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OFDM CHANNEL ESTIMATION USING BAYESIAN REGULARIZED DEEP LEARNING

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ABSTRACT

Orthogonal Frequency Division Multiplexing (OFDM) has clearly emerged as one of the most potent enablers for high data rate and high spectral efficiency communication systems. Most wireless communication systems consisting of large number of users sharing a common channel with limitations in bandwidth opt for OFDM transmission. However, due to the frequency selective nature of wireless channels, OFDM often faces degradation in the Bit Error Rate (BER) and hence Quality of Service. This paper proposes a channel estimation mechanism for OFDM based on Bayesian Regularized ANN. It has been shown that the proposed approach attain low BER and lesser number of iterations for training compared to conventional systems. The deep learning algorithm used is the Bayesian Regularization which is an effective algorithm for analyzing large and complex patterns in data. The performance metrics are the BER, mean square error (MSE) and number of epochs.

KEYWORDS: Orthogonal Frequency Division Multiplexing (OFDM), Bit Error Rate (BER), Signal to Noise Ratio (SNR), Mean Square Error (MSE), Epochs, Deep Learning.

INTRODUCTION

Controllers are Orthogonal Frequency Davison Multiplexing has the advantage of higher amount of spectral efficiency compared to frequency division multiplexing and the comparative spectral are shown as:[7].

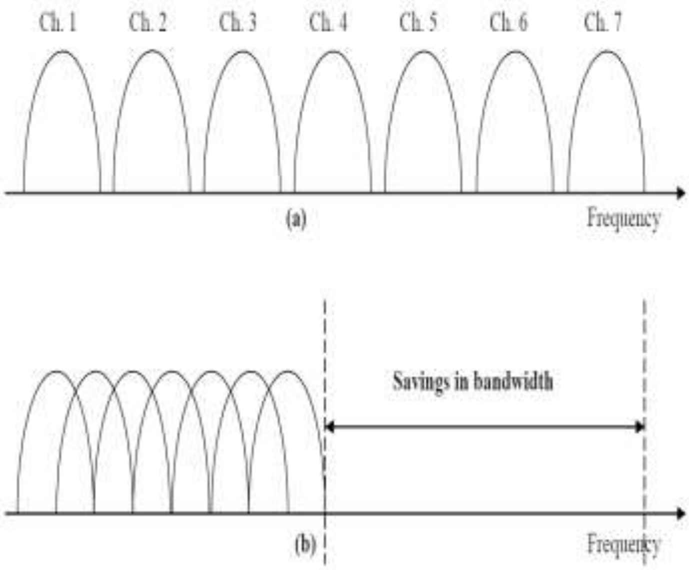

Fig.1 Comparative Spectrum of FDM and OFDM

If two signals are orthogonal, then:

$$\int_0^T x1(t).x2(t)dt = 0 \quad (1)$$

Here,
x1(t) represents signal1

x2(t)represents signal 2
T represents the period

For, N signals, the modified condition is given by:

$\int_0^T x1(t).x2(t)x3(t) \ldots \ldots .xn(t)dt = 0$ (2)

Considering the case if sin(t) and cos(t), the orthogonality check can be done as:
$y = \int_0^{2\pi} \sin(t) . \cos(t)\, dt$ (3)
y= $\int_0^{2\pi} \frac{1}{2} . 2\sin(t) . \cos(t)\, dt$ (4)
y= $\frac{1}{2} \int_0^{2\pi} 2\sin(t) . \cos(t)\, dt$ (6)
$y = \int_0^{2\pi} \sin(2t)\, dt$ (7)
$y = -\cos(2t)/t_0^{2\pi}$ (8)
y=0 (9)
Here,
n is the number of signals

The major challenge with OFDM data transmission is the frequency selective nature of wireless channels. This results in high bit error rates and degraded Quality of Service. Hence it becomes mandatory to estimate the OFDM channels. The mathematical representation of such a channel is given by:
The impulse response can be given by:

$$himp(t) = \sum_{i=1}^{k} \delta_i(t) \quad (10)$$

Here,
himp(t) represents the impulse response
δ denotes the Kronekar delta function [13]
In the frequency domain counterpart of the formulation, the Fourier Transform is used for time-frequency translation given by:

$$H(f) = \int_{-\infty}^{\infty} himp(t) e^{-j\omega t}\, dt \quad (11)$$

Here,
The time-frequency translation is done using the Fourier Transform
$H(f)$ is the f-domain representation of the channel
himp(t) is time varying impulse response
ω denotes the variable called angular frequency
t denotes time

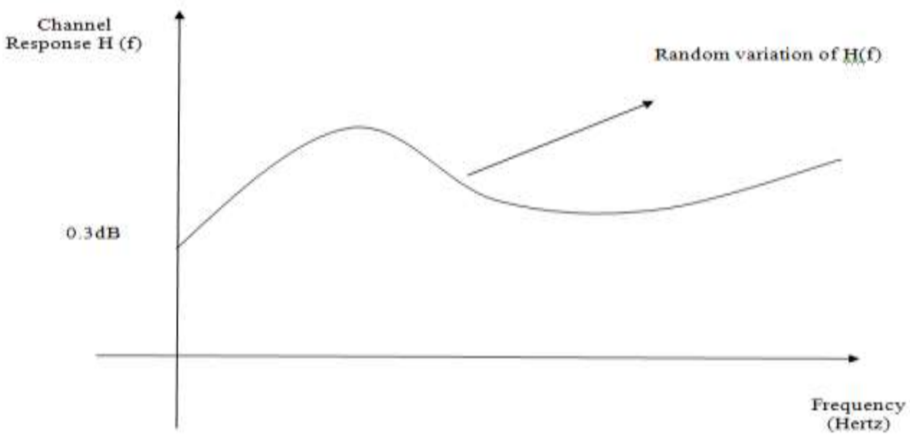

Fig.2 Response of Frequency Selective Channels

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MATERIALS AND METHODS

Neural Networks and Deep Learning

Artificial neural networks tend to follow the attributes of human data processing and handling capability. The fundamental attributed of artificial neural networks is the fact that they try to adapt just like the human intelligence. ANN resembles human intelligence in the following ways:

1. Parallel data processing
2. Recognition of patterns and correlating them.
3. Evolving as pr the changes in the training data in terms of the withheld experiences called weights. This attribute makes the artificial neural network learn and adapt just like humans in data analysis. The following is the biological model of a neuron. The biological model is further converted to a mathematical model so as to facilitate the translation into actual code.

ANN basically tries to follow the patterns followed by human intelligence to inherit and copy the attributes of human intelligence for the sake of dat analysis and making predictions and classifications. By monitoring the data and information flow, it is easy to predict the workload extent and its quantity. This helps in building elasticity and also enhances the scalability of the system. The workload plays a crucial role and it must be flexible enough so that different programs can use it according to its changing requirements. The resource management and resource based allocation is very important area of work. With the advent of machine learning approaches and mechanisms, it is viable option to use them for the energy efficient resource handling for cloud based environments. There is no second thought to the fact that cloud services provides plethora of benefits in many form of environments. The major attributes of such a system can be considered to be a fact that it can handle data in different way compared to statistical techniques. Cloud computing domain has been witnessing a large traffic and users dependent on it. With most of the work being shifted to the internet platform, the cloud services have become dominant in all aspects of business and technology. In this work, the authors proposed a novel study of cloud tasks dispatching. There are allocation schemed and algorithms that have been used as a part of the model. The response time that is computed has been reduced considerably in this work. Hence the following attributed of ANN is necessary for cloud workload estimates.

The way in which a neural network is designed depends on several parameters. The fundamental attributes are the number of neurons in each layer of the neural network. Also the number of hidden layers is also a critical aspect. In this sense, there is no fixed paradigm to assume the number of hidden layers which can render accurate prediction results. The output of the neural network is obtained from the output layer of the ANN. Another aspect that affects the decision making capability of the ANN is the choice of the activation function used for the neural network. The activation function is necessary for a mapping of the neural network parameters with the final output. Such activation functions try to mimic the human decision making ability in the sense that there can be cases where there can be a clear boundary of prediction or decision class which would be useful for the decision type. Moreover, the bas or the logic is also mandatory for the patterns fitting into a fitting model. The mathematical model of the ANN is shown subsequently:

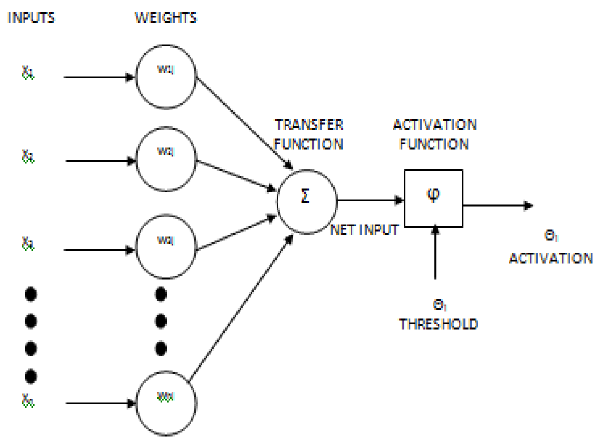

Fig.3 Mathematical Model of ANN

Work on ANN has become indispensible these days due to the fact that the data size and the complexity of the data has grown manifold. Moreover, cloud based services need to handle and cater to relatively very large data sets and data processing mechanisms. The attributes of the ANN mentioned above make the ANN architecture exactly apt for workload prediction purposes with higher accuracy compared to conventional models. The mathematical relation for the output of an ANN is given by:

$$Y = \sum_{i=1}^{n} X_i . W_i + \theta_i \tag{12}$$

Here,
X is the input
Y is the output
W is the weight
θ_i is the bias

The general model of the ANN also needs to be followed by a critically important aspect of ANN design and it is the choice of the training algorithm. The training algorithm is the mathematical relation relating present and subsequent weights and errors. It is the way in which it is decided to deed the neural network with data and manipulate the experiences or weights accordingly. There are several algorithms which can be used for training an ANN, but the following features of any algorithm need to be considered prior to choosing any particular one. Such parameters are:
1) Time Complexity
2) Space Complexity
3) Accuracy

Deep Learning and Back Propagation
Deep Learning is specific domain of neural network based machine learning in which the number of hidden layers are large. This helps the neural network to analyze and find patterns in extremely large and complex data. The conceptual structure of deep leaning is shown below:

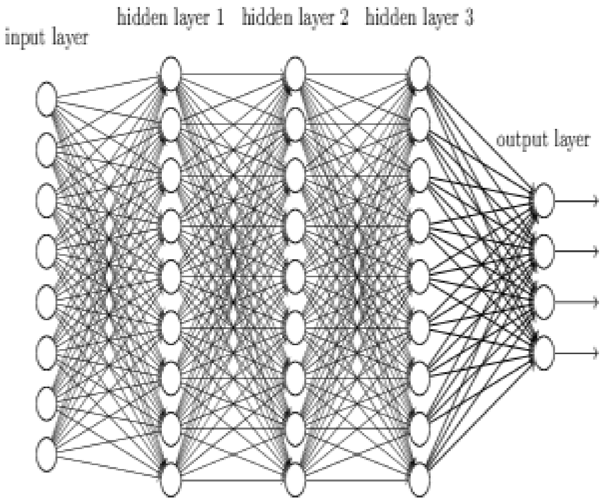

Fig.4 Physical representation of DNN

The training algorithm used also plays a crucial role in attaining high accuracy. There are several approaches to train a neural network, and one needs to choose one that is effective in achieving low execution time, high speed and overall high accuracy. High accuracy is basically a function of low attained errors. The back propagation approach is often a good choice for attaining the above requirements and is explained in the following section using the flow diagram of back propagation that uses errors to be fed back to the system in each iteration. The major reason for the choice of this algorithm is the fact that the algorithm exhibits fast rate of convergence and needs relatively less memory for execution. The fast rate of convergence is due to the gradient descent approach in which the gradient of the error with respect to the weights is maximized in the negative direction thereby making the searching for appropriate weights for pattern recognition of the trends in the data quicker. The following figure illustrates the concept.

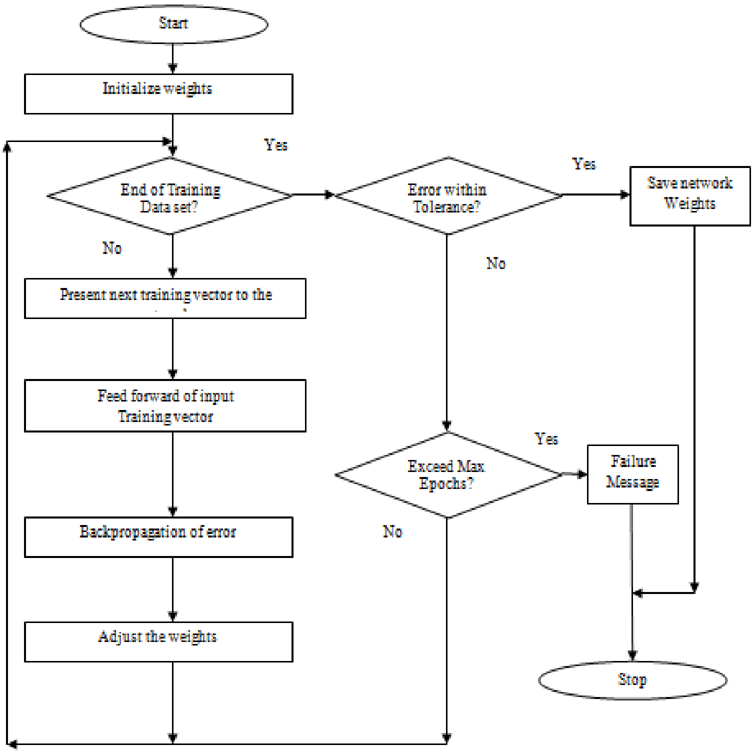

Fig.5 Designed Back Propagation Model

The weight updating rule for the Bayesian Regularization algorithm is given by:

$$W_{k+1} = W_k - [J_K{}^T J_k + \mu I]^{-1} J_K{}^T e_k \qquad (13)$$

Where,
W_k represents current weight,
W_{k+1} represents next weight,
I represent the identity matrix
e_k representslast error,
μ represents combination coefficient

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

$$P\frac{A}{B} = \frac{P(A).P\frac{B}{A}}{P(B)} \qquad (14)$$

Here,

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

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

$P(B)$ 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. The evaluation parameters considered are:

The erroneous reception of bits cause bit error rare or BER of the system. A bit error at the receiving end is defined as:

$$BER = \frac{Number_{error\ bits}}{Numner_{total\ bits}} \qquad (15)$$

Here,
$Number_{error\ bits}$ represents the number of bits containing errors
$Numner_{total\ bits}$ represnets the total number of bits transmitted

Mean Absolute Percentage Error:

$$MAPE = \frac{100}{N} \sum_{t=1}^{N} \frac{|A_t - \hat{A}_t|}{A_t} \qquad (16)$$

The Mean Square Error:

$$MSE = \frac{1}{N} \sum_{t=1}^{N} {e_t}^2 \qquad (17)$$

Here,
N is the number of test samples,
A_t is the actual value and
$\hat{A}_t$is the forecasted value

RESULTS AND DISCUSSION
The results have been simulated on Matlab 2017a. 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.

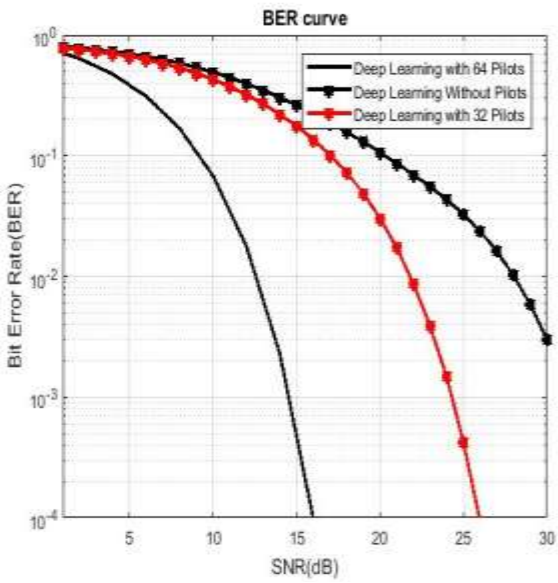

Fig.6 BER performance of the Proposed System

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}

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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.

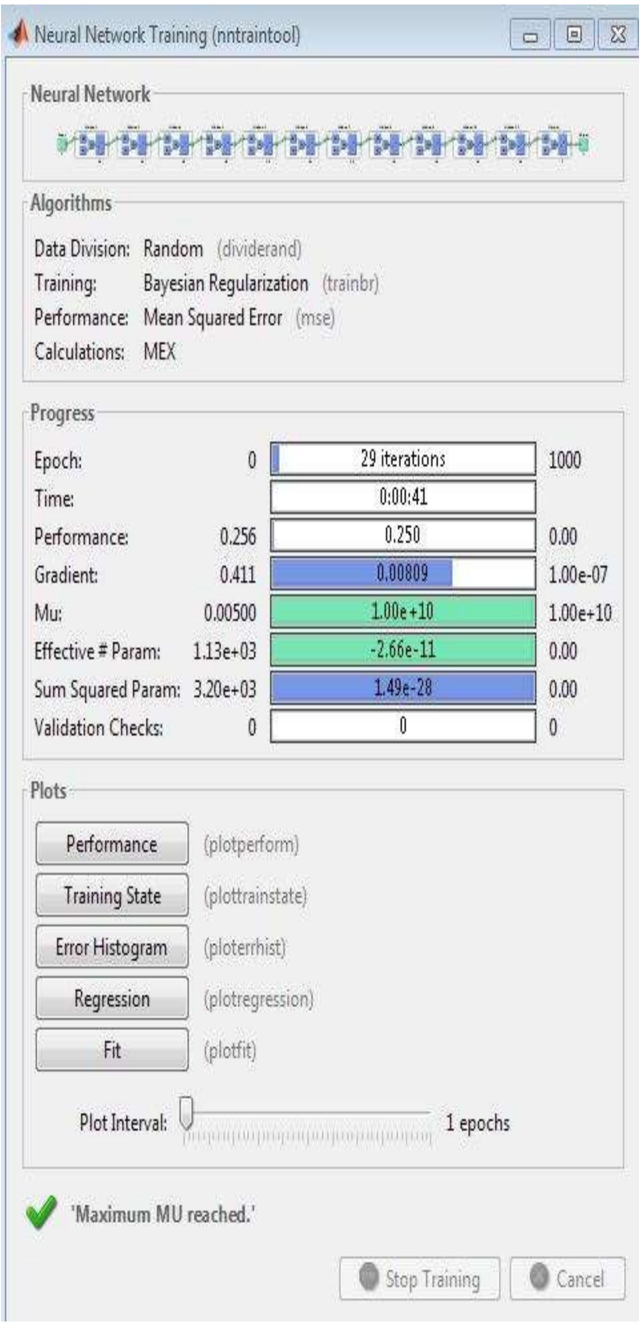

Fig.7 Training and epoch performance of the proposed system

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.

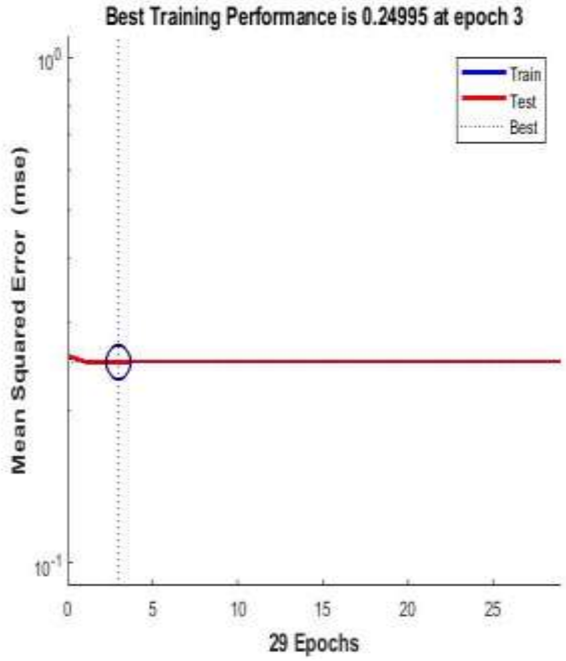

Fig.8 mse of proposed system as a function of number of epochs.

CONCLUSION

It can be concluded form the above discussions that Deep Neural Networks can be effectively used for OFDM channel estimation even though channel parameters may exhibit complex time series behavior. In the proposed work, the back propagation based Bayesian Regularization algorithm is used to train the Deep Neural Network. It has been shown that the proposed technique performs better than previous technique in the following respects: MSE, BER, number of iterations and number of pilots needed. The SNR requirement is however the same. Hence it can be concluded that the proposed system performs better than the previously existing technique.

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