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OFDM Channel Estimation Using Bayesian Regularization Algorithm

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Abstract- *Orthogonal Frequency Division Multiplexing is a multi carrier system which owing to its spectral efficiency has evolved as the primary solution to high speed data networks. The fundamental problem still lies in the fact that wireless channels exhibit frequency selectivity thereby rendering high bit error rate (BER) to the system. The present work presents a technique used for deep learning based on the Bayesian Regularized Deep Neural Network (BRDNN) for channel estimation of an OFDM based network. The performance is evaluated based on the mean square error found in channel estimation. Moreover the number of epochs has also been considered as an evaluation parameter for judging the performance of the system. It is found that the proposed system attains a mean squared error of 0.25% and a BER of 10-4. It has been observed that the variation in the number of pilots results in a variation in BER of the system.*

Keywords- Orthogonal Frequency Division Multiplexing (OFDM), Channel Estimation, Artificial Neural Network (ANN), Levenberg Marquardt Back propagation, Deep Neural Network (DNN).

I. INTRODUCTION

Orthogonal Frequency Division Multiplexing is a special form of multicarrier modulation which is particularly suited for transmission over a dispersive channel. [3] 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. 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.[14] 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.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.[7]

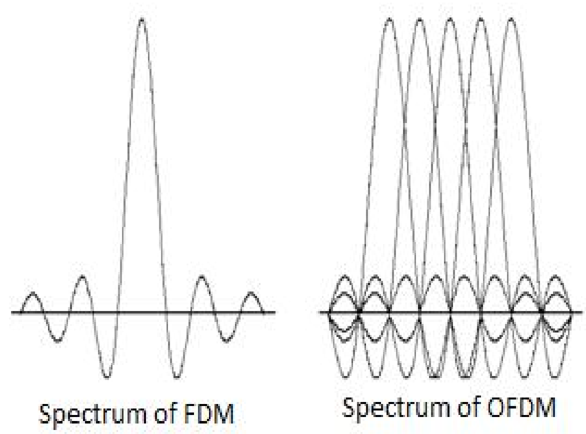

Fig.1 Spectrum of FDM and OFDM

II. DEEP NEURAL NETWORKS

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. 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. It resembles the brain in two respects:

1. Knowledge is acquired by the network from its environment through a learning process.
2. Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge. [6]

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. Other advantages include:

1. **Adaptive learning:** An ability to learn how to do tasks based on the data given for training or initial experience.
2. **Self-Organization:** An ANN can create its own organization or representation of the information it receives during learning time.
3. **Real Time Operation:** ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.

The output of the neural network is given by:

$$\sum_{i=1}^{n} XiWi + \theta \qquad (1)$$

Where Xi represents the signals arriving through various paths, Wi represents the weight corresponding to the various paths and Θ is the bias. The above diagram exhibits the derived mathematical model of the neural network. It can be seen that various signals traverssing different paths have been assigned names X and each path has been assigned a weight W. The signal traverssing a particular path gets multiplied by a corresponding weight W and finally the overall summation of the signals multiplied by the corresponding path weights reaches the neuron which reacts to it according to the bias Θ. Finally its the bias that decides the activation function that is responsiblefor the decision taken upon by the neuralnetwork.Neural networks can be used for tracking complex patterns in wind speed and subsequently predicting wind speed.

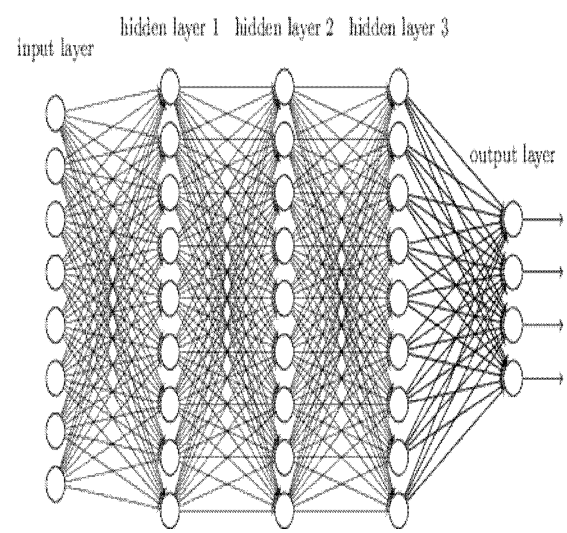

Fig.2 Physical Representation of a Deep Neural Network

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 hissedn layer seccction for the sake of simolicaty and the ease of analysis.[6] The common rule for the deep neural network's size is the chocie of hidden layers for the analysis of data depending the complexity and theh size of the data that needes to be handled.

III. SYSTEM DESIGN

The proposed system design uses the bayesian regularization algorithm as the learning rule for the system. The fundamental steps in the design of the system are put forth:

1. Generate a random serial data set that is to be transmitted in the form of 0s and 1s. Let it be given by:

$$X_{Serial} = (rand(1, n) \qquad (2)$$

Here,

X_{Serial} represents the serial data.
Rand(1,n) exhibits a serial data stream of n-bits.

Rand signifies that the data is completely random owing to the fact that the data arriving at the transmittig end is from users and is to be considered random.

2. Narrowly spaced sub-channles are to be generated which would be orthogonal in nature given by:

$$X_{IFFT} = ifft(X_{Serial}) \quad (3)$$

Here,

X_{IFFT} is the parallel modulated data at narrow orthogonal subchannels after the inverse fast fourier transfrom operation on serail data.

3. Addition of Pilots.

Pilots are added to safeguard bits at appended part of the data packet. It is chosen as a matrix vector given by:

$$X_{Pilot} = X_{end} - N \quad (4)$$

Here,
X_{Pilot} reppresentsthe number of pilot bits.
X_{end} represents the ending bit of the data stream
N persents the appended bit size.

4. The signal to be sent via the wireless channel is given by:

$$Y_{OUT} = f(X_{IN}) \quad (5)$$

Here,

f represents the channel function governing the input output channel mapping.
X_{IN} represents the input data stream of the channel and is given by;

$$X_{IN} = X_{IFFT} + X_{PILOT} \quad (6)$$

The nature of the channel is also to be designed as an Additive Whiite Gaussian Noise Channel, such that its power spectral density is constant over a range of frequencies that comes unser data transmission.

5. In such a case, the disturbances in the channel can be governed by:

$$Y_{OUT} = X_{IN} + Noise_{Channel} \quad (7)$$

Here,

Y_{OUT} represents the channel's output
X_{IN} represents the channels input
$Noise_{Channel}$ represnets the noise or disturbance effects added in the channel.

6. Design a deep neural network (DNN) with Bayesian Regularized Training. The weight updating rule for the Bayesian Regularizationis given by:

$$w_{k+1} = w_k - (J_k J_k^T + \mu I)^\wedge - 1(J_k^T e_k) \quad (8)$$

Here,

w_{k+1} is weight of next iteration,
w_k is weight of present iteration
J_k is the Jacobian Matrix
J_k^T is Transpose of Jacobian Matrix
e_k is error of Present Iteration
μ is step size
I is an identity matrix.

Moreover for the predictive classification of ant data set, the Baye's Rule is followed, which is given by:

$$P\frac{A}{B} = \frac{P(A).P\frac{B}{A}}{P(B)} \quad (9)$$

Here,

$P\frac{A}{B}$ is the probability of occurrence of A given B is true.

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$P(B)$ is the probability of occurrence of B

$P(A)$ is the probability of occurrence of A

In the present case the, 70% of the data has been taken for training and 30% of the data has been taken for testing.

IV. 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:

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

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

$$BER = \frac{No.ofErrorBits}{TotalNumberofBits}$$

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

V. RESULTS

In the present case, the BER of the system is computed for 3 cases,

1) Without adding pilot bits.
2) With adding 32 Pilot bits.
3) With adding 64 Pilot bits.

A superimposed BER curve depicts the results.

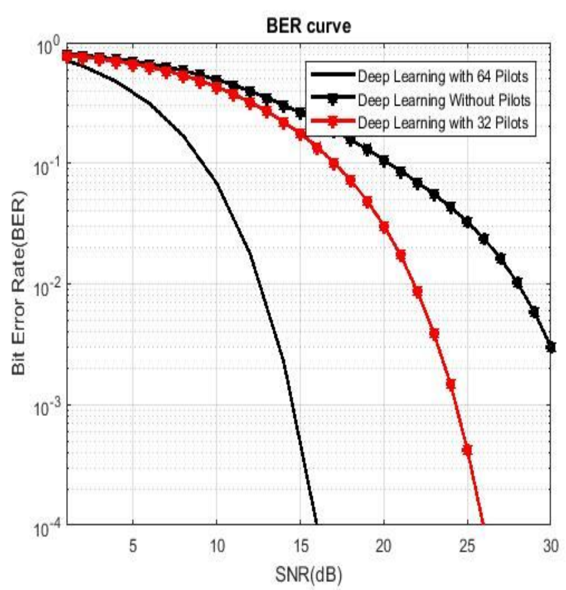

Fig.3 BER performance of the Proposed System

It can be observed that the BER falls the fastest for 64 pilot bits and falls the slowest for no pilot addition.

The BER attained in the three cases is:

1) 16 dB for 64 pilot bits, with a BER of 10^{-4}
2) 26 dB for 32 pilot bits, with a BER of 10^{-4}
3) 30 dB for no pilot bits, with a BER of 10^{-3}

It can be seen that the increase in the number of Pilot Bits decreases the BER performance of the system and simultaneously decreases the SNR need to attain the desired value of BER.

The Deep Neural Network designed has a configuration of 1-11-1, signifying 1 input and output layer and 11 hidden layers.

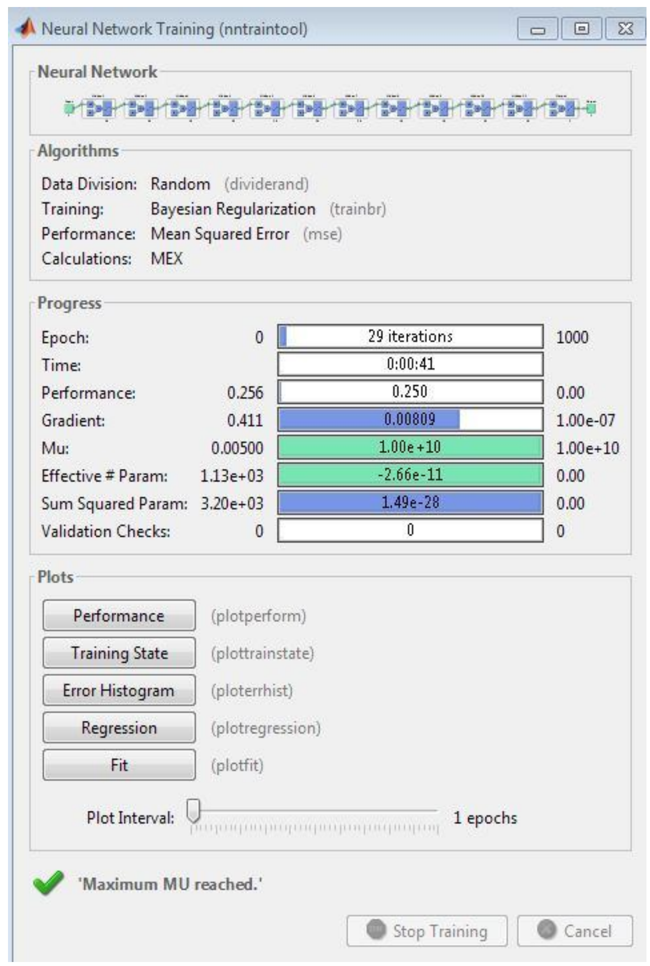

Fig.4 Training and epoch performance of the proposed system

The variation of the mean squared error as a function of the number of epochs is shown in the subsequent figure. It can be seen that the MSE stabilizes at a value of 0.25% after 29 iterations.

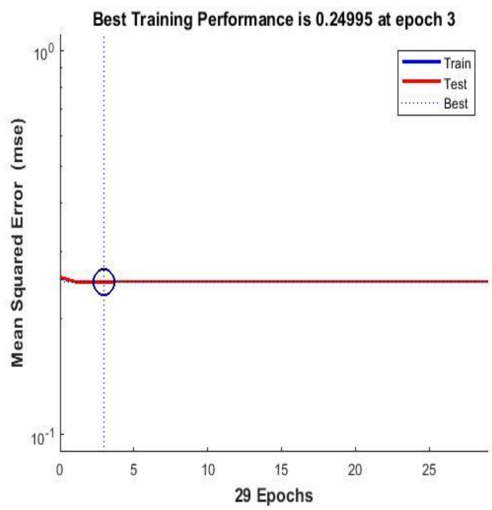

Fig.5 mse performance of proposed system as a function of number of epochs.

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 Neural Network Architectures 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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