid Precoding achieved the best energy efficiency, spectral efficiency performance, and bit error rate with increased transmitter and receiver antennae and fewer users. The RLS Kalman Hybrid Precoding improved the spectral efficiency by almost 4.105 bps/Hz at 20dB with ten channel paths compared to the Zero Forcing (ZF) Hybrid Precoding and almost 3.758 bps/Hz, 3.159 bps/Hz, 2.107 bps/Hz, and 0.57 bps/Hz for the MMSE, Kalman, NLMS Kalman, and MSE Fully Digital Hybrid Precoding techniques, respectively, under the same conditions.

Key words: Bit error rate, Energy Efficiency, Massive MIMO, Millimeter-Wave, Normalized Least Mean Squares Kalman Hybrid precoding, Spectral Efficiency.

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the Study

Over the past few decades, especially in wireless communication, global communication technologies have seen rapid growth and have come to be regarded as essential by modern society. The growth of mobile services over the last few years has greatly improved coverage, speed and flexibility. However, there is a growing demand for mobile data access due to the widespread usage of smartphones, tablets, and personal computers. In regard to this, the fifth-generation (5G) mobile system has garnered a lot of interest as a way to offer greater mobility support, reduced latency, higher reliability, and higher capacity(N. Chen et al., 2016). The fundamental difficulty in the era of 5G is effectively meeting the rising demand for mobile data services while the limited amount of spectrum resources continues to be of more concern. One of the interesting technologies that can be employed in 5G to improve network throughput is millimeter wave(Osman & Zaki, 2020).

Millimeter wave (mmWave) systems with frequency limits between 30 GHz and 300 GHz provide high data rates on cellular networks. Due to the short wavelength of mmWave systems, transceivers can support many antenna arrays(Kasai, 2019). Due to its higher frequencies, millimeter wave can attain a high data rate, a greater accessible bandwidth, and low latency. However, mmWave experiences significant path loss because of interference and noise. To solve this issue, massive MIMO and antenna beamforming can be implemented(N. Chen et al., 2016). Beamforming is the most widely used technique for enhancing Massive MIMO systems spectral efficiency and suppress the interference between different data streams with in different number of antenna array(Tao et al., 2019). The signal transmission range can be further extended by beamforming technology. Beamforming prepares the antenna to focus its transmission only in the intended direction (Nalband et al., 2022).

As these promising technologies are implemented, network complexity rises, which encourages the virtualization of network services. Designing the antenna beamforming is the main challenge in mmWave system deployment. The use of basic phase shifters makes it possible to build analog beamforming, but it does not improve system performance. Even with a high SNR, it provides a very poor average throughput(Chophel et al., 2020).

In the mmWave system, digital beamforming is also possible, but it requires a lot of power because of the use of numerous RF chains. Additionally, it increases the complexity of the hardware. The new beamforming technique should be taken into consideration in order to enhance the systems performance and energy efficiency. The management of spatial information and the coordination of complex antennas are the two remaining issues with the deployment of mmWave systems and massive MIMO systems(Faragallah et al., 2021). Thus, managing, recovering, and storing spatial information becomes challenge(Ramírez-Arroyo et al., 2021). To deploy and properly manage the 5G mobile network, several new issues must be resolved.

The conventional Multiple Input Multiple Output systems use either fully analog beamforming or fully digital precoding at the radio frequency (RF), with baseband circuitry controlling both the amplitude and phase shift of the input signal. This makes it difficult to assign a separate RF chain containing components to each antenna, resulting in high power consumption and high hardware costs in Massive MIMO systems. Hybrid precoding is the most effective method for resolving this issue by combining large-dimensional analog precoding with low-dimensional digital baseband precoding via phase shifters(Kasai, 2019).

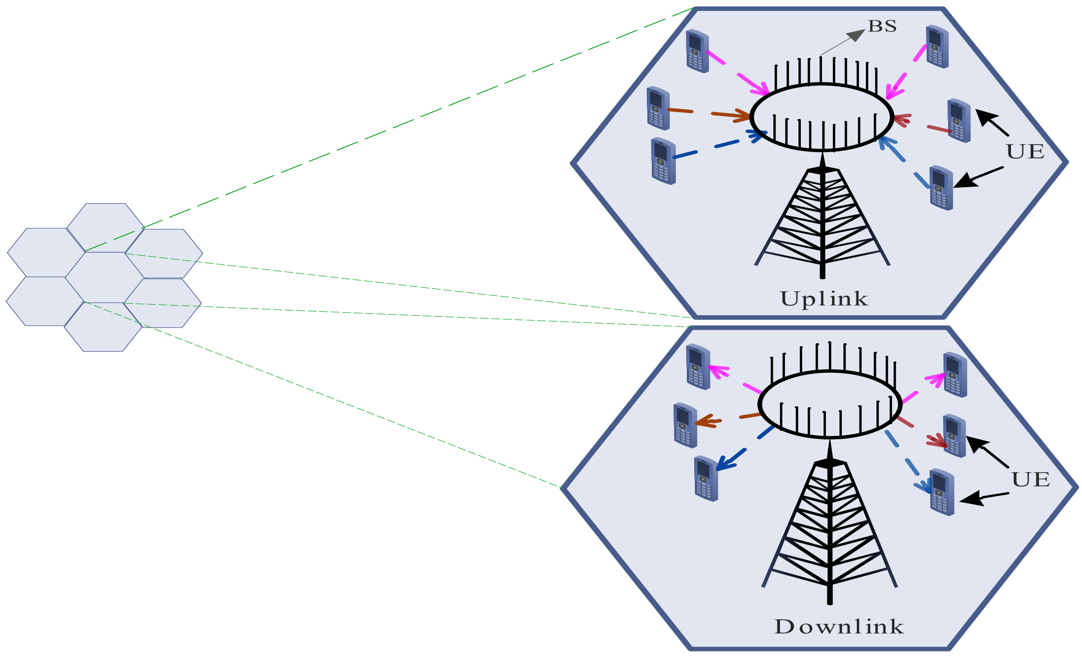

Figure 1.1: Massive MIMO Uplink and Downlink (Chataut & Akl, 2020)

In general, Massive MIMO technology in 5G offers a variety of benefits, including higher spectral efficiency, higher data rates, low latency, robustness, high link reliability, higher energy efficiency and enhanced security. Although this massive MIMO system have some difficulties during deployment. These difficulties are precoding, pilot contamination and channel estimation. Many studies are being carried out to find solutions for mitigation techniques for these difficulties. This research focuses on the Precoding challenge and its mitigation techniques.

1.2 Motivation

The motivation behind this approach is the effectiveness of hybrid beamforming depends on accurate channel estimation, which is challenging in mmWave systems due to the rapidly changing nature of the channel. By using RLS Kalman filter-based approach to estimate the channel state, hybrid beamforming can be optimized for the current channel conditions, leading to improved performance in Millimeter Wave Massive MIMO systems. This can lead to better communication quality, increased range, and reduced interference, making it a promising technology for future wireless communication systems.

1.3 Problem Statements

Millimeter waves Massive MIMO systems support several antennas at both the receiver and transmitter side to serve several users in a communication system. Because of its several antennas, the channel estimation is challenging and the system cost is very high and Millimeter Wave face some challenges such as blockage and path loss due to the non-stationary nature of the channel and small wavelengths. Also, interference results from using several antennas and phase shifter in the base station. Therefore hybrid beamforming has been created for massive Multiple Input Multiple Output systems to get the benefits of digital and analog beamforming by reducing the number of RF chains significantly below the number of antennas while maintaining the gain of spatial multiplexing. To solve the above interference problem beamforming technology and an optimized Kalman filter are used in Millimeter Wave Massive MIMO system by directing the signal in the desired direction and to achieve better estimates of the channel state information with a reduced bit error rate. Therefore RLS Kalman Hybrid Beamforming is used in massive Multiple Input Multiple Output systems to address the problem of the channel can change rapidly over time in mmWave massive MIMO systems.

1.4 Objective of the Study

1.4.1 General Objective

The main objective of this thesis is to achieve the Recursive Least Squares based Kalman Hybrid Precoding for Multi-User Millimeter Wave Massive Multiple Input Multiple Output Systems.

1.4.2 Specific Objectives

- To analyze the Spectral efficiency of the system by varying Signal to noise ratio (SNR), number of channel paths, and the number of Users.
- To evaluate the Spectral efficiency of the system by varying the number of Transmitter and Receiver antennas
- To evaluate the energy efficiency of the system by varying Signal to Noise Ratio
- To evaluate the energy efficiency of the system by varying the number of channel paths.
- To compare the bit error rate of the proposed RLS Kalman Hybrid precoding with the existing precoding.

1.5 Significance of the Study

As higher bandwidth is used in millimeter Wave Systems, the propagation losses are considerable in the mmWave band. To counteract the problem massive MIMO System is used to overcome high propagation loss. This thesis provides a better performance in the Energy and Spectral efficiency of the proposed precoding. Therefore, the RLS Kalman hybrid precoding in Millimeter Wave massive Multiple Input Multiple Output will provide better System Performance and reduced bit error rate in wireless communication systems.

1.6 Scope of the Study

This thesis focused on the performance analysis of hybrid precoding in mmWave Massive MIMO System. The performance of existing precoding such as ZF, MMSE, MSE Fully digital, and Kalman hybrid precoding is compared with the Proposed algorithm. The performance of the precoding algorithm is compared in terms of energy energy, spectral efficiency, and bit error rate in Millimeter Wave (mmWave) Massive Multiple Input Multiple Output System (MIMO) System. Finally, the proposed model can be simulated with Matlab software.

1.7 Thesis Contribution

The main contribution of this thesis is the deployment of a hybrid beamforming technique in a mmWave massive MIMO system. This technique combines the advantages of both analog and digital beamforming, while also addressing the challenges associated with millimeter wave frequencies, such as high path loss and susceptibility to blockage. The proposed technique involves using the RLS Kalman filter to estimate the channel state information (CSI) of the system, which is then used to optimize the beamforming weights. The proposed precoding show that it outperforms existing Kalman-based hybrid beamforming techniques in terms of Spectral efficiency, Energy efficiency and bit error rate. It is also shown to be more robust to channel estimation errors and blockages, which are common challenges in millimeter wave systems.

1.8 Limitation of the Thesis

This thesis is limited only to simulation-based results.

1.9 Thesis Organization

The following is a summary of this thesis structure:

Chapter 1 Introduction: This chapter mainly focuses on the background of the study, statement of the problem, objectives, contribution of the study, scope of the study, and limitations of the study.

Chapter 2 Literature Review: This chapter mainly focuses on Introduction to mmWave communication, Millimeter Wave Channel Model, Overview of Massive MIMO System, mmWave Massive MIMO Beamforming, Benefits of Beamforming in Massive MIMO System, Challenges of Massive MIMO System and review of related works.

Chapter 3 Materials and Methods: This chapter mainly focuses on materials and methods used to accomplish the research work and the performance metrics.

Chapter 4 Result and Discussion: This chapter mainly focuses on simulation parameters, simulation results, and a discussion of obtained results.

The last part mainly focuses on the conclusion and recommendations for future work.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Introduction to mmWave Communication

Millimeter-wave wireless communication, which offers a high gigabits per second data rate and supports millisecond latency, has been gaining significant consideration due to the rising demand for higher data rate services. The large spectral channels provided by mmWave bands, which allow for high data rate communications, are the main benefit of employing these bands. However, these mmWave bands experience diffuse scattering, reduced diffraction, and very high propagation and penetration losses, all of which reduce communication performance. Directional phased array antennas with narrow beam width and high gain that can allow electrical beam-steering are typically utilized at both transmitters and receivers to ensure adequate link margin. Therefore, in mmWave communications, proper beam management at both transmitters and receivers becomes crucial to provide good communication link (Bang et al., 2021). Millimeter Wave is a viable technology for cellular networks in the future. There is a certain amount of spectrum that cellular networks can use. Therefore, a variety of methods are employed to improve spectral efficiency. These include interference coordination, multiple input multiple output (MIMO), orthogonal frequency division multiplexing (OFDM) and efficient channel coding methods. In addition to the utilization of heterogeneous infrastructure including macro, pico, femtocells, relays, and distributed antennas, network densification has recently been studied to enhance the area spectral efficiency(Philip et al., 2020). Regarding fulfilling the capacity needs of the next 5G network, millimeter wave communication solutions have gained a lot of interest. The mmWave systems operate at frequencies range of 30 GHz and 300 GHz, with a total bandwidth of about 250 GHz. Although the mmWave frequencies potential bandwidth is encouraging, the propagation characteristics which include path loss, blockage and diffraction, rain attenuation and air absorption behaviors are very different from those of microwave frequency bands. For a point-to-point link, the overall loss of mmWave systems is typically much higher than that of microwave systems. However, the mmWave frequencies short wavelengths make it possible to deploy numerous antenna elements in similar form factor, leading to substantial spatial processing gains, in theory, can compensate for at least the isotropic path loss. To maintain the predicted the effectiveness of mmWave systems, a variety of computing and implementation issues occur due to the fact that mmWave systems are equipped with many antennas(Bogale et al., 2017).

2.2 Propagation characteristics of mmWave

Millimeter wave frequencies have different propagation properties. Additionally, because the high millimeter wave spectrum has a variety of propagation properties, examining the traits of the possible bands for 5G contributes to a greater understanding and accurate modeling of mmWave channels for various 5G deployment scenarios. This section provides a review of the primary propagation characteristics of millimeter waves, which include free space loss, rain attenuation, and material penetration (Seraj, 2019).

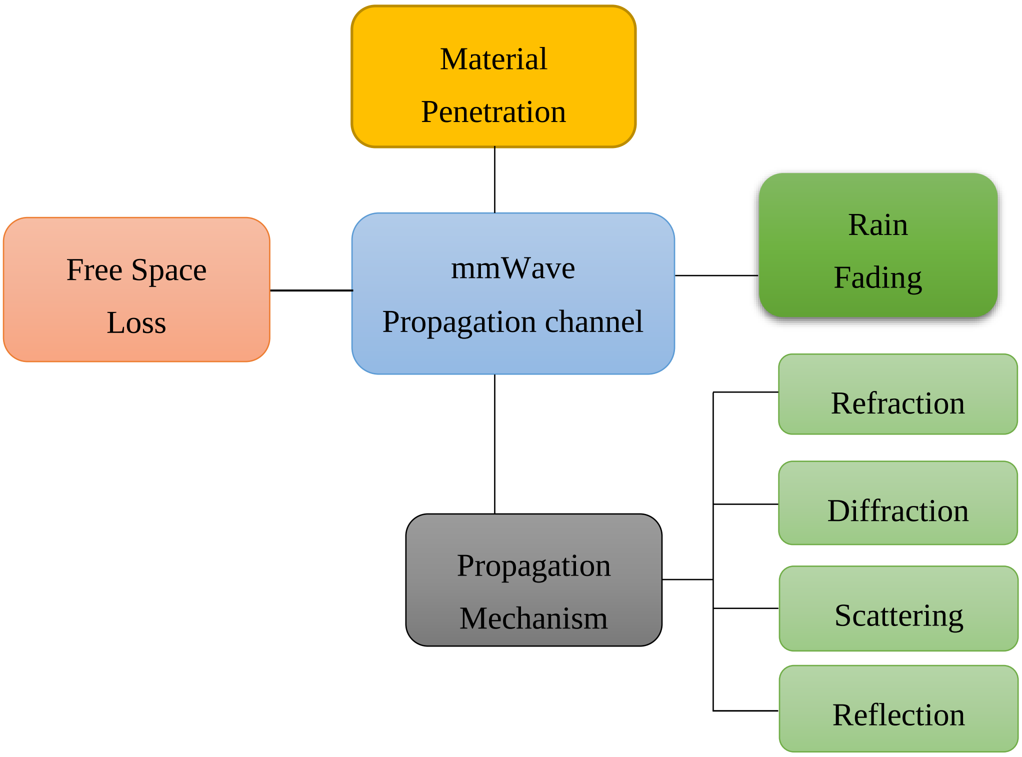

Figure 2.1: Millimeter Wave Propagation Characteristics

2.2.1 Free-Space Loss

Free-Space Loss, also known as path loss, is a radio waves experience a loss of signal strength as they move through free space. It is a natural phenomenon that occurs as the energy of the wave is dispersed over an increasingly larger area as it propagates away from the source.

2.2.2 Rain attenuation

Rain attenuation, also known as rain fade, is a phenomenon that occurs in wireless communication systems where the signal strength is reduced due to the scattering, absorption and reflection of radio waves by raindrops in the atmosphere. It is one of the major causes of signal degradation in satellite communication systems and other wireless systems operating at frequencies above 10 GHz. In millimeter waves, the losses and attenuation from precipitation are significant. Raindrops and Radio wavelengths are roughly the same size at millimeter wave frequencies. Raindrops can therefore easily block millimeter wave communications, scattering the signal energy and reducing its power. The rain's attenuation is influenced by the rate of rainfall(Seraj, 2019).

2.2.3 Material Penetration

Material penetration refers to the capacity of electromagnetic waves to pass through a material. When an electromagnetic wave encounters a material, it may be reflected, absorbed, or transmitted through the material, depending on the properties of the material and the frequency of the wave. Compared to low frequency waves, Millimeter wave frequencies are also prone to penetration loss and are unable to pass through most solid objects such as walls, doors, and furniture. As a result, millimeter wave transmissions are easily obstructed, particularly in densely populated urban areas with numerous buildings and large populations (Seraj, 2019).

2.2.4 Propagation Mechanisms

Propagation mechanisms are the ways in which electromagnetic waves travel through different mediums, including air, water, and solid materials. The propagation mechanism that occurs depends on the properties of the medium and the frequency of the wave it is traveling through. The ray's specular reflection, diffraction , and diffuse scattering are represented in Figure 2.2 and make up the propagation mechanisms seen in Figure 2.1. These methods have been found to significantly affect mmWaves. Understanding the mmWave channel requires extensive study and modeling of the mmWave channels propagation mechanisms due to the short wavelengths of Millimeter Wave signals, which range from 1 mm to 10 mm. As depicted in Figure 2.2, small structures with sizes corresponding to millimeter wavelengths undergo extensive diffused scattering, where each reflected ray has a distinct direction, leading to a dispersed power reception and a weaker specular reflection from a smooth surface. Another commonly held notion is that Millimeter Wave signals are more prone to diffraction mechanisms than their counterparts in reflection, as illustrated in Figure 2.2. This can be explained by the fact that their millimeter-scale wavelengths prevent them from reflecting or scattering off large buildings and flat surfaces. This is caused by the first Fresnel zone of the mmWaves, which is smaller and directly proportional to the wavelength. As a result, objects that are only a few tens of centimeters in size appear to be larger than the signals wavelength, resulting in more shadowing effects and less ray diffraction. But, mmWave communication may depend on the diffracted beams in specific interior situations, especially in an NLOS environment. Contrarily, communications in outdoor settings must depend on reflected pathways rather than easily diffracted ones. Additionally, communication nodes use narrow-beam directional broadcast and receive antennas to overcome high FSL in mmWave communications (El-hajjar et al., 2018).

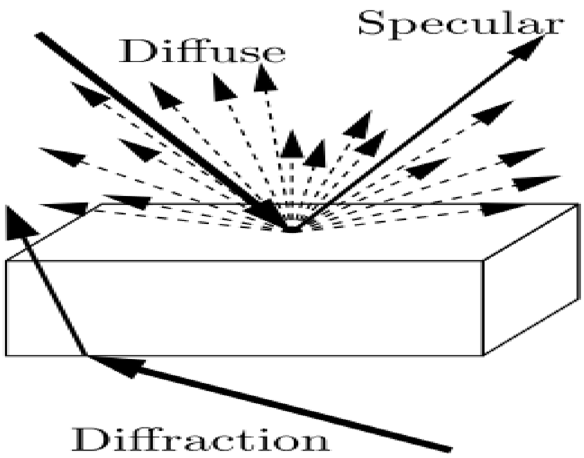

Figure 2.2: An illustration of different propagation mechanisms, namely specular reflection, diffuse scattering and diffraction(El-hajjar et al., 2018)

2.3 Overview of Massive MIMO Systems

MIMO systems have gained significant attention due to the increasing number of customers being served and the growing demand for vast amounts of data. Multi-user MIMO system may offer an innovative technique for enhancing wireless communications spectrum efficiency. Since there is a limited amount of spectrum and there are growing demands for wireless services, MIMO has become an essential technology for upcoming communication systems. Massive MIMO system are described as a configuration of Multi-user MIMO systems with extensive deployment of antenna components at both terminals and base stations. Massive MIMO system use several antennas (hundreds or thousands) connected to a base station to concurrently serve a few terminals (tens or hundreds) while sharing the same carrier frequency and time resources (Larsson et al., 2014). Massive MIMO systems increased capacity is made possible by the several antennas that are used. Beamforming antennas can be used in place of traditional antennas to reduce interference issues that arise from utilizing many antennas. To enhance system performance and capacity, beamforming is a signal processing technique utilized in systems with multiple antenna arrays at both the transmitter and receiver, allowing for the simultaneous transmission or reception of multiple signals from several desired terminals. Beamforming and Massive MIMO techniques have been the primary area of current studies on 5G wireless systems. However, beamforming technology remain capable of improving wireless communication systems in the future(Ali et al., 2017).

2.4 Millimeter Wave Massive MIMO Beamforming

To improve massive MIMO communication systems spectral efficiency, beamforming is utilized. This technique utilizes the interference cancellation concept to enhance wireless system performance(Abdelghany et al., 2021). Utilizing the feasible spatial degrees of freedom, beamforming entails pre-processing signals before transmission in order to maximize network reliability and performance in a Multiple Input Multiple Output system. Additionally, it provides a high beam gain for wireless systems, enabling them to address the challenges imposed by mmWave significant path loss and massive MIMO schemes hardware requirements. Essentially, there are Beamforming architectures fall into three kinds: digital, hybrid, and analog beamforming architectures(Kebede et al., 2022).

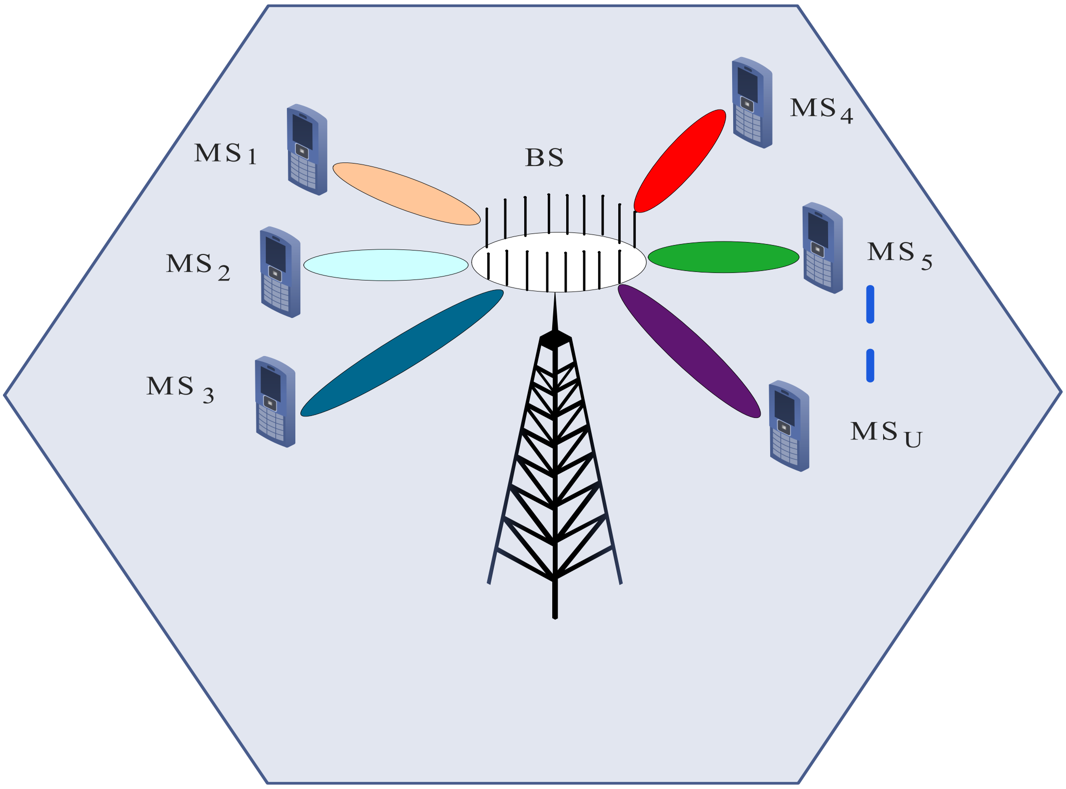

Figure 2.3: Massive MIMO Beamforming (Yarrabothu & Telagathoti, 2019)

2.4.1 Digital Beamforming

All signal processing for digital beamforming takes place at baseband, When every single RF chain is coupled to every single antenna element, with $N_{RF} = N_{BS}$. The transmitter in digital beamforming can send one data stream, multiple data streams Ns to one receiver, or multiple data streams spatially multiplexed to various receivers. The fundamental idea underlying digital precoding is to successfully remove interferences by controlling the amplitudes and phases of the original signals(Kebede et al., 2022). In addition, there are two types of digital precoding: single-user precoding and multiuser precoding. Figure 2..4 shows the Digital precoding system architecture for a multi-user mmWave massive MIMO system.

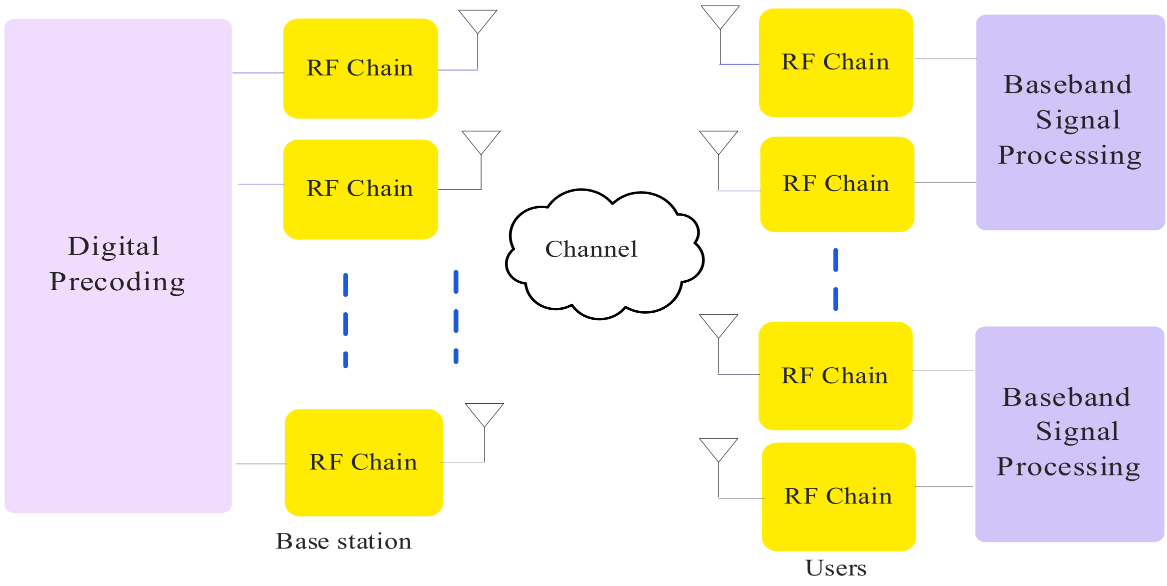

Figure 2.4: Digital precoding system architecture for a multi-user mmWave massive MIMO system (Kebede et al., 2022)

2.4.2 Analogue Beamforming

All signal processing for analog beamforming is carried out in the RF domain. Each antenna element has a phase shifter attached to it, as shown in Figure 2.5. In order to transmit a single data stream, each phase shifter is applied to a single RF chain. The weights of the phase shifters are digitally controlled to direct the beam in a specified direction based on the strongest received signal power and high data rate (Kebede et al., 2022). It is impossible to take advantage of the multi-stream or multi-user benefits of MIMO while using a single beamformer for analog beamforming because it only allows single-user and single-stream transmission.

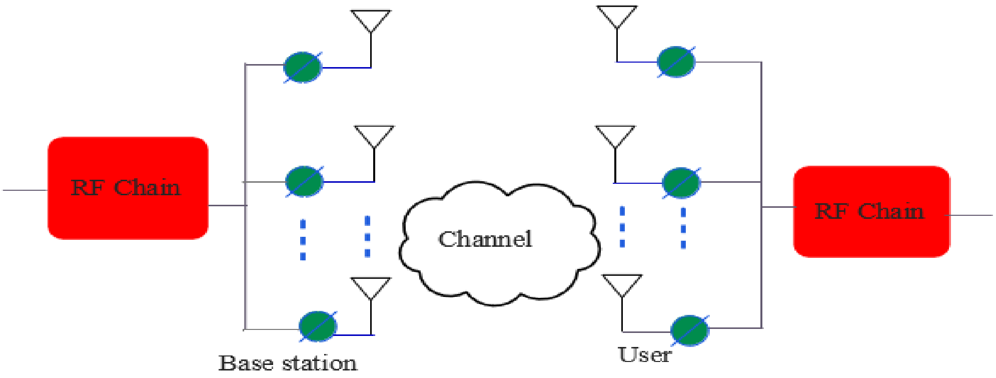

Figure 2.5: Analog beamforming architecture for single-user mmWave massive MIMO systems(Kebede et al., 2022)

2.4.3 Hybrid Beamforming

Hybrid beamforming employs both analog and digital beamforming techniques. Therefore, it offers good performance with less complicated hardware due to the fact that it implements its architecture in both the analog and digital domains. Additionally, its effectiveness is comparable with that of unrestricted digital beamforming. Figure 2.6 illustrates how the hybrid precoding is applied in digital and analog domains, producing the precoders F^{DB} (baseband precoder) and F^{AB} (RF precoder) respectively(Zilli, 2021). In hybrid precoding the number of transmitter antennas N_{BS} is greater than the number of RF chains. This makes it possible for the transmitter to connect with one receiver while utilizing different data streams, or with several receivers while using a single data stream, depending on the situation where, $N_s \leq N_{RF} \ll N_{BS}$ Consequently, hybrid beamforming results in increased spatial multiplexing.

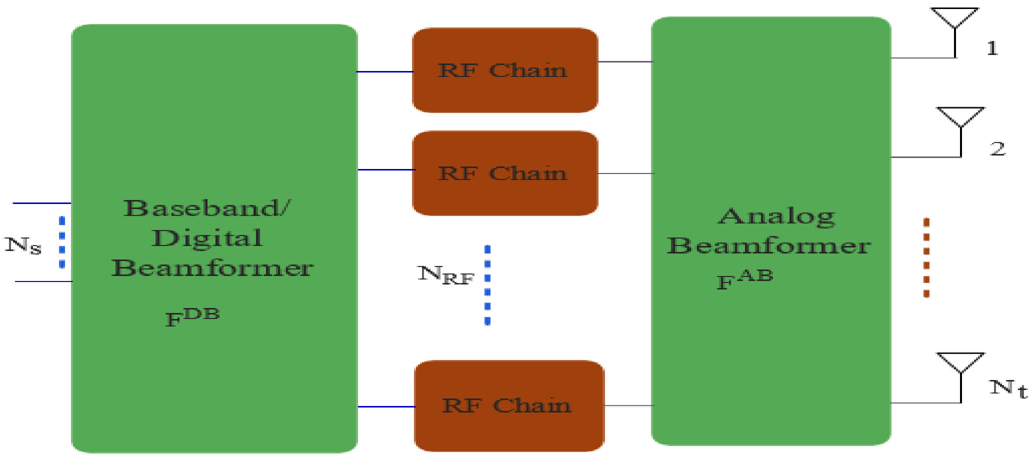

Figure 2.6: Hybrid analog/digital architectures for mm-wave massive MIMO systems (Zilli, 2021)

2.4.3.1 Hybrid Beamforming Benefits and Drawbacks

Hybrid precoding enables performance improvements while maintaining hardware complexity. It enables employing fewer RF chains than antennas, saving both energy and cost. Due to its extra digital layer, hybrid precoding gives developers of precoding matrices greater flexibility than analogue beamforming. Therefore, hybrid precoding can accommodate multiuser transmission, multi-stream multiplexing, as well as more complex processing. Furthermore, by adding a digital layer, mmWave systems with broadband channels may perform tasks like frequency domain equalization for space-time with greater reliability.

Table 2.1: Comparison of beamforming techniques(Busari et al., 2018)

Features	Beamforming types		
	Analog Beamforming	Digital Beamforming	Hybrid beamforming
Energy consumption	Least	Highest	Intermediate
Number of users	Single-user	Multi-user	Multi-user
Complexity	Least	Highest	Intermediate
Cost	Least	Highest	Intermediate
Implementation	Phase shifters	Mixer, ADC/DAC	Phase shifters, mixer and ADC/DAC
Number of streams	Single stream	Multi-stream	Multi-stream
Signal control capability	Phase control Only	amplitude & Phase Control	amplitude and Phase Control
Suitability for mmWave massive MIMO	Unsuitable	Impractical	Is realistic
Hardware requirement	Least	Highest	Intermediate

2.5 Benefits of Beamforming in Massive MIMO Systems

Beamforming is a signal processing technique used to focus the transmitted signals towards the desired terminal while eliminating unwanted signal components from the antenna radiation patterns. The advantages of implementing beamforming in massive MIMO systems are as follows: higher system security, improved energy efficiency and improved spectral efficiency(Ali et al., 2017).

2.5.1 Improved Energy Efficiency

Massive MIMO systems require less electrical power and have reduced amplifier costs due to the lowered power requirements of beamforming antennas for transmitting signals to specific users. Beamforming techniques aid Massive MIMO systems in determining the optimal number of antenna elements required to meet several criteria for managing energy-efficient systems. There is little impact on the cell performance from the number of operational antenna elements for each Base Station specified power consumption; as a result to achieve great cost-effectiveness and total energy efficiency, the systems cells can use a common number of functional antennas. In order to meet the throughput requirements of the terminals, optimization methods such as power control must be used in beamforming techniques to decrease the power consumption at the Base Station.

2.5.2 Improved Spectral Efficiency

To enhance the spectral efficiency of wireless communication networks, Massive MIMO systems utilize beamforming antenna arrays with multiple serving antenna elements at the base station, along with coherent precoding and detector processing. The efficiency of spectrum utilization in cellular networks is impacted by the distribution of carrier-to-interference ratios at the mobile devices. By transitioning from traditional omnidirectional antenna arrays to beam steering antenna arrays and dynamic cell sectored construction using time division duplex (TDD) techniques, traffic performance in wireless system designs has been considerably improved. Instead of omnidirectional antennas at BSs, beamforming techniques are used to increase the efficiency of dynamic cell sectoring.

2.5.3 Higher System Security

The purpose of beamforming is to focus the transmitted signal in the direction of the desired user, making it possible for only the receiver to differentiate between the essential signal and the overlay signal. Physical security is possible since there is less chance of unauthorized persons receiving the transmitted signal than there is with conventional antennas.

2.6 Massive MIMO Uplink System

In uplink channel transmission, the user terminal transmits the pilot signal and data to the base station, as depicted in Figure 2.7. The base station in the UL with M antennas receives sent data using the same frequency-time resource from all N user terminals. Let's imagine a massive MIMO uplink system that has M base station antennas and can interact with N (M ≫N) single-antenna users(Chataut & Akl, 2020).

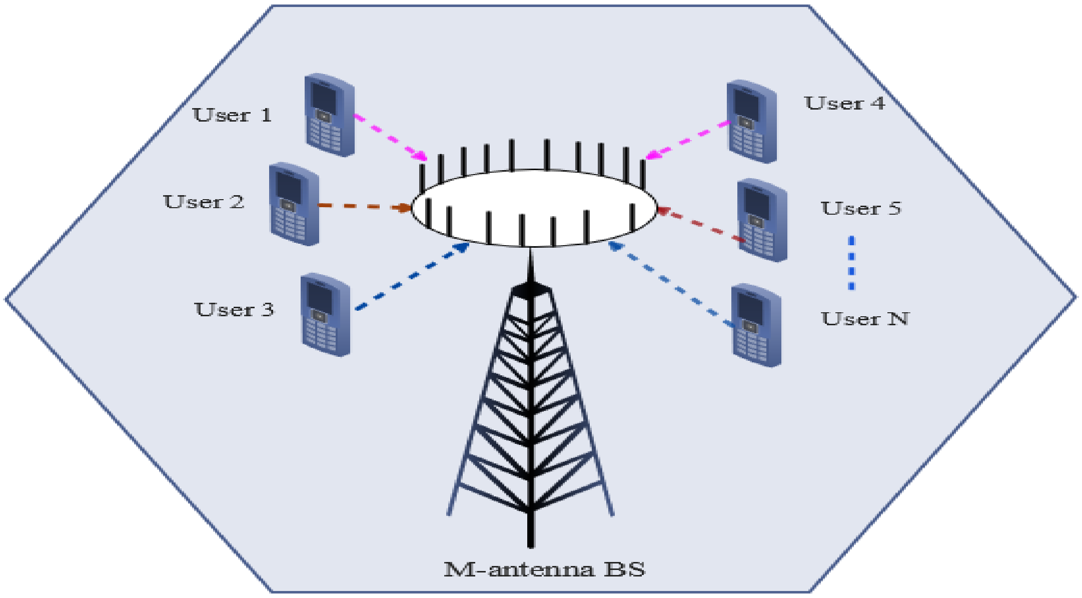

Figure 2.7: Massive MIMO uplink operation(Wang, 2017)

2.7 Massive MIMO Downlink System

In Massive MIMO System, the downlink transmission channel is utilized to send data from the base station to the mobile stations. Data transmission between transmitter and receiver take place over downlink channels. The channel is estimated by the base station through the use of training pilots. Figure 2.8 depicts a downlink transmission involving numerous base station antenna and users. Imagine a downlink massive MIMO system where N users are served simultaneously by M base station antenna, each of which has a single antenna (Chataut & Akl, 2020). The base station provides independent information to several users.

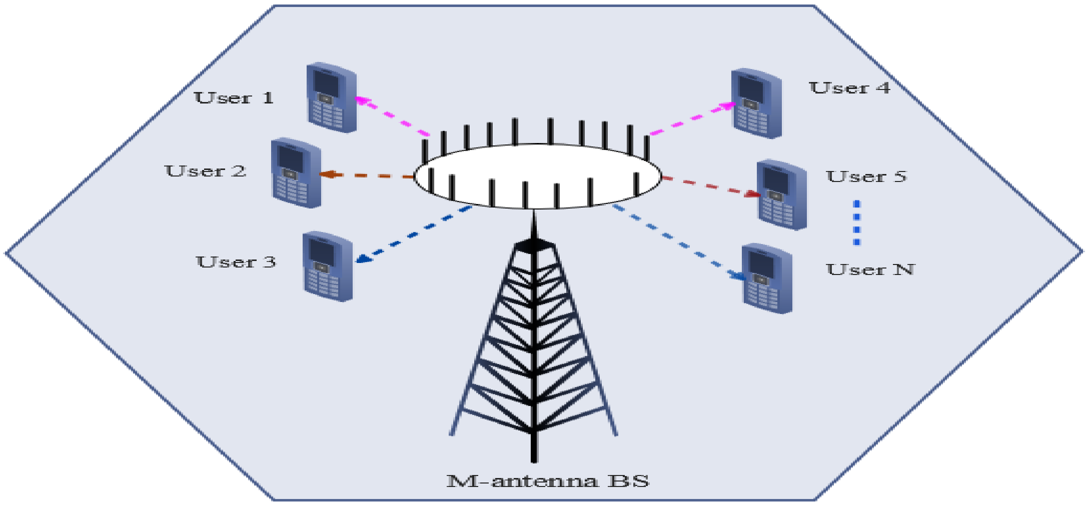

Figure 2.8: Massive MIMO downlink operation(Qiu et al., 2018)

2.8 Challenges of massive MIMO system

2.8.1 Pilot Contamination

In actuality, there are a lot of cells that make up cellular networks. Numerous cells share frequency resources due to a shortage of frequency spectrum. Due to the short channel coherence period, it is challenging to allocate orthogonal pilots to all users in a Massive MIMO system. These orthogonal sequences between the various cells are typically recycled. As a result, as illustrated in figure 2.9, the pilot sequences communicated to other cells can change how a particular cell performs channel estimation. The pilot contamination problem may result in decreased system performance. A significant issue reducing the efficiency of massive MIMO systems is pilot contamination. Its effect cannot be diminished, even if the number of BS antennas increases.

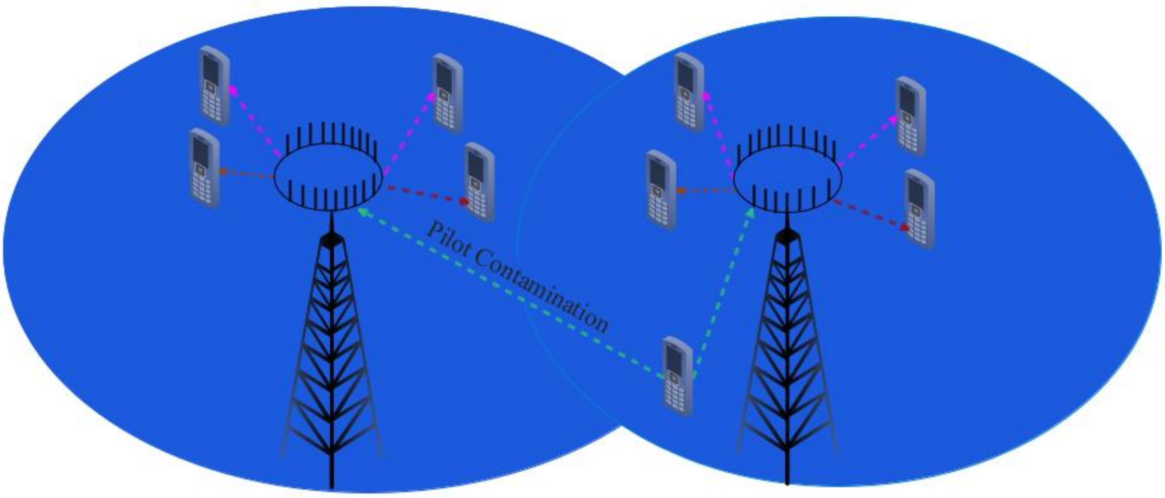

Figure 2.9: Massive MIMO pilot contamination effect(Chataut & Akl, 2020)

2.8.2 Channel Estimation

The detection and decoding of signals in Massive MIMO systems rely on the availability of Channel State Information (CSI). CSI pertains to the collective influence of fading, scattering, and other phenomena on the state of communication between the transmitter and receiver in a system. In the event of perfect CSI, the performance of Massive MIMO systems improves linearly with the number of sending or receiving antennas, whichever is less. In a frequency division duplexing system, CSI needs to be estimated for both the uplink and the downlink. During uplink channel estimation, the Base Station utilizes orthogonal pilot signals that are transmitted by the user terminal. During the downlink, the user terminal receives pilot signals from the base station and then employs the estimated channel information to receive the downlink transmissions. In Massive MIMO systems with a large number of antennas, the frequency division duplexing (FDD) downlink channel estimation approach becomes increasingly difficult and impractical to use in real-world applications (Chataut & Akl, 2020). Figure 2.10 depicts the Time Division Duplexing (TDD) and Frequency Division Duplexing (FDD) modes used in wireless communication, whereas Figure 2.11 shows the CSI feedback and standard pilot transmission method in TDD and FDD mode. Time Division Duplexing (TDD) provides a solution to the challenge of downlink transmission in FDD systems. The base station in a Time Division Duplexing (TDD) system can estimate the downlink channel by utilizing information from the uplink channel and the reciprocity property of the channel. During the uplink transmission, the user terminal sends orthogonal pilot signals to the base station, which then utilizes these signals to estimate the Channel State Information (CSI) for the user terminal. After estimating the CSI for the user terminal, the base station will use beamforming to transmit downlink data in the direction of the user terminal. The pilot contamination problem is a significant challenge during channel estimation in Massive MIMO systems, as there is a limited number of orthogonal pilots that can be reused across different cells (Chataut & Akl, 2020). Another issue is that more antennas lead to more complicated hardware and processing. A channel estimation technique with low complexity and overhead is therefore extremely desired for large MIMO systems.

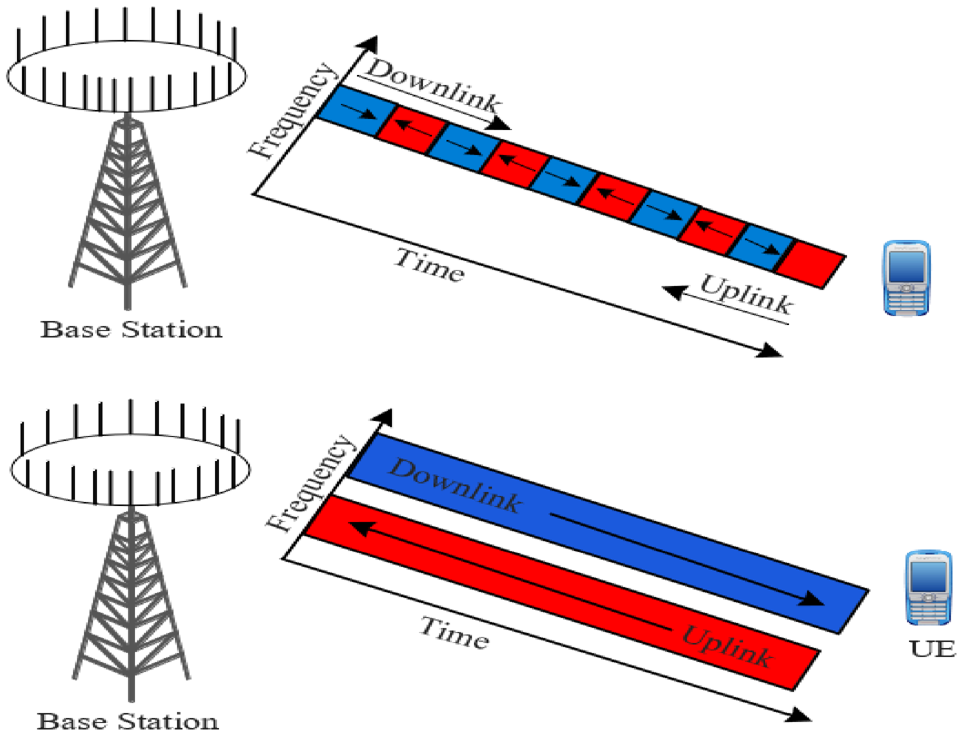

Figure 2.10: Frequency Division Duplexing (FDD) and Time Division Duplexing (TDD) mode (Chataut & Akl, 2020)

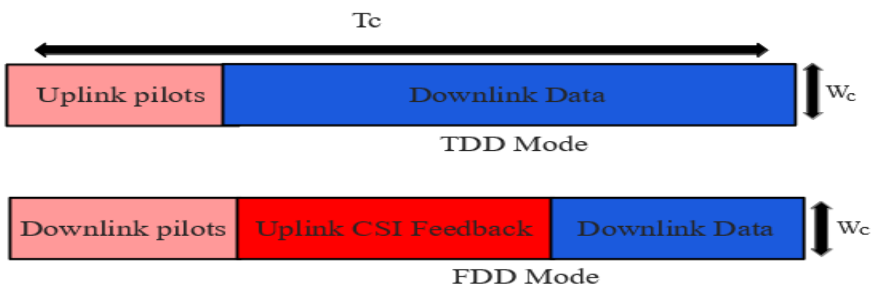

Figure 2.11: Typical pilot transmission and CSI feedback mechanism in FDD and TDD mode (Chataut & Akl, 2020)

2.8.3 Precoding

The concept of precoding involves beamforming and allows for multi-stream transmission in systems that have multiple antennas. Precoding is essential as it increases throughput while minimizing the effects of path loss and interference in massive MIMO systems. Massive MIMO systems employ channel state information estimation by the base station using feedback from the user equipment. With the estimated CSI and precoding technique, the base station can mitigate interference and improve spectral efficiency. The effectiveness of downlink massive MIMO is reliant on both the accuracy of CSI estimation and the choice of precoding technique. Massive MIMO systems gain greatly from the precoding technique, but by adding more computations, it also makes the systems total computations more difficult. As antennas number increases, the computational complexity also increases. Hence, it is more feasible to utilize straightforward and efficient precoding techniques for Massive MIMO systems. Figure 2.12 depicts the precoding in massive MIMO system with M-Antenna and N-users.

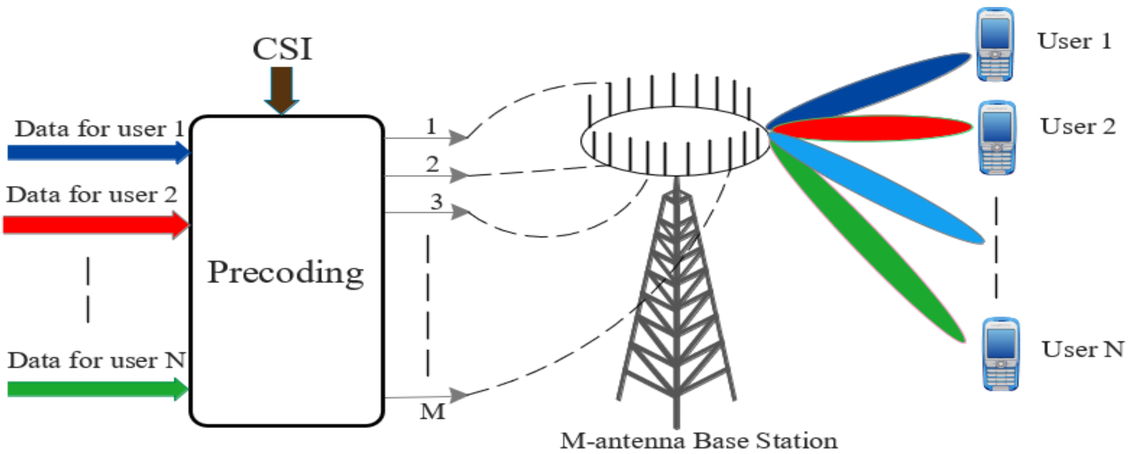

Figure 2.12 Precoding in a Massive MIMO system with M antennas at the base station communicating with N users(Mukubwa et al., 2017)

Massive MIMO systems benefit greatly from the precoding method, but it also adds additional computations that raise the computational complexity of the system as a whole. The number of antennas directly relates to the increase in computing complexity. To address this problem, different precoding techniques have been used including ZF, MMSE ,MSE Fully digital and Kalman hybrid precoding (Mukubwa et al., 2017).

2.8.4 User Scheduling

Massive MIMO technology employs a large number of antennas to enable simultaneous communication with multiple users. Simultaneous communication with several users leads to reduce the throughput performance and multi-user interference. Figure 2.13 illustrates the use of precoding techniques to mitigate the effects of multi-user interference during the downlink. If the number of users exceeds the allowed amount of antennas for the massive MIMO system, an efficient user scheduling mechanism is put in place prior to precoding to attain greater performance in throughput and spectral efficiency.

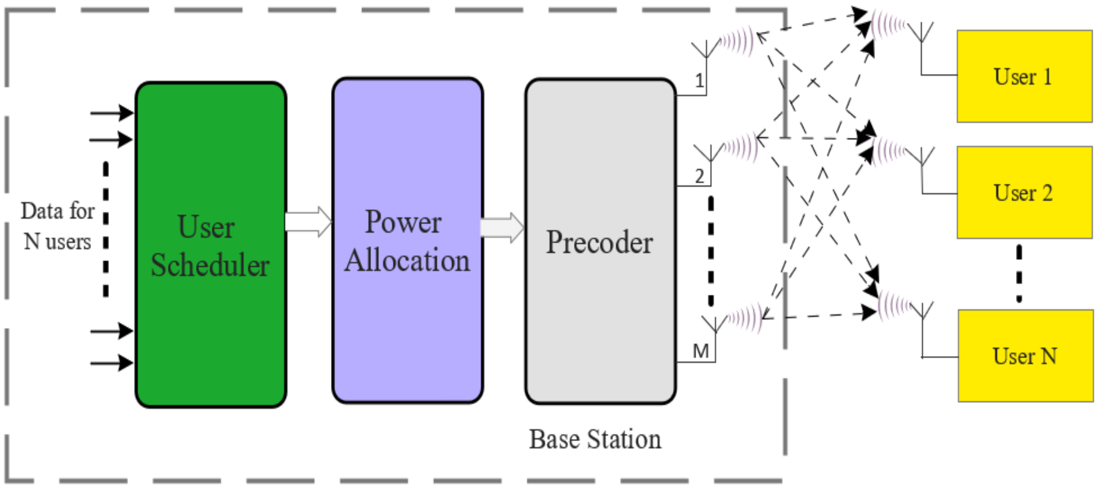

Figure 2.13: Massive MIMO user scheduling (Chataut & Akl, 2020)

The optimum scheduling algorithm for massive MIMO has been the subject of several studies. At various times, many methods have been proposed, including ZF, MMSE, MSE Fully digital and Multi-user Grouping (Meng et al., 2018).

2.9 Previous Works

Some of the materials that I have reviewed to do this thesis are the following.

In literature (H. Huang et al., 2019), the author of this paper provides The primary drawbacks of the current hybrid precoding techniques including their complicated computational complexity and incomplete exploitation of spatial information. This paper offers a deep learning enabled mmWave massive MIMO System for efficient hybrid precoding, where each precoder choice for achieving the optimum decoder is viewed as a mapping relation in the deep neural network (DNN). They also provide thorough simulation results to support the suggested scheme's superior performance. The outcomes show that DNN-based approach can significantly reduce the required computational complexity while improving spectral efficiency and reducing the bit error rate of the mmWave massive MIMO, which performs better in hybrid precoding compared to conventional schemes. Since this research paper didn’t considers energy efficiency analysis.

The authors of (J. Chen et al., 2020), The various hybrid mmWave MIMO system types are converted into the relevant autoencoder (AE) based neural networks in the proposed neural hybrid beamforming/combining (NHB) MIMO system. They can implement a machine learning-based design technique using this technology, which is suitable for a variety of beamforming/combing architectures. Additionally, they provide an iterative training method for updating neural network parameters that can successfully ensure quick convergence of the built NHB model. The suggested NHB can provide a significant performance improvement over current approaches in terms of bit error rate, according to simulated results.

mmWave communication and massive MIMO are the technology needed to realize 5G design objectives. Taking into account their beamforming and precoding techniques. In contrast, the usage of numerous antennas and radio frequencies (RFs) raises the complexity of these technologies. In order to find the proper precoding and beamforming techniques with minimal costs, power, and complexity, many investigations are now being conducted. As we do in this research, RLS Kalman was not considered (Kebede et al., 2022). The paper in literature (Vizziello et al., 2018), provides A promising approach is hybrid analog/digital beamforming, Particularly when applied in a multiples user environment. This work proposes a Kalman-based hybrid precoding in a multi-user context. Simulation findings demonstrate that the suggested method significantly improves spectral efficiency and bit error rate, the spectral efficiency at 20 dB obtaining about 9.8 b/s/Hz with 12 channel paths for Kalman-based hybrid precoding which outperform other precoding. For performance comparison, a Kalman-based approach is considered but Energy efficiency analysis is not considered.

Research Paper (Abid et al., 2022), Massive multiple input multiple output (MIMO) systems for millimeter-wave (mmWave) technology can considerably increase their spectrum and energy efficiency with hybrid beamforming while suffering not substantial performance consequences. However, the primary drawback of current hybrid beamforming is the presence of powerful, high-resolution analog-to-digital converters (ADCs). This work proposes an energy and spectrum efficient mmWave massive MIMO transmission system that simultaneously enhances the quantity of ADC bits and the hybrid combiner's performance to get over this fundamental restriction. Comparing the proposed Kalman hybrid combiner with zero-forcing (ZF) and minimum mean square error (MMSE) receivers, Simulation outcomes demonstrate that it performs with the best spectrum and energy efficiency but, the bit error rate aspect was not considered in their work.

Fully digital baseband precoding methods are typically inefficient in massive MIMO systems operating at millimeter waves because of their high costs and power requirements. Hybrid precoding techniques so emerge as interesting alternatives. The significant phase information of the channels is captured since the resulting eigenvectors correspond to the bigger singular values. By doing so, the iterative search procedure for finding the analog precoding vectors is eliminated, enabling the parallel realization of the hybrid precoding. A hybrid precoder is created by employing the generated vector set by including more significant vectors in terms of the unconstrained optimal precoder's correlation values to increase its spectral efficiency. The outcomes of the simulation demonstrate that the suggested technique accomplishes almost similar performance to the orthogonal matching pursuit, but at a significantly lower cost and with a lot less complexity than the OMP, allowing parallel implementation. This research focuses on improving spectral efficiency but linear precoding was not considered(Liu et al., 2019).

For mmWave massive multiple input multiple output (MIMO) systems hybrid beamforming is a promising method that can lower power consumption and offer great spectrum efficiency. However, due to limitations in hardware architecture, it is impossible to find the optimum character of such hybrid beamforming optimization issues. In this study, they introduced a hybrid beamforming method for mmWave massive MIMO systems based on constrained deep neural networks (constrained-DNN), with End-to-end autonomous hybrid beamforming is possible by using neural networks in place of the beamforming matrices used in traditional hybrid beamforming. The traditional hybrid beamforming optimization problem is changed into a neural network optimization problem, which increases the complexity of the optimization problem. Additionally, they provide numerical findings on the algorithms' performance, showing a notable improvement in bit error rate performance when compared to current hybrid beamforming techniques. But in this paper RLS Kalman hybrid precoding was not considered (Tao et al., 2019).

With the public introduction of 5G, mmWave frequency communications are seen as a new wireless communications era. The hybrid beamforming transceivers, which are made up of a large number of analog phase shifters and a lesser number of RF chains, are typically used to implement massive MIMO with Millimeter Wave. The hybrid beamforming design combines digital and analog beamforming, which reduces both cost and power usage. The primary goal of this research is to present a hybrid beamforming architecture based on deep learning to complement combiner and the precoder optimization in mmWave massive MIMO communication systems. But this paper did not consider the energy and spectral efficiency of the communication system (Osama et al., 2021).

A critical step in the design of mmWave MIMO systems is hybrid beamforming. Conventional Hybrid Beamforming techniques, on the other hand, continue to be highly complex and heavily rely on the accuracy of channel status data. To jointly improve the transmitting and receiving beamformer, they suggest an extreme learning machine (ELM) framework. They first suggest a factional programming and majorization-minimization-based HBF method (FP-MM-HBF) in order to generate accurate labels for training. Then, a framework for extreme learning machine based hybrid beamforming (ELM-HBF) is suggested to improve beamformer robustness. Comparing the two FP-MM-HBF and ELM-HBF can both offer a greater system total rate. Additionally, ELM-HBF takes up relatively little computing time and offers solid HBF performance. But the linear precoding is not taken into account in this study(S. Huang et al., 2020).

Table 2.2: Contribution and gap of different related works

Title	Contributions	Gap
Spectrum and energy efficient kalman-based hybrid combiner for mmWave massive MIMO systems(Abid et al., 2022)	Kalman-based beamforming has been considered	The bit error rate aspect not addressed.
A Kalman Based Hybrid Precoding for Multi-User Millimeter Wave MIMO Systems(Vizziello et al., 2018)	For performance analysis, they looked at multi-cell millimeter wave systems	Energy efficiency analysis not addressed
Hybrid Precoding for Massive mmWave MIMO Systems(Liu et al., 2019)	Reduce the complexity	As we do in this research, Linear precoding was not considered
Precoding and Beamforming Techniques in mmWave-Massive MIMO (Kebede et al., 2022)	The energy efficiency of hybrid precoding was examined	As we do in this research, RLS Kalman was not considered
Deep-Learning-based Millimeter-Wave Massive MIMO for Hybrid Precoding(S. Huang et al., 2020)	Contributing to lowering computational complexity	Linear precoding was not considered

CHAPTER THREE

3. METHODOLOGY

3.1 Introduction

In this thesis, different related papers and articles are reviewed from various journals such as IEEE, Springer and Elsevier and also the books that are related to Hybrid Precoding in mmWave Massive MIMO System are highlighted. Researchers applied their own proposed techniques to obtain high performance and reduced bit error rate channel estimation methods in hybrid precoding mmWave massive MIMO systems. Depending on the reviewed papers the methodology of this study is illustrated as follows, based on inputs obtained through a review of related literature, a problem statement, and bearing in mind the problem of existing Precoding algorithms.

3.2 Materials

Software materials used in this thesis are MATLAB R2018a, Concept Draw Office, and MathType 6.9 equation editor is utilized. MATLAB R2018a, which is a computing software that consists of Editor, which is used to write a code for entire system. Concept Draw DIAGRAM is drawing software that includes ready-to-use templates, a professional set of drawing tools, a range of custom printing and file export options and a large object library. Math Type 6.9, is an integrated writing environment. It is writing tool which is recommended to write mathematical equations.

3.3 Method of the Study

3.3.1 System Design

- Analyzing the Mathematical Model for various Precoding algorithm in order to calculate the spectral efficiency.
- Analyzing the Mathematical Model for various Precoding algorithm in order to calculate the energy efficiency.
- Evaluate the Mathematical Model for various Precoding algorithm in order to calculate the bit error rate.

3.3.2 Simulation Methods

- Perform the Spectral efficiency versus SNR simulation to compare the Proposed RLS Kalman based Hybrid precoding with other precoding algorithm.
- Perform Performance Comparison of the Proposed RLS Kalman based Hybrid

precoding with other precoding algorithm interms of Spectral efficiency versus Number of Users.

- Perform the Spectral efficiency versus Number of Base station antenna simulation to compare the Proposed RLS Kalman based Hybrid precoding with other precoding algorithm.
- Perform Performance Comparison of the Proposed RLS Kalman based Hybrid precoding with other precoding algorithm interms of Spectral efficiency versus Number of Mobile station antenna.
- Compare the Proposed RLS Kalman based Hybrid precoding Performance to that of other precoding algorithm based on Energy efficiency versus SNR.
- Perform a BER versus SNR simulation to compare the proposed precoding algorithm performance to that of other precoding algorithms.

The procedure used throughout this thesis study can be summarized in Figure 3.1, which shows the workflow of whole Simulation of Energy, Spectral efficiency and bit error rate Result.

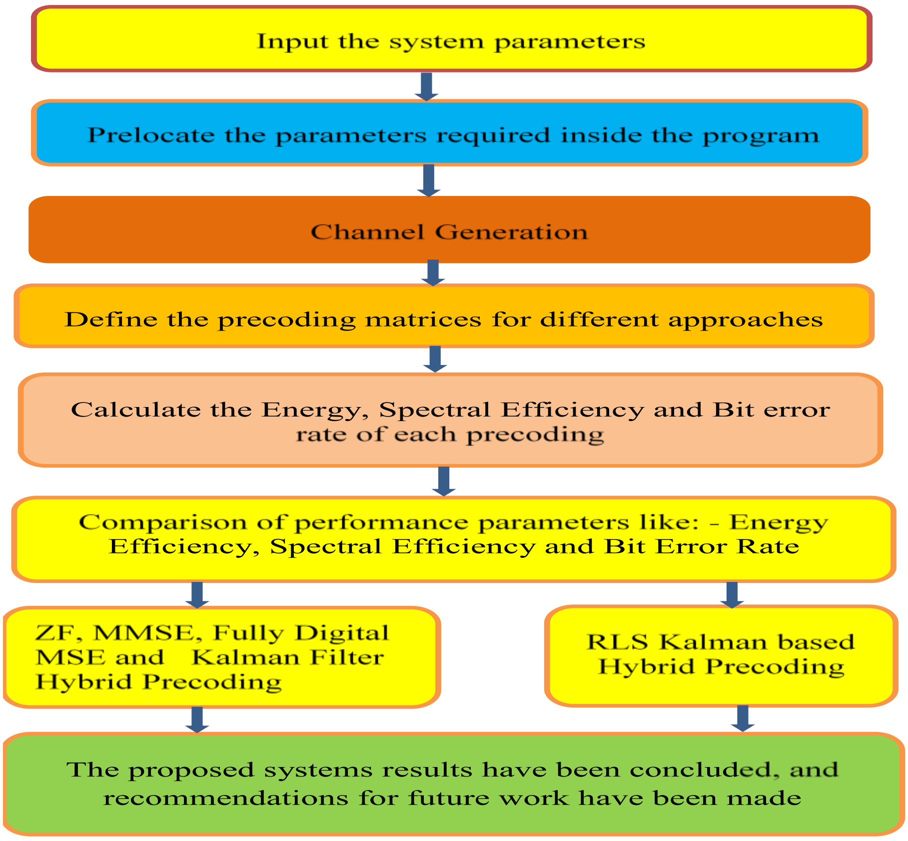

Figure 3.1: Flow chart for Simulation of Spectral, Energy efficiency and Bit error rate

3.4 Adaptive Filter Algorithm

Adaptive filter algorithms can be used in hybrid precoding to adjust the beamforming weights and optimize the system's performance. The goal of hybrid precoding is to maximize the signal-to-noise ratio (SNR) at the receiver while minimizing the number of RF chains required. However, finding the optimal beamforming weights is a complex optimization problem, especially in massive MIMO systems with a large number of antennas. An adaptive filter algorithm, such as Normalized Least Mean Squares (NLMS) and Recursive Least Squares (RLS) algorithm, can be used to estimate the optimal beamforming weights by adjusting the filter coefficients.

3.4.1 Normalized Least Mean Squares Algorithm

The Normalized LMS (NLMS) algorithm is a variation of the Least Mean Squares (LMS) algorithm used in adaptive filtering. The NLMS algorithm updates the coefficients of an adaptive filter by using the following equation(Martinek et al., 2018):

$$W(\mathrm{k}+1) = W(\mathrm{k}) + \mu e(\mathrm{k})\frac{\mathrm{x}(\mathrm{k})}{\|\mathrm{x}(\mathrm{k})\|^2} \tag{3.1}$$

Where W(k) is the filter coefficient vector, x(k) is the input filter vector, μ is the step size of the adaptive filter that satisfies the condition $0 < \mu < 2$. The convergence rate of the adaptive filter can be improved by adjusting the filter step size, which is a crucial parameter.

The error of Normalized LMS (NLMS) algorithm is given by the following equation:

$$e(\mathrm{k}) = \mathrm{d}(\mathrm{k}) - \mathrm{y}(\mathrm{k}) \tag{3.2}$$

Where $d(k)$ is the desired signal and $y(k)$ indicates the existing output of the adaptive filter.

3.4.2 Recursive Least Squares Algorithm

The Recursive Least Squares (RLS) algorithm is an adaptive filtering algorithm that estimates the filter coefficients by minimizing the sum of the squared errors between the predicted output and the actual output. The algorithm updates its filter coefficients recursively based on the current input and output signals(Martinek et al., 2018).

$$W(\mathrm{k}+1) = W^T(\mathrm{k}) + G(\mathrm{k})e(\mathrm{k}) \tag{3.3}$$

Where G(k) is a gain vector, and e(k) is the error

The gain of Recursive Least Squares Algorithm can be calculated as:

$$\mathrm{G}(\mathrm{k}) = \frac{\mathrm{P}(\mathrm{k})\,\mathrm{x}(\mathrm{k})}{\lambda + \mathrm{x}^T(\mathrm{k})P(\mathrm{k})\,\mathrm{x}(\mathrm{k})} \tag{3.4}$$

Where P(k) is the inverse correlation matrix, λ is the forgetting factor should be selected as one. Otherwise, it should be less than one.

The error e(k) of Recursive Least Squares Algorithm can be calculated as:

$$e(\mathrm{k}) = \mathrm{d}(\mathrm{k}) - \mathrm{y}(\mathrm{k}) \tag{3.5}$$

Where d(k) is the desired signal and y(k) is the output signal

The output signal of the adaptive filter is calculated as follows using the RLS algorithm:

$$\mathrm{y}(\mathrm{k}) = \mathrm{W}^{T}(\mathrm{k}-1)\,\mathrm{x}(\mathrm{k}) \tag{3.6}$$

Where x(k) is the input filter vector, $\mathrm{W}^{T}(\mathrm{k}-1)$ are the transpose of filter coefficients at time k-1

3.5 System model and Mathematical Formulation

3.5.1 System Model

We list the notations used throughout the work below for simplicity of explanation: A is a matrix, $\|A\|_F$ is the Frobenius norm of A, whereas A^{-1}, A^{H}, A^{T} are its inverse, Hermitian and transpose respectively. E[·] is used to denote expectation. N (m, R) is a complex Gaussian random vector with mean m and covariance R and I is the identity matrix (Fabiana Meijon Fadul, 2019).

Compared to fully digital methods, hybrid solutions may use a less Radio Frequency chains than antennas number, which reduces the energy consumption and the complexity of signal processing of Radio Frequency chains. The network structure is a Millimeter Wave based massive MIMO cellular system where the base station transmits number of data streams N_s through number of BS antenna N_{BS} and number of Radio Frequency chains N_{RF} for serving M mobile stations, each with N_{MS} antennas and one Radio Frequency chain, with $N_s < N_{RF} < N_{BS}$. We make the assumption that the MS has a simplified configuration with just one RF chain. This assumption makes sense considering how essential low cost, power consumption and complexity requirements are for user device implementation. In contrast, the BS might be equipped with more advanced Digital Signal Processing capabilities to enable many parallel data streams. The BS communicates with every single MS via a single stream, making the total number of streams equal to M (N_s = M). The maximum number of users M that the BS serve concurrently is equal to the number of RF chains at the BS, or M ≤ N_{RF}. It should be noted that the hybrid scheme, which permits multi-user Massive MIMO and spatial multiplexing, makes this architectural assumption achievable. This allows the Base Station can communicate with numerous MS simultaneously using various beams.

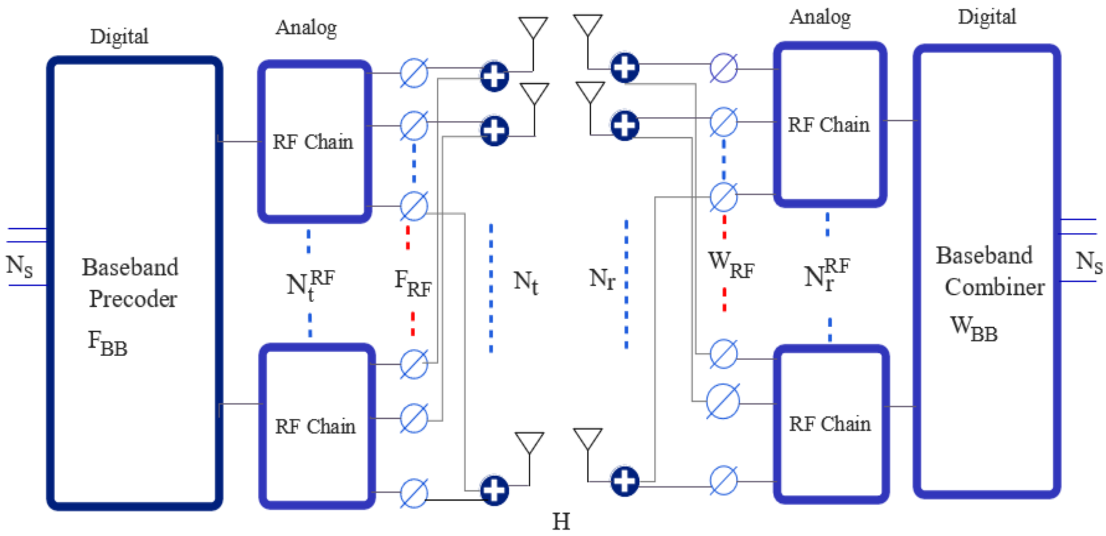

Figure 3.2: mmWave Hybrid Beamforming System (Thurpati & Muthuchidambaranathan, 2022)

The base station transmits a synchronization message at the downlink utilizing baseband precoder F_{BB} with size N_{RF} × N_s and analog precoder F_{RF} with size N_{BS} × N_s so that the sampled transmitted signal in (Vizziello et al., 2018) is:

$$x = F_{RF} F_{BB} s \tag{3.7}$$

where s is the N_s × 1 transmitted symbol vector

Thus, the received signal at MS-m is:

$$r_m = H_m F_{RF} F_{BB} s + n_m \tag{3.8}$$

where H_m is the $N_{MS} \times N_{BS}$ matrix of the mmWave channel between the BS and the MS-m, and n_m ~ N (0, σ^2 I) is the Gaussian noise vector. The received signal r_m in (3.8) can be rewritten showing the desired contribution and the interference as follows:

$$r_m = H_m F_{RF} F_{BBm} s_m + H_m \sum_{j \neq m}^{M} F_{RF} F_{BBj} s_j + n_m \tag{3.9}$$

where F_{RF} F_{BBm} is the BS precoding vector for MS-m, F_{BBm} is the column m of the matrix F_{BB} and s_j is the j^{th} element of s.

Since the MS employ only RF analog combining $w_{RFm} = w_m$, after the combining process, the estimated symbol of the MS-m can be expressed as:

$$\hat{s} = w_m^H H_m F_{RF} F_{BB} s + w_m^H n_m \tag{3.10}$$

The estimated signal $\hat{s}$ in (3.10) can be written showing the desired contribution and the interference ones:

$$\hat{s} = w_m^H H_m F_{RF} F_{BBm} s_m + w_m^H H_m \sum_{j \neq m}^{M} F_{RF} F_{BBj} s_j + w_m^H n_m \tag{3.11}$$

The signal model on the uplink is comparable to that in (3.10), but the task of the precoders and combiners changes. Hence, we replace H_m with H_m^T, where $(.)^T$ represents the transpose.

3.5.2 Millimeter Wave Channel Model

It is anticipated that scattering will be minimal in millimeter-wave channels. Each scatterer in mmWave is anticipated to add a single propagation path between the transmission and reception. An extended Saleh-Valenzuela model is frequently employed when modeling mmWave channels. Due to its low spatial selectivity and high antenna correlation, this model is utilized in our research(Kebede et al., 2022). The use of a geometric channel model with L_k scatters is applied for the channel of the k^{th} user. In this model, the *k-th* user channel matrix $H_k \in \mathbb{C}^{N_r \times N_t}$ can be expressed as

$$H_k = \sqrt{\frac{N_t N_r}{L_k}} \sum_{l=1}^{L_k} \alpha_{k,l} \alpha_{k,r}\left(\theta_{k,l}\right) \alpha_{k,t}^H\left(\phi_{k,l}\right) \tag{3.12}$$

where $\alpha_{k,l}$ is the complex gain of the l^{th} path including the path loss between the BS and the MS-m, with $E[|\alpha_{k,l}|^2] = \beta$ (normalization constant). The variables $\theta_{k,l}$ and $\phi_{k,l} \in [0, 2\pi]$ are the l-th path's angles of arrival and departure (AoAs/AoDs) respectively. $\alpha_{k,t}(\phi_{k,l})$ and $\alpha_{k,r}(\theta_{k,l})$ are the antenna array response vectors at the BS and MS-m, respectively.

If uniform linear arrays (ULA) are assumed at BS and MSs, $\alpha_{k,t}(\phi_{k,l})$ can be expressed as:

$$\alpha_{k,t}(\phi_{k,l}) = \frac{1}{\sqrt{N}}\left[1, \exp^{j\frac{2\pi}{\lambda} d \sin(\phi_l)}, \ldots\ldots, \exp^{j(N_t - 1)\frac{2\pi}{\lambda} d \sin(\phi_l)}\right]^T \tag{3.13}$$

On the other hand, the receiver's array response vectors is

$$\alpha_{k,r}(\phi_{k,l}) = \frac{1}{\sqrt{N}}\left[1, \exp^{j\frac{2\pi}{\lambda}d(x\sin(\phi)\sin(\theta)+y\cos(\theta))}, \ldots\ldots \times \exp^{j\frac{\pi}{\lambda}d(W_1-1)\sin(\phi)\sin(\theta)+(W_2-1)\cos(\theta))}\right]^T \quad (3.14)$$

where λ denotes the wavelength, d is the spacing between two antennas commonly, $d = \frac{\lambda}{2}$

ϕ = azimuth angle, θ =elevation angle and N = antenna elements number.

3.5.3 Zero Forcing Precoding schemes

ZF precoding prevents interference by transmitting signals in the direction of the desired user and nulls in the direction of other users. The ZF precoder is given:

$$F^{ZF} = H^{+} \quad (3.15)$$

Where $H^{+} = H^{H}(HH^{H})^{-1}$ is the pseudo inverse of the channel matrix H.

The instantaneous per stream SE_k is well known to be expressed as follows(Israr et al., 2017):

$$SE_k = \log 2(1 + SINR_k) \quad (3.16)$$

given the fact that the instantaneous Signal to Interference and Noise Ratio (SINR) for UT k in case ZF Hybrid beamforming is applied, is expressed as follows:

$$SINR_k^{ZF} = \frac{\beta}{\left\| f_k^{ZF} \right\|^2} \quad (3.17)$$

where β is the transmit Signal to Noise Ratio (SNR). According to (3.11), $\left\| f_k^{ZF} \right\|^2$ can be represented as:

$$\| f_k^{ZF} \|^2 = ((HH^{H})^{-1})_{(k,k)} \quad (3.18)$$

substituting Equation (3.12) in (3.11), then $\left\| SINR_k^{ZF} \right\|$ is expressed as

$$SINR_k^{ZF} = \frac{\beta}{((HH^{H})^{-1})_{k,k}} \quad (3.19)$$

3.5.4 Minimum Mean Square Error Precoding scheme

In MMSE pre-coding, signal power efficiency and interference reduction can be matched. The following describe the ideal MMSE pre-coder:

$$W_{MMSE} = H^{H}(HH^{H} + \alpha I)^{-1} \quad (3.20)$$

Where $\alpha = K/p$ is the regularization factor to be optimized.

Minimum mean squared error hybrid precoder is trying to minimize the sum MSE off data streams $E\left\|s-\hat{s}\right\|^2$ it is simple to obtain by an orthogonal matching pursuit algorithm explained in this section. The γ as a power scaling factor and unnormalized baseband precoder V_{BB} such that $F_{BB}=\sqrt{1/\gamma}V_{BB}$. Considering $V=F_{RF}V_{BB}$, the sum MSE equation can be expressed as (Thesis & Yll, 2020):

$$E\left\|s-\hat{s}\right\|^2=\left\|I-HF_{RF}V_{BB}\right\|_F^2+K\gamma\sigma^2 \tag{3.21}$$

The following optimization will get the hybrid precoder that minimizes this sum MSE.

$$\begin{aligned}&\underset{F_{RF},F_{BB},\gamma}{minimize}\ Tr\left\{\left(I-HF_{RF}V_{BB}\right)\left(I-HF_{RF}V_{BB}\right)^H\right\}+K\gamma\sigma^2\\&Subject\ to\left\|F_{RF}F_{BB}\right\|^2=Ns\end{aligned} \tag{3.22}$$

This problem is nonconvex due the multiplication of the variables F_{RF} and V_{BB}. For a known F_{RF}, the optimal baseband precoder F_{BB} can be obtained. The optimal solution to V_{BB} can be estimated as:

$$V_{BB}^*=H^HF_{RF}^H(HF_{RF}H^HF_{RF}^H+\frac{K\sigma^2}{Ns}F_{RF}^HF_{RF})^{-1} \tag{3.23}$$

Finally the optimal baseband digital precoder $F_{BB}=\sqrt{1/\gamma*}V_{BB}^*$ where $\gamma^*=\left\|F_{RF}V_{BB}\right\|_F^2/Ns$

3.5.5 MSE Fully Digital Precoding

Maximizing the received signal quality and reducing interference between the transmitted signals of various users are the primary goals of MSE fully digital precoding. A separate radio-frequency chain is needed for each antenna. The current state of technology makes it impractical for many antennas to implement a fully digital precoder because of the high power requirements. However, because of its considerable flexibility, this fully digital precoder delivers better performance.

Imagine γ is a power gain factor such that $F_{BB}=\sqrt{1/\gamma}V_{BB}$ satisfies the power constrain $\left\|F_{BB}F_{BB}^H\right\|^2=Ns$ and V_{BB} as unnormalized digital precoder. Assuming that the MS applies a simple equalizer by multiplying the power scaling factor $\sqrt{\gamma}$ with each baseband signal. From the following optimization, the MSE fully digital precoder can be obtained(Thesis & Yll, 2020).

$$\begin{aligned}&\underset{F_{BB},\gamma}{minimize}\ E\|s-\hat{s}\|_F^2\\&Subject\ to\left\|V_{BB}V_{BB}^H\right\|^2=\gamma Ns\end{aligned} \tag{3.24}$$

This optimization is convex, so the optimal MMSE digital precoder can be obtained with a standard optimization technique.

$$V_{BB}^{*} = H^{H}(HH^{H} + \frac{K\sigma^{2}}{Ns} I)^{-1} \tag{3.25}$$

Finally the optimal baseband digital precoder $F_{BB_F D} = \sqrt{1/\gamma *} V_{BB}^{*}$ where $\gamma * = \|V_{BB}\|_F^2 / Ns$

3.5.6 Kalman based Hybrid Beamforming

Kalman filter is a signal processing method applied to wireless communications to enhance data transfer through several antennas. In order to respond to changes in the wireless channel and optimize the precoding matrix, Kalman hybrid precoding uses the Kalman filter to estimate the channel state information (CSI). As a result, the wireless communication system may operate better and have higher transmission rates with fewer interference. The baseband precoding matrix $V_{BB}(\mathrm{k}\,|\,\mathrm{k})$ can be used to describe the Kalman filter state.

The Kalman state equation can be calculated at the k^{th} iteration as follows:

$$V_{BB}(\mathrm{k}\,|\,\mathrm{k}) = V_{BB}(\mathrm{k}-1\,|\,\mathrm{k}-1) + G(\mathrm{k})E\{diag[err(\mathrm{k})]\} \tag{3.26}$$

Where G(k) is the Kalman gains, $diag[err(\mathrm{k})]$ is the matrix representation of $err(\mathrm{k})$ and $E\{diag[err(\mathrm{k})]\}$ is represent the mean of error.

For the k^{th} iteration of the Kalman filter the error err(k) can be expressed as:

$$err(k) = \frac{s(k) - \hat{s}(k)}{\| s(k) - \hat{s}(k) \|_F^2} \tag{3.27}$$

The mean of error $err(\mathrm{k})$ which can be calculated as follows:

$$E[diag\left[err(k)\right] = \frac{I - H\, V_{BB}(\mathrm{k}-1\,|\,\mathrm{k}-1)}{\| I - H\, V_{BB}(\mathrm{k}-1\,|\,\mathrm{k}-1) \|_F^2} \tag{3.28}$$

Where H is the equivalent channel and G(k) is the Kalman gain.

The Kalman state matrix V_{BB} at iteration *k*, given as follows:

$$\begin{aligned} &V_{BB}(\mathrm{k}\,|\,\mathrm{k}) = V_{BB}(k-1\,|\,k-1) + G(k)\frac{I - H\, V_{BB}(\mathrm{k}-1\,|\,\mathrm{k}-1)}{\| I - H\, V_{BB}(\mathrm{k}-1\,|\,\mathrm{k}-1) \|_F^2} \\ &\mathrm{G(k)} = R(\mathrm{k}-1\,|\,\mathrm{k}-1)H^{H}[H\ R(\mathrm{k}-1\,|\,\mathrm{k}-1)H^{H} + Q_n]^{-1} \\ &\mathrm{R(k\,|\,k)} = [I - G(\mathrm{k})H\ ]\mathrm{R(k}-1\,|\,\mathrm{k}-1) \end{aligned} \tag{3.29}$$

Where $V_{BB}(\mathrm{k}\,|\,\mathrm{k})$ is Kalman baseband matrix at time step k, $V_{BB}(\mathrm{k}-1\,|\,\mathrm{k}-1)$ is the predicted Kalman precoding baseband matrix at time k-1, $\mathrm{R(k\,|\,k)}$ is the variance at time step k, Q_n is the covariance matrix of the noise that can be expressed as $Q_n = (1/SNR)*I$ and H is the equivalent channel.

The limitation of Kalman hybrid precoding is that it is sensitive to noise in the system, which can affect the accuracy of the channel state information and degrade system performance.

3.5.7 NLMS Kalman based Hybrid Beamforming

Normalized Least Mean Squares (NLMS) Kalman filter hybrid precoding is a technique used in wireless communication systems to optimize the transmission of data over multiple antennas in a multi-user scenario. It combines the NLMS algorithm, which is a popular adaptive filtering technique, with the Kalman filter, which is an optimal estimator, to achieve efficient and adaptive precoding for wireless transmissions. The base band precoding matrix NLMS Kalman hybrid precoding can be calculated as:

$$W_{BB}(\mathrm{k}|\mathrm{k}) = W_{BB}(\mathrm{k}-1|\mathrm{k}-1) + \mu G(k) E\{diag[e(\mathrm{k})]\} \frac{N_s}{\| N_s \|^2} \tag{3.30}$$

Where $W_{BB}(\mathrm{k}|\mathrm{k})$ is NLMS Kalman base band precoding matrix at time step k, μ is the time varying step size, N_s is the input data streams and G(k) is the NLMS Kalman gain.

For the k^{th} iteration of the NLMS Kalman filter the error e(k) can be expressed as:

$$e(k) = \frac{s(k) - \hat{s}(k)}{\| s(k) - \hat{s}(k) \|_F^2} \tag{3.31}$$

The mean of error $e(\mathrm{k})$ which can be calculated as follows:

$$E[diag[e(k)]] = \frac{I - H_e W_{BB}(\mathrm{k}-1|\mathrm{k}-1)}{\| I - H_e W_{BB}(\mathrm{k}-1|\mathrm{k}-1) \|_F^2} \tag{3.32}$$

$$\begin{aligned} W_{BB}(\mathrm{k}|\mathrm{k}) &= W_{BB}(k-1|k-1) + \mu G(k) \frac{I - H_e W_{BB}(\mathrm{k}-1|\mathrm{k}-1)}{\| I - H_e W_{BB}(\mathrm{k}-1|\mathrm{k}-1) \|_F^2} \left(\frac{N_s}{\| N_s \|^2} \right) \\ \mathrm{G(k)} &= R(\mathrm{k}-1|\mathrm{k}-1) H_e^H [H_e R(\mathrm{k}-1|\mathrm{k}-1) H_e^H + Q_n]^{-1} \\ \mathrm{R(k|k)} &= [I - G(\mathrm{k}) H_e] \mathrm{R(k-1|k-1)} \end{aligned} \tag{3.33}$$

Where $W_{BB}(\mathrm{k}|\mathrm{k})$ is NLMS Kalman baseband matrix at time step k, $W_{BB}(\mathrm{k}-1|\mathrm{k}-1)$ is the predicted NLMS Kalman precoding baseband matrix at time k-1, $\mathrm{R(k|k)}$ is the variance at time step k, Q_n is the covariance matrix of the noise that can be expressed as $Q_n = (1/SNR)*I$ and H_e is the equivalent channel.

NLMS Kalman Hybrid precoding may be limited in its flexibility to adapt to changing channel conditions.

3.5.8 Proposed RLS Kalman based Hybrid Beamforming

Recursive Least Squares (RLS) is a more advanced adaptive filtering algorithm that estimates the filter coefficients using a recursive method based on minimizing the error signal in a least-squares sense. Proposed RLS Kalman hybrid architecture involves first processing N_s data stream and then applying RLS Kalman hybrid precoding for estimate of channel state information for each users with the baseband signal processing and Analog Precoding in the analog stage through the number of RF chain $N_{RFchain}$. The RF chains are typically connected to the outputs of the analog precoding block and are responsible for transmitting the analog Precoded signals over the air. The analog Precoded signals from the RF chains are fed to the N_t antennas for transmission, and the received signals from the antennas are combined and fed to the RF chains for reception. Finally, the baseband combiner is to combine the output signals from the RF chains and generate the final output signal. The number of transmitter antennas is much higher than the number of RF chains. This approach uses less RF chains compared to the number of antennas, this simplifying implementation complexity and cost. A mmWave massive MIMO system model is presented with a transmitter or BS with N_t antennas, N_{RF}^t an RF chain for transmitting N_s data streams simultaneously, and a receiver or MS with N_r antennas and N_{RF}^r RF chains.

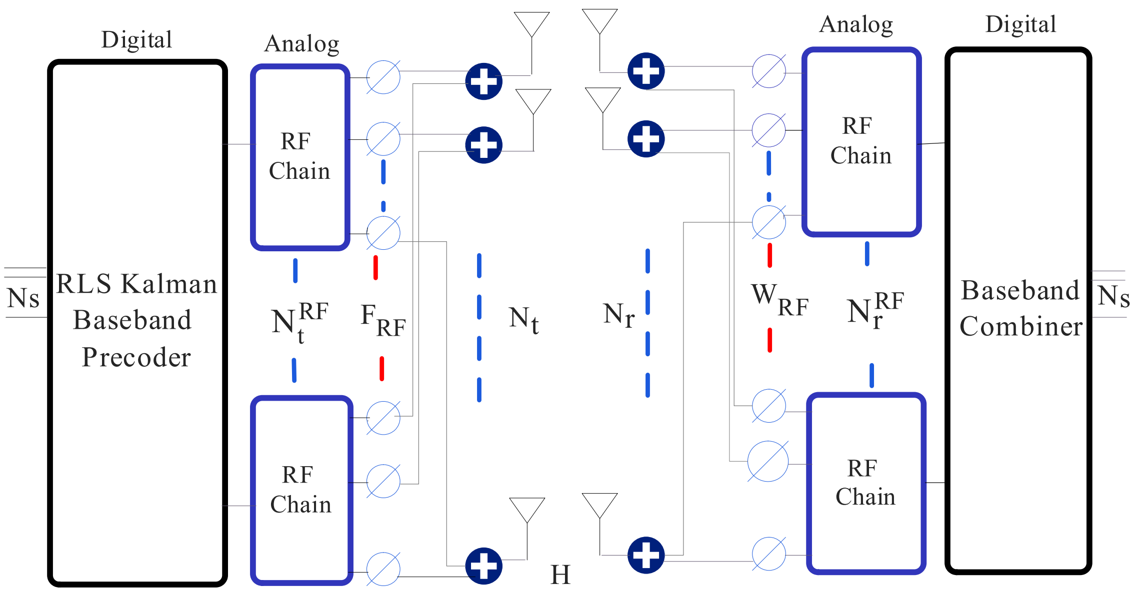

Figure 3.3: Proposed RLS Kalman Hybrid precoding in mmWave Massive MIMO system

The hybrid precoding solution based on RLS Kalman analysis is discussed in this section.

The preamble message s is sent by the base station (BS), and the estimated signal at the receiver is sent as $\hat{s} = [\hat{s}_1, \ldots, \hat{s}_M]^T$, where s(k) is the training vector at iteration k. The mean squared error of the training vector between the transmitted signal s and the predicted signal $\hat{s}$ is reduced by the RLS Kalman filter technique $E\| s-\hat{s} \|^2$.

$$\begin{aligned} &\underset{F_{RF},\mathrm{F}_{BB}}{minimize}\ E\| s-\hat{s} \|^2 \\ &Subject\ to \left\| F_{RF}F_{BB} \right\|^2 = N_S \end{aligned} \tag{3.34}$$

knowing that $\hat{s} = [\hat{s}_1, \ldots, \hat{s}_M]$ at the MS the observation vector can be defined at the k iteration as $\hat{s}_m(\mathrm{k}) = (w_m^H H_m F_{RF} F_{BB}) s(\mathrm{k}) + n_m(\mathrm{k})$ the minimization problem can be expressed as:

$$\begin{aligned} &\underset{F_{RF},\mathrm{F}_{BB}}{minimize}\ E\| I - H_e F_{BB}(\mathrm{k}\,|\,\mathrm{k}-1) \|_F^2 \\ &Subject\ to \left\| F_{RF}F_{BB} \right\|^2 = N_S \end{aligned} \tag{3.35}$$

The baseband precoding matrix F_{BB} is the term we use to describe the RLS Kalman filter state. RLS Kalman State recommended equation is as follows:

$$F_{BB}(\mathrm{k}\,|\,\mathrm{k}) = \beta F_{BB}^T(\mathrm{k}-1\,|\,\mathrm{k}-1) + G(k)E\{diag[e(k)]\} \tag{3.36}$$

The value of the power normalization parameter β in adaptive filters is typically in the range of 0 to 1.

The error e(k) during the k-th RLS Kalman iteration is therefore expressed as:

$$e(k) = \frac{s(k) - \hat{s}(k)}{\| s(k) - \hat{s}(k) \|_F^2} \tag{3.37}$$

where diag $s(k) - \hat{s}(k)$ is the error's matrix representation, G(k) is the RLS Kalman gains, and the effective channel is represented by H_e , so that

$$E[diag\left[e(k)\right] = \frac{I - H_e F_{BB}(\mathrm{k}-1\,|\,\mathrm{k}-1)}{\| I - H_e F_{BB}(\mathrm{k}-1\,|\,\mathrm{k}-1) \|_F^2} \tag{3.38}$$

$$\begin{aligned} &F_{BB}(\mathrm{k}\,|\,\mathrm{k}) = \beta F_{BB}^T(\mathrm{k}-1\,|\,\mathrm{k}-1) + G(k)\frac{I - H_e F_{BB}(\mathrm{k}-1\,|\,\mathrm{k}-1)}{\| I - H_e F_{BB}(\mathrm{k}-1\,|\,\mathrm{k}-1) \|_F^2} \\ &\mathrm{G(k)} = R(\mathrm{k}-1\,|\,\mathrm{k}-1)H_e^H[H_e R(\mathrm{k}-1\,|\,\mathrm{k}-1)H_e^H + Q_n]^{-1} \\ &\mathrm{R(k\,|\,k)} = [I - G(\mathrm{k})H_e]\mathrm{R(k-1\,|\,k-1)} \end{aligned} \tag{3.39}$$

Where $F_{BB}(\mathrm{k}\,|\,\mathrm{k})$ is RLS Kalman baseband matrix at time step k, $F_{BB}(\mathrm{k}-1\,|\,\mathrm{k}-1)$ is the predicted RLS Kalman precoding baseband matrix at time k-1, based on the previous estimate of the state of the system, $\mathrm{R}(\mathrm{k}|\mathrm{k})$ is the variance at time step k, β is the power normalization parameter, Q_n is the covariance matrix of the noise n(n) that can be expressed as $Q_n = (1/SNR)*I$ and H_e is the equivalent channel.

Algorithm for Proposed RLS Kalman Hybrid Precoding

1. Input: BS RF codebook $\mathcal{F}$, MS RF codebook $\mathcal{W}$
2. Output: F_{BB}, F_{RF} and w_m $\forall_m =$ 1,....,M
3. Step 1- RF Analog Design: define F_{RF} and w_m $\forall_m$ such that
4. BS and MS-m choose v_m, g_m $\forall_m$ so that
5. g_m, v_m = arg max $\left\| g_m^H H_m v_m \right\|$ $\forall g_m \in w, \forall v_m \in F$
6. BS define $F_{RF} = [\mathrm{v}_1, ..., \mathrm{v}_M]$ and MS-m define $w_m =$ $\mathrm{g}_m \forall m$
7. Step 2- Baseband Digital Design: define F_{BB}
8. MS-m estimates h_m^H = $\mathrm{w}_m^H H_m F_{RF}$ where h_m^H has dimension $M \times 1$ and quantizes h_m using a codebook $\mathcal{H}$ $\forall m$
9. MS-m calculate and sends to BS $\hat{h}_m$ $\forall$m where
10. $\hat{h}_m$ = $\underset{\hat{h}_m \in H}{\arg\max}$ $\left\| h_m^H \hat{h}_m \right\|$
11. BS sets $H_e = \hat{H} = [\hat{h}_1, ..., \hat{h}_M]^H$
12. At BS: for $k \le ITER$ calculate
13. $e(k) = \dfrac{s(k) - \hat{s}(k)}{\| s(k) - \hat{s}(k) \|_F^2}$ where $s(k) - \hat{s}(k)$ $= I - H_e F_{BB}(\mathrm{k}-1|\mathrm{k}-1)$
14. Define RLS algorithm: $W(\mathrm{k}+1) = W^T(\mathrm{k}) + G(\mathrm{k}) e(\mathrm{k})$ where $W^T(k)$ is transpose of filter coefficient vector
15. optimize Kalman hybrid precoding by RLS algorithm by mapping kalman hybrid precoding with RLS algorithm
16. $F_{BB}(\mathrm{k}|\mathrm{k}) = \beta F_{BB}^T(\mathrm{k}-1|\mathrm{k}-1) + G(k) e(k)$
17. $\mathrm{G(k)} = R(\mathrm{k}-1|\mathrm{k}-1) H_e^H [H_e R(\mathrm{k}-1|\mathrm{k}-1) H_e^H + Q_n]^{-1}$
18. $\mathrm{R}(\mathrm{k}|\mathrm{k}) = [I - G(\mathrm{k}) H_e] \mathrm{R}(\mathrm{k}-1|\mathrm{k}-1)$
19. $Q_n = (1/SNR)*I$
20. end

3.6 Performance Metrics of Precoding Algorithm

The performance of Precoding techniques in Millimeter Wave massive MIMO systems can be measured using metrics such as Energy efficiency, Spectral efficiency and bit error rate.

3.6.1 Spectral Efficiency

Spectral efficiency is a measure of amount of data that can be transmitted over a communication channel per unit of bandwidth. It is typically expressed in bit per second per hertz(bps/Hz). The system's spectral efficiency will increase with increased signal power. On the other hand, as signal power rises, the system's power consumption also rises, dramatically reducing the system's energy efficiency.

$$\mu_{SE} = \frac{R}{B} \tag{3.40}$$

We define R as achievable sum rate and B is the transmission bandwidth

3.6.2 Energy Efficiency

Energy efficiency measures how effectively a system uses energy to carry out a specific operation or function. Energy efficiency is an important performance parameter in the context of wireless communication systems because it shows how well the system can transfer data while using minimizing energy consumption.

$$\mu_{EE} = \frac{B\mu_{SE}}{P_T} \tag{3.41}$$

We define P_T as the receiver power consumption, μ_{SE} is a spectral efficiency, μ_{EE} is a energy efficiency and B is a transmission bandwidth

3.6.3 Signal to Noise Ratio (SNR)

The signal to noise ratio in a digital communication system is the ratio of signal power in a symbol P_s to its noise power p_w. signal to noise ratio is a measure of the strength of the desired signal in comparison to undesired signal.

$$SNR = \frac{p_s}{p_w} \tag{3.42}$$

Where p_s is signal power and p_w is noise power

3.6.4 Bit Error Rate (BER)

In a wireless communication system, the bit error rate is the ratio of the number of incorrectly received bits to the total number of bits transmitted in a given time period. BER is a crucial factor For evaluating the effectiveness of different precoding techniques.

$$BER = \frac{No.\text{ of bit in error}}{Total\text{ No. of transmitted bits}} \tag{3.43}$$

CHAPTER FOUR

RESULT AND DISCUSSION

In this chapter, the simulation result of different specific objectives is presented. The simulation results and discussion on the performance of proposed precoding and other precoding in the millimeter wave massive MIMO system are presented. The comparison is based on performance parameters like:- Energy efficiency, Spectral efficiency, and Bit error rate. The simulation parameters used to analyze the effectiveness of the suggested precoding algorithm with other precoding algorithms in mmWave massive MIMO system are listed below.

Table 4.1: Value of different parameters

Parameters	Values
SNR(Range)	-10 to 20dB
SNR(When fixed)	20dB
Range of BS antenna (When varied)	4 to 256
Number of BS antenna (When fixed)	64
Number of MS antenna (When varied)	4 to 256
Number of Propagation Path	L=4,8,12
Number of Iteration	500
Number of Users (When fixed)	4
Range of Users(When varied)	2 to 14
Number of RF chain	4

4.1 Spectral Efficiency Comparison

Spectral efficiency is one of the performance indicators in mmWave massive MIMO System, it measures the amount of data that can be transmitted over a given amount of spectrum. For performance comparison, the input parameters used for simulations are 64 transmitter antenna N_{Tx}, 4 Number of users,4 data streams N_s and 10 Number of channel paths are considered.

4.1.1 Spectral Efficiency Comparison of the Proposed Precoding with the Existing Precoding by Varying SNR

Figure 4.1 compares the Spectral Efficiency of the Proposed Algorithm with Other Precoding Algorithms for 64 transmitter antenna N_{Tx}, 4 Number of users and 4 data streams N_s in multi-path scenario (L=10) at SNR= [-10,8]dB. The Proposed RLS Kalman Hybrid Precoding achieved a Spectral Efficiency of 7.411 bps/Hz at SNR=8dB, Whereas MSE Fully digital, NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding achieved a Spectral Efficiency of 7.031 bps/Hz, 5.491 bps/Hz, 4.66 bps/Hz, 4.519 bps/Hz, and 3.64 bps/Hz at the same SNR=8dB respectively. From the below figure, we conclude that the Proposed RLS Kalman Hybrid Precoding Improved the Spectral efficiency by 0.38 bps/Hz at 8 dB with 10 channel paths with respect to MSE Fully digital Hybrid Precoding, and almost 1.92 bps/Hz, 2.751 bps/Hz, 2.892 bps/Hz and 3.771 bps/Hz with respect to the NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding respectively under the same conditions.

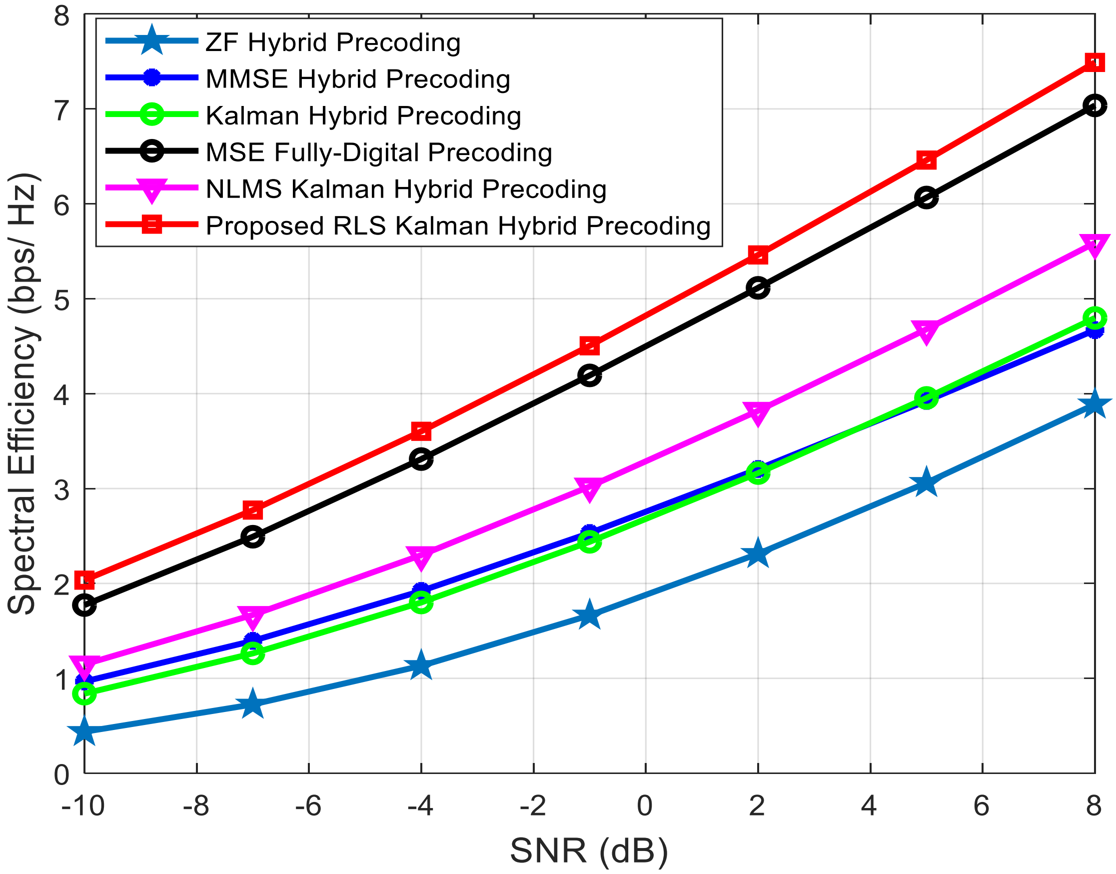

Figure 4.1: Spectral efficiency varying SNR in the range SNR =[-10, 8]dB in multi-path scenario (L=10) with 64 transmitter antenna and 4 users

Figure 4.2 and Figure 4.3 depicts the Spectral efficiency versus signal-to-noise ratio of different precoding techniques for 64 transmitter antenna N_{Tx}, 4 Number of users and 4 data streams N_s in multi-path scenario (L=10) and the same Precoding algorithm is used as Previous Figure. In Figure 4.2 SNR in the range [-10,14]dB, the proposed Precoding algorithm obtained Spectral Efficiency=9.651 bps/Hz at SNR=14dB Where as ZF, MMSE, Kalman, NLMS Kalman and MSE Fully digital hybrid Precoding achieved Spectral Efficiency of 5.714 bps/Hz, 6.246 bps/Hz, 6.66 bps/Hz, 7.612 bps/Hz and 9.043 bps/Hz at the same SNR=14dB respectively. The Proposed RLS Kalman Hybrid Precoding Improved the Spectral efficiency by 3.937 bps/Hz at 14 dB with 10 channel paths with respect to ZF digital Hybrid Precoding and almost 3.405 bps/Hz, 2.991 bps/Hz, 2.039 bps/Hz and 0.608 bps/Hz with respect to the MMSE, Kalman, NLMS Kalman, and MSE Fully digital hybrid Precoding respectively under the same conditions. In Figure 4.3 SNR in the range [-10,20]dB, the proposed algorithm attained Spectral Efficiency=11.6 bps/Hz at SNR=20dB Where as ZF, MMSE, Kalman, NLMS Kalman and MSE Fully digital hybrid Precoding achieved Spectral Efficiency of 7.495 bps/Hz, 7.842 bps/Hz, 8.441 bps/Hz, 9.493 bps/Hz and 11.03 bps/Hz at the same SNR=20dB respectively. The Proposed RLS Kalman Hybrid Precoding improved the Spectral efficiency by 4.105 bps/Hz at 20 dB with 10 channel paths with respect to ZF Hybrid Precoding and almost 3.758 bps/Hz, 3.159 bps/Hz, 2.107 bps/Hz, and 0.57 bps/Hz with respect to the MMSE, Kalman, NLMS Kalman, and MSE Fully digital hybrid Precoding respectively under the same conditions. From the results, it can be concluded that as the signal-to-noise ratio increases the performance of spectral efficiency also increase. In Figure 4.2 and Figure 4.3, the spectral efficiency performance of RLS Kalman Hybrid precoding outperforms all other precoding algorithms.

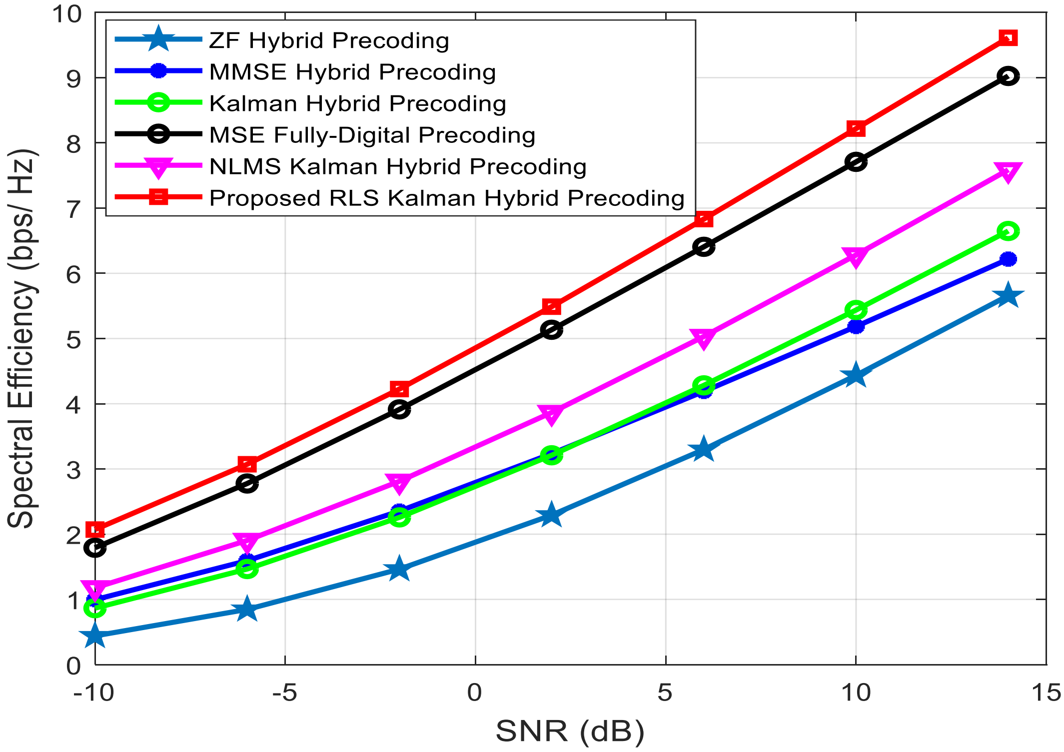

Figure 4.2: Spectral efficiency varying SNR in the range SNR =[-10,14]dB in multi-path scenario (L=10) with 64 transmitter antenna and 4 users

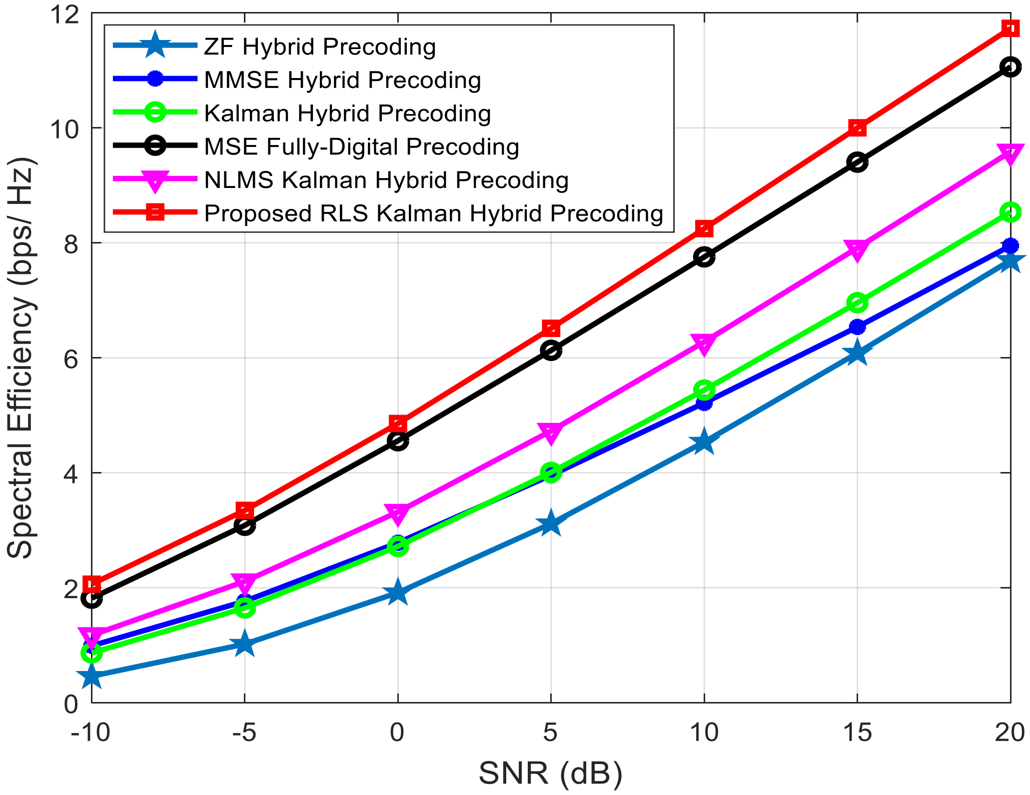

Figure 4.3: Spectral efficiency varying SNR in the range SNR =[-10,20]dB in multi-path scenario (L=10) with 64 transmitter antenna and 4 users

Table 4.2 shows the performance comparison of proposed precoding and existing precoding techniques for the 64 transmitter antenna N_{Tx}, 4 Number of users and 4 data streams N_s in multi-path scenario (L=10) at SNR= -10dB to 20dB. As we observed from the table the performance of the proposed precoding is better than all other precoding. The table below indicates the tabular representation of Figure 4.3 by considering some values of SNR.

Table 4.2: Data collection of spectral efficiency by varying SNR

SNR (dB)	Spectral efficiency(bps/Hz)					
	ZF	MMSE	Kalman	NLMS Kalman	MSE Fully digital	Proposed
-5	0.9562	1.742	1.614	2.079	3.061	3.3
5	2.985	3.947	3.947	4.663	6.101	6.407
10	4.376	5.15	5.366	6.196	7.725	8.124
15	5.9	6.452	6.876	7.821	9.373	9.869
20	7.495	7.842	8.441	9.493	11.03	11.6

4.1.2 Spectral Efficiency Comparison of the Proposed Precoding with the Existing Precoding by Varying Number of Channel Paths

Spectral efficiency comparison is a performance metric to evaluate the performance of different precoding algorithms in communication systems. Figure 4.4, Figure 4.5, and Figure 4.6 illustrate the performance comparison of Spectral efficiency versus SNR by varying the number of channel paths (L=4,8,12). In Figure 4.4 the Proposed RLS Kalman Hybrid precoding with 64 base station antennas and 4 channel path performance is better than ZF, MMSE, Kalman, NLMS Kalman, and MSE fully-digital Hybrid precoding. The outcomes depict that the spectral efficiency of ZF, MMSE, Kalman, NLMS Kalman, MSE fully-digital, and RLS Kalman hybrid precoding at SNR of 20dB can be 9.21bps/Hz, 9.213bps/Hz, 9.581 bps/Hz, 10.44 bps/Hz, 11.08 bps/Hz and 12.29 bps/Hz. The Proposed RLS Kalman Hybrid Precoding Improved the Spectral efficiency by 3.08 bps/Hz at 20 dB with 4 channel paths with respect to ZF Hybrid Precoding and almost 3.077 bps/Hz, 2.709 bps/Hz, 1.85 bps/Hz and 1.21 bps/Hz with respect to the MMSE, Kalman, NLMS Kalman, and MSE Fully digital Hybrid Precoding respectively under the same conditions.

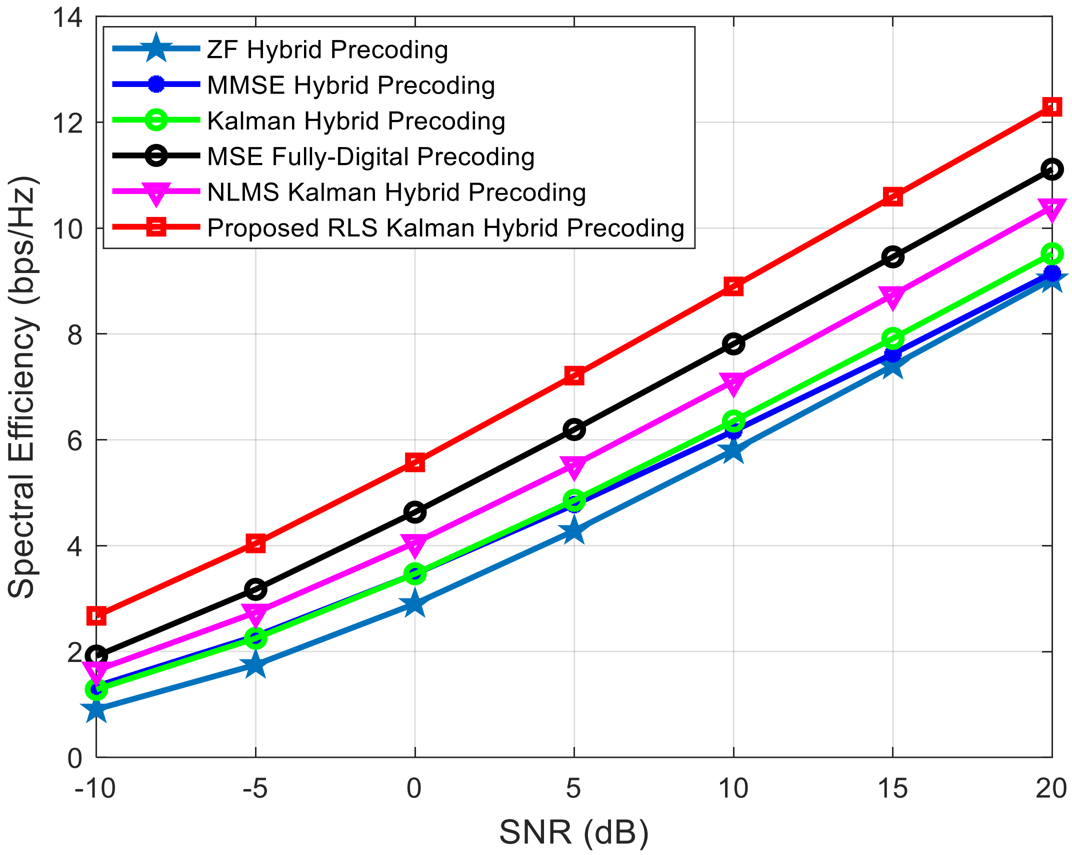

Figure 4.4: Spectral efficiency varying number of channel paths(4 paths scenario)

In Figure 4.5 the Proposed RLS Kalman Hybrid precoding with 64 base station antennas and 8 channel path performance is better than ZF, MMSE, Kalman, NLMS Kalman, and MSE fully-digital Hybrid precoding. The outcomes depict that the spectral efficiency of ZF, MMSE, Kalman, NLMS Kalman, MSE fully-digital, and RLS Kalman Hybrid precoding at SNR of 20dB can be 7.986 bps/Hz, 8.225 bps/Hz, 8.795 bps/Hz, 9.777 bps/Hz, 11.07 bps/Hz and 11.85 bps/Hz respectively. The Proposed RLS Kalman Hybrid Precoding Improved the Spectral efficiency by 3.864 bps/Hz at 20 dB with 8 channel paths with respect to ZF Hybrid Precoding and almost 3.625 bps/Hz, 3.055 bps/Hz, 2.073 bps/Hz and 0.78 bps/Hz with respect to the MMSE, Kalman, NLMS Kalman, MSE fully-digital Hybrid Precoding respectively under the same conditions.

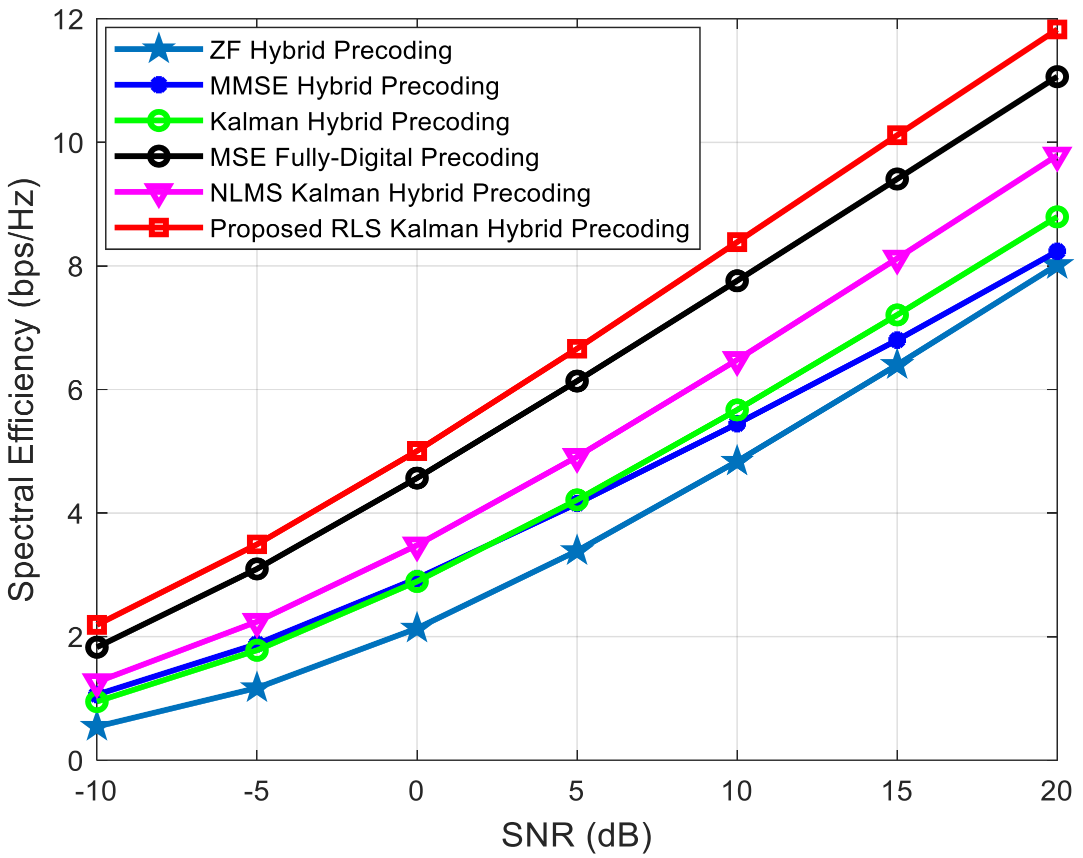

Figure 4.5: Spectral efficiency varying number of channel paths (8 paths scenario)

In Figure 4.6 for RLS Kalman Hybrid precoding with 64 base station antennas and 12 channel path performance is better than ZF, MMSE, Kalman, and NLMS Kalman. MSE fully-digital Hybrid precoding is very close to RLS Kalman Hybrid precoding. The results show that the spectral efficiency of ZF, MMSE, Kalman, NLMS Kalman, MSE fully-digital, and RLS Kalman Hybrid precoding at SNR of 20dB can be 7.244 bps/Hz, 7.57 bps/Hz, 8.264 bps/Hz, 9.377 bps/Hz, 10.99 bps/Hz and 11.55 bps/Hz respectively. The Proposed RLS Kalman Hybrid Precoding Improved the Spectral efficiency by 4.306 bps/Hz at 20 dB with 12 channel paths with respect to ZF Hybrid Precoding and almost 3.98 bps/Hz, 3.286 bps/Hz, 2.173 bps/Hz, and 0.56 bps/Hz with respect to the MMSE, Kalman, NLMS Kalman and MSE Fully digital Hybrid Precoding respectively under the same conditions.

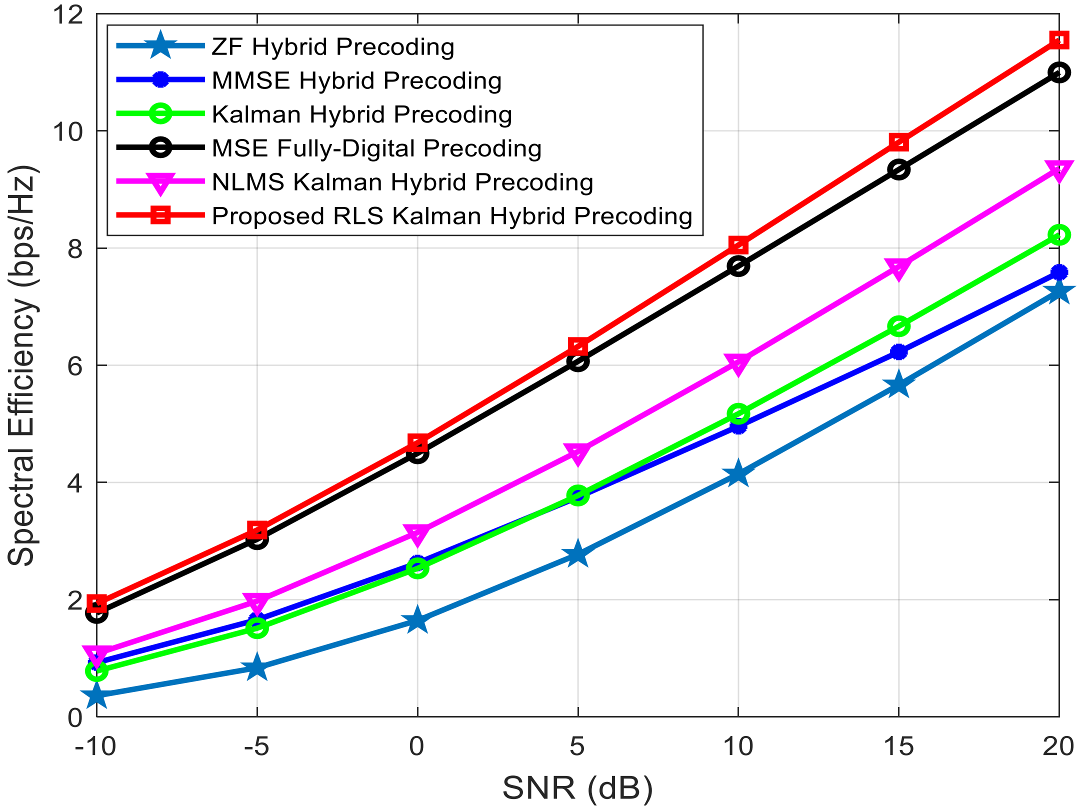

Figure 4.6: Spectral efficiency varying number of channel paths (12 paths scenario)

Figure 4.4, Figure 4.5, and Figure 4.6 illustrate the Spectral efficiency versus Signal to noise ratio by varying the Number of channel paths of different Precoding algorithms. From the result, it can be concluded that as the number of channel path increase the Spectral efficiency performance decrease and vice versa. And also as Signal to noise ratio increases the Spectral efficiency performance increase. From Figure 4.4, Figure 4.5, and Figure 4.6 the Spectral efficiency performance of RLS Kalman Hybrid Precoding outperforms all other Precoding.

4.1.3 Spectral Efficiency Comparison of the Proposed Precoding with the Existing Precoding by Varying Numbers of Users

Figure 4.7 demonstrate the Spectral efficiency versus the Number of users of different precoding techniques for 64 transmitter antenna N_{Tx}, 4 Number of users and 4 data streams N_s in multi-path scenario (L=10) for a fixed SNR = 20dB. The simulation results in Figure 4.8 shows the performance of all precoding decrease as the number of users increases. When the numbers of users increase, the interference also increases in the mmWave massive MIMO System, which results in a reduction in spectral efficiency. From Figure 4.7 the MSE Fully digital Hybrid precoding is quite near to the Proposed RLS Kalman Hybrid precoding and superior to NLMS Kalman, Kalman, MMSE, and ZF Hybrid precoding. The results depict that the spectral efficiency of RLS Kalman, MSE fully-digital, NLMS Kalman, Kalman, MMSE, and ZF hybrid precoding for 2 users at SNR of 20dB can be 8.996 bps/Hz, 8.924 bps/Hz, 8.143 bps/Hz, 8.235 bps/Hz, 8.068 bps/Hz and 6.854 bps/Hz respectively. And also from Figure 4.7, all precoding with 14 users performance shows a significant reduction as compared to 2 users. The results show that the spectral efficiency of RLS Kalman, MSE fully-digital, NLMS Kalman, Kalman, MMSE, and ZF Hybrid precoding for 14 users at SNR of 20dB can be 4.551 bps/Hz, 4.393 bps/Hz, 3.93 bps/Hz, 3.33 bps/Hz, 2.83 bps/Hz, and 2.587 bps/Hz respectively. From the figure, we conclude that the Spectral efficiency decrease as the number of users increases.

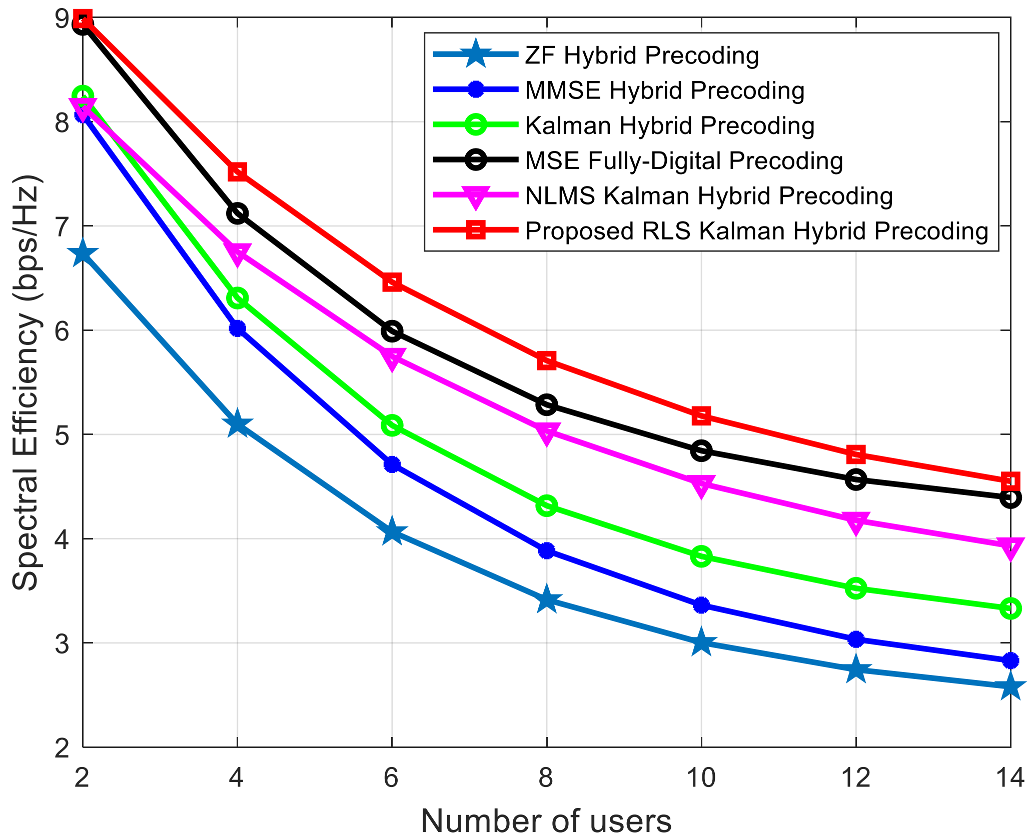

Figure 4.7: Spectral efficiency varying number of users with SNR=20dB

Table 4.3 indicates the performance comparison of RLS Kalman Hybrid precoding and other precoding for fixed SNR=20dB, 64 transmitter antennas N_{Tx}, 4 Number of users and 4 data streams N_s in multi-path scenario (L=10). As we observed from the table, the proposed precoding achieved better spectral efficiency performance. ZF Hybrid precoding performs poor spectral efficiency performance compared to other precoding as indicated in the below table. From the below table, we conclude that the Proposed RLS Kalman Hybrid Precoding improves the Spectral efficiency by 0.158 bps/Hz at 20 dB with 10 channel paths and 14 users concerning MSE Fully digital Hybrid Precoding and almost 0.621 bps/Hz, 1.221 bps/Hz, 1.721 bps/Hz, and 1.964 bps/Hz concerning the NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding respectively under the same conditions. The table below indicates the tabular representation of Figure 4.7 by considering some value of a number of users.

Table 4.3: Data collection on the system performance by the effect of varying number of users

Number of Users	Spectral efficiency(bps/Hz)					
	ZF	MMSE	Kalman	NLMS Kalman	MSE Fully digital	Proposed
2	6.854	8.068	8.235	8.143	8.924	8.996
4	5.173	6.018	6.302	6.749	7.114	7.522
8	3.44	3.885	4.314	5.032	5.282	5.709
10	3.022	3.363	3.829	4.528	4.842	5.178
14	2.587	2.83	3.33	3.93	4.393	4.551

4.1.4 Spectral Efficiency Comparison of the Proposed Precoding with the Existing Precoding by Varying the Number of BS antennas

The number of transmitter antennas has an impact on its spectral efficiency. As more antennas are used, the spectral efficiency increases. Figure 4.8 demonstrates the Spectral efficiency Performance by varying the number of Transmitter antenna in a multi-path scenario (L = 10) for a fixed SNR = 20dB. This simulation takes into account a situation with 64 receiver antennas, 4 users, and a fixed SNR of 20 dB. As the transmitter antenna number increases, it is known that the spectral efficiency in this instance shows a logarithmic pattern. As the number of transmitter antennas increases, the spectral efficiency of the Proposed RLS Kalman Hybrid precoder and existing hybrid precoders is increase. The results show that the spectral efficiency of RLS Kalman, MSE fully-digital, NLMS Kalman, Kalman, MMSE, and ZF Hybrid precoding for 256 BS antenna at SNR of 20dB can be 13.3624 bps/Hz, 12.7716 bps/Hz, 12.3459 bps/Hz, 11.8012bps/Hz, 11.2724 bps/Hz and 10.8327 bps/Hz respectively. From the below figure, we conclude that the Proposed RLS Kalman Hybrid Precoding Improved the Spectral efficiency by 0.5908 bps/Hz at 20 dB with 10 channel paths and 256 BS antenna concerning MSE fully-digital Hybrid Precoding and almost 1.0165 bps/Hz, 1.5612 bps/Hz, 2.09 bps/Hz and 2.5297 bps/Hz concerning the NLMS Kalman, Kalman, MMSE and ZF Hybrid precoding respectively under the same conditions. In Figure 4.8 the Proposed Precoding outperforms all other precoding techniques.

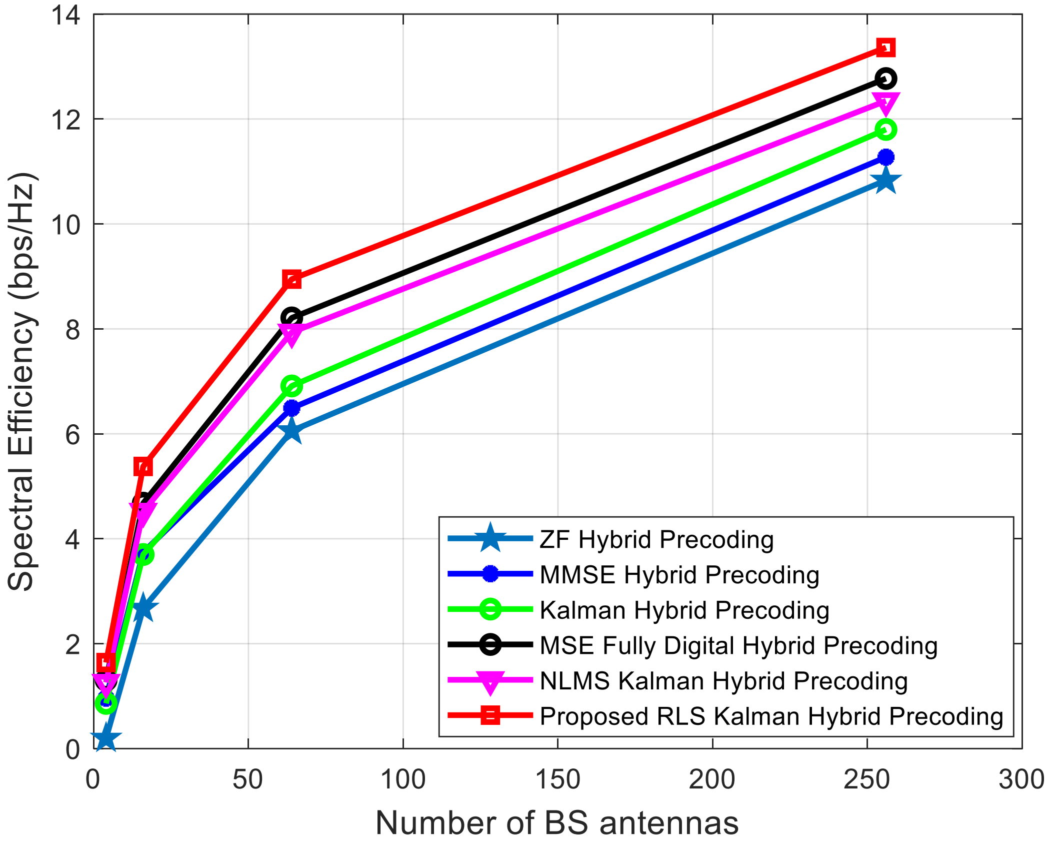

Figure 4.8: Spectral efficiency versus the Number of BS antenna , with Number of MS antenna=64, fixed SNR=20dB

Table 4.4 depicts the Spectral efficiency performance comparison of proposed precoding and other precoding for fixed SNR=20dB, 64 receiver antennaN_{Rx}, 4 Number of users and 4 data streams N_s in multi-path scenario (L=10). As indicated in the below table, the proposed precoding outperformed all other precoding. The table below indicates the tabular representation of Figure 4.8 by considering the number of Base station antenna.

Table 4.4: Data collection on the system performance by varying numbers of BS antennas

Number of BS antenna	Spectral efficiency(bps/Hz)					
	ZF	MMSE	Kalman	NLMS Kalman	MSE Fully digital	Proposed
4	0.1965	0.9607	0.8621	1.2602	1.3037	1.6397
16	2.6745	3.7408	3.6994	4.5218	4.6777	5.3779
64	6.0573	6.4895	6.9119	7.9354	8.2090	8.9478
256	10.8327	11.2724	11.8012	12.3459	12.7716	13.3624

4.1.5 Spectral Efficiency Comparison of the Proposed Precoding with the Existing Precoding by Varying Numbers of MS antennas

The number of receiver antennas has an impact on its spectral efficiency. As the number of antennas increases, the spectral efficiency also increases. Figure 4.9 demonstrates the Spectral efficiency Performance by varying the number of Receiver antenna in a multi-path scenario (L = 10) for a fixed SNR = 20dB. This simulation takes into account a situation with 64 transmitter antennas, 4 users, and a fixed SNR of 20 dB. As the receiver antenna number increases, it is known that the spectral efficiency in this instance shows a logarithmic behavior. The spectral efficiency of the proposed RLS Kalman-based hybrid precoder and the existing hybrid precoders increases with increasing the number of receiver antennas. The outcomes demonstrate that the spectral efficiency of RLS Kalman, MSE fully-digital, NLMS Kalman, Kalman, MMSE, and ZF Hybrid precoding for 256 MS antenna at SNR of 20 dB can be 10.8793 bps/Hz, 10.5028 bps/Hz, 10.3609 bps/Hz, 10.3151 bps/Hz 10.0067 bps/Hz and 9.7617 bps/Hz respectively. The Proposed RLS Kalman Hybrid Precoding Improves the Spectral efficiency by 0.3765 bps/Hz at 20 dB with 10 channel paths and 256 MS antenna concerning MSE Fully digital Hybrid Precoding and almost 0.5184 bps/Hz, 0.5642 bps/Hz, 0.8726 bps/Hz and 1.1176 bps/Hz concerning the NLMS Kalman, Kalman, MMSE and ZF Hybrid precoding respectively under the same conditions. In Figure 4.9 RLS Kalman-based Hybrid precoder outperforms all other precoding techniques.

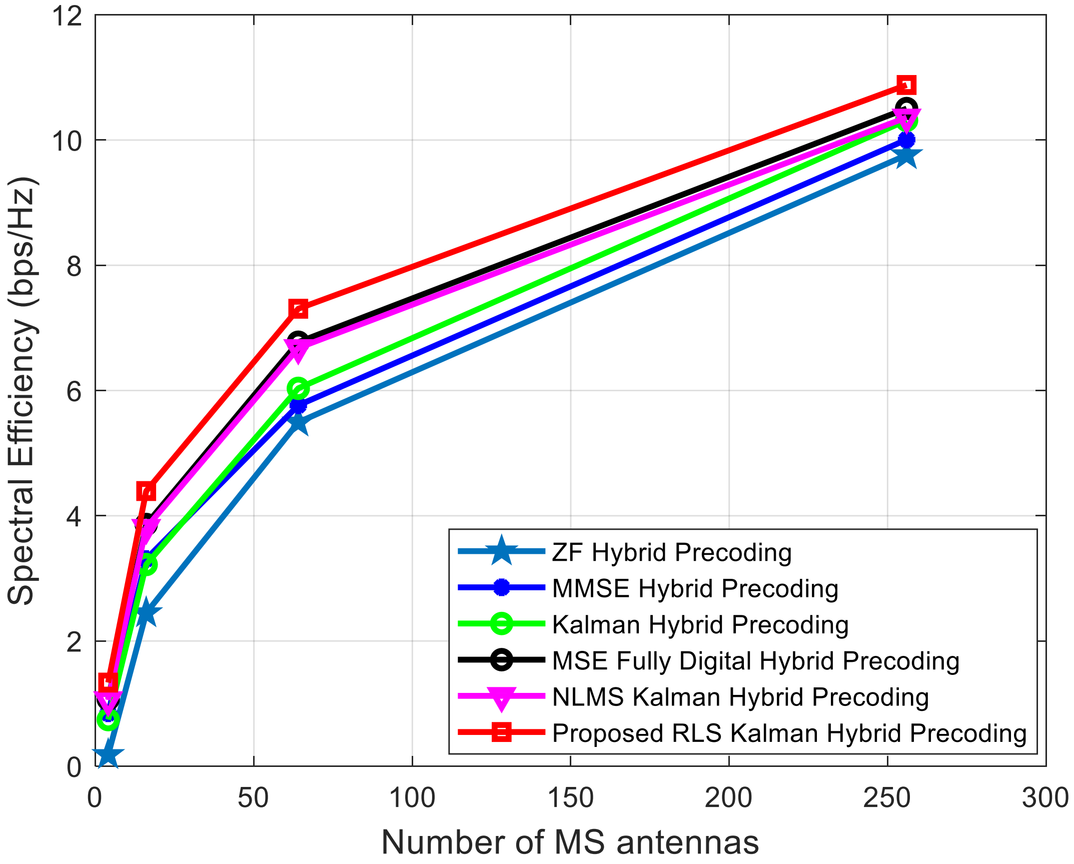

Figure 4.9: Spectral efficiency versus the Number of MS antenna , with Number of BS antenna=64, fixed SNR=20dB

Generally, in comparison to the number of transmitter antennas, the simulation indicates that the number of receiver antennas enables all precoding in approaching the behavior of the RLS Kalman Hybrid precoder.

Table 4.5 shows the performance comparison of the proposed precoding with other precoding for fixed SNR=20dB, 64 transmitter antennaN_{Tx}, 4 Number of users and 4 data streams N_s in multi-path scenario (L=10) based on Spectral efficiency. The table below indicates the tabular representation of Figure 4.9 by considering the number of Mobile station antenna. Generally, from the below table, the proposed precoding achieved the best Spectral efficiency performance compared to all other precoding.

Table 4.5: Data collection on the system performance by varying numbers of MS antennas

Number of MS antenna	Spectral efficiency(bps/Hz)					
	ZF	MMSE	Kalman	NLMS Kalman	MSE Fully digital	Proposed
4	0.1827	0.8452	0.7448	1.0570	1.0715	1.3357
16	2.4471	3.3091	3.2221	3.8085	3.8606	4.3948
64	5.4929	5.7633	6.0349	6.6799	6.7714	7.3061
256	9.7617	10.0067	10.3151	10.3609	10.5028	10.8793

4.2 Energy Efficiency Comparison

To evaluate the performance of mmWave massive MIMO Hybrid precoding, the simulations presented below are based on the Energy efficiency versus signal-to-noise ratio. The spectral efficiency, fixed bandwidth, and power are used to calculate the Energy Efficiency. The performance is shown below in terms of Energy efficiency versus signal-to-noise ratio by varying the signal-to-noise range and the number of channel paths.

4.2.1 Energy Efficiency Comparison of the Proposed Precoding with the Existing Precoding by Varying SNR

Figure 4.10 shows the Performance Comparison of the Proposed Algorithm Energy Efficiency with other Precoding Algorithm for transmitter antenna 64, receiver antenna 16, 4 number of users in multi-path scenario (L= 10), and Signal to noise ratio in the range [-10,8]. The Proposed algorithm attained an Energy Efficiency of 37.7297 Mbit/joule at SNR=8dB, While MSE Fully digital, NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding achieved an Energy Efficiency of 35.3803 Mbit/joule, 28.3912 Mbit/joule, 24.3721 Mbit/joule, 23.5371 Mbit/joule and 19.7609 Mbit/joule at SNR=8dB respectively. From the below figure, we conclude that the Proposed RLS Kalman Hybrid Precoding Improved the Energy efficiency by 2.3494 Mbit/joule at 8 dB with 10 channel paths concerning MSE Fully digital Hybrid Precoding and almost 9.3385 Mbit/joule, 13.3576 Mbit/joule, 14.1926 Mbit/joule, and 17.9688 Mbit/joule concerning the NLMS Kalman, Kalman, MMSE and ZF Hybrid Precoding respectively under the same conditions. The Zero forcing (ZF) Hybrid Precoding performs poorly performance. The figure below shows that the proposed precoding outperforms all other precoding in terms of Energy efficiency.

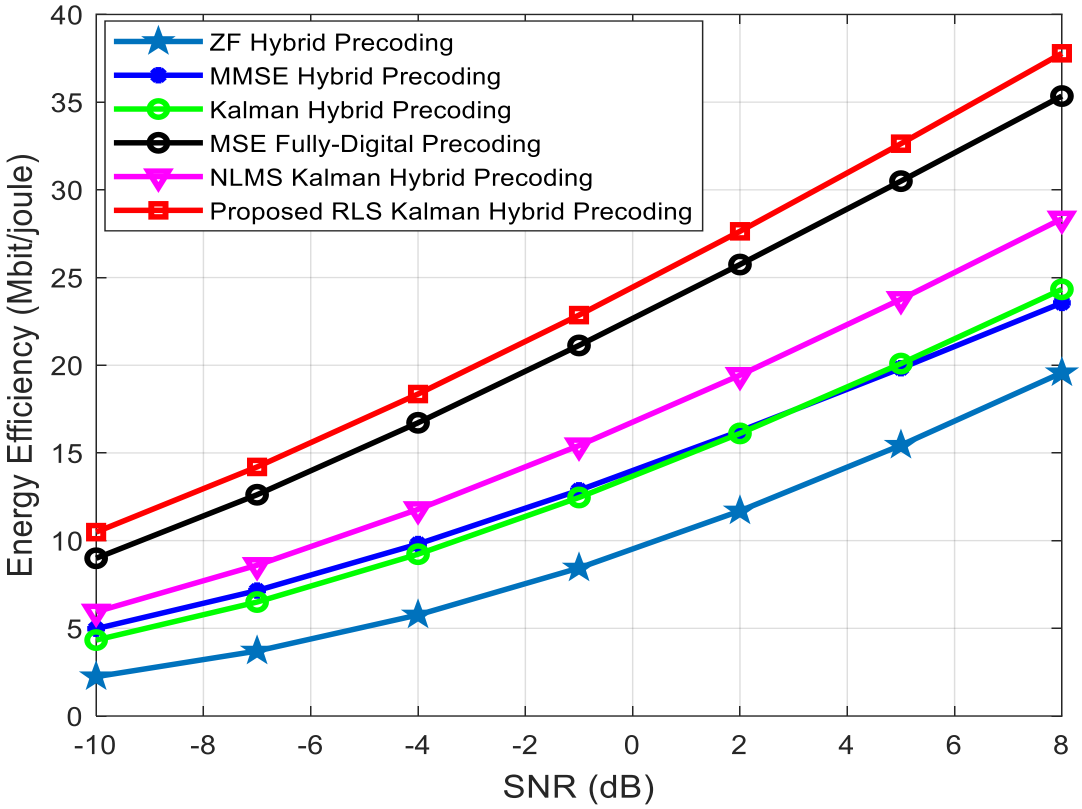

Figure 4.10: Energy efficiency varying SNR in multi-path scenario (L=10) in the SNR range=[-10,8]dB with 64 transmitter antenna and 4 users

Figure 4.11 and Figure 4.12 depicts the Performance Comparison of the Proposed Algorithm Energy Efficiency with other Precoding Algorithm for transmitter antenna 64, receiver antenna 16, and 4 users in a multi-path scenario (L= 10). The simulation results presented below are obtained by changing the range of SNR from [-10,14]dB to [-10,20]dB. Figure 4.11 compares the efficiency of the suggested precoding algorithm to other precoding algorithms for Signal to noise ratio in the range [-10,14]dB, the Proposed RLS Kalman-based Hybrid Precoding achieved an Energy Efficiency of 48.1934 Mbit/joule at SNR=14dB, Whereas MSE Fully digital, NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding achieved an Energy Efficiency of 45.1877 Mbit/joule, 37.8573 Mbit/joule, 33.2199 Mbit/joule, 31.2184 Mbit/joule and 28.3491 Mbit/joule at the same SNR=14dB respectively. The Proposed RLS Kalman Hybrid Precoding Improved the Spectral efficiency by 3.0057 Mbit/joule at 14 dB with 10 channel paths concerning ZF Hybrid Precoding and almost 10.3361 Mbit/joule, 14.9735 Mbit/joule, 16.975 Mbit/joule and 19.8443 Mbit/joule concerning the MMSE, Kalman, NLMS Kalman and MSE Fully digital Hybrid Precoding respectively under the same conditions.

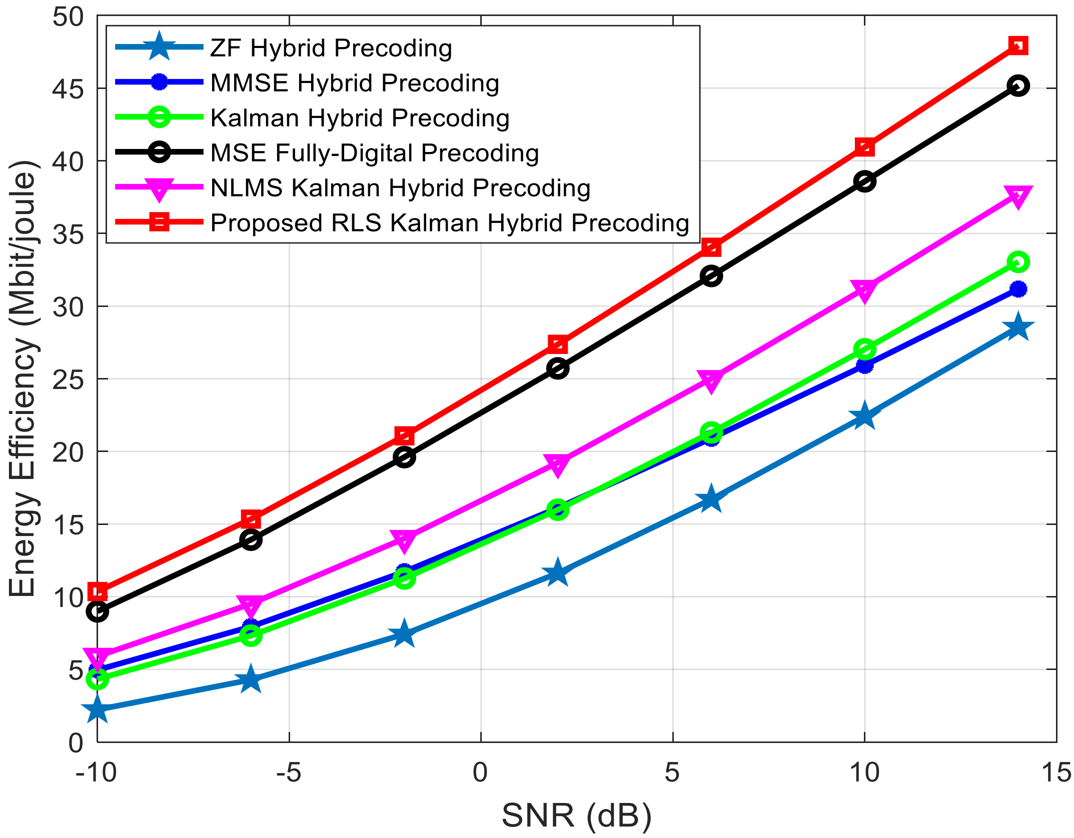

Figure 4.11: Energy efficiency varying SNR in multi-path scenario (L=10) in the SNR range=[-10,14]dB with 64 transmitter antenna and 4 Number of users

Figure 4.12 compares the efficiency of the proposed precoding algorithm to other precoding algorithms for Signal to noise ratio in the range [-10,20], the Proposed RLS Kalman-based Hybrid Precoding achieved an Energy Efficiency of 58.0168 Mbit/joule at SNR=20dB, Whereas MSE Fully digital, NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding achieved an Energy Efficiency of 55.1497 Mbit/joule, 47.4659 Mbit/joule, 42.2028 Mbit/joule, 39.2087 Mbit/joule, and 37.4752 Mbit/joule at the same SNR=20dB respectively. The Proposed RLS Kalman Hybrid Precoding Improved the Spectral efficiency by 2.8671 Mbit/joule at 20 dB with 10 channel paths concerning MSE Fully digital Hybrid Precoding and almost 10.5509 Mbit/joule, 15.814 Mbit/joule, 18.8081 Mbit/joule, and 20.5416 Mbit/joule concerning the NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding respectively under the same conditions. As shown in Figure 4.12 below, the proposed precoding Outperformed all other precoding.

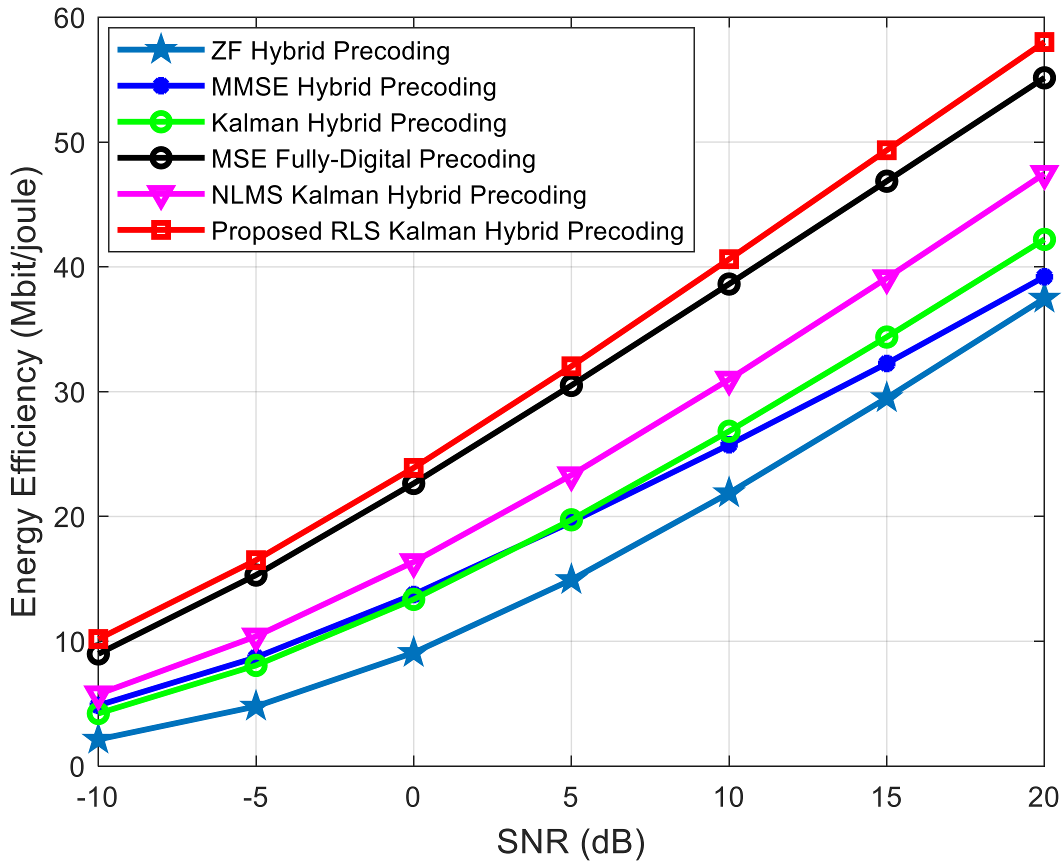

Figure 4.12: Energy efficiency varying SNR in multi-path scenario (L=10) in the SNR range=[-10,20]dB with 64 transmitter antenna and 4 Number of users

From the above two figures Zero forcing (ZF) Hybrid Precoding showed poor Energy efficiency performance as compared to other precoding. MSE Fully digital hybrid precoding showed better performance as compared to NLMS Kalman, Kalman Filter, MMSE, and ZF Hybrid Precoding but less performance as compared to the proposed precoding. Generally, as the signal-to-noise ratio increases the performance of all precoding Energy efficiency also increases.

Table 4.6 compares the proposed precoding algorithm performance to that of other precoding algorithms at SNR= -5dB to 20dB, 64 transmitter antenna N_{Tx}, 4 Number of users and 4 data streams N_s in multi-path scenario (L=10) based on Energy efficiency. The table below indicates the tabular representation of Figure 4.16 by considering some values of SNR. As shown in the below table, Compared to existing precoding, the proposed precoding has the highest energy efficiency performance.

Table 4.6: Data collection of energy efficiency by varying SNR

SNR (dB)	Energy Efficiency(Mbit/joule)					
	ZF	MMSE	Kalman	NLMS Kalman	MSE Fully digital	Proposed
-5	4.7812	8.7087	8.0688	10.3956	15.3060	16.5012
5	14.9263	19.5531	19.7359	23.3166	30.5039	32.0343
10	21.8797	25.7491	26.8302	30.9804	38.6263	40.6177
15	29.4996	32.2605	34.3777	39.1046	46.8663	49.3472
20	37.4752	39.2087	42.2028	47.4659	55.1497	58.0168

4.2.2 Energy Efficiency Comparison of the Proposed Precoding with the Existing Precoding by Varying Number of Path

Energy efficiency comparison is a performance metric to compare the performance of different precoding algorithms in communication systems. Figure 4.13, Figure 4.14, and Figure 4.15 depict the performance comparison of Energy efficiency versus Signal to noise ratio for transmitter antenna 64, receiver antenna 16, 4 number of users, and SNR in the range [-10,20] by varying the number of channel path (L=4,8,12). Figure 4.13 compares the effectiveness of the proposed precoding algorithm to other precoding algorithms for Signal to noise ratio in the range [-10,20]dB, the Proposed RLS Kalman-based Hybrid Precoding achieved an Energy Efficiency of 61.2525 Mbit/joule at SNR=20dB, Whereas MSE Fully digital, NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding achieved Energy Efficiency of 55.6683 Mbit/joule, 51.9768 Mbit/joule, 47.6038 Mbit/joule, 45.8093 Mbit/joule and 45.0434 Mbit/joule at SNR=20dB respectively. From the below figure, we conclude that the Proposed RLS Kalman Hybrid Precoding Improved the Energy efficiency by 5.5842 Mbit/joule at 20 dB with 4 channel paths concerning MSE Fully digital Hybrid Precoding and almost 9.2757 Mbit/joule, 13.6487 Mbit/joule, 15.4432 Mbit/joule, and 16.2091 Mbit/joule concerning the NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding respectively under the same conditions.

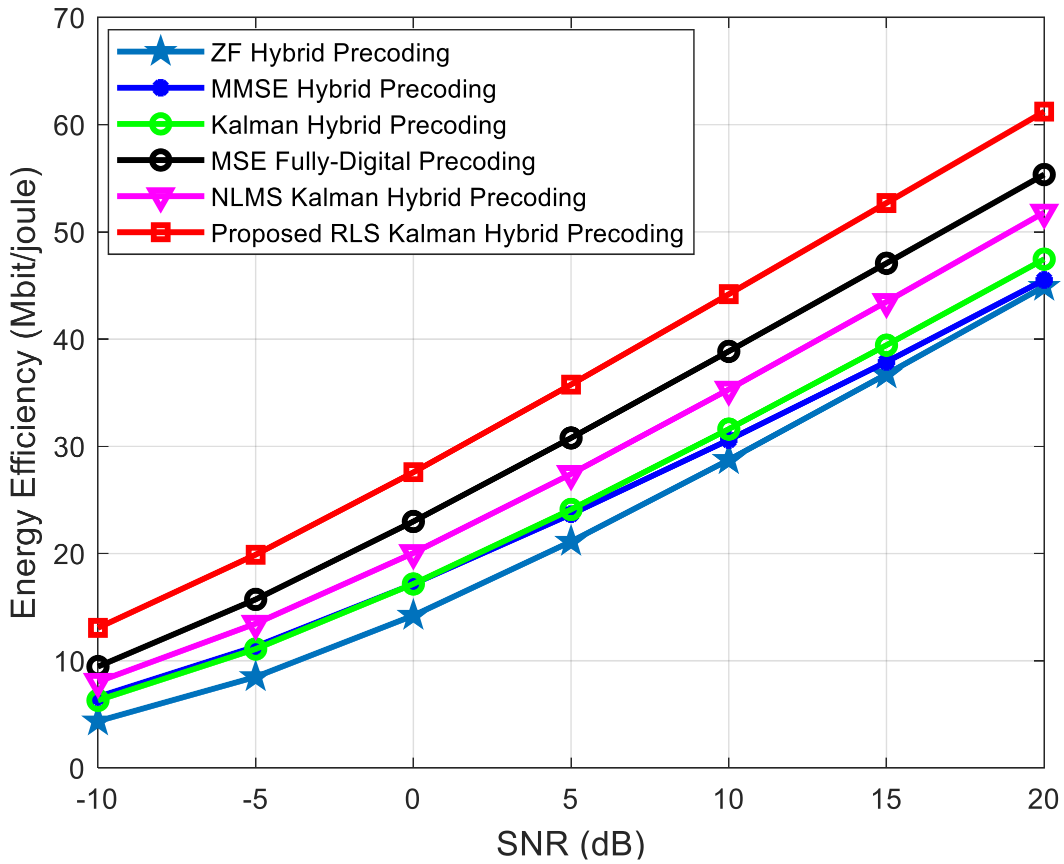

Figure 4.13: Energy Efficiency varying number of channel paths (4 paths scenario)

Figure 4.14 evaluates the effectiveness of the proposed precoding algorithm Energy efficiency to other precoding algorithm Energy efficiency for SNR in the range [-10,20] with 64 transmitter antenna, 16 receiver antenna, 4 users, and 8 channel paths. At SNR=20dB, the Proposed RLS Kalman Hybrid Precoding obtained an Energy Efficiency of 59.2605 Mbit/joule, Whereas MSE Fully digital, NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding achieved an Energy Efficiency of 55.0699 Mbit/joule, 48.9159 Mbit/joule, 43.8252 Mbit/joule, 40.8291 Mbit/joule and 39.8014 Mbit/joule at SNR=20dB respectively. The Proposed RLS Kalman Hybrid Precoding Improved the Spectral efficiency by 4.1906 Mbit/joule at 20 dB with 8 channel paths concerning MSE Fully digital Hybrid Precoding and almost 10.3446 Mbit/joule, 15.4353 Mbit/joule, 18.4314 Mbit/joule, and 19.4591 Mbit/joule concerning the NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding respectively under the same conditions.

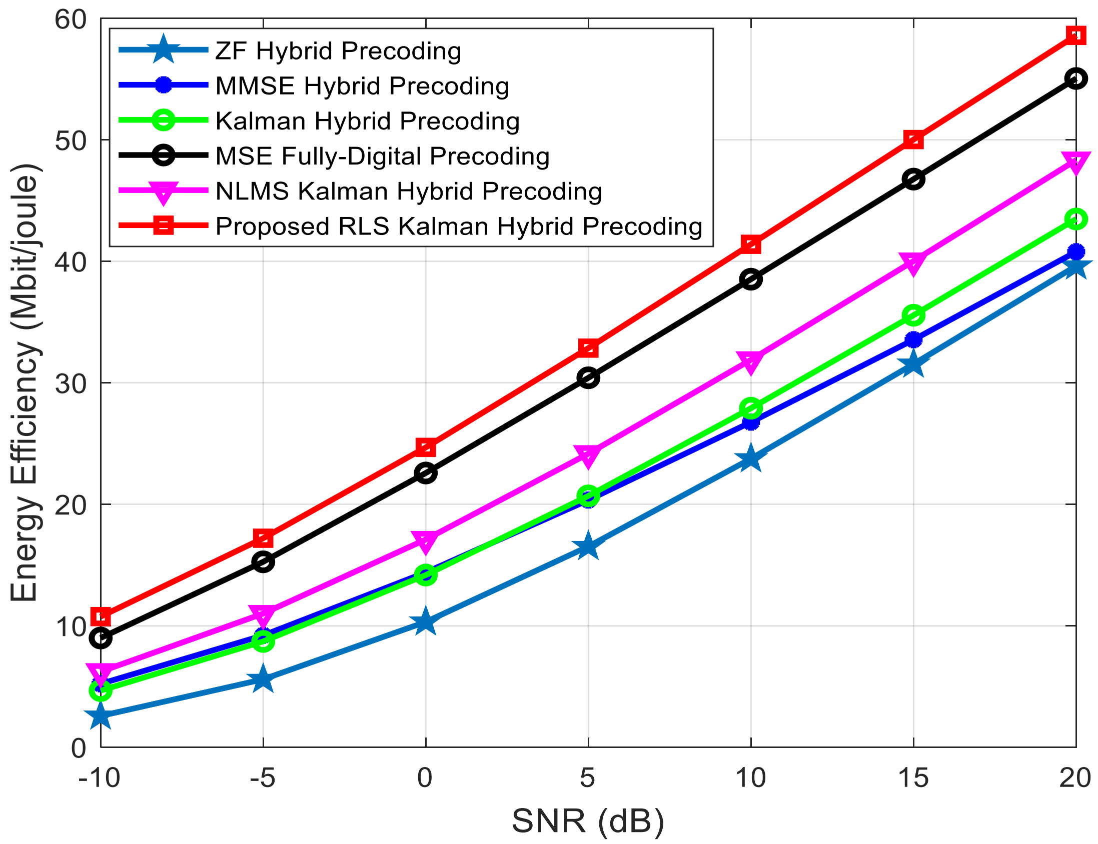

Figure 4.14: Energy Efficiency varying number of channel paths (8 paths scenario)

Figure 4.15 compares the Energy efficiency performance of the proposed precoding algorithm to other precoding algorithms for SNR in the range [-10,20]dB, the Proposed RLS Kalman-based Hybrid Precoding achieved an Energy Efficiency of 58.1403 Mbit/joule at SNR=20dB, Whereas MSE Fully digital, NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding achieved Energy Efficiency of 55.1480 Mbit/joule, 47.3609 Mbit/joule, 41.8221 Mbit/joule, 38.6232 Mbit/joule and 37.0103 Mbit/joule at SNR=20dB respectively. The Proposed RLS Kalman Hybrid Precoding Improved the Spectral efficiency by 2.9923 Mbit/joule at 20 dB with 12 channel paths concerning MSE Fully digital Hybrid Precoding and almost 10.7794 Mbit/joule, 16.3182 Mbit/joule, 19.5171 Mbit/joule, and 21.13 Mbit/joule concerning the NLMS Kalman, Kalman, MMSE and ZF Hybrid Precoding respectively under the same conditions. MSE Fully digital Hybrid precoding is very close to the proposed RLS Kalman hybrid precoding.

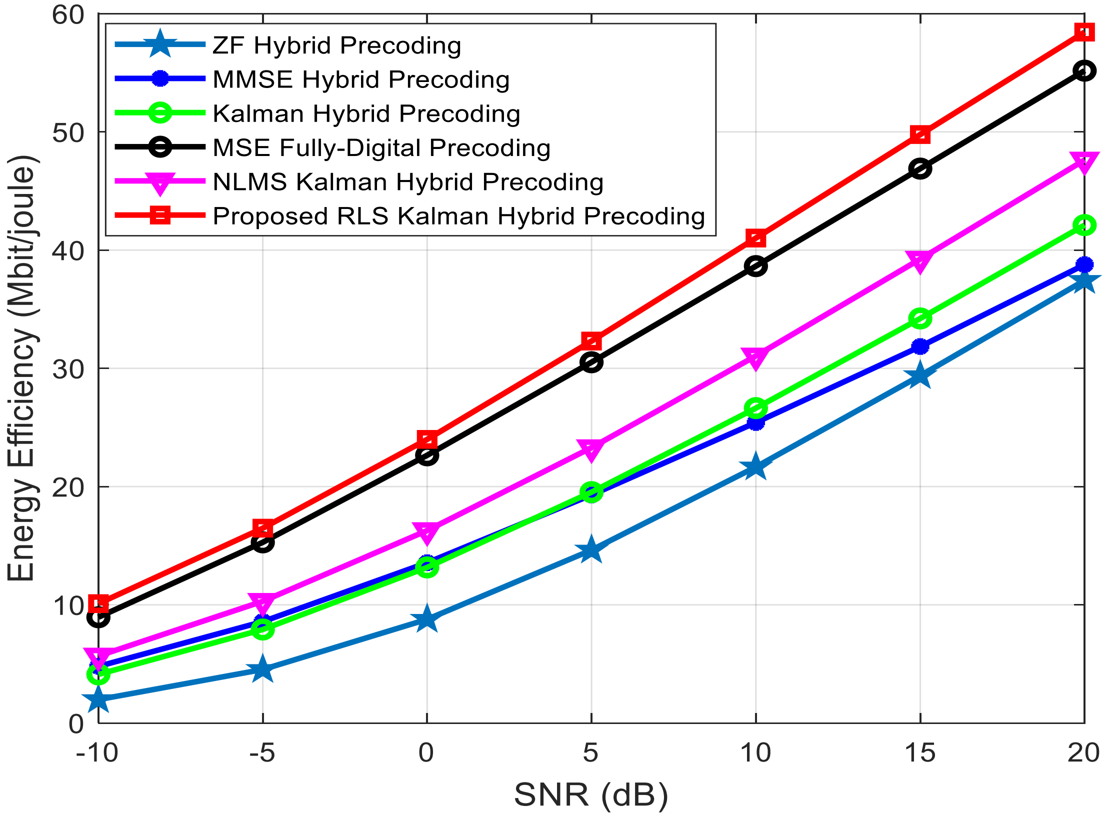

Figure 4.15: Energy Efficiency varying number of channel paths (12 paths scenario)

Figure 4.13, Figure 4.14, and Figure 4.15 show the Energy efficiency versus Signal to noise ratio by varying the number of channel paths of different Precoding algorithms. From the result, it can be concluded that as Signal to noise ratio increases the Energy efficiency performance also increase but, as the Number of channel path increase the Energy efficiency performance is decrease. In Figure 4.13, Figure 4.14, and Figure 4.15 the Energy efficiency performance of RLS Kalman-based Hybrid Precoding outperforms than all other Precoding.

4.3 Bit Error Rate Comparison

Bit Error Rate is one of the performance metrics to compare the performance of different precoding in wireless communication systems. Figure 4.16 depicts the bit error rate versus signal-to-noise ratio comparison of ZF, MMSE, Kalman, MSE Fully digital, NLMS Kalman, and Proposed RLS Kalman Hybrid Precoding for QPSK modulation schemes. The Proposed algorithm attained BER= 1.02×10^{-5} at SNR=20dB, While MSE Fully digital, NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding achieved BER of 1.88×10^{-5}, 6.28×10^{-5}, 2.19×10^{-4}, 7.29×10^{-4} and 4.22×10^{-3} at SNR=20dB respectively. From the below figure, we conclude that the Proposed RLS Kalman Hybrid Precoding reduced the bit error rate by 8.6×10^{-6} at 20 dB with 10 channel paths concerning MSE Fully digital Hybrid Precoding and also reduced by 5.26×10^{-5}, 2.088×10^{-4}, 7.188×10^{-4} and 4.21×10^{-3} concerning the NLMS Kalman, Kalman, MMSE, and ZF Hybrid Precoding respectively under the same conditions. From Figure 4.16 the bit error rate decrease as the signal-to-noise ratio increase and the bit error rate of all precoding decrease as the signal-to-noise ratio increase. The proposed RLS Kalman Hybrid precoding shows the best performance and is close to MSE Fully digital Hybrid precoding.

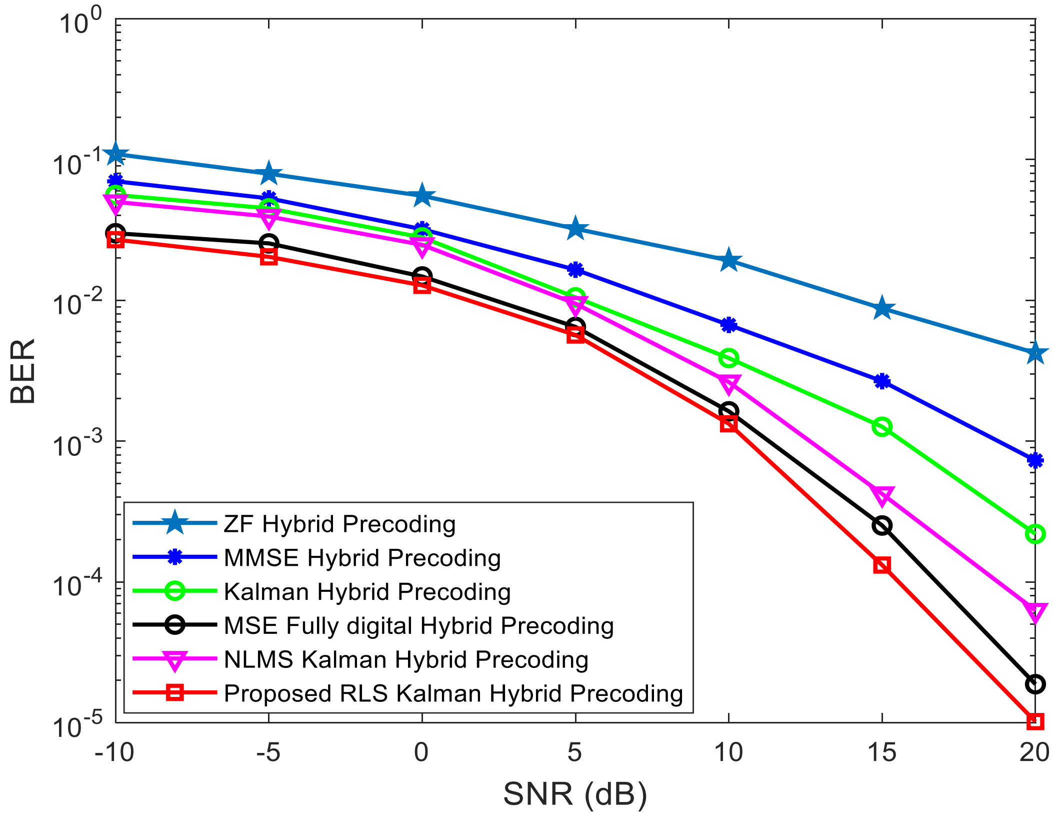

Figure 4.16: Bit error rate performance of different precoding

Table 4.7 shows the performance comparison of proposed precoding and existing precoding techniques for the 64 transmitter antenna N_{Tx}, 4 Number of users and 4 data streams N_s at SNR= -10dB to 20dB. The table below indicates the tabular representation of Figure 4.20 by considering some values of SNR. As we observed from the below table the bit error rate of proposed RLS Kalman precoding is less and better than all other precoding thus resulting in the proposed precoding giving better channel estimation and reduced interference.

Table 4.7: Data collection of bit error rate by varying SNR

SNR (dB)	BER					
	ZF	MMSE	Kalman	NLMS Kalman	MSE Fully digital	Proposed
-10	1.09×10^{-1}	7.00×10^{-2}	5.59×10^{-2}	4.99×10^{-2}	2.99×10^{-2}	2.69×10^{-2}
-5	7.92×10^{-2}	5.30×10^{-2}	4.49×10^{-2}	3.94×10^{-2}	2.54×10^{-2}	2.04×10^{-2}
0	5.52×10^{-2}	3.20×10^{-2}	2.79×10^{-2}	2.48×10^{-2}	1.48×10^{-2}	1.28×10^{-2}
5	3.22×10^{-2}	1.65×10^{-2}	1.05×10^{-2}	9.47×10^{-3}	6.47×10^{-3}	5.67×10^{-3}
10	1.92×10^{-2}	6.69×10^{-3}	3.89×10^{-3}	2.63×10^{-3}	1.63×10^{-3}	1.33×10^{-3}
15	8.76×10^{-3}	2.67×10^{-3}	1.27×10^{-3}	4.22×10^{-4}	2.52×10^{-4}	1.32×10^{-4}
20	4.22×10^{-3}	7.29×10^{-4}	2.19×10^{-4}	6.28×10^{-5}	1.88×10^{-5}	1.02×10^{-5}

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

Millimeter Wave Massive MIMO systems support several antenna at both the receiver and transmitter side to serve several users in a communication system. mmWave face some challenges such as blockage and path loss due to the non-stationary nature of the channel. To solve the above problem beamforming technology and optimized Kalman filter is used in mmWave massive MIMO system by directing the signal in the desired direction and to achieve better estimates of the channel state information. Optimize the Kalman filter using NLMS Kalman Hybrid Precoding but the performance is less compared to MSE Fully digital hybrid precoding. Therefore RLS Kalman hybrid beamforming is used in Massive MIMO systems to address the issue of the channel can change rapidly over time in Millimeter Wave massive MIMO systems. The performance of the proposed precoding algorithm has been compared with other precoding including MSE Fully digital, NLMS Kalman, Kalman, MMSE, and ZF hybrid precoding.

According to the outcomes of the simulation, in a multi-path scenario, the Spectral efficiency of the Proposed Precoding algorithm and all beamformer increased with increasing transmitting and receiving antennas and decreased with an increasing number of users. For 256 transmit antenna at SNR of 20dB the spectral efficiency of ZF, MMSE, Kalman, NLMS Kalman, MSE Fully digital and the proposed RLS Kalman hybrid precoding is around 10.8327 bps/Hz, 11.2724 bps/Hz, 11.8012 bps/Hz, 12.3459 bps/Hz, 12.7716 bps/Hz and 13.3624 bps/Hz respectively. The Proposed RLS Kalman Hybrid Precoding Improved the Spectral efficiency by 2.5297bps/Hz at 20 dB with 10 channel paths and 256 BS antenna concerning ZF Hybrid Precoding and almost 2.09 bps/Hz, 1.5612 bps/Hz, 1.0165 bps/Hz and 0.5908 bps/Hz concerning the MMSE, Kalman, NLMS Kalman, MSE Fully digital Hybrid precoding respectively under the same conditions. The simulation result demonstrates the performance of the proposed RLS Kalman hybrid precoding demonstrates superior performance in terms of energy efficiency, spectral efficiency, and bit error rate compared to other precoding.

5.2 Recommendation

In this thesis, we analyze the Performance of different hybrid precoding algorithms in the mmWave massive MIMO System. The performance analysis is carried out using performance metrics like Energy efficiency, Spectral efficiency, and Bit error rate. The precoding algorithm used for performance analysis comparison is Zero Forcing(ZF), Minimum mean square error (MMSE), Kalman, Normalized Least Mean squares (NLMS) Kalman, Fully digital mean square error (MSE Fully digital), and Proposed Recursive Least squares Kalman (RLS Kalman) hybrid Precoding. In the future work of this thesis, deep learning and machine learning-based Optimized Kalman Filter Based Hybrid Beamforming in Millimeter Wave Massive MIMO System algorithms will be developed and the computational complexity analysis of existing hybrid precoding and Proposed algorithm are recommended.

REFERENCES

Abdelghany, M., Farid, A. A., Rasekh, M. E., Madhow, U., & Rodwell, M. J. W. (2021). A Design Framework for All-Digital mmWave Massive MIMO with per-Antenna Nonlinearities. *IEEE Transactions on Wireless Communications*, *20*(9), 5689–5701. https://doi.org/10.1109/TWC.2021.3069378

Abid, W., Hajjaj, M., & Bouallegue, R. (2022). Spectrum and energy efficient kalman-based hybrid combiner for mmWave massive MIMO systems. *IET Communications*, *16*(1), 100–109. https://doi.org/10.1049/cmu2.12320

Ali, E., Ismail, M., Nordin, R., & Abdulah, N. F. (2017). Beamforming techniques for massive MIMO systems in 5G: overview, classification, and trends for future research. *Frontiers of Information Technology and Electronic Engineering*, *18*(6), 753–772. https://doi.org/10.1631/FITEE.1601817

Bang, J., Chung, H., Hong, J., Seo, H., Choi, J., & Kim, S. (2021). Millimeter-Wave Communications: Recent Developments and Challenges of Hardware and Beam Management Algorithms. *IEEE Communications Magazine*, *59*(8), 86–92. https://doi.org/10.1109/MCOM.001.2001010

Bogale, T. E., Le, L. B., & Mimo, M. (2017). *mmWave communication enabling techniques for 5G wireless systems Detection of Explosives by Millime- ter-wave Imaging*.

Busari, S. A., Huq, K. M. S., Mumtaz, S., Dai, L., & Rodriguez, J. (2018). Millimeter-Wave Massive MIMO Communication for Future Wireless Systems: A Survey. *IEEE Communications Surveys and Tutorials*, *20*(2), 836 – 869. https://doi.org/10.1109/ COMST.2017.2787460

Chataut, R., & Akl, R. (2020). Massive MIMO systems for 5G and beyond networks—overview, recent trends, challenges, and future research direction. *Sensors (Switzerland)*, *20*(10), 1–35. https://doi.org/10.3390/s20102753

Chen, J., Feng, W., Xing, J., Yang, P., Sobelman, G. E., Lin, D., & Li, S. (2020). Hybrid Beamforming/Combining for Millimeter Wave MIMO: A Machine Learning Approach. *IEEE Transactions on Vehicular Technology*, *69*(10), 11353–11368. https://doi.org/10.1109/TVT.2020.3009746

Chen, N., Sun, S., Kadoch, M., & Rong, B. (2016). SDN controlled mmWave massive MIMO hybrid precoding for 5G heterogeneous mobile systems. *Mobile Information Systems, 2016*. https://doi.org/10.1155/2016/9767065

Chophel, T., Duraikannan, S., Thiruchelvam, V., Abdulla, R., Selvaperumal, S. K., & Susiapan, Y. (2020). Hybrid Precoding for Energy Conservation in HetNets. *Solid State Technology*, *63*(1S), 1003–1014. http://www.solidstatetechnology. us/index.php/JSS T/article/view/789

El-hajjar, M., Member, S., & Hanzo, L. (2018). Millimeter-Wave Communications : Physical Channel Models , Design Considerations , Antenna. *IEEE Communications Surveys & Tutorials*, *20*(2), 870–913. https://doi.org/10.1109/COMST.2017.2783541

Fabiana Meijon Fadul. (2019). *済無 No Title No Title No Title*. *4*(2), 438–457. https://doi.org/10.5281/zenodo.7264799

Faragallah, O. S., El-Sayed, H. S., & El-Mashed, M. G. (2021). Performance Enhancement of MmWave MIMO Systems Using Deep Learning Framework. *IEEE Access*, *9*, 92460–92472. https://doi.org/10.1109/ACCESS.2021.3092709

Huang, H., Song, Y., Yang, J., Gui, G., & Adachi, F. (2019). Deep-Learning-Based Millimeter-Wave Massive MIMO for Hybrid Precoding. *IEEE Transactions on Vehicular Technology*, *68*(3), 3027–3032. https://doi.org/10.1109/TVT.2019.2893928

Huang, S., Ye, Y., & Xiao, M. (2020). Hybrid Beamforming for Millimeter Wave Multi-User MIMO Systems Using Learning Machine. *IEEE Wireless Communications Letters*, *9*(11), 1914–1918. https://doi.org/10.1109/LWC.2020.3007990

Israr, A., Rauf, Z., Muhammad, J., & Khan, F. (2017). Performance Analysis of Downlink Linear Precoding in Massive MIMO Systems Under Imperfect CSI. *Wireless Personal Communications*, *96*(2), 2603–2619. https://doi.org/10.1007/s11277-017-4314-0

Kasai, H. (2019). Fast optimization algorithm on complex oblique manifold for hybrid precoding in millimeter wave MIMO systems. *2018 IEEE Global Conference on Signal and Information Processing, GlobalSIP 2018 - Proceedings*, 1266–1270. https://doi.org/10.1109/GlobalSIP.2018.8646553

Kebede, T., Wondie, Y., Steinbrunn, J., Kassa, H. B., & Kornegay, K. T. (2022). Precoding and Beamforming Techniques in mmWave-Massive MIMO: Performance Assessment.

IEEE Access, *10*, 16365–16387. https://doi.org/10.1109/ACCESS.2022.3149301

Liu, X., Li, X., Cao, S., Deng, Q., Ran, R., Nguyen, K., & Tingrui, P. (2019). Hybrid Precoding for Massive mmWave MIMO Systems. *IEEE Access*, *7*, 33577–33586. https://doi.org/10.1109/ACCESS.2019.2903166

Martinek, R., Kahankova, R., Nedoma, J., Fajkus, M., & Skacel, M. (2018). Comparison of the LMS, NLMS, RLS, and QR-RLS algorithms for vehicle noise suppression. *ACM International Conference Proceeding Series*, 23–27.https://doi.org/10.1145/3177457. 3177502

Meng, X., Chang, Y., Wang, Y., & Wu, J. (2018). Multi-user grouping based scheduling algorithm in massive MIMO uplink networks. *2018 IEEE 4th International Conference on Computer and Communications, ICCC-2018*, 409–413. https://doi.org/10.1109/ CompComm.2018.8780961

Mukubwa, E., Sokoya, O. A., & Ilcev, D. S. (2017). Comparison and analysis of massive MIMO linear precoding schemes in the downlink. *2017 IEEE AFRICON: Science, Technology and Innovation for Africa, AFRICON 2017*, 187–191. https://doi.org/10.1109/AFRCON.2017.8095479

Nalband, A. H., Sarvagya, M., & Ahmed, M. R. (2022). Optimization of precoder and combiner in mmwave hybrid beamforming systems for multi-user downlink scenario. *Journal of Applied Science and Engineering (Taiwan)*, *25*(2), 257–265. https://doi.org/10.6180/jase.202204_25(2).0002

Osama, I., Rihan, M., Elhefnawy, M., & Eldolil, S. (2021). Deep learning based hybrid precoding technique for millimeter-wave massive MIMO systems. *ICEEM 2021 - 2nd IEEE International Conference on Electronic Engineering*, 4419–4424. https://doi.org/10.1109/ICEEM52022.2021.9480386

Osman, R. A., & Zaki, A. I. (2020). Energy-efficient and reliable internet of things for 5g: A framework for interference control. *Electronics (Switzerland)*, *9*(12), 1–18. https://doi.org/10.3390/electronics9122165

Philip, A. S., James, J. E., Antony, J., Varghese, J. A., & Sreenath, M. (2020). Millimeter Wave Communications for 5G: Theory and Applications. *International Research Journal of Engineering and Technology*, *5*(May), 365–383. www.irjet.net

Qiu, S., Chen, D., Qu, D., Luo, K., & Jiang, T. (2018). *Downlink Precoding with Mixed Statistical and Imperfect Instantaneous CSI for Massive MIMO Systems*. *April*. https://doi.org/10.1109/TVT.2017.2774836

Ramírez-Arroyo, A., González-Macías, J. C., Rico-Palomo, J. J., Carmona-Murillo, J., & Martínez-González, A. (2021). On the spectral efficiency for distributed massive MIMO-systems. *Applied Sciences (Switzerland)*, *11*(22). https://doi.org/10.3390/app 112210926

Seraj, A. S. (2019). *Study on Propagation Characteristics of 5G Millimeter-Wave Wireless Communication Systems for Dense Urban Environments*.

Tao, J., Wang, Q., Luo, S., & Chen, J. (2019). Constrained Deep Neural Network Based Hybrid Beamforming for Millimeter Wave Massive MIMO Systems. *IEEE International Conference on Communications*, *2019-May*, 1–6. https://doi.org/ ICC. 2019.8761742

Thesis, M., & Yll, D. N. (2020). *Kalman Hierarchical Hybrid Precoding for mmWave MIMO system submitted to the Faculty of the by*.

Thurpati, S., & Muthuchidambaranathan, P. (2022). Design of Hybrid Precoding for Millimeter-Wave Massive MIMO System. *Wireless Personal Communications*, *127*(4), 3363–3377. https://doi.org/10.1007/s11277-022-09922-5

Vizziello, A., Savazzi, P., & Chowdhury, K. R. (2018). A kalman based hybrid precoding for multi-user millimeter wave MIMO systems. *IEEE Access*, *6*, 55712–55722. https://doi.org/10.1109/ACCESS.2018.2872738

Wang, X. (2017). *Spectrum and Energy Efficiency of Uplink Massive MIMO System with D2D Underlay*. https://doi.org/10.3390/fi9020012

Zilli, G. M. (2021). *HYBRID BEAMFORMING DESIGN FOR MILLIMETER WAVE MASSIVE MIMO COMMUNICATIONS Concordia University*. *April*.

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