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Design and Implementation of Deep Neural Network (DNN) using Bayesian Regularization for OFDM Channel Estimation

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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

Artificial Neural Networks have made their presence felt in several applications where finding relations and patterns is complex in nature. One such application is that of finding channel nature for computer and wireless networks. For such a time varying channel response, an artificial neural network consisting of multiple hidden layers needs to be used. These days, Orthogonal Frequency division multiplexing (OFDM) has become an effective multiplexing technique for several applications. The need for channel estimation lies in the fact that data transmission is computer networks are prone to errors arising out of the nature of the wireless channels. Networks such as LANs, MANs or WANs tend to have multiple devices connected to each other, which may move with time. If the nature of the channel is known, then corrective measures for circumventing the errors can be deigned.[2] However, this is a challenging task as wireless channels keep changing their nature over time. Moreover, spectrally efficient techniques such as OFDM tend to transmit data in narrowly spaced channels. Hence it is extremely difficult to find out the exact nature of the channel by analyzing the patterns existing in the input and output data streams. [3]The match between the input and output data streams need to be done. Let the input data stream be X and the output data stream be Y. The relation between input X to the channel and output Y of the channel decides the channel response 'H'

Deep neural network (DNN) is a special category of artificial neural networks specially designed for analyzing complex data patterns. Still it is challenging to keep the error low and accuracy high for the OFDM based channel estimation.

II Deep Neural Networks

An Artificial neural network is the computational mechanism to implement artificial intelligence practically for purposes where the capabilities of human or natural intelligence fail. The mathematical model for an artificial neural network is given below.

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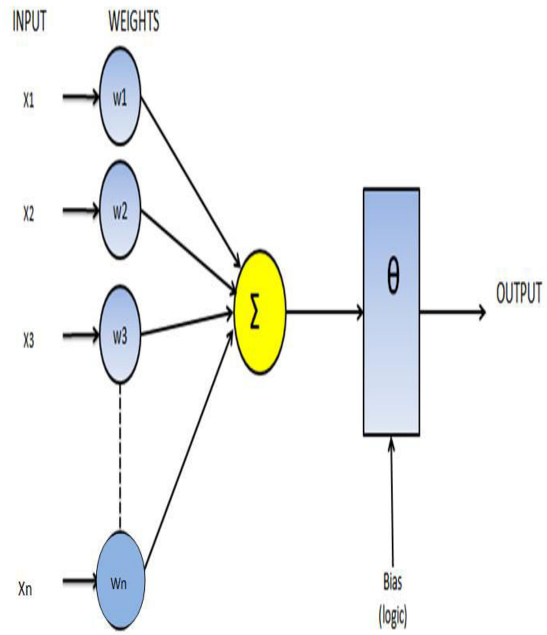

Fig. 1 Mathematical Model of ANN

Owing to the parallel data processing technology of the artificial neural network, the mathematical relation relating the input and output variables is given below. [7] The output of the neural network is given by:

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

Here,

Xi represents the signals arriving through various paths,
Wi represents the weight corresponding to the various paths and
Ɵ is the bias.
The representation of the computational intelligence as in terms of weights is explained below. The adaptive learning rule is decided by the variation of the weights with the epochs based on the system errors given by:

$$w(i) = f(i, e) \qquad (2)$$

Here,

w (i) represents the instantaneous weights
i is the iteration
e is the prediction error
The deep neural architecture can be given by the diagrammatic representation given below:

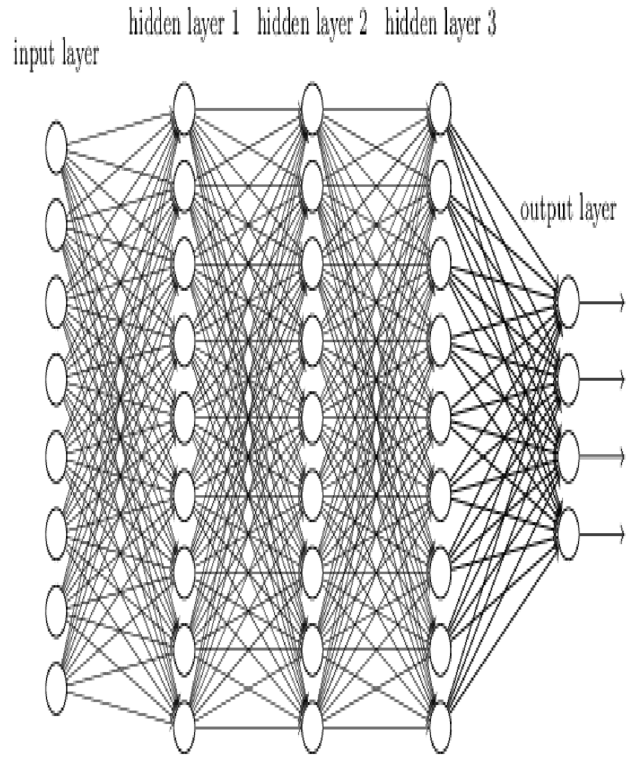

Fig.2 Physical Representation of a Deep Neural Network

Deep neural networks generally tend to increase the system complexity by insertion of several hidden layers between the input and output layers. The Deep Neural Network is used only in cases where the complexity and size of the data needs a DNN architecture.

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:

$$X_{Serial} = (rand(1, n)) \qquad (3)$$

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 transmitting end is from users and is to be considered random.

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

$$X_{IFFT} = ifft(X_{Serial}) \tag{4}$$

Here,
X_{IFFT} is the parallel modulated data at narrow orthogonal sub channels after the inverse fast Fourier transform operation on serial 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:

$$X_{Pilot} = X_{end} - N \tag{5}$$

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

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

$$Y_{OUT} = f(X_{IN}) \tag{6}$$

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;

$$X_{IN} = X_{IFFT} + X_{PILOT} \tag{7}$$

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

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

$$Y_{OUT} = X_{IN} + Noise_{Channel} \tag{8}$$

Here,
Y_{OUT} represents the channel's output
X_{IN} represents the channels input
$Noise_{Channel}$ represents 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 Regularizations given by:

$$w_{k+1} = w_k - (J_k J_k^T + \mu I)^\wedge - 1(J_k^T e_k) \tag{9}$$

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:

$$P\frac{A}{B} = \frac{P(A).P\frac{B}{A}}{P(B)} \tag{10}$$

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:

$$MSE = \frac{1}{n}\sum_{i}^{n}$$

(11)

Here,

N is the total number of error samples.

E is the error between the predicted and actual value.

The bit error rate can be defined as:

$$BER = \frac{No.of\ Error\ E}{Total\ Number\ o} \quad (12)$$

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.

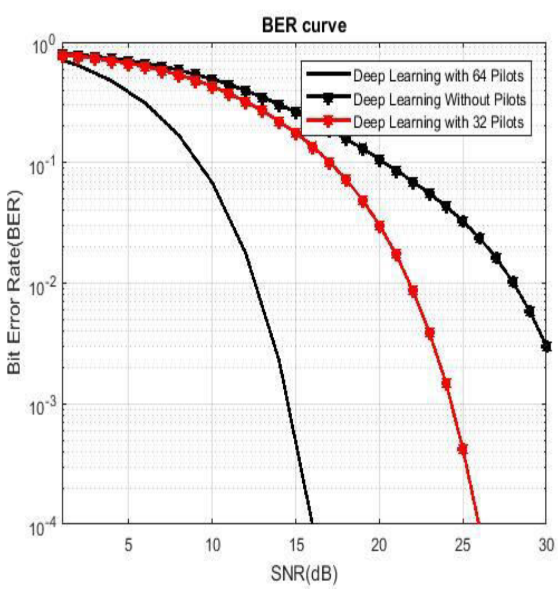

Fig.3 BER performance of the Proposed System

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.

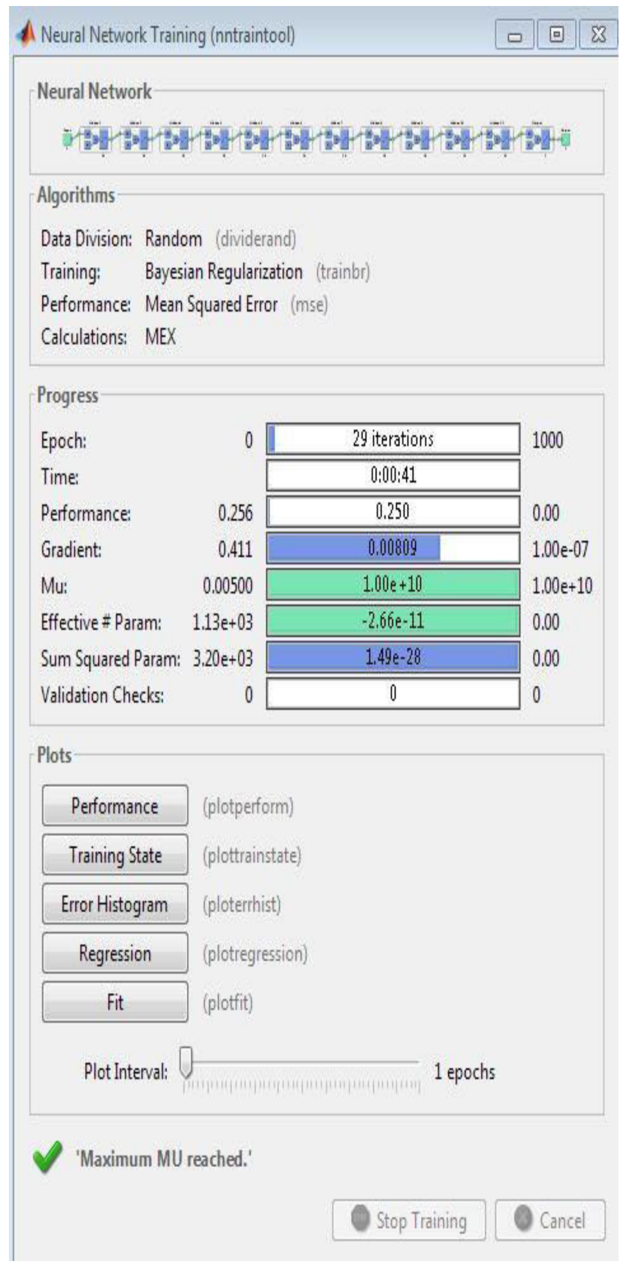

Fig.4 Training and epoch performance of the proposed system

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.

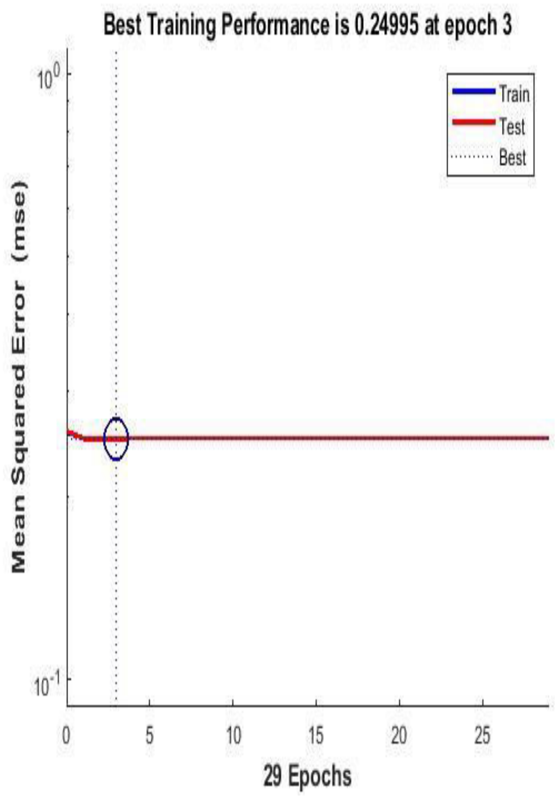

Fig.5 MSE performance of proposed system as a function of number of epochs.

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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