https://doi.org/10.26682/sjuod.2023.26.2.46

Journal of University of Duhok., Vol. 26, No.2 (Pure and Engineering Sciences), Pp 502 - 514, 2023
(Special Issue)

DEEP LEARNING BASED CHANNEL ESTIMATION FOR 5G AND BEYOND

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(Accepted for Publication: November 27, 2023)

ABSTRACT

As the demand for high-speed and reliable wireless communication continues to grow, 5G technology has emerged as a promising solution to meet these requirements. However, accurate channel estimation is essential for reliable and efficient data transmission in 5G and beyond. Traditional channel estimation techniques face challenges as a result of the time-varying nature of channels for wireless communication, frequency-selective fading, and interference from neighboring subcarriers. To address these challenges, deep learning models have emerged as promising solutions for channel estimation in 5G systems and beyond. Leveraging the powerful representation learning capabilities of neural networks approach have been adopted to learn the underlying channel characteristics directly from the received signals, without relying on explicit mathematical models. This approach offers several advantages, including improved estimation accuracy, reduced computational complexity, and enhanced robustness against channel variations. In this paper, a DL network for Long- Short- Term - Memory (LSTM) is utilized in channel estimation approach and compare the results with traditional approaches like Minimum- Mean- Square- Error (MMSE) and Least Squares (LS). Results demonstrate that deep learning models can achieve superior estimation accuracy, especially with low number of pilots leading to increased spectral efficiency, enhanced system capacity, and reduce the latency, even in challenging channel conditions, which is the main requirements in 5G and beyond.

KEYWORDS: Deep learning; channel estimation; 5G; OFDM; MMSE; LS; and LSMT.

1. INTRODUCTION

The increasing complexity of upcoming cellular networks necessitates the implementation of robust and cost-effective technologies that can efficiently handle substantial data traffic and improve overall network performance. Channel estimation is a critical process in coherent receivers for accurately recovering transmitted data (Hammed et al., 2023). A portion of the transmitted signals, known as pilot's symbols, they are recognized by the receiver and used to estimate the channel. Traditional approaches for channel estimation rely on mathematical models of the wireless channel that are often based on idealized assumptions that might not accurately reflect the complexity of wireless channels in the actual universe (Mahmood et al., 2020).

The conventional approaches of estimation, including LS and MMSE have been extensively explored and improved under different circumstances (Mei et al., 2021). The least squares technique is independent of any prior understanding of channel statistics, but it may not achieve satisfactory performance. On the other

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hand, estimation demonstrates enhanced detection performance through the effective utilization of the channels' second-order statistics (Mei et al., 2021). These approaches are considered as pilot-based estimation, where sufficient number of pilots should be used to achieve accurate channel estimation and maintaining link quality (Munshi & Unnikrishnan, 2021).

The recent advancements in the field machine learning (ML) and artificial intelligence (AI), particularly the notable achievements in reinforcement learning (RL) and deep learning (DL), have led to significant advancements and applications across various research fields. These include robotic and autonomous management, communication and networking (Xin et al., 2018), self-organized systems, autonomous Internet of Things(IoT), computer vision, and healthcare (Saravanan Understanding of the channel., 2019).

Recently, more research has focused on applying learning algorithms to different communication scenarios. DL has gained much attention in communication systems. Some approaches have used DL to improve the performance of various traditional algorithms, such as detection of the signal (Yi & Zhong, 2020), Recognition of modulation (Zhou et al., 2020), feedback from Channel State Information (CSI) modulation recognition(Wang et al., 2019), channel equalization (Ji et al., 2020), and channel estimation (Le et al., 2021). An end to end DL architecture had used for transmission and receiving of signals in this case, and communication system operates as black box. Channel estimation, encoding, decoding, and all other functionalities of a communication link are implicitly embedded in the DL block.

When DL-based channel estimation is used, a neural network is trained to modify a parameter in accordance with pilot data under various channel conditions. This trained model is then utilized in online deployments in order to effectively recover the sent data.

The following list summarizes the primary objectives provided by this work.

- To enhance channel estimation's accuracy in challenging environments, such as those with high levels of noise or interference.
- To reduce the complexity of channel estimation algorithms, making them more suitable for real-time applications.
- To develop new deep learning algorithms that are specifically tailored addresses the issue of wireless networks channel estimation.

According to the following structure, paper is organized as follows: Section 2 the literature review discusses. Section 3 describes the basic system architecture. A various channel estimation methods used in wireless communication system explains in section 4. In the last part, section 5, results of the simulation and an explanation of those results are given. While section 6 discusses the conclusions.

2. RELATED WORK

In any wireless communication systems, a major issue is estimating the channel. In order to provide receiver ends channel status information (CSI) and prevent substantial SNR losses, researchers developed a variety of strategies for predicting wireless channel characteristics (Hammed et al., 2021) (Althahab & Alrufaiaat, 2019). As described in (Gao et al., 2018),(Yi & Zhong, 2020), initially, channel estimate LS is delivered to estimate a channel network, which subsequently feeds its output to signal detection network responsible for data recovery. In this section, an overview of several methodologies for assessing the characteristics of wireless communication channels is presented.

In (Althahab & Alrufaiaat, 2019) the study involved a comparison of three established MIMO techniques for channel estimation: non-blind, semi-blind, and blind estimation strategies. Non-blind methods, which depend on pilot symbols, exhibit a lower transmission rate, making them suitable for applications with low data rates. However, their advantage lies in their straightforward implementation and minimal computational complexity. In the context of non-blind (pilot-based) techniques, various approaches can be employed, including calculated LMS, MMSE, and ZF (Bandari et al., 2017) (Hashimoto et al., 2021), which demonstrate favorable performance but necessitate SNR estimation. To enhance channel estimation in OFDM modulation, an alternative transformation, such as the discrete wavelet transform, is explored (Ramadan et al., 2020) (Tang et al., 2018).

In the study conducted by Dong et al. (Dong et al., 2019), convolutional neural network (CNN) was employed to improve channel estimate accuracy while maintaining high performance levels in comparison to conventional approaches, all while utilizing fewer pilots signals. Numerical findings demonstrated that this data-driven approach significantly enhanced the accuracy of channel prediction.

Liao Y. et al. (Liao et al., 2019), channel estimation network utilizes convolutional neural network (CNN) for extracting feature vectors from channel response and employs recurrent neural network (RNN) to estimate channel parameters. By conducting offline training on the deep learning network and leveraging its nonlinear mapping capabilities, the model effectively incorporates channel state information (CSI) from training samples to adapt to the dynamic and non-stationary characteristic of high-speed mobile environments. Furthermore, a related work (Jiang & Schotten, 2019) specifically explored channel estimation using recurrent neural networks (RNNs).

Based on prior research, this paper's primary objective is to develop cost-effective algorithms that leverage machine learning techniques for signal processing in mm-Wave communication system. As 5G wireless networks and future technologies are expected to employ bands of higher frequencies such as mm-Wave, to achieve enhanced bandwidths and data rates, innovative approaches are necessary to effectively manage and control these advanced networks. Specifically, the focus of this paper centers around the implementation of LSTM algorithms, which aim to enhance effectiveness and accuracy of processes for identifying the signal and estimating the channel in OFDM systems. By exploring potential of machine learning, this paper aims to elevate the performance of these crucial functions, thereby boosting the overall reliability and throughput of OFDM communication systems.

3. SYSTEM ARCHITECTURE

The fundamental system model is illustrated in Figure 1. Within this model, User Equipment (UE) and Base Station (BS) both utilize a singular antenna for communication purposes. The OFDM system is comprised of N subcarriers. The Base Station (BS) encodes a binary data stream into symbols using specific modulation coding scheme(MC)scheme (MCS) like Quadrature Phase Shift Keying(QPSK), which is already known at UE. These modulated symbols then converted into parallel steams and transformed into time domain signals using Inverse Fast Fourier Transform(IFFT). To deal with Inter Symbol Interference(ISI), Cyclic Prefix (CP) appended to resulting time domain signals. Importantly, the CP's length must be equal to or longer than the channel impulse response to effectively counteract ISI.

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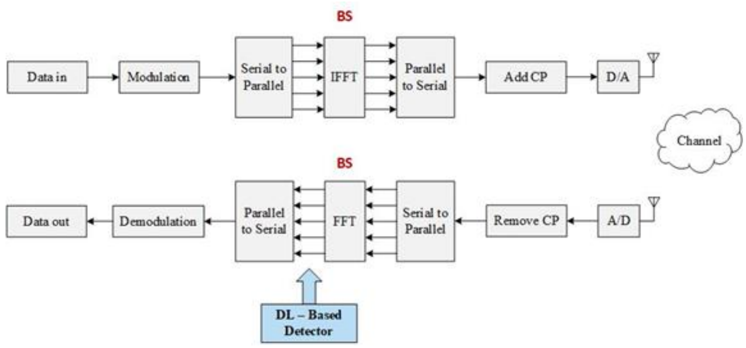

Fig.(1):- System model

The multipath channel $\{h(l)\}_{l=0}^{L-1}$, is made up of resolvable paths L. Signal then transmitted through antenna after passing through digital to analog convertor (DAC). UE then receives signal $\tilde{y}(l)$

$$\tilde{y}(l) = \tilde{x}(l) \otimes h(l) + \tilde{n}(l) \quad (1)$$

Let us denote circular convolution operation as $\otimes$,with $\tilde{y}(l)$ representing the received signal, $\tilde{x}(l)$ representing the transmitted signal, and $\tilde{n}(l)$ denoting the presence of Additive White Gaussian Noise (AWGN). Once CP eliminated and Fast Fourier Transform (FFT) applied, a resulting received signal at subcarrier ´k´ could be expressed as

$$y(k) = x(k)\,H(k) + n(k),\; k = 1, 2, \ldots \quad (2)$$

The discrete Fourier transforms of the variables $\tilde{y}(l)$, $\tilde{x}(l)$, and $\tilde{n}(l)$ are represented as y(k), x(k), and n(k) correspondingly. DFT is also utilized to acquire the channel at subcarrier k.

$$H(k) = \sum_{l=0}^{L-1} h(l)\left(e\right)^{-j\frac{2\pi l}{N}k} \quad (3)$$

Additionally, transmitted symbol is considered to be of unit power $E\left[|x(k)|^2\right] = 1$, and a random noise at k subcarrier is distributed as $CN(0, \sigma_n^2)$.

The proposed model integrates channel estimation and detection to retrieve transmitted symbol on specific subcarrier after FFT. Pilot symbols situated in initial OFDM block, while transmitted data follows in subsequent OFDM blocks. When combined, these elements create a cohesive framework. The channel is considered constant across the pilot and data blocks within a frame, but it varies from frame to frame. In model, the DNN receives data consisting of one pilot block and one data block as input and recovers transmitted data end to end.

4. Channel Estimation and Detection

This section begins by discussing conventional Methods for channel estimation and signal identification, which are then put to use in the performance comparison that follows. DL-based detectors are then constructed for SISO communication systems according to the procedure outlined in Section 4.2, which details the format of training data as well as the DNN training process.

4.1. Traditional Algorithms for Channel Estimation

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In traditional channel estimation the LS used to minimize squared distance between original and received data (Hammed et al., 2021). The errors like MSE and BER can be minimized. In OFDM systems, LS channel estimation approach is simple to implement. LS algorithms are well-known for their cheap computing costs, robustness, and simplicity of implementation. The LS channel estimating approach employs block type pilots to estimate channel state information (Far, 2020). It can be seen that the LS method's predicted channel frequency response (CFR) at pilots is represented as

$$\widehat{h}_{LS}(K_p) = \frac{Y(K_p)}{X(K_p)} \tag{4}$$

The transmitted pilot signal, denoted as $X(k_P)$, and the received pilot signal, denoted as $Y(k_P)$, correspond to the k_P-th pilot symbol. By employing one-dimensional linear interpolation, it becomes possible to derive channel coefficients for all data symbols in frequency domain $\widehat{h}_{LS}$. In order to reduce Mean Square Error(MSE), an MMSE channel estimation scheme has been developed. Although more intricate than the LS estimator, this approach yields superior outcomes. MMSE technique consists of matrix inversions and multiple multiplications but exhibits faster performance compared to the LS estimator(Gayathri et al., 2021).

$$\widehat{\mathrm{h}}_{u,s}^{MMSE} = R_{hh}^{u,s}\left(R_{hh}^{u,s} + \sigma_n^2 \mathrm{I}_N\right)^{-1} \widehat{\mathrm{h}}_{u,s}^{LS} \tag{5}$$

$$R_{hh}^{u,s} = \mathbf{E}\left[\mathrm{h}_{u,s}\mathrm{h}_{u,s}^{H}\right], s = 1, 2, 3, ..., N_{TX}, u = 1, 2, 3, ..., N_{RX},$$

The noise variance is denoted by σ_n^2, while auto correlation matrix of the N1 frequency domain channel $h_{u,s}$ is denoted by $R_{hh}^{u,s}$. Both the LS and MMSE techniques may be used to estimate channels in SISO system with $N_{TX} = N_{RX} = 1$. In contrast to MMSE approach, which relies on channel's second order statistics to improve performance, LS approach may be used with no knowledge of such data in advance.

4.2. Deep Learning Techniques for Detection and Channel Estimation

The architecture of a DNN model shown in the form of a schematic that can be seen in Figure 2. It is possible to think of DNNs as an improved version of ANNs. This improvement is achieved by including more hidden layers in DNNs in order to enhance their capacity for representation and recognition. Each layer of network is made up of several neurons, and output of each neuron is a nonlinear function of a weighted sum of the outputs of neurons in the layer that comes before it. This shown graphically in figure 2, which could be seen below (Narengerile, 2022).

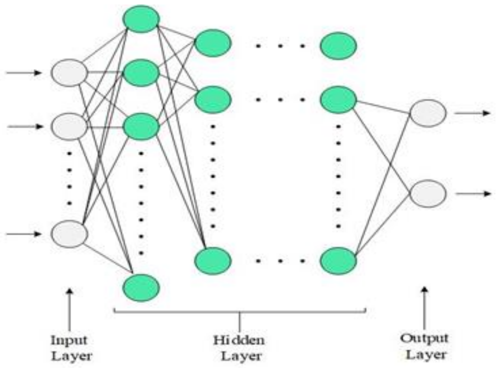

Fig.(2):- An example of a three-layer ANN

The nonlinear function used in deep learning models can be either the Sigmoid function is referred to as in the following definition:

$$f_s(a) = \frac{1}{1+e^{-a}} \qquad (6)$$

As well as; Rectified Linear Unit (ReLU) function, defined as

$$f_R(a) = \max(0, a) \qquad (7)$$

As a result, these nonlinear transformations are sequentially applied to the input data I to produce output of network, indicated as Z. This may be described mathematically as a series of nonlinear transformations.

$$Z = f(I;\theta) = f^{(L-1)}(f^{(L-2)}(\cdots f^{(1)} \qquad (8)$$

where, L stands for the total number of layers in the network, and θ is the weight used by the network. Before a model can be used in production, its parameters—specifically, the weights given to its neurons—must be fine-tuned. Training using a collection of labeled training data, where the intended outputs are known, is often used to learn the appropriate weights. The model may then fine-tune its weights in order to reduce error and maximize efficiency.

A DNN that has been trained to retrieve symbols of transmitted at a particular subcarrier, such as k subcarrier, is used to represent the DL-based detector. The application of DL based detector for OFDM receiver with single receiver antenna is shown in Figure 3. DL based detector, which executes integrated channel estimation and signal detection in end to end manner, effectively performs channel estimation procedure. The problem of joint channel estimation and detection approached as classification problem, with signal received categorized into Q categories. DNN learns a CSI implicitly by off-line training utilizing many labeled training samples produced by 3GPP TR 38.91channe1 model operating at mm-Wave frequencies (Rumney et al., 2018). DNN could recognize symbols and data transmitted immediately without need for explicit channel estimate during the online deployment phase.

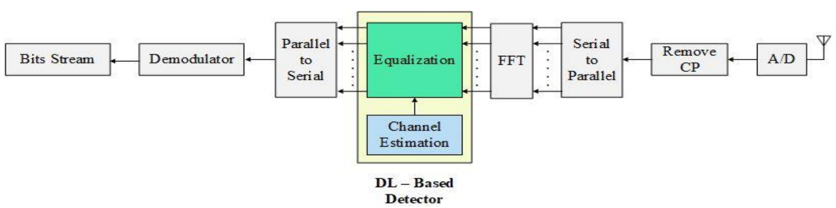

Fig.(3):- OFDM receiver with a DL-based detector

https://doi.org/10.26682/sjuod.2023.26.2.46
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4.2.1 *Training Data Structure.*

Each data transfer utilizes OFDM packets, which are made up of OFDM blocks. While it is expected that the channel will stay the same from OFDM block to OFDM block inside a packet, between packets, the channel may change. Each packet's data symbols are sent in the very last OFDM block after pilot symbols for channel estimate have been sent in the previous (J-1) OFDM blocks. There are N complex symbols in the frequency domain that make up an OFDM symbol block. Within a same OFDM block, both data symbols and pilot symbols may be interleaved. When attempting to determine the state of the channel, each transmitter sends out its own unique sequence of pilot symbols. Maintaining a constant pilot sequence is crucial throughout both preparation and deployment. Data symbols are created at random in each packet transfer and sent across the wireless channel. This paper assumes the usage of digital Quadrature Phase Shift Keying (QPSK) as digital modulation scheme offers M=4 complex symbols. The training data is made up of training samples, and their labels.

4.2.2 *The Training of DNN*

The input layer, LSMT layer, Fully Connected Layer (FCL)) with softmax activation function¸ and classification layer¸ are four layers that make up a DNN. Input layer has (J×N×2) neurons, which is same as dimension of a feature vector. Because it can learn information between time steps, LSTM layers are frequently employed to process sequential data (Van Houdt et al., 2020) in this study, u-th receive antenna treated as a time step, Moreover, a data from the N_{RX} receiver antennas are processed in order using an LSTM layer. The structures of the LSTM layer, as illustrated in Figure 4, includes elementwise addition (⊕), elementwise multiplication (⊗), non-linear operations such as Sigmoid (σ), and Hyperbolic Tangent (tanh)are also supported. Functioning of the LSTM layer could be expressed as recursive function¸ denoted by

$$(g_u, c_u) = f_{LSTM}(g_{u-1}, c_{u-1}, s_{u,i}; \Theta_{u-1}) \quad (9)$$

Both the hidden cell state (c_u)and state (g_u) are essential components in the operation of LSTM layer. Input data at step u represented by $s_{u,i}$, while Θ_{u-1} represents the LSTM layer parameters from the previous iteration (u-1). The g_u acts as the output from each neuron within the LSTM layer, whereas each neuron's cell state (c_u) stores information learned in a previous phase(Wu et al., 2021).

Since NRX = 1 in the SISO, the LSTM layer only processes information once. Therefore, the prior hidden state and cell state are set to zero, or c_{u-1} = 0 and, g_{u-1} =0, respectively.

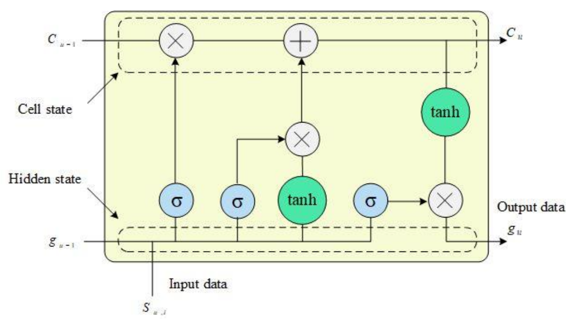

Fig.(4):- LSTM DL Network

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5. SIMULATION RESULTS

To substantiate the effectiveness of employing DL techniques for estimation of the channel and detection of symbols in OFDM wireless communication systems, we conducted series of experiments using NYUSIM system simulator. These experiments involved training Deep Neural Network (DNN) model using simulation data and comparing its performance with conventional techniques in terms of Bit- Error Rates (BERs) across varying signal to noise ratios (SNRs). In these experiments, the deep learning approach exhibited greater robustness compared to MMSE and LS approaches, especially in cases when there are fewer pilots are training, without CP, or nonlinear clipping noise is present. Considered OFDM system comprised 64 subcarriers and 20 CP length with 30 GHz a carrier frequency, a specified number of paths, and actual urban channels with a delay maximum of 16 sampling periods. The modulation method employed was Quadrature Phase Shift Keying (QPSK). Table 1 lists all of simulation parameters for three different detectors.

Table(1):- The simulation parameters for the DL-based SISO detector

Parameters	values
RF Bandwidth	800 MHz
Frequency Carrier	30 GHz
MCS	QPSK
Number of N subcarriers	64
Environment	LOS
Number of Paths L	20
Number of Testing Samples	100,000
DNN Learning Rate	0.01
Number of Training Epochs	100
SNR in Training	0-30 dB
Pilot's Number	8, 64
CP 's length	0,20
DNN input size and output size	256 , 4
Number of training samples	400,000
Number of Neurons	864
Batch Size	2,000

The chart of accuracy and loss entropy, taken from the iterative fitting of data that occurs during the training of a DNN is shown in Figure 5. The curve in the graph goes down and then back up quickly, which demonstrates that some neurons have a large influence on the weight mutation that occurs throughout the process of model training. Eventually, the curve converges on itself. The entire amount of elapsed time that has passed is one minute and nine seconds. The findings from the simulation demonstrate that the enhanced receiver not only requires a decreased amount of training time but also delivers satisfactory outcomes.

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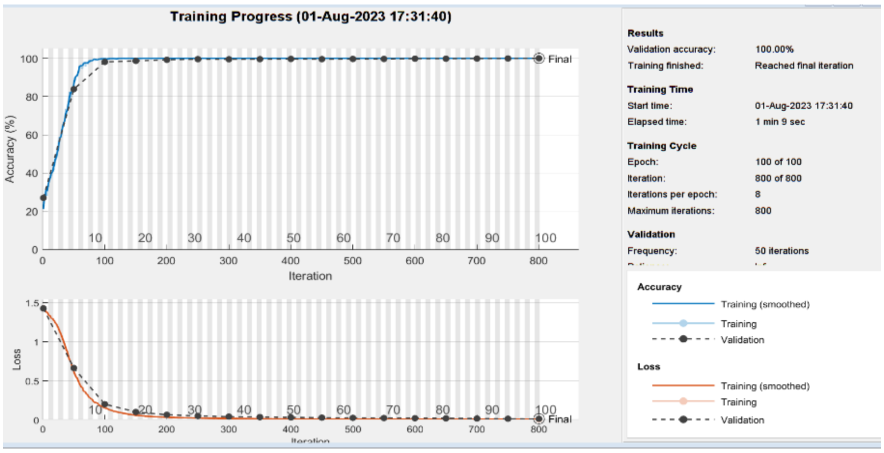

Fig.(5):- DNN offline training progress diagram

5.1. Impact of Pilot Numbers

To assess the effectiveness of the suggested approach to estimate and detect channels, we conducted comparative and analysis against the LS and MMSE techniques. The number of pilots used in channel estimation have substantial effect on performance of channel estimation algorithms. Two pilot number 8 and 64 were utilized for estimating channels using DL, LS, and MMSE algorithms. As depicted in figures 6, 7 and 8 using only 8 and 64 pilots for channel estimation, the pilot overhead is relatively low, allowing for more efficient utilization of the available bandwidth for data transmission. However, a lower number of pilots may result in less accurate channel estimation compared to higher pilot numbers. DL-based channel estimation methods, can handle the estimation task with a limited number of pilots. DL models has potential to learn complex mappings between the received signals and the corresponding channel responses. With proper training, DL can capture the channel characteristics effectively, even with a reduced pilot number. LS can estimate the channel coefficients by solving a system of linear equations. However, the accuracy of the estimation may be lower compared to methods that utilize more pilots. While, MMSE estimation may encounter challenges in accurately estimating the channel parameters due to the limited pilot information available.

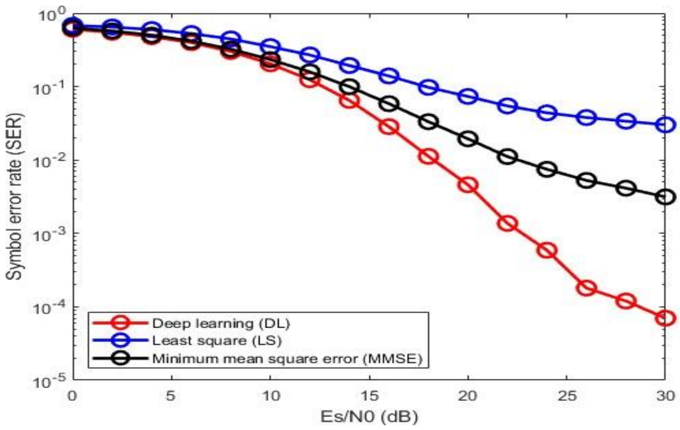

Fig.(6):- 64 Pilot without CP.

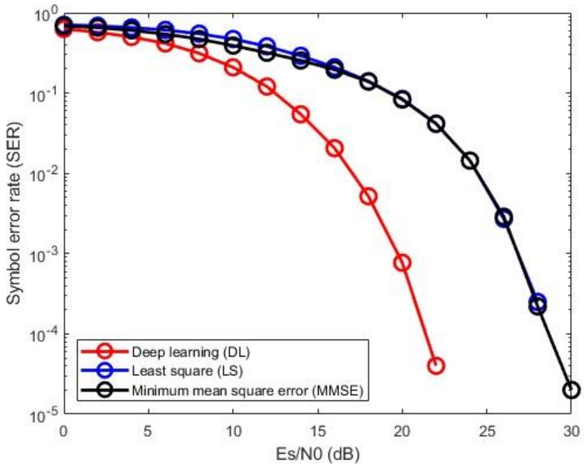

Fig.(7):- 8 Pilot with CP

Increasing the number of pilots to 64 provides more reference points for channel estimation as show in figure 8. This allows for better characterization of the channel and can lead to improved estimation accuracy. DL models can benefit from additional pilot information and may produce more accurate channel estimates compared to the case with 8 pilots. The increased pilot density provides more training samples, which can enhance the learning capability of DL algorithms. LS with 64 pilots can obtain a more refined estimation of the channel coefficients. The additional pilot symbols provide more equations to solve, resulting in better estimation performance compared to the case with 8 pilots. Additionally; MMSE estimation can exploit the increased pilot density to achieve better channel estimation. MMSE with 64 can estimate the channel by considering the additional pilot information and better account for the noise and interference in the system. In most cases, increasing number of pilots improves the accuracy of channel estimation algorithms. However, it is accompanied by increased pilot overhead, reducing the available bandwidth for data transmission. It's worth mentioning that DL-based approaches have shown promise in channel estimation, as they can learn complex mappings and exploit the available pilot information efficiently. Moreover, LS and MMSE are classical estimation techniques that provide computationally efficient solutions and can benefit from increased pilot density.

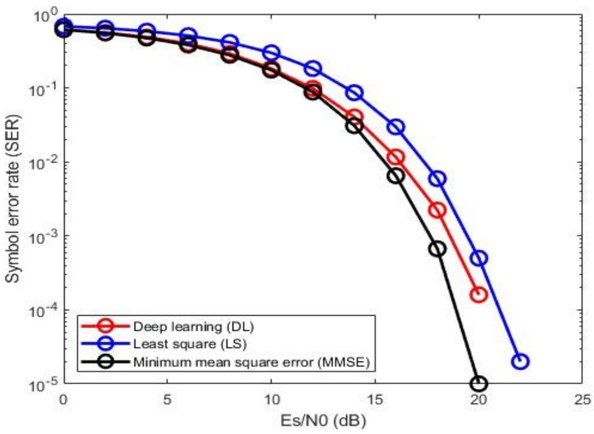

Fig.(8):- 64 Pilot with CP.

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5.2. Impact of CP

As mentioned earlier, to reduce Inter Symbol Interference (ISI), CP required to transform the physical channel's linear convolution into a circular one. However, this comes at the cost of increased amount of time and energy required for transmission. We investigated the system's performance in this experiment without CP. For an OFDM system without CP, Figure 6 shows the Symbol-Error Rate (SER) curves. The graph clearly demonstrates neither MMSE nor LS techniques could successfully channel estimation. When SNR reaches 13 dB, their accuracy begins to saturate. In contrast, the deep learning approach continues to perform effectively even without the CP. This result confirms that during the training stage, DNNs may learn and exploit the intrinsic properties of the wireless channel. In conclusion, figure 6 compares DL-OFDM channel estimation with and without CP to traditional techniques provides valuable insights into the performance differences. The DL-OFDM, particularly with the inclusion of the CP, generally outperforms traditional techniques in terms of estimation accuracy and SNR. These results highlighted the potential of DL-OFDM as a powerful technique for accurate and reliable channel estimation in challenging wireless environments. Figures demonstrate that the advantages of the DL approach become particularly apparent in cases where conventional channel estimation methods are ineffective due to severe interference produced by Inter-Symbol Interference (ISI) or an insufficient pilot symbols.

5.3. Performance Evaluation in term of MSE

Another comparison is made to assess the effectiveness of suggested DL algorithm in term of Mean Squared Error (MSE), which represent the measure of average squared difference between estimated channel response and true response of channel. In the context of channel estimation, a lower MSE indicates that the estimated channel response is closer to actual response channel, signifying higher accuracy. Figure 9 shows the results indicate that the DL estimator is a more accurate channel estimate approach than the LS and MMSE estimators at all SNR levels due to its ability to accomplish lower MSE. With enough training data and a high SNR, DL techniques may perform better than conventional techniques like LS and MMSE, leading to lower MSE values. However, the MMSE may provide more estimating accuracy than LS in low SNR conditions. This is due to MMSE's capacity to reduce external noise. Additionally, MSE of MMSE estimator is less than LS estimator when the SNR is increased. When trained on large and varied datasets, DL techniques have the potential to perform better than both LS and MMSE.

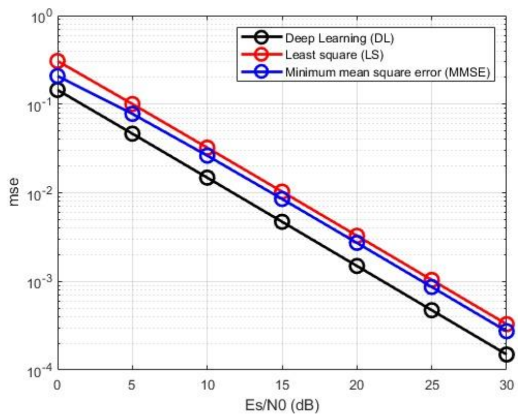

Fig.(9):- Channel MSE vs SNR for channel estimator.

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6. CONCLUSION

In this article, DNNs channel estimation and symbol detection in OFDM system is presented and investigated. To train the model, offline simulation data used., which treats wireless channels and OFDM as black box. DL network for LSTM utilized in channel estimation approach have been investigated and compared MMSE with LS. Results demonstrate that deep learning models can achieve superior estimation accuracy, especially with low number of pilots leading to increased spectral efficiency, enhanced system capacity, and reduce the latency, even in challenging channel conditions, which is the main requirements in 5G and beyond. The simulation results show that when wireless channels afflicted by considerable interference and distortion, the deep learning technique demonstrates clear benefits. This result demonstrates the DNNs' capacity to store and evaluate the varied characteristics of wireless channels. DNN models used in real-world applications must have strong generalization capabilities. This ensures successful performance even when the system is utilized online in situations that vary from the channel models used during training. A basic experiment was done in this paper to demonstrate DNN model's generalizability with regard to channel model parameters. Furthermore, for practical utility, it would be beneficial to collect sample created from actual wireless channels. These samples could be employed to adjust or retrain model, aiming to enhance performance in real-world scenarios.

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