Performance Analysis for Hybrid Beamforming using Deep Learning

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***Abstract*—Hybrid beamforming is an approach that is used in huge MIMO systems to create a balance between the advantages of digital and analog beamforming. Hybrid beamforming merges analog and digital beamforming to lower the complexities and cost. However, designing the analog and digital precoders in a hybrid beamforming system is a difficult task. Knowledge about several factors such as channel state information (CSI) is required for optimization. The proposed method in this paper is that of an unsupervised deep learning model that utilizes RSSI (received signal strength indicator) measurements. Instead of relying on complex CSI feedback and optimization, the proposed method leverages RSSI measurements and deep learning techniques to simplify the design process, reduce costs, and improve spectral efficiency, especially in FDD communication systems.**

***Index Terms*—hybrid beamforming, MIMO, RSSI, unsupervised learning, deep learning**

I. Introduction

Upcoming application like Iot and vehicular communications require faster data rates. A huge number of antennas at the base station is required for massive MIMO and is also important for cellular systems in the time to come. Some of the benefits of massive MIMO include the ability to overcome fast fading and interference which ultimately leads to increased multiplexing and diversity gains, spectral efficiency, and energy efficiency.

However, massive MIMO arrays contain multiple antennas, each of which requires an Rf chain, resulting in increased system costs and energy-inefficiency [1]. Hybrid beamforming was introduced to address these issues. HBF is a combination of analog and digital beamforming. Digital beamforming includes manipulating the signals at baseband using complex digital processing, On the other hand while analog beamforming is performed at radio frequency (RF) using analog components like phase shifters. HBF thus, helps in reducing the number of RF chains required and keeping the performance in acceptable ranges.

Channel state information (CSI) is one particular requirement for designing HBF and several channel estimation techniques have been developed using CSI. These models, however, are entirely dependent on CSI [2] , which causes signal overhead and a reduction in spectral and energy efficiency is observed, particular frequency division duplex (FDD) communication.

In order to overcome these challenges, we can use RSSI measurements over CSI for the design of HBF. RSSI is a single real-valued metric, which can easily be measured from the received signal by the user, thus explicit CSI feedback will no longer be required, and the problems of signal overhead and spectral inefficiency will be addressed.

In earlier models where deep neural networks have been explored for HBF assume perfect CSI. They also make use of supervised learning [3], for which labelled targets and large computing resources are needed. These systems were also mainly designed for base stations where full CSI was obtainable. We have proposed unsupervised learning approach for designing HBF for massive MIMO and this method does not require perfect CSI.

We have implemented a DNN architecture for both digital and analog components of the HBF to address computational efficiency. Using the deepMIMO library available, we have also generated our own dataset for training the architecture. Optimization of the synchronization signals transmitted by the base station is done to maximise the information carried by the RSSI measurements. Finally, three different channels are inspected to judge the model's reliability and robustness.

II. Literature Survey

In this paper, author Peihao Dong et al.[4] discusses the applicability of CNNs for channel estimation in mmWave MIMO systems, concentrating on spatial, frequency and temporal connections. The systems suggested in the paper assure high data rates but cannot deliver due to inaccurate channel estimation because of the mmWave's unique characteristics. The author discusses three main approaches-

a) Spatial-frequency CNN (SF-CNN): this approach uses spatial and frequency correlations to approximate channel information by making use of corrupted matrices from neighbouring subcarriers. This method shows improved accuracy.

b) Spatial-Frequency-Temporal CNN (SFT-CNN): this approach extrapolates on SF-CNNs by introducing temporal correlations in dynamic channels, thus increasing accuracy and addressing the rapid variations common in mmWave environments.

c) Spatial Pilot-Reduced CNN (SPR-CNN): this method lessens the spatial plot overhead required for channel estimation. Grouping of channels is involved across successive coherence intervals, thus reducing complexity and maintaining performance.

These approaches enable efficient control of channel correlation, promising enhanced channel estimation performance in mmWave massive MIMO systems across various propagation scenarios, and facilitating the advancement of mmWave communication technologies.

The next generation of wireless communication rests on millimeterwave (mmWave) massive multi- input multi-output (MIMO) technology. Precoding hybrid analog-digital is essential to reduce the hardware complexity and energy consumption. Nevertheless, existing hybrid precoding approaches suffer from high computation complexity and insufficient utilization of spatial information. In this paper, author Yiwei Song et al [5]. conducts a literature review to study the implementation of deep learning in the hybrid precoding for massive MIMO systems at mmWave frequencies.

In the suggested methodology, precoder selection is considered to be a mapping relation inside a deep neural network (DNN). By DNN training, it improves the hybrid precoding in mmWave massive MIMO by optimally choosing precoders for signal transmission.

Results from the simulations showed effectiveness this DNN-based method. It decreases the Bit Error Rate (BER), improves Spectrum Efficiency (SE) and dramatically decreases Computational Complexity as compared to other. As one of the crucial technologies, deep learning can enhance the efficacy and throughput in the millimetre Wave Massive MIMO communications system.

Over the past several years, massive MIMO has been touted as one of the key enablers of advanced wireless communication system. It uses many antennae at the base-station to achieve high Spectral Efficiency and a low error rate in the wireless links. Hybrid beamforming is indispensable for Massive MIMO systems to strike the right notes between performance enhancements and complexity management. This approach permits a better insight into the present status of research and development in hybrid beamforming solutions regarding such systems. In the introduction, the author Molisch et al. [6] discusses why we want Massive MIMO, why it's a big deal, and why it's hard. It makes clear the needed use of hybrid beamforming to get over the drawbacks of fully digital beamforming in Massive MIMO systems which are too complex hardware wise and consuming great power.

The author also discusses a taxonomy of hybrid beamforming techniques comprising digital and analog precoding/combining, quantization methods, and phase shifters. This classification helps readers understanding the different strategies analysed across the literature. The authors therein further explore into digital pre-coding and combination schemes, with advantages and limitations stated. That encompasses Zero Forcing, MMSE and other algorithms applied in the digital domain. It is designed for both novice traders as well as advanced traders and offers 24/7 customer support. This brief describes the basics of analog beamforming, giving you, some understanding about phase shifter design and optimization. Furthermore, this paper investigates Quantization schemes for Channel State Information (CSI) and feedback Strategies with respect to Overhead vs Performance trade-off. In the remaining two sections, the authors describe prospective use cases for hybrid beamforming and highlight its importance in next-generation communication systems such as 5G and onwards. They present an overview of research on-going, along with possible avenues for the future, including hardware-friendly beamforming schemes, and machine-learning based methods. The author Sohrabi et al. [7] addresses an important aspect of next-generation wireless communication systems, specifically the design of hybrid beamforming techniques for large-scale antenna arrays. The paper starts by pointing out that with growing need of high data rates in wireless communication systems and difficulties encountered while configuring large scale antenna array, the problems are discussed in this paper. This highlights the importance of developing beamforming strategies that can effectively utilise these huge arrays. In this paper, Sohrabi and Yu present the idea of hybrid beam forming, mixing some aspects of digital beam forming with others of its analog counterpart to find a good trade-off between performance, signal processing complexity and hardware implementation difficulties.

The authors presents the architecture of hybrid beamforming systems that consist of both analog and digital precoding/combining units and highlights the role of analog precoding in decrease of the number of RF chains and simplification of hardware structure. Sohrabi and Yu study the joint optimization problem of digital and analog beam forming matrices. They provide a complete approach on how to optimize these matrices with practical considerations, such as memory & hardware limits, and quantization. Performance evaluation measurements were done along with the analog beamforming, fully and compared. With these, they show the advantages of hybrid beam forming for obtaining an attractive compromise between spectral efficiency and hardware complication.

This paper introduces hybrid beamforming as a promising method for massive MIMO systems, mmWave communications, and future wireless techniques. This demonstrates that the idea is operationally viable and can be scaled.

Accordingly at any rate, they propose potential headings for further developed exploration into half breed beaming frameworks incorporating propelled streamlining strategies, equipment-accommodating executions, and combination with

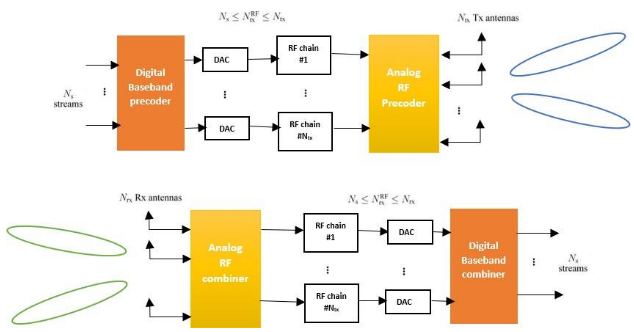

Fig. 1. system Model Diagram

impending intercommunication norms like 5G and past.

This author shuangfeng et al.[8] explores the role of large-scale antenna systems (LSAS), in addressing the shortage of frequencies in traditional cellular bands and meeting the increasing demands of mobile traffic in the 5G era especially in the millimeter wave (mmWave) frequency bands. However, implementing LSAS comes with challenges related to beamforming, such as complexity, energy consumption and cost. To overcome these challenges this article focuses on optimizing analog and digital beamforming structures for LSAS deployments. Specifically, it examines the configuration of N (number of transceivers) by M (number of antennas per transceiver) hybrid beamforming.

The authors discuss designs for both analog and digital beamforming in a scenario where multiple users are involved. It also investigates the energy efficiency. Spectrum efficiency of the N × M beamforming structure by analyzing their interaction at a point called the green point. The green point represents the energy efficiency on an energy efficiency spectrum efficiency curve. Moreover it analyzes how changing N affects energy efficiency at a given spectrum efficiency value and its impact on achieving energy efficiency at the point. These findings offer insights for LSAS design allowing for an optimal balance, between energy consumption and spectrum utilization.

Moreover, the authors highlight a signal design, for the beamforming structure, which exhibits better channel estimation performance than approaches that solely depend on analog beamforming. These findings emphasize the importance of utilizing LSAS with beamforming structures in the mmWave band and its potential to have an impact, on 5G communication.

III. SYSTEM MODEL

We have opted for a model that is comprised of massive MIMO BS in a single cell that has NT antennas that serve Nu single antenna users. The system uses hybrid beamforming precoders for uplink as well as downlink transmission. Every RF chain at the BS is coupled through 2-bit phase shifters to all antennas.

As In the system described in [9] we have broken down the model into 3 steps-

1) SS bursts Transmissions-
   The BS broadcasts K SS (Single Stream) bursts in this step, using various $A_{\mathrm{SS}}^{(k)}$ 2-bit phase-shift analogue precoders.
   $r_{\mathrm{u}}^{(k)}$ is given by-

$$r_u^{(k)} = h_u^{(k)H} A_{\mathrm{SS}}^{(k)} + \eta_u^{(k)} \tag{1}$$

   The BS broadcasts K SS (Single Stream) bursts in this step, using various $A_{\mathrm{SS}}^{(k)}$ 2-bit phase-shift analogue precoders. All users within the cell are able to receive these SS bursts. The sent signal, channel, and noise are combined linearly to form the received signal, r(k)_u, at the u-th user for the k-th burst.
2) RSSI feedback-
   Each user measures the averaged Received Signal Strength Indicator (RSSI) value $\alpha_u^{(k)}$ for the k-th SS burst after receiving $r_u^{(k)}$. Thus,

$$\alpha_u^{(k)} = |h_u^{(k)H} A_{\mathrm{SS}}^{(k)}|^2 + \sigma^2 \tag{2}$$

   These RSSI readings are employed as feedback data. Due to measurement accuracy issues and feedback channel restrictions, the RSSI values have been quantized.
3) Downlink data transmission-
   In this step, the BS uses digital precoders to relay data to each user. For each user, the digital precoder matrix W is made to encrypt data symbols. Based on the selected hybrid beamformer (A, wu), the SINR (Signal-to-Interference-Noise Ratio) is computed for each user.

$$\mathrm{SINR}(A, w_u) = \frac{|h^H A w_u|^2}{\sum_{j \neq u} |h_u^H A w_j|^2 + \sigma^2} \tag{3}$$

   The SINR values for each user are used to calculate the system's spectral efficiency. The sum of the logarithms of (1 + SINR) for each user yields the sum-rate (R).

$$R(A, W) = \sum_{u=1}^{NU} \log_2(1 + \mathrm{SINR}(A, w_u)) \tag{4}$$

   The noise power and channel coefficients are not directly known to the BS. The received RSSIs contain partial channel state information (CSI), which is embedded. The HBF precoders are to be designed using Deep Neural Network (DNN) approaches, utilising the RSSI feedback data. This method takes into account the practical constraints of quantization and feedback while attempting to maximise the spectral efficiency of a huge MIMO system utilising HBF. An innovative solution to the problems of channel prediction and optimisation in wireless communication systems is the use of DNNs for precoder design.

IV. Parameters

A. Input Parameters:

1) A dictionary containing various parameters for dataset generation.
2) Simulated transmitted data (complex symbols).
3) channel_matrix: Simulated channel matrix.
4) learning_rate: Learning rate for gradient descent.
5) epochs: Number of optimization iterations.

B. Output Parameters:

1) beamforming_weights: Optimized beamforming weights.
2) mse: Mean Squared Error.
3) mean_snr_db: Mean Signal-to-Noise Ratio in dB.
4) sinr_db: Signal-Interference-Plus-Noise Ratio in dB.
5) mean_sinr_db: Mean SINR in dB.

V. Algorithm

1) Generate DeepMIMO Dataset:
   a) Input: parameters
   b) Generate the DeepMIMO dataset based on the provided parameters.
2) Neural Network Model Hyperparameter Tuning:
   a) Input: X_train, y_train
   b) Define a custom loss function with Elastic Net regularization.
   c) Define the hyperparameter search space.
   d) Start hyperparameter tuning.
   e) Get the best hyperparameters.
   f) Build the best model based on the hyperparameters.
   g) Train the best model.
3) Beamforming Optimization using Gradient Descent:
   a) Input: transmitted_data, channel_matrix, learning_rate, epochs
   b) Initialize beamforming weights.
   c) Perform gradient descent to optimize beamforming weights.
      i) For each epoch:
         A) Initialize error and gradient.
         B) For each symbol in transmitted data calculate received signal using current weights.
         C) For each symbol in transmitted data calculate error (MSE) and gradient for this symbol.
         D) For each symbol in transmitted data update weights using gradient.
         E) Calculate average error.
         F) Print progress.
   d) Calculate the optimized beamforming weights.
   e) Calculate Mean Squared Error (MSE).
4) Calculate SINR and Mean SINR:
   a) Input: transmitted_data, mse
   b) Calculate Signal-to-Interference-Plus-Noise Ratio (SINR) in dB.
   c) Calculate Mean SINR in dB.

VI. methodology and implementation

In this extensive section, we explore the challenges of our experimental application and methodology with special emphasis on building a beamforming model for massive multiple-input-multi-output (MIMO) systems using deep learning methods use the right. Specifically, we will discuss parameter setting, datasets generation, synthetic training data for beamforming models, hyperparameter tuning process, beamforming weight optimization, and the Signal-to- noise ratio (SNR) of our method) will discuss the evaluation of the project. and signal-to-interference noise ratio (SINR) specification.

1) Consideration of optimal parameter settings:
   The analysis begins with a comprehensive collection of parameter settings to ensure reproducibility and rigor in our analyses. The characteristics in question are critical to defining the scope and design of our study. The choice of wireless communication scenario is the main basis of our research. The DeepMIMO framework is used in our study as a versatile simulation tool to help evaluate various wireless communication scenarios. We chose ”Scenario O1_60” because of its comprehensive coverage of many factors such as antenna configuration, subcarrier information and channel characteristics. Antenna configuration: The efficiency of beamforming depends largely on the antenna configuration. We carefully specify the number of antennas, their spacing, and radiation for both the base station (BS) and the operating equipment (UE). These settings significantly affect the performance of our beamforming model. Orthogonal Frequency Division Multiplexing (OFDM) Parameters: OFDM is an integral part of our communication infrastructure. To ensure the accuracy of the configuration, we define the necessary OFDM parameters such as the number of subcarriers, bandwidth allocation, and receive filter configuration. Hybrid beam forming (HBF): An important aspect of our research is the use of hybrid beam forming techniques. In our example, each BS antenna is connected to all antennas by a 2-bit phase shifter. This system enables signal-steering accuracy, which is an important feature of beamforming.
2) Dataset Generation:
   Our analysis is based on the availability of a comprehensive dataset that reflects real-world wireless communication scenarios. For this we use the DeepMIMO algorithm to generate a data set covering the wireless channel characteristics between the BS and the UE in our chosen environment It is assumed that the discovery of multiple channels will bring diversity to our training data.
3) Generation of Synthetic Training Data for Beamforming Model:
   The development of a deep learning-based beamforming model requires the generation of synthetic training data. The complex procedure unfolds over a series of pivotal stages:

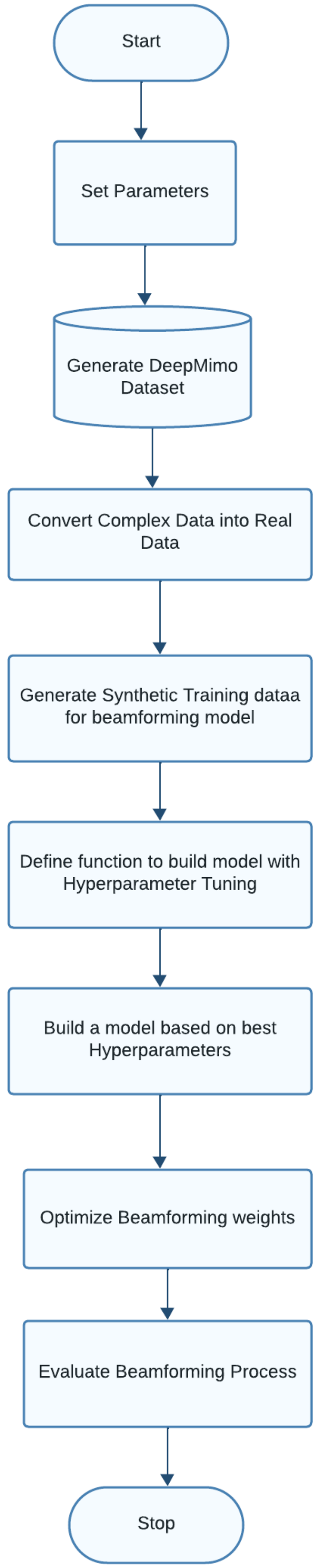

Fig. 2. workflow of the system [10]

Fig. 3. Scenario O1_60

a) The process commences with the extraction of channel matrices from the dataset, with a particular emphasis on the combinations of Base Stations (BS) and User Equipment (UE) that are pertinent to our investigation.
b) The conversion from complex to real values is a fundamental process in neural networks, as these networks are designed to operate exclusively with real-valued data. In order to meet this criterion, we perform a conversion of the channel matrices with complex values into their respective real and imaginary components.
c) Standardization plays a crucial role in ensuring that our data adheres to uniform scaling and distribution patterns. The process is conducted with great attention to detail, as we ensure that the real and fictional components are standardized independently. This change facilitates the process of training models effectively.
d) The input data for deep learning is represented by the standardized channel matrices, while the goal output is represented by the ideal beamforming weights. The organization of this data serves as the fundamental basis upon which our model will undergo training.

4) Hyperparameter Tuning
Architectural optimization of the deep learning model is essential to achieve optimal performance. To go through this complex process more efficiently, we use a hyperparameter tuning technique, which involves tuning several parts of the model. The important elements of this process are: The model builder tool plays an important role in our hyperparameter tuning method.
The work in question is a foundational framework for neural networks, which provides the opportunity to explore structures and their flexibility Hyperparameters requiring tuning include the number of convolutional layers, the number of units per layer, and selection of activation functions The implementation of the Keras

tuner library is implemented in an attempt to find optimal hyperparameters.

Motivated by a predefined search location, we systematically investigate several systems with the ultimate goal of minimizing the fidelity loss. The aforementioned procedure concludes with the determination of the optimal hyperparameters of our beam formation model.

5) Optimization of Beamforming Weights
The deep learning model, now primed with the knowledge of optimal hyperparameters, takes center stage in our quest to optimize beamforming weights. These weights are instrumental in directing signals with precision from the BS to the UEs, thereby maximizing system performance.

6) Evaluation Using SNR and SINR The end of our research effort is to evaluate the efficiency of our beamforming model. This analysis is done by considering two important indicators.
The Signal-to-Noise Ratio (SNR) is a fundamental metric used to evaluate the quality of a signal. The aforementioned statement pertains to the quantification of the ratio between the power of the signal and the power of the noise in the received signal. Within the scope of our investigation, the signal-to-noise ratio (SNR) functions as a fundamental metric for assessing the excellence of the signal that is received.
The Signal-to-Interference-Noise Ratio (SINR) expands upon the concept of Signal-to-Noise Ratio (SNR) by incorporating the additional factor of interference originating from various sources. The utilization of this metric provides a more comprehensive assessment of the operation of the communication system by considering potential sources of interference. To provide a detailed understanding of these metrics, we use a rigorous approach to estimate signal-to-noise ratio (SNR) and signal-to-interference-plus-noise ratio (SINR) values under different communication conditions into by the optimum Beamform weights. These metrics are indicators that help us assess the spectral efficiency and the overall performance of the system.
Our study undertakes a systematic and carefully designed approach in both the execution and methodology. The research context is established by defining a set of parameter settings at the outset. To generate the dataset, we utilize the DeepMIMO architecture. The generation of artificial training data is a crucial process that encompasses the conversion of complex data into realistic representations and the establishment of standardized formats. The optimization of hyperparameters plays a crucial role in determining the most effective architecture for our model. The optimization of beamforming weights is a significant milestone, enabling the realization of the complete capabilities inherent in our deep learning-based beamforming methodology. Ultimately, our system undergoes a comprehensive evaluation, employing SNR and SINR as guiding metrics to navigate the unfamiliar terrain of practical wireless communication settings. The present complete methodology provides us with the necessary tools to analyse the complexities of beamforming in the context of massive MIMO systems. This analysis aims to elucidate the practical consequences and possible benefits of beamforming in improving wireless communication.

TABLE I
MEAN SQUARED ERROR (MSE) RESULTS

Model Configuration	Mean Squared Error (MSE)
Initial Model (No Hyperparameter Training)	500.007
Hyperparameter Tuned Model	2.004
With L1 and L2 Regularization	1.004

TABLE II
SIGNAL QUALITY FOR DIFFERENT CHANNEL MATRIX SIZES

Channel Matrix size	SNR	SINR
8X8	9.06	10.04
16X16	9.01	10.08
32X32	8.9	10.15
64X64	8.85	10.4
128X128	9.62	10.02
256X256	12.43	12.44

VII. RESULTS

Our thorough analysis of developing a beamforming model based on deep learning for massive MIMO systems has led to significant improvements in its performance. The vital elements that have contributed to our methodology's success include the integration of elasticNet regularization algorithm and adjusting hyperparameters.

Our investigation started with an initial model that had not undergone hyperparameter training and we got an MSE value of 500.007. We used this value to gauge the accuracy of our model's predictions during massive MIMO communication optimization, specifically with respect to beamforming weights. We the started the process of fine tuning the hyper parameters of our model. By deliberately experimenting with the model's configuration and settings, we achieved a significant decrease in the MSE. The fine tuning resulted in an MSE of 2.004. To enhance our model, we integrated L2 and L1 regularisation techniques. Regularisation is essential to prevent overfitting and improve generalisation capacity. These tactics strike a balance between model complexity and performance. Consequently, we observed a significant drop in the MSE, reaching a rock-solid value of 1.004, thus establishing the dependability and accuracy of our model. Fundamental metrics used to evaluate the effectiveness of wireless communication systems include Signal-to-Noise Ratio (SNR) and Signal-to-Interference-plus-Noise Ratio (SINR). They are extremely important in evaluating how effective the communication link is.

SNR is a measure of the strength of the signal to noise ratio. A higher SNR indicates better signal quality and a greater chance of effective data transfer with few errors because the signal power is stronger relative to the background noise.

On the other hand, SINR quantifies the ratio of signal power to total noise and interference power. It is a more thorough statistic that takes into account the overall signal quality as well as the effect of noise and other interfering signals. The ability of the system to retain signal integrity in the presence of interference is highlighted by a greater SINR value, which shows that the signal is stronger than both the interference and the background noise.

According to the table II, SNR and SINR tend to get better as channel matrix size grows. This improvement is due to the system's increasing capacity and sophistication in managing bigger amounts of data, which has improved signal quality and communication performance. The 256x256 channel matrix size's noticeably higher SNR and SINR values represent the notable improvements in performance and signal quality possible with bigger matrices, demonstrating a durable and dependable communication link even in challenging wireless situations.

VIII. CONCLUSION

Our research, both in execution and method, is carried out in a systematic manner and with due diligence. The first step defines a set of initial parameter settings, which creates the context for the study. DeepMIMO for Deep Learning Dataset Formation. One important part in transforming complicated data in to practical representation and in building a standardized form comes with artificial training data. It is crucial to optimize hyperparameters in order to select the right architecture for our model. Optimization of the beamforming weights is also an essential step in unlocking the maximum benefits of our deep learning-based beamforming technology. Lastly, the solution is reviewed using the SNR and SINR. Using the current comprehensive theory enables us to dig into the internal workings of beamforming at large MIMO system. The main purpose of this paper is to discuss actual benefits of a phenomenon named beamforming applied for increasing wireless communications.

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