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Channel Estimation and BER Reduction Using Artificial Neural Network

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Abstract- The work proposes Inter-Symbol Interference (ISI) reduction scheme, ISI being a major problem in Optical systems, which produces various type of non-linear distortions. So the implementation of OFDM system using Artificial Neural Network (ANN) scheme with M-QAM modulation technique is proposed and compared with the conventional OFDM system without using ANN. This proposed scheme is implementation of Backpropagation (BP) algorithm over AWGN channels to achieve an effective ISI reduction in orthogonal frequency division multiplexing (OFDM) systems. Simulation results prove that ANN equalizer can further reduce ISI effectively and provide acceptable BER and better MSE plot compared to conventional OFDM system.

Keywords- OFDM, Artificial Neural Network (ANN), FFT, QAM, BER, ISI, MMSE.

I. INTRODUCTION

OFDM is becoming a very popular multi-carrier modulation technique for transmission of signals over wireless channels. Now OFDM is widely used for high-speed communications over frequency selective channels. OFDM divides the high data rate stream into parallel lower data rate and hence prolongs the symbol duration, thus helping to eliminate Inter Symbol Interference (ISI). It also allows the bandwidth of subcarriers to overlap without Inter Carrier Interference (ICI) as long as the modulated carriers are orthogonal. Therefore OFDM is considered as an efficient modulation technique for broadband access in a very dispersive environment. The frequency selective fading, is caused by multipath could lead to carriers used, being heavily attenuated due to destructive interference at the receiver. The result of this is the carriers being lost in the noise [1].

To increase performance of OFDM system under frequency selective channels; the channel estimation is required before demodulation of OFDM signals [2]. The channel estimation is a process of characterizing the effect of the transmission medium on the input signal. In OFDM system there are several techniques for channel estimation [2-14]. Among these techniques; Block type Pilot based channel estimation technique is more popular. The Block type Pilot based estimation techniques can be based on Least-Square (LS). The LS estimators have low complexity.

II. PROBLEM FORMULATION

Nonlinear mapping is better done through Neural Networks than through other methods. Hence signals can be effectively processed through nonlinear channels using neural networks. The natural structure of neural network which has multiple inputs and multiple outputs is more suitable for MIMO systems [4].

Conventional feed forward neural networks viz., radial basis function(RBF), back propagation (BP), multilayer perception(MLP) have been employed for MIMO-OFDM system channel equalization[4-7]. Blind equalization using multilayer feed forward perceptron ANN is applied to avoid the Inter Symbol Interference (ISI) which is produced by the bandwidth limited channel with multipath propagation. Three-layer ANN is utilized with the feedback for describing the channel estimation and equalization. The second and third ANN layer comprises of gradient algorithm and kalman filter respectively. These two layers are combined with the feedback of the turbo iteration process to improve the estimation accuracy [8-2].

However, the noise encountered in practical applications is more impulsive in nature than that predicted by Gaussian distribution. Underwater acoustic noise, low frequency atmospheric noise and many types of man made noises are few examples. To model these types of noises α-stable distribution is used [2].

Authors of [3-4] proposed a Fractional Lower-Order Multi-User Constant Modulus Algorithm (FLOS-MU-CMA) to handle robustly α-stable noise and interference in the data. FLOS_MU_CMA is developed for removing the non-Gaussian impulsive noise. The system performance is resolved by the fractional lower order constant. The multiuser constant modulus algorithm cost function was generalized and a new blind equalization algorithm was defined [5] in impulsive noise environment.

III. PROPOSED METHODOLOGY

1. Artificial neural networks (**ANNs**):
Usually simply called **neural networks** (**NNs**), are computing systems vaguely inspired by the biological neural networks that constitute animal brains.[1]

An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called edges.

Neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the layers multiple times.

2. Training:
Neural networks learn (or are trained) by processing examples, each of which contains a known "input" and "result," forming probability-weighted associations between the two, which are stored within the data structure of the net itself. The training of a neural network from a given example is usually conducted by determining the difference between the processed output of the network (often a prediction) and a target output. This is the error.

The network then adjusts its weighted associations according to a learning rule and using this error value. Successive adjustments will cause the neural network to produce output which is increasingly similar to the target output. After a sufficient number of these adjustments the training can be terminated based upon certain criteria. This is known as supervised learning.

Such systems "learn" to perform tasks by considering examples, generally without being programmed with task-specific rules. For example, in image recognition, they might learn to identify images that contain cats by analyzing example images that have been manually labeled as "cat" or "no cat" and using the results to identify cats in other images. They do this without any prior knowledge of cats, for example, that they have fur, tails, whiskers, and cat-like faces. Instead, they automatically generate identifying characteristics from the examples that they process.

3. Components of ANNs:
3.1 Neurons: ANNs are composed of artificial neurons which are conceptually derived from biological neurons. Each artificial neuron has inputs and produces a single output which can be sent to multiple other neurons. The inputs can be the feature values of a sample of external data, such as images or documents, or they can be the outputs of other neurons. The outputs of the final output neurons of the neural net accomplish the task, such as recognizing an object in an image. To find the output of the neuron, first we take the weighted sum of all the inputs, weighted by the weights of the connections from the inputs to the neuron. We add a bias term to this sum. This weighted sum is sometimes called the activation. This weighted sum is then passed through a (usually nonlinear) activation function to produce the output. The initial inputs are external data, such as images and documents. The ultimate outputs accomplish the task, such as recognizing an object in an image.[4]
3.2 Connections and Weights: The network consists of connections, each connection providing the output of one neuron as an input to another neuron. Each connection is assigned a weight that represents its relative importance.[9] A given neuron can have multiple input and output connections.[2]
3.3 Propagation function: The propagation function computes the input to a neuron from the outputs of its predecessor neurons and their connections as a weighted sum. [9] A bias term can be added to the result of the propagation.[3]
3.4 Organization: The neurons are typically organized into multiple layers, especially in deep learning. Neurons of one layer connect only to neurons of the immediately preceding and immediately following layers. The layer that receives external data is the input layer. The layer that produces the ultimate result is the output layer. In between them are zero or more hidden layers. Single layer and unlayered networks are also used. Between two layers, multiple connection patterns are possible. They can be fully connected, with every neuron in one layer connecting to every neuron in the next layer. They can be pooling, where a group of neurons in one layer connect to a single neuron in the next layer, thereby reducing the number of neurons in that layer.[4] Neurons with only such connections form a directed acyclic graph and are known as feedforward networks.[5] Alternatively, networks that allow connections between neurons in the same or previous layers are known as recurrent networks.[6]

IV. PROPOSED SIMULATION MODEL

For estimation of channel in OFDM system for pilot based arrangement using QAM modulation evaluation has done in MATLAB. The steps involved in the work are:

- Step 1. Random data is taken Step 2. QAM modulation is done

- Step 3. Modulated signal is obtained which is passed to serial to parallel converter. Step 4. Modulated signal after parallelization is obtained.
- Step 5. Pilot tone is inserted. The pilot symbols are used to correct the phase error and for data security using carrier frequency set and channel estimators.
- Step 6. The obtained signal is optimized by bacterial foraging optimization and classified by feed forward back propagation neural network.
- Step 7. Estimation is done by using minimum mean square error estimator.
- Step 8. At last performance of two parameters are calculated i.e MSE and BER.

MSE: The mean-squared error (MSE) between two signals is

MSE=$(newdata - olddata)$ **2** $/lengthof data$.

BER: Total number of errors during transmission of data.

V. RESULT AND ANALYSIS

The most interesting case for Anns is the deployment in tougher channel conditions. The deep slope profile with matlab and a sandy bottom was chosen. A plot of a simulated channel impulse response is found in Figure 5.1 With multiple simulation instances both the Ann and lstm could not converge, reaching an accuracy below 50%. By using a single simulation instance, the training of the networks could converge. After the training, the trained networks were used to perform equalization via a transmission in the specified channel using the same small scale simulation, and the resulting ber was calculated. The result is presented in Figure 5.1.

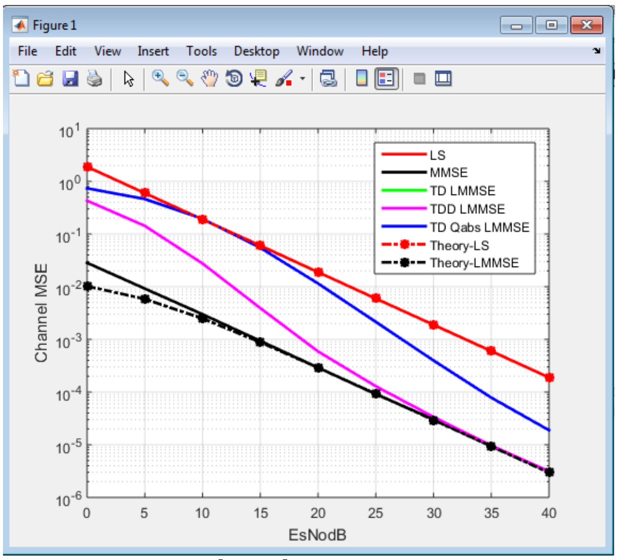

Fig 1. Channel estimation curve.

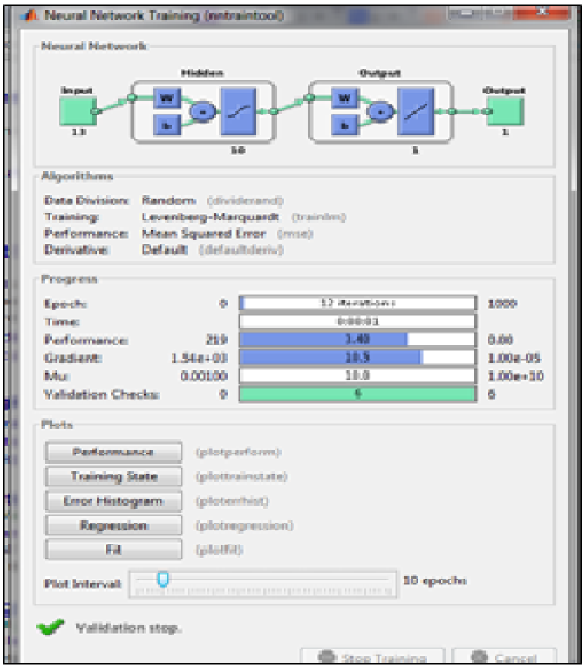

Fig 2. NN Training State.

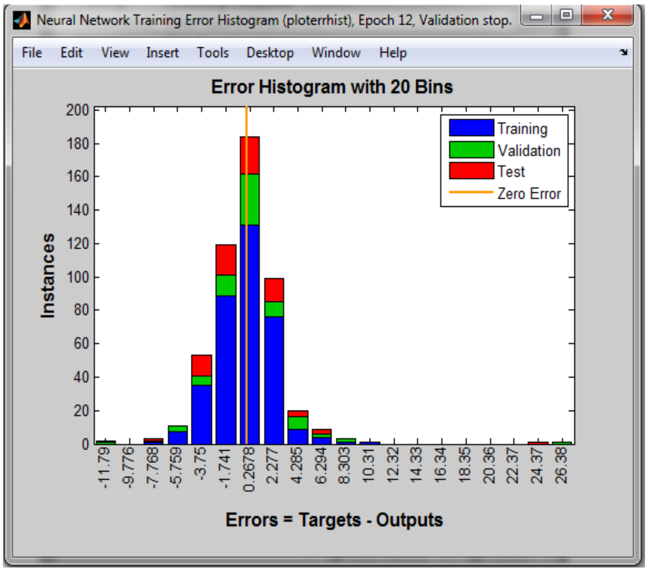

Fig 3. Error of histogram.

MSE Analysis represents histogram for multiple layer option. The irregular result provide to neural network. So 0.2678 Error histogram with 20 bins is the highest value of this graph represent.

VI. CONCLUSION AND FUTURE SCOPE

This paper proposed, Back-propagation (BP) based ANN channel estimator which is further combined with OFDM system. This proposed combined technique provides better ISI reduction performance than an OFDM system without adding ANN. In this work, ISI is directly proportional to BER and inversely proportional to SNR.

The future scope of this paper is to apply ANN with MIMO-OFDM system or use of other modulation technique.

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