DEEP LEARNING TECHNIQUES FOR CHANNEL ESTIMATION AND SIGNAL DETECTION IN OFDM SYSTEMS

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Abstract— This paper lays emphasis on the application of Deep learning Techniques in Channel Estimation and Signal Detection in Orthogonal Frequency Division Multiplexing (OFDM) systems. The performance of the Deep Learning Techniques is compared with the conventional methods: Least Square Error (LSE) and Minimum Mean Square Error (MMSE) estimation methods. Unlike the conventional OFDM receivers that first estimate the Channel System Information (CSI) and then detect the transmitted signal using the estimated CSI, a Deep learning based approach allows the estimate of CSI implicitly and recovers the transmitted signal directly. To understand and estimate the channel distortion, Deep Neural Network is first trained offline and then used for recovering the transmitted data. The performance of a Deep learning based approach is comparable to the MMSE method. Hence Deep learning based Approach can be thought of a potential tool for channel estimation and signal detection in Wireless Communication.

Keywords— Deep learning, Channel Estimation, OFDM.

I. INTRODUCTION

Orthogonal frequency-division multiplexing (OFDM) modulation is a promising modulation technique for achieving the high bit rates required for a wireless multimedia service due to its flexibility and robustness against multipath fading [1],[2]. OFDM is a special case of multi-carrier transmission where a single data stream transmits over a number of lower rate subcarrier [3]. OFDM based systems combat frequency selective fading in wireless channels and reduces the Inter-Symbol Interference (ISI). Channel State Information (CSI) plays a vital role in the detection of OFDM systems. CSI is estimated by means of pilots prior to detection of the transmitted data and with the help of the estimated CSI, the transmitted signal is decoded at the receiver.

The investigation of the traditional methods: LSE and MMSE are done along with the Deep Learning based techniques in this paper. The LSE estimation method requires no prior information of the system characteristics but does not perform well whereas the MMSE estimation which makes full use of the correlation of the channel frequency response at different times and frequencies performs much better compared to the LSE method.

Ever since the advent of Deep Neural Networks they have found their applicability in different fields. They have made their presence felt in the field of wireless communications too. To name a few: Localization based on CSI [4], channel Decoding [5] and Channel Equalization [6] in communication systems. With improving computational resources and large availability of data the Deep Learning is expected to find more applications.

In this paper, training a Deep Neural Network (DNN) model that predicts the data in different channel conditions is done in Deep learning based technique which is then deployed for the recovery of transmitted signals.

The paper is organized as follows: Section II introduces the OFDM system, Section III deals with the Deep learning, Section IV shows the Training of the DNN Model, in Section V Simulation Results are shown and discussed followed by the conclusion.

II.OFDM SYSTEM

The OFDM system used for channel Detection and Signal Estimation using Deep Learning Techniques is illustrated in figure 1. The OFDM system is the same as the traditional OFDM system. On the transmitter side, the symbols to be transmitted are first generated, then they are inserted with pilot bits. They are next converted from Serial to Paralleled data stream. After this, an Inverse Discrete Fourier Transform (IDFT) is performed that converts frequency domain signal into the Time domain signal. To mitigate Inter-Symbol Interference (ISI) a Cyclic prefix (CP) is inserted after this stage. Then the signal is converted back into a Serial data stream and is set through a Channel whose Impulse response is represented by h(n) and an Additive White Gaussian Noise (AWGN) is added.

The received signal at the receiver y(n) is then expressed as

$$y(n)=x(n)*h(n)+w(n) \tag{1}$$

Where x(n) is the transmitted signal, w(n) is the Additive White Gaussian Noise (AWGN) respectively. At the receiver, the frequency domain signal after the removal of CP and performing Discrete Fourier Transform (DFT) the frequency domain signal is expressed as

$$Y(k)=X(k)\,H(k)+W(k) \quad (2)$$

Where Y(k), X(k) and H(k) are the DFT of y(n), x(n) and w(n) respectively. The pilot bits are the first OFDM block while the following blocks of OFDM consist of transmitted data. Together they form a frame. The channel can be thought of as a constant span over the pilot block and the data blocks. The DNN model takes the input consisting of one pilot block and one data block for initial training and then detects the transmitted signal from an end-to-end manner.

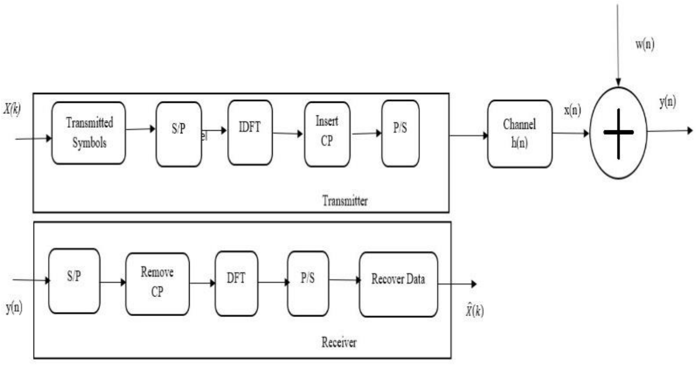

Figure 1: OFDM Transmitter and Receiver with Channel and Noise representation

III DEEP LEARNING

Deep learning is a machine learning technique that tells a computer to do what comes to human naturally: to learn by example. This has made them very popular in various fields with significant performance improvement, including computer vision [7], natural language processing [8], speech recognition [9]. Basically, DNN is a deeper version of Artificial Neural network (ANN) with a greater number of hidden layers, which improves the ability to recognize or represent. Each layer consists of the network of neurons, as shown in figure 2. In figure 2 each circle in each layer represents a neuron and the oriented lines indicate weights from the neuron of one layer to the neurons of the next layer. The input to each neuron is a nonlinear function, a Relu function or a Sigmoid function of the weighted sum of responses from previous layer neurons. Hence the output of a neural network is a cascade nonlinear transformation of the input. Deep learning refers to the optimization of the weights of the neural networks during the training phase on a training set with known outputs before the deployment of the DNN model in real time.

To obtain an effective DNN model for Channel Estimation and Signal Detection, the received OFDM samples generated with given random input samples under diversified channel conditions are used along with the originally transmitted data for offline training of the network. During the online deployment stage, the network is made to generate the output that recovers the transmitted data without explicitly estimating the channel.

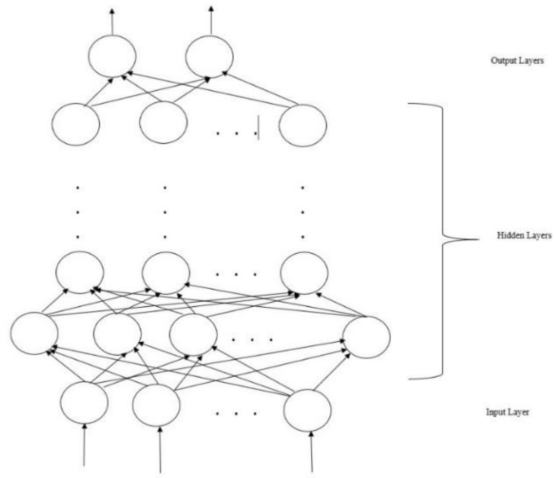

Figure 2: Deep Neural Network

IV TRAINING OF THE DEEP NEURAL NETWORK MODEL

The DNN model to be trained treats the OFDM generation methods and the channel as black boxes. Using any of the traditional generation and channel models, a random sequence is first generated called the transmitted symbols, the corresponding OFDM frame is formed with a sequence of pilot symbols. This frame is sent through a channel model. The received OFDM symbols will now characterize the channel distortion and noise. This received data and the original transmitted data are given as the training data. The received data of the pilot and data block that forms a frame is the input to the DNN model to be trained. The model is trained to minimize the difference between the output of the neural network and the transmitted data. The difference can be characterized in a number of ways out of which Mean Square Error (MSE) is used here.

$$MSE = \frac{1}{N}\sum_{k}\left(\hat{X}(k) - X(k)\right)^2 \quad (3)$$

where $\hat{X}(k)$is the predicted signal and X(k) is the transmitted signal known as the supervision signal.

The DNN model used here is a seven-layer network consisting of five hidden layers. The number of neurons used in the layers are 10,256,500,120,256,10. The activation function used in all the layers is a Sigmoid function. The specifications of the DNN used for simulation are shown in Table I.

Table I: Specifications of the DNN model.

Parameter	Specification
Training Function	Gradient Descent
Performance/Cost function	Mean Square Error (MSE)
Learning Rate	0.01
Epochs	1000

The MATLAB generated model of the above mentioned DNN network is shown in figure 3. This is a seven-layered feed forward back propagation network with the first layer being the input layer and the last being the output layer.

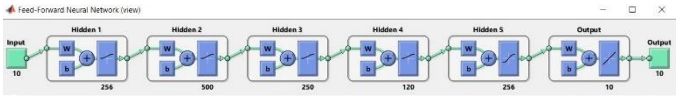

Figure.3.: MATLAB generated Deep Neural Network model

V SIMULATION RESULTS

The demonstration of the performance of Deep Learning based Channel Estimation and Signal Detection is done by simulating the Deep Neural Network in figure 3 in MATLAB and training the DNN based on simulated data as shown figure 4.

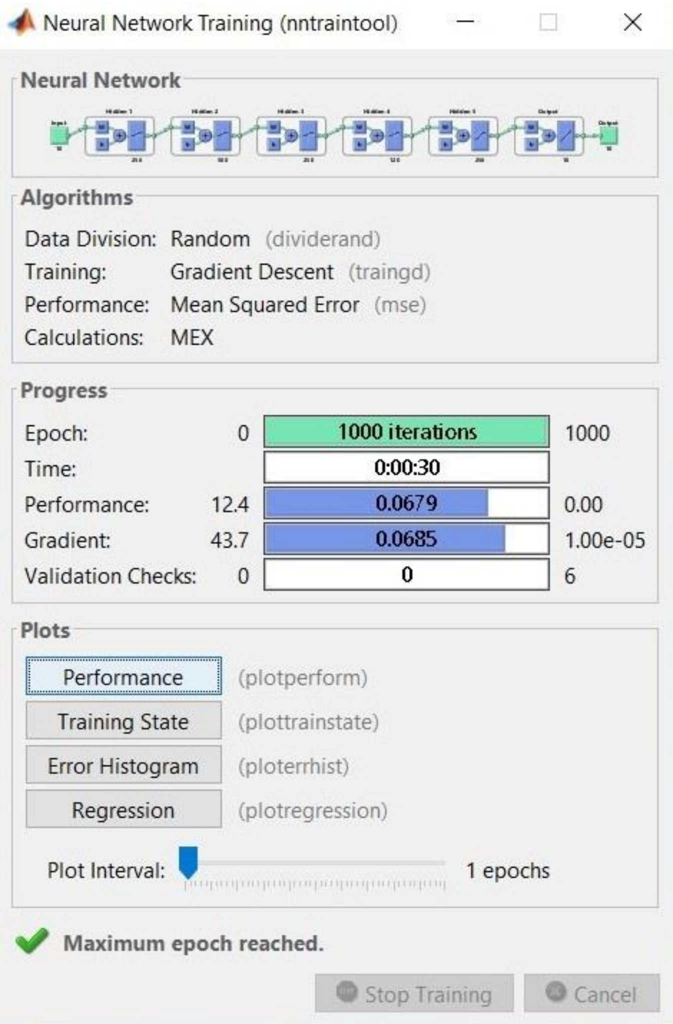

Figure 4: Training the Deep Neural Network

The performance of the Deep Learning based method is compared with traditional methods LSE and MMSE in terms of Bit Error Rate (BER) under different Signal to Noise ratios (SNR) when 32 pilots are used for Channel Estimation. The LSE method has the worst performance since it uses no prior statistics of the channel during detection. The MMSE performs the best because of its assumption that the second order statistics of the channel are known for signal detection. The performance of the Deep Learning based method is much better than LSE and is comparable to MMSE as shown in figure 5.

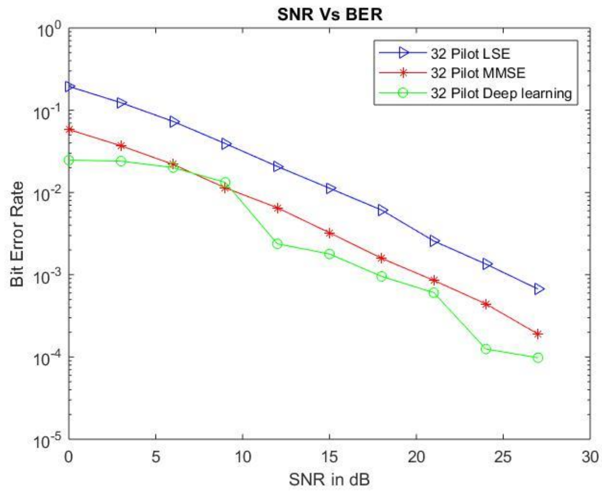

Figure 5: BER curves of Deep Learning based approach, LSE and MMSE

VI CONCLUSION

This paper shows a comparison between the Deep Learning based Approach for Channel Estimation and Signal Detection in OFDM systems with the traditional LSE and MMSE techniques. The DNN is trained offline based on the simulated data that treats the OFDM generation and the Channel as black boxes. Then the Deep neural network is made to recover the transmitted symbols during online deployment. The simulation results show that the Deep Learning based approach shows a performance that is comparable to MMSE, which is the better one of the compared traditional methods. This shows the ability of DNNs to remember and analyze the complicated wireless channel characteristics. However, in real life scenarios, it is important for the DNNs to have good generalization capabilities to work effectively when the conditions in the online deployment do not exactly match with the channel models in the offline training stage. This creates a need to further analysis and understand the Deep Learning Technique under various realistic conditions.

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