A Survey and Taxonomy on OFDM Channel Estimation

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Abstract- *Orthogonal Frequency Division Multiplexing (OFDM) has emerged as a key enabler in high speed data transmission. The term channel estimation means finding out a mathematical relation regarding the transformation caused by the channel on the signal that is passed through it. The OFDM channel be designated by it's impulse response. The various approaches used thus far for OFDM channel estimation have been enlisted with their pros and cons. The performance indices have been described to evaluate the performance of different existing techniques. Focus has been the use of machine learning based approaches for OFDM channel estimation.*

Keywords- Orthogonal Frequency Division Multiplexing (OFDM), Channel Estimation, Bit Error rate, Mean Square Error,

I. INTRODUCTION

Deep learning is a category of machine learning where the learning ANN structure has multiple hidden layers. Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on learning data representations, as opposed to task-specific algorithms. Learning can be supervised, semi-supervised or unsupervised. Typically, deep learning is used for applications where the data is:

1) Very Large
Or
2) Very Complex
3) Both very large and complex

A Deep Neural Network (DNN) is a category of Artificial Neural Network (ANN) which has a multitude of hidden layers.[1] The fundamental concepts of the Deep Neural Network (DNN) resemble the human brain in the following aspects. Deep neural networks may have a variable speed of learning for each hidden layer. It is customary to use the same learning rule for each layer in the hidden layer section for the sake of simplicity and the ease of analysis.[6]

A typical illustration of the deep learning architecture is shown in the figure below:

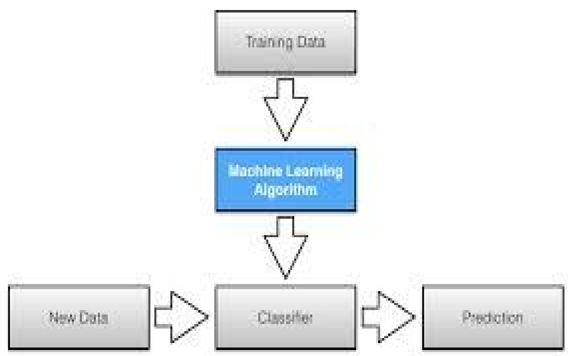

Fig. 1 Structure for Machine Learning based Chanel Estimation

The common rule for the deep neural network's size is the choice of hidden layers for the analysis of data depending the complexity and the size of the data that needed to be handled.

Trying to mimic the nature of the human brain needs a clear understanding of the functioning of the human brain, which happens to be the following.[16] The brain is a highly complex, nonlinear and parallel information processing system. It has the capability to organize its structural constituents, known as neurons, so as to perform certain computations many times faster than the fastest digital computer in existence today. The brain routinely accomplishes perceptual recognition tasks, e.g. recognizing a familiar face embedded in an unfamiliar scene, in approximately 100-200 ms, whereas tasks of much lesser complexity may take days on a conventional computer. A neural network is a machine that is designed to model the way in which the brain performs a particular task. The network is implemented by using electronic components or is simulated in software on a digital computer. A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use.

II. OFDM THEORY

Orthogonal Frequency Division Multiplexing is a special form of multicarrier modulation which is particularly suited for transmission over a dispersive channel. Here the different carriers are orthogonal to each other, that is, they are totally independent of one another. This is achieved by placing the carrier exactly at the nulls in the modulation spectra of each other.

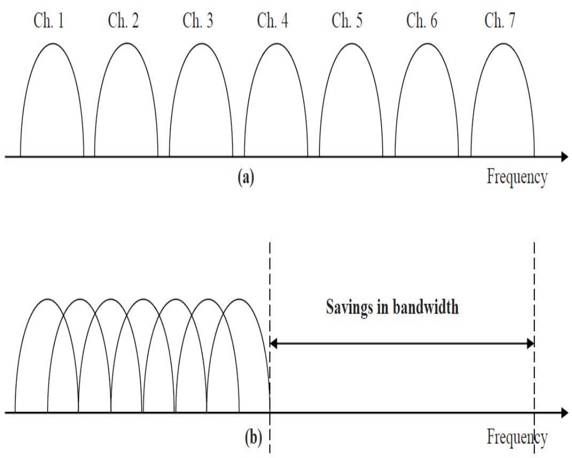

Fig. 2 Spectrum of FDM and OFDM

The transceiver structure for the implementation of OFDM is shown in figure 2. At the outset, the Analog to digital converter (A/D) converts the analog signal to digital signal or in the form of data stream, then source encoding is used to compress the digital data up to an extent such that it can be received without any loss. Then, the information symbol is obtained from source encoder which is passed through a channel encoder which adds the redundant bits to the data sequence for reliable communication or to make the data transmission robust to disturbances which are present in the transmission channel. Now, the information sequence at the output of the channel encoder is passed through the digital modulator which outputs the signal waveform. The modulation may be binary or m-array. In Binary modulation, bit 1 and 0 uses distinct waveform and m-array modulation, uses m number of distinct waveform and this modulated waveform is transmitted. In the channel, the modulated signal is affected by the addition of random noise which is probabilistic in nature. [14]

At the receiver side, the demodulator demodulates the received signal into binary sequence and matched filter is also used at receiver side to increase SNR. Now the output of the demodulator is passed through the channel decoder to recovers information sequence. This information sequence is fed to the source decoder to reconstruct the signal which was actually transmitted by source. Then that signal is converted to analog signal and received by the user. Throughout this process the channel introduces the attenuation in the signal which increases the probability of error /BER as decrease in SNR.

III. NEED FOR DEEP NEURAL NETWORKS IN OFDM CHANNEL ESTIMATION

The fundamental reason why Deep Neural Networks for OFDM channel estimation is the fact that OFDM data is extremely complex and un-correlated for conventional channel estimation techniques. Conventional techniques have yielded high errors in estimation of OFDM channel models. Typically OFDM channels exhibit a random nature of variation in nature and hence the input and output data are extremely uncorrelated.

The deep neural network can find patterns in highly uncorrelated data using its training rule. The successive iterations try to reduce the errors monotonically given by:

$$g = \frac{\partial e}{\partial w} \qquad (1)$$

Here,
g represents the error gradient.
e represents the estimation error
w represents the weights

The second order error rate can be given by a cascade of individual learning rates, typically formulated as:

$$\prod_{i=1}^{N} \frac{d^2 e_i}{d w_i^2} \qquad (2)$$

Here,

N is the number of hidden layers in the deep neural network.

Thus an appropriate number of hidden layers and an effective training algorithm can find significant patterns in the data fed to the deep neural network which is yielded by the OFDM system. The estimation process in to be done based on 70% training and 30% testing data bifurcation.

IV. PREVIOUS WORK

In 2018, C Hager et al. in [2] proposed an approach that used the concept of deep learning for high speed optical networks in which the non-linear interference (NLI) was proposed to be mitigated by the use of a differential learning rule based on deep neural networks. The need for deep learning as cited was the complexity of the digital data that was being transmitted in the optical fibers.

In 2017, H Ye et al. in [3] proposed a technique that used the technique of deep learning for OFDM channel estimation and signal detection. It was shown that the addition of pilots would affect the BER of the system. The necessity of the deep neural networks was because of the extremely non-linear and frequency selective nature of OFDM systems wherein small or extremely narrowband spectrum is allocated to each user.

In the year 2017, C Jiang et al. in [4] laid down machine learning platforms for next generation systems communication in networks. The focus was on 5G networks and the use of machine learning for the performance enhancement of such network using machine learning techniques. The areas of focus were the channel state information (CSI) data extraction from typical channel sounding mechanisms. The use of machine learning was also jumping from one configuration to the other estimating the BER of the system.

In the year 2016, Eliya Nachmani et al. in [5] proposed deep learning for the use of decoding linear codes that are used in the belief propagation approach. The performance metric used was the Bit Error Rate. The property that was leveraged in this case was the independence of the code word that is transmitted in the case of belief propagation mechanisms. The training data set is a self created bit stream of the zero codeword.

In the year 2016, X Wang et al. in [6] proposed a technique that incorporated digital fingerprinting using channel state information (CSI) and deep neural networks (DNN). The technique was termed as Deep-Fi. The areas of focus were the channel state information data extraction from typical channel sounding mechanisms. The use of machine learning was also jumping from one configuration to the other estimating the BER of the system.

V. EVALUATION PARAMETERS

Since errors can be both negative and positive in polarity, therefore its immaterial to consider errors with signs which may lead to cancellation and hence inaccurate evaluation of errors. Therefore we consider mean square error and mean absolute percentage errors for evaluation. Mean Square Error is defined as:

$$MSE = [\sum_{i=1}^{n}(X - X')^2]/n \qquad (3)$$

Here, X is the predicted value and X' is the actual value and n is the number of samples.

$$BER = \frac{No.of\ Error\ Bits}{Total\ Number\ of\ Bits} \qquad (4)$$

Bit Error Rate (BER) is a metric that indicates the reliability of the system. Low values of BER are envisaged.

VI. CONCLUSION

It can be concluded form the above discussions that Artificial Neural Networks can be effectively used for electrical OFDM channel estimation even though channel parameters may exhibit complex time series behaviour. Various previous appraoches have been discussed with their salient features. Finally the evaluation parameters used for the evaluation of any prediction model to be designed have been explained with their physical significance and need.

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