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On the Performance of Beamforming for Massive MIMO Architectures in 5G Systems

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On the Performance of Beamforming for Massive MIMO Architectures in 5G Systems

A Dissertation Submitted

By

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Abstract

Elevation beamforming allows elevational cooperation, which is one of the essential features in the development of FD-MIMO systems. This study investigates the incorporation of artificial intelligence into FD-MIMO systems to make the theoretical base of the beamforming algorithms stronger and improve their performance.

It provides a better approach that combines artificial intelligence methods with reinforcement learning to achieve adaptive beamforming in dynamically changing network scenarios. Horizontal and vertical beamforming strategies are compared using ULA and URA. The simulations take place in urban-inspired distribution.

Performance evaluation is based on the key metrics of BER, throughput, and Eb/No. The results show improvements in signal integrity and spectral efficiency. BER analysis indicates close performance to theoretical limits with an increase in throughput from 2.2 Mbps at -25 dB Eb/No to 3.8 Mbps at 5 dB Eb/No. SINR improvements in the order of 80 dB could enable themselves with the application of optimized beamforming weights.

The results show that the role of AI-empowered beamforming strategies can play in surmounting high-density urban deployment challenges and give the opportunity to work further on wireless network optimization.

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List of Abbreviations

1. **AI - Artificial Intelligence**
2. **AoA - Angle of Arrival**
3. **BER - Bit Error Rate**
4. **BS - Base Station**
5. **CSI - Channel State Information**
6. **CQI - Channel Quality Indicator**
7. **D2D - Device-to-Device**
8. **DOA - Direction of Arrival**
9. **DRL - Deep Reinforcement Learning**

10. FD-MIMO - Full Dimension Multi-Input Multi-Output

11. Gb/s - Gigabit per second

12. IoT - Internet of Things

13. KPI - Key Performance Indicators

14. LTE - Long Term Evolution

15. MIMO - Multiple Input Multiple Output

16. mmWave - Millimeter Wave

17. NOMA - Non-Orthogonal Multiple Access

18. OMA - Orthogonal Multiple Access

19. QoS - Quality of Service

20. RA - Resource Allocation

21. RF - Radio Frequency

22. SC - Successive Cancellation

23. SE - Spectral Efficiency

24. SIC - Successive Interference Cancellation

25. SINR - Signal plus Interference to Noise Ratio

26. SNR - Signal to Noise Ratio

27. UE - User Equipment

28. ULA - Uniform Linear Array

29. URA - Uniform Rectangular Array

30. URLLC - Ultra-Reliable Low-Latency Communications

31. mMTC - Massive Machine-Type Communications

32. QAM - Quadrature Amplitude Modulation

33. QPSK - Quadrature Phase Shift Keying

34. GoB - Grid of Beams

35. SSB - Synchronous Signal Block

36. SRS - Sounding Reference Signal

37. TDD - Time Division Duplexing

38. HB - Hybrid Beamforming

List of Symbols

1. **($\boldsymbol{\lambda}$) - Wavelength**
2. **($\boldsymbol{\theta}$) - Angle of Arrival (AoA)**
3. **($\boldsymbol{P}$) - Power**
4. **($\boldsymbol{w}$) - Weight applied to the received signal**
5. **($\boldsymbol{x_t}$)- Received signal vector at the antenna elements**
6. **($\boldsymbol{\sigma^2}$) - Noise power**
7. **($\boldsymbol{a(\theta)}$) - Steering vector**
8. **($\boldsymbol{E_n}$) - Noise eigenvector matrix**
9. **($\boldsymbol{H}$) - Hermitian transpose**
10. **($\boldsymbol{t}$) - Time**
11. **($\boldsymbol{d}$) - Element spacing**
12. **($\boldsymbol{h_k}$) - Channel coefficient vector**
13. **($\boldsymbol{s_{k(t)}}$) - Signal destined for the ($\boldsymbol{k}$)-th user**
14. **($\boldsymbol{x_{k(t)}}$) - Received vector at ULA by the ($\boldsymbol{k}$)-th user**
15. **($\boldsymbol{\gamma}$) - Signal-to-Interference-plus-Noise Ratio (SINR)**
16. **($\boldsymbol{R_k}$) - Minimum data rate requirement for user ($\boldsymbol{k}$)**
17. **($\boldsymbol{E_b/N_0}$) - Energy per bit to noise power spectral density ratio**
18. **($\boldsymbol{k}$) - Wavenumber**
19. **($\boldsymbol{f_c}$) - Carrier frequency**
20. **($\boldsymbol{\phi}$) - Phase shift introduced by the channel**
21. **($\boldsymbol{n_t}$) - Noise at time ($\boldsymbol{t}$)**
22. **(AF($\boldsymbol{\theta}$)) - Array factor**
23. **($\boldsymbol{P}_{\text{total}}$) - Total transmitted power**
24. **($\boldsymbol{w_n}$) - Weight for the ($\boldsymbol{n}$)-th element**
25. **($\boldsymbol{Q(x)}$) - Q-function, the tail probability of the Gaussian distribution**
26. **($\boldsymbol{R_b}$) - Bit rate**

27. ($\boldsymbol{B}$) - **Bandwidth of the channel**

28. ($\mathbf{log_2}$) - **Logarithm base 2**

29. ($\mathbf{cos}(\boldsymbol{\theta})$) - **Cosine of angle** ($\boldsymbol{\theta}$)

30. ($\boldsymbol{\mu}$) - **Mean**

31. ($\boldsymbol{\rho}$) - **Correlation coefficient**

32. ($\boldsymbol{\sigma}$) - **Standard deviation**

33. ($\boldsymbol{\alpha}$) - **Angle of elevation**

34. ($\boldsymbol{\beta}$) - **Slope**

35. ($\boldsymbol{\delta}$) - **Delta, small change**

36. ($\boldsymbol{\epsilon}$) - **Permittivity**

37. ($\boldsymbol{\eta}$) - **Efficiency**

38. ($\boldsymbol{\theta_{az}}$) - **Azimuth angle**

39. ($\boldsymbol{\theta_{el}}$) - **Elevation angle**

40. ($\boldsymbol{\omega}$) - **Angular frequency**

41. ($\boldsymbol{\Gamma}$) - **Reflection coefficient**

42. ($\boldsymbol{\zeta}$) - **Impedance**

43. ($\boldsymbol{\kappa}$) - **Propagation constant**

44. ($\boldsymbol{\chi}$) - **Susceptibility**

45. ($\boldsymbol{\nu}$) - **Frequency**

CHAPTER ONE

INTRODUCTION

1.1 Preface

At the current time, wireless networks are required to deliver more than just higher data rates are, also, expected to offer new frontiers of reliability, coverage, and energy efficiency. Full dimension-multi-input multi output (FD-MIMO) is revolutionary as it unlocks spatial dimension using elevation beamforming and provides a way to see and use wireless networks. These systems will become increasingly essential for overcoming the difficulties of urban densification, which is marked not only by large consumer demand but also by the various demands for the service quality of the individual user [1]. The transition to Fifth Generation (5G) was driven by a search for novelty and elevation. One of the major drivers has been beamforming. The basic point of this procedure is that it helps in adapting the information that is to be sent, thus making it possible for the power of transmission to be concentrated towards its intended recipients, thereby leading to much more efficient and effective wireless communication systems. By making good use of such a spatial dimension, elevation beamforming will make network Resource Allocation (RA) more realistic, thereby enhancing user experience through better signal quality and network capacity improvement.

As a broadband opportunity for 5G cellular networks, there is great interest in the ability of millimeter-wave (mm-Wave) beamforming to deliver extremely high Gigabit per second (Gb/s) data rates [1].

Massive MIMO is one of the most promising technologies for improving the spectral efficiency (SE) of cellular networks. Beamforming technology is used to equip a Base Station (BS) with an antenna array with hundreds of active elements to perform coherent processing on both the transmitter and receiver sides [1].

The main components that provide current wireless communications include beamforming in millimeter wave (mmWave) and massive MIMO systems. The usage of the mmWave technologies, which leads to a significant increase of data rate, throughput, and capacity, also plays a role in increasing the bandwidth available when applying the required output goals SE.

The massive MIMO mmWave systems may reach the required output goals by applying multiple frequencies and three different beamforming techniques: conjugate beamforming, minimum mean squared error, and zero-forcing over mmWave channel. However, even though the available beamforming techniques provided the needed requirements; they consumed excessive power and did not allow limitless use of the electromagnetic spectrum [2].

Some cases might require the communication link of the network to be available while the User Equipment (UE) is using some applications and at the same time it might be moving as pedestrian/using a car, so according to 5G system beamforming facility, the beam must follow to the user’s movement, which means that we need to track the user movement accordingly. This is done by Channel Quality Indicator (CQI) in Forth Generation Long Term Evolution (4G-LTE) or by proximity discovery using Device-to-Device (D2D) [3], [4]. This chapter sets the stage for the dissertation to outline the motivation, objectives, and structure of the research. It provides a preliminary overview of elevation beamforming and its significance in the context of 5G networks.

1.2 Literature Review

The conceptual foundation underpinning Elevation Beamforming (EB) in Full Dimension - Multiple Input Multiple Output (FD-MIMO) systems is rooted in early thoughts on spatial multiplexing as well as the possibilities of antenna arrays which followed significantly soon. The early generation research is mostly based on the azimuth dimension and gives less emphasis to the elevation one. Nonetheless, as soon as the knowledge of the two-dimensional planar antenna system's incapacity to fulfill the growing needs of the wireless network services grew, so did the focus on exploitation of the elevation dimension in a bid to elicit improved discrimination and more multiplexing.

- In 2019, Q.-U.-A. Nadeem *et al.* discussed FD MIMO status and standardization. They mentioned the history of FD-MIMO, from its conceptualization to its latest standardization within the Third Generation Partnership Project (3GPP) releases. They outlined the development of FD-MIMO in literary text as one of the most significant technological advances in the field of wireless communication. Utilizing 3D beamforming, FD-MIMO has enabled this as a way to curb the unprecedented rise in data consumption. The breakthrough marks a leap in the grasp of the potential for wireless networks to guarantee high – risk communication in high density urban settings and beyond. Furthermore, the paper discussed the use of advanced antenna technologies and the integral role of elevation beamforming in helping to fully unlock FD-MIMO systems [5].
- In 2020, S. Kalamkar *et al.* proposed system-level stochastic geometry model that includes various aspects of beam management, such as frequencies, antenna configuration, physical layer, wireless links, network geometry, interference, and resource sharing. This model aims

to find an optimal balance between beamforming gains and the operational overheads associated with beam management. The model led to a simple analytical expression for the effective rate of the typical user. This expression helps in determining the optimal number of beams per cell and per Mobile Terminal (MT) [6].

- In 2021 April, Joan Palacios *et al.* focused on the challenging problem of interference management in dense wireless networks, enabled by elevation beamforming in the context of FD-MIMO architectures. In particular, this part examined a set of algorithmic solutions and system designs get designed to reduce the impact of cross-channel interference while simultaneously increasing the aggregate network capacity. In relation to this, the key importance of Coordinated Multi-Point (CoMP) transmission and reception and Non-Orthogonal Multiple Access (NOMA) and many more to improve the Signal-to-Interference-plus-Noise Ratio (SINR) platform across the network. Such strategies illustrate that FD communication may be used to not only boost the performance of a Person-to-Person (P2P) link but also to enhance the efficiency and availability of the network [7].
- In 2021 Dec, K. Ma *et al.* discussed the motivations, and the challenges in implementing deep learning for beam control in millimeter-wave communications. They, also, spotlighted their research vector and the main peculiarities. However, in addition to making them remarkable due to the benefits of narrow beams for high interaction gains, it also distinguishes some limitations, such as overhead in training and susceptibility in comparison with blockages, shown under the utilization of thinner currents. Deep Learning (DL) design lessons were summarized by drawing readers' attention to the problems and future opportunities for such insights to support innovative concepts on novel

mechanisms for beam management that can stimulate novel ideas and contributions into DL-assisted beam management [8].

- In 2022, Spyros *et al.* developed an adaptive beamforming approach that utilizes a predefined set of configurations to generate highly directional beams on demand. This approach is designed to handle various traffic scenarios effectively. They incorporated a Machine Learning (ML) beamforming approach based on the k-Nearest Neighbors (k-NN) approximation. This ML model is trained to generate the appropriate beamforming configurations according to the spatial distribution of throughput demand [9].
- In 2023 Jan, the idea of how complicated the problem of beam management in massive MIMO arrived. The authors showed that it is complicated to find efficient beamforming schemes that maximize Spectral Efficiency (SE) to enhance network performance. In this case, adaptive beam steering and dynamic resource allocation as well as advanced signal processing approaches and machine learning indicate the direction beam management strategies should evolve in the context of dynamic wireless environments. It will help to ensure the required high throughput and low latency of next generation wireless networks [10].
- In 2023 July, J. Kaur *et al.* investigated the idea of contextual beamforming, its pros and cons as well as its interpretation. They showed a significant 53% improvement of Signal-to-Noise Ratio (SNR) by using with and without beamforming implemented scenarios. The importance of localization in implementing contextual beamforming was argued by them [11].
- In 2023, S. Lavdas *et al.* studied an adaptable mixed analog-digital beamforming technique for such networks and shown proof of the potential of the concept to aid 5G MIMO mmWave broadband networks

in meeting dynamic traffic demands. Using vertical antenna arrays and ON OFF antenna mode, this work has shown remarkable enhancement in the annual cumulative distribution function of the throughput, the blockage probability, and downlink transmission power. The mixed digital-analog beamforming versatile nature considerably decreases the active radiating components, hence indicating a path towards hardware-efficient broadband wireless networks [12].

- In 2023 Nov, the utilization of elevation beamforming in various environments, including satellite communications to urban canyons and disaster recovery operations occurred. As a result, some examination points to the commonality and uniqueness of the challenges faced in each scenario, such as high mobility, severe multipath fading, and line-of-sight obstructions were discussed. The extensive overview of such diverse applications offers comprehensive insights into the wide-reaching potential of elevation beamforming in substantially increasing communication reliability and coverage. Therefore, the exploration impacts an enhanced understanding of how the elevation beamforming can be used to strengthen the resilience and operation of wireless networks in the various domains [13].
- In 2024, Chary *et al.* proposed a deep learning-based hybrid beamforming approach for massive MIMO systems, integrating the Improved Extreme Learning Machine-Adaptive Orthogonal Matching Pursuit (IELM-AOMP) algorithm for accurate channel estimation and the Improved Proximal Policy Optimization (IPPO) algorithm for hybrid beamforming. Their method effectively reduces pilot overhead and power consumption but introduces significant computational complexity and requires substantial training data [14].

1.3 Aims of the Dissertation

This dissertation sets out with the primary objective of demystifying the complexities and unraveling the potential of elevation beamforming within FD-MIMO architectures in the evolving landscape of 5G networks. The research aims to bridge the theoretical concepts with practical applications, thereby contributing to the body of knowledge in the following ways:

1. **Theoretical Exploration and Validation:** is used to thoroughly investigate the theoretical underpinnings of elevation beamforming in FD-MIMO systems. This involves a detailed examination of the signal processing mechanisms, antenna array configurations, and the spatial dynamics that govern the effectiveness of elevation beamforming.
2. **Algorithmic Development and Optimization**: is used to develop and optimize algorithms that enhance the performance of elevation beamforming in FD-MIMO systems. This includes creating adaptive beamforming strategies that can dynamically adjust to varying network conditions, user distributions, and traffic demands.
3. **Performance Analysis and Benchmarking**: is used to conduct a comprehensive performance analysis of elevation beamforming in FD-MIMO systems across a range of scenarios and conditions. This analysis will focus on key performance indicators such as throughput, SINR, and energy efficiency.
4. **Future Directions and Innovations**: is used to identify future research directions and potential innovations that can further enhance the performance and applicability of elevation beamforming in 5G and beyond. This includes investigating the integration of emerging technologies such as Artificial Intelligence (AI) and ML in the optimization and management of elevation beamforming.

1.4 Layout of Dissertation

The dissertation is structured to provide a coherent and comprehensive exploration of elevation beamforming in FD-MIMO systems, structured as follows:

- **Chapter Two – Theoretical Background and Technologies**: Delving into the theoretical aspects, covers the principles of beamforming, FD-MIMO architectures, and the role of elevation beamforming. It includes a review of the state-of-the-art technologies and methodologies relevant to the dissertation.
- **Chapter Three – Algorithmic Framework and Optimization**: Focusing on the algorithmic advancements, presents the development, implementation, and optimization of beamforming algorithms tailored for elevation beamforming in FD-MIMO systems.
- **Chapter Four – Performance Evaluation and Analysis**: This chapter details the simulation setup, performance metrics, and analysis of elevation beamforming under various scenarios. It aims to validate the theoretical models and algorithmic approaches through rigorous testing and benchmarking.
- **Chapter Five – Conclusion and Future Work**: The final chapter summarizes the key findings, contributions, and limitations of the dissertation. It also outlines future research directions that can further advance the field of elevation beamforming in wireless communication systems. Through this structured approach, the dissertation aims to provide a holistic understanding of elevation beamforming in FD-MIMO systems, contributing valuable insights and innovations to the field of wireless communications.

CHAPTER TWO
THEORETICAL BACKGROUND

2.1. Introduction

5G introduction had a huge impact on the telecommunication world by shifting the focus from network-centric designs to user-centric ones. This shift was caused by the demand for data rates, Ultra-Reliable Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC), which underlies the principal concepts on the Internet of Things (IoT), smart cities, autonomous vehicles, and Augmented Reality (AR) 5G applications. The technology cornerstone enabling the full coverage of high spectrum efficiently and signal directivity are beamforming techniques [1]. Beamforming is utilized in signal processing techniques in radio signals' transmission and reception direction alike applications. Beamforming was used in 5G networks due to high-frequency bands, e.g., millimeter waves, posing obstacles to mobile communication design. Even though these frequencies can carry huge data, they have major cons including large propagation loss and vulnerability to obstacles. Beamforming resolves these demerits by concentrating the signal power on certain directions which improves signal strength and minimizes interference leading to efficient wireless networks. The role of beamforming in 5G is widespread including boosting signal quality and network capacity. However, the technology is a product of promoting energy usage and preserving battery lifespan [1]. As such, since in 5G physical infrastructure last-mile link is a key challenge, keeping beams steered enables flexible network coverage to be achieved.

Indeed, such adaptive properties are crucial if 5G is to realize its potential especially considering its large spectrum and anticipated applications from video streaming to mission critical communications. Moving on from fixed-beam antennas to advanced adaptive beamforming and massive MIMO systems symbolizes the powerful drive of the industry to make 5G's visions a reality. These innovations also prove the essential significance of beamforming in linking the disparity among the network's theoretical capability and actual, competent, and scalable wireless communication [15].

2.2. Overview to 5G System

The 5G wireless system is a significantly revolutionary technological advancement in the telecommunications sector. A number of factors summarize the characteristics of 5G that include advanced architectural development, superior network capability performance, and revolution for internet connection for over billions of devices [16].

Central to the transformation of 5G are some core technologies anchored in the massive MIMO, beamforming, mmWave communication, and network slicing. Massive MIMO technology reflects significant capacity and efficiency improvements arising from support for several antennas in the BS. The technology enables the BS to manage multiple data streams simultaneously, thus elevated throughput and diminishing interference. In close association with massive MIMO technology, beamforming enables systems to manage added streams sent to specific users.

In addition to enhancing the signal strength and quality, focused transmissions approach reduces energy use per bit and the consequences of signals among different users as well [2].

Another important feature of 5G is the utilization of mmWave frequencies to send huge amount of data at high data rates. However, the large attenuation of signals transmitted using mmWave frequency bands, compel using beamforming to ensure adequate performance and reliable communication of these higher frequencies. Beamforming is made conceivable by the shrewd plan of receiving wire exhibits and all the more particularly through phased array antennas. This allows the real time changing of the directionality of transmitted or received signals. By utilizing mmWave, beamforming increments the availability and reliability of such systems considerably, in crowded urban areas [2]. Network slicing, another concept made possible with 5G, includes the division of the communications network into multiple virtual networks that utilize an identical physical infrastructure. Each of these networks can, at that point, be assigned committed levels of network assets such as transmission capacity or ways, with a direct association to their necessities and prerequisites. The assets include the radio, the sending force of the BS, and indeed the potential directions through which they are transmitted or received [2].

2.2.1. Key Performance Indicators (KPI)

The deployment of 5G networks sets several new milestones in the wireless communication technology and introduces particular key performance indicators which are applicable metrics to evaluate the efficiency and effectiveness of the new systems. Thus, in contrast to the traditional ones that measure throughput, latency and reliability, the new performance of 5G is provided by its qualities to effectively deploy and integrate mmWave technology, massive MIMO architecture, sophisticated beamforming techniques, mobile edge computing, small cell BSs, and D2D communications. Every item is some of the bases for the success of 5G networks that have to address the growing challenge of high data rates, high system capacity, low latency, power consumption, device costs, and massive intercommunications [4].

- **Millimeter Wave (mmWave) Technology:** mmWave technology, shown in Figure 2.1, points to the use of extremely high frequencies ranging from 30 GHz to 300 GHz in 5G networks, allow large volumes of data to be transmitted at high speeds. In this case, SE is the most important KPI associated with mmWave technology, thus testing the performance of high quality connections over short distances overcoming high propagation loss and blockage at the same time. Therefore, in the case of mmWave, beamforming and antenna technology should be more advanced to guarantee the specified level of signal directivity and reliability which makes this metric very crucial for 5G networks testing performance in an urban environment and places with large number of people [16]. Figure 2.1 shows the mmWave ranges.

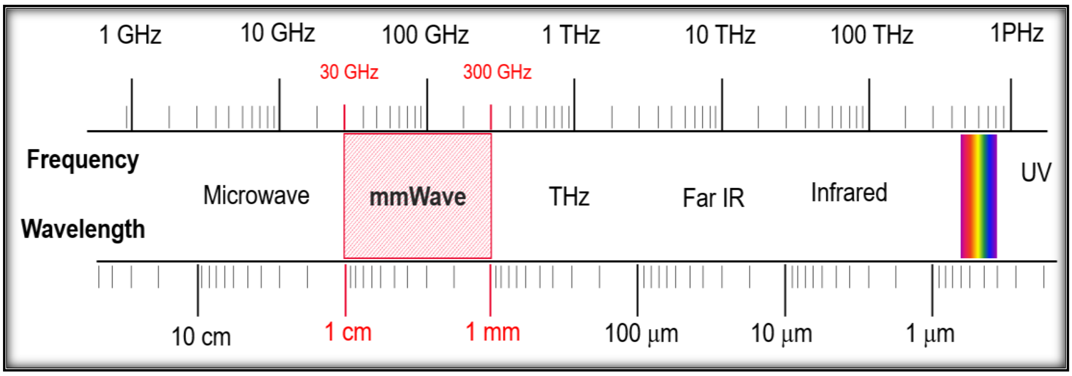

Fig 2.1: mmWave

- **Massive MIMO (Multiple Input Multiple Output):** Massive MIMO technology, as shown in Figure 2.2, enhances network capacity and efficiency by deploying hundreds of antennas at a single BS to serve multiple users simultaneously. Massive MIMO technology's ultimate performance indicator includes network throughput and energy efficiency. Massive MIMO systems drive up throughput through spatial multiplexing, which means higher data rates need not more bandwidth or transmit power [16].

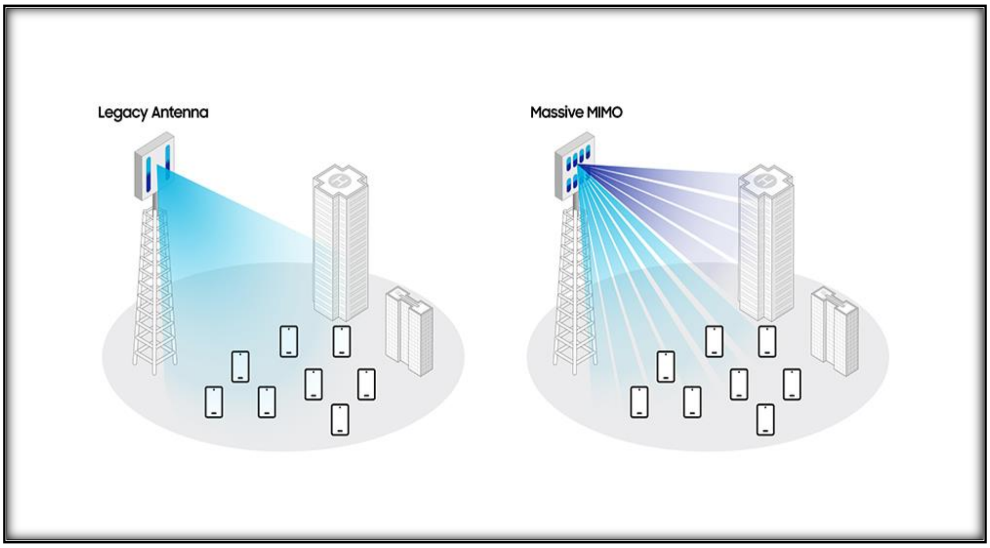

Fig 2.2: Massive MIMO.

- **Mobile Edge Computing (MEC):** as shown in Figure 2.3, MEC is implemented to get computational resources and storage closer to the endpoint of the network, lessening latency and traffic congestion. Therefore, the performance KPIs for MEC are set for end-user applications and the effectiveness of resource usage. Locating data at the endpoint allows real-time applications and is one of the promising solutions for URLLC implementation in 5G [16].

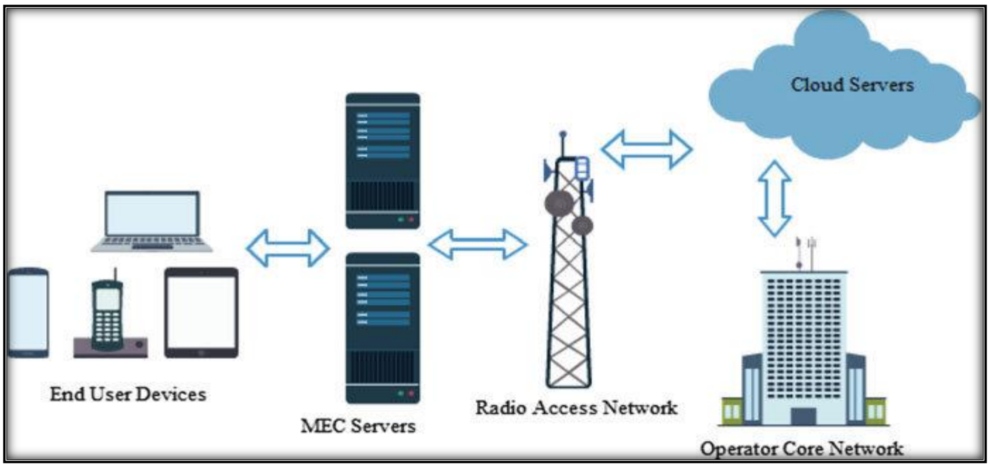

Fig. 2.3: Mobile Edge Computing [17].

- **Small Cell Base Stations (SCBSs):** Small cell BSs, as shown in Figure 2.4, are essential to expand network's reach and capacity, highly used in congested user areas and indoor environments. The small cell KPIs are their ability to integrate with macro networks to improve coverage and high data rate capabilities. Deploying small cells is a policy that will guarantee steady and dependable connectivity across the 5G network by achieving the limitations of mmWave because small cell connectivity is more growth-oriented [16].

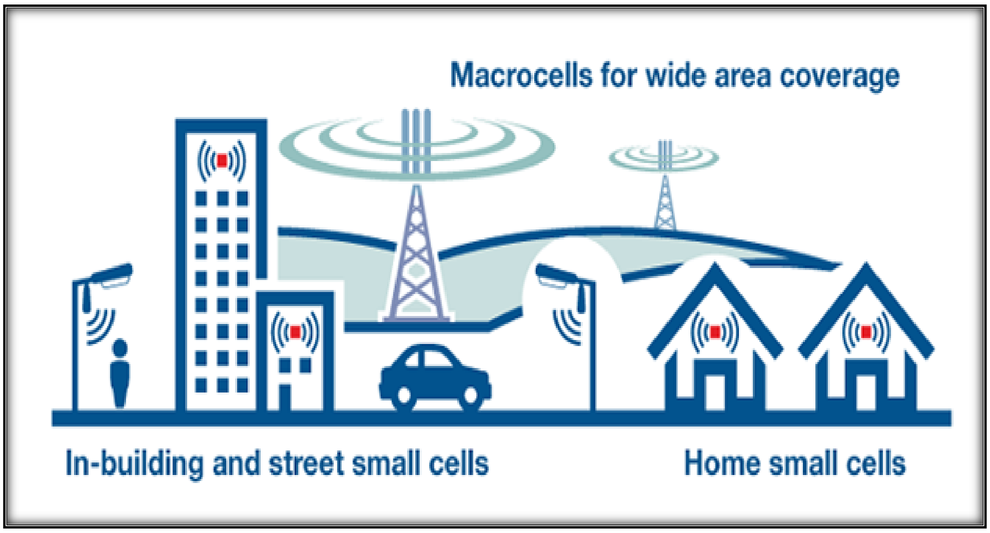

Fig. 2.4: Small Cell Stations [18].

- **Non-Orthogonal Multiple Access (NOMA):** Non-Orthogonal Multiple Access, shown in Figure 2.5, ensures that the same frequency resource transmits to multiple users all at the same time. A drastic difference to Orthogonal Multiple Accesses (OMA)s, which operate through orthogonal spectral uses, are recognized by a distinction in its power domain multiplexing implementation. Such is possible through the Successive Cancellation (SC) and the Successive Interference Cancellation (SIC). Evidently, the BS has the ability to serve as many users as it can as it results in efficient use of the spectrum. When coupled with the MIMO technology, the 5G network's aim to achieve higher data rates and user density. It promises further improvements and energy advancement for the 5G systems and widespread use in the IoT [19].

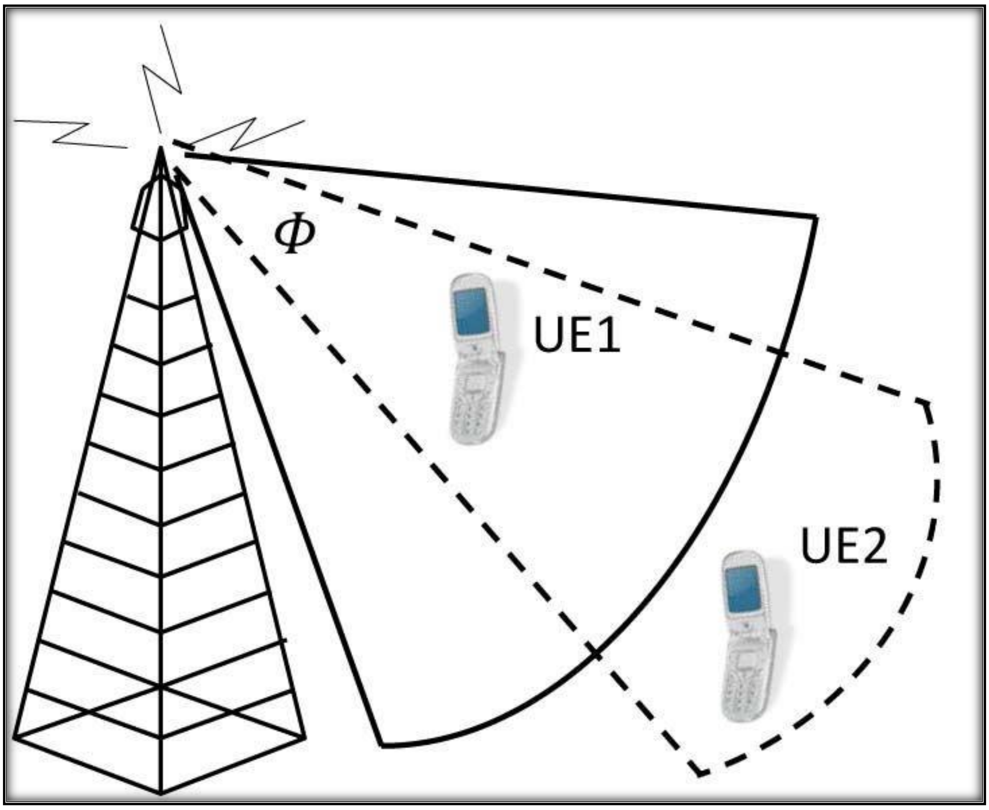

Fig. 2.5: Non-Orthogonal Multiple Access [20].

- **Beamforming:** Beamforming technology, shown in Figure 2.6, is necessary for radio wave propagation focused on specified users either when transmitting or receiving, which lead to signal impact and minimal interference. Success of the beamforming methods is measured by the increased signal to noise ratio, as well as minimal reduction of power usage. These measures define the perfect measure for the potentiality of focusing that characterize the power usage ability of the 5G. Sophisticated beamforming is therefore critical in addressing the technologies of mmWave and massive MIMO due to the assumed potentiality concerning the power usage ability metric [16].

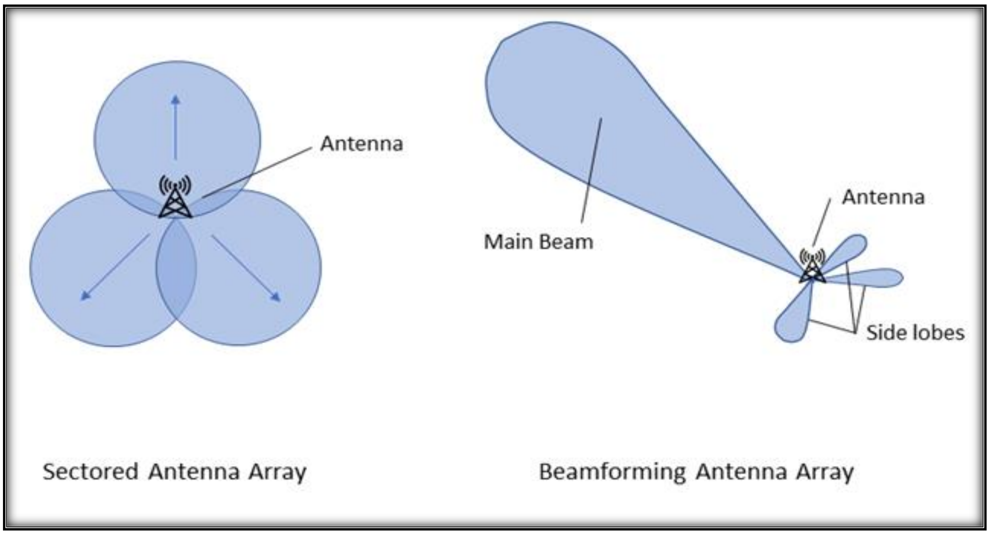

Fig. 2.6: Beamforming.

2.3. Introduction to Elevation Beamforming

Elevation beamforming is integral to making the revolutionary massive MIMO systems entirely realize the 5G and future wireless potentials. It is even more fundamental in high-mobility and continued mmWave operations since the conventional beam steering techniques are limited by fluctuations in the channel conditions, side communication, fast signal blockage, and interference systems. This study presents an overview of elevation beamforming from the basics, showing how it is expected to solve these challenges and take the wireless communication systems to a new level of efficiency and reliability.

As such, it is correct to describe massive MIMO systems as revolutionary since they will provide enough bandwidth to meet the increasing demand for high-data services like virtual/augmented reality and vehicle-to-everything systems. A classic challenge of these systems is how to maintain strong links between the fast-moving UE and the BS. This requires effective interference suppression and directional control, which is a process known as beamforming. Although traditional fully digital beamforming architectures may be formidable, the costs are prohibitive and overhead of energy consumption is enormous. Under the combined pressure, developers have come up with an answer in hybrid beamforming- the best of both systems that uses digital signal processing on baseband end to suppress interference and employs analog mechanisms such as phase shifters in Radio Frequency (RF) front while steering beams. Hybrid beamforming is particularly effective in large-scale MIMO systems because it reduces the number of required RF chains and thus itemizes both system complexity and cost. This new way of using AI for beamforming, together with Deep Reinforcement Learning (DRL), is a profound departure. It not simply promises better than theory communication ability in Massive MIMO projects over traditional beamforming approached but even development of underlying algorithms is simplified locally for everyone. This is especially important in edge computing scenarios, where computational resources are expensive, and good communications is crucial [21]. Figure 2.7 shows Elevation beamforming.

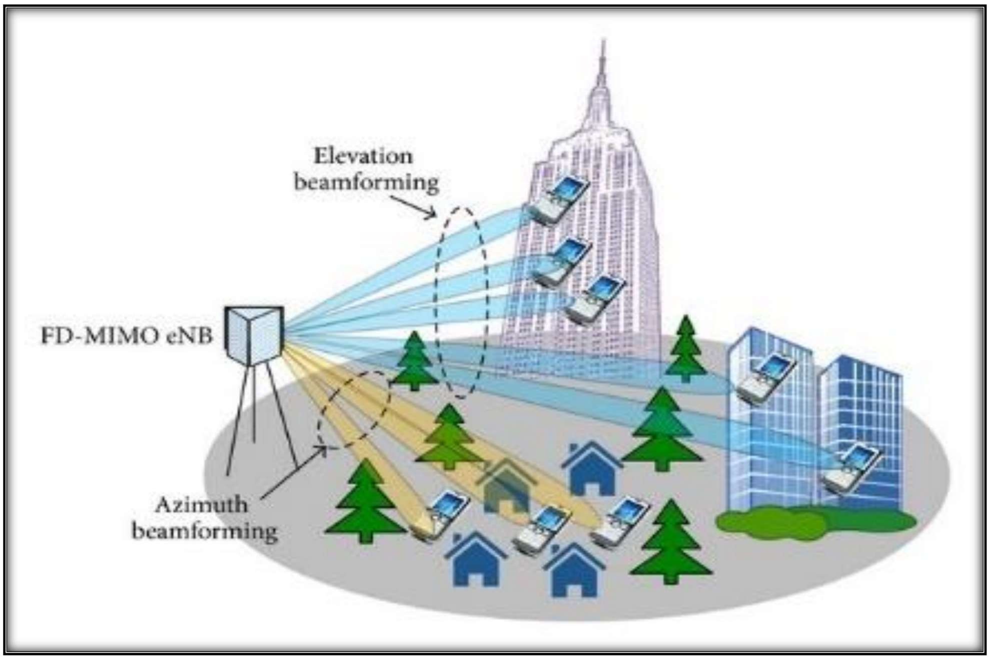

Fig. 2.7: Elevation Beamforming [22]

If hybrid beamforming in FD-MIMO systems is to succeed in practical operation, the intricate adaptation of beamforming vectors according to daily changing channel conditions is vital; this is an achievement that prior methods cannot accomplish, especially in cases as fluid as those involving high levels of mobility. Born out of this kind of consideration, recent advances have utilized deep learning methodologies, especially DRL, to design and then control the process of transmitting radio waves in space. These techniques allow beamforming vectors to adjust dynamically towards the source, leading to maximal energy efficiency and Quality of Service (QoS) network wide. The incorporation of DRL into beamforming reflects the general trend towards bettering machine learning for administering ever-more complicated wireless network systems.

Therefore, elevation beamforming, through the power of high-dimensional reinforced learning and hybrid radio communications means, has come to dominate technology that defines the shape wireless communications will take tomorrow. It also embodies the ongoing journey from hardware-defined to software-configurable radio systems; in this way a great leap forward is made toward at last realizing the full power of 5G and beyond [23].

2.4. Fundamentals of Beamforming

In Massive MIMO systems, beamforming is a technology that improves the signal processing capability of 5G and future 6G networks. In order to shape the signal radiation from antenna arrays dynamically, we use electronic networks, such as that given in Figure 2.8, to control amplitudes and phases at individual antennas on BS. SNR is critical for a receiver's performance. Through manipulation of antenna pattern--its power gain in various directions--beamforming accomplishes this end by improving reception quality. The result is that multiple UE can be served simultaneously over the same time-frequency resources through space-domain multiple access [24].

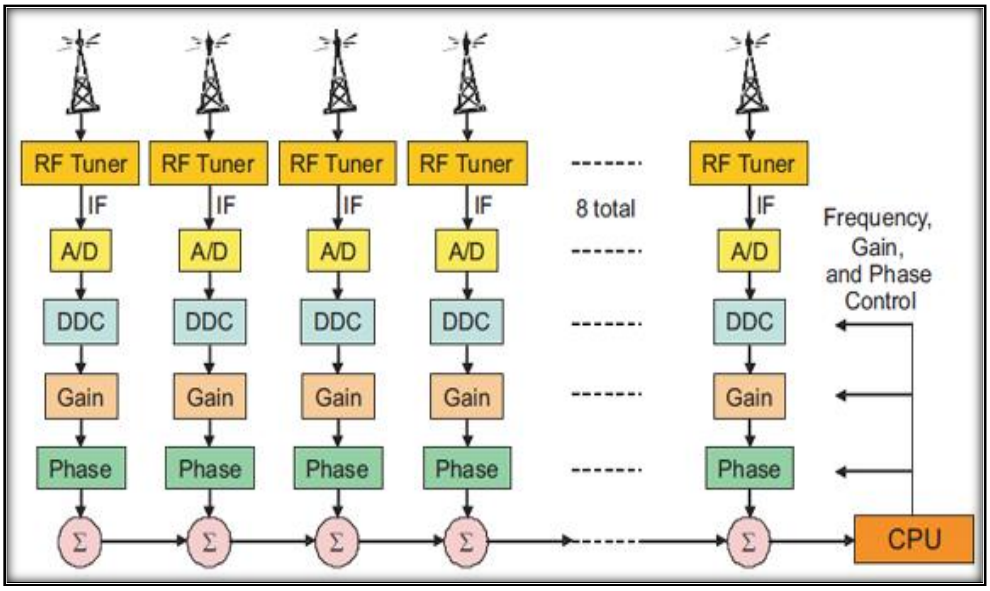

Fig 2.8: Channel Beamforming.

2.4.1. Beamforming Approaches

There are primarily two beamforming strategies in the context of massive MIMO systems: Grid of Beams (GoB) and adaptive beamforming.

- In GoB, the very important downlink Reference Signal Received Power (RSRP) measurement mainly depends on the Synchronous Signal Block (SSB) sent by BS. This method has the advantage of simplicity, ease in implementing--and it is well-suited for high mobility scenarios where the channel status goes through rapid periodic changes making real-time adaptive beamforming difficult. Figure 2.9 shows the GoB.
- Whereas in adaptive beamforming, the beamforming weight for Adaptive Beamforming demands accurate channel estimation, which has to be calculated from Sounding Reference Signals (SRS) in hope that by Time-Division Duplexing (TDD) systems. Although this method can lead to greater user throughput through increased accuracy of channel information, it needs sophisticated signal processing and

control, because the quickly outdated channel estimates of high-speed UE products makes it unsuitable for such equipment. [24].

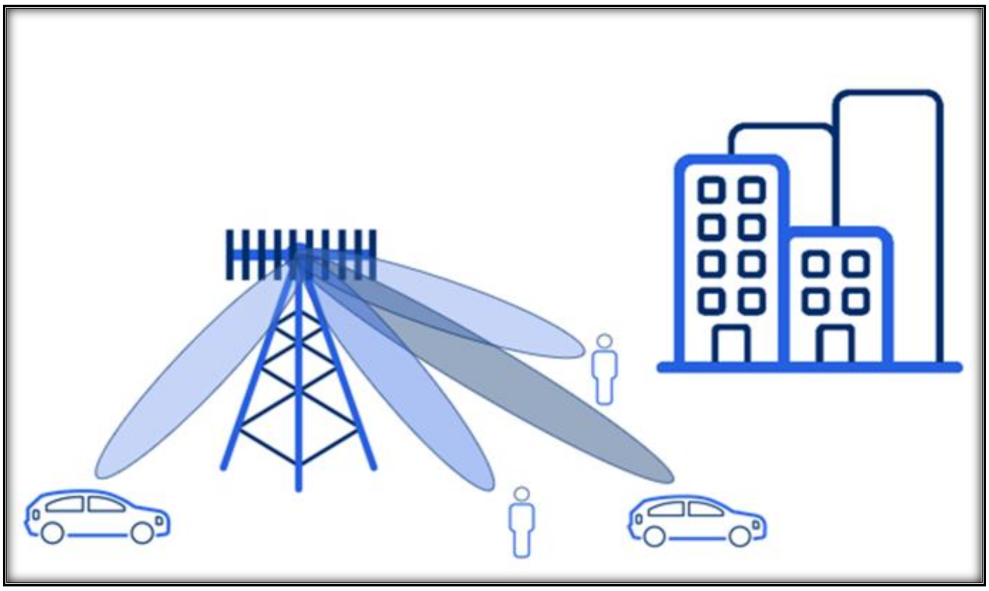

Fig 2.9: Grid of Beams [24].

2.4.2. Evolution from MU-MIMO to Massive MIMO

5G massive MIMO contextual help to support more users than ever before processing higher data rates with lower latency and higher need for reliability. When using traditional MIMO, both the transmitter and the receiver normally include as many as 8 antennas; but massive MIMO can support up to 256 BS antennas and 32 UE ones. An additional increase in the number of antennas makes a marked addition to the amount of throughput and coverage that can be had by cellular networks.

The next step, is to explain how massive MIMO overcomes the higher path losses during its use of high-frequency bands, thus achieving extended coverage. Using an integrated technology, which we call beamforming, to angle radio energy into more angular sectors proportionally improves the SE of this process.

2.4.3. FD-MIMO and 3D-MIMO

FD-MIMO not only enhances azimuthally, but adds the angle of inclination as 3D MIMO, antennas cytologically arranged within both horizontal and vertical dimensions. This approach vastly improves performance and use range at the BSs, therefore, transmission direction in both azimuth and elevation has been resolved into a task helpfully taken on by special chips. One of the more significant challenges in deploying FD-MIMO systems is the complex radio system that must be put in place.

To fully take advantage of this technology, radios are needed. It not only can handle 3D beamforming operations but do so in ways only possible through use of Native Instruments (NI) tools and modules right for the task. This includes having the accurate electric state feedback needed to improve the Channel State Information (CSI) and employ the quantum algorithms in advanced mode-forming techniques to efficiently drive beams towards users [25].

2.5. 3D Channel Modeling Approaches

Advances in 3D channel modeling methods have greatly raised the stakes for developing and applying Full Dimension-Multiple Input Multiple Output (FD-MIMO) technologies for 5G and beyond networks. It should be clear that these methods are necessary for Hybrid Beamforming (HB), which is crucial to harvesting the mmWave spectrum and massive MIMO communications, and these are both core technologies of 5G and beyond.

2.5.1. HB and Channel Modeling

The widespread adoption of HB strikes a balance between power, complexity, and cost for mmWave massive MIMO communications. Sometimes transiently through a variety of streams at the same time, this technique leverages both Digital Beamforming (DB) and Analog Beamforming (AB) benefits to create the possibility for mmWave communications with less computational overhead as well as lower cost.

2.5.2. Reasons for HB System's 3D Channel Modeling

- **Spectral Efficiency Optimization**: Effective HB requires precise modeling of the mmWave propagation environment, including considerations of path loss, shadowing, and multipath effects, to optimize SE.
- **Hardware Complexity and Energy Efficiency**: because the channel model used in a certain system is different from that of others, it will affect directly on how many RF chains and the physical and digital architecture of beamformers are needed. Accurate 3D channel modeling can reduce how much hardware there is and improve the energy efficiency.
- **Channel State Information (CSI) Accuracy**: The performance of HB significantly relies on the accuracy of CSI. Advanced 3D channel models enable more precise estimation of CSI, facilitating improved alignment of beams in both azimuth and elevation dimensions and enhancing the system's overall performance.
- **Adaptation to Environment Variability**: 3D channel models account for the variability in propagation environments, from urban high-rise scenarios to rural open spaces. This adaptability is essential for designing HBF strategies that can dynamically adjust to changing conditions to maintain optimal performance [26].

2.5.3. Beam Management in mmWave Communications

In mmWave communications, beam management includes three processes: beam selection, beam switching, and beam tracking. These are very important for keeping up a high-quality communication link with often quickly changing environmental conditions. With signals transmitted in such high frequencies and pinpoint directions, even if there is a slight shift in where the user equipment (UE) is located or what direction it faces, then this will have a big effect on channels. For this reason, efficient beam management strategies must be used if robust and reliable communication is to be achieved using FD-MIMO systems in the new mmWave spectrum. Figure 2.10 shows the beam management.

- **Beam Selection**: is the process of choosing the most appropriate transmit and receive beams from a predefined set or codebook to establish the initial communication link. Beam selection aims to maximize the received signal strength by considering the spatial correlation and the propagation.
- **Beam Switching**: when the UE is in motion, the initially selected beam may not be best. Changing beams means moving to a different beam or beams that is/are better performing under the new conditions, thus ensuring spatial correlation, which has been invented for both conditions, are managed and maintained through link quality, which is unaffected by pushes and pulls on noise characteristics.
- **Beam Tracking**: to sustain high-quality communication links in the face of UE mobility and dynamic channel conditions, beam tracking continuously monitors the channel and adjusts the beam direction and width. This adaptability is crucial for compensating for the spatial correlation effects and ensuring that the beamforming strategy remains aligned with the optimal communication path [27].

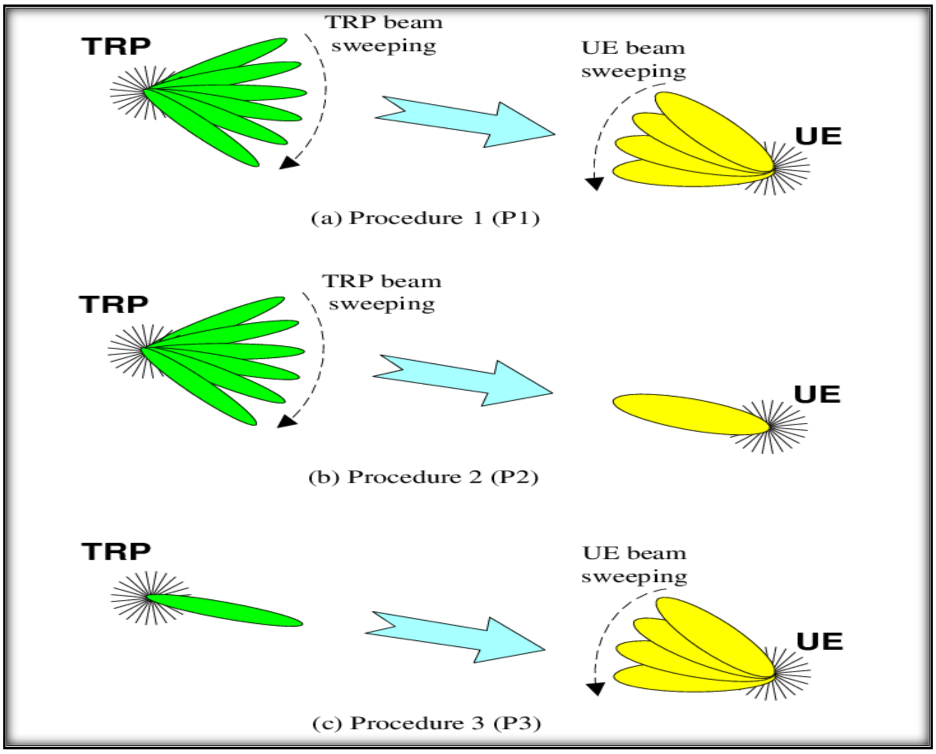

Fig. 2.10: Beam Management[27].

CHAPTER THREE

AI-ENHANCED BEAMFORMING FOR POWER-EFFICIENT IN 5G NETWORKS USING REINFORCEMENT LEARNING

3.1 Introduction

In the quest for optimizing 5G networks, this study introduces an innovative AI based beamforming technique, which focused on power efficiency and signal integrity. By combining Reinforcement Learning (RL) and adaptive signal processing, the system achieves optimal beamforming towards the user with the lowest power signature. The system starts at the BS which conducts an omnidirectional scan to identify and direct beams towards the UE exhibiting the lowest power signature, and optimizing the network's performance and efficiency.

In this chapter, extensive simulations are conducted using a Uniform Linear Array (ULA) at 28 GHz with Quadrature Amplitude Modulation (QAM) to authenticate the process. AI algorithm dynamically adjusted the beamforming weights, which were then applied to synthetic user signals to simulate real-world conditions. This study will conclude that AI based steering towards the least power-intensive user is not only viable but also enhances overall network efficiency and reliability.

3.2 System Architecture

The architecture of a system, which is suitable for setting up an elevation beam comprises all the hardware and software components needed to perform a beamforming operation. These components include the antenna array, RF radio-frequency chains and digital signal processing circuitry, and a means of acting over these components.

The architecture, which varies depending on the given application cellular communication, satellite communication, or radar system, mainly includes the following [28]:

- **Antenna Array**: The configuration of the antenna array (linear, planar, etc.) and the number of elements significantly influence the beamforming capabilities, particularly in elevation. The physical design and spacing of the antenna elements are crucial for achieving the desired beamforming performance.
- **RF Chains**: In a digital system, each antenna element is connected to the input of its dedicated RF chain. RF chain consists of amplifiers, mixers, and analog-to-digital and digital-to-analog converters. In analog and hybrid systems, several elements might share the same RF chain or use phase shifters and variable gain amplifiers for beam steering.
- **DSP Units**: Digital signal processors perform the calculations for generating the beamforming weights and adjusting them in real-time to steer the beam. The complexity of the DSP algorithms can vary from simple phase adjustment to more sophisticated techniques that account for channel conditions, interference, and optimization objectives.
- **Control Mechanisms**: Software-defined radios (SDRs) or other control systems are used to dynamically adjust the beamforming parameters based on feedback from the environment or system objectives. This includes changing the beam direction, shape, and other characteristics to optimize performance.

3.3 Algorithm Design

The design of the beamforming algorithm is critical for achieving the desired control over the beam's direction and shape, especially in the elevation plane. The algorithm must consider the array geometry, desired beam pattern, and environmental factors. Key considerations includes [29]:

- **Beam Steering Algorithms**: they are algorithms such as phase-shift beamforming, which adjusts the phase of the signal at each antenna element to steer the beam in a desired direction.
- **Beam Shaping Algorithms**: they are techniques that optimize the amplitude and phase weights to achieve a specific beam shape, such as reducing sidelobes or achieving a flat-top beam.
- **Adaptive Beamforming Algorithms**: these algorithms adjust the beamforming weights in real-time based on the received signal characteristics, and optimizing for metrics such as SINR.

The following pseudocode shows the system algorithm:

ALGORITHM 1 BEAMFORMING OPTIMIZATION ALGORITHM

```
Initialize reinforcement learning agent
Initialize URA array with parameters
    for each time step do
    Collect signals from users
    Estimate DOA and AOA for each user
    State ← Current network conditions (user positions, SNR,
            channel conditions)
    Action ← RL agent selects optimal beamforming direction and
            power level
    Apply beamforming to URA based on selected action
    Reward ← Compute reward based on signal quality and power
            efficiency
        if reward is below threshold then
        Adjust beamforming parameters
        Update RL agent with new state, action, and reward
    else
        Continue with current beamforming parameters
    end if
    if user mobility detected then
        Recalculate user positions
        Update state space with new positions
    end if
    Log performance metrics (BER, throughput, power efficiency)
end for
```

3.3.1 Simulation Environment

To evaluate the performance of the elevation beamforming system, a simulation environment is set up, which models the signal propagation, antenna array behavior, and environmental effects. The simulation environment allows for testing under various scenarios, including different array configurations, elevation angles, and channel conditions.

- **Simulation Tools**: Software tools such as MATLAB or Python libraries (e.g., NumPy, SciPy) are commonly used for simulating beamforming systems. These tools offer extensive libraries for signal processing, matrix calculations, and visualization.
- **Performance Metrics**: The simulation environment must be capable of calculating key performance metrics, including beamwidth, sidelobe level, and gain. These metrics are crucial for evaluating the effectiveness of the elevation beamforming design.
- **Scenario Testing**: The environment should allow for the simulation of different scenarios, including varying numbers of users, mobility patterns, and physical obstructions. This helps in understanding the system's performance in real-world conditions.

3.4 Artificial Intelligence and Reinforcement Learning

Certain AI algorithms are commonly referred to when considering wireless communications systems and beamforming when studying complex systems for which simple algorithms are unsuitable due to the high dimension or non-linear nature of the system [30].

RL is that part of machine learning, concerned with the question of how intelligent agents should take actions in an environment to maximize some cumulative reward. In the case of wireless communications and, more particularly, beamforming optimization for 5G systems, RL has emerged as a very powerful tool because of its ability to learn optimal policies in complex and dynamic environments without explicit programming. The basic idea of RL involves a learning agent in an environment that includes one series of observations, actions and rewards. The simple objective of the agent is to learn such a policy that is able to maximize the expected cumulative reward over time. Therefore, this learning process will turn out to be very useful in beamforming optimization where the wireless environment may change frequently and, correspondingly, the optimal beamforming strategy may have to change during real-time.

In a typical RL framework for beamforming, the components can be defined as follows:

- **State (S):** Represents the current condition of the wireless environment, including channel state information, user locations, and traffic demands.
- **Action (A):** Corresponds to adjustments in beamforming weights or directions.
- **Reward (R):** A scalar feedback signal that measures the quality of the action taken, such as achieved throughput or SINR.
- **Policy (π):** A strategy that the agent follows to select actions based on the current state.
- **Value Function (V):** Estimates the expected cumulative reward from a given state under a specific policy.
- **Q-Function (Q):** Estimates the expected cumulative reward for taking a specific action in a given state under a policy.

The RL agent will learn from the interaction with the environment, updating its policy according to the received rewards. In such a way, the agent will have the capability to improve over time the beamforming strategy and change it with respect to variations of the wireless environment or user's behavior.

Several RL algorithms have been applied to beamforming optimization in 5G systems:

1. **Q-Learning:** is a model-free algorithm that learns an optimal action-value function (Q-function) to determine the best policy.
2. **Deep Q-Networks (DQN):** is an extension of Q-Learning that uses deep neural networks to approximate the Q-function, enabling learning in high-dimensional state spaces.
3. **Policy Gradient Methods:** are algorithms that directly optimize the policy function, such as REINFORCE (Monte Carlo Policy Gradient) and Trust Region Policy Optimization (TRPO).
4. **Actor-Critic Methods:** Combine value function estimation with policy optimization, examples include Advantage Actor-Critic (A2C) and Deep Deterministic Policy Gradient (DDPG).
5. **Proximal Policy Optimization (PPO):** is a policy gradient method that uses a clipped surrogate objective to ensure stable learning.

Compliance with these requirements in beamforming optimization can be done by adaptation of these algorithms with regards to the unique characteristics of the wireless environment and the constraints of the beamforming system.

3.4.1 Advantages of Reinforcement Learning in Beamforming

Reinforcement Learning offers several key advantages when applied to beamforming optimization in 5G systems:

1. **Adaptability to Dynamic Environments:** Due to their ability of continuous learning, RL algorithms can adapt to changes in network conditions and are, hence, well-suited for the dynamism in wireless communications. For example, such adaptability is of utmost importance when users are mobile, while traffic patterns keep on changing and channel conditions vary.

2. **Model-Free Learning:** In contrast to other optimization techniques, that require an accurate model of the system, RL is able to learn optimal policies directly from the interaction with the environment. This will turn out to be particularly useful in complex wireless scenarios wherein exact modeling is either difficult or requires large computational effort.
3. **Handling High-Dimensional State and Action Spaces:** Advanced RL algorithms, more specifically, deep-learning-based ones, are able to accommodate large-dimensional state and action spaces typical in massive MIMO beamforming systems.
4. **Long-Term Optimization:** RL mostly focuses on maximizing the cumulative rewards over time, deriving strategies that optimize long-term performance and not myopic short-term gains. This is valuable in scenarios in which short-term optimizations may result in suboptimal overall network performance.
5. **Multi-Objective Optimization:** The reward function of RL may be designed to obtain as many objectives as desired. During training, it tries to maximize the throughput, decreases energy consumption and takes care of fairness between the different users.
6. **Exploration-Exploitation Balance:** By design, RL algorithms manage a smart tradeoff between the exploration of new strategies and the exploitation of known good solutions. That helps to find new beamforming techniques that might not come out from traditional optimization techniques.
7. **Scalability:** The RL approaches can be scaled to tackle large-scale MIMO systems with huge numbers of antennas and users, so as to fit very well into the next generation of wireless networks.
8. **Transfer Learning Capabilities:** Knowledge acquired through training in one scenario might be transferred to similar environments

and evading the need for extensive retraining every time deployment of beamforming systems is done in new locations.

9. **Handling Partial Observability:** Some of the RL algorithms are designed to work in a partially observable environment, such as in most cases in wireless systems when the whole channel state information is unavailable.
10. **Integration with Other AI Techniques:** It is possible to integrate RL with other machine learning methods; for example, using supervised learning to train the initial policy or unsupervised learning to obtain the state representation for establishing more powerful and efficient beamforming.

Such are some of the gains that make reinforcement learning very promising for tackling the beamforming optimization complex challenge of 5G and beyond systems related, specifically, to scenarios with massive MIMO, millimeter-wave communications, and ultra-dense network deployments.

3.4.2 Hybrid Reinforcement Learning with Domain Knowledge for Beamforming Optimization

From the practical standpoint, an ideal example of RL algorithms being efficiently used to optimize the beamforming vectors in the MIMO systems. Properly adjusting the weights of antenna elements in an array allows radiation pattern shaping. It ensures maximize of the desired signal while the further interference propagation is minimized. This factor is of the utmost importance considering the ongoing evolution of wireless networks [31].

This dissertation presents a brand-new approach, based on a Hybrid RL method enhanced with domain knowledge, toward beamforming optimization in the 5G system. To be more exact, by fusing the adaptive learning capabilities of RL, the researcher manages to put into practice knowledge from the area of wireless communications and beamforming.

The proposed method can be characterized as follows:

1. **Hybrid Nature:** It integrates reinforcement learning principles with domain-specific heuristics and optimization techniques from beamforming and wireless communications.
2. **Adaptive Learning:** Quite like the traditional methods based on RL, it learns and refines the beamforming strategy by continuous interaction with the wireless environment.
3. **Domain Knowledge Integration:** Domain knowledge builds in the knowledge on beamforming, channel characteristics, and wireless network dynamics to guide the learning and speed up its convergence.
4. **Feedback-Driven Optimization:** It uses the BER and throughput of the system for performance metrics, thus acting as feedback signals that tune and fine-tune the beamforming parameters.
5. **Iterative Improvement:** Iterative improvement improves its beamforming strategies in cycles to find a better performance through repeated actions, observation of the environment and adaptation.

In these complex and dynamic 5G surroundings, this hybrid approach makes it possible to efficiently optimize beamforming parameters by use of both reinforcement learning's adaptability and the reliability of established domain expertise.

3.5 Mathematical System Model

The mathematical equations provided are recognized in the communications engineering discipline and represents a fundamental resource for the proposed model. The system utilizes RL for dynamic scaling of user signals. A persistent state switches between different scaling factor sets, allowing the system to explore different configurations and optimize performance over time. The adaptive signal processing component includes phase shift beamforming and the MUSIC estimator for DOA estimation. These adaptive algorithms align with the principles of machine learning, facilitating dynamic adjustments for optimal beamforming [32], [33].

3.5.1 Mathematical Model for Beamforming

The mathematical model of the simulated AI based beamforming system can be described mathematically just as follows; consider a ULA with " N " antenna elements spaced at half the wavelength $\left(\frac{\lambda}{2}\right)$ apart. The array factor for a ULA can be expressed in Eq. (1):

$$[\boldsymbol{AF(\theta)} = \sum_{\boldsymbol{n=0}}^{\boldsymbol{N-1}} \boldsymbol{w_n e^{-jkn\cos(\theta)d}}] \qquad \textbf{(3-1)}$$

Where (w_n) is the complex weight, applied on the ninth elements, represented here as $(k = \frac{2\pi}{\lambda})$, where (d) signifies for the distance between elements and (θ) is taken to be the arrival of angle of signal. The received signal (x(t)) at the ULA from a user can be modeled as shown in Eq. (2):

$$[\boldsymbol{x(t) = A(t)s(t)e^{j(2\pi f_c t+\phi)} + n(t)}] \qquad \textbf{(3-2)}$$

Where $(A(t))$ is the signal amplitude, $(s(t))$ is the transmitted signal, (f_c) is the carrier frequency, (ϕ) is the phase shift introduced by channel and $(n(t))$ stands for noise is the signal amplitude.

An AI based beamforming algorithm should strive to optimize the weights ($\mathrm{w_n}$) such that SNR, is maximized, and power consumption is minimized at the user; it is done by reducing the overall radiated power(P_{total}), which is to be transmitted while making sure that the signal strength picked up by the intended user fall over a threshold(γ). It can be formulated into an optimization problem as in Eqns. (3,4):

$$[\boldsymbol{W_{min}P_{total}} = \boldsymbol{W_{min}} \sum_{n=0}^{N-1} |\boldsymbol{w_n}|^2] \tag{3-3}$$

$$[\ \mathbf{s.t.}\ \frac{|\mathbf{AF(\theta)A(t)}|^2}{\boldsymbol{\sigma}_\mathbf{n}^2} \geq \boldsymbol{\gamma}\ ] \tag{3-4}$$

Where (σ_n^2) is the noise power.

AI algorithm adjusts according to the characteristics of the received signals and difference between users' locations by iterative updating weights(w_n). The feedback mechanism used by the AI includes Bit Error Rate (BER) and throughput measurements; that are adjusted by means of tuning of beamforming weights for the network to adjust accordingly to any changes around it or in user behavior.

3.5.2 Mathematical Model for AI Training

Consider a case of (K) users and ($s_k(t)$) represents the signal destined for the (k^{th}) user, while ($x_k(t)$) indicates the received vector at ULA by the (k^{th}) user. The ULA has (N) antenna elements. The channel between the array and each user indicated by(h_k), which is itself a complex vector that specifies the channel coefficients.

The AI algorithm operates in two phases: training and execution. In (Training Phase), the AI uses a set of training signals to learn the optimal beamforming weights. The CSI for each user is estimated and stored. In this stage, the AI employs a bunch of training signals in order to compute the most appropriate beamforming weights. CSI for each user, i.e.,(h_k), is valued and preserved. In (Execution Phase), the AI applies the learned weights and calculates estimated CSI to adapt it in real time for beamforming vector according to changing conditions. An optimization issue of beamforming is the minimization of power with Quality of Service (QoS) constraints related to each user as in Eq. (5).

$$[\min_{W} = \sum_{k=1}^{K} |\, w_k|^2] \tag{3-5}$$

Subject to the following constraints for each user(k), Eq. (6) is representing SINR constraint for user(k):

$$[\frac{\left|h_k^H w_k\right|^2}{\sum_{i \neq k}\left|h_k^H w_i\right|^2 + \sigma^2} \geq \gamma_k] \tag{3-6}$$

Where $(w_k)$the beamforming vector for user is(k), (γ_k) is the minimum SINR required for user(k), and (σ^2) is the noise power.

QoS constraints such as the minimum data rate requirement modeled in Eq. (7):

$$[\log_2(1 + SINR_k) \geq R_k] \tag{3-7}$$

Where $(R_k)$is the minimum data rate required for user(k). The objective function seeks to minimize the sum of transmit power for all users without damaging their QoS. The real-time channel estimations and the QoS requirements change accordingly, while the AI algorithm adjusts in time by adjusting its weights($W = [w_1, w_2, \ldots, w_K]$).

The AI could potentially use RL techniques to learn the optimal policy for adjusting beamforming weights. For instance, one might train deep neural network with the given CSI and QoS specifications as an input and the optimal beamforming weights for accessing best BS transmitting state if any or only one user at a time is in a traffic jam. While functional, the network would extract current CSI and QoS demands during operation that would feed-in to present weights of minimum power with constraints gratified. These elements significantly increase the complexity of the mathematical model; however, they contribute to greater adaptability and efficiency of AI driven beamforming strategy in a mobile multi-user environment. This model paves the way for a powerful system, which can achieve power optimal usage in such an environment that relies heavily on energy-use appliances and people with user satisfaction.

3.5.3 Mathematical Model for 16-QAM System's Modulation

For the proposed system, the following 16-QAM modulation equations have been used for beamforming and signal transmission. The BER for a 16-QAM modulation in an Additive White Gaussian Noise (AWGN) channel can be approximated in Eq. (8):

$$[\boldsymbol{BER \approx \frac{4}{log_2(M)}\left(1 - \frac{1}{\sqrt{M}}\right) Q\left(\sqrt{\frac{3\,log_2(M)\cdot E_b}{(M-1)N_0}}\right)} \tag{3-8}$$

Where (M) is the modulation order (16 for 16-QAM), ($Q(x)$) is the Q-function, which represents the tail probability of the Gaussian distribution, (E_b) is the energy per bit, (N_0) is the noise power spectral density, and the (E_b/N_0) ratio is a normalized measure of the signal energy per bit to the noise power spectral density. The relationship between (E_b/N_0) and the SNR for 16-QAM is given by Eq. (9):

$$[\boldsymbol{SNR = \frac{E_b}{N_0}\cdot\frac{R_b}{B}}] \tag{3-9}$$

Where (R_b) is the bit rate, (B) is the bandwidth of the channel. Eq. (10) can be rearranged to express (E_b/N_0) in terms of SNR:

$$[\frac{\boldsymbol{E_b}}{\boldsymbol{N_0}} = \frac{\boldsymbol{SNR}}{\boldsymbol{R_b/B}}] \qquad \textbf{(3-10)}$$

The SNR can be converted to decibels (dB) in Eq. (11):

$$[\boldsymbol{SNR(dB)} = \mathbf{10} \cdot \boldsymbol{log_{10}}(\boldsymbol{SNR})] \qquad \textbf{(3-11)}$$

3.5.4 Throughput Calculation

Throughput is the rate of successful message delivery over a communication channel. The throughput can be affected by the BER as errors require retransmission or error correction. The theoretical throughput without considering errors can be expressed in Eq. (12):

$$[\boldsymbol{Throughput} = \boldsymbol{R_b} \cdot (\mathbf{1} - \boldsymbol{BER})] \qquad \textbf{(3-12)}$$

However, considering retransmissions because of errors, the effective throughput becomes as shown in Eq. (13):

$$[\boldsymbol{Throughput_{effective}} = \frac{\boldsymbol{R_b} \cdot (\mathbf{1} - \boldsymbol{BER})}{\mathbf{1} + \boldsymbol{Retransmissions\ due\ to\ errors}}] \qquad \textbf{(3-13)}$$

3.5.5 Array Gain and Beamforming

The gain of an antenna array due to beamforming is related to the number of elements and their patterns. The array gain (G) can be approximated by applying Eq. (14):

$$[\boldsymbol{G} = \boldsymbol{N} \cdot \boldsymbol{G_e} \cdot \boldsymbol{AF}(\boldsymbol{\theta})] \qquad \textbf{(3-14)}$$

Where (N) is the number of antenna elements, (G_e) is the gain of a single element, ($AF(\theta)$) is the array factor, and (θ) is a function of the direction relative to the beam's main lobe.

For a ULA, the array factor for broadside direction can be simplified as in Eq. (15):

$$[\boldsymbol{AF(\theta)} = \frac{\boldsymbol{sin(N\pi d\, sin(\theta)\,/\lambda)}}{\boldsymbol{N\, sin(\pi d\, sin(\theta)\,/\lambda)}}] \qquad \textbf{(3-15)}$$

Where (d) is the distance between elements, (λ) is the wavelength of the carrier signal, and (θ) is the angle relative to the array axis.

3.5.6 Beam Steering

The phase shift (Φ) required for beam steering towards a particular user can be calculated by the following Eq. (16):

$$[\boldsymbol{\Phi_n} = \frac{\{\boldsymbol{2\pi}\}\{\boldsymbol{\lambda}\}}{\boldsymbol{(n-1)dsin(\theta_d)}}] \qquad \textbf{(3-16)}$$

Where (Φ_n) is the phase shift for the (N)-th element, (θ_d) is the desired steering angle, and(n) is the element index in the array.

3.5.7 MUSIC Algorithm

The AI uses statistical methods and signal processing algorithms. Thus, when noise is present the AI uses an algorithm known as MUSIC for determining the direction of signal by leveraging orthogonality between signal and noise subspaces. The MUSIC estimator locates peaks in the spatial spectrum that correspond to directions of incoming signals.

For signal model, each user signal can be represented as a delta function in time. For the (i)-th user, the signal ($s_i(t)$) at time (t) is given by Eq. (17):

$$[\boldsymbol{s_i(t)} = \boldsymbol{\delta(t - t_{0i})}] \quad \textbf{(3-17)}$$

Where (δ) is the Dirac delta function, and (t_{0i}) is the time of arrival for the (i)-th user's signal.

The AOA for the (i) -th user is represented as a vector ($\theta_i = [\theta_{az,i}; \theta_{el,i}]$), where ($\theta_{az,i}$)is the azimuth angle and ($\theta_{el,i}$) is the elevation angle. The AOA determines the phase shift across the antenna elements and is critical for beamforming.

The response of an antenna array can be mathematically described by its array factor($AF(\theta)$). For a ULA, the array factor is given by Eq. (18):

$$[\boldsymbol{AF(\theta)} = \sum_{\boldsymbol{n=1}}^{\boldsymbol{N}} \boldsymbol{e^{-j\frac{2\pi}{\lambda}d(n-1)sin(\theta)}}] \quad \textbf{(3-18)}$$

Where (N) is the number of elements, (d) is the element spacing, (λ) is the wavelength, and (θ) is the AoA. The beamforming levels assigned to all antenna elements direct the beam towards a certain direction. These weights (w) are complex numbers applied to the phase and amplitude of the received signal on each element. The weights for the (N)-th element to direct the beam towards (θ) are given by Eq. (19):

$$[\boldsymbol{w_n} = \boldsymbol{e^{j\frac{2\pi}{\lambda}d(n-1)sin(\theta)}}] \quad \textbf{(3-19)}$$

The power (P) of the signal after applying the scaling factor (a) is calculated using Eq. (20):

$$[\boldsymbol{P} = \sum_{\boldsymbol{t}} |\boldsymbol{a} \cdot \boldsymbol{s(t)}|^2] \quad \textbf{(3-20)}$$

The MUSIC algorithm estimates the DOA by forming a spatial spectrum and identifying its peaks. The spatial spectrum for MUSIC is given by Eq. (21):

$$[\boldsymbol{P}(\boldsymbol{\theta}) = \frac{\mathbf{1}}{\boldsymbol{a}(\boldsymbol{\theta})^{\boldsymbol{H}}\boldsymbol{E}_{\boldsymbol{n}}\boldsymbol{E}_{\boldsymbol{n}}^{\boldsymbol{H}}\boldsymbol{a}(\boldsymbol{\theta})}] \qquad \textbf{(3-21)}$$

Where $(a(\theta))$is the steering vector, (E_n) is the noise eigenvector matrix, and (H) denotes the Hermitian transpose.

The beam is steered by adjusting the weights applied to the received signals. The beamforming output (y) is shown in Eq. (22):

$$[\boldsymbol{y}(\boldsymbol{t}) = \boldsymbol{w}^{\boldsymbol{H}}\boldsymbol{x}(\boldsymbol{t})] \qquad \textbf{(3-22)}$$

Where $(x(t))$ is the received signal vector at the antenna elements, and (w) is the weights vector.

3.6 Brief Overview for the Models

Generally, in the current study, the researcher applies two different system models with different configurations. The first model is designed on the bases of horizontal users and the second model is more advanced to cover vertical users as well in the elevation section.

3.6.1 Horizontal System Model

The strategy involves guiding the beam to those users and detecting the user which has an extremely low measurement of power under the preservation of signal integrity. Figure 3.1 shows how machine learning algorithms (MLAs) can be used to look at and change beamforming weights in real time with a phased array system that works at 28 GHz carrier frequency for two users.

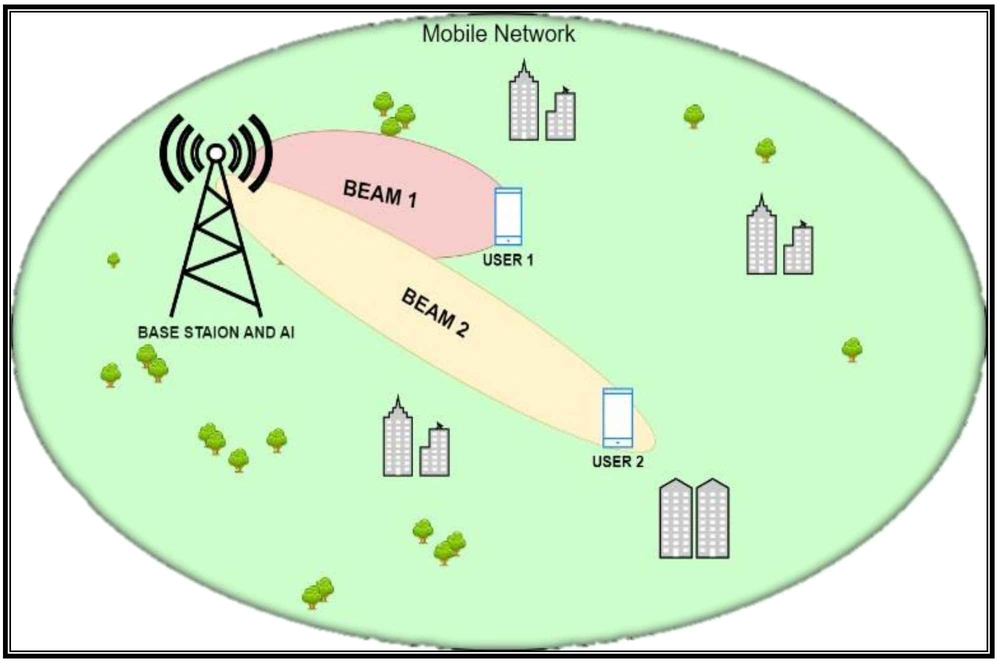

Fig. 3.1. Beamforming System Model

Referring to Figure 3.2, the system starts by collecting the signals from the users in the network, then calculates their AoA and sets a scaling factor based on their distance relative to the power level of the users.

After the operation is done, the AI chooses the user with the least power in the network and adjusts the beam towards the user with the least power.

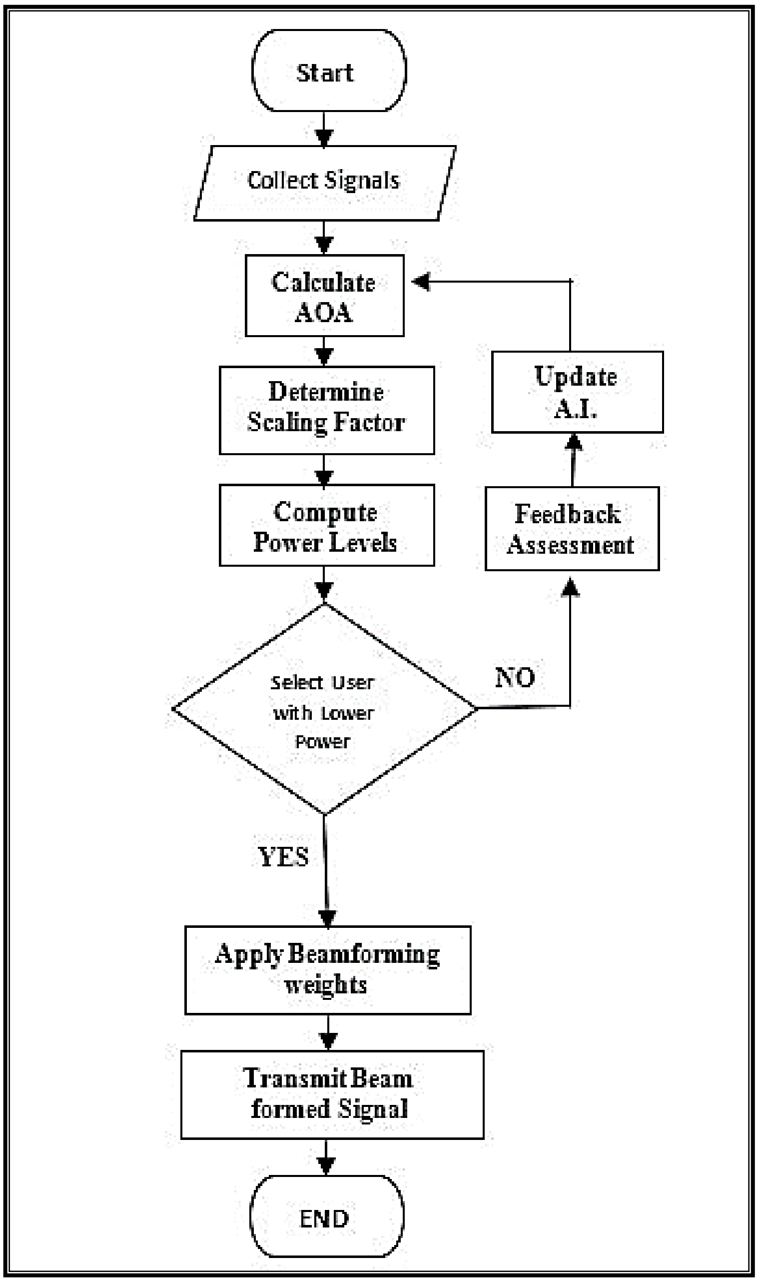

Fig. 3.2. Horizontal System's Flowchart.

If the user moves or changes, UE power is restored; a recalibration happens by sending feedback to the station, which makes the system re-do the scaler calculation.

3.6.2 Vertical System Model

The system model, as shown in Figure 3.3, is placed within a mobile network context, where the central communication hub is a BS, interacts with a number of UEs within a defined coverage area. The BS is equipped with complex signal processing systems and it is responsible for guiding the beam and maintaining a dependable link to the UE. In such network, mobile users (referred to as User 1 and User 2) are mobile all the time and make the direction of arrival (DoA) of the signal dynamic; hence, there is a need for an adaptive signal processing. On the contrary User 3 and User 4 are static, being inside a building of different heights, where signal transmission meets multipath propagation effects caused by reflections, causing phase and time delays. The model shows the realities of signal propagation in the real world and the need for advanced beamforming methods to meet the complex communication needs within a 5G network environment.

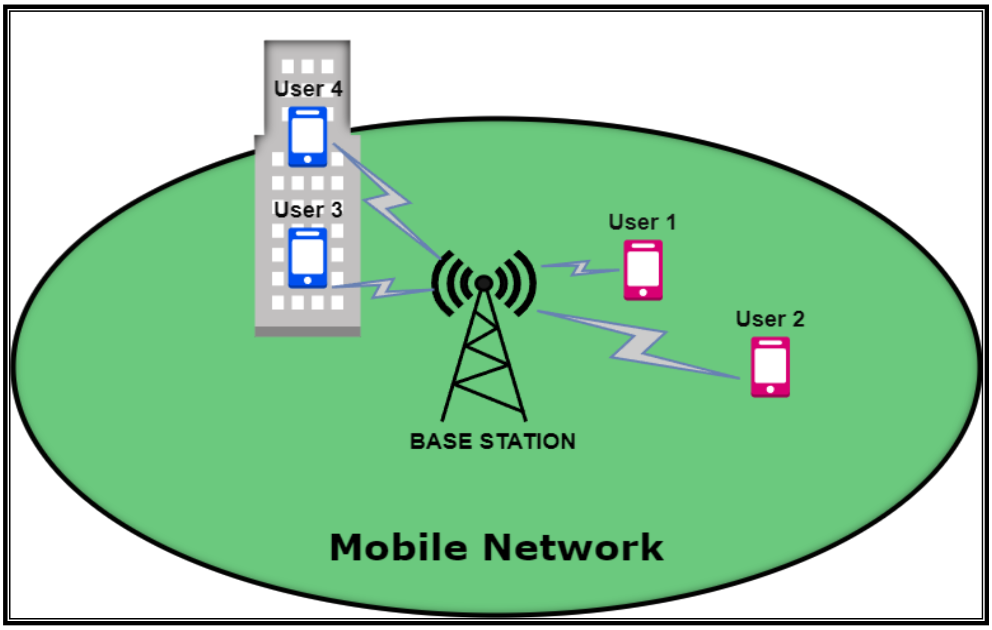

Fig. 3.3 Proposed System Model

The flowchart in Figure 3.4 outlines an AI-enhanced beamforming system designed for 5G networks, starting with the initialization of a URA, crucial for capturing and processing signals in a multi-user environment. Signals for multiple users are generated and then subjected to a unique set of scaling factors, optimizing their power levels for improved reception and processing efficiency. These signals undergo a beamforming process where the system dynamically selects the optimal direction based on the lowest power signal, demonstrating the adaptive nature of the system to focus on weaker signals and enhance overall network performance.

A feedback loop is incorporated to evaluate the system's performance continually, with BER and throughput calculations serving as key metrics. This loop allows for real-time adjustments to the beamforming strategy, ensuring the system's adaptability to varying network conditions and user requirements. Additionally, the system employs DoA and AoA estimation techniques, further refining the beamforming process by accurately determining the signal's origin. This precise localization is essential for targeting the beamforming efforts more effectively and is indicative of the system's capability to handle complex urban scenarios.

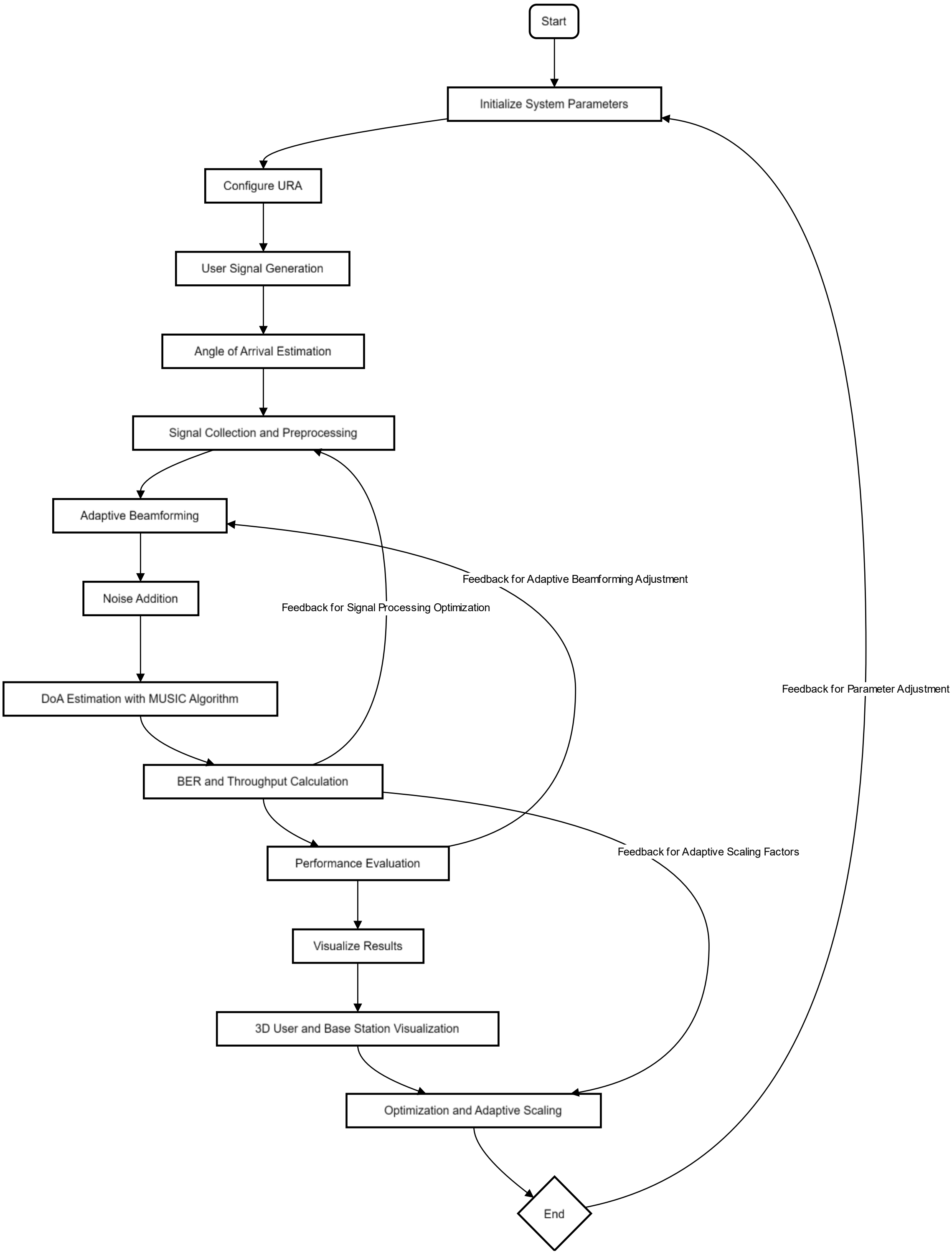

Fig. 3.4. Vertical System's Flowchart

3.7 System Assumption and Configuration

The following section contain system assumption, configuration the simulated MATLAB model, and the designed system's flowchart as follows:

3.7.1 System Assumptions

- Modulation Scheme (16-QAM)
- Beamforming Algorithm is Hybrid Phased
- AI Algorithm for Beam Steering for optimizing power consumption and maintaining signal integrity.
- Distinct signals are generated to represent users, each with a unique time of arrival.
- The angles of arrival (AoA) for each user are randomized within a range of -90 to 90 degrees.
- The AI algorithm assigns scaling factors to the signals, which adjust their amplitude and, consequently, their power.
- Power calculations for each user's signal are performed to determine which user has the lower power signal.
- Noise is artificially added to the signals to simulate a realistic communication environment.
- The signals for both users are received through an antenna array with noise components.
- A beamforming algorithm is applied to the noisy signals and combining them in such a way to form a single beam directed towards the chosen user's signal.
- The AI employs a DOA estimation algorithm (MUSIC estimator) to find the direction from which the signals are arriving amidst the noise.
- The AI uses the calculated power to decide which user to direct the beam towards and opting for the user with the lower power signal to optimize system performance.
- The AI controlled system dynamically adjusts the beam direction to align with the estimated DOA of the selected user.

3.7.2 System Configurations

The systems implemented in this dissertation have similar properties, but there are few distinct differences between them. The most distinct difference between the two systems is the different uses of array model. The horizontal system utilizes ULA and the vertical system utilizes Uniform Rectangular Array (URA). Further explanation about their usage will be discussed in the results section in this dissertation.

3.7.2.1 Horizontal System Configuration

Referring to Table I shown below, which shows the configurations parameters that has been used for the MATLAB simulated modeled system, along with their direct impacts and effects on the calculated results.

Table 3.1: Parameters Impact on the Results

Parameter	Setting	Impact on Results
Carrier Frequency	28 GHz	Affects wavelength and antenna design
Signal Amplitude	1V	Influences power calculation and beam direction
Antenna Array Elements	10	Impacts the array's ability to form and steer beams
Element Spacing	λ/2	Affects the array's spatial resolution and side
Modulation Order (M)	16	Affects BER and throughput
SNR	-25 to 25 dB	Challenges the AI in correctly estimating DOA
Angle of Arrival (AoA)	MUSIC	Determines beam steering direction
Scaling Factors	0-1	Used by the AI to prioritize users based on power
Frame Duration/s	1ms	Affects the data transmission
Symbol Rate / Hz	1 MHz	Rate at which symbols are transmitted

3.7.2.2 Vertical System Configuration

Table II shows a summary for the important parameters and techniques used in the MATLAB simulation. It is also worth to mention that the main numerical parameters including frequency values, element layout, signal characteristics, noise level and the methods employed for signal processing, beamforming, and angle of arrival estimation in the context of a phased array system simulation are also included.

Table 3.2: Parameters Assumptions of the Chosen Modeled System

Parameter/Technique	Value/Description
Carrier Frequency	28GHz
Number of Elements in Array	8x8
Element Spacing	$(\lambda/2)$
Frequency Range	27GHz to 29GHz
Angle of Arrival (Horizontal)	Random integer between -90 and 90 degrees
Angle of Arrival (Vertical)	Random integer between 0 and 70 degrees
Noise Power	1.5 (1.76 dB)
Beamforming Direction	Based on the user with the lowest power signal
Phased Array Technique	Uniform Rectangular Array (URA)
DoA Estimation	MUlti SIgnal Estimator (MUSIC Estimator)
Modulation Order (M)	16 (QAM)
Symbol Rate	1 MHz
Frame Duration	1 ms
Eb/No Values	-25 to 25 dB
Number of Symbols Per Frame	100

CHAPTER FOUR

RESULTS EVALUATION AND DISCUSSION

4.1 Introduction

In this chapter, the researcher initiates the evaluation of findings of the study, focusing on the performance of the AI-driven system in handling complex signal environments. This part of the dissertation is dedicated to exploring how artificial intelligence manages noise and enhances signal clarity, thereby improving communication efficiency under varied and challenging conditions.

The analysis not only underscores the AI's utility in signal processing, but also showcases its potential applications in real-world scenarios. By examining the system's ability to maintain high integrity and precision in signal handling, this section provides critical insights into the technological advancements that drive modern communication systems. The results discussed here lay the groundwork for understanding the broader implications of AI in enhancing network performance and reliability.

4.2 ULA and URA Choice of Matter

The choice between ULA and URA in beamforming is largely determined by the specific requirements of the system and the environment in which it operates. A ULA, which consists of antennas arranged in a line, is capable of forming beams in one dimension (azimuth), but it lacks the ability to form beams in the elevation dimension. This is because the antennas in a ULA are aligned along a single axis, which limits their ability to steer the beam in multiple dimensions.

On the other hand, a URA, which has antennas arranged in a rectangular grid, can form beams in both azimuth and elevation dimensions, making it suitable for 3D beamforming or Massive MIMO [34]. This is particularly useful in urban environments where users may be located at different heights, such as in multi-story buildings [35].

The ability of URAs to perform 3D beamforming is due to their two-dimensional structure, which allows them to steer the beam in both horizontal and vertical directions. This provides more degrees of freedom and increases the number of high-throughput users [36].

However, it's important to note that the choice between ULA and URA isn't about one being "better" than the other, but rather about choosing the right tool for the job based on the specific requirements of the system and the environment. Both ULA and URA have their own advantages and can be effectively used in different scenarios. For instance, ULA might be preferred in environments where the users are spread out in the horizontal plane, while URA might be more suitable in environments where users are distributed in three dimensions.

4.3 Horizontal System

System analysis starts with Figure 4.1, which illustrates a time-domain signal depiction for two different users. Figure 4.1 shows the users being spread out in time domains, and they are separated from each other to make them more distinct.

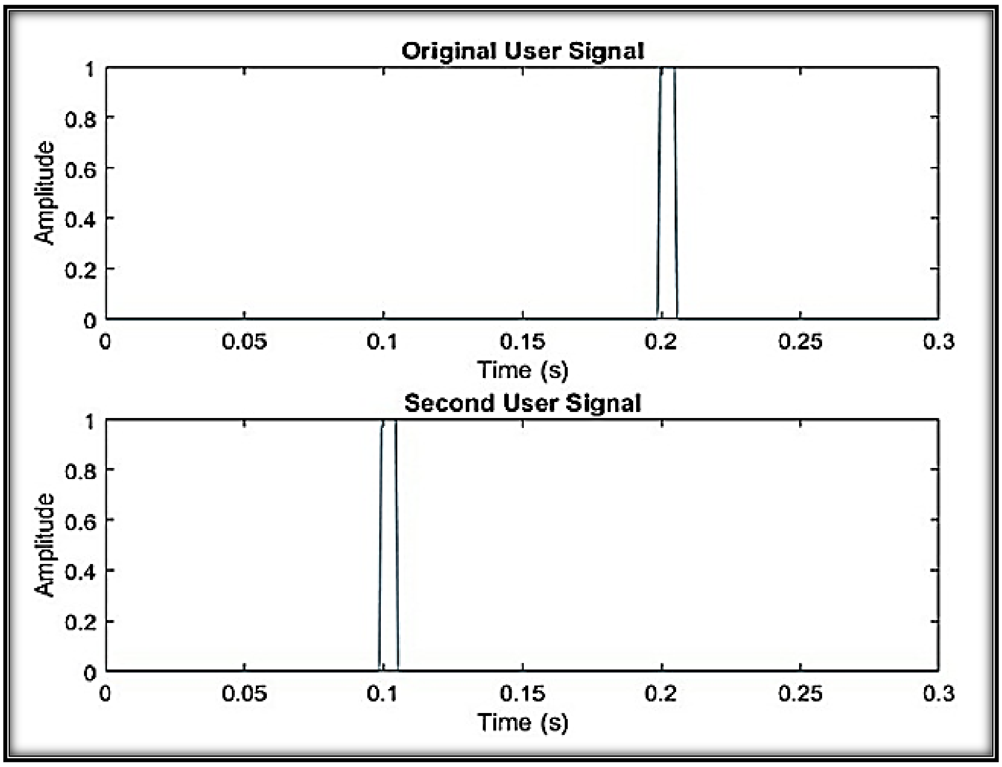

Fig. 4.1: Time-Domain Signal for Two Users

In Figures 4.2 and 4.3, noise has been added to the received signals at each antenna element to emulate these real-world conditions. This addition lets us make a thorough assessment of the AI system's ability to handle noise and filter it out while it concentrates on the desired signal. The simulation of the noise addition process includes the generation of a noise signal that resembles the characteristics of real noise—random, unpredictable, and of different magnitudes. This noise signal is then added to the signal collected by the antenna elements. The AI system processes the combined signal (the original signal coupled with noise).

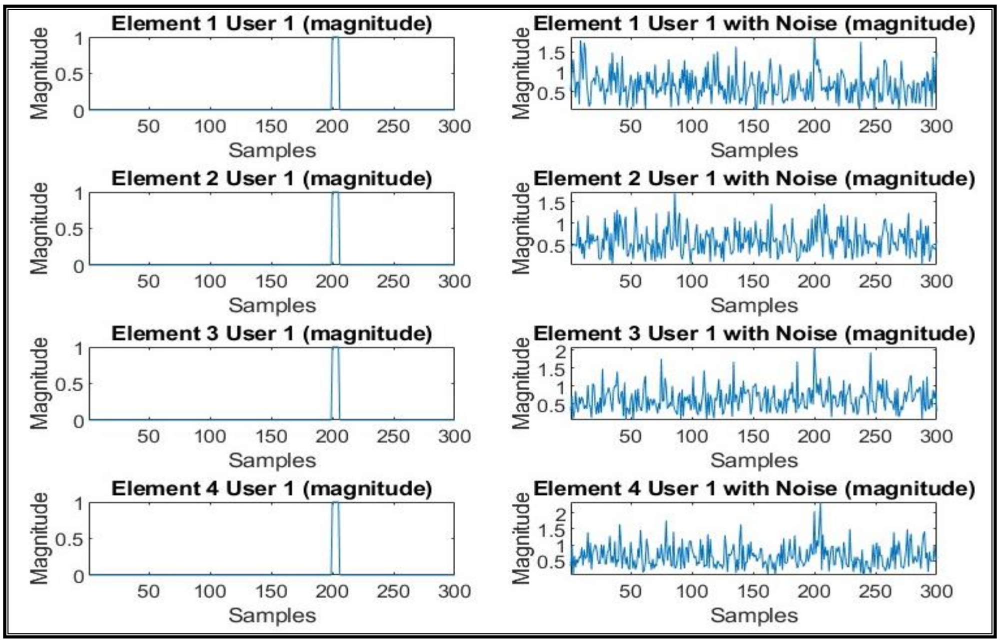

Fig. 4.2: Noise Signal Added to Users1

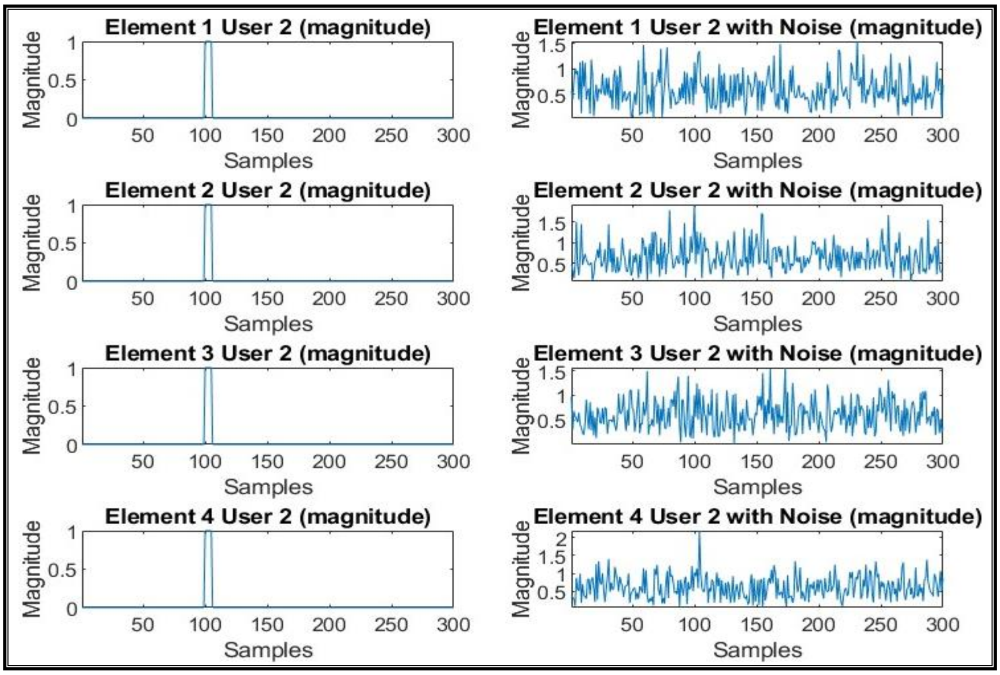

Fig. 4.3: Noise Signal Added to Users2

Figures 4.4 and 4.5, draw polar plots that depict the adopted angles of arrival (AOA) for their respective users. In hindsight, these plots are very important for showing how well the AI fixes on AOA, which is a big part that is needed and it is enough to keep power usage low while signal integrity stays high.

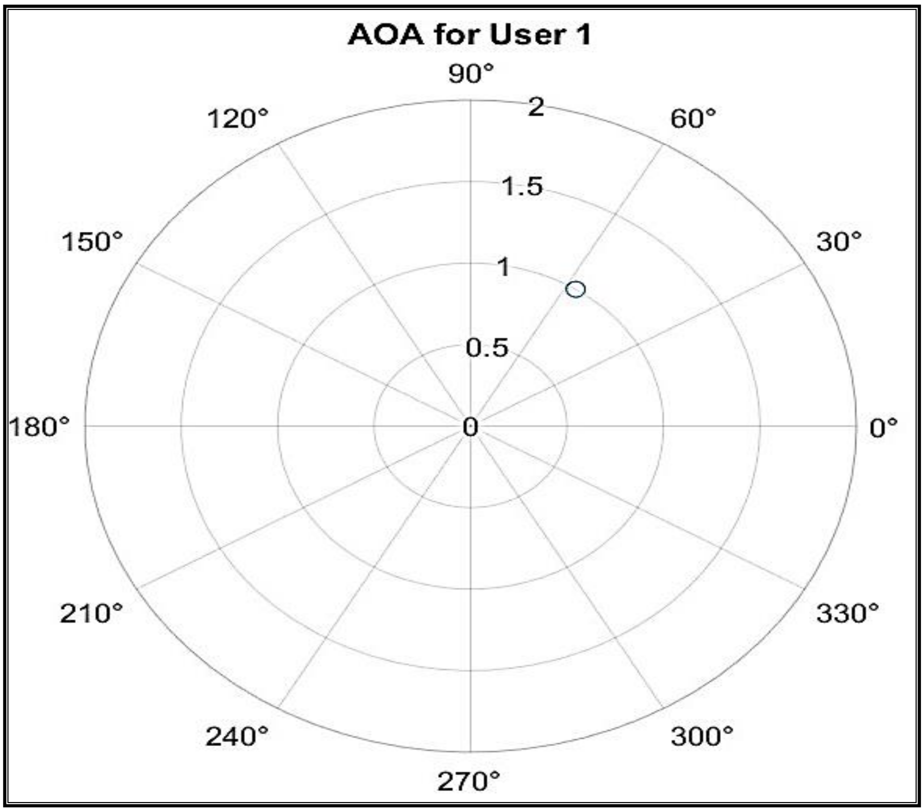

Fig. 4.4: Angles of Arrival (AoA) for Users1

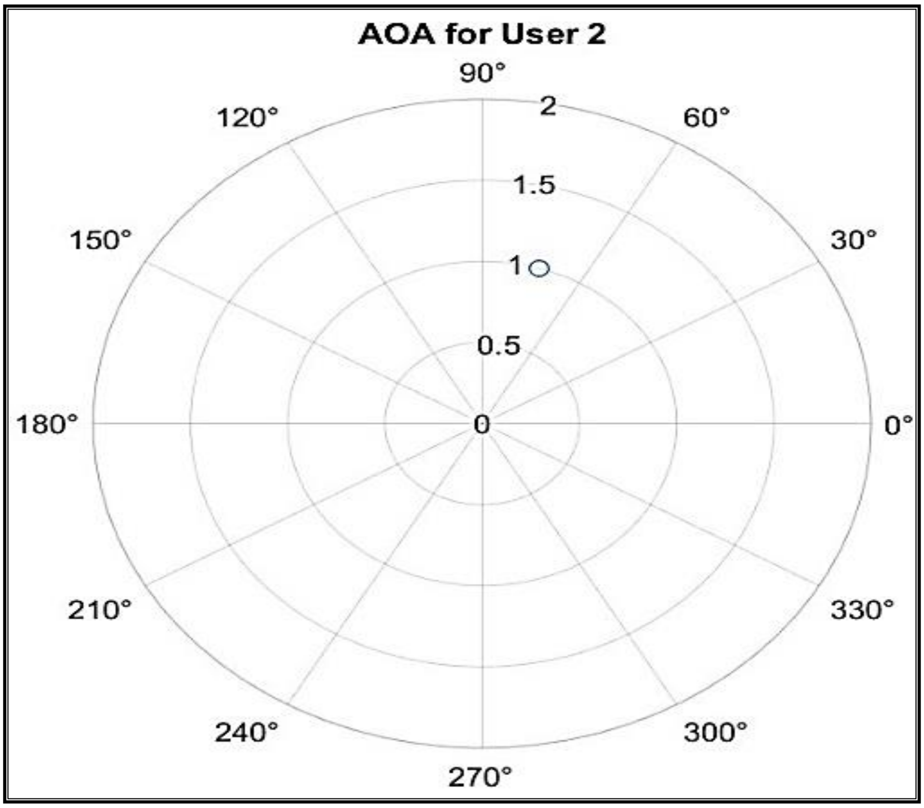

Fig. 4.5: Angles of Arrival (AoA) for Users2

Figures 4.6 and 4.7 give detailed DOA estimation plots, which are practically very useful to the successful beam steering mechanism of the system. These plots represent a kind of graphical proof that the AI can precisely pinpoint the location of the user. Discussing such a figure comprehensively would also require addressing the accuracy level of the DOA estimation for different conditions and special cases like non-line-of-sight scenarios and dynamically changing environments.

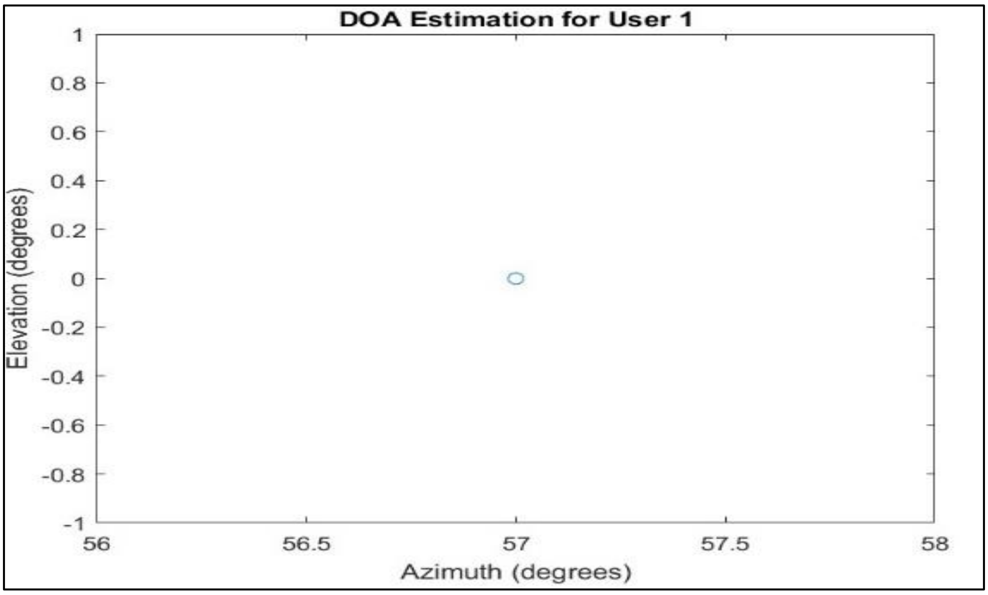

Fig. 4.6: Direction of Arrival (DOA) for Users1

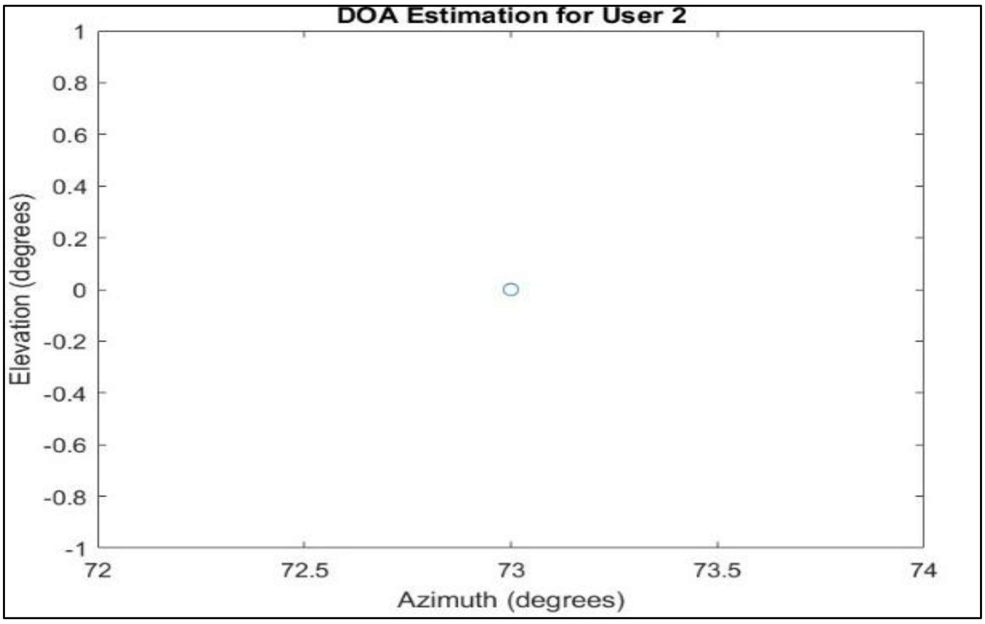

Fig. 4.7: Direction of Arrival (DOA) for Users2

Figure 4.8 is a key illustration in depicting the effect of AI driven beamforming iterations on signal integrity after post-processing. The enhanced clarity of the user's signal in one distinct peak above any ambient level is illustrated in Figure 4.8 when a beamforming operation has been applied to it. This peak is not just a graphical construction but also stands for a measurable manifestation of the AI's ability to enhance controllable features and eliminate unwanted noise and interference. In a detailed analysis of this figure, one must elaborate on the AI algorithms that can adaptively optimize beamforming weights. This optimization is essential to ensuring the high signal clarity in Figure 4.1. The AI system also uses state-of-the-art techniques like machine learning models that have been trained to comprehend all the essential substances in different signal environments.

The system can do this by using models that allow the beamforming weights to be adjusted in real-time based on dynamic feedback about such things as signal environment, user location, etc. In addition, it is necessary to consider the trade-offs that the AI system may make in its quest for such clarity in a signal. For example, when the system aims at improving the signal for a given user or group of users, it can assign less power or attention to other sections of the network. One of the fundamental approaches to providing a realistic view of the abilities and potential outcomes generated by this AI system is discussing how it balances these trade-offs. In addition, the analysis should consider the technical details of how it is possible for AI to maintain signal integrity.

One of the important facets that may be considered for a dialog is how the AI handles situations such as multipath propagation, where signals bounce off several surfaces before reaching a receiver, and how the same would lessen if any were understood about what is happening by the AI algorithm to isolate or strengthen only the desired signal path.

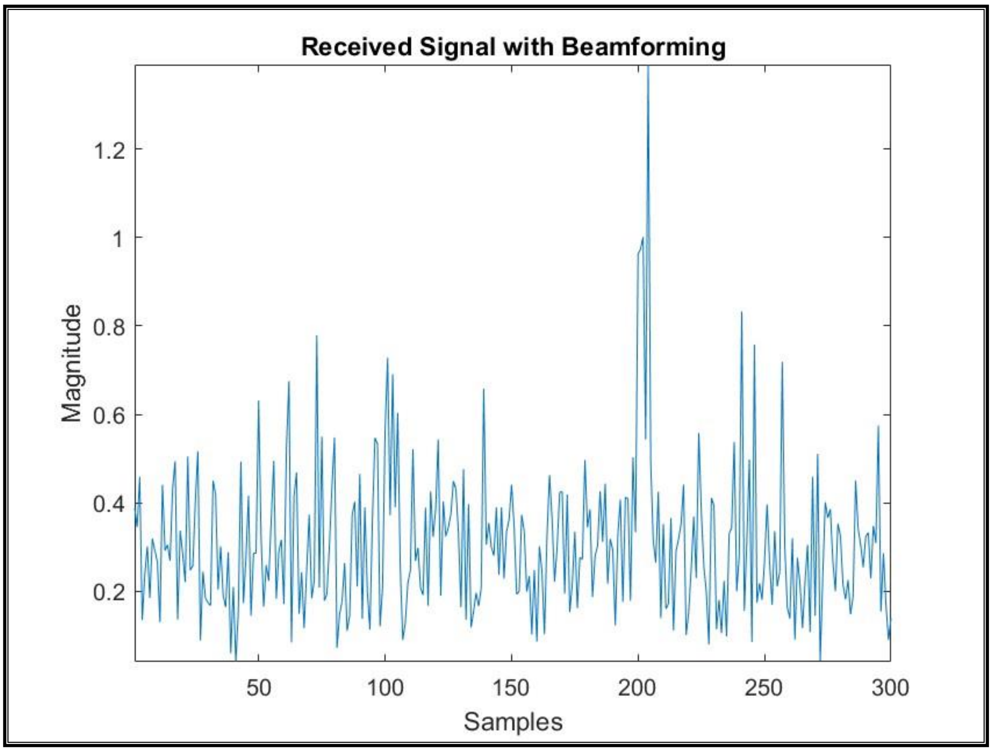

Fig. 4.8: Received Signal after Beamforming

In Figures 4.9 and 4.10, the focus of analysis is on power distribution vs. different azimuth angles for two cases with and without beamforming weights. Of course, the increase in the concentration of the central lobe when using beamforming is a vivid proof that AI-driven steering is successful in steering to the correct UE.

A more detailed analysis here will be made to compare the side lobe levels in different scenarios, which gives some valuable indications on the efficiency of the ML algorithm's work in interference cancellation and estimator precision as well. Furthermore, the establishment of the gain obtained from this process and how it augmented total network production results in a complete picture of system capabilities.

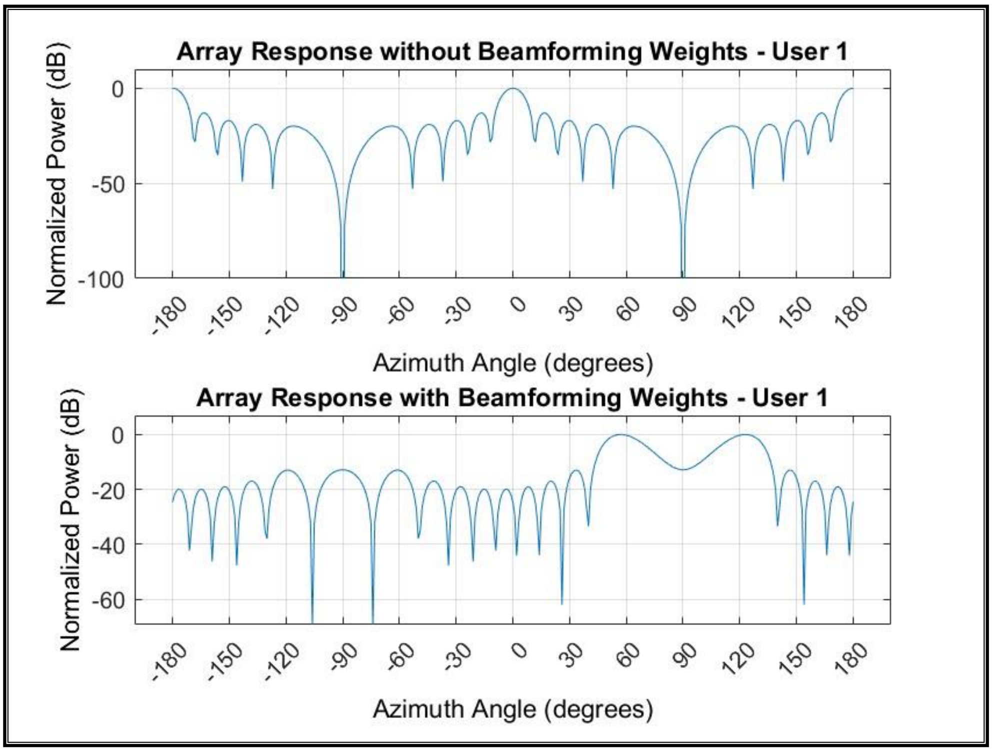

Fig. 4.9: Azimuth Angles for User1

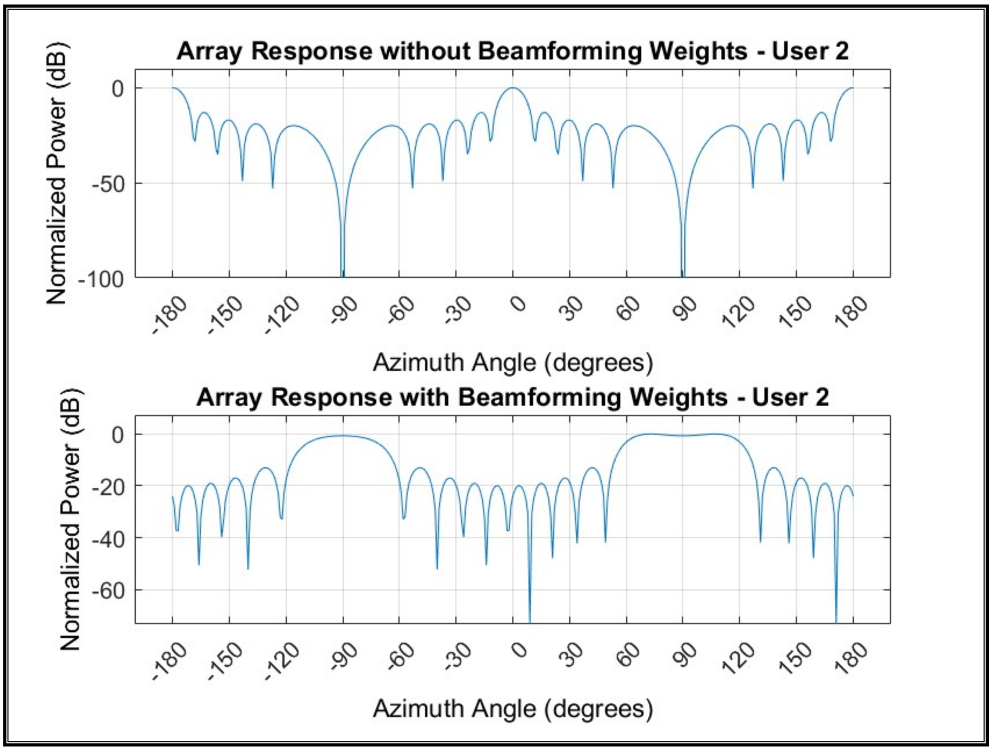

Fig. 4.10: Azimuth Angles for User2

The simulated BER analysis for the system is shown in Figure 4.11. The points of blue stars represent the results of the BER simulation using the AI algorithm for beam steering. In fact, the performance is excellent at high Eb/No. This means that when a signal is much more powerful than noise, the AI algorithm runs precisely and steers the beam towards the user. At the lower Eb/No values, it can be observed a slight departure from the theoretical curve because there are imperfections in the real world, which include quantization errors, phase noise, and non-linearity within the system. The red curve shows the theoretical BER, which also helps determine the quality of performance of the system. That is because BER establishes an ideal 16-QAM modulation without including any impairments or loss systems—particular losses. There are multiple factors that may be the reason behind this gap between the estimated BER and theoretical BER, including imperfections in the AI algorithm that are not allowing it to align the beam perfectly, practical constraints of the hardware of the phased array for physical realization, signal processing errors and delays, etc. However, the minimization of power while steering the beam by the AI algorithm should not compromise BER beyond acceptable levels.

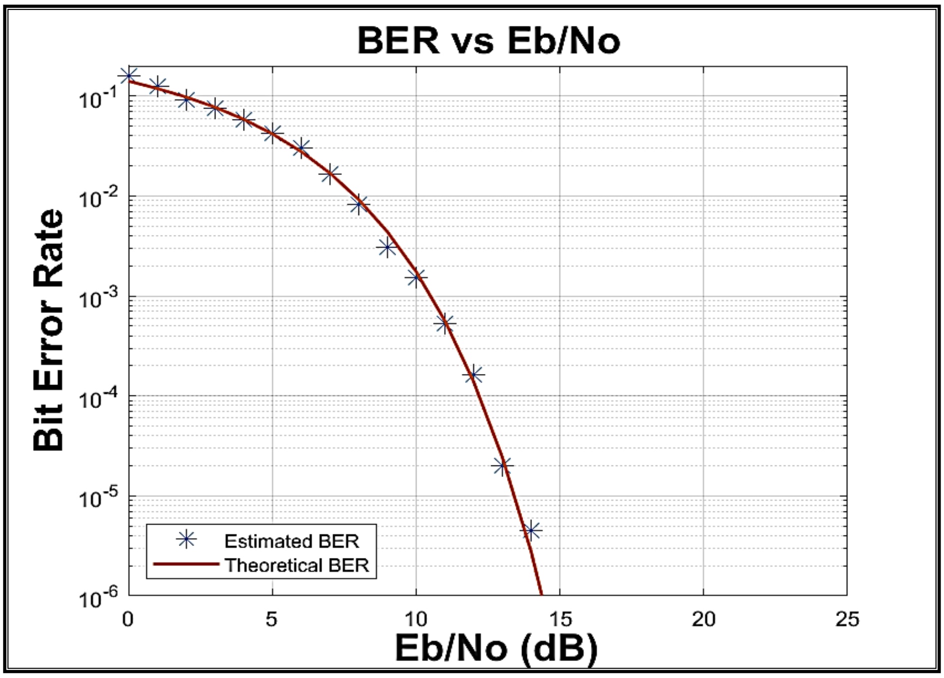

Fig. 4.11: BER vs. EbNo. (dB)

Figure 4.12 indicates the throughput, which shows that despite its Eb/No being in the negative region, the system is able to sustain data transmission. In theory, as the value of Eb/No decreases, errors tend to rise, therefore reducing the overall throughput through retransmissions and error correction overheads.

However, if the system uses strong error correction and retransmission techniques, it can hold a base throughput. The robustness of the system is observed at negative Eb/No values of throughput. This is because the AI algorithm can keep the beam alignment despite less-than-full signal-to-noise ratio levels. Error-correcting codes can allow for data recovery.

It can be seen that the throughput is sufficiently increasing until it reaches saturation at 10 Eb/No. The reason behind that might be due to system limits like the maximum symbol rate, finite modulation levels (16-QAM), or a constraint in the processing capacity of the AI algorithm. However, the AI can still guide the beam properly by utilizing peeks from these noises. The detailed plots and much of the obtained results clearly show how effective it is to have precise implementation of these algorithms and estimate very accurate signal parameters. These visuals show that the AI can work in a noisy environment and will ensure beam steering to maximize communication between the intended users.

This paves the way for beamforming to couple with numerous parameters such as complex interaction and an ever-changing acoustical signal environment; therefore, the system will manage to control it.

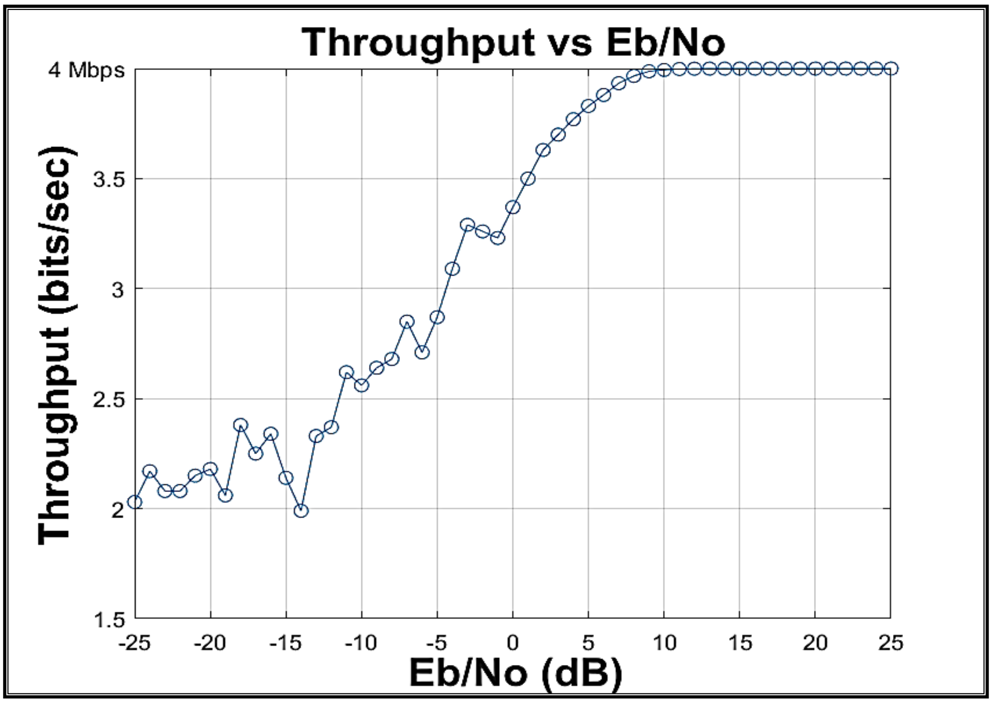

Fig. 4.12: Throughput vs. Eb/No

4.4 Vertical System

The actual signal representation for four different users is shown in Figure 4.13. The signals are generated and sampled over a 0.3s and a carrier frequency of 28 GHz, and thus represents signals used in millimeter-wave communications. Each subplot depicts a single, brief high-amplitude pulse submerged in mostly 1V amplitude signal; these are digital pulses visualized in the time-domain. Each of the signal is further aligned with an element in a URA. The signals are timed in such a way that each time at most one user signal is present; thus, the ultra-wide band spectra correspond directly to the spectrum for the four signals.

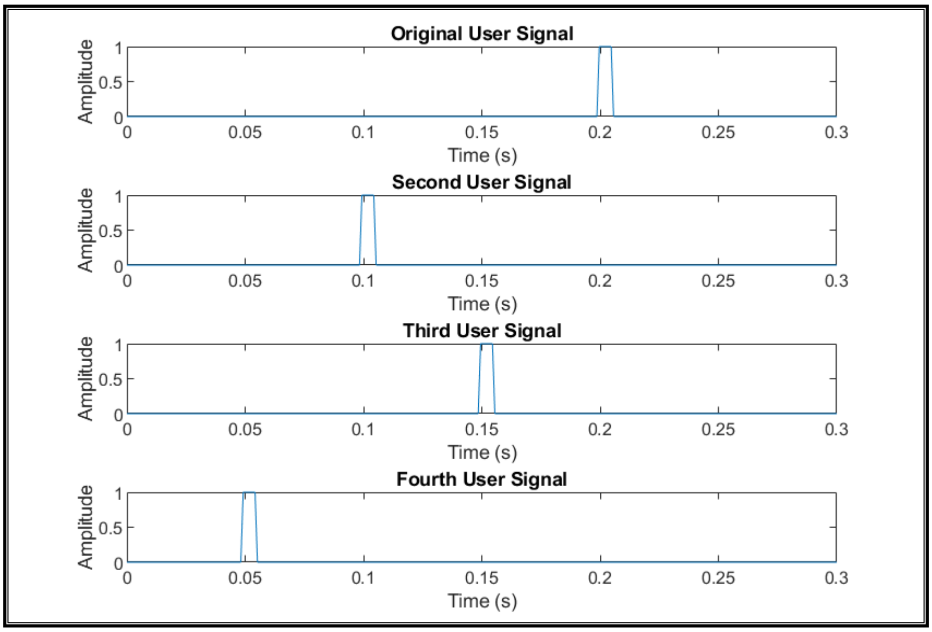

Fig. 4.13: Four Signals for End Users

Proceeding to Figure 4.14, which shows a three-dimensional spatial representation of user distribution with respect to a BS positioned at the center. The BS is defined at the coordinate origin to enable beamforming operations. The horizontal users (User 1 and User 2) exhibit the proximity of the BS in the XY plane and the vertical users (User 3 and User 4) are positioned along the Z axis reflecting a multi-story user environment that represents the urban high-rise conditions.

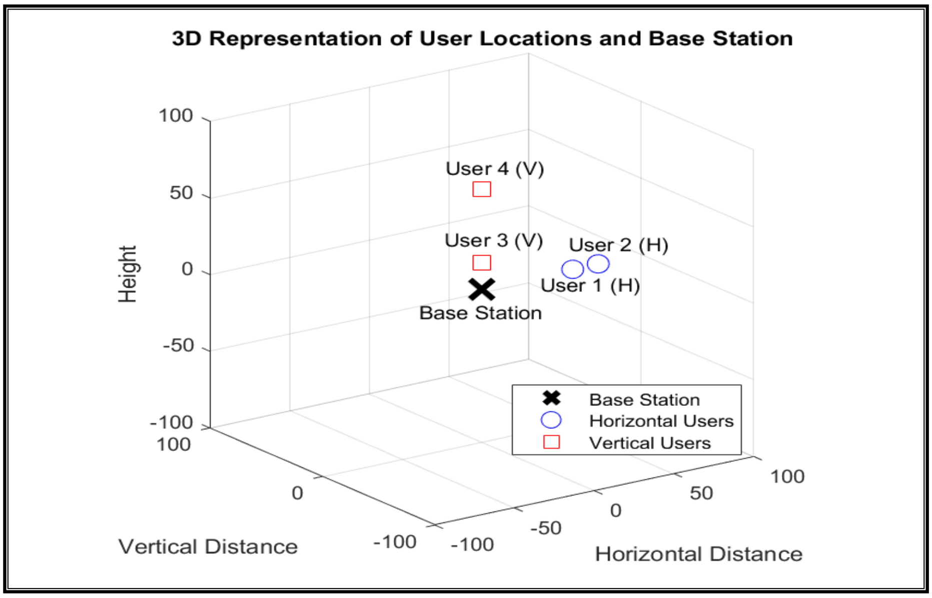

Fig. 4.14: 3D Representation of Users Locations

Figures 4.15, 4.16 and 4.17 present the spatial spectrum analysis utilized to infer the DOA for each user and their spectrum. Peaks are discernible for User 1 at approximately +57 azimuth degrees, User 2 at +73 azimuth degrees, User 3 at -8 azimuth and +9 elevation degree, and User 4 at -15 azimuth and +63 elevation degrees, with spectral magnitudes approaching unity. This precision in peak detection exemplifies the system's adeptness at resolving UE directions amidst a high noise backdrop, attributable to the MUSIC algorithm's high-resolution capabilities. DOA estimation in azimuth and elevation further validates the MUSIC estimator's proficiency.

Horizontal user’s exhibit closely clustered azimuthal estimates, while vertical users are close at azimuth angles.

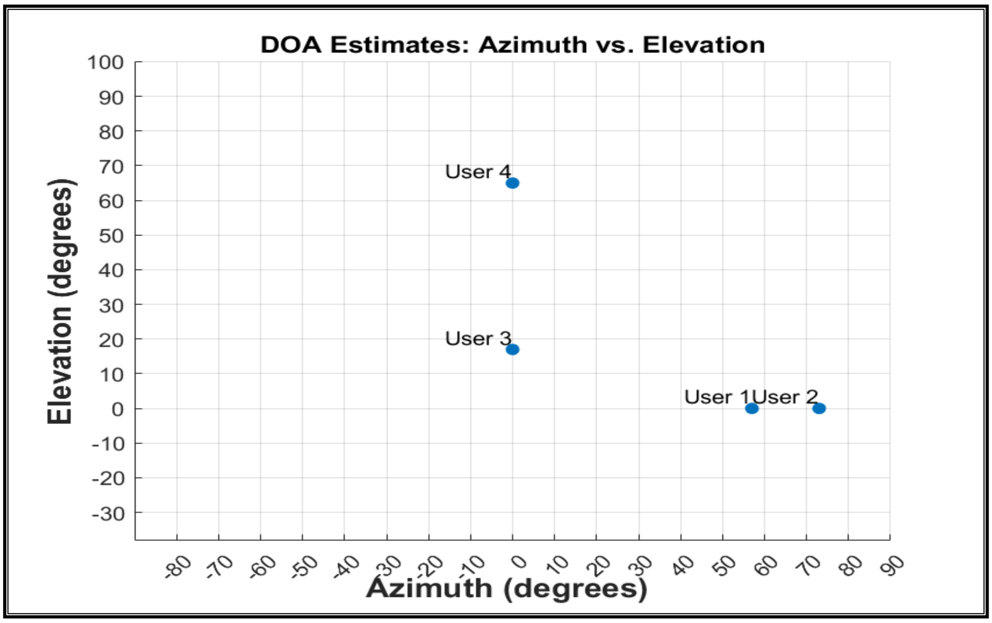

Fig. 4.15: DOA Presentation in 2D

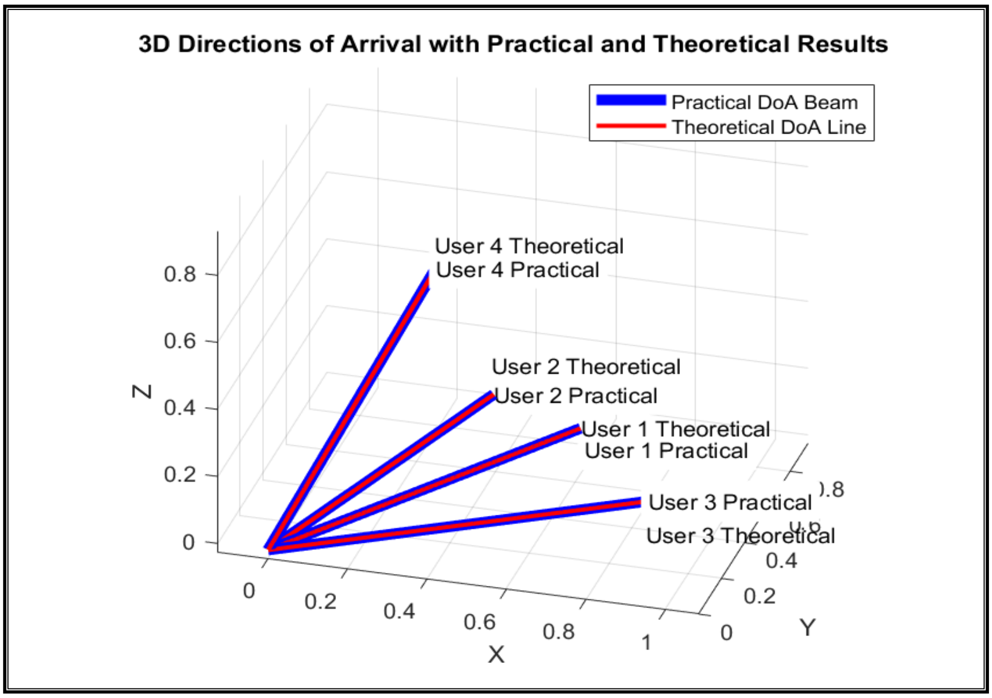

Fig. 4.16: 3D Representation of DOA

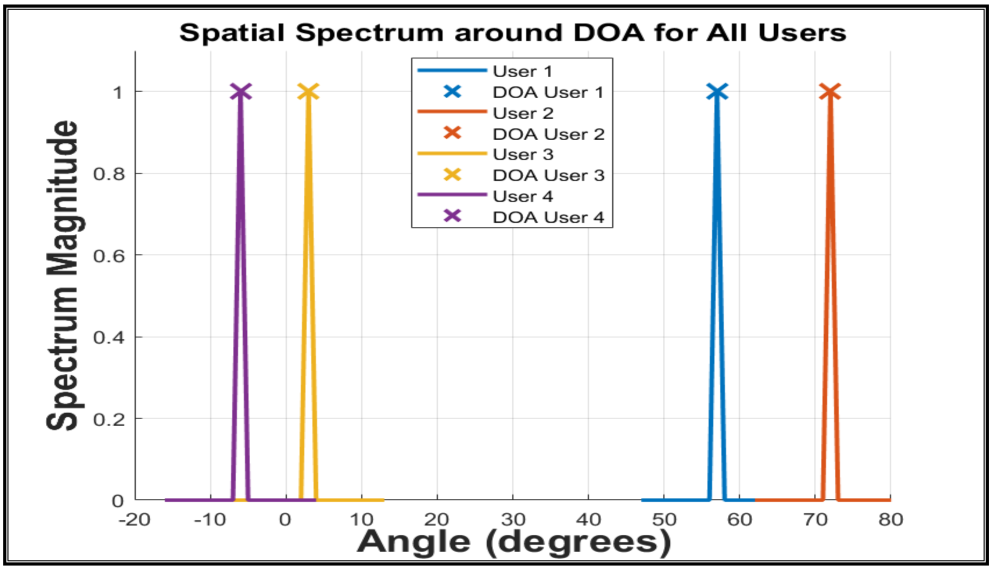

Fig. 4.17: Spatial Spectrum for all Users

Figure 4.18, shows the original signal with heavy noise added to it to make it more challenging for the system to detect the signal. The right side shows that the signal is altered heavily beyond recognition as the noise figure added to the signal is 1.76 dB to imitate real environment scenario. The noise is added to every element in the array before transmitting the signal out.

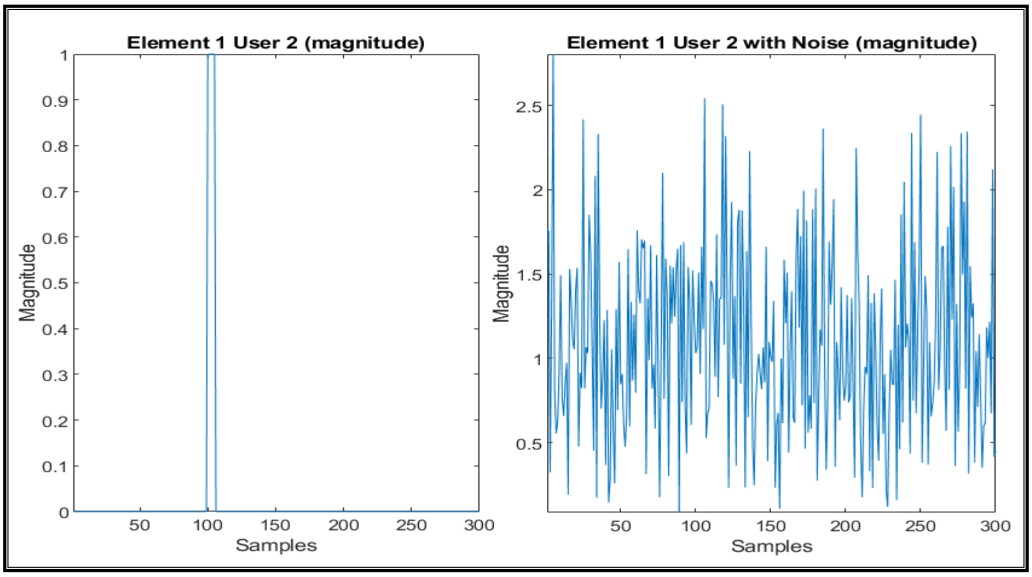

Fig. 4.18: Signal with Heavy Noise Addition

Figures (4.19 to 4.22), show the response of azimuth and elevation arrays with and without beamforming weights implementation. The normalized power in the beamforming application are significantly improved from an average level of -100 dB to a central peak at -20 dB, which is a strong 80 dB gain. This fact supports the effectiveness of the beamforming strategy in signal directivity improvement.

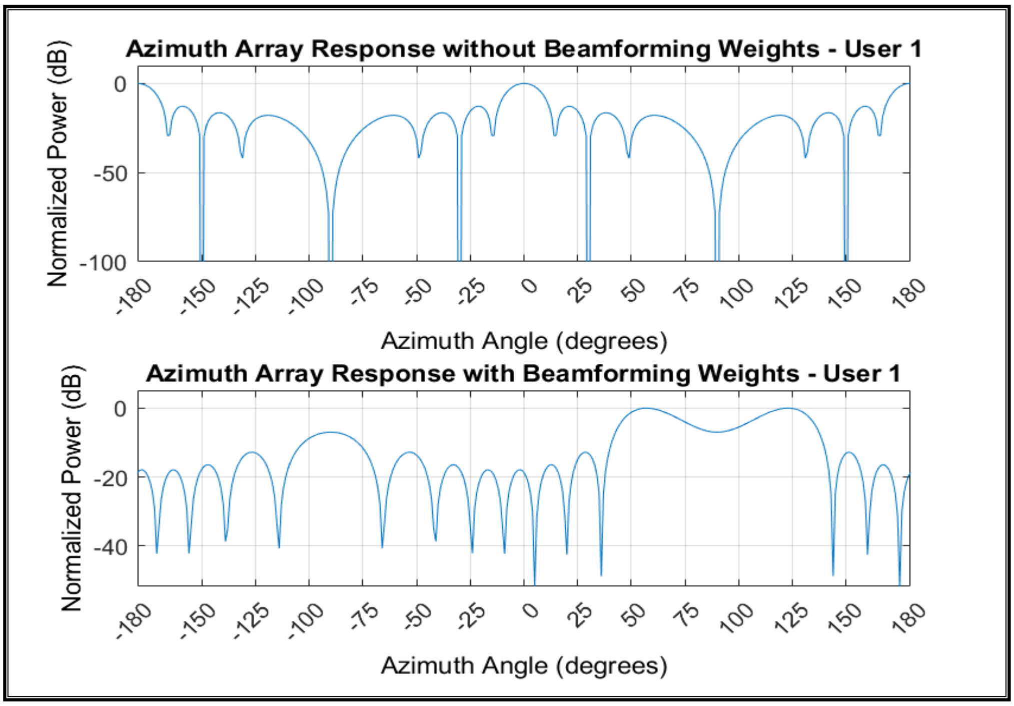

Fig. 4.19: Array Response for User1

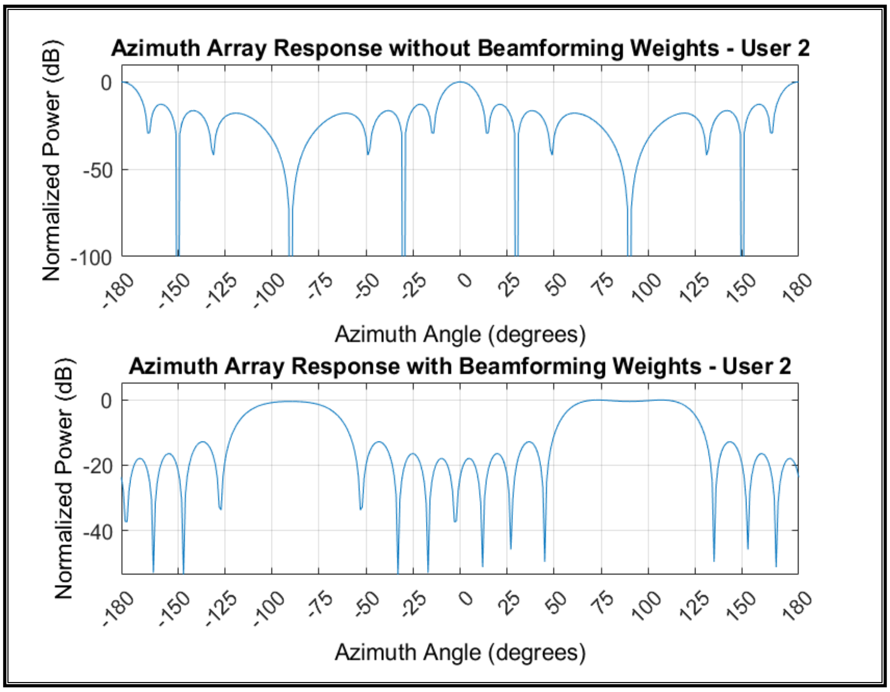

Fig. 4.20: Array Response for User 2

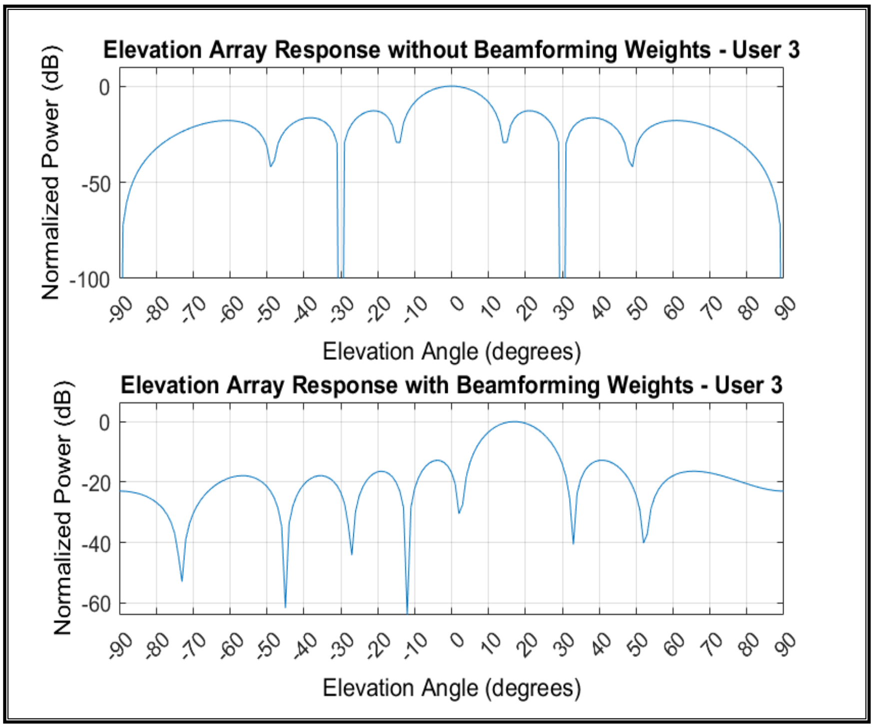

Fig. 4.21: Array Response for User3

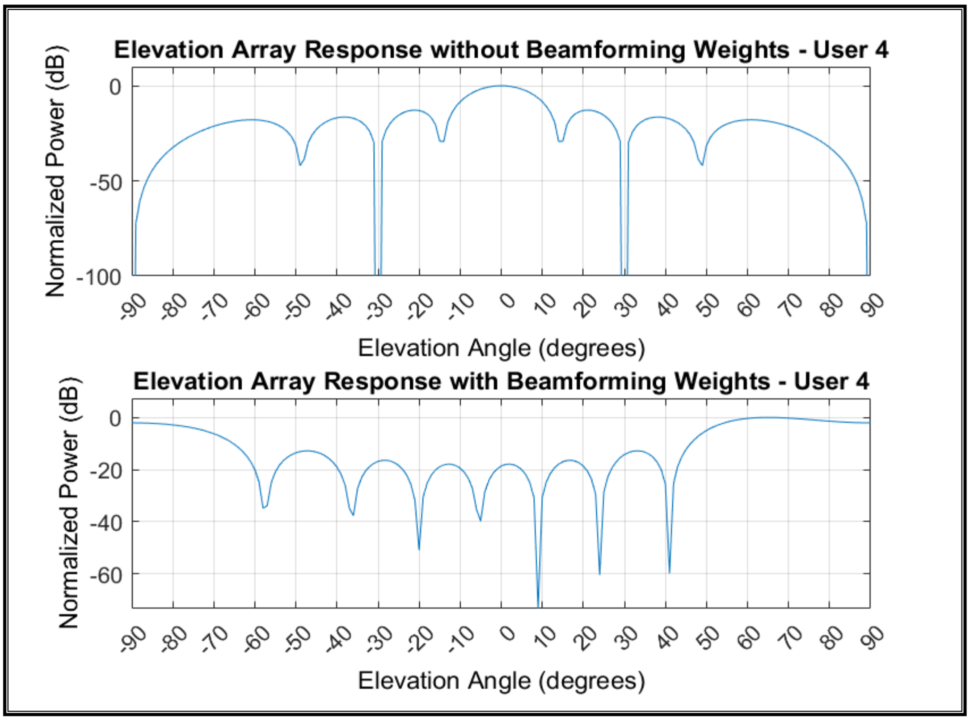

Fig. 4.22: Array Response for User 4

Figure 4.23 represents the temporal characteristic of the magnitude of the received signal after applying beamforming. Sporadic peaks ranging over 1.2 magnitudes break the plot and show that the system is a dynamic adaptation to the best beam alignment in the face of temporal changes in channel conditions.

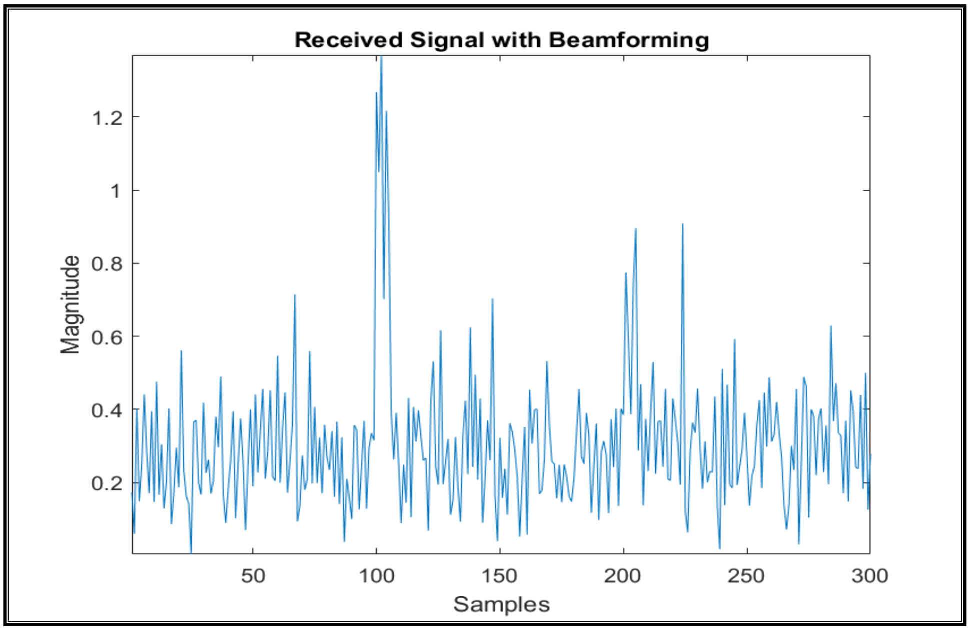

Fig. 4.23: Beamforming User's Signal

Figure 4.24 evaluates BER performance with respect to Eb/No which is a quantitative measure of data integrity. The BER estimates closely aligns with the theoretical BER with a clear exponential improvement seen as Eb/No grows. The BER falls under an acceptable 10^{-5} level at about 13 dB Eb/No which is suitable for reliable digital communications.

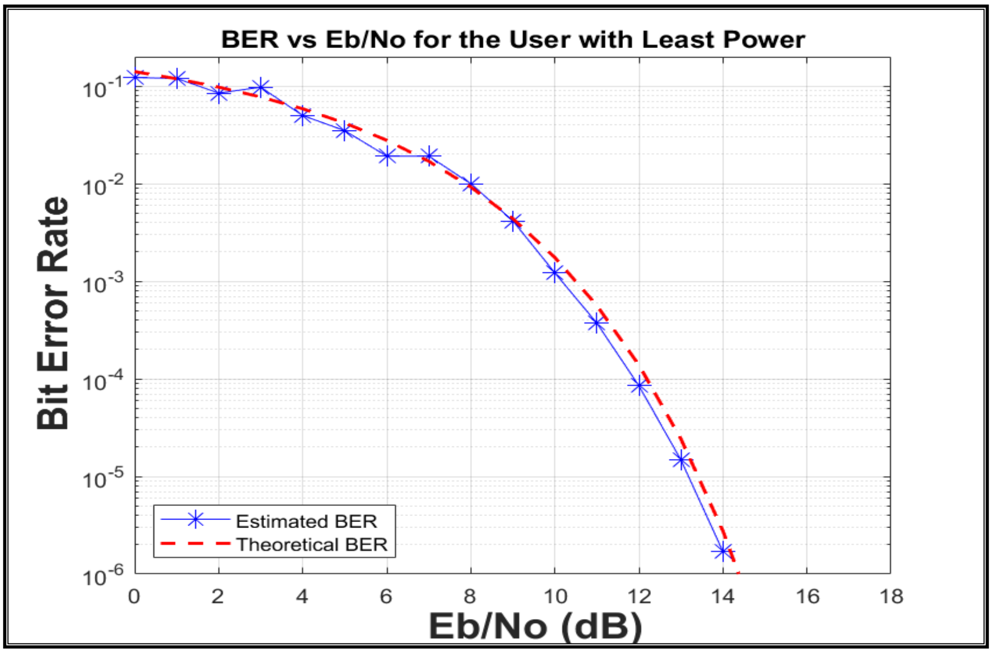

Fig. 4.24: Bit Error Rate Analysis

Finally, Figure 4.25 represents throughput comparison between azimuth and elevation beamforming with respect to the energy per bit to noise power spectral density ratio (Eb/No). It's observed that both strategies exhibit an increasing throughput with the rising Eb/No levels, eventually reaching a saturation point. The curve shows a vertical growth from 2.2 Mbps throughput at -25 dB Eb/No to a peak where it reaches its saturation at 3.8 Mbps, from 5 dB Eb/No. Notably, despite a higher noise figure in elevation beamforming, the use of an URA allows for spatial diversity utilization, enabling the elevation strategy to match the performance of azimuth beamforming at higher Eb/No values and outperforming the azimuth by 3.45% at lower Eb/No. Meanwhile, the azimuth approach, with its lower noise power, outperforms elevation beamforming by 6.25% at higher Eb/No; however, the gap closes as the Eb/No ratio improves, indicating effective compensation mechanisms within the system for noise.

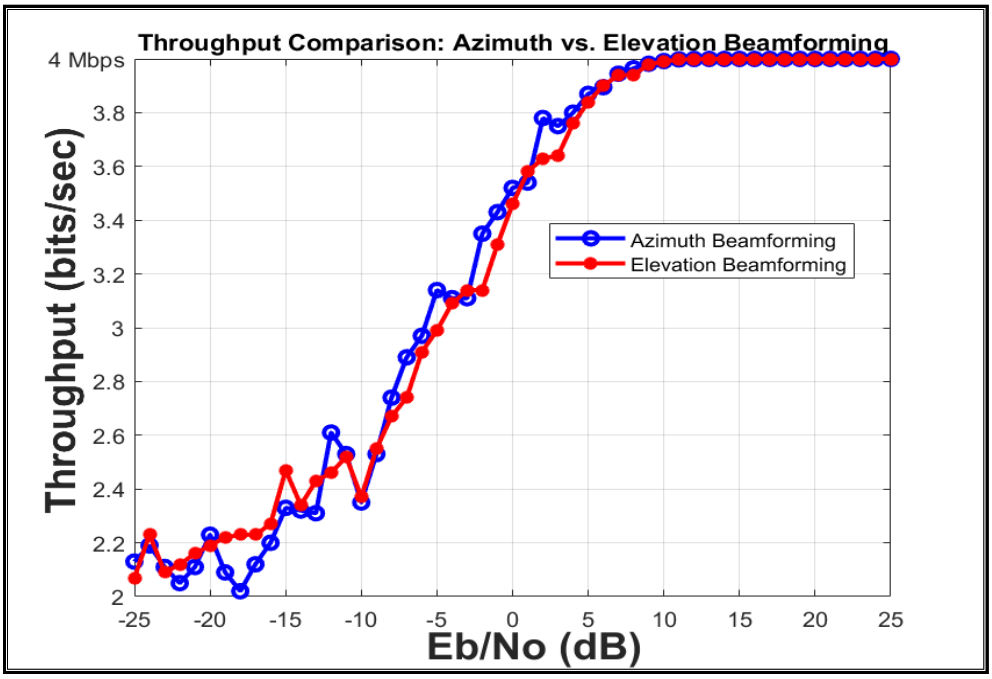

Fig. 4.25: Throughput Analysis

4.5 Various Evaluation Settings

In this section the researcher explores more settings for the selected system and observe its work under simpler modulation schemes, more amount of array elements and different frequencies. Table III shows the different settings changed to the system structure.

Table 4.3: Parameters of the Chosen System

Parameter/Technique	Value/Description
Carrier Frequency	26, 28, 30 GHz
No: of Elements in Horizontal ULA Array	8, 10, 12
No: of Elements in Array Vertical URA Array	8x8, 10x10, 12x12
Element Spacing	$(\lambda/2)$
Frequency Range	25GHz to 31GHz
Angle of Arrival (Horizontal)	Random integer between -90 and 90 degrees
Angle of Arrival (Vertical)	Random integer between 0 and 70 degrees
Noise Power	0.5 - 1.5
Beamforming Direction	Based on the user with the lowest power signal
Modulations schemes	QPSK, QAM, 8QAM, 16QAM
DoA Estimation	MUlti SIgnal Estimator (MUSIC Estimator)
Modulation Order (M)	4, 4, 8, 16
Symbol Rate	1 MHz
Frame Duration	1 ms
Eb/No Values	-25 to 25 dB
Number of Symbols Per Frame	100

The researcher starts first by changing the number of elements in the horizontal system’s array under the influence of different frequencies and observe the changes in the system results. Figures 4.26, 4.27, and 4.28 show the BER under different frequencies and elements respectively. From the BER results, it can be seen that the system is independent on frequency, but rather dependent on the number of elements in the array.

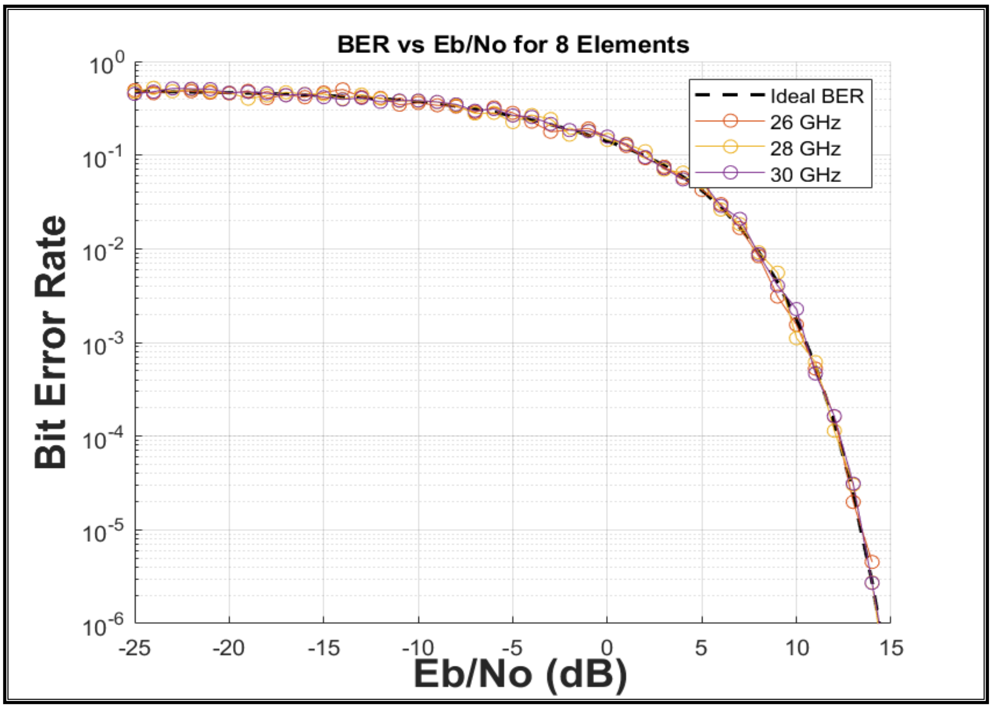

Figure 4.26: BER for 8 Elements

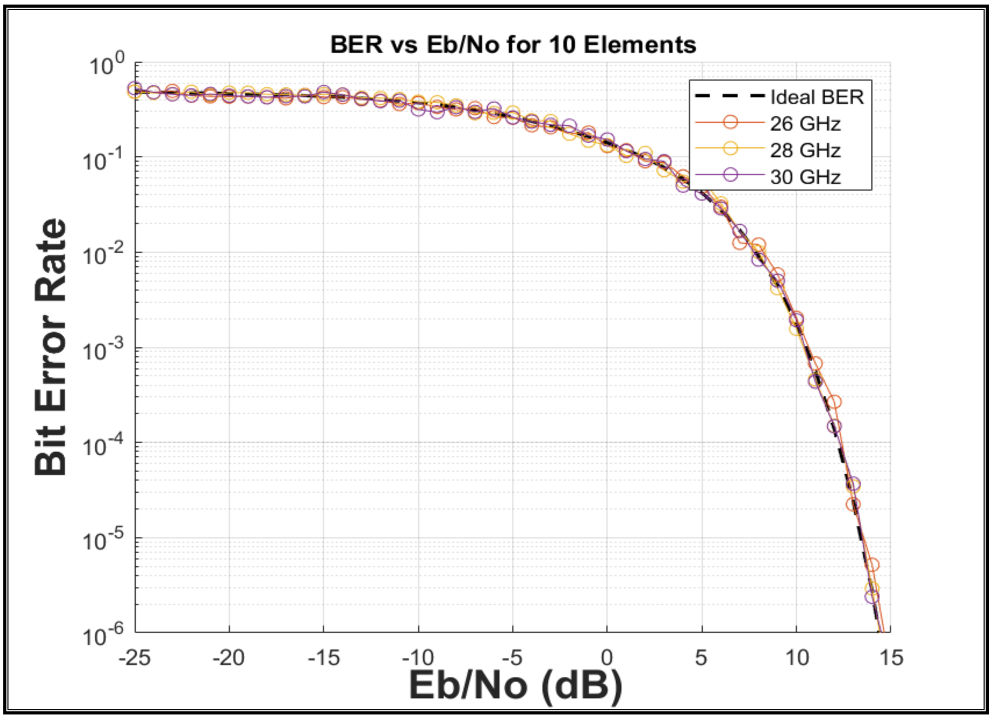

Figure 4.27: BER for 10 Elements

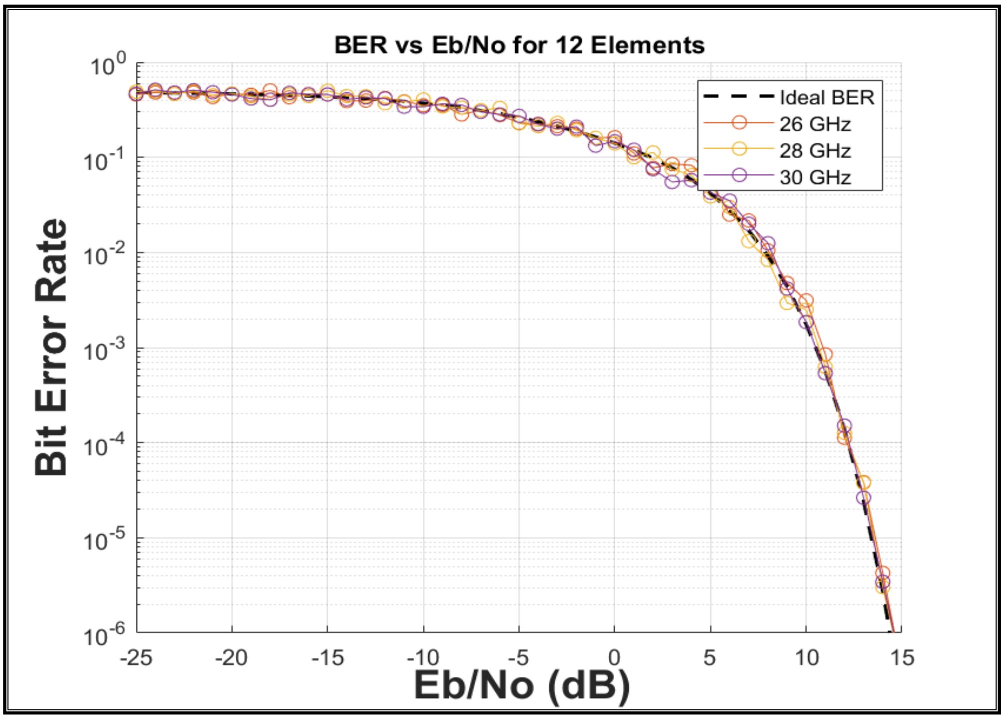

Figure 4.28: BER for 10 Elements

Then, a simulation run with the throughput under the same environment. Figures 4.29, 4.30, and 4.31 show the throughput simulated under different number of elements and frequencies. The results show that the system throughput increases as the number of elements in the array increase and this is due to increasing in gain and efficiency, thus increasing the overall performance of the system.

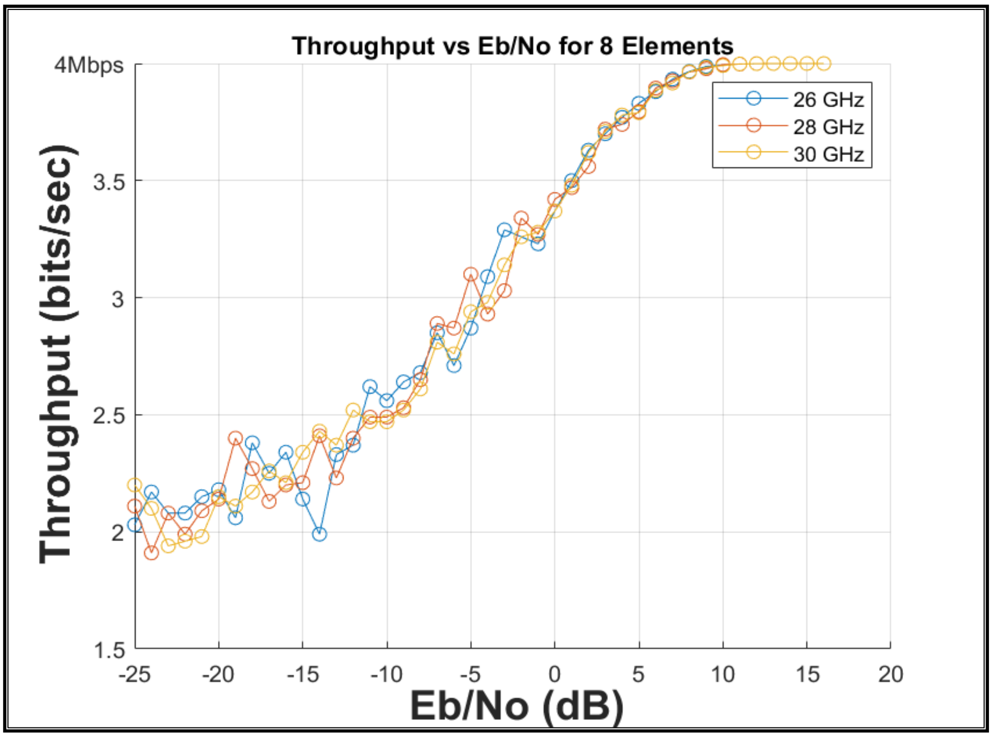

Figure 4.29: Throughput for 8 Elements

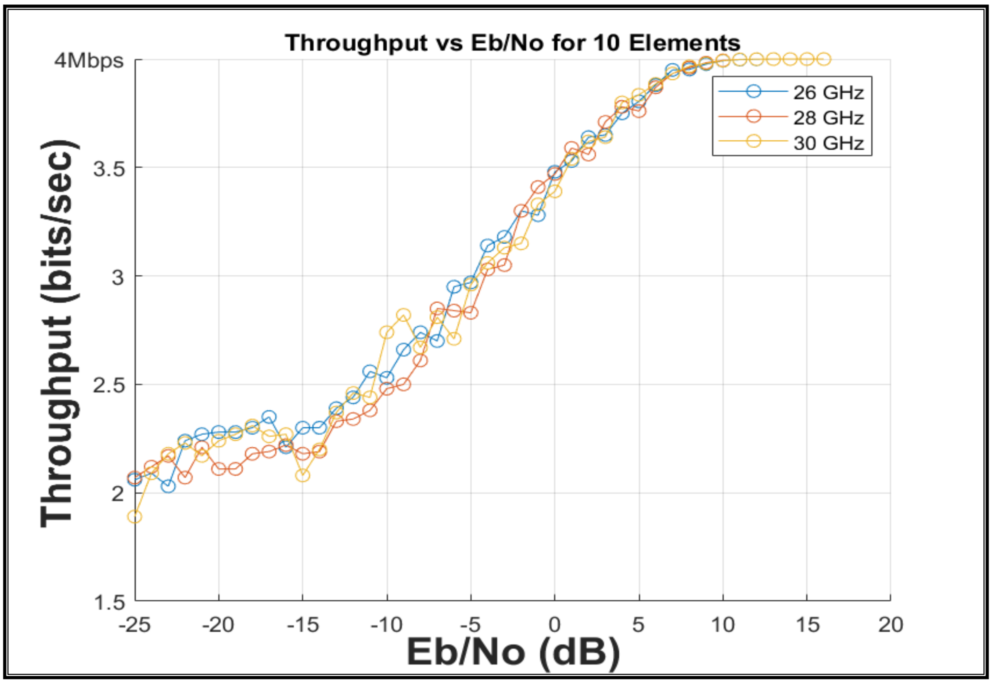

Figure 4.30: Throughput for 10 Elements

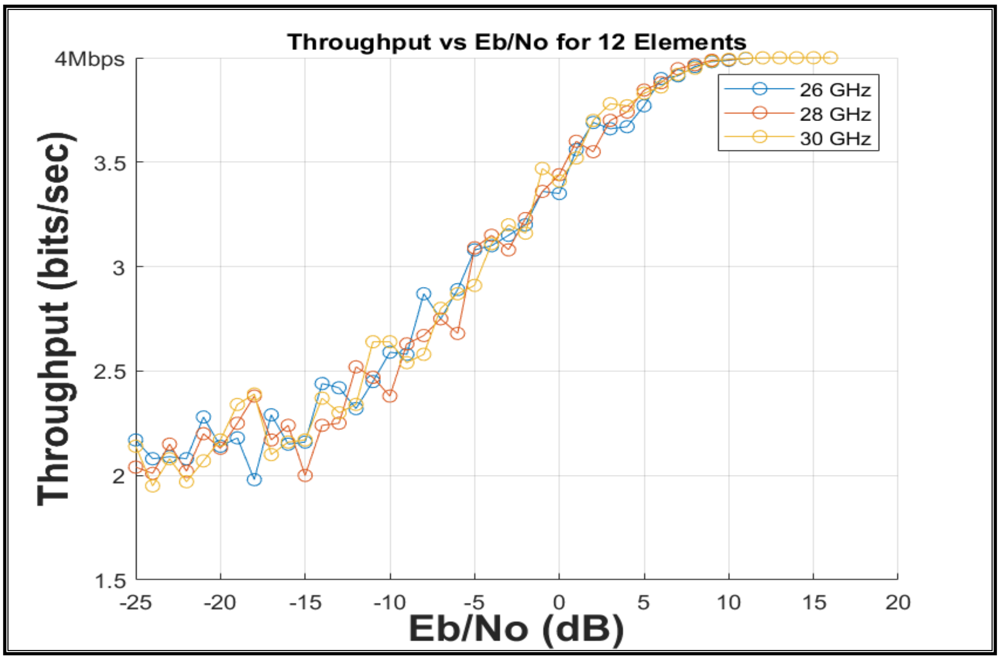

Figure 4.31: Throughput for 12 Elements

As for the analog beamforming signal, its clarity increases and the noise gets reduced for every increase in the elements in the system's array. Figures 4.32, 4.33, and 4.34 shows the beamforming signal at different number of array elements.

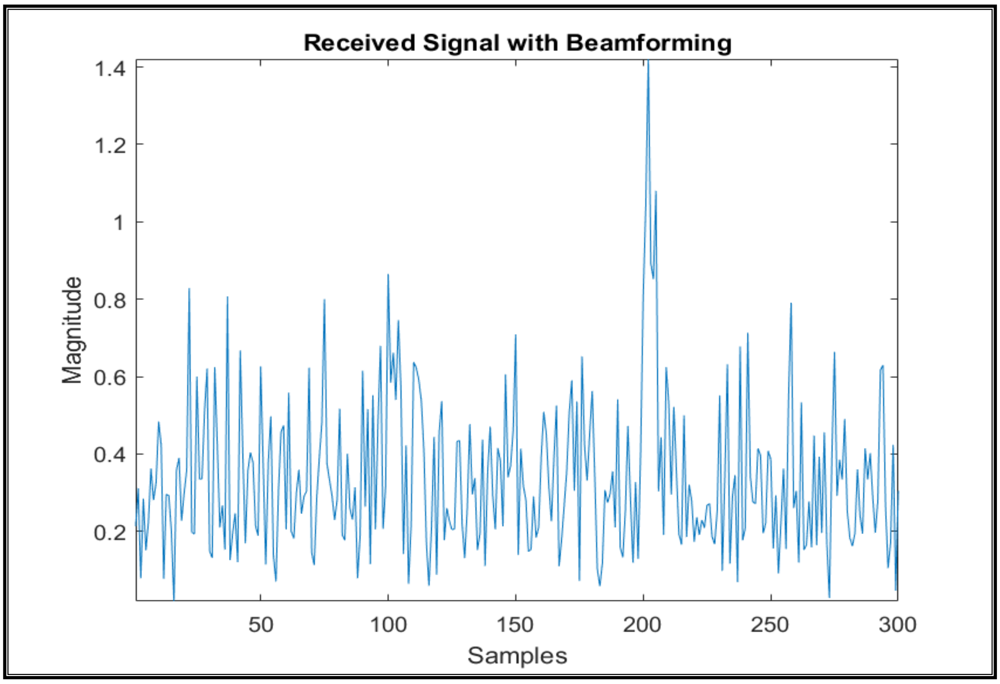

Figure 4.32: Beamforming Signal for 8 Elements

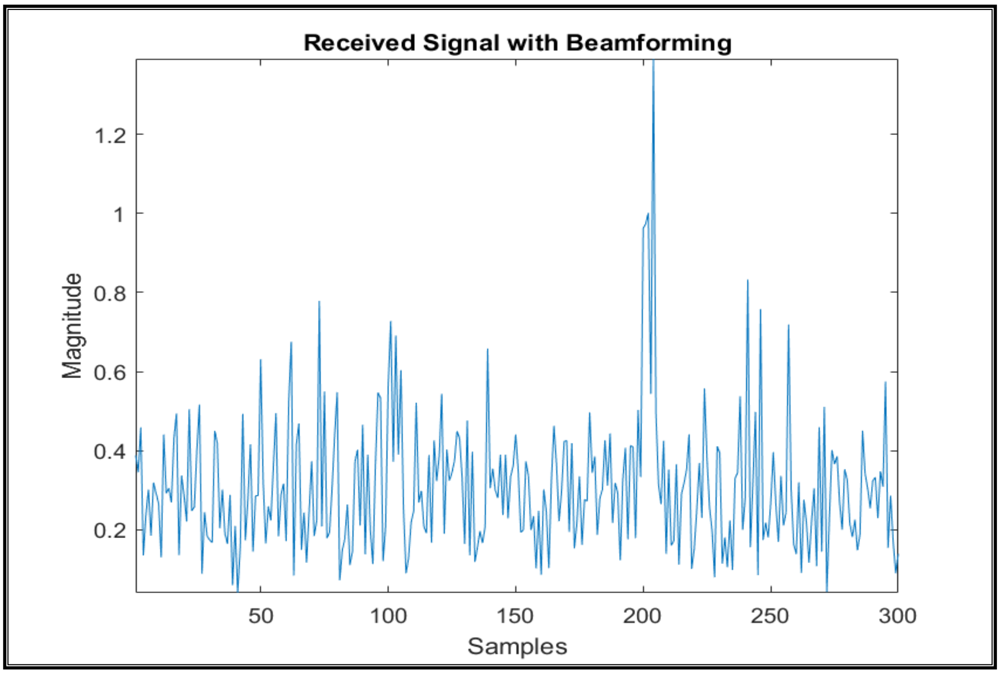

Figure 4.33: Beamforming Signal for 10 Elements

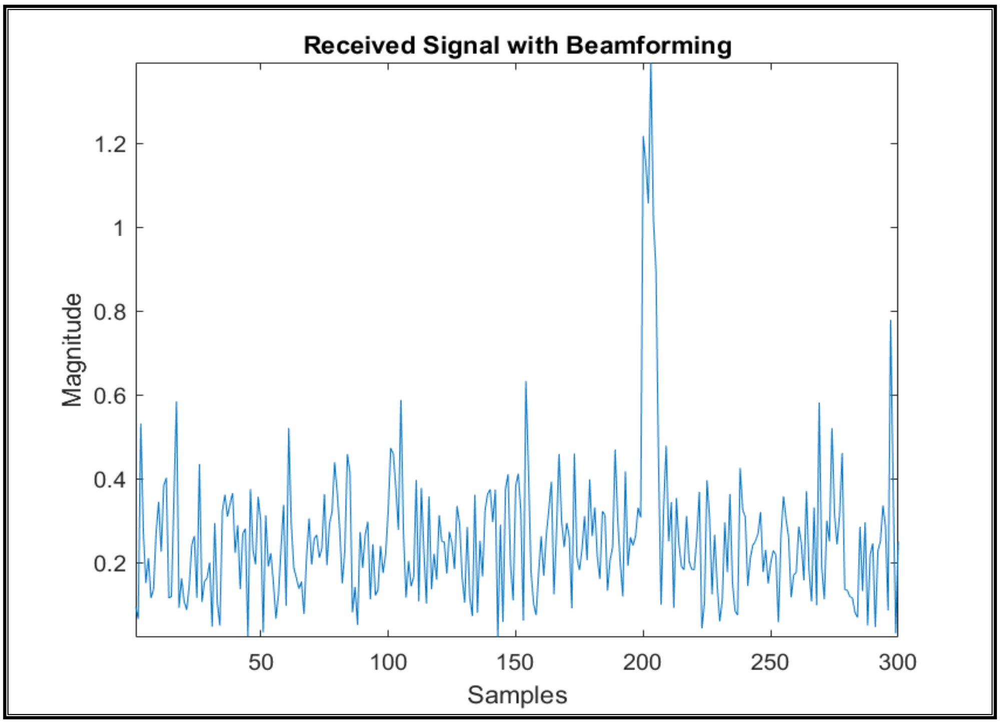

Figure 4.34: Beamforming Signal for 12 Elements

The same settings were placed for the vertical system excluding the frequency because the system is independent on the frequency as was shown previously. Starting with calculating the BER for the system under different number of array elements, Fig 35 shows BER performance under different number of array elements, then evaluating the throughput of the system under the same conditions. Figure 4.36 shows the throughput of the system under different number of array elements. It is noticed that there is a slight improvement in BER and throughput at a higher number of array elements. The overall performance of the vertical system is slightly better because it has a rectangular array and not linear. The number of arrays is much higher compared to the horizontal system, where the rectangular system takes [NxN] number of elements. The horizontal system can run with only [N] number of elements reducing the cost and simplicity of the system by a large amount.

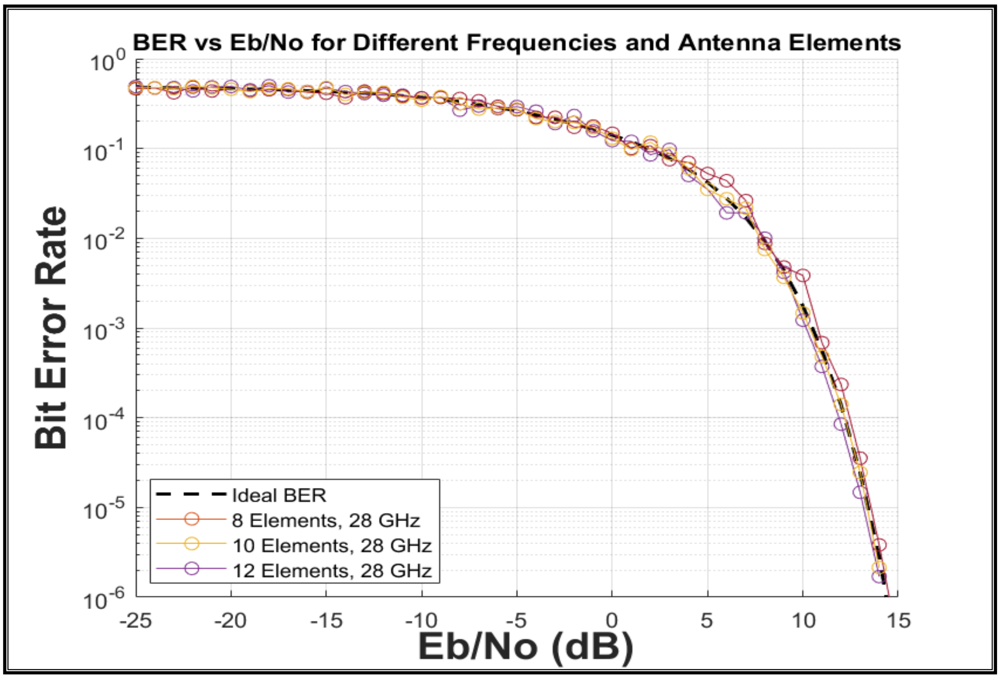

Figure 4.35: BER for Different Number of Elements

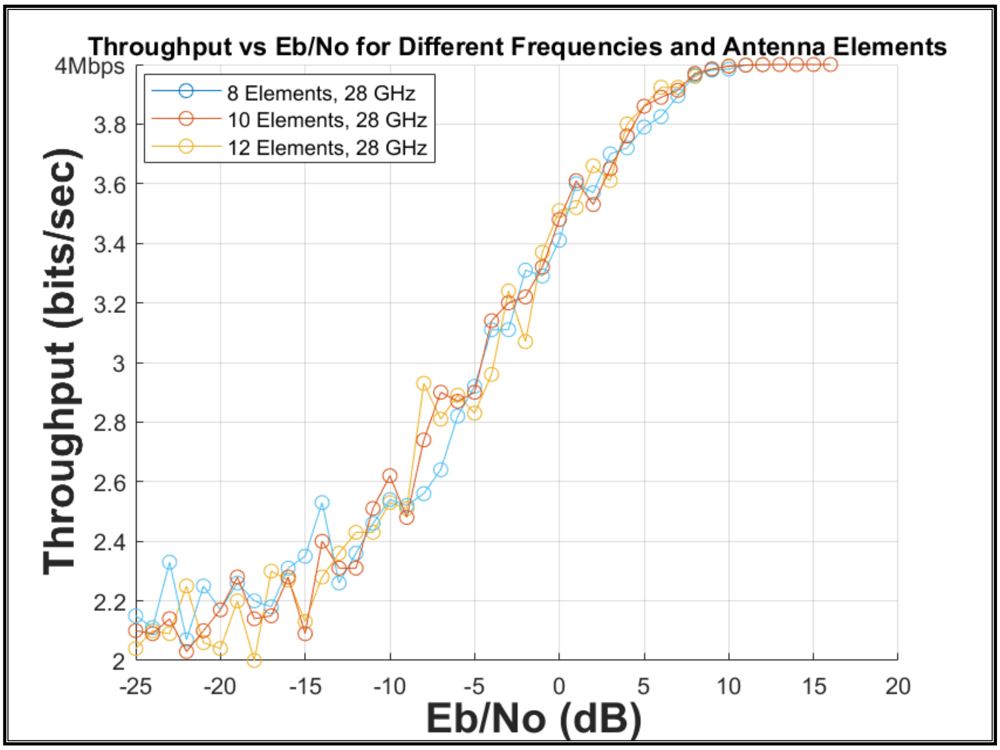

Figure 4.36: Throughput for Different Number of Elements

Continuing to test the clarity of the analog beamforming signal, the researcher ran the model at previous conditions and observed the signal clarity.

Figures 4.37, 4.38, and 4.39 shows the analog beamforming signal at different number of array elements. As it is assumed, the system's performance at receiving signals is slightly better than the horizontal system, as of the increase system's resilience to noise.

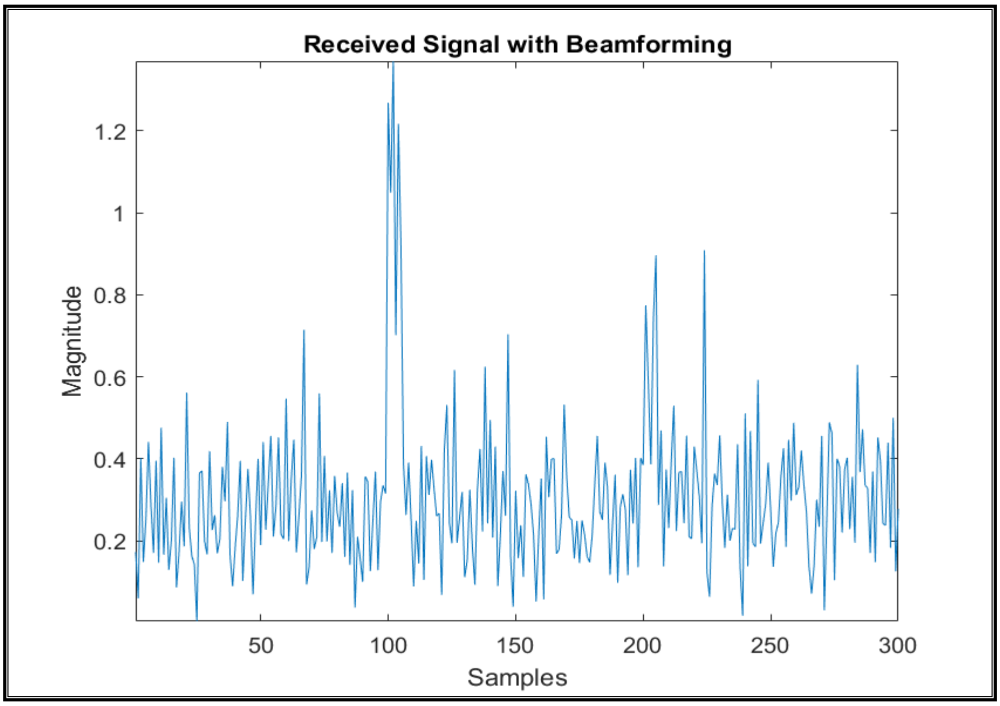

Figure 4.37: Beamforming Signal for 8 Elements

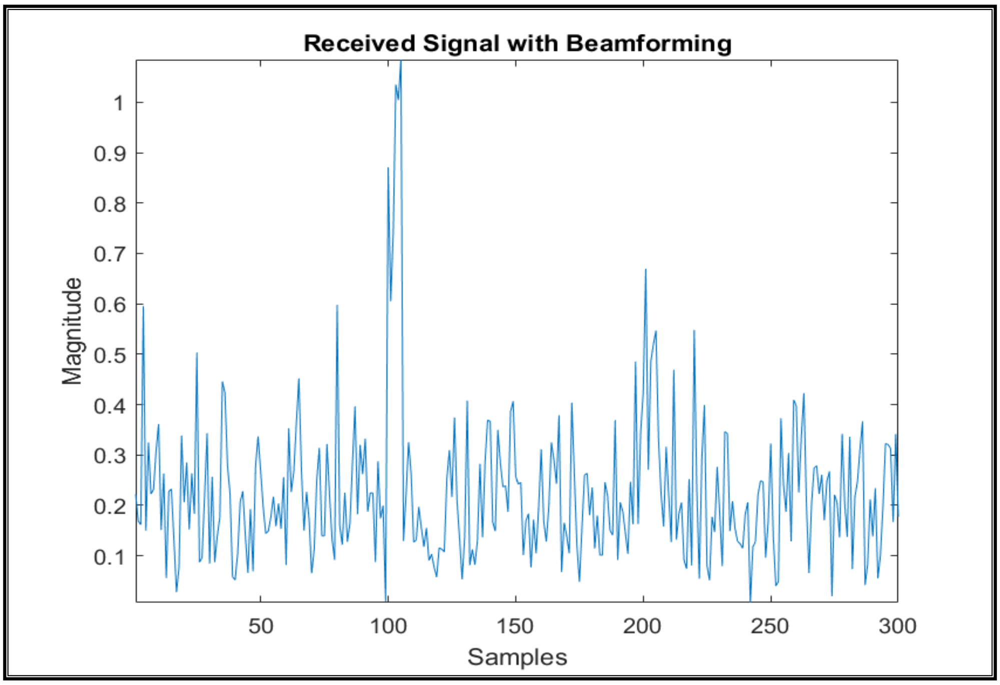

Figure 4.38: Beamforming Signal for 10 Elements

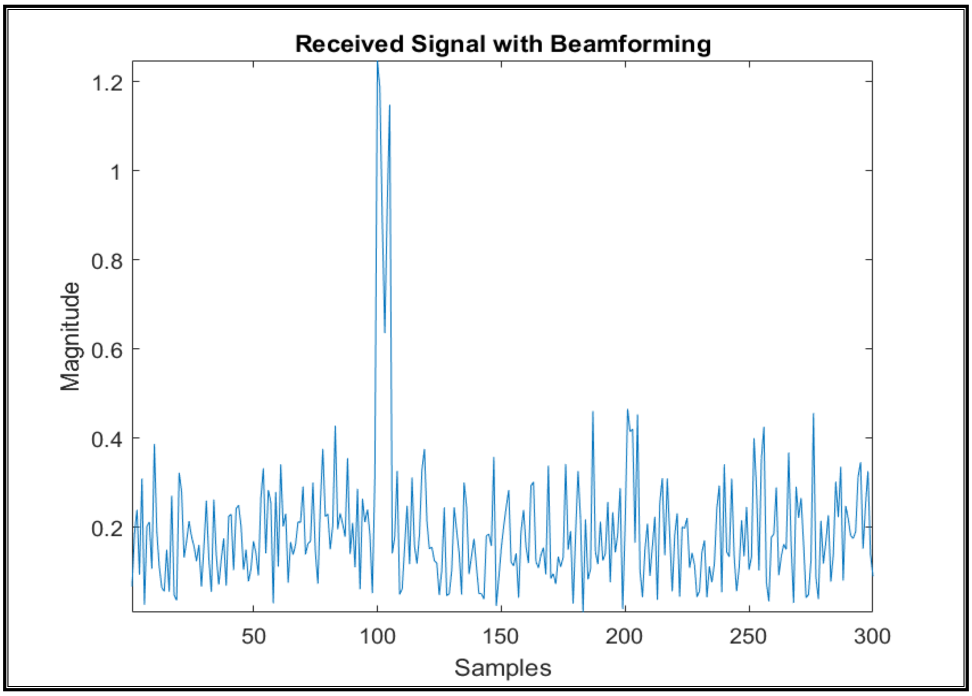

Figure 4.39: Beamforming Signal for 10 Elements.

Finally, a different modulation schemes, QPSK, QAM, 8QAM, and 16 QAM, were investigated to study the effect of modulation on the beamforming process into the system. Figure 4.40 Shows the BER for the system under the standard conditions mentioned in table I and II.

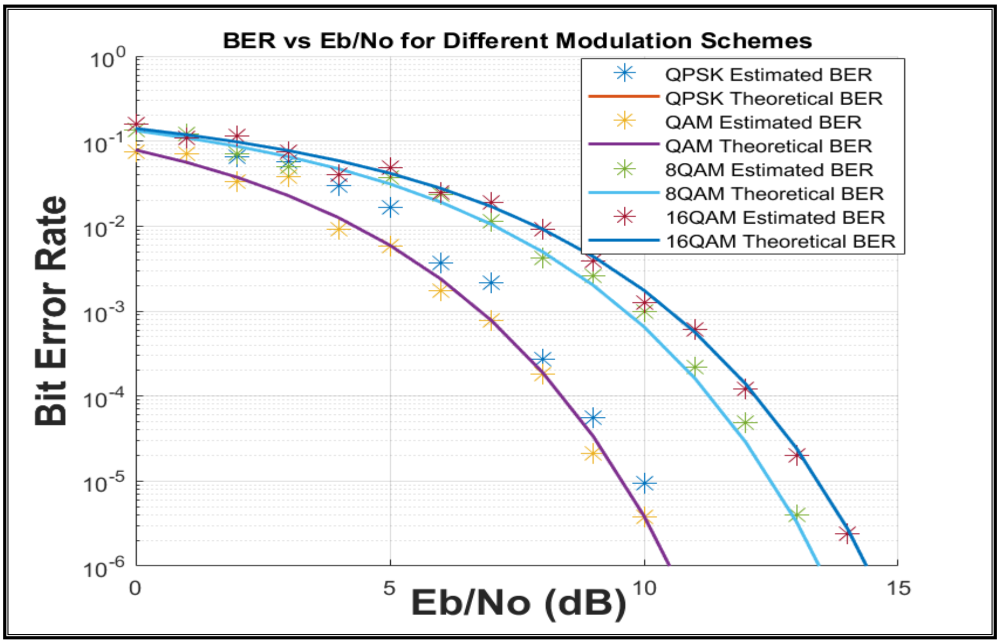

Figure 4.40: BER for Vertical and Horizontal Systems

From the observation, it can be noticed that the QPSK is of the worst performance, but of course, since beamforming is a technique that utilizes phase domain and QPSK works on the same domain so it is expected to be of reduced performance, but as the Eb increase, it follows the path of normal QAM and takes a steady steep. 8QAM comes after them being suitable for modulation at a lower cost, and then, ideally, the 16QAM is performing well in the system. Moving on to verify the throughput of the systems under different modulation schemes, Figure 4.41 shows the systems throughput under different modulation schemes.

An interesting effect can be noticed on the system. When observing the system's throughput, one can see that QPSK being the lowest then followed by QAM at certain Eb point, but the important point is that the stability of the system is constant at 6dB. Moreover, a limitation can be observed on the amount of data the system can absorb. QPSK and QAM being capped at 2Mbps, 8QAM being capped at 3Mbps, and lastly and ideally the 16QAM at 4Mbps.

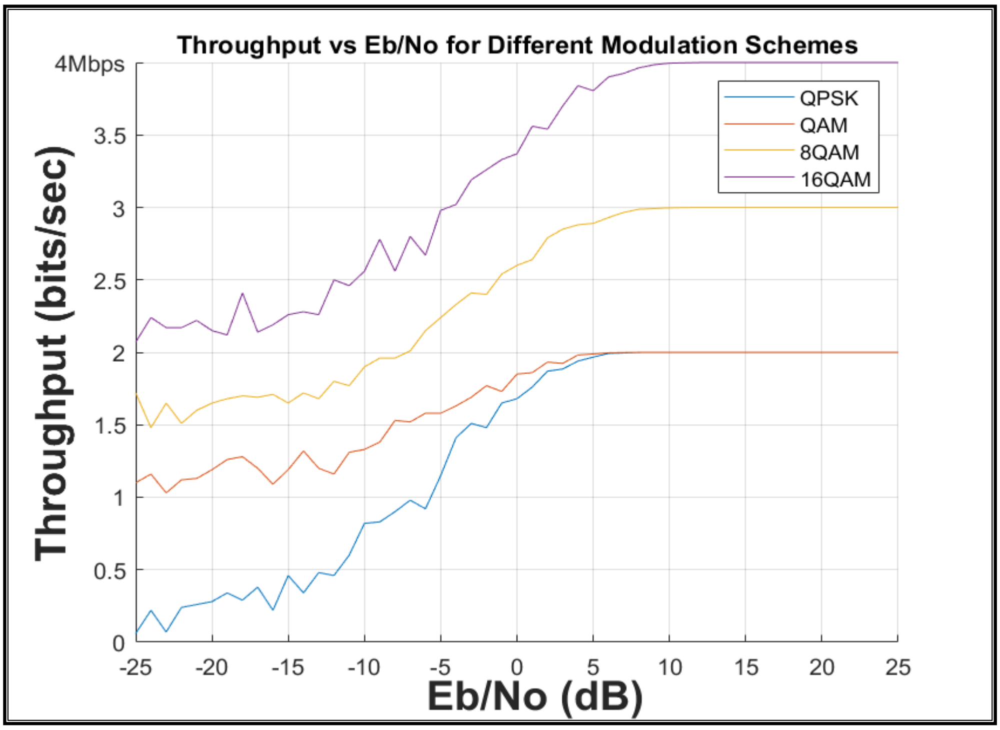

Figure 4.41: Throughput for Vertical and Horizontal Systems

CHAPTER FIVE

CONCLUSION AND FUTURE WORK

5.1. Conclusion

This dissertation thoroughly explored the central role of elevation beamforming in Full Dimension Multiple Input Multiple Output systems and extensively demonstrated the potential of such an approach for revolutionary improvement of future wireless networks. The combination of elevation and azimuth plane of one of the vital degrees of freedom in signal processing opened opportunities for solving most pressing issues related to signal quality, resilience to interference, and scalability in settings with extreme density like multiflora buildings in urban configurations that cause signal blockage and destructive path loss.

The dissertation utilized comprehensive simulations to show that elevation beamforming does not only help create network coverage and capacity but also allows avoiding expensive and complicated infrastructure enhancements to increase data rates and coverage at the same time by using fewer BSs or antenna systems. However, the employment of advanced beamforming strategies has one serious obstacle because they are very computation-expensive and require the most sophisticated real-time signal processing capacity.

Moreover, beamforming algorithms need to be adapted to different network conditions that change in minutes or even faster, which requires solid software tools and even more robust hardware solutions. It is both a challenging and promising direction for the improvement of global communication systems.

The simulation results provided robust evidence supporting the efficacy of elevation beamforming.

- Signal enhancement was notable, with beamforming user signal magnitudes reaching peaks over 1.2V. BER performance showed a significant improvement, with BER falling below the acceptable 10^{-5} level at 13 dB Eb/No and closely aligning with theoretical estimates.
- Throughput analysis indicated a substantial increase from 2.2 Mbps at -25 dB Eb/No to a peak of 3.8 Mbps at 5 dB Eb/No, with elevation beamforming outperforming azimuth beamforming by 3.45% at lower Eb/No levels and matching azimuth performance at higher Eb/No.
- Power distribution analysis revealed a significant 80 dB gain in central peak power when applying beamforming weights, improving from an average level of -100 dB to a central peak at -20 dB.
- The system's ability to dynamically adapt to optimal beam alignment in response to temporal changes in channel conditions was evident from the signal integrity improvements.

5.2. Future Work

The results of this dissertation establish the basis for extensive academic research to advance the implementation and operational use of elevation beamforming in FD-MIMO. It is reasonable to expect more research works to try to find optimal solutions to overcome the obstacles discussed in this work and unlock the full capacity of this technology for future-generation wireless systems.

As future work, there are areas that provide a roadmap for continued research and development in the field of AI-enhanced adaptive vertical beamforming for 5G networks and beyond:

- Increasing the users is a difficult task as it requires increasing demands on managing the interference between them and raises higher concerns when facing environments with same or higher noise.
- Focusing on the deployment of elevation beamforming in urban settings to overcome challenges related to high-rise buildings and dense infrastructures.
- Exploring quantum computing methods to handle the complex calculations required for real-time beamforming in dense network environments.
- Reducing the computational complexity of current beamforming algorithms to facilitate faster processing and lower power consumption.

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الخلاصة

تبحث هذه الدراسة في امكانية دمج تقنيات الذكاء الاصطناعي الحديثة في أنظمة الاتصالات من نوع FD-MIMO لجعلها قاعدة نظرية يستند عليها في خوارزميات تشكيل الحزم (Beamforming) وتحسين أدائها, وهي أحد الميزات الأساسية في تطوير أنظمة FD-MIMO.

توفر هذه الدراسة نهجًا أفضل يجمع بين أساليب الذكاء الاصطناعي والتعليم المعزز (Reinforcement Learning) وذلك لتحقيق افضل اداء ممكن في خوارزميات تشكيل الحزم التكيُفية وفق سيناريوهات الشبكة المتغيرة ديناميكيًا، حيث تمت مقارنة مختلف استراتيجيات تشكيل الحزم بنوعيها الأفقية والرأسية باستخدام مصفوفات ULA وURA.

اعتمد تقييم الأداء على اهم المقاييس الرئيسية وهي BER، وسرعة نقل البيانات، وEb/No. وقد اظهرت النتائج تحسينات جيدة من حيث سلامة الإشارة والكفاءة الطيفية، وقد لوحظ قرب نتائج المحاكات من تلك القيم التي نتجت من النتائج النظرية مع زيادة واضحة في سرعة نقل البيانات والتي كانت بحدود من 2.2 ميجابت في الثانية عند -25 ديسيبل لكل Eb/No إلى 3.8 ميجابت في الثانية عند 5 ديسيبل لكل Eb/No وايضا اظهرت النتائج تحسينات في SINR في حدود 80 ديسيبل من خلال تطبيق عناصر تشكيل الحزم (Beamforming Weights) المُحسّنة.

اظهرت النتائج النهائية لهذه الدراسة قدرتها في التغلب على اهم التحديات في المناطق السكنية عالية الكثافة واتاحة فرصة جيدة للعمل باداء افضل على تحسين الشبكة اللاسلكية من خلال تطبيق استراتيجيات تشكيل الحزم المدعمة بالذكاء الاصطناعي.

عن أداء تشكيل الحزم لبنيات MIMO الضخمة في أنظمة 5G

رسالة تقدم بها

يوسف ماهر عبد الحميد

إلى

مجلس كلية هندسة الالكترونيات / جامعة نينوى وهي جزء من متطلبات نيل درجة الماجستير في العلوم في

هندسة اتصالات

إشراف

أ. م. د. علي عثمان الجنابي

1446هـ **2024م**

جامعة نينوى
كلية هندسة الالكترونيات
قسم هندسة الاتصالات

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يوسف ماهر عبد الحميد

رسالة ماجستير
هندسة الاتصالات

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2024م 1446هـ