Machine Learning-Driven Blind Carrier Offset Estimation for OFDM Systems

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Abstract
As wireless networks continue to evolve with the emergence of sixth-generation networks and beyond, OFDM technology is expected to be an essential system component for providing reliable connectivity in an increasingly complex environment. Its high spectrum efficiency, efficiency against impulse noise, and resilience against frequency-selective multipath fading channels make it an invaluable component. Although OFDM technology has various capabilities and uses and is widely used, it has some issues and challenges, and one of these challenges is Carrier Frequency Offset (CFO). The CFO destroys orthogonality between subcarriers and causes subcarrier misalignment at the receiver, resulting in inter-carrier interference (ICI) in OFDM systems. This interference impairs system performance by introducing errors and degrading signal-to-noise ratios. In this paper, a new Deep Neural Network (DNN) algorithm has been proposed for estimating the CFO in OFDM systems. The architecture is precisely designed for regression tasks, with a focus on accurately estimating the continuous parameter based on the input features. The multiple hidden layers facilitate the extraction of intricate patterns, while careful training options ensure efficient optimization and monitoring of the training process. The performance of the proposed DNN algorithm is assessed and compared with other subspace-based methods, ESPRIT, PM(MUSIC), and QR. Remarkably, the results demonstrate that the DNN algorithm consistently outperforms all subspace methods, especially in low SNR scenarios.

Keywords:
OFDM, 6th generation, ICI, CFO, Blind Estimation, dataset, training, Machine Learning (ML), Deep Learning (DL), Neural Network (NN), Loss function,

I. Introduction

With the tremendous growth of wireless and mobile services and the revolution in artificial intelligence applications, the next generations of wireless networks are expected to offer low latency transmission, higher data rates, higher bandwidth efficiency, energy-efficient transmission, and better quality of services. Orthogonal frequency division multiplexing (OFDM) has been the most preferred multicarrier modulation technique for most standards, including 802.11, long-term evolution LTE, and 5th generation mobile networks due to its benefits and advantages, such as high spectrum efficiency, efficiency against impulse noise, and resilience against frequency-selective multipath fading channels [1]. As we look toward the future of wireless networks with the emergence of sixth-generation networks and beyond, OFDM technology is expected to play a crucial role in providing reliable connectivity in an increasingly complex environment [2]. Although the basic requirements for 6G technology are still under research and development, the OFDM technology, with its adaptability and versatility, makes it suitable for fulfilling the needs of many emerging applications such as the Internet of Things (IoT), artificial intelligence-based applications, and 3D communications. Although OFDM technology has various capabilities and uses and is widely used, it has some issues and challenges. Some of these challenges include high Peak-to-average Power ratio (PAPR), Inter-Symbol Interference (ISI), and Carrier Frequency Offset (CFO) [2],[3]. High PAPR in OFDM systems results in low power efficiency. Complex signal processing techniques such as amplitude clipping and filtering can be used to reduce the impact of PAPR in OFDM systems; however, these sequences increase cost and system complexity. Despite OFDM's capability to reduce ISI within each OFDM subcarrier, ISI may still occur due to multipath propagation in wireless networks.

The cause of CFO can be attributed to two main factors: the Doppler shift of the mobile channel and inconsistency between the transmitter and receiver [4]. The CFO destroys orthogonality between subcarriers and causes subcarrier misalignment at the receiver, resulting in inter-carrier interference (ICI) in OFDM systems. This interference impairs system performance by introducing errors and degrading signal-to-noise ratios, especially in situations with high mobility or frequency-selective fading channels. Over the last two decades, several techniques have been developed to mitigate the impact of CFO on OFDM [5]-[10]. These methods fall into three categories: pilot-aided schemes, semi-blind, and blind ones [5]. The paper in [5] addresses blind carrier frequency offset estimation for MIMO-OFDM systems, which is crucial for optimal system performance. The proposed approach leverages the banded structure of covariance matrices for constant modulus signals, enabling CFO estimation without the need for pilot or training symbols.

A subspace-based semi-blind CFO estimation method was proposed in [6], where a multi-antenna redundancy is

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exploited at the receiver. The proposed method requires the number of receiving antennas to be larger than that at the transmitting side [6].

The cyclic prefix (CP) preceding OFDM symbols contains no information and can be utilized for CFO estimation for OFDM operating over multipath channels, as presented in [7]. This innovative approach effectively reduces the estimation's theoretical mean squared error (MSE) without any extra pilot symbols. In [8], a technique was suggested for estimating the frequency offset in the OFDM system by constraining the criteria function for covariance fitting. Based on the covariance fitting criteria between two neighboring symbols, a cost function was generated assuming that the channel's influence over the OFDM symbols is the same across two close sub-carriers. The results demonstrated that this approach is less reliant on the channel conditions and provides greater precision.

Many existing CFO estimation techniques currently in use are limited to certain carrier assignment schemes (CAS) and cannot be used with others. However, the paper in [9] presented a blind CFO estimation for uplink orthogonal frequency division multiple access (OFDMA) systems by exploiting the virtual carrier (unused subchannels) for CFO estimation. Moreover, the proposed scheme requires a single OFDM block to perform the CFO estimation, thereby reducing the system complexity.

In [10], an estimation bound for frequency offset estimator in OFDM systems with single relay networks over multipath receptions was presented. In multipath fading channels, it is necessary to estimate the frequency offset of the source-relay and relay-destination links independently, unlike flat fading channels where the CFOs of two hops can be combined as a single estimation parameter. The Authors in [11] proposed a blind frequency offset estimation based on signal characteristics for OFDM under a doubly selective fading channel. According to their results, this method successfully resolved the CFO and compensated for its impact on the OFDM system. However, the main weakness of this approach was its computational complexity and rate of convergence compared to data-aided methods [11]. In [12], a joint CFO and channel estimation problem for OFDM/OQAM systems over an additive white Gaussian noise (AWGN) channel was presented. The first step involves estimating the carrier phase offset using an unconditional machine learning estimator. Then, a data-aided approach based on the preamble was used to improve carrier frequency offset estimation accuracy, and the received signal was used to estimate the channel impulse response.

Authors in [13] presented a frequency domain pilot symbol-based data-assisted CFO estimation method by leveraging pilot symbols to precisely estimate and compensate for CFO in constant-envelope OFDM satellite systems. The pilot symbol-based CFO estimator can obtain an extensive estimation range with a small pilot overhead. Furthermore, [13] explored the impact of pilot symbols on estimation accuracy. A sparse recovery-based CFO blind estimation scheme for an uplink OFDMA system was proposed in [14]. This scheme utilized sparse recovery in OFDMA data to optimize CFO estimation with high resolution. The estimator mitigated background noise and sampling errors by utilizing noise covariances matrix structure and asymptotic distribution of sampling errors. The regularization parameter employed by the estimator was obtained to manage the trade-off between data fitting error and the sparsity of the solution.

Using the pilot grid that is available for channel state information (CSI) estimation, an iterative frequency domain maximum likelihood (ML) CFO algorithm in [15] produces ML and least square (LS) iterative estimators.

Utilizing a limited number of noisy observations of the received OFDM signal, authors in [16] proposed a subspace CFO estimation scheme. The estimation was obtained by solving a quadratic eigenvalue problem using the linear prediction property of a complex sinusoidal.

In [17] and [18], the authors compared various CFO estimate schemes in OFDM systems. The papers examined the cyclic prefix and the training sequence methods in the time domain, while the training symbol and the pilot methods were investigated in the frequency domain. The comparison criteria were the mean squared error (MSE). According to their results, the CFO estimate methods in the frequency domain outperform CFO estimation methods in the time domain in terms of MSE. Furthermore, It was shown that the performance of the pilot tone approach surpasses the cyclic prefix method and a two identical blocks training sequence method.

In recent years, Artificial intelligence (AI) technologies have shown remarkable potential in wireless networks for the fifth generation and beyond. Research has shown two possible applications for artificial intelligence in communications networks. The first is to improve the performance of particular functions within the wireless network, such as signal detecting, error-correcting and detection, modulation and demodulation, and channel estimation. The second is to replace function modules with an intelligent system, creating an end-to-end (E2E) communication system that improves transmission efficiency between the ends [19].

The upcoming 6th generation technologies are expected to handle high transmission rate wireless communication networks with massive data and low latency communications. OFDM is expected to play a crucial role in the 6th generation and beyond due to its versatility in integrating with other technologies [1]. AI techniques like machine learning (ML) and deep learning (DL) are inevitable in OFDM-based communication networks. Research has indicated that applying ML to OFDM systems can improve performance compared to signal processing-based systems. DL algorithms can be employed in OFDM systems to estimate the channel coefficient for equalization purposes, as outlined in [20]. One major issue in OFDM systems is the large PAPR in the transmitted OFDM signal, which reduces the OFDM system's power efficiency. In [21], an OFDM system with a DL-based autoencoder was proposed to reduce the PAPR; the proposed method outperforms conventional PAPR reduction schemes such as partial transmit scheme and clipping methods [21], [22].

Various artificial intelligence techniques have recently been adopted to address the challenge of carrier frequency offset in OFDM-based wireless networks [23-26]. A supervised DL-based CFO estimation was proposed in [23], where four different neural networks (NN) were considered: a convolutional NN, a feedforward NN, a residual NN, and a recurrent NN. Findings demonstrated that NN learning can be enhanced by utilizing quantized training datasets with low signal-to-noise ratio (SNR). A deep neural network (DNN) with three layers, an input linear layer, one hidden layer, and one output layer, was proposed in [24] to handle CFO in OFDMA systems. Ninkovic et al. in [25] proposed CFO estimation and packet detection for IEEE 802.11 ah standard using machine learning. The recurrent neural network (RNN) RNNs were shown to be the most influential architecture for CFO estimate, matching the accuracy of conventional techniques at low to medium SNRs. Nevertheless, their complexity is consistently lower than that of conventional approaches. In [26], Hussien et al. proposed an ML-based CFO estimation technique. The training of the NN utilizes datasets taken from the received primary synchronization signal and secondary synchronization signal.

This paper presents a deep learning-based carrier frequency offset estimation approach. Specifically, a feedforward neural network (FFNN) consisting of input, hidden, and output layers is utilized for deep learning training purposes. The collected dataset underwent a prepossessing procedure to guarantee consistency and simplify model training. Blind CFO-OFDM estimator using propagator method (PM) in conjunction with the well-known MUSIC based high resolution searching algorithm introduced in [27]. Another blind CFO estimator based on the Matrix Pencil (MP) method was proposed in [28, 29], where a closed-form solution of the generalized eigenvalue problem using the MP method was solved by Rank Revealing QR factorization (RRQR). The structure of the paper is as follows: The problem formulation is described in Section II. Part III describes the suggested model's evolution in depth. Discussions and simulation results are given in Section IV. The article is finally concluded in Section V

II. Problem Formulation

We're examining an OFDM system implemented using both inverse discrete Fourier transform (IDFT) and discrete Fourier transform (DFT) for modulation and demodulation, respectively, each of size N. To avoid aliasing effects at the edges of the transmission spectrum, only P subcarriers out of the total N are utilized. Let $\boldsymbol{s}_P(k)$ i represent a QPSK or QAM data symbol to be transmitted in the k^{th} block, typically known as Used Carriers (UC):

$$\boldsymbol{s}_P(k) = [s_0(k)\ s_1(k) \dots \dots s_{P-1}(k)]^T \tag{1}$$

Where $[\blacksquare]^T$ denotes transpose. The vector $\boldsymbol{s}_P$ of size P is extended to the vector $\boldsymbol{s}$ of size N by padding *N-P* zeros, to accommodate the Virtual Carrier (VC) or unused carriers, ensuring avoidance of aliasing problems at the receiver.

$$\boldsymbol{s}(k) = \Bigg[\underbrace{s_0(k)\ s_1(k) \dots \dots s_{P-1}(k)}_{P}, \underbrace{0,0,\dots,0}_{N-P}\Bigg]^T \tag{2}$$

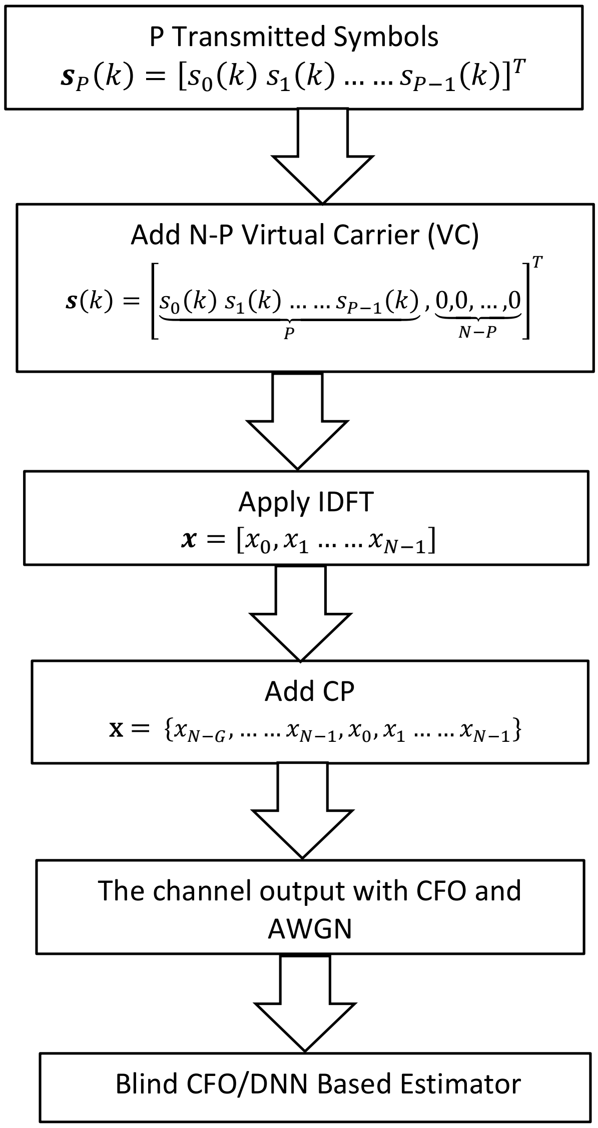

Fig.1. Simple OFDM System.

The N samples of the IDFT output with $\boldsymbol{s}(k)$ as input are expressed as follows:

$$\boldsymbol{x}(k) \triangleq \boldsymbol{W}.\boldsymbol{s}(k) = \boldsymbol{W}_P.\boldsymbol{s}_P(k) \qquad (3)$$

where $\boldsymbol{W}_P$ consists of the first P columns of the $N \times N$ IDFT matrix $\boldsymbol{W}$ which is given by:

$$\boldsymbol{W} = \frac{1}{\sqrt{N}}.\begin{bmatrix} W^{0.0} & W^{1.0} & W^{2.0} & \cdots & W^{(N-1).0} \\ W^{0.1} & W^{1.1} & W^{2.1} & \cdots & W^{(N-1).1} \\ W^{0.2} & W^{1.2} & W^{2.2} & \cdots & W^{(N-1).2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ W^{0.(N-1)} & W^{1.(N-1)} & W^{2.(N-1)} & \cdots & W^{(N-1).(N-1)} \end{bmatrix}$$

where $W = e^{j\omega}$. To mitigate Inter-Symbol-Interference (ISI) between successive OFDM symbols, cyclic prefix (CP) symbols are appended at the beginning of each frame. Consequently, the OFDM system is denoted as:

$$\mathbf{x} = \{x_{N-G}, \dots \dots x_{N-1}, x_0, x_1 \dots \dots x_{N-1}\} \qquad (4)$$

At the receiver end, removing the CP symbols transforms the received sequence into the circular convolution of the transmitted sequence with the channel impulse response $h(l),\ l = 0,1, \dots L_c - 1$, where L_c is the channel length. Given that, the channel length $L_c < G$, Inside the k^{th} block only the guard portion of the signal will be distorted. The channel output based on used subcarriers for the k^{th} block in the existence of a CFO and AWGN, is given by:

$$\boldsymbol{y}(k) = [y_0(k)\ y_1(k) \dots \dots y_{N-1}(k)]^T$$

$$\boldsymbol{y}(k) = \boldsymbol{E}\boldsymbol{W}_P\boldsymbol{H}\boldsymbol{s}(k)e^{j(k-1)\varphi(N+G)} + \boldsymbol{z}(k) \qquad (5)$$

where

$$\boldsymbol{E} = diag(1, e^{j\varphi}, \dots, e^{j(N-1)\varphi})$$

and φ is the carrier offset, $\boldsymbol{H}$ is the frequency domain channel matrix representation and given by:

$$\boldsymbol{H} = diag[H(0), H(1), \dots \dots H(P-1)]$$

The channel frequency response is represented as:

$$H(i) = \sum_{l=0}^{L_c-1} h(l)\omega^{-il} \qquad (6)$$

. To sustain orthogonality among the sub-channel carriers and to mitigate Inter-Carrier Interference (ICI), the matrix E needs estimation and compensation before applying the Discrete Fourier Transform (DFT) to equation (5). The current objective is to propose a Deep Neural Network (DNN) to estimate φ, given that the K received noisy data blocks only are the sole available measurements, assuming that φ is constant during the K blocks. Having tackled the blind CFO estimation problem previously, we'll maintain the identical setup described in [29]. Our goal is to demonstrate the effectiveness of the proposed method relative to various reference subspace-based methods.

III. Development of Proposed Method

The K blocks of the received data are collected in matrix $\boldsymbol{Y}$ of size $(N \times K)$

$$\boldsymbol{Y} = [\boldsymbol{y}(1)\ \ \boldsymbol{y}(2) \dots \dots \boldsymbol{y}(K)] + \boldsymbol{Z} \qquad (7)$$

where the kth block of the received signal in (3) is given by $\boldsymbol{y}(k) = [y_0(k)\ y_1(k) \dots \dots y_{N-1}(k)]^T$, and the $\boldsymbol{Z}$ is the corresponding additive white gaussian noise matrix. The real matrix ***YY*** is formulated by concatenating the real and imaginary parts of ***Y*** as:

$$\boldsymbol{YY}\text{=[Real(}\boldsymbol{Y}\text{); imaginary(}\boldsymbol{Y}\text{)]} \qquad (8)$$

Then the real matrix ***YY*** reshaped to have *2NK* elements in the input features vector to the DNN.

Recently, there has been a growing interest in leveraging machine learning models to supplant conventional CFO estimators. These models can be trained on extensive datasets of CFO measurements, enabling them to provide more precise estimates of the Carrier Frequency Offset (CFO) compared to traditional statistical models. Utilizing a machine learning model in lieu of a conventional CFO estimator offers several potential advantages. Firstly, machine learning models tend to exhibit superior accuracy, particularly in scenarios involving intricate or rapidly evolving CFOs. Secondly, these models boast greater adaptability, allowing them to learn and adjust to changes in the CFO dynamics over time.

[1] Datasets Generation

In the foundational phase of the research, a synthetic dataset closely emulating the complexities of actual CFO scenarios is generated. CFO values are randomly sampled from a uniform distribution spanning zero to one, while the channel gain is assumed to follow a random complex normal distribution with 10 taps, as described in [*]. A total of twenty thousand received block signals, each of size 2NKfeatures as described in Eq. (8), are generated.

[2] Dataset Preprocessing

Following generation, the dataset underwent preprocessing procedures to ensure consistency and facilitate model training. Subsequently, the dataset was partitioned into training (75%) and testing (25%) subsets, as detailed in [30].

[3] *Neural Network Architecture*

A feedforward neural network, a form of artificial neural network, operates by transmitting information in a singular direction—forward—starting from the input layer, passing through the hidden layers, and concluding at the output layer. Each layer is comprised of nodes, also known as neurons, with interconnecting weights governing the connections between nodes. Throughout the training process, these weights are iteratively modified to reduce the disparity between the predicted output and the actual output.

The neural network as shown in Fig. 2 begins with an input layer created using the feature Input Layer function, acting as the gateway for input data into the network. This layer is designed to accommodate the varying number of features present in the input dataset, where each input sample has a size of *2NK*. Following the input layer, the architecture incorporates four hidden layers, each consisting of fully connected neurons. The first hidden layer comprises 256 neurons, serving as an initial processing stage for the input data. Subsequent hidden layers progressively reduce the number of neurons, with 128, 64, and 32 neurons in the second, third, and fourth layers, respectively. Rectified Linear

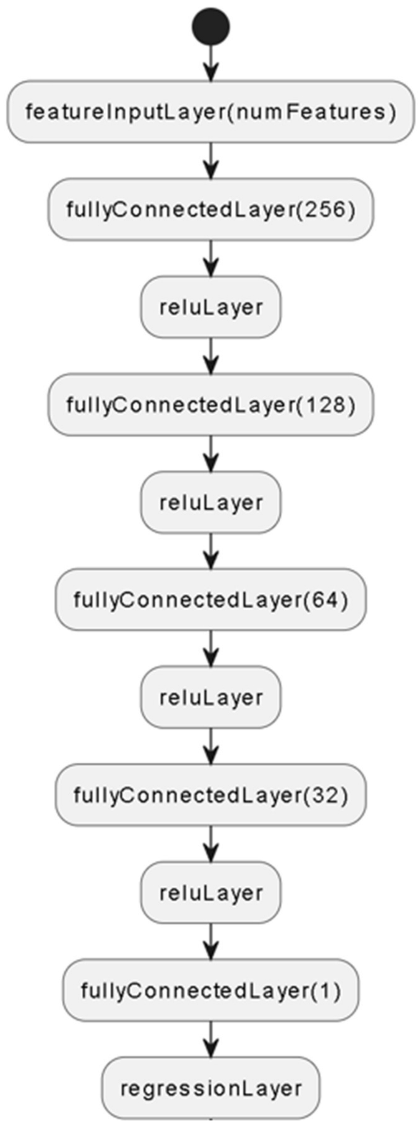

Fig 2. Feedforward Neural Network (FNN) architecture, the diagram automatically generated by ChatUML

Unit (ReLU) activation functions are applied after each hidden layer, facilitating the introduction of non-linearities, and enabling the network to capture intricate patterns within the data. The output layer of the network is composed of a single neuron, tasked with producing the final estimation of the parameter φ. Since the objective is regression, no activation function is applied to the output neuron. Instead, it directly outputs continuous values representing φ.

[4] *Neural Network Training Process*

The training process utilizes the Adam optimizer, a robust algorithm suitable for optimizing deep neural networks. The initial learning rate is set to 3e-4, determining the magnitude of weight updates during training. Training progresses through a maximum of 50 epochs, with the dataset shuffled before

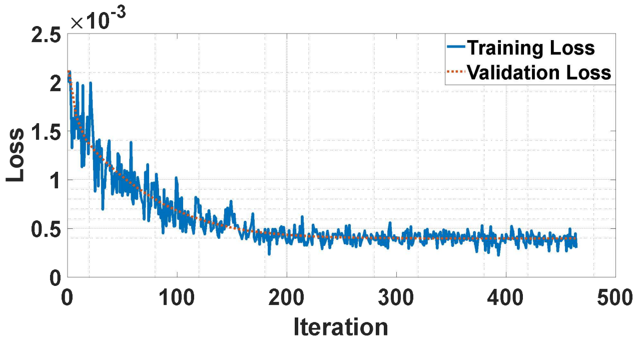

Fig.3.a. Training and Validation loss curves for K=1

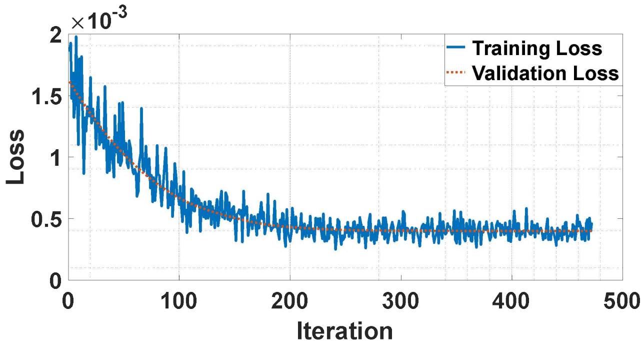

Fig.3.b. Training and Validation loss curves for K=5

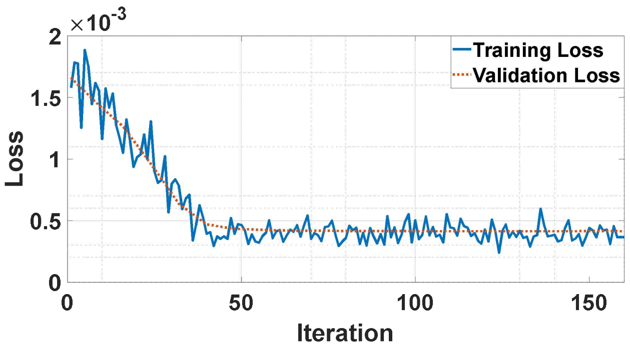

Fig.3.c. Training and Validation loss curves for K=10

data, comprising input features and corresponding labels, is utilized to assess the network's performance at regular intervals, with validation performed every 8 mini-batches. If validation performance fails to improve for 5 consecutive epochs, training may halt prematurely to prevent overfitting. These parameters collectively optimize the neural network training process, ensuring effective learning and performance evaluation while mitigating the risk of overfitting. each epoch to prevent the network from memorizing sample order. Each training iteration involves mini batches containing 32 samples, enhancing computational efficiency. Training Loss curves and accuracy curves is generated in Fig. 3 for different frame sizes. In various cases, the loss curves for both training and validation data exhibit a decreasing trend as the number of iterations increases during the neural network training process. This indicates that the model is effectively learning from the training data, as evidenced by the decreasing training loss. Additionally, the decreasing validation loss suggests that the

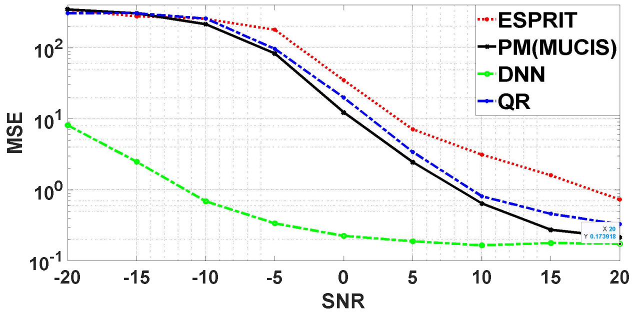

Fig.4. MSE vs. SNR curves for K=10

model's performance is improving not only on the training set but also on unseen data, indicating generalization capability. Consequently, the observed trend signifies a successful training process, where the neural network is iteratively adjusting its parameters to better capture the underlying patterns in the data, ultimately leading to improved performance on both the training and validation sets.

IV. Simulation Results

In the conducted simulations, the proposed method tested, validated and compared with reference methods [27-29]. Same experiment setup for all methods is assumed. An OFDM system characterized by 64 carriers. Among these carriers, 40 were allocated as used subcarriers, while the remaining 24 were designated as virtual carriers. The transmitted symbols were drawn from a QPSK constellation, ensuring equiprobable distribution. The cyclic prefix (CP) length was set to eleven symbols to accommodate channel delay spread, and we assumed a uniform random frequency offset φ to simulate real-world conditions accurately. These parameters were carefully chosen to mimic the complexities of practical OFDM systems, allowing us to assess the effectiveness and robustness of the proposed method under realistic operating conditions. The experiment was conducted in an Additive White Gaussian Noise (AWGN) environment, employing a total of 10,000 independent Monte Carlo realizations. The estimator performance was evaluated using the normalized mean square error (MSE) as a unified performance metric for all shown algorithms and is given by:

$$MSE_{dB} = \frac{1}{N_t} \sum_{i=1}^{N_t} \left(\frac{\varphi - \widehat{\varphi}}{\omega} \right)^2 \qquad (9)$$

Fig.4 illustrates the normalized Mean Square Error (MSE) of the CFO, plotted against the Signal-to-Noise Ratio (SNR) for a assumed number of blocks, K=10. The DNN algorithm proposed in this study is evaluated alongside other subspace-based methods such as ESPRIT, PM(MUSIC), and QR [27- 29]. The performance of the proposed DNN algorithm outperforms all subspace methods, particularly in low SNR scenarios [30, 31].

V. CONCLUSION

A new Deep Neural Network (DNN) algorithm has been proposed for estimating the Carrier Frequency Offset (CFO) in Orthogonal Frequency Division Multiplexing (OFDM) systems. The architecture is carefully designed for regression tasks, with a focus on accurately estimating the continuous parameter φ based on the input features. The multiple hidden layers facilitate the extraction of intricate patterns, while careful training options ensure efficient optimization and monitoring of the training process. The performance of the proposed DNN algorithm is assessed with other subspace-based methods, ESPRIT, PM(MUSIC), and QR. Remarkably, the results demonstrate that the DNN algorithm consistently outperforms all subspace methods, especially in low SNR scenarios.

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