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Intelligent Beamforming for 5G Communication Systems Using AI-Based Deep Learning

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ABSTRACT

Recently, one of the critical challenges in beamforming is beam selection in modern communication systems, especially for large antenna arrays, due to the significant training overhead for exhaustive beam sweeping results. This paper presents a proposed model-driven convolutional neural network (CNN)-based beam selection framework that depends on physical channel modeling and data-driven learning together to reduce the requirements for full channel estimation and lower the system overhead. CNN is trained offline in a supervised manner to converge the mapping between beam power patterns and optimal beam index. This enables fast beam selection during inference with minimal computational complexity. Monte Carlo simulations are employed to evaluate the performance of the proposed framework. The results confirmed that the proposed system achieves accuracies exceeding 99% and 93.8% under ideal and realistic channel conditions, respectively and 93.65% for the multi-user framework. Furthermore, the loss curve converges rapidly to zero, which indicates that the degradation in physical layer performance is insignificant, while Top-K accuracy demonstrates that the optimal beam is included in predicted candidates. Additional analyses such as reproducibility assessment over ten independent executions, sensitivity to measurement error, and multi-user performance validation were performed. All these metric analyses validate that the proposed framework is reliable, robust and effective under noise- free and multipath noisy channels. The system supports scalability due to its stable performance without noticeable degradation in the multi-user framework.

1. INTRODUCTION

First and foremost, the main goal of massive multiple-input multiple-output (MIMO) and beamforming in 5G communication systems is to meet the requirements of high data rate and very high capacity. These two factors lead to enhancing the services of 5G systems [1].

MIMO is employed as a key in 5G by using a massive number of antennas at the base station. Massive MIMO enables the base station to serve many users simultaneously by applying the concepts of spatial multiplexing and beamforming. In addition to higher capacity and data rate, energy efficiency and spectral efficiency will be enhanced, and interference will be reduced. Therefore, the overall performance of the network will be improved by applying these techniques.

Subsequently, the main idea of beamforming is directing the transmitted energy (including the sent message) from the sender to the receiver instead of spreading it in all directions. On the other hand, when the receiver listens to the signals sent from the transmitter directly. This way of communication improves the strength of the signal, and the effect of interference and noise will be decreased; these conditions will lead to higher throughput. It is important to note that beamforming is more suitable to be applied in the base station than in the user equipment (UE) due to its complexity and requirements [1].

Based on the definition of 3GPP, massive MIMO is used when the system has more than eight transmitters. It is an extended MIMO in order to have a large number of transmitters. Its main concept is based on the ability to use beams to send signals in different ways. This is evidenced if the system has an antenna with two transceiver branches; the transmitter can send two streams simultaneously to single user (RX) and when the transmitter has four antenna branches its ability is improved and he can send four streams at the same time to a certain user furthermore sending dual of two streams to two users working on the principle of Multi User MIMO (MU-MIMO). Along those lines, if the system has 64 antenna branches, it is able to transmit data to multiple users simultaneously.

On the whole, the number of transceivers is an important point in designing MIMO antennas. When the system has a higher number of transceivers, it needs to generate more beams to cover the required capacity. On the other hand, this situation will increase the cost of implementing the system. Figure 1 shows an example with 192 elements arranged as 12 vertical and 8 horizontal antennas, while each antenna has two different polarizations. Antenna gain is defined by the number of antenna elements; increasing the number of antennas will increase the gain. Moreover, the frequency is responsible for determining the antenna spacing. At low frequencies, the antenna's physical size will be larger.

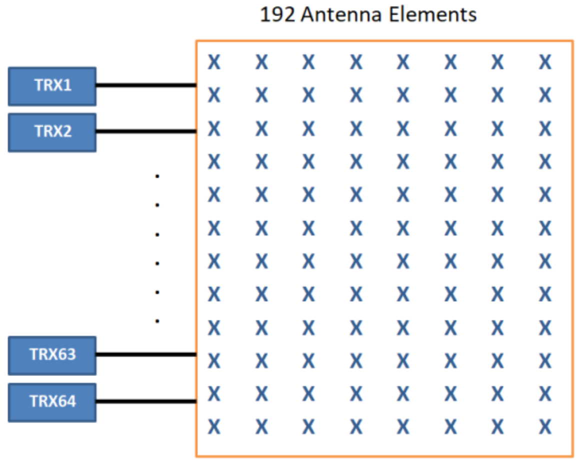

Figure 1. The relation between the number of transmitters and the number of antenna elements in a massive multiple-input multiple-output (MIMO) system

In fact, the antenna gain and size are controlled by the number of antenna elements. Furthermore, the antenna size depends on the frequency. For example, at high bands, the antenna becomes smaller.

Subsequently, the number of antenna elements is an important point at the transmitters/receivers, even if it can be lower or equal to the number of antenna elements to cover the required capacity with a suitable gain.

Likewise, the number of MIMO streams can be lower than or equal to the number of transmitters/receivers because these streams define the capability of peak data rate, which depends on the capability of baseband processing.

Finally, in the situation where antenna elements are larger (in number) than transmitters/receivers, these additional elements will be added as more rows. Typically, a MIMO system has 192 antenna elements and 64 transmitters, which can support up to 16 streams; in this case, each transmitter/ receiver has three rows [2].

Even more important is the mechanism of controlling beamforming. The UE establishes a radio link, then starts to use Synchronization Signal Blocks (SSBs), which are used in determining the initial configuration of the beam for the device. For 5G new radio networks below 6 GHz, it can be up to eight beams. Each beam has an SSB, and all these SSBs are sent in different directions but with the same strength. On the other hand, a UE will receive each signal block of synchronization with a different strength. After that, the UE will inform the network of the best signal identifier (SSB ID) when it wants to connect to the network. This is done through the use of the Random Access Channel request way, which will be linked to the particular SSB.

When there is a radio bearer, it is important to modify the configuration of the beam so the network can keep tracking the device while it is moving out of the coverage area of the initial beam. Also, the strength of the signal can be improved by making the beam narrow to a particular device during the transmission to this device. This is done by including Channel State Information Reference Signal (CSI-RS) while transmitting data and asking the device at the same time to report back the status of the received data.

Moving on, beamforming has two ways of steering the beam: Either configuring the UE with a Radio Resource Control reconfiguration (RRC-Reconfiguration) message; the role of this step is beam reporting on the MAC layer of the protocol stack. As a result, the network will be able to collect information and manage signal energy. Now, there is an indication that there is an entry from the standard precoding matrix codebook (this will be returned as feedback to the network on the MAC layer). This codebook can be referenced as the Precoding Matrix Indicator (PMI). Subsequently, the UE will analyze all the incoming signals and prepare the required network guidelines to modify the beam properly. There is another way of beam steering; this method is done through instructing the UE to radiate periodic Sounding Reference Signals (SRSs). On the other hand, the base station knows the look of SRS transmissions, so it will compare them with the received signals and will update the status of the beam according to these signals.

In fact, using these two ways includes RRC messaging to make the beam active and update its controls only. After completing the configuration, the beam will send feedback reports in the uplink and commands in the downlink direction. These two controls will be included in the MAC layer without depending on more RRC messaging. This way will make feedback production and processing as fast as possible.

In case the UE loses the beam, a beam failure recovery procedure should be initiated. It is done by indicating a new SSB ID during the procedure of random access.

Additionally, RRC measurement reports will include all the results of beam measurement, which will be used for inter-cell mobility. For example, if the strength of the beam signal of the neighbor cell is higher than the strength of the signal in the current cell, then the signal should be treated on the MAC layer and the mobility level of the cell should be handled in the RRC layer [3].

The main contributions of this work can be summarized as follows: The proposed model-driven convolutional neural network (CNN) framework is used for intelligent beam selection in 5G communication systems by integrating physical channel modeling with supervised deep learning. Furthermore, synthetic beam power measurements are generated from a physics-based channel model and are used for training instead of relying on extensive measurement-based datasets. Also, the proposed system is evaluated and compared with conventional exhaustive beam search. In the proposed framework, the trained CNN directly predicts the optimal beam during online operation, so the beam sweeping overhead is reduced. On the other hand, to cover the evaluation in terms of practical applicability, the framework is validated under multipath fading channels and multi-user scenarios. The obtained evaluation was comprehensive under varying conditions, and the system is assessed using various metrics such as beam prediction accuracy, confusion matrix analysis, Top-K accuracy, beamforming gain loss, and cumulative distribution function (CDF) analysis. This way of assessment demonstrates the framework's effectiveness for accurate and efficient beam prediction.

The paper includes a comprehensive literature review of deep learning architectures for the intelligent beamforming technique in Section 2. All the details of the proposed model and its equations are included in Section 3, while the definitions of the proposed system performance metrics are clarified in Section 4. The results and comparisons with related state-of-the-art are discussed in Section 5. Finally, all the conclusions from this work are assessed and clarified in Section 6.

2. LITERATURE REVIEW OF DEEP LEARNING ARCHITECTURES FOR INTELLIGENT BEAMFORMING TECHNIQUE

In fact, deep learning has been increasingly integrated into the beamforming technique in 5G networks because it optimizes the direction of signal transmission and reception. There are many architectures that are used for improving the status of the network and optimizing its behavior. Here are some of these approaches:

2.1 Deep neural networks

Deep neural networks (DNNs) are widely used to optimize 5G systems, including beam direction optimization, by reducing computational complexity. For instance, Lv et al. [4] applied DNNs in optimizing beamforming design and reduced the complexity of computations, as they got good performance at low values of Signal-to-Noise Ratio (SNR). But on the other hand, the important factor that affects the performance of this technique is the quality and quantity of the dataset.

Moreover, CNNs are adopted to produce effective beamforming vectors. Xia et al. [5] show how CNN is used for beamforming optimization (to be specific, for the SINR balancing problem, power minimization problem). The complexity is reduced, and the simulation results demonstrate that the proposed system makes a good balance between performance and complexity. On the other hand, it needs a lot of work to ensure user mobility, feasibility and other related issues.

Abir et al. developed a CNN algorithm for beamforming in massive MIMO systems. The algorithm, named CNNBiLSTM, was based on Received Signal Strength Indicator (RSSI) without knowing CSI. Furthermore, incremental Principal Component Analysis (PCA) is adopted to reduce the dimensions of the dataset. They achieved significant improvement in spectral efficiency and good performance compared to other models and a very high accuracy [6].

Additionally, Deep Reinforcement Learning (DRL) starts to take an important role in beamforming optimization. It differs from traditional methods because it doesn't need complex mathematical models to optimize the strategy, and it can adapt to real-time environment changes, such as updating the policy and user allocation. Furthermore, it can deal with a huge amount of data, and it is suitable for multi-objective optimization problems. This type of learning reduces the latency and computation complexity, and finally, it has the ability to make decisions with incomplete information [7]. As a result of all these advantages, many researchers have applied DRL in beamforming optimization. For example, Tarafder and Choi [8] proposed a model that enabled a complete system with high-mobility mmWave applications with low latency and minimum training overhead.

The main aim of beamforming development is to reduce the complexity of computations, as mentioned earlier. Unsupervised deep learning algorithms were introduced for beamforming to ensure this aim. Many research papers adopt this type of algorithm, and they have enhanced the performance of beamforming, such as the proposed systems in references [9-11].

Overall, all the previous studies show that deep learning has the ability to improve beamforming performance efficiently through the reduction of computational complexity and enhancement of the accuracy of beam prediction. On the other hand, many of the existing papers focus on network architecture optimization or the application scenario with limited emphasis on the practical beam selection problem. Motivated by this research gap, the proposed system adopts a model-driven CNN framework that combines a physically motivated channel model with supervised learning to predict the beam with the optimal index, keeping the computational complexity low.

2.2 AI-based deep learning for beamforming in 5G systems

In fact, there are many conventional beamforming techniques such as maximum ratio transmission, minimum mean square error, and zero forcing. The performance of these techniques degrades in practical scenarios, even though they are optimal under ideal assumptions; they have channel estimation errors, large antenna arrays, and high mobility, particularly in mmWave and massive MIMO systems [12, 13]. The best way to address these challenges is deep learning because of its ability to learn complex mappings and its ability to optimize beamforming decisions.

The role of AI and deep learning in beamforming can be highlighted in beam selection, vector prediction, and beam management:

First of all, beam selection can be implemented by training the deep learning model to map received pilot signals, partial CSI, and RSSI or SNR measurements. One of them is mapped to the best beam index, and as a result, it will maximize the quality of the link, reduce beam training overhead, and lead to reduced latency [14, 15]. Fully connected DNNs, CNNs, attention-based models, and transformer models can be used for these purposes [16].

The second way of using deep learning is in vector prediction. This method deals with estimating the beamforming vector, which is used to steer the antenna array toward the required user. This way avoids matrix inversion and is able to learn nonlinear beam patterns [17, 18].

In fact, RL also has an important role in solving dynamic beamforming problems, like beam tracking and mobility-aware beam switching [19, 20].

Moving on, hybrid beamforming systems can be implemented through analog RF beamforming and digital baseband precoding, and AI techniques are used in optimizing the analog beamforming by reducing search complexity and RF chain requirements when digital precoding is implemented through basic methods [21, 22]. This way of AI use is really attractive for mmWave and massive MIMO systems.

In summary, AI-based beamforming enhances robustness to channel uncertainty, reduces dependence on perfect CSI, lowers computational complexity, and improves adaptability in high-mobility systems.

In this paper, a model-driven CNN is suggested to enhance the performance of beamforming in 5G systems, as will be discussed in the next sections.

Based on all the above literature review, the existing AI-based beamforming techniques use various input features such as CSI, RSSI, location information, and camera images. On the other hand, the proposed framework predicts the optimal beam index directly from the measurements of beam power, which is generated by a physically motivated channel model. Moreover, the proposed work produces a comprehensive evaluation through ideal and realistic channel conditions, Top-K accuracy, beamforming gain loss, reproducibility analysis, measurement sensitivity, and multi-user performance. All these evaluation analyses provide a complete assessment of the beam selection framework.

3. PROPOSED SYSTEM MODEL

This section includes the proposed model-driven CNN specifications and methodology for beam selection, which is unified because the learning framework is derived depending on physical channel and beamforming models.

3.1 Channel model and beamforming

The channel and beamforming model is first introduced. The system has a single-user downlink beamforming system, and the base station has a uniform linear array (ULA) of antennas (N_t) for transmission. Beam selection is performed using the following weights [23]:

$$W = [w_l, w_2, w_3, \dots, w_{N_b}], \text{with } \mathrm{N}_b = \mathrm{N_t} \tag{1}$$

The assumed model has narrowband propagation with a dominant line of sight (LoS) component, while the channel vector is [24, 25]:

$$h = \frac{1}{\sqrt{N_t}} a(\theta) \tag{2}$$

where, θ is the angle of departure (AoD); the value was set to a random value between -60 and 60° and this range is a practical and physical choice [23]. Subsequently, $a(\theta)$ is the ULA steering vector and can be defined as:

$$a(\theta) = \left[1, e^{j\frac{2\pi d}{\lambda}\sin(\theta)}, \dots, e^{j\frac{2\pi d}{\lambda}(N_t-1)\sin(\theta)}\right]^T \tag{3}$$

Note that d = $\lambda/2\mathrm{d}$, while λ is the carrier wavelength.

Furthermore, the system depends on the discrete Fourier transform (DFT) due to orthogonality, and it is suitable for beam sweeping as mentioned in a previous study [26]. The received beamforming power according to beam b is [26]:

$$P_b = |w_b^H h|^2, b = 1, \dots, N_b \tag{4}$$

Finally, for the beamforming model, the index of the optimal beam will be:

$$b^* = \arg arg_b^{max} P_b \tag{5}$$

This equation demonstrates that the index of the optimal beam corresponds to the beam with maximum received beamforming power among all candidate beams. Due to this, the ground-truth label for each training sample is the index of the beam with the highest received power. Sometimes, multiple beams exhibit identical received power, which is the maximum (rare case). In this situation, the function max in MATLAB will choose the first occurrence of the maximum value and it will have a unique class label for CNN training and testing.

On the other hand, it is important to present the details of model-driven data generation and feature construction so that the whole system will be clear and integrated. The mentioned physical channel and beamforming models are used to generate training data, and this is the point that makes the proposed framework different from purely data-driven approaches. The beamforming powers are computed for each channel realization and all beams in dB. So the beam power vector will be:

$$P = [P_1, P_2, \dots, P_{N_b}] \tag{6}$$

In the designed beam selection framework, a CNN is employed. The difference from the existing related CNN works in the following important aspects:

1. Most of the existing works use full CSI or complex channel matrices as the input to the CNN. The proposed model uses beam power measurements obtained from the beamforming codebook as input feature representation. Each sample includes the received power values, which correspond to the candidate beam. The used way of representation reduces the requirements for full channel estimation and lowers the system overhead.
2. The other meaningful difference is training with variable SNR (-5 dB to 15 dB) using random values within this range. This approach enables the CNN to learn how to predict the beam under different noise conditions and leads to improved robustness of the proposed model.
3. The dataset generation considers a multipath channel, which converges to practical wireless environments and allows the CNN model to learn beam selection behavior under realistic channel conditions.

So the novelty of the proposed framework lies in these three points, which enable low complexity and robust beam prediction without requiring full CSI estimation.

3.2 Measurement and estimation model

In fact, we consider the beam power vector defined in Eq. (6) as the measured input to the proposed CNN. Each element of the vector P represents the beamformed received power of the beam in the DFT beamforming codebook. These values are obtained from applying each beamforming vector to the received channel and computing the corresponding received power. In the offline dataset generation stage, the beam power is generated directly from the physical channel for all values. All these values are considered to be ideal and without any impairments, in order to enable the proposed CNN to learn the actual relationship between the measured beam power distribution and the optimal beam index.

On the other hand, the proposed framework is designed to work as a practical wireless communication system in which the beam power measurements may be affected by receiver thermal noise, channel estimation errors, analog-to-digital converter quantization, and hardware calibration imperfections. So, in practical implementation, the measured power of the beam can be expressed as

$$\hat{P}_b = P_b + \varepsilon_b \tag{7}$$

where, P_b is the b-th element of the ideal beam power vector defined in Eq. (6), and ε_b is the measurement error, which is modeled as an additive zero-mean Gaussian random variable in this practical work environment. The robustness of the proposed beam selection system is further evaluated and clarified later in the sensitivity analysis in Section 5.

3.3 Model-driven convolutional neural network-based beam selection

CNN is a way to learn the relation between the beam power vector and the optimal beam index. CNN is used to implement this task because it is able to exploit the correlations among adjacent beams, and these correlations arise from the structure of ULA [27, 28].

The training was offline and supervised to obtain the predicted beam index $\hat{b}$ and to approximate the function:

$$f_{\Theta} = P \rightarrow \hat{b} \quad (8)$$

where, Θ represents network parameters. CNN selects the beam through inference, and this task enables fast selection with minimal computations. The design of the CNN architecture is designed to capture the spatial structure of beam power patterns. It is a one-dimensional structure and has two convolutional layers; the kernel sizes are small in order to extract the correlations of local beams, and then batch normalization and ReLU activation are included in order to improve the stability and nonlinearity of training. Furthermore, fully connected layers are included to perform a high level of beam classification. This lightweight CNN achieves high accuracy and low computational complexity. Figures 2 and 3 show the flowcharts of the offline training phase and online (real-time) beam selection phase.

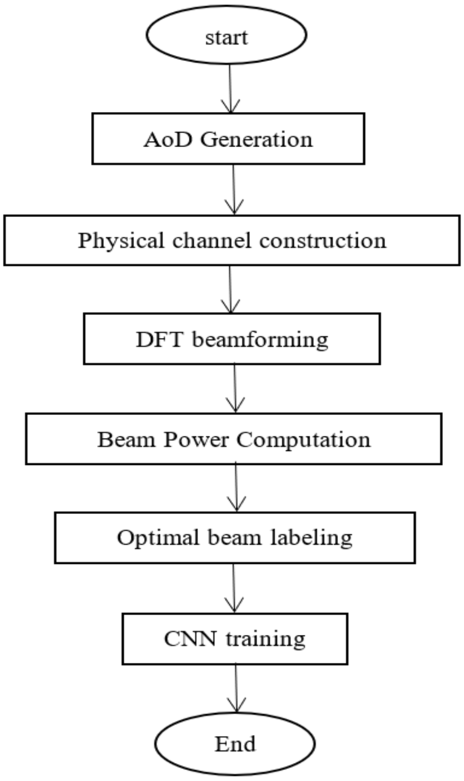

Figure 2. Offline training phase

The proposed framework supposes that the input to the CNN is available, which is the received beam power measurements corresponding to the predefined beam codebook. Also, the proposed model does not remove the initial beam measurement stage, which is required to obtain these observations; instead, its main objective is to reduce the complexity of computations and the latency of decision by replacing iterative beam search in conventional beam selection with a single forward inference in the trained CNN. As a result, the reported overhead reduction relates to the beam selection process and the decision-making process instead of the beam measurement procedure. Therefore, the investigation of beam prediction from beam measurements represents an important direction for future work.

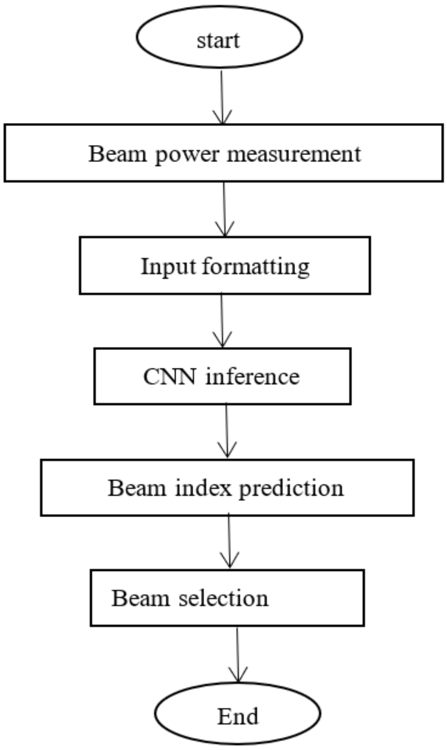

Figure 3. Online beam selection phase

According to the reproducibility of the proposed framework, the following algorithm is included. It summarizes the implementation procedure completely during the online phase, i.e., model-driven dataset generation, CNN training, and beam prediction. Also, Table 1 includes all implementation details and hyperparameters to support any other assessment or comparison.

Algorithm 1. Model-driven convolutional neural network (CNN) beam prediction procedure

1: Generate random AoD samples
2: Construct the physical channel using the steering vector of ULA
3: Generate the DFT of the beamforming codebook
4: Compute the received beamforming power for all the candidate beams
5: Convert the beam power measurements to dB scale
6: Assign the beam with maximum power as the ground truth beam label
7: Split the dataset into three sets: training, validation, and testing
8: Reshape the beam power vectors to form CNN input tensors
9: Initialize the CNN architecture and training hyperparameters
10: Train the CNN using the Adam optimizer
11: Predict beam indices for the test set
12: Evaluate the performance in terms of prediction accuracy, Top-K accuracy, beamforming gain loss, and confusion matrix

Table 1. The proposed convolutional neural network (CNN) architecture and training hyperparameters

Parameter	Value
Deep learning framework	MATLAB R2023a Deep Learning Toolbox
CNN architecture	Model-driven CNN
Input size	16 × 1 × 1 beam power vector
Number of convolution layers	2
Convolution layer 1	32 filters, kernel 3 × 1
Convolution layer 2	64 filters, kernel 3 × 1
Padding	Zero padding
Stride	1
Batch normalization	After each convolution layer
Activation	ReLU
Fully connected layer	128 neurons
Output layer	Softmax
Loss function	Cross-entropy classification loss
Optimizer	Adam
Initial learning rate	0.001
Learning rate schedule	Constant
Mini-batch size	64
Maximum epochs	20
Validation frequency	Every 50 iterations
Data shuffling	Every epoch
Weight initialization	Glorot/Xavier
Regularization	None
Data split	70%, 10%, 20%
No. of training samples	7000
No. of validation samples	1000
No. of testing samples	2000

4. PROPOSED SYSTEM PERFORMANCE METRICS

In this work, classification-based and physical metrics are used to evaluate the proposed system and make a comprehensive assessment. The following metrics are defined before discussing their values and graphs for the proposed framework.

4.1 Classification accuracy

This metric measures the proportion of the correctly selected beams [28].

$$Accuracy = \frac{1}{N}\sum_{i=1}^{N} 1(\hat{b}_i = b_i^*) \quad (9)$$

4.2 Confusion matrix

A confusion matrix is used to show the behavior of beam prediction and detect misclassification patterns [27].

4.3 Top-K accuracy

This value reflects practical beam refinement strategies in a 5G system.

$$Top\text{-}K = \frac{1}{N}\sum_{i=1}^{N} 1(\, b_i^* \in B_i^{(K)}) \quad (10)$$

where, $B_i^{(K)}$ is the set of the K most probable beams [26].

4.4 Beamforming gain loss

This metric determines the physical layer performance degradation by incorrect beam selection [29].

$$\Delta G = P_{b^*} - P_{\hat{b}} \quad (11)$$

4.5 Cumulative distribution function of beamforming gain loss

CDF of ΔG assesses the reliability of the system and the worst-case behavior, which is important and critical for latency-sensitive services [29].

5. RESULTS AND DISCUSSION

5.1 Simulation setups

The framework of beam selection is evaluated by repeating it many times with a random AoD; for this reason, the system is evaluated through Monte Carlo simulations. As mentioned earlier, for a single-user downlink system, the base station is equipped with a ULA of 16 antennas. Also, the LoS channel model is considered, and the range of AoD within -60º to 60º.

The dataset has 10000 samples, which is partitioned into training, validation, and testing with ratios of 70%, 10%, and 20%, respectively. CNN is trained using the Adam optimizer; the learning rate is 0.001, the mini-batch size is 64, and the training epochs are 20. The training is offline and supervised, and the noise is considered free for all beams.

To cover all possible scenarios, the proposed framework was evaluated in two stages. Stage 1 used a noise-free beam power dataset to establish the upper-bound beam prediction performance under ideal conditions. Stage 2 used a more realistic dataset with multipath fading and an additive white Gaussian noise (AWGN) channel, with SNR values ranging from −5 to 15 dB to evaluate robustness in practical environments.

The noise was added during training and testing phases; each generated sample was corrupted by a randomly selected SNR value from the interval [-5,15] dB before beam power computation. This step is needed to cover realistic cases and to ensure that the CNN has the ability to predict beams with a high level of robustness under varying channel conditions (heterogeneous channel conditions), not only in ideal conditions.

Finally, for statistical robustness analysis, it is important to demonstrate that the experiment was completely repeated using ten independent random seeds. Each one of them generated different realizations of the channel, dataset portions, and CNN initialization and the mean and standard deviations were computed across independent runs.

5.2 Performance evaluation

5.2.1 Performance evaluation under ideal channel conditions

The evaluation of the proposed model-driven CNN is based on the evaluation of the performance metrics mentioned earlier. The first metric is accuracy, which is high, as shown in Figure 4.

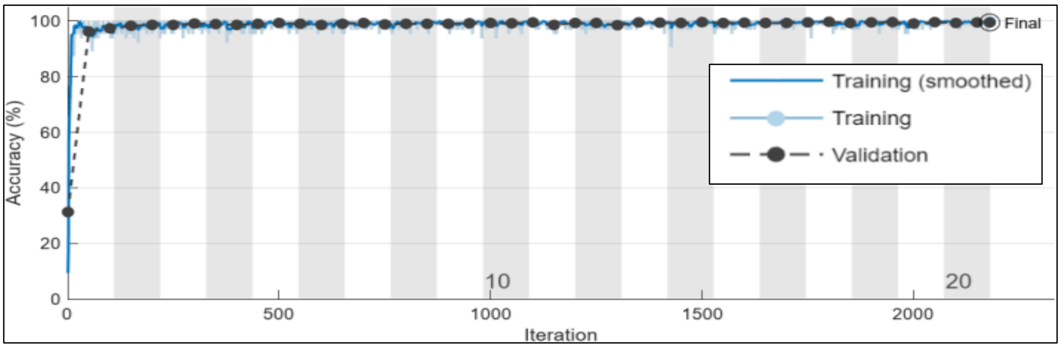

Figure 4. Classification accuracy of the proposed model-driven convolutional neural network (CNN) under ideal channel conditions

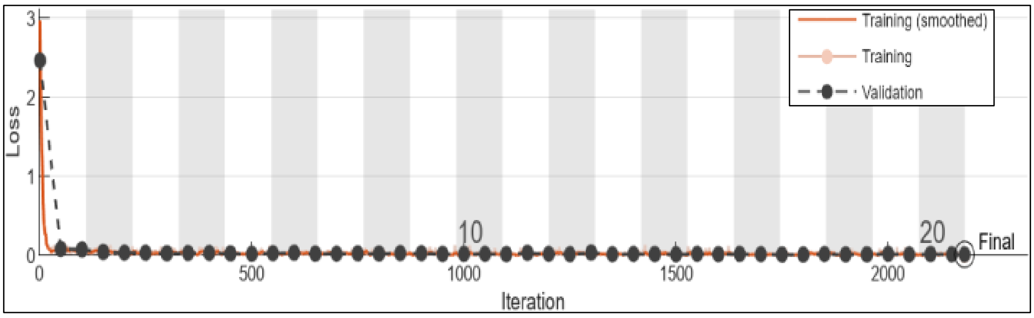

Figure 5. Training loss of the proposed model-driven convolutional neural network (CNN) under ideal channel conditions

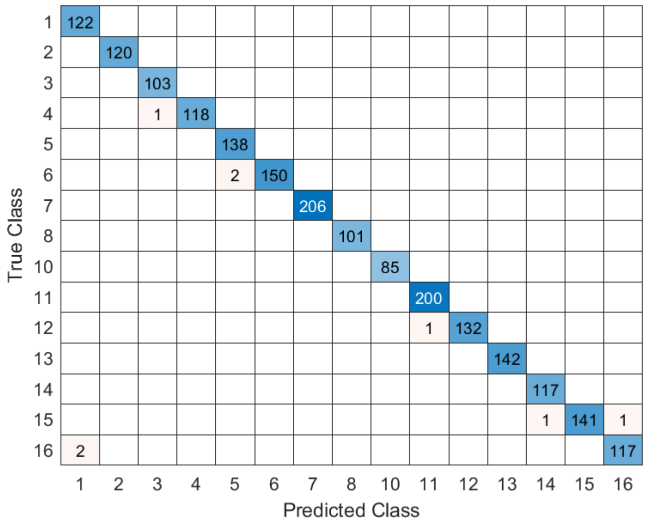

Figure 6. Confusion matrix for beam selection

It is clear that accuracy rapidly converges to 99.6% within early training epochs, and it is stable throughout the training process.

On the other hand, Figure 5 shows the training loss, which decreases sharply and approaches zero; this means the learning is effective, and the prediction is confident.

The system has no overfitting during the training process because of the agreement between training and validation accuracy. Also, the training time was short (1 minute and 6 seconds) for a single CPU, and this highlights the computational efficiency of the proposed system.

Figure 6 illustrates the confusion matrix of beam classification of the proposed system. It is clear that the major predictions are correct (along the main diagonal), which means the optimal beam index is identified properly for most channel realizations.

Figure 7 illustrates the Top-K beam selection accuracy. When K = 1, the accuracy is 99.6%, which means the predicted beam index matches the optimal beam, but when K is increased to 2 and 3, the accuracy reaches 100%, and this indicates the optimal beam is always included within the Top-K predicted candidates. In fact, this is a sign of the proposed system's robustness, which makes it suitable for practical beam management.

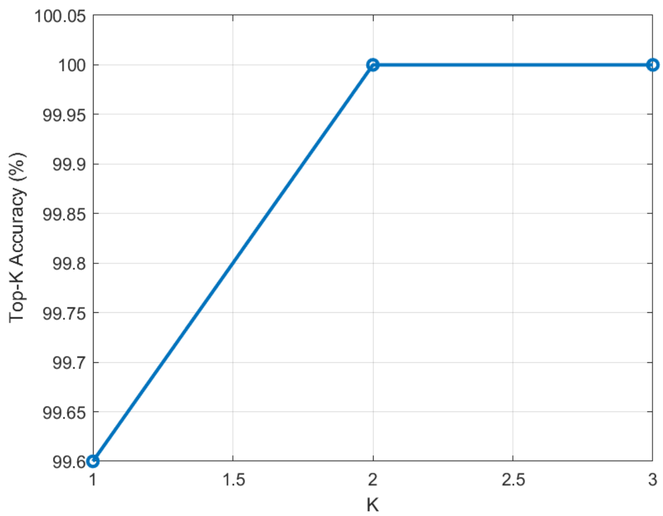

Figure 7. Top-K beam selection accuracy

Figure 8 shows the histogram of beamforming gain loss between the optimal beam and the selected one (by the proposed system). The distribution around 0 dB indicates that the predicted beam is close to the optimal one. This highlights the effectiveness of the proposed model in maintaining beamforming gain because the misclassifications occur infrequently.

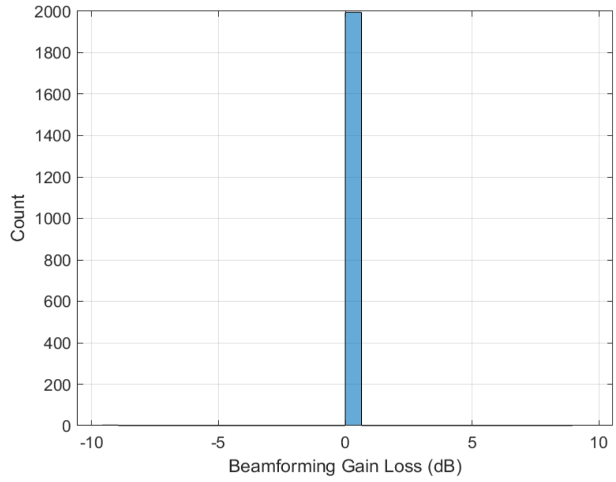

Figure 8. Histogram of beamforming gain loss

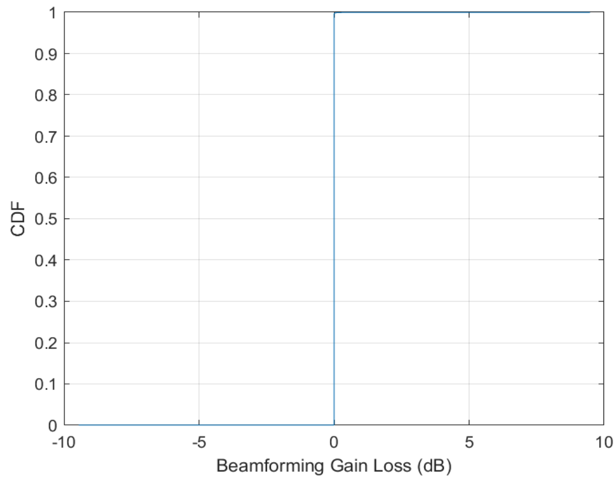

Figure 9. Cumulative distribution function (CDF) of beamforming gain loss

Table 2. Beamforming gain loss statistics for misclassified samples

Metric	Value
Total test samples	2000
Misclassified samples	13
Misclassification rate	0.65%
Average gain loss	5.25 dB
Maximum gain loss	9.82 dB
Standard deviation	4.91 dB

Figure 9 shows the relation between the CDF and the beamforming loss. It is clear that beamforming gain loss remains near zero for most of the test samples, which indicates that the proposed CNN predicts the optimal (or near optimal) beam successfully in most cases. Subsequently, the beamforming gain loss was analyzed only for misclassified samples to assess the practical impact of prediction errors, as demonstrated in Table 2.

It is demonstrated in Table 2 that only 13 out of 2000 test samples were misclassified, i.e., for 0.65% of the samples, the average beamforming gain loss was 5.25 dB, while the maximum loss was 9.82 dB. Note that if multiple candidate beams exhibit nearly identical received power values, then zero gain loss occurs for a small number of misclassified samples. In fact, in these cases the predicted beam index differs from the reference label, but it has the same beamforming performance. For this reason, a conflict will appear between the beam prediction accuracy and the CDF due to the small proportion of sample misclassification and the existence of nearly equivalent beam candidates.

5.2.2 Performance evaluation under realistic channel conditions

To enrich simulation environments and have the best assessment of the system performance, realistic channel conditions are used:

1) Two paths are used with random angles and random gains to have a multipath channel.
2) Gaussian noise is added, which is scaled by SNR, so that the channel will be noisy.
3) Normalization is used to ensure the channel has unit power.

The proposed system is tested on a multipath fading channel with AWGN and the accuracy under these situations is shown in Figure 10.

It is clear that the proposed system performance is stable and the accuracy has fast convergence to 93.8% in validation over a realistic channel with varying SNR (-5 to 15 dB) along 2,180 iterations. For reproducibility, the number of training iterations is determined by dividing the training set size, which is 7000 (according to Table 1), by the mini-batch size, which is 64 (also taken from Table 1), so (7000/64) = 109 complete mini-patches, and with 20 epochs the total number of training iterations will be 109 × 20 = 2180 iterations. The remaining 24 samples (7000 – 109 × 64) do not form a complete mini-patch and are discarded for that epoch.

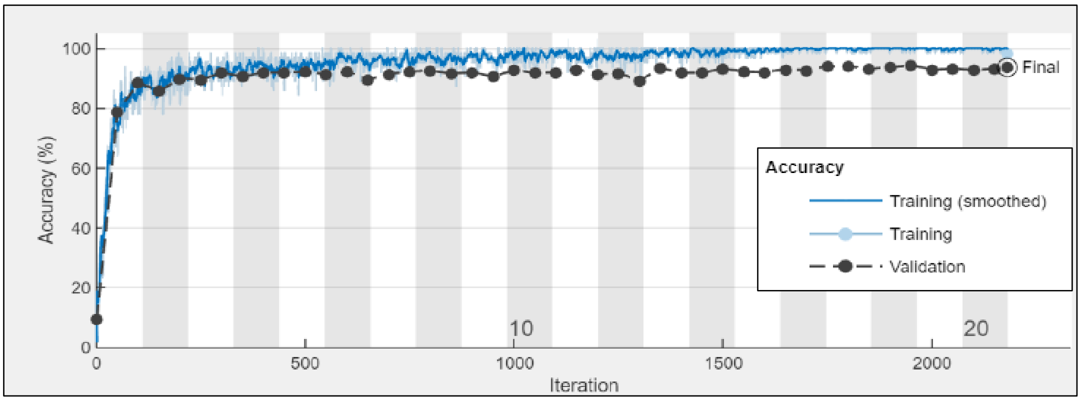

Figure 10. Classification accuracy of the proposed model-driven convolutional neural network (CNN) under realistic channel conditions

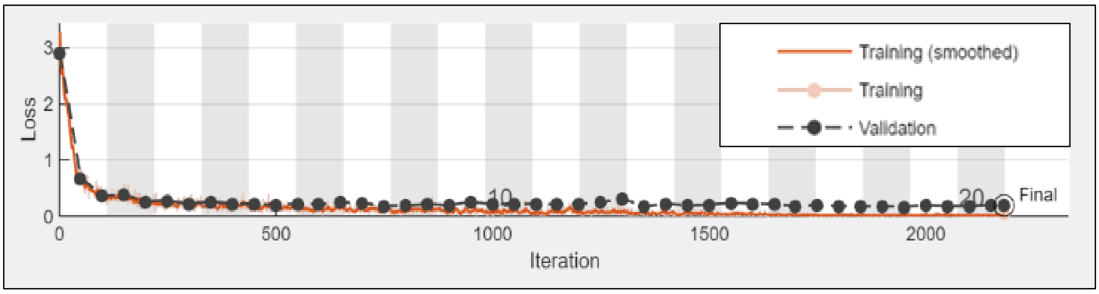

Figure 11. Training loss of the proposed model-driven convolutional neural network (CNN) under realistic channel conditions

On the other hand, the loss factor was also assessed under a multipath AWGN channel, and it was stable; the learning was also effective, and the loss converged to a near-zero value quickly, as shown in Figure 11. This value indicates that the degradation in physical layer performance is insignificant because the predicted beam is becoming very close to the target (optimum beam).

Subsequently, Table 3 demonstrates the principal performance indicators obtained under realistic channel conditions. The best achieved validation accuracy was 93.8% even when multipath propagation with AWGN existed, with random variations of SNR from -5 dB to 15 dB. Moreover, the decrease of training and validation loss was rapid and the levels converged to near-zero values, which proves that the learning behavior of the proposed framework was stable and the employed optimization technique was effective. Furthermore, the convergence and agreement between the training and validation curves, as shown in Figures 4 and 10, confirm that the proposed framework has no overfitting and generalizes well to unseen channel realizations. Overall, these results show that the proposed beam prediction framework is robust under practical channel conditions and environments and the system maintains reliable learning performance.

Table 3. Convolutional neural network (CNN) performance under realistic channel conditions

Performance Metric	Value
Best validation accuracy	93.8%
Final training loss	Near zero
Final validation loss	Near zero
Channel Model	Multipath and additive white Gaussian noise (AWGN)
Training Signal-to-Noise Ratio (SNR) range	-5 dB to 15 dB
Learning Stability	Stable convergence
Generalization Performance	No noticeable overfitting

5.2.3 Sensitivity to measurement errors

One of the most important metrics to assess the system is the robustness of the proposed framework under realistic environments, as mentioned earlier. For this reason, a sensitivity analysis was presented in this section and tested by introducing additive measurement errors into beam power measured values through the testing phase. As described in Section 3, the measurement error was modeled as an additive zero-mean Gaussian random variable in the dB domain, which represents the combined effects of all practical errors such as ADC quantization, thermal noise, and hardware calibration defects. The training of the CNN was done using the original dataset, while the measurement errors were introduced during the testing phase to highlight their impact on beam prediction performance.

Figure 12 shows that the standard deviation of measurement error was varied from 0 to 1 dB, while the corresponding beam prediction accuracies are summarized in Table 4.

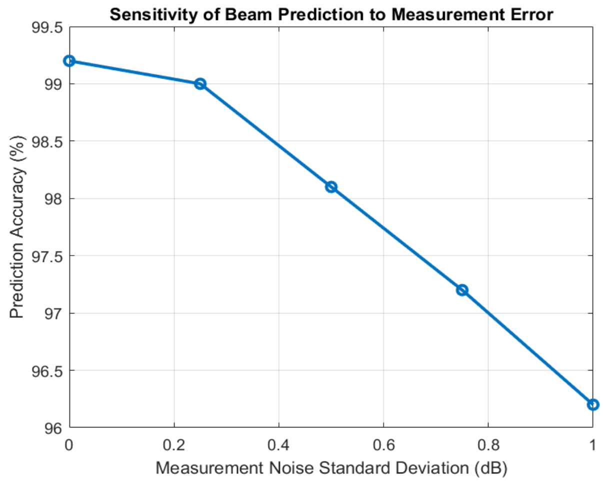

Figure 12. The sensitivity of the proposed beam selection framework to measurement noise standard deviation

Table 4. Sensitivity of beam prediction accuracy to measurement errors

Measurement Noise Standard Deviation (dB)	Prediction Accuracy (%)
0	99.6
0.25	98.9
0.5	97.9
0.75	97.3
1	95.75

It can be demonstrated from Figure 12 and Table 4 that the proposed framework has a gradual degradation in prediction accuracy when the uncertainty of measurements increases, but the worst case has 95.75%, which means an absolute reduction of only 3.85 points. So the framework maintains prediction accuracy exceeding 95% and this indicates the framework demonstrated satisfactory robustness for practical beamforming systems.

5.2.4 Scalability potential

Scalability potential is beneficial to assess the performance of the proposed beamforming prediction for multi-user broadcasting on a multipath AWGN channel. The proposed framework is used to predict the beams of four users instead of one user as in previous simulations. The system is executed over 8,740 iterations to achieve stable convergence in the training process. Figure 13 illustrates how training accuracy increases rapidly and improves gradually to reach 93.65%, which means that the predicted beam is very close to the optimal beam, even when multiple users are present within the coverage area. The results indicate that the proposed model-driven CNN achieves scalability with accuracy comparable to that of the single-user scenario.

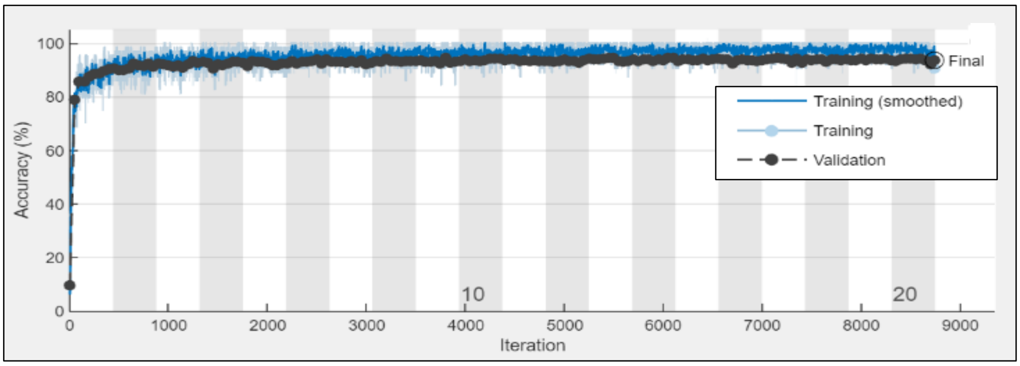

Figure 13. Classification accuracy of the proposed model-driven convolutional neural network (CNN) across four users

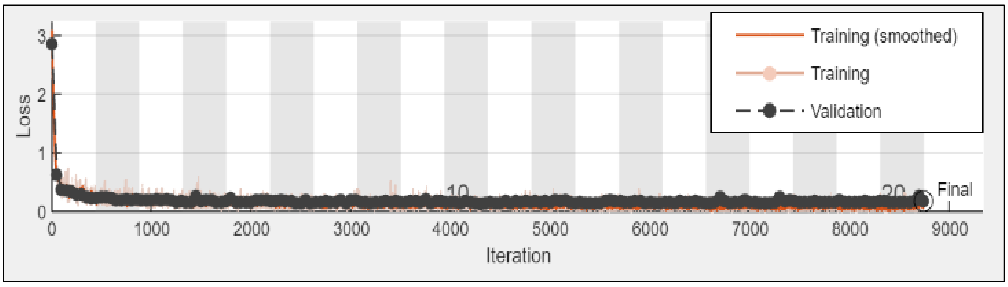

Figure 14. Training loss of the proposed model-driven convolutional neural network (CNN) across four users

Loss must be assessed to judge the performance fairly. The curve shown in Figure 14 supports the idea of scalability because of its sharp decrease to a near-zero value rapidly during the early iterations.

Furthermore, it is important to mention that the small gap between the accuracy curves in training and validation means that the model performs well on unseen data without overfitting. As a conclusion from these curves, they confirm that the proposed beam prediction framework achieves reliable learning performance and stable convergence for a multi-user (4 users) scenario.

Table 5. Convolutional neural network (CNN) performance in multi-user uniform linear array (ULA)-based beamforming scenario

Performance Metric	Value
No. of users	**4**
Best validation accuracy	93.65%
Final training loss	Near zero
Final validation loss	Near zero
Channel model	Multi-user multipath additive white Gaussian noise (AWGN) channel based on ULA
Learning stability	Stable convergence
Generalization performance	No noticeable overfitting
Scalability	Successfully scalable

Subsequently, Table 5 summarizes the principal quantitative results for the multi-user beam selection scenario. The proposed framework has the best validation accuracy of 93.65%, while the gain loss remains stable and near zero in the validation and testing phases. This level of performance (for single and multi-user scenarios) ensures the robustness, reliability, and scalability of the proposed model-driven CNN beam prediction framework.

5.2.5 Latency evaluation of beam selection

Latency means the required time to predict the optimal beam. It can be measured using the inference stage only because training is offline. The average inference time (total inference time/number of samples) is 20.3 µs per sample (on a PC with a Core i7 processor and 16 GB RAM). This value demonstrates that the proposed framework enables fast beam prediction suitable for real-time wireless communication systems.

In order to produce a practical perspective, the proposed CNN framework is compared with conventional beam sweeping. The optimal beam in the conventional approach is identified by evaluating all candidate beams sequentially, while the proposed framework predicts the optimal beam index through a single forward propagation when the beam power measurements are acquired. In this case, the latency of the reported beam selection is approximately 20 µs, which corresponds to the CNN inference stage measured in a MATLAB environment only without including beam measurement, signal acquisition, or hardware processing delays. As a result, this latency represents the computational cost of the beam prediction stage, not the end-to-end beam management latency and the result demonstrates that the proposed model provides an efficient mechanism with high beam prediction accuracy.

5.2.6 Reproducibility and statistical robustness analysis

In order to check the reproducibility and assess the statistical robustness of the proposed CNN-based beam prediction framework, the training and evaluation procedure was repeated over ten independent runs using different random seeds.

During data generation, SNR was independently sampled for each generated sample from a uniform distribution between -5 dB and 15 dB. The other hyperparameters, such as CNN architecture and evaluation setting, were kept unchanged throughout the experiments. This procedure ensures that the reported performance does not depend on a single experiment realization or random initialization.

Table 6. Statistical robustness of the proposed beam prediction framework over 10 independent runs

Performance Metric	Mean ± Standard Deviation
Validation accuracy	91.34 ± 0.93%
Beam selection latency	0.0203 ± 0.0018 ms
Training time	47.57 ± 6.72 s

Table 6 demonstrates the statistical results obtained from the independent ten executions. The mean validation accuracy achieved by the proposed framework was 91.34 ± 0.93%, which indicates highly consistent convergence during training, even when the inherent randomness is introduced by channel generation, SNR sampling, and parameter initialization. Moreover, the average latency of beam selection was 0.0203 ± 0.0018 ms, which indicates that the system had a highly stable inference time, making it suitable for real-time beam prediction applications. Finally, the average training time was 47.57 ± 6.72 s, which means that the variation was moderate among different executions because of the stochastic optimization process employed by the Adam optimizer.

All these small deviations confirm the robustness and repeatability of the proposed CNN-based model and show that the model converges to similar performance for independent runs, so the reliability and reproducibility of the reported findings were improved.

5.2.7 The proposed framework comparison with baseline beam selection methods

In order to cover the performance of the proposed framework, a comparison with two baseline beam selection approaches is presented in this section using the same dataset and identical input features. The first baseline method depends on the conventional exhaustive beam sweeping, i.e., the selected beam has the maximum measured beam power. On the other hand, the second baseline is a lightweight multilayer perceptron (MLP) which is trained using the same beam power vector employed in the proposed framework. The main outcome from this comparison is the effectiveness of the proposed framework, which is evaluated under identical conditions.

Table 7 includes the quantitative comparison in terms of accuracy, Top-K accuracy, average beamforming gain loss, and inference time.

Table 7. Proposed framework comparison with baseline beam selection methods

Method	Top-1 Accuracy (%)	Top-2 Accuracy (%)	Average Gain Loss (dB)	Average Inference Time/Selection Time (ms)
Exhaustive beam sweeping	100	100	0	Sequential beam sweeping (16 beam measurements): very high
Lightweight multilayer perceptron (MLP)	99.6	100	0	0.1528
Proposed model-driven convolutional neural network (CNN)	99.6	100	0.0341	0.0203

The results show that the whole approach achieves high accuracy exceeding 99% and this indicates that the proposed model-driven CNN dataset enables highly reliable beam classification. On the other hand, the lightweight MLP achieves the higher Top-1 accuracy, but the difference to the proposed method is only 0.25%, which can be considered insignificant in practical applications. The important point is the inference time, which achieves 0.0203 ms for the proposed framework, i.e., the proposed CNN requires only this amount of time per prediction. In fact, the exhaustive beam sweeping method achieves perfect selection accuracy due to its direct evaluation of all candidate beams. As a result of sequential measurement of every beam in the codebook, the latency amount is proportional to the number of candidate beams and will be higher than that of learning-based inference. In contrast, the proposed framework needs a single forward propagation after acquiring the beam power measurements to predict the beam; this way reduces the computational complexity associated with the decision stage while near-optimal beam selection performance is maintained.

Putting it all together, the comparison demonstrates that the proposed model-driven CNN framework achieves a balance between prediction accuracy and computational complexity efficiency. After adding robustness analyses presented earlier, the results confirm the suitability of the proposed framework for practical beam selection applications due to its prediction reliability and low latency.

5.2.8 Computational complexity

The computational complexity of the proposed beam prediction system can be determined by the CNN that is used for 16-beam classification. Table 1 includes the proposed CNN architecture and training hyperparameters in calculations of the computational complexity.

Computational complexity is mainly determined by the convolution and fully connected layers during inference. The beam codebook size was 16, so convolution layer 1 has 1,536 multiplications, convolution layer 2 has 98,304 multiplications, fully connected layer 1 has 131,072 multiplications, and the output layer has 2,048 multiplications. Therefore, the total represents the computational complexity for one beam prediction, which is 232,960 (approximately 2.33 × 105).

The proposed model has a low level of computational complexity for the beam prediction scheme, which makes it efficiently implemented for real-time beam selection in mmWave communication systems.

5.2.9 Performance comparison vs. recent state-of-the-art

Table 8 illustrates the differences between the proposed model and recent related works. Even though the proposed work has a competitive level of performance compared to related approaches, there are two important advantages. Firstly, the system predicts the optimal beam using only beam power measurements, not camera images or location data. Moreover, the system operates under realistic channel conditions with random SNR, which ensures robustness in various communication environments. These advantages are observed through a comprehensive performance analysis of different metrics, including accuracy, loss, Top-K accuracy, beamforming gain loss, and CDF.

Table 8. Comparison of the proposed system with recent state-of-the-art methods

Ref.	AI Model	Input Features	Communication Scenario	Channel Model	Baseline Method	Performance Indicators	Computational Complexity
[30]	LSTM-based deep learning	Historical beam information and situational awareness information	mmWave ITS	Vehicular mmWave channel	Conventional beam prediction	Prediction accuracy, throughput	Not analyzed
[31]	CNN, channel attention and LSTM	Wide beam received signals	mmWave MIMO beam alignment	COST 2100 channel model	CNN, CNN-LSTM, Fully connected-based, and active learning beam alignment methods	CDF, normalized beamforming gain, beam alignment performance	Qualitative discussion
[32]	Modified ResNet-50 CNN/Multimodal DNN	RGB images; RGG + wireless + position information	Real-world V2I beam prediction	Geometric mmWave channel	Conventional beam sweeping (beam training)	Top-1, Top-K beam prediction accuracy	Not analyzed
[33]	KNN, SVM, Decision Tree	GPS coordinates	DeepSense 6G V2I	Real-world mmWave channel	Comparison among ML classifiers	Prediction accuracy, precision, recall, F1 score, ROC-AUC	Not analyzed
[34]	Multimodal Mixture of Experts	RGB images and GPS coordinates	THz ISAC V2I	Deep sense 6G	Vision only, position only, early fusion methods	Top-1 accuracy, Top-1 accuracy	Not analyzed
The proposed work	CNN	Beam power measurements	Multi-user MIMO beam	Noise-free/Noisy channel; Multipath channel; Random SNR (-5 to 15 dB)	Optimal beam obtained by exhaustive search over the DFT beamforming codebook	Accuracy, loss, Top-K accuracy, gain loss, confusion matrix, latency, and CDF	Low complexity offline training with fast online inference

Note: LSTM = Long Short-Term Memory, ITS = Intelligent Transportation System, MIMO = Multiple-Input Multiple-Output, CNN = Convolutional Neural Network, CDF = Cumulative Distribution Function, ResNet-50 = Residual Network with 50 layers, DNN = Deep Neural Network, RGG = Random Geometric Graph, V2I = Vehicle-to-Infrastructure, KNN =K-Nearest Neighbors, SVM = Support Vector Machine, GPS = Global Positioning System, ROC-AUC = Receiver Operating Characteristic – Area Under the Curve, ISAC = Integrated Sensing and Communication, DFT = Discrete Fourier Transform, SNR = Signal-to-Noise Ratio.

6. CONCLUSIONS

In this paper, a comprehensive evaluation of the proposed model- driven deep learning framework for beam selection is presented. The system incorporates a physically motivated channel model and DFT-based beamforming in the data generation step; it connects classical signal processing and data-driven learning. As mentioned earlier, the training of the CNN was supervised to map the received power patterns to the optimal beam index to enable fast and accurate beam selection.

The Monte Carlo simulations show that the proposed model has very high beam selection accuracy, 99.6% under an ideal channel; then a multipath AWGN channel was used to provide a realistic channel and the achieved accuracy was 93.8%. Moreover, the multi-user scenario achieved an accuracy of 93.65%. While the Top-K accuracy analysis shows the robustness of the proposed framework. Furthermore, the CDF of the beamforming gain loss shows that the gain loss remains concentrated near 0 dB for the evaluated samples, indicating that the predicted beam is the optimal or near-optimal beam under the considered channel, which is noise-free (ideal channel). All these evaluations and analyses verify that the proposed model is reliable and captures the optimal beam with light computations and low latency.

The proposed model demonstrates robust performance across the channel conditions investigated in this work. The training process has ranging SNR from -5 to 15 dB, testing the framework under both ideal and realistic channel conditions (including noise-free and noisy environments as well as single-path and multipath propagation scenarios). Different angles of arrival are generated to represent diverse spatial channel conditions. These evaluations indicate the reliability and robustness of the proposed framework.

Furthermore, the analysis of reproducibility over ten runs demonstrates that the proposed framework has a stable performance with low variance. Also, the analysis of sensitivity to measurement errors confirmed that the proposed framework has high prediction accuracy under practical measurement uncertainty. Finally, multi-user evaluation verified the scalability of the proposed framework for ULA-based beamforming scenarios.

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