Channel Estimation and Signal Detection in OFDM Systems using Deep Learning

Manoj Kumar Ojha

Abstract— ***this article presents "channel estimation and signal detection in OFDM systems by using deep learning". OFDM stands for "Orthogonal Frequency Division Multiplexing". This paper exploits end to end handling of wireless OFDM channels by deep learning. It is different from the existing OFDM receivers as it estimates the channel state information (CSI) explicitly and then estimated CSI is used to recover the transmitted symbols, thee proposed approach of deep learning implicitly estimates CSI and the transmitted symbols are recovered directly. The online transmitted data is directly recovered by the offline training a deep learning model using simulation based channel statistics generated data for addressing channel distortion. The performance comparable to "minimum mean square error" (MSME) estimator with transmitted symbols is detected by using deep learning based channel distortion. Using fewer number of pilots, omitting cyclic prefix and in the existence of nonlinear clipping noise, the approach of deep learning is more robust as compared to traditional methods.***

Keywords— ***OFDM, MSME, channel state information, DNN model.***

I. INTRODUCTION

Wireless broadband systems employ orthogonal frequency division multiplexing (OFDM) for combatting frequency selective fading in wireless channels. Decoding and detection in OFDM systems is rationalized by channel state information (CSI). Prior of detecting the transmitted data, estimation of CSI is done by pilots. The transmitted symbols at receiver are recovered with the help of estimated CSI. Thorough study of estimation of channel in OFDM system has been done. The "least squares (LS)" and "minimum mean square error (MMSE)" are the traditional methods of estimation that are used and enhanced in several situations[1]. No prior channel statistics is needed by LS estimation but it may lead to inadequate performance. The statistics of channels are of second order that are utilized for much better detection performance by MSME estimation. This channel introduces an approach of deep learning for the estimation and detection of symbol in OFDM system. Numerous application of deep learning and "artificial neural networks (ANNs)" are seen. A successful application of these is found in equalization of channel[2], channel decoding [3] and localization based on CSI [4] in systems of communication. More applications of deep learning in communication systems are expected with the improvement of computational resources on devices. The demonstration of ANNs for equalization of channel with online training for adjusting parameters according to online pilot data is done. It is not possible to directly apply the deep neural networks (DNNs) because there are a lot of parameters requiring long training period for training large number of training data. The transmitted data is recovered by using the model in online deployment. The ability of learning and analysing wireless channel's characteristics that face interference and nonlinear distortion in addition to frequency selectivity has been demonstrated here. Without the use of online training, wireless channels are dealt with learning methods for the first time. The simulation results illustrates that the performance achieved by models of deep learning can be compared to conventional methods if there are sufficient pilots in OFDM systems and it has the capability of working well with CP removal, nonlinear noise and limited pilots. Applications of deep learning are found in communications and signal processing.

II. DETECTION AND ESTIMATION BASED ON DEEP LEARNING

A. *Methods of Deep Learning:*

Significant applications of deep learning in wide areas having significant improvement in performance, including computer vision[5], speech recognition[6], processing of natural language[7] and so on. The literature work[8] presents a comprehensive introduction to machine learning and deep learning. The fig. 1 illustrates the structure of a DNN model. The ability in recognition and representation is improved by DNN because they are deeper versions of ANNs and they have increase number of hidden layers. Multiple neurons are comprised in every layer of a network. The Relu function may be a nonlinear function or Sigmoid function which is defined as fS(a)=1

1+e−a, and fR(a) = max(0, a), respectively.

The cascade of nonlinear transformation of input data I produces the network z output, which is mathematically represented as

$$\mathbf{z} = f(\mathbf{I}, \boldsymbol{\theta}) = f^{(L-1)}(f^{(L-2)}(\cdots f^{(1)}(\mathbf{I}))) \tag{1}$$

L=number of layers, _ = weights of a neural network.

The weights for neurons are the parameters of a model that should be optimized before online deployment. With knowing the desired outputs, optimal weights are learned on a training set.

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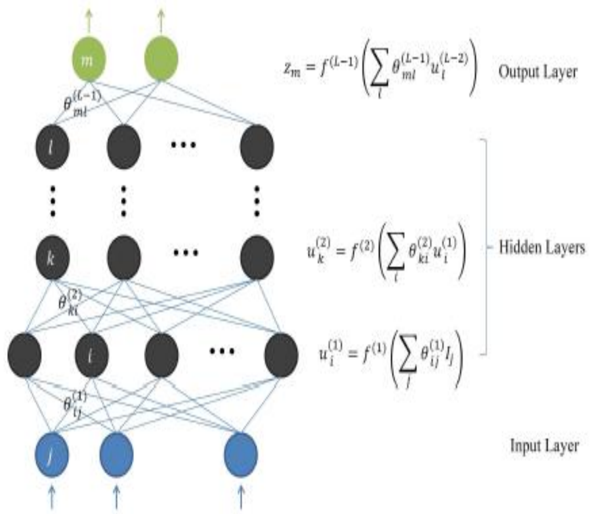

Fig. 1 An example of deep learning model

B. System Architecture:

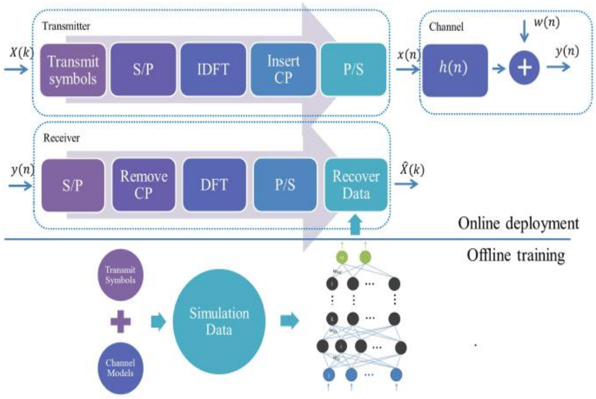

Fig. 2 System Model

Figure 2 illustrates an architecture of OFDM system with channel estimation based on deep learning and signal detection. There is a similarity between baseband OFDM system and conventional ones. At the transmitter end, a parallel data stream conversion is done by inserting the symbols with pilots and then the signal is transformed from frequency domain to time domain by performing the inverse discrete Fourier transform (IDFT). The inter-symbol interference (ISI) is mitigated by inserting a cyclic prefix (CP). The length of cyclic prefix's (CP) should be equal to or greater than maximum delay spread of channel. A complex random variables $\{h(n)\}_{n=0}^{N-1}$ is a complex random variables that describe a sample spaced multi-path channel. The expression of a received signal is

$$y(n) = x(n) \otimes h(n) + w(n) \quad (2)$$

x(n) represents the transmitted signal, *w(n)* represents the AWGN and $\otimes$ represents the circular convolution. The received frequency domain signal obtained after removing CP and performing DFT is as given below:

$$Y(k) = X(k)H(k) + W(k) \quad (3)$$

The discrete Fourier transform of x(n), h(n) and w(n) are represented by X(k), Y(k) and W(k) respectively. The first block of OFDM consist of the pilot symbols whereas rest blocks of OFDM consist of transmitted data. Together, a *frame* is formed. The channel can be referred as "spanning over pilot block and data blocks but changing from one frame to another". During initial study, data consisting of one pilot and one data block is taken as input and the transmitted data is recovered in an end-to-end manner. The figure 2 illustrates the inclusion of two stages for the estimation of joint channel and detection of symbol for obtaining an effective DNN model. The output of DNN is generated in online deployment stage that does not estimates wireless channel for recovering transmitted data.

C. Model Training

The OFDM modulation and wireless channels are viewed as black boxes for training the models. The description of real channels in ways of channel statistics is done by many channel models developed by researchers. Simulation is used to obtain training data by these channel models. The transmitted symbols are first generated by a random sequence of data and a sequence of pilot symbols forms corresponding OFDM frame and during the training and deployment stages, pilot symbols should be fixed. The channel model is used for the simulation of current random channel. The OFDM frames that undergo current channel distortion is used as basis for the simulation of current random channel. L2 loss has been used in the settings of this experiment.

$$L_2 = \frac{1}{N}\sum_k (\hat{X}(k) - X(k))^2 \quad (4)$$

Here *X(k)* denotes the supervision message and also a symbol transmitted in this situation. Three out of five layers in DNN model are hidden layers. There are 256, 500, 250, 120, 16 neurons in each layer respectively. The 2 blocks of OFDM contain pilot and transmitted symbols and the input number corresponding to this number corresponds to number of real and imaginary parts. A single model is trained independently for grouping and predicting every 16 bits of data that is transmitted, which for getting final output is concatenated. The Sigmoid function is applied to last layer for doing mapping pf output to [0,1] interval. Except in the last layer, most of the layers use Relu function as an activation function.

III. SIMULATION RESULTS

The methods of deep learning for estimation of joint channel and detection of symbol were demonstrated by various experiments in OFDM wireless communication systems. The simulation data was used to train DNN model and comparison under different values of signal to noise ratios (SNRs) was done with traditional methods for different bit-error rates (BERs). The conditions using fewer number of training pilots, omitting CP and presence of nonlinear clipping noise, the approach based on deep learning is more robust in comparison with LS and MMSE. This paper is based on experiments based on 64 sub-carriers OFDM system and length 16 cyclic prefix. The wireless channel follows [9] "the wireless world initiative for new radio model (WINNER II) is based on a carrier frequency of

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2.6 GHz with path number 24 and maximum delay of 16 sampling period in urban channels is used". The method of modulation used is QPSK.

A. Influence of Pilot Numbers:

For estimating channel in each frame, 64 pilots are used and comparison of method proposed here is done for detection and estimation of channel by using LS and MMSE. Figure 3 illustrates the worst performance of LS method because detection does not utilizes prior statistics of a channel. The best performance is observed by MMSE because the second-order statistics of channels are used for symbol detection as they are known. The performance of deep learning is comparable to MMSE method and is much better than LS method. A maximum delay of 16 sampling periods is seen in the channel model and better spectrum is utilized by estimating much fewer pilots. 8 pilots and transmitted data are comprised in first block of OFDM when 8 pilots were only used. There is no change in the output and input of DNN. Figure 3 illustrates the saturation of BER curves of methods of LS and MMSE which have SNR value higher than 10 dB when number of pilots utilized is 8 pilots are utilized. The BER of deep learning is reduced with an increase in SNR, which states that "DNN is robust with the quantity of pilots used for estimation of channel". The training data which is obtained from model is used to learn characteristics of wireless channels. This is the reason behind enhanced performance of DNN.

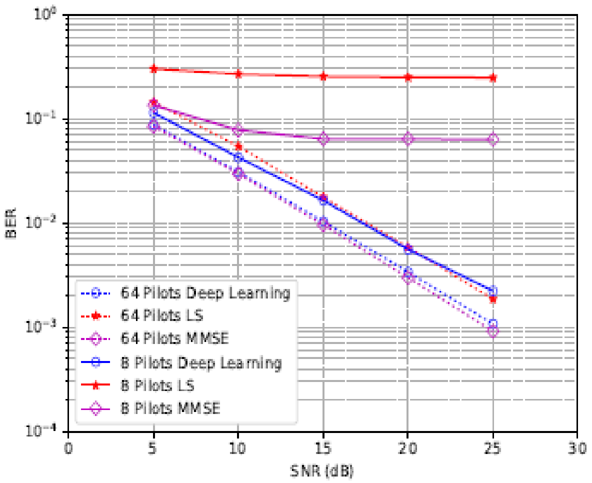

Fig. 3 BER curves of approach based on deep learning and traditional methods

B. Impact of CP

- The conversion of physical channel's linear convolution into its circular convolution is done by CP and mitigation of ISI. The transmission of time and energy effected by this. The performance is evaluated with the removal of CP. The BER curves for an OFDM system without the removal of CP is illustrated in figure 4. The channel cannot be effectively estimated neither LS nor by MMSE. When SNR reaches above 15 dB then SNR is saturated. The method of deep learning functions well. Thus, DNN can be used to reveal the characteristics of wireless channel.

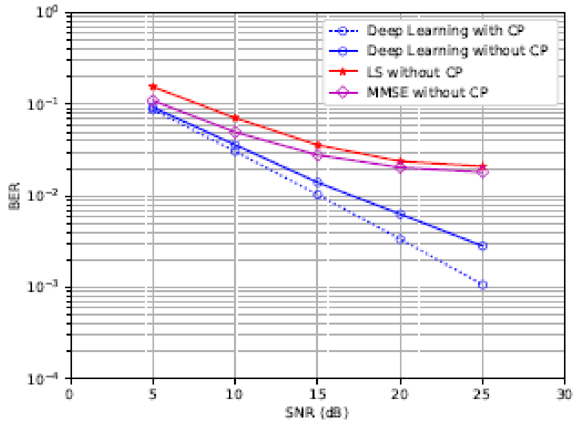

Fig. 4 "BER curves without CP"

C. Effect of Clipping and Filtering Distortion

The high "peak-to average power ratio" (PAPR) is the biggest drawback of OFDM system [10].

The effective and simple approach for reducing PAPR is the filtering and clipping. The nonlinear noise gets introduced after clipping by which the performance detection and estimation are degraded. The clipped signal is as following

$$\hat{x}(n) = \begin{cases} x(n), & \text{if } |x(n)| \leq A, \\ Ae^{j\phi(n)}, & \text{otherwise}, \end{cases} \quad (5)$$

Here, A denotes the threshold value and $\phi(n)$ represents the phase of *x(n).*

In the presence of clipping noise, the detection performance of deep learning method and MMSE of OFDM system is illustrated in figure 5. It also illustrates that at the clipping ratio of 1, deep learning method is preferable in comparison with MSME at a SNR value greater than 15 dB. This proves the robustness of deep learning method to nonlinear clipping noise. After combining all adversities together, comparison between DNN and MSME is illustrated in figure 6 after omitting CP and clipping noise and using only 8 pilots. It also illustrates that it is preferable to use DNN than MMSE but under the ideal circumstances, it has a drawback of gap with detection performance.

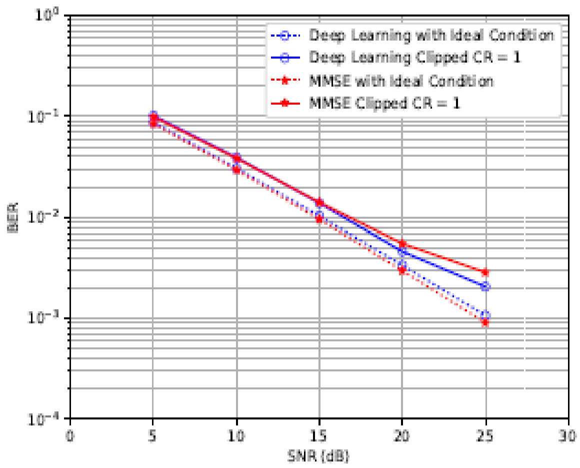

Fig. 5 "BER curves with clipping noise"

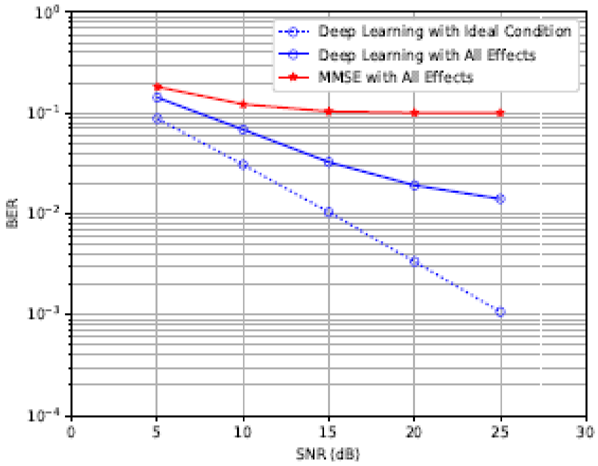

Fig. 6 BER curves after combining all adversities

D. ROBUSTNESS ANALYSIS

The simulations above show the channel having similar statistics as in offline training stage is used for generation of online deployment. But there may occur mismatches between two stages in real-world applications. The analysis of this simulation the impact of varying the statistics of channel nodes that are used during deployment and training stages. The variation of number of paths and maximum delay in test stage from the training stage is described here. The performance of symbol detection is not significantly damaged by the variations of channel's models statistics.

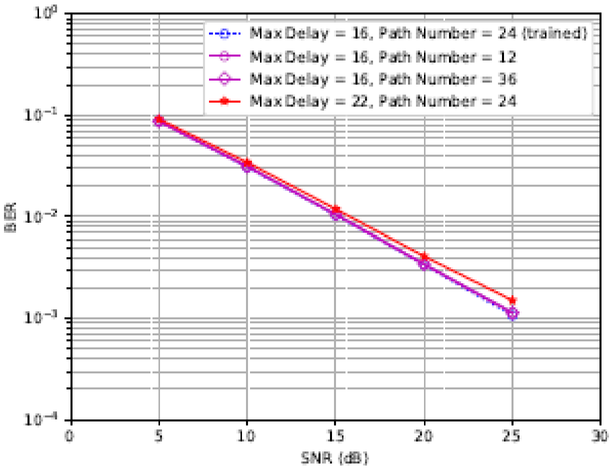

Fig. 7 BER mismatch between deployment stages and training

IV. CONCLUSION

This paper demonstrates the initial efforts for employing estimation of channel and symbol detection in OFDM by DNNs. The wireless channels and OFDM channels are viewed as "black boxes" by training the model offline by using simulation data. The advantages offered by deep learning methods is that wireless channels get complexed by interference and serious distortion as shown in simulation results. This proves the ability of DNN to analyse and remember the complicated characteristics of wireless channels. It is important to have a good ability of generalization of DNN models for effective working of DNN when there is no exact agreement between online deployment with models of channel that are used in training stage.

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