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Deep Learning Techniques for Channel Estimation in MIMO-OFDM System for 5G

Somalaxmi Vasa[1], Dr. V. Chandrasekhar[2], Dr. P. Naveen Kumar[2]

[1]*Department of ECE, CMRIT Hyderabad, T.S, India, vasasomalaxmi431ece@gmail.com*
[2]*Department of ECE, MECS, Osmania University, Hyderabad, T.S, India*

Wireless network performance depends extensively on channel estimation (CE). Moreover, the application of deep learning (DL) has demonstrated significant developments in improving communication reliability and reducing the computing complexity of 5G and subsequent networks. While CE is frequently produced using least squares (LS) estimation, which is susceptible to relatively large estimation errors, it is a cost effective method that does not require prior statistical knowledge about the channel. In order to enhance the precision of channel estimates produced by the LS methodology, the research proposes an innovative method for CE using DL. A multiple-input multiple-output (MIMO) system with a multi-path channel is used to achieve the goal by simulating scenarios in 5G and future networks while accounting for the degree of mobility suggested by doppler effects. A variety of transceiver antennas can be employed with the system model, while the machine learning (ML) module's flexibility allows for the use of various neural network (NN) architectures. The results show that the newly developed DL-based CE framework is more effective than the conventional methods that were frequently employed in earlier research. Furthermore, the long short-term memory (LSTM) architecture offers the lowest bit error rate (BER), peak to average power ratio (PAPR) and the highest level of channel estimate accuracy among all the artificial neural network (ANN) designs that were examined.

Keywords: channel estimation, deep learning, LSTM, Machine learning, MIMO, MMSE, OFDM, Signal detection.

1. Introduction

Wireless data communication systems are increasingly demanding higher data speed and efficient utilization of the available spectrum. These objectives have been met by the application of orthogonal frequency division multiplexing (OFDM) modulation technology. OFDM is increasingly being favored as the modulation technology in many current high-speed wireless communication systems (WCSs). This is due to its resilience to multipath fading and ability to decrease inter-symbol interference (ISI) brought on by the wireless channel's delay spread [1]. Channel state estimation (CSE) is a key component of communication systems due to its substantial impact on system quality. The estimation of channel state in OFDM systems is a significant challenge because of the fluctuating channel response resulting from transmitter, receiver, or propagation barrier mobility. By incorporating predefined pilot carriers into the OFDM signal transmission, CSE is achieved. However, this inclusion of pilot carriers requires extra spectrum resources. However, it is necessary to assess and offset the effects of the CSE at the receiving end in order to properly recover the target signal. While the addition of additional pilots in the OFDM symbol improves estimation accuracy, it also leads to increased occupation of spectrum resources by the inserted pilot signals. This, in turn, makes the pilot signals more susceptible to noise, resulting in a decline in the recovery of the original signal and a loss of bandwidth. The LS estimator is well recognized in conventional channel estimating approaches for its minimal computing cost, since it does not need any previous channel statistics. Nevertheless, in several real-world scenarios, particularly in multipath channels, LS estimation yields considerable inaccuracies in channel estimate [2]. As a good substitute for the LS estimator, the minimum mean square error (MMSE) estimating method produces better CE quality. However, the MMSE method requires the knowledge of operational noise power and channel statistics, resulting in a substantial computing burden.

The use of MIMO in wireless communication is a major technological advancement in current communication technology. Multiple antenna components are included at the sending and receiving ends, which sets MIMO systems distinguishable. The core concept of MIMO is the aggregation of signals broadcast from all transmitting antennas at each receiving antenna element, with the goal of enhancing the BER performance or data rate for communication. This eventually leads to an improvement in the overall communication quality for each MIMO user. By making use of this advantage, the operator's earnings and the networks' Quality of Service (QoS) could both be significantly improved [3]. Since MIMO offers higher data rate than SISO, MISO, or SIMO systems, they can potentially attain high data speeds. There is a widespread need for wireless connectivity that can handle large amounts of data quickly. Historically, in order to achieve larger data rates during transmission, it has been necessary to provide more bandwidth. WCSs may achieve significant channel capacities in situations with many signal paths by using the extra spatial dimension. The transmit signal's shape and the channel conditions determine the actual volume and performance. The attainment of this goal is affected by the structure of the MIMO system, which has an effect on the intricacy of both the sender and also recipient. Three categories can be used to group MIMO coding techniques: beamforming, space division multiplexing (SDM), or space time coding (STC). The underlying principle of space-time processing is essential to MIMO systems [4]. Time is the fundamental aspect of digital communication data, whereas space refers to the spatial component involved in using many antennas that are scattered in space. According to the literature study, current methods for estimating channels have not produced sufficient outcomes. Therefore, in order to reduce the BER and increase the MSE, in the MIMO-OFDM system, we suggest a unique approach that integrates ML techniques for CE. Improving the system's overall adaptability and efficiency in real-world scenarios is the primary objective of this approach.

DL approaches have emerged as a current and popular trend in a wide range of wireless communication applications, as shown by studies [5-9]. Applications have been identified [10–15] for channel equalization, radio allocation of resources, physical security, and channel decoding. DL is supported by several aspects across various domains. One crucial aspect is that DL-based algorithms are driven by data, which makes them more equipped to address obstacles in real-world applications. In addition, DL-based techniques exhibit reduced computational complexity, necessitating many layers of fundamental operations such as matrix-vector multiplications. In addition, DL algorithms may be parallelized to a great degree and can be developed utilizing low-precision data types with ease.

In [16], the authors presented a deep neural network (DNN) architecture that performs symbol identification in the strongest channel and precisely predicts channel state details within OFDM wireless networks through the use of hyper parameter optimization. The DNN model performs better than the MMSE estimation method. An LSTM approach to CSI estimation in OFDM is presented in the literature [17]. The comparative study showed that the proposed estimate outperformed both MMSE and LS estimators whereas utilizing a small number of pilots and taking previous channel condition uncertainty into account. A DNN-based channel equalization method was proposed by the researchers in [18] for channels with dual selective fading. According on the simulation results, the suggested DNN estimator performs more effectively and robustly than the linear MMSE (LMMSE) estimate. The authors of the article demonstrated various DNN model architectures operating within a 5G MIMO-OFDM system. These patterns were created especially for channel estimation when frequency selective fading is present. Additionally, the effectiveness of the suggested DNN estimators was assessed by contrasting them with the traditional MMSE and LS estimation methods with respect to the BER as a function of the channel estimate errors and the signal to noise ratio (SNR). The DNN-assisted estimation approach demonstrated superior performance compared to previous methods in reducing errors in CE. The authors of the study in [19] used a variety of DNN architectures, including a fully connected DNN, bi-LTSM, and convolutional neural network (CNN), to help with the CSE process in MIMO-OFDM system. They investigated several fading multi-path channel model scenarios based on the 5G network's TDL-C model. The simulation results indicates DNN-based estimators perform effective than the conventional LS and MMSE estimation methods. A recurrent neural network (RNN) comprising a CNN, batch normalization (BN) layer, and BiLSTM architecture was presented by the authors in [20]. This network was specifically created to perform signal detection functions in upstream OFDM systems that operate in channels that change over time. In order to reduce noise in the IEEE 802.11p standard, the paper [21] proposed to use DL LSTM-based data-pilot assisted (DPA) estimation, then temporal averaging (TA) processing. This method was used in a situation including a vehicular channel with different mobility conditions. A DL Bi-LSTM architecture was employed by the authors in [22] to perform symbol recognition functions in a MIMO-OFDM system. They specifically looked into how the quantity of pilots affected the system's functionality.

2. SYSTEM MODEL

2.1. Multiple Input Multiple Output System

Without the requirement for additional bandwidth or higher transmission power, a MIMO system can increase bandwidth efficiency as well as system stability very effectively by using many antennas on both sides of the wireless connection. MIMO systems, which have many broadcast and receive antennas, are the focus of extensive research. MIMO describes the process of delivering data from several devices using the same frequency/time channel utilizing many antennas as the transmitter and reception ends. These systems are highly desirable because they have the potential to increase the capacity of WCSs. MIMO technology is employed to maximize SNR in mobile WiMAX when line-of-sight is not direct and SNR adjustment is required. It's clear that MIMO systems are capable of offering higher capacities than SISO systems. Due to its many advantages, MIMO communication which makes use of several transmit and receive antenna to maximize the physical channel is currently attracting a lot of attention [23]. In addition, the capacity of the system may be significantly enhanced by using several broadcast and receive antennas to create MIMO channels. It has the ability to change multipath propagation often viewed as a drawback of wireless transmission into an advantage for the user. Moreover, it can simultaneously encode and decode multiple streams intended for the identical user. Integration of OFDM with MIMO systems has attracted a lot of interest and is thought to be a promising technique for wireless communications in the future.

2.2. Orthogonal Frequency Division Multiplexing

It is generally recognized that OFDM is a robust modulation method for wireless communication. In broadband WCS, OFDM represents a very promising data transmission technique.Without the need for complex equalization, this multi-carrier technique successfully handles the problems of multipath and frequency selective fading. Because OFDM/QAM systems incorporate a cyclically prefixed guard time between consecutive signals, inter-symbol interference (ISI) is eliminated, making them effective for multipath communications. For OFDM to preserve the orthogonality between subcarriers, time and frequency must be precisely synchronized [24]. It is also very prone to frequency offset, that can be brought on by either the difference in local oscillator frequencies at the receiver and transmitter, or doppler shift brought on by the distance that exists across the two devices. In order to provide resilience against frequency-selective fading channels, OFDM implementation uses fast fourier transform (FFT) and inverse fast fourier transform (IFFT) techniques. By splitting the channel in flat fading subchannels, this is accomplished. N orthogonal sub bands that overlap with one another are used in OFDM. They are separated by 1/T and have a single sub-band with a baud rate of 1/T.

The effective IFFT and FFT techniques are used for modulation and demodulation, respectively. OFDM has been employed in numerous broadband wireless systems to meet the QoS requirements of future multimedia applications. It is acknowledged as one of the WCs' robust technologies. Systems that use orthogonal transmission, like TDMA, FDMA, and CDMA, are inefficient since they only allow the base station to communicate to one user at a time while consuming a given resource. Due to OFDM's outstanding multipath performance and noise and interference handling capabilities, it is frequently utilized.It is not the best option, though, in situations where deliberate attempts are made to obstruct communication, like in strategic settings. A collection of parallel time-dependent frequency-flat subcarriers is created from a time-dependent frequency-selective channel using the OFDM technology. Figure 1 displays the MIMO-OFDM block diagram. The channel's frequency response must be estimated for OFDM transmission. Thus, obtaining a reliable and precise channel estimate is essential to enabling coherent demodulation and offering trustworthy data recovery.

Figure 1: Block Diagram Of MIMO-OFDM System

The symbols modulated using OFDM and transformed using IFFT may be represented as:

$$s(n) = \frac{1}{N}\sum_{k=0}^{N-1} S(k) e^{\frac{j2\pi nk}{N}}$$

where N denotes the orthogonal sub-carriers, whereas S(k) represents the symbols modulated using M-QAM. The variables k and n respectively denote the index of subcarrier and index of sample. The frame period may be calculated as the sum of N and N_C, denoted as M. The last samples of the N_C IFFT are used as a CP in order to mitigate ISI. Now we examine a time-varying multipath frequency selective fading channel with a channel impulse response (CIR) represented as

$$h(t,T) = \sum_{i=0}^{I-1} \beta_i(t)\delta(t - T_i)$$

The complex amplitude of the i^{th} route and time delay are $\beta_i(t)$ and T_i, respectively. CIR frequency response is expressed as

$$H(f) = \int_{-\infty}^{\infty} h(t,T) e^{-2j\pi Tf}$$

The signal s(n) is the result of the IFFT block, as seen in Figure 2. The channel output is represented as:

$$s(n) = \sum_{i=0}^{I-1} h(i) s(n-i)$$

The signal that has been received is represented as the result of being sampled by the DAC, frequency up-converted by a mixer, and received via the receive antennas.

$$R(n) = s(n - n_s) e^{\frac{j2\pi n f_{cfo}}{N}} + w(n)$$

The symbol timing offset n_s, arises due to mismatches in the sampling frequencies of the DAC and ADC, as seen in Figure 2. f_{cfo} stands for carrier frequency offset resulting from a mismatch in the local oscillator frequency of the transceiver. The signal s(n) that is transmitted additionally undergoes nonlinear distortion due to the high peak-to-average power ratio (PAPR) of the multicarrier signal induced by the high power amplifier (HPA). The characteristics of a nonlinear high power solid-state power amplifier (SSPA) may be expressed as follows:

$$R_{SSPA}(n) = \frac{|R(n)|}{\left[1 + \left(\frac{|y(n)|}{A}\right)^{2m}\right]^{\frac{1}{2m}}}$$

where m represents the smoothness parameter from linear to saturation region. The base-band received signal is

$$R(k) = \frac{1}{N}\sum_{n=0}^{N-1} r_{sspa}(n) e^{\frac{-j2\pi nk}{N}}$$

2.3. Channel Estimation (CE)

CE is a crucial undertaking in coherent communication systems. Furthermore, it poses a significant challenge for the integrity of coherent OFDM systems. CE is more complicated in contrast to SISO systems because the increased number of channels that have must be calculated.TheCE approach is created based on the correlation of signals and reduction of multiple access interference (MAI). The signal amplitude and propagation delay of each user are estimated. The combination of diversity and receiver performance optimization are affected by the use of CE. The CE approach significantly affects the receiver's overall BER performance. Adaptive MIMO detectors use channel estimations from the previous data block to demodulate the current block. These estimates are paired with phase tracking for improved accuracy. When a time domain channel estimate knows the length of the CIR ahead of time, it can produce much better channel estimates in MIMO-OFDM systems. In actuality, though, the dimension of the CP is frequently used to determine the necessary CIR length. The time domain CE performs much worse if the projected CIR length is substantially longer than the actual CIR length. Coherent demodulation can be made possible in OFDM systems with the use of precise channel estimate. Effective use of CE enhances LTE OFDMA system performance [25]. CE may be conducted in the absence of a training sequence via the use of a method known as blind CE. One advantage of using statistical data from the received symbol in blind CE is that it can save bandwidth. Effective use of CE enhances LTE OFDMA system performance [25]. Strategies for blind CE seek to estimate the channel without requiring any prior information about the delivered data. DFT-based techniques comprise the vast majority of CE methodologies. These methods include obtaining LS channel estimations in frequency domain and utilizing the IFFT block to convert them to the time domain (TD) in order to estimate the CIR.After that, the anticipated impulse response is analyzed and the FFT is used to convert it back to the FD.

2.3.1 Pilot Based CE Methods

A channel estimator for OFDM systems with numerous transmitters was introduced in [26]. The usage of pilot symbols, low complexity, and bandwidth efficiency define this estimation. The pilot symbols have non-overlapping frequencies in order to allow multiple channels to sound simultaneously. By interpolating a sequence of estimations acquired from periodically transmitted pilot symbols, the time-varying channel responses were found. Using simulation data, the accuracy of the suggested estimator has been verified and its limitations have been investigated. Moreover, it is demonstrated that for OFDM transmitter diversity systems, the pilot symbol assisted (PSA) CE performs better and has less processing complexity than the existing decision-directed MMSE CE.

A PSA CE method was presented in [27] for OFDM wireless channel estimation when synchronous noise is present. It is shown that in the synchronous case, employing prior knowledge of the interference structure can lead to a large reduction in the total amount of covariance parameters. To limit the amount of unknown parameters, basis functions have been used to represent the interference channel and user replies. As a result, the previously indicated approximations have produced a structured covariance model that has fewer parameters and no discernible drop in detection performance. These parameters have then been computed through the application of asymptotic MLE and Maximum Likelihood Estimation (MLE) approaches.

In the study [28], the application of the MMSE pilot-aided channel estimate method to broadband OFDM systems was investigated. The OFDM symbol has been painstakingly designed to yield a TD MMSE estimator. By employing the TD received signal sample as input for the MMSE filter, which is based upon the fourier properties of the symbol, the studied technique eliminates the necessity for DFT/IDFT prior to CE. Additionally, estimating in TD enables a simple and efficient estimation of the filter parameters.

The comb-type pilot arrangement used in the paper [29] was an introduction to the CE technique. This technique uses interpolation to figure out the channel's frequency response (CFR) for data frequencies after estimating the channel for pilot frequencies. One advantage of utilizing a comb-style pilot setup is that it can identify changes in the channel's timing. According to the simulation results, low-pass interpolation combined with comb type pilot based CE worked better than any other interpolation technique. Consequently, the MSE has been effectively reduced by the low pass interpolation.

In [30] presented a technique for precisely predicting OFDM channels in a time-frequency-selective fading context by using the Kalman filter. An assumed AR model is used to model the fading process of a time-varying channel. The estimation process has been carried out using the comb-type pilot frequency setup. After computation, the channel coefficients correlating to the pilot subcarriers were interpolated. When compared to other methods, the low-pass interpolation methodology proved better performance. Furthermore, the MSE that exists between interpolated points with their ideal values is successfully minimized by this technique. Inter-Carrier Interference (ICI) is the effect of the doppler frequency causing the subcarriers' orthogonality to be broken. The estimate process's efficiency and accuracy are severely impacted by this interference.

2.3.2 Blind Channel Estimation Methods

Two partially sighted methods for multiuser MIMO channel estimation were presented in [31].

When using Orthogonal Space Time Block Codes (OSTBCs) for data transmission, these methods are advantageous. The proposed methods tackle the problem of multiuser MIMO CE by expanding on the ideas of the popular Capon and MUSIC algorithms. We have developed a new intrinsic framework for OSTBCs that can independently identify the subspace containing the user channel matrices. From this subspace, the user channels are then extracted using the fewest possible training blocks. Compared to the standard non-blind LS-based channel estimator, the proposed methods require less training blocks, which leads to improved bandwidth efficiency.

A method integrating subspace-based approaches and second order statistical analysis was developed in [32] for blind CE in MIMO OFDM systems. The recommended technique has the advantage of being able to estimate the channel even in cases when the total amount of transmit antennas is equal to or more than the total number of receiving antennas. This is in contrast to typical subspace-based methods, which cannot be used in such cases. The channel estimates have been analyzed, taking into account both matrix ambiguity and scalar ambiguity. The outcomes of simulations have clearly demonstrated the recommended approach's efficacy in a variety of scenarios.

In reference [33], a method for estimating blind channels in OFDM systems operating over time-dispersive channels was developed utilizing subspace analysis.Using the block Toeplitz structure of the channel matrix, the proposed blind estimate technique shows good performance when applied to a small number of received OFDM blocks. The suggested technique has been shown to outperform previously published algorithms in the literature via numerical simulations. Their suggested approach has obtained a high spectrum efficiency because to its lack of need for a CP.

An approach for estimating channel attributes in a blind manner, along with a reduced complexity version based on the cyclostationarity features produced by the CP in an OFDM system, was presented in [34]. To independently identify the channel, the proposed method examines the spectrum data of the send and receive signals at a specific frequency. The suggested approach exhibits superior performance in comparison to the prior Two-Cyclic algorithm. Furthermore, a more effective method has been developed, greatly lowering the amount of computation required.

2.3.3 LMS and RLS Channel Estimation Methods

An LMS and RLS methodology was used in [35] to offer an adaptive channel estimation method for OSTBC-OFDM systems having three transmit antennas. The results of the BER obtained using the suggested Recursive LS (RLS) algorithm method demonstrate accurate recognition of the channel coefficients at the three-transmitter side, with a satisfactory level of precision.

For MIMO-OFDM systems, [36] suggested using adaptive CE techniques such normalized LMS (NLMS) and RLS. These CE techniques do away with the need for understanding channel state noise statistics by utilizing an adaptive estimator that may upgrade the estimate's parameters on a regular basis. All that is needed for the recommended NLMS/RLS CE approach is the received signal's information.According to their simulation results, in MIMO OFDM systems, the RLS CE approach performs better than the NLMS CE technique. Furthermore, compared to utilizing fewer antennas, a higher degree of performance has been achieved by using many antennas at the transmitter and/or receiver.

A technique for CE in frequency selective fading channel OFDM communication was presented in [37], with a focus on pilots. The channel responses in the equalizer have been calculated primarily utilizing three prediction algorithms: LMS, NLMS, and RLS. Three equalization strategies have been employed to reduce the fading induced by multipath delay: NLMS, RLS, and LMS. Plots of SNR against BER have been created and examined for every equalization strategy. The efficacy of algorithms in tracking may be clearly shown by showing the actual and anticipated values of channel coefficients.

2.3.4 MMSE and LS Channel Estimation Methods

A CE method that makes use of a time frequency quadratic model to simulate the properties for fading multipath channels was presented in [38]. Compared to algorithms that merely use the time or frequency polynomial model, this approach uses correlations of the channel signals across the time and frequency domains, leading to a larger reduction of noise.Moreover, the estimator shows better efficiency than the existing methods that utilize the Fourier transform. A nearly 5 dB improvement in MSEE has been demonstrated by the simulation for certain realistic channel conditions. Prior knowledge of the channel's delay and fading qualities is necessary for the algorithm. The technique may be iteratively built and adapt itself to the changing channel statistics.

A receiver technique for MIMO networks with frequency-selective fading channels was presented in [39] using an iterative approach. The proposed method performs (SISO) MAP decoding, soft interference cancellation via MMSE post-filtering, and iterative channel estimation. The decoder has computed the log-likelihood ratio of coded symbols in each iteration, which is both extrinsic and a-posteriori. We have created a channel estimator that uses soft estimations for every one the data symbols and is based on the LMMSE method. Initializing the estimator with the pilot symbols, it was then adjusted for each iteration based on a-posteriori based soft data choices obtained from the output of the decoders. Simulations have been used to assess the performance of two channel estimators: one centered around LMMSE and the other on LS solution.

In [40] developed a unique channel estimate method for pilot tones based MIMO-OFDM systems in the time domain. The time-domain signals generated by the receiver and transmitter pilots have been used to approximate the time-domain channel replies. The optimum pilot sequence (OPS), developed by the researchers, reduces the MSE of LS CE. It has been demonstrated that the OPS has three essential characteristics: position orthogonality, equal power, and equal spacing. Considering that virtual subcarriers are not employed for transmission, a maximum guard band-width (MGB) has been developed to alleviate the MSE issue. By changing the OPS's starting location, a MIMO-OFDM system can prevent interfering in the guard band if its guard bandwidth is below or equal to the MGB. According to the simulations, the derived OPS performs better in terms of MGB and MSE than the old OPS.

3. DL / ML BASED CE

This section introduces a proposed receiver that uses ML and DL algorithms to perform signal detection. The algorithms are used to i) compensate for non-linear distortion (NLD), ii) mitigate the impact of the multipath channel through estimation and equalisation, and iii) simultaneously compensate for carrier frequency offset (CFO) and sampling frequency offset (SFO) while detecting the received OFDM signal in the presence of the mentioned channel imperfections, as shown in Figure 2. The ML/DL-based receiver is implemented by offline training of the receiver and then online deployment, as shown in Figure 2. During the offline step, the models' parameters, such as the neuron weights, are acquired and refined using the training data set. This data set is obtained from the received OFDM symbols that have been subjected to different channel effects [41]. The main goal is to reduce the error function by optimizing the weights. Once trained, the model has acquired the capability to counteract and minimise the impact of different channel flaws while identifying the received OFDM signals. It is important to note that there are no extra steps or blocks needed for channel equalisation, reduction of PA nonlinearity, or compensation for CFO/SFO. OFDM systems do not need additional blocks for successive interference cancellation (SIC). The suggested DL/ML-based method offers a solution with decreased complexity for addressing the channel defects in OFDM.

Figure 2. System model for ML/DL aided OFDM system

The LS estimation minimizes the Euclidean distance between the received signal and the original signal. The channel matrix is estimated using the LS method.

$$H_{LS} = R_m S_m^H \left(S_m S_m^H \right)^{-1}$$

$$S_{LS} = R H_{LS}^H \left(H_{LS} H_{LS}^H \right)^{-1}$$

where H_{LS} refers to the predicted channel frequency response at pilots using LS method, whereas S_{LS} represents the recognized symbol using LS method. The pilot channel estimate and signal identification are performed using the LMMSE method, which use the second-order statistics of the channel state to minimise the MSE. The LMMSE estimate may be computed using the following procedure:

$$H_{LMMSE} = R_m S_m^H \left(S_m S_m^H + \frac{1}{SNR} \right)^{-1}$$

$$S_{LMMSE} = R H_{LMMSE}^H \left(H_{LMMSE} H_{LMMSE}^H + \frac{1}{SNR} \right)^{-1}$$

where $S_m$is the matrix represents the sent pilot signal, while the R_m represents the received signal. This matrix takes into account various channel imperfections.

Long short term memory (LSTM): The basic RNN technique has strong performance when used to short sequences. Nevertheless, when the sequence is quite lengthy, some crucial challenges emerge, including the disappearing gradient, expanding gradient, and long-term dependency problem. The LSTM architecture, described in [42], is used as an enhanced version of RNN to address these concerns. The RNN cells have been substituted with LSTM cell units to enhance the ability to learn from sequential, memory-based, and nonlinear input. LSTMis a kind of RNN that offers more versatility in managing the outputs. The LSTM model provides us with a higher level of control, resulting in improved outcomes. However, it also entails more intricacy and higher operational expenses. Each LSTM unit is equipped with a forget gate, denoted as ft, which acts as a window between 0 and 1 to control the flow of information. The forget gate determines the amount of information that will be discarded from the previous cell state by selectively setting part of the weights to zero.

Convolutional Neural Network (CNN) :

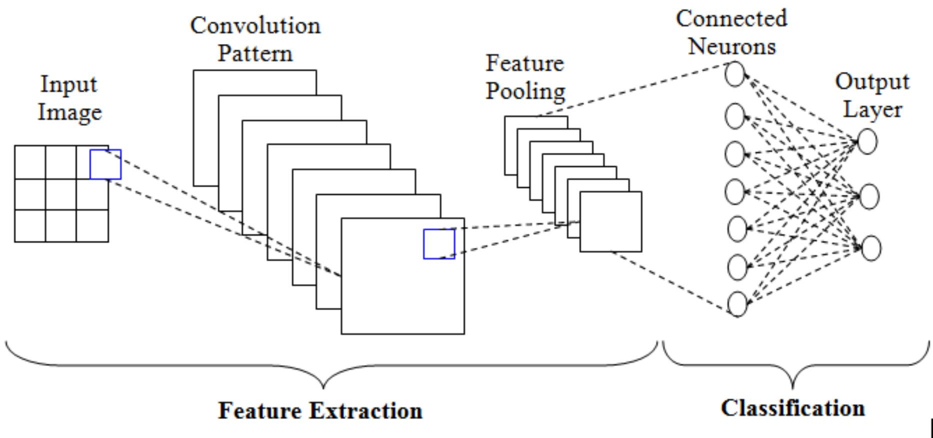

Figure3 . Basic CNN Architecture.

The input layer specifies the input for pictures. The dimensions of each picture are anticipated to be 16x16 pixels, with a single channel representing grayscale. The input layer establishes the dimensions for the pictures that will be sent to the network.The convolution 2D Layer is a layer that performs 2D convolution using 20 filters, each having a size of 5x5. Convolutional layers use filters to extract features from the input picture. The layer has 20 filters that will identify and analyse different patterns and characteristics within the input photos.The Rectified Linear Unit (ReLU) Layer is an activation function that introduces non-linearity into the network. An element-wise function is used to set all negative values to zero and keep positive ones unaffected. This helps the network in acquiring knowledge about intricate connections within the data.Max pooling layers reduce the size of the feature maps by down-sampling the spatial dimensions, while preserving the most significant information. This layer does max pooling using a 2x2 window and a stride of 2, resulting in a halving of the spatial dimensions.The Fully connected Layer consists of a set of 4 neurons that are fully linked (dense). The output from the preceding levels is processed using normal feed-forward connections. The purpose of this layer is to apply changes to the acquired characteristics before transmitting them to the ultimate output layer.The Softmax Layer, much like the previous explanation, performs the computation of the softmax activation function in order to generate a probability distribution over the various classes. The Classification Layer is the last layer of the network, particularly tailored for classification tasks. The softmax activation function is applied to the output of the preceding layer, and the loss for the classification job is computed. To summaries, the architecture receives 16x16 grayscale pictures as input and passes them through a series of layers for processing. The convolutional layer is responsible for extracting features, which are then subjected to ReLU activation to introduce non-linearity. Max pooling decreases the size of the spatial dimensions, while a fully linked layer handles the characteristics prior to classification. The softmax layer generates probabilities for each class, whereas the classification layer calculates the training loss.

4. SIMULATION RESULTS AND DISCUSSION

A dataset consisting of 255 and 860 instances was collected for the purpose of training and testing the FDNN model. For training, we used 70% of the data, allocated 15% for validation, and reserved another 15% for testing. We used a dataset consisting of 12,000 instances for both the CNN model and LSTM model. The proportions of the training set, validation set, and test set were kept identical to those of the FDNN. The training parameters for such models are shown in Table 1.

Table 1

Training Option	Value
Optimizer	Adam
Epochs	10^2
Mini Batch size	10^3
Learning Rate	10^{-2}
Learn rate Drop Factor	10^{-1}
Working frequency	10^8 Hz
Non-compressed latency	1.67 ms
Compressed latency	33 μs
Data symbol	96
IFFT	128
CP	32
Null symbol	23
Pilot symbol	9
Modulation	QAM

In order to assess the effectiveness of the suggested estimators, a simulation was conducted. The obtained results were then compared to those of the traditional LS estimation and MMSE estimation. This comparison was based on the evaluation of the BER and MSE as a function of the SNR.

Figure 4 shows the MSE vs SNR of various channel estimates. The simulation used the QAM technique to modify the delivered data. The channel estimation approaches resulted in a progressive decrease in the MSE as the SNR increases. LS estimation performed the poorest in terms of MSE in both instances due to its failure to use statistical channel information during channel estimation. In contrast, LMMSE estimation utilizes the mean and covariance matrices, leading to superior MSE performance compared to the LS method. The CNN+LSTM estimators we suggested outperformed the standard approaches in terms of MSE performance. At a SNR of 10 dB, the MSE values are 1.5×10^{-3}, 8×10^{-2}, 1×10^{-1}, 3×10^{-1}, 5×10^{-1} and 9×10^{-1} for CNN+LSTM, FDNN, LSTM, CNN, MMSE and LS, respectively.

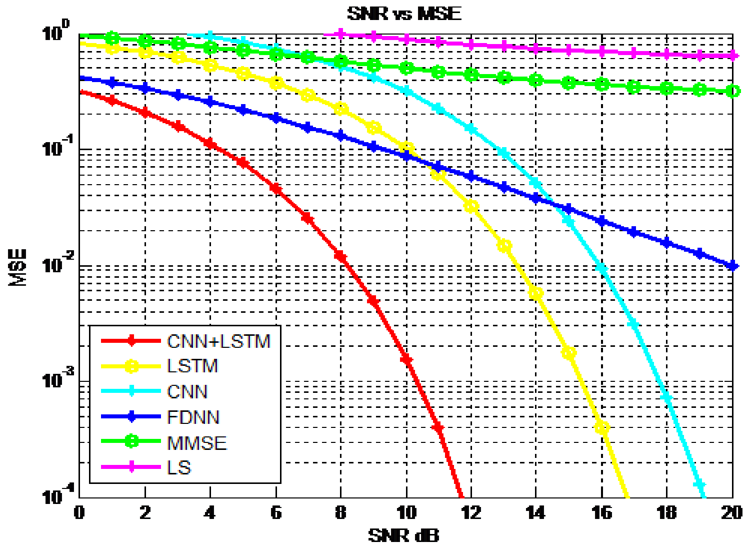

Figure 4: SNR vs MSE

Figure 5 displays the BER performance of the examined situations using various channel estimate approaches. The BER performance of the analyzed estimators exhibits a similar pattern to that of the MSE performance. Nevertheless, in both situations, the BER performance of the CNN model is somewhat worse than that of the CNN+LSTM technique when the SNR is set to 20 dB. The reason for this is because the loss function has been specifically developed to minimize mistakes in channel estimate, rather than focusing on the BER measure. At a SNR of 8 dB, the BER values are $1.9x10^{-4}$, $2x10^{-2}$, $3.8x10^{-2}$ and $1.8x10^{-1}$ for CNN+LSTM, LSTM, CNN, and LS, respectively.

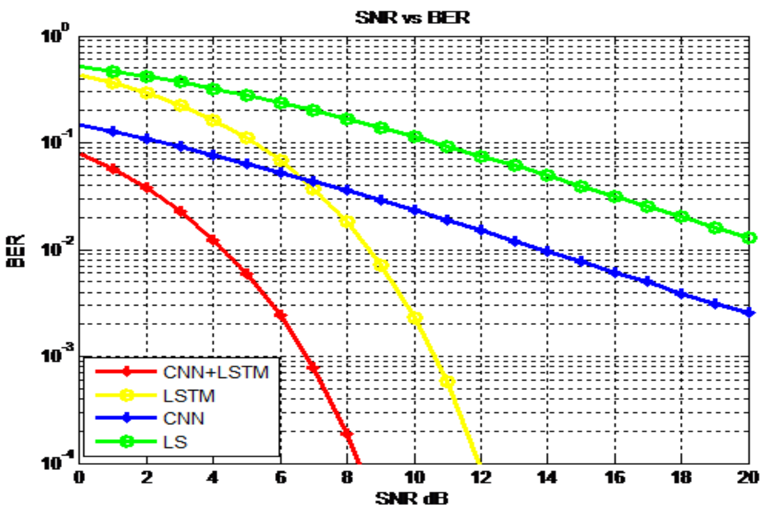

Figure 5. SNR vs BER

Figure 6 shows the PAPR performance of various channel estimators. The CNN+LSTM gives better performance and LS provides the poor performance. At a CCDF of 10-3, the PAPR values are 4.41dB, 7.52 dB, 8.34 dB, 9.82 dB and 10.8 dB for CNN+LSTM, LSTM, CNN, MMSE and LS, respectively.

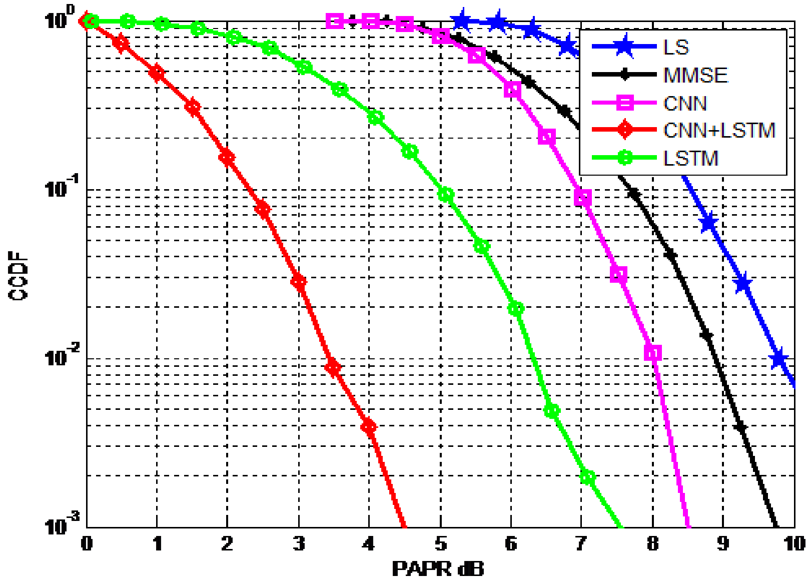

Figure 6. PAPR Analysis

5. CONCLUSIONS

This research explores alternative DNN architectures, including as fully-connected DNN, CNN, and LSTM, to assist in the CE process in a MIMO-OFDM system. The study focuses on various fading multi-path channel situations, in 5G networks. The CNN+LSTM based CE framework was trained using least squares estimation channel estimates and perfect channels. The parameters were determined as weights and biases. We evaluated the performance of the suggested estimates using the QAM modulation scheme, and compared it with standard LSTM and CNN estimations. We measured the MSE and BER as functions of SNR levels. Upon properly learning the channel parameters, we noticed a considerable reduction in MSE and BER with the implementation of the suggested hybrid DL-aided estimations. Out of the suggested DL-hybrid methods, the LSTM and CNN models demonstrated the most significant decrease in MSE. This is because they can effectively use the temporal and frequency correlation among the channels. Moreover, the suggested channel estimation techniques based on DL exhibited strong and consistent performance under different pilot densities and variations in doppler frequency.

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