DEVELOPMENT OF QUALITY OF SERVICE (QOS) PROVISIONING FOR MASSIVE MIMO BASED 5G NETWORKS

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<u>DECLARATION</u>

I hereby declared that the presented work in the thesis entitled "**Development of Quality of Service (QoS) Provisioning For Massive MIMO Based 5G Networks**" in fulfilment of degree of **Doctor of Philosophy (Ph.D.)** is outcome of research work carried out by me under the supervision of Dr.Manwinder Singh, working as Professor, in the School of Electronics and Electrical Engineering of Lovely Professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigator. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled "**Development of Quality of Service (QoS) Provisioning For Massive MIMO Based 5G Networks**" submitted in fulfillment of the requirement for the award of degree of **Doctor of Philosophy (Ph.D.)** in the Electronics and Communication Engineering, is a research work carried out by Sandhya Bolla, 42000294, is bonafide record of his original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.

Signature of the Supervisor

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ABSTRACT

Massive MIMO is a key technology enabling 5G networks to deliver high data rates, low latency, offering enhanced capacity, spectral efficiency and massive connectivity. However, ensuring Quality of Service (QoS) for diverse applications, such as real-time video streaming, autonomous vehicles, energy efficiency and Peak-to-Average Power Ratio (PAPR) management remain a key challenge in such systems.

This thesis aims to develop advanced QoS provisioning mechanisms tailored for Massive MIMO systems. We propose a novel framework that leverages machine learning techniques to allocate resources and optimize system performance dynamically. By analyzing real-time channel conditions and traffic patterns, our approach enables intelligent resource allocation, interference mitigation, and power control. An energy-efficient harvesting algorithm for massive MIMO systems (EHMMS) is proposed to maximize energy harvesting while maintaining system performance. Additionally, a novel PAPR reduction technique is developed to improve signal quality and reduce power consumption.

Through extensive simulations and experiments, it demonstrates the effectiveness of our proposed techniques in improving QoS metrics such as throughput, latency, residual energy, and reliability. Our findings provide valuable insights for the design and deployment of future 5G networks, ensuring a seamless and efficient user experience. Comparative analysis with existing approaches demonstrates that the proposed framework offers superior performance, providing a scalable and efficient solution for next-generation wireless networks. This thesis contributes significantly to advancing energy-efficient and high-performance communication in 5G systems. This thesis investigates energy-efficient techniques for Massive MIMO systems.

Firstly, this thesis can analyze using state-of-the-art massive MIMO techniques, including precoding and channel estimation, to identify opportunities for energy savings. This thesis aims to study and analyze various massive MIMO techniques to identify their strengths and limitations. The Hybrid Spider Wasp Fick’s Law algorithm appears to offer an innovative approach to tackling the challenges of joint optimization in communication systems.

Its name likely draws inspiration from the behavior of spider wasps and Fick's law, suggesting a combination of principles from nature and mathematical models to achieve its objectives. ZF with Symbol-level linear precoding, particularly when coupled with the Stacked Convolution Sparse BiLSTM Auto Encoder (SCS-BiLSTMAE) network, presents an effective solution for decreasing the PAPR in massive MIMO techniques. It employs a huge number of antennas to serve multiple users simultaneously, often encountering high PAPR, leading to distortion and inefficiencies in the transmission process. By integrating ZF precoding with advanced signal processing techniques like SCS-BiLSTMAE, it becomes feasible to mitigate PAPR efficiently. When integrated with techniques like Zero-Forcing with SLLP and SCS-BiLSTMAE network, adaptive constellation mapping and demapping provide a holistic solution for optimizing massive MIMO systems.

During the second part, this thesis proposes a novel energy harvesting algorithm that maximizes energy extraction from ambient RF signals, thereby reducing the reliance on traditional power sources. Based on the findings, an energy-efficient harvesting algorithm for massive MIMO systems (EHMMS) is proposed to maximize energy harvesting while ensuring optimal system performance using SWIPT antenna switching and power splitting.

Thirdly, to mitigate the adverse effects of high PAPR, we develop a novel PAPR reduction technique that is tailored for Massive MIMO systems. This technique effectively reduces PAPR while preserving system performance. Despite its potential, challenges such as energy efficiency and Peak-to-Average Power Ratio (PAPR) reduction persist. Additionally, a novel PAPR reduction technique is developed to enhance signal quality and minimize power consumption. Moreover, PAPR reduction not only enhances energy efficiency but also aids in reducing the BER by improving signal quality, thereby contributing to overall system performance and reliability. The EIBO algorithm emerges as another innovative approach for bolstering energy efficiency and curtailing PAPR in communication methods, especially within the realm of massive MIMO. Leveraging this algorithm suggests the system's capability to intelligently allocate resources, optimize power usage, or adjust transmission parameters to enhance energy efficiency effectively.

Moreover, it appears adept at reducing PAPR, a pivotal aspect in preserving signal quality and mitigating interference in wireless communication. By harnessing the Enhanced Influencer Buddy Optimization algorithm, communication systems can potentially achieve higher levels of performance, reliability, and sustainability. Conducting experiments in MATLAB enables researchers to analyze the performance of various algorithms, compare them against benchmarks, and validate their efficacy in achieving desired objectives.

Finally, through rigorous simulations and analysis, it can evaluate the performance of the proposed techniques in terms of QoS, energy efficiency, and throughput. The results demonstrate significant improvements over existing methods, paving the way for more energy-efficient and sustainable 5G networks. The proposed methods are evaluated through comprehensive performance analysis using metrics such as throughput, energy efficiency, and residual energy. Comparative results demonstrate that the proposed framework significantly outperforms existing approaches, offering a scalable and efficient solution for next-generation wireless communication systems.

1. Analyze different Massive MIMO techniques for 5G networks using linear precoding.
2. Proposed an energy-efficient algorithm to maximize energy harvested from massive MIMO systems (EHMMS) using SWIPT.
3. Proposed a novel PAPR reduction technique for the massive MIMO system
4. Compared the performance analysis of the proposed technique to existing methods using potential parameters like throughput, energy efficiency, and residual energy.

PREFACE / ACKNOWLEDGEMENT

This thesis would not have been possible without the support of glorious people who motivated me during my doctoral study. I am thankful from bottom of my heart towards the numerous persons who assisted me while conducting this study. First of all, I would like to thank my supervisor, Dr. Manwinder Singh, for his worthy guidance, support, and suggestions, in every step of this research project during my Ph.D. journey. Dr. Manwinder Singh has an optimistic personality with a helpful nature, he has always made himself ready to clarify my doubts and it was a great opportunity to work under his supervision. He always shed light whenever I was feeling stuck in my path of research ambitions.

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List of Abbreviations

5G	5th Generation
ABM	Adaptive Beam Forming
ACE	Active Constellation Extension
AGNN	Alternating Graph Regularized Neural Network
AMP	Approximated Message Precoding
BDMA	Beam Division Multiple Access
BER	Bit Error Rate
BiLSTM	Bidirectional Long Short Tem Memory
BS	Base Station
CCDF	Complementary Cumulative Distribution Function
CNN	Convolutional Neural Network
CP	Cyclic Prefix
CRN	Cognitive Radio Networks
CSI	Channel State Information
CSS	Cooperative Spectrum Sensing
CT	Circular Transformation
DFT/IDFT	Discrete Fourier Transform/Inverse DFT
DL	Deep Learning
DL-QL	Deep Learning based Q-Learning
EE	Energy Efficiency
EHMMS	Energy Harvesting Massive MIMO System
EIBO	Enhanced Influencer Buddy Optimization
FBMC	Filter Bank Multi Carrier
FGWO	Fuzzy Grey Wolf Optimization
HCN	Heterogeneous Cellular Networks
HPT-SSAE	Hyper parameter Tuned SSAE
HSWFL	Hybrid Spider Wasp Fick's Law
ICIBS	Inter Channel Interference Based Selection
ICI	Inter Carrier Interference
IMT	International Mobile Telecommunication
ISI	Inter Symbol Interference
LCA	Low Complexity Algorithm
LMMSE	Linear Minimum Mean Square Error
LSTM	Long Short term Memory
LTE	Long Term Evaluation
MCN	Multi Cellular Network
MDOA	Modified Dragonfly Optimization Algorithm
MF	Matched Filtering
MIMO	Multiple Input Multiple Output
ML	Maximum Likelihood

m-MIMO	Massive MIMO
MMSE	Minimum Mean Square Error
MRC	Maximum Ratio Combining
MRT	Maximum Ratio Transmission
MT	Mobile Terminal
MTC	Machine Type Communication
NOMA	Non-Orthogonal Multiple Access
OFDM	Orthogonal Frequency Division Multiplexing
OQAM	Orthogonal Quadrature Amplitude Modulation
PAPR	Peak to Average Power Ratio
PDF	Power Spectral Density
PS	Power Splitting
PSO	Particle Swarm Optimization
PTS	Partial Transmit Sequence
QAM	Quadrature Amplitude Modulation
QoS	Quality of Service
QPSK	Quadrature Phase Shift Keying
RE	Residual Energy
RF	Radio Frequency
RNN	Recurrent Neural Network
SC	System capacity
SC-QAM	Single Carrier QAM
SCS-BiLSTM AE	Stacked Convolutional Sparse BiLSTM Auto Encoder
SDN	Software Define Networking
SE	Spectral Efficiency
SER	Symbol Error Rate
SFB	Synthesis Filter Bank
SINR	Signal-to-Interference-plus-Noise Ratio
SISO	Single Input Single Output
SLLP	Symbol Level Linear Precoding
SLM	Symbol Level Mapping
SNR	Signal to Noise Ratio
SSAE	Stacked Sparse Auto Encoder
ST-PAPR	Spatio Temporal PAPR
SVD	Singular Value Decomposition
SWIPT	Simultaneous Wireless Information Power Transfer
TDD	Time Division Duplex
THz	Tera Hertz
TOA	Tyrannosaurus Optimization Algorithm
TR	Tone Reservation
TS	Time Switching
UAV	Unmanned Aerial Vehicle
UDN	Ultra Dense Network
UE	User Equipment
UFMC	Universal Filtered Bank Multi-Carrier
URLLC	Ultra-Reliable Low-Latency Communication
ZF	Zero Forcing

List of Symbols

Symbol	Description
α	Power splitting ratio
$\hat{\boldsymbol{p}}$	Discrete-time signal or a vector of complex samples
$\lvert\hat{\boldsymbol{p}}\rvert^{\mathbf{2}}$	Instantaneous power of the signal
η	Antenna efficiency
σ	Trainable weight matrix

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Chapter 1

INTRODUCTION

1.1 Overview

Massive MIMO is a momentous pillar in 5G networks because it uses a greater number of antennas. It provides many advantages to present communication systems in spectral efficiency, energy efficiency, and quality of service [1]. The complexity of signal processing for data detection in these systems is indeed a significant challenge. In massive MIMO scenarios, the number of parameters that need to be estimated and the complexity of operating these parameters grow rapidly [1]. This complexity becomes even more pronounced when high-order modulation schemes are used and multiple users are multiplexed simultaneously.

To address this challenge, researchers have been exploring various suboptimal detection algorithms that strike a balance between performance and complexity. These algorithms include linear detection techniques like ZF and MMSE detection, as well as iterative detection and decoding techniques such as message-passing algorithms [1-2]. Additionally, machine learning and neural network approaches are gaining attention for their ability to handle the difficulty of massive MIMO systems more efficiently.

Despite the challenges, it remains a key technology for 5G and beyond due to its ability to significantly increase spectral efficiency, enhance coverage, and improve overall network performance. Continued research and development in signal processing techniques will be essential to completely realize the potential of massive MIMO in future wireless communication systems. In this system, the primary focus is on facilitating large data transfers that are not feasible in 4G for a greater number of users [3].

Here are some key multi-carrier transmission techniques commonly used or considered for future generation wireless systems, such as Orthogonal Frequency Division Multiplexing (OFDM), Filter Bank Multi Carrier (FBMC), Non-Orthogonal Multiple Access (NOMA), GFDM (Generalized Frequency Division Multiplexing), and UFMC (Universal Filter Multi Carrier) [4].

If the number of customers overshoots the quantity of offered antenna terminals (a scenario known as an underdetermined system), scheduling becomes essential to efficiently utilize the limited resources. Overall, user scheduling like ZF, multi-objective optimization, QoS-based scheduling, adaptive scheduling, MRT, and greedy scheduling algorithms plays a critical role in maximizing the throughput and efficiency of these systems, especially when the number of users increases [5].

By intelligently selecting users and allocating resources, scheduling algorithms can optimize system performance and enhance the user experience in 5G networks. Overall, achieving both more throughput and fairness in massive MIMO systems requires careful algorithm design and consideration of various factors, including channel conditions, QoS requirements, and fairness constraints. Continued research and innovation in scheduling algorithms are essential to address these challenges and unlock the full potential of this technology in the future [5-6].

1.2 Motivation

4G, such as LTE, has been globally deployed, but ongoing research aims to develop fifth-generation (5G) technologies. The current 4G technology struggles to accommodate the exponential increase in data rates and the propagation of connected devices [6]. The advent of 5G seeks to address these challenges by enhancing wireless data rates, expanding coverage areas, and accommodating a vast array of devices.

In the realm of wireless communications, effectively managing resources to meet the varied quality of service (QoS) demands is critical. These demands differ across services, particularly in terms of latency and data throughput. Tailoring resource allocation to accommodate these varied requirements ensures that all types of services maintain high performance and reliability, a necessity for modern communication networks [7].

OFDM, the modulation technique utilized in 4G mobile communication systems, faces certain limitations that may render it unsuitable for the next generation. Consequently, numerous researchers are exploring alternative modulation methods capable of overcoming OFDM's drawbacks.

Among these alternatives, generalized frequency division multiplexing and FBMC have emerged as promising candidates for next-generation wireless communications. GFDM and FBMC offer several advantages over OFDM. Firstly, they exhibit lower out-of-band emissions, addressing a key limitation of OFDM [8].

Moreover, 5G facilitates robust machine-to-machine (M2M) communications, crucial for automating industrial processes and improving efficiency across various sectors. The expansion of the Internet of Things is another critical application, where 5G enables countless devices to connect, communicate, and exchange data with minimal latency, supporting smart cities and automated homes [8-9].

5G technology stands as a cornerstone for transformative digital experiences, offering significantly higher data rates coupled with dependable connectivity. This next-generation wireless standard is pivotal for enhancing device-to-device (D2D) interactions, allowing for seamless communication between devices without the need for intermediary network services [9].

Additionally, 5G plays a transformative role in healthcare, improving telemedicine services, enabling remote monitoring, and supporting advanced technologies such as augmented reality for surgical procedures, thereby revolutionizing patient care and medical interventions. 5G is envisioned as an integration of various techniques and technologies, all aimed at revolutionizing wireless statement capabilities to meet the weight of present connectivity. Multi-carrier transmission techniques play a crucial role in future-generation communication systems, especially in massive MIMO environments.

GFDM employs circular convolution with prototype filtering across individual subcarriers, thereby enhancing frequency localization and reducing interference. On the additional pass, FBMC achieves SE by eliminating the cyclic prefix (CP) present in OFDM, resulting in a more efficient use of available bandwidth. Through their unique characteristics and design principles, GFDM and FBMC present viable alternatives to OFDM for future wireless communication systems [9].

1.3 Background

This technology improves spectral efficiency and high communication reliability. Previous research works have extensively investigated OFDM systems, demonstrating the effectiveness of this technology for multimedia data transfer [10]. OFDM's high spectral efficiency and robustness make it well-suited for multimedia data transfer applications, including image transmission. The combination of OFDM with massive MIMO technology enables efficient and reliable transmission of large amounts of multimedia data over wireless channels, meeting the increasing demands of next-generation communication networks.

OFDM's robustness against frequency-selective fading and multipath propagation, coupled with the spatial diversity provided by massive MIMO systems, enhances communication reliability [10-12]. By leveraging a greater number of antennas for transmission and reception, these systems with OFDM combinations can further improve link reliability and mitigate the impact of fading and interference, resulting in more robust wireless communication links.

This thesis study reveals significant enhancements in image quality metrics within massive MIMO systems when employing FrFT and DWT compared to traditional FFT-based MIMO-OFDM configurations. This makes OFDM particularly effective for massive MIMO systems operating in environments with challenging channel conditions [10]. Specifically, when both FrFT and DWT are integrated into massive MIMO systems, there is a notable improvement in both PSNR and Structural Similarity Index Measure (SSIM) across various Signal-to-Noise Ratios (SNRs) and user counts. This indicates that such transformations may offer more robust and efficient alternatives for handling multi-user scenarios and maintaining high-quality signal transmissions in wireless communication environments [11]. These techniques offer several advantages in terms of spectral efficiency, robustness to channel impairments, and flexibility in resource allocation.

It explores the performance of a hybrid amalgamation of these combination schemes augmented with different transform techniques (FFT, FrFT, and DWT) for reliable image communication in 5G systems. Here's a breakdown of the key points and findings.

Hybrid Amalgamation: The combination of massive MIMO and OFDM is recognized as an effective methodology for fulfilling the requirements of modern-day wireless communication systems.

Evaluation Parameters: The performance of these systems is evaluated using metrics such as SNR vs. peak SNR and SNR vs. SSIM at the receiver.

Simulation Environment: The analysis is conducted over Rayleigh fading channels, which are commonly encountered in wireless communication environments. M-ary phase-shift keying is measured to appraise the presentation of the planned systems under varying conditions.

Table 1.1: Comparison of 1G to 5G [11]

Generation	**Year of Introduction**	**Key Features**	**Data Speeds**	**Latency**	**Applications**
1G	1980s	Analog voice calls	2.4 Kbps	High	Voice calls
2G	1990s	Digital voice calls, SMS	14.4 - 217.6 Kbps	Medium	Voice calls, SMS, basic data
3G	2000s	Mobile internet access, video calls	384 Kbps - 2 Mbps	Low	Mobile internet, video calls, basic mobile apps
4G	2010s	High-speed data, HD video streaming, online gaming	100 Mbps - 1 Gbps	Very low	High-definition streaming, online gaming, advanced mobile apps
5G	2019	Ultra-fast speeds, low latency, massive capacity	Up to 20 Gbps	Ultra-low (<1 ms)	IoT, AR/VR, autonomous vehicles, high-definition streaming

Table 1.1 shows the comparison of 1G to 5G in terms of the parameters of data bandwidth, technology, multiplexing, switching, and core network.

5G has a data rate of up to 1 Gbps with packet switching**.** Each generation builds upon the previous one, offering increased capabilities and faster speeds [11]. The evolution from analog to digital and broadband technologies has significantly improved network performance. The shift from circuit switching to packet switching has enabled more efficient and flexible data transmission. The integration of the internet as a core network component has revolutionized mobile communication. In conclusion, each generation of mobile networks has brought significant advancements [12-13].

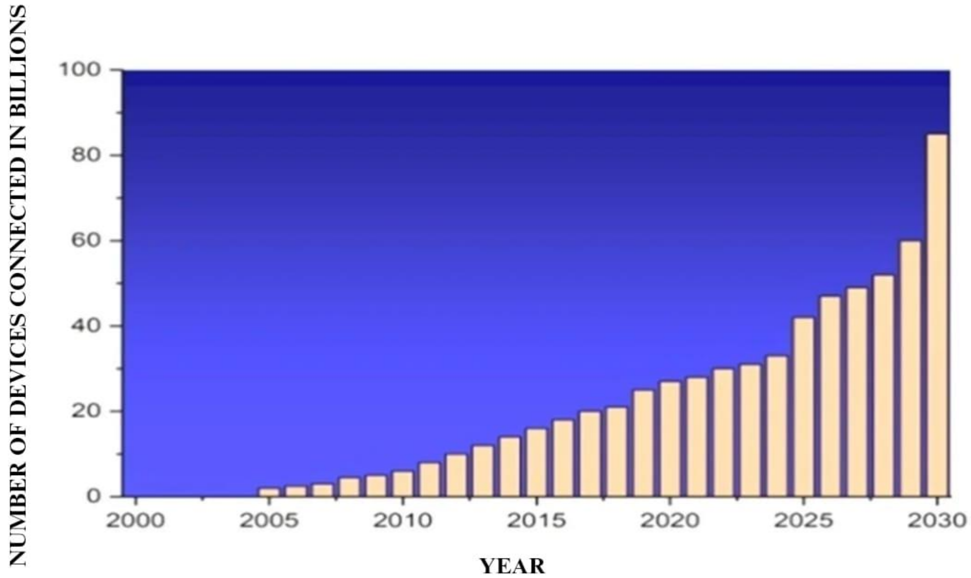

Figure 1.1: Overview of technology

Figure 1.1 shows the number of connected devices, in billions, on a year-by-year basis. For example, Marzetta introduced the term "large MIMO" in 2010 in conjunction with multiple cells and time-division duplexing (TDD) in order to describe some of the features of single cells and constrained antennas. One hundred or even hundreds of antennas are often deployed at each of the base stations in massive MIMO technology, which are several orders of magnitude more powerful than the previous communication technique. The fundamental model of this network is illustrated in Figure 1.1, highlighting the architecture that supports the exponential growth in wireless data traffic. Over the last decade, various innovative communication technologies, including massive MIMO, have experienced significant development to address this increasing demand [12].

1.4 Massive MIMO Model

Typically, massive MIMO systems comprise hundreds of antennas, representing a substantial increase in the number of antennas compared to traditional communication systems. Both 5G and 6G mobile communication systems accept it as a comprehensive tool. Its ability to deploy large-scale antenna arrays at the base station enables significant improvements in system performance, including increased spectral efficiency, enhanced capacity, and improved reliability. In large-scale MIMO systems, the base station employs antenna arrays consisting of hundreds to several hundreds of elements (typically between 100 and 300). These antenna arrays enable the exploitation of spatial diversity and multiplexing gains, allowing for efficient communication with multiple users simultaneously. Overall, massive MIMO technology represents a primary shift in the design and implementation of these systems [12]. By deploying large-scale antenna elements at the BS, massive MIMO systems can achieve unprecedented levels of performance in 5G and 6G.

Massive MIMO network architecture has evolved to accommodate large-scale antenna arrays at base stations, allowing for the exploitation of spatial multiplexing, spatial diversity, and advanced beamforming techniques. Implementing these advanced transformations allows for the simultaneous accommodation of numerous user equipments on identical time and frequency resources, enhancing the system capacity. Yet, this progress is not without its hurdles. Variability in service quality and persistent difficulties in cell-edge performance remain significant challenges, complicating the full-scale deployment of cellular networks [13].

These issues underscore the need for ongoing research and optimization strategies to ensure that advancements in technology translate into uniformly improved user experiences across all network areas [14-15].

To address these challenges, the DL framework has been engaged to discover this system. By integrating deep learning algorithms with massive MIMO technology, researchers aim to further optimize network performance and meet the growing demands of modern wireless systems [15].

Advanced research into THz ultra-massive MIMO (UM-MIMO) systems is critical for the evolution of 5G and future networks. This includes developing new technologies such as plasmonic very small array antennas and creating optimal channel evaluation techniques.

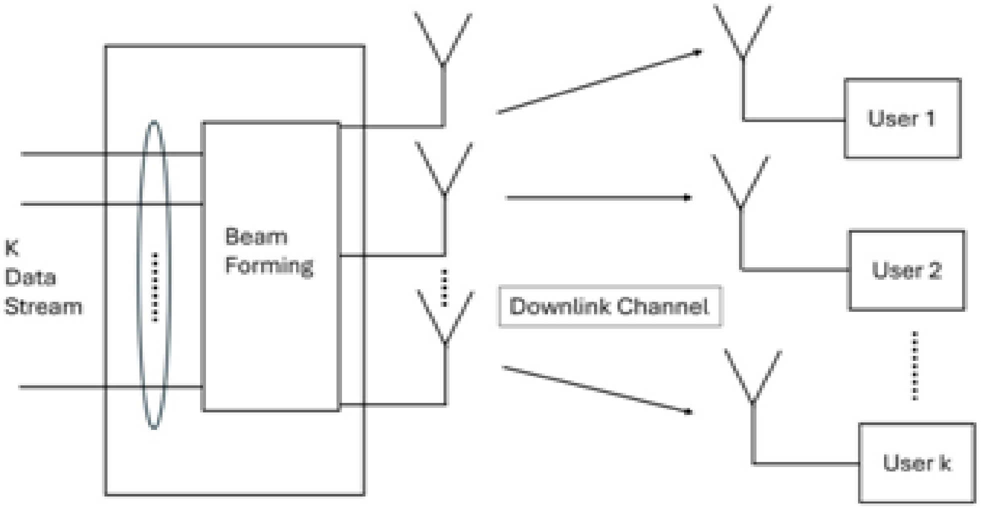

Figure 1.2: Basic model of massive MIMO [16]

Massive MIMO network architecture has evolved to accommodate large-scale antenna arrays at base stations, allowing for the exploitation of spatial multiplexing, spatial diversity, and advanced beamforming techniques, as shown in figure 1.2 for different users [16-17]. These properties enable CF-massive MIMO systems to achieve robust and reliable communication performance, even in challenging wireless environments. Overall, the integration of this algorithm with CF-massive MIMO systems represents a promising approach to address key challenges in wireless communication, offering improved performance, reduced complexity, and enhanced reliability for next-generation networks. This is essential for maintaining communication quality, especially in scenarios with challenging channel conditions or high levels of interference [18-20].

It is also an essential area of research. Overall, continued research and innovation in user scheduling algorithms are essential to address the complex trade-offs between throughput, fairness, and system performance in massive MIMO systems.

By developing more efficient and fair scheduling algorithms, we can unlock the full potential of this technology and enhance the overall user experience in future wireless communication networks.

To address these challenges and improve overall system performance, further research is indeed necessary to develop more efficient and fair scheduling algorithm designs [20]. Concentrating on these areas of research paves the way for the creation of innovative scheduling algorithms that not only enhance the data throughput but also ensure equitable access for all users within these systems. This approach will be instrumental in achieving the high-performance standards expected from future wireless infrastructures. Accurate channel state information is essential in these systems for effective beamforming, user signal detection, and resource management. The challenge intensifies as the user equipment must discern signals from a multitude of antennas at the BS, significantly increasing the burden of pilot signaling [21].

An efficient channel estimation strategy that balances accuracy with pilot overhead, particularly in Frequency Division Duplexing (FDD) systems, presents a promising research opportunity. Integrating massive MIMO with quantum communication technologies, particularly at frequencies above 300 GHz, represents an innovative research frontier. This combination could potentially unlock new paradigms in secure and ultra-fast wireless communications, exploring the quantum properties of electromagnetic waves at extremely high frequencies.

Furthermore, efforts to devise low-complexity, high-efficiency precoding and signal detection techniques, alongside precise beamforming and steering, are essential for leveraging THz communications at their full potential. Employing ML and DL for channel inference in massive MIMO could revolutionize how networks predict and adapt to channel conditions [22]. These technologies could improve the accuracy of predicting statistical channel characteristics, enhancing beam forming, and signal detection processes through intelligent algorithms.

Exploring key technologies that could underpin 6th generation networks, such as terahertz communication, visible light communication, and holographic radio, is another exciting field of this system. These technologies could dramatically increase the bandwidth and efficiency of future wireless networks, offering novel communication mediums and capabilities. The current generation of smartphones lacks support for massive MIMO technologies, posing a significant challenge for device manufacturers.

There is a critical need to develop more affordable mobile devices capable of supporting massive MIMO, alongside designs for systems that are backward compatible with existing 4G networks [22]. The practical deployment of massive MIMO involves users equipped with numerous antennas, necessitating rigorous testing of transceiver designs.

1.5 Massive MIMO comparison with traditional MIMO performance

If the capacity of the antennas is more in a system, the spectral efficiency experiences a continuous rise, accompanied by a corresponding increase in EE up to a convincing threshold. However, beyond this threshold, the energy efficiency begins to decline, creating a trade-off relationship between the two parameters. This inherent contradiction makes it challenging to achieve simultaneous optimization. Consequently, for these systems, exploring the joint optimization of SE and EE remains an important area of investigation [22].

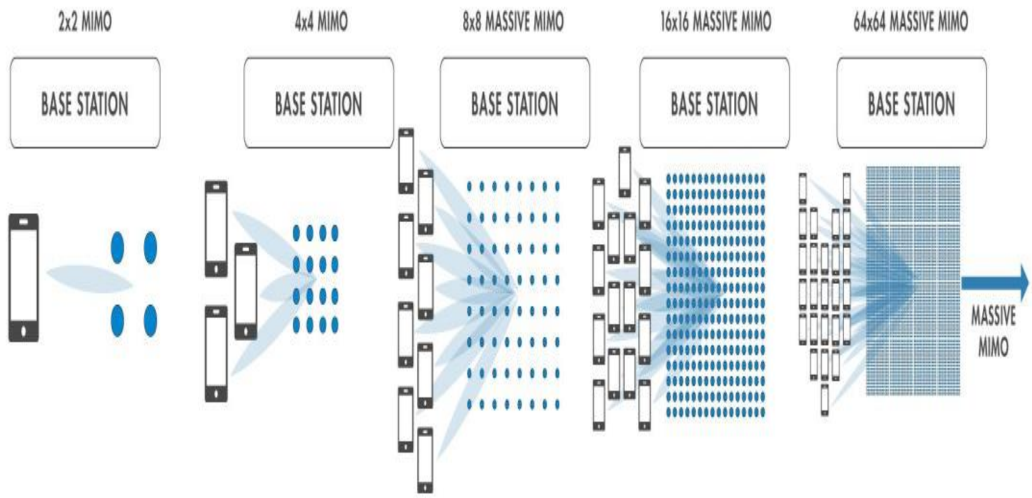

Figure 1.3: Massive MIMO comparison with traditional MIMO performance [22]

Given the constraints of restricted band possessions and the growing need for vast capacity, efficiency has been extensively studied as a conventional performance metric in the field of mobile communication [22].

1.5.1 MIMO system

It is a fundamental transmission technology pivotal in advancing wireless systems, aiming to bolster information transport rates and elevate overall system performance. Figure 1.4 shows the MIMO system.

This ingenious setup capitalizes on the spatial diversity inherent in radio channels and the multipath propagation phenomenon, effectively mitigating signal fading effects and bolstering system reliability [23].

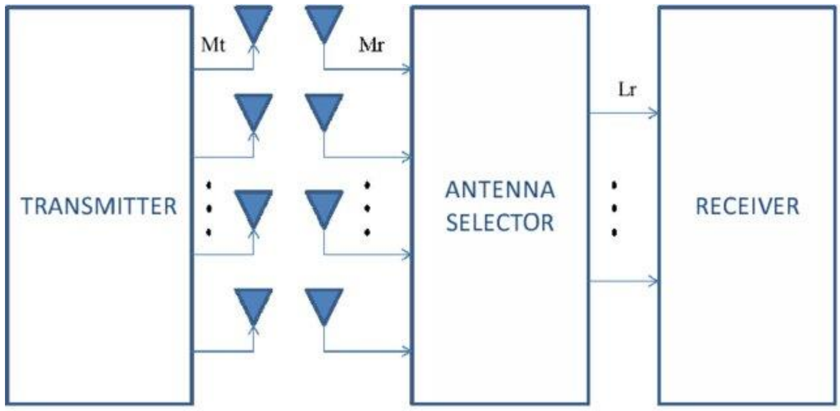

Figure 1.4: MIMO system [24]

Leveraging the spatial dimensions, MIMO systems yield substantial enhancements in data throughput, amplification of spectral efficiency, and reinforcement of signal robustness. MIMO technology aims to enhance system throughput and link reliability, and it has been widely adopted in recent communication standards.

While implementing OFDM on MIMO channels is relatively straightforward, extending FBMC to MIMO channels remains a topic of advanced research. In a MIMO system, there are Mt transmitter antennas responsible for data transmission and Mr receiver antennas for data reception. The channel coefficients, denoted as H, represent the characteristics of the communication channel and are of size Mr × Mt elements. The capacity analysis of MIMO systems has been conducted considering various combinations of transmitter-receiver antenna configurations [24]. Harnessing the power of more antennas, MIMO systems revolutionize wireless communication by enabling the instantaneous communication of various data streams across the same rate band. This innovative approach dramatically enhances the system's throughput, allowing for the concurrent delivery of more data compared to traditional single-antenna systems. By leveraging spatial multiplexing techniques, MIMO systems exploit the spatial variety of the radio channel, effectively increasing the capacity and efficiency of wireless transmissions.

As a result, this technology has become a cornerstone of modern wireless standards, facilitating higher data rates and improved network performance across a variety of applications and environments [25], [27].

MIMO technology has become integral to modern communication standards and is utilized in various applications, including Wi-Fi, LTE, and 5G networks. It offers significant advantages such as enlarged information charges, better coverage, and enhanced spectral efficiency compared to traditional single-antenna systems. The implementation of MIMO requires sophisticated signal processing techniques to decode and separate the transmitted data streams at the receiver accurately. Overall, MIMO technology plays a crucial role in gathering the growing demand for quick and reliable wireless communication services [26-27]. If the capacity of the antennas is more in a system, the spectral efficiency experiences a continuous rise, accompanied by a corresponding increase in EE up to a convincing threshold [$EE = SE \,/\, Total\ Power\ Consumption$] with this mathematical relation and $SE = K.\log_2\left(1 + \frac{M*(SNR)}{K}\right)$

Where M = number of base station antennas, K = number of users

1.5.2 Massive MIMO system

Massive MIMO represents a highly developed iteration of wireless technology that extends the capabilities of MIMO by integrating a multitude of antennas at both the Tx and Rx ends. By deploying hundreds or even thousands of antennas at BSs, Massive MIMO facilitates simultaneous transmission to multiple users, thereby amplifying SE. Vital for the progression of 5G networks, Massive MIMO leverages spatial techniques to bolster throughput and network capacity [26]. Massive MIMO and millimeter-wave (mmWave) communication stand as pivotal technologies in achieving the design objectives of 5G networks. Remarkably, these two technologies complement each other synergistically.

Their integration gives rise to mmWave massive MIMO, a paradigm that markedly enhances spectral and energy efficiency while achieving substantial gains in multiplexing and mobile network capacity. The foundational principles of massive MIMO technology are depicted in the accompanying figure 1.5.

However, this thesis takes a comprehensive approach by exploring these three key 5G techniques collectively, with a particular focal point on their precoding and beamforming strategies. Yet, the difficulty of these techniques escalates significantly when deploying a huge amount of antennas and exploiting higher RFs. Consequently, ongoing investigations aim to develop precoding and beamforming strategies that strike a balance between optimal performance and considerations such as cost, power consumption, and complexity [27].

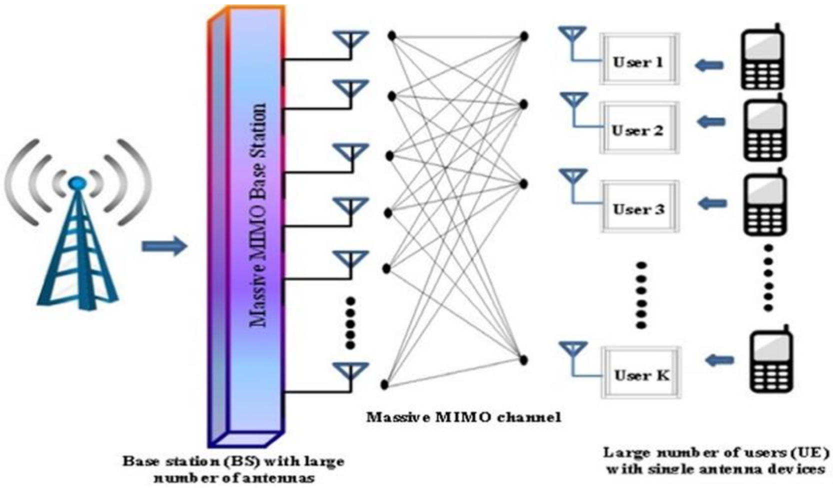

Figure 1.5: A basic massive MIMO system [27]

This thesis outlines potential future directions and highlights forthcoming challenges in the realm of mm wave massive MIMO precoding and beamforming, paving the way for continued advancements in this exciting field of research. To tackle these challenges head-on, this work delves into a range of linear precoding techniques tailored for these systems. The exploration encompasses well-established methodologies such as ZF, MRC, RZF, truncated polynomial expansion, and PZF [27]. Furthermore, it delves into non-linear precoding schemes like DPC, THP, and vector perturbation. Analytical analyses and simulation results presented in the thesis demonstrate that the partially connected hybrid analog/digital beamforming architecture emerges as a frontrunner in terms of overall performance for mmWave massive MIMO communications.

Moreover, a comprehensive analysis of beamforming techniques is provided, spanning analog, digital, and hybrid schemes. Special emphasis is placed on the potential of hybrid beamforming, considering both fully connected and sub-connected architecture approaches, in harnessing the capabilities of mmWave massive MIMO systems. Evaluation metrics encompass a broad spectrum of performance indicators, including BER, SNR, complexity, SE, and EE.

Table 1.2: Differences between traditional MIMO and Massive MIMO [27]

Technical Content	**Traditional MIMO**	**Massive MIMO**
Antenna numbers	≤ Eight	>100
Channel medium	Lower order	Higher order
Channel Facility	Weak signal compared to noise leads to errors	Clear signal leads to reliable communication.
Mixture Gain	Less spatial resolution and multiplexing ability.	Higher chance of selecting users with strong instantaneous channels)
Symbol Error Rate	More	Less
Pilot contamination	Not used	Used
Deployment	Used in 3G/4G wireless systems	Key technology in 5G and future 6G networks
Spatial Multiplexing	Limited parallel data streams	Many simultaneous users/data streams
Energy Efficiency	Limited	High (via focused beamforming and power scaling)
Spectral Efficiency	Moderate	Extremely high due to spatial reuse.

Scalability	Not easily scalable	Highly scalable for dense user environments.
Interference Management	Limited capabilities	Improved interference suppression (via precoding, beamforming)
Spatial Multiplexing	Limited parallel data streams	Many simultaneous users/data streams
Energy Efficiency	Limited	High (via focused beamforming and power scaling)

Table 1.2 shows that massive MIMO builds upon the foundations of MIMO, offering significant advantages in terms of capacity, coverage, and reliability [28]. This can be achieved through the utilization of a device known as an energy harvester. For the development of QoS(Quality of Service) provisioning for massive MIMO-based 5G networks, it is to increase energy. The study and simulation results have shed important light on how well these methods work to increase transmission rates, boost signal quality, and control interference. The comparative examination of MIMO with beamforming and classic MIMO and single-antenna systems demonstrated the supremacy of MIMO with precoding in requisites of capacity, signal quality, and interference management, according to the study's conclusions.

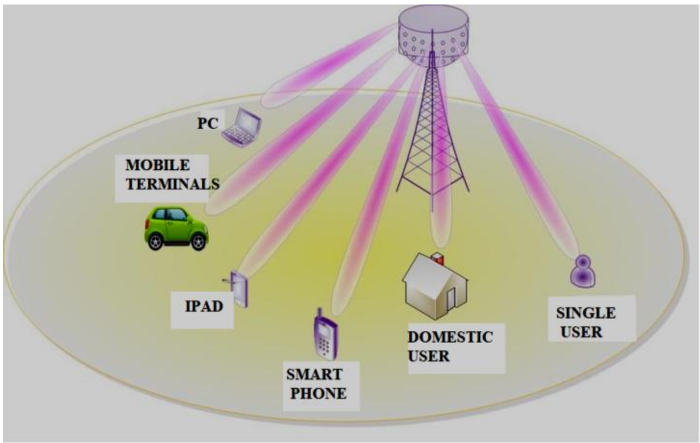

Figure 1.6: Massive MIMO system BS to all users [28].

The massive MIMO system is designed to achieve high data throughput and low latency as shown in the figure 1.6. By utilizing a large array of antennas, massive MIMO facilitates spatial multiplexing, enabling the simultaneous transmission of multiple data streams. This significantly enhances system capacity, achieving data rates of up to 20 Gbps. Furthermore, the integration of advanced beamforming and channel estimation techniques—potentially incorporating algorithms such as Least Mean Squares (LMS)—ensures precise signal detection and minimizes retransmissions. These features collectively contribute to reduced latency and improved spectral efficiency, positioning massive MIMO as a critical technology for fulfilling the performance requirements of 5G networks.

These results highlighted the potential of massive MIMO, precoding, and beamforming to satisfy the growing need for fast and dependable communication services in 5G and other wireless networks in the future. Figure 1.6 shows the base station with a greater number of users. The utilization of large-scale MIMO holds the possibility to extensively enhance the presentation of wireless power transmission systems. The fundamental objective of wireless energy transmission is to fulfill the energy requirements of the receiver, which aligns with intuitive reasoning. This technology opens up possibilities such as wirelessly charging medical implants and facilitating the transmission of checkup data to an out-of-the-way beneficiary by harnessing the acquired energy. With the burgeoning growth in data traffic, the forefront of next-generation systems is anticipated to be mmWave communication [28].

In these systems, the proliferation of BS antennas enables beamforming, directing communicated signals towards specific points in space. This precision allows the BS to efficiently distinguish linking entity users, thereby attracting spatial declaration. Massive MIMO configurations typically feature a base station equipped with a multitude of antennas, facilitating concurrent service to numerous active users within the same time-frequency block. This technology is poised to be instrumental in the development of new networks that are both spectral and energy-efficient. By concentrating transmitted signal energy into localized areas, massive MIMO promises significant enhancements in system performance.

1.6 Key Enabling Technologies for 5G

5G mobile communication systems are projected to support improved ultra-broadband, ultra-reliable, and low-latency communication, reflecting the diverse requirements of modern connectivity.

Meeting these demands will necessitate a significant paradigm shift in network infrastructure to accommodate larger data rates, lower network latencies, improved EE, and dependable omnipresent connectivity. To bring 5G into practical fruition, several key technological breakthroughs are essential [29]. Figure 1.7 illustrates the essential techniques required to realize the 5G specifications in practice.

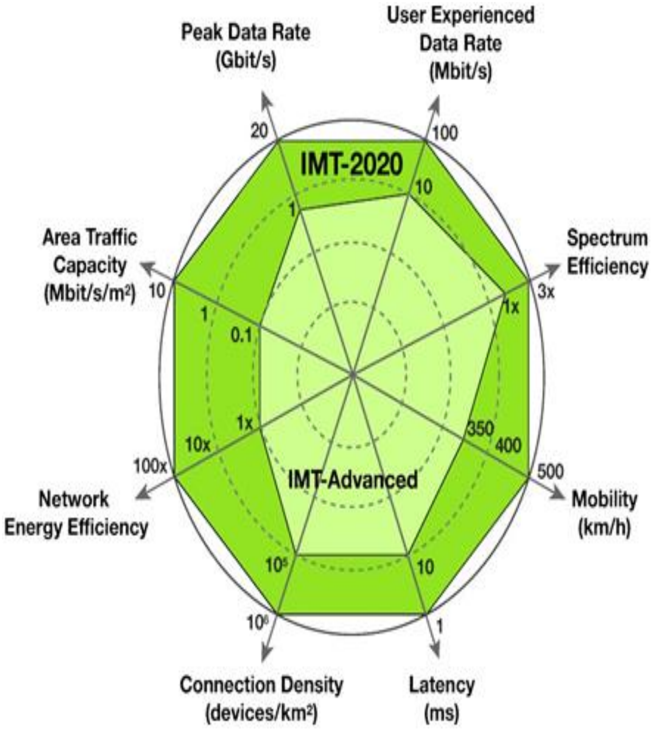

Figure 1.7: Key parameters for IMT2020 [29]

The (IMT-Advanced) International Mobile Telecommunications-Advanced facility, endorsed by the (ITU) International Telecommunication Union, signifies an important bound forward in transportable statement technology, surpassing the capabilities of its predecessor, IMT-2000 (3G). Although labeled as a 4G technology by the ITU, it's important to note the absence of a universally accepted definition for "4G." LTE, used in the 3rd Generation Partnership Project (3GPP), serves as a fully 4G-capable movable broadband stage [29].

Utilizing OFDM as its cornerstone, LTE ropes variable transmission bandwidths of up to 20 MHz and incorporates highly developed multi-aerial communication techniques. The evolution of these systems underscores the importance of global collaboration among mobile communication companies and governments.

Various entities, including the Electronics and Telecommunication Research Institute, Samsung, Nokia Siemens Networks (NSN), and others, have been actively engaged in the growth of 4th generation systems and beyond [29]. The pursuit of "Giga Korea" and advancements in mm-wave wireless communication exemplify the ongoing efforts to establish hyper-connected IT infrastructure.

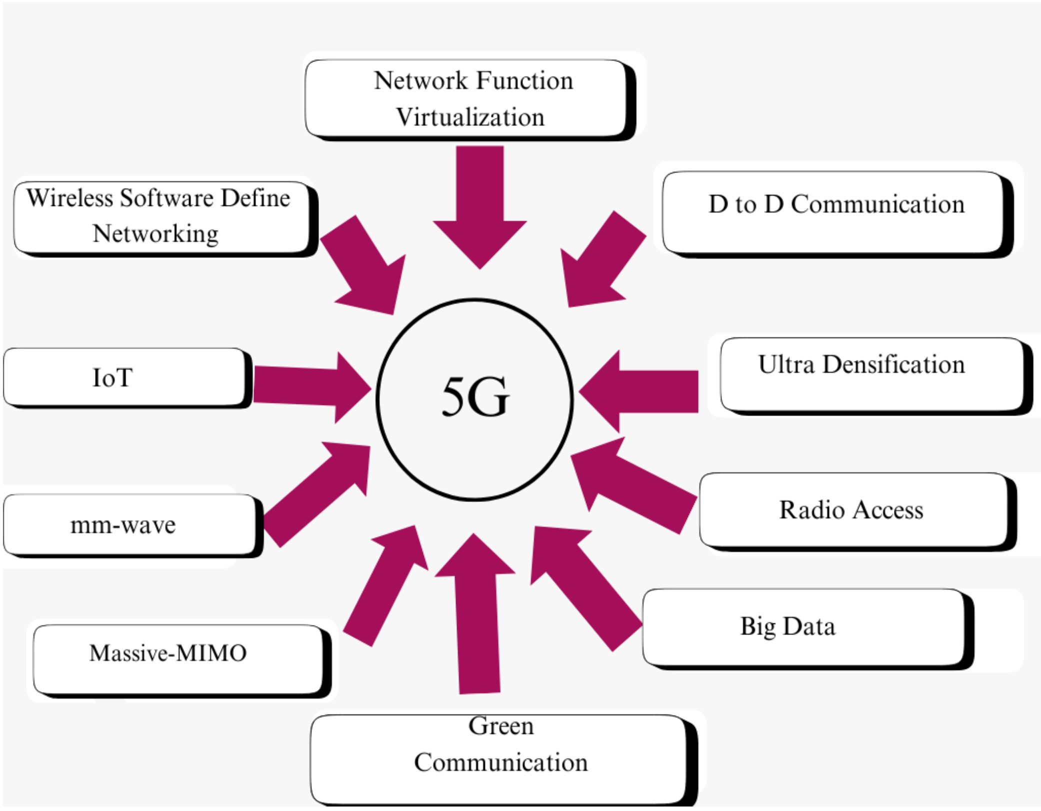

Figure 1.8: 5G key enabling technologies [30]

Central to the more data charge in 4G systems is MIMO technology, facilitating multi-stream communication, enhancing SE, and improving link quality. Adaptive beamforming using antenna arrays enables MIMO to adapt emission patterns for signal gain and noisiness improvement [30].

However, the exponential growth in cellular phone traffic demands, with a projected thousand-fold increase by 2020, necessitates continuous research into enhancing capacity and exploring new wireless spectrum.

LTE Advanced embraces heterogeneous networks comprising macro, micro, and picocells alongside Wi-Fi APs. Self-organizing capabilities and repeaters/relays facilitate cost-effective deployment. Anticipated disparities between 4G and the upcoming fifth-generation (5G) technology include leveraging untapped millimeter-wave frequency bands for greater spectrum allocations, deploying directional beamforming antennas, prolonging battery life, minimizing outage probability, achieving superior bit charges, reducing infrastructure costs, and enhancing aggregate capacity.

Future networks are expected to support significantly higher traffic volumes with peak rates exceeding 10 Gbps and latency below 1 ms, necessitating diverse radio access technologies and continuous innovations to meet growing demands.

Furthermore, combining MIMO with cutting-edge beamforming techniques improves system capacity and coverage but necessitates the use of complex algorithms and optimization approaches [30]. Massive MIMO systems can serve several customers at the same time-frequency resource to the base station's many antennas. So, the main goal is to provide sufficient baseline knowledge on multi-carrier transmission techniques that might be applied in a massive MIMO context and in MIMO and other next-generation wireless systems. In wireless systems, there is always a need to improve performance and QoS.

Simultaneously, in line with the imperative of advancing green communication practices, the sole pursuit of spectrum efficiency in communication systems has given way to a more balanced consideration of energy efficiency [30]. The emergence of energy efficiency as an optimization metric signifies a focus on decreasing the overall energy consumption of the system.

1.7 The Main Advantages of the Massive MIMO Technique:

This technology offers a multitude of advantages in wireless communication systems. Firstly, it significantly enhances spectral efficiency by exploiting the spatial domain through the utilization of a huge number of antennas at the BS [30]. This allows for concurrent transmission to multiple users, effectively increasing the system's throughput. Furthermore, it enables efficient utilization of available spectrum resources, leading to improved network capacity and coverage. Moreover, massive MIMO systems exhibit robustness against various propagation conditions, making them suitable for deployment in diverse environments. Lastly, the technology holds promise for enhancing EE in wireless networks by optimizing the utilization of resources and reducing overall power consumption.

- **Increased Spectral Efficiency**: This technology enhances spectral efficiency by leveraging a huge array of antennas at the BS, allowing for instantaneous transmission to numerous users and maximizing the utilization of available spectrum.
- **Improved Throughput**: By exploiting spatial multiplexing, these systems can achieve higher data rates and throughput compared to traditional MIMO systems, thereby meeting the growing demand for quick information for armed forces.
- **Robustness Propagation Conditions**: Massive MIMO systems exhibit robustness against various propagation conditions, including multipath fading and shadowing, making them suitable for deployment in diverse environments with challenging RF conditions.
- **Increased Energy Efficiency**: Through advanced signal processing techniques and optimized resource allocation, massive MIMO technology contributes to improved energy efficiency in wireless networks, reducing overall power consumption and operational costs.
- **Improved Coverage:** Beamforming can extend the coverage of the network by directing the signal towards users located at the cell edge.
- **Reduced Energy Consumption:** By reducing interference and improving spectral efficiency, precoding and beamforming can contribute to lower energy consumption.
- **Enhanced User Experience:** Improved signal quality and reduced interference lead to a better user experience in terms of voice and data services.

1.8 Research Problem:

The rapid evolution of wireless communication has led to the deployment of fifth-generation (5G) networks, which aim to meet the growing demands for high data rates, ultra-low latency, massive connectivity, and enhanced reliability. Massive Multiple-Input Multiple-Output (Massive MIMO) technology plays a crucial role in realizing these goals by significantly increasing spectral and energy efficiency. However, despite its potential, ensuring consistent and reliable Quality of Service (QoS) provisioning in Massive MIMO-based 5G networks remains a significant challenge. The complexity of channel estimation, dynamic user mobility, interference management, and resource allocation in highly dense and heterogeneous environments hinders optimal QoS delivery.

Therefore, there is a critical need for robust frameworks and techniques that can address these challenges and ensure efficient QoS provisioning in Massive MIMO-enabled 5G networks.

Massive MIMO systems can serve several customers at the same time-frequency resource to the base station's many antennas. So, the main goal is to provide sufficient baseline knowledge on multi-carrier transmission techniques that might be applied in a massive MIMO context and in MIMO and other next-generation wireless systems.

In wireless systems, there is always a need to improve performance and QoS. When evaluating the performance of MIMO and beamforming systems, simulation is a crucial tool to have at your disposal. Because of its flexibility and user-friendliness, the MATLAB simulation environment is utilized by a large number of people.

This methodological framework serves as a blueprint for researchers to systematically investigate the intricacies of massive MIMO, ensuring methodical execution and rigorous examination of results. Through this approach, researchers can gain deeper insights into the capabilities, limitations, and potential applications of massive MIMO systems.

The research methodology for massive MIMO outlines the systematic approach employed to investigate and analyze various aspects of massive MIMO technology. This methodology serves as a roadmap for researchers to navigate through the complexities of massive MIMO studies, ensuring methodical execution and robust analysis of findings.

When evaluating the performance of MIMO and beamforming systems, simulation is a crucial tool to have at your disposal. In the research that has been done on this topic, several different simulation approaches have been suggested as possible ways to investigate the functioning of the system and evaluate its capabilities [30].

1.9 Parameter Initialization*:*

This technology study begins by configuring a number of parameters, including the number of base station antennas (n Antennas), the total number of system users (n Users), and an array of angular degrees (angular degree) that represents the angles at which the users are positioned [30]. Additionally, it initializes a transmission rate matrix to store user transmission rates at various angles. Zeros are used to initialize the matrix. The thesis then moves into a nested loop where transmission rates are simulated for various users and angle degrees.

It uses the function to simulate the transmission rate to determine the transmission rate based on the specified angular degree.

- **SNR, BER, Transmission Rate, Throughput, PAPR, Antenna Efficiency, EE, PAPR, Sum rate, SE, Residual Energy, SER, CCDF, System Capacity for QoS Calculation*:***

The study computes the BER, EE, SNR, and QoS based on the calculated transmission rates after simulating transmission rates.

• **SNR:** It quantifies the relationship between the signal powers to the noise power within the channel.

$$\mathbf{SNR(in\ dB) = 10 * \log_{10}\left(\frac{P\_signal}{P\_noise}\right)} \tag{1.1}$$

Where: P_signal is the power of the transmitted signal [30].

P_noise is the power of the noise in the channel.

• **BER:** It signifies the amount of incorrectly received bits relative to the full amount of transmitted bits sent.

$$BER = \frac{\text{Number of bits received in error}}{\text{Total number of communicated bits}} \tag{1.2}$$

• **Transmission Rate:** The data transfer speed refers to how quickly information is conveyed through the channel and is typically spoken in bits per second (bps).

$$\text{Transmission Rate} = \text{Modulation scheme} * \text{Symbol rate} \tag{1.3}$$

• **Throughput**: Throughput is the actual data rate achieved by a communication system, considering overhead and possible errors.

$$\text{Throughput} = \text{Transmission Rate} \times (1 - \text{BER}) \qquad (1.4)$$

- **Signal Power (P_signal):** The power of the input signal is related to the transmit power and the antenna gain.

$$\mathrm{P_{signal}} = \text{Transmit Power} \times \text{Antenna Gain} \qquad (1.5)$$

• **PAPR:** It is a measure of the peak power compared to the average power in a transmitted signal.

$$PAPR = \frac{(\textbf{Peak Power of the Signal})^2}{(\textbf{Average Power of the Signal})^2} \qquad (1.6)$$

• **The antenna efficiency:**

$$\text{Antenna Efficiency} = \left(\frac{\text{RF Output Power}}{\text{DC Input Power}}\right) * 100\% \qquad (1.7)$$

• **Spectral Efficiency (SE):**

$$SE = K.log2(1 + \frac{M(SNR)}{K}) \qquad (1.8)$$

Where K: number of users, M : number of antennas at the base station.

• **Energy Efficiency (EE):**

Energy efficiency in a massive MIMO system measures how effectively the system utilizes energy to transmit and receive data while maintaining a specific level of performance.

$$EE = SE \,/\, Total\ Power\ Consumption \qquad (1.9)$$

- **Achievable sum rate (R_{sum}):** For a massive MIMO system with K users and perfect CSI, the achievable sum rate can be given by: $R_{sum} = \sum_{k=1}^{K}(1 + \log_2(1 + SNR_k)$ (1.10)

• **Residual Energy:** Residual energy (RE) in this system refers to

• the unused energy remaining after a specific process or transmission.

$$RE = Initial\ Energy - Consumed\ Energy \qquad (1.11)$$

- **Symbol Error Rate (SER):** It is a measure of the likelihood that a transmitted symbol is incorrectly detected at the receiver. Here, P is the number of symbols modulation scheme.

$$SER = BER * (\log_2 P) \tag{1.12}$$

- **Complementary Cumulative Distribution Function (CCDF):**

It is a statistical tool used to characterize the probability that a random variable exceeds a specific threshold. Specifically, in wireless communications, the CCDF is commonly applied to metrics such as the SNR, PAPR, or achievable sum rate.

$$CCDF(x) = P_r(\mathrm{X} > x) = 1 - \mathrm{F_X}(\mathrm{x}) \tag{1.13}$$

Where: P_r (X>x) is the probability that X exceeds the value x,

$\mathrm{F_X}(\mathrm{x})$, the cumulative distribution function (CDF) of X.

$$CCDF = (P_r(PAPR > PAPR_O) \tag{1.14}$$

- **System Capacity (SC) :**

Massive MIMO enhances system capacity significantly by allowing simultaneous transmission to multiple users over the same frequency band through spatial multiplexing, thereby efficiently utilizing available spectrum and improving spectral efficiency.

$$SC = \log_2\left(det\left(1 + \frac{SNR}{K}\right)\right) \tag{1.15}$$

Maximizing the capacity of a system hinges on the adept utilization of massive MIMO precoding techniques.

These methodologies entail sophisticated signal processing strategies implemented at the transmitter, enabling efficient management of the complexities inherent in large-scale MIMO systems.

Among the array of precoding methods commonly employed are zero forcing (ZF), which nullifies interference from other users' signals; matched filtering, which optimally combines received signals; MRC, aimed at maximizing the signal power; and MMSE, which minimizes the error between transmitted and received signals [30].

Additionally, techniques such as matched filter precoding and PAPR precoding are deployed to address specific challenges encountered in the system, ensuring robust and efficient signal transmission.

Moreover, various nonlinear methods are tailored to further enhance system performance by effectively mitigating nonlinear distortions and optimizing spectral efficiency [30]. Through the strategic implementation of these pre-coding techniques, massive MIMO systems can unlock their full potential, delivering enhanced capacity and improved overall performance in wireless communication networks. Zero-forcing, also referred to as no interference, is a spatial pointer giving out approach frequently employed in MIMO wireless communication systems to mitigate multiuser interference [30].

1.10 Research Objectives

1. Study and analyze various massive MIMO techniques for 5G networks.

2. To propose an energy-efficient algorithm to maximize energy harvested in massive MIMO systems (EHMMS).

3. To develop a novel PAPR reduction technique for the proposed system.

4. Performance analysis of the proposed technique compared to existing methods using potential parameters like throughput, energy efficiency, and residual energy.

The first objective focuses on an in-depth exploration of diverse massive MIMO techniques that form the backbone of 5G wireless communication systems. It leverages a large number of antennas at the base station to serve multiple users simultaneously, significantly enhancing spectral and energy efficiency.

This stage of the study involves a comprehensive review of the current state-of-the-art technologies, including advanced precoding methods such as zero-forcing (ZF), maximum ratio transmission (MRT), and minimum mean square error (MMSE). It also covers aspects like channel estimation strategies, pilot contamination mitigation, beamforming techniques, and hybrid architectures using the ZF-SSLP method. By analyzing the performance trade-offs, complexities, and deployment challenges of each technique, this step lays a strong theoretical foundation for the development of optimized solutions tailored for 5G environments.

The second objective is to develop an innovative algorithm that enhances energy harvesting in massive MIMO systems, thereby improving the overall energy efficiency of 5G networks. The proposed energy harvesting in massive MIMO systems algorithm will be designed to optimally allocate resources such as power and, antennas while also supporting SWIPT. The algorithm aims to intelligently balance the trade-off between data transmission and energy harvesting by leveraging channel state information and user distribution. Advanced optimization techniques, including convex optimization and machine learning, may be employed to dynamically adapt to varying network conditions. The ultimate goal is to create a scalable and energy-efficient solution that aligns with the growing demand for green communication technologies.

High PAPR remains a significant challenge in massive MIMO systems, leading to power inefficiencies and signal distortion. The third objective addresses this issue by introducing a novel PAPR reduction technique specifically tailored for the proposed SCS-BiLSTMAE framework. The technique will aim to minimize PAPR without compromising data integrity or increasing system complexity. Potential approaches may include signal distortion methods like clipping and filtering, coding techniques such as SLM, or intelligent algorithms utilizing artificial intelligence to predict and mitigate high peaks in the signal. This innovative solution is expected to improve power amplifier efficiency and extend the operational life of communication hardware.

The final objective involves a thorough performance evaluation of the proposed system in comparison with existing state-of-the-art methods. The assessment will be conducted using key performance indicators such as throughput, energy efficiency, and residual energy. Additional metrics like BER, PAPR levels, and spectral efficiency may also be considered to provide a comprehensive understanding of the system’s effectiveness.

Simulations will be carried out using platforms such as MATLAB to validate the proposed algorithm under realistic 5G scenarios. This analysis will not only demonstrate the practical viability of the proposed solutions but also highlight their advantages over conventional approaches using the SCS-BiLSTMAE method.

1.11 Key contributions of the thesis

1.11.1 Analyzing massive MIMO precoding and beamforming techniques

- **Hardware Complexity:** Implementing complex precoding algorithms and beamforming techniques can increase the hardware complexity and cost of the base station.
- **Pilot Contamination:** In dense networks, pilot signals used for channel estimation can interfere with each other, leading to performance degradation.
- **Channel Estimation:** Accurate channel estimation is crucial for the effectiveness of precoding and beamforming, especially in rapidly changing environments. To support accurate data detection and beamforming, we have implemented the BiLSTM channel estimation algorithm**.** This method is selected due to its suitability for low complexity, real-time adaptation, and accuracy, and is applied in the simulation/modeling of the 5G massive MIMO system to ensure accurate CSI acquisition and reliable performance evaluation. The MMSE estimator is a sophisticated statistical technique that aims to provide the most accurate possible channel estimate. Its primary goal is to minimize the mean square error (MSE) between the true, unknown channel coefficients and their calculated estimates.

1.11.2 Key Techniques for Maximizing Energy Harvesting in Massive MIMO

Massive MIMO enables joint transmission of energy and data, allowing receivers to decode information and harvest energy simultaneously by the SWIPT method with power splitting and antenna switching. These technologies have emerged as a cornerstone in modern wireless communication, promising unprecedented energy efficiency and spectral gains. Energy harvesting in massive MIMO refers to the process of collecting ambient energy from transmitted signals and converting it into usable power for low-energy devices.

A key technique in maximizing energy harvesting in massive MIMO systems is optimal beamforming. It enables the precise direction of radio waves to maximize the power transfer to energy-harvesting nodes. By tailoring beam patterns to align with the positions of target devices, the harvested energy efficiency can be substantially improved. Another strategy involves power-splitting and time-switching protocols. These methods allow devices to dynamically allocate received signal power between information decoding and energy harvesting. Adaptive algorithms ensure that the split ratio or switching duration is optimized in real-time, considering the channel conditions and energy requirements [30].

The SWIPT method dynamically switches between energy harvesting and data transmission phases to optimize the overall system performance. Algorithms can be developed to determine the optimal time allocation for each user based on their energy needs and channel conditions. It divides the received signal into two streams: one for energy harvesting and the other for information decoding. Optimizing the power splitting ratio can maximize energy harvesting while ensuring adequate signal quality for data reception. It utilizes efficient energy storage mechanisms to store harvested energy for later use, allowing for continuous operation even during periods of low energy availability.

Employing machine learning algorithms to predict and adapt to changing energy harvesting conditions, optimize power allocation, and improve overall system performance.

1.11.3 Key Techniques in Improvement of PAPR Reduction in Massive MIMO Systems

One prominent method for PAPR reduction is the use of precoding techniques. Precoding allows signal optimization before transmission, ensuring that the signal's peaks are minimized while maintaining the desired quality of service. Selected Level Mapping (SLM), Partial Transmit Sequence (PTS), Particle Swarm Optimization (PSO), and SCS-BiLSTMAE are probabilistic approaches widely adopted for PAPR reduction. In these methods, multiple signal sequences are generated, and the one with the lowest PAPR is selected for transmission.

This approach significantly improves the PAPR profile without degrading the signal quality. Deep learning (DL) has recently been integrated into PAPR reduction strategies to optimize the performance of traditional methods. ML models, trained on system-specific data, can dynamically adjust parameters to achieve better PAPR reduction in real-time scenarios. Lastly, hybrid techniques combining multiple PAPR reduction methods have emerged as a comprehensive solution.

For instance, combining SLM with precoding or integrating companding with PTS can yield superior results. These hybrid methods leverage the strengths of individual techniques while compensating for their weaknesses.

1.11.4 Key Techniques in Performance Analysis of Parameters

In modern wireless communication systems, the evaluation of performance parameters is essential to ensure reliability, efficiency, and sustainability. Among these parameters, throughput, energy efficiency, and residual energy play pivotal roles in determining the overall system effectiveness. A comprehensive analysis of these metrics is crucial for designing next-generation communication networks.

- **Throughput** represents the amount of data successfully transmitted over a network within a given time frame. It is a critical indicator of system capacity and performance. In systems like massive MIMO and IoT networks, achieving high throughput requires optimizing resource allocation, reducing interference, and enhancing spectral efficiency. Factors such as channel conditions, modulation schemes, and traffic patterns significantly influence throughput. Adaptive modulation and coding techniques, as well as advanced scheduling algorithms, have proven effective in maximizing throughput under varying network conditions.
- **Energy Efficiency** metric is particularly important in energy-constrained systems, such as sensor networks and mobile devices. Improving energy efficiency involves minimizing power consumption while maintaining acceptable quality of service. Techniques such as energy-aware routing, power control and beamforming are commonly employed to enhance EE. Additionally, the integration of renewable energy sources and hybrid energy-harvesting systems further boosts energy efficiency in sustainable network designs.
- **Residual Energy** is a crucial parameter for ensuring the longevity of energy-constrained systems, particularly in wireless sensor networks and battery-powered devices. Residual energy is influenced by factors such as transmission power, operational cycles, and energy-harvesting capabilities.

1.12 Proposed methodology:

Proposed methodology block diagram is presented in figure.1.9

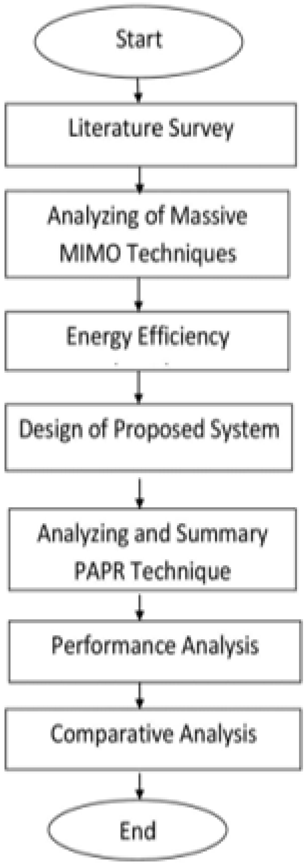

Figure 1.9: Flow Chart of Proposed methodology

Stage I: Analyze the conventional techniques and understand the gaps.

Stage II: Design of proposed technique for energy harvesting using optimization.

Stage III: Implementing the proposed techniques.

Stage IV: Adding PAPR techniques for the proposed technique.

Stage V: Using the proposed optimization techniques in one or two intrusive applications.

Tools: MATLAB R2024b simulation tool can be used as platform for compilation and simulation.

Modeling the MIMO channel, creating random channel realizations, simulating beamforming methods, and computing presentation metrics such as transmission rate and SINR are all possible with the help of MATLAB R2024b, which offers a comprehensive collection of functions and tools for these purposes. Modeling the MIMO channel, creating random channel realizations, simulating beamforming methods, and computing performance metrics such as data rate and SNR are all possible with the help of MATLAB, which offers a comprehensive collection of functions and tools for these purposes. These proposed methodologies are then evaluated through simulations or practical implementations to assess their effectiveness in enhancing QoS parameters, as shown in figure 1.9.

Based on the findings, novel methodologies tailored to the specific requirements of 5G networks are proposed, focusing on aspects such as supply distribution, noisiness management, and beamforming strategies. Finally, iterative refinement and optimization of the proposed methodologies are performed based on feedback and performance evaluations, ensuring continuous improvement and adaptation to evolving network conditions and user demands. Through this approach, the QoS capabilities of massive MIMO systems in 5G networks can be maximized, ultimately leading to better system presentation and consumer contentment.

1.13 Thesis organization

The thesis is presented in the following manner. The introduction will be presented in chapter one. The literature review will be presented in chapter two. Algorithms for the proposed methods will be discussed in chapters three through six. A conclusion and future scope will be offered in chapter seven.

In the second chapter, the literature review and review table will be discussed. This chapter has presented a comprehensive review of relevant literature and identified key themes and gaps that inform the current research. The inclusion of a review table provides a structured and summarized representation of the literature consulted. The insights gained from this chapter contribute directly to the development of the research framework and the justification for undertaking the present study.

In the third chapter, precoding and beamforming are fundamental techniques for realizing the full potential of these systems. Linear precoding methods like ZF and hybrid ZF with SLLP strike a balance between performance and complexity, while hybrid beamforming offers a practical compromise for high-frequency deployments. Overcoming challenges such as pilot contamination and hardware limitations will be pivotal in advancing these technologies. By carefully designing and implementing these techniques, it is possible to achieve significant improvements in system performance, energy efficiency, and user experience.

In the fourth chapter, advanced channel state information (CSI) acquisition is crucial for energy harvesting. Massive MIMO systems rely on accurate CSI to predict the optimal transmission parameters. Techniques such as deep learning-based CSI prediction have been explored to enhance energy transfer accuracy, reducing the impact of channel fading and noise. Additionally, the integration of hybrid energy-harvesting systems combining radio frequency (RF) energy harvesting with solar or vibration energy harvesting offers a robust solution. These systems ensure reliable operation even in environments with fluctuating RF signal strengths. Maximizing energy harvesting in massive MIMO systems is a multidisciplinary challenge requiring innovations in hardware design, algorithm development, and system optimization. Future advancements in artificial intelligence, green communication technologies, and energy-efficient circuit designs are expected to further elevate the potential of this transformative approach.

In the fifth chapter, improving PAPR reduction in massive MIMO systems is pivotal for the efficient operation of next-generation wireless networks. As research continues, advancements in hardware capabilities, optimization algorithms, and intelligent systems are expected to revolutionize PAPR reduction techniques, ensuring sustainable and high-performance communication systems. By employing a combination of digital and analog techniques, along with machine learning approaches, it is possible to mitigate the impact of high PAPR and improve the overall system performance. Here, a BiLSTM system is employed to capture high-range chronological dependencies inherent in the signal. Long-range dependencies denote relationships between distant elements within the signal sequence, which may span over considerable time intervals.

By leveraging the BiLSTM network, the system effectively captures and learns these intricate temporal dependencies, thereby refining the PAPR reduction achieved by the SCS-AE compression.

Sixth chapter: The interdependence between throughput, EE, and RE requires careful optimization to achieve a balanced system performance. For example, maximizing throughput often involves higher power consumption, potentially reducing energy efficiency and depleting residual energy. Conversely, focusing solely on energy efficiency may compromise throughput. Advanced optimization techniques, such as multi-objective algorithms and machine learning-based approaches, are increasingly employed to balance this trade-offs and achieve an optimal performance profile. Throughput, EE, and RE are critical performance metrics in wireless communication systems. By carefully analyzing and optimizing these parameters, it is possible to design systems that are efficient, reliable, and sustainable.

In the seventh chapter, the conclusion and the future scope of the future generation system can be explained. Adaptive constellation mapping and demapping serve as additional contributors to system enhancement by dynamically adjusting the signal constellation in response to changing channel conditions. This adaptive approach ensures optimal signal transmission and reception, maximizing spectral efficiency and minimizing, as was explained in the last chapter.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

Many researchers have done work related to 5G and Massive MIMO consideration of various technological implementations in it to improve the system; the below gives an overview of research gaps found in the literature survey.

Pioneering green networking techniques, energy efficiency maximization schemes, intervention exposure and improvement strategies, and connectivity administration approaches have emerged to establish efficient wireless systems capable of meeting the escalating demand for traffic while ensuring the continuous evolution of wireless technologies.

Zhang et al. (2019) paper introduces a comprehensive framework for optimizing resource allocation in 5G mobile wireless networks leveraging mmWave multi-input multi-output (m-MIMO) technology, catering to both asymptotic and non-asymptotic scenarios. By integrating statistical quality-of-service (QoS) considerations, the proposed methods offer versatile strategies tailored to the distinctive characteristics of mmWave communication. Our model delineates the intricate interplay between network parameters and QoS metrics to maximize actual capacity, ensuring efficient utilization of resources while meeting stringent performance requirements. Through meticulous analysis and innovative approaches, our suggested schemes aim to propel mmWave m-MIMO-based 5G networks towards their full potential [31].

Kayyali et al. (2020) paper introduces, before delving into resource management and quality-of-service (QoS) provisioning, this study meticulously examines the features and specifications inherent in 5G networks. By comprehensively understanding the intricacies of 5G technology, the research aims to lay a solid foundation for optimizing resource utilization. Subsequently, a survey is conducted, focusing on various aspects of resource management and QoS provisioning within the realm of 5G networks [32].

In 2021, Lavdas et al. have suggested an adaptive hybrid beamforming method for 5G millimeter wave MIMO wireless cellular networks. Here, assess the performance of the adaptive hybrid A-D beamforming technique in 5G mmWave wireless cellular networks with massive MIMO. Here, generated beams were created dynamically in response to traffic demands by means of analog on-off activation of burning essentials for each perpendicular aerial collection. This eliminates the need for a costly, mechanically complex steering antenna system, thereby serving active users who request high data rate services. Every vertical array has a dedicated RF chain, making it a radiating element in circular array design. When analyzed with static grid of beams scenario, the suggested adaptive process is able to drastically lower the number of active radiating antenna elements. In same setting, it was possible to drastically lower both the overall downlink transmission power and the blocking probability by maintaining a fixed number of radiating elements. It attains a low bit error rate, and it provides a high normalized mean square error [33].

In 2021, Ahmed et al. have presented ML depending on the selection of beams with lower complexity hybrid beamforming design for 5G massive MIMO systems. Here, provide a low-difficulty hybrid beamforming and energy-effectual joint ML-dependent beam-user selection for a multiuser massive MIMO downlink system. The 5G technology that was being employed in vehicle-to-everything communications and other IoT applications was greatly facilitated by massive MIMO systems; the radio frequency (RF) chain's high power consumption was a result of the base station's numerous antennas. Here, present ML depend beam-user selection strategy that facilitates creation of an orthogonal hybrid beamforming design with low complexity. Using Householder (HH) reflectors, an orthogonal analogue beamforming (ABF) matrix was produced. For beam-user selection, it employs a feedforward neural network (FFNN) approach. It provides low computation complexity, and it attains low blocking probability [34].

Zhang et al. (2021) pioneer the establishment of these networks within the context of 6G wireless technology, augmented by instantaneous wireless information and power transfer capabilities. Through meticulous planning and analysis, we aim to strike an optimal balance that maximizes the benefits of both energy harvesting and data transmission, ensuring efficient resource utilization while meeting stringent QoS constraints. To validate the efficacy of our proposed techniques, extensive simulations are conducted, providing empirical evidence of the performance gains achieved by the developed systems [35].

Liu et al. (2021) introduced a novel approach to address low-complexity detection by leveraging Neumann series expansion for approximate matrix inversion. By truncating the series to limit elements, they achieved a significant reduction in complexity. However, this method's performance suffers from increased complexity with a higher number of elements and lowers BER due to truncation [36].

Lavdas et al. (2022) A novel approach for machine learning (ML) beamforming involves leveraging a k-nearest neighbors (k-NN) approximation method, presenting an alternative paradigm to traditional techniques. This approach entails training the system to generate optimal beamforming configurations based on the spatial distribution of throughput demand, effectively adapting to varying network conditions. Rigorous evaluation of this method is conducted using a specially designed system-level simulator capable of executing parallel Monte Carlo simulations, ensuring comprehensive assessment across diverse scenarios. The results obtained from this evaluation reveal that the potential SE and EE values achieved through the k-NN approximation method are comparable to those attained by existing state-of-the-art methodologies. Notably, this is accomplished while minimizing hardware and algorithmic complexity, as user-specific beamforming computations are obviated. This underscores the efficacy of the proposed approach in optimizing beamforming performance while streamlining implementation, thus contributing to advancements in ML-based beamforming techniques [37].

In 2022,Gholami-Dadkan, et al. have presented reducing jamming effects in multicellular massive MIMO systems. Here, assess the multi-cell scenario's Ma-MIMO systems' sum spectral efficiency (SE) with respect to jamming effects. Initially, a closed-form expression for the sum SE in the presence of a jammer was found utilizing dual detectors, maximum ratio combining, and zero-forcing. Next, system performance was determined in relation to overcrowding energy, number of BS aerials, SNR, and lengths of coherence blocks.

Finally, the challenge of enhancing fairness trade-off among middle awful users and cell edge rightful users was showed by employ log barrier functions in order to optimize SINR of cell edge users. Numerical studies demonstrated that sum SE better with suggested approaches, also by increasing number of antennas at BS while taking into account similar nosiness strength and energy of legal users. It provides low normalized mean square error and it attains low energy efficiency [38].

In 2023,Nguyen et al. have presented a DL framework about the selection of beams with power in these systems. The beam-steering technique was applied to assess the user's signal intensity coming from the BS. In the case when the channel was unknown, suggest a unique learning framework to identify the optimal beam for a given user, transmit power to minimize total cost, which includes both transmit power and dissatisfaction rate. It also solves problem of missing data and uses LSTM on temporal processed inputs to choose the appropriate beam. In addition, create a learning agent that considers the necessary transmission rate while predicting the appropriate transmit power from transmitted SSBs [39].

In a similar vein, Fang et al. proposed a low-complexity detection method based on MMSE parallel interference cancellation, also utilizing Neumann series to avoid complex matrix inversions. Despite its simplicity, this approach tends to exhibit a high BER in 2023 [40].

Contrarily, Gao et al. proposed an alternative solution where matrix inversion is circumvented, and detection vectors are directly formed by solving linear equations. Employing the Successive Over Relaxation (SOR) algorithm, they achieved complexity reduction, albeit at the cost of increased iteration requirements for improved BER performance. Each method presents trade-offs between complexity and performance, highlighting the ongoing challenge of achieving an optimal balance in low-complexity signal detection techniques [41].

Other studies, such as that by Alonzo et al. investigated the energy efficiency of cell-free mmWave technology, providing valuable insights into environmentally sustainable wireless network design [42].

Gao et al. conducted a thorough investigation into the energy efficiency of SWIPT-aided NOMA networks, shedding light on the potential of such networks. They explored the integration of CF massive MIMO and SWIPT technologies to enhance the EE of wireless communication networks [43].

In 2023, Bartsiokas et.al, presented networks built on the 5G/B5G that use a number of advanced physical layer methods, like relaying-aided transmission, with the goal of enhancing network performance and expanding multi-cellular orientations' coverage region. Nevertheless, the implementation of using such strategies increases the computing complexity of radio resource management (RRM) activities in cellular environments with higher levels of interference and multivariate channel representations. Given that ML or DL methods can lessen computational load linked with RRM, they were suggested as an effective means of supporting E2E user applications in extremely complex contexts. Here, examines the combined issue of relay node placement with selection in 5G/B5G networks, taking into account subcarrier allotment and power management restrictions. Both sub-problems were solved by combining and analyzing different DL-based approaches. It provides high energy efficiency, and it attains low blocking probability [44].

In 2023, Taghavi, et al. has suggested joint active-passive beamforming with user association in IRS-aided mmWave cellular networks. Here, it provides a novel strategy for user-aiding mmWave cellular networks assisted by multiple IRSs that considers cell interference. By simultaneously enhancing active beamforming at BSs, passive beamforming at IRSs, user-BS association while taking the effect of IRSs into account, establish network spectrum efficiency maximization issue. Active beamforming at BSs, and passive beamforming at IRSs, and are optimized using a fractional programming technique, and the optimal solution for the UA optimization was achieved by combining the penalization technique by successive convex programming. By enhancing mmWave propagation routes in non-line of sight conditions and extending coverage region to blind spots, intelligent reflecting surfaces (IRSs) hold great promise for the development of next-generation WNs. It provides low latency, and it attains ahigh bit error rate [45].

Meanwhile, Hamdi, Qaraqe, and colleagues proposed power collaboration and management strategies specifically designed for CF-massive MIMO systems, further advancing the field. These efforts collectively contribute to the development of energy-efficient networks, laying the groundwork for future wireless systems in 2024 [46].

P. Lohan et al. proposed that achieving the goals of next-generation wireless networks—such as global connectivity, energy-efficient and sustainable communication, massive device integration, ultra-reliable performance, and minimal latency—requires the development of a variety of complementary enabling technologies. These include UAV-assisted networks, vehicular communications, heterogeneous cellular networks (HCNs), the Internet of Things (IoT), device-to-device (D2D) communication, millimeter wave MIMO (mmWave-MIMO), non-orthogonal multiple access (NOMA), and terahertz (THz) communication. Each of these technologies has unique characteristics that must be carefully addressed for effective deployment. Among the primary challenges, interference management emerges as a critical factor in optimizing the utilization of limited bandwidth and power resources, ultimately enhancing overall network performance and the user's quality of experience (QoE). To tackle this issue, the integration of artificial intelligence (AI) and machine learning (ML) into 5G and beyond (5GB) networks is becoming increasingly important, offering promising solutions for interference management in dynamic and complex network environments in 2024 [47].

M. N. Hossain et al. presented a comprehensive framework for the design and implementation of a transceiver in a reconfigurable intelligent surface (RIS)-assisted, UAV-enabled, secure multi-user full-duplex spatial spreading (FDSS)-based DCT-spread massive MIMO-OFDM system. The primary focus is on enhancing physical layer security (PLS), with an evaluation of the performance of CD-ZF and LR-MMSE signal detectors to improve the bit error rate (BER). The study also explores the application of both lower- and higher-order digital modulation schemes, specifically 4-QAM and 16-QAM. The proposed system exhibits negligible out-of-band (OOB) spectral power leakage, significant PAPR reduction, and enhanced SE in 2025 [48].

2.2 Literature Review Table:

Massive MIMO, which is being investigated as a critical technique to improve SE in future generation cellular systems, is described in Table 2.1 compared with existing methods.

Table 2.1: Literature Survey

AUTHORS AND YEARS	METHODOLOGY	FINDINGS
Zhang et al., (2019)	Develop the 5G mobile wireless networks model based on millimeter wave m-MIMO in particular to maximize the actual capacity for our suggested schemes in both asymptotic & non-asymptotic regions.	When it comes to ensuring a bounded QoS for heterogeneous statistical delay/error rate, the proposed schemes perform better than the other current systems. An improvement of up to 28% in energy efficiency has been observed compared to conventional systems under stringent QoS requirements.
Kayyali (2020)	This study went over the features and specifications of 5G networks before conducting a survey on resource management and QoS provisioning to better manage resource consumption in 5G networks.	The management of network resources should be the top priority in order to prevent network congestion and performance deterioration during peak hours and traffic spikes and to enable more users to access network services when demand is high. On the other hand, a significant challenge in 5G networks is meeting the QoS requirements for a wide variety of emerging services. An overall improvement of approximately 57% has been achieved in average user throughput.
Zhang et al., (2021)	This study established CF (cell-free) m-MIMO 6G wireless networks with SWIPT-enabled FBC (finite block length coding)-based statistical delay and error	The trade-offs between gathered energy and ϵeffective capacity should be optimized for the suggested statistical QoS provisioning. The

	rate-constrained QoS provisioning techniques[27].	simulation findings serve as a final validation and assessment of the developed systems. Under FBC and statistical QoS constraints, the proposed system achieves an effective capacity of 4.05 bps/Hz and harvests 3.9 µJ of energy at the optimal power splitting ratio.
Bolla & Singh, (2022)	The implementation of secure long-distance wireless energy transmission necessitates the utilization of energy beam-generating methodologies within these systems. The letter maximizes information transmission's energy efficiency (bits per joule) while considering QoS, a latency limitation. This includes maximizing transfer length and transmitting power. This example uses block diagonalization (BD) at the source to minimize relay-destination channel interference and maximize relay energy. As a final phase, this analysis simulates conventional circuit power needs. This work is supplemented by basic online guidelines for all possible situations.	When considering the circuit's maximum power consumption, numerical findings demonstrate that the intention of a nearest online approach can perform the same function as its offline version. Energy harvesting efficiency can be enhanced by reducing the network size and the number of RF chains. The duration required to harvest energy from different users varies. Studies show that when the number of radio users exceeds 30, configurations with fewer RF chains (L = 1) outperform those with a higher number of RF chains (L = 16). Moreover, the significance of scheduling for energy harvesting increases with the number of users.

Lavdas et al., (2022)	An alternative approach for machine learning (ML) beamforming is the utilization of a k-nearest neighbors (k-NN) approximation method. This approach involves training the system to generate suitable beamforming configurations by considering the spatial allocation of throughput demand. The performance of this method is rigorously calculated using a specially designed system-level simulator capable of running parallel Monte Carlo simulation results.	The obtained results show that the potential SE and EE values exhibit a level of comparability to those achieved by other state-of-the-art methodologie"s. This is accomplished while minimizing both hardware and algorithmic complexity by eliminating the need for user-specific beamforming computations. Specifically, the standard deviation of the effective capacity is 2.5/3.2 bps/Hz for Traffic Scenario 1 and 4.6/5.4 bps/Hz for Traffic Scenario 2 when considering 5 and 15 PRBs per mobile station (MS), respectively.
Y. Yan et.al., (2023)	It faces challenges such as high complexity and scalability issues, particularly in dense network environments. However, it benefits from structured policy updates, which contribute to faster convergence and reduced variance in Q-value approximation.	It proposes a novel model-assisted decentralized multi-agent reinforcement learning (MADRL) framework for the joint optimization of hybrid beamforming in massive MIMO mmWave systems. Extensive simulations have been conducted, and the numerical results demonstrate that Model-Assisted Decentralized Multi-Agent Reinforcement Learning (MAD-MARL) significantly accelerates the learning process and substantially enhances

		overall performance compared to existing approaches.
M.M.Kesargheh,. et.al.,(2024)	The power-splitting SWIPT (PS-SWIPT) method impacts the optimization problem's primary constraints based on energy and power limits.	This paper is Collocated massive MIMO SWIPT for wireless communication networks. Numerical results show that the proposed scheme reduces federated learning training time by up to 70.01% and 21.29% compared to CF-TDMA mMIMO and S2FL schemes, respectively, while maintaining comparable accuracy.
S. Dey ,. et.al., (2024)	The user equipment (UE) supports simultaneous wireless information and power transfer (SWIPT) and is capable of ultra-reliable low-latency communication (URLLC). To address challenges caused by hardware impairments, we propose novel distortion-aware minimum mean square error (MMSE) and regularized zero-forcing (RZF) precoders that effectively mitigate the negative effects of low-cost RF chains and coarse quantization from ADCs/DACs.	This paper numerically demonstrates that: (i) the energy harvested by user equipment (UE) increases with higher spatial correlation; (ii) the proposed distortion-aware precoders effectively mitigate the spectral efficiency (SE) loss caused by URLLC implementation; and (iii) the proposed optimization framework achieves near-optimal performance with significantly lower computational complexity compared to exhaustive grid-based search methods. During the WPT phase, the UEs experience high received signal strength, enabling them to harvest sufficient energy for data transmission even

		within a short charging duration. This results in an extended data transmission interval and allows the UEs to achieve high spectral efficiency.
M. H. Adeli et.al., (2025)	"This article investigates the energy-efficient design of downlink transmission in a simultaneous wireless information and power transfer (SWIPT) massive MIMO (mMIMO) system, incorporating a nonlinear energy harvesting (EH) model. The objective is to jointly determine suboptimal values for the allocated power coefficients and power splitting (PS) ratios by formulating and solving an optimization problem."	"To achieve this, we first derive statistical expressions for the signal-to-interference-plus-noise ratio (SINR) and harvested power, assuming that base stations (BSs) utilize statistical 3D beamforming. These expressions are then used to formulate an optimization problem aimed at maximizing energy efficiency (EE), subject to user quality-of-service (QoS) requirements, including data rate and harvested power constraints, as well as a total transmit power limit. Simulation results validate the effectiveness of the proposed design, demonstrating a 2- to 5-fold improvement in EE compared to conventional methods employing equal power allocation and fixed power-splitting (PS) ratio algorithms. Moreover, the growth rate of EE is significantly higher when varying design parameters such as the number of antennas and the Rician factor, in

		contrast to the aforementioned baseline algorithms.

2.3 Problem Statement

This includes evaluating the complexity, performance, and scalability of systems to ensure they can efficiently handle increased antenna counts on both ends of the communication link.

- **Machine learning-based approaches**: Utilize machine learning techniques, such as reinforcement learning or deep learning, to learn optimal scheduling policies from historical data and adaptively adjust scheduling decisions based on changing network conditions. Machine learning-based approaches can improve the efficiency and fairness of scheduling algorithms by leveraging advanced data analytics and predictive modeling techniques [47].

- **Qos aware scheduling**: Explore QoS-aware scheduling algorithms that prioritize users based on their definite quality of service requirements. By considering factors such as data rate, latency, and with reliability, QoS-aware scheduling algorithms can ensure that each user receives a satisfactory level of service while maximizing overall system throughput. The objectives have been reviewed based on research problem [48].

- **Multi-objective optimization**: Explore these techniques to concurrently optimize multiple conflicting objectives, such as throughput maximization and fairness enhancement. Multi-objective optimization approaches can provide a systematic framework for balancing competing objectives and finding Pareto-optimal solutions that trade-off between different performance metrics [49-50].

Chapter 3

MASSIVE MIMO PRECODING, BEAMFORMING TECHNIQUES

3.1.1 Introduction

The utilization of hybrid ZF with SLLP precoding techniques is indispensable in maximizing the system's ability, particularly in reducing interference and improving signal quality. These techniques play a fundamental role in managing the complexity of large MIMO systems by optimizing the transmission of data from terminals to base stations [51]. Understanding the intricacies of massive MIMO communication systems is paramount in addressing fundamental technical concerns and laying the groundwork for the future generation systems.

Commonly utilized precoding methods include Zero-Forcing (ZF), matched filtering (MF), MRC (Maximum Ratio Combining), MRT (Maximum Ratio Transmitter), ML (Maximum Likelihood), LMMSE (Linear Minimum Mean Square) , Bi-LSTMAE, peak-to-average power precoding, and various nonlinear techniques tailored to specific challenges[51-52]. To address the underlying technical intricacies, it's imperative to comprehend the operations of massive MIMO communication systems, laying the groundwork for the evolution of next-generation systems. This understanding also underpins the development and deployment of diverse applications and services within smart sensing systems.

This technique extensively compares linear precoders, considering their performance and complexity profiles. Nonlinear precoding methods are also examined; despite their higher computational demands, they can achieve satisfactory performance levels. Furthermore, the research explores the potential integration of machine learning techniques into precoding methods [53]. Moreover, the utilization of massive MIMO technology aids in comprehending and advancing various applications and services within smart sensing systems. Below are outlined some of the principal objectives of this technology within 5G networks. In figure 3.1, M antennas are used at the base station**,** and each of the N users is typically equipped with a single antenna**.**

While linear precoders may experience presentation dilapidation in certain scenarios, their relative simplicity remains pivotal in transmitter design, thus contributing significantly to system efficiency. This thesis extensively compares linear precoders, elucidating their performance-complexity profiles [54].

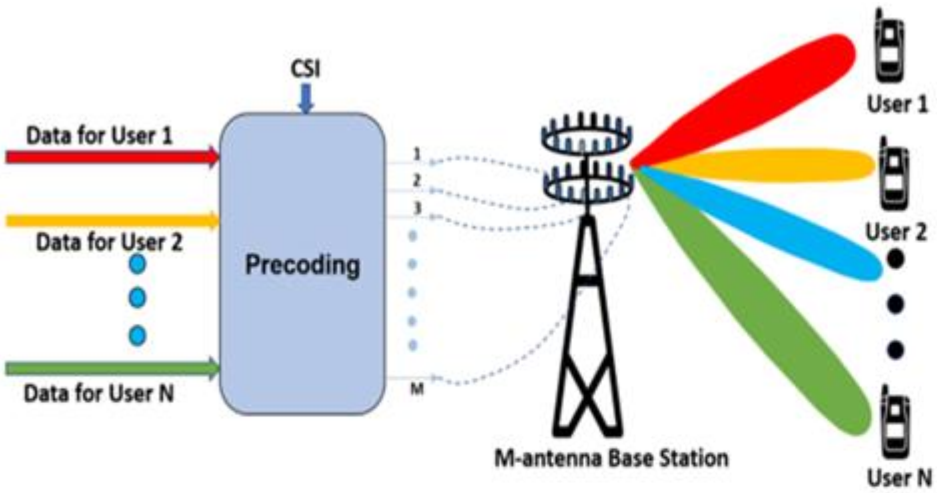

Figure 3.1: Massive MIMO BS to all users by using precoding techniques

It's worth noting that cell collaboration may not always be advantageous across all deployment scenarios, with the effectiveness of such approaches heavily dependent on organizational distinctiveness, such as in figure 3.1 and the positioning of M transmit antennas and N users.

3.2 Massive MIMO Beamforming Techniques

The utilization of mmWave spectrum allows for the integration of large multi-antenna arrays into compact base stations (BS) and consumer electronics devices, enabling thousands of antenna components on user equipment (UE). This property facilitates the creation of highly directional beams with maximum gain, particularly beneficial for multi-user applications leveraging extensive MIMO technology [55]. In large MIMO networks, digital beamforming emerges as the most advanced method to maximize spectral efficiency.

A single-carrier system that doesn't have the same PAPR capabilities, however, would be of enormous benefit. When using multiple taps and high-level modulation for higher data rates, a system with more antennas may be demonstrated to be less complicated, but full-fledged time domain equalization is required for a frequency-selective channel. Research is needed to compare this system to the standard MIMO system under less-than-ideal conditions.

Beamforming is a critical technique in these MIMO systems for directing signal energy toward desired users while reducing interference. In massive MIMO, three main types of beamforming techniques are employed: analog, digital, and hybrid beamforming [56].

- **Analog Beamforming**:

It relies on the manipulation of signals in the analog domain. A single RF chain is used to process all antenna signals, which makes it energy-efficient and less complex. It can adjust the phase of the signal at each antenna to form a directional beam. Since only one RF chain is needed, the hardware is simpler and consumes less power compared to digital beamforming [57]. It has the advantage of **r**educed power consumption and hardware cost. It has a disadvantage of limited flexibility, as it cannot support multiple data streams simultaneously. It is not having an opportunity for suboptimal performance in scenarios with dynamic multi-user environments.

- **Digital Beamforming**

It operates in the digital domain, providing high flexibility and performance by processing signals independently for each antenna using separate RF chains and baseband units. Each antenna element has its own RF chain and baseband processing unit. Amplitude and phase can be adjusted at each antenna element to achieve precise beam patterns. It allows simultaneous transmission to multiple users by creating independent beams for each. It has high performance and flexibility in beam forming. It has the advantage of being ideal for scenarios requiring multi-user support or dynamic beamforming. It has the disadvantage of high power consumption and hardware cost due to the need for multiple RF chains with complex signal processing requirements [58].

- **Hybrid Beamforming**

Hybrid beamforming combines the strengths of analog and digital beamforming to balance performance and hardware complexity. It divides the beamforming process between analog and digital domains. It uses fewer RF chains than digital beamforming while still achieving multi-user support. It reduces hardware complexity without compromising much on performance. It is suitable for cost-effective and power-efficient compared to fully digital beamforming and for mmWave communications where antenna arrays are large and RF chain costs are significant. It supports multi-user scenarios more effectively than pure analog beamforming. It has the disadvantage of increased complexity compared to analog beamforming. It is more prominent in performance that may not match fully digital beamforming in highly dynamic environments [59].

- **Adaptive Beamforming:** In 5G Massive MIMO systems, it is a dynamic technique that continuously adjusts the direction and shape of the transmitted beams based on real-time channel conditions and user locations. Unlike fixed or static beamforming methods, adaptive beamforming uses CSI to optimize signal transmission, thereby enhancing signal quality and reducing interference. This approach allows the system to focus energy more precisely toward intended users while minimizing leakage toward others. As a result, adaptive beamforming significantly improves key QoS metrics, such as throughput, reliability, and spectral efficiency.

Table 3.1: Comparison of beamforming techniques

Beam forming Technique	**Description**	**QoS Benefits**
Analog beamforming	Employs phase shifters to steer the beam using a single RF chain.	Low complexity and power-efficient for mm
Digital beamforming	Uses a separate RF chain per antenna; allows full flexibility in beam control.	High spectral efficiency interference reduction.
Hybrid beamforming	Combines analog and digital beamforming to balance complexity and performance.	Scalable for mmWave, balances cost, power, an throughput.

Adaptive beamforming	Dynamically adjusts beam patterns based on real-time channel conditions.	Responsive to mobility, channel conditions and changing environments.

In conclusion, the choice of beamforming technique depends on the application scenario. Analog beamforming is suitable for low-cost systems, digital beamforming is ideal for high-performance applications, and adaptive beamforming dynamically adjusts beam patterns, making it well-suited for massive MIMO systems operating at mmWave frequencies [60].

3.3 Types of linear precoding techniques

In these systems, several precoding techniques are employed to optimize signal transmission and reception.

3.3.1 ZF Precoding: It is a widely used precoding method that aims to eliminate noisiness between customers by setting the prevailing conditions such that the interference seen at each user is nullified. This technique effectively suppresses interference but may lead to noise amplification, particularly in scenarios with high SNR imbalances [60-61]. For large SNRs, the sum rate will be increased in this technique. It is a commonly utilized precoding method that aims to nullify nosiness among users by selecting the precoding matrix to cancel out interference at each user's receiver. ZF precoding aims to completely eliminate interference between users. It achieves this by designing the transmitted signals in such a way that the interference from other users is nullified at the intended receiver. Mathematically, ZF precoding vectors are chosen to be orthogonal to the interference channels [61].

➢ **Benefits of ZF precoding in Massive MIMO**

- **Eliminates Interference Suppression:** Effectively eliminates interference between users, improving system capacity and user experience.
- **Relatively Simple Implementation:** Compared to some other precoding techniques, ZF can be relatively straightforward to implement.
- **Improved Throughput:** By reducing interference, ZF enables simultaneous transmission to multiple users, maximizing system throughput.

- **Simplicity:** The linear nature of ZF makes it computationally very simple.

In conclusion, ZF is a powerful tool in massive MIMO systems, offering significant benefits in interference management and throughput enhancement. Ongoing research into hybrid methods and computational optimizations continues to extend its applicability to next-generation communication networks.

3.3.2 MRT Precoding: It is another precoding technique that focuses on maximizing the received signal power at each user. It achieves this by setting the precoding matrix to be the Hermitian transpose of the channel matrix, scaled by the inverse of its Frobenius norm. MRT is known for its simplicity and robustness against noise amplification compared to ZF [62]. MRT aims to maximize the received signal power at the user equipment. Mathematically, the MRT precoding vector is proportional to the conjugate of the channel vector. The data symbols for each user are multiplied by their corresponding MRT precoding vectors and then transmitted through the antenna array. MRT is a computationally simple technique and is relatively easy to implement. By matching the transmitted signal to the channel, MRT maximizes the received signal power at the user equipment.

➢ **Benefits of MRT precoding in Massive MIMO**

- **Good performance in high SNR regimes:** MRT performs well in high signal-to-noise ratio (SNR) conditions, where maximizing received power is crucial.

➢ **Limitations of MRT**

- **Susceptibility to interference:** MRT does not explicitly address interference from other users, which can limit its performance in multi-user scenarios.
- **Limited performance in low SNR regimes:** In low SNR conditions, maximizing received power may not be the most effective strategy, and techniques like MMSE precoding may offer better performance.

MRT is a fundamental precoding technique in massive MIMO systems. While it may not always be the optimal choice in all scenarios, its simplicity and effectiveness in maximizing received signal power make it a valuable tool in many applications.

3.3.3 MMSE Precoding: It decreases the mean square error between the communicated signal and the desired received signal, considering both interference and noise. Unlike ZF, MMSE takes into account the noise variance and channel conditions, making it more suitable for scenarios with imperfect channel state information. However, MMSE precoding involves more computational complexity than ZF and MRT [63].

MMSE is a powerful tool for signal and channel estimation and interference management in massive MIMO systems. Its ability to optimize performance by minimizing errors makes it an integral part of modern wireless communication. Despite its computational challenges, ongoing research into optimization techniques and hybrid approaches continues to enhance the practical applicability of MMSE in hyper MIMO systems.

3.3.4 ML Precoding: It is a powerful technique for enhancing the performance of massive MIMO systems but for low SNR values. By addressing the limitations and exploring innovative solutions, we can unlock the full potential of Massive MIMO and achieve significant improvements in wireless network capacity and reliability. Mathematically, this can be formulated as follows: Maximize P(y|x,H), where y is the received signal vector, x is the transmitted signal vector, and H is the channel matrix. Directly evaluates the likelihood function for all possible transmit symbol combinations. It is computationally intensive, especially for large modulation orders and high-dimensional signal spaces [64].

Table 3.2: Comparison of ML, MMSE and ZF

Precoding	**Performance**	**Complexity**	**SNR Behavior**
ML	Highest Accuracy (Lowest BER)	Highest	Best performance across all SNRs
MMSE	Good balance of accuracy	Medium	Outperforms ZF at low SNR, approaches ML at high SNR
ZF	Good balance of accuracy	Lowest	Performs well at high SNR, struggles at low SNR

3.3.5 MRC Precoding: This method aimed at improving the received signal strength by optimally combining the signals taken from various aerials at the receiver. By weighting and summing the received signals, MRC enhances the overall received signal quality [64].

3.3.6 MF Precoding:

It involved modifying the transmitted signal to conform to the properties of the channel. By convolving the transmitted signal with the complex conjugate of the channel impulse response, the SNR at the receiver is maximized, enhancing signal detection and reducing the impact of noise [65].

3.3.7 PAPR Precoding: It is designed to minimize the amplitude variations of the transmitted signal, thereby reducing the likelihood of signal clipping and distortion in the nonlinear components of the transmitter [66]. PAPR precoding reshapes the signal envelope to maintain a more uniform power distribution, ensuring efficient power amplifier operation and minimizing signal degradation.

3.3.8 Continuous Envelope Precoding: It is a technique that ensures the transmitted signal maintains a continuous amplitude envelope, facilitating efficient power amplification and reducing signal distortion. It minimizes signal clipping and distortion, improving overall transmission quality [67].

3.3.9 Quantized Precoding: It involves quantizing the precoding coefficients or CSI feedback to reduce the amount of information exchanged between the transmitter and receiver [67]. By quantizing the precoding parameters, quantized precoding reduces the overhead associated with channel feedback and simplifies the implementation of precoding algorithms. Despite the quantization-induced loss of precision, quantized precoding remains effective in enhancing spectral efficiency and reducing signaling overhead in massive MIMO systems.

3.3.10 AMP Precoding: Approximate Message Passing is a sophisticated method that leverages iterative algorithms to estimate the transmitted signals based on received measurements and prior information. AMP precoding iteratively refines its estimates, incorporating feedback from the receiver to enhance the accuracy of signal transmission. This iterative process enables AMP precoding to achieve near-optimal performance while efficiently handling the computational complexity associated with massive MIMO systems.

These precoding techniques play crucial roles in optimizing the presentation of massive MIMO systems, balancing trade-offs between interference suppression, noise amplification, and computational complexity to ensure efficient and reliable signal transmission [68].

3.4 Types of Non-Linear precoding Technology

·**Dirty Paper Coding** (**DPC)** mitigates interference by precoding the transmitted signal to cancel out the interference effects at the receiver. It achieves near-optimal performance by exploiting knowledge of both the transmitted symbols and the interference structure.

·**Tomlinson-Harashima Precoding (THP)** is a nonlinear precoding technique that pre-compensates for the distortion introduced by the transmission channel. By iteratively refining the transmitted symbols based on feedback from the receiver, THP minimizes the impact of channel distortion on signal quality.

·**Vector Perturbation Precoding (VPP)** introduces controlled perturbations to the precoded transmit signal to improve performance in nonlinear channels. By intelligently perturbing the transmitted symbols, VPP can enhance spectral efficiency and mitigate the effects of nonlinear distortion.

·**Geometric precoding** optimizes signal transmission by exploiting the geometric properties of the channel. It designs precoding matrices to take advantage of SNR while considering the spatial characteristics of the channel.

·**Nonlinear generalized precoding:** encompasses a broader class of precoding techniques that exploit advanced signal processing methods to optimize system performance. NGP techniques encompass a range of nonlinear transformations applied to the transmitted signals to achieve interference suppression and improve spectral efficiency [69].

These nonlinear precoding techniques typically come with higher computational complexity compared to linear precoding methods like ZF or MF. The most effective proposed technique used in this massive MIMO system is the hybrid zero forcing (ZF) with symbol-level linear precoding (SLLP) method.

3.5 Proposed System Model:

The increasing demand for high-capacity, energy-efficient wireless communication has driven the adoption of Massive Multiple Input Multiple Output technology. Among all linear precoding techniques, zero-forcing (ZF) precoding combined with advanced methods such as hybrid ZF and SLLP offers enhanced performance. Despite its significant potential to enhance data communication efficiency in modern networks, massive MIMO faces challenges due to the complexity of managing numerous antennas, which adversely impacts signal quality, PAPR, and energy efficiency [70]. To overcome these obstacles, this research work proposes a joint optimization-based framework for these systems.

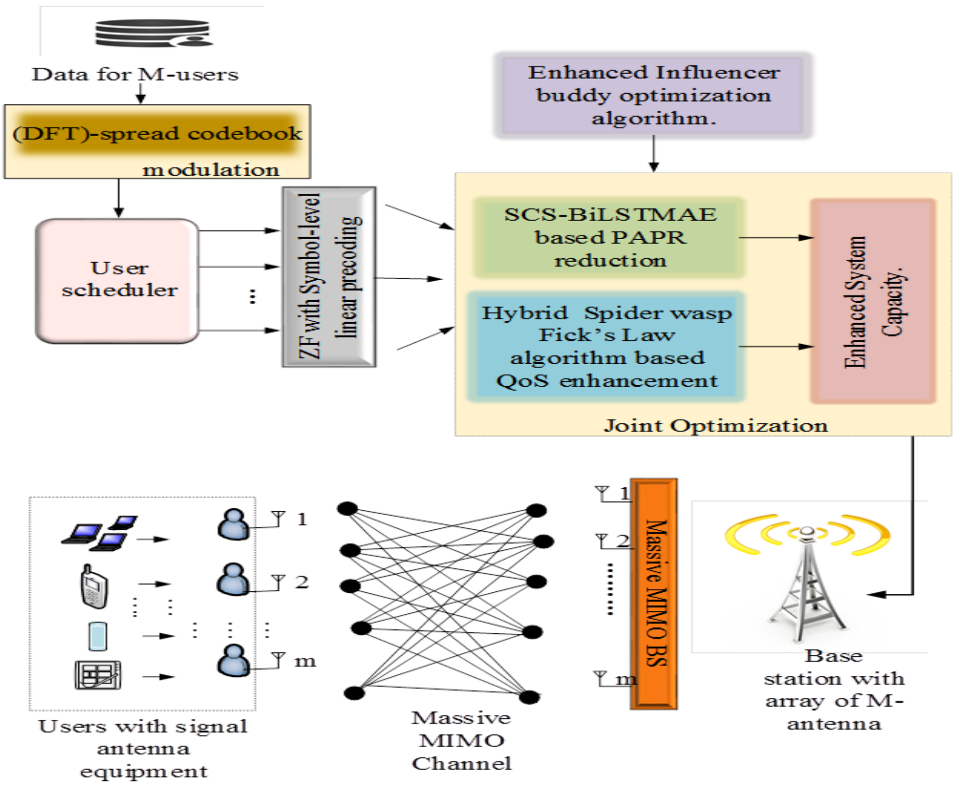

Figure 3.2: System Model for joint optimization [71]

In the first phase, the framework employs a hybrid spider wasp Fick's law algorithm to maximize system capacity through optimal power distribution while maintaining quality of service.

In the second phase, the SCS-BiLSTMAE network is integrated with zero-forcing and symbol-level linear precoding techniques, as shown in figure 3.2.

This approach effectively reduces the PAPR and BER by utilizing adaptive mapping strategies. Additionally, the model's performance is fine-tuned through precise hyper parameter optimization using the EIBO algorithm. The proposed joint optimization-based technique provides a robust solution for enhancing massive MIMO systems, establishing it as a crucial enabler for future high-performance wireless communication networks.

3.6 Joint Optimization using SLLP:

SLLP represents a paradigm shift in signal manipulation within communication systems. Unlike conventional approaches that operate at the antenna level, SLLP delves into the granularity of individual symbols, affording unprecedented control over both amplitude and phase. This optimization extends beyond mere PAPR reduction, as it also contributes to bolstering system performance in scenarios where stringent PAPR constraints are paramount.

Symbol-Level Linear Precoding (SLLP) inherits and expands upon these advantages, transcending the limitations of block-level precoding. SLLP's superiority is evident in its ability to achieve superior BER performance while necessitating poorer transmit power to meet particular BER targets. Furthermore, SLLP strategically harnesses intervention dynamics, exploiting constructive interference to bolster signal strength. This strategic approach not only enhances spectral efficiency but also contributes to a poorer PAPR [71].

In essence, the adoption of symbol-level precoding represents a pivotal step towards optimizing communication system performance across multiple dimensions, heralding a new era of efficiency and reliability.

$$P_{precoded}=\mathrm{M}.P_{original} \tag{3.1}$$

Here $P_{precoded}$ is the precoded sign vector, M is the precoding template, and $P_{original}$ is the unique representation vector. The crafting of the precoding template is a meticulous process aimed at strategically manipulating symbols to optimize specific performance metrics within the communication system. This formula suggests that the power generated is obtained by multiplying the required power by a constant factor M. Here M is called as scaling factor. The precise structure and composition of this matrix are inherently tied to the overarching goals of the system, which could range from minimizing interference to reducing PAPR. Whether it involves exploiting interference dynamics, enhancing SNR, or mitigating PAPR, the precoding matrix serves as a versatile tool for achieving optimal performance across various operational scenarios.

3.7 Hybrid ZF SLLP Algorithm:

ZF precoding effectively removes multi-user interference, while SLLP specializes in refining signal shaping. The synergistic combination of both techniques not only optimizes signal quality but also enhances precoding concurrently, ensuring superior presentation and SE in wireless announcement systems. Equation (3.2) signifies the amalgam procedure for precoding, representing the amalgamation of ZF precoding and SLLP to achieve maximal effectiveness in managing interference and shaping signals for improved system performance.

$$F = Z_F * P * i \tag{3.2}$$

Here, F is the preceded pointer vector (M x 1), P is the symbol-level preceding template (N x N), and is i the participation sign vector (N x 1).Here, M is the number of antennas, and N is the number of users.

Z_F is a scalar quantity. The subscript 'F' might indicate a specific property or point. Zero Forcing Spatial Modulation with SSLP enriches wireless systems by effectively decreasing noisiness, thereby enhancing Signal-to-Noise Ratio (SNR) for improved indicator superiority and advanced information charges. By concomitantly serving multiple users, this approach boosts SE, maximizing the utilization of available bandwidth resources. Furthermore, efficient precoding techniques contribute to reduced energy utilization, conserving power and increasing the piece of equipment's series life, thus promoting sustainability in wireless networks. The adaptability of SSLP ensures robust performance even in dynamic conditions, making it a versatile solution well-suited for the evolving landscape of wireless communication technologies.

Massive MIMO downlink system defined as

$$y = HW_x + n \tag{3.3}$$

- y is the received signal at K users

- H is the channel matrix (Rayleigh fading) = $K \times N_t$
- W_x is the precoding matrix
- n is the AWGN noise
- N_t: Number of transmit antennas (at BS)
- K: Number of users (receivers)
- Perfect CSI

➢ **BER for Zero-Forcing (ZF) precoding**

In a massive MIMO system with $N_t \gg K$, the ZF precoding effectively cancels inter-user interference. The approximate BER expression for QPSK with ZF is

$$BER = Q\left(\sqrt{\frac{(SNR \times (N_t - K))}{K}}\right) \tag{3.4}$$

$$Q(x) = \left(\frac{1}{\sqrt{2\pi}}\right)\int_x^{\infty} e^{-\frac{t^2}{2}2}\, dt \tag{3.5}$$

Valid when $N_t > K$ and high SNR

➢ **BER for SLLP :**

SLLP (Symbol Level Linear Precoding) typically uses subset matched filtering or a simplified precoder on a reduced number of antennas $N_{SLLP} = N_t/2$ so it performs worse than ZF that is $BER_{SLLP} > BER_{ZF}$.

➢ **BER for Hybrid ZF–SLLP:**

The hybrid precoding combines ZF and SLLP linearly:

$$W_{Hybrid} = \alpha\, W_{ZF} + (1 - \alpha) W_{SLLP} \tag{3.6}$$

The resulting SNR and BER are more difficult to derive exactly but can be approximated by modeling the effective SNR as a weighted combination of the ZF and SLLP performance.

Where:

$\alpha \in [0,1]$ is the interpolation weight (closer to ZF when $\alpha \to 1$ to SLLP

when $\alpha \to 0$

Sum rate of ZF:

$$R_{ZF} = K \ \log_2\left(1 + \frac{SNR(N_t - K)}{K}\right) \tag{3.7}$$

Sum rate of Hybrid ZF:

$$R_{Hybrid\ ZF} = K \ \log_2\left(1 + \frac{SNR(N_{RF} - K)}{K}\right) \tag{3.8}$$

Sum rate of Symbol-Level Linear Precoding (SLLP)

SLLP designs the transmit vector x=W_{SLLP} * S (3.9)

S is the data symbol vector (known at transmitter)

Approximate sum-rate for SLLP can be modeled as:

$$R_{\{SLLP\}} == \sum_{k=1}^{K} log_2\,(1 \ + \ SNR_k^{SLLP}) \tag{3.10}$$

where SNR typically improves over ZF due to symbol-aware design. SLLP SNR is approximated or numerically computed.

Sum rate of hybrid ZF-SLLP :

Sum-rate of Hybrid ZF SLLP precoding computed similarly:

$$R_{hybrid} = \sum_{k=1}^{K} \log_2(1 \ + SNR_{hybrid}\ ) \tag{3.11}$$

3.8 Results and Discussions:

➢ Figure 3.3 shows the BER of a massive MIMO system in terms of SNR in theory and simulation. For large SNR values, BER will be decreased. In theory, if SNR increases, BER will linearly decrease, while in simulation, BER will decrease nonlinearly as SNR increases. At SNR=10 dB BER=10^{-5} in theory, but in simulation it is $10^{-3.}$ But as long as SNR increases BER is decreasing in simulation.

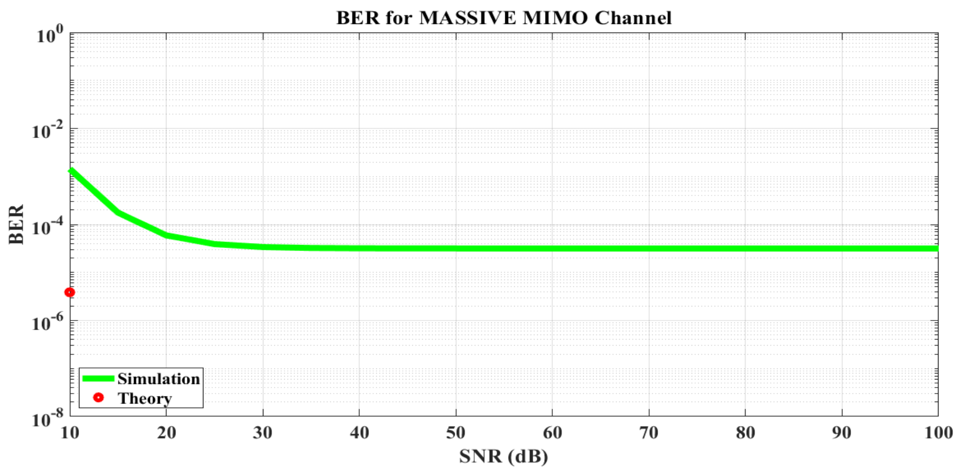

Figure 3.3: BER for Massive MIMO System with SNR (dB).

➢ Figure 3.4 shows sum rate for massive MIMO with SNR (dBm). The specific characteristics of the massive MIMO system (number of antennas 64-256 and 4-12 users in a cell, etc.) can influence the relative performance of the algorithms.

Computational complexity is another important factor to consider when choosing an algorithm.

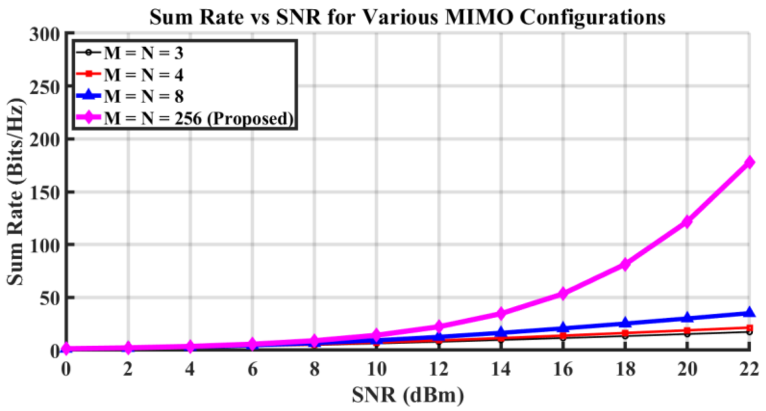

Figure 3.4: SNR versus sum rate for massive MIMO system with number of antennas

➢ Figure 3.5 plots the sum rate (bits/Hz) against the SNR in dBm for four different configurations:

- **M=N=3**: This likely represents a system with 3 transmit antennas and receive antennas.
- **M=N=4**: This configuration has 4 transmit antennas and 4 receive

antennas.

• **M=N=8**: This configuration has 8 transmit antennas and 8 receive antennas.

• **M=N=256 (Proposed)**: This configuration has 256 transmit antennas and 256 receive antennas, and it is labeled as "Proposed," suggesting it's a novel or optimized design.

Increasing Sum Rate with SNR**:** For all three configurations, the sum rate increases as the SNR increases. The configuration with the highest number of antennas (M=N=256 proposed) consistently achieves the highest sum rate across all SNR values. This demonstrates the benefit of having more antennas, as it allows for better spatial multiplexing and beamforming, leading to higher data rates. The M=N=4 configuration performs better than the M=N=3, further supporting the positive impact of increasing antenna numbers. The proposed configuration with M=N=256 might represent a new or optimized antenna array design or beamforming technique. In figure 3.5, the number of users and the sum rate can be shown.

- Figure 3.5 illustrates the relationship between the achievable sum rate and the number of users for three different precoding techniques: MRT, MMSE, and ZF

Table 3.3: Number of users with sum rate of ZF, MMSE and MRT

Number of Users	**ZF sum rate (Bits/Hz)**	**MMSE sum rate (Bits/Hz)**	**MRT sum rate (Bits/Hz)**
10	100	50	70
20	150	80	120
30	200	120	180
40	270	180	250
50	300	250	320
60	280	350	330
70	250	330	350
80	270	350	350

90	300	370	360
100	330	400	380
110	360	420	400
120	400	450	420

This is likely due to the multiplexing gain that can be achieved by serving multiple users simultaneously. ZF shows a relatively good performance, especially at lower user numbers. However, its sum rate growth tapers off and even starts to decrease at higher user numbers. This technique aims to completely eliminate interference between users by forcing the signals from other users to be zero at the desired receiver. However, it may not be as robust as MMSE in the presence of noise.

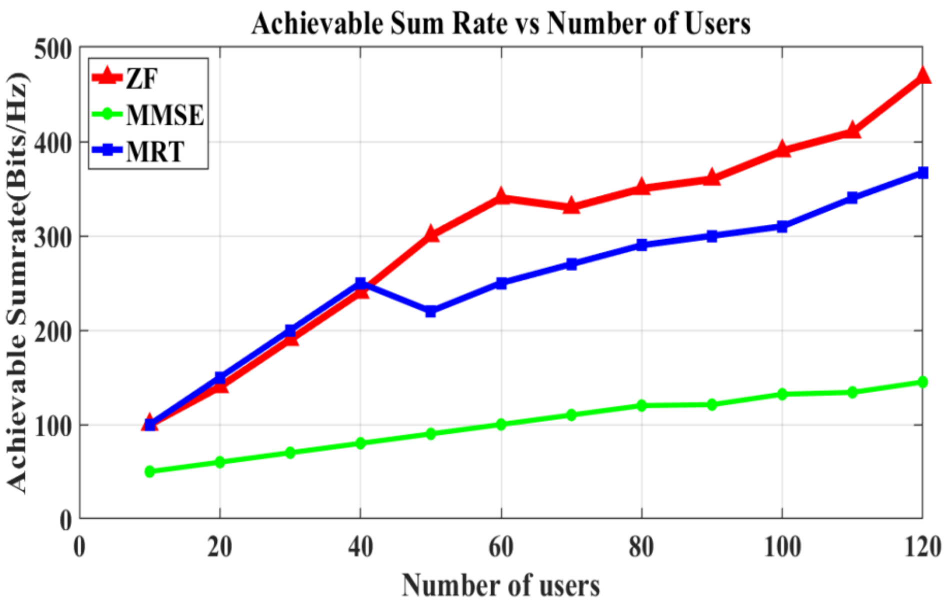

Figure 3.5: Achievable sum rate for linear precoding

MMSE consistently achieves the average sum rate across the range of user numbers. This indicates that MMSE precoding is the most effective in maximizing the overall data rate in this scenario. Its superior performance suggests that it effectively mitigates interference between users and maximizes the signal quality for each user.

MRT has the lowest sum rate among the three techniques. Its performance increases at a slower rate compared to MMSE and ZF, and it saturates at a lower Sum rate value. This technique simply maximizes the received signal power at each user. While simple to implement, it may not be as effective as MMSE or ZF in managing interference and maximizing overall system performance. The graph suggests that MMSE precoding is the most suitable choice for maximizing the overall data rate in this multi-user communication scenario, as shown in figure 3.5.

- Hybrid ZF, also known as hybrid precoding based on ZF, is utilized in millimeter-wave massive MIMO systems, where deploying a full set of RF chains for all antennas is impractical due to power and cost limitations. To overcome this constraint, a two-stage precoding structure is adopted by using analog precoding implemented in the RF domain and digital ZF precoding applied in the baseband and is limited by the number of available RF chains. In this configuration, the system's performance follows a trend similar to that of traditional ZF; however, the performance expression is adjusted to account for the effective channel after analog precoding. This leads to a modified SNR, which significantly influences the overall system performance. According to all this precoding, hybrid ZF combined with SLLP will give the best result. The table 3.5 below presents the BER expressions in relation to SNR, accompanied by figure 3

Table 3.4: The BER expressions are presented as a function of SNR for different methods.

Precoding Method	**BER Expression in terms of SNR**
ZF	$Q\left(\sqrt{\frac{(SNR \times (N_t - K))}{K}}\right)$
Hybrid ZF	$Q\left(\sqrt{\frac{(SNR \times (N_{RF} - K))}{K}}\right)$
SLLP	$Q\left(\sqrt{\frac{(SNR \times N_{SLLP})}{K}}\right)$

Hybrid ZF SLLP	$Q\left(\sqrt{\frac{(SNR \times [\alpha \times (N_t - K) + (1 - \alpha) \times N_{SLLP}])}{K}}\right)$

- **BER versus SNR for ZF, Hybrid ZF, Hybrid ZF with SLLP**

Hybrid ZF SLLP shows in figure 3.6 as a relatively good performance, especially at higher values of SNR. However, its sum rate growth tapers off and even starts to decrease at the lowest values of SNR shown in table 3.5.

Table 3.5: BER verses SNR for Z, SLLP, and Hybrid ZF SLLP precoding methods

SNR in dB	BER for ZF	BER for SLLP	BER for Hybrid ZF SLLP
0	1.39	1.39	1.39
5	5	1.28	1.28
10	10	1.09	1.09
15	15	0.85	0.82
20	20	0.48	0.35
25	25	0.05	0.04
30	30	0.00	0.00
35	35	0.00	0.00
40	40	0.00	0.00
45	45	0.00	0.00
50	50	0.00	0.00
55	55	0.00	0.00
60	60	0.00	0.00

As long as SNR increases, BER will decrease to approximately zero as shown in figure 3.6 with table 3.6.

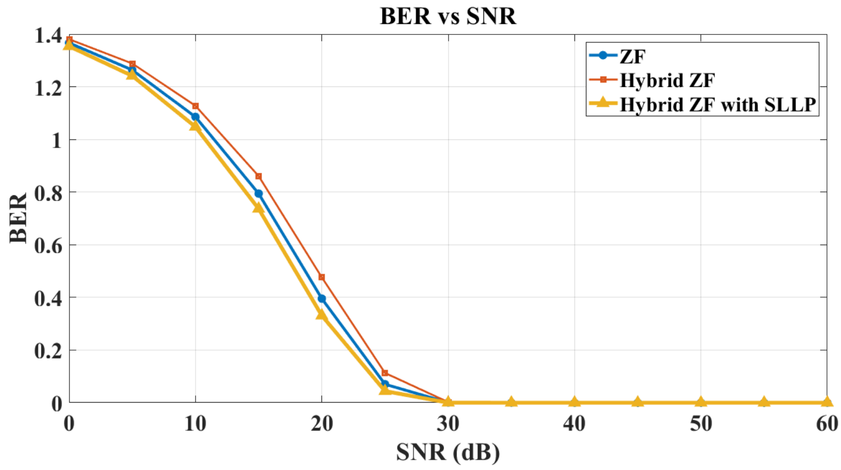

Figure 3.6: BER verses SNR for ZF, Hybrid ZF, Hybrid ZF with SLLP precoding methods.

- **Sum rate versus SNR for ZF, Hybrid ZF, Hybrid ZF with SLLP**

In the BER versus SNR analysis, an inverse relationship is consistently observed: as SNR increases, the BER for all evaluated methods decreases.

Table 3.6: Sum rate expressions as a function of SNR for various methods.

Precoding Method	**Sum rate Expression in terms of SNR**
ZF	$K\ \log_2\left(1+\frac{SNR(N_t-K)}{K}\right)$
Hybrid ZF	$K\ \log_2\left(1+\frac{SNR(N_{RF}-K)}{K}\right)$
SLLP	$\sum_{k=1}^{K} log_2\,(1\ +\ SNR_k^{SLLP})$
Hybrid ZF SLLP	$\sum_{k=1}^{K}\log_2(1\ + SNR_{hybrid}\ )$

At SNR=20 dB sum rate for hybrid ZF-SLLP 21bps/Hz with number of users are 4. In This behavior is anticipated, as a stronger signal relative to noise inherently facilitates more accurate bit decoding by the receiver.

Table 3.7: Users with sum rate for ZF, SLLP, Hybrid ZF SLLP precoding methods.

Number of Users (K)	sum rate for ZF(bps/Hz)	sum rate for Hybrid ZF(bps/Hz)	sum rate for Hybrid ZF with SLLP(bps/Hz)
4	20	19	21
8	30	28	32
12	39	36	43
16	47	43	52
20	53	49	58
24	58	54	64
28	62	58	69
32	66	61	73
36	70	64	77
40	74	67	81
44	78	69	85
48	79	70	88

Notably, beyond approximately 30 dB SNR, the BER for all depicted methods approaches zero, indicating that at these very high SNR levels, the systems operate with negligible errors, rendering further increases in SNR largely inconsequential for BER improvement.

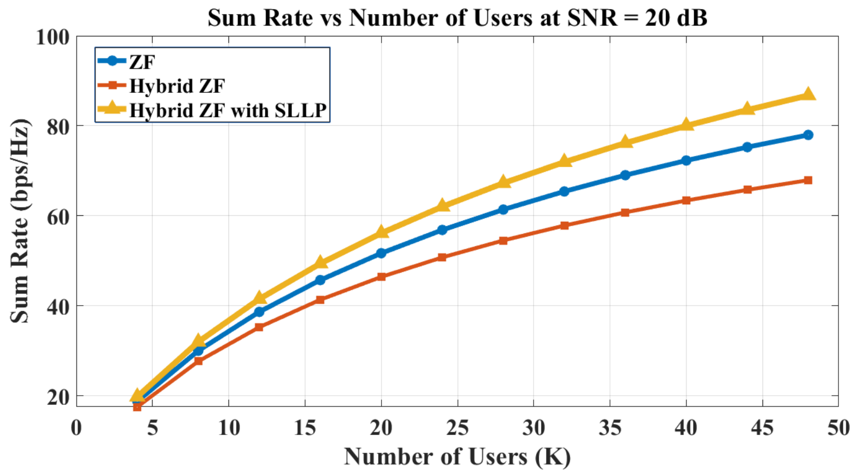

Figure 3.7: Number of users with sum rate for ZF, hybrid Z, hybrid ZF with SLLP precoding methods.

Within this context, Hybrid ZF with SLLP consistently demonstrates superior performance, exhibiting the lowest BER at higher SNR values. This underscores the significant advantage of SLLP in enhancing error rate performance.

In figure 3.7, the sum rate compared with SNR for ZF, hybrid ZF, and hybrid ZF-SLLP is shown in table 3.8. At SNR=20 dB sum rate for hybrid ZF-SLLP has 52bps/Hz with number of users at 16, as shown in figure 3.7. As shown in figure 3.7 and Table 3.7, the sum rate increases gradually as the number of users increases. When compared with hybrid ZF, with SLLP has a higher sum rate compared to other methods.

- **Sum rate verses SNR at K=16 for ZF, Hybrid ZF, Hybrid ZF with SLLP**

Conversely, in the **s**um rate analyses**,** different dynamics are observed. When examining **the** sum rate's dependence on the number of users, a notable trend emerges: the performance disparity between Hybrid ZF with SLLP and the other two methodologies (ZF and Hybrid ZF) widens as the user count increases, as shown in table 3.8 with the figure 3.8.

Table 3.8: SNR with sum rate for ZF and Hybrid ZF SLLP precoding methods.

SNR (dB)	**Sum rate for ZF (bps/Hz)**	**Sum rate for Hybrid ZF (bps/Hz)**	**Sum rate for Hybrid ZF with SLLP (bps/Hz)**
0	0	0	0
5	10	9	9.5
10	22	20	21
15	36	34	35
20	52	49	50
25	70	66	67
30	90	85	87
35	112	106	109
40	135	129	132
45	160	153	157
50	185	178	182

55	210	202	207
60	235	227	232

This observation highlights the compelling scalability benefits that SLLP offers within multi-user communication environments, enabling greater throughput as the user base expands. However, when the focus shifts to the sum rate's relationship with SNR at a fixed, moderate number of users (K=16), the advantages of SLLP in terms of sum rate become less pronounced, as shown in figure 3.8.

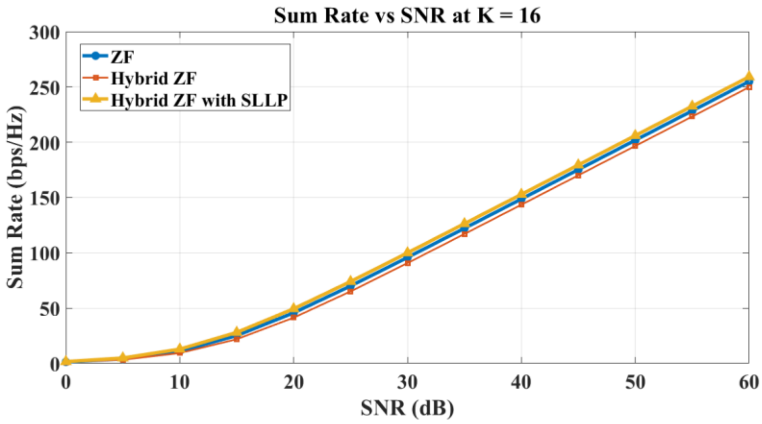

Figure 3.8: Sum rate and SNR for ZF, SLLP, Hybrid ZF SLLP precoding methods.

In this specific scenario, the sum rate performance of all three methods tends to converge across a broad range of SNRs. This convergence suggests that for this particular user count, the trade-off between complexity and performance inherent in hybrid architectures can be justified, as they achieve sum rates comparable to a fully digital ZF approach without a significant loss in efficiency.

- **Sum rate versus number of antennas for ZF, hybrid ZF, hybrid ZF with SLLP**

The figure 3.9 titled "Sum Rate vs. Number of BS Antennas at SNR=20 dB" illustrates the performance of three techniques—ZF (Zero Forcing), hybrid ZF, and hybrid ZF with SLLP-as the number of base station antennas increases. Among these, Hybrid ZF with SLLP consistently outperforms both ZF and Hybrid ZF across all antenna configurations.

Table 3.9: Antennas with sum rate for ZF, SLLP, Hybrid ZF SLLP precoding methods in massive MIMO at N_t=256

Number of BS Antennas (Nt)	Sum rate for ZF	Sum rate for Hybrid ZF	Sum rate for Hybrid ZF with SLLP
32	108	104	112
64	132	128	137
96	145	139	150
128	152	147	157
160	158	152	163
192	163	157	168
224	167	161	172
256	171	164	175

This improvement is likely due to the use of long-term statistical learning in the precoder, which enables better adaptation to varying channel conditions.

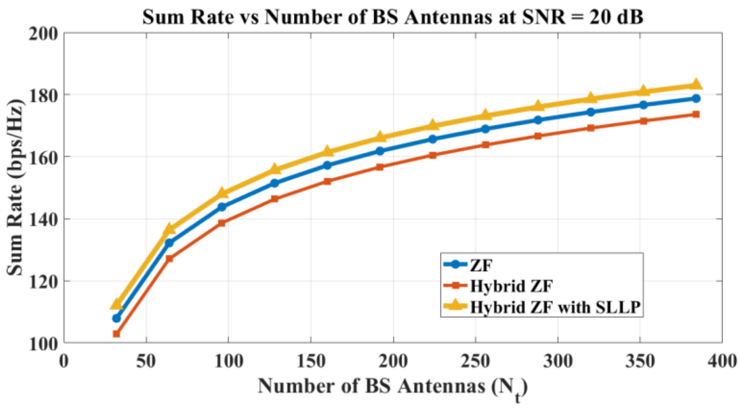

Figure 3.9: Number of BS stations with sum rate for ZF, hybrid ZF, hybrid ZF with SLLP

As in figure 3.9, increasing the number of BS antennas significantly enhances the sum rate, and integrating statistical learning into hybrid precoding methods offers the most effective performance in massive MIMO systems, as shown in table 3.9.

3.9 Conclusion:

Finally, hybrid zero forcing with symbol-level linear precoding is very useful in massive MIMO. Objective 1 has been studied with the help of more precoding techniques and analyzed in massive MIMO with parameters like SNR, BER, achievable sum, and data rate for the hybrid ZF-SLLP precoding technique. These observations are based on the specific graph provided.

The actual energy efficiency values and trends may vary depending on factors such as the specific implementation, system parameters, and operating conditions. Research efforts should focus on developing innovative precoding techniques that can achieve high performance while minimizing energy consumption, especially as the number of antennas continues to increase in future wireless communication systems.

It is concluded that ZF-SLLP precoding is the best precoding technique in massive MIMO. Hybrid ZF with SLLP is modeled with a 20% SNR gain over conventional hybrid ZF for illustration. Here, the sum rate has been calculated with the number of antennas at the BS being 256 at SNR = 20 dB.

CHAPTER 4

ENERGY HARVESTING TECHNIQUES IN MASSIVE MIMO

4.1 Introduction

Recent advancements in extremely well-organized radio frequency energy harvesting hardware offer several advantages: precise energy transfer control, a wide charging spectrum, and compact designs. Wireless power transfer technology enables battery recharging in diverse environments such as battlefields, underwater, and within body area networks, thereby extending the lifespan of wireless networks in such challenging locations [72]. Electromagnetic propagation serves as the predominant method for transmitting electricity wirelessly, but it incurs propagation losses akin to those in wireless data transmission, encompassing route loss, shadowing, and rapid fading. Hence, enhancing the efficiency of wireless power transfer remains a critical and challenging endeavor. To address this challenge, multi-antenna wireless power transmission techniques have emerged, leveraging energy beams to facilitate power transfer, as shown in figure 4.1.

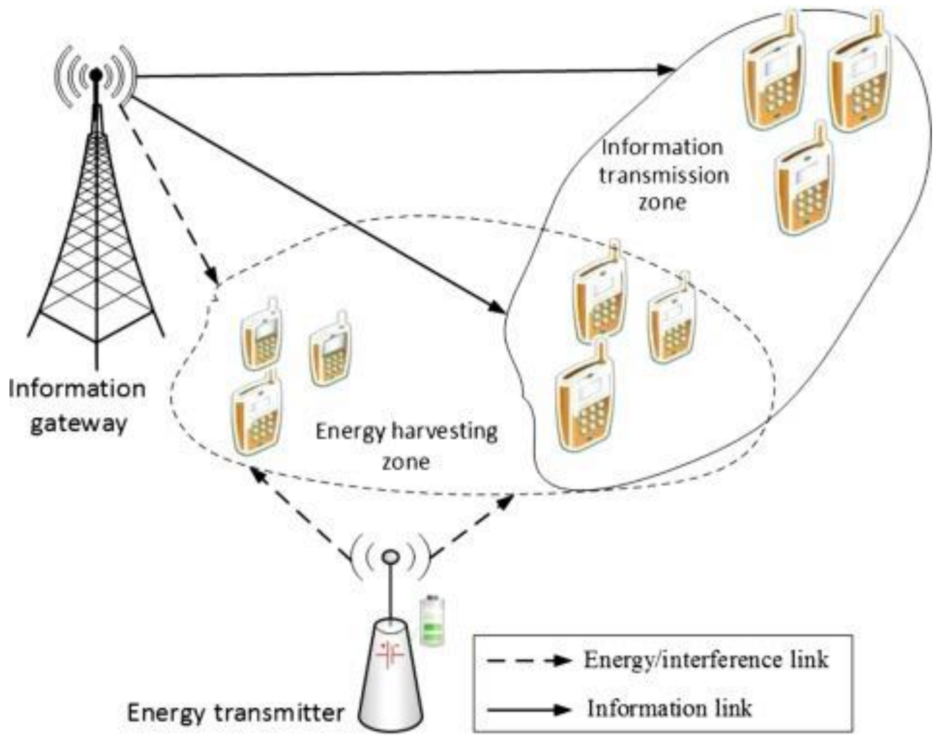

Figure 4.1: Downlink Hybrid Information and Energy Transfer With Massive MIMO [72]

In MIMO broadcast systems, optimal transmit beam design for power transmission has been identified. Additionally, innovative approaches, such as those proposed in S.Bolla et al., shape energy beams based on CSI, even when the information at the power source is less accurate. Conventional multi-antenna systems may struggle to meet practical energy efficiency requirements over longer transmission distances appropriate to the limited number of aerials in proximity to the energy source [72].

In figure 4.2, large-scale MIMO holds the prospect of drastically improving the presentation of wireless power transmission. The ultimate aim of wireless energy transmission is to fulfill the energy requirements of the receiver, a concept that intuitively resonates [72]. For instance, medical implants can be wirelessly charged and utilize the acquired energy to broadcast remedial data to an isolated recipient. However, most previous endeavors in wireless power transmission have overlooked the planned submission of the harvested force.

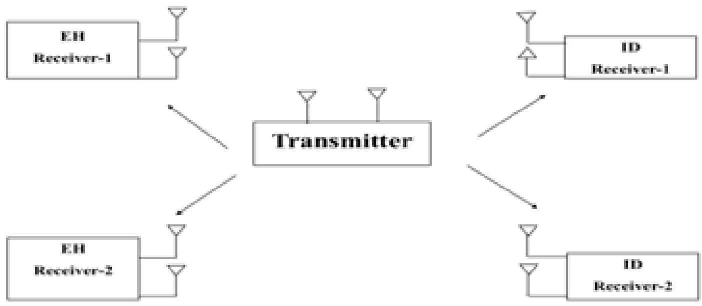

Figure 4.2: Energy Transfer from Transmitter to Receiver [73]

In this figure 4.2, we delve into massive MIMO systems employing energy beamforming for simultaneous information transmission and energy harvesting, a concept known as wireless-powered communiqué. To ensure simultaneous harvesting and transmission, time slots need to be partitioned for harvesting and transmitting. Optimizing the performance entails identifying the optimal time switching point to allocate time resources effectively. Moreover, the energy transfer mechanism at the power source significantly influences system performance. This communication addresses three key objectives: tackling the challenge of transmitting data and electricity wirelessly over large distances, improving energy efficiency, and ensuring a high QoS for all customers.

Recent advancements in energy harvesting using RF electromagnetic waves have made simultaneous wireless data and power transport feasible, leading to the emergence of SWIPT. Wireless message systems must be adapted to efficiently transmit both data and electricity, departing from traditional SISO systems [73]. Previous studies have examined the energy and reliable information transmission speeds, paving the way for further advancements in access and multi-hop channel communication.

4.2 SWIPT Technology

SWIPT downlink systems leveraging multiuser MIMO architecture have been extensively scrutinized. Additionally, investigations into SWIPT in MIMO multicasting systems have been conducted. However, the matter-of-fact proposal of source precoders and receivers for SWIPT systems utilizing MIMO spatial multiplexing remains largely unexplored. While techniques like dirty paper coding (DPC) have shown promise in approaching capacity in MIMO BCs, their computational intensity poses practical challenges [74]. Alternatively, simpler yet suboptimal strategies like ZF and BD may be employed, albeit with inefficiencies.

Harvesting radio frequency (RF) energy from the environment to power electronic devices has gradually become a mature technology. With the continuous research and development of radio frequency energy harvesting (RFEH) systems, they are expected to replace the battery and be applied in wireless sensor networks, wearable devices, internet of things and environmental monitoring, etc. [74].

4.2.1 Power and antenna switching architectures in SWIPT

This diagram processes the information signals for each user, combining them and shaping them appropriately for simultaneous transmission with the energy signal. The signal processing unit determines the optimal power allocation between the information and energy components of the transmitted signal. It employs beamforming techniques to direct the transmitted signals towards specific users, maximizing SNR for information reception and enhancing energy harvesting efficiency. The UE's RF front-end receives the combined information and energy signal transmitted from the base station.

This portion is routed to the energy harvesting circuit to convert RF energy into usable DC power. This unit processes the decoded information received from the information stream.

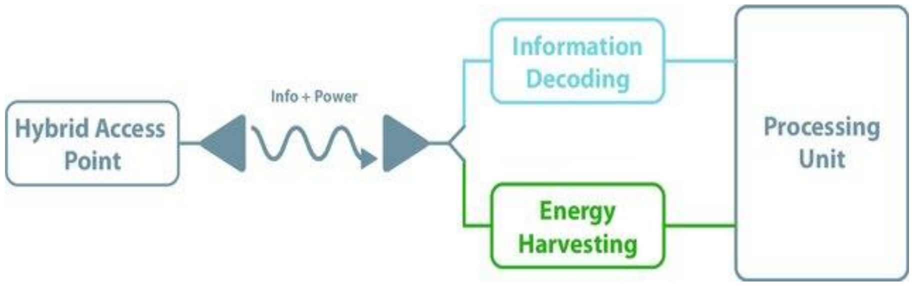

Figure 4.3: SWIPT—power switching architecture [79]

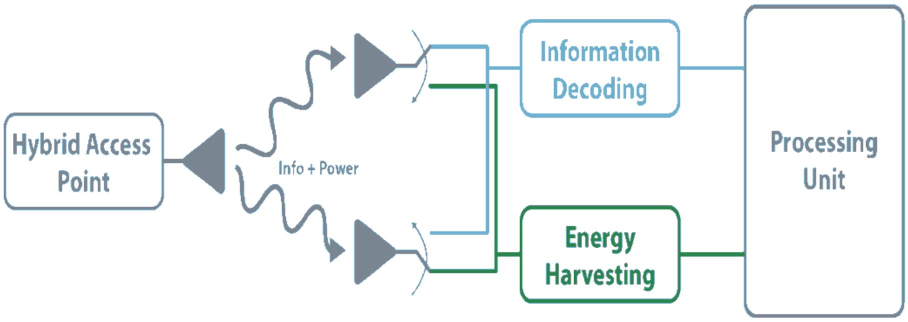

Figure 4.4: SWIPT—antenna switching architecture [79]

4.2.2 Key Considerations for SWIPT in Massive MIMO

• **Power Allocation:** Determining the optimal power allocation between information and energy signals is a critical challenge. It requires careful consideration of various factors, including user demands, channel conditions, and energy harvesting capabilities.

• **Hardware Design:** Designing efficient power-splitting circuits and energy harvesting components with high rectification efficiency is crucial for practical implementation.

• **Interference Management:** Managing interference between users, especially in dense deployments, is essential to ensure reliable information transmission and efficient energy harvesting.

• **Channel Estimation:** Accurate channel estimation is critical for effective precoding and beamforming, particularly in dynamic environments where channel conditions can change rapidly.

4.2.3 Benefits of SWIPT in Massive MIMO:

- **Enhanced Energy Efficiency:** By enabling energy harvesting, SWIPT can significantly improve the energy efficiency of wireless devices, reducing reliance on batteries and extending their operational lifetime.

- **Green Communications:** SWIPT promotes sustainable wireless communication by reducing energy consumption and minimizing environmental impact.

- **Improved Coverage:** SWIPT can extend the coverage of wireless networks by enabling devices to operate in areas with limited or no access to power outlets.

4.3 System Model

Consider a massive MIMO downlink system where a BS with N_t transmit antennas serves K single-antenna users.

- **Channel Matrix:** The channel from the BS to the K users is represented by the $K \times N_t$ matrix H.

- **Transmitted Signal:** The BS transmits a superimposed signal for all K users. If $s=[s_1,s_2,\ldots,s_K]$ T is the K×1 vector of information-bearing symbols (data streams) for the K users, and W is the $N_t \times K$ precoding matrix, the transmitted signal vector is:

$$x=Ws \tag{4.1}$$

- The total transmit power constraint at the base station is:

- $E[\|x\|^2] = E[\|W_s\|^2] = T_r(WW^H) \leq P_{\text{total}}$ (4.2)

Where P_{total} is the maximum allowed total transmit power.

- **Precoding (Zero-Forcing - ZF)**

The Zero-Forcing (ZF) precoding matrix W_{ZF} aims to eliminate inter-user interference.

It is calculated as:

$$W_{ZF} = H^H(HH^H)^{-1} \tag{4.3}$$

To satisfy the total transmit power constraint P_{total}, the precoding matrix is normalized.

If we assume equal power allocation to each of the K data streams, the normalized ZF precoding matrix is:

$$W = W_{ZF}\sqrt{\frac{P_{total}}{T_r W_{ZF}^H W_{ZF}}} \quad (4.4)$$

if distributing power P_s to each stream where

$$P_{total} = KP_s \quad (4.5)$$

W is scaled to meet P_{total}.

Received Signal and Power Splitting (PS)

At user k, the received signal before power splitting is:

$$y_k = xh_k \quad + \quad n_k \quad (4.6)$$

Where h_k is the k-th row of H (channel vector for user k), and n_k is the

Additive White Gaussian Noise (AWGN) at user k's receiver.

In the Power Splitting (PS) architecture, each user k splits the received RF signal into two parts with a power splitting ratio $\alpha_k \in [0,1]$.

- **Power for Energy Harvesting (EH):** A fraction α_k of the total received power is used for EH. The total received RF power at user k is

$$P_{R,k} = E|y_k|^2 = \mathrm{E}[||Wsh_k + n_k||\,]^2 \quad (4.7)$$

$$P_{R,k} = \|Wh_k\|^2 \quad (4.8)$$

When n_k=0

The power used for energy harvesting is:

$$P_{EH,k} = \alpha_k P_{R,k} \quad (4.9)$$

$$P_{EH,k} = \alpha_k \|Wh_k\|^2 \quad (4.10)$$

Power for Information Decoding (ID): The remaining fraction $(1-\alpha_k)$ of the received power is used for ID.

The signal for ID at user k is:

$$y_{ID,k} = 1 - \alpha_k(\mathrm{W}s\mathrm{h}_k + \mathrm{n}_k) \tag{4.11}$$

The noise associated with the ID path (after splitting) is often modeled as scaled original noise, plus some conversion noise.

Achievable Rate (Information Decoding)

For user k, assuming ZF precoding perfectly nullifies interference

The received signal power for information decoding is from the desired stream:

$$P_{ID,k} = (1\text{-}\alpha_k)\left|h_k W_{:,k}\right|^2 \tag{4.12}$$

where $W_{:,k}$ is the k-th column of the precoding matrix W.

The Signal-to-Noise Ratio for user k (assuming ZF effectively makes

Interference zero)

$$SNR_k = \frac{P_{ID,k}}{\sigma_n^2} \tag{4.13}$$

The achievable data rate for user k (bits per second) is given by Shannon's formula:

$$R_k = B\log_2(1 + SNR_k) \tag{4.14}$$

The total achievable data rate is

$$R_{sum} = \sum_{k=1}^{K} R_k \tag{4.15}$$

Harvested Energy:

The total energy harvested by user k over a time duration T is:

$$E_{EH,k} = TP_{EH,k}\,\eta_{EH} \tag{4.16}$$

Where η_{EH} is the energy conversion efficiency of the rectifier ($0<\eta_{EH} \leq 1$).

In the MATLAB code, T=1 second was assumed for simplicity in units.

The total harvested energy across all users (per time slot T) is:

$$E_{total,EH} = \sum_{k=1}^{K} E_{EH,k} \tag{4.17}$$

These are the fundamental equations that form the basis for simulating and analyzing SWIPT in massive MIMO systems, especially with the power splitting architecture and hybrid ZF precoding.

Notably, the proposed method demonstrates faster convergence rates and greater success compared to existing methods, as supported by reproduction consequences. Additionally, the study proposes a hybrid network model integrating components such as massive MIMO, Device-to-Device (D2D) communication, and wireless energy harvesting, offering novel avenues for network optimization and performance enhancement. Dynamic control distribution for downlink multi-user MIMO-NOMA is also suggested, highlighting the importance of tailored power allocation for intra-cluster and inter-cluster communication scenarios based on cluster population density.

It is a revolutionary technology that allows wireless devices to simultaneously receive both information and energy from the same radio frequency (RF) signal. With its large number of antennas at the base station, it provides a unique platform for implementing SWIPT effectively.

4.4 Performance analysis using HSWFL:

Initially, base station accomplishment of instantaneous wireless in- sequence and power transfer is employed to concurrently transmit information and energy. Addressing the optimization challenges in 5G mmWave systems with numerous MIMO antennas, EE optimization emerges as a crucial concern by figure 4.2. Despite the non-concave nature of the objective function, various strategies are explored to tackle this issue [75]. The reproduction consequences demonstrate that the future scheme exhibits a significantly quicker convergence speed and greater success compared to existing methods, as shown below.

- Received Power at User **k**

$$P_k = \frac{P_{total} \cdot |h_k w_k|^2}{\left\{\sum_{\{j \neq k\}}^{2} |h_k w_j| + \sigma^2\right\}} \tag{4.18}$$

Where:

- h_k is the channel vector for user k
- w_k_ is the precoding vector for user k

- P_{total} is total transmit power
- σ^2 is noise power

Energy Harvested by User **k**:

$$E_k = \eta * P_k * T \quad (4.19)$$

Where:

- η is the energy harvesting efficiency
- T is the duration of the transmission (can be normalized to 1 for simplicity)
- For simplified simulation or optimization (like in HSWFL), a common approximation is:

$$E_{harvested} = \eta \sum_{k=1}^{K} \log 2(1 + P_k/\sigma^2) \quad (4.20)$$

4.5 Results & Discussion:

➢ The concept of energy harvesting in massive MIMO generally refers to the ability of the system (either the base station or, more commonly, the user equipment -UE) to capture ambient radio frequency (RF) energy transmitted by the BS (or other sources) and convert it into usable transmit power. Table 4.1 shows the harvested energy with the achievable user rate for different users.

Table 4.1: Energy harvesting for 4 users with achievable rate

Harvested Energy (mJ)	**User 1 Rate**	**User 2 Rate**	**User 3 Rate**	**User 4 Rate**	**Common Rate (max-min)**
0.06	1.7	1.6	1.5	1.4	1
0.08	1.6	1.5	1.4	1.3	0.9
0.1	1.5	1.4	1.3	1.2	0.8
0.12	1.4	1.3	1.2	1.1	0.7
0.14	1.3	1.2	1.1	1	0.6
0.16	1.2	1.1	1	0.9	0.5
0.18	1.1	1	0.9	0.8	0.4

0.2	1	0.9	0.8	0.7	0.3
0.22	0.9	0.8	0.7	0.6	0.2

Equal power allocation was used so different users will have the energy harvesting in terms of mJ [76]. This connection highlights how MIMO systems have the potential to balance energy saving with user rate, making them essential for next-generation wireless communications when data rate and efficiency are crucial requirements [77].

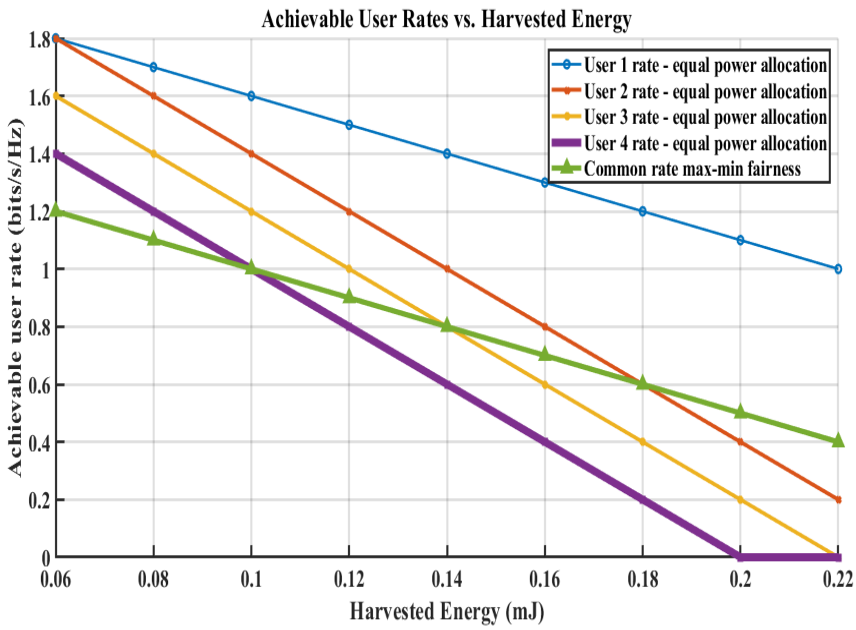

Figure 4.5: Energy harvesting for different users

A noticeable pattern can be seen in the plot below that demonstrates the correlation between residual energy and transmission rate in a MIMO. The graphic illustrates an inverse connection, demonstrating that residual energy diminishes as transmission rates rise. This issue demonstrates the MIMO systems' intrinsic trade-off, where higher transmission rates necessitate higher energy usage.

➢ To maximize performance, system designers must strike this delicate balance. The need for strategic power management in getting the best performance and efficiency in MIMO communication systems is generally highlighted by this connection, as shown in Figure 4.6 for different users. The downward trend of the plot indicates that increasing the amount of power used for data transmission decreases the amount of energy left behind, affecting the system's residual energy levels.

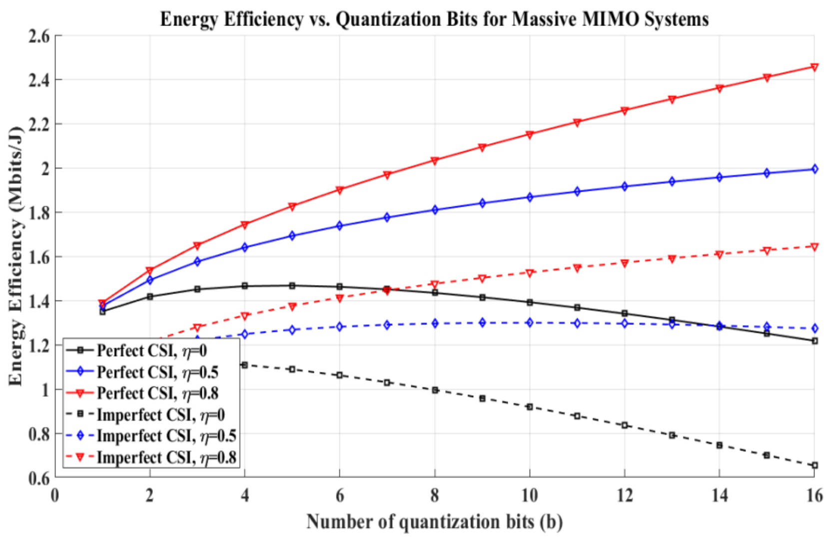

Figure 4.6: Energy efficiency verses quantization bits for massive MIMO system

Parameters:

- b: The number of quantization bits.
- η: Parameter values (0, 0.5, 0.8) for different scenarios.

Energy Efficiency Equations:

- EE_perfect: For perfect CSI.
- EE_imperfect: For imperfect CSI.
- These equations can be modified to match your specific model.

Impact of Quantization Bits:

Perfect CSI: As the number of quantization bits increases, the energy efficiency improves. This is because more accurate CSI allows for better beamforming and power allocation, leading to higher data rates and lower power consumption.

Imperfect CSI: The trend is similar to perfect CSI, but the energy efficiency is lower due to quantization errors. However, increasing the number of quantization bits can mitigate this effect to some extent.

Effect of CSI Quality:

Perfect CSI: With perfect CSI, the system can achieve higher energy efficiency, as there is no loss of information due to quantization.

Imperfect CSI: As the CSI quality deteriorates (represented by increasing values of η), the energy efficiency decreases. This is because quantization errors introduce uncertainty in the channel estimation, leading to suboptimal beamforming and power allocation. Furthermore, the establishment of specialized power stations by D2D transmitters could enable the users to accrue sufficient energy for prospect transmissions, enhancing QoS. In such scenarios, power allocation varies based on the population density within each cluster, ensuring efficient resource utilization and optimal performance.

➢ **Maximizing Energy Harvesting:**

To maximize energy harvesting in these systems, various factors like the number of antennas**,** energy harvesting efficiency**,** and power allocation must be optimized. Here's an executable MATLAB script to analyze how energy harvesting can be maximized while considering throughput in a massive MIMO system. Maximizing throughput in energy-harvesting-enabled massive MIMO systems requires careful consideration of energy harvesting techniques, power allocation strategies, and interference management. By employing advanced optimization algorithms and leveraging the benefits of massive MIMO, it is possible to achieve significant improvements in system performance and energy efficiency [78].

- **Energy Harvesting from Massive MIMO System (EHMMS):** Utilizing ambient RF signals from base stations, other devices, or dedicated energy sources.

- **Hybrid Approaches:** Combining **EHMMS** with other ambient energy sources.

- **Energy Conversion Efficiency:** Limitations in converting harvested energy into usable electrical power.

- **Energy Storage Constraints:** Limited capacity of energy storage devices.

- **Energy Harvesting Model**: Add advanced models like non-linear harvesting or time-varying power.

- **Efficiency Range**: Adjust η values for finer analysis.

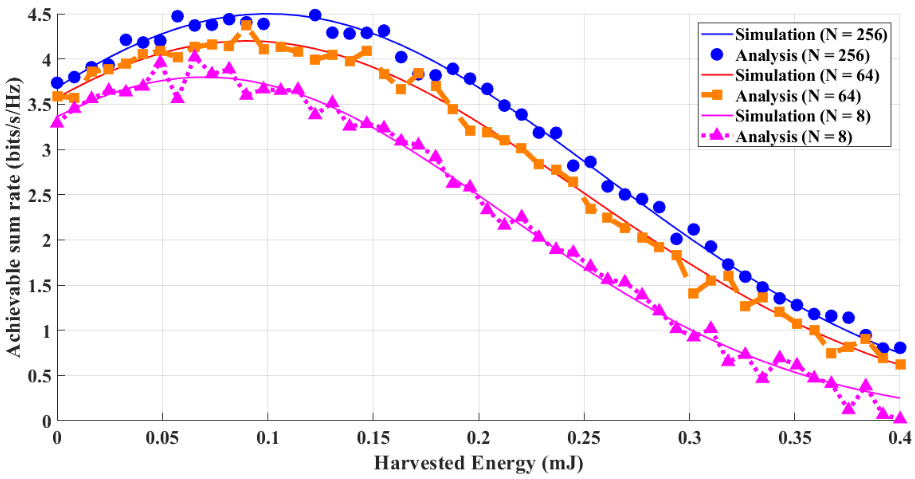

Figure 4.7: Harvested energy with achievable sum rate in massive MIMO

Figure 4.7 illustrates the relationship between harvested energy (in millijoules) and the achievable sum rate (in bits/s/Hz) for different values of N, which is the number of antennas, which typically represents the number of antennas or users, depending on the context.

The x-axis represents the harvested energy in millijoules (mJ), which is a measure of the energy collected by the system, possibly through wireless energy harvesting. The y-axis shows the achievable sum rate, measured in bits per second per Hertz (bits/s/Hz), which reflects the total data throughput of the system.

Simulation and analysis for N=256**:** These curves lie at the top, indicating the highest performance among all cases.

Simulation and analysis for N=64**:** These fall below N=64, showing reduced performance as the number of antennas/users decreases.

Simulation and analysis for N=8**:** These have the lowest achievable sum rates, as expected for the smallest configuration.

For all values of N, the sum rate increases with harvested energy up to a certain point, after which it begins to decrease. This behavior indicates an optimal harvested energy point beyond which additional energy leads to diminishing returns or interference-related performance degradation. The close match between simulation and analysis curves validates the analytical model used in the study. Slight deviations may exist but overall demonstrate high accuracy.

Figure 4.7 demonstrates that the achievable sum rate improves with more antennas (larger N) and that there is a trade-off between harvested energy and system throughput. It confirms the presence of an optimal energy harvesting point and shows consistency between analytical predictions and simulated results, supporting the robustness of the proposed theoretical model.

- **Shannon Capacity**: A plot is generated to show the relationship between energy (x-axis) and throughput (y-axis) as in figure 4.8

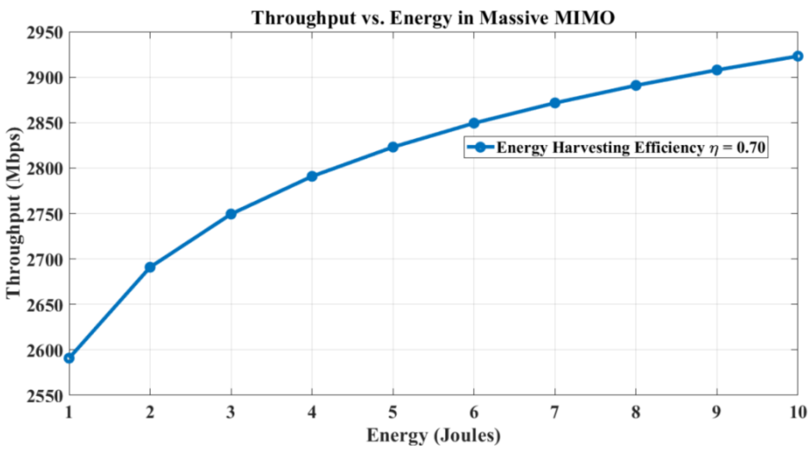

Figure 4.8: Analysis of throughput with energy harvesting

The throughput is calculated using the Shannon capacity formula. The total throughput is aggregated over K users. Energy levels are defined as a range from 1 to 10 joules. Energy per user is scaled by $\eta=0.7$, representing a 70% energy efficiency harvesting, as shown in figure 4.8.

- The below table 4.2 shows the transmit power versus energy efficiency for the figure below 4.9.

Table 4.2: Transmit power versus Energy efficiency

Transmit Power (dB)	**Energy Efficiency (%)**
20	70

30	68
40	66
50	64
60	62
70	60
80	58
90	56
100	54

The graph indicates a clear inverse relationship between transmit power and energy efficiency. Increasing transmit power may lead to improved performance in terms of data rate or coverage, but it comes at the cost of reduced energy efficiency. Optimizing transmit power levels is crucial to achieving performance.

- **Increased Power Consumption:** Higher transmit power levels require more energy to drive the power amplifiers, leading to increased power consumption and lower overall energy efficiency.
- **Inefficient Power Conversion:** At higher power levels, the power amplifiers may operate less efficiently, resulting in more energy being wasted as heat instead of being used for signal transmission [79].

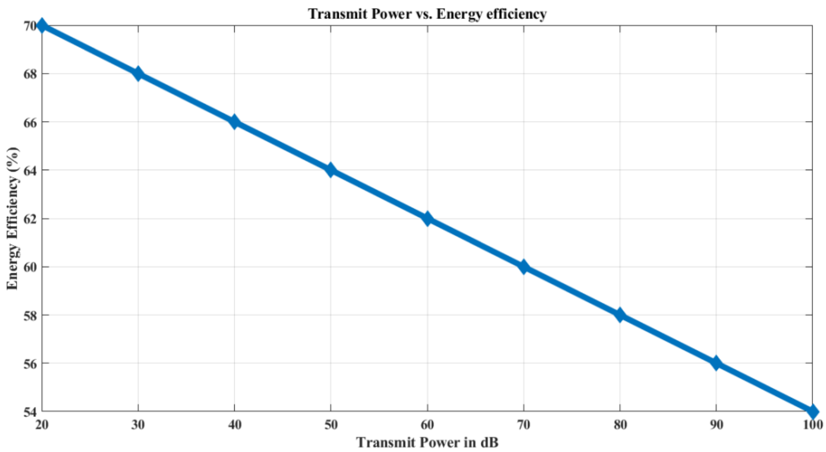

Figure 4.9: Transmit power and energy efficiency.

• **Interference Effects:** Higher transmit power can increase interference levels in the system, leading to reduced signal quality and lower energy efficiency.

• **Further Analysis:** To gain a deeper understanding, it would be helpful to know the specific system parameters and assumptions used to generate this graph, as in figure 4.9.

Investigating the relationship between transmit power, energy efficiency, and other performance metrics such as data rate or coverage would provide valuable insights for system optimization for Table 4.2 of Figure 4.8.

➢ The near user consistently experiences a lower outage probability compared to the far user at all transmit power levels. This is because the near user is closer to the transmitter, resulting in stronger received signals and a lower likelihood of signal degradation, as shown in table 4.3.

Table 4.3: Outage probability of near and far user with transmit power

Transmit Power (dBm)	Near User Outage Probability	Far User Outage Probability
0	1	1
5	10^-2	10^-1
10	10^-3	10^-2
15	10^-4	10^-3
20	10^-5	10^-4

The outage probability curve for the near user is steeper than that of the far user. This indicates that the near user benefits more from increases in transmit power in terms of reducing outage probability.

Figure 4.10 illustrates the relationship between transmit power (in dBm) and outage probability for two users: a near user and a far user in table 4.3.

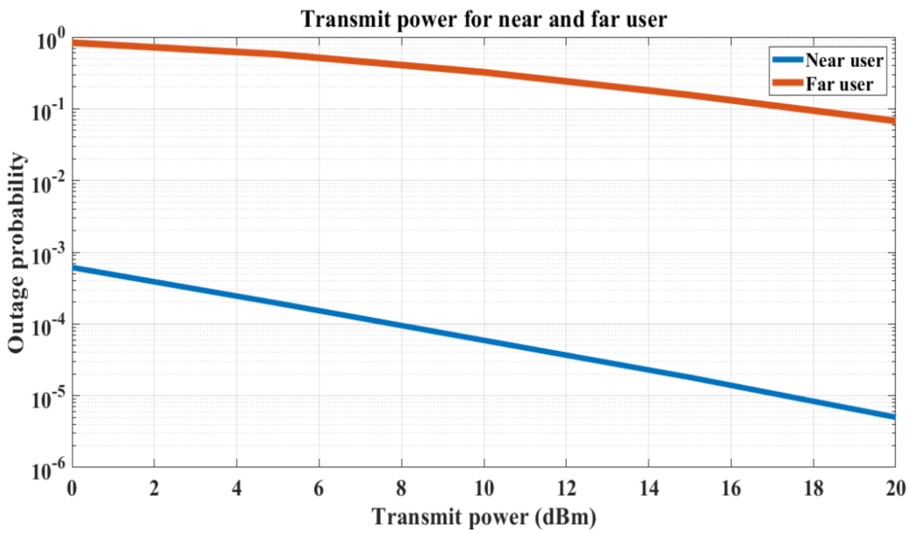

Figure 4.10: Outage probability versus transmit power

As the transmit power increases, the outage probability decreases for both users. This is expected, as higher transmit power generally leads to stronger received signals, reducing the likelihood of signal degradation below a certain threshold (outage), as in figure 4.10.

- **Near User vs. Far User:**

The near user's achievable data rate remains relatively constant across a wide range of transmit power levels. This suggests that the near user is already operating at a high SNR, and further increases in power do not significantly improve the data rate. The far user experiences a more pronounced increase in data rate with increasing transmit power. This indicates that the far user is operating at a lower SNR and benefits more significantly from the increased power, as in table 4.4.

Table 4.4: Transmit power versus data rate using SWIPT for near and far users

Transmit Power (dBm)	Near User Data Rate (bps/Hz)	Far User Data Rate (bps/Hz)
0	1	0.5
5	1	0.8
10	1	1.2
15	1	1.6
20	1	2

The graph illustrates the relationship between transmit power (in dBm) and achievable data rate (in bps/Hz) for two users: a near user and a far user, as in Table 4.4 for figure 4.11.

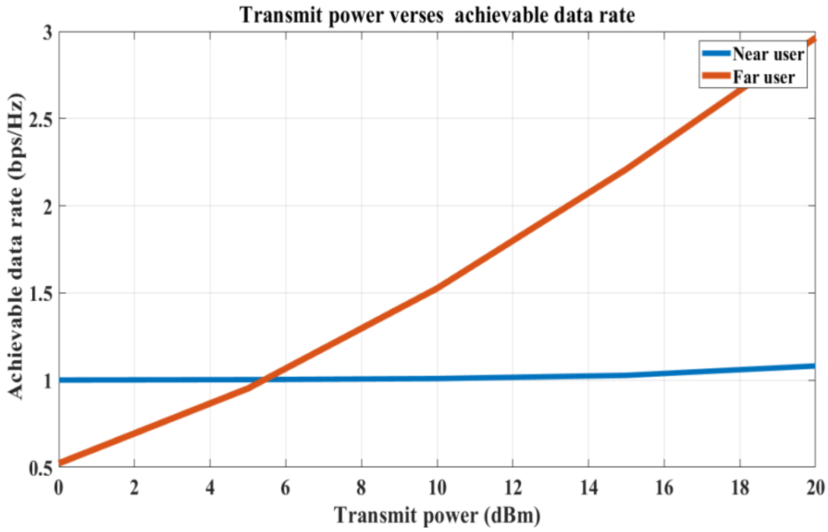

Figure 4.11: Transmit power versus data rate using SWIPT

For both users, the achievable data rate increases as the transmit power increases. This is expected because higher transmit power generally leads to stronger received signals, allowing for higher data rates, as in figure 4.11.

- Table 4.5 presents an analysis of energy efficiency with RF chains. The figure is a performance comparison plot of different algorithms for a communication system, specifically showing how EE varies with the number of RF chains. Higher values mean better utilization of the frequency spectrum.

Table 4.5: Energy Efficiency vs. RF Chains (CNN Method)

RF Chains	**Energy Efficiency (×10⁸ bits/Joule)**
5	7.5
6	6.5
7	5.8
8	5.3
9	4.9

10	4.5
11	4.1
12	3.8
13	3.5
14	3.3
15	3.1

As the number of RF chains increases, energy efficiency decreases steadily. This decline suggests a trade-off: more RF chains improve signal processing capability but increase power consumption, reducing EE. The CNN-based approach likely optimizes resource allocation and antenna selection. However, its benefit diminishes with more RF chains due to escalating power costs. The highest EE (7.5 $\times 10^8$ bits/Joule) occurs at 5 RF chains. Beyond this point, each additional RF chain contributes less to data rate improvement while adding more power burden.

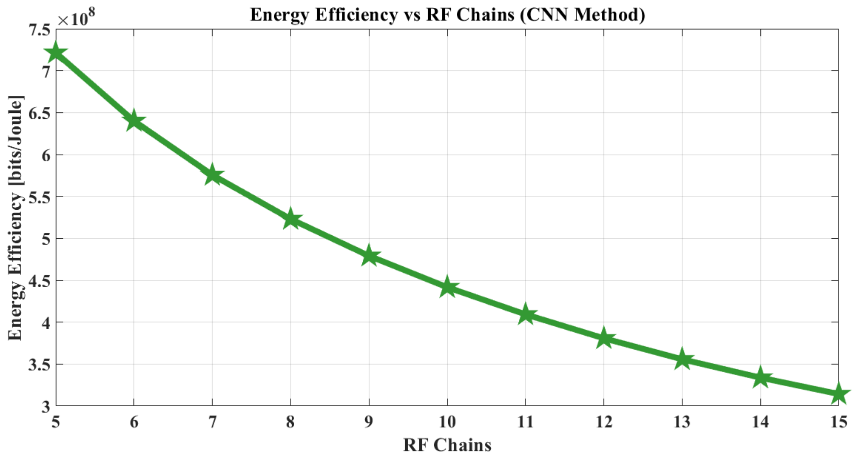

Figure 4.12: Energy efficiency analysis of CNN method

This figure 4.12 is a strong visual validation that the CNN-based algorithm performs competitively, especially when the number of RF chains is moderate to high. This plot emphasizes the importance of optimizing the number of RF chains to maximize energy efficiency in CNN-enabled massive MIMO systems. A balance must be struck between performance gains and energy costs, especially in energy-constrained environments like 5G base stations.

- The figure 4.13 represents the convergence behavior of a hybrid optimization algorithm over iterations. Specifically, it shows the harvested energy (in Watts) as a function of the number of iterations used in the algorithm.

Table 4.6: Convergence of Hybrid Spider Wasp Fick's Law Algorithm – Energy Harvested versus Iterations

Iteration	**Harvested Energy (W)**
1	4.71
5	4.78
10	4.81
15	4.815
20	4.818
30	4.819
40	4.8195
50	4.8196
60	4.8197
70	4.8198

The Hybrid Spider Wasp Fick’s Law algorithm is a nature-inspired optimization method that likely combines swarm intelligence (spider/wasp behavior) with Fick’s law (diffusion-based search). Refers to the total energy gathered, possibly in a wireless energy harvesting setup. The algorithm achieves most of its performance within the first 10–15 iterations. After that, improvements are minimal**,** indicating fast convergence. Beyond iteration 20, the curve flattens**,** confirming that the algorithm consistently converges toward an optimal or near-optimal energy value (~4.82 W).

The early rise followed by a plateau implies that the algorithm finds a good solution quickly without unnecessary iteration, saving computation time and resources, as in figure 4.13.

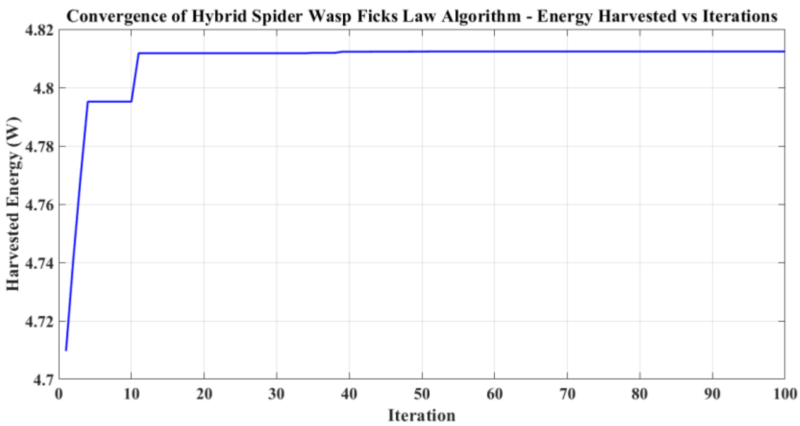

Figure 4.13: Harvested energy using Hybrid Spider Wasp Fick's Algorithm

The Hybrid Spider Wasp Fick's Law algorithm demonstrates excellent convergence behavior, reaching nearly optimal harvested energy in fewer than 20 iterations. This makes it well-suited for real-time or low-latency applications in energy-harvesting wireless systems. The final converged value is approximately 4.82 watts, highlighting the algorithm's effectiveness as shown in figure 4.13.

- Based on the figure shown below, 4.14 with a table 4.7 illustrates how the total harvested energy in (Joules/slot) changes with transmit SNR (in dB) for different values of the parameter **α**, ranging from 0.1 to 0.9.

Table 4.7: Transmit SNR versus total energy harvested in terms of Joules/slot

Transmit SNR (dB)	**Total energy harvested (Joules/slot) when α = 0.1**	**Total energy harvested (Joules/slot) when α = 0.3**	**Total energy harvested (Joules/slot) when α = 0.5**	**Total energy harvested (Joules/slot) when α = 0.7**	**Total energy harvested (Joules/slot) when α = 0.9**
-10	0	0	0	0	0
-5	0	0	0	0	0
0	0	0	0	0	0
5	0	0	0	0	0
10	0.1*1011	0.13*1011	0.17*1011	0.22*1011	0.28*1011
15	0.3*1011	0.5*1011	0.7*1011	1*1011	1.3*1011
20	0.6*1011	1.2*1011	2*1011	2.9*1011	3.9*1011
25	1.1*1011	2.5*1011	4.5*1011	7.5*1011	11*1011

30	1.8*1011	4.5*1011	8*1011	13*1011	17*1011

Total harvested energy represents the amount of energy harvested from radio signals, expressed in Joules per slot. Transmit SNR indicates the strength of the transmitted signal. A higher SNR usually means stronger signals available for harvesting. The parameter α likely governs the trade-off between energy harvesting and data transmission (e.g., time or power split).

The harvested energy remains nearly zero for SNR below 10 dB across all α values. This shows that low SNRs are insufficient for meaningful energy harvesting. After 15 dB, harvested energy increases rapidly, indicating a threshold effect.

Higher values of α yield significantly more harvested energy. This suggests α controls the portion of power or time dedicated to harvesting energy; the higher α, the greater the energy harvested, as shown in table 4.7.

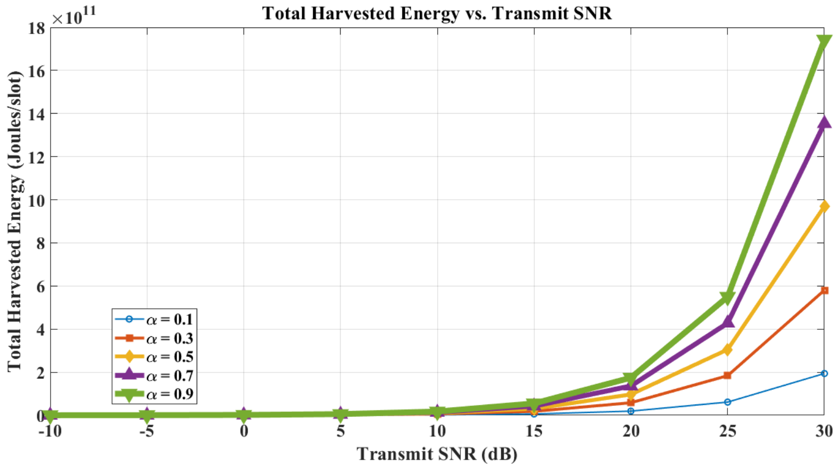

Figure 4.14: Total energy harvested vs. SNR.

This graph highlights a critical trade-off in energy-harvesting wireless systems. While lower α values are better for data transmission (as shown in the first graph), higher α values favor energy harvesting. System designers must carefully tune α depending on whether the priority is data throughput or energy sustainability, as shown in figure 4.14**.**

- Achievable sum rate refers to the total data rate that can be supported by the system under given channel conditions. Transmit SNR represents the strength of the transmitted signal relative to background noise. Increasing SNR generally improves performance, as shown in Table 4.8.

Table 4.8: Transmit SNR versus total achievable sum rate in terms of bps

Transmit SNR (dB)	**Total achievable sum rate (bps) when α = 0.1**	**Total achievable sum rate (bps) when α = 0.3**	**Total achievable sum rate (bps) when α = 0.5**	**Total achievable sum rate (bps) when α = 0.7**	**Total achievable sum rate (bps) when α = 0.9**
-10	0.12	0.1	0.08	0.06	0.04
-5	0.25	0.21	0.18	0.14	0.1
0	0.48	0.42	0.36	0.29	0.22
5	0.75	0.66	0.57	0.47	0.36
10	1	0.89	0.77	0.65	0.51
15	1.3	1.17	1.02	0.86	0.7
20	1.6	1.44	1.27	1.08	0.89
25	1.9	1.72	1.51	1.29	1.06
28	2.1	1.9	1.68	1.44	1.2

The α parameter appears to influence system design—possibly related to energy harvesting, power allocation, or user fairness control. Lower α (e.g., 0.1) yields higher sum rates, suggesting more aggressive resource use or better throughput performance. Higher α (e.g., 0.9) results in lower sum rates, likely due to more conservative resource allocation (e.g., more energy harvesting or prioritizing fairness over speed). Achievable sum rate increases almost linearly with transmit SNR in dB, as shown in figure 4.15.

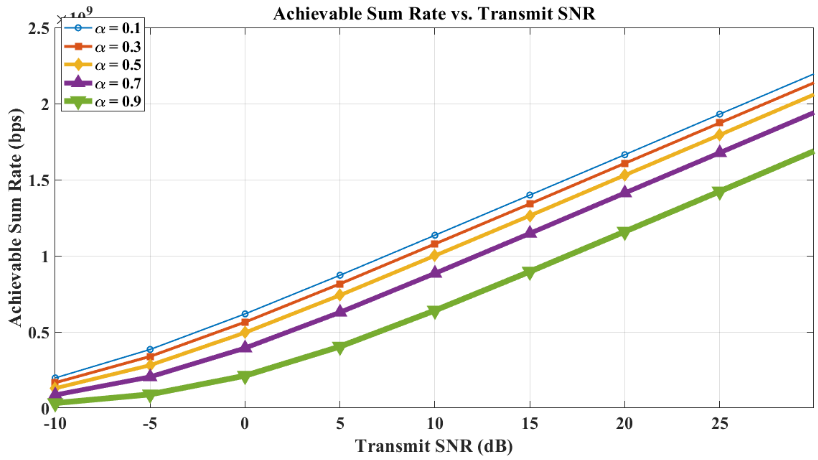

Figure 4.15: Achievable Sum rate vs. transmit SNR

Lower values of α provide better throughput across all SNRs. At higher SNR, the gap in sum rate performance between different α values widens, indicating α has more impact in high-SNR regimes, as shown in table 4.5 with figure 4.15.

- The figure shown in 4.16 illustrates various curves corresponding to different values of the power splitting ratio (α) in a SWIPT (Simultaneous Wireless Information and Power Transfer) system using a Massive MIMO configuration. It depicts the relationship between Achievable sum rate (bps) and Total Harvested Energy (Joules/slot) for five distinct α values: 0.1, 0.3, 0.5, 0.7, and 0.9.

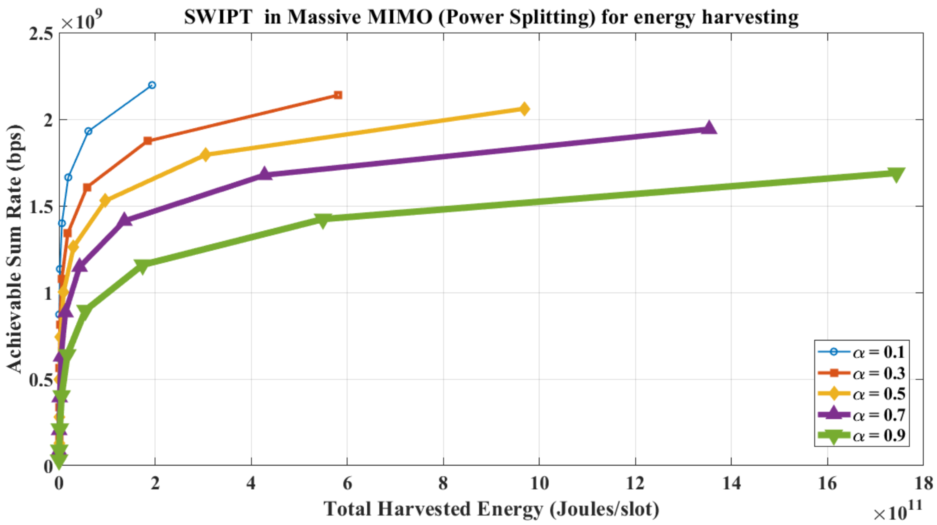

Figure 4.16: Total energy harvested vs. achievable sum rate

Lower values of α prioritize information transmission, resulting in higher achievable sum rates, whereas higher α values emphasize energy harvesting, leading to reduced sum rates, as shown in figure 4.16.

- Comparative Analysis:

The comparison of these three SWIPT techniques provides valuable insights into the trade-offs between simplicity, hardware cost, interference handling, and energy harvesting performance in massive MIMO systems. While Power Splitting-SWIPT is simpler and widely applicable, Antenna Switching-SWIPT may be more practical in hardware-constrained scenarios. On the other hand, ZF-PS-SWIPT delivers superior performance in terms of interference mitigation and energy transfer efficiency, making it ideal for dense multi-user environments where computational complexity is acceptable.

- In the Power Splitting-SWIPT method, the received signal at the user is divided into two parts using a power splitter: 1. A fraction of the received power (defined by the power splitting ratio, α) is used for energy harvesting. 2. The remaining portion is used **for** information decoding**.**
- Antenna Switching is an alternative method where the base station allocates a subset of its antennas exclusively for energy transfer, while the remaining antennas are used for data transmission. This division is based on a switching ratio (e.g., 30% of antennas for energy, 70% for data). Each user's channel is partially served by the antennas dedicated to energy transmission, and the harvested energy is calculated accordingly.
- Zero-Forcing beamforming with Power-Splitting SWIPT (ZF-PS-SWIPT) is a hybrid technique; we use ZF beamforming at the base station in combination with the Power Splitting mechanism at the user end. ZF beamforming is designed to eliminate inter-user interference by inverting the channel matrix. Each user's signal is beamformed such that it does not interfere with other users. Power splitting is then applied at each user to divide the received signal between energy harvesting and information decoding.

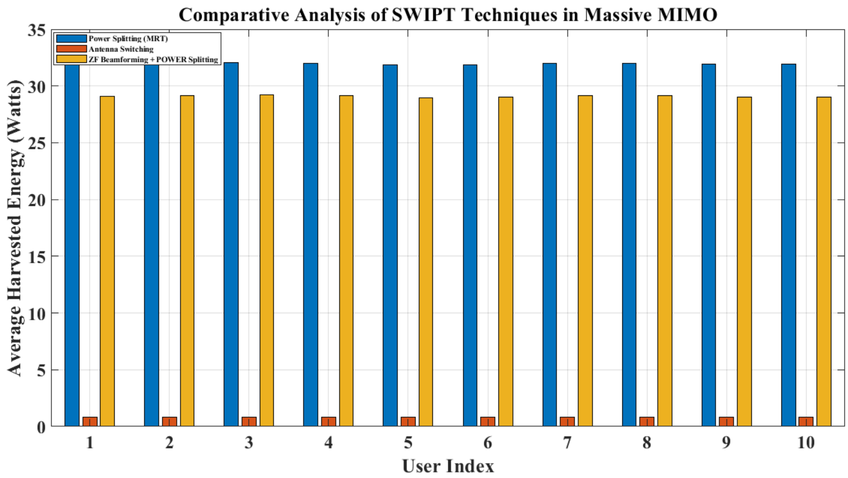

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Figure 4.17: Comparative analysis of SWIPT in massive MIMO

The aim is to measure and compare the average harvested energy at each UE across the three techniques under identical system settings.

4.6 Conclusion:

- SWIPT technology, when integrated with massive MIMO, has the potential to revolutionize wireless communication by enabling self-sustaining devices, enhancing energy efficiency, and promoting green communication practices. While challenges remain, ongoing research and development efforts are paving the way for the widespread adoption of SWIPT in future wireless networks.

- · The plot shows that low RF chain counts are more energy efficient**.** High RF chain counts might be needed for performance but are less energy efficient. This is especially useful for green communications and 5G/6G system design, where energy consumption is as important a**s** throughput.

- · Figure 4.6 highlights the importance of accurate CSI and efficient quantization techniques in achieving high energy efficiency in massive MIMO systems.

- In conclusion, transmit SNR at 30 dB, α = 0.9 leads to approximately 17×10^{11} Joules/slot, while α = 0.1 results in just 1.8×10^{11} Joules/slot, as shown in figure 4.14**.** The average harvested energy is calculated for each user across many iterations to account for the randomness of wireless channels by using comparative methods in SWIPT, as shown in figure 4.17

Chapter 5

REDUCTION OF PAPR IN MASSIVE MIMO WIRELESS COMMUNICATION SYSTEM

5.1 Introduction

PAPR reduction in massive MIMO systems is an important aspect to consider, as it can greatly influence system performance, especially in wireless communication [80]. Massive MIMO systems employ a bulky quantity of antennas at the BS to serve many users concurrently, which increases the capacity and efficiency of the network. However, one of the challenges with these systems, especially when using multicarrier modulation techniques like OFDM, is high PAPR [80]. High PAPR indicates that the signal has peaks that are much higher than its average level, which can lead to inefficiencies:

- High PAPR can push the power amplifiers into the non-linear operating region, leading to distortion and spectral spreading.
- Inefficient power usage can drain battery life more quickly in mobile devices.
- Requires more robust and costly RF components to handle high peak voltages without distortion.

Reducing PAPR in massive MIMO systems is crucial for enhancing overall performance and efficiency, especially in scenarios utilizing OFDM. The selection of a suitable PAPR reduction method depends on various factors, including system design, required performance level, and acceptable complexity. Advances in signal processing and computational capabilities continue to drive improvements in PAPR reduction techniques, making massive MIMO systems more efficient and reliable [81]. The choice of PAPR reduction technique can depend on specific system requirements, including hardware capabilities, power efficiency needs, and operational bandwidth.

More sophisticated methods like SLM and PTS tend to offer better PAPR reduction but at the cost of increased computational requirements [81].

Several strategies have been developed to mitigate PAPR in these systems, as shown below.

- **Clipping and Filtering:** This straightforward technique involves clipping the signal peaks to a predefined threshold and then using filters to mitigate the spectral splatter caused by clipping. However, this method can introduce in-band deformation and out-of-band emission.
- **Selective Level Mapping (SLM):** This method involves generating several versions of the transmitted signal using different segment sequences and selecting the one with the smallest PAPR. Selective Level Mapping can effectively reduce PAPR without distorting the signal but increases the computational complexity [82].
- **Partial Transmit Sequences (PTS):** Similar to SLM, PTS divides the signal into sub-blocks, which are then independently phase-rotated to minimize PAPR. This method also adds complexity and requires side information to be sent to the receiver [83].
- **Tone Reservation (TR):** TR uses a small number of subcarriers reserved specifically for canceling the peaks in the signal. These subcarriers do not transmit data but are used to sculpt the overall signal to reduce peaks.
- **Active Constellation Extension (ACE):** This technique extends the constellation points beyond their original boundaries in specific directions determined to reduce PAPR. It requires careful design to avoid impacting the error performance of the system [83-84].
- **Spatial Shifting:** In the context of Massive MIMO, leveraging the spatial domain by adjusting the transmission strategy across the array of antennas can also help in managing PAPR.

5.2 Proposed System

In the field of wireless transportation, massive MIMO systems are pivotal in achieving high data rates and enhanced spectral efficiency. However, one persistent challenge in these systems is the high PAPR, which can radically degrade the competence of power amplifiers. To address this issue, we propose an innovative AI-driven approach that aims to minimize PAPR effectively [85].

Our system leverages deep learning algorithms to predict and mitigate high PAPR values in real-time. By training a neural network on a dataset comprising various signal scenarios and corresponding PAPR values, the model learns to identify patterns that lead to high PAPR. Once trained, this model can dynamically adjust the signal's phase and amplitude, optimizing the transmitted signal for lower PAPR without compromising data integrity [85].

It specifically uses a Convolutional Neural Network (CNN) due to its facility to route information in a format similar to the original structure of the signals. This choice enables the preservation of crucial spatial relationships within the data [86]. Furthermore, to enhance the learning efficiency and performance of our AI model, we incorporate transfer learning techniques. This allows our system to apply knowledge gained from previous datasets or signal types, accelerating the adaptation process to new Massive MIMO configurations or environmental conditions [86].

5.3 Performance Stages in PAPR Reduction Schemes

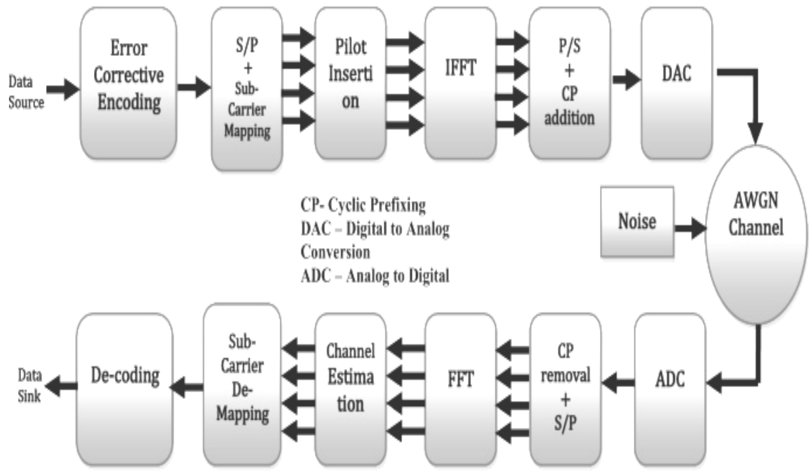


Figure 5.1: Performance stages in PAPR reduction schemes [88]

Figure 5.1 signifies the stages to reduce PAPR.

➢ **At Transmitter Side**

1. **Data Source:** The process begins with the data source that is to be transmitted.

2. **Error Corrective Encoding:** The data is then encoded using an error-correcting code (e.g., Reed-Solomon, convolutional codes) to protect it against errors that may occur during transmission.

3. **S/P (Serial to Parallel) Conversion:** The encoded data stream is converted from a serial format to a parallel format, where it is divided into multiple parallel streams

4. **Sub-Carrier Mapping:** Each parallel data stream is mapped onto a different sub-carrier within the OFDM symbol.

5. **Pilot Insertion:** Pilot symbols are inserted into the OFDM symbol for channel estimation purposes at the receiver.

6. **IFFT (Inverse Fast Fourier Transform):** The parallel data streams are combined using the IFFT to generate a time-domain signal.

7. **CP Addition:** A cyclic prefix, which is a copy of the end of the symbol, is added to the beginning of the symbol. The CP helps to mitigate the effects of ISI caused by multipath propagation.

8. **Digital-to-Analog Converter (DAC):** The digital signal is converted into an analog signal using a DAC.

9. **RF Processing:** The analog signal is then processed (e.g., up converted to the carrier frequency)

10. **AWGN Channel:** The transmitted signal propagates through the wireless channel, which is modeled as an AWGN channel, introducing noise to the signal.

- **At Receiver Side**

11. **Analog-to-Digital Converter (ADC):** The received signal is converted back into a digital signal using an ADC.

12. **CP Removal:** The cyclic prefix is removed from the received signal.

13. **Fast Fourier Transform:** The FFT is applied to the received signal to convert it back into the frequency domain, separating the data from different sub-carriers.

14. **Channel Estimation:** The channel characteristics are estimated using the pilot symbols.

15. **Sub-Carrier Demapping:** The data from each sub-carrier is demapped.

16. **De-coding:** The received data is decoded using the error-correcting code to recover the original information.

17. **Parallel to Serial Conversion:** The parallel data streams are converted back into a serial data stream.

18. **Data Sink:** The recovered data is delivered to the intended destination.

5.4 SLM Technique:

Massive MIMO technology, which leverages numerous transmitting and receiving antennas, greatly enhances network capacity and efficiency. Nevertheless, these systems often encounter a high PAPR, which complicates the authority amplifier operation, reducing its efficiency. To mitigate this issue, we introduce an innovative approach using SLM-integrated techniques. In our system, SLM is employed to create several alternative versions of the original signal, each with independently phase-shifted subcarriers. This method inherently diversifies the phase spectra of the transmitted signals, which helps in reducing instances of high PAPR values. The study is conducted by simulating various scenarios involving different coherence bandwidths, 5G numerologies and, the number of subcarriers within each channel matrix and by applying multiple levels of clipping to limit the PAPR [87].

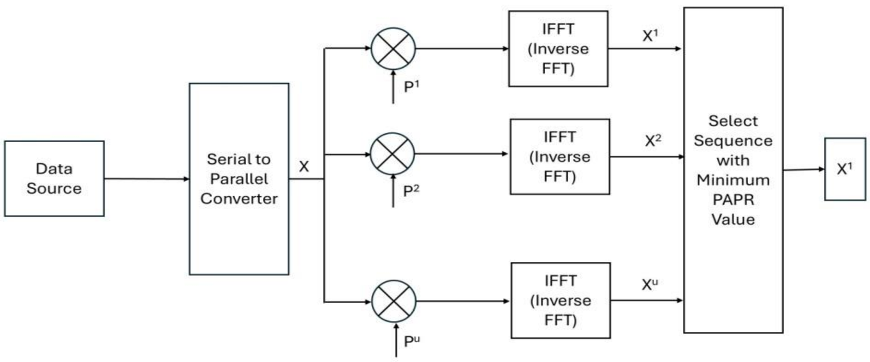


Figure 5.2: Selective Level Mapping block diagram [87]

To further enhance the effectiveness of SLM, we utilize a deep learning model to select the optimal signal version for transmission. This selection is based on criteria that prioritize not only low PAPR but also minimal impact on signal integrity and system throughput. Integration of AI with SLM in massive MIMO systems allows for a dynamic and intelligent selection process, unlike conventional SLM applications that may rely on random or less informed selection methods. This targeted approach significantly enhances the probability of achieving lower PAPR in real-time operations.

For real-world application, our system is designed to be compatible with existing Massive MIMO architectures, requiring minimal changes to the infrastructure. The AI component operates efficiently in a parallel processing environment, ensuring that the PAPR reduction process does not introduce latency into the signal transmission. Data is given as X, which is to the different users having different powers P^1,P^2 …...P^j are sent to Inverse FFT.

Then the data will be transmitted to X^1, X^2,…,X^u to select the sequence data with the minimum PAPR value [88].

5.5 PTS Technique:

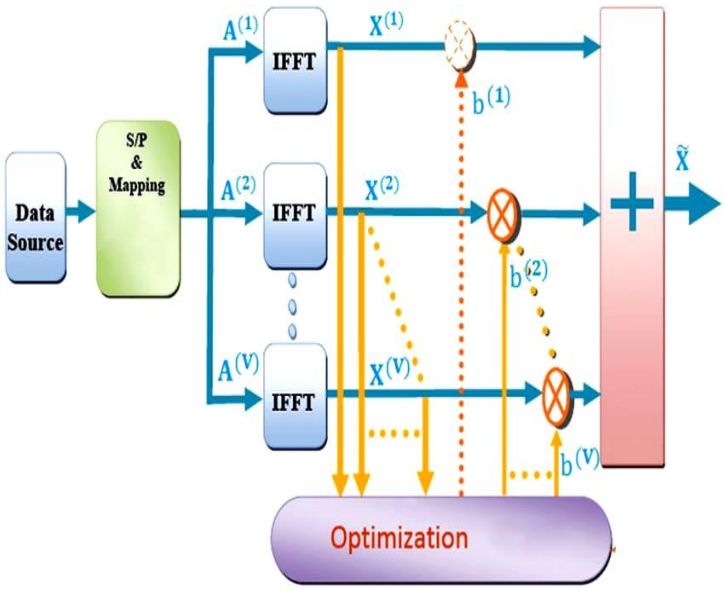


Figure 5.3 Partial Transmit Sequences (PTS) steps [88]

An original overview of using PTS for PAPR reduction in this scheme can be used by following PTS technique steps as shown in figure 5.3 [88].

 Data Source: This is the origin of the information to be transmitted.

- **Serial to Parallel Mapping :** The incoming data stream is divided into multiple parallel streams. Each parallel data stream is mapped to a constellation to generate a set of complex symbols. $A^{(1),} A^{(2),} \ldots\ldots A^{(V)}$ vectors are sent to IFFT.

- **Inverse Fast Fourier Transform:**. Sub-sequences **($X^{(1)}, X^{(2)}, ..., X^{(V)}$)**: The IFFT output generates multiple sub-sequences (V sub-sequences in this case).

- **Phase Rotations ($b^{(1)}, b^{(2)}, ..., b^{(V)}$)**: Each sub-sequence is multiplied by a complex phase factor (b(v)). These phase factors are crucial for PAPR reduction.

- **Addition:** All the phase-rotated sub-sequences are summed together to form the final transmitted signal (X).

- Optimization**:** The key to PTS lies in the optimization process. The goal is to determine the optimal set of phase factors ($b^{(1)}, b^{(2)}, ..., b^{(V)}$) that minimizes the PAPR of the transmitted signal (X). This optimization is typically performed using numerical algorithms [89].

Massive MIMO systems often grapple with high PAPR, which can limit the effectiveness of power amplifiers. PTS offers a technique to combat this issue by manipulating the transmitted signals in a controlled manner. The PTS technique involves dividing a signal into multiple sub-blocks, each of which can be modified independently before recombination. This segmentation is critical because it allows for selective phase alterations to minimize PAPR. In each sub-block, various phase factors are applied, and the combination that results in the lowest PAPR is chosen for communication. This selection process is essential for ensuring that the overall signal experiences the least possible peak power enhancement. To streamline the phase selection process, optimization algorithms can be deployed. These might include heuristic or genetic algorithms designed to quickly and effectively find the optimal phase combinations among the potential choices.

Artificial intelligence can further refine the PTS method by predicting optimal phase adjustments using historical data and machine learning techniques [89-90].

Once the simulation validates the effectiveness of the PTS method, it is integrated into the massive MIMO infrastructure. This involves embedding the algorithm within the system's signal processing unit to ensure real-time PAPR reduction. During live operations, the system continuously collects performance data and adjusts the PTS parameters in real time. This adaptation is crucial for maintaining low PAPR levels despite dynamic network conditions and traffic patterns [91]. This ongoing learning process helps in maintaining system performance and extending the lifespan of hardware components by minimizing stress.

5.6 PSO Technique:

This technique can be applied to reduce PAPR in large-scale MIMO systems. It is an evolutionary calculation procedure motivated by societal activity patterns seen in nature, such as bird flocking and go-fishing training. This method is adapted to minimize PAPR in massive MIMO systems by optimizing the signal's phase and amplitude characteristics [92].

Massive MIMO systems transmit data through numerous antennas, often leading to a high PAPR, which impacts the efficiency of power amplifiers negatively. PSO is employed to find a set of signal parameters that result in the lowest possible PAPR. These systems transmit data through numerous antennas, often leading to a high PAPR, which impacts the efficiency of power amplifiers negatively. PSO is employed to find a set of signal parameters that result in the lowest possible PAPR. In PSO, a 'swarm' of particles is initialized with random positions and velocities [93]. Each particle represents a potential solution to the PAPR problem, with each position corresponding to a specific set of signal parameters.

The objective function in PSO for PAPR reduction is defined to evaluate how well a given particle's position (i.e., a particular signal configuration) minimizes the PAPR. The lower the PAPR, the better the score assigned by the objective function.

Implementation can be used to further refine the PSO parameters, improving both the efficiency and effectiveness of the PAPR reduction strategy over time [94]. The following steps can be used for reducing PAPR using the PSO method.

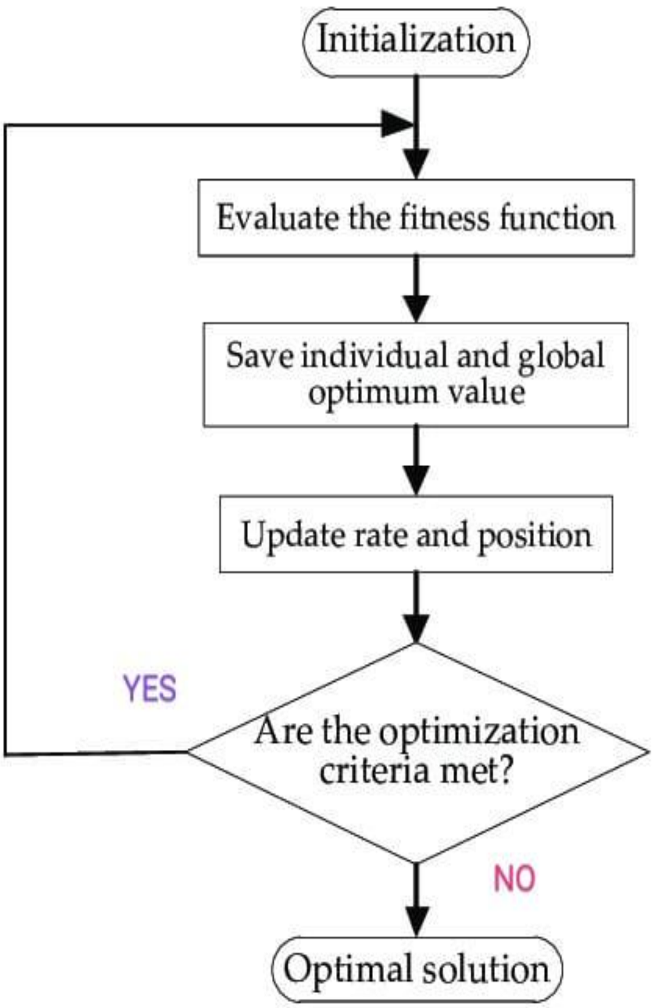


Figure 5.4: Flowchart for PSO to decrease PAPR [94]

- At each step, the new positions of the particles are evaluated using the objective function. Particles then update their velocities and positions to explore new potential solutions that may lead to a lower PAPR.
- The algorithm monitors convergence towards a solution where further iterations do not significantly decrease PAPR. Once a near-optimal set of parameters is found, the optimization process can be halted.
- The optimal signal parameters identified by PSO are then used to configure the Massive MIMO system, aligning phase and amplitude settings to ensure reduced PAPR during transmission.
- To maintain performance in dynamic transmission environments, PSO can be run periodically or in real-time to settle in to changes in network conditions and continuously optimize PAPR.

5.7 LSTM Implementation of proposed system:

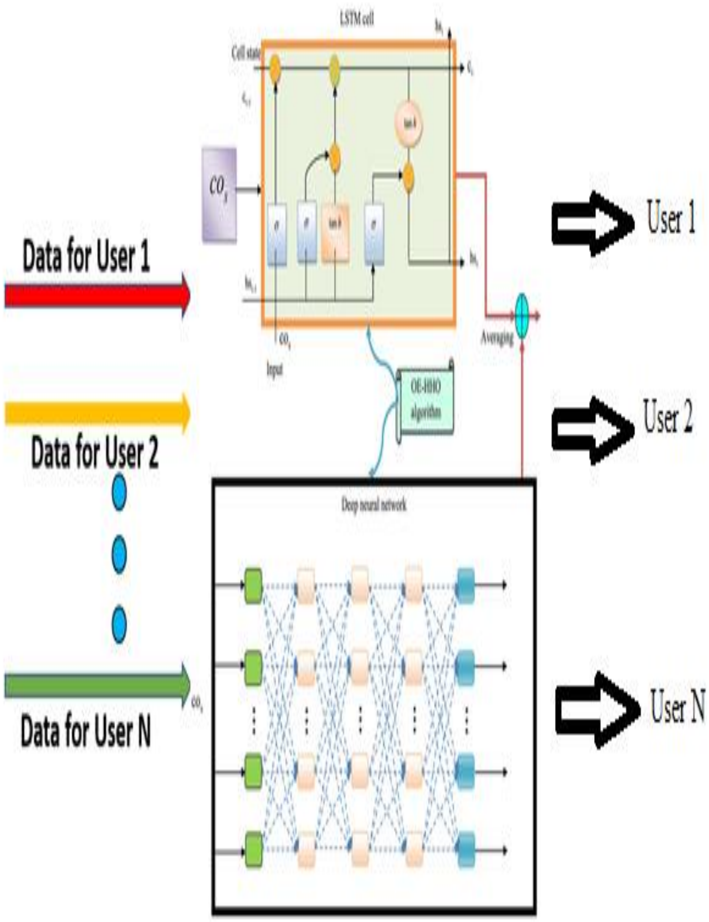


Figure 5.5: LSTM based analysis

Analysis using LSTM networks involves leveraging these specialized recurrent neural networks to process sequential data, as shown in figure 5.5.

LSTMs are considered to efficiently confine long-term dependencies within sequences, making them particularly useful for tasks such as time series prediction and speech recognition [95]. In an LSTM-based analysis, sequential data is fed into the network, which processes it step by step, maintaining an internal state that allows it to remember past information for an extended period [96]. This ability to retain memory over long sequences enables LSTMs to learn intricate patterns and relationships within the data.

In LSTM-based analysis, data is fed into the network sequentially, allowing it to process each element while retaining an internal memory state.

This memory mechanism enables LSTMs to learn and understand intricate patterns and relationships within the data over extended sequences.

The applications of LSTM-based analysis span across various fields. For instance, in time series prediction, LSTMs can forecast future values based on past observations, which finds applications in areas similar to stockpile marketplace calculation, climate prediction, and stipulate prediction [97].

Similarly, in speech recognition, LSTMs are utilized to process audio signals and convert them into text. By modeling the temporal dependencies inherent in speech data, LSTMs contribute to improving the accuracy and robustness of speech recognition systems. Additionally, LSTMs find application in anomaly detection tasks, where they learn the normal patterns within sequential data and identify deviations from these patterns [97].

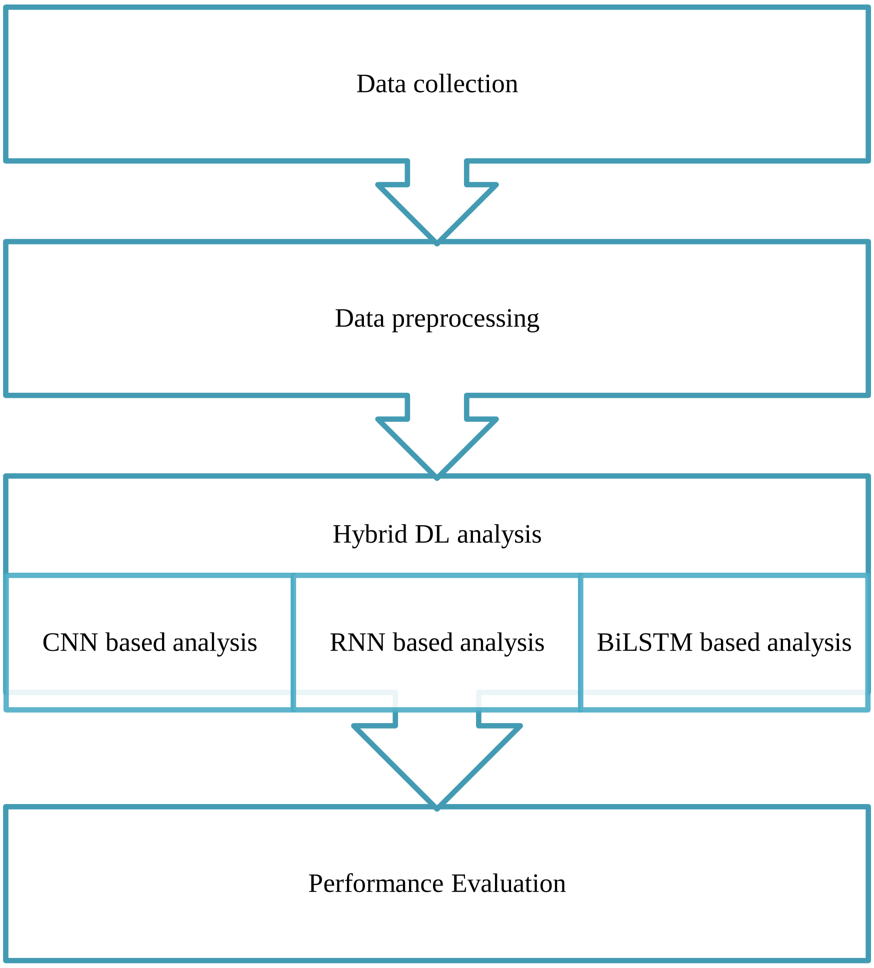


Figure 5.6: Stages in proposed system [97]

This capability is valuable in various domains, including detecting anomalies in network traffic, manufacturing processes, and financial transactions. Overall, leveraging LSTM-based analysis provides a powerful framework for modeling and analyzing sequential data, enabling the development of sophisticated solutions across diverse domains.

Evaluation of a Massive MIMO-Based 5G Communication Framework Using an Integrated Deep Learning Approach Incorporating CNN, RNN, and BiLSTM Layers [97].

The outlines of these stages are as shown in figure 5.6.

(i) **Data Collection**: Initially, data relevant to this 5G system is gathered. This data may include CSI, user feedback, network performance metrics, and environmental variables. Following collection, the data is preprocessed to ensure uniformity, normalization, and removal of noise or irrelevant features.

(ii) **Data Preprocessing**: Once the data is collected, it needs to be pre processed to prepare it for Data cleaning analysis.

(iii) **Hybrid DL analysis**: Hybrid deep learning (DL) analysis represents a cutting-edge approach that combines multiple DL techniques, such as CNNs, RNNs, and LSTM networks, to address the complexities of modern data analysis tasks. In the realm of telecommunications, particularly in the context of large-scale, 5^{th} generation networks, an amalgam. DL approach offers unprecedented capabilities for extracting insights from diverse data sources and optimizing network performance. By integrating CNNs for spatial feature extraction, RNNs for capturing temporal dependencies, and LSTM networks for handling long-term dependencies, analysts can effectively analyze complex spatial-temporal data generated by massive MIMO systems [98]. This enables tasks such as channel prediction, user behavior analysis, and resource allocation optimization to be performed with enhanced accuracy and efficiency. Through the synergy of different DL techniques, hybrid DL analysis empowers telecommunications researchers and practitioners to unlock new possibilities in understanding and optimizing the performance of 5G networks, ultimately paving the way for the advancement of communication technologies.

(iv) **CNN based analysis:** Analyzing massive MIMO 5G networks through a CNN-based approach involves key steps tailored to the intricacies of this advanced communication system. Initially, relevant data encompassing channel state information and user mobility patterns is collected and preprocessed to ensure consistency. The CNN model is then utilized to extract spatial features from channel matrices, effectively capturing spatial correlations among antennas. These features aid in optimizing beamforming strategies and mitigating interference, thereby enhancing spectral efficiency. Rigorous evaluation and validation of the trained CNN model are conducted to ensure accuracy and generalization capabilities, particularly in predicting channel states under diverse conditions. Upon successful validation, the CNN-based analysis framework is deployed for continuous tracking and enhancement of the massive MIMO 5G network, continuously adapting to dynamic changes and improving overall network efficiency [99].

(v) **RNN based Analysis**: Analyzing a massive MIMO system within the context of 5G using an RNN-based approach involves a series of critical steps customized to the complexities of this cutting-edge communication technology. Initially, pertinent data related to the massive MIMO system, including channel state information, user mobility patterns, and network performance metrics, is collected and prepared for analysis. The RNN model is then employed to capture temporal dependencies within the data, particularly focusing on sequential information such as user movements and channel variations over time. By leveraging the inherent ability of RNNs to retain memory of past inputs, the model effectively learns and predicts future states of the massive MIMO system, facilitating tasks such as optimizing resource allocation, predicting user behavior, and mitigating interference [100]. Following training, the RNN model undergoes rigorous evaluation to ensure its accuracy and robustness in handling diverse scenarios and datasets. Once validated, the RNN-based analysis framework is deployed in real-world environments for continuous monitoring and optimization of the massive MIMO system, enabling adaptive and efficient operation in dynamic 5G networks.

(vi) **BiLSTM based analysis**: Networks represent a specific type of system; LSTM networks hold significant promise for analyzing time-series data due to their ability to successfully confine and expect multi-part patterns in excess of unlimited periods. Leveraging LSTM architecture entails constructing, training, and evaluating models tailored to the unique characteristics of this 5G set-up data. This involves understanding the intricate spatial and temporal dynamics inherent in such networks and devising LSTM-based approaches that can efficiently process and interpret this information for tasks like channel prediction, resource allocation optimization, and interference mitigation. Through the utilization of LSTM linkages, analysts can gain deeper insights into the behavior and performance of 5G networks, ultimately contributing to the advancement of further adaptive, proficient, and trustworthy communication systems [101].

(vii) By following these steps, a CNN-based analysis approach facilitates comprehensive insights into the spatial characteristics and performance optimization of massive MIMO 5G networks, ultimately contributing to their enhanced functionality and scalability in modern telecommunications systems.

5.8 PAPR Reduction by using SCS-BiLSTMAE :

PAPR levels potentially inducing nonlinear deformation in authority amplifiers, thereby compromising in general system presentation. Hence, decreasing PAPR is essential to improve the model’s effectiveness.

Now define the rearranged signal as $\hat{p}$ and the squeezed-together symbol after the SCS-AE stage as q_L. Equation (4.1) signifies the PAPR computation procedure.

$$PAPR(\hat{p}) = 10 * \log_{10}\left(\frac{max(|\hat{p}|^2)}{E(|\hat{p}|^2)}\right) \tag{5.1}$$

In the subsequent SCS-AE compression step, the input signal is compressed using Sparse Coding-based Autoencoder (SCS-AE) to generate a sparse representation. This compression process aims to create a representation wherein fewer high-amplitude peaks are present in the signal, thereby contributing to a reduction in PAPR. Meager characterizations are distinguished by having a significant near-zero value, which effectively mitigates peak power. The sparse characterization of the sent image is innovated by Equation (4.2), encapsulating the mathematical transformation that generates the compressed representation while minimizing information loss and preserving signal quality.

$$q_L = \text{SCS-AE}(p) \tag{5.2}$$

BiLSTM represents a type of RNN planning utilized in this stage. This stage plays a crucial role in enhancing the overall performance of the system by enabling it to better understand and process complex temporal patterns in the signal sequence.

$$(h_t, c_t) = BiLSTM(p_t, h_{t-1}, c_{t-1}) \tag{5.3}$$

where, c signifying hidden state, c_t shows cell state signifies the BiLSTM operations. Equation below delineates the solution for a BiLSTM unit at the designated time step. This equation encapsulates the intricate computations and transformations performed within the BiLSTM unit to process sequential data efficiently while capturing long-range dependencies. By incorporating both forward and backward information flows, BiLSTM units excel in modeling complex temporal patterns and relationships in diverse datasets. Equation (5.3) serves as a fundamental building block in the architecture of recurrent neural networks, enabling robust learning and prediction tasks across a variety of domains like AI, NLP, and ML.

Following firmness and communicating through this stage, the system proceeds to reconstruct the signal. This rebuilding process is meticulously designed to preserve the original information while achieving a lower PAPR. Preserving information holds paramount importance in transmission systems, ensuring that the decoded signal remains realistic to the innovative result after decreasing PAPR. By maintaining the integrity of the signal throughout the compression and reconstruction stages, the system guarantees the reliability and accuracy of the transmitted data, ultimately enhancing the overall performance and efficiency of the communication network.

The output stage of the process is responsible for reconstructing the signal using the information obtained from the BiLSTM stage. This reconstruction process aims to generate an accurate representation of the original signal based on the insights and features extracted by the BiLSTM stage. The formula for the reconstructed image $\hat{p}$ is derived from equation (5.4), which incorporates the learned representations and parameters to recreate the signal with minimal loss of information. This reconstruction step is crucial in ensuring the fidelity and quality of the output signal, enabling downstream analysis and applications to effectively utilize the processed data.

$$\hat{p} = Decoder(h_t \,, c_t) \tag{5.4}$$

Subsequently, the PAPR reduction step involves calculating the reduction in PAPR achieved by the entire process. Equation (5.5) is formulated to represent the mathematical expression for calculating PAPR reduction, providing a quantitative measure of the effectiveness of the signal processing techniques employed.

$$PAPR\ REDUCTION = PAPR\ (\hat{p}))\text{-PAPR}(p) \tag{5.5}$$

Where , the $PAPR\left(\hat{p}\right)$ is PAPR of the reformed signal (the output signal after PAPR reduction), $PAPR(p)$is the Peak to Average Power Ratio of the original input signal.

$$\text{CCDF}=P_r[PAPR > PAPR_O] \tag{5.6}$$

5.9 Results and Discussion

- **PAPR verses CCDF analysis for different techniques**

Massive MIMO demonstrates the most effective PAPR reduction among the three modulation techniques considered in this graph. NOMA appears to have the highest PAPR, which could potentially lead to increased distortion in the power amplifier, as shown in Table 5.1.

Table 5.1: PAPR Vs CCDF for massive MIMO, FBMC, NOMA

Modulation Technique	PAPR Reduction Effectiveness
Massive MIMO	Highest PAPR reduction
FBMC	Moderate PAPR reduction
NOMA	Lowest PAPR

The CCDF curves provide valuable insights into the PAPR distribution of each modulation technique and can be used to assess their suitability for different applications, as shown in Figure 5.7 with Table 5.1.

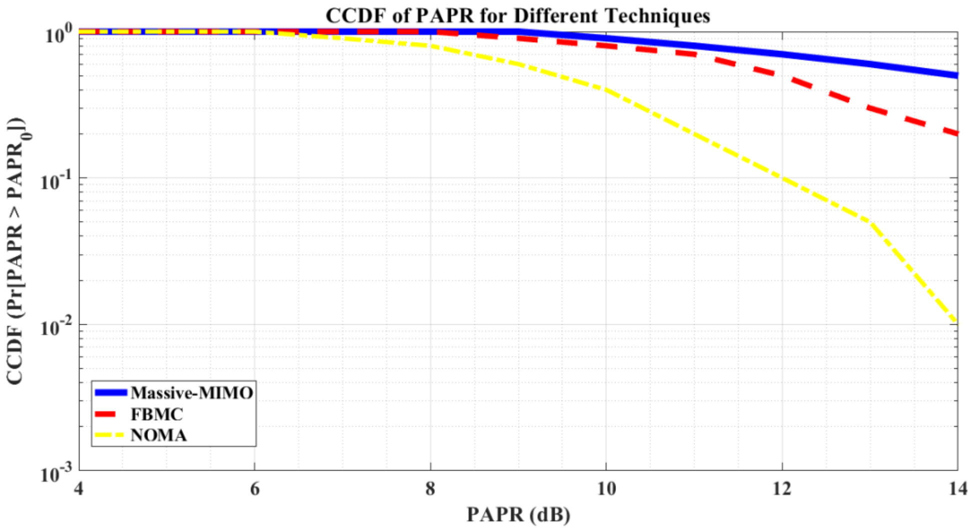


Figure 5.7: PAPR vs. CCDF analysis for massive MIMO, NOMA and FBMC

To gain a deeper understanding, it would be beneficial to investigate the specific characteristics of each modulation technique and how they contribute to the observed PAPR behavior.

➢ **Comparison of PAPR methods**

PAPR can lead to nonlinear distortions in the power amplifier, resulting in degraded signal quality and reduced transmission efficiency for different methods shown below in figure 5.8.

• **PTS (Partial Transmit Sequence):** This technique divides the symbol into multiple segments, which are then added together with different phase shifts to reduce the peak power.

• **PSO-PTS (Particle Swarm Optimization-based PTS):** This technique uses a meta-heuristic optimization algorithm to optimize the phase shifts in the PTS method, leading to improved PAPR reduction.

• **Scaled PSO-PTS:**

This is a variation of PSO-PTS where the amplitude of the segments is also optimized, and then PAPR will be reduced. As PAPR decreases, received power will be increased. As PAPR increases, received power will be decreased. From the graph, we can see that scaled PSO-PTS generally outperforms PSO-PTS and PTS in terms of PAPR reduction. This is because it has more degrees of freedom to optimize the signal. While these techniques can effectively reduce PAPR, they often come with increased computational complexity and potential overhead in terms of additional signaling. The graph demonstrates the effectiveness of different PAPR reduction techniques in mitigating the high PAPR problem in these systems.

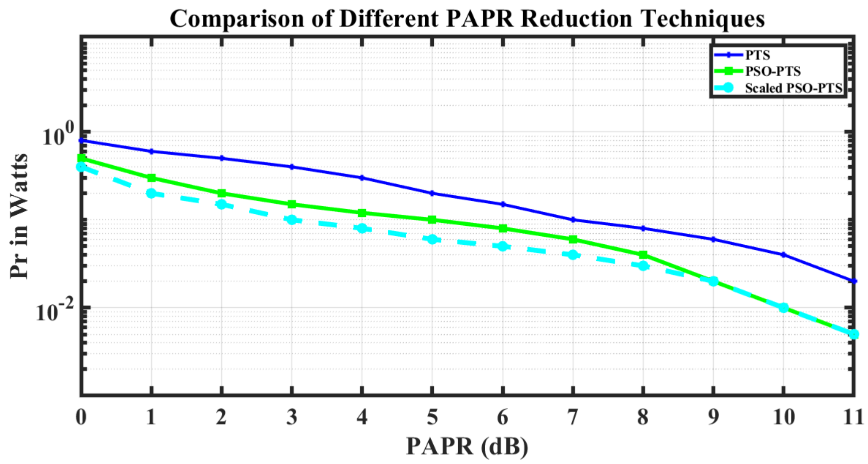


Figure 5.8: Comparison of PTS and PSO Methods

➢ A CCDF graph is a graphical representation of the probability that a random variable exceeds a certain threshold. Figure 5.9 compares the PAPR performance of the different techniques as shown in figure 5.9.

Without PAPR Reduction: This is the baseline, showing the original PAPR distribution of the signal.

With Partial Transmit Sequence (PTS): This technique reduces PAPR by dividing the signal into multiple segments and combining them with different phase shifts.

With Tone Reservation (TR): TR reserves some subcarriers for additional signal power, reducing the peak power.

As we move to the right on the x-axis (higher PAPR thresholds), the CCDF values decrease for all techniques. The techniques with PAPR reduction (PTS, TR) consistently outperform the "without PAPR reduction" case.

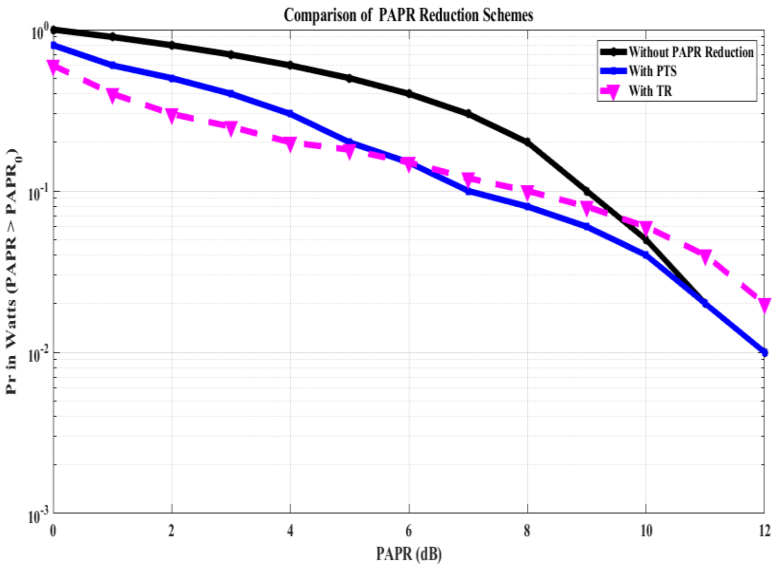


Figure 5.9: Comparison of PAPR reduction schemes

Among the reduction techniques, PTS seems to be the most effective, followed by TR. While PAPR reduction techniques can improve the signal quality, they may introduce additional complexity and overhead, as shown in figure 5.9.

- The figure 5.10 shows the CCDF of the PAPR for different PAPR reduction techniques in a Massive MIMO-OFDM system**.**

Table 5.2: CCDF versus PAPR for three different methods

Technique	**Approximate PAPR (dB) at CCDF=10^{-3}**
Original	~9.5 dB
SLM	~7.5 dB
PTS	~6.2 dB

Tone Reservation	~5.5 dB

The Original method has a high PAPR (~9.5 dB), which can stress power amplifiers**.** SLM reduces PAPR by around 2 dB, making it suitable for many practical systems. PTS offers better performance (~3.3 dB reduction), balancing complexity and gain. Tone Reservation is the most effective among the three, cutting PAPR by up to 4 dB, but at the cost of some spectral efficiency.

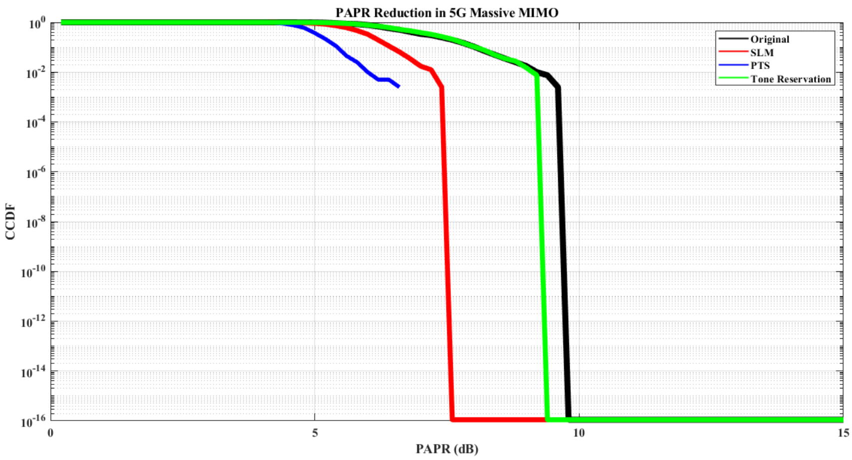


Figure 5.10: PAPR reduction in massive MIMO with SLM, PTS and TR different methods

The goal is to compare the effectiveness of SLM**,** PTS**,** and tone reservation methods against the original unprocessed OFDM signal as shown in figure 5.10 with table 5.2.

➢ Among these techniques, the proposed method consistently requires the least transmission power across all SNR thresholds. This indicates that the proposed method is more efficient in terms of power usage. It makes it the best choice for applications where power consumption is a critical factor, such as wireless communication systems. The graph shown in figure 5.11 illustrates the CCDF of PAPR for three different scenarios.

- **Original Performance:** This likely represents the PAPR distribution of the original transmitted signal without any PAPR reduction techniques applied.
- **Performance in ZF:** This curve shows the PAPR distribution after

applying ZF precoding.

- **Performance in MMSE:** This curve shows the PAPR distribution after applying Minimum Mean Square Error (MMSE) precoding.

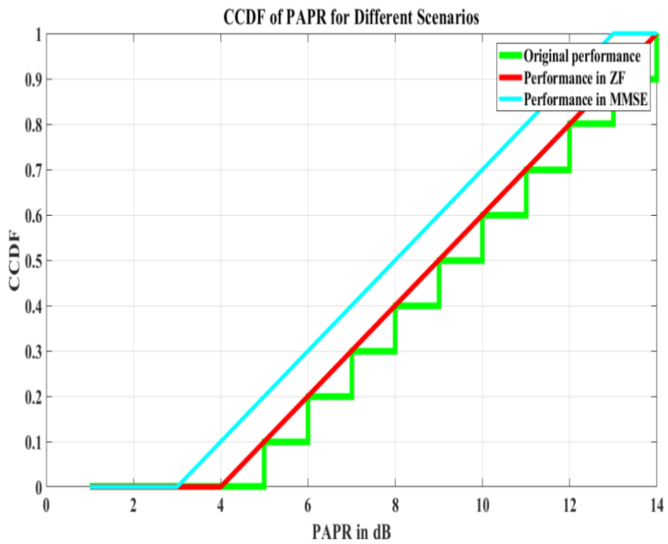


Figure 5.11: CCDF of PAPR in different precoding techniques

Both ZF and MMSE precoding techniques effectively reduce the PAPR compared to the original signal. This is evident from the shift of the curves to the left, indicating a lower probability of higher PAPR values. The MMSE precoding technique generally results in a lower PAPR compared to ZF. This is indicated by the MMSE curve being shifted further to the left compared to the ZF curve. This suggests that MMSE is more effective in reducing PAPR. The reduction in PAPR achieved by these techniques is likely to improve the performance of the power amplifier and reduce distortion in the transmitted signal.

- The shape of the curve suggests that the PAPR distribution is skewed towards lower values. ZF precoded Signal represents the PAPR distribution of a signal precoded using the ZF technique, as shown in table 5.3.

Table 5.3: PAPR reduction effectiveness

Scenario	**PAPR Reduction Effectiveness**
PAPR-Aware-Secure-massive MIMO	Highest PAPR reduction

ZF Precoded Signal plus Random AN	Intermediate PAPR reduction
ZF Precoded Signal	Moderate PAPR reduction

Graph 5.12 illustrates the CCDF of Peak-to-Average Power Ratio (PAPR) for three different scenarios. PAPR-Aware-Secure-massive MIMO likely represents the PAPR distribution of a signal precoded using a technique that aims to both reduce PAPR and enhance security in a massive MIMO system for figure 5.12.

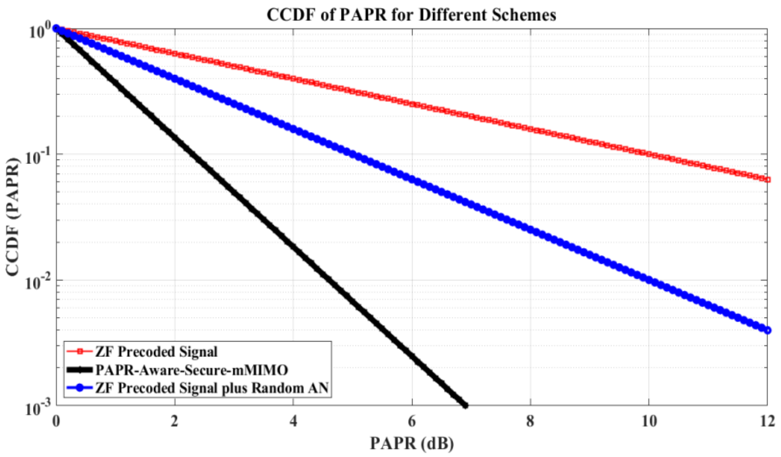


Figure 5.12: CCDF of PAPR for different schemes

At, the proposed method likely represents the PAPR distribution of a ZF-precoded signal with the addition of some form of artificial noise (AN) to further enhance security or reduce PAPR, as shown in the table. This technique demonstrates the most effective PAPR reduction among the three scenarios. Adding random artificial noise to the ZF precoded signal can slightly increase the PAPR.

The CCDF curves provide valuable insights into the PAPR distribution and can be used to assess the impact of different precoding and security techniques on system performance. To gain a deeper understanding, it would be beneficial to investigate the specific techniques employed in the "PAPR-Aware-Secure-mMIMO" approach.

➢ Table 5.4 illustrates the complementary CCDF of PAPR for four different scenarios: SLM shows the PAPR distribution after applying the Selective Mapping (SLM) technique. The interleaved curve likely represents the PAPR distribution after applying an interleaving technique. The PTS curve likely represents the PAPR distribution as in figure 5.13.

Table 5.4: PAPR reduction in SLM, PTS, interleaved methods with original

Technique	**PAPR Reduction Effectiveness**
Original	Baseline
SLM	Moderate PAPR reduction
Interleaved	Highest PAPR reduction
PTS	Least PAPR reduction

This is evident from the shift of the curves to the left, indicating a lower probability of higher PAPR values. Among the techniques, the interleaved method appears to have the most pronounced effect on PAPR reduction.

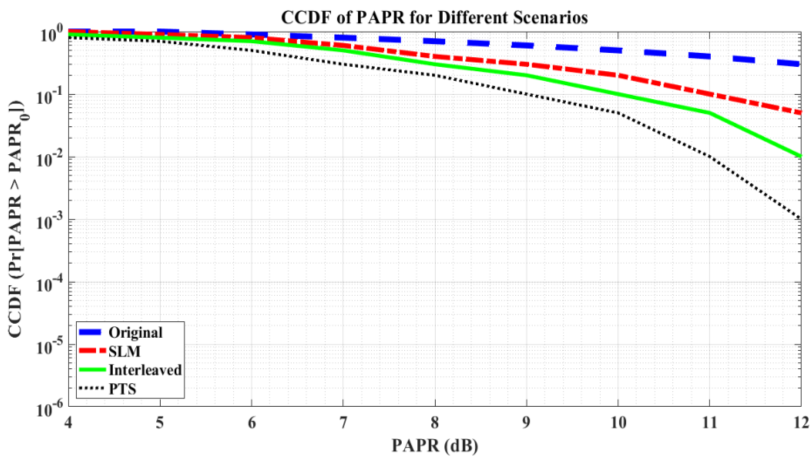


Figure 5.13: Comparisons of CCDF and PAPR for SLM, PTS, and interleaved methods.

This simulation incorporates a hybrid ZF precoding scheme, commonly used in massive MIMO systems, to evaluate its impact on PAPR. It calculates the PAPR for each transmit antenna individually as well as for the aggregated signal across all antennas, which is critical for assessing the demands on power amplifiers and ensuring linear system performance. By comparing the CCDF curves under different scenarios, such as without precoding, with hybrid ZF precoding for individual antenna signals, and for the combined output, the analysis provides a clear understanding of how precoding strategies influence PAPR behavior in massive MIMO transmissions, as shown in figure 5.13 of table 5.4. Its CCDF curve lies farthest to the left, indicating the lowest probability of high PAPR values.

➢ In a massive MIMO system with M=256 antennas with K=8 users, spatial diversity can be leveraged, potentially enabling PAPR reduction through advanced signal processing or precoding techniques.

Table 5.5: PAPR versus CCDF in massive MIMO

CCDF (Probability)	**Individual Antenna PAPR (dB)**	**Aggregated Signal PAPR (dB)**
100 (100%)	~5.5	~5.5
10−1 (10%)	~7.5	~7.5
10−2 (1%)	~9.5	~9.4
10−3 (0.1%)	~11	~10.8

The close alignment of both curves implies that signal aggregation introduces minimal PAPR degradation.

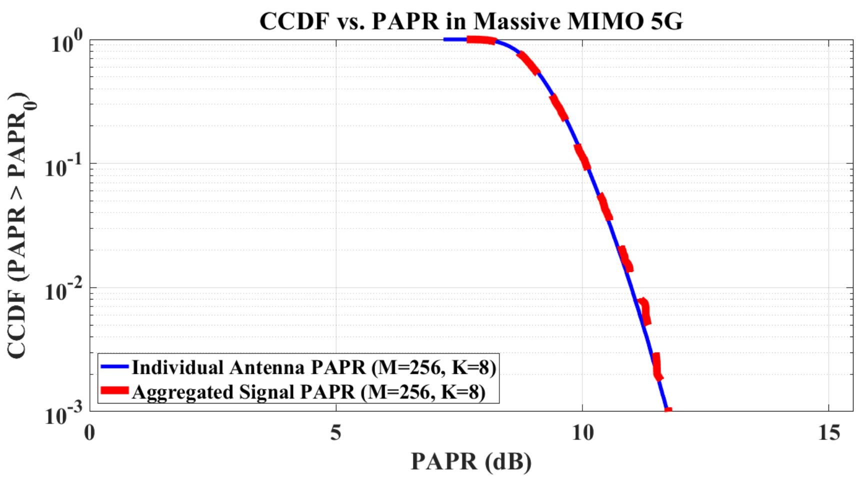


Figure 5.14: Comparisons of CCDF versus PAPR in massive MIMO

This is encouraging for practical implementations, where baseband signal combination is common, as in table 5.5 with figure 5.14.

Both curves exhibit similar behavior, indicating that signal aggregation across antennas (represented by the red line) does not significantly increase the PAPR compared to the individual antenna signals (represented by the blue line). The curves begin at higher probabilities and decline sharply beyond approximately 9 dB, suggesting that high PAPR occurrences are relatively rare.

Given the limitations associated with techniques like SLM, PSO, and PTS, the SCS-BiLSTMAE method emerges as a more effective solution. This model is designed to process signal sequences and is trained using a regression-based approach, specifically, the mean squared error loss function, to accurately capture the relationship between signal features and their corresponding PAPR values.

- In a massive MIMO system, each antenna transmits a modulated signal. The time-domain signal generated by applying IFFT to the modulated data often suffers from a high PAPR. This high PAPR leads to nonlinear distortion when signals pass through power amplifiers, resulting in spectral spreading and performance degradation, as in figure 5.15.

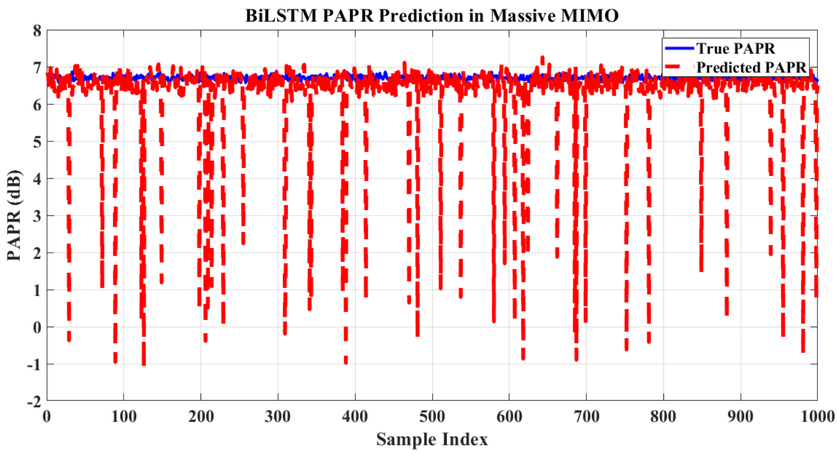


Figure 5.15: BiLSTM PAPR reduction in massive MIMO

To address this, a BiLSTM neural network is trained to predict the PAPR from the real and imaginary parts of the time-domain signals. The BiLSTM model learns temporal dependencies across the time-domain samples for each symbol. By mapping input sequences to scalar PAPR values, the model can assist in real-time PAPR prediction or even be extended for reduction strategies. During training, the average PAPR per symbol (across all antennas) is computed and used as the target output.

5.10 Conclusion:

- The CCDF plot provides a clear visual representation of the effectiveness of different PAPR reduction techniques. By analyzing the CCDF curves, we can assess the performance of each technique and make informed decisions about their suitability for specific applications.

- Higher CCDF values at lower PAPR levels indicate better PAPR reduction performance.

- PAPR-Aware-Secure-mMIMO likely represents the PAPR distribution of a signal precoded using a technique that aims to both reduce PAPR and enhance security in a massive MIMO system.

- Thus, the reduction of PAPR leads to the increase in the system efficiency with accurate performance in transmitting and receiving data at the base station.

- Overall, the plot 5.14 illustrates that the PAPR distribution in a massive MIMO 5G system (with 256 antennas and 8 users) remains well-regulated, even after signal aggregation. This is crucial for maintaining power amplifier efficiency and minimizing signal distortion in 5G communication systems.

- The BiLSTM processes these sequences and is trained using a regression loss (mean squared error) to learn the correlation between the signal characteristics and PAPR values.

Chapter 6

PERFORMANCE ANALYSIS OF THE PROPOSED TECHNIQUE TO EXISTING METHODS USING POTENTIAL PARAMETERS LIKE THROUGHPUT, ENERGY EFFICIENCY AND RESIDUAL ENERGY.

6.1 Introduction

Employing an Alternating Graph regularized Neural Network (AGNN) in conjunction with joint optimization strategies presents a compelling approach for addressing the complexities inherent in these systems [110]. In the circumstance of 5th generation communication networks, where maximizing spectral efficiency and minimizing interference are paramount, this hybrid methodology offers promising avenues for enhancing performance. The AGNN framework integrates the strengths of regularized neural networks, which excel in learning complex patterns and relationships within data, with the principles of joint optimization, which consider multiple system parameters simultaneously to achieve optimal solutions [111-112].

Through joint optimization, factors such as power allocation, beamforming, and user scheduling can be optimized concurrently, leading to improved energy efficiency, increased network capacity, and enhanced user experience. Integrating alternating regularized neural networks (AGNNs) with joint optimization techniques presents a novel approach for enhancing the performance of these systems. AGNNs offer a unique framework for learning complex relationships within the massive MIMO environment by alternating graphs between different regularization strategies like sparsity and preventing overfitting. By incorporating joint optimization principles, which consider multiple factors like QoS, system capacity, and energy efficiency simultaneously [113].

Through iterative optimization iterations, the AGNNs adaptively adjust their parameters to maximize system efficiency while meeting QoS requirements for multiple users. This innovative methodology facilitates the design of robust and efficient massive MIMO systems capable of handling diverse communication scenarios with improved spectral efficiency, reduced interference, and enhanced energy efficiency. By leveraging the complementary strengths of AGNNs and joint optimization, researchers can propel the development of further-invention wireless communiqué systems that meet the evolving demands of 5G and beyond [114].

6.2 Block Diagram:

In recent years, the conception of UDN has emerged as a gifting strategy for improving both EE and SE within confined geographical areas. On the other hand, deploying a huge number of APs presents challenges, primarily concerning the acquisition of accurate CSI, which leads to heightened signaling overhead and vulnerability to pilot contamination effects. To mitigate these challenges, we propose an innovative solution known as the AGNN for proposed adaptive beamforming in 5G millimeter wave massive MIMO multi cellular networks (AGNN-ABM-MIMO-MCN).

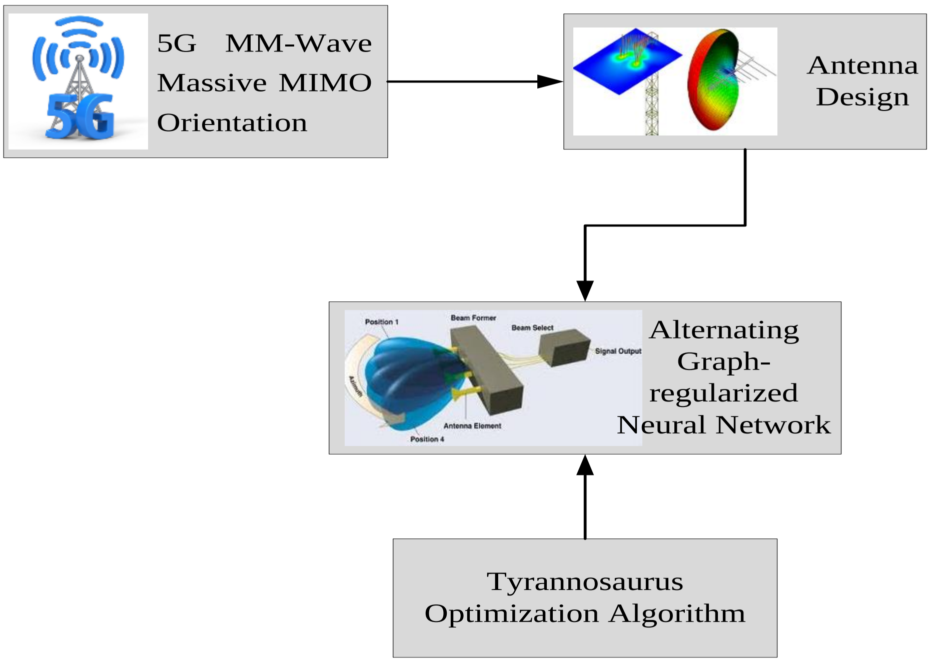


Figure 6.1: Proposed Block diagram of alternating graph regularized neural network [AGNN]

In this framework, each active base station leverages extensive multiple-input, multiple-output (MIMO) setups, enabling adaptive beamforming through the generation of higher directional beams as per demand to accommodate diverse traffic scenarios.

The beamforming strategy relies on AGNN, trained to determine optimal beamforming configurations. However, the AGNN classifier inherently lacks optimization techniques for identifying optimal parameters for beamforming configuration. To remedy this, the technique introduced the TOA to maximize the AGNN, ensuring precise generation of beamforming configurations. The proposed method is evaluated across various metrics, including EE, SE, blocking probability, NMSE, latency, and BER. As illustrated in figure 5.1, the proposed method encompasses four main procedures: 5G millimeter wave massive MIMO orientation, antenna design, beamforming configuration, and optimization. Each stage is elaborated upon in detail below [114].

5G millimeter wave massive MIMO orientation: This initial stage involves determining the orientation of the 5G MM-Wave massive MIMO system. It encompasses the selection of suitable locations for base stations and the arrangement of antenna arrays to maximize coverage and capacity within the network.

Antenna Design: The antenna design phase focuses on configuring the antenna arrays for optimal presentation in the 5G massive MIMO system. This includes selecting the number and arrangement of antennas, as well as optimizing antenna parameters such as beam width and directivity to enhance signal transmission and reception capabilities.

Beamforming Configuration: In this stage, beamforming configurations are determined to adaptively steer antenna beams towards desired users or areas of interest within the network. This involves generating directional beams to maximize signal strength and minimize interference, thereby optimizing the overall network performance.

Optimization: The final stage involves optimization techniques to refine the beam-forming configurations and further enhance system efficiency. This may include adjusting beamforming parameters based on feedback from the network environment, optimizing power allocation, and minimizing signal distortion and interference using TOA to improve the spectral efficiency, signal quality, and overall network performance [115].

6.3 Millimeter Wave Massive MIMO Orientation for 5G:

5G elevates the energy demands, leading to heightened energy consumption by users. This can be achieved through the utilization of a device known as an energy harvester. For the development of QoS provisioning for massive MIMO-based 5G networks is to increase energy. The study and simulation results have shed important light on how well these methods work to increase transmission rates, boost signal quality, and control interference. The comparative examination of MIMO with beamforming and classic MIMO and single-antenna systems demonstrated the supremacy of MIMO with precoding in conditions of capacity, signal quality, and interference management, according to the study's conclusions. These results highlighted the potential of massive MIMO, precoding, and beamforming to satisfy the growing need for fast and dependable communication services in 5G and other wireless networks in the future [115].

In this phase, the downlink of the multi-cellular 5G massive MIMO direction is investigated, focusing on communication with multiple base stations. The entire bandwidth D is allocated for transmission. Mobile stations (MSs) sequentially join the network based on predetermined geographic dispersion. Each MS requests a specific data rate from its serving base station (BS), which is achieved through the allocation of appropriate PRBs and into nation instructions for every PRB. The communicated signal is mathematically represented as equation (6.1).

$$Z_k(r) = \sum_{b \in U_k} \sqrt{D_{k,b}} r_{k,b} Z_{k,b} e^{i2\pi t h_b} \tag{6.1}$$

The transmitted signal is represented by an equation, ensuring efficient utilization of resources and effective communication between BSs and MSs in the multi-cellular 5G massive MIMO orientation. Consequently, when averaged over frame duration, the SNR for each PRB can be appropriately calculated.

This calculation is vital for assessing the superiority of the expected indicator and determining the effectiveness of the transmission scheme. The formulation of the SNR for each PRB is typically expressed in equation (6.2).

These physical resource blocks (PRBs) represent the specific time-frequency resources allocated by the base station to a UE for data transmission, determining the bandwidth and transmission opportunities available within the system.

The notation U_k denotes the physical resource blocks (PRBs) assigned to the k^{th} user or mobile station. U_k as the set of physical resource blocks (PRBs) assigned to a specific Mobile Station (MS). $N_r \times 1$ denotes the transmission vector, which encompasses the symbols to be transmitted by the MS. $D_{k,b}$ signifies the owed authority to the b^{th} PRB of the k^{th} MS. $z_{k,b}$ indicates the transmission symbol selected from a predefined constellation, conveying the information to be transmitted, h_b represents the symbol period, dictating the duration of each symbol as in equation (6.2). $r_{k,b}$ represents a routing variable or flow variable, indicating the proportion of flow or decision variable for using path b^{th} from source k.

$$SNR_{r,f} = \frac{Q_{r,f}}{KL_{r,\sec(r)}} \left| t_{r,f} S_{r,\sec(r),f} k_{r,f} \right|^2 \tag{6.2}$$

$S_{r,\sec(r),f}$ indicates the channel matrix of r^{th} MS concerning its allocation segment, $Q_{r,f}$ indicates expected signal, $t_{r,f}$ signifies maximal ratio combining multiplying vector [100]. This can be done by calculating downlink transmission powers per PRB in equation (6.3).

Where $t_{r,f}$ could be a transmission coefficient**,** transfer function**,** or time duration associated with the r-th signal and *f*-th frequency. L $_{r,\sec(r)}$ in this L could be related to a modulation scheme's parameters, and sec(i) might indicate a specific secant type being applied to the *i*-th signal.

Equation (6.3) facilitates the calculation of downlink transmission powers allocated per PRB. This computation is essential for optimizing resource allocation strategies, ensuring efficient spectrum within the network. By dynamically adjusting the transmission powers per PRB based on channel conditions and system constraints, the network can mitigate interference, enhance signal quality, and improve overall system performance, thereby delivering a reliable and high-quality communication experience to users.

$$Q_f = B_f^{-1} * C_f \tag{6.3}$$

Here, Q_f represents the $M_f \times 1$ downlink communication vector of the M_f that assigned with f^{th} PRB. The matrix is given in equation (6.4)

$$G_f(t,1) = SNR_{t,f} k_{t,f}^{H} L_o \tag{6.4}$$

Here, $SNR_{t,f}$ states the lowest amount SINR entrance for the maintenance of the measured communication rate above the s^{th} PRB of the t^{th} mobile station, L_o represents the downlink transmission, H represents the linear system. Then the advanced boundary of the Shannon method is determined in equation (6.5)

$$k_{t,f} = \frac{Q}{M_{PRB}} \log_2(1 + SNR_{r,f}) \tag{6.5}$$

Where, $k_{t,f}$ indicates the most advantageous communication, M_{PRB} states the PRBs per BS, equal super natural allocation, Q denotes polarized emission, $SNR_{t,f}$ states the lowest amount SNR threshold for help of measured conduction time over s^{th} PRB of t^{th} MS. The primary objective is to maximize both EE and SE, with additional consideration given to optimizing other metrics such as the Jain's fairness index, the number of glowing fundamentals comprising explicit base stations (BSs), and the minimization of jamming possibility. Influence thresholds associated with these metrics provide greater constraints for all premeditated authority levels. On the other hand, in practical wireless scenarios, the approach of MSs measuring the systematic trait of all snooping MSs' acknowledged waveforms poses challenges. To address this, machine learning techniques offer valuable assistance in most advantageous communication power distribution, particularly in the context of 5G UDN [116].

Every BS is equipped with three massive MIMO configurations, strategically spaced apart by degrees to guarantee comprehensive spatial exposure. Additionally, to evaluate the efficacy of the recommended adaptive beamforming procedure in real-world MU orientations, two layers of cells neighboring the central part cell are taken into account, enhancing the practical applicability and robustness of the proposed approach. Therefore, the set $BC_{b,l}$ shall signify a set of communicating antennas for l^{th} configuration of b^{th} BS throughout the remainder of this work [117].

6.4 Adaptive beamforming using AGNN:

In this phase, we delve into the discussion of AGNN, which serves the purpose of generating the appropriate beamforming configuration. AGNN operates by addressing a semi-supervised classification problem using a deposit of moderately labeled samples, along with their matching position accuracy surrounding substance. This process entails harnessing outcomes derived from multiple hops of locality relations to determine the model's last prediction. Furthermore, AGNN employs a fragile classifier to generate graph representations with dimensions akin to those of the input data, thereby aiding in effective beamforming configuration determination within multi-cellular 5G massive MIMO networks. As described in Equation (5.6), this calculation integrates the graph representations generated by the weak classifier, enabling the model to leverage spatial and temporal information to make informed decisions regarding beamforming configurations. This approach enhances the network's adaptability and performance, contributing to improved communication efficiency and reliability in 5G environments. Softmax is applied to normalize the outputs into a probability distribution.

$$a(M^{(f)}) = \mathrm{Softmax}(\sigma(M^{(f)}P_a + c)) \tag{6.6}$$

Where, P_a denotes the probability distribution dimension or projection matrix, c indicates the ray forming, a signifies the overexcited constraint, $M^{(f)}$ states the spherical divergence, c signifies the aerial and σ represents the activation function. The consequent sets representing the physical resource blocks accessible for communication for each BS are determined. Each base station produces and categorizes their canal growth vector medium. The PRBs billed to mobile stations (MSs) are stored in the transmission vector matrix, which also regulates the power allocation for each MS [118]. The system of MIMO is represented by an equation, encapsulating the allocation and regulation processes involved in optimizing data transmission within the multi-cellular 5G massive MIMO network in equation (6.7).

$$D=\sum_{f=1}^{r}(\alpha^{(f)}\, b\left(M^{(f)}\right) + \beta^{(f)} b(X^{(f)})) \tag{6.7}$$

Here, $\alpha^{(f)}$ denotes burden of classifier with reverence to $M^{(f)}$, $\beta^{(f)}$ signifies heaviness of classifier with reverence to $Z^{(f)}$, c defines aerial, and D signifies the marked nodes. In scenarios where there is no energy intermission at the base station or mobile station point, a fresh MS is introduced to the network, prompting the update of all associated sets. Subsequently, the classifier weights are computed, as outlined in Equation (6.8). This process ensures that the network remains dynamic and adaptable to changes, such as the addition of new MSs, while maintaining the integrity and accuracy of the classification system. The computation of classifier weights is a crucial step in optimizing the performance of the network and ensuring efficient and effective communication between BSs and MSs.

$$\alpha^{(f)} = \frac{1}{2}\log\frac{1-e_M^f}{e_M^f} + \log(T-1) \tag{6.8}$$

Where, T defines the number of classes, $\alpha^{(f)}$ denotes weight of classifier, M shows the circular polarization [96]. By the side of this juncture, it's crucial to highlight that the prospective base stations (BSs) store every set in mounting order. The intention here is to ascertain the lowest number of resource elements required to ensure agreeable QoS for every mobile station. Every appropriate constraint is reorganizing to its preliminary setting, and a prospective mobile station is disinterested in the association if none of the base stations are capable of accomplishing this objective. Subsequently, the regularization of all classifier weights is defined in (6.9), ensuring consistency and accuracy in the classification process within the multi-cellular 5G massive MIMO network.

$$\eta_i = exp\left(\log\left(\frac{k_{i,t}}{\max\,(\sum_{i=1,j\neq t}^{T} \epsilon, k_{i,j,}}\right)\right) \tag{6.9}$$

Here, $k_{i,t}$ shows the possibility of i^{th} sample belonging to t^{th} class, $\in$ indicates tiny value avoiding divide by zero error. Here, η_i signifies efficiency of i^{th} sample accepting to t^{th} in the base station.

This clarifies that selecting the right beamforming codebook can be an algebraically challenging procedure since dissimilar statistic values might be conducted on the direction and throughput command of mobile stations.

The choice of beamforming codebook is crucial in optimizing the performance of wireless communication systems, as it directly impacts signal transmission, reception, and overall network efficiency [116]. This encoding strategy aims to eliminate redundancy by avoiding duplicate spatial distributions among the entries. The decisive factor in this selection process is the minimization of overall downlink transmission power. To achieve this, a beamforming configuration derived from the AGNN technique is commonly employed. This configuration, encapsulated by equation (6.10), embodies the optimal beamforming strategy identified through the neural network's classification process.

$$S = -\sum_{i\epsilon\Omega}\sum_{j=1}^{a} Z_{i,j} \ln L_{i,j} \tag{6.10}$$

Here, S indicates the failure occupation, Ω states the nodes in the instruction set, a signifies the subjective node, $Z_{i,j}$ denotes the high-order area embeddings, and $L_{i,j}$ indicates the directly combined node [117]. These variables play essential roles in various machine learning and network analysis tasks, contributing to the understanding and optimization of complex systems. The relationship between the seemed throughput within the pointed liberty of a base station and the resultant beamforming configuration is pivotal in optimizing wireless communication systems. In recent studies, the AGNN approximation has emerged as particularly effective in uncovering insights in this domain. AGNN's prowess lies in its ability to accurately capture the intricate connections between throughput demand distributions and the optimal selection of BSs, thereby facilitating exhaustive searches for the most suitable BC once the training phase concludes. Through AGNN, the identification of the optimal BS for a given throughput demands distribution becomes feasible, thanks to its reliance on advanced AI-driven optimization techniques.

In a recent investigation, the integration of the TOA further elevates AGNN's capabilities [107-117]. This synergistic approach, coupling AGNN with TOA, showcases a promising avenue for achieving practical and efficient optimization in wireless communication systems, ultimately advancing the frontier of 5G network optimization.

6.5 Step-by-Step Procedure for TOA

The TOA, which serves as a cornerstone for generating the beamforming configuration. Inspired by the predatory behavior of the Tyrannosaurus receiver, this approach mirrors the predator-prey poaching dynamics observed in apex predators. The TOA collaborates to optimize the beamforming process. The TOA's stepwise procedure is divided into distinct phases, as illustrated in figure 6.2 accompanying flowchart. By leveraging this innovative methodology, the TOA algorithm significantly enhances the efficiency and efficacy of beamforming configuration within the multi-cellular 5G massive MIMO network.

Step 1: Initialization

(TOA) initializes a set of prey individuals within the search space through a population-based approach, where these individuals are randomly generated. This initialization process is precisely defined by equation (6.11) to ensure a systematic and unbiased start to the algorithm's execution.

$$Z_i = rand(mv, dim) * (ud - kd) + kd \tag{6.11}$$

In the equation, Z_i, signifies the location of the ith prey the total number of dimensions, m represents the dimension; mv indicates the upper limit in the population; ud indicates upper limits; and kd represents the lower limit in the search space.

Step 2: Random Generation

Following the initialization phase, the TOA method facilitates the random generation of beamforming configurations to optimize communication system performance.

Step 3: Robustness Function

The results stem from operated judgments and accidental responses. The personal property of heaviness constraint optimization is incorporated into the fitness function assessment. By integrating weight parameter optimization into the fitness function, the evaluation accounts for the impact of varying weights on the overall performance metrics. This approach ensures a comprehensive assessment that considers not only the initial conditions but also the optimization process, providing insights into the effectiveness of weight parameter adjustments in improving system performance. It is calculated using equation (6.12)

$$fitness\ function = Otimizing\left[\alpha^{(f)} . \eta_i\right] \tag{6.12}$$

Here, $\alpha^{(f)}$ represents the weight of classifier, η_i represents the importance of the i^{th} sample. In this formulation, $\alpha^{(f)}$ denotes the weight assigned to the classifier, while η_i indicates the significance attributed to each sample.

Step 4: Exploration Phase

Initially, the value emerges over a period of time. When this algorithm detects its nearest prey, it initiates a hunt. Sometimes, the prey might defend itself against predators or try to escape. Juveniles participate in the chase and capture of prey, a dynamic described in equation (6.13).

$$Z_{new} = \begin{cases} z_{new} & if\ rand(1) < Ft \\ Random & else \end{cases} \tag{6.13}$$

In this context, Z_{new} symbolizes the successful capture of prey, Ft denotes the control challenges encountered, and $rand$ represents the random exploration factor. Equation (6.14) outlines the process of updating the location based on these variables.

$$z_{new} = z + rand(1) * uv * (rpos * rs - target * kl) \tag{6.14}$$

In this scenario, uv signifies the achievement speed of searching, constrained within the range of [0.1,1], kl denotes the lowest amount position, rs denotes the scattered prey, and $rpos$ signifies the searching position.

Step 5: Development Phase

The development phase marks the culmination, aiming to pinpoint the optimal choices within promising regions. Equation (5.15) delineates the TOA's strategy during this exploitation phase.

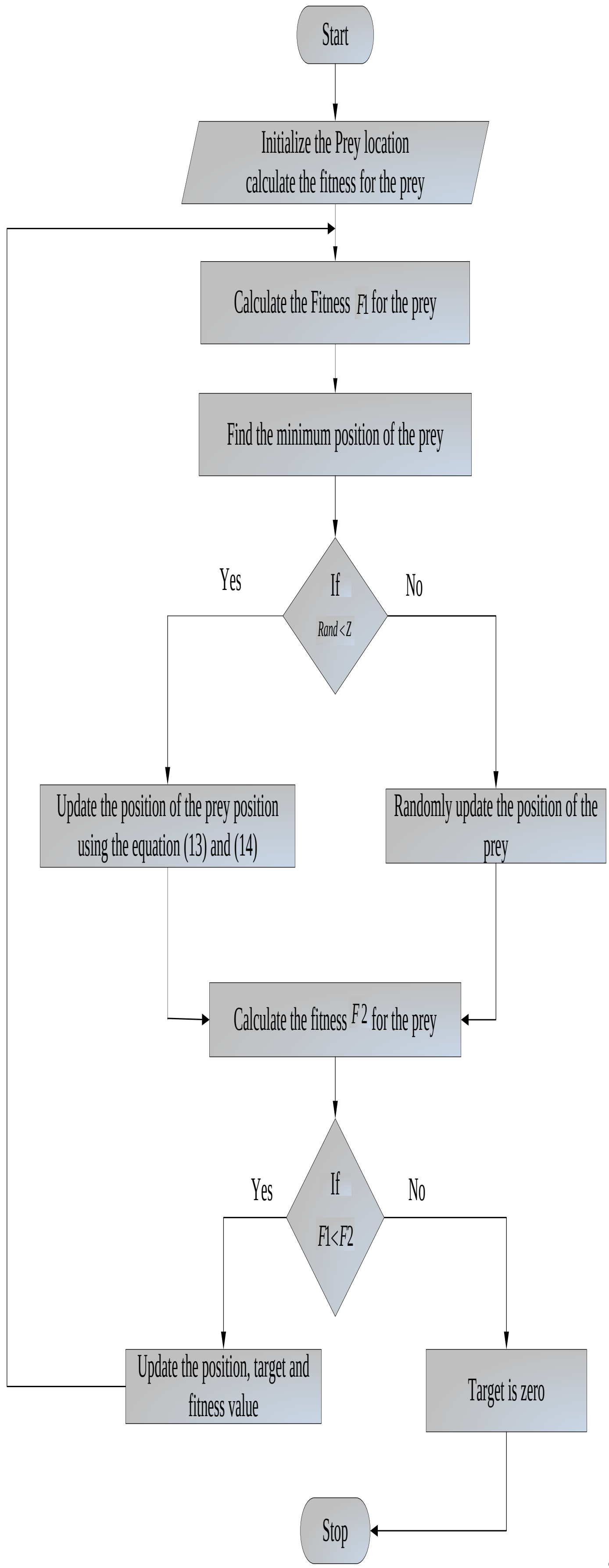
$$Z_i^{t+1} = \begin{cases} update\ the\ target\ position\ if & f(Z) < f(Z_{new}) \\ target\ is\ zero & otherwise \end{cases} \tag{6.15}$$

In this, $f(Z)$ denotes the strength function evaluated for the initial location, while fupdated $f(Z_{new})$ denotes the strength occupation computed for the reorganized position.

Step 6: Execution Phase

The heaviness constraint of the producer within the AGNN is optimized through the TOA, iterating through step 3 until it satisfies the specified halting criteria $Z_i = Z_i + 1$. Consequently, this algorithm efficiently generates beamforming configurations with heightened accuracy and reduced computational time.

Figure 6.2: Flowch



art for TOA [118]

6.6 Performance Enhancement using EIBO Algorithm:

Furthermore, in order to boost the implementation of the SSAE model, a constraint optimization procedure is conducted using the EIBO algorithm. This approach aims to fine-tune the parameters of the SSAE model systematically, leveraging the capabilities of the EIBO algorithm to explore and adjust external configuration settings iteratively. By optimizing parameters through the EIBO algorithm, the execution efficiency of the SSAE model is enhanced, ultimately leading to improved performance and efficacy in various tasks and applications. Equation (6.16) formulates the EIBO formula for performance enhancement.

$$P_c(t+1) = a_1\big(P_C(t) - P_c(t)\big) + a_2\big(P_{best}(t) - P_c(t)\big) + a_3\big(P_B(t) - P_c(t)\big) \quad (6.16)$$

To enhance the SSAE model's performance, a parameter optimization process was implemented using the EIBO algorithm. This algorithm is particularly effective in fine-tuning hyperparameters, which are external configuration settings that significantly impact the model's behavior. By iteratively exploring and adjusting these hyperparameters, EIBO helps optimize the SSAE system's overall effectiveness [109]. By employing the EIBO algorithm for strategic optimization, we aimed to improve key execution metrics like correctness and productivity. EIBO's ability to handle complex tasks effectively allowed us to fine-tune the SSAE model to meet specific requirements. This optimization resulted in a significantly enhanced model performance, as outlined in Equation (6.16).

Where $P_c(t)$ is the current solution (individual) in the population at iteration t, $P_C(t)$ is the influential individual selected based on its fitness or other criteria, $P_{best}(t)$ is the best individual in the population at iteration t, $P_B(t)$ is the buddy individual selected based on interactions or other criteria, a_1, a_2 and a_3 are randomization factors.

Figure 6.3 illustrates the EIBO algorithm flowchart. The process begins with the initialization of massive MIMO parameters, including the number of antennas and SNR. A random population of precoding matrices is then generated for user signal beamforming.

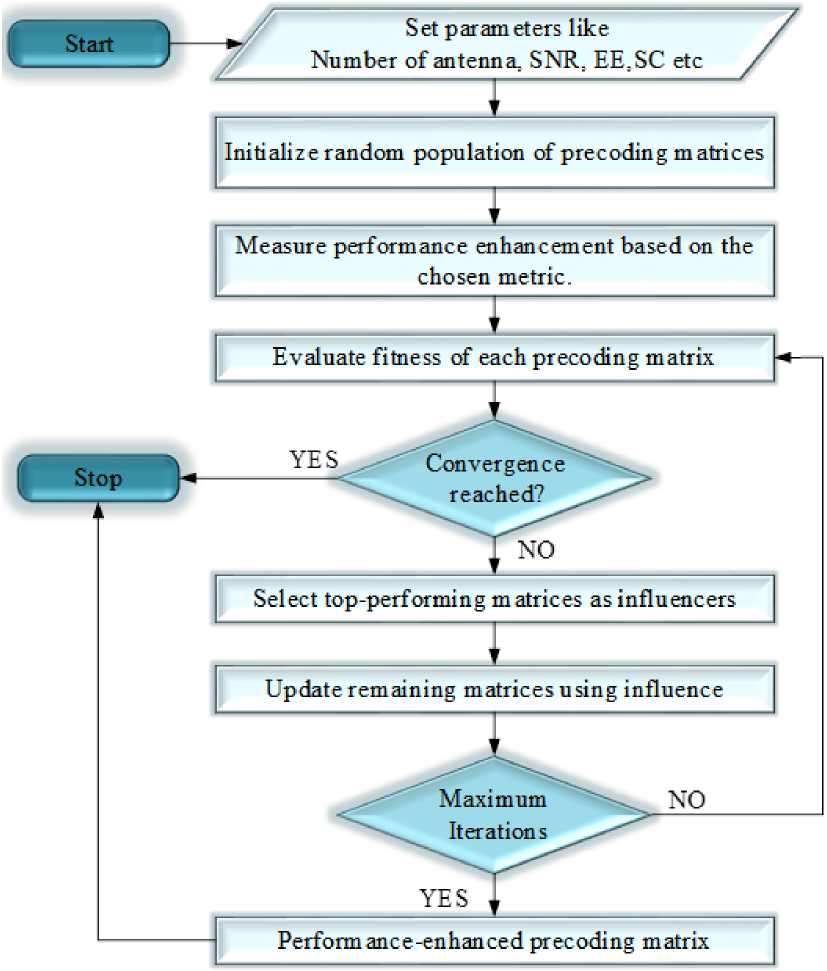


Figure 6.3: Flowchart for EIBO [119]

In the main loop, the fitness of each matrix is evaluated, and the top performers are selected as influencers for the next generation. This iterative process continues until convergence, resulting in an optimized precoding matrix that significantly improves massive MIMO performance.

6.7 Performance Metrics

The assessment includes an evaluation of key performance metrics, such as BER, throughput, energy efficiency, system capacity, and residual energy as explained in section 1.9.

The analysis is performed under Rayleigh fading channels, with varying SNR ranging from 10 dB to 50 dB. These conditions reflect typical scenarios in massive MIMO systems, where the signal experiences multipath fading, which is common in wireless communication environments.

6.8 Results and Discussions:

The new outcomes of the future technique are deliberated, with the technique simulated using Python and assessed across various performance metrics. The results obtained from the AGNN-ABM-MIMO-MCN technique are compared against existing methodologies such as MLAB-MMWM-MIMO [111], DL-ERN-MCN [112], and DLF-BSPC-MIMO [113]. The number of users served per cell in a massive MIMO system depends on the system's spatial multiplexing capabilities. Typically, each cell can support between 10 and 40 users simultaneously. In a multi-cell scenario, a standard assumption is that each cell is surrounded by six neighboring cells, forming a hexagonal layout. As a result, simulation models often consider a total of seven cells in that one central cell and seven adjacent cells, as shown in table 6.1. For more comprehensive performance evaluations, larger configurations such as 19-cell clusters are used. Inter-cell interference becomes a significant factor in such environments, particularly when a frequency reuse factor of 1 is employed. Its ability to concurrently serve multiple users within a single cell is a key advantage, often supporting tens of simultaneous users in sub-6 GHz deployments, with common figures ranging from 8 to 32 users. In the context of massive MIMO, "channel gains" precisely describe how the power of a transmitted signal is altered (either amplified or attenuated) as it propagates through the wireless medium from the transmitter to the receiver.

Table 6.1: Replication Parameter

Parameter	**Value**
Tiers of cells around the middle cell	7
Cell radius	500m
Total bandwidth	100MHz
Subcarrier spacing	60KHz
Carrier frequency	28GHz
Antenna essentials per MS	2
Beam forming configuration (M_{BC})	51
Necessary $E_b / N_o\,(dB)$ for QPSK modulation	9.6
Traffic scenario	50% of mobile stations by QPSK modulation per Block

Figures below illustrate the replication results of the AGNN-ABM-MIMO-MCN method, with the performance of the projected AGNN-ABM-MIMO-MCN method assessed in comparison to existing methods such as MLAB-MMWM-MIMO, DL-ERN-MCN, and DLF-BSPC-MIMO [110]-[119].

- **Spectral Efficiency**

The spectral efficiency of a cellular network, denoting the maximum data communicated to a particular figure of users for each moment whilst preserving a satisfactory level of service, is expressed mathematically by equation (6.20) in section 1.8.

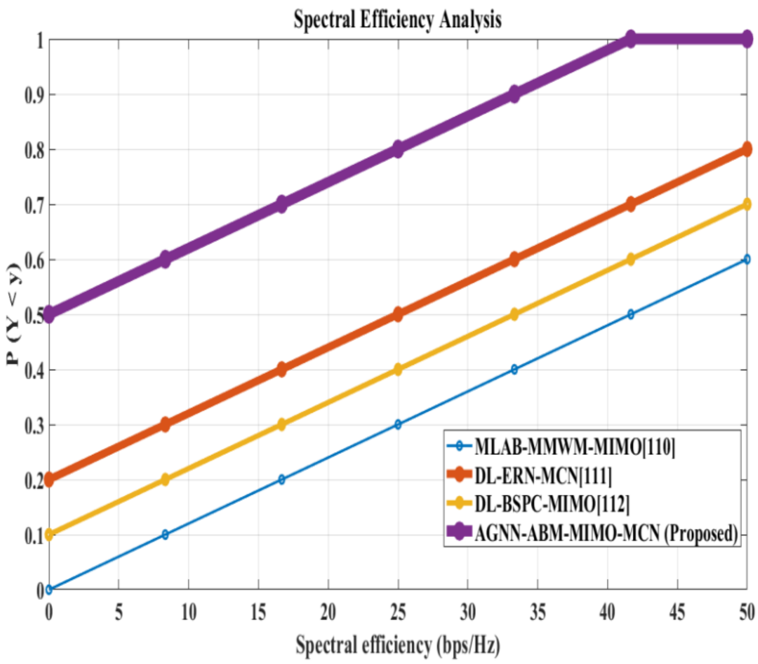


Figure 6.4: Spectral Efficiency Analysis

The figure shows these results highlight the effectiveness of the AGNN-ABM-MIMO-MCN approach in enhancing spectral efficiency within the multi-cellular 5G massive MIMO network, paving the way for improved data throughput and network performance. These findings highlight the superior performance of the AGNN-ABM-MIMO-MCN approach in optimizing spectral efficiency within the multi-cellular 5G massive MIMO network, underscoring its effectiveness in maximizing data throughput and network capacity.

- **Energy Efficiency Analysis**

The concept of achieving the same task with reduced energy consumption, thereby lowering energy costs and minimizing pollutants, is encapsulated by the equation in section 1.8.

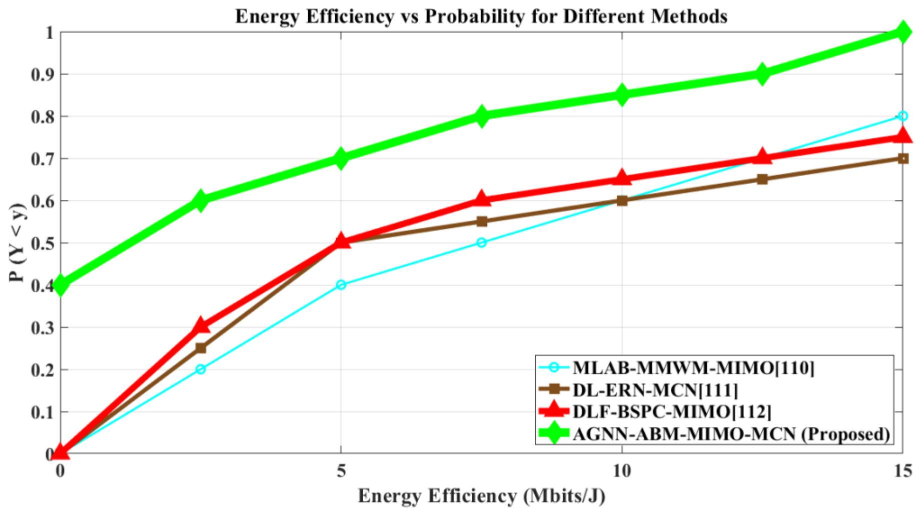


Figure 6.5: Energy Efficiency Analysis

• These results shown above underscore the efficacy of the AGNN-ABM-MIMO-MCN approach in enhancing energy efficiency within the multi-cellular 5G massive MIMO network, contributing to more sustainable and environmentally friendly communication systems.

➢ **BER analysis**

This evaluation reflects the system's ability to transmit data with minimal errors, despite potential challenges like interference and channel fading, with the equation defined in section 1.8.

These findings in the above figure underscore the superior performance of the AGNN-ABM-MIMO-MCN approach in reducing bit errors and enhancing the overall reliability of data transmission within the multi-cellular 5G massive MIMO network, as shown in figures 6.6 and 6.7.

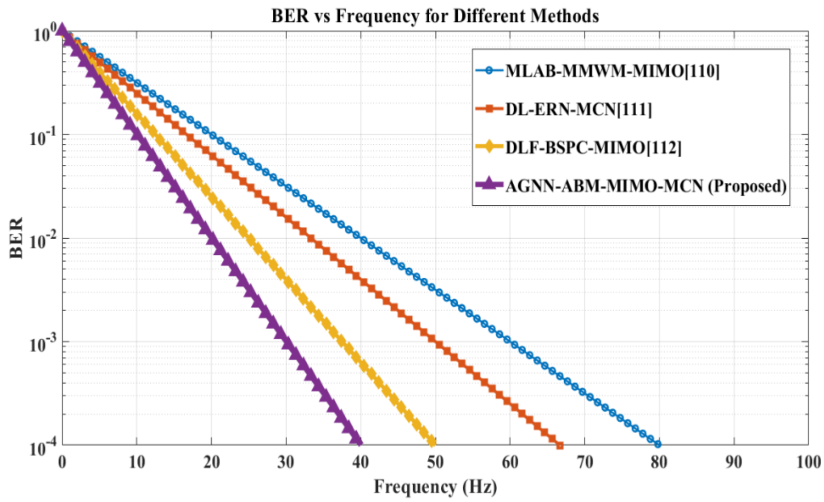


Figure 6.6: BER analysis with frequency

- **Figure 6.7** indicates the BER analysis. The proposed approach achieves a lower BER than the existing methods with SNR Bi-LSTMAE has BER is decreasing with high SNR values.

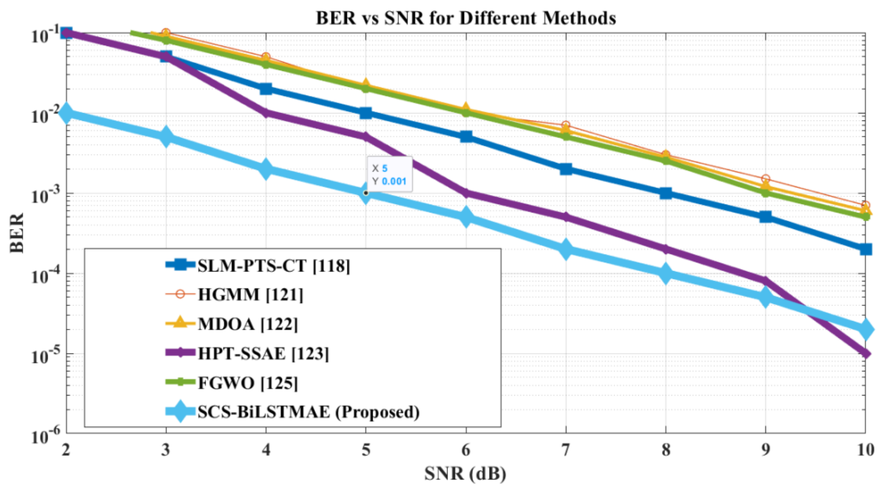


Figure 6.7: Bit Rate Error analysis with respect to SNR

- Throughput analysis was compared to established methods, including Hybrid EH, DL-QL, and ICIBS, as shown in Table 6.2 for Figure 6.8. The result shows that the proposed approach extensively outperforms these existing methods in terms of throughput.

Table 6.2: Throughput analysis for different methods

No. of Antennas	Hybrid EH (bps/Hz)	DL-QL (bps/Hz)	ICIBS (bps/Hz)	SCS-BiLSTM-AE (bps/Hz)

0	0	0	0	0
50	15	20	10	25
100	25	35	20	40
150	30	45	25	50
200	35	50	30	60
250	38	55	35	65
300	40	58	40	70
350	42	60	45	75
400	44	62	48	80
450	45	64	49	86
500	46	65	50	90

As shown in figure 6.8 below, throughput will be maximized when the number of antennas is increased for different methods. The proposed method is best for maximizing throughput in these networks. The number of antennas used in the simulations ranges from 100 to 500 antennas, which is consistent with standard MIMO configurations and ensures a fair comparison with the existing methods.

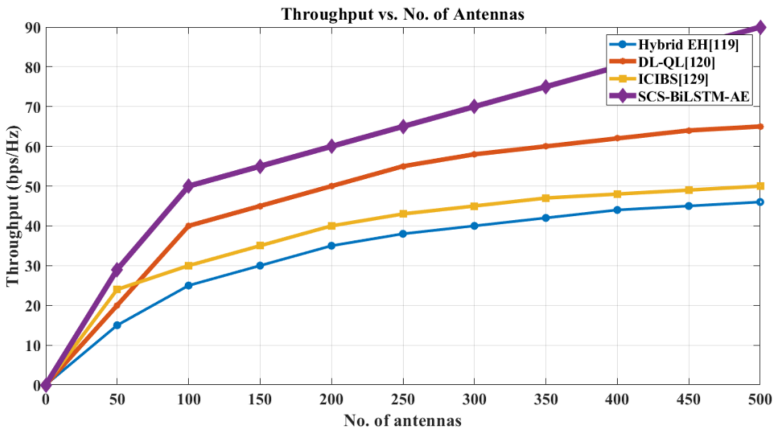


Figure 6.8: Throughput analysis for number of antennas

- **Residual Energy**

Residual energy (RE) in this system refers to the unused energy remaining after a specific process or transmission. The figure below illustrates an analysis of residual energy. Table 6.4 shows the residual energy for different methods.

Table 6.3: Residual energy for different methods

Method	Residual Energy (%)
MDOA [122]	35
LCA [124]	40
FGWO [125]	42
SCS-BILSTMAE (Proposed)	60

Residual energy analysis for various methods was described in figure 6.9, which shown in table 6.3. The proposed method used for more residual energy percentage.

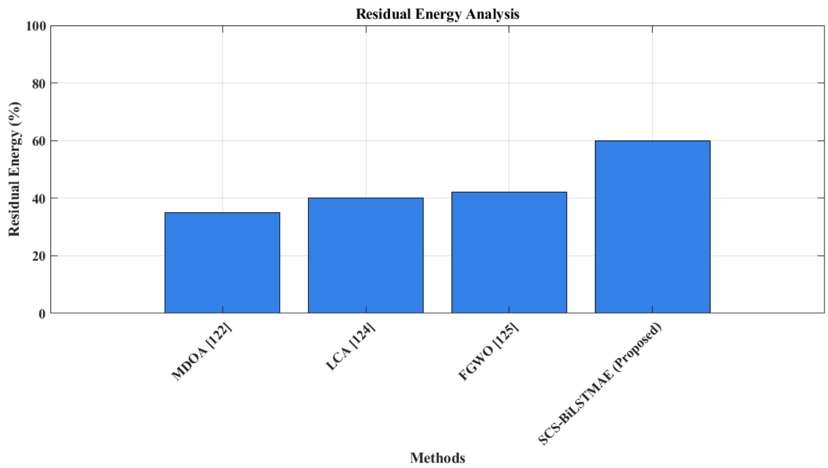


Figure 6.9: Residual Energy analysis for various methods

- Higher throughput often involves advanced modulation and coding techniques that are more energy-efficient. Efficient power allocation strategies can ensure that energy is used judiciously for data transmission [120].

Table 6.4: SNR versus SER for different neural network methods

SNR (dB)	SER for Conventional Hybrid Precoding	SER for CNN-Based Hybrid Precoding	SER for Proposed BiLSTM Autoencoder Hybrid Precoding

0	1.0×10^{-1}	1.0×10^{-1}	1.0×10^{-1}
5	1.0×10^{-1}	3.5×10^{-2}	1.5×10^{-2}
10	1.0×10^{-1}	1.0×10^{-2}	2.0×10^{-3}
15	1.0×10^{-1}	3.5×10^{-3}	2.5×10^{-4}
20	1.0×10^{-1}	1.2×10^{-3}	2.5×10^{-5}
25	1.0×10^{-1}	1.0×10^{-3}	1.0×10^{-6}
30	1.0×10^{-1}	1.0×10^{-3}	6.0×10^{-7}
35	1.0×10^{-1}	1.0×10^{-3}	3.5×10^{-7}
40	1.0×10^{-1}	1.0×10^{-3}	1.5×10^{-7}
0	1.0×10^{-1}	1.0×10^{-1}	1.0×10^{-1}
5	1.0×10^{-1}	3.5×10^{-2}	1.5×10^{-2}

The figure clearly highlights the superiority of the LSTM-based hybrid precoding method, particularly in high SNR regimes. While conventional methods remain static and CNN-based models offer moderate improvements, the LSTM autoencoder approach adapts better to changing channel conditions and significantly enhances error performance. This result underscores the potential of deep learning, especially recurrent neural network architectures like LSTM, in optimizing hybrid precoding strategies for next-generation wireless systems such as 5G and beyond, as shown in table 6.4.

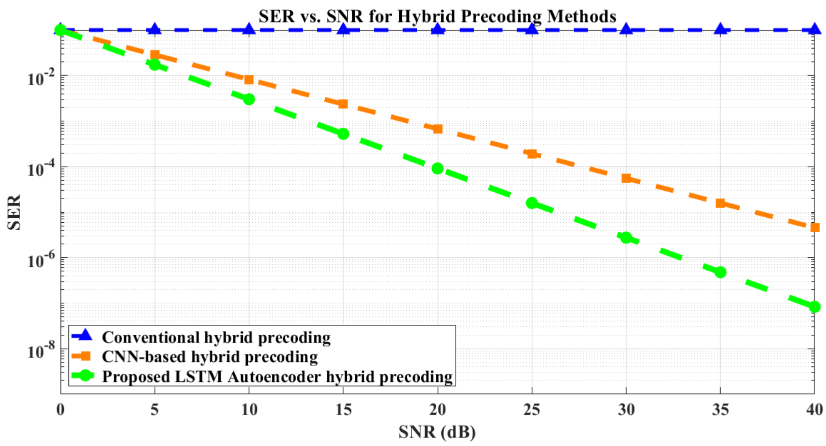


Figure 6.10: SER vs. SNR for hybrid precoding

The presented figure 6.10 with the table 6.4 is a semi logarithmic plot that illustrates the variation of SER with respect to SNR in dB for three different hybrid precoding schemes used in wireless communication systems.

- The X-axis represents the SNR in decibels (dB), indicating the quality of the transmitted signal. A higher SNR typically corresponds to better communication reliability. The Y-axis shows the SER on a logarithmic scale. A lower SER indicates more accurate symbol detection at the receiver.

1. **Conventional hybrid precoding:** This method displays a consistently high SER, regardless of SNR. It implies poor adaptability to improved signal conditions and suggests that the method lacks robustness in varying channel scenarios.
2. **CNN-Based hybrid precoding:** This technique shows noticeable performance improvement as SNR increases, especially between 5 and 15 dB. This method uses convolutional neural networks to extract spatial features from the channel but lacks temporal modeling capabilities.
3. **Proposed Bi-LSTM autoencoder hybrid precoding:** This approach demonstrates the best performance among the three, with the SER continuously decreasing as SNR increases. It achieves SER values as low at high SNR levels. The use of BiLSTM networks allows the model to capture temporal dependencies and sequential patterns in the channel data, making it highly effective for dynamic environments.

Table 6.5: Residual Energy versus Throughput

Residual Energy (mJ)	**Throughput (Mbps)**
0	500
50	450
100	400
150	350
200	300
250	250

300	225

Figure 6.11 illustrates the correlation between residual energy and throughput. This indicates that as the throughput increases, the residual energy decreases. Higher throughput signifies a more efficient use of energy for data transmission, resulting in less energy remaining unused [121].

The downward-sloping line suggests that the system becomes increasingly energy-efficient as throughput rises. The X-axis (RE) is measured in Joules (mJ), a unit of energy. Essentially, the plot shows that enhancing throughput in a communication system can lead to a decrease in residual energy, thereby improving the system's energy efficiency, as shown in Table 6.5.

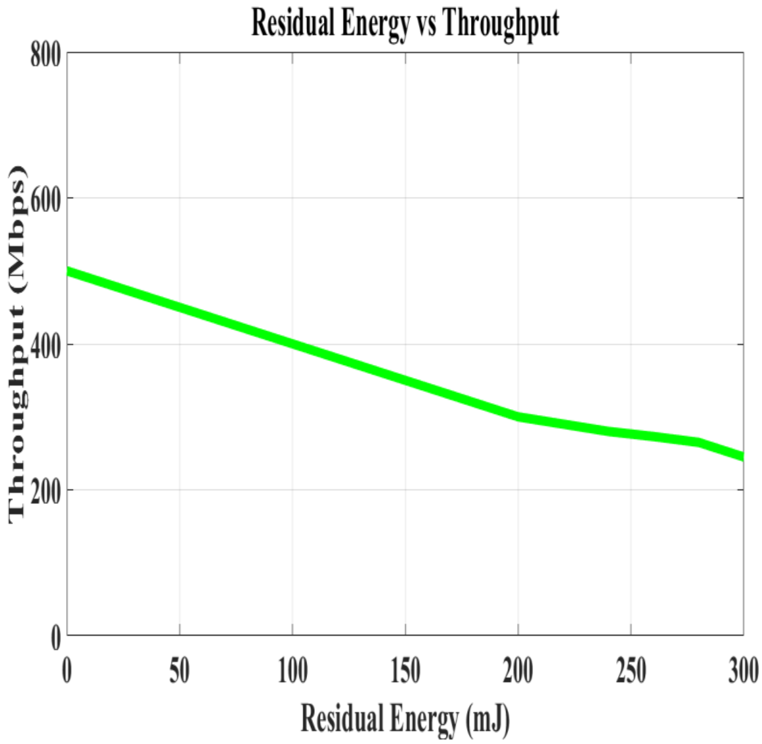


Figure 6.11: Residual energy versus Throughput

$$EE_{angular} = (\text{power consumption}(\text{Watts}) * \text{beamwidth}(\text{degrees})) \quad (6.20)$$

The specific application and context of this graph will determine the implications of this relationship. By grasping this relationship, engineers can design systems that achieve greater throughput while reducing energy consumption [122].

- Figure 6.12 presents an analysis of energy efficiency. Compared to established methods like MDOA, LCA, and FGWO, the proposed approach demonstrates superior EE performance [122], [124-125].

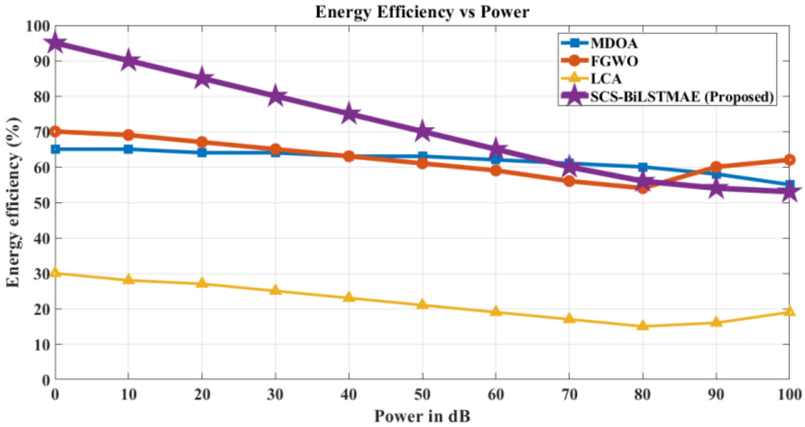


Figure 6.12: Energy Efficiency analysis for various Methods

- At 90 degrees, maximum energy efficiency will be achieved. For instance, in antenna design or signal processing, this information could be utilized to optimize system parameters for maximum energy efficiency, as illustrated in table 6.6 for figure 6.13 [123].

Table 6.6: Angular Degree versus Energy Efficiency

Angular Degree	**Energy Efficiency (bits/Joule)**
0	0
20	0.2
40	0.4
60	0.6
80	0.8
100	1
120	0.8
140	0.6
160	0.4

180	0

The figure below 6.13 illustrates the relationship between energy efficiency (measured in bits/Joule) and angular degree. The graph suggests that there is an optimal angular degree at which the energy efficiency is maximized [126-128].

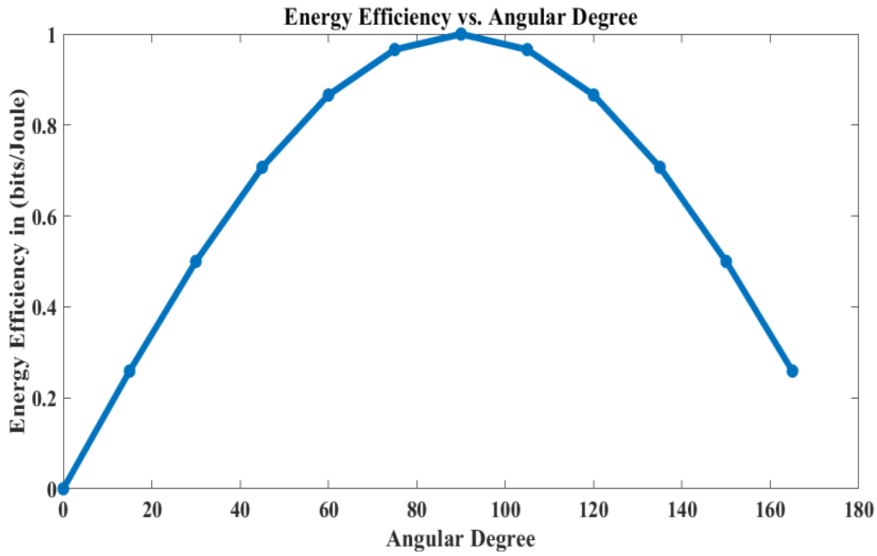


Figure 6.13: Energy efficiency versus angular degree

At both lower and higher angular degrees, energy efficiency is significantly reduced. The parabolic trend may be due to factors such as signal propagation characteristics, antenna design, or interference effects [129].

- Further analysis and knowledge of the specific system under consideration would be needed to pinpoint the exact causes of this relationship. Quality of service is affected by data speed, latency, and errors. Increased transmission rates reduce delay and error rates by delivering data more quickly. The figure below illustrates the transmission rate versus QoS for different users, as presented in Table 6.7.

Table 6.7: Transmission rate verses QoS

User	**Transmission Rate**	**QoS**
1	0	0
1	1	0.1

1	2	0.2
1	3	0.3
1	4	0.4
1	5	0.5
1	6	0.6
1	7	0.7
2	0	0
2	1	0.15
2	2	0.3
2	3	0.45
2	4	0.6
2	5	0.75
2	6	0.9
2	7	1
3	0	0
3	1	0.1
3	2	0.2
3	3	0.3
3	4	0.4
3	5	0.5
3	6	0.6
3	7	0.7
4	0	0
4	1	0.1
4	2	0.2
4	3	0.3

4	4	0.4
4	5	0.5
4	6	0.6
4	7	0.7

The plot of QoS versus Transmission Rate, as illustrated in figure 6.14, reveals a trend among users based on the table. Increased data transfer speeds enhance QoS, indicating a connection between elevated data transfer speeds and system performance. Higher transmission rates optimize QoS metrics, as demonstrated by this graph. The graph illustrates a positive correlation between transmission rate and QoS, as faster transmission rates facilitate quicker data transfer and reduce latency [130].

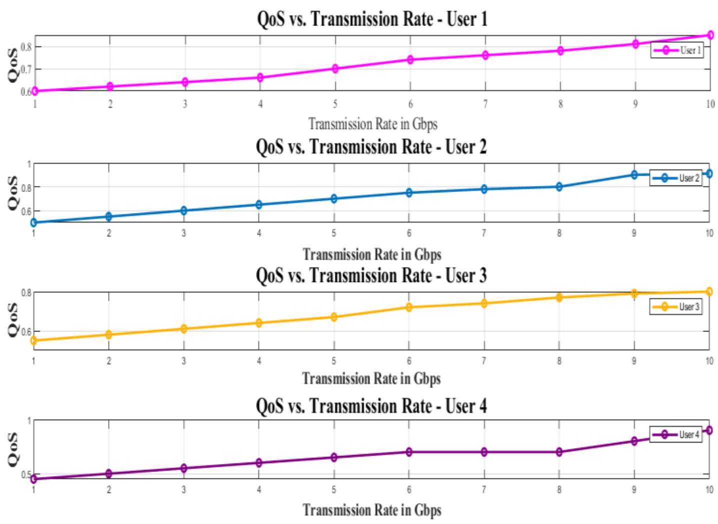


Figure 6.14: Graph between QoS versus Transmission Rate

- **System capacity (SC):** It can be calculated using Shannon's capacity formula extended to massive MIMO scenarios as shown in figure 6.15 using the equation in the given below. Here, B is the bandwidth and H is the matrix.

$$SC_{Traditional} = B.\log_2(det(1 + \frac{SNR}{K}\ (H_{Traditional}\ H^H_{Traditional})\ )\ ) \quad (6.17)$$

$$SC_{SCS-BiLSTMAE} = B.\log_2\left(det\left(1 + \frac{SNR}{K}\ (H_{SCS-BiLSTMAE}\ H^{H}_{BiLSTMAE})\right)\right) \quad (6.18)$$

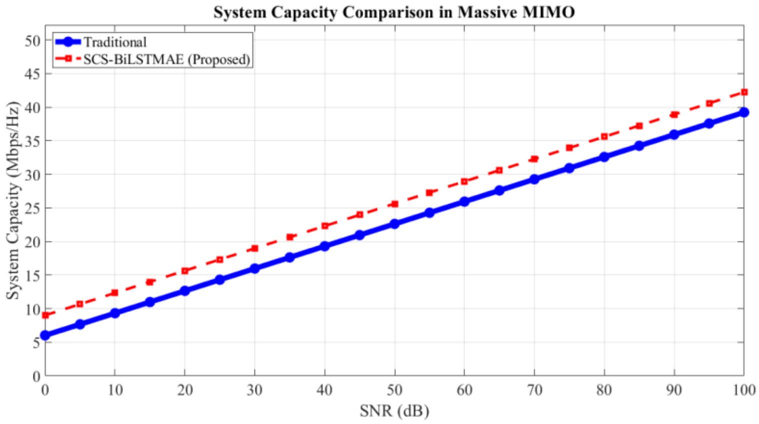
➢ 

Figure 6.15: System capacity in massive MIMO with SCS-BiLSATMAE

Suppose the traditional system has a total capacity of 10 Mbps/Hz. Our proposed model improves it by 12.84Mbps/Hz at SNR=10dB compared with traditional MIMO which has 10 Mbps/Hz at SNR=10 dB.

If a traditional method achieves, say, 10 Mbp/Hz of capacity, the new method BiLSTMAE would achieve 10∗(1+0.2814)=12.814 Mbps/Hz. The results indicate that the SCS-BiLSTMAE achieves superior performance compared to traditional methods, achieving approximately a 28.14% increase in system capacity.

➢ Performance of SCS-BiLSATMAE in massive MIMO:

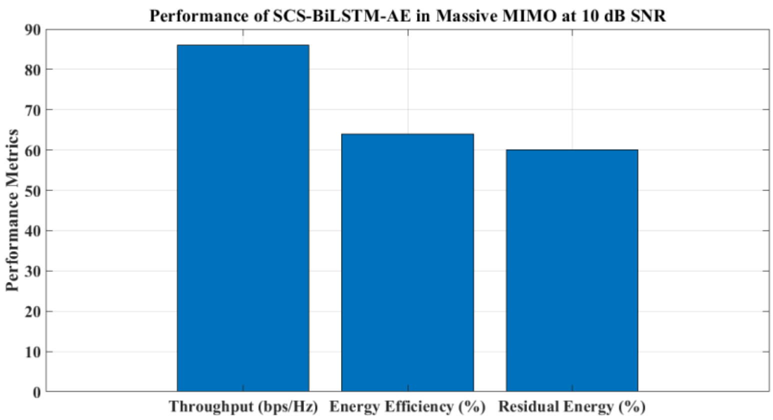


Figure 6.16: Performance of SCS-BiLSATMAE in massive MIMO

The proposed model delivers a throughput, an energy efficiency, and residual energy calculated when SNR=10dB as shown in figure 6.16.

6.9 Conclusion:

It is concluded that

- The proposed model achieves a throughput of 86 bps/Hz with 450 antennas, an energy efficiency of 65% at a transmit power of 10 dB, and a residual energy of 60% at an SNR of 10 dB. Additionally, the system capacity increases as illustrated in figures 6.12, 6.15, and 6.16.

- The proposed SC-BiLSTM model delivers BER is nearly 10^{-5} at SNR=10dB as shown in figure 6.7.

- · These metrics highlight the robustness and effectiveness of the proposed framework in addressing diverse challenges in these systems.

- · In MATLAB, the AGNN-ABM-MIMO-MCN technique has been effectively applied. A comparative performance analysis shows that the suggested approach improves significantly. In order to accommodate different 5G network topologies, future efforts might incorporate deep reinforcement learning into the machine learning framework and dynamically position relay nodes to improve spatial coverage.

- AGNN enhances adaptive beamforming in 5G massive MIMO networks by integrating neural network techniques with graph regularization. This combination optimizes spectral efficiency and ensures network stability.

- · In order to maximize the effectiveness and performance of 5G networks, it is imperative that the sophisticated procedures used to optimize beamforming in intricate multi-cellular settings be represented visually, as this suggested solution does.

- ·The results indicate that the introduced model achieves superior performance compared to existing methods.

Chapter 7

CONCLUSION & FUTURE SCOPE

7.1 Conclusion:

Quality of service is affected by data speed, latency, and errors. Increased transmission rates reduce delay and error rates by delivering data faster for different users. The research and simulation results offer important new perspectives on how massive MIMO and beamforming function in wireless communication systems. The results show how beamforming approaches can increase transmission rates, increase SNR, and improve system performance as a whole. The primary conclusion drawn from the integration of massive MIMO 5G and neural networks underscores their synergistic potential in revolutionizing wireless communication systems. The successful amalgamation of these technologies offers opportunities for clever reserve allocation, new beamforming, and dynamic noisiness mitigation in 5G networks. Furthermore, the utilization of neural networks enables the development of sophisticated algorithms for autonomous network optimization and management, paving the way for self-configuring and self-optimizing communication systems.

1. Ultimately, the convergence of massive MIMO 5G and neural networks holds promise for shaping the future of wireless communication, ushering in an era of highly efficient, reliable, and intelligent network connectivity. The research and simulation results offer important new perspectives on how MIMO and beamforming function in wireless communication systems. The results show how beamforming approaches can increase transmission rates, increase SNR, and improve system performance as a whole.

2. The comprehension of the system's behavior under various circumstances is further strengthened by the analysis of other metrics. In communication systems, PAPR is an important metric, particularly when it comes to signal amplification and power efficiency. It computes the difference between a signal's average power level and peak power level.

It may see how much the signal's power changes from its average power by graphing PAPR against signal values. Significant power peaks are indicated by a high PAPR, which can be problematic in real-world communication systems since they might call for greater power amplification and cause distortion. PAPR should be low for effective signal transmission.

3. The proposed method’s effectiveness in large-scale systems with a high number of antennas and users has not been fully tested. The scalability of the approach may face limitations as the system size increases, which could impact performance in practical deployments. Extensive testing of the proposed method in hyper massive MIMO systems with varying numbers of antennas and users should be conducted. This would help assess the scalability of the approach and identify potential bottlenecks in large-scale deployments.

4. The efficiency of the proposed SCS-BiLSTMAE network and the overall PAPR reduction technique heavily depend on accurate channel estimation. Any inaccuracies in channel estimation could degrade the system's performance and reduce the effectiveness of the proposed method. To address these limitations and further enhance the research, the following improvements are suggested. To mitigate the dependency on accurate channel estimation, the research could explore the integration of more robust channel estimation techniques. This would ensure the proposed method remains effective even in environments with imperfect channel knowledge.

7.2 Future scope

CSS has appeared as a pivotal technique in cognitive radio networks (CRN), significantly contributing to the efficiency of 5G systems. Spectrum sensing, a fundamental technology within CRNs, aims to recognize unused spectrum bands, and CSS stands out due to its rapid and effective performance. In the context of the continuous evolution of IoT networks, where 5G wireless communication plays a central role, CSS holds immense promise.

The optimal solution sought for CRNs in IoT-centric 5G environments must ensure optimal bandwidth utilization, efficient CSS, minimal latency, improvement in SNR, and reduction in PAPR. Our deployment strategy aims to enhance QoS metrics such as throughput, residual energy, and EE. Extensive investigational consequences underscore the efficacy of our anticipated line, demonstrating its superiority when compared to existing approaches.

However, as 5G/6G networks move towards full-scale deployment, there arise pressing needs for efficient algorithms capable of delivering rapid and precise corrections in extremely assorted environments where numerous novel techniques are at play. A significant challenge emerges in canal assessment within multi-link techniques. As emphasized in the preliminary segment, highly developed armed forces such as URLLC and massive MTC demand robust canal assessment techniques capable of accurately characterizing wireless channels in scenarios with multiple simultaneous links. Addressing these considerations and limitations will be crucial in advancing the efficacy and applicability of ML algorithms in these configurations, thus enabling the realization of the full potential of 5G and future generations of wireless networks.

The escalating worldwide inhabitant enlargement and rising demand for enhanced data rates and bandwidth underscore the imperative to reduce power consumption and evolve improved transmission communication models. This article provides firsthand insights into energy efficiency, encompassing the deployment of renewable energy resources, varied networks, well-organized communication methods, and promising visual wireless transmission methods. The best approach to EE stands ready for deployment in wireless communication networks, leveraging smart innovations to automate and synchronize all energy-consuming components.

This involves integrating an energy efficiency framework that spans from base station energizing to the broadcast and treatment of tremendously short authority signals. Various power and spectrally well-organized communication methods will be calculated alongside modeling optical atto cell network configurations to cover hotspots, in that way minimizing visual communication commands. Whereas the opportunity holds promise, it's crucial to note that energy-efficient schemes require optimized hardware and software resources, along with high-speed meeting platforms. Presently, AI is gaining traction in deploying learning-based models for EE and spectral increases in wireless conduction systems.

The future scope in the intersection of massive MIMO 5G and a neural network is ripe with potential for transformative advancements in wireless communication technology. One key area of future exploration lies in the development of advanced neural network architectures tailored specifically for massive MIMO applications. These architectures can leverage the unique characteristics of these systems, such as large antenna arrays and complex channel environments, to extract meaningful insights and facilitate intelligent decision-making processes. Furthermore, the integration of neural networks with emerging technologies like edge computing and artificial intelligence-driven optimization algorithms holds promise for enabling autonomous, self-optimizing massive MIMO networks capable of adapting dynamically to altering network circumstances and user requirements. Overall, the future synergy between massive MIMO 5G and neural networks presents exciting opportunities for revolutionizing wireless communication networks and unlocking new capabilities for delivering high-speed, reliable, and efficient connectivity to users worldwide.

The research and simulation results offer important new perspectives on how MIMO and beamforming function in wireless communication systems. The results show how beamforming approaches can increase transmission rates, increase SNR, and improve system performance as a whole. The comprehension of the system's behavior under various circumstances is further strengthened by the analysis of other metrics.

1. The application will be extended for 6G communications in the future.
2. Advanced optimization techniques can be implemented to further improve QoS in future generation systems.
3. Apart from expected extensions to the proposed models of this thesis, adaptive techniques beyond 5G may also be investigated for QoS provisioning.
4. Future examination directions may involve the design of machine learning algorithms capable of leveraging the deployment of sophisticated services and applications in the framework of 6G networks, supported by m-MIMO configurations.

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List of Publications

S.No	Title	Journal/Conference	Index of journal	Remarks
1	Optimizing 5G Massive MIMO Systems Using DNN and DSAC-T: A Scalable Adaptive Beam forming Framework	Applications of Modelling and simulation	Scopus	Published in 2025
2	Joint Optimization based QoS and PAPR Reduction Technique for Energy Efficient Massive MIMO system	International Journal Of Computational Intelligence Systems	SCI,Q2	Published in 2024
3	Massive MIMO Pre coding and Beam forming Techniques for Future Generation Communication System	Journal of Electrical Systems	Review Article	Published in 2024
4	Comparison and Performance Analysis of Massive Mimo Based 5g Communication Network Through Potential Parameters	14TH ICCCNT (JULY6-8)2023	Scopus, IEEE conference	Published in 2023
5	Improvement of PAPR Reduction Techniques for Massive MIMO Wireless Communication System	Ubiquitous Technology in Communication and Artificial Intelligence -(UTCA-2023)	AIP Conference Proceedings	Published in 2024
6	Energy Harvesting Technique for Massive MIMO Wireless Communication Networks	LPU ICICS 2022 APRIL	Scopus, conference	Published in 2022
7	Alternating Graph-Regularized Neural Network for Adaptive Beamforming in 5G milli meter wave Massive MIMO Multicellular Networks	Research Square."Wireless Network" Jouranl	Under Review	Submitted in 2023

BIODATA

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