Enhanced OFDM Signal Detection via Hybrid MMSE and Deep Neural Network Architecture

1st Muhammad Usman
Dept. of Information and Communication Engineering and Dept. of Convergence Engineering for Intelligent Drone, Sejong University
Seoul, Republic of Korea
m_usman@sju.ac.kr

2nd Iqra Hameed
Dept. of Information and Communication Engineering and Dept. of Convergence Engineering for Intelligent Drone, Sejong University
Seoul, Republic of Korea
iqrahameed@sejong.ac.kr

3rd Md Habibur Rahman
Dept. of Information and Communication Engineering and Dept. of Convergence Engineering for Intelligent Drone, Sejong University
Seoul, Republic of Korea
habibur@sju.ac.kr

4th Mohammad Abrar Shakil Sejan
Dept. of Information and Communication Engineering and Dept. of Convergence Engineering for Intelligent Drone, Sejong University
Seoul, Republic of Korea
sejan@sejong.ac.kr

5th Md Abdul Aziz
Dept. of Information and Communication Engineering and Dept. of Convergence Engineering for Intelligent Drone, Sejong University
Seoul, Republic of Korea
aziz@sju.ac.kr

6th Hyoung-Kyu Song
Dept. of Information and Communication Engineering and Dept. of Convergence Engineering for Intelligent Drone, Sejong University
Seoul, Republic of Korea
songhk@sejong.ac.kr

***Abstract*—In wireless systems, orthogonal frequency-division multiplexing (OFDM) is often used because it can handle channel fading well. To detect the transmitted signals, receivers usually use methods like least squares (LS) or minimum mean square error (MMSE). MMSE gives better results than LS, but it still makes errors, especially when there is noise. In this work, we improve signal detection by combining MMSE with a deep neural network (DNN). First, we use MMSE to estimate the received symbols. Then, we use a DNN to refine these estimates and reduce errors. The DNN takes the MMSE output as input and learns to predict the original signal more accurately. We test our method using both binary phase-shift keying (BPSK) and quadrature phase shift keying (QPSK) modulation in an OFDM system over different signal-to-noise ratios (SNRs). Our results show that the MMSE + DNN approach gives lower bit error rates (BER) than using LS or MMSE alone. This shows that deep learning (DL) can help improve signal detection when used with traditional methods.**

***Index Terms*—MMSE estimation, Deep Neural Networks (DNNs), signal detection, and OFDM systems**

I. INTRODUCTION

Reliable signal detection is a critical task in modern wireless communication systems. Among these systems, orthogonal frequency-division multiplexing (OFDM) has become widely adopted due to its robustness against multipath fading and its spectral efficiency [1]. However, the performance of OFDM heavily depends on accurate detection of transmitted symbols at the receiver side, especially in the presence of noise and fading [2]. In conventional receivers, detection typically follows channel estimation using methods such as least squares (LS) or minimum mean square error (MMSE) [3]. LS estimation is simple and does not rely on channel statistics, but it often suffers from poor performance under noisy conditions. MMSE significantly improves over LS by exploiting noise variance and statistical channel knowledge [4] [5]. For many years, MMSE has been the standard approach to enhance LS and enable more accurate signal recovery.

Recently, deep learning (DL) has gained attention for signal processing tasks, including channel estimation and signal detection [6]. Researchers have shown that neural networks can learn complex mappings and outperform traditional algorithms in challenging scenarios. For instance, Ye et al. [3] used a deep neural network (DNN) to jointly perform channel estimation and detection in OFDM systems. Other works such as [7] and [8] introduced end-to-end neural detection architectures or cascaded networks that learn corrections over conventional estimators like Zero-Forcing or MMSE.

Despite these advances, many DL based detectors ignore the useful structure that conventional methods provide [7]. Instead of replacing MMSE entirely, we believe that MMSE can offer a strong starting point for learning-based refinement. In this work, we integrate MMSE equalization with a DNN that enhances symbol estimates in a data-driven manner. Our approach first uses MMSE to equalize the received signal and then applies a fully connected DNN to improve the output. The DNN learns to denoise and correct the MMSE output, leading to

This research was supported by Basic Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education(2020R1A6A1A03038540), by Institute of Information & communications Technology Planning & Evaluation (IITP) under the metaverse support program to nurture the best talents (IITP-2025-RS-2023-00254529) grant funded by the Korea government(MSIT), and by the IITP(Institute of Information & Communications Technology Planning & Evaluation)-ITRC(Information Technology Research Center) grant funded by the Korea government(Ministry of Science and ICT)(IITP-2024-RS-2024-00437191)

lower bit error rates (BER).

We implement and test this system in an OFDM simulation framework using quadrature phase shift keying (QPSK) modulation and frequency-selective fading. We compare various DNN architectures using different activation functions and optimizers. Our results show that the MMSE+DNN hybrid approach consistently outperforms both MMSE and LS detectors across a wide range of SNR values. The DNN acts as a nonlinear post-equalizer that effectively learns the mapping between noisy estimates and clean symbols. This work contributes to the growing body of literature on combining model-based and data-driven methods in wireless communication. Rather than replacing traditional techniques, we show that DL can complement and enhance them when properly integrated.

II. SYSTEM MODEL

In this section, we present the system model as shown in Fig. 1. for the simulated OFDM transmission chain, incorporating QPSK modulation, frequency-selective fading, MMSE equalization, and a DNN-based symbol refinement stage.

A. OFDM Transmission

We consider a single-antenna OFDM system with N subcarriers. Each OFDM frame comprises N complex-valued QPSK symbols generated from $2N$ random bits. The baseband transmitted OFDM signal is obtained by applying an N-point inverse fast fourier transform (IFFT) to the modulated symbol vector $\boldsymbol{x} \in \mathbb{C}^N$, resulting in the time-domain vector $\boldsymbol{s} = \text{IFFT}(\boldsymbol{x})$. To mitigate inter-symbol interference (ISI), a cyclic prefix (CP) of length L_{cp} is appended to each OFDM symbol, forming the transmit signal $\tilde{\boldsymbol{s}} \in \mathbb{C}^{N+L_{\text{cp}}}$.

B. Channel Model

The wireless channel is modeled as a frequency-selective fading channel with complex Gaussian coefficients. In our simulation, the frequency-domain channel is assumed flat per subcarrier and modeled as:

$$\boldsymbol{h} = [h_1, h_2, \dots, h_N]^\top, \quad h_k \sim \mathcal{CN}(0,1), \quad k = 1, \dots, N. \tag{1}$$

The channel is constant over the duration of each OFDM frame and perfectly known at the receiver for the MMSE equalizer.

C. Receiver Model and Channel Equalization

At the receiver, the CP is removed and an fast fourier transform (FFT) is applied to recover the received frequency-domain symbol vector:

$$\boldsymbol{y} = \text{FFT}(\boldsymbol{r}) \tag{2}$$

where $\boldsymbol{r} \in \mathbb{C}^N$ is the received OFDM symbol after CP removal. The received vector is modeled as:

$$\boldsymbol{y} = \boldsymbol{h} \odot \boldsymbol{x} + \boldsymbol{n} \tag{3}$$

where $\odot$ denotes element-wise multiplication, and $\boldsymbol{n} \sim \mathcal{CN}(0, \sigma^2 \boldsymbol{I})$ is the complex additive white Gaussian noise (AWGN) vector. We first estimate the transmitted symbol vector $\boldsymbol{x}$ using the MMSE equalizer [9]:

$$\hat{x}_k^{\text{MMSE}} = \frac{H_k^*}{|H_k|^2 + \sigma^2} y_k, \quad k = 1, \dots, N \tag{4}$$

After applying the MMSE equalizer to obtain an initial estimate of the transmitted symbols, we enhance the detection performance using a DNN trained to refine symbol estimates and suppress residual noise and distortion.

III. HYBRID MMSE AND DNN-BASED ESTIMATION AND DETECTION

A. DNN-Based Signal Detection Enhancement

To further refine the MMSE output, we apply a fully connected feedforward DNN. The DNN is trained to map the imperfect MMSE estimates $\hat{x}_k^{\text{MMSE}}$ to the original transmitted symbols x_k. Each input sample to the DNN consists of the real and imaginary parts of the MMSE estimate:

$$\boldsymbol{u}_k = \left[\Re\left(\hat{x}_k^{\text{MMSE}}\right), \Im\left(\hat{x}_k^{\text{MMSE}}\right)\right], \tag{5}$$

and the corresponding output is trained to match the real and imaginary parts of the true QPSK symbol:

$$\boldsymbol{v}_k = \left[\Re(x_k), \Im(x_k)\right]. \tag{6}$$

B. Deep Neural Network Architecture

In this section, we discuss DNN models. DL is a modern technique widely used in communication systems. The DNN consists of multiple hidden layers that enable it to make accurate predictions. Each layer contains multiple neurons. Increasing the number of hidden layers can improve the accuracy of the results.The output is calculated by summing the weighted outputs of neurons in each layer, which helps the model predict a non-linear function. Common non-linear activation functions include ReLU, Sigmoid, and GELU. The **ReLU (rectified linear unit)** function is defined by the output range $[0, \infty)$, and its formula is given by:

$$\text{ReLU}(z) = \max(0, z) \tag{7}$$

The **sigmoid activation function** is often used at the output layer because it produces values in the range of

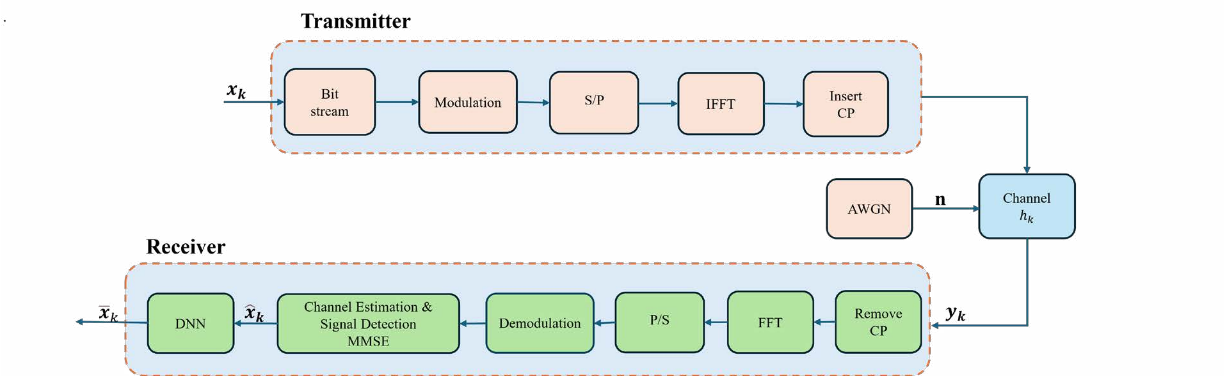

Fig. 1: Block diagram of the OFDM system with neural network-based receiver.

0 to 1, which is suitable for many applications such as binary classification. The sigmoid function is defined as:

$$\phi\left(z_i^{(l)}\right) = \frac{1}{1+e^{-z_i^{(l)}}} \tag{8}$$

where $z_i^{(l)}$ represents the output vector of the i-th sample at layer l of the DNN, and $\phi(\cdot)$ denotes a nonlinear activation function. The model uses the *Adam* optimizer, which updates the model's weights (parameters) to minimize the loss function during training.The MSE loss function $J(\boldsymbol{\theta})$is used to guide the DL model toward optimal performance, particularly under complex Gaussian distributed channels and noise. It also serves as an effective metric for evaluating how closely the estimated bit stream matches the transmitted bit stream. The MSE loss function is defined as:

$$J_{\text{MSE}}(\boldsymbol{\theta}) = \frac{1}{D}\sum_{k=1}^{D}(v_k - z_k)^2 \tag{9}$$

Here, $J_{\text{MSE}}(\boldsymbol{\theta})$, v_k, and z_k represent the MSE loss function, the transmitted bits, and the predicted bits generated by the DL model, respectively. Therefore, the output of the network, denoted as z_k, is a cascade of nonlinear transformations applied to the input data I, which can be mathematically expressed as:

$$z_k = f(u, \boldsymbol{\theta}) = f^{(L-1)}\left(f^{(L-2)}\left(\cdots f^{(1)}(u)\right)\right) \tag{10}$$

Here, L represents the total number of layers in the network, and $\boldsymbol{\theta}$ denotes the weights (parameters) of the neural network. These parameters correspond to the weights assigned to the neurons and must be optimized prior to online deployment. Typically, the optimal weights are learned using a training dataset with known target outputs.

C. DNN Model Training

The models are trained by treating OFDM modulation and wireless channels as black boxes. Traditionally, researchers have developed various channel models that accurately represent real-world channels based on statistical properties. Using these models, training data can be generated through simulation. In each simulation, a random data sequence is first generated to represent the transmitted symbols, and an OFDM frame is constructed by inserting a sequence of pilot symbols. These pilot symbols must remain fixed during both training and deployment. The current random channel is then simulated according to the selected channel model. The received OFDM signal is obtained by passing the constructed OFDM frame through the simulated channel, which introduces channel distortion and noise.The received signal is first processed using the LS estimation technique, and the results are evaluated. Next, the MMSE estimation method is applied, and its performance is also assessed. A comparison between LS and MMSE shows that MMSE provides improved results. These MMSE estimates are then used as inputs to the DL model. In this work, we propose a hybrid receiver that combines MMSE equalization with a DNN to improve symbol detection using data-driven learning. First, the received signal is equalized using MMSE. Then, a fully connected DNN refines the symbol estimates to reduce remaining errors. The DNN is trained to minimize the difference between its output and the original transmitted data. The neural network used in this system has five layers, including three hidden layers. For binary phase-shift keying (BPSK) modulation, the hidden layers contain 64, 64, and 1 neuron(s), respectively. For QPSK modulation, the layers have 128, 64, and 2 neurons. The input to the model includes the real and imaginary parts of two consecutive OFDM blocks, which contain both pilot and data symbols. To handle the input efficiently, every 16 bits of transmitted data are grouped and processed by a separate trained model. The outputs from these models are then combined to produce the final result. By learning to clean and correct the MMSE estimates, the DNN effectively BER.

IV. SIMULATION RESULTS

The simulation investigates the BER performance of OFDM systems under BPSK and QPSK modulation using three channel estimation techniques: LS, MMSE, and MMSE enhanced with a DNN employing ReLU activation. The experiments were conducted over a range of SNR values from 10 dB to 30 dB with 10 Monte Carlo runs for each point. The results clearly demonstrate that MMSE outperforms LS in both BPSK and QPSK scenarios due to its superior noise suppression capabilities. Moreover, integrating a DNN with MMSE further improves performance, especially at higher SNR levels. For instance, at 30 dB SNR, the BER for BPSK reduces from approximately 1.5×10^{-4} (MMSE) to below 1.0×10^{-4} with MMSE+DNN. Similarly, QPSK shows a reduction from around 9×10^{-4} (MMSE) to 6×10^{-4} using MMSE+DNN. These results validate that the combination of MMSE estimation followed by a learned DNN regression stage leads to a more accurate symbol detection, thus improving the system's overall reliability. The BER performance trends for all methods are illustrated in Fig. 2.

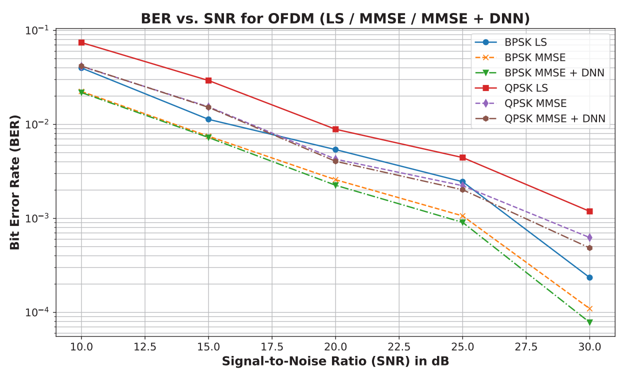

Fig. 2: BER vs. SNR for OFDM using LS, MMSE, and MMSE+DNN under BPSK and QPSK.

A. Effect of CP Length and DNN Activations on BER Performance in OFDM

The performance evaluation of the QPSK-OFDM system was conducted under two different CP lengths, namely CP = 16 and CP = 32, to assess the impact of channel estimation techniques and CP duration on BER. As shown in Fig. 3, the LS estimator yields the highest BER in both CP scenarios, indicating its vulnerability to noise and its lack of statistical noise modeling. Although it performs adequately at higher SNR values, the BER remains significantly higher compared to MMSE and MMSE+DNN. In contrast, the MMSE estimator shows considerable improvement by utilizing the noise variance in its formulation, offering lower BER across all SNRs. Additionally, the MMSE performance is further improved when the CP is extended from 16 to 32, suggesting that a longer CP helps reduce ISI and enhances channel estimation accuracy.

The most notable improvement is observed when MMSE is followed by a DNN. This hybrid approach leverages the nonlinear learning capabilities of the neural network to refine the symbol estimates obtained from MMSE, correcting residual estimation errors. As a result, the MMSE+DNN model consistently achieves the lowest BER for all tested SNR values. Particularly at high SNRs, the BER reduction is substantial, confirming the ability of the DNN to approximate the ideal QPSK constellation mapping even in the presence of channel distortion. Furthermore, the comparison between CP=16 and CP=32 shows that the longer CP results in slightly better performance for all three methods, particularly for MMSE and MMSE+DNN, as it effectively mitigates ISI. In summary, the simulation results confirm that the MMSE+DNN model with CP = 32 provides the best overall performance in terms of BER. It demonstrates the strength of combining statistical estimation with data-driven deep learning techniques. The results also highlight the importance of CP length, showing that increasing the CP improves robustness against ISI at the cost of spectral efficiency. These findings, illustrated in Fig. 3, support the integration of machine learning-based post-equalization in OFDM systems and suggest that careful tuning of physical layer parameters such as CP length can further enhance system reliability in practical communication scenarios.

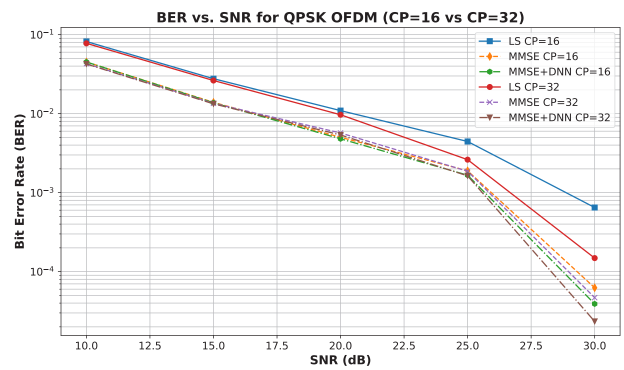

Fig. 3: BER vs. SNR for QPSK-OFDM with LS, MMSE, and MMSE+DNN under CP lengths 16 and 32.

V. CONCLUSION

In conclusion, this paper presented a DL based approach for signal detection in OFDM systems by combining MMSE estimation with DNN. First, we applied the MMSE technique to obtain more accurate signal estimates. These results were then used as input to the DNN model, which was trained to predict the transmitted symbols. This hybrid MMSE-DNN method showed very good performance and achieved significantly better results than traditional LS and MMSE techniques and the DNN model alone. Simulation results confirm that our deep learning model performs especially well in the presence of severe distortion and interference. For future work, we plan to conduct more detailed evaluations and use real wireless channel data to retrain or fine-tune the model. This will further improve its performance in practical scenarios and support its deployment in real-world communication systems.

REFERENCES

[1] D. Hasini and K. R. L. Reddy, "Channel estimation and signal detection in ofdm systems using deep learning," in *2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS)*, vol. 1, 2023, pp. 1337–1340.

[2] Y. Zhang and H. Liu, "Impact of time-selective fading on the performance of quasi-orthogonal space-time-coded ofdm systems," *IEEE Transactions on Communications*, vol. 54, no. 2, pp. 251–260, 2006.

[3] H. Ye, G. Y. Li, and B.-H. Juang, "Power of deep learning for channel estimation and signal detection in ofdm systems," *IEEE Wireless Communications Letters*, vol. 7, no. 1, pp. 114–117, 2018.

[4] M. K. Ozdemir and H. Arslan, "Channel estimation for wireless ofdm systems," *IEEE Communications Surveys Tutorials*, vol. 9, no. 2, pp. 18–48, Second 2007.

[5] J.-J. van de Beek, O. Edfors, M. Sandell, S. Wilson, and P. Borjesson, "On channel estimation in ofdm systems," in *1995 IEEE 45th Vehicular Technology Conference. Countdown to the Wireless Twenty-First Century*, vol. 2, 1995, pp. 815–819 vol.2.

[6] M. Khani, M. Alizadeh, J. Hoydis, and P. Fleming, "Adaptive neural signal detection for massive mimo," *IEEE Transactions on Wireless Communications*, vol. 19, no. 8, pp. 5635–5648, 2020.

[7] K. Albagami, N. Van Huynh, and G. Ye Li, "A universal deep neural network for signal detection in wireless communication systems," in *2024 IEEE International Conference on Machine Learning for Communication and Networking (ICMLCN)*, 2024, pp. 1–6.

[8] Q. Huang, C. Zhao, M. Jiang, X. Li, and J. Liang, "Cascade-net: a new deep learning architecture for ofdm detection," 2018. [Online]. Available: https://arxiv.org/abs/1812.00023

[9] W. Y. Y. C. G. K. Yong Soo Cho, Jaekwon Kim, *MIMO-OFDM Wireless Communications with MATLAB*. John Wiley & Sons, 2010.