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Original Article

Enhanced Performance with Neural Network Based Hybrid Beamforming in Sparse MIMO Systems

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Abstract *- The Millimeter-Wave (mmWave) Multiple-Input Multiple-Output (MIMO) systems offer high data rates and capacity but face challenges in sparse propagation environments. Beamforming is one of the techniques by which these challenges can be addressed. It can be done by searching for an appropriate beam and accurately aligning the beam in the direction of User Equipment (UE). Hybrid Beamforming (HBF) has emerged as a promising solution, combining analog and digital processing to improve performance and by minimizing hardware requirements. Compared to an exhaustive search, the overhead in the beam selection can be reduced by using machine learning and the subset of it, Neural Networks (NN). This paper presents a novel approach to enhance the performance of mmWave MIMO systems by integrating Neural Networks (NNs) with hybrid beamforming. Our proposed Neural Network Hybrid Beamforming (NHBF) method combines multiple streams into a single beam, transmitted via high-order transmission, achieving improved Bit Error Rate (BER) performance compared to traditional Hybrid Beamforming (HBF). By optimizing power distribution, the NHBF beamforming approach eliminates the need for tedious hardware requirements, simplifying the implementation process. Simulation results demonstrate significant performance enhancements, including up to 18% gain in spectral efficiency, a minimum 50% decrease in bit error rate, a 25% increase in energy efficiency, and a 20% reduction in total power consumption compared with Hybrid Beamforming (HBF).*

Keywords *- Bit error rate, Energy efficiency, Hybrid beamforming, MIMO, Neural network, Spectral Efficiency.*

1. Introduction

Millimeter wave (mmWave) communication is regarded as a promising technology for future cellular networks due to its large available bandwidth and potential to offer gigabits-per-second communication data rates. The increasing demand for high-speed wireless communication has driven the need for innovative solutions that balance hardware costs and transmission performance. To combat the higher free-space path loss compared to microwave signals below 6 GHz, a large antenna array is essential. The large antennas make channel estimation a challenging issue because of the large number of channel matrices [1-4].

To address the challenges, mmWave channel estimation face, beam scanning, beamforming and alignment methods are studied in the literature. Beamforming is a technique used in modern wireless systems that directs the radio signal on a specific device/User Equipment (UE) [5]. For the effectiveness of directional beamforming, reliable Channel State Information (CSI) is required. However, because of the mobility of the UE, transmitter, and the presence of scattering objects, the channel conditions vary over time, and acquiring CSI is a challenging task in wireless communication. The use of large antenna arrays and complex hardware architecture of transceivers is another reason which makes it difficult to acquire CSI [6]. These challenges have driven the recent efforts in developing hardware-efficient transceivers, supported with efficient beamforming algorithms that reduce the overhead in beam selection tasks. The initial proposal in the literature is analog beamforming, supported with a phase shifter network to give different phases to the signal fed to each antenna called analog beamforming which has low complexity and is used for indoor mmWave systems [7]. However, analog beamforming only supports single-stream transmission, so available spatial resources are underutilized. To further improve performance, hybrid beamforming (HBF) has been proposed as a cost-effective approach to support spatial multiplexing with the limited number of RF chains whose potential is demonstrated in [8, 9]. HBF technology has emerged as a promising solution to meet this demand, particularly at Millimeter-Wave (mmWave) frequencies where losses are high. HBF balances hardware complexity and transmission performance by combining analogue and digital beamformers, making it an attractive solution for next-generation wireless communication systems. It achieves spectral efficiency comparable to fully digital beamforming with much-reduced hardware complexity. The use of Machine Learning (ML) for the next-generation wireless network has been explored in recent studies to address various problems, such as network management, self-organization, self-healing, and optimizations in our physical layer [10, 11]. Deep Learning (DL), a special category of ML, has given the best performance in the domain of speech processing and computational vision. This paper explores another subset of machine learning: Neural network (NN) for beamforming applications. As mentioned earlier, the mmWave channels are dynamic and suffer from huge path loss; hence, a technical challenge is beam alignment from the base station to the user equipment to get the initial access. During initial access, the UE establishes a physical connection with the base station, which must be completed before any data transmission begins.

Using large antenna arrays at mmWave requires an extensive search over all beams presented in [12]. In [13], authors have presented a categorized beam search where the base station starts scanning a wider beam and then iteratively comes down to a narrower beam. Such a method decreases latency compared with extensive search but provides the worst coverage to the users on the cell boundary. Another study in [14, 15] presents that the base station steers the beam towards UE when UE locations are known, and such an approach will be susceptible to the errors caused by scattering objects present between the base station and UE. The study on the application of ML to the beam training problem is carried out in the literature. In [16], authors have shown that the CNN technique solves a non-convex problem with the analog beamformer as the final optimization aim. Another self-defined network layer guarantees the result meets the constant frequency condition. The increasing demand for high-speed wireless communication has driven research into efficiency beamforming techniques.

The conventional approach to beam scanning and searching includes iterative algorithms and gradient-based methods that make computations expensive. This leads to complexity as the number of antennas grows in large MIMO systems. Compared with the neural network-based approach, where the bulk of computation is moved offline during the training phase, once the neural network is trained, the task of beam searching is much faster and more efficient even in the interference and for the fast fading channel conditions. Additionally, training neural networks for the large dataset can help learn more non-linear mappings from channel conditions to beamforming vectors, capturing the range of practical channel impairments. Also once the network is designed, the same network architecture can be fine-tuned for the new conditions like different SNR levels, antenna array sizes, new channel conditions and user mobility patterns.

This paper explores the potential of neural networks in beam searching and beam selection tasks, which reduces the overhead of the network. The neural network will be trained with UE locations, and the output will be the optimal beam pair index, which will reduce the overhead in searching the beam in the selected beam pair index instead of exhaustive search over all the beam pairs. Neural Network Hybrid Beamforming (NHBF) optimizes the performance of Hybrid Beamforming (HBF) for a MIMO system to enhance spectral efficiency, considering the transmitter's power limitation and the typical continuous modulus restriction of phase shifters. In the context of wireless communication, Spectral Efficiency (SE) refers to the efficient use of available bandwidth to maximize data transmission rates. The performance of the model is evaluated by computing parameters like spectral efficiency, energy efficiency, total power consumption and Bit Error Rate (BER) for the different values of signal-to-noise ratio.

The rest of the paper is organized as follows. Related work in the form of a literature survey is presented in section 2. The methodology and design of neural networks are presented in section 3. Performance parameters of model evaluation are described in section 4, the result and discussion are presented in section 5, followed by conclusion and future work in section 6.

2. Literature Survey

In massive Multiple-Input Multiple-Output systems, HBF is a crucial technique for minimizing hardware and computational expenses. However, its effectiveness depends on various factors, including Channel State Information (CSI), bandwidth, and complexity. Understanding the trade-offs between these factors is essential to achieve optimal performance, as they directly impact the system's ability to meet its objectives. By considering these factors, researchers can identify research gaps, develop innovative solutions, and advance the state-of-the-art in HBF for massive MIMO systems, ultimately enhancing network capacity and performance [17].

The enormous number of base station transmitters at mmWave frequencies makes CSI problematic. Effective channel estimates may be produced via step-length reduction. [18]. Compared to traditional beamforming approaches employing faculty CSI and hardware constraints, a deep learning-based neural network for mmWave MIMO system may improve beamforming designs and boost spectrum efficiency [19]. Considering the amount of BS antenna components, scheduling many UEs concurrently maximises spectral efficiency in MIMO systems. Downlink (DL) and Uplink (UL) may have equal spectral effectiveness, enabling cooperative connection efficiency without real-time user entity location [20].

MIMO-NOMA systems have been the subject of extensive research due to their ability to greatly increase the number of supportable users, improving the system sum capacity [21]. The HBF large-scale MIMO system offers a favourable trade-off between system performance and hardware complexity, making it a potential communication technology [22]. To calculate frequency band gain, sent information properties, noise, and received signal were used. In [23], the authors evaluated downlink Rayleigh propagation network completeness.

The simulation illustrates that the idea works better and suggests a new channel estimate method to improve 5G MIMO efficiency. The wavelength estimation method for large MIMO mmWave technology is used in [24]. The study recommended super-resolution-based channel prediction using a hybrid present code structure.

Incremental mesh upgrade includes azimuth and elevation angles for off-grid settings. Simple weighted average values and data combining inaccuracy for channel prediction were new purpose challenges. The proposed research has good spectrum effectiveness, AoD/AoD, prediction reliability, and NMSE.

Incorporating restricted data into channel predictions decreased overhead [25]. This study assessed downstream channels using pilot signals. Downstream frequencies are mostly computed from response data. Smoothing standard reduction solved joint sparsity. Testing showed the suggested work had better accuracy and pilot costs. Researchers used neural networks to forecast mmWave MIMO channels [26].

Using a uniform planar antenna array, a blind multiuser identification technique creates strong MIMO systems. As a sparse matrix with non-zero coefficients forming clusters, researchers model the channel in the angular domain. By integrating the MRF model into the bilinear framework, authors have constructed a robust messaging system.

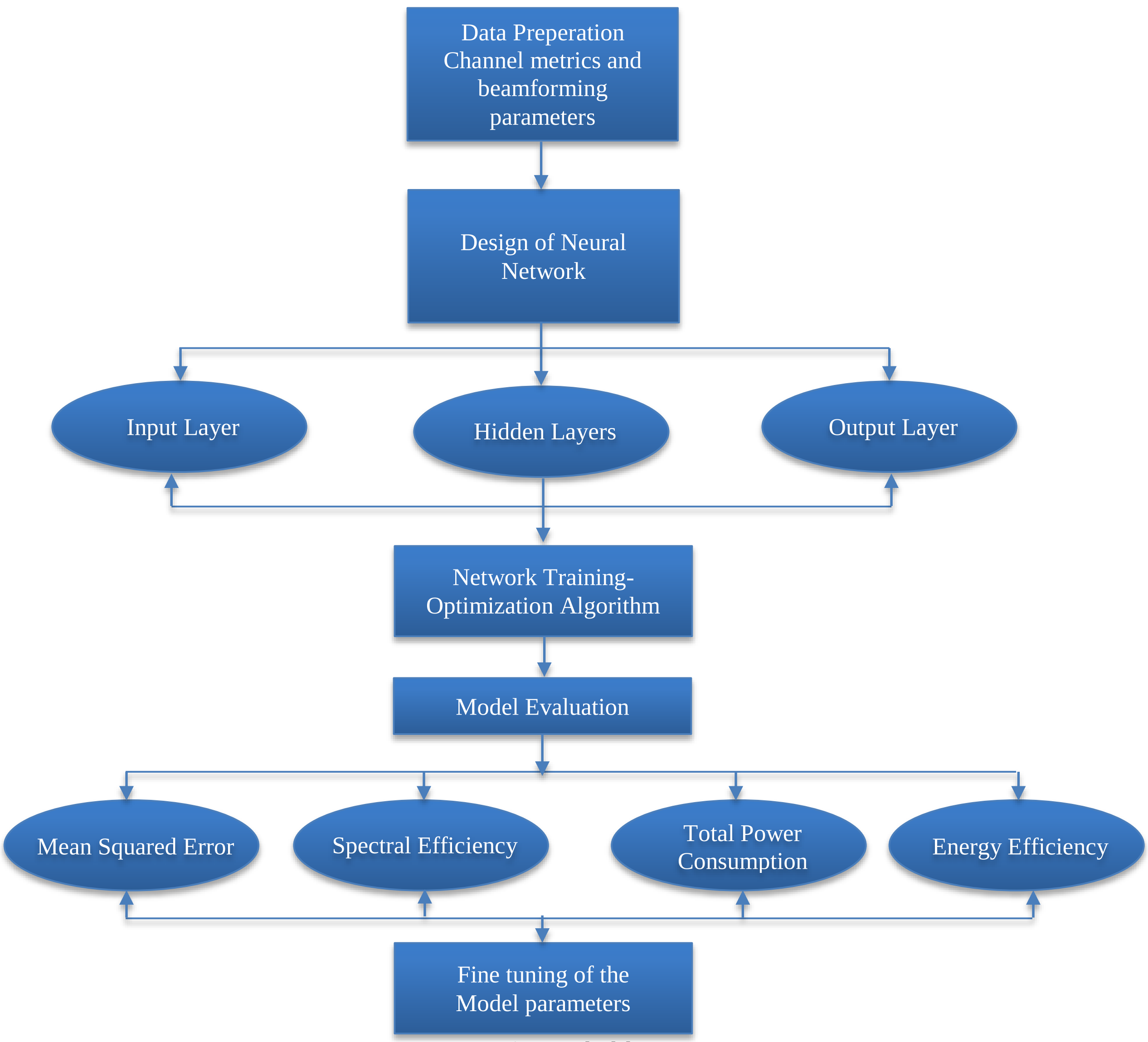


Fig. 1 Methodology

3. Research Methodology

3.1. Data Preparation

To estimate Channel State Information (CSI) in a sparse transmission MIMO scenario, a comprehensive data preparation process is undertaken. Beamforming parameters and channel matrices are collected and organised into separate databases for testing, training, and validation.

The databases are structured to include beamforming parameters resulting from categories and channel matrices as input parameters, enabling the development and evaluation of accurate CSI estimation. Through this process the power of machine learning is harnessed to improve beamforming and overall system performance in sparse transmission MIMO systems. Figure 1 shows the methodology used.

3.2. Designing Neural Network Architecture

3.2.1. Input Layer

The input layer receives the 64 X 64 channel matrix, which represents the complex interactions between transmits and receives antennas. This later serves as the foundation for the neural network, providing the raw data that will be processed and refined in subsequent layers.

3.2.2. Hidden Layer

The two hidden layers are where the neural network's complexity and learning capabilities shine. The first hidden layer consists of 128 neurons with *ReLU* activation, extracting initial features from the channel matrix.

The second hidden layer has 256 neurons with *Tanh* activation, refining feature extracting and learning nonlinear relationships between inputs and outputs.

3.2.3. Output Layer

The output layer produces the 64 X 64 beamforming weights, which combine signals from individual antennas and form the beams. This layer takes the refined features and learned relationships from the hidden layers and generates the final output, enabling accurate beamforming decisions that enhance system performance. The network designed in MATLAB is shown in Figure 2.

3.3. Network Training

The Mean Squared Error (MSE) loss function measures the average squared difference between predicted and actual beam formation data. This loss function is used to quantify the error between the neural network's predictions and actual beamforming weights.

$$Loss = \frac{1}{N}\sum_{i=1}^{N}(Actual_i - Predicted_i)^2 \qquad (1)$$

Where N is the total number of data points, $Actual_i$ is actual beamforming weights for data point i and $Predicted_i$ is predicted beamforming weights for data point i, Loss is Mean Squared Error (MSE).

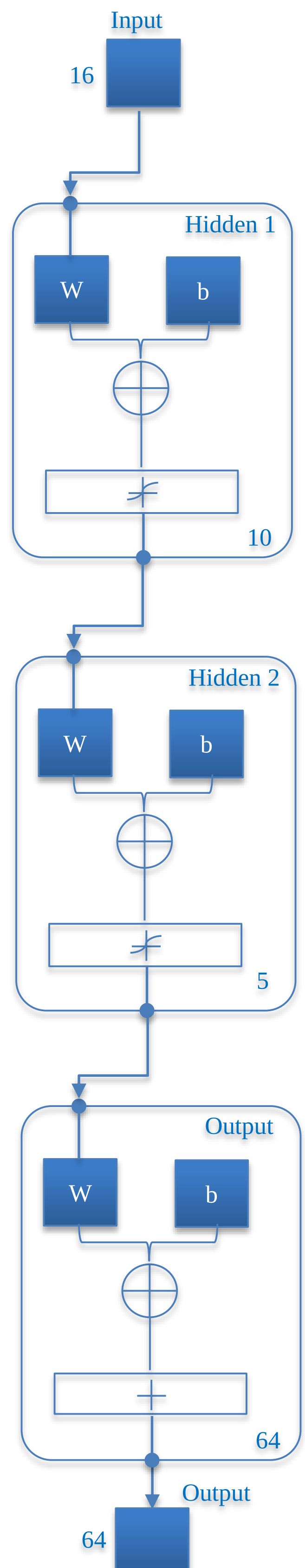


Fig. 2 Design of neural network

3.3.1. Optimization Algorithm

The Levenberg-Marquardt (LM) algorithm is a popular optimization technique used in neural network training. It is a variant of the Gauss-Newton method, which combines the benefits of gradient descent and Newton's method. LM is particularly effective for nonlinear least squares problems, making it suitable for neural network optimization.

The optimization iteration technique collection focuses on solving complex least-square problems. A prediction error or loss function is developed in neural network development, and the LM approach reduces variation between real and projected nonlinear function outcomes.

Algorithm 1: The Iterative LM Algorithm
Input: Model parameters (θ), Damping factor (λ)
Output: updating 'θ'
1: Initialize: θ and λ;
2: Compute: Jacobian matrix (J) of the loss function w.r.t 'θ';
3: Compute: Gradient of the loss (g) w.r.t 'θ' ;
4: Compute: Hessian matrix (H) w.r.t 'θ';
5: Update: 'θ' using LM update rule;
6: $i \leftarrow i + 1$;
7: repeat
8: until all data points are covered;
9: update final value of 'θ'

The Levenberg-Marquardt (LM) method calculates the Jacobian matrix for each iteration, which can be computationally expensive when dealing with complex functions or large dimensions.

To reduce the computational cost, [] proposed a modified LM method that reuses the evaluated Jacobian to compute both an exact LM step and an approximate LM step at each iteration.

This approach was further extended to a multi-step LM method, where the k^{th} iteration, one exact LM step and $p - 1$ approximate LM steps are computed, reducing the number of Jacobian evaluations and linear algebra operations.

3.3.2. Training Process

The channel matrix is input to the neural network, and network weights are adjusted during training to minimize the discrepancy between predicted and actual beamforming weights. The network is trained using a dataset of labelled examples, where each example consists of a channel matrix and corresponding beamforming weights. After training, the network's performance is validated using a separate dataset to ensure it generalizes well to unseen data and avoids overfitting. By iteratively updating the network weights and validating its performance, the neural network learns to accurately predict beamforming weights from channel matrices, enabling efficient beamforming in the system. This process enables the network to adapt to varying channel conditions and optimize beamforming for improved system performance.

3.4. Neural Network Hybrid Beamforming (NHBF)

Neural network hybrid beamforming uses analog and digital beamforming to improve performance. The neural network minimizes the system's loss function, which is usually linked to signal quality, interference, and noise.

As shown in Figure 3, the traditional hybrid beamforming system can be modified into a neural network-based hybrid beamforming system. Single-user MIMO system with N_s data stream followed by ${N_t}^{rf}$ radio frequency (RF) chains going through N_t antennas on the transmitting side. On the receiving side, the there N_r antennas followed by ${N_r}^{rf}$ RF chains.

Digital beamformer (F_{bb}) consists of the hardware architecture of ${N_t}^{rf} \times N_s$, followed by $N_t \times {N_t}^{rf}$ analog beamformer (F_{rf}). To recover the transmitted symbol vector, the receiver employs an analog combiner (W_{rf}) and a digital combiner (W_{bb}). A neural network with trainable parameters $\theta = \{W, b\}$ is used to define digital beamformer function.

$$X^{bb} = f_\theta(s) = \sigma(W \cdot s + b) \quad (2)$$

For a traditional digital beamformer, the signal processing is a matrix-vector multiplication as $X^{bb} = F_{bb}s$, where both X^{bb} and s represent the magnitude and phase of the signal.

The digital beamformer output is $X^{bb} \in \mathbb{R}_{N_t^{rf} \times 1}$, where σ is the activation function, which is the hyperbolic tangent function$\sigma(x) = \tanh(x)$. The weight and bias of the neural network is denoted as W and b. With several neural network layers, the NN-based digital beamformer function is

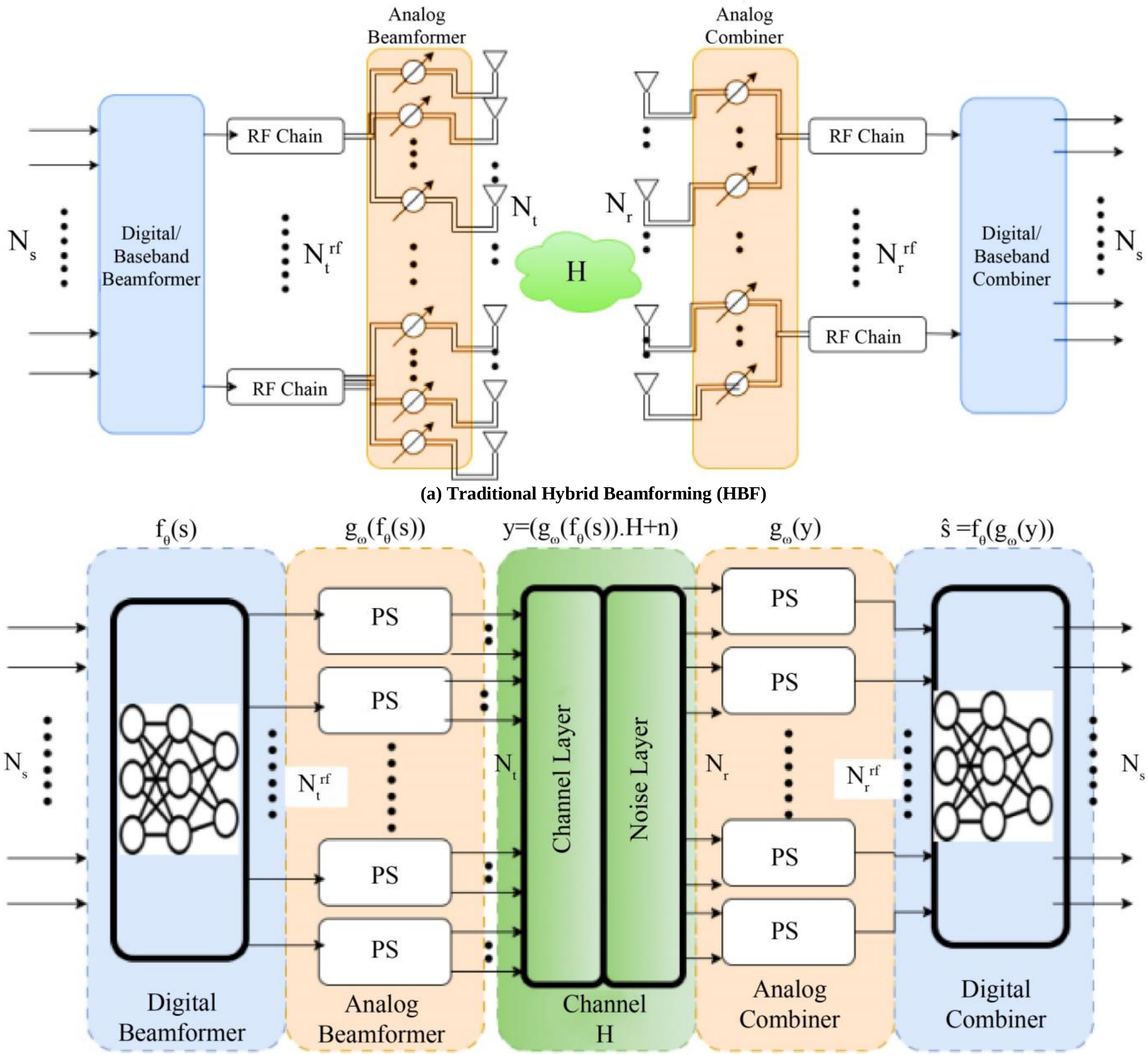
$$X^{bb} = f_\theta(\dots. f_\theta(f_\theta(s))) \quad (3)$$

Further additive channel noise is added to the NHBF system's channel layer.

$$y = HX^{bb} + n \quad (4)$$

$$y = \left(P^{pow}\left(g_w(f_\theta(s))\right)\right) H + n \quad (5)$$

Where y is the received signal at the receiver end, $P^{pow}$is the power of the signal transmitted with non-linear effects of the amplifier, g_w are complex weights applied to the signal to steer the beam in a specific direction, H is the channel matrix, which represents complex interactions between the transmit and receive antennas, n is the noise vector, which represents the random noise added to the signal.



(a) Traditional Hybrid Beamforming (HBF)

(b) Neural Network Hybrid Beamforming (NHBF)

Fig. 3 Illustration of hybrid beamforming (a) Traditional Hybrid Beamforming (HBF) and (b) Neural Network Hybrid Beamforming (NHBF)

Algorithm 2: Neural Network Hybrid Beamforming (NHBF)
Input: Transmitter signal (X), channel state information (CSI), Beamforming weights (W)
Output: Predicted signal (Y)
1: NN_Output: NN (X, CSI), predict beamforming weights using the neural network;
2: W_Hybrid: combine (W, NN_Output), combine traditional and neural network weights;
3: Y: beamform (X,W_Hybrid), beamforming using hybrid weights;
4: Output: Y

4. Model Evaluation

A test dataset is a separate collection of data used to evaluate the performance of a trained machine learning mode, typically consisting of 20-30% of the total data. This dataset assesses the model's accuracy and testing on unseen data.

To evaluate the beamforming model's performance, metrics such as Mean Squared Error (MSE) and Signal Noise Ratio (SNR) are used.

By maximizing SNR and minimizing MSE, the model can produce accurate beamforming weights, ensuring reliable and high-quality signal transmission.

4.1. Mean Squared Error (MSE)

Mean Squared Error is the mean squared deviation between the reality (desired) signal and the normal (received) signal.

$$MSE = E[(y - \hat{y})] \tag{6}$$

Where MSE is a mean squared error, E is the expected value, y is the actual value, $\hat{y}$ is the predicted value output of the model or estimator.

4.2. Spectral Efficiency (SE)

Spectral efficiency measures the amount of data delivered across a network with a given bandwidth without affecting service. It is also known as channel capacity, transmission efficiency, or bandwidth efficiency. It is expressed in bps/Hz.

$$SE = \frac{Channel\ bitrate}{Channel\ bandwidth} \tag{7}$$

4.3. Energy Efficiency (EE)

Implementing machine learning and neural networks optimizes the beam search to selected beam pair indices instead of an exhaustive search of all beam pair indices. Hence, it focuses signal energy in the desired directions while minimizing interference and maintaining link quality. It is defined as the number of bits sent per power consumption unit. It's expressed in bits/joules.

5. Results and Discussion

This section presents the performance evaluation of the proposed Neural Network Hybrid Beamforming (NHBF) and its results. We use conventional Hyperparameter settings for individual user systems in NHBF modelling.

The simulation network design is based on mathematical principles, with accidental Laplacian allocation determining arrival and departure locations and standardized sampling determining collection angles from$[0,2\pi]$ as described in [12]. We assume systematic coordination and channel estimations.

The number of data channels and RF signal chains are equal. We set the connection size and hyperparameters according to Table 1. The time and complexity of back-propagation in the neural network depend on the number of neurons in each layer, epochs (N), and training samples (M).

Figure 4 demonstrates the validation of a machine learning model's performance on unseen data, ensuring its ability to generalize well. The validation curve shows the model's performance metrics, such as accuracy and MSE, over time. A comparison between training and validation performance reveals any potential overfitting. Figure 2 provides a comprehensive evaluation of the model's strengths and weaknesses, allowing for informed decisions to improve its performance.

Table 1. Setting of hyperparameters

Configuration	Values
Number of base station Tx antennas	16
Number of mobile station Rx antennas	16
Antenna configuration	Uniform rectangular array
Antenna spacing	0.5λ
Position of UE	Azimuth angle: [-180 180] Elevation angle: [-90 90]
Position of BS	[0 0]
Maximum range of MS	1 km
Carrier frequency (GHz)	28
Modulation scheme	16-QAM
Channel sampling rate	100×10^6 samples/sec
Channel type	MIMO, sparse propagation
Noise figure (dB)	5-10
Number of rays for partitioning F_{rf}, F_{bb}	500

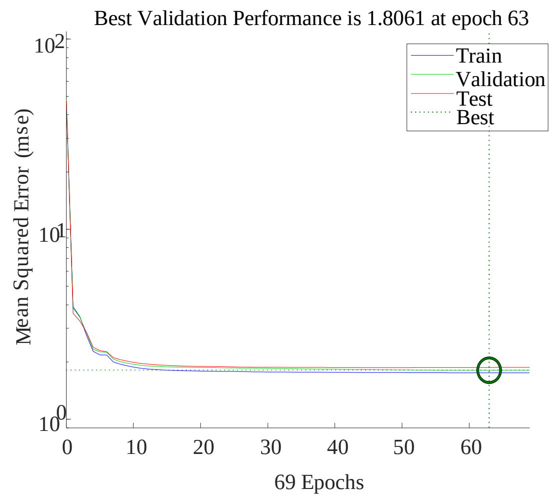


Fig. 4 Validation of performance

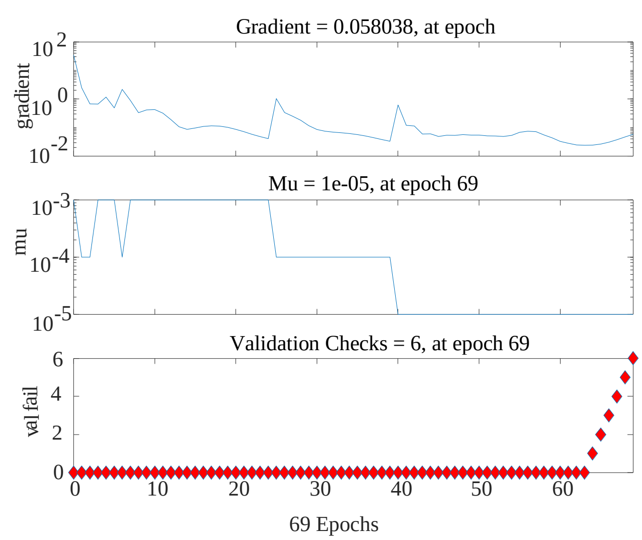


Fig. 5 The training states for gradient, MSE and validation

Figure 5 illustrates the interplay between gradient, MSE and validation during model training. As the gradient decreases, indicating improved parameter optimization, the MSE also decreases, which reflects reduced error between predicted and actual values. The validation curve tracks the model's performance on unseen data, ensuring good generalization. The closely related gradient and MSE curves demonstrate improved performance of the model, and validation curves confirm its ability to generalize well to new unseen data.

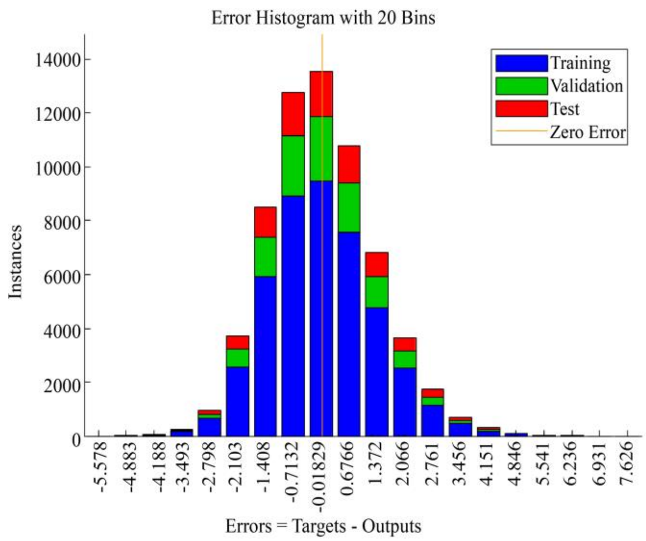


Fig. 6 Error histogram with 20 bins

Figure 6 presents an error histogram with 20 bins, providing a visual representation of the distribution of errors in the regression model. The histogram reveals a skewed distribution, indicating that the errors are not normally distributed. Most errors are concentrated in the central bins, with fewer errors in the outer bins. However, there are noticeable peaks in the higher error bins, suggesting the presence of outliers or anomalies in the data. This histogram offers valuable insights into the model's performance, highlighting areas that require improvement to achieve more accurate predictions.

Figure 7 compares the recommended and present regression bin training stages. It presents the comparative analysis of the recommended and present regression bin training stages, revealing a notable discrepancy in performance. The recommended approach, depicted by the solid line, exhibits a steady and consistent increase in accuracy as the training stage progresses, whereas the present approach, represented by the dashed line, displays a more erratic and variable performance. This divergence suggests that the current training process can be optimized to achieve better accuracy and model performance by adopting the recommended approach. By doing so, the training process can be refined to yield more consistent and reliable results, leading to improved overall performance.

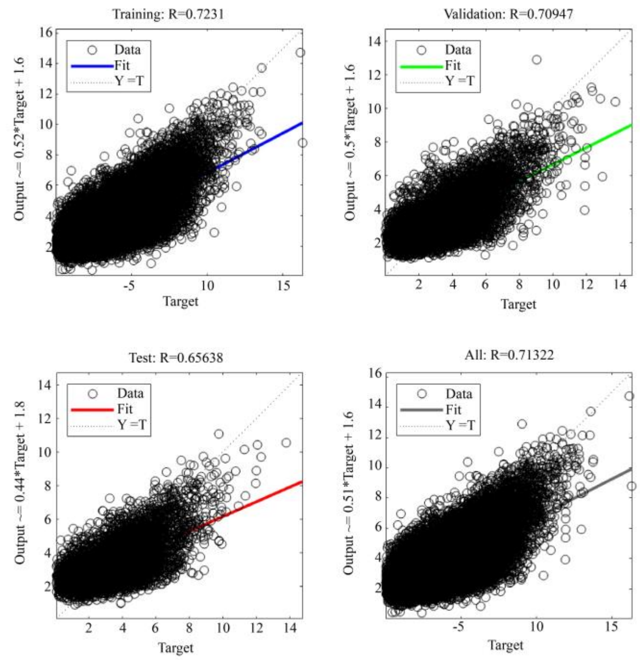


Fig. 7 Regression validation

5.1. Performance Comparison of 16 X 16 MIMO (SNR Range -20 to 10)

Parameters are set as per Table 1, and simulations are done in MATLAB by designing a neural network for hybrid beamforming (NHBF) with 16 transmitting antennas and 16 receiving antennas. The performance of various parameters such as spectral efficiency, BER, energy efficiency and total power consumption is plotted for the positive and negative values of SNR, and results are compared with hybrid beamforming (HBF) shown in the figure below.

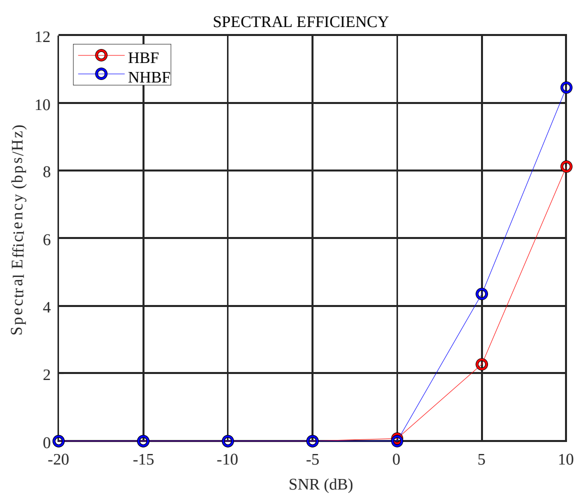


Fig. 8 Spectral efficiency vs SNR for 16 X 16 MIMO system

As seen in Figure 8, the values of spectral efficiency are near 0 bps/Hz for the negative values of SNR and a significant difference in the values is seen between HBF and NHBF for the positive values of SNR. For SNR=5, HBF provides a spectral efficiency of 2.27 bps/Hz, and NHBF provides a higher value of 4.35 bps/Hz, which is further improved to 10.46 bps/Hz for SNR =10 compared to NBF, which has a maximum value of 8.12.

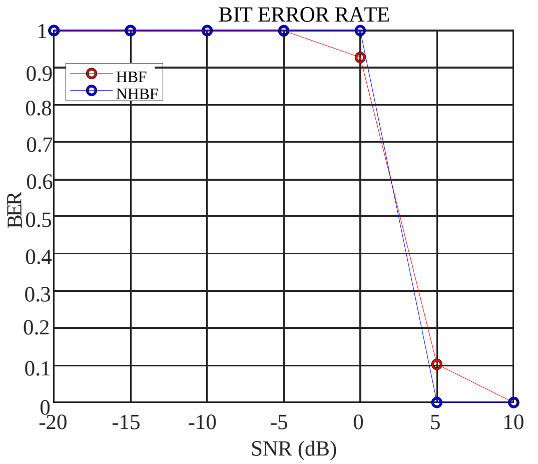


Fig. 9 BER vs SNR for 16 X 16 MIMO system (SNR range -20 to 10)

As seen in Figure 9, a similar variation in the bit error rate is seen for the negative values of SNR as that of spectral efficiency. However, BER is 1.04×10^{-6} for SNR of 5dB, and a further lower value of BER is obtained at SNR of 10 dB as 3.66×10^{-46} for NHBF compared to HBF.

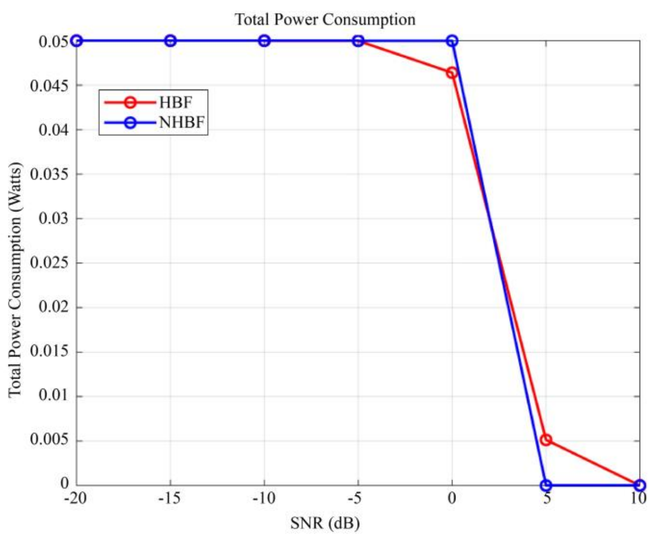


Fig. 10 SNR vs Total power consumption for 16 X 16 MIMO system

The curve of total power consumption is plotted for the different values of SNR, which are shown in Figure 10. From the figure, it can be seen that when the value of SNR is 0, power consumption for NHBF is high, 0.049 watts, compared to HBF, which is 0.046 watts. However, when the SNR value increases further, the power consumption of the proposed NHBF method reduces to 5.28×10^{-8} compared to 0.005 of HBF. It shows the improvement in total power consumption of our proposed method, NHBF.

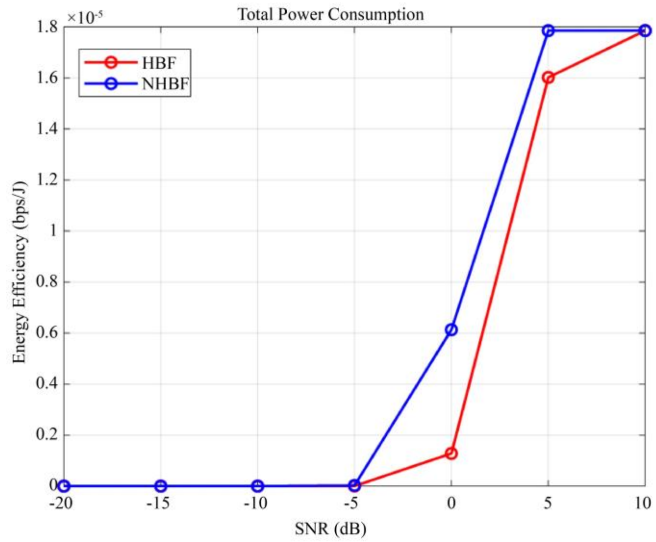


Fig. 11 SNR vs Energy efficiency for 16 X 16 MIMO system

Figure 11 shows the energy efficiency curve vs. SNR for the 16×16 MIMO system. There is a significant improvement in the energy efficiency of NHBF compared with HBF at the lower positive value of SNR of 5dB.

Further, the value of energy efficiency is 1.78×10^{-5} bps/J for the proposed NHBF model, which is higher than HBF at an SNR of 10.

5.2. Performance Comparison of 16 X 16 MIMO (SNR Range 0 to 30)

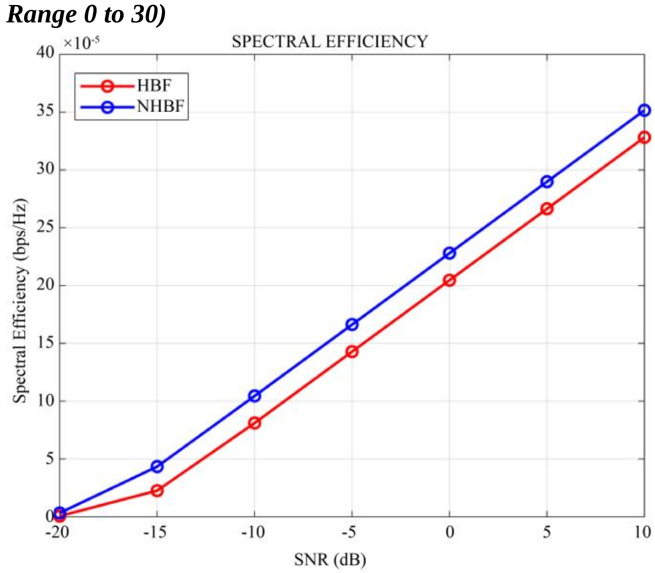


Fig. 12 Spectral efficiency vs SNR for 16 X 16 MIMO system

Figure 12 shows the spectral efficiency curve for the positive range of SNR from 0 to 30 dB. It has been observed that the value of spectral efficiency is higher for NHBF compared to HBF for all the values of SNR. The maximum value is obtained for NHBF of 35.17 bps/Hz compared with 32.83 bps/Hz of HBF.

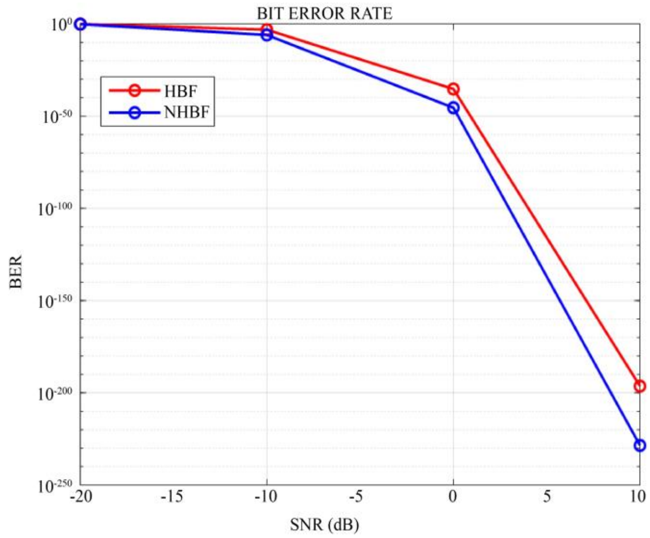


Fig. 13 BER vs SNR for 16 X 16 MIMO system (SNR range 0 to 30)

Figure 13 shows the plot of BER for the positive values of SNR. It is observed that the proposed NHBF model has less BER than the HBF model.

Figure 14 shows the total power consumption for positive values of SNR of the NHBF model compared with the HBF model. It is observed that for positive values of SNR, there is no difference in power consumption between the HBF and NHBF models. However, a difference is observed for negative values of SNR, and when SNR is 0 dB, 0.046 watts is consumed by the HBF model, which is higher compared with 0.035 watts of the NHBF model.

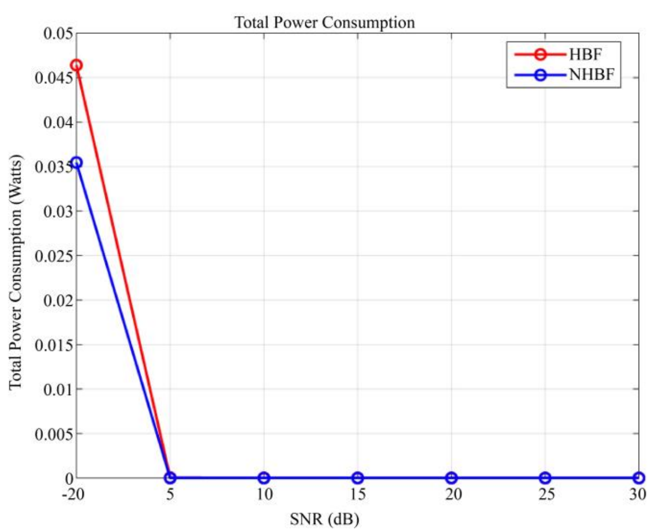


Fig. 14 Total power consumption vs SNR for 16 X 16 MIMO system

Figure 15 above shows the plot of energy efficiency. It is observed that the value of energy efficiency is nearly the same for the HBF and NHBF models. However, a significant difference is observed in the value of energy efficiency 5.19 X 10^{-6} bps/J for NHBF, which is higher compared to HBF of 1.28 X 10^{-6} bps/J for the same SNR.

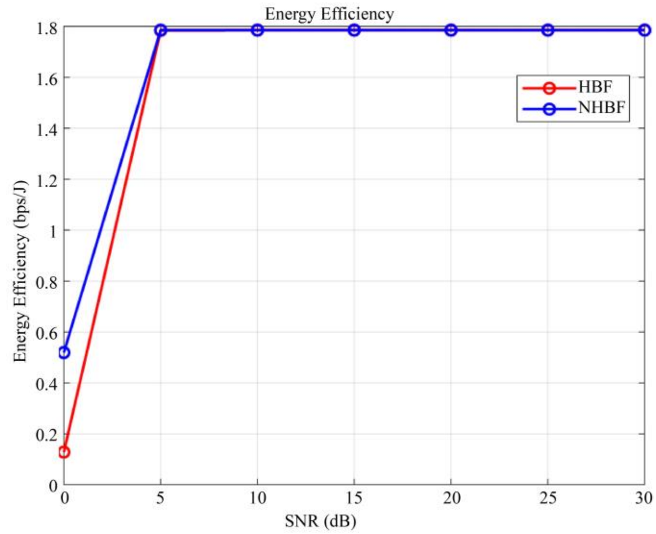


Fig. 15 SNR vs Energy efficiency for 16 X 16 MIMO system

6. Conclusion

Millimeter wave frequency bands for next-generation wireless networks have several advantages, such as increased data rate, spectral efficiency, etc. However, the challenge is to acquire channel state information in a dynamic channel at these frequencies. Beamforming is one of the techniques by which an accurate beam can be aligned in the required direction where the user is present. The use of neural network based hybrid beamforming is presented in this paper for beam searching and beam alignment. The designed model is evaluated on different performance parameters and compared with the traditional hybrid beamforming method. The simulations are done for 16 transmitters and 16 receiver antenna systems operating at a frequency of 28 GHz. The neural network is designed in MATLAB, and different performance metrics are calculated and presented in this paper. Such a neural network-based hybrid beamforming method will find applications in high frequencies and short wavelength mmWave bands for precise beamforming. Another application could be multiuser MIMO systems where users simultaneously attempt to transmit data, and neural networks can help dynamically adjust the beamforming weight and allot optimal signal power to each user based on their location, channel conditions and mobility scenarios, thus improving overall system capacity. The authors conclude that neural Network-Based Hybrid Beamforming (NHBF) is an excellent solution for achieving reliable wireless links and diverse scenarios for the MIMO systems. Specifically, NHBF yields a high spectra efficiency of 35.17bps/Hz compared with Hybrid Beamforming (HBF), which has 32.83bps/Hz at 20 dB SNR. Furthermore, NHBF achieves a minimum bit error rate of 6.2×10^{-6} at 15 dB SNR. Additionally, a high energy efficiency gain of 5.19 X 10^{-6} bps/J is obtained. These remarkable metrics underscore the system's ability to optimize wireless communication performance in the sparse propagation environment, making it an attractive solution for various applications, including 5G and beyond, IoT, and mission-critical communications and paving the way for future wireless networks that are faster, more reliable, and more energy-efficient. Future research directions include exploring the system's application in emerging wireless technologies like Terahertz (THz) communications and massive MIMO. Investigating advanced neural network architectures to enhance performance and adaptability is also crucial. Additionally, examining scalability and robustness in complex environments and integration with other wireless technologies is necessary.

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