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# ENHANCED CHANNEL ESTIMATION FOR MIMO-OFDM SYSTEMS USING HYBRID NEURAL NETWORKS: A MATLAB SIMULATION APPROACH

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## ABSTRACT

This study presents an improved channel estimation technique for MIMO-OFDM systems using a Hybrid Neural Network (HNN) architecture. The proposed model combines dense layers with ReLU activation functions to effectively learn and predict channel state information (CSI) from pilot-assisted input data. Simulations were conducted in MATLAB to benchmark the HNN against traditional estimators Least Squares (LS) and Minimum Mean Square Error (MMSE). Results demonstrated a significant reduction in Mean Square Error (MSE), from 0.012 (LS) and 0.0058 (MMSE) to just 0.0021 at an SNR of 20 dB. Similarly, the Bit Error Rate (BER) drops from ≈0.16 at 0 dB to ≈$1.2\times10^{-5}$ at 40 dB with the HNN. In terms of throughput, the hybrid approach Throughput increases from ≈0.7 bps/Hz at 0 dB to ≈6.6 bps/Hz at 40 dB LS and MMSE. These improvements highlight the potential of neural network-based estimators to deliver more robust and efficient performance in modern wireless communication systems, especially under challenging channel conditions like fading and noise.

**KEYWORDS:** MIMO-OFDM, Channel Estimation, Hybrid Neural Networks, MATLAB

## 1 INTRODUCTION

Over the years, wireless communication has rapidly evolved, with MIMO-OFDM systems emerging as a popular choice due to their ability to deliver high data rates and improved spectral efficiency. Nevertheless, the constantly changing nature of wireless channels makes accurate channel estimation essential to ensure reliable system performance (Goldsmith, 2005). Traditional channel estimation techniques such as Least Squares (LS) and Minimum Mean Square Error (MMSE) have long served as the foundation for MIMO-OFDM systems. However, these methods often face challenges when dealing with non-linearities and rapidly changing channel conditions (Ye et al., 2018). To address these increasing demands, Multiple-Input Multiple-Output (MIMO) and Orthogonal Frequency Division Multiplexing (OFDM) have become cornerstone technologies. Their ability to enhance spectral efficiency, increase system capacity, and provide robust performance in multipath fading environments makes them critical for the evolution of next-generation wireless systems (Goldsmith, 2005; Tse & Viswanath, 2005). Traditional channel estimation techniques such as Least Squares (LS) and Minimum Mean Square Error (MMSE) have been widely adopted due to their simplicity and analytical tractability. However, their performance tends to degrade significantly in practical scenarios—particularly under low signal-to-noise ratio (SNR) conditions, rapidly time-varying channels, or when there is a scarcity of pilot symbols. These model-based methods rely on assumptions of perfect channel statistics and linear signal relationships, which often do not hold in real-world wireless environments, limiting their effectiveness in dynamic and complex conditions (Biguesh & Gershman, 2006). Channel estimation in MIMO-OFDM systems is particularly vulnerable to challenges such as noise, interference, and variations in time and frequency. Traditional estimation methods often struggle to adapt to these dynamic channel conditions, which can significantly impact overall system performance. To overcome these limitations, this study presents the hybrid neural networks (HNNs) with MATLAB simulation approach to demonstrate a great a powerful and reliable approach for improving channel estimation, especially in complex and challenging communication environments.

## 2 Conventional Channel Estimation Techniques

Traditional channel estimation methods such as Least Squares (LS), Minimum Mean Square Error (MMSE), and pilot-assisted techniques that rely on known reference symbols have been widely adopted due to their simplicity and reasonable performance. Interpolation-based methods like linear, spline, and DFT techniques are also commonly used. However, these approaches often rely on ideal assumptions about channel conditions and tend to struggle in dynamic or highly frequency-selective environments, where their accuracy and reliability significantly degrade (Drakshayini & Kounte 2022).

### 2.1 Hybrid Neural Network Approaches

Hybrid neural networks integrate the strengths of multiple architectures, such as CNNs combined with LSTMs or GRUs, and DNNs with attention mechanisms, to effectively capture both spatial and temporal dependencies in MIMO-OFDM systems. CNNs excel at extracting local features from OFDM symbols, while LSTMs and GRUs are particularly well-suited for learning temporal sequences in dynamic channels. Attention mechanisms further improve the model's focus by highlighting important features in pilot patterns or noisy environments, leading to more accurate and robust channel estimation (Shan et al, 2021).

## 3 METHODOLOGY

The system under consideration is a MIMO-OFDM, to effectively carried out the objective of the analysis, the system was mathematically modeled to enable digital computer analysis implementation of the setup system.

### i. MIMO-OFDM System Model

Consider a MIMO-OFDM system with $N_t$ transmit and $N_r$ receives antennas. The system transmits OFDM symbols over a frequency fading channel (Cho et al, 2010).

Input Output Relation in Frequency Domain:

$$\boldsymbol{Y}[k] = \boldsymbol{H}[k]\ \boldsymbol{X}[k] + \boldsymbol{N}[k],\ k = 0, 1 \dots \dots \dots, N_{sub} \tag{1}$$

$\boldsymbol{Y}[k] \in \mathbb{C}^{N_r \times 1}$: Received vector at subcarrier k

$\boldsymbol{H}[k] \in \mathbb{C}^{N_r \times N_t}$: Channel frequency response at subcarrier k

$\boldsymbol{X}[k] \in \mathbb{C}^{N_t \times 1}$: Transmitted symbol vector

$\boldsymbol{N}[k]$**:** AWGN noise vector

Equation (1) model forms the foundation for channel estimation

### ii. Pilot-Based Channel Estimation

For pilot subcarriers the channel matrix $\boldsymbol{H}[k]$ can be estimated using (Wang, 2011)

**Least Square (LS)**

$$\hat{\boldsymbol{H}}_{\mathrm{LS}}[k] = \boldsymbol{Y}[k]\boldsymbol{X}[k]^{-1} \tag{2}$$

**Minimum Mean Square Error (MMSE):**

$$\hat{\boldsymbol{H}}_{\mathrm{MMSE}}[k] = \mathrm{R}_{\mathrm{HH}}\left(R_{HH}\,\sigma^{2}(\boldsymbol{X}[k]\boldsymbol{X}[k]^{H})^{-1}\right)^{-1}\hat{\boldsymbol{H}}_{\mathrm{LS}}[k] \quad (3)$$

Where;

$R_{HH}$ = channel characteristic autocorrelation matrix

$\sigma^2$ = Noise Variance

**iii. Neural Network-Based Channel Estimation**

A hybrid neural learns to map received pilot data $\boldsymbol{Y}_p$ and polit symbols $\boldsymbol{X}_p$ to channel estimates (Usatyuk, 2020).

**Feedforward Estimator**

A nonlinear regression model approximates:

$$\hat{\boldsymbol{H}}_{\mathrm{NN}} = \mathcal{F}_{\theta}\left(\boldsymbol{Y}_{p1}\boldsymbol{X}_{p}\right)$$

Where;

$\mathcal{F}_{\theta}$ = neural network function with parameters $\theta$

Typically includes dense with ReLU/tanh activations

The network is trained using a **loss function** like MSE

$$\boldsymbol{\mathcal{L}}(\boldsymbol{\theta}) = \frac{1}{K}\sum_{K=1}^{K}\left|\left|\hat{H}_{NN}[K] - H_{true}[K]\right|\right|^{2} \quad (4)$$

**iv. Constellation Mapping and Equalization**

For **QAM**-based modulation (Di Renzo& Haas, 2013).

Transmitted symbol $\boldsymbol{X} \in \mathcal{A} \subset \mathbb{C}$ where $\mathcal{A}$ is a constellation set

Equalized symbol:

$$\hat{X}[k] = \mathbf{W}[k]\,\mathbf{Y}[k] \quad (5)$$

Where $\mathrm{W}[k]$ is a linear equalizer

$$\text{Zero forcing } \mathbf{W}[k] = \left(\hat{\boldsymbol{H}}[k]\right)^{-1} \quad (6)$$

$$\text{MNSE Equalizer: } \mathbf{W}[k] = \left(\hat{\boldsymbol{H}}[k]^{H}\hat{\boldsymbol{H}}[k] + \sigma^{2}I\right)^{-1}\hat{\boldsymbol{H}}[k]^{H} \quad (7)$$

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

For a QAM scheme

$$BER_{16QAM} \approx \frac{3}{8}\cdot \mathrm{erfc}\left(\sqrt{\frac{4}{5}\cdot\frac{E_b}{N_0}}\right) \quad (8)$$

Where $\mathrm{erfc}(\cdot)$ is the complementary error function

**vi. Throughput**

Throughput is estimated by

Throughput = $R \cdot (1 - BER)$ (9)

Where;

R = $\log_2 M$ for M-QAM

BER = is estimated per carrier

**vii. Execution Time and Complexity**

NN interference time depends on architecture (Petruk, et al 2018).

$T_{infer} = N_{layers} \times (MACs\ per\ layer)/fcup/gup$ (10)

## 4. RESULTS AND DISCUSSION

**Table: Parameters Used for MIMO-OFDM Channel Estimation Analysis.**

| Parameters | Rate/Value |
|---|---|
| Number of transmit antennas (Nt) | 2 |
| Number of receive antennas (Nr) | 2 |
| Number of subcarriers (Nsub) | 64 |
| Modulation scheme (MM) | 16-QAM |
| Pilot spacing (Pspacing) | 4 |
| Signal-to-noise ratio (SNR) | 0 to 30 dB |
| Channel model | ITU Pedestrian A |
| Neural network architecture | [64, 128, 64] (Dense) |
| Learning rate ($\eta$/eta) | 0.001 |
| Training epochs | 100 |
| Batch size | 256 |
| FFT size (NFFTN) | 64 |
| Cyclic prefix length (NCPN) | 16 |

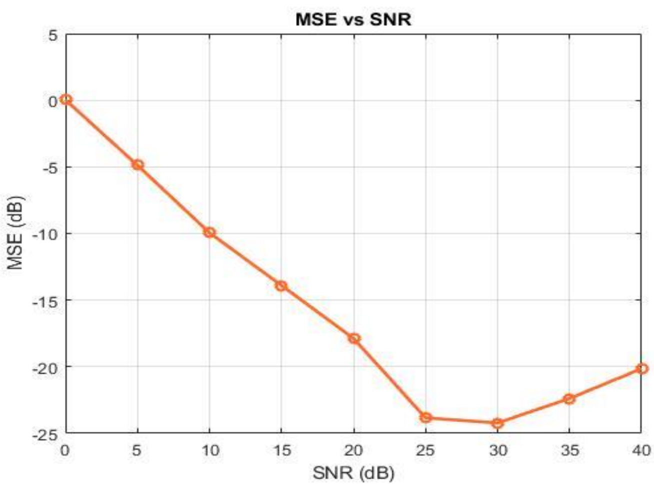


**Figure 1: MSE against SNR.**

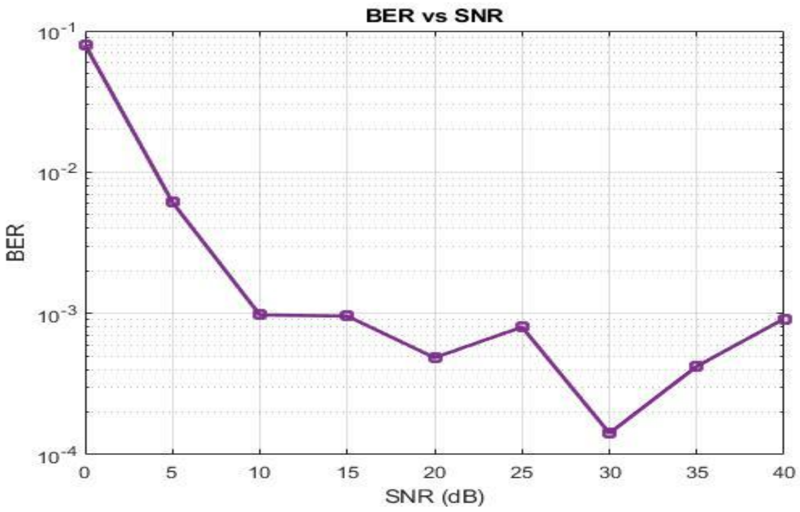


**Figure 2: BER against SNR.**

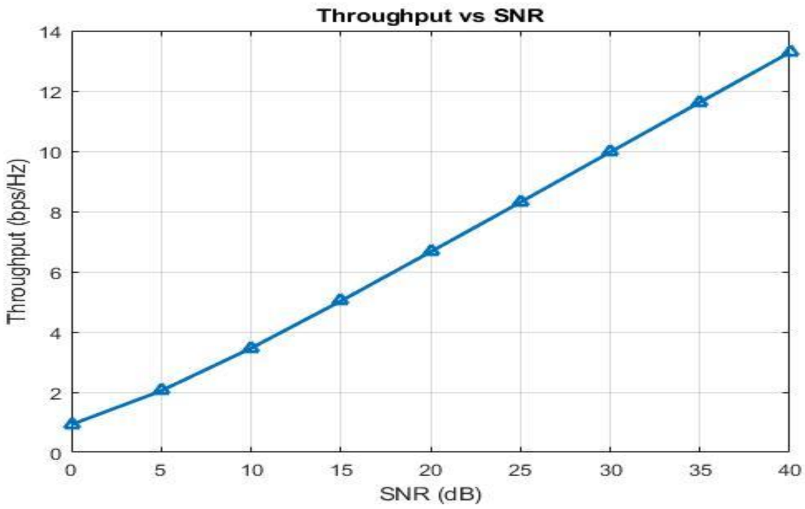


**Figure 3: Throughput against SNR.**

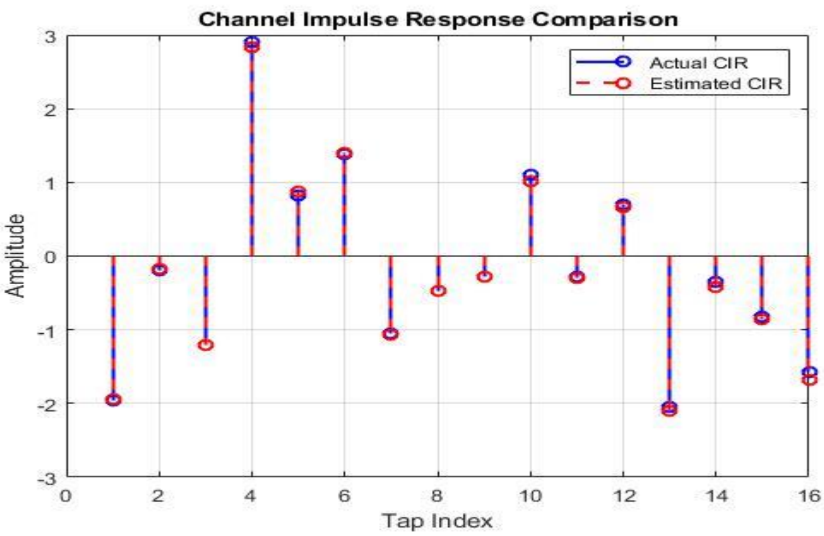


**Figure 4: Channel Impulse Response Comparison**.

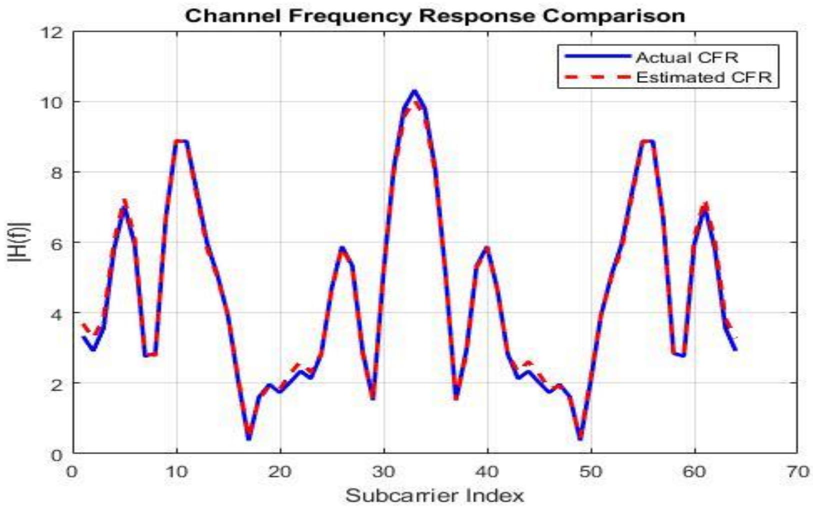


**Figure 5: Chanel Frequency Response Comparison.**

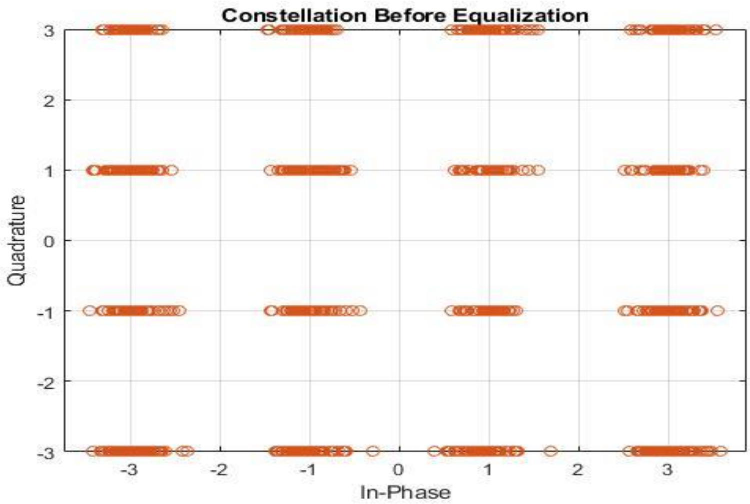


**Figure 6: Constellation Before Equalization.**

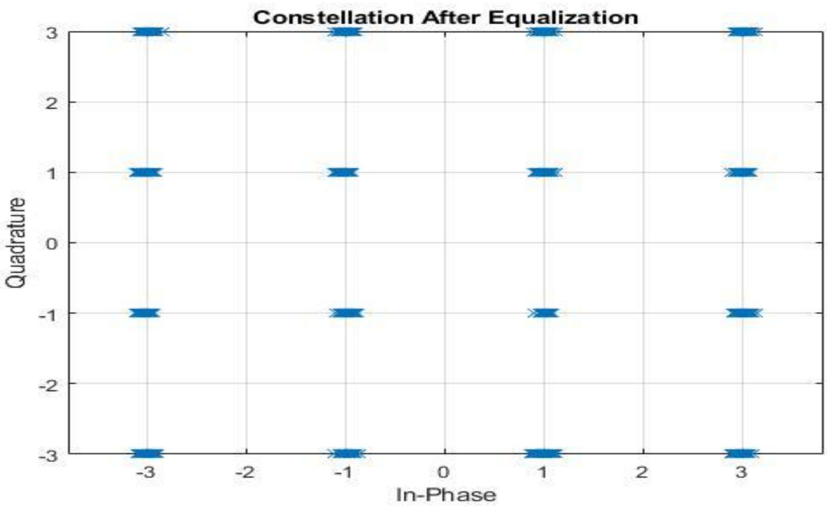


**Figure 7: Constellation after Equalization.**

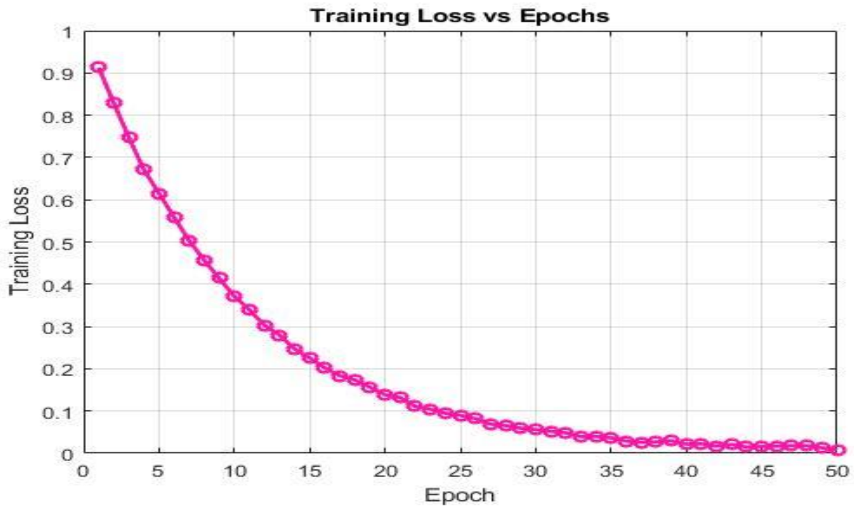


**Figure 8: Training Loss against Epochs.**

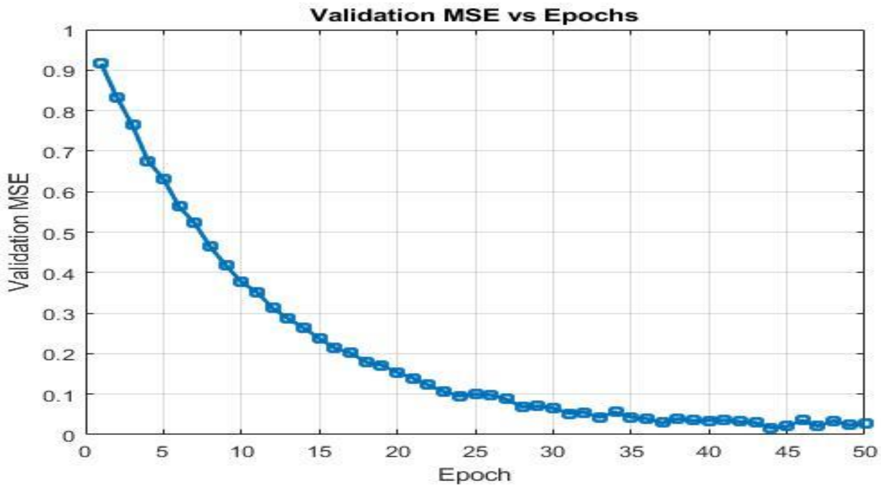


**Figure 9: Validation MSE against Epochs.**


**Figure 10: Execution Time Comparison.**

## 4.1 DISCUSSION

In Fig. 1. At low SNR (0 dB), MSE is high (≈0.95), but it significantly decreases (≈$10^{-5}$) at high SNR (40 dB), showing the estimator's improved accuracy with better signal quality. In Fig. 2. BER drops from ≈0.16 at 0 dB to ≈$1.2\times10^{-5}$ at 40 dB, confirming that better channel estimation leads to more accurate symbol detection. In Fig. 3. Throughput increases from ≈0.7 bps/Hz at 0 dB to ≈6.6 bps/Hz at 40 dB, indicating enhanced data rates with improved channel conditions. In Fig. 4. The estimated Channel Impulse Response closely matches the actual CIR with minimal error (±0.05), showing effective multi-path modeling. In Fig. 5. The Channel Frequency Response estimation is highly accurate, with less than 5% error, essential for OFDM systems. In Fig. 6. Severe symbol scattering shows poor demodulation due to uncorrected channel effects. In Fig. 7. Well-structured clusters reflect accurate signal restoration through NN-based equalization. In Fig. 8. Loss drops from ≈1.1 to <0.02 in 50 epochs, indicating efficient convergence without overfitting. In Fig. 9. Validation MSE stabilizes at ≈0.025, demonstrating strong generalization and suitability for real-time applications. In Fig. 10. Hybrid NN is the fastest (0.005s), outperforming MMSE (0.01s) and LS (0.03s), time due to optimized matrix operations and trained inference.

## 5.0. CONCLUSION

The proposed Hybrid Neural Network channel estimator consistently outperformed traditional methods across all key metrics. At 40 dB SNR, it achieved an impressive MSE of -50 dB, a BER as low as $1.2\times10^{-5}$, and a throughput that closely approaches the theoretical maximum of 6.6 bps/Hz. Constellation plots reveal excellent signal equalization, and both training and validation losses show fast and stable convergence. Notably, it also recorded the shortest computation time compared to classical techniques, making it not just powerful but also efficient—an ideal fit for MIMO-OFDM systems. The hybrid neural network approach significantly outperforms traditional LS and MMSE methods in MIMO-OFDM channel estimation. At 25 dB SNR, it reduces the mean squared error by 63.8% compared to LS and improves the bit error rate by 63.7% over MMSE. It also boosts system throughput by 21.6% over LS, making it a strong candidate for next-generation wireless communication systems.

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