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Performance Evaluation of UFMC System using Neural Networks for BER Prediction and Efficiency Optimization

Kiran Kumar Padakanti [a], R. Mohandas [b], N. Sivapriya [c], Karthik Kumar Vaigandla [a, *]

[a] Department of Electronics and Communication Engineering, Balaji Institute of Technology and Science, Warangal, Telangana, India.

[b] Department of Electronics and Communication Engineering, Chennai Institute of Technology, Chennai, Tamil Nadu, India

[c] Department of Computer Applications, Cauvery College for Women, Trichy, Tamil Nadu, India

* Corresponding Author Email: vkvaigandla@gmail.com

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Abstract: In this article, we explore the use of neural networks (NNs) to enhance the performance evaluation of Universal Filtered Multi-Carrier (UFMC) systems, a key technology for modern communication networks such as 5G and beyond. Traditional methods of evaluating the Bit Error Rate (BER) and system efficiency in UFMC system can be computationally intensive and less accurate under dynamic conditions. To address these challenges, we propose a NN based approach that not only improves the accuracy of BER prediction but also significantly optimizes the system's overall efficiency. Channel state estimation (CSE) plays a major role for UFMC system to address the phenomenon of multipath channel fading. In order to achieve a high data rate using UFMC technology, it is necessary to have an effective CSE and very accurate signal detection. Recently, there has been significant interest in utilizing deep learning (DL) to enhance channel estimations. This article introduces a new method for channel estimation (CE) in UFMC system. The suggested approach utilizes DL models to improve the CE. For the UFMC system, we propose a detector based on bidirectional long short-term memory (Bi-LSTM). To identify the transmitted symbols, the suggested detector uses DL training data directly. Currently, a significant drawback of UFMC systems is the presence of a high peak-to-average power ratio (PAPR). The approach aims to reduce the BER and enhances the efficiency of the UFMC system. This is achieved by dynamically setting the constellation mapping and symbol damping on each subcarrier and sub-symbol. The results illustrate that the proposed model can accurately and efficiently recognize UFMC signals. The suggested model is being compared to Least Square (LS), LSTM, and Minimum Mean Square Error (MMSE) channel estimators. Through extensive simulations, our results demonstrate that the NN model reduces BER and enhances efficiency. The proposed model gives more effective performance in terms of enhanced efficiency and reduction of BER. The findings offer valuable insights for the design and optimization of next-generation communication systems, where accurate and efficient performance evaluation is critical.

Keywords: BER, Bi-LSTM, Channel Estimation (CE), LS, LSTM, MMSE, Neural network (NN), UFMC.

1. Introduction

Current 4G networks utilize the Orthogonal Frequency Division Multiplexing (OFDM) technology, which is a modulation method that utilizes multiple carriers. Although OFDM offers several benefits, it suffers from a high PAPR and significant Out-Of-Band (OOB) radiation [1]. Future wireless communication systems (WCSs) are anticipated to facilitate novel services and a various kind of use scenarios, including the Internet of Things (IoT). These new services necessitate many prerequisites, including extremely minimal latency, the capacity to accommodate a vast number of devices, as well as increased data rates. Many waveforms, prompted by OFDM, have been suggested for the future wireless networks. OFDM offers substantial improvements in bandwidth efficiency and effectively reduces the impact of time and frequency dispersion caused by the channel. Therefore, OFDM was the preferred modulation technique for DSLs, the 4G long term evolution (LTE) and wireless standards. Nevertheless, within the intricate framework of 5G and future networks, OFDM must confront the difficulties posed by carrier frequency offset and temporal offset [2, 3]. To fulfill a various kinds of needs, it is essential to utilize alternative data transmission methods apart than OFDM. UFMC is characterized as a more comprehensive iteration of OFDM. UFMC is a highly promising waveform for future wireless networks. In [4], the UFMC system's performance is evaluated in comparison to other waveforms.

Wireless data communication systems requires an enhanced need to provide data speed and efficiently use the existing spectrum. The UFMC modulation technology has been used to achieve these objectives. UFMC is increasingly being preferred as the modulation technique of choice for recent high-speed wireless communication systems (WCSs) [5]. This is due to its flexibility against multipath fading and its capacity to minimize the inter-symbol interference (ISI) induced by the delay spread of the wireless channel. In communication systems, CSE plays a crucial role due to its direct impact on the quality of the system. CSE is a substantial problem in UFMC systems due to the varying channel response caused by the mobility of the transmitter, receiver, or difficulties due to propagation. CSE is accomplished by including predetermined pilot carriers into the transmission of UFMC signals, however this does need additional spectrum resources. However, it is necessary to evaluate and offset the effects of the CSE at the point of receiver in order to properly recover the desired signal. While the addition of more pilots in the UFMC symbol improves estimation accuracy, it also leads to the occupation of more spectrum resources by the inserted pilot signals. Moreover, these signals are more susceptible to noise, resulting in a deterioration of the original signal recovery and a loss of bandwidth [6]. DL greatly enhances the concepts, patterns, techniques, and means of WCSs. Several interesting discoveries have been discovered in the area of physical and network layers of communication, encompassing CE, reduction of channel state information (CSI) feedback, signal recognition, and managing resources. Among the DL applications for WCSs, CE has become a significant study focus. An initial effort has been undertaken to employ advanced DL algorithms in order to comprehend the aspects of frequency-selective wireless channels (FSWCs), combat nonlinear distortion and interference in UFMC systems [7].

1.1 Research Gap

In the field of UFMC systems, traditional methods of evaluating BER and system efficiency are well-explored, but these methods have limitations. Conventional approaches for BER evaluation in UFMC systems are often based on analytical models or simulations, which can lack precision under rapidly changing conditions, such as in 5G networks. These methods also tend to be computationally expensive. Evaluating efficiency in real-time applications is crucial for communication systems, yet many existing methods are slow and not optimized for modern high-speed networks. While NNs and other ML techniques have been applied to performance evaluation in WCSs, their application to UFMC systems specifically is still limited. Most of the research has focused on other types of multicarrier systems, leaving a gap in the use of NNs for performance optimization and BER prediction in UFMC.

1.2 Highlighting the Gap

The gap this research addresses is the lack of an efficient, real-time performance evaluation method that leverages neural networks to predict BER and optimize efficiency in UFMC systems. While traditional methods are available, there is limited research on how NNs can be applied to UFMC systems, especially to improve the accuracy of BER prediction, Reduce computational complexity and increase system efficiency.

1.3 Objectives

The objective of this study is to evaluate the performance of UFMC system using NNs. Specifically, the research aims to improve the accuracy of BER prediction and optimize the overall system efficiency compared to traditional methods of performance evaluation.

- Develop a model of the UFMC system.
- Design and implement a neural network model specifically tailored for predicting the BER in UFMC systems, utilizing relevant input parameters from the system model.
- Assess the accuracy of the neural network in predicting BER by comparing its predictions with actual simulation data and traditional analytical methods.
- Analyze the efficiency of the neural network-based approach in performance evaluation, focusing on the time taken for evaluations and the resource utilization compared to conventional methods.

1.4 Motivation and Contributions

The motivation behind the research likely stems from the need to enhance the performance of UFMC systems, which are a promising waveform for next-generation communication systems like 5G and beyond. BER is a critical performance metric in communication systems, determining the reliability of data transmission. Accurate prediction of BER helps optimize system performance under varying channel conditions. The use of neural networks for BER prediction allows for non-linear and complex models to improve the accuracy of these predictions, even under adverse communication scenarios. UFMC systems are designed to overcome issues such as spectral leakage in OFDM systems. However, there are still trade-offs between complexity, power efficiency, and error rates. Optimizing system parameters like filter design, power allocation, and modulation schemes to enhance efficiency is crucial, especially as data demand increases in modern wireless systems. Machine learning, particularly neural networks, can be utilized to optimize these parameters dynamically based on real-time network conditions. NNs provide the ability to model complex, non-linear relationships between input parameters and performance metrics, which is beneficial in adaptive communication systems. Integrating machine learning in the performance evaluation of UFMC systems allows for automated adjustments to system parameters to maintain optimal performance, ensuring better spectral efficiency, reduced power consumption, and minimized latency. As wireless communication moves toward 6G, systems must accommodate a wide range of services, including URLLC and massive machine-type communications (mMTC). UFMC is seen as one of the waveforms capable of supporting these diverse requirements. Research that explores the use of neural networks for BER prediction and system optimization contributes to the broader goal of building more intelligent and autonomous 6G networks.

The primary contributions of this paper involve the proposal and evaluation of a DL based LSTM model for estimating CSI. Additionally, the paper compares the MMSE, LS, and DL approaches for determining the impulse response (IR) of various channels in the context of 5G WCSs, specifically focusing on the UFMC system. Bi-LSTM architectures provide the capability to retain information for an extended duration. This attribute is exceedingly valuable when working with time-series or sequential data. It processes both individual data points and whole data sequences. It outperforms MMSE and LS conventional-state estimators with lower complexity.

2. Related Work

Recent research has demonstrated that DL methods are very suitable for CE, and DL is being progressively employed in WCSs. Therefore, this part examines prior research conducted on our main focus. Extensive research on 5G communications was conducted in response to the need for wireless communication with ultra-high capacity and great reliability. The advancements achieved in the development of DL solutions for 5G communications are represented in [8]. Following this, they put forth efficient approaches for 5G scenarios that are predicated on DL. The text concentrates on the fundamental principles underlying diverse DL-based communication methods, in addition to the potential for research advancements and challenges that are linked to them. (Balevi & Andrews 2019) Presented a novel DL-based CE method that is training-independent. This method has been developed with high-dimensional communication signals in mind [9]. The deep channel estimator optimizes its parameters using a Deep Neural Network (DNN) that has been specifically designed for this purpose; as a consequence, the received signal is de-noised. Similar to an LS estimation, the generated signal is partitioned into pilot symbols to estimate the channel. In (Ye *et al,* 2017) forward to resolve concerns regarding nonlinear distortion and interference in OFDM systems while gaining knowledge about the characteristics of FSWCs through the use of sophisticated DL algorithms [10]. Traditional OFDM receivers are distinguished from the proposed DL method by the fact that it indirectly estimates CSI and retrieves the broadcast symbols directly. In order to rectify channel distortion, a DL model is initially trained offline using simulated data derived from channel statistics. Following that, the model is implemented directly in order to real-time restore the transmitted data [10]. (Liao *et al,* 2019) have proposed a DL-based estimation method for doubly selective channels (DSC) by utilizing a DNN [11]. The results obtained numerically demonstrate that the proposed DL-based methods outperforms the existing methods in terms of robustness and efficiency. This is particularly true when temporal variations in channel statistics are considered. Artificial neural networks (ANNs) are becoming increasingly prominent in an effort to simulate the operations of the human brain. In addition to CSI-based localization, channel decoding, image recognition, user localization, traffic information, service requests, channel usage, and CE and recognition, artificial neural networks (ANNS) have been implemented in a multitude of other applications [12–16].

In (Ye et al, 2017) a combined symbol identification and channel estimation strategy based on a feed-forward NN (FFNN) was proposed for the OFDM method with the ability to pick frequency channels [10]. When evaluating imperfect communication networks, the suggested algorithms outperform traditional estimators. Yang *et al*, [16], a DL-enabled estimator for DSCs was suggested. The suggested technique effectively function conventional linear MMSE estimators in all test scenarios. A study introduced a methodology for 1D convolutional neural networks (CNNs) in DL to estimate the channel and recover the equalized information [16]. Currently, recurrent neural network (RNN) are efficiently employed in the fields of voice and recognition of handwriting [17, 18]. The fundamental RNN is impacted by the vanishing or exploding gradient issue. The research introduced a hybrid model and data-driven receiver approach that employs LS estimation and zero-point equalization to remove initial characteristics for channel estimation and data identification [19]. The study successfully demonstrated accurate CE by utilizing an enhanced version of the extreme learning machine (ELM). The GRU is a less complex variation of the LSTM. The GRU architecture employed for solving RNN issues with LSTM exhibits a highly complex framework [20, 21].

A comprehensive examination of UFMC was conducted for 5G networks in [22]. Explored the application of deep learning to classify modulation in filtered multicarrier waveforms in [23]. Sun *et al,* [24] presents an enhanced approach to time series forecasting using a composite LSTM network that incorporates adaptive weighting. Explored the successful performance of Bi-LSTM networks in modeling RF power amplifiers for 5G WCSs in [25]. Developed a technique for predicting ship motion altitude using Bi-LSTM networks in [26]. Implemented LSTM and Bi-LSTM networks to forecast wind speed in [27]. Time-varying OFDM signal detection is achieved by the use of RNN and Bi-LSTM networks in [28]. A convolutional LSTM model is proposed for the prediction of global traffic patterns in [29]. Table 1 represents the contributions to UFMC, LSTM and Bi-LSTM. Table 2 gives analysis of literature about DL-based MCM systems and novelty analysis is given in Table 3.

Table 1. Contributions to UFMC, including LSTM and BiLSTM

Reference	Contribution
[30]	Introduced UFMC.
[31]	Based on UFMC, the 5G air interface was developed.
[32]	UFMC was examined as a potential waveform for short-burst and low-latency applications.
[22]	A comparative examination of UFMC was conducted for 5G networks.
[33]	An investigation of UFMC performance for 5G wireless networks was conducted.
[23]	Examined DL-assisted modulation classifications for filtered multicarrier waveforms.
[24]	Enhanced time series forecasting with a composite LSTM network with adjustable weighting.
[25]	Examined the efficacy of Bi-LSTM networks in simulating RF power amplifiers for 5G wireless systems.
[34]	Examined the efficacy of LSTM and Bi-LSTM in time series forecasting.
[26]	Developed a ship motion altitude forecasting system utilizing Bi-LSTM networks.
[27]	Utilized LSTM and Bi-LSTM networks for forecasting wind speed.
[28]	Detection of time-varying OFDM signals with RNN and Bi-LSTM networks
[29]	Developed a convolutional LSTM model for forecasting global traffic.

Table 2. Analysis of literature about DL-based MCM systems

Reference	Channel	DL Technique	Purpose	Modulation
[10]	Winner II	DNN	Channel Estimation (CE) & Signal Detection (SD)	QPSK
[35]	Winner II	FC-SD and BiLSTM	CE & SD	64-QAM
[36]	Rayleigh Fading	Adaptive Ensemble	CE & SD	BPSK/ QPSK/ QAM
[37]	Exponential /IEEE802.11g	CELM with SLFN	CE & Equalization	4-QAM
[38]	WinnerII	DNN	CE & SD	QAM
[39]	Rayleigh Fading	Meta-learning	CE	16-QAM
[40]	3GPPUrban Micro/EPA/WinnerII	ReEsNet	CE	NA
[41]	VehAandPedA	CENet and CCRNet	CE & SD	256-QAM
[42]	Rayleigh Fading	SVM classifier	SD	4-QAM
[43]	Tappeddelayline ModelC (TDL-C)	NN	Channel Equalisation	16-QAM
[44]	Rayleigh Fading	DNN	CE	QPSK
[45]	Doubly Selective	NN	CE	16-QAM
[46]	Rayleigh Fading	DNN	CE & SD	4-QAM
[47]	PedB	ML	CE	QPSK
[48]	Rayleigh Fading/EPA/ETU	DNN & CNN	CE	4-QAM

Table 3. Novelty Analysis

Reference	Method/ Technique	Key Features	Performance Metrics	Results/ Outcomes	Novel Contributions
[49]	Integrates Image Super-Resolution with Image Restoration Methods	Improved CE with the utilization of image processing techniques	MSE, Computational Complexity (CC)	Attains performance similar to MMSE, effective in low-SNR conditions	Combines DL with conventional image processing techniques to enhance CE
[50]	Learned Network for Approximate Message Passing	Near-field CE for XL-MIMO systems	Normalized MSE (NMSE), CC	Effective estimate with reduced complexity	AMP-based learning is used for near-field channels
[51]	ADMM-Based CE for XL-MIMO	Alternating Direction Method of Multipliers (ADMM)	NMSE, Computational Time	Efficient estimation with minimal pilot overhead	ADMM technique for minimizing pilot overhead in XL-MIMO systems
[52]	SWOMP Algorithm for Hybrid-Field CE	Joint near-field and far-field estimation; Low complexity	NMSE, SNR	Improved accuracy in hybrid-field channels; Decreased complexity	Introduces a joint hybrid-field CE using SWOMP
[53]	FSRCNN-Based CE	Rapid super-resolution CNN; Scenarios with enhanced mobility and SNR	MSE, SNR, BER	Superior performance in high-mobility scenarios; Real-time applicability	Novel application of FSRCNN for CE in 5G/B5G

3. System Model

3.1 UFMC System

In a standard UFMC system, the input data go through modulation using a digital modulation method. Subsequently, pilots are introduced to form UFMC symbols. The symbol is partitioned into M subbands. Zero-padding is applied to the samples in each subband, followed by the N-FFT procedure. Ultimately, the output of the FFT undergoes filtration and is then combined with another filtered sub-bands. The primary concept of UFMC is the partitioning of the signal into several subbands [54], as seen in Figure 1. This is distinct from OFDM, which utilizes only one filter for the entire signal. The primary cause of low OOB emission in UFMC is the implementation of sub-band filtering.

The resulting time-domain(TD) signal y(n) can be represented in Equation (1) and Equation (2),

$$y(n) = \sum_{m=0}^{M} y_m(n) \tag{1}$$

$$y(n) = \sum_{m=0}^{M} h_m(n) * x_m(n) \tag{2}$$

Here, $y_m(n)$ refers to the output of the m^th^ sub-band in the TD is given in Equation (3), the index of the time sample is n, the IR of the filter utilized for sub-band m is represented by the term $h_m(n)$, TD signal is $x_m(n)$ and linear convolution operation is indicated by *.

$$y_m(n) = \sum_{a=0}^{L-1} h_m(a)\, x_m(n-a) \tag{3}$$

where, number of filter taps are represented by L, length of $y_m(n)$ is N+L-1 samples.

The signal is extended by N-L+1 zeros at the receiving end, resulting in a sequence of length 2N. The representation of the 2N-FFT result is represented in Equation (4) and Equation (5).

$$Y_m(p') = \sum_{n=0}^{2N-1} y_m(a)\, e^{\frac{-j2\pi p'n}{2N}} \tag{4}$$

$$Y_m(p') = \sum_{n=0}^{2N-1} \sum_{a=0}^{L-1} h_m(a)\, x_m(n-a)\, e^{\frac{-j2\pi p'n}{2N}} \tag{5}$$

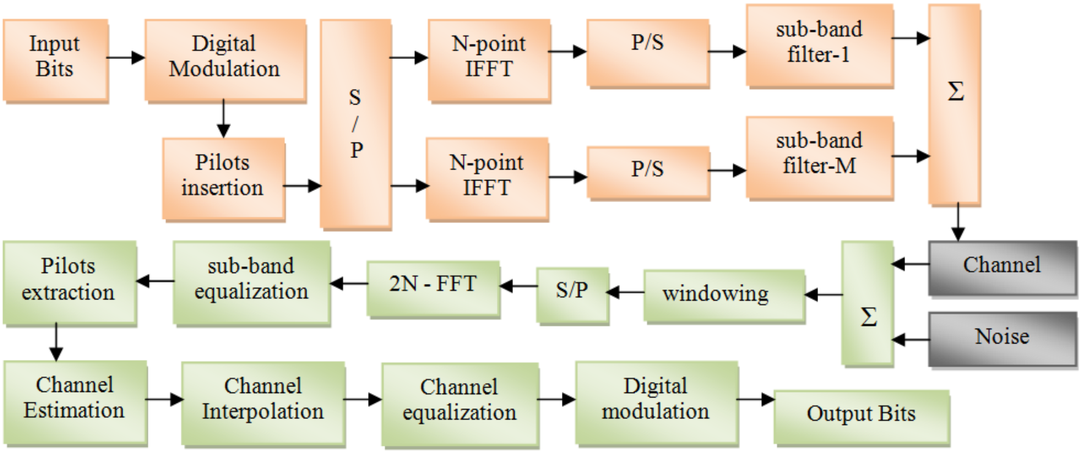

Figure 1. UFMC System

The signal received at sub-carrier p' can be expressed as in Equation (6):

$$Y_m(p') = \frac{1}{N}\sum_{n=0}^{2N-1}\sum_{p=0}^{N-1} H_m(p)\, X_m(p)\, e^{\frac{j2\pi n(2p-p')}{2N}} \tag{6}$$

If p' is an even number (i.e, p'=2l) ; then

$$Y_m(2l) = \begin{cases} 2H_m(p)\, X_m(p); & p = l \\ 0\ ; & otherwise \end{cases} \tag{7}$$

3.1.1 Channel estimation (CE)

This section covers about channel estimate for UFMC systems. CE is a crucial approach in UFMC. CE can be accurately described as the representation of a mathematically formulated channel [55]. CE Techniques are commonly employed for the purpose of finding the CIR or FR. Figure 2 illustrates the fundamental idea of CE.

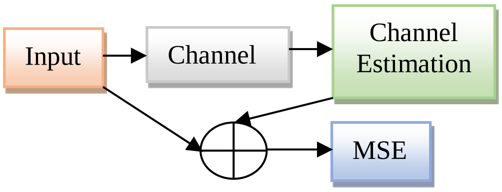

Figure 2. Basic model of CE

The requirements for the channel estimator include the reduction of the MSE and the reduction of computing complexity (CC). CE may be categorized into three types: PACE, BCE, and DDCE, is shown in Figure 3. PACE is a widely used technique for broadcasting a predetermined signal from a transmitter. The pilot refers to the reference signal that is utilized by both the transmitter and the receiver. This may be applied to any WCS and has minimal computing complexity (CC). However, one major drawback is the reduction in the transmission rate due to the inclusion of pilots. One of the design challenges for PACE is to simultaneously reduce the number of pilots and accurately estimate the channel.

The channel is estimated using the Conventional LS estimator. The received signal is expressed in Equation (8),

$$Y_m(2l) = 2\, F_m(l)\, H_m(l)\, X_m(l) \tag{8}$$

$F_m(l)$ represents the FR of the channel at subcarrier l and subband m. An estimation of the channel can be achieved by utilizing the transmitted and received pilots, as well as the FR of the filter implemented for sub-band m on the receiving end. LS channel estimation can be implemented at the pilot sub-carriers using even indexes $(2l)$, as denoted in Equation (9) by

$$F_m^{LS}(l) = \frac{Y_m(2l)}{2\, F_m(l)\, X_m(l)} \tag{9}$$

In UFMC systems, the channel estimation approach usually relies on pilot signals, where only the samples with even indices are utilized. According to the literature examination, UFMC systems have never utilized odd-indexed samples for CE. Moreover, an analytical formula for CE utilizing the odd indices is not presented, despite the fact that these indices contain crucial wireless channel information that can be utilized to increase the estimation's precision. Therefore, we propose in this study the utilization of NNs to enhance the CE by employing both the odd and even indexes of the received signal [56].

3.2 Proposed System

The schematic of the proposed UFMC transceiver system is depicted in figure 4. The UFMC transmitter allows for filtering based on subbands. Filtering may be applied with flexibility to any desired quantity of subcarriers. The subband splitter is used to convert the source bits to the subband symbols.

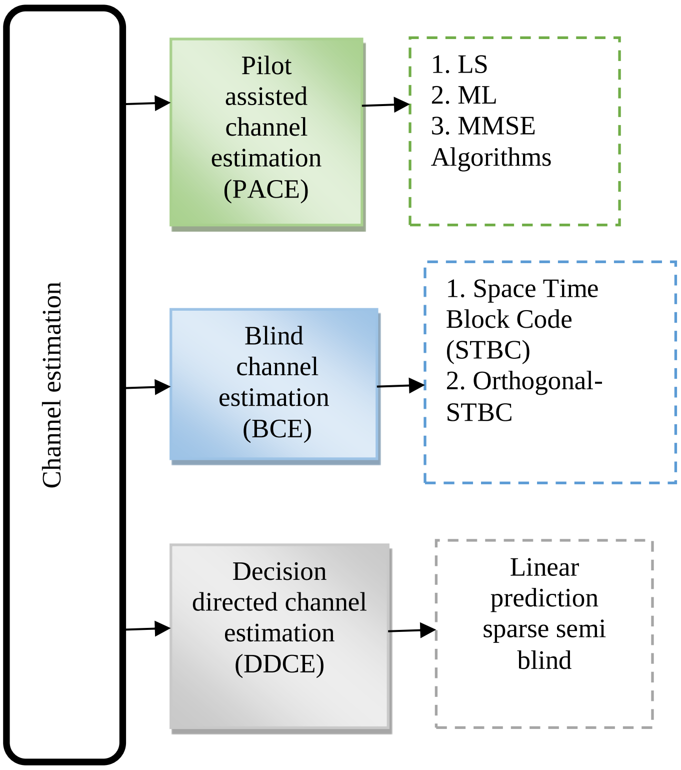

Figure 3. Various types of CE

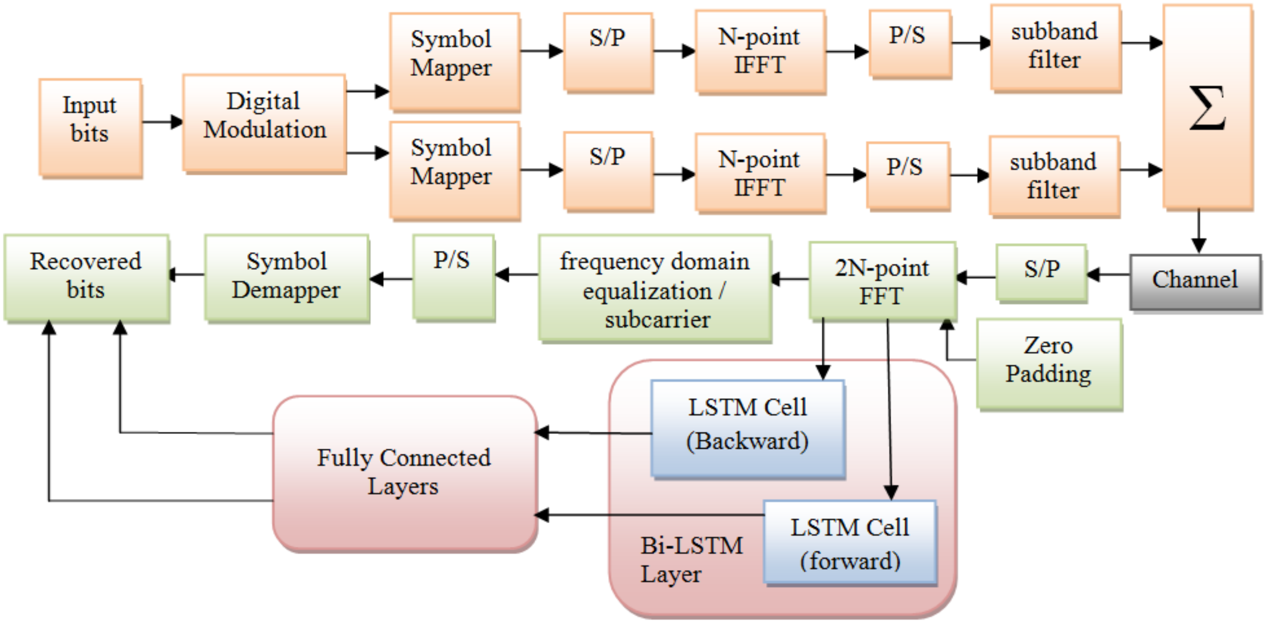

Figure 4. DL-based UFMC system

The symbols, which have been mapped to subbands, undergo a parallel modulation similar to OFDM. Following this, the subcarriers within each subband are filtered, and the merged subband symbols constitute the broadcast signal. After augmenting the signal received at the UFMC receiver with ZP, it is subsequently converted back to the frequency domain via a double-scale FFT operation. The suggested DL-based detector utilizes the symbols from the odd subcarriers and discards the symbols from the even subcarriers to generate the output bits [57].

The QAM symbols are utilized by the UFMC transmitter in order to alter the incoming bits. An total of M subbands comprise the symbols. The subcarriers are subsequently allocated the subband symbols in an appropriate fashion. Moreover, in the case of an IFFT comprising a length of N and a frequency offset length of N_{OL} on both sides of the frequency band, the subband symbols that remain are assigned to the subcarriers $N-2N_{OL}$. Once the appropriate subband symbol mapping has been implemented, the N-point IFFT is performed on every subband, resulting in the filtration of the TD symbols. Following this, the filtered subband symbols are merged in preparation for transmission across the channel. The TD UFMC signal may be calculated as, shown in Equation (10) - Equation (11).

$$x = \sum_{m=0}^{M} F_m V_m^A X_m \tag{10}$$

$$x = F \ V^A X \tag{11}$$

Where $F = [F_1, F_2, F_3, F_4, .., F_M]$, $X = [X_1 \ X_2 \ \mathrm{X}_3 \ \mathrm{X}_4 ... \ X_M]^T$ and

$$V^A = \begin{bmatrix} V_1^A & 0 & ... & 0 \\ 0 & V_2^A & ... & 0 \\ & & . & \\ 0 & 0 & . & 0 \\ & & . & \\ 0 & 0 & 0 & V_M^A \end{bmatrix}$$

Here X_m represents the m^th^ subband symbol vector, V_N^A is NxN IFFT matrix, V_1^A represents M columns of the matrix V_N^A, the Eplitz matrix is formed by the finite IR of the m^th^ prototype filter, which has a length of L_f and a frequency response of F_m. The received TD UFMC signal y is expressed in terms of transmission across the frequency-selective channel, $y = h * x + \eta$, where length of the CIR is h, convolution operator is * and Additive White Gaussian Noise (AWGN) is η. The 2N-point FFT is executed at the receiver after zero-paging the TD signal y. After ignoring the even subcarriers, the FD signal may be represented as $y = s \ V_{2N} [y \ \ 0]^T$. Here, V_{2N} refers to the 2N×2N FFT matrix and s represented only for odd subcarriers and it may be considered as $s = [s_1 \ s_3 \ s_5 ... \ s_{2N-1}]^T$. By utilizing the channel estimations, the FD UFMC symbols that are linked to the odd subcarriers are equalized. Conventionally, either the pilot-assisted LS method or the MMSE method is utilized to estimate the channel. The utilization of the OFDM pilot structure in UFMC is suggested in reference [58]. The implementation of CE and equalization in UFMC is analogous to that in OFDM, except for the modification of the prototype filter response in UFMC.

3.2.1 Methodology

The study employs a NN-based approach to evaluate the performance of UFMC systems. The following steps were involved in the methodology: We first model the UFMC system, including all relevant parameters such as subcarrier spacing, filter design, and modulation schemes. Next, we simulate various communication scenarios, generating data on system performance, particularly focusing on BER under different conditions. Then, a NN model is designed to predict BER based on the input parameters from the UFMC system. The network architecture includes multiple layers optimized for learning system behavior. Further, the NN is trained using a portion of the simulated data and tested on a separate dataset to evaluate its predictive accuracy. Finally, the results are compared with traditional performance evaluation methods to measure the accuracy of BER prediction and the system's efficiency.

3.2.2 Recurrent Neural Networks (RNNs)

RNNs are frequently employed for processing sequential data. A RNN is a sort of NN in which the output from the previous step is used as the input for the next phase. The RNN structure is shown in figure 5. In CNNs, the inputs and outputs are completely unrelated to one another. Although, when it is essential to anticipate the subsequent word in a phrase, it is essential to have knowledge of the preceding words, therefore necessitating the requirement to retain the prior words. Therefore, the problem was resolved by the introduction of RNN, which utilized a Hidden Layer (HL). The essential and fundamental characteristic of RNN is its Hidden state (HS), which retains relevant information regarding a sequence [59].

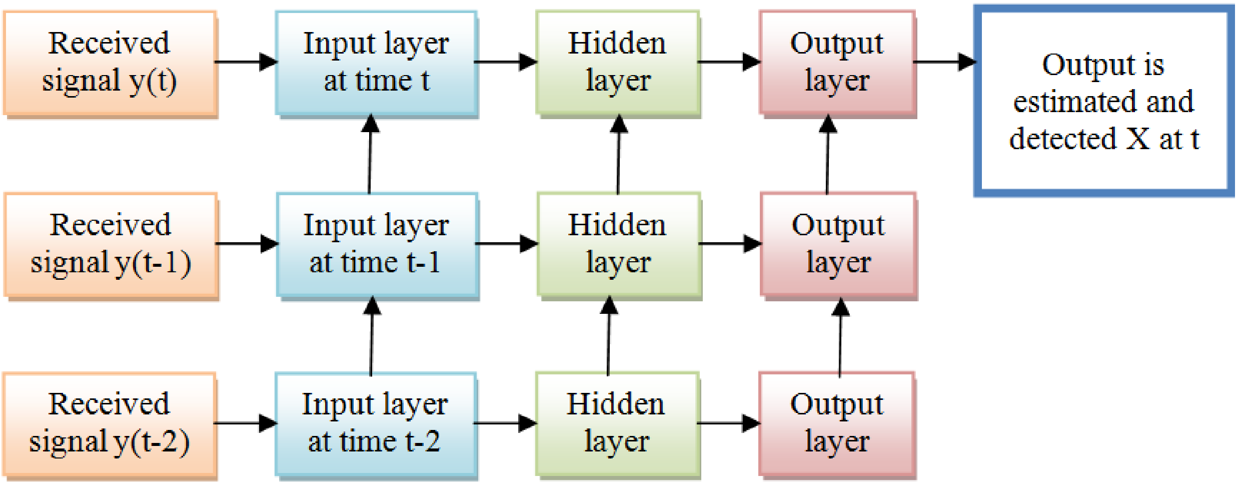

Figure 5. RNN with memory

The state is commonly known as the Memory State (MS) as it retains information about the previous input to the network. The algorithm utilizes consistent parameters for each input and performs an identical operation on all inputs or HLs in order to produce the outcome. This feature mitigates the intricacy of parameters, in contrast to other NNs.

RNNs are a type of NN designed for processing sequential data, such as time series, natural language, or any data where the order of elements matters. Unlike traditional feedforward networks, RNNs have loops that allow information to persist across steps in a sequence. This enables RNNs to maintain a "memory" of previous inputs and use that to inform predictions at each step. RNNs are widely used in applications like language modeling, speech recognition, and time-series prediction, but they can struggle with long-term dependencies. Variants like LSTM and Gated Recurrent Units (GRU) are designed to address this issue. The key features of RNNs includes, RNNs process input data one element at a time, maintaining a hidden state that carries information about previous elements in the sequence. The same set of weights is applied at each step of the sequence, making RNNs efficient for handling variable-length inputs. RNNs can theoretically capture dependencies over time by using their internal state, although in practice, this is limited to short sequences due to vanishing gradient problems.

3.2.3 LSTM architecture

LSTM is a specialized type of RNN designed to overcome the limitations of standard RNNs, particularly the vanishing gradient problem, which makes it difficult for RNNs to learn long-term dependencies. LSTMs introduce a more complex architecture that includes gates to control the flow of information. An LSTM unit is composed of four key components: cell state, forget gate, input gate, and output gate. These gates allow the LSTM to selectively remember or forget information over time, making it effective for modeling long sequences. The Forget gate is controls what information from the previous cell state to discard, the Input gate is controls what new information to add to the cell state and the Output gate controls what part of the cell state to output as the hidden state [60]. By managing the flow of information through these gates, LSTMs can capture long-term dependencies in data, making them effective for tasks like time-series prediction, natural language processing, and speech recognition.

RNNs are specifically intended to acquire knowledge from sequential input and have demonstrated remarkable efficacy in a variety of time series scenarios. However, when the sequence is significantly longer, a number of crucial hurdles arise, including problems with long-term reliance and concerns with disappearing or expanding gradients. The LSTM structure was introduced as an improved iteration of RNN in response to these concerns [61]. LSTMs are effective at using information from preceding time sequences and addressing the extended relationships within time sequences, particularly when formulating predictions and categorizing data based on sequence.

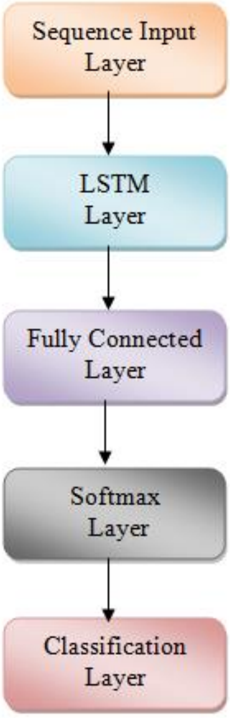

Figure 6. The layout of the DL-LSTM

Figure 6 represents the layout of the DL-based channel estimator and figure 7 illustrates a typical LSTM cell and the associated computation of the gates. The gate terminals of this system consist of three types: the input gate (I_g), the forget gate (F_g), and the output gate (O_g). The input gate (IG) determines the specific information that has to be saved. The forget gate(FG) is responsible for choosing the information that is not necessary to be stored or should be intentionally forgotten. Every individual cell retains the feedback data across certain time intervals. The gates regulate the flow of data by utilizing the weighted sum of the associated activation function. The resultant output and network state at time t are calculated based on the previous state ($\boldsymbol{c}_{t-1}$, $\boldsymbol{h}_{t-1}$) of the network. The weight vectors for the input W, recurrent R, and bias B are represented as in Equation (12),

$$W = \begin{bmatrix} W_i \\ W_f \\ W_g \\ W_o \end{bmatrix},\ \mathrm{R}=\begin{bmatrix} R_i \\ R_f \\ R_g \\ R_o \end{bmatrix},\ \mathrm{B}=\begin{bmatrix} B_i \\ B_f \\ B_g \\ B_o \end{bmatrix} \quad (12)$$

where *i* indicates to the IG, *f* is the FG, g refer to cell candidate and o represented by OG. The mathematical expressions that describe the design and functionality of the LSTM-NN cell as shown in Equation (13) - Equation (18).

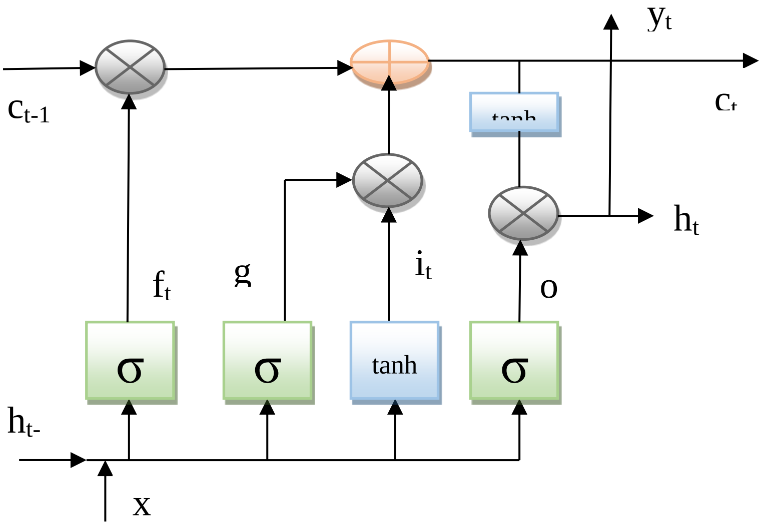

Figure 7. The LSTM cell structure demonstrates the computational operations performed at the gates estimator algorithms

$$f_t = \sigma_f \left[W_f \; x_t + R_f \; h_{t-1} + B_f \right] \quad (13)$$

$$i_t = \sigma_i \left[W_i \; x_t + R_i \; h_{t-1} + B_i \right] \quad (14)$$

$$g_t = \sigma_g \left[W_g \; x_t + R_g \; h_{t-1} + B_g \right] \quad (15)$$

$$c_t = f_t \odot c_{t-1} + g_t \odot i_t \quad (16)$$

$$o_t = \sigma_o \left[W_o \; x_t + R_o \; h_{t-1} + B_o \right] \quad (17)$$

$$h_t = o_t \odot \tanh(c_t) \quad (18)$$

A FG output of 1 signifies that the data from the previous state should be retained, whereas an output of 0 indicates that the data should be deleted. The IG provides in determining which new data conveyed by the input may be incorporated and how the cell state should be modified. A sigmoid function is employed to calculate the values that will be modified based on the current input x_t and the preceding HS h_{t-1}. A hyperbolic tangent (tanh) layer produces a novel candidate vector g_t, which is considered for constitution into the state. A cell state c_t update is then produced by combining these two vectors.

The new HS h_t is determined by the OG. Data from earlier stages is stored in this state. Using the data from the previous HS h_{t-1} and the current state input x_t, a sigmoid activation function is executed to determine which portion of the cell state is to be output. Subsequently, the newly generated cell state undergoes the tanh function. The outputs are determined by multiplication. The network determines the necessary information for the HS based on its final value. The hidden state is employed for forecasting. Subsequently, the newly updated cell state and HS are transmitted for the further step.

3.2.4 Bidirectional LSTM (Bi-LSTM)

A Bi-LSTM is an extension of the standard LSTM architecture, which improves its ability to capture context from both past and future time steps in a sequence. While a regular LSTM processes data in one direction (usually from past to future), Bi-LSTMs process data in two directions: forward and backward. The key concepts of Bi-LSTM includes, one LSTM processes the input sequence from the beginning to the end (left to right), learning dependencies from past time steps. Another LSTM processes the input sequence from the end to the beginning (right to left), learning dependencies from future time steps. At each time step, the outputs from the forward and backward LSTMs are combined, typically by concatenating them. This provides the network with both past and future context for each point in the sequence [62].

The Bi-LSTM design form with two unidirectional LSTMs (ULSTMs) that analyze the sequence in both the forward (F_{LSTM}) and backward (B_{LSTM}) orientations. This design may be understood as consisting of two various LSTM networks. A network processes the token sequence in its reversed order, whereas another network processes the sequence in its original order. The output of each of these LSTM networks is a probability vector; the final output is achieved through the combination of these two probability vectors. Figure 8 represents the structure of the Bi-LSTM network.

The Bi-LSTM is employed to improve the LSTM model's dependability and the acquisition of long-term data. The UFMC data is inputted into the FG, IG, and OG of the forward and backward LSTM networks in a sequential fashion. The training data is generated by the gates of each LSTM using LSTM-specific equations that include non-linear sigmoid and tanh activation functions. In the suggested Bi-LSTM-based framework, the input UFMC symbol sequence X is initially passed through the

F_{LSTM} cell, followed by the B_{LSTM} cell, resulting in the collection of the equivalent predicted output sequences, $O_F=F_{LSTM}(X)$ and $O_B=B_{LSTM}(X)$. The evaluation of the Bi-LSTM output may be achieved by mixing the outputs of the two cells, that can be represented as $O=[O_F, O_B]$. Both the forward and reverse flow of the data series contribute to enhanced and expedited learning. During the training phase, the network is optimized through precision adjustments to the weights. The performance of the network can then be evaluated using the validation dataset. In order to construct the UFMC frames, a random sequence of data and pilot symbols is generated during the training phase. The training datasets are generated by the DL network through the implementation of appropriate channel models and UFMC-related subband-based parallel modulation and filtering. The training datasets have been labeled to identify suitable characteristics based on the constellation map. The procedures entailed in generating a trained LSTM estimator through an offline DL process are depicted in Figure 9 and the flowchart for suggested model is shown in Figure 10. Table 4 gives comparisons among LS, MMSE, LSTM and BiLSTM.

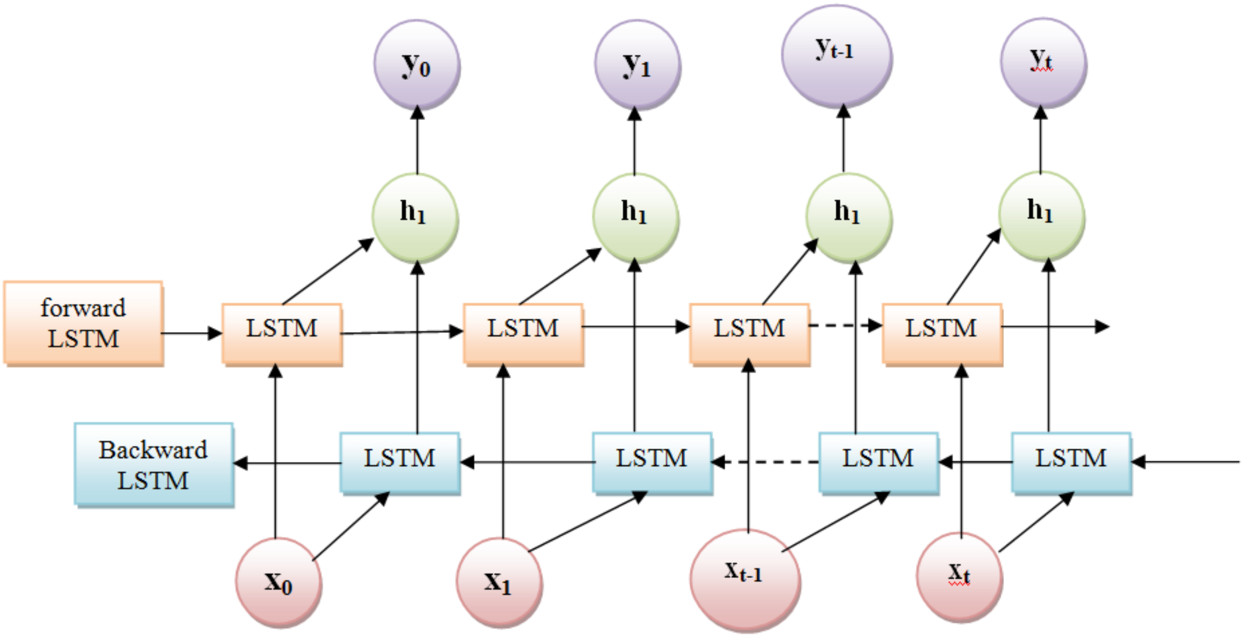

Figure 8. Architecture of a Bi-LSTM Layer

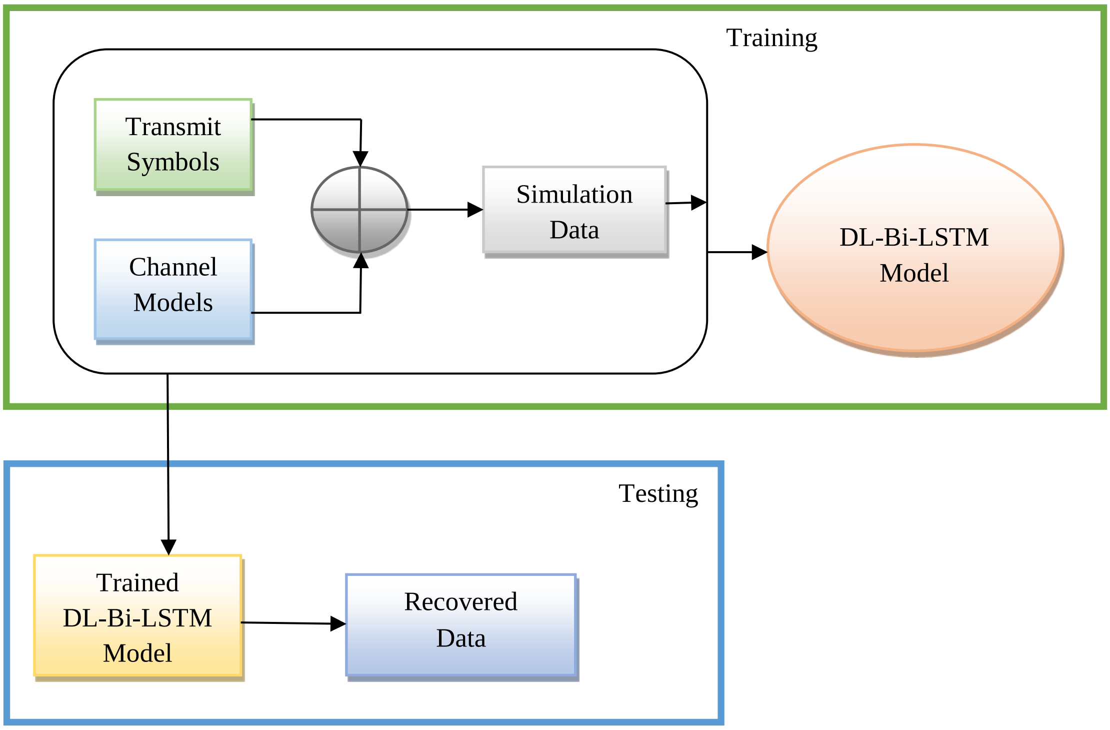

Figure 9. The training and testing phases

The various advantages of Bi-LSTM includes**,** Bi-LSTMs capture information from both past and future time steps, making them especially effective for tasks where understanding the full context of a sequence is important. This dual-direction processing can lead to better performance in tasks like speech recognition, machine translation, and natural language processing, where context from both before and after a word or time step is important. Bi-LSTMs are widely used in NLP tasks, as they can use both previous and following words to better understand meaning. When predicting values based on sequential data, both past and future values can be useful for accurate predictions.

The algorithm is designed to automate the process of evaluating and optimizing the UFMC system's performance. The algorithm integrates key components of the UFMC system, data collection, neural network training, and optimization to achieve an optimal balance between spectral efficiency and BER performance. This algorithm leverages neural networks for accurate BER prediction and applies optimization techniques to enhance the overall efficiency of UFMC systems.

Algorithm 1:

Step 1: System Setup and Initialization

(i) Input System Parameters:

- Modulation scheme (e.g., 16-QAM)
- Filter length for sub-band filtering
- Subcarrier spacing
- Signal-to-noise ratio (SNR)
- Channel conditions (e.g., AWGN)

(ii) Initialize UFMC Simulation:

- Configure the UFMC transmitter and receiver models.
- Set the number of subcarriers, sub-band filters, and carrier frequencies.

(iii) Specify Target Metrics:

- Define performance goals: BER and Spectral Efficiency (bps/Hz).
- Choose a trade-off factor between BER and system efficiency.

Step 2: Data Collection and Preprocessing

(i) Simulate the UFMC System:

- Run the UFMC system simulation under different SNR levels, modulation schemes, and other system parameters.

(ii) Collect Performance Data:

- For each configuration, record the input features (SNR, modulation, filter length, etc.) and the resulting BER.

(iii) Preprocess Data:

- Normalize or standardize the input features to ensure consistent scaling.
- Split the data into training, validation, and test sets (e.g., 80% training, 20% testing).

Step 3: Neural Network Design for BER Prediction

(i) Choose the Neural Network Architecture:

- Use a RNN, LSTM, LS, BiLSTM.
- Define the number of layers, neurons per layer, and activation functions (e.g., ReLU, Tanh).

(ii) Define the Input and Output:

- Input: System parameters (SNR, modulation scheme, filter length, etc.).
- Output: Predicted BER.

(iii) Initialize Weights:

- Randomly initialize the weights for the neural network.

Step 4: Neural Network Training

(i) Define the Loss Function:

- Use MSE to minimize the difference between actual and predicted BER.

(ii) Select an Optimizer:

- Use Adam to update the network's weights and minimize the loss function.

(iii) Train the Model:

- Use the training dataset to train the NN over multiple epochs.
- Monitor training and validation loss to ensure the model is not overfitting.

(iv) Evaluate the Model:

- Test the model using the validation dataset to tune hyperparameters.
- Use the test dataset to evaluate the accuracy of BER predictions.

Step 5: Efficiency Optimization

(i) Define the Efficiency Objective Function:

- The goal is to optimize spectral efficiency while minimizing BER.

(ii) Run Optimization Algorithm:

- Use an optimization technique to maximize the objective function.

- For each system configuration, calculate the predicted BER using the trained neural network and optimize for the configuration that maximizes system efficiency.

Step 6: System Parameter Tuning

(i) Adjust UFMC System Parameters:

- Based on the optimization results, adjust system parameters such as modulation scheme, filter length, subcarrier spacing, and power levels to achieve the best trade-off between BER and spectral efficiency.

(ii) Simulate and Verify:

- Simulate the UFMC system with the optimized parameters to verify the predicted performance.
- Record the actual BER and spectral efficiency to check if they meet the target performance.

Algorithm 2:

Input: Training data produced through simulation, transmit symbols.

Training Output: NN-Bi-LSTM

Final Output: Determined symbols

1. **Generation of training data**: create the training data, validation data, simulation parameters, and channel matrices.
2. **Training the NN**: The training and validation data are utilized to train the Bi-LSTM network. The training data and pilot symbols are used to effectively optimize the NN.
   i) Specify the initial learning rate, optimizer, maximum number of epochs, number of hidden units, and learning rate drop factor. Choose the value of the error threshold E.
   ii) If error > Threshold value E
   iii) Apply the optimizer settings to the training input sequence in order to train the NN.
   iv) Update the weights and output of the NN
   v) If error =< Threshold value E
   vi) end if
   vii) Return the Bi-LSTM layer structure
3. **Testing:** The system has been evaluated with randomly generated input symbols using the pre-trained Bi-LSTM network.
   i) The UFMC receiver extracts features and labels from the received symbols.
   ii) The DL network is used to classify the data and create the expected symbols.
   iii) By using the estimated symbols, it is possible to approximate the UFMC signal and calculate the BER.

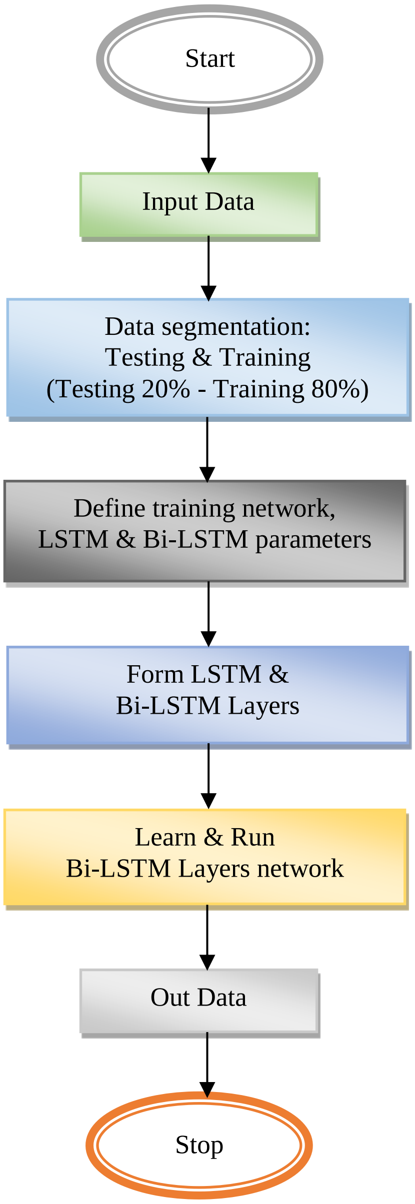

Figure 10. Flowchart of suggested model

4. Simulation Results and Discussions

In the simulation results, the primary goal is to analyze how well the neural network predicts BER and to assess the efficiency optimization in terms of system performance. The results generally focus on key performance indicators like BER prediction accuracy, spectral efficiency, and overall system optimization. The purpose of this section is to evaluate the effectiveness of the proposed NN-Bi-LSTM detector in detecting the UFMC waveform. The proposed estimator is compared to the LS, LSTM, and MMSE is performed. At various SNRs, the SERs of the proposed estimator were evaluated in comparison to those of the conventional LS and MMSE CS estimators, which were trained using simulated datasets.

Table 4. Comparisons among LS,MMSE, LSTM and BiLSTM

Feature	**LS**	**MMSE**	**LSTM**	**BiLSTM**
Principle	Minimizes squared error	Minimizes mean squared error with statistical knowledge	Captures time-dependence with neural networks	Captures bidirectional time-dependence with neural networks
Complexity	L	M	H	VH
Noise Sensitivity	H	L	M	M
Time-Dependence Modeling	N	N	Y	Y (bidirectional)
Data Requirement	L	M	H (for training)	H (for training)
Computational Load	L	H	H	VH (for training)
Performance (SNR)	Poor at low SNR	Excellent	Good, depending on training data	Excellent, depending on training data
BER	H (low SNR)	L (across SNRs)	Medium (depends on training)	L (better than LSTM)
SER	H (low SNR)	L (across SNRs)	Medium (depends on training)	L (better than LSTM)
PAPR Impact	Indirect (can increase)	Indirect (helps lower)	Indirect (can increase)	Indirect (can increase)
SNR Performance	Good at high SNR	Good at low and high SNR	M (depends on data)	Good at both high and low SNR
Efficiency (Runtime)	H	M (depends on complexity)	M (after training)	L (due to bidirectional nature)
Adaptation to Dynamic Channels	P	M	Good (learns from past data)	Very Good (learns from past and future)
Training Required	N	N	Y (data-driven)	Y (data-driven)
N : No, Y : Yes, P : Poor, L : Low, M : Moderate, H : High, VH: Very High				

The parameters used in the simulation are detailed in Table 5. We conducted a comprehensive simulation using MATLAB to demonstrate the performance of the suggested method in compensating and reducing distortions and offsets during symbol detection. Every model undergoes testing in same channel circumstances. The efficacy of the four estimators will be assessed through testing on prototypes of sizes 8, 16, and 64. This simulation is being executed using the Adam optimizer [63]. The proposed Bi-LSTM-assisted UFMC detector establishes an appropriate arrangement for complexity and performance. The Bi-LSTM offers enhanced performance in comparison to the unidirectional LSTM (U-LSTM) due to its ability to process symbol sequences in both directions. Nevertheless, due to the bidirectional nature of data flow and the extraction of features in both ways, the computational expenditure associated with Bi-LSTM is higher in comparison to U-LSTM. We utilized a significantly greater quantity of training packets, wherein each packet comprises data symbols of a predetermined length. The suggested estimator exhibits improved performance in comparison to the conventional modes.

Figure 11 illustrates the BER effectiveness of the proposed DL-based UFMC detector, and it is compared to LS, MMSE and LSTM. The result typically reported is how well the neural network predicts the BER for different system configurations and channel conditions. One of the most important results for evaluating communication systems like UFMC is the BER vs. SNR curve [64]. The neural network predictions are compared with actual BER performance for different SNR values. Within the range of SNRs from 0 to 22 dB, as shown in Figure 11, the suggested estimator has much better performance than LS estimator.

Table 5. Simulation Parameters

Parameter	**Value**
Carrier frequency	2.6 GHz
Channel model	Rayleigh Fading
FFT size	64
Fully connected layer size	4
Filter	Dolph–Chebyshev
Initial learning rate	0.01
Input data size	256
Learning rate drop factor	0.1
Modulation order	16-QAM
No. transmit frames	10000
No. of hidden layers	16
No. of subcarriers	64
No. of pilots	64, 16, 8
Noise	AWGN
No. of paths	20
Optimizer	Adam
Side lobe attenuation	40 dB
Training frames	8000
Test frame	2000

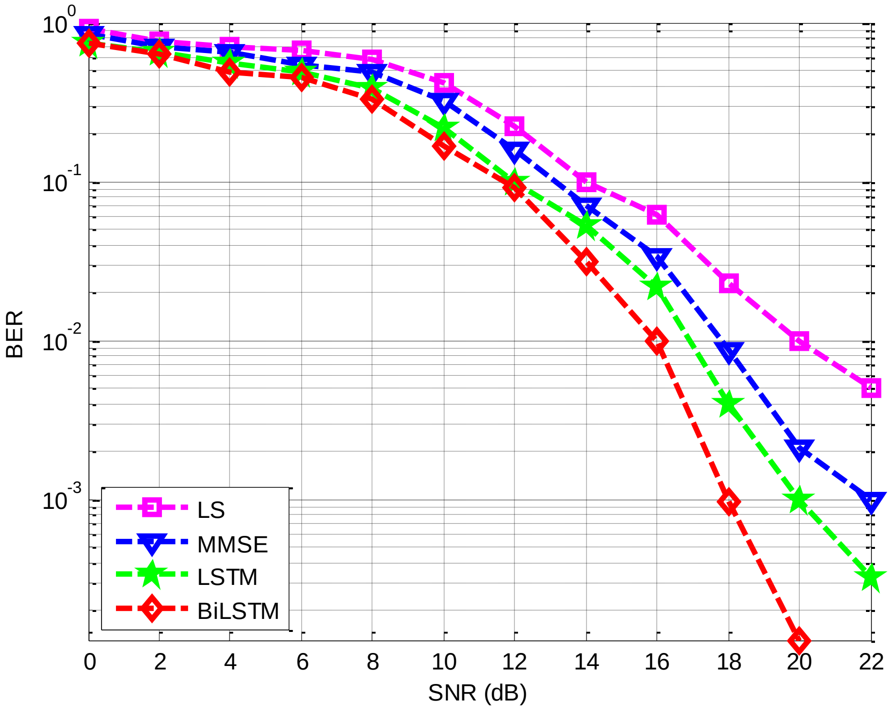

Figure 11. BER performance for 64 pilots

Table 6. BER analysis

	BER value at 64 pilots and SNR 20dB	BER value at 16 pilots and SNR 20dB
LS	0.01	0.098
MMSE	0.00213	0.0695
LSTM	0.0010063	0.017
Bi-LSTM	0.0001314	0.0063

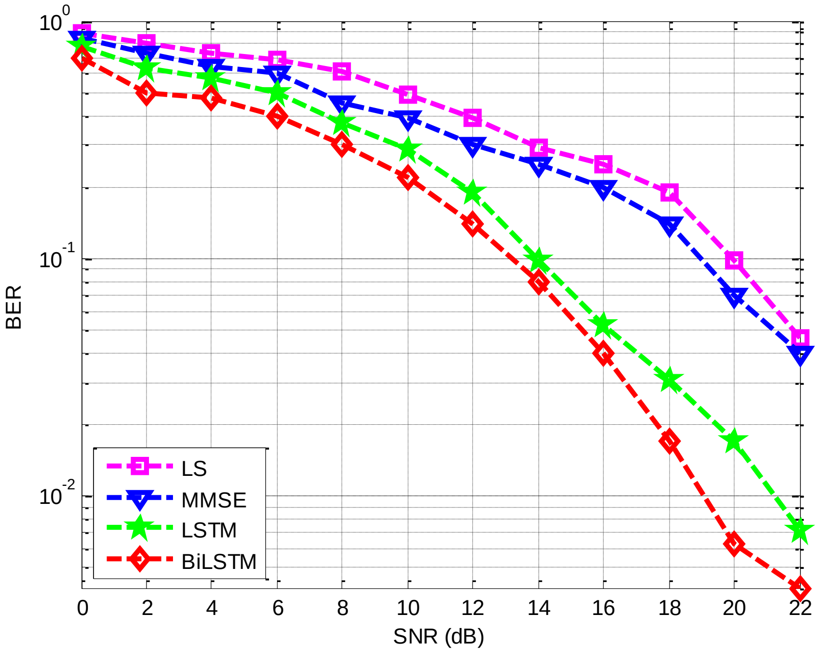

Figure 12. BER performance for 16 pilots

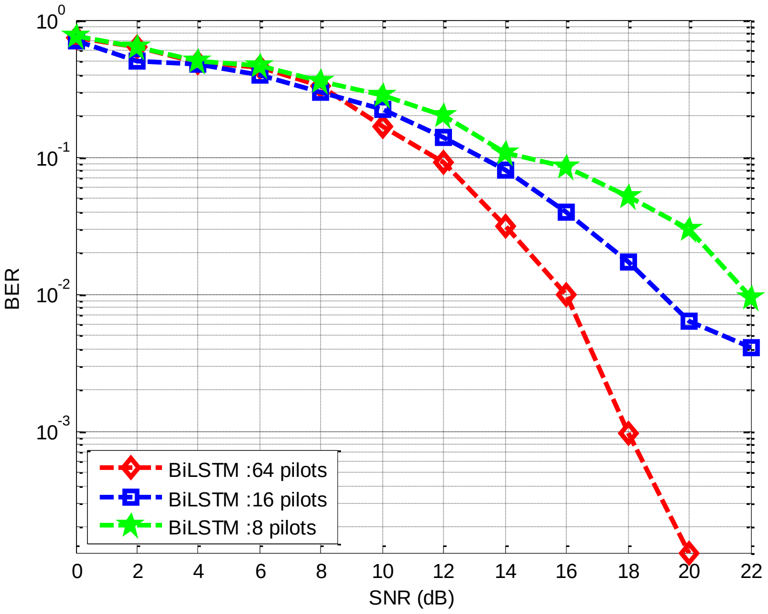

Figure 13. BER performance for 64, 16 and 8 pilots

Additionally, within the SNR range of 0 to 12, it performs the same to the LSTM estimator. Furthermore, the proposed estimator demonstrates superior performance compared to the LS and MMSE, particularly in situations with high SNR values. The MMSE estimator consistently performs greater than the LS estimator across all SNR levels. At a CCDF of 10^{-2}, the SNR values are approximately 16 dB, 17.1dB, 18dB and 20dB for the proposed model, LSTM, MMSE and LS. The suggested model improves performance by 4 dB, 2 dB and 1.9 dB over the LSTM, MMSE and LS, respectively.

Based on Figures 12, the suggested estimator demonstrates higher performance compared to the LS and MMSE estimators while the number of pilots reduces to 16. The results shows that the proposed model compares to all existing estimators for SNRs ranging from 0 to 22 dB. Figure 12 demonstrates that the standard LS and MMSE estimators, along with DL-Bi-LSTM, exhibit reduced effectiveness at low SNR levels when just 16 pilots are employed. As the SNR increases, the estimator has the ability to improve the SER. Table 6 shows the relation between BER and SNR at different pilots.

The performance of the suggested estimator can be increased with a rise in the number of pilots. Figure 13 reflects the effectiveness of the suggested estimator for pilot numbers of 64, 16 and 8. In a UFMC system, pilots are reference signals inserted into the transmitted data to assist the receiver in estimating the channel state for more accurate demodulation. Increasing the number of pilots in UFMC systems has both positive and negative impacts on system performance, including BER. The optimal number of pilots depends on the specific channel conditions and system requirements. More pilots provide better channel estimation accuracy. With a higher number of pilot symbols, the receiver can more precisely estimate the channel's response, which is especially important in frequency-selective or time-varying channels. Improved channel estimation accuracy leads to better equalization at the receiver, reducing errors in detecting the transmitted symbols. This generally lowers the BER, particularly in harsh channel conditions. While adding more pilots helps with channel estimation, it also reduces the number of subcarriers available for transmitting actual data (i.e., payload). This creates an overhead as pilots occupy part of the transmission resources. The increased overhead can affect the efficiency of power allocation and limit the number of data symbols sent, reducing overall data rate. This trade-off does not directly increase BER but could affect overall system efficiency and throughput. As SNR increases, the benefit of adding more pilots decreases because the channel can already be estimated reasonably well with fewer pilots in high-quality (low-noise) channels. In high SNR environments, increasing the number of pilots beyond a certain point provides marginal BER improvement. The system may reach a point where additional pilots do not significantly further reduce the BER. UFMC systems rely on filtering to reduce inter-carrier interference (ICI) and OoB emissions [65]. With more pilots, the impact of filtering on pilot symbols must be considered. Improper filtering could introduce distortions in the pilot signals themselves, which could negatively impact channel estimation. If the filtering process distorts the pilots, this could lead to inaccurate channel estimation and potentially increase the BER in certain scenarios.

The figure 14 depicts the performance of the suggested model, in contrast with existing techniques. SNR vs. Accuracy is a critical relationship in communication systems, particularly in systems like UFMC and other wireless systems. This relationship can be explored in terms of accuracy of detection, which includes the BER, channel estimation accuracy, and overall system performance. In digital communication systems, accuracy typically refers to how reliably the transmitted data is detected at the receiver. The accuracy is often measured in terms of BER or the probability of correctly detecting transmitted bits. At low SNR values, the noise has a significant impact on the transmitted signal. The receiver struggles to differentiate the signal from the noise, leading to incorrect bit detection and, consequently, a high BER. In channel estimation, poor SNR means less accurate channel state information, further degrading detection accuracy. As SNR increases, the signal becomes more distinguishable from the noise, leading to better detection accuracy. BER decreases significantly as the noise impacts the signal less, and the system can more accurately decode the transmitted information. At high SNR values, the signal is much stronger than the noise, leading to highly accurate detection with minimal errors. The BER approaches zero, meaning the accuracy of the system is maximized, as the noise has little impact on the signal. The figure 14 clearly illustrates the superiority of the suggested technique over the performance of existing techniques. The DL-Bi-LSTM model attains an accuracy over 90% when the SNR is 25 dB. Table 7 represents relation between SNR and accuracy.

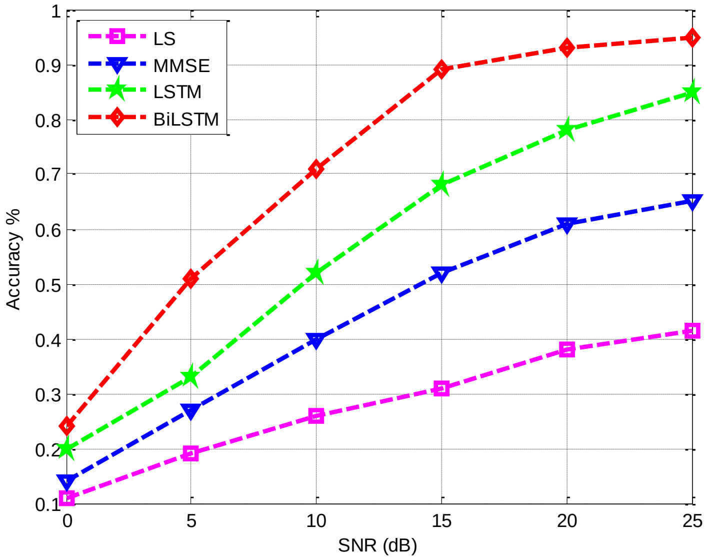

Figure 14. SNR vs Accuracy

Table 7. SNR vs Accuracy

	Accuracy at SNR 10dB	Accuracy at SNR 20dB
LS	26%	38%
MMSE	40%	61%
LSTM	52%	78%
BiLSTM	71%	93.1%

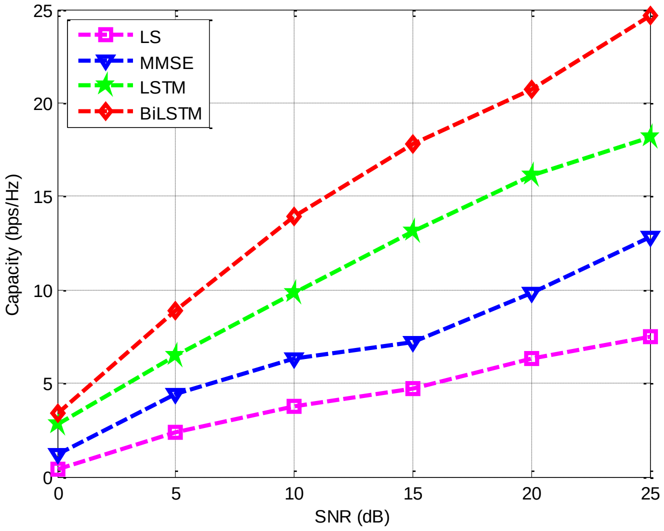

Figure 15. SNR vs Capacity

Table 8. SNR vs Capacity

	Capacity at SNR 10dB	Capacity at SNR 20dB
LS	3.73	6.3
MMSE	6.3	9.8
LSTM	9.8	16.1
BiLSTM	13.9	20.7

In Figure 15, the correlation between capacity and SNR is illustrated. Table 8 represents relation between SNR and capacity. The relationship between SNR and capacity is critical for evaluating system performance, particularly when neural networks are used for BER prediction and efficiency optimization. Capacity in wireless communication systems refers to the maximum data rate that can be transmitted reliably over a channel, and it is directly influenced by the SNR. In UFMC systems, the relationship between SNR and Capacity is influenced by several factors, such as filtering, modulation, and the interference management mechanisms that UFMC provides [66]. The system's capacity in UFMC is typically higher than other multi-carrier systems due to the reduced out-of-band emissions and better interference handling. At low SNR (e.g., 0-5 dB), the capacity of the UFMC system is limited due to high noise levels. The filtering techniques in UFMC reduce some interference, but the low SNR still restricts data transmission rates. Neural networks used for BER prediction and efficiency optimization can help configure the system to operate more efficiently under these challenging conditions by adjusting parameters such as power allocation, modulation schemes, and subcarrier filtering. As SNR improves (e.g., 10-20 dB), the UFMC system can handle more data, leading to higher capacity. The UFMC's filtering reduces ICI and OoB emissions, allowing better exploitation of the available bandwidth. The neural network can optimize the UFMC system for moderate SNR conditions by selecting higher-order modulation schemes (like 16-QAM) and optimizing the subcarrier allocation, balancing BER and capacity. At high SNR (e.g., >20 dB), the capacity of the UFMC system reaches near its maximum potential. The signal is much stronger than the noise, allowing the system to use higher-order modulation schemes and maximize spectral efficiency. Neural networks can ensure the system operates at peak efficiency in high-SNR scenarios by using complex modulation schemes and optimizing power allocation, which maximizes both the capacity and efficiency of the system. As the SNR increases, the capacity correspondingly increases. The current CSE technique of LS has a lower capacity, about 6.3 bits/second/Hz at a SNR of 20 decibels. The capacity of suggested model is significantly higher about 20.7 bps/Hz at 20dB compared to existing methods due to the flexible structure of the neural network, which effectively retains and recalls all information. Therefore, proposed strategy achieved a higher channel capacity.

These simulation results demonstrate the effectiveness of using neural networks for BER prediction and system efficiency optimization in UFMC systems. By leveraging the predictive power of neural networks, the UFMC system can be dynamically optimized for various channel conditions and system configurations, ultimately improving both performance and efficiency.

5. Limitation and Future Directions

5.1 Limitations

The system model requires large, diverse datasets to generalize well across different channel conditions. It is susceptible to noise and adversarial conditions without explicit mechanisms to ensure robustness. Networks may not generalize well to different deployment environments without retraining. The BER-focused networks may not address PAPR, a critical issue in multi-carrier systems like UFMC. It has high computational cost, lengthy training time, and difficulty in hyper-parameter tuning. NNs are black boxes, making it hard to understand predictions and optimizations. NNs may not generalize well to different or unseen channel conditions (e.g., dynamic channels). Difficulty in handling rapidly changing channels in real-time without retraining. It may struggle in predicting BER accurately in extreme conditions (e.g., low SNR scenarios). NNs can be resource-intensive, leading to power and computational inefficiency. The potential latency issues may occur when optimizing for BER or efficiency in real-time applications.

5.2 Practical Applications

The insights gained from our study can be utilized by engineers and designers to optimize the performance of UFMC system in next-generation telecommunications networks, including 5G and beyond. By implementing our neural network-based BER prediction model, network operators can enhance signal reliability and improve overall service quality. Our neural network model can be integrated into real-time monitoring systems to continuously predict and analyze BER in operating networks. This capability allows for proactive adjustments to be made to system parameters, thereby maintaining optimal performance and user experience. The findings can aid in developing strategies for efficient resource allocation in telecommunications networks. By accurately predicting BER, network operators can allocate bandwidth and other resources more effectively, reducing operational costs while ensuring high-quality service. The study promotes the integration of machine learning techniques into communication system design. Telecommunications companies may adopt our approach to develop smarter systems that adapt to varying conditions, ultimately leading to more resilient and efficient networks.

5.3 Future Research Directions

Future research could explore the application of the NN-based approach to other modulation techniques beyond UFMC, such as OFDM or SC-FDMA (Single-Carrier Frequency Division Multiple Access). This would provide a broader understanding of the applicability and effectiveness of ML in diverse scenarios. Researchers should focus on testing the generalization of the suggested NN model across different environments and channel conditions. Understanding its robustness and adaptability could enhance its real-world applicability. Future studies could investigate the integration of our neural network model with other emerging technologies, such as edge computing or the Internet of Things (IoT). This exploration could lead to innovative solutions for optimizing communication in complex, interconnected systems. Conducting longitudinal studies that monitor the performance of UFMC systems using the neural network model over time would provide insights into its long-term viability and effectiveness in various operational conditions. Future research could include a comparative analysis of different ML techniques (e.g., deep learning, reinforcement learning) in predicting BER for UFMC systems. This would contribute to understanding which methods provide the best performance under varying conditions.

6. Conclusions

The use of neural networks for BER prediction and efficiency optimization in UFMC systems offers a promising approach to tackle the challenges of non-linear modeling and dynamic channel environments. Neural networks, particularly deep learning models, can learn complex relationships between input features and system performance, allowing for improved BER prediction and system efficiency. However, the approach has notable limitations, including high data dependency, significant computational and energy costs, and generalization challenges across different channel conditions and environments. While neural networks can outperform traditional methods like LS and MMSE in certain scenarios, their high training complexity, and the need for extensive data pose substantial challenges for real-time, low-latency, and resource-constrained UFMC applications. A novel technique for estimating UFMC channel using the NN method has been proposed. Utilization of DL-Bi-LSTM neural networks was accomplished. By training the proposed estimator offline and subsequently employing it online to monitor channel statistics in a WCS, it is possible to estimate CSI parameters and reconstruct transmitted symbols. The evaluation of the suggested estimator's performance was conducted on three various pilots 64, 16, and 8. The results indicate that the suggested methodology exhibits improved performance as the quantity of pilots increases. UFMC signals can be accurately identified by the proposed model even in the absence of explicit CE. For the proposed model the obtained BER values are 0.0001314 and 0.0063 for 64 and 16 pilots at a SNR of 20dB. The proposed model attains an accuracy over 95% when the SNR is 25 dB. The capacity of suggested model is significantly higher about 20.7 bps/Hz at 20dB compared to existing models. The proposed methodology has exhibited its adaptability and improved the system's performance. The results of the simulation demonstrated that the suggested model is dependable and that its performance is superior to that of the alternative estimators. The proposed model is suggested for optimizing spectrum, energy, and data transmission rates in UFMC systems.

Future research could focus on developing hybrid models that combine the strengths of traditional methods with neural networks. These models could use traditional estimators for initial predictions and neural networks for further refinement, enhancing both prediction accuracy and efficiency. To improve the generalization of neural networks across various channel conditions, researchers can explore transfer learning. Pre-trained models can be fine-tuned on new channel environments, minimizing the need for extensive retraining and improving adaptability to diverse deployment environments. Developing neural network architectures that are more robust to noise, interference, and adversarial conditions is crucial for UFMC systems. In addition, integrating methods for uncertainty estimation within neural networks could provide insights into how confident the model is in its predictions, which would enhance system reliability. Future research should focus on multi-objective optimization frameworks that not only predict BER but also optimize key system parameters like PAPR, latency, and spectral efficiency. Neural networks can be trained to balance multiple performance metrics, ensuring that UFMC systems are optimized holistically rather than focusing solely on BER. As 6G and beyond wireless technologies develop, research should focus on how neural networks for UFMC can be integrated with massive MIMO, intelligent reflecting surfaces (IRS), and other emerging technologies. This would enhance both the performance and robustness of future wireless systems.

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Authors Contribution Statement

Kiran Kumar Padakanti: conceptualization, methodology design, data and formal analysis. R. Mohandas: conceptualization, data collection and preliminary analysis. Karthik Kumar Vaigandla: drafting the manuscript and visualizing the data, Writing -Original Draft, Review & Editing. N. Sivapriya: Formal analysis, Writing Original Draft, Review & Editing. All authors collaboratively contributed to the manuscript and approved its final version.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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