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Artificial-Intelligence-Enhanced Beamforming for Power-Efficient User Targeting in 5G Networks using Reinforcement Learning

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Abstract: In the quest for optimizing 5G networks, this study introduces an innovative Artificial Intelligence (A.I.)-based beamforming technique 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 base station (BS) which conducts an omnidirectional scan to identify and direct beams towards the user equipment (UE) exhibiting the lowest power signature, optimizing the network's performance and efficiency. Extensive simulations conducted using a Uniform Linear Array (ULA) at 28 GHz with QAM modulation to authenticate the process, A.I. algorithm dynamically adjusted the beamforming weights, which were then applied to synthetic user signals to simulate real-world conditions. The results, validated through Bit Error Rate (BER), Throughput, Angle of Arrival (AOA), Direction of Arrival (DOA), and Array Response metrics demonstrated that the A.I.-driven approach not only reduces power consumption but also maintains signal fidelity with high precision. A.I.'s decision-making process was exactly analyzed showing its capability to fine-tune beam direction in the presence of noise and interference. The study concluded that A.I.-based steering towards the least power-intensive user is not only viable but also enhances overall network efficiency and reliability.

Keywords: A.I.,Beamforming,BER,Throughput,5G.

1. INTRODUCTION

There has been a lot of interest in millimeter-wave (mm-wave) beamforming's ability to deliver extremely high data rates of gigabits per second (Gb/s) as a broadband possibility for fifth generation (5G) cellular communications networks. Massive multi-input multi-output (MIMO) is one of the most promising techniques for boosting the spectral efficiency (SE) of cellular networks. It involves using beamforming technology to outfit the base station (BS) with antenna arrays that have hundreds or thousands of active elements and perform coherent processing on both the transmitter and receiver sides [1].

The key components that enable current wireless communications are beamforming with millimeter-wave (mmWave) and massive MIMO systems. Using mmWave technology, which significantly increases the data rate, throughput, and capacity, is a key component in resolving throttling congestion in the available bandwidth. Massive MIMO mmWave communication achieves the desired output results SE by employing multiple frequencies with three different beamforming techniques: conjugate beamforming (CB), Minimum Mean Squared Error (MMSE), and zero-forcing (ZF) across mm-Wave channel [2]. However, conventional beamforming techniques, while effective, often require significant power consumption and may not optimize the use of the electromagnetic spectrum.

Despite these advancements, current beamforming techniques, as discussed in the works of Thakur et al., often focus on optimizing sparse array configurations to enhance the Output Signal to Noise Ratio (OSINR) without adequately addressing the dynamic conditions of mobile environments. Their approach introduces additional constraints in the beamforming process to control sidelobe levels, which is crucial for reducing interference in densely populated network areas [3].

The integration of Artificial Intelligence (A.I.) with beamforming presents a novel solution to these challenges. A.I. algorithms can dynamically adapt to the environment, users' positions, and channel conditions, enabling more efficient and intelligent beam steering [4].

This research introduces an innovative A.I.-based beamforming technique that focuses on steering the beam towards users with the least power consumption while maintaining the integrity of the signal. The suggested method

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uses a phased array system with a carrier frequency of 28 GHz and machine learning algorithms to look at the beamforming weights and change them in real time. In this study, we utilize a combination of Reinforcement Learning (RL) and adaptive signal processing to enhance beamforming in 5G networks. The RL component dynamically adjusts scaling factors for user signals, while adaptive signal processing techniques are used for optimal beamforming and Direction of Arrival (DOA) estimation. This approach not only promises significant improvements in power efficiency but also in the accuracy of the signal's directivity, which is crucial for high-density environments where 5G deployment is most beneficial [[5]-[6]]. The primary objectives of this research are to develop a novel A.I.-based beamforming algorithm that enhances power efficiency and signal integrity and evaluate the performance of the proposed algorithm through extensive simulations.

Contributions to the 5G networks:

- **Novel Approach**: This system model is distinct in its combination of adaptive signal processing with machine learning-driven dynamic adjustments. It exemplifies a novel approach to solving traditional problems in 5G network management, such as power efficiency and signal integrity, by integrating AI directly into the physical layer of network architecture.
- **Specific Algorithms**: The research employs a combination of RL for dynamic signal scaling and adaptive signal processing for beamforming and DOA estimation, which optimizes the system's performance.
- **Unique System Model**: The paper introduces a unique system model that combines the use of a Uniform Linear Array (ULA) at 28 GHz with AI-driven beamforming strategies.
- **Practical Implications**: The study demonstrates how AI-enhanced beamforming can enhance power efficiency, signal fidelity, and overall network performance, with potential applications in high-density environments.

The rest of this paper is as the following way, the previous works related to beamforming presented in section II. Section III presents the mathematical model of the proposed AI beamforming. Section IV explains the system assumptions and configuration of proposed model. Section V presents simulation evaluation and results assessment. Finally, the paper presents the conclusions and future work in Section VI.

2. Related Works

The beamforming problems have heightened the demand for technical solutions to overcome the technical problems associated with directing the beam at certain points. Some developing centers have suggested solutions for these problems such as enhancement of Signal-to-Noise Ratio (SNR), while others suggested different solutions.

In [7], the authors explored the concept of contextual beamforming, advantages, disadvantages and implications. Their study presented an impressive 53% improvement in SNR by implementing the adaptive beamforming (MRT) algorithm compared to scenarios without beamforming. They examined the importance of localization in implementing contextual beamforming. In [8], the author studied and analyzed the overall FEDS approach performance and tried to find its optimal window length for adaptive beamforming applications. The author used the channel in a Rayleigh fading model with Jake's power spectral density, which is a popular choice for wireless communications systems which has a Doppler frequency and the user's mobility parameters. In [9], authors elaborated on the motivations and difficulties faced in implementing Leep Learning (DL) for beam control in millimeter-wave communications. 3GPP provides a glimpse of big-antenna arrays and directional beamforming as ways to counteract the poor free space loss that mmWave signals have and reviews the current state-of-the-art techniques for DL-assisted beam management. They also touch on their research vector and major characteristics. In addition to the advantages of narrow beams for large beamforming gains, it also points out some drawbacks, such as training overhead, and sensitivity compared to blockages associated with the use of thin channels. By summarizing the challenges and future opportunities of DL design insights, novel beam management mechanisms for stimulating innovative ideas and contributions in DL-assisted beam management are proposed.

In [10], authors compared the performance of mm-wave frequencies (28 GHz and 73 GHz) in terms of spectrum efficiency using massive MIMO and two beamforming methods. Its results are that in different cases with an increasing number of antennas, there are significant improvements on the spectrum using 28 GHz compared to 73 GHz. 28 GHz performed better than 73 GHz, in which beamforming technology consists of two main classes, namely, conjugate beamforming (CB), also referred to as spatial multiplexing vector, and zero-forcing (ZF) carried out for null. In general, the paper has proposed that mm-wave frequencies coupled with massive MIMO and beamforming techniques would significantly improve the spectrum efficiency of cellular communication networks. 28 GHz depicts that it outperforms in this case by giving greater performance. In [11], the paper compared many resources scheduling schemes in the 5G system with network slicing. The paper compared many resource scheduling algorithms, best Channel Quality Indicator (CQI), Round Robin (RR), proportional fair (PF), to assess each scheme performance. Then they proposed an adaptive scheduling scheme that dynamically chooses the scheduling algorithm among mentioned schemes that optimized the traffic, user throughput, and cell capacity.

In [12], the system is composed of four stages: antenna array, channel model, spatial multiplexing, and hybrid beamforming. An array of antennas is constructed and used for the sub channel model. The outputs are then used to simulate spatial multiplexing and hybrid beamforming. The result of each model concludes that both transmission methods are reliable for merging 5G cellular systems. In [13], the authors proposed an integrated system utilizes the 5G wireless cellular integrated with satellite communication systems by taming many downlink channels of the satellite link to manage the new 6G system. With the terrestrial's satellite, the satellite receivers will be directed to the LEO-system are communicated to the 5G systems or base stations. The new system will be able to support all user services and applications.

While previous studies have demonstrated significant advancements in beamforming techniques for 5G networks, they often rely on static models or focus solely on optimizing specific aspects of beamforming. For instance, the ResNeSt-based approach, while effective in static scenarios, does not address the challenges of dynamic network environments which are crucial for real-time applications [14]. Similarly, while stochastic geometry provides a robust framework for analyzing beam management, it does not accommodate the real-time adaptation required in rapidly changing conditions [15]. Furthermore, while deep RL has been explored for optimizing beam selection, the integration with adaptive signal processing remains underexplored, which is crucial for enhancing the overall system responsiveness and efficiency [16].

Chary et al. [17] 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. Our approach leverages reinforcement learning for dynamic beamforming weight adjustment, aiming to balance computational efficiency with high performance in real-time applications, another study done by Hamid et al. [18] explored hybrid beamforming in massive MIMO systems, comparing analog, digital, and hybrid techniques. Their study demonstrated that hybrid beamforming, which connects a group of antennas to a single RF chain, offers a balance of flexibility, power efficiency, and cost-effectiveness. While hybrid beamforming shows improved performance over purely analog methods, it still faces challenges related to signal processing complexity and hardware implementation. Our approach also employs hybrid beamforming but focuses on optimizing computational efficiency and real-time application performance through reinforcement learning.

Our proposed method addresses these gaps by introducing a hybrid model that combines RL with adaptive signal processing, enabling dynamic scaling and real-time adjustment of beamforming strategies. This approach not only enhances system adaptability in changing environments but also improves computational efficiency, making it highly suitable for 5G networks where flexibility and responsiveness are paramount

3. System Assumption And Configuration

The following section contain system assumption, configuration of the simulated MATLAB model, and the designed system's flowchart as follows. MATLAB and the Phased Array System Toolbox were used to conduct all the simulations

A. *System Assumptions*

- Modulation Scheme (16-QAM)
- Beamforming Algorithm is Hybrid Phased
- A.I. Algorithm for Beam Steering for optimizing power consumption and maintaining signal integrity.
- Two distinct signals are generated to represent two 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 A.I. 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, combining them in such a way to form a single beam directed towards the chosen user's signal.
- The A.I. employs a DOA estimation algorithm using MUltiple SIgnal Classification (MUSIC) estimator to find the direction from which the signals are arriving amidst the noise.
- The A.I. uses the calculated power to decide which user to direct the beam towards, opting for the user with the lower power signal to optimize system performance.
- The A.I.-controlled system dynamically adjusts the beam direction to align with the estimated DOA of the selected user.

B. System Configurations

Referring to Table I shown below, which it 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 I. System Configuration Parameters and Their Impact on 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	$\lambda/2$	Affects the array's spatial resolution and sidelobe levels
Modulation Order (M)	16	Affects BER and throughput
SNR	-25 to 25 dB	Challenges the A.I. in correctly estimating DOA
AOA	MUSIC	Determines beam steering direction
Scaling Factors	0-1	Used by the A.I. to prioritize users based on power
Frame Duration / s	1 ms	Affects the data transmission
Symbol Rate / Hz	1 MHz	Rate at which symbols are transmitted

C. System Model And Flowchart

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 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.

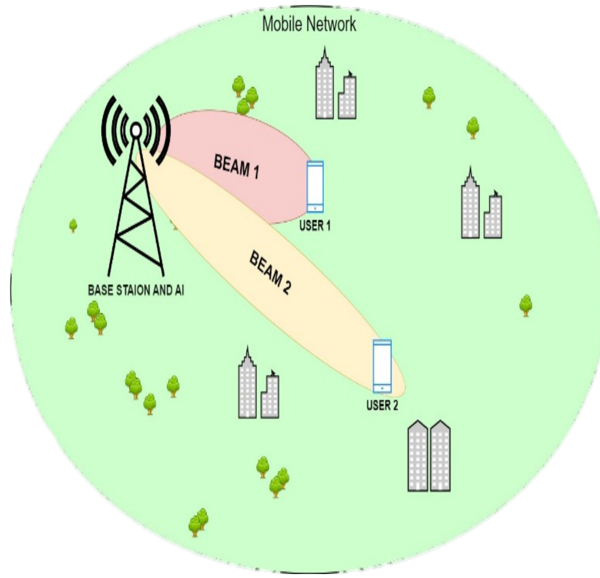

Figure 1. Beamforming System Model

Referring to Figure 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 A.I. chooses the user with the least power in the network and adjusts the beam towards the user with the least power.

The system incorporates RL for dynamically scaling the signals. The scaling factors are adjusted iteratively based on varying states to optimize performance. Additionally, adaptive signal processing techniques, such as the MUSIC estimator, are used for beamforming and DOA estimation, allowing the system to steer beams towards the user with the least power. If the user moves or changes, its power is restored; a recalibration happens by sending feedback to the station, which makes the system redo the scaler calculation.

D. System Model Components

Our system model is designed to harness the capabilities of AI to enhance beamforming techniques in 5G networks, focusing on power efficiency and signal integrity. Below is a detailed description of each key component involved in the system:

1- **ULA**:
The core of our beamforming system is a ULA consisting of 10 antenna elements. These elements are spaced half a wavelength ($\lambda/2$) apart, which is crucial for minimizing interference and maximizing the directionality of the beam. The ULA operates within a frequency range of 27 GHz to 29 GHz, with a focus on the 28 GHz carrier frequency for optimal performance in high-frequency 5G applications.

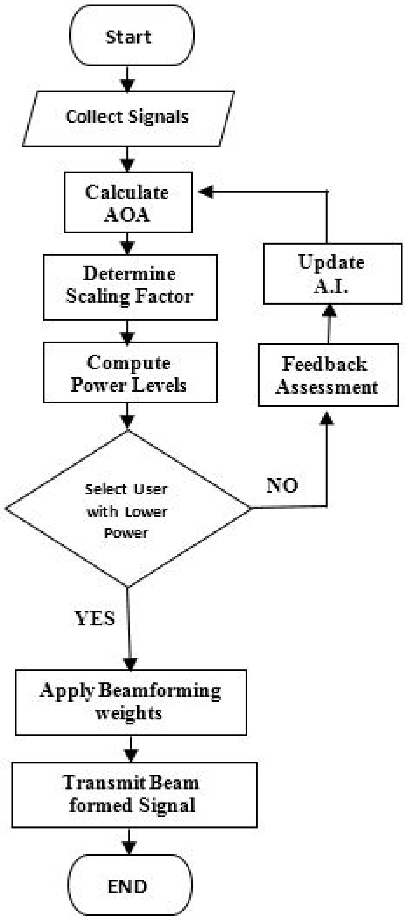

Figure 2. System's Flowchart

2- **AI Algorithm for Beam Steering**:
Beam steering is executed through a sophisticated AI algorithm that dynamically adjusts beamforming weights. This algorithm utilizes RL to iteratively modify the scaling factors of the signals based on real-time performance metrics. This approach enables the system to adapt to changing environmental conditions and user positions, optimizing the beam's direction towards users with the lowest power consumption.

3- **Signal Generation and Processing**:
Multiple user signals are generated to simulate real-world scenarios. These signals are modified by the AI algorithm to ensure that the beam is directed at the optimal angle. Each signal's power is calculated, and the AI chooses the direction for beamforming based on the user with the lowest power signal, thus maintaining system efficiency and integrity.

4- **DOA and AOA Estimation**:
The system employs the MUSIC estimator for precise DOA and AOA estimation. This advanced signal processing technique helps in accurately determining the directions from which signals arrive, which is critical for effective beamforming.

5- **Modulation and Transmission**:
The system utilizes a 16-QAM modulation scheme to modulate the user signals. This choice of modulation balances complexity and performance, providing a good trade-off between data rate and error performance in a congested network environment.

6- **Noise and Interference Management**:
To simulate realistic communication scenarios, artificial noise is added to the user signals. This component of the model tests the robustness of the AI-driven beamforming in noisy environments, ensuring that the system can maintain high signal integrity under adverse conditions.

E. Machine Learning Algorithms Utilized

1- **Reinforcement Learning**:

The study utilizes a RL-like approach to dynamically adjust scaling factors for different user signals. The operation uses a persistent state to toggle between different configurations, optimizing the system's performance based on user power levels.

2- **Adaptive Signal Processing**:

The study employs adaptive signal processing techniques, such as a phase shift beamformer and the MUSIC estimator, for beamforming and DOA estimation, respectively. These algorithms help steer the beam towards the desired user with the least power while minimizing interference.

4. Mathematical System Model

The mathematical equations provided are recognized in the communications engineering discipline and represents a fundamental resource for the proposed model paper. The system utilizes RL for dynamic scaling of user signals. A persistent state toggles 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. [[19]-[20]].

A. Mathmatical Model For Beamforimg

The mathematical model of the simulated A.I. 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):

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

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):

$$[x(t) = A(t)s(t)e^{j(2\pi f_c t+\phi)} + n(t)] \tag{2}$$

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, is the transmitted signal, is the carrier frequency, is the phase shift introduced by the channel, and represents the noise.

An A.I.-based beamforming algorithm should strive to optimize the weights (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 Eqs. (3,4):

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

$$[\ s.t. \ \frac{|AF(\theta)A(t)|^2}{\sigma_n^2} \ \geq \ \gamma\ ] \tag{4}$$

Where (σ_n^2) is the noise power.

A.I. 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 A.I. 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.

B. Mathmatical Model For A.I. 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 A.I. algorithm operates in two phases: training and execution. In (Training Phase), the A.I. uses a set of training signals to learn the optimal beamforming weights. The channel state information (CSI) for each user is estimated and stored. In this stage, the A.I. 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 A.I. 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).

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

Subject to the following constraints for each user(k), Eq. (6) is representing Signal-to-Interference-plus-Noise Ratio (SINR) constraint for user(k):

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

Where (w_k)the beamforming vector for user is(k), (γ_k) is the minimum signal to interference plus noise ratio (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):

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

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 A.I. algorithm adjusts in time by adjusting its weights($W = [w_1, w_2, \ldots, w_K]$).

The A.I. 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 in cases of traffic concentration. 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 A.I.-driven beamforming strategy in a mobile multi-user environment. This model paves 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.

C. Mathmatical 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):

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

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):

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

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:

$$[\frac{E_b}{N_0} = \frac{SNR}{R_b/B}] \tag{10}$$

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

$$[SNR(dB) = 10\cdot\log_{10}(SNR)] \tag{11}$$

D. 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):

$$[Throughput = R_b\cdot(1-BER)] \tag{12}$$

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

$$[Throughput_{effective} = \frac{R_b\cdot(1-BER)}{1+Retransmissions\ due\ to\ errors} \tag{13}$$

E. Array Gain And Beamforming

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

$$[G = N\cdot G_e\cdot AF(\theta)] \tag{14}$$

Where (N) is the number of antenna elements, (G_e) is the gain of a single element, and ($AF(\theta)$) is the array factor, 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):

$$[AF(\theta) = \frac{\sin(N\pi d\sin(\theta)/\lambda)}{N\sin(\pi d\sin(\theta)/\lambda)}] \tag{15}$$

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.

F. Beam Steering

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

$$[\Phi_n = \frac{\{2\pi\}\{\lambda\}}{(n-1)d\sin(\theta_d)}] \tag{16}$$

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

G. MUSIC Algorithm

The A.I. uses statistical methods and signal processing algorithms. Thus, when noise is present the A.I. 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):

$$[s_i(t) = \delta(t-t_{0i})] \tag{17}$$

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):

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

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 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):

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

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

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

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):

$$[P(\theta) = \frac{1}{a(\theta)^H E_n E_n^H a(\theta)}] \quad (21)$$

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 beam formed output (y) is shown in Eq. (22):

$$[y(t) = w^H x(t)] \quad (22)$$

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

5. Simulation Evaluation and results Discussion

System analysis starts with Figure 3, which illustrates a time-domain signal depiction for two different users. Figure 3 shows the users being spread out in time domains, and they are separated from each other to make them more distinct.

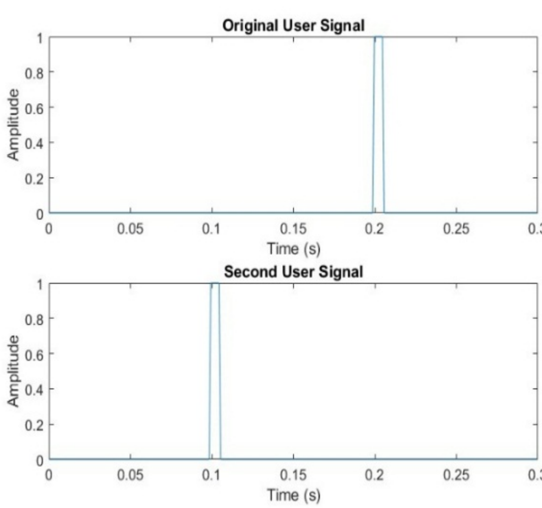

Figure 3. Time-Domain Signal for Two Users1

In Figures 4 and 5, 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 A.I. 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 A.I. system processes the combined signal (the original signal coupled with noise).

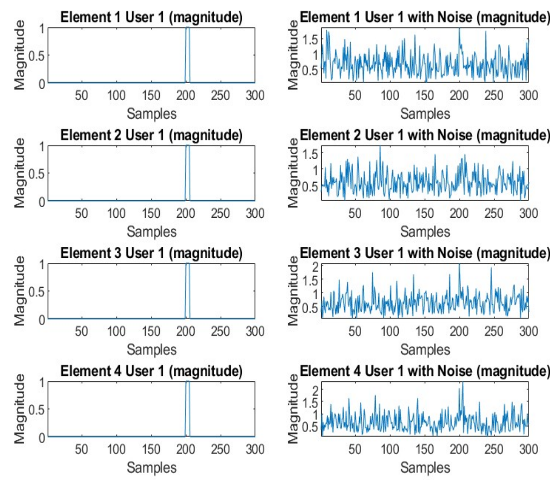

Figure 4. Noise Signal added to Users1

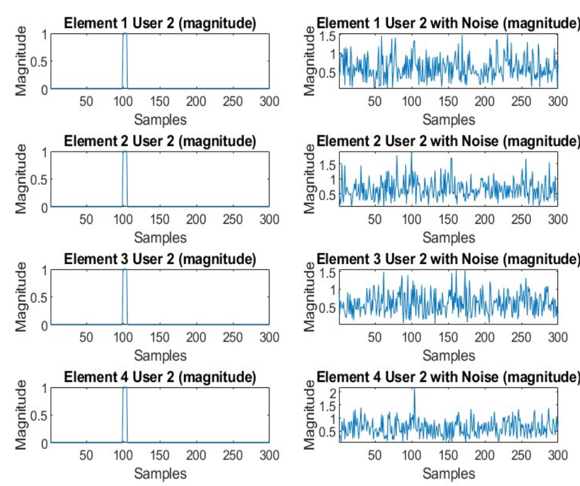

Figure 5. Noise Signal added to Users2

Figure 6 and 7, on the other hand, draw polar plots that depict the adopted AOA for their respective users. In hindsight, these plots are very important for showing how well the A.I. fixes on AOA, which is a big part that is needed and enough to keep power usage low while signal integrity stays high.

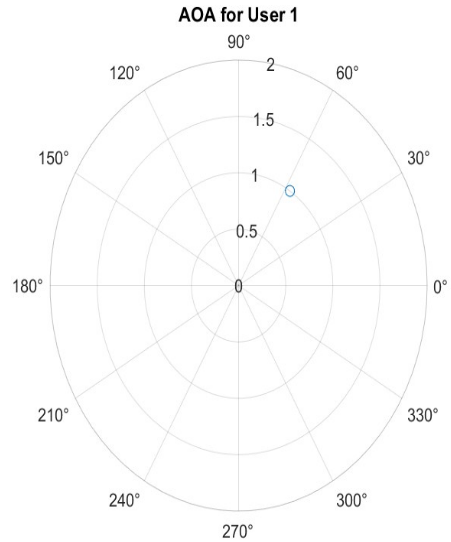

Figure 6. AoA for Users1

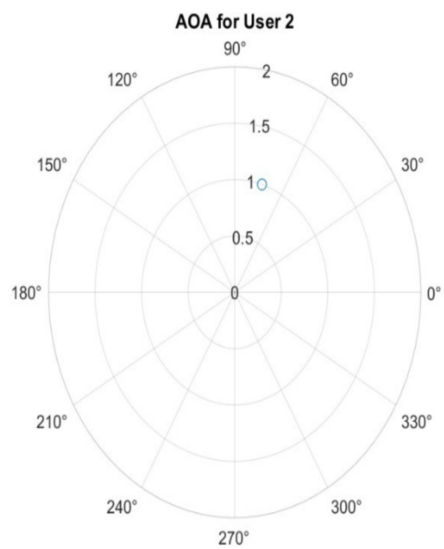

Figure 7. AoA for Users2

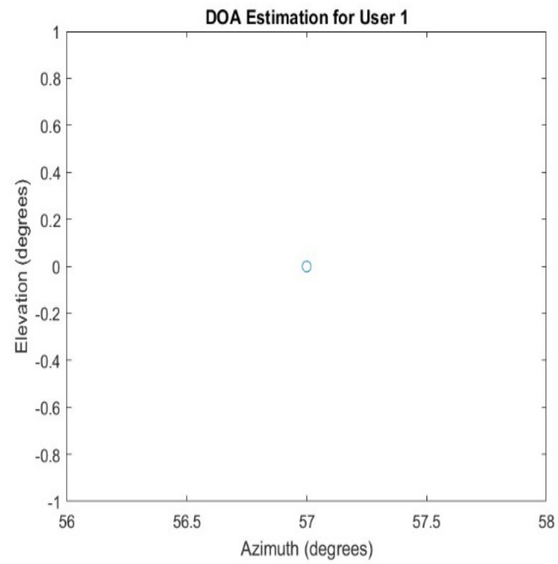

Figure 8. Fig. 8. DOA for users1

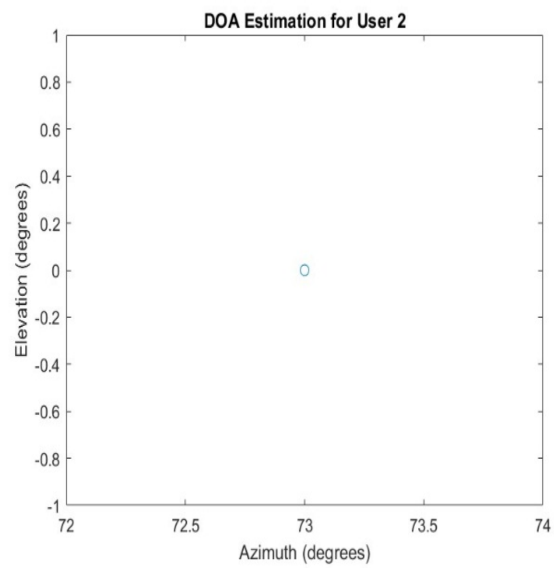

Figure 9. DOA for users2

Figures 8 and 9 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 A.I. 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.

Figure 10 is a key illustration in depicting the effect of A.I.-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 10 when a beamforming operation has been applied to it. This peak is not just a graphical construction but stands for a measurable manifestation of the A.I.'s ability to enhance controllable features and eliminate unwanted noise and interference. In a detailed analysis of this figure, one must elaborate on the A.I. algorithms that can adaptively optimize beamforming weights. This optimization is essential to ensuring the high signal clarity in Figure 3. The A.I.

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 A.I. 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 A.I. to maintain signal integrity. One of the important facets that may be considered for a dialog is how the A.I. 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 A.I. algorithm to isolate or strengthen only the desired signal path.

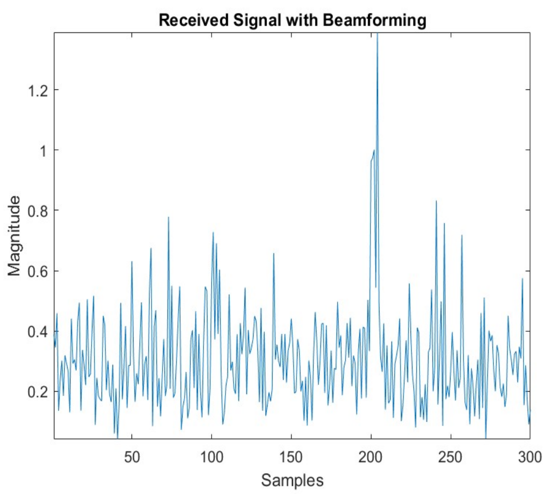

Figure 10. Received Signal after Beamforming

In Figures 11 and 12, 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. A more detailed analysis here will be 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 result in a complete picture of system capabilities.

Figure 11. Azimuth Angles for user1

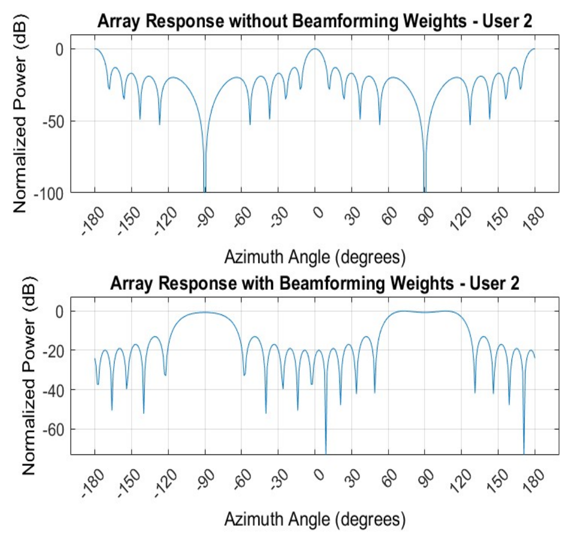

Figure 12. Azimuth Angles for user2

The simulated BER analysis for the system is shown in Figure 13. The points of blue stars represent the results of the BER simulation using the A.I. 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 A.I. 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 it 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 A.I. 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 A.I. algorithm should not compromise BER beyond acceptable levels.

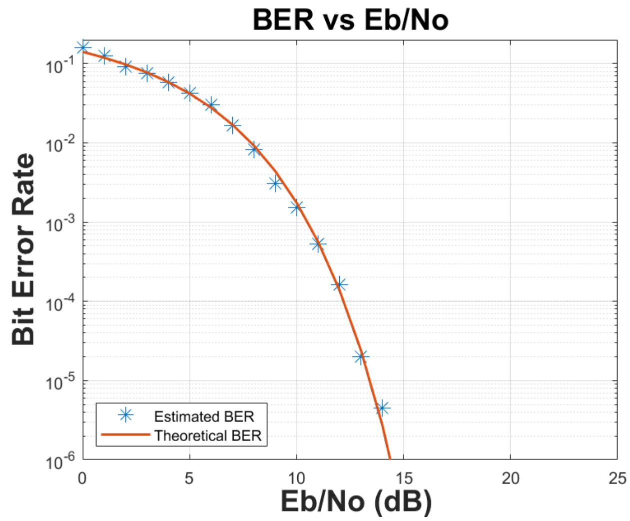

Figure 13. BER vs. EbNo. (dB)

Figure 14 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 A.I. algorithm can keep the beam alignment despite less-than-full SNR 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 A.I. algorithm.

However, the A.I. 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 A.I. 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.

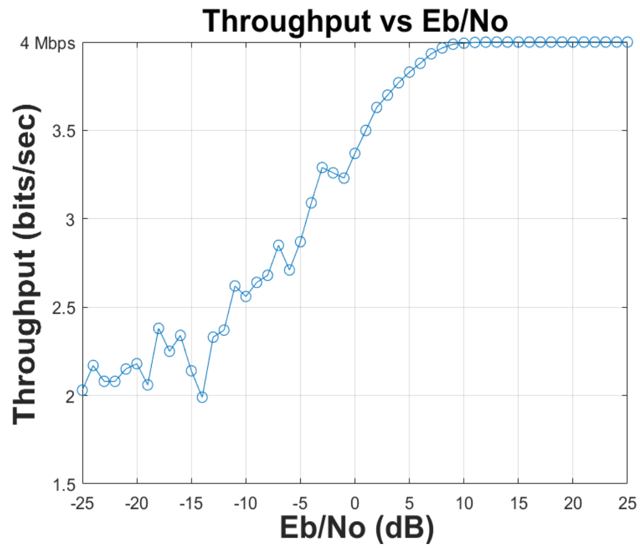

Figure 14. Throughput vs. Eb/No

6. Conclusion

This paper introduces an innovative AI-based beamforming technique by focusing on power efficiency and signal integrity. Using a machine learning algorithm, the BS did an all-around scan to find and direct beams towards the user equipment (UE) with the lowest power signature. This improved the budget link for that user and enhanced the network performance. Extensive simulations were conducted using ULA at 28 GHz with QAM modulation to authenticate the process. The A.I. algorithm dynamically adjusted the beamforming weights, which were then applied to synthetic user signals to simulate real-world conditions. BER, Throughput, AOA, DOA, and Array Response metrics were used to confirm the results. They show that the A.I.-driven approach not only cuts down on power use but also keeps signal quality very accurate. The A.I.'s decision-making process was exactly analyzed, showcasing its capability to fine-tune beam direction in the presence of noise and interference. The study concluded that AI-based steering towards the least power-intensive user is not only viable but also enhances overall network efficiency and reliability. In the very near future, A.I.-based beamforming in vertical elevation will enhance power efficiency, network capacity, and the user's throughput.

A. Limitations

While the results of this study are promising, several limitations should be noted. First, the simulations were conducted in a controlled environment, which may not fully capture the complexities of real-world conditions. Second, the performance of the AI algorithm may vary depending on the specific hardware and network configurations used in practical implementations. Finally, the study focused on a limited number of users and signal scenarios, and scalability to larger networks with more users remains to be investigated. Future work should address these limitations by validating the proposed approach in real-world 5G network deployments and exploring the integration of AI-driven beamforming with other advanced technologies.

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