Inter-symbol Anti-interference Algorithm for 5G Communication System Based on Deep Learning

Yangbin Zhou *

School of Resources and Environment, University of Electronic Science and Technology of China, Chengdu, China

* Corresponding author: 2021070903011@std.uestc.edu.cn

Abstract. As a matter of fact, the fifth generation (5G) wireless technology requires huge capacity to ensure normal use of communications, and a large amount of data will cause interference between wireless communication systems. With this in mind, to reduce inter-symbol interference in wireless systems, MIMO-OFDM is employed, the rapid growth of deep learning has the potential to significantly enhance wireless system performance. In reality, applying deep learning to estimate channels in MIMO-OFDM systems can reduce channel errors as well as improve channel quality, thereby greatly reducing inter-code interference between systems. On this basis, this paper introduces various DL-based channel estimation and demonstrates its improvement in the efficiency of the system. According to the analysis, the usage of deep learning in 5G wireless communication systems has great advantages. In addition, the limitations and defects are also discussed at the same time. Overall, these results shed light on guiding further exploration of 5G communication.

Keywords: Deep learning, channel estimation, MIMO-OFDM, 5G mobile communication.

1. Introduction

Fifth-generation (5G) wireless technology was created to keep up with the reliability of wireless data and communications as it continues to rise exponentially. The rapid development of mobile Internet has created huge challenges for 5G wireless networks. Therefore, the wireless communication system requires the ability to send and receive large capacity, and a large amount of data will cause interference to the communication system. To minimize the communication system's inter-symbol interference, the current network has been using the Orthogonal Frequency Division Multiplexing (OFDM) method [1]. Compared with traditional single carrier, OFDM improves system capacity. In OFDM, dividing data into different channels and Inter-symbol interference can be significantly reduced by employing orthogonal subcarriers to transport the data [2]. In addition, given its many benefits, OFDM is an effective application approach for 5G communication networks, including easy channel equalization, resistance to frequency selective fading, and excellent spectral efficiency [3]. Wireless multipath channels, however, can have a number of detrimental effects, including mutual interference brought on by shared radio resources, multipath propagation, and local scattering, thereby distorting the signal sent to a specific receiver.

In order to reduce data distortion, it is crucial to continuously search for more efficient techniques. One of the key innovations for large-scale machine communications and improved mobile broadband 5G situations is multiple-input multiple-output (MIMO). MIMO is an advanced wireless transmission method that increases dependability and offers high data speeds by using numerous antennas at both the transmitter and the receiver without consuming more bandwidth or power consumption [3]. MIMO can be used in combination with OFDM to generate a MIMO-OFDM system. The benefits of MIMO and OFDM are combined in the MIMO-OFDM to provide higher quality services and greatly reduce interference between channels. Therefore, MIMO-OFDM has become the most suitable technology choice for wireless communication systems [4]. In the process of signal transmission, the signal will encounter the interference of obstacles, or be affected by the mutual interference between channels. Consequently, to enhance the signal transmission quality and reduce the inter-symbol interference between 5G communication systems, accurate calculation of the channel state information (CSI) is required. In calculating channel's channel state information, the pilot symbols of the receiver and transmitter are needed. The pilot symbol structure is determined by different communication systems.

In the traditional channel estimation algorithm, the algorithm with lower computational complexity is the least squares estimation (LS). The statistical channel's previous data are not required for the least squares estimation, so its complexity is low and easy to use [5], but in many complex Its insufficient performance in scenarios makes it difficult to use widely. Another channel estimation algorithm, minimum mean square error estimation (MMSE), has superior effectiveness to least squares estimation, but the closed-form expression of minimum mean square error estimation is based on the assumption that the channel is regarded as a linear channel following a complex Gaussian distribution. In the case of the system, the derivation of MMSE for the general channel estimation is more complicated, and its computational complexity is much greater than that of the least squares estimation [6]. Contemporarily, the emergence of machine learning has enabled some problems to be solved well. With the widespread popularity of deep learning, deep learning has also greatly improved wireless communication systems [7]. Deep learning technology is applied to MIMO-OFDM systems to enhance efficiency and greatly reduce computational complexity [8]. Deep learning techniques such as fully connected deep neural network (FC-DNN) and convolutional neural network (CNN) are used to improve the performance of channel estimation, weakening the inter-code interference between communication systems [9].

In this study, by analyzing a variety of channel estimation algorithms under the structure of deep learning algorithms, and calculating their BER and signal-to-noise ratio (SNR), they are compared with two traditional channel estimation algorithms: least squares estimation Comparative analysis with the minimum mean square error estimate reveals the quality of channel estimation under the deep learning algorithm. This study first gives an overview of MIMO-OFDM, then analyzes the channel estimation under the deep learning algorithm, and then simulates the above channel estimation algorithm to calculate its performance indicators. By comparing the channel estimation under DL technology with the traditional channel estimation A comparative analysis was conducted to obtain the differences between channel estimation under DL technology and previous channel estimation algorithms. The 5G wireless communication system requires fast signal transmission with less interference, and the current signal processing algorithm is less efficient and more complex, making the transmission efficiency of the communication system lower. However, methods based on deep learning can Helping handle signal transmission in complex situations, improving the efficiency of 5G wireless communication systems. It can be predicted from the application of deep learning in communication systems in recent years that the wireless physical layer framework based on deep learning will bring new directions to communication theory. Promoting wireless communication systems to move in a better direction [10].

2. MIMO-OFDM Model

The MIMO-OFDM model consists of a transmitter and a receiver and Fig. 1 indicates the structural block diagram of MIMO-OFDM. At the transmitter, the input signal is modulated by using a modulation technique to map the input data to the constellation points, and there are numerous methods of modulation, including BPSK (Binary Phase Shift Keying), QAM (Quadrature Amplitude Modulation), etc. [11]. After the input data is modulated, it is divided into symbols corresponding to different transmitting antennas by the Layer Mapping module (Layer Mapping), and then the coded symbols of each antenna pass through the serial-to-parallel converter (S/P) is converted from the serial form to the parallel form. After the conversion, for channel estimation, the pilot symbols are placed into the coded symbols. After the pilot symbols are inserted, the frequency domain signal is transformed into the time signal through the inverse Fourier transform (IFFT). domain signal, and finally converted to serial form (P/S) again through a serial-to-parallel converter. Finally, in order to reduce inter-symbol interference during transmission, the OFDM symbol will have a cyclic prefix (CP) attached [12].

At the receiver, after receiving the data transmitted from the transmitter, the cyclic prefix (CP) of the data is first removed, and then converted into different parallel subcarriers through the serial-to-parallel converter (S/P). Next, Fourier transform is used to the parallel subcarriers to transform the carrier into the frequency domain. The frequency domain signal can be used to extract the pilot signal for channel estimation, and then the serial-to-parallel conversion is carried out once more. After conversion, through the layer mapping module, the signal is equalized and merged into a serial sequence. Finally, a signal is demodulated through a demodulation scheme corresponding to the modulation scheme of the transmitter, and the signal is brought back to the initial input data stream.In the above process, the application of deep learning in channel estimation has greatly improved the efficiency of MIMO-OFDM systems. In addition to its application in channel estimation, deep learning also has extensive applications in signal recovery [13].

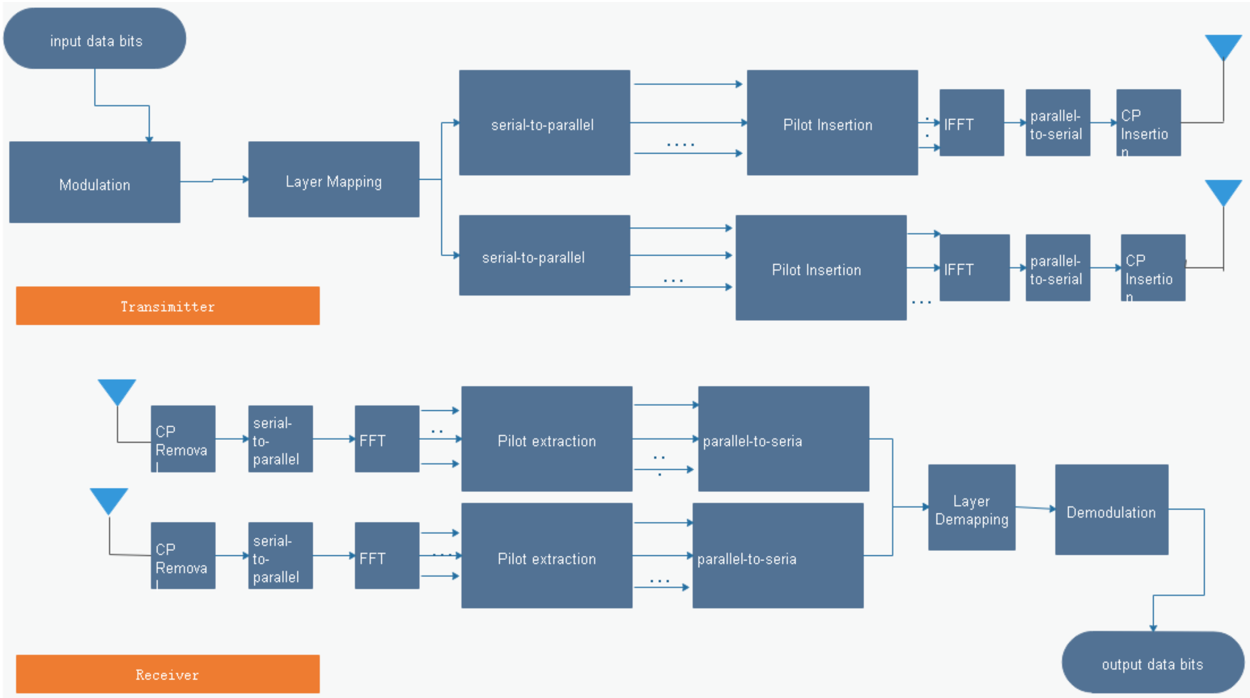

Figure 1. Model of the MIMO-OFDM system with the transmitter and receiver.

3. DL-Based Channel Estimation

This section introduces and analyzes methods for estimating channels using deep learning in different circumstances. There are many methods to apply deep learning in channel estimation. This section introduces two different channel estimation methods in detail, compares them with traditional channel estimation methods through simulation, and then summarizes and analyzes different deep learning-based methods.

3.1. DNN-Based Channel Estimation

In the DNN model, as shown in Fig. 2, the input layer, hidden layer, and output layer are the three components. For MIMO-OFDM system, three hidden layers with multiple neurons need to be designed. as the picture shows. Each neuron performs the following calculations:

$$o = f(z) = f(\sum_{i=1}^{M} w_i x_i + b), \tag{1}$$

Where o represents a neuron's output and M is the amount of neuron inputs, x_i is the i-th input of a specific neuron, where i=1,2,3…M. Here, w_i indicates the weight of the i-th input; the activation function f(.) and the deviation b are employed to describe the nonlinearity of the channel data [14]. Tanh is used as the activation function in the DNN-based channel estimation model defined as:

$$f(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}, \tag{2}$$

In order to learn DNN channel estimation model, the channel estimation data acquired via LS estimation is employed as input. So, the mean square error can be minimized. Specifically, the input process for training can be defined as:

$$M_{n-DNN} = \left\{Re\left\{\left[\hat{h}_{LS}^{n}(t)\right]_0\right\}, Im\left\{\left[\hat{h}_{LS}^{n}(t)\right]_0\right\}, \dots, Re\left\{\left[\hat{h}_{LS}^{n}(t)\right]_K\right\}, Im\left\{\left[\hat{h}_{LS}^{n}(t)\right]_K\right\}\right\} \tag{3}$$

where $\hat{h}_{LS}^{n}(t)$ represents the channel data collected by the receiving antenna and obtained by LS estimation, where n is the number of realizations. $Re\{.\}$ and $Im\{.\}$ represents the real and imaginary components of the inputs, K stands for the number of samples processed for the model. The output process of a neuron can be defined as:

$$O_{n-DNN} = \left\{Re\left\{\left[\hat{h}^{n}(t)\right]_0\right\}, Im\left\{\left[\hat{h}^{n}(t)\right]_0\right\}, \dots, Re\left\{\left[\hat{h}^{n}(t)\right]_K\right\}, Im\left\{\left[\hat{h}^{n}(t)\right]_K\right\}\right\} \tag{4}$$

where $\hat{h}^{n}(t)$ denotes the result of DNN from the nth implementation. Eq. (3) and Eq. (4) divide the channel estimation into real and imaginary components, which facilitates the DNN neural network to process complex numbers. In the learning process, the one-to-one mapping is:

$$\left(Re\left\{\left[\hat{h}_{LS}^{n}(t)\right]_r\right\}, Im\left\{\left[\hat{h}_{LS}^{n}(t)\right]_r\right\}\right) \to \left(Re\left\{\left[\hat{h}^{n}(t)\right]_r\right\}, Im\left\{\left[\hat{h}^{n}(t)\right]_r\right\}\right), r = 0, \dots, K. \tag{5}$$

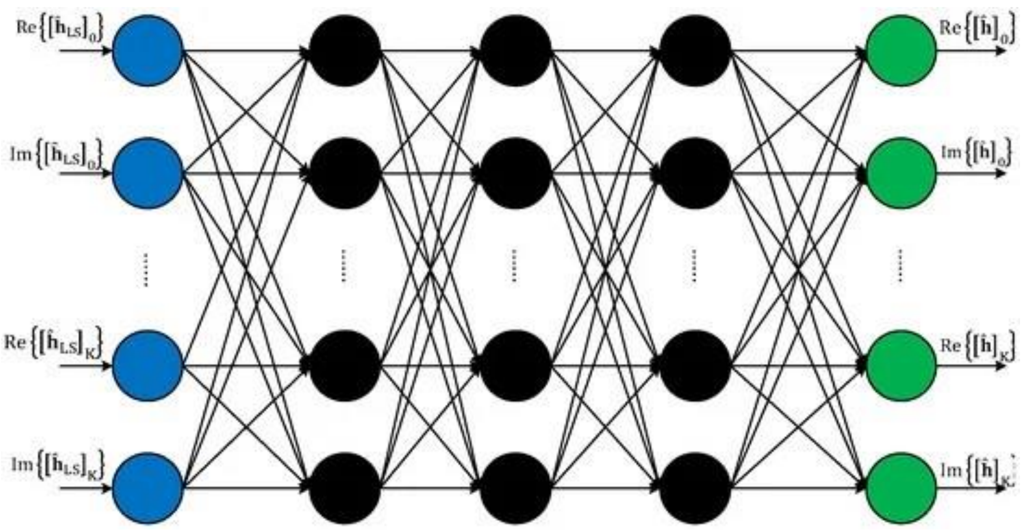

Figure 2. Picture of the DNN-based channel estimation.

Outputs obtained by DNN-based channel estimation should be well fitted to the actual channel, that is, the MSE should be as low as possible when using DNN-based channel estimation. Therefore, in the DNN training process, the definition of the loss function is:

$$L_{DNN}(W, B) = \frac{1}{NT} \sum_{n=1}^{N} \sum_{t=1}^{T} \left\|\hat{h}^{n}(t) - h^{n}(t)\right\|_2^2, \tag{6}$$

Here, W and B represent the weights and biases in the network, N represents the amount of training executions, $\hat{h}^{n}(t)$ represents the actual channel of $h^{n}(t)$ obtained by estimation, and the minimum of forward and backward transmission. The loss function is used to correct the weight and bias of the initial value [15].

3.2. CNN-Based Channel Estimation

The CNN model has been extensively studied in image processing, and the CNN model can be used to map a noisy image to a clean image, thereby making the image clear [16, 17]. By sharing weights and biases, CNN can decrease down on the number of variables, thereby simplifying the system and increasing the quality of channel estimation. From this, the mapping of the LS estimated noise channel to the real channel can be learned based on CNN. Fig. 3 depicts the CNN model's construction. According to the image, the components of the CNN construction are: 2D input layer, convolutional layer, activation layer and linear layer. The 2D input layer receives the LS estimated channel. The 2D input layer divides the channel calculated by LS into two parts, the real component and the imaginary component, and merges them once again into a matrix. Then the matrix is input into the convolution layer as follows calculate:

$$O_l = Conv(I_l, w_l) + b_{l,} l \in L, \tag{7}$$

Where L represents the convolutional layer set of CNN, L represents each convolutional layer, L includes a convolution kernel cl of size kl×kl, l and the input layer $I_l \in R^{a_{l-1}^1 \times a_{l-1}^2 \times c_{l-1}}$ performs convolution, where a_{l-1}^1 and a_{l-1}^2 represent the dimensions of the $l-1$th convolution layer, and the output $O_l \in R^{a_l^1 \times a_l^2 \times c_l}$, where$w_l$ and $I_l$represent the weight and bias of the lth convolutional layer. In the CNN-based channel estimation model, the activation layer comes after the convolution layer, and the modified linear unit (ReLU) can be employed as the activation layer, it is defined:

$$ReLU(r) = max(0, r) \tag{8}$$

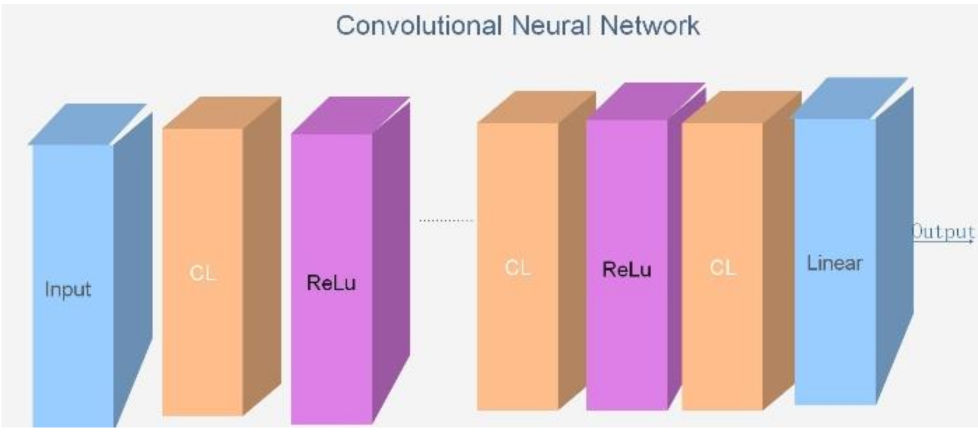

Figure 3. Picture of the CNN channel estimation

During the training process in this model, the channel estimated by LS is reshaped into the matrix form $\widehat{H}_{LS}^n \in C^{N_t N_r \times N_{FFT}}$, and split into the real and the imaginary parts. Therefore, the training process' input can be described as:

$$M_{n-CNN} = \left\{Re\{[\widehat{H}_{LS}^n]\}, Im\{[\widehat{H}_{LS}^n]\}\right\} \tag{9}$$

The resulting output of the CNN channel estimation model is:

$$O_{n-CNN} = \{Re\{[\widehat{H}^n]\}, Im\{[\widehat{H}^n]\}\} \tag{10}$$

where O_{n-CNN} contains the real and imaginary components. From this one can get the matrix mapping in the CNN model as: $(Re\{[\widehat{H}_{LS}^n]\}, Im\{[\widehat{H}_{LS}^n]\}) \rightarrow (Re\{[\widehat{H}^n]\}, Im\{[\widehat{H}^n]\})$. CNN-based channel estimation minimizes the MSE, consequently, the loss function is described as:

$$(W, B) = \frac{1}{N}\sum_{n=1}^{N}\left\|\widehat{H}^n - H^n\right\|_F^2 \tag{11}$$

Among them, N is the amount of training sessions, H^n represents the actual channel of $\widehat{H}^n$ obtained by estimation, and W and B represent the weights and biases. The weights and biases are modified. through the loss function. In order to make the CNN model application easier, the training data is organized into a matrix.

3.3. Analysis and S

To assess the effectiveness of deep learning-based channel estimation, MSE and SNR are employed to compare the CNN-based channel estimation model with the LS estimator; BER and SNR are employed to compare DNN-based channel estimation models with LS estimators and MMSE estimators. In order to calculate the effectiveness of all channel estimations in the 5G channel model, two different situations are simulated based on different moving speeds: In the first scenario, the receiver speed is slower, so that the maximum Doppler frequency is 50Hz, In the second case, the system travels quickly, so that the maximum Doppler frequency is 100 Hz, and the details of the system are displayed in Table 1.

Table 1. MIMO-OFDM details.

Parameters	Values
MIMO	2×2
FFT size	512
CP length Modulation Channel PDP Maximum Doppler frequency	64 $16\ QAM$ $TDL - A$ $50Hz, 100Hz$

Fig. 4 and Fig. 5 show the MSE and SNR of the two channel estimates in the two scenarios. The transmission data in analog is modulated by using a 16QAM modulation method. As shown, the MSE of each channel estimation method decreases with increasing SNR. It can be seen from the two figures that the MSE values of CNN-based channel estimation is significantly lower than the MSE values of LS channel estimation. The reason is that LS does not count channel information when performing channel estimation, while CNN-based channel estimation fully counts channel information, resulting in Better MSE performance, under the condition of lower SNR, can show the superiority of channel estimation under deep learning.

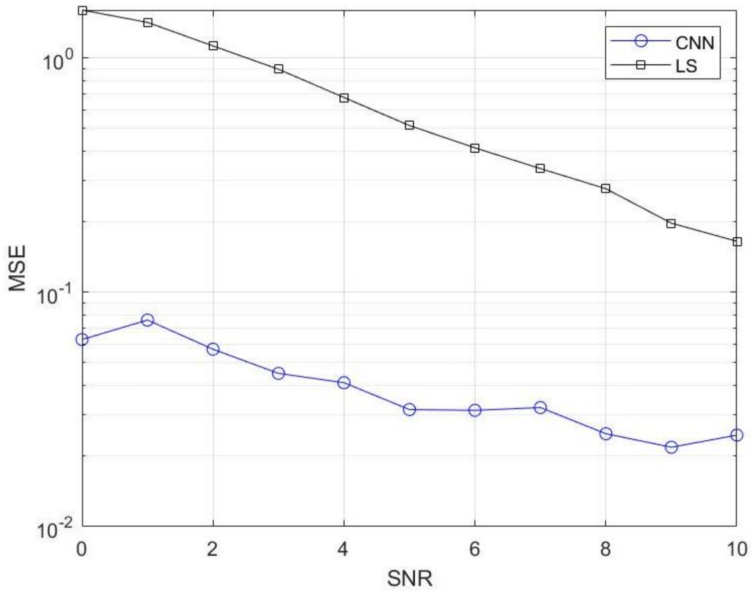

Figure 4. The MSE of the estimated channel in relation to the SNR(fd=50 Hz).

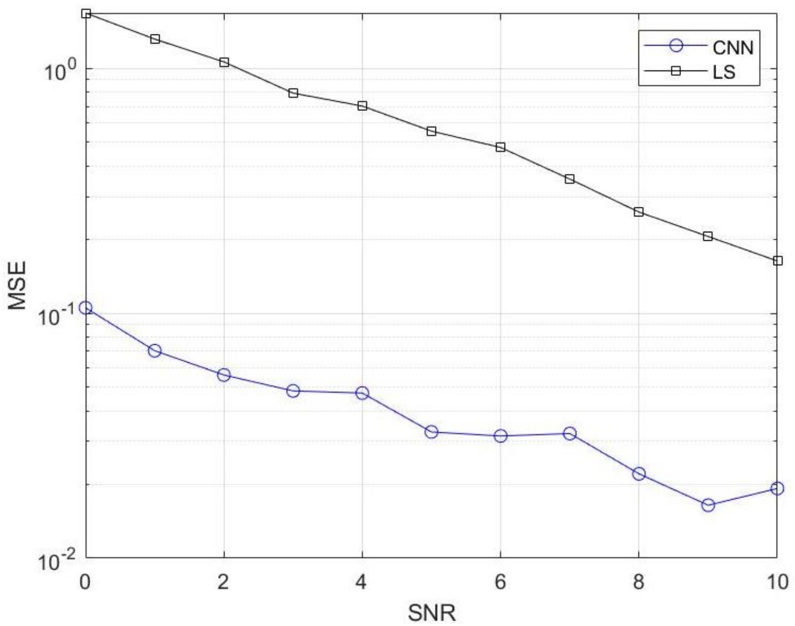

Figure 5. The MSE of the estimated channel in relation to the SNR(fd=100 Hz)

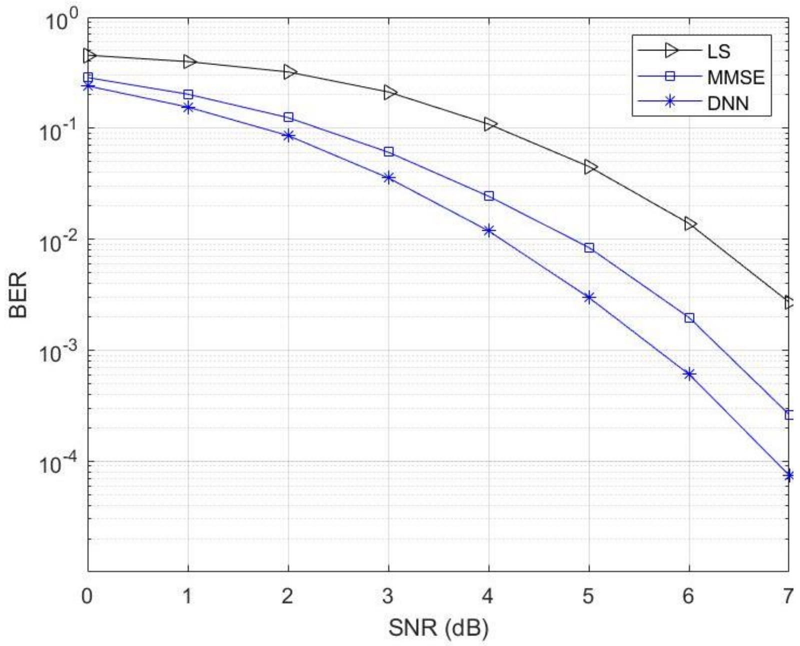

Figure 6. The channel estimate's BER in relation to the SNR level (fd=50 Hz).

Fig. 6 and Fig. 7 show the BER and SNR of three channel estimates in two cases. From the two figures, it is clear that there are not numerous distinctions between the three channel estimation approaches in terms of BER performance. Among them, the LS estimation has the worst BER performance. The channel estimation based on DNN is almost equal to the MMSE estimation. Despite the LS estimate method's subpar BER performance, the difference with the two channel estimation methods is not very big. Although the channel estimation based on deep learning has not greatly enhanced BER performance, it can be improved by increasing the SNR. As can be seen from the results, when the SNR increases a little, the BER performance will increase significantly.

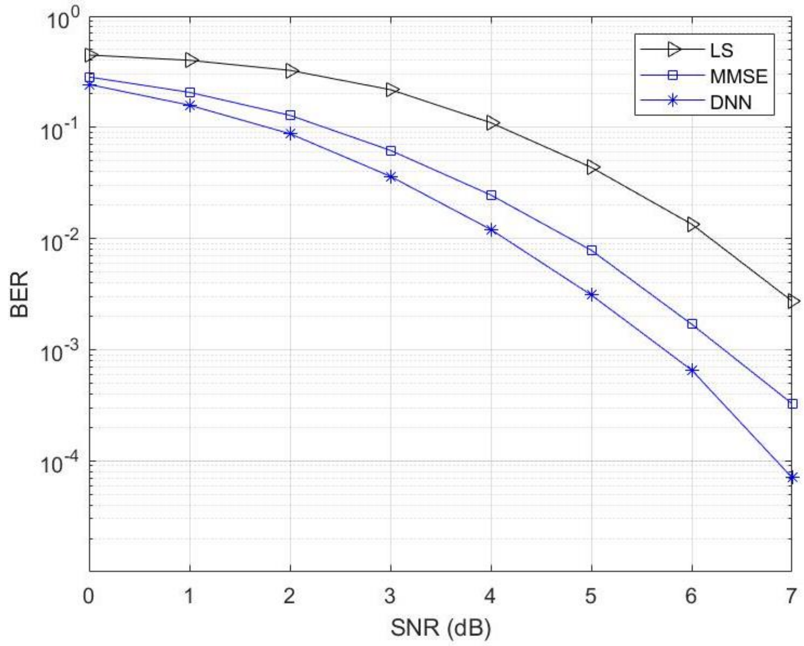

Figure 7. The channel estimate's BER in relation to the SNR level (fd=100 Hz).

In addition to these methods, other DL-based channel estimation is also widely used in MIMO-OFDM. In the OFDM system, the Bi-LSTM model is designed for channel estimation. Following much practice, it has been proved that its learning capacity and channel estimation quality are superior. It is trained with forward and backward input directions, consequently, it performs more effective in OFDM systems [10]. In MIMO-OFDM systems at high mobile speeds, channel estimation becomes extremely difficult, therefore, to deal with these highly mobile situations [9], created a model by fusing the CNN and Bi-LSTM networks. CNN is employed to imitate frequency-domain interpolation procedures, while Bi-LSTM is used to anticipate time-domain channels, then estimating the correlation coefficients of time-domain and CSI. Several highly mobile situations and pilot structures are used to assess the efficiency of the proposed network. The findings demonstrate that it significantly enhances the efficiency of the system. Pilot symbol cost rises in MIMO-OFDM systems because of the multiple antennas, so a pilot symbol-based compressed sensing technique is proposed [18]. A Bi-LSTM network is also implemented into an RNN model to enhance signal detection,which hugely enhance the system's efficiency. Based on the fast learning of extreme learning machines, proposed a 2×2 MIMO-OFDM receiver,which has a better BER perfoemence [19].

4. Conclusion

To sum up, this study analyzes and introduces DL-based channel estimation, which can reduce inter-symbol interference between communication systems by improving the performance of channel estimation. This research introduces in detail channel estimation methods based on DNN and CNN, and compare the efficiency of these two methods with traditional channel estimation methods. After analysis and comparison, it can be seen that the DL-based channel estimation has great advantages in MSE performance, but the BER performance is not much different from the traditional method, but it can be improved by increasing SNR, and then summarize and analyze other methods based on deep learning. Finally, it can be concluded that DL-based channel estimation has greatly improved the performance of channel estimation, making the code between 5G communication systems Interference is greatly reduced, and more deep learning methods will be applied to channel estimation in the future, which will make wireless communication systems develop more rapidly

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