

A Novel Machine Learning Approach for Blind Carrier Offset Estimation in OFDM Systems

Mahmoud M. Qasaymeh

Computer Engineering and Communication Department, Faculty of Engineering, Tafila Technical University,
Tafila, Jordan

Email: qasaymeh@ttu.edu.jo (M.M.Q.)

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 (SNR). In this paper, a novel approach to estimate the CFO in OFDM systems via Feedforward Neural Network (FNN) has been proposed. The architecture is precisely 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 FNN algorithm is assessed and compared with other subspace-based methods, ESPRIT, PM(MUSIC), and QR. Remarkably, the results demonstrate that the FNN algorithm consistently outperforms all subspace methods, especially in low SNR scenarios.

Index Terms—6G, blind estimation, Carrier Frequency Offset (CFO), dataset, Deep Learning (DL), Inter-Carrier Interference (ICI), loss function, Machine Learning (ML), Feedforward Neural Network (FNN), OFDM, training

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 improved service quality. Orthogonal Frequency Division Multiplexing (OFDM) has been the most preferred multicarrier modulation technique for most standards [1], including 802.11, Long-Term Evolution (LTE), and Fifth Generation (5G) cellular networks [2] due to its benefits and advantages, such as high spectrum efficiency, efficiency against impulse noise, and resilience

against frequency-selective multipath fading channels [3]. As we look toward the future of wireless networks with the emergence of Sixth Generation (6G) networks [4, 5] and beyond, OFDM technology is expected to play a crucial role in providing reliable connectivity in an increasingly complex environment [6]. 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 as 3D communications, the Internet of Things (IoT), and Artificial Intelligence-Based (AI) applications. 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) [7, 8]. High PAPR in OFDM systems results in low power efficiency. Complex signal processing techniques such as amplitude clipping and filtering can be employed to decrease 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.

Doppler shift of the mobile channel and inconsistency between the transmitter and receiver are the two main causes of CFO [9]. The CFO destroys orthogonality among subcarriers leading to 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 [9–14]. These methods are divided into three categories: pilot-aided schemes, semi-blind, and blind ones. The paper in [9] addresses blind CFO estimation for Multi-Input, Multi-Output (MIMO)-OFDM systems, which is crucial for optimal system performance. The proposed approach leverages the 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 [10], where a multi-antenna redundancy is exploited at the receiver. The proposed method requires

that the antennas number at the receiver to be greater than those at the transmitter [10].

The cyclic Prefix (CP) preceding OFDM symbols contains No information and can be utilized for CFO estimation for OFDM operating under multipath channels, as presented in [11]. This innovative approach effectively reduces the estimation's theoretical Mean Squared Error (MSE) without any extra pilot symbols. In [12], 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 [13] presented a blind CFO estimation for uplink multiple access OFDM 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.

An estimation bound for frequency offset estimator in OFDM systems with single relay networks over multipath receptions was presented [14]. 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 Zhao and Chen [15] 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 [16]. A joint CFO and channel estimation problem for OFDM/OQAM systems over an Additive White Gaussian Noise (AWGN) channel was presented [17]. 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.

Huang *et al.* [18] 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, Huang *et al.* [18] 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 [18]. This scheme utilized sparse recovery in OFDMA data to optimize CFO estimation with high resolution. Applying noise covariances matrix

structure and asymptotic distribution of sampling errors, the estimator mitigated sampling errors and background noise. The regularization factor 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 Maximum Likelihood (ML) CFO method in frequency domain produces ML and Least Square (LS) iterative estimators [19].

Utilizing a limited number of noisy observations of the received OFDM signal, Eslahi *et al.* [20] proposed a subspace CFO estimation scheme. The linear prediction property of a complex sinusoidal was used to solve a quadratic eigenvalue problem.

Raboh *et al.* [21, 22] compared various CFO estimate schemes in OFDM systems. Also, examined the training symbol along with the Cyclic Prefix (CP) methods in the time domain, while the training symbol and the pilot methods were investigated in the frequency domain. The comparison criteria were the MSE according to their results, the CFO estimate methods in the frequency domain outperform those 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 5G and beyond. Research has shown two possible applications for artificial intelligence in communications networks. The first is to improve the performance of functions within the wireless network, such as signal detection, error-correction, modulation, 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 [23].

The upcoming 6th generation technologies are expected to handle high transmission rate wireless communication networks with massive data and low latency communications. OFDM is presumed to have a substantial impact on 6G and beyond due to its versatility in integrating with other technologies [4]. 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 [24]. One major issue in OFDM systems is the large PAPR in the transmitted OFDM signal, which reduces the OFDM system's power efficiency. In [25], 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 [25, 26].

Various artificial intelligence techniques have recently been adopted to address the challenge of carrier frequency offset in OFDM-based wireless networks [27–30]. A supervised DL-based CFO estimation was proposed in

[27], 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 [28] to handle CFO in OFDMA systems. Ninkovic *et al.* in [29] 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. The performance of the proposed CAD method in [30] shows performance enhancement under low SNR while it has a steady-state MSE performance over high SNR. Nevertheless, their complexity is consistently lower than that of conventional approaches. Hussien *et al.* [31] 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. The performance of the proposed CAD method in [32] shows performance enhancement under low SNR while it has a steady-state MSE performance over high SNR.

CFO estimation in [33] was achieved by acquiring signal characteristics from in-phase and quadrature signal components. These features were then used to train a residual network (ResNet). Various modulation schemes were used in the training procedure to enable the model to handle new signals effectively.

Blind CFO-OFDM estimator introduced, using Propagator Method (PM) with Multiple Signal Classification (MUSIC) [34]. Matrix Pencil (MP) was suggested [35, 36] as another blind CFO estimator based, where a closed-form solution of the generalized eigenvalue problem was solved by Rank Revealing QR factorization (RRQR).

This paper presents a novel 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. In the proposed method, we utilized a P subcarriers raw data consisting solely of received vectors from used carriers only, without the need for pilot symbols. The collected dataset underwent a preprocessing procedure to guarantee consistency and simplify model training.

The structure of the paper is as follows: The problem formulation is described in Section II. Section III describes the suggested model's evolution in depth. Discussions and simulation results are given in Section IV. The article is lastly concluded in Section V.

II. PROBLEM FORMULATION

We study an OFDM system that utilizes pairs of inverse discrete Fourier transform (IDFT) for modulation and discrete Fourier transform (DFT) for demodulation, each of size N , as shown in Fig. 1.

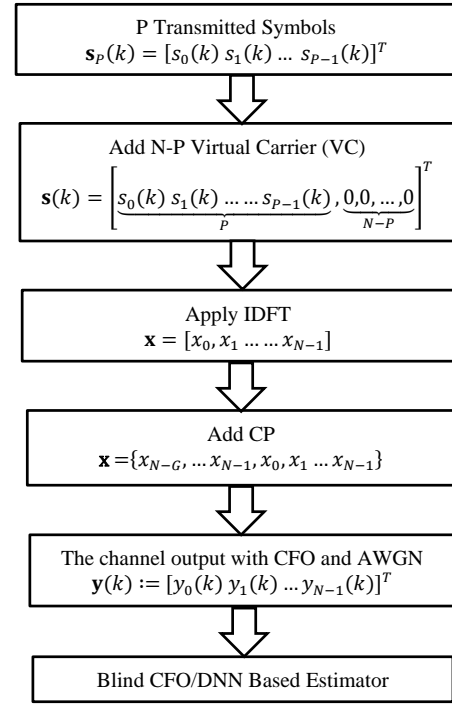


Fig. 1. Block Diagram of OFDM system

To avoid aliasing effects at the edges of the transmission spectrum, Only P subcarriers are utilized among all N components, identified as Used Carriers (UC). Let the k th UC block to be transmitted $\mathbf{s}_p(k)$ represented by a QPSK or QAM data symbol as

$$\mathbf{s}_p(k) = [s_0(k) s_1(k) \dots s_{p-1}(k)]^T \quad (1)$$

where T denotes transpose. The vector \mathbf{s}_p of length P is extended to the vector \mathbf{s} of length N by padding $N-P$ zeros, to accommodate the Virtual Carrier (VC) or unused carriers, ensuring avoidance of aliasing problems at the receiver:

$$\mathbf{s}(k) = \left[\underbrace{s_0(k) s_1(k) \dots s_{p-1}(k)}_P, \underbrace{0 \ 0 \ \dots \ 0}_{N-P} \right]^T \quad (2)$$

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

$$\begin{cases} \mathbf{x}(k) \triangleq \mathbf{W}\mathbf{s}(k) = \mathbf{W}_p\mathbf{s}_p(k) \\ \mathbf{x} = \{x_0 \ x_1 \ \dots \ x_{N-1}\} \end{cases} \quad (3)$$

where \mathbf{W}_p contains the first P columns of $N \times N$ IDFT matrix \mathbf{W} as:

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

where $W = e^{j\omega}$. Cyclic Prefix (CP) symbols are appended in front of each frame to mitigate Inter-Symbol-Interference (ISI) between consecutive OFDM symbols. Consequently, the OFDM system is expressed as:

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

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

$$\begin{aligned} \mathbf{y}(k) &= [y_0(k) \ y_1(k) \ \dots \ y_{N-1}(k)]^T \\ &= \mathbf{E} \mathbf{W}_P \mathbf{H} \mathbf{s}(k) e^{j(k-1)\varphi(N+G)} + \mathbf{z}(k) \end{aligned} \quad (5)$$

where

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

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

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

The channel frequency response is represented as:

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

To sustain orthogonality among the sub-channel carriers and to mitigate Inter-Carrier Interference (ICI), the matrix \mathbf{E} needs estimation and compensation before applying the Discrete Fourier Transform (DFT) to (5). The current objective is to propose a Deep Neural Network (DNN) to estimate φ , given that the K received noisy data blocks are only 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 [31]. Our goal is to demonstrate the effectiveness of the proposed method relative to various reference subspace-based methods.

III. DEVELOPMENT OF ML METHOD

The K blocks of the received data are collected in matrix \mathbf{Y} of size $N \times K$:

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

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

$$\mathbf{Y}\mathbf{Y} = [\text{Real}(\mathbf{Y}); \text{imaginary}(\mathbf{Y})] \quad (8)$$

Then the real matrix $\mathbf{Y}\mathbf{Y}$ reshaped to have $2NK$ elements in the input features vector to the FNN.

Recently, there has been an expanding interest in leveraging machine learning models to replace 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.

A. 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 [30]. A total of twenty thousand received block signals, each of size $2NK$ features as described in (8), are generated.

B. 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].

C. 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 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 outputs continuous values that represent φ directly.

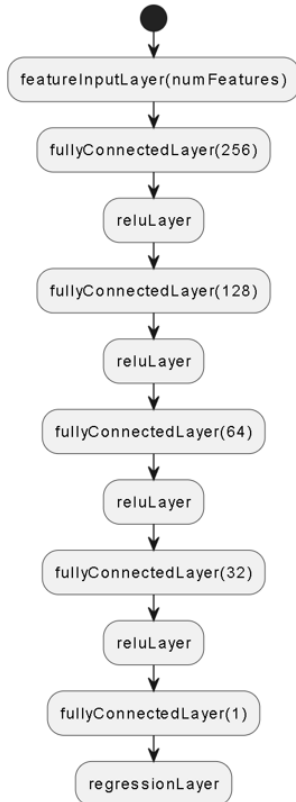


Fig. 2. Feedforward Neural Network (FNN) architecture, the diagram automatically generated by ChatUML.

D. 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 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 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.

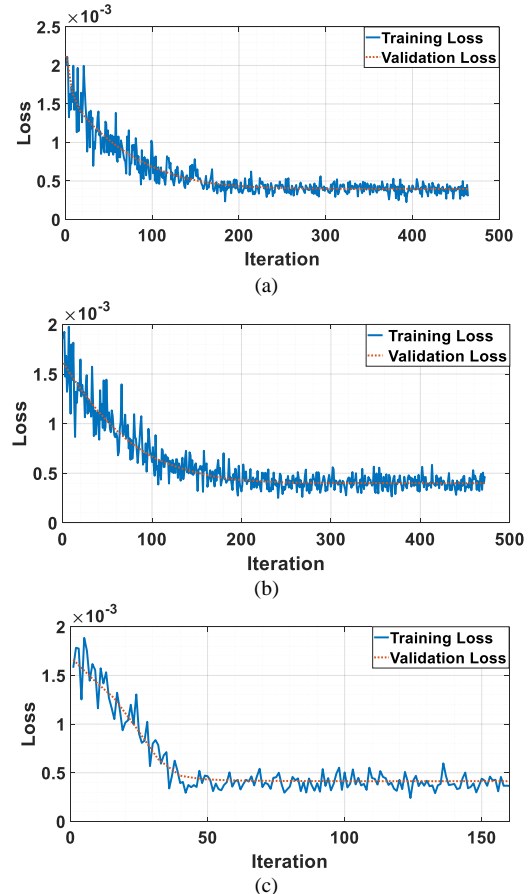


Fig. 3. Training and validation loss curves for (a) $K=1$, (b) $K=5$, and (c) $K=10$.

IV. SIMULATION RESULTS

In the conducted simulations, the proposed method was tested, validated, and compared with reference methods [28–30]. 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. To simulate real-world conditions accurately, frequency offset ϕ was drawn from a uniform random distribution. 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 practical conditions. The experiment was conducted in an AWGN environment, employing a total of 10,000 independent Monte Carlo realizations. The estimator performance was evaluated using the normalized MSE as a unified performance metric for all shown algorithms and is given by

$$\text{MSE} = \frac{1}{N_t} \sum_{i=1}^{N_t} (\phi - \hat{\phi}_i)^2 \quad (9)$$

Fig. 4 illustrates the normalized MSE of the CFO, plotted against the signal-to-noise ratio (SNR) for an assumed number of blocks, $K=10$. The FNN algorithm proposed in this study is evaluated alongside other subspace-based methods such as ESPRIT, PM(MUSIC), and QR [34–36]. At an SNR of zero dB, the MSE of the DNN is 2.25375×10^{-3} , and of 0.12298 to 0.3489 of the other methods, marking a one hundredfold enhancement. Conversely, at higher SNR levels such as 20 dB, the FNN achieves a performance of 1.73918×10^{-3} compared to the next best reference method PM (MUSIC) as 2.14405×10^{-3} . Remarkably, the performance of the proposed FNN algorithm outperforms all subspace methods, particularly in low SNR scenarios [37, 38].

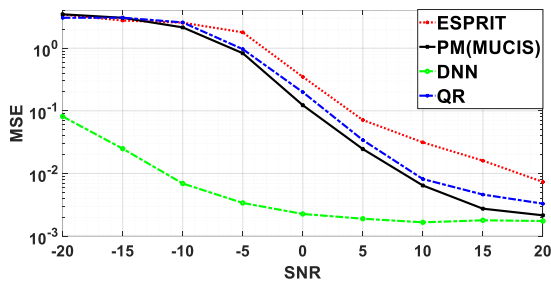


Fig. 4. MSE vs. SNR curves for $K=10$.

V. CONCLUSION

A novel Feedforward Neural Network (FNN) 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 FNN algorithm is assessed with other subspace-based methods, ESPRIT, PM(MUSIC), and QR. Remarkably, the results demonstrate that the parameter estimation using FNN algorithm consistently outperforms all subspace methods, especially in low SNR scenarios.

CONFLICT OF INTEREST

The author declares no conflict of interest.

REFERENCES

[1] S. Ali, D. Zheng, and B. Jiao, "A new pilot shared method for saving bandwidth cost of OFDM," *Sci. Rep.*, vol. 14, 2024. <https://doi.org/10.1038/s41598-024-55153-y>

[2] M. Hussien, A. Abdelmoaty, M. Elsaadany *et al.*, "Carrier frequency offset estimation in 5G NR: introducing gradient boosting machines," *IEEE Access*, vol. 11, pp. 34128–34137, 2023.

[3] H. Harkat, P. Monteiro, A. Gameiro, F. Guiomar, and H. Farhana Thariq Ahmed, "A survey on MIMO-OFDM systems: Review of recent trends," *Signals*, vol. 3, no. 2, pp. 359–395, 2022.

[4] L. Mohjazi, B. Selim, M. Tatipamula *et al.* "The journey towards 6G: A digital and societal revolution in the making," *IEEE Internet of Things Magazine*, vol. 7, no. 2, pp. 119–128, 2024.

[5] R. Liu, H. Lin, H. Lee, F. Chaves, H. Lim and J. Skögl, "Beginning of the journey toward 6G: Vision and framework,"

IEEE Communications Magazine, vol. 61, no. 10, pp. 8–9, October 2023.

[6] F. H. Juwono and R. Reine, "Future OFDM-based communication systems towards 6G and beyond: Machine learning approaches," *Green Intell. Syst. Appl.*, vol. 1, no. 1, pp. 19–25, 2021.

[7] M. Z. Asghar, S. A. Memon, and J. Hämäläinen, "Evolution of wireless communication to 6G: Potential applications and research directions," *Sustainability*, vol. 14, no. 10, #6356, 2022.

[8] S. Sharma and K. Thakur, "Carrier frequency offset in OFDM systems," presented at 2018 2nd International Conference on Inventive Systems and Control (ICISC), 2018.

[9] L. Yang, H. Zhang, Y. Cai, and H. Yang, "Blind carrier frequency offset estimation for MIMO-OFDM systems based on the banded structure of covariance matrices for constant modulus signals," *IEEE Access*, vol. 6, pp. 51804–51813, 2018.

[10] W. Zhang, Q. Yin, and F. Gao, "Computationally efficient blind estimation of carrier frequency offset for MIMO-OFDM systems," *IEEE Trans. Wirel. Commun.*, vol. 15, no. 11, pp. 7644–7656, 2016.

[11] T.-C. Lin and S.-M. Phoong, "MSE-optimized CP-based CFO estimation in OFDM systems over multipath channels," in *Proc. 2017 Asia-Pacific Signal and Information Processing Association Annual Summit and Conf.*, 2017. doi: 10.1109/APSIPA.2017.8282146

[12] A. Jayaprakash and G. R. Reddy, "Covariance-fitting-based blind carrier frequency offset estimation method for OFDM systems," *IEEE Trans. Veh. Technol.*, vol. 65, no. 12, pp. 10101–10105, 2016.

[13] S.-S. Li and S.-M. Phoong, "Blind estimation of multiple carrier frequency offsets in OFDMA uplink systems employing virtual carriers," *IEEE Access*, vol. 8, pp. 2915–2923, 2020.

[14] C.-C. Chen and M.-L. Ku, "Carrier frequency offset estimation bound for OFDM-based single relay networks with multipath receptions," *IEEE Access*, vol. 7, pp. 63900–63912, 2019.

[15] Y. Zhao and X. Chen, "Blind CFO estimation for OFDM/OQAM systems over doubly-selective fading channels," *J. Commun.*, vol. 10, no. 11, pp. 870–875, 2015.

[16] Y. Liu and X. Chen, "Joint carrier frequency offset and channel estimation for OFDM/OQAM systems on AWGN channel," in *Proc. 2019 IEEE 11th Int. Conf. on Communication Software and Networks*, 2019. doi: 10.1109/ICCSN.2019.8905324

[17] W. Cheng, C. Yushi, and W. Weidong, "Data-aided frequency offset estimation for CE-OFDM broadband satellite systems," *Appl. Sci. (Basel)*, vol. 9, no. 11, #2310, 2019.

[18] M. Huang, L. Huang, C. Guo, P. Zhang, J. Zhang, and L.-L. Yang, "Carrier frequency offset estimation in uplink OFDMA systems: An approach relying on sparse recovery," *IEEE Trans. Veh. Technol.*, vol. 66, no. 10, pp. 9592–9597, 2017.

[19] V. Stanković, "Iterative frequency domain maximum likelihood OFDM carrier frequency offset estimation," *Wirel. Pers. Commun.*, vol. 91, no. 2, pp. 975–987, 2016.

[20] Eslahi, Amin, A. Mahmoudi, and H. Kaabi, "Carrier frequency offset estimation in OFDM systems as a quadratic eigenvalue problem," *Radio Engineering*, vol. 26, no. 4, #1139, 2017.

[21] M. S. Raboh, H. M. Abd, A. A. M. Zakaria, and M. M. E. Bassiouni, "Carrier frequency offset (CFO) estimation methods, A comparative study," presented at 16th Int. Conf. on Aerospace Sciences & Aviation Technology, ASAT, 2015.

[22] J. S. Raj, A. Bashar, and S. R. Jino Ramson, *Innovative Data Communication Technologies and Application: ICIDCA 2019*, 1st ed. Cham, Switzerland: Springer Nature, 2020.

[23] S. Liu, T. Wang, and S. Wang, "Toward intelligent wireless communications: Deep learning-based physical layer technologies," *Digit. Commun. Netw.*, vol. 7, no. 4, pp. 589–597, 2021.

[24] B. A. Jebur, S. H. Alkassar, M. A. M. Abdullah, and C. C. Tsimenidis, "Efficient machine learning-enhanced channel estimation for OFDM systems," *IEEE Access*, vol. 9, pp. 100839–100850, 2021.

[25] M. Kim, W. Lee, and D.-H. Cho, "A novel PAPR reduction scheme for OFDM system based on deep learning," *IEEE Commun. Lett.*, vol. 22, no. 3, pp. 510–513, 2018.

[26] M. Vahdat, K. P. Roshandeh, M. Ardakani, and H. Jiang, "PAPR reduction scheme for deep learning-based communication systems using autoencoders," in *Proc. 2020 IEEE 91st Vehicular*

- Technology Conf., 2020. doi: 10.1109/VTC2020-Spring48590.2020.9128513
- [27] R. M. Dreifuerst, R. W. Heath, M. N. Kulkarni, and J. Charlie, "Deep learning-based carrier frequency offset estimation with one-bit ADCs," in *Proc. 2020 IEEE 21st Int. Workshop on Signal Processing Advances in Wireless Communications*, 2020. doi: 10.1109/SPAWC48557.2020.9154214
- [28] A. Li, Y. Me, S. Xue, N. Yi, and R. Tafazolli, "A carrier-frequency-offset resilient OFDMA receiver designed through machine deep learning," in *Proc. 2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications*, 2018. doi: 10.1109/PIMRC.2018.8580824
- [29] V. Ninkovic, A. Valka, D. Dumic, and D. Vukobratovic, "Deep learning-based packet detection and carrier frequency offset estimation in IEEE 802.11ah," *IEEE Access*, vol. 9, pp. 99853–99865, 2021.
- [30] M. S. Chaudhari, S. Majhi, and S. Jain, "CNN-Attention-DNN design for CFO estimation of non-pilot-assisted OFDM system," *IEEE Communications Letters*, vol. 27, no. 2, pp. 551–555, 2022.
- [31] M. Hussien, A. Abdelmoaty; M. Elsaadany *et al.*, "Carrier frequency offset estimation in 5G NR: Introducing gradient boosting machines," *IEEE Access*, vol. 11, pp. 34128–34137, 2023.
- [32] M. S. Chaudhari, S. Kumar, R. Gupta, M. Kumar, and S. Majhi, "Design and testbed implementation of blind parameter estimated OFDM receiver," *IEEE Trans. Instrum. Meas.*, vol. 71, 2021. doi: 10.1109/TIM.2021.3124833
- [33] T. Chen, S. Zheng, J. Zhu, Q. Xuan, and X. Yang, "Deep learning-based frequency offset estimation," arXiv:2311.16155, 2023.
- [34] G. Hiren, M. M. Qasaymeh, N. Tayem, R. Pendse and M. E. Sawan, "Subspace based blind CFO estimation for OFDM by exploiting used carriers," in *Proc. 2009 IEEE Sarnoff Symp.*, Princeton, 2009. doi: 10.1109/SARNOF.2009.4850278
- [35] M. M. Qasaymeh, T. Nizar, G. Hiren, M. E. Sawan and R. Pendse, "RRQR based closed-form blind carrier offset estimator for OFDM systems," in *Proc. 2009 Int. Conf. on Telecommunications*, Marrakech, Morocco, 2009, pp. 369–3726.
- [36] G. Hiren, M. M. Qasaymeh, T. Nizar, R. Pendse and M. E. Sawan, "Efficient structure-based carrier offset estimator for OFDM system," in *Proc. IEEE 69th Vehicular Technology Conf.*, Barcelona, 2009. doi: 10.1109/VETECS.2009.5073527
- [37] M. Jin, Q. Guo, J. Xi, Y. Li and Y. Li, "On spectrum sensing of OFDM signals at low SNR: New detectors and asymptotic performance," *IEEE Trans. on Signal Processing*, vol. 65, no. 12, pp. 3218–3233, June, 2017.
- [38] C. Wang, X. Wang, H. Lin, and J.-Y. Chouinard, "Low SNR timing and frequency synchronization for PIP-OFDM system," in *Proc. 2010 IEEE 71st Vehicular Technology Conf.* 2010. doi: 10.1109/VETECS.2010.5493827

Copyright © 2024 by the authors. This is an open access article distributed under the Creative Commons Attribution License (CC BY-NC-ND 4.0), which permits use, distribution and reproduction in any medium, provided that the article is properly cited, the use is non-commercial and no modifications or adaptations are made.



Mahmoud Qasaymeh is an associate professor in Computer and Communication Engineering Department, Tafila Technical University Jordan, Jordan. He received his Ph.D. degree in electrical engineering, wireless communication from Wichita State University, KS, USA and the M.S. degree communications and electronics from Jordan University of Science and Technology, Jordan. His research interests are in the wireless communication system, array signal processing, radio communication systems, blind estimation techniques, frequency hopping systems, OFDM, MIMO and coding techniques.