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Enhancing Spectral Efficiency in 5G MIMO Networks Through Adaptive Beamforming Techniques

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Abstract—**The evolution of 5G networks is driving advancements in data rates, latency reduction, and connectivity, with adaptive beamforming emerging as a core technology to enhance spectral efficiency. This study demonstrates how integrating beamforming with spatial filtering can effectively optimize signal quality in 5G MIMO networks. Through simulations, we show that our approach achieves significant improvements in Signal-to-Noise Ratio (SNR) by optimizing beam directions. Specifically, results indicate that optimal beamforming angles can yield SNR values as high as 78 dB, substantially outperforming lower SNRs observed at less favorable angles. These findings underscore the potential of combined beamforming and spatial filtering to enhance communication reliability and network performance, particularly in high-density settings.**

Keywords—Beamforming, Interference Management, Multiple Input Multiple Output (MIMO), Resource Allocation, Spatial Filtering, 5G Networks

I. Introduction

Mobile communications have been revolutionized by the rapid advancements in the deployment of Fifth Generation (5G) networks. These promise improved data rates, reduced latency, and extensive device connectivity, leading the digital transformation of various industries and societies. However, realizing the full potential of 5G networks requires overcoming complex technical challenges, particularly in signal transmission and management.

Beamforming is a key technology in this context, enabling directional transmission of radio waves to enhance signal strength at the receiver, thereby improving the network's overall spectral efficiency. This directional transmission is crucial in scenarios with limited bandwidth and high User Equipment (UE) density, optimizing the use of scarce radio resources.

Alongside beamforming, spatial filtering plays an essential role by precisely directing transmission beams toward intended UE while minimizing signals in unintended directions. This capability is crucial for reducing interference, enhancing signal quality, and ensuring efficient use of the radio spectrum.

The importance of spatial filtering is even more pronounced in densely populated urban areas or environments with numerous IoT devices [1], [2], where managing interference is a significant challenge. By directing transmission beams, spatial filtering avoids non-target areas and concentrates signal power on specific UE or devices, maintaining high-quality service across the network.

Additionally, spatial filtering increases system capacity by servicing more UE within the same spectrum, achieved by minimizing interference and enabling more simultaneous data transmissions. This capacity increase is further supported by spatial filtering's ability to extend Base Station (BS) coverage areas, efficiently allocating signal power where it is most needed.

The dynamic nature of spatial filtering allows for flexible resource allocation, enabling real-time adjustments to beam patterns in response to changing network demands and UE mobility. This dynamic resource allocation optimizes the use of available network resources across various applications, from high-speed video streaming to ultra-reliable low-latency communications for autonomous vehicles and industrial automation.

Moreover, spatial filtering supports the deployment of advanced BS technologies like massive Multiple Input Multiple Output (MIMO) systems, which use hundreds of BS elements to create highly directional beams, significantly enhancing throughput and reducing latency.

Finally, spatial filtering is crucial for spectrum sharing among different services and operators, a necessity as the radio spectrum becomes increasingly crowded. By managing transmission directionality, spatial filtering ensures that multiple operators can coexist within the same spectral band, maximizing spectrum efficiency without causing harmful interference.

Given these transformative capabilities this paper explores the roles of beamforming and spatial filtering in improving signal reception for UE in modern mobile networks. Beamforming helps direct signal transmission toward specific users, which strengthens the signal and reduces interference. Spatial filtering further improves this by blocking unwanted signals, making communication clearer. The strength of this method lies in the adaptive nature of spatial filtering, which can adjust in real-time to changes in UE movement—a capability that traditional beamforming lacks. This study aims to improve user experience by providing more stable and higher-quality connections, meeting the growing demand for data and connectivity. These techniques are paving the way for more efficient and reliable mobile networks [3], [4], [5], [6], [7].

The rest of the paper is organized as follows: In Section II related work is presented through various studies which focus on beamforming optimization. In Section III, the mathematical model utilized in the simulation environment is introduced. Moving to Section IV, the algorithm analysis that

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forms the basis for constructing the experiment scenarios is delved into. Section V outlines the simulation setup and methodology employed to assess the performance of Spectral Efficiency in MIMO 5G Heterogeneous Networks (HetNets). Following that, in Section VI, the simulation results are presented, and a comprehensive analysis of the findings is conducted. Lastly, Section VII concludes the paper and offers insights into potential avenues for future research.

II. RELATED WORK

There have been studies focused on optimizing beamforming in 5G MIMO networks, such as paper [8], in which a Convolutional Neural Network (CNN) is trained on data from a fading communication channel model to predict beamforming weights, simplifying the estimation process. The study shows that deep learning reduces complexity and improves efficiency in both digital and hybrid beamforming. Results indicate that deep learning achieves spectral efficiency close to conventional methods, especially as the number of antennas increases, highlighting its potential in optimizing 5G MIMO systems. Moreover, in paper [9] a link-level model is developed to relate antenna array elements and spatial separation distance, while a system-level model relates inter-site distance with SINR. The study demonstrates that even with increasing device density, beamforming maintains efficient Space-Division Multiple Access (SDMA) capabilities. Additionally, the research establishes a relationship between Half-Power Beam Width (HPBW) and spatial separation, suggesting an ellipse as a measure for positioning accuracy in location-aware beamforming.

Further advances in the optimization of beamforming are explored in paper [10], where Reinforcement Learning (RL) is introduced as a dynamic solution to continuously adjust beam directions in real-time based on fluctuating user locations and network conditions. This approach is particularly beneficial in high-mobility scenarios, such as vehicular networks or users in densely populated areas. By using reinforcement learning, the beamforming system learns from the environment, continuously optimizing its performance to enhance Signal-to-Noise Ratio (SNR) and minimize interference. This adaptive approach not only improves the spectral efficiency of 5G MIMO systems but also offers substantial energy efficiency benefits. The study showcases how RL can transform beamforming from a static, predefined process into a dynamic and self-learning system capable of responding to network variations in real time. In doing so, the system provides a more reliable and efficient communication experience, even in the most challenging network environments.

In addition to adaptive beamforming, paper [11] delves into the integration of millimeter-wave (mmWave) technology with beamforming techniques in 5G MIMO systems. The use of mmWave frequencies, which range from 30 GHz to 300 GHz, offers the promise of dramatically increased bandwidth and data rates, making them a cornerstone for achieving the ultra-high speeds expected from 5G. However, mmWave signals suffer from high attenuation and susceptibility to physical obstacles, which can significantly reduce their effective range. To mitigate these issues, beamforming becomes a critical technology for directing mmWave signals with pinpoint accuracy, ensuring that signal power is focused on specific users and improving both signal reliability and range. Paper [11] further discusses hybrid beamforming techniques, which combine digital and analog beamforming components to provide a more cost-effective and scalable solution. By splitting the beamforming process between digital baseband processing and analog radio-frequency components, hybrid beamforming enables mmWave MIMO systems to strike a balance between performance and cost, making widespread deployment of 5G networks more feasible.

Existing research on 5G MIMO networks has extensively explored both beamforming and spatial filtering as effective techniques for improving signal quality and managing interference. Beamforming is crucial for directing signals accurately toward specific users, concentrating energy to strengthen transmission. However, in densely populated network environments, beamforming alone may not sufficiently reduce interference from surrounding devices. Spatial filtering complements beamforming by refining signal reception, adjusting angles to block out noise from unintended directions and further enhancing signal clarity.

Despite the recognized value of these methods individually, few studies have investigated their combined implementation to achieve optimal noise reduction and signal clarity. This paper addresses this gap by proposing a novel approach that integrates beamforming with spatial filtering, aligning their strengths to minimize interference and boost SNR across network nodes. By synchronizing signal directionality with precise filtering at the BS, our method achieves significantly clearer transmission and more reliable communication.

This integrated approach proves particularly beneficial in high-density environments, where interference from multiple devices can severely impact network performance. The proposed solution merges the precision of beamforming with the interference-canceling abilities of spatial filtering, offering a scalable approach to enhance spectral efficiency and increase network capacity, especially in complex urban and IoT-rich settings.

III. MATHEMATICAL MODEL

This section gives a detailed explanation of the mathematical model used to set up and carry out the simulations in subsequent scenarios. In the mathematical model proposed, the signal received by each BS element in the array is represented by equation 1 [10]:

$$x[n] = s[n] \cdot a(\theta) + n[n] \tag{1}$$

The term x[n] captures the essence of the received signal, in which s[n] denotes the transmitted signal, a(θ) is the steering vector dependent on the direction of arrival θ, and n[n] represents the noise. The configuration of the BS array is defined as a linear array with N elements, a spacing of d, and an operating frequency f. The steering vector a(θ) is derived as in equation 2 [11]:

$$\begin{aligned} a(\theta) \;=\; [1, e\hat{}(j * 2\pi * d/\lambda * sin(\theta)), e\hat{}(j * 2\pi \\ * d/\lambda * 2 * sin(\theta)), \dots, e\hat{}(j \\ * 2\pi * d/\lambda * (N-1) \\ * sin(\theta))]\hat{}T \end{aligned} \tag{2}$$

where λ is the wavelength corresponding to the carrier frequency. The steering vector a(θ) provides a mathematical representation of how the phase of the received signal varies across the array elements for a signal arriving from angle (θ). This vector is crucial for beamforming and spatial filtering as it captures the geometric alignment of the array elements relative to the incoming signal. To direct the main lobe of the beam pattern towards the desired angle θ0, the beamforming weights w are calculated as in equation 3 [12]:

$$w = a(\theta 0)H \tag{3}$$

The array factor AF(θ) describes the combined radiation pattern of the BS elements as a function of angle and is given by the equation 4 [13]:

$$AF(\theta) = | \, wHa(\theta) \, | \tag{4}$$

In essence, these mathematical expressions encapsulate the foundation of the mathematical model, providing a comprehensive framework for analyzing beamforming and spatial filtering techniques within BS arrays to optimize signal reception in wireless communication systems.

The mathematical model encapsulated in these equations forms the foundation for analyzing beamforming and spatial filtering techniques within BS arrays. By incorporating the steering vector and beamforming weights, the model provides a comprehensive framework for optimizing signal reception in wireless communication systems.

Also, the optimal angle for transmitting signals from the BS to the UE is determined by calculating the angle that maximizes the SNR and the angle that minimizes it. Furthermore, calculating the SNR necessitates determining the minimum path loss distance, which involves utilizing equations 5, 6, 7. The model evaluates the Path Loss (PL) in various scenarios, considering both Line-Of-Sight (LOS) and Non-LOS conditions.

$$PL_{\text{RMa-LOS}} = \begin{cases} PL_1 & 10m \leq d_{\text{2D}} \leq d_{\text{BP}} \\ PL_2 & d_{\text{BP}} \leq d_{\text{2D}} \leq 10\text{km} \end{cases} \tag{5}$$

$$\begin{gathered} PL_1 = 20\, log_{10}(\, 40\pi d_{\text{3D}} f_c 3) + \\ min(\, 0.03h^{1.72}, 10)\, log_{10}(\, d_{\text{3D}}) - \\ min(\, 0.044h^{1.72}, 14.77) + 0.002\, log_{10}(\, h) d_{\text{3D}} \end{gathered} \tag{6}$$

$$PL_2 = PL_1(d_{\text{BP}}) + 40\, log_{10}(\, d_{\text{3D}}/d_{\text{BP}}) \tag{7}$$

However, delving into the analysis of these equations is beyond the scope of the current paper. For further insights, you can refer here [14].

The SNR, which indicates the quality of the received signal, is calculated using equation 8:

$$\text{SNR} = \text{Psignal/Pnoise} \tag{8}$$

Eventually, this process helps demonstrate how adjusting the angle optimizes signal reception using beamforming techniques, ultimately improving network throughput, and facilitating interference-free communication between antennas and UEs.

IV. Algorithm Analysis

This section presents the analysis of the theoretical algorithm which was evaluated through simulations. The algorithm starts by setting up the foundational parameters required for the simulation. These parameters include essential aspects such as the operating frequency, speed of light, antenna configuration, and UE distribution within the coverage area. Once the initialization is complete, the algorithm proceeds to the core of its functionality. It calculates the angles and SNR for each UE in relation to each BS. This involves determining how each UE's position affects their signal strength and quality concerning the BSs.

Algorithm 1 Best and Worst SNR Calculation for UE at Each BS

Step 1: Initialization

- Set parameters including the frequency of operation, speed of light, wavelength, BS spacing, number of BSs, total number of UEs, path loss constant, transmitter power, BS gain, and noise power.
- Generate random UE positions within a defined area.
- Define the positions of BSs.

Step 2: Calculate Angles and SNR for Each UE Relative to Each BS

- For each BS:
  - For each UE:
  - Calculate the angle between the UE and the BS.
  - Compute the steering vector for the calculated angle.
  - Evaluate the array factor for the steering vector across a range of angles.
  - Determine the maximum and minimum array factors, corresponding to the best and worst angles, respectively.
  - Calculate the distance between the UE and the BS.
  - Compute the path loss using the distance and path loss constant.
  - Determine the effective power at the best and worst angles by adding the transmitter power, BS gain, and maximum/minimum array factor.
  - Convert the effective power from dBm to Watts for SNR calculation.
  - Convert the noise power from dBm to Watts.
  - Calculate the SNR at the best and worst angles.

Step 3: Plot Results for One Example UE

- Select an example UE.
- Plot the array factor against angle for the selected UE.

Step 4: Plot Comparison of Best and Worst SNR for a Specific UE at Each BS

- Select a specific UE for analysis.
- Create a plot to compare the best and worst SNR for the selected UE at each BS.
- For each BS:
  - Plot the best SNR value against the corresponding angle with a blue circle marker.
  - Plot the worst SNR value against the corresponding angle with a red cross marker.
- Annotate the legend to indicate "Best SNR" and "Worst SNR".
- Label the axes and provide a title for the plot.
- Show a grid on the plot for clarity.

Through a series of calculations, the algorithm evaluates the array factor for each UE at every angle. This factor essentially represents how much the antenna array amplifies or attenuates the signal based on the direction it's coming from. By analyzing the array factor, the algorithm identifies the angles where the received signal is strongest (best angle) and weakest (worst angle) for each UE. Once the best and worst angles are determined, the algorithm computes the corresponding SNR values. SNR is a crucial metric in wireless communication systems as it indicates the quality of the received signal relative to the background noise. The algorithm calculates the SNR considering factors such as transmitter power, BS gain, path loss, and noise power. After completing the SNR calculations, the algorithm provides visual representations of the results. It first plots the array factor against angle for a randomly selected UE. This plot offers insights into how the antenna array responds to signals from different directions. Additionally, the algorithm generates a comparison plot for a specific UE, showcasing the best and worst SNR values at each BS. Also, offers a clear visualization of how the UE's location relative to the BSs affects their signal quality. By displaying both the best and worst scenarios, the algorithm provides a comprehensive understanding of the system's performance variability.

Overall, the proposed algorithm addresses the issue of optimizing beamforming in multi-BS 5G systems by calculating the optimal angles and SNR for each UE in relation to the base stations. Traditional methods often struggle to adapt to changing user positions and environmental factors, which can lead to inefficient signal quality and resource use. By examining the array factor and identifying the angles with the strongest and weakest signals, the algorithm improves signal strength and quality, providing a more effective solution for managing complex network conditions.

V. SIMULATION ENVIRONMENT

This section outlines the simulation environment, structured to align closely with the algorithm and mathematical model presented earlier. The experiments were conducted in a simulated 5G HetNet within a 2 x 2 km urban area, depicted in Fig. 1. Unlike prior research, this study employs a MIMO configuration with each BS equipped with 2000 antennas, enabling each antenna to serve as a dedicated link to an individual UE. This setup allows UEs to connect to multiple antennas, significantly boosting system performance and spectral efficiency through adaptive beamforming.

The primary goal of this configuration is to enhance spectral efficiency within 5G MIMO networks, providing UEs with multiple connection options and thereby surpassing conventional resource allocation methods in flexibility and effectiveness. Adaptive beamforming enables optimized network performance by accommodating varying user demands and improving connectivity across the network. The network operates at a frequency of 140 GHz with 60 New Radio (NR) resource blocks and a subcarrier spacing of 120 kHz. Each BS transmits at 45 dBm, with a gain of 21 dBi. These key parameters, summarized in Table I, were selected to replicate real-world mmWave 5G conditions, ensuring that the simulation environment accurately reflects the demands and constraints of practical deployment.

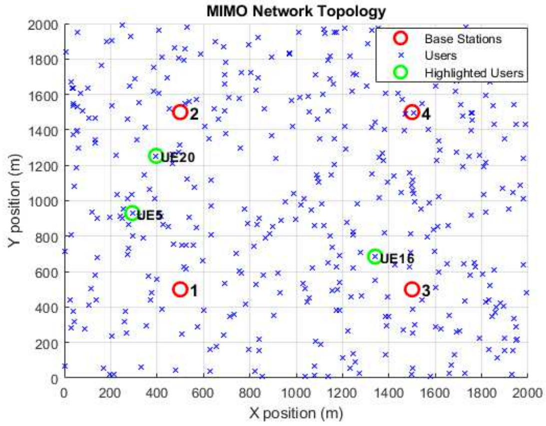

Fig.1. MIMO Network Topology

TABLE I. SIMULATION PARAMETERS

Parameter	Value
Transmit power(dbm)	45 dbm
BS height (m)	6 m
BS/UE gain (dbi)	21 dbi, 0 dbi
Number Of UEs	16,5,20
Power Noise	Pnoise= -74+10log(Bandwidth(hz))
Number of NR	60
Subcarrier spacing	120 KHz
Frequency	140 GHz

VI. SIMULATION RESULTS

In this section, the outcomes of the experiments are reviewed in order to assess whether the algorithm effectively enhances the transmission of signals from the antenna to the UE through beamforming. Before analyzing the results, it is important to note that the selection of UEs for our analysis is random, because the effectiveness of our results is not influenced by the user's selection. Our goal is to demonstrate that a better angle improves beamforming efficiency and that applying a spatial filter ideally reduces noise in the communication between the user and the antenna. This outcome remains consistent regardless of the user's choice. This is because all users in our experiments exhibit similar performance.

More specific, Fig. 2 is pivotal in understanding the directional aspects of beamforming, a technique that focuses and steers the wireless signal in specific directions to maximize signal strength and minimize interference. The visualization showcases the effectiveness of beamforming by illustrating the optimal angles at which the signal is transmitted or received to achieve the highest SNR. By analyzing the angular distribution, researchers can identify the most favorable angles for directing the beamformed signals, thereby enhancing the SNR and improving communication performance. This figure underscores the critical role of beamforming in spatial filtering, demonstrating how precise angular adjustments can lead to significant improvements in signal quality and system efficiency. The insights gained from this analysis are instrumental in refining beamforming strategies, ultimately contributing to the development of more robust and efficient wireless communication systems.

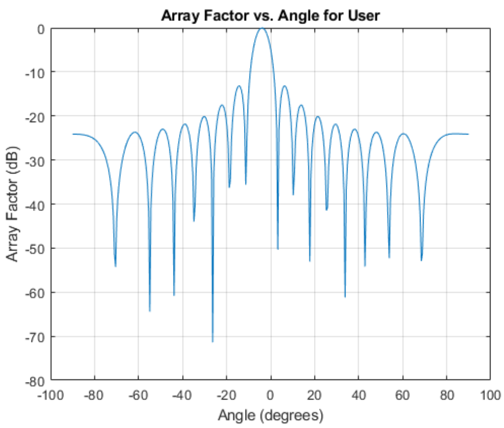

Fig.2. Noise base on angles for UE=16

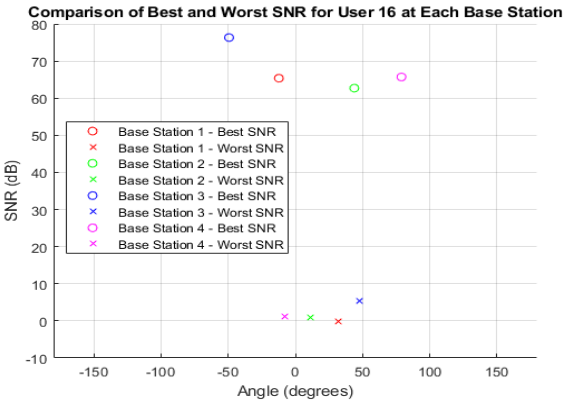

Fig.3. Best and Worst SNR for UE=16

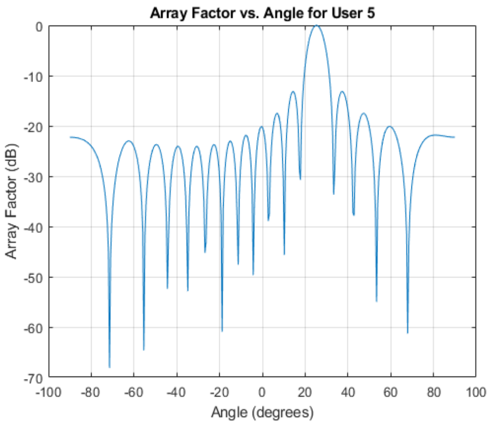

Fig.4. Noise base on angles for UE=5

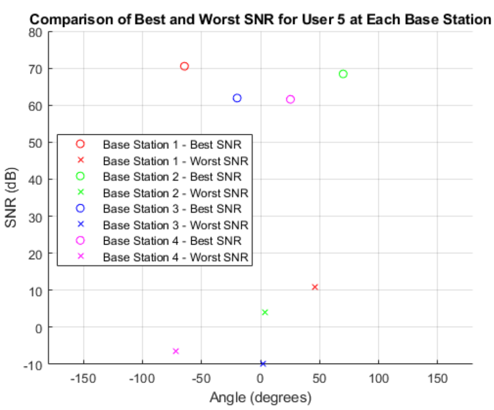

Fig.5. Best and Worst SNR for UE=5

Also, to prevent confusion, Fig.2, Fig. 4 and Fig.6 illustrate the noise levels and their variations as beamforming technology is applied in the network. Then, keeping this in mind, we utilize our analysis to modify the angle direction in which the directional signal is sent. Ideally, this will allow us to apply the spatial filter and optimize the signal performance between the UE and the BS. In addition, by identifying the direction with the least noise, we determine the optimal angle to send the signal for the best SNR. Conversely, by analyzing the direction with the highest noise, we calculate the angle (for the worst SNR) to illustrate the difference between the best and worst angles. This comparison highlights the impact on SNR and, consequently, the quality of communication between the UE and the BS and the results are presented in Fig.3, Fig.5 and Fig.6.

Also Fig. 3 serves to highlight the efficacy of spatial filtering and beamforming techniques employed to enhance the SNR across different spatial locations. The visualization reveals areas with varying SNR values, providing insights into the regions where the signal quality is superior or inferior. Higher SNR values indicate regions where the signal is strong and less corrupted by noise, whereas lower values signify areas with significant noise interference. Analyzing this figure allows researchers to assess the performance improvements achieved through the applied spatial filtering and beamforming methods, thereby validating their effectiveness in optimizing SNR and enhancing overall communication reliability.

Furthermore, for UE 16, the best SNRs across the BSs are recorded at -12 degrees (65 dB), 49 degrees (61 dB), -49.5 degrees (78 dB), and 78 degrees (66 dB) for BSs 1 through 4 respectively. The worst SNRs for these BSs occur at 32 degrees (-0.2 dB), 11 degrees (0,7 dB), 47 degrees (5.3 dB), and -8 degrees (1,2 dB). The array factor analysis indicates that the optimal beamforming direction after spatial filtering for UE 16 is at 78 degrees, where the array factor peaks, suggesting this angle as the most effective for enhancing SNR. These findings underscore the importance of directional signal optimization in improving communication quality through beamforming and spatial filtering.

The array factor for UE 5, shown in Fig. 4, reveals the directionality of the signal strength. The peak array factor is observed in the optimal beamforming direction for minimum level Noise. Moreover, for UE 5 in Fig.5, the SNR performance across four BSs reveals significant variability, with the best SNRs observed at -64 degrees (70 dB), 69 degrees (68 dB), -19 degrees (61 dB), and 25 degrees (61 dB) for BSs 1 through 4 respectively. The worst SNRs for these BSs occur at 46 degrees (10 dB), 3.7 degrees (4 dB), 2.2 degrees (-9 dB), and -71 degrees (-6.5 dB).

The beamforming analysis for UE 20 is illustrated in two figures. Fig.6 displays the array factor in decibels (dB) as a function of angle, revealing the directional properties of the antenna array used for beamforming. It shows the direction of the strongest signal transmission or reception, along with several side lobes and nulls that highlight points of reduced signal strength to minimize interference. The main lobe's width reflects the beamwidth of the array, illustrating its ability to focus the signal on UE 20 efficiently. In order to maximize the UE 20's communication effectiveness with the network BSs, the precise angle at which the signal should be transmitted is determined by taking into account the direction first, using the data from this diagram.

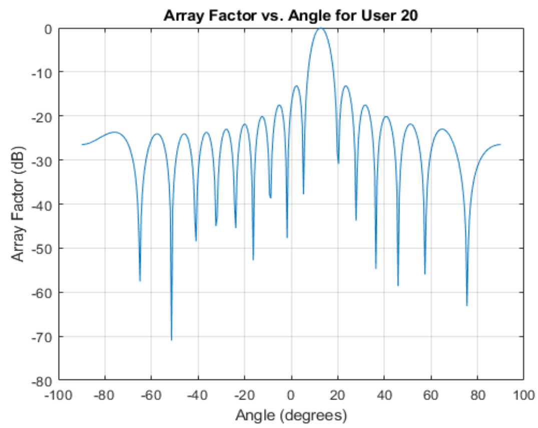

Fig.6. Noise base on angles for UE=20

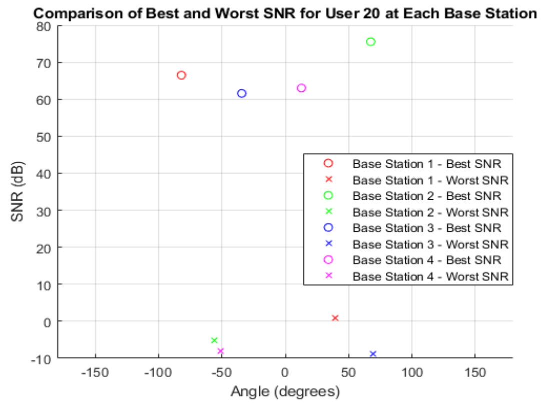

Fig.7. Best and Worst SNR for UE=20

Furthermore, Fig.7 compares the SNR for UEs 20 at various angles across four BSs, with best and worst SNR values indicated by circles and crosses, respectively. This comparison reveals the unique performance profiles of each BS, with significant SNR variations across different angles. Optimal beamforming directions are identified by the highest SNR values, which can reach up to 75 dB, while the lowest SNR values can be as low as -8.9 dB. This comprehensive analysis underscores the importance of selecting optimal beamforming directions to enhance signal quality for UE 20.

In conclusion, the beamforming analysis for UEs highlights the critical role of directional optimization in enhancing signal quality. For UE 20, the analysis demonstrated a prominent main lobe around 67 degrees, indicating optimal signal transmission and reception direction, supported by a comprehensive SNR comparison across four BSs. Similarly, UE 5's optimal beamforming direction is around -64 degrees, as indicated by the array factor analysis and supported by the SNR performance across BSs, with notable best SNR values observed at various angles. For UE 16, the optimal direction is at 78 degrees, where the array factor peaks, and SNR performance is maximized. These findings collectively highlight the importance of selecting precise beamforming directions (through the application of spatial filtering) to improve signal quality and communication efficiency through beamforming. The variability in SNR at different angles and BSs for each UE reinforces the need for tailored beamforming strategies to achieve optimal signal strength and reduce interference, ultimately enhancing the overall communication experience.

VII. Conclusion and Future Work

In conclusion, this research aimed to demonstrate that using a spatial filter in beamforming technology not only directs the signal appropriately but also optimizes the angle. This enhancement significantly maximizes communication between the UE and the BS by greatly reducing noise levels. By strategically applying beamforming zones, the study demonstrates a substantial improvement in signal transmission from antennas to UEs, resulting in elevated SNR values. This optimization leads to superior communication quality with minimal losses and interference, underscoring the critical role of intelligent beamforming strategies in maximizing network performance and user satisfaction in 5G environments.

The results of this research are significant due to the marked improvements in spectral efficiency and signal quality achieved through adaptive beamforming with spatial filtering. By precisely directing transmission beams and nullifying unwanted signals, the study effectively mitigates interference, extends coverage, and enhances system capacity. These improvements are particularly crucial in densely populated urban areas and environments with numerous IoT devices, where efficient spectrum utilization and interference management are essential.

Future research will focus on exploring how beamforming can prevent jamming attacks. In addition, future research will focus on implementing the algorithm in real-world scenarios, addressing UE interference and varying environmental conditions (for example urban vs. rural environments, varying device densities, etc.). Conducting experiments in authentic settings will provide deeper insights into the algorithm's performance and validate the findings. This practical application will refine techniques to address challenges in dynamic environments. Additionally, there will be efforts to refine beamforming techniques to adapt to evolving network dynamics and technological advancements. This includes integrating machine learning models to predict optimal beamforming weights in real-time, enhancing efficiency and reducing complexity.

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