VOLUME OF INTERNATIONAL DISCOVERIES AND YOUTH ACADEMIC WORKS, ACHIEVEMENTS, AND NOVELTIES - VIDYAWAN

VIDYAWAN - Volume of International Discoveries and Youth Academic Works, Achievements, and Novelties | Vol. 1, Issue 1

Optimized MIMO-OFDM Channel Estimation Using Convolutional Neural Networks

Snehasish Biswas[1], Sumon Pramanik[1]

[1]*Department of Electronics and Communication Engineering, JIS School Polytechnic, West Bengal, INDIA — snehasishbiswas1611@gmail.com, sumonpramanik2005@gmail.com*

Abstract—Multiple Input Multiple Output-Orthogonal Frequency Division Multiplexing (MIMO-OFDM) has become a fundamental transmission technique for modern wireless communication systems due to its high spectral efficiency and robustness against multipath fading. Accurate channel estimation is essential for reliable data transmission in MIMO-OFDM systems. Traditional estimation methods such as Least Squares (LS) and Minimum Mean Square Error (MMSE) suffer from performance degradation under low Signal-to-Noise Ratio (SNR) conditions and rapidly varying channels. Recent advancements in deep learning have demonstrated promising capabilities in wireless signal processing tasks. This paper proposes an optimized Convolutional Neural Network (CNN)-based channel estimation framework for MIMO-OFDM systems. The proposed model learns channel characteristics directly from received pilot signals and estimates channel coefficients with improved accuracy. Simulation results demonstrate that the CNN-based estimator significantly outperforms conventional LS and MMSE estimators in terms of Mean Square Error (MSE) and Bit Error Rate (BER). The proposed approach provides enhanced robustness in dynamic wireless environments and is suitable for future 5G and 6G communication systems.

Keywords—MIMO-OFDM, Channel Estimation, Deep Learning, Convolutional Neural Networks, Wireless Communications, 5G, 6G, BER, MSE.

I. INTRODUCTION

II. RELATED WORK

Traditional channel estimation approaches have been extensively studied over the last two decades. LS estimation is simple but highly sensitive to noise. MMSE estimation provides better performance but requires prior channel statistics and matrix inversion, resulting in high computational complexity. Recent studies have introduced machine learning-based channel estimation methods:

- Ye et al. applied deep neural networks for OFDM signal detection.
- Soltani et al. proposed CNN architectures for wireless channel estimation.
- Wen et al. investigated deep learning for massive MIMO systems.
- Huang et al. explored hybrid CNN-LSTM channel prediction techniques.

These studies indicate that CNNs can efficiently learn channel structures and outperform conventional methods.

III. PROPOSED METHODOLOGY

A MIMO-OFDM system consists of multiple transmit and receive antennas. Signal Model The received signal can be represented as: genui{“math*block*widget*always*prefetch_v2”:{“content”:”Y = HX + N”}} Where:

- Y = Received signal vector
- H = Channel matrix
- X = Transmitted signal vector
- N = Additive White Gaussian Noise (AWGN)

For OFDM transmission: y(k)=H(k)x(k)+n(k) where k denotes the subcarrier index. The objective is to estimate H(k) accurately using pilot symbols.

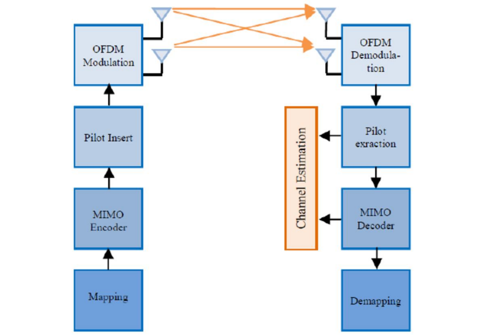


Fig. 1. MIMO-OFDM Communication Architecture

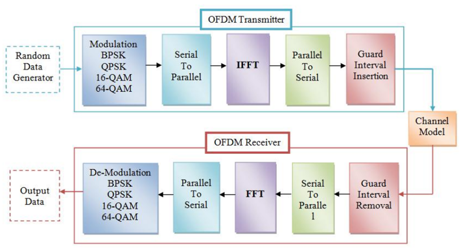


Fig. 2.

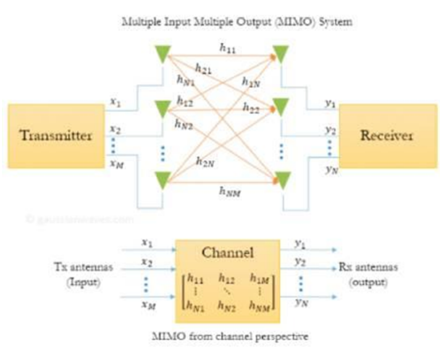


Fig. 3.

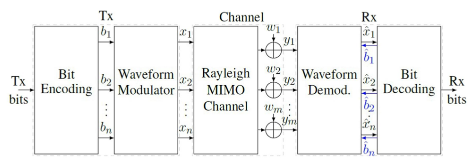


Fig. 4.

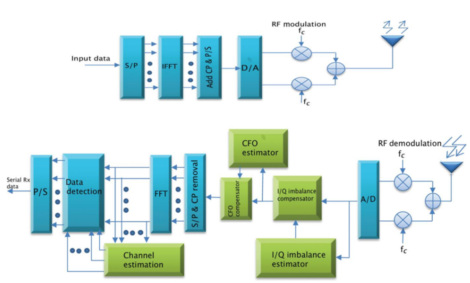


Fig. 5. General architecture of a MIMO-OFDM communication system.

IV. CONVENTIONAL CHANNEL ESTIMATION TECHNIQUES

4.1 Least Squares (LS) LS estimation minimizes the squared error between received and transmitted pilot signals. Formula: \hat{H}_{LS}=Y/X Advantages:

- Low complexity
- Easy implementation

Disadvantages:

- Poor performance at low SNR

4.2 MMSE Estimation MMSE minimizes the mean square estimation error. Advantages:

- Better accuracy

Disadvantages:

- High computational complexity
- Requires channel statistics

V. PROPOSED CNN-BASED CHANNEL ESTIMATION FRAMEWORK

5.1 Framework Overview The proposed framework uses a CNN to estimate wireless channel coefficients directly from pilot symbols. Input:

- Received pilot signals
- Real and imaginary channel components

Output:

- Estimated channel matrix

The CNN automatically learns:

- Spatial correlations
- Frequency-domain characteristics
- Noise patterns

Architecture The proposed CNN consists of:

1. Input Layer
2. Convolution Layer 1 (32 filters)
3. ReLU Activation
4. Convolution Layer 2 (64 filters)
5. Max Pooling Layer
6. Fully Connected Layer
7. Output Layer

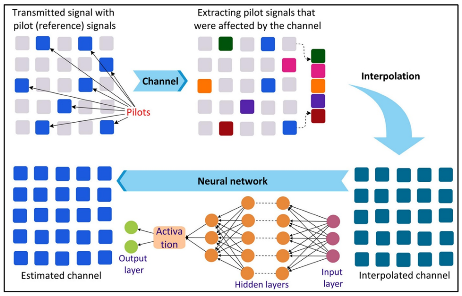


Fig. 6. Proposed CNN Channel Estimator

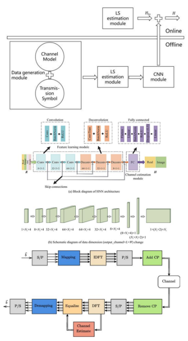


Fig. 7. CNN architecture used for channel estimation.

5.2 Training Procedure Dataset generation steps:

1. Generate random bit streams.
2. Perform OFDM modulation.
3. Simulate Rayleigh fading channels.
4. Add AWGN noise.
5. Store received pilots and actual channel coefficients.

Loss Function:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(H_i-\hat{H}_i)^2 \quad (1)$$

Optimizer:

- Adam Optimizer

Training Parameters:

TABLE V

Parameter	Value
Epochs	100
Batch Size	128
Learning Rate	0.001
Optimizer	Adam

VI. SIMULATION SETUP

Simulation parameters used in the study are shown below.

TABLE VI

Parameter	Value
OFDM Subcarriers	128
Cyclic Prefix	16
Modulation	QPSK
Transmit Antennas	4
Receive Antennas	4
Channel Model	Rayleigh Fading
SNR Range	0–30 dB
CNN Epochs	100

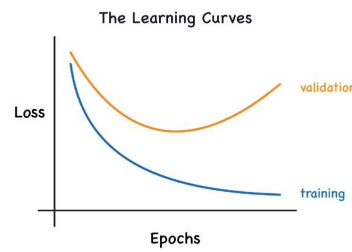


Fig. 8. Training and Validation Process

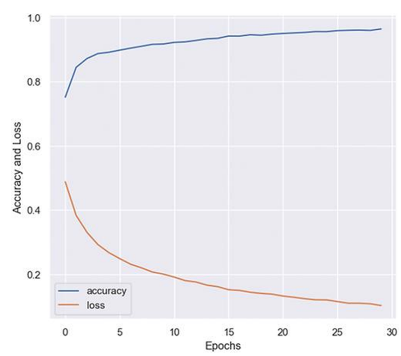


Fig. 9. Accuracy and Loss

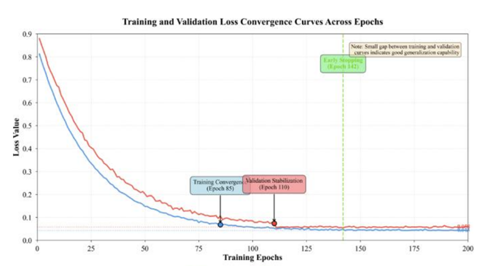


Fig. 10. Training and validation Loss convergence Curves across Epochs

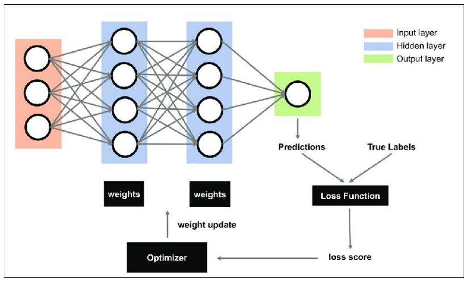


Fig. 11.

VII. RESULTS AND DISCUSSION

7.1 Mean Square Error Performance The CNN estimator demonstrates significantly lower MSE compared to LS and MMSE.

TABLE VII — MSE COMPARISON

SNR (dB)	LS	MMSE	CNN
0	0.290	0.180	0.110
5	0.180	0.110	0.060
10	0.100	0.060	0.025
15	0.050	0.030	0.010
20	0.020	0.012	0.004
25	0.010	0.006	0.002
30	0.005	0.003	0.001

Analysis The CNN model consistently achieves lower estimation errors because it learns nonlinear channel characteristics that traditional estimators cannot capture effectively. 7.2 BER Performance The CNN-based estimator also improves BER performance.

TABLE VIII — BER COMPARISON

SNR (dB)	LS	MMSE	CNN
0	0.42	0.34	0.25
5	0.28	0.20	0.12
10	0.16	0.10	0.05
15	0.08	0.04	0.015
20	0.03	0.015	0.004

The proposed CNN estimator provides superior BER performance across all SNR levels.

BER and MSE Performance Comparison

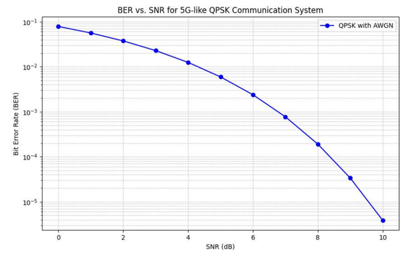
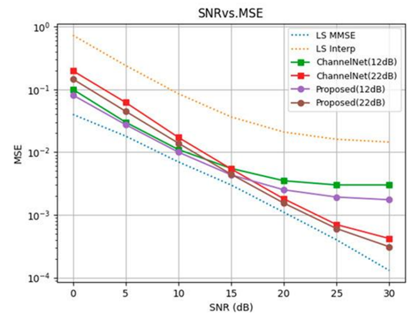


Fig. 12. BER and MSE Performance Comparison



(b)

Fig. 13. SNR VS MSE

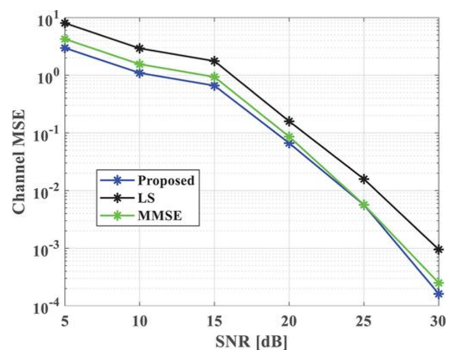


Fig. 14.

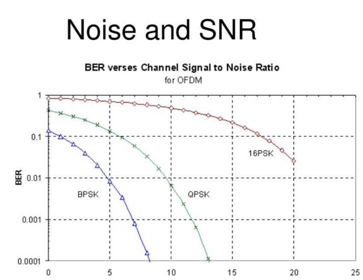


Fig. 15. Performance comparison of LS, MMSE, and CNN estimators.

VIII. ADVANTAGES OF CNN-BASED CHANNEL ESTIMATION

The proposed approach offers several benefits:

- Improved estimation accuracy
- Reduced BER
- Robust performance in low SNR environments
- Adaptability to dynamic channels
- Scalability for massive MIMO systems
- Suitable for 5G and future 6G networks

IX. FUTURE RESEARCH DIRECTIONS

Future work may focus on:

- CNN-LSTM hybrid models
- Transformer-based channel estimation
- Federated learning for distributed communication systems
- Intelligent reflecting surface (IRS)-assisted MIMO networks
- Deep reinforcement learning for adaptive pilot allocation

X. CONCLUSION

This paper presented an optimized CNN-based channel estimation framework for MIMO-OFDM systems. The proposed model leverages deep learning techniques to learn channel characteristics directly from received pilot signals. Simulation results demonstrate substantial improvements over conventional LS and MMSE estimators in terms of MSE and BER. The CNN estimator exhibits strong robustness under noisy and dynamic channel conditions, making it a promising solution for future wireless communication technologies, including 5G, beyond-5G, and 6G networks.

REFERENCES

[1]S. Haykin, *Communication Systems*. Wiley, 2019.

[2]A. Goldsmith, *Wireless Communications*. Cambridge University Press, 2005.

[3]T. S. Rappaport, *Communications*. Prentice Hall.

[4]D. Tse and P. Viswanath, "Fundamentals of Wireless Communication," *Cambridge University Press*, 2005.

[5]Y. S. Cho et al., *MIMO-OFDM Wireless Communications with MATLAB*. Wiley, 2010.

[6]O. Edfors et al., *Adaptive and Iterative Signal Processing in Communications*. Cambridge, 2006.

[7]J. Choi, "Adaptive and Iterative Signal Processing in Communications," *Cambridge*, 006.