Deep Learning-Based Channel State Estimation Approach for OFDM System

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***Abstract*—This paper introduces a hybrid, low-complexity channel estimation scheme that integrates pilot-aided channel estimation with Machine Learning (ML) to obtain the Channel State Information (CSI) for an Orthogonal Frequency Division Multiplexing (OFDM) system. The proposed method eliminates the need for channel statistics at data subcarrier positions, while still achieving performance comparable to that of classical pilot-aided channel estimation schemes. The CSI is fully determined by first obtaining channel coefficients at subcarrier positions where pilot symbols are transmitted; these coefficients are then used to obtain channel coefficients at data subcarrier positions. Thus, in the proposed method, pilot symbols are inserted among data symbols. The pilot symbols are used to estimate channel coefficients at pilot subcarrier positions using the Linear Minimum-Mean-Square-Error (LMMSE) estimator. The estimated coefficients are then used as an input to a Feed-Forward Neural Network (FFNN). The FFNN is trained to learn and capture channel characteristics from the estimated coefficients at subcarrier positions where pilot symbols are transmitted. The trained neural network can predict channel coefficients at data subcarrier positions where pilot information is unavailable. In some conventional pilot-aided channel estimation schemes, the cross-correlation matrix of channel coefficients at the positions of data subcarriers is an essential parameter for estimating channel coefficients at those positions. However, this statistical information may not be available. In the proposed scheme, channel coefficients at data subcarrier positions can be predicted using a trained FFNN, without requiring statistical information about coefficients at those positions. Also, the proposed method avoids high computational complexity in statistical-based channel estimation methods. For example, the computational complexity of the classical LMMSE mainly stems from the matrix inversion and multiplication operations it involves. Computer simulations in MATLAB show that the Mean-Squared Error (MSE) of the proposed estimation method can achieve performance comparable to classical systems, especially at low Signal-to-Noise Ratio (SNR).**

***Index Terms*—dataset, Feed-Forward Neural Network (FFNN), machine learning, mean squared error, neural network, pilot symbols, training**

I. INTRODUCTION

Orthogonal Frequency Division Multiplexing (OFDM) is a multicarrier transmission technique widely used for broadband wireless communication due to its robustness against inter-symbol interference. In recent decades, OFDM technology has been adopted in many wireless standards, such as the worldwide interoperability for Microwave Access (WiMAX), Long-Term Evolution (LTE) cellular systems, and 5G cellular communications. With the emergence of the Sixth-Generation (6G) wireless networks and beyond, OFDM technology is expected to play a critical role in ensuring dependable connectivity in an increasingly complex transmission environment. Even though the fundamental requirements for the next 6th generation technology are still under research and development, the versatility of OFDM and adaptability allow it to meet the needs of numerous emerging applications, including Artificial Intelligence (AI)-based applications, the Internet of Things (IoT) applications, 3D communications such as three-dimension visualization and modeling, 3D printing, and holography [1–4].

Channel estimation is crucial for accurately detecting transmitted symbols at the receiver side for an OFDM wireless communication system operating in a multipath environment. For this purpose, a sequence of pilot symbols containing no information can be inserted among data symbols to track the variations in the fading channel [5–10]. The Least-Squares (LS) and the Linear Minimum Mean-Squared Error (LMMSE) estimation rules are commonly used in pilot-aided channel estimation techniques. When channel statistics are known, employing the LMMSE can significantly reduce the estimation error. Theoretically, the LMMSE estimator is the optimal solution for minimizing the Mean Squared Error (MSE) of the channel estimator. Thus, the channel estimation scheme with LMMSE outperforms its LSE counterpart [7–10]. Furthermore, the performance of the LSE estimator is greatly affected by noise [10]. Although LMMSE outperforms LSE, the computational complexity of channel estimation with LMMSE is higher than that with LSE. Singular Value Decomposition (SVD) can reduce the computational complexity of the LMMSE estimator, but at the cost of increasing performance attenuation [11]. In addition to the noise power, LMMSE includes a channel correlation matrix that relies solely on channel statistical information. However, in many systems, the receiver cannot access these statistical characteristics [12].

Over the past few years, the potential of Artificial Intelligence (AI), especially Machine Learning (ML), has impressed many researchers from various fields. It has shown promise in multiple fields, including the industrial,

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medical, educational, agricultural, communications, and other vital sectors. In wireless communication, machine learning can be used to enhance the performance of specific functions, such as symbol recovery, demodulation, channel equalization, channel estimation, and more. It can also revolutionize the field by replacing traditional signal processing units with ML neural networks that achieve the optimal overall performance required of the communications system [13]. Many studies have examined the use of artificial intelligence in channel calculations, either by combining it with classical methods that rely on channel statistical information or by using it alone without that statistical information [14–22].

A deep learning approach that utilizes known channel characteristics at the pilot location for channel estimation was presented in [14]. The time-frequency response is treated as a two-dimensional image using deep learning techniques like Image Restoration (IR) and image Super-Resolution (SR). Channel parameters at pilot locations are low-resolution images. The proposed scheme demonstrates estimation performance comparable to that of classical estimation systems based on the Minimum Mean Square Error (MMSE) method. A deep learning scheme with a non-uniform pilot design scheme in [15] estimated the channel response and defined the optimal pilot pattern. The suggested method first identifies the most valuable pilots in the time-frequency grid using a concrete autoencoder and then trains ChannelNet on the selected pilots [15]. Without prior knowledge of channel statistics or models, the suggested channel estimation system described in [16] can dynamically estimate the time-selective fading channels' Channel State Information (CSI).

Yang *et al*. [17] proposed a deep learning-based channel estimation approach for a communication system operating over time-frequency-selective fading channels. The approach has significant practical implications, as it can predict channel fluctuations based on prior channel estimations. Furthermore, the DNN implicitly learns the temporal correlation of time-varying channels from previous channel estimates, thereby improving channel estimation accuracy. This is particularly critical in high-mobility scenarios, where channel estimation can be challenging due to multi-path fading, rapid time fluctuations, and non-stationary characteristics. A deep learning-based channel estimation approach for an OFDM system is introduced in [18]. The proposed scheme utilizes an Initial Denoise Network (IDN) and a Resolution Enhancement Network (REN). The IDN uses a unique two-stage noise reduction structure, while the REN consists solely of fully connected layers.

Recent DL-based channel estimation studies have concentrated on its transformative role in modern wireless communication systems, especially for 5G and beyond [19–25]. Various studies have shown that DL-based channel estimation models, such as CNNs or RNN-based schemes, significantly outperform traditional LS and MMSE estimators by efficiently handling complex, dynamic, and doubly selective channels [19, 20]. Several works, such as one by Lv and Luo [20], have presented comprehensive reviews on data-driven and model-driven approaches, while other works have explored specialized scenarios like Intelligent Reflecting Surfaces (IRS) assisted Multiple-Input Single-Output (MISO) systems [21], and ultraviolet Multiple-Input and Multiple-Output (MIMO) links using CNN-attention hybrids. The high-mobility environment has motivated proposals based on Bidirectional Recurrent Neural Networks (Bi-RNN) and Gated Recurrent Unit (GRU) to mitigate the Doppler and multipath effects with lower complexity [22]. Furthermore, several recent surveys emphasize that deep learning can be integrated into massive MIMO and RIS-aided systems by overcoming challenges due to pilot overhead, hardware constraints, and non-stationary conditions [23, 24]. In general, these studies confirm that deep learning provides robust, scalable, and accurate channel estimation, opening the door for intelligent physical-layer designs in next-generation networks.

Qasaymeh *et al*. [26] investigated an intelligent receiver for frequency-hopping systems from the perspective of performance and reliability enhancement. The proposed DL-enabled intelligent receiver enhances signal detection and adaptability in dynamic environments. Whereas Qasaymeh [27] introduced machine-learning-based channel estimation methods that do not employ traditional statistical models, precise channel prediction is ensured independent of changing conditions. These articles collectively address the effectiveness of ML-based approaches to combat non-stationary channel and interference problems in frequency-hopping communications.

Channel estimation in high-mobility OFDM systems is a challenging task due to fast time variations and Doppler shift [28, 29]. Ai *et al*. in [28] addressed this challenge by using a Super-Resolution Convolutional Neural Network (SRCNN) to extract dynamic channel features for MIMO-OFDM systems in a high-speed mobile environment. A different approach for channel estimation with a DL-based technique was proposed in [29] for an OFDM system operating in a high-speed railway. The proposed technique uses a one-dimensional convolutional neural network (1-D CNN) to reduce the MSE of the Least Squares (LS) estimator. However, this approach is applicable only to OFDM systems that utilize full pilot symbols, which results in reduced transmission efficiency and increased computational complexity [29].

Makhlasawy *et al*. [30] proposed a Long Short-Term Memory (LSTM) based Recurrent Neural Network (RNN) channel estimation scheme that combines interference cancellation and channel estimation. The proposed scheme significantly enhances the system's performance and reduces its Bit Error Rate (BER). Humse and Anjanappa [31] proposed a method that employs a Cascaded Convolutional Neural Network (Cs-CNN) to estimate the channel response. Their experimental results show that their proposed method outperforms traditional channel estimation methods, including LMMSE and LS-based methods.

In this paper, we propose a hybrid, low-complexity channel estimation scheme that integrates pilot-aided channel estimation with Machine Learning (ML) eliminating the need for channel statistics at data subcarriers while achieving performance matching that of classical pilot-aided channel estimation schemes. In the proposed scheme, the CSI can be completely determined in two steps. First, the channel coefficients are estimated at selected subcarrier positions by sending pilot symbols that convey no information. The Linear Minimum-Mean-Squared-Error (LMMSE) estimator employs these symbols to estimate channel coefficients at pilot subcarrier positions. Second, the estimated channel coefficients at pilot subcarrier positions are fed to the FFNN. The FFNN is trained to learn and capture channel characteristics. The trained neural network can be used to predict channel coefficients at data subcarrier positions where pilot information is unavailable. Thus, the main task of the FFNN is to learn the channel characteristics from pilot-based estimates to accurately predict channel coefficients at data subcarrier positions. The proposed scheme offers an alternative to conventional statistical-based methods that require channel coefficient statistics at data subcarrier positions; however, such statistics may not be available. Also, the proposed model avoids the high computational complexity of statistical-based channel estimation methods, which arises from matrix inversion and multiplication operations.

The rest of this paper is organized as follows: Section II presents the system model and deep learning approach. Section III discusses the simulation results. Section IV concludes the paper.

II. System Model and Deep Learning-Based Channel Estimation

This section elaborates the pilot aided with deep learning-based channel estimation scheme. The section consists of three parts: the first part introduces the system model, the second part presents channel estimation at pilot positions, and the third part discusses the development of the DL-based channel estimation approach.

A. System Model

Consider an OFDM system with pilot aided and deep learning channel estimation as illustrated in Fig. 1.

As figure shows, the considered system scheme consists of K_p pilot symbols injected among K_d data symbols to form a symbol sequence consisting of K symbols, where $K = K_p + K_d$. In vector format, the composite symbols sequence can be expressed as:

$$\mathbf{s} = (\mathbf{s}_d\mathbf{C}_d + \mathbf{s}_p\mathbf{C}_p)^T, \tag{1}$$

where $(\cdot)^T$ represents a matrix transpose, $\mathbf{s}_d = [s(0), s(1), s(K_d)]$ is a row vector of length K_d and contains the data symbols, $\boldsymbol{s}_p = [p(0), p(1), \cdots, p(K_p)]$ is a pilot symbols row vector of length K_p, and finally $\mathbf{C}_d$, and $\mathbf{C}_p$ represent pilot symbols injection matrix and data symbols insertion matrix, respectively. The matrices $\mathbf{C}_d, \mathbf{C}_p$ can be defined as $\mathbf{C}_d \stackrel{\text{def}}{=} \left(\mathbf{I}_{K_d} \otimes [1\ \ 0]\right)$, and $\mathbf{C}_p \stackrel{\text{def}}{=} (\mathbf{I}_{K_p} \otimes [0\ \ 1])$ with $\otimes$ being the Kronecker tensor product, and $\mathbf{I}_{K_p}$,and $\mathbf{I}_{K_d}$ are identity matrices of size K_p and K_d , respectively. All elements of vector $\mathbf{s}$ were selected from an M-ary phase shift keying (MPSK) constellation. The symbols slot $\mathbf{s}$ of length K is then used to modulate K orthogonal subcarriers using K-points an inverse discrete Fourier transform (IDFT) as $\mathbf{x} = \mathbf{W}^H\mathbf{s}$, where $\mathbf{W}$ is a $K{\times}K$ square IDFT matrix and given in equation (2), $\mathbf{x} = [x(0), x(1),\ x(2), \cdots, x(K-1)]$ is the time-domain OFDM samples, and $(\cdot)^H$ is the matrix Hermitian.

$$\mathbf{W} = \frac{1}{\sqrt{K}}\begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & w & w^2 & \dots & w^{(K-1)} \\ 1 & w^2 & w^4 & \dots & w^{2(K-1)} \\ 1 & w^3 & w^6 & \dots & w^{3(K-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & w^{K-1} & w^{2(K-1)} & \cdots & w^{(K-1)(K-1)} \end{bmatrix} \tag{2}$$

where is $w = e^{-j2\pi/K}$. After adding a cyclic prefix sequence, to prevent block interference, the time-domain samples are filtered processing before transmitted over channel with multipath fading characteristics. At the receiver, the signal is first passed through filtering before sampling at a rate equal to that at the transmitter side. The sampled signal at the receiver can then be presented as:

$$\mathbf{r} = \mathbf{H}\mathbf{x} + \mathbf{n} \tag{3}$$

where $\mathbf{r} = [r(0), r(1), \cdots, r(K-1)]^T$ contains the discrete-time signal samples at the receivers, $\mathbf{n} = [n(0), n(1), \cdots, n(K-1)]^T$ is the time-domain noise vector, and $\mathbf{H}$ represents the time-domain channel matrix. To obtain the frequency-domain representation of equation (3) we apply a K-point DFT as expressed in (4):

$$\mathbf{y} = \mathbf{W}\mathbf{r} = \mathbf{W}\mathbf{H}\mathbf{x} + \mathbf{W}\mathbf{n} = \mathbf{G}\mathbf{s} + \mathbf{z} \tag{4}$$

where $\mathbf{y}$ is the frequency-domain version of $\mathbf{r}$, $\mathbf{G} = \mathbf{W}\mathbf{H}\mathbf{W}^H$ is the frequency-domain channel matrix, and $\mathbf{z}$ is the corresponding frequency domain noise samples.

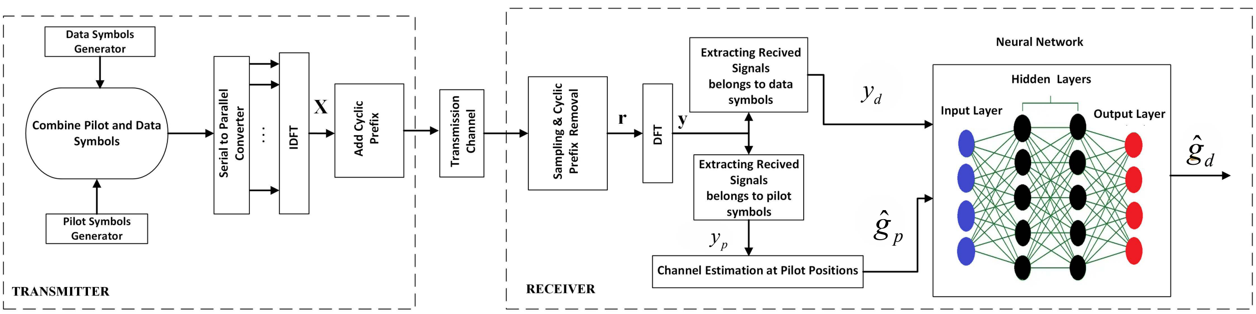

Fig. 1. OFDM system with the proposed channel estimation scheme.

Before starting the channel estimation process, whether in the traditional way or using the proposed pilot aided combined with Machine Learning (ML), the frequency-domain vector, $\mathbf{y}$, is split into two parts, one part represents the received signal at data positions and can be obtained as $\mathbf{y}_d = \mathbf{C}_d\mathbf{y}$, while the second part is related to the received signal at pilot-symbol positions and can be extracted as $\mathbf{y}_p = \mathbf{C}_p\mathbf{y}$. The received signal at pilot positions is used to estimate the channel coefficients at pilot positions, $\hat{\mathbf{g}}_p$. The estimate coefficients at pilot position, $\hat{\mathbf{g}}_p$, and the received signal at data positions, $\mathbf{y}_d$, are then fed to a neural network for channel coefficient estimation at data positions, $\hat{\mathbf{g}}_d$. Next, channel coefficients estimation at pilot positions is introduced.

B. Channel Estimation at Pilot-Symbol Positions

At the receiver, the frequency-domain signal at pilot positions, $\mathbf{y}_p$, is used to estimate channel coefficients at pilot positions. In terms of channel coefficients at pilot positions, the signal $\mathbf{y}_p$ can be expressed as,

$$\mathbf{y}_p = \sqrt{E_p}\mathbf{S}_p \cdot \mathbf{g}_p + \mathbf{z}_p \tag{5}$$

where $\mathbf{g}_p$ is the channel coefficients vector at pilot symbol positions, S_p is a diagonal matrix with diagonal being the pilot symbols vector, $\mathbf{s}_p$, and $\mathbf{z}_p = \mathbf{C}_p\mathbf{z} = [z(1),\ z(3),\ z(5), \cdots, z(1+2(K_p-1))]$ is the frequency-domain AWGN vector at pilot symbols positions. Suppose that the relationship between the received signal at pilot locations and the estimated channel coefficients can be described as $\hat{\mathbf{g}}_p = \mathbf{X}^H\mathbf{y}_p$, where $\mathbf{X}$ is the channel estimation matrix. When we employ the principle of orthogonality between the accurate channel coefficients vector $\mathbf{g}_p$, and the estimate one, $\hat{\mathbf{g}}_p$, and by minimizing the mean-squared error between the two vectors, the channel estimation matrix can be found as $E\left[(\hat{\mathbf{g}}_p - \mathbf{g}_p)\mathbf{y}_p^H\right] = 0 \rightarrow E\left[(\hat{\mathbf{g}}_p\mathbf{y}_p^H - \mathbf{g}_p\mathbf{y}_p^H)\right] = E\left[((\mathbf{X}\mathbf{y}_p)\mathbf{y}_p^H - \mathbf{g}_p\mathbf{y}_p^H)\right] = 0$ from which the estimation matrix X can be written as [11]:

$$\mathbf{X} = {E_p}^{\frac{3}{2}}((\mathbf{S}_p\mathbf{R}_{pp})\mathbf{S}_p^H + \frac{1}{\mathrm{snr}}\boldsymbol{I}_{L_p})^{-1}\mathbf{S}_p\mathbf{R}_{pp} \tag{6}$$

where $\mathrm{snr} = \frac{E_p}{N_0}$, $\mathbf{R}_{pp}$ is the autocorrelation function of channel coefficients vector $\mathbf{g}_p$, $\boldsymbol{I}_{L_p}$ is an identity matrix of size L_p, where $L_p = LK_p$ with L being the channel length, and K_p is the number of pilot symbols . Thus, the estimated channel coefficients at pilot-symbol locations can be expressed as:

$$\hat{\mathbf{g}}_p = \left({E_p}^{\frac{3}{2}}((\mathbf{S}_p\mathbf{R}_{pp})\mathbf{S}_p^H + \frac{1}{\mathrm{snr}}\boldsymbol{I}_{L_p})^{-1}\mathbf{S}_p\mathbf{R}_{pp}\right)^H \mathbf{y}_p \tag{7}$$

C. Development of the DL-Based Channel Estimation Approach

Over the past few years, the importance of employing machine learning in various areas of life has increased, including wireless communications. Since channel estimation was, and still is, one of the vital matters in wireless communications, using machine learning in channel estimation can bring many potential benefits and advantages compared to classical methods. For example, machine learning-based methods have the potential to outperform the classical and statistical-based schemes in dealing with dynamic channel environments. Furthermore, machine learning-based models have the potential to be more flexible than classical statistical-based schemes, as they can gradually adjust to rapid variations in the actual channel. Finally, compared to classical and statistical-based channel estimation models, ML-based channel estimation techniques can capture and predict a wider variety of channel information.

Nevertheless, there are several drawbacks to using machine learning-based techniques in the channel estimation process. First, the training and operation of machine learning-based models can be computationally costly. Second, the quality of data used to train and validate the neural network can significantly affect the accuracy of the outputs of the trained model; in other words, models may only function successfully if the training data accurately represents the channel circumstances. This section will discuss the deep learning model, and the neural network architecture used to predict channel coefficients at data symbol positions.

1) Traoining data generation

As shown in Fig. 1, at the receiver end, the signal corresponding to the pilot symbols and the signal corresponding to the data symbols are separately extracted from the sampled observed signal. The pilot symbol signal is then utilized to estimate the channel coefficients at pilot-symbol positions, as described in (7). After obtaining these coefficients, they are fed to the neural network along with the observed signal at data positions for training after being preprocessed to become suitable for training the network

2) Training data preparation

The training dataset consists of the sampled-observed signal at the data position and the estimated channel coefficients at the pilot positions; both vectors contain complex data. The data set is then reshaped to form the input-output pairs $(\mathbf{x}_{\mathrm{neu}}, \mathbf{y}_{\mathrm{neu}})$ for the neural network training.The vector $\mathbf{x}_{\mathrm{neu}}$comprises the imaginary part of vector $\hat{\mathbf{g}}_p$, the real part of $\hat{\mathbf{g}}_p$, their difference, i.e. $\mathrm{real}\{\hat{\mathbf{g}}_p\} - \mathrm{imag}\{\hat{\mathbf{g}}_p\}$, and the real and imaginary parts of vector $\mathbf{y}_d$. At the same time, the vector $\mathbf{y}_{\mathrm{neu}}$ contains the real and the imaginary parts of the desired channel coefficients. Using the real and imaginary components of the channel coefficients at pilot symbol positions as separate input features enables the FFNN to efficiently learn complex-valued channel behavior using real-valued operations. This representation preserves phase and magnitude information while maintaining low computational complexity.

In vector format, the training data preparation can be expressed as:

$$\mathbf{x}_{\mathrm{neu}} = [\mathrm{real}\{\hat{\mathbf{g}}_p\}, \mathrm{imag}\{\hat{\mathbf{g}}_p\}, \mathrm{real}\{\hat{\mathbf{g}}_p\} - \mathrm{imag}\{\hat{\mathbf{g}}_p\}, \mathrm{real}\{\mathbf{y}_d\}, \mathrm{imag}\{\mathbf{y}_d\}] \tag{8}$$

$$\mathbf{y}_{\mathrm{neu}} = [\mathrm{real}\{\mathbf{g}_d\}, \mathrm{imag}\{\mathbf{g}_d\}] \tag{9}$$

The training dataset is then split into training and validation sets, the training part is used to train the model, while the validation part is used to evaluate the model. In our model the 80% of data set is used for training and 20% for validation process.

3) Neural network architecture

In this project, we employ a Feed-Forward Neural Network (FFNN) with multiple cascaded layers, as shown in Fig. 2. The architecture of the deployed FFNN consists of three cascaded layers: input, hidden, and output. Next, each layer and its role in training process will be discussed.

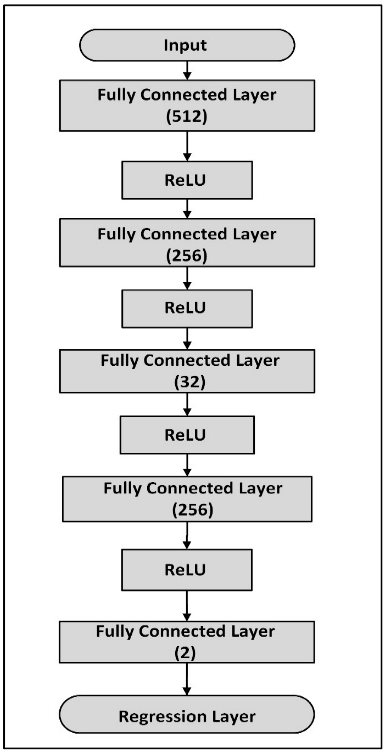

Fig. 2. Neural network architecture for the proposed model.

a) Input layer

The input layer serves the starting point in the structure of the deployed FFNN, whereby the network receives and processes all information regarding the characteristics of the channel. The adaptive feature representation approach helps the neural network to adapt to the different channel conditions, which ensures that estimation is robust. Incorporating both real and imaginary components of channel response at every pilot position increases the feature space, significantly enhancing the network's ability to learn the spatial and frequency diversities associated with the OFDM system.

The general feature representation at the input helps the network to learn the specific subtle relationships between the features and the responses in the channel to obtain accurate estimated results in the presence of noise and fading. The hidden layers represent the core of the neural network, as they serve to extract and refine abstract features based on the input representation. These layers are fully connected and utilize ReLU activation functions to allow the learning of complex nonlinear mappings between input features and the channel responses.

b) Hidden layers

The hidden layers are the architecture core of the feed-forward neural network. These layers can capture and refine the complex features extracted from the input data set. These layers are fully connected with ReLU activation functions, allowing them to learn complex, nonlinear mappings between the input features and channel coefficients. The hierarchical structure for these layers allows the FFNN to progressively obtain essential information that may aid in retrieving prominent features necessary to predict channel coefficients accurately. The dense hidden layers, having 1568 neurons, provide expressive power to the neural network. This architecture helps it capture minor details about the channel characteristic so that its estimate becomes accurate and can tolerate deviations in channel conditions. Additionally, by employing variable numbers of neurons in every hidden layer, we make it possible for the network to grasp diverse levels of abstraction or complexity found in the training data set

c) Output layers

In the output layer, the neural network synthesizes learned representations into estimates of the channel coefficients. Using a fully connected layer filled with neurons representing the real and imaginary parts of the estimated channel coefficients the output layer synthesizes the network's predictions in a coherent output format. By applying regression techniques like mean squared error minimization, the output layer further refines network parameters to minimize mean square errors. The This configuration makes the design of the output layer very much in coordination with standard practice for channel estimation and easily integrates into real-world communication systems.

d) Training Strategy

The architecture of the FFNN is structured to process and interpret complex-valued channel coefficients at pilot positions ($\hat{\mathbf{g}}_p$) and observed frequency domain sampled signal at the data position, ($\mathbf{y}_d$) which serve as critical inputs for predicting the channel coefficients at data positions ($\hat{\mathbf{g}}_d$). The network starts with an input layer that can capture the unique characteristics of channel coefficients, specifically tailored to handle the dual real and imaginary components inherent in the channel coefficients at pilot positions. First the network has an input layer that is designed to handle the real and imaginary components that are inherent in the channel coefficients at pilot positions and can capture the special characteristics of those coefficients. With this setup the network is guaranteed to be able to efficiently gather and process the complex phase and amplitude data that is essential for an accurate channel coefficients prediction. The architecture of the proposed neural network comprises densely interconnected multiple fully connected layers interspersed with Rectified Linear Unit (ReLU) activation functions, ending with a regression layer to predict the real and imaginary parts of channel coefficients. The architecture includes multiple hidden layers configured with varying dimensions strategically optimizing the network's ability to extract outstanding features from the input data.

During neural network training, we employ the Root Mean Square Propagation (RMSprop) optimizer with an initial learning rate of 0.00009, which is scheduled to decrease by 0.6 per epoch to fine-tune the learning process. A regularization factor of 0.00034 is used to prevent overfitting, while a maximum of 30 epochs and a mini-batch size of 256 balance computational efficiency and gradient stability. We also use data shuffling in each epoch to enhance generalization. Validation data guides early stopping, set with a patience of 20 epochs, to avoid overfitting. The final output layer has a dimension of 2, specialized to predict two channels, corresponding to the real and imaginary parts of a single data subcarrier channel coefficient. Therefore, the FFNN predicts the channel coefficient for a single data subcarrier at a time rather than all K_d data subcarrier coefficients simulteneously. This further simplifies the network's complexity and reduces the difficulty of training the network compared to predicting all $K_d$outputs simultaneously.

Fig. 3 and Fig. 4 show performance curves of the training process for BPSK with K = 512 and fading channel with three taps. In Fig. 3, we present the loss curves for both the training and validation stages. As shown in the figure, the training loss decreases rapidly, indicating an efficient training and learning options set. The training loss reaches its minimum value, 4×10^{-5} after 5271 iterations. Furthermore, the validation loss curve indicates that the validation loss is slightly higher than the training loss. The validation process is an important metric for assessing model generalization.

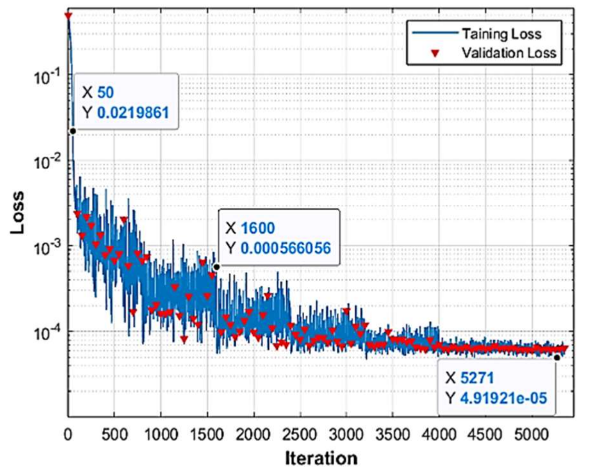

Fig. 3. Training and validation loss curves for the proposed scheme.

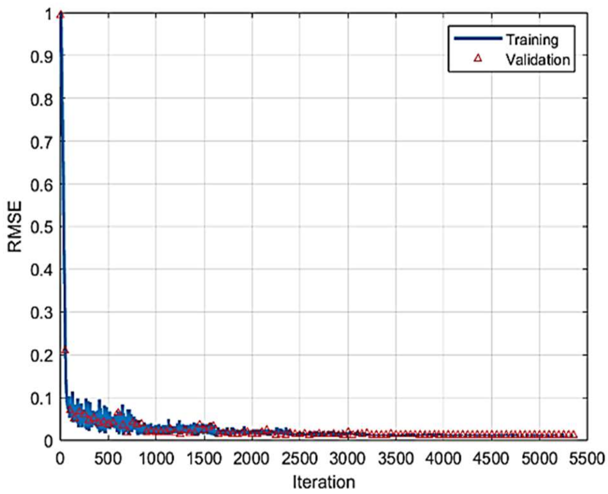

Fig. 4. Training and validation RMSE curves for the proposed scheme.

Fig. 4 shows the root mean-squared error (RMSE) performance curves for the training and validation stages. The curves show that training and validation stages start with high RMSE values but decrease over time. The reduction indicates that the model learns from the training dataset, improving performance as the iteration increases. Both curves flattened after high and close iteration values, meaning there was no overfitting during the learning process.

Fig. 5 shows the convergence behavior of the Root Mean Square Error (RMSE) as a function of the number of iterations under different values of slot length (i.e., K = 32, K = 64, and K = 128) for training stage of the proposed scheme. It can be oserved from the figure that arger values of K lead to faster convergence and lower RMSE values. The blue curve where K = 128 achieves the lowest RMSE in the shortest number of iterations, followed by the red curve at K = 64, and the black curve K = 32, which converges more slowly and stabilizes at a higher RMSE value. This suggests that increasing the transmitted slot length improves the accuracy and efficiency of the estimated algorithm. However, the computational complexity associated with larger values of K should be considered when selecting an optimal trade-off between performance and efficiency.

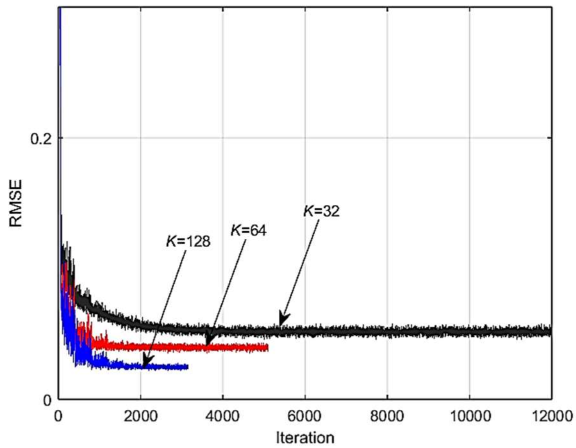

Fig. 5. RMSE for Training stage of the proposed scheme under different transmitted slot length values.

III. RESULT AND DISCUSSION

In this section, we present the computer simulations conducted to validate the proposed model's performance. In Fig. 6, the estimated channel coefficients were compared with the true ones for a system with QPSK, L = 4, K = 128. The main observation is that the predicted channel coefficients' real and imaginary parts are very close to the true ones.

In Fig. 7, we calculate the mean-squared error (MSE) between the proposed DL-based predicted channel coefficients and the true ones for different modulation techniques, BPSK, QPSK, and 8 PSK, over the multipath fading channel with two taps. The transmitted slot was set to 128 for all systems The MSEs for the proposed model is also compared with the analytical and simulated ones for an equivalent system with LMMSE interpolation [32, 33].

Also, we can observe an excellent matching between the MSE of the proposed model and the analytical and simulated MSEs of the LMMSE interpolation method, especially at low SNR. The trained DL-based model can be used to obtain channel coefficients without any extra statistical information between channel coefficients at data positions and pilot positions, as should be in the LMMSE interpolation approach [34].

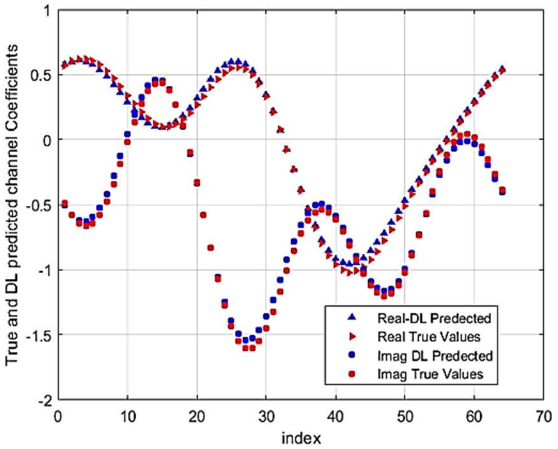

Fig. 6. Comparison between the true channel coefficients and the predicted ones using the proposed model.

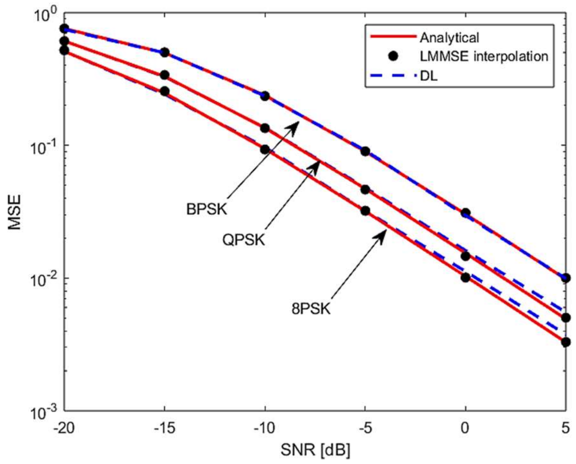

Fig. 7. The MSE for the proposed model as a function of SNR for different modulation techniques.

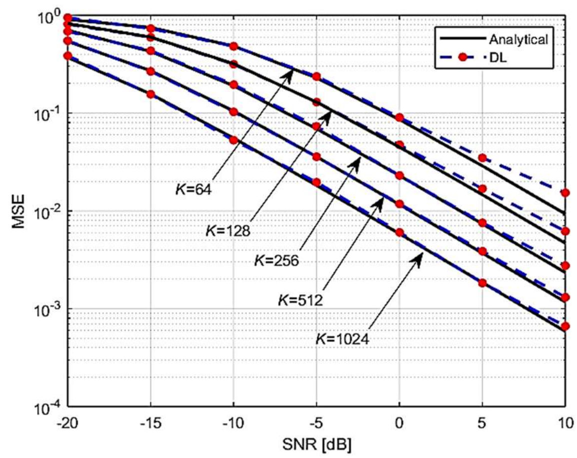

Fig. 8. The MSE for the proposed model as a function of SNR under various *K* values.

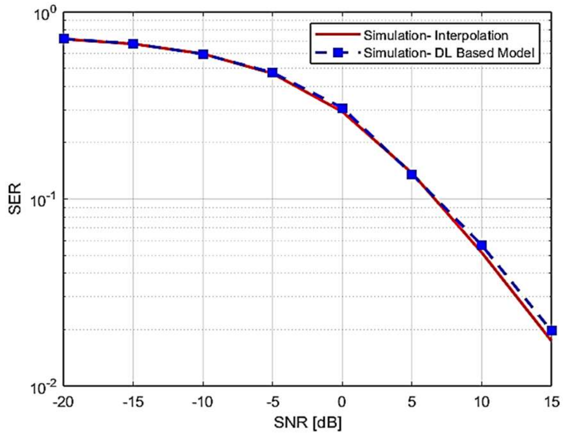

Fig. 9. SER for the proposed model as a function of SNR.

Fig. 8 presents the MSE for the proposed model under different numbers of transmitted slot lengths. As is evident from the figure, the MSE value for the estimated DL-based model improves as the slot length increases. This improvement is understandable and is due to the improvement in the RMSE of the proposed model's learning process, as explained in Fig. 5. Finally, Fig. 9 presents the performance curve of the OFDM system with QPSK and DL-based channel estimation. For comparison, the performance curve for an equivalent system utilizing LMMSE is also presented in the figure. The two curves match excellently, especially at low SNR.

IV. Conclusion

This paper introduced a pilot-aided DL-based channel estimation for an OFDM system operating under a multipath fading channel. First, the channel coefficients at pilot symbol positions were estimated by using the LMMSE channel estimation method. These coefficients are then fed to a neural network, which subsequently estimates channel coefficients at data symbol positions, without requiring statistical information about channel coefficients at data positions. Results showed that increasing the transmitted slot length can enhance the accuracy and speed of the neural network learning. The MSE of the proposed model indicated that it can be an alternative method for estimating channel coefficients at data positions, especially at low SNR. For future work, we will explore alternative deep learning architectures to improve performance. We can also consider neural network-based channel estimation in high-mobility scenarios. Finally, we will explore extending the proposed channel estimation method to a multi-input multi-output (MIMO) OFDM system.

Conflict of Interest

The author declares no conflict of interest.

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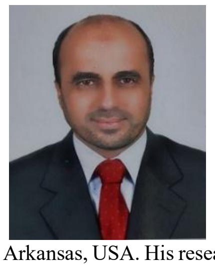

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