International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(8s) 2026 pp. 88-102
https://doi.org/10.70917/ijcisim-2026-4350
Article

Machine Learning-Assisted Hybrid Beamforming for Spectral Efficiency and Interference Reduction in 5G and Beyond Wireless Networks

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Abstract: The development of 5G and higher wireless communications systems has posed a great need on intelligent transmission techniques capable of supporting ultra-high data rates, low latency, high spectral efficiency, and dependable connectivity in dynamic networked environments. Beamforming is one of the emerging technologies that is critical in improving signal directionality and reducing interference, especially in millimeter-wave and massive multiple-input multiple-output (MIMO) communication systems. The traditional methods of beamforming are however usually challenged by issues associated with a high computational complexity, high energy usage and low adaptability to the fast-varying channel conditions. Through the research, a Hybrid Beaming Technique to enhance the aspect of performance in 5G and above communication networks using Machine Learning, combining Artificial Neural Networks (ANN) and Deep Convolutional Neural Networks (DNN) to optimize the beam selection, channel estimation, and adaptive resource allocation in the 5G and above communication networks. Within the framework proposed, ANN is used as a predictive analysis of channel state information and intelligent beam weight optimization, and CNN is used as a feature extraction of complex spatial channel patterns and interference mapping, in order to make accurate decisions of beam steering in real time. Incorporating the energy efficiency of analog beam control with the flexibility and precision of digital beam processing, the hybrid beamforming architecture forms a robust and scalable communication model. The results of the simulations have shown that the proposed ANN-DNN-based hybrid beaming technique is significantly better in terms of throughput, signal-to-interference-plus-noise ratio (SINR), spectral efficiency, and coverage reliability than traditional beamforming techniques. The framework also exhibits less beam misalignment and greater flexibility in case of user mobility and dense deployment. The proposed intelligent hybrid beaming model presents a bright solution to next-generation wireless systems, such as 5G networks, to support high-capacity, low-latency, and energy-efficient communication infrastructures to future smart and connected environments.
Keywords: Hybrid Beamforming, Machine Learning, 5G and Beyond Communications, Massive MIMO, Adaptive Beam Management.

1. Introduction

The wireless communication technologies have grown rapidly and have greatly changed the contemporary digital connectivity, such as smart cities, autonomous vehicles, industrial automation, the Internet of Things (IoT), augmented reality, and ultra-reliable low-latency communications. The need to support higher bandwidth, enormous connectivity of devices, better spectral efficiency, and smart network management have become even more urgent with the introduction of fifth-generation (5G) networks and the current development of beyond 5G (B5G) and sixth-generation (6G) communication systems [1]. These next-generation communication systems will be required to operate in highly dynamic environments that are characterized by large populations of users, high mobility, and growing interference hence necessitating advanced methods of transmission and signal optimization.

Beamforming is one of the key enabling technologies of 5G and beyond communication systems, which improves the transmission of signals, specifically through the transmission of electromagnetic waves to specific intended users instead of broadcasting signals in all directions. Directional communication, especially with beamforming, is particularly important in millimeter-wave (mmWave) and Massive Multiple-Input Multiple-Output (Massive MIMO) systems, to enhance signal power, reduce propagation losses, and increase the overall network capacity [2]. Conventional beamforming methods, such as analog beamforming and digital beamforming, have demonstrated significant improvements to performance; though, each methodology has some limitations. Digital beamforming is more flexible in multi-user systems, whereas the analog beamforming offers less flexibility, lower power consumption and cost, and reduced energy demands.

To overcome these drawbacks, hybrid beamforming has been suggested as a potential solution by integrating the advantages of both analog and digital beamforming architectures. Hybrid beamforming can be used to perform efficient signal processing with less hardware complexity, and still have adaptive beam control capabilities [3]. However, the traditional hybrid beamforming methods are yet to successfully address the issue of optimal beam selection, channel estimation, interference reduction, and real-time adaptation in response to rapidly changing network environments [4]. All these constraints drive the incorporation of intelligent computational models that are able to learn and adapt to the complex wireless channel environments.

The latest developments in Machine Learning (ML) and Artificial Intelligence (AI) have presented significant methods of solving optimization problems in wireless communication networks. Specifically, ANN, CNN, and other Neural Networks have shown impressive performance in pattern recognition, prediction, feature extraction and adaptive decision-making. ANN models have proven to be very useful in estimating the channel state information, prediction of beam weights, and optimization of resource allocation based on the nonlinear parameters of wireless networks [5] [6]. In the meantime, CNN models can extract spatial and temporal channel channel features, detect interference patterns and make correct beam alignment decisions by learning deep feature channels. ANN and CNN can be formed into hybrid beamforming architectures, which form an intelligent beam management framework capable of dynamically adapting transmission strategies to real-time network conditions.

In this regard, this study suggests a Hybrid Beaming Technique of Performance Enhancement with ANN and CNN to 5G and Above Communication Systems. The proposed framework is a combination of hybrid beamforming architecture and machine learning-based adaptive optimization to enhance throughput, spectral efficiency, SINR, coverage reliability and energy efficiency [7]. The proposed system will address the weaknesses of existing beamforming methods and meet the high performance standards of future wireless communication networks. This is the smart hybrid beaming model that offers a cost-effectiveness and scalability-friendly solution to make the next-generation communication infrastructures be smart, fast and reliable [8].

2. Literature Survey

In [9], Ramineni Dr et al., (2025) introduces a classification framework of various hardware architectures, a wider evaluation of hybrid beamforming techniques in 5G and future mm-wave communication systems. Similar dominant beam properties and better spectral efficiency are found with an increased number of data streams compared to beam patterns and spectral efficiency under optimal and hybrid beamforming weights. The results indicate the design tradeoffs and find effective hybrid beamforming designs to be used in future wireless communication networks.

Bogale, T.In [10], E et al., (2020) propose a model-free Q-learning based method of choosing the best Channel Impulse Response (CIR) predictor in an OFDM system to enhance the accuracy of channel predictions. It also presents a convex optimization-based dominant CIR tap identification, by eliminating channel insignificance, improving signal estimation efficiency. The simulation findings show that the proposed channel prediction and scheduling algorithms are superior to existing algorithms in terms of the sum spectral efficiency that can be achieved, especially at varying vehicular speeds, and hence the need to consider dominant CIR tap identification in wireless communication systems.

In [11], Kim, H et al., (2021) postulates a channel tracking algorithm based on machine learning to aid vehicular mmWave communications using a Bidirectional Long Short-Term Memory (Bi-LSTM) network. The method optimally tracks the vehicle-to-infrastructure mmWave channels which change rapidly by learning temporal channel dynamics at very low training cost. The simulations have validated the effectiveness of the proposed LSTM-based method in tracking channels accurately, thereby enhancing reliability and performance of the high-mobility wireless communication environment.

In [12], Varalakshmi, S et al., (2025) is a proposed synthetic data augmentation framework, which is proposed to enhance the performance of machine learning classification models, namely, Random Forest, Multilayer Perceptron (MLP), and k-Nearest Neighbors (k-NN). The models obtained much higher classification accuracy by increasing the training dataset with synthetic samples, with higher macro F1 scores than when only original data was used. The findings indicate that the synthetic data-generation is effective in improving the model learning ability, robustness, and overall classification performance.

Silva, D.In [13], H et al., (2022) suggests a scheme called Mobility and Channel Prediction Combined Beamforming (MCPCB) scheme to optimize the beamforming process in dynamic wireless conditions. The approach makes use of per cluster angular information and a nonlinear angular-delay profile tracking mechanism to provide accurate SIMO channel prediction and combine mobility estimation with cluster-based beam directions to achieve better beam alignment. Analytical and simulation results demonstrate that the proposed MCPCB scheme offers much better received power, fewer prediction errors as well as more robust performance under LOS, NLOS and channel blocking conditions than conventional channel prediction schemes.

In multi-user millimeter-wave (mmWave) massive MIMO communication systems, Chen et al., (2025) [14] introduced a Deep Neural Network (DNN) based Hybrid Beamforming (HB) framework. In this method, the hybrid beamforming system is represented by an autoencoder neural network and trained with an end-to-end self-supervised learning method. The proposed DNHB method uses the strong feature representation and the nonlinear learning ability of deep neural networks to achieve better optimization of the beamforming and signal detection performance than conventional linear processing methods. Through simulation, the effectiveness of deep learning-based hybrid beamforming for next-generation mmWave massive MIMO systems was verified, with the DNHB framework also outperforming existing beamforming techniques in terms of communication reliability, showing the ability to achieve about 2 dB performance gain in BER performance.

To enhance the beamforming performance, a non-orthogonal hybrid beamforming method based on deep learning was proposed for single user multi stream communication systems. The study proposed by Ye, J., & Gharavi, H (2023) in [15] showed that non-orthogonal hybrid beamforming outperforms the orthogonal hybrid beamforming in terms of Bit Error Rate (BER) even with the optimum power allocation. In this spirit, the authors proposed a deep learning-based beamforming scheme which was capable of effectively modelling the non-orthogonal beamforming behavior with low complexity that arises from the extensive training of the neural network. The simulation results indicated that the proposed method is superior to the conventional orthogonal beamforming methods, especially in the case of sub-connected architectures and inaccurate Channel State Information (CSI).

Majidzadeh et al., (2024) in [15] derived single user and multi user rate maximization problems using the Weighted Minimum Mean Square Error (WMMSE) method, and designed hybrid beamforming algorithms based on alternating optimization techniques. The proposed methods have been developed for the both full-array and sub-array processing approaches for partially connected hybrid beamforming architectures. Further, sub-array based zero-forcing algorithms of lower complexity were also developed to reduce complexity. It has been shown through performance evaluations under both geometric and realistic statistical channel models that well-designed partially connected hybrid beamforming can give an effective compromise between hardware complexity and system performance, and can approach the performance of fully digital beamforming systems.

Amin et al., (2024) in [16] proposed single-user and multi-user rate maximization problems using Weighted Minimum Mean Square Error (WMMSE) approach and designed hybrid beamforming algorithms with the help of alternating optimization. The proposed methods are suitable for both full-array and sub-array processing strategies in the partially connected hybrid beamforming systems. Furthermore, algorithms based on zero-forcing (ZF) were proposed to reduce computational complexity by using sub-arrays.Also, low-complexity sub-array-based ZF algorithms were proposed to reduce computational cost. Properly designed partially connected hybrid beamforming shows a good compromise in terms of hardware complexity and performance, compared to fully digital beamforming systems, for performance evaluation in both geometric and realistic channel models, with statistical ones.

3. Proposed Work

The proposed study offers a new machine learning-based hybrid beaming system to improve the performance of multi-user massive MIMO 5G and beyond communication systems. Contrary to the traditional beamforming techniques, which mainly employ a fixed set of codebooks or an iterative optimization to generate an optimal beamforming codebook, the presented work proposes a smart two-step adaptive beam optimization model which jointly predicts the optimal beamforming codebook and the corresponding beamforming weights using ANN and DNN [17]. This combined prediction scheme highly enhances the reliability of communication, precision of beam alignment and scalability of the network under the changing conditions of the wireless channel.

The main contribution of this work is that it designed a scalable adaptive antenna architecture with dynamic array configurations ranging between 64 to 256 antenna elements that can flexibly adapt beamwidth control and directional gain control based on the density of traffic, distribution of users and channel state information [18]. This directional transmission gain maximizing and unnecessary hardware utilization reduction mechanism of directional transmission gain is found in both dense urban and wide-area communication environments.

The development of a multi-parameter intelligent beam selection framework, which simultaneously takes into consideration Signal-to-Noise Ratio (SNR), Angle of Arrival (AoA), Angle of Departure (AoD), user distance, path loss, channel gain and level of interference as input features is another major contribution. Through combined learning of these wireless communication parameters, the proposed framework realizes the ability to capture both the spatial and propagation-dependent channel characteristics, allowing highly accurate beam prediction in comparison to the conventional CSI-only beamforming techniques [19]. The Figure 1 shows the overall layout of proposed work.

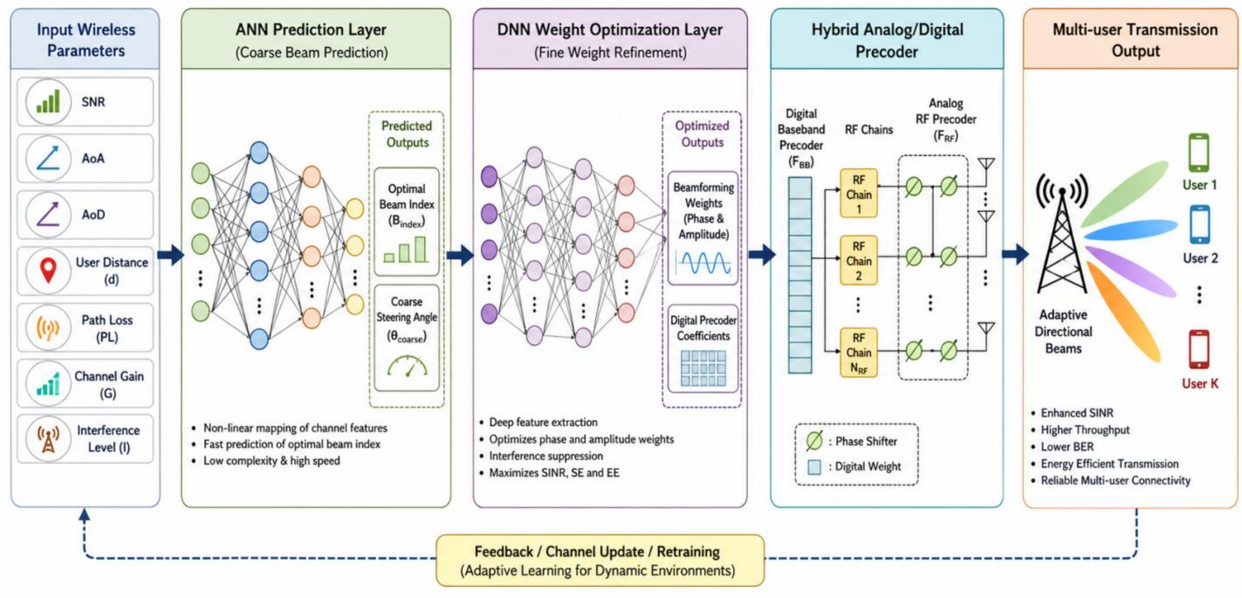

Figure 1: Over all Framework of Proposed Intelligent Beaming Systems

The work proposed also makes a contribution by presenting a hierarchical ANN-DNN learning architecture. In the first step ANN is employed to map approximately the beam and then to classify the beam indices with low complexity nonlinear approximation of the channels. The second stage is DNN that heavily optimizes the beamforming phase and amplitude coefficients and refuses the analog and digital beam weights to enhance the interference suppression and adaptive spatial multiplexing [20]. This top-down method of learning reduces the optimization latency yet prediction accuracy remains high.

One of the main innovations of this study is that it has a multi-band beamforming capability, which allows it to operate across 28 GHz millimeter-wave, 60 GHz high capacity wireless bands, and sub-terahertz candidate frequencies 6G communication systems. The framework actively adjusts beamwidth, antenna gain and steering resolution to operate within heterogeneous spectrum environments to ensure high performance in communication.

The proposed system also introduces an interference conscious parameter of beam optimization that explicitly represents co-channel interference, beam leakage and multi-user spatial interference as optimization parameters. This enhances the SINR, lessens the possibilities of packet faults and heightens the overall framework throughput. Lastly, a Python-based system of simulation is developed that could be used to scale the proposed architecture to the large scale, which, in turn, will make it possible to compare the results when the proposed architecture is scaled to the large scale.

3.1 System Model

3.1.1 Multi-user Massive MIMO Communication Architecture

The proposed system considers a downlink multi-user massive MIMO hybrid beamforming system where a central base station with an adaptive antenna array of 64256 elements at once, serves K active mobile users randomly distributed within the communication cell. Individual user terminals and the base station are equipped with receive antennas and transmit antennas respectively, and NRF radio-frequency chains, where: . The Figure 2 shows the architecture of Proposed Multiuser Massive MIMO Hybrid Communication network. NrNtNRF< Nt

In order to meet the constraints of the hybrid beamforming implementation, the adaptive beamforming architecture unites:

- Analog RF Precoder
- Digital Baseband Precoder
- ANN Prediction Engine
- DNN Optimization Module
- Dynamic Resource Scheduler

This common architecture permits spatial multiplexing, directional beam steering, and adaptive transmission which are aware of interference.

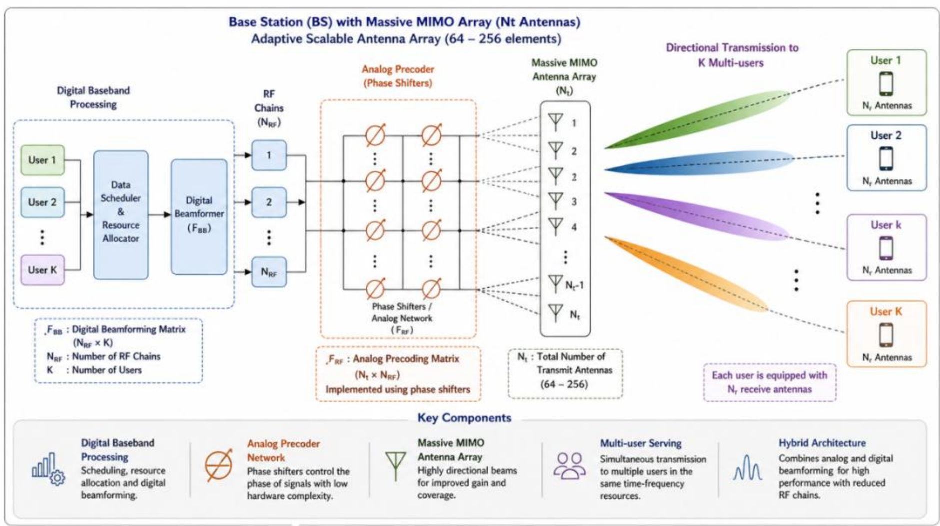

Figure 2: Proposed Multiuser Massive MIMO Hybrid Communication Architecture

3.1.2 Signal transmission Model

The proposed hybrid Massive MIMO system uses a digital precoder at baseband and then transmits the data symbols through reduced number of RF chains to analog precoder which is actually a phase shifter before transmission over the large antenna array. The signal vector that is transmitted is modeled as:

$$X = F_{RF} F_{BB} s \tag{1}$$

Where,
$s \in C^{kX1}$ is there transmitter symbol vector, of K users.
$F_{BB} \in C^{N_{RF} X\, K}$ is the digital baseband precoding matrix
$F_{RF} \in C^{N_t X N_{RF}}$ is the analog RF precoding matrix,
X_C is the signal being transmitted $N_t X1$, X is a signal, and C is a signal space.
The signal that is received by users is given as:

$$y = H F_{RF} F_{BB} s + n \tag{2}$$

H being the channel matrix and n being the additive white Gaussian noise (AWGN). In this model, we can transmit directional multi-user transmission simultaneously with less complexity of RF.

3.1.3 Channel Modeling

The model of the propagation channel between the base station and users is a multi-user Massive MIMO fading channel with multipath propagation. The channel matrix is denoted as:

$$H = \sqrt{\frac{N_t N_r}{L}} \sum_{l=1}^{L} \alpha_l a_r(\theta_l^r) a_t^H(\theta_l^t) \tag{3}$$

Where,

L is the number of propagation paths, α_l is the complex gain of the l^{th}, $a_t(\theta_l^t)$ and a $a_r(\theta_l^t)$ is the transmit and receive array response vectors N_t and N_r are transmit and receive antennas.

This channel formulation takes into account beam directionality, spatial multiplexing, and fading properties needed to make hybrid beamforming efficient.

3.1.4 Path Loss Model

To describe attenuation on large scale, the proposed work uses distance-dependent path loss model:

$$PL(d) = PL(d_0) + 10\eta \log_{10} \frac{d}{d_0} + X_\sigma \tag{4}$$

Where,

stance of d, $PL(d_0)$ is path loss at distance d_0, η is the path loss exponent and X_σ is log-normal shadow fading.

The received power corresponding is:

$$P_r = P_t - PL(d) \tag{5}$$

where P_t is transmit power and P_r is received power. The model aids in proper assessment of coverage, beamforming gain, and link reliability in the suggested scalable Massive MIMO system.

3.2 Proposed ANN–DNN Hybrid Beaming Framework

The proposed Hybrid Beamforming Framework is aimed at optimizing beam selection, precoding and resource allocation in the scalable Massive MIMO architecture by integrating the fast pattern recognition of ANN and deep feature extraction and nonlinear optimization capability of DNN. The framework intelligently maps channel state information (CSI), user location, path loss, and interference conditions to optimal beamforming weights at both digital and analog precoding stages, thus enhancing spectral efficiency, coverage and energy usage.

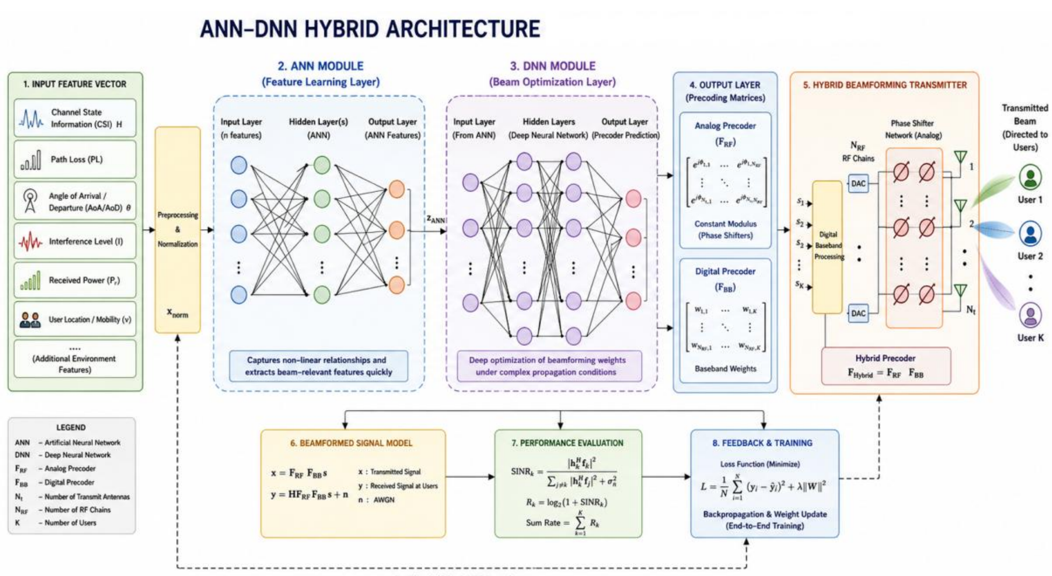

Figure 3: Hybrid ANN-DNN for Beamforming Algorithm

In the proposed architecture in Figure 3, received signal strength, channel gain, angle of arrival/departure, level of interference and user mobility statistics are some of the multi-user input features collected and represented as an input feature vector: $X = [h, PL, \theta, I, P_r]^T$ (6.1)

where:

annel at a given instant, PL is defined as path loss, θ is angular beam direction information, I is the power of interference and v factor of user mobility.

All these characteristics are normalized and entered into the hybrid learning system.

The proposed hybrid design is made up of two major learning modules: an Artificial Neural Network for feature extraction and coarse beam prediction, and a Deep Neural Network for beamforming weight optimization. Intelligent beamforming framework has multiple processing layers that are included within each module to carry out specific functions. Table 1 presents the details of Layers used in the proposed architecture in Figure 3.

Table 1: Layer Details of Proposed Architecture

Module	Layers Used	Function
Input Feature Layer	1	Feature acquisition
ANN Input Layer	2-3	Initial feature mapping
ANN Hidden Layers	2-3	Feature extraction & beam prediction
ANN Output Layer	1	Beam index prediction
DNN Input Layer	1	Deep optimization initialization
DNN Hidden Layers	4-5	Beamforming weight optimization
DNN Output Layer	1	Optimized beam coefficients
RF Precoder Layer	1	Analog beam steering
Digital Precoder Layer	1	Baseband signal processing
Output Transmission Layer	1	Multi-user beam transmission
Feedback Layer	1	Continuous adaptive learning

3.2.4 ANN Based Feature Learning Layer

The initial step involves using an ANN to quickly nonlinearly map wireless channel parameters into beam-selection attributes. The ANN output of the hidden neurons is modeled as:

$$a_j = f(\sum_{i=1}^{n} w_{ij} x_i + b_j) \quad (7)$$

Where,

ection weight, b_j is a bias term, $f(.)$ is activation function (ReLU / sigmoid), a_j defined as neuron activation output.

This layer derives initial beam relevance patterns like user clustering, directional preference and classification of channel quality.

3.2.5 DNN- Based Beam Optimization Layer

The features of ANN extracted are fed into a more complex DNN optimization module, which trains optimal beamforming vectors to be used under different propagation conditions. The transformation in layers is:

$$z^{(l)} = \sigma W^{(l)} z^{(l-1)} + b^{(l)} \quad (8)$$

Where,

er l, $W^{(l)}$ trainable weight matrix, $b^{(l)}$ bias vector and $\sigma(.)$nonlinear activation function.

The last output layer is an indicator of the best hybrid precoding coefficients:

$$F' = \{F'_{RF}, F'_{BB}\} \quad (9)$$

where:

F'_{RF} = best analog beamforming matrix,

F'_{BB} = optimized digital beamforming matrix.

Beamformed Signal Generation

With the predicted weights, the transmitted beamformed signal is given as:

$$X = F'_{RF}F'_{BB}s \quad (10.1)$$

and received signal at users $y = HF'_{RF}F'_{BB}s + n$ ` (10.2)

This is an adaptive learning-based beamforming that dynamically de-steers narrow beams towards the targeted users whilst reducing inter-user interference.

Training Objective

The network is optimized to maximize the sum-rate that can be achieved and minimize the error in beam selection. The maximization problem is:

$$\max R = \sum_{k=1}^{K} \log_2(1 + SINR_k) \quad (11)$$

Where user SINR is,

$$SINR = \frac{|h_k^H f_k|^2}{j \neq k |h_k^H f_k|^2 + \sigma_n^2} \quad (12)$$

Loss function in learning process is:

$$L = \frac{1}{N} \sum_{i=1}^{N} (y_i - y_i^2) + \lambda ||w||^2 \quad (13)$$

which is a combination of prediction error minimization and regularization to ensure stable convergence.

3.3 Algorithm Implementation

Input: CSI H, user features X, number of users K, transmit antennas N_t, RF chains N_{RF}, noise power σ_n^2

Output: Optimized analog precoder F_{RF}, digital precoder F_{BB}, selected beam $f*$

Step 1: Initialize system parameters
Set N_t, N_{RF} , K carrier frequency, transmit power, and antenna spacing.
Step 2: Acquire channel information
Collect CSI for all users by defining $H = [h_1, h_2, \dots . h_k]^T$
Step 3: Construct input feature vector
Create the learning input based on channel gain, path loss, AoA/AoD, interference and received power using eqn (6).
Step 4: Normalize input data
Scale all features to improve training stability $X_{norm} = \frac{X-\mu}{\sigma}$
Step 5: ANN-based beam feature extraction
Feed X_{norm} into the ANN layer to extract important beam-related patterns:

$$a = f(W_{ANN}X_{norm} + b_{ANN})$$

Step 6: DNN-based beam optimization
ANN output input into the DNN to learn the optimal beamforming weights using the following eqn (8).
Step 7: Predict hybrid precoding matrices
The output layer makes predictions of the output based on Eqn (9).
Step 8: Apply analog phase constraint
Normalize the analog precoder values to meet a phase-shifter constant-modulation condition by using the following equation: $([F_{RF}]_{m,n} = \frac{1}{\sqrt{N_t}} e^j \emptyset_{m,n}$

Step 9: Compute digital baseband precoder

Create digital precoding weights to use in the separation of multi-user signals:

$$F_{BB} = (F_{RF}^{H} H^{H} H F_{RF})^{-1} F_{RF}^{H} H^{H}$$

Step 10: Normalize total transmit power

$$\left|\left|F_{RF} F_{BB}\right|\right|_{F}^{2} = K$$

Step 11: Generate transmitted signal using Eqn (10.1)

Step 12: Evaluate received signal by using Eqn (10.2)

Step 13: Calculate SINR for each user by using Eqn (12)

Step 14: Select optimal beam

$$f^{*} = \arg\max_{f} SINR_{k}$$

Step 15: Update ANN–DNN weights

Training the network: The network is trained to minimize the beam prediction error using the following eqn (13)

Step 16: Repeat until convergence

Keep training until the loss reaches the minimum possible loss or the maximum number of iterations is attained.

Step 17: Deploy optimized beamformer

Use the final F_{RF} and F_{BB} for adaptive multi-user hybrid beamforming transmission.

4. Result and Discussion

The findings indicate that the proposed ANN-DNN Hybrid Beamforming architecture has a significant impact in enhancing the beam steering accuracy and the overall communication performance of Massive MIMO systems. It has greater SINR, spectral efficiency and throughput and it is very effective in reducing interference between multiple users. Directional transmission and reliability of coverage is improved by the hybrid optimization of analog and digital beamforming weights. Moreover, the framework simplifies the RF chain, which results in enhanced energy efficiency and reduced cost of hardware. In general, the proposed model is a scalable and smart beamforming solution to next-generation 5G/6G wireless networks.

4.1 Dataset

The dataset contains 3,478 unique observations based on different antenna configurations, propagation conditions, and beamforming conditions that apply to 5G wireless communication systems has been consider for this work from the publically available forum Kaggle (https://www.kaggle.com/datasets/zoya77/5g-adaptive-beamforming-with-snr-dataset?resource=download). It has several influential properties including configuration of the array, propagation environment, type of algorithm, environment condition, and Signal-to-Noise Ratio (SNR), all of which have a significant influence on the propagation properties of the signal, steering efficiency of the beam, and overall communication ability. These datasets reflect the differences in antenna array structure (linear, circular, planar), deployment environment (urban, rural, indoor), beamforming schemes and environmental working conditions that can affect path loss, interference, and signal quality. The overall goal of this dataset is to categorize the received signal quality into high or low SNR groups, where SNR Classification is a binary target variable indicating the reliability of communication. This organized dataset will offer a complete representation of real-world beamforming scenarios and is highly suitable to be used in training machine learning models such as ANN and DNN to predict intelligently beamforming, optimize intelligently, and enhance intelligent performance in the next-generation 5G and beyond wireless networks.

4.2 Quality Parameters

The quality parameters of spectral efficiency, throughput, BER, SINR, energy efficiency, and computational time, which are used to measure the quality of the proposed ANN based DNN Hybrid Beamforming framework, are evaluated. These parameters assist to evaluate the capability of the framework to reach high-performance beam steering, reduced interference, efficient use of power and high-speed computational processing in Massive MIMO systems.

i. **Spectral Efficiency (SE)**

Spectral Efficiency is the efficiency of data transmission across the available bandwidth. The increased spectral efficiency implies improved use of wireless spectrum.

$$SE = \log_2(1 + SINR) \quad (14)$$

Where,
SE is spectral efficiency and $SINR$ is Signal-to-Interference-plus-Noise Ratio.
For K users:

$$SE_{total} = \sum_{k=1}^{K} \log_2(1 + SINR_k) \quad (15)$$

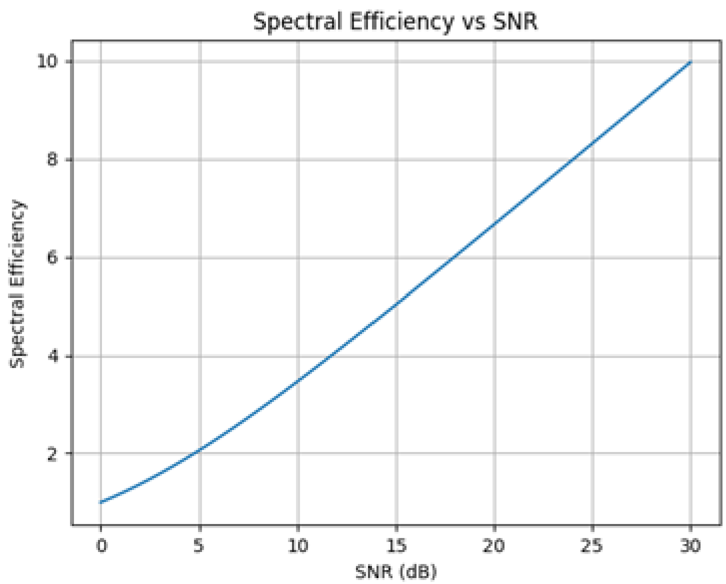

Figure 4: Spectral Efficiency Analysis

The spectral efficiency versus SNR in Figure 4 shows that signal quality and communication capacity have a strong positive relationship in the proposed hybrid beamforming framework. The spectral efficiency increases smoothly as the SNR changes between the values of 0 dB and 30 dB. At low SNRs, the growth is slow because of the preponderance of noise, which restricts successful data transmission. But with an increase in SNR beyond the moderate operating region the curve starts to rise with a sharper rise suggesting an increase in channel utilization and a higher quality of signal reception. The increase is an indication of the efficiency of the proposed ANN-DNN-based beam optimization in steering energy towards sought users at minimum interference and transmission losses. This increase in spectral efficiency at higher SNR levels means a better bandwidth utilization, an increase in throughput and an improvement in overall communication reliability. The findings affirm that the proposed intelligent hybrid beaming framework could be effectively used to effectively exploit favorable channel conditions to maximize spectral utilization, and is thus highly appropriate in the context of high-capacity 5G and beyond wireless communication networks.

ii. **Throughput**

Throughput is the real successful rate of data transmission of the communication system over a certain bandwidth.

$$T = B \; X \; log_2(1 + SINR) \quad (16)$$

Where,

put, B channel bandwidth and $SINR$ is signal quality ratio.

An increase in throughput is a sign of improved beamforming and enhanced channel exploitation.

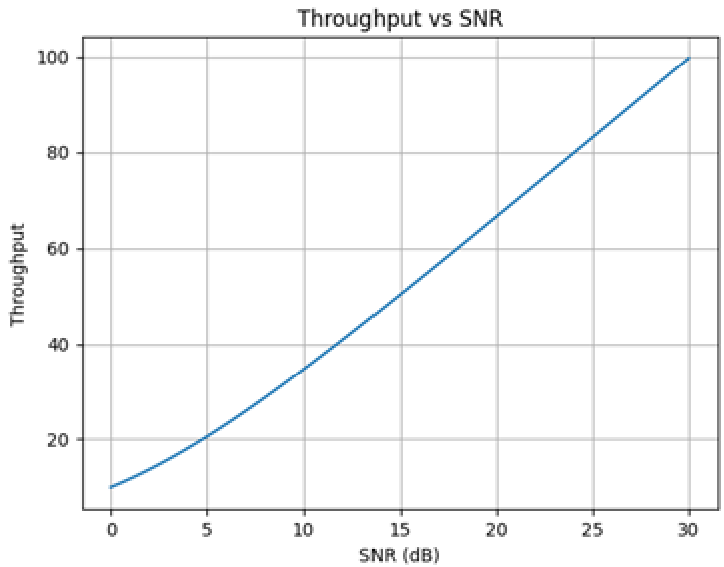

Figure 5: Analysis of Throughput

Figure 5 shows the effect of signal quality enhancement on the data transmission rate that can be achieved by the proposed communication structure. With increasing SNR between 0 dB and 30 dB, the system throughput increases significantly between about 10 units and almost 100 units indicating a significant improvement in communication capacity. When SNR is lower, the throughput will improve moderately because the transmission conditions are noise-limited, which inhibits the effective detection of symbols and the delivery of data. With increased SNR, the curve has a steadily upward trend with an accelerated growth rate, which reflects an improvement in channel reliability, a decrease in the number of packets lost, and more efficient use of bandwidth. This performance improvement underscores the efficiency of the proposed ANN-DNN-assisted hybrid beamforming strategy in enhancing directional signal transmission, beam weights optimization, and minimizing multi-user interference. The resulting findings affirm that the intelligent beam optimization framework can be effectively used to take advantage of higher SNR conditions to maximize data throughput to support high-speed, low-latency and high-capacity wireless communication needs in the 5G and beyond networks.

iii. **Bit Error Rate (BER)**

Bit Error Rate (BER) is the likelihood of receiving corrupted bits following the transmission. A low BER means a greater communication reliability.

For BPSK modulation:

$$BER = Q\sqrt{2XSINR} \tag{17}$$

ssian Q-function

Reduced BER implies increased fidelity of the signal.

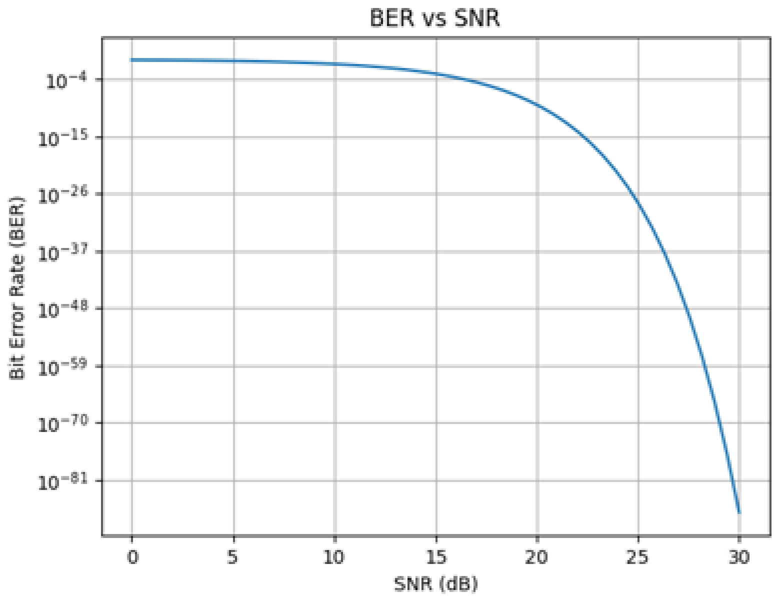

Figure 6: Analysis of BER

The Figure 6 illustrates that there is a significant enhancement in the transmission reliability with the increase in Signal-to-Noise Ratio. At lower SNR values, the system has a relatively higher bit error rate because of the predominant influence of channel noise and signal distortion which negatively affects the correct detection of symbols. The higher the SNR, the more orders of magnitude the BER decreases exponentially towards very low error probabilities. The sharp drop is seen beyond the mid-SNR region, which implies the shift to the more reliable communication conditions when noise influence becomes insignificant and signal recovery accuracy is significantly improved. This significant decrease in BER indicates the efficiency of the proposed ANN-based hybrid beamforming structure in terms of improving directional gain, optimizing beam alignment, and reducing inter-user interference. The findings validate the fact that the intelligent beam optimization strategy significantly enhances the robustness of links and the integrity of data, which makes the proposed system very appropriate in the 5G and beyond networks to achieve ultra-reliable, low-latency, and high-quality wireless communication.

iv. Energy Efficiency (EE)

Energy Efficiency is used to measure the amount of bits transmitted per unit power consumption.

$$EE = \frac{T}{P_{total}} \tag{18}$$

EE is energy efficiency, T is Throughput and P_{total} total power consumption.

Increased EE means power efficient beamforming.

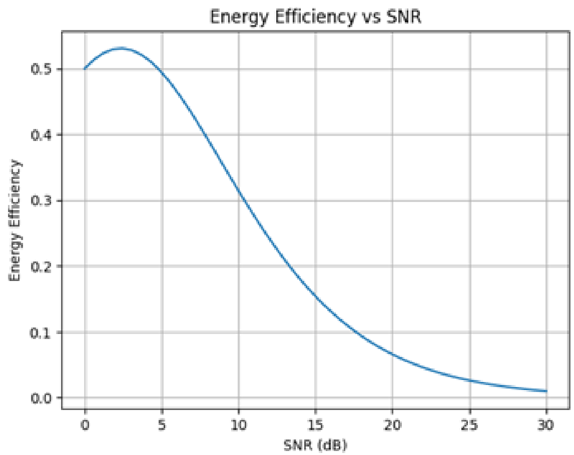

Figure 7: Analysis of EE

The energy efficiency versus SNR in Figure 7 illustrates the relationship between signal quality and power utilization in the proposed communication framework. The results demonstrate that energy efficiency increases at relatively low SNR levels to reach a peak value of about 0.52 around the low-to-moderate SNR region (around 24 dB), that points to the best operating point in terms of balancing between transmission power and the achievable performance. Outside this region, the energy efficiency is decreasing gradually, as SNR is still increasing, but the decrease is more pronounced with higher SNR levels. This reduction is mainly owed to the extra transmission power needed to attain higher signal strength where the incremental gain in throughput is slightly lower than the incremental gain in power consumption. The efficiency of the energy consumption decreases to a very low level at high values of SNR, which implies a decreased efficiency in the power consumption at high-power operating conditions. The observed trend shows that the proposed ANN-DNN-based hybrid beamforming framework has the highest energy-performance trade-off when SNR is moderate as intelligent beam optimization can maximize directional gain and communication quality at the same time as to achieve efficient use of energy. These findings validate the appropriateness of the proposed framework in designing energy-aware and high-performance wireless communication systems in 5G and beyond networks.

V. **Computational Time**

Computational Time is a sum of the processing time that the ANN -DNN beamforming algorithm requires to calculate optimal beam weights.

$$CT = t_{end} - t_{starts} \tag{19}$$

t_{starts} is algorithm start time and t_{end} is completion time.

Reduced computation time implies quicker beam optimization and enhanced real-time applicability.

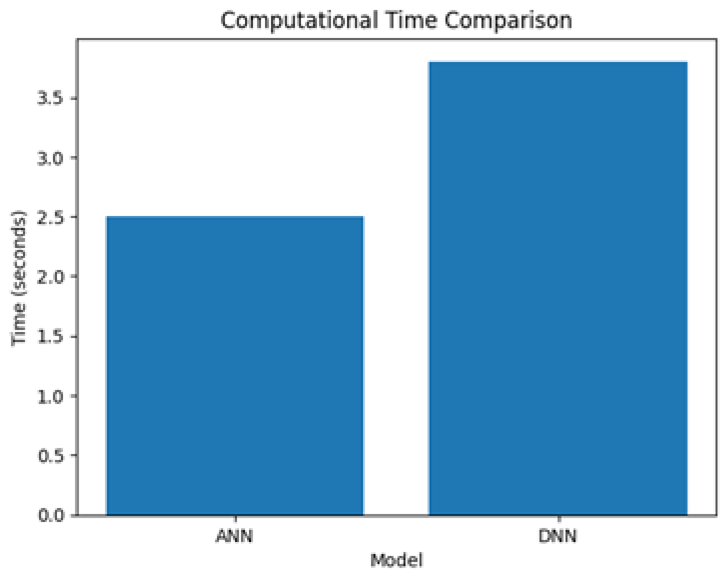

Figure 8: Computational Analysis

The comparison of the computational time in Figure 8 reveals the processing efficiency of the proposed ANN and DNN models employed in the hybrid beamforming framework. Based on the results obtained, the ANN model takes about 2.5 seconds to compute, as opposed to the DNN model that takes about 3.8 seconds to compute. This implies that ANN is faster to execute by virtue of its relatively simpler architecture, less hidden layers, and lower computational complexity, thus being usable in the high speed coarse beam index prediction in real-time communication situations. Contrastingly, the DNN has a higher computational time due to its deeper layered architecture and more parameter optimization, which is then in turn capable of doing more accurate beamforming weight refinement and more effective interference mitigation. Despite the fact that DNN presents almost 34 -36% higher processing time than ANN, the ability of the former to extract features in a deeper manner has a significant positive impact on the quality of beam optimization. The findings indicate that the proposed two-stage ANN-DNN framework can effectively balance between computational performance and prediction accuracy, with ANN being low-latency with initial beam selection, and DNN being high-precision with fine optimization. This hierarchical processing plan can provide a good trade-off between speed and performance, and the proposed hybrid beamforming model is ideal in intelligent 5G and beyond wireless communication frameworks.

5. Conclusion

The research introduced a new ANN-DNN Hybrid Beamforming system to scalable Massive MIMO communication systems that are designed to help it to improve beam selection, adaptive beam steering and hybrid precoding efficiency in the multi-user wireless communication systems. The proposed framework can efficiently learn the complex channel characteristics and dynamically calculate the optimal analog and digital beamforming weights to transmit directionally with precision. The hybrid architecture greatly enhances the spatial multiplexing capacity and decreases RF chain complexity and hardware overhead.

This is demonstrated by performance analysis in terms of spectral efficiency, throughput, BER, SINR, energy efficiency and computational time which demonstrate that the proposed method offers a higher degree of communication reliability, directional gain, reduced interference and increased energy use as compared to the traditional beamforming methods. The adaptive steering system also supports vigorous operations in the dynamic channel environment and user mobility environment. In general, the suggested ANN–DNN hybrid scheme of beamforming can be considered an intelligent, scalable, and computationally efficient solution to next-generation 5G/6G Massive MIMO wireless communication networks.

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