Deep Learning-Powered Beamforming for 5G Massive MIMO Systems

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Abstract — In this study, a ResNeSt-based deep learning approach to beamforming for 5G massive multiple-input multiple-output (MIMO) systems is presented. The ResNeSt-based deep learning method is harnessed to simplify and optimize the beamforming process, consequently improving performance and efficiency of 5G and beyond communication networks. A study of beamforming capabilities has revealed potential to maximize channel capacity while minimizing interference, thus eliminating inherent limitations of the traditional methods. The proposed model shows superior adaptability to dynamic channel conditions and outperforms traditional techniques across various interference scenarios.

***Keywords* — 5G, digital beamforming, hybrid beamforming, massive MIMO, ResNeSt**

1. Introduction

The rapid development of wireless communication systems has given rise to an increasing demand for efficient and reliable transmission methods [1]. Beamforming is a key technique deployed in these systems. It boosts channel capacity by maximizing the received signal power and minimizing interference from other users [2]. Traditional beamforming approaches, including digital and hybrid beamforming, all have their own advantages and limitations.

In this study, a novel approach to beamforming in massive multiple-input multiple-output (MIMO) systems is proposed. The capabilities of convolutional neural networks (CNNs) are leveraged to address the intricacies of estimating beamforming weights. Machine learning techniques are employed to simplify and optimize the beamforming process, with the aim of enhancing system's performance and efficiency.

Convolutional neural networks (CNNs) have multiple applications beyond the field of image processing [3], [4]. They have been successfully employed in such areas as face recognition [5]–[7], Arabic handwriting recognition [8], and in many other fields. These networks are distinguished by their ability to automatically learn data features and patterns, which makes them highly valuable in a variety of domains.

The primary goal of beamforming in wireless communication systems is to concentrate the transmitted signal's power in a specific direction or towards a particular receiver, thereby enhancing signal quality, reducing interference, and extending coverage. The main advantages of using beamforming techniques in 5G and beyond networks include:

- improved signal quality – beamforming enhances signal strength and quality for users aligned with the beam's direction, leading to higher data rates and better connectivity,
- increased coverage – by directing signals towards specific areas, beamforming may extend coverage and reach previously underserved regions,
- reduced interference – beamforming can mitigate interference by focusing transmission energy where it is needed, minimizing interference in other directions,
- enhanced capacity – beamforming increases network capacity by enabling simultaneous communication with multiple users on the same frequency, without significant interference,
- energy efficiency – by concentrating energy where it is needed, beamforming reduces energy waste, thus contributing to improved network efficiency.

In Section 2, the related works focusing on beamforming techniques used in wireless communication systems are reviewed. The advancements and limitations of digital and hybrid beamforming approaches are explored, and previous studies that utilized deep learning in the context of beamforming for 5G massive MIMO systems are examined. In Section 3, the deep learning-based beamforming model for 5G Massive MIMO systems is described. In Section 4, experimental results are presented and the performance of the proposed deep learning-based beamforming model for 5G massive MIMO systems is analyzed. In Section 5, the conclusions are drawn and implications of the deep learning-based approach to beamforming for 5G massive MIMO systems are summarized.

2. Related Work

Klautau *et al.* [9] proposed a deep learning-based approach for beam selection in 5G networks. Their method leveraged machine learning techniques to optimize the process of selecting the best beam for communication, leading to improved system performance. In [10], Xu *et al.* introduced a 3D scene-based beam selection method for millimeter-wave (mmWave) communications. By utilizing deep learning, they improved the efficiency of beamforming in mmWave systems, achieving enhanced transmission quality. Klautau *et al.* [11] utilized light detection and ranging (LIDAR) data for mmWave beam selection. Their approach further improved the accuracy of beamforming by incorporating LIDAR information into the selection process.

In article [12], Ayvasik *et al.* investigated reliable wireless communication approaches using depth images. While not directly focused on beamforming, their work demonstrated the potential of utilizing depth images to enhance the quality of wireless communications. Paper [13] explored the application of computer vision techniques, with a particular emphasis placed on deep learning, in beam prediction for wireless communications. That specific study highlighted the effectiveness of deep learning models in accurately predicting optimal beams, thereby improving system performance.

In [14], novel deep learning models were introduced to predict beamforming and blockage in mmWave communication systems. The research utilized sub-6 GHz channels and successfully demonstrated precise beamforming and blockage prediction capabilities in mmWave systems.

Paper [15] integrated vision-aided beam and blockage prediction using cameras at millimeter-wave base stations. The approach demonstrated the practical implementation of vision-based techniques for improved beam prediction. In a study conducted by Aljohani *et al.* [16], an implementation of deep learning in beamforming for a 5G multiple-input multiple-output (MIMO) system was introduced. The primary aim of this particular study was to streamline the estimation of beamforming weights through the application of deep learning methodologies. Through the training of convolutional neural networks on a fading communication channel model, their work showcased promising capabilities of deep learning in reducing complexity and enhancing performance of beamforming techniques.

3. Digital Beamforming

In a MIMO system, digital beamforming allows to precisely control the transmitted signal's amplitude and phase to optimize signal reception and transmission. Its primary objective is to enhance received signal power and minimize interference through efficient adjustment of beamforming weights. Figure 1 illustrates the structure of digital beamforming in a MIMO system [17]. In this approach, a digital beamforming matrix denoted as FDB is estimated based on the channel model. The matrix is designed to achieve constructive interference of each data stream at specific scatterers. The digital beamforming process involves several key steps. Firstly, FDB is estimated using the channel model and the desired beamforming characteristics. This estimation process relies on the decomposition of the channel matrix using the singular value decomposition (SVD) method:

$$H = USV^H , \tag{1}$$

where H is the channel matrix with dimensions $N_t \times N_r$, representing N_t transmit antennas and N_r receive antennas,

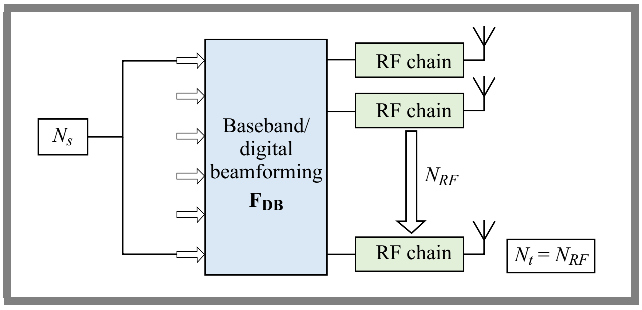

Fig. 1. Digital beamforming technique in MIMO systems.

x is a $1 \times N_t$ row vector for the transmitted signal, and y is a $1 \times N_r$ row vector for the received signal. $\mathbf{F_{DB}}$ is constructed by selecting the first N_s singular values and corresponding columns of the unitary matrices $\mathbf{U}$ and $\mathbf{V}$ obtained from SVD. On the transmitter side, precoding is performed using the first N_s rows of the Hermitian transpose of $\mathbf{U}$. This step directs the transmitted beams towards the N_s strongest scatterers, thereby enhancing signal reception at desired locations.

On the receiver side, shaping is performed using the first N_s columns of the unitary matrix $\mathbf{V}$, thus enabling the retrieval of desired data streams from the received signals. Digital beamforming may, however, be resource-intensive due to its reliance on many radio frequency (RF) chains, which leads to high energy consumption and increased cost. To overcome these challenges, hybrid beamforming techniques have emerged, combining digital and analog beamforming to strike a balance between performance and complexity.

3.1. Hybrid Beamforming

Hybrid beamforming is an advanced technique used in massive MIMO systems to reduce the number of the required RF chains, thus simplifying the system's design, lowering costs, and decreasing power consumption. Unlike traditional digital beamforming approaches which demand a dedicated RF chain for each antenna, hybrid beamforming optimizes large-scale antenna arrays by employing a smaller number of RF chains. Hybrid beamforming may be implemented through different connectivity schemes. In a fully connected structure, each RF chain connects directly to all antennas, providing maximum flexibility in terms of beamforming patterns and optimization. In contrast, a partially connected structure uses RF chains connected to a subset of antennas, forming smaller sub-arrays. This approach efficiently utilizes RF chains while still providing good performance. Fast-fading channels prove to be challenging, however, as the prevailing channel conditions change rapidly over time and the degree of complexity increases with the number of antennas in massive MIMO systems.

To cope with this, a deep learning network is trained using a vast dataset containing channel information and the corresponding optimal beamforming weights. This dataset is meticulously curated from real-world scenarios, ensuring that the network learns to adapt to diverse channel conditions. During the training phase, the network refines its weight estimation by iteratively adjusting its parameters to minimize the error between predicted and actual beamforming weights, thus

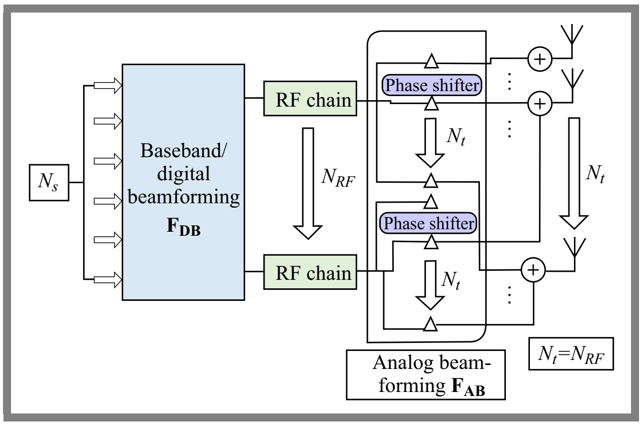

Fig. 2. Fully connected hybrid network architecture.

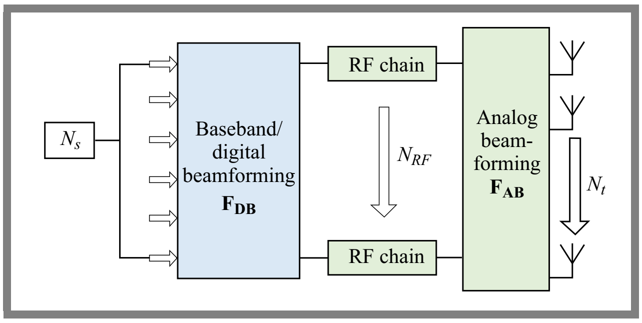

Fig. 3. Partially connected hybrid network architecture.

creating a highly accurate and adaptive model. The power of neural networks is exploited by harnessing the power of deep learning in the algorithm to adapt to and learn from dynamic channel conditions. The training phase is performed with the use of a vast dataset of channel parameters and the corresponding optimal beamforming weights, allowing the most suitable beamforming weights for various channel states to be predicted. This, in turn, results in a reduction in computational overhead and ensures real-time adaptability to changing channel conditions, making it suitable for fast-fading environments.

Figure 2 presents a hybrid structure utilizing full connectivity, while Fig. 3 shows a hybrid, partially connected structure [18]. These figures exemplify the versatility and potential of hybrid beamforming in fulfilling the ever-increasing demands of next-generation wireless communication systems.

3.2. ResNeSt Block

In ResNeSt, the ResNeSt block introduces a novel approach to handling feature grouping. Unlike prior ResNeXt blocks, where the features were divided into several groups based on a cardinality hyperparameter K, ResNeSt introduces a new hyperparameter R called "radix".

This R parameter indicates the number of splits within a cardinal group, resulting in a total of $G = KR$ feature groups [19]. Figure 4 illustrates the concept of the split-attention method deployed within a cardinal group. When configuring the radix with $R = 2$, the split-attention block utilizes SKNet-like attention for each cardinal group [20]. This means that there will be a series of transformations $\{F_1, F_2, \ldots, F_G\}$ to each

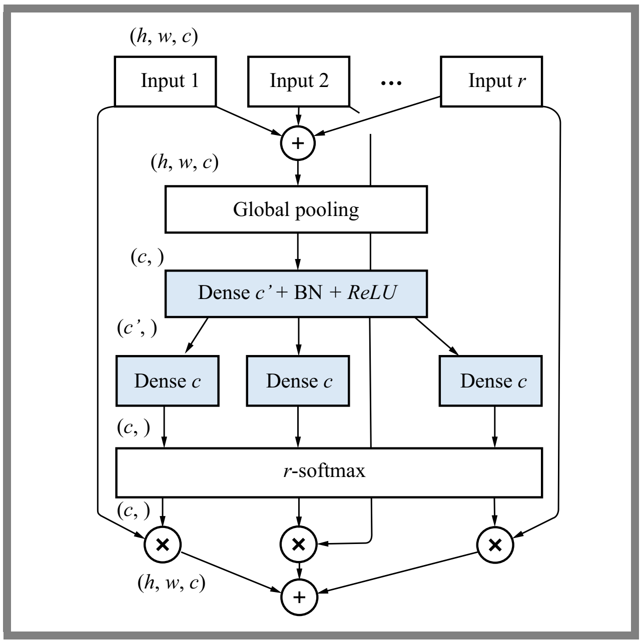

Fig. 4. Split-attention mechanism within a cardinal group.

individual group, resulting in intermediate representations $U_i = F_i(X)$, where i takes values from 1 to G.

The novel aspect of ResNeSt lies in its approach to gathering embedded channel-wise statistics. This is accomplished by conducting global average pooling across the spatial dimensions. The calculation of the c-th component in this pooling operation can be expressed as [21]:

$$S^k_c \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} \widehat{U^k_c}(i,j) \ . \tag{2}$$

The attention mechanism in ResNeSt encompasses a weighted fusion of the representation of the cardinal group V^k, with dimensions of $H \times W \times C/K$. This fusion process employs channel-wise soft attention, where each feature map channel is created by applying a weighted combination over splits within the cardinal group. The value of the c-th channel is then computed as:

$$V^k_c = \sum_{i=1}^{R} a^k_i(c) U_{R(k-1)+i} \ . \tag{3}$$

The assignment weight, a^k_i, determines the soft assignment weight and is defined as follows:

$$a^k_i(c) = \begin{cases} \dfrac{e\Big(G^c_i(s^k)\Big)}{\sum_{j=1}^{R} e\Big(G^c_j(s^k)\Big)}, & \text{if } R > 1 \\ 1 + e\Big(-G^c_i(s^k)\Big), & \text{if } R = 1 \ . \end{cases} \tag{4}$$

The function G^c_i calculates the weight of each split for the c-th channel based on global context representation s^k.

To generate the final output Y of the split-attention block, a shortcut connection is employed $Y = V + X$, where V represents the weighted fusion of the cardinal group representation, and X is the input to the block [22].

In practical terms, the operation denoted as F_i, representing the group transformation, involves a 1×1 convolution fol-

lowed by a 3×3 convolution. The attention weight function G is defined using two fully connected layers with ReLU activation.
While the cardinality-major implementation is conceptually straightforward, it presents challenges concerning modularity and acceleration when utilizing standard CNN operators. To tackle these challenges, we introduce a radix-major implementation of the ResNeSt block as a more effective solution.

3.3. Radix-major Implementation of ResNeSt Block

In the radix-major implementation of the ResNeSt block, feature map groups are physically arranged so that those with the same radix index but different cardinalities are positioned adjacent to each other. This strategic arrangement facilitates the combination of feature map groups that share the same cardinality index but have different radix indices, resulting in a fusion of these groups.
To effectively predict attention weights for each split, a global pooling layer is utilized to aggregate information across the spatial dimension. Following this, two consecutive fully connected (FC) or dense layers are introduced, with the number of groups matching the cardinality.
This implementation allows for the consolidation of the initial 1×1 convolutional layers into a single layer. Furthermore, the 3×3 convolutional layers can be achieved using a single-grouped convolution, with the number of groups set to RK. This modularization using standard CNN operators significantly enhances the efficiency and effectiveness of the split-attention block. Figure 5 illustrates the radix-major implementation of the ResNeSt block. After introducing the concept of the ResNeSt Block, let us elaborate on its specific implementation this paper focuses on, namely ResNeSt-50. It is a variant of the ResNeSt architecture comprising 50 layers. The selection of ResNeSt-50 was driven by the need to strike a balance between model complexity and performance, ensuring sufficient depth for capturing intricate data features relevant to beamforming in 5G massive MIMO systems.
The ResNeSt-50 model architecture adheres to the same principles as the ResNeSt block and utilizes radix and cardinality hyperparameters for feature grouping. Its design incorporates multiple ResNeSt building blocks, thus facilitating the transformation and aggregation of features across various groups and splits.
Moreover, the ResNeSt-50 model leverages the depth and expressive power inherent in convolutional neural networks (CNNs). CNNs possess the capability to automatically learn hierarchical representations from input data, a critical aspect in complex tasks such as beamforming. Accurate estimation of beamforming weights is essential for optimizing communication performance, and the ResNeSt-50 architecture is well suited to meet this demand.

3.4. 5G Massive MIMO Hybrid Beamforming System

Figure 6 shows a block diagram of the transmission chain for the proposed hybrid beamforming system. The diagram consists of two parts related to digital and hybrid beamforming, to emphasize the differences.
The proposed system starts with input data representing the digital information to be transmitted. The data are processed in the digital baseband processor, where such operations as modulation, coding, and data formatting are performed to prepare the data for transmission.

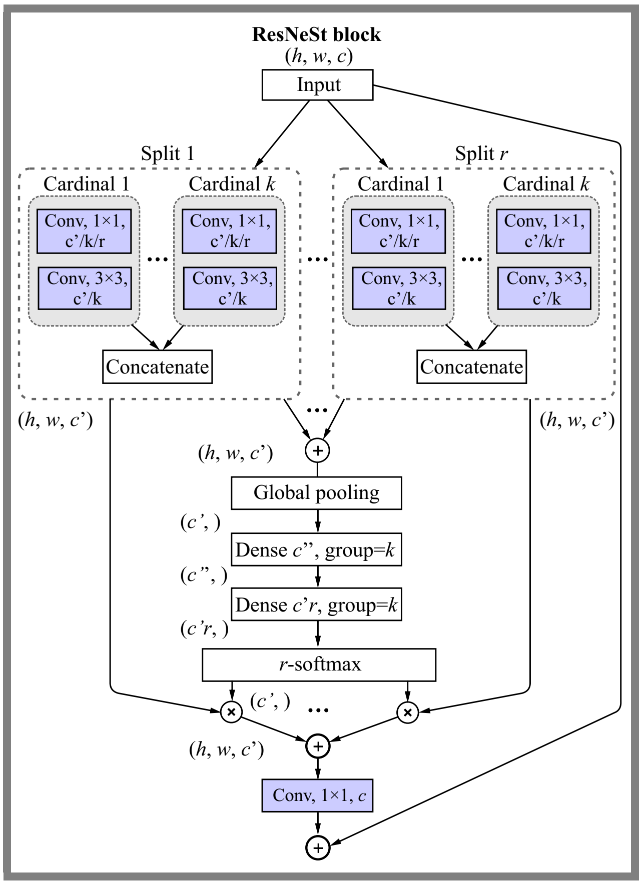

Fig. 5. Illustration of the radix-major implementation of the ResNeSt block.

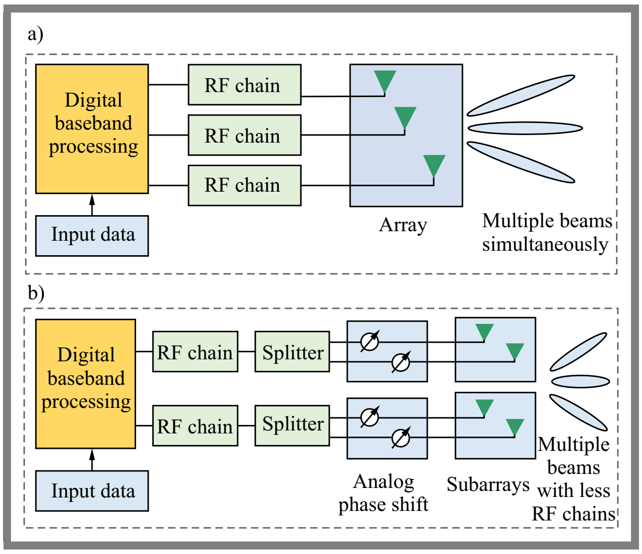

Fig. 6. Block diagram of the transmission chain for 5G massive MIMO with: a) digital beamforming and b) hybrid beamforming.

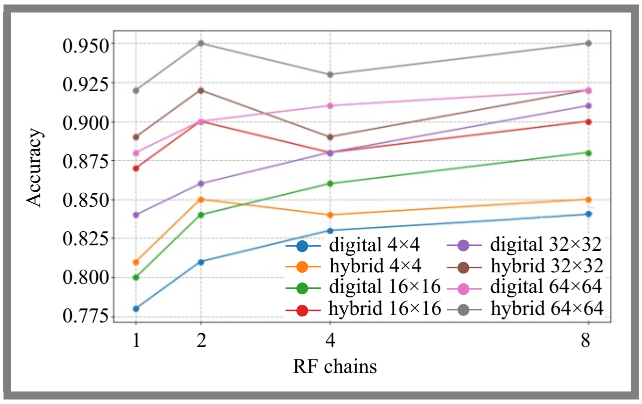

Fig. 7. Accuracy vs. RF chains for different channel sizes.

The hybrid beamforming algorithm analyzes the channel information and calculates optimal beamforming weights to improve signal reception and transmission. On the RF side, the system operates in the mmWave frequency band at 28 GHz.

3.5. Experimental Setup

For experiments, 90 scatterers were selected to simulate a complex scattering environment which is crucial for evaluating the performance of the proposed model. These scatterers were strategically distributed to create diverse and challenging channel conditions. Additionally, a dataset of 15,000 samples was employed to ensure a comprehensive evaluation of the proposed approach. The choice of 90 scatterers enabled the emulation of real-world scenarios with a sufficient level of complexity, allowing the system's performance to be thoroughly tested under various interference and noise conditions. Different configurations with varying numbers of transmitters and receivers were explored to assess the scalability and adaptability of the proposed model. To establish a benchmark, a digital beamforming scheme was also implemented using the singular value decomposition (SVD) method which is widely used in 5G massive MIMO systems. This classical method served as a reference point to evaluate the performance improvements achieved by the hybrid beamforming approach.

Throughout the experiments, data from the generated channel were extracted and utilized, enabling the fine-tuning of the model. By leveraging this data-driven approach, the beamforming weights were implemented, resulting in enhanced channel estimation and signal transmission in 5G massive MIMO scenarios.

In the experimental setup for ResNeSt-50, the training process spanned a total of 60 epochs, employing a batch size of 32. To optimize the model's performance during training, the Adam optimizer was utilized with a learning rate set at 0.001. Mean squared error (MSE) served as the chosen loss function for training. To enhance training efficiency and mitigate overfitting, the early stopping technique was implemented. Throughout the training procedure, the model's performance on a separate validation set was monitored on a continuous basis. If the model's performance on the validation set did not exhibit any improvement for a specified number of consecutive epochs, the training process was terminated prematurely. This precautionary measure aimed to ensure that the model does not overfit the training data and maintains good generalization capabilities for new, unseen data.

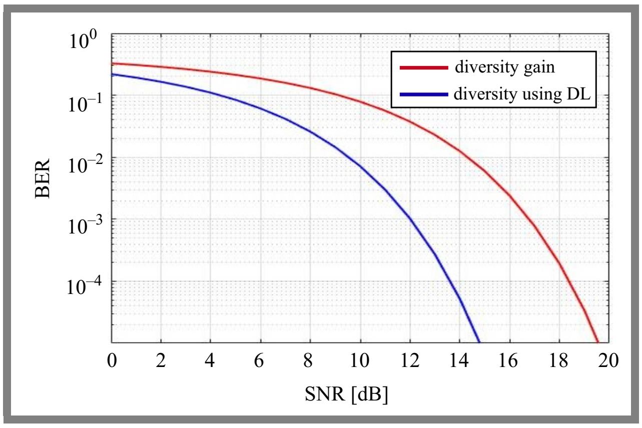

Fig. 8. BER vs SNR comparison using DL and diversity gain.

4. Results and Discussion

The experimental evaluations and analyses presented in this study were carried out using Matlab. Throughout the experimentation phase, the system's performance metrics, including spectral efficiency, bit error rate (BER), recall, F1 score, precision, and validation accuracy, were monitored. Testing was conducted under various interference conditions, noise scenarios, and channel configurations to obtain the results. In addition, the performance of the model was compared against the digital beamforming scheme based on singular value decomposition (SVD) for further analysis.

4.1. Performance Comparison

Table 1 compares the performance of digital and hybrid beamforming models under various channel sizes. The research has yielded remarkable achievements, highlighting the potential of hybrid beamforming combined with deep learning, which may serve as an alternative to traditional digital beamforming methods.

Upon analysis, the hybrid beamforming model outperformed the digital beamforming model across all channel sizes. It achieved lower values for loss, indicating better accuracy, and higher values for recall, F1 score, precision, and validation accuracy, showcasing its effectiveness in handling different scenarios.

At low channel sizes (4×4), the digital beamforming model exhibits higher loss values (0.27) compared to the hybrid beamforming (0.21). However, as the channel size increases, both models show improvements in various performance metrics, including recall, F1 score, precision, and validation accuracy. Hybrid beamforming outperforms the digital variant across all channel sizes. It achieves higher recall, F1 score, precision, and validation accuracy values, improving

Tab. 1. Performance comparison of digital and hybrid beamforming models under different channel sizes.

Model	Channel size	Loss	Recall	F1 score	Precision	Validation accuracy
Digital beamforming	4×4	0.27	0.77	0.78	0.80	0.81
	16×16	0.20	0.80	0.81	0.84	0.84
	32×32	0.18	0.82	0.84	0.87	0.86
	64×64	0.16	0.86	0.88	0.90	0.90
Hybrid beamforming	4×4	0.21	0.81	0.82	0.84	0.85
	16×16	0.15	0.88	0.88	0.87	0.90
	32×32	0.13	0.90	0.91	0.89	0.92
	64×64	0.10	0.93	0.94	0.92	0.95

the accuracy of estimating beamforming weights and handling diverse channel data.

4.2. RF Chains

Figure 7 demonstrates a comparison of the accuracy of both models across different channel sizes and RF chains. It demonstrates the performance evaluation of different beamforming models for various channel sizes and the number of RF chains using accuracy metrics for each configuration. The hybrid beamforming model consistently outperforms its digital counterpart across all channel sizes and RF chain configurations. The proposed model achieves higher accuracy values, reaching up to 0.95 for a 64×64 channel size with 8 RF chains, while the digital beamforming model achieves lower accuracy values of up to 0.84 for the same configuration.
The improvements in accuracy result from the fact that beamforming weights are estimated using deep learning and leverage diverse channel data.

4.3. Performance Evaluation Under Various Interference Conditions

The following analysis is based on a channel size of 64×64 and 2 RF chains. Table 2 illustrates the performance evaluation under various interference conditions.
The model achieves high accuracy across all metrics, with a recall of 0.93, F1 score of 0.94, and precision of 0.92. Validation accuracy equals 0.95, indicating that the model accurately predicts the beamforming weights in the absence of interference. The model maintains strong performance even in the presence of Gaussian noise, with a recall of 0.91, F1 score of 0.91, and precision of 0.91. Validation accuracy also remains high at 0.92, demonstrating the model's robustness in terms of handling Gaussian noise. The model exhibits resilience against renewal noise, achieving a recall of 0.88, F1 score of 0.90, and precision of 0.89. Validation accuracy remains high at 0.91, indicating the model's ability to cope with challenges posed by renewal noise.
Even under moderate interference conditions, the model maintains competitive performance, with a recall of 0.86, F1 score of 0.87, and precision of 0.86. Validation accuracy is 0.89, indicating that the model can effectively predict beamforming weights despite the presence of moderate interference.
Overall, the hybrid beamforming model with a channel size of 64×64 and two RF chains shows remarkable adaptability and robustness across various interference scenarios. It achieves high accuracy and precision in predicting beamforming weights, which is crucial for optimizing the performance of massive MIMO systems. These results underscore the potential of hybrid beamforming and its effectiveness in reducing the required number of RF chains while maintaining high-quality communication in challenging wireless environments.

Tab. 2. Performance evaluation of hybrid beamforming model under various interference conditions.

Model	Loss	Recall	F1 score	Precision	Validation accuracy
No interference	0.10	0.93	0.94	0.92	0.95
Gaussian noise	0.14	0.90	0.91	0.91	0.92
Renewal noise	0.15	0.88	0.90	0.89	0.91
Moderate interference	0.19	0.86	0.87	0.86	0.89

4.4. BER versus SNR Comparison

Figure 8 shows the BER versus SNR comparison using DL and diversity gain. It illustrates the performance of both models under varying signal-to-noise ratio (SNR) conditions.
BER values, which are as low as 10^{-5} for both models, demonstrate the effectiveness of the deep learning-based hybrid beamforming massive MIMO system in handling noise and interference.
The diversity using DL gives a BER of 14.9 and diversity gain gives a BER of 19.3 at 10^{-5}. This signifies the remarkable capability of the deep learning model in mitigating signal degradation and improving spectral efficiency.

Tab. 3. Spectral efficiency comparison using a 4×4 array size ($N_s = 2$).

Paper	Method	SNR [dB]	Spectral efficiency [bits/Hz]
[18]	Deep learning in digital and hybrid beamforming	0	~3.4
[23]	OMP HBF	0	~12
[24]	OMP HBF	0	18
	MO HBF	0	20
Proposed	Deep learning powered beamforming	0	25

Tab. 4. Spectral efficiency comparison using a 16×16 array ($N_s = 2$).

Paper	Method	SNR [dB]	Spectral efficiency [bits/Hz]
[23]	OMP HBF	0	~17.5
[24]	OMP HBF	0	24
	MO HBF	0	36
Proposed	Deep learning powered beamforming	0	40

4.5. Comparison of Spectral Efficiency with Other Methods

Table 3 presents a comparison of beamforming methods evaluated at an SNR of 0 dB with a frequency of 28 GHz and using a 4×4 array size ($N_s = 2$). The presented comparison highlights the varying levels of spectral efficiency achieved by different beamforming methods. The deep learning-based method [18] exhibits a spectral efficiency of approximately 3.4 bits/Hz, which is comparatively limited compared to other techniques. The OMP HBF [23] achieves a higher spectral efficiency of around 12 bits/Hz, making it a promising approach for 5G massive MIMO systems. The combination of OMP HBF and MO HBF [24] shows improved performance, achieving spectral efficiencies of 18 bits/Hz and 20 bits/Hz, respectively. The proposed method achieves the highest spectral efficiency of 25 bits/Hz, surpassing all other presented techniques.

Table 4 provides a comparison of various beamforming methods, including manifold optimization hybrid beamforming (MO HBF), orthogonal matching pursuit hybrid beamforming (OMP HBF), and the proposed method. The evaluation was conducted under an SNR of 0 dB, 28 GHz, and on a 16×16 array with $N_s = 2$.

In the evaluation of different beamforming methods, OMP HBF achieved a notable spectral efficiency of approximately 17.5 bits/Hz in [23], showcasing its effectiveness in enhancing data transmission rates. Paper [24] demonstrated the outstanding performance of OMP HBF, achieving a remarkable spectral efficiency of 24 bits/Hz. The combination of OMP HBF and MO HBF in [24] led to even higher spectral efficiency of 36 bits/Hz, further underscoring the capability of MO HBF to optimize multiple parameters for superior beamforming performance.

However, the most significant improvements come from the proposed deep learning powered beamforming method, which achieved an impressive spectral efficiency of 40 bits/Hz.

5. Conclusions

This research has demonstrated the potential of the proposed 5G massive MIMO hybrid beamforming model based on the ResNeSt-50 architecture. Leveraging advanced deep learning techniques, the model efficiently optimized beamforming weights, which resulted in enhanced channel estimation and signal transmission performance. The experimental evaluations showcased the model's adaptability and effectiveness in handling diverse interference and noise conditions, particularly in complex scattering environments. The hybrid beamforming model consistently outperformed traditional digital beamforming methods utilizing SVD, achieving higher spectral efficiency, lower BER, as well as improving recall, F1 score, precision, and validation accuracy. These findings underscore the significant impact of the proposed approach in transforming wireless communication systems. Despite the promising results, there are several challenges that warrant further investigation. One such challenge is the need to scale the proposed model to handle larger antenna arrays and more complex real-world scenarios. Additionally, exploring the impact of various environmental factors, such as mobility and frequency-selective fading, will be crucial to ensure robust performance in practical deployment scenarios.

Future work should focus on optimizing the deep learning architecture for even better performance, considering such factors as computational efficiency and model complexity. Additionally, the proposed model can be extended to multi-user scenarios, addressing interference management challenges in dense and highly populated communication networks.

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