The Comparative Study of Adaptive Channel Equalizer Based on Feed Forward Back Propagation, Radial Basis Function Neural Network(RBFNNs) & Least Mean Square (LMS) Algorithm

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Abstract
Artificial Neural networks (ANNs) have been extensively used in many signal processing applications. Linear & Nonlinear adaptive filters based on a variety of neural network models have been used successfully for system identification in a wide range of applications. Due to their capacity to form complex decision regions, ANNs have been most popularly applied, in particular, for channel equalization of digital communication channels. The mean square error (MSE) criterion, which is usually adopted in neural learning, is of interest in the channel equalization. In this paper, we introduce a novel approach to adaptive channel equalization using feed forward & Radial Basis Function neural network (RBFNNs) that exploits the principle of discriminative learning while minimizing error function. The performance of proposed method has been compared with gradient based algorithms such as LMS (Least Mean Square) which are often characterized by slow convergence. ANNs technique using fast learning feed forward configuration based on Back Propagation Algorithm, offers high speed of convergence w.r.t. LMS adaptive filtering algorithm. Computer simulation for the equalization of QAM signals in AWGN transmission channel is presented, which demonstrates the effectiveness of the proposed technique vis-à-vis LMS algorithm.

Keywords - LMS, MSE, ANN, RBF, Artificial Neural Network

I. INTRODUCTION

Artificial neural networks (ANNs) takes their name from the network of nerve cells in the brain.Recently,ANNs has been found to be an important technique for classification and optimization problem. Neural networks (NNs) have been extensively used in many signal processing applications. Linear & Nonlinear adaptive filters based on a variety of neural network models have been used successfully for system identification in a wide class of application. NNs have been most popularly applied to channel equalization of digital communication channels, in particular, due to their capacity to form complex decision regions. The mean square error(MSE) criterion, which is usually adopted in neural learning is of interest in the channel equalization

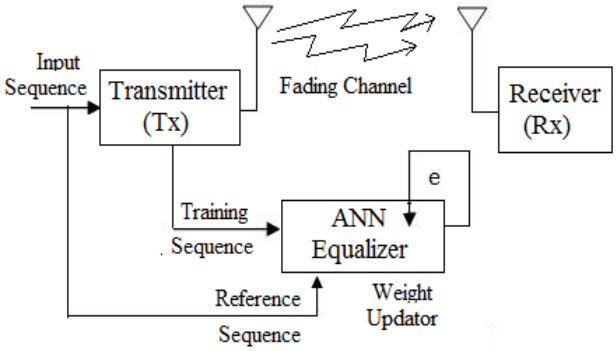


Fig: (1) A Block Diagram of Digital Communication System using Artificial Neural Network based Equalizer [2].

ANNs are non–linear data driven &follows self adaptive approach as opposed to traditional model based methods.They are powerful tools for modelling,specially when the underlying data relationship is unknown.ANNs can identify and learn correlated patterns between input data sets and corresponding target values. ANNs can be used to predict

the outcome of new independent input data after training ANNs imitate the learning process of human brain & can process problems involving non-linear & complex data even if the data are imprecise & noisy.

A very important feature of these networks is their adaptive nature,where "learning by example"replaces "programming" in solving problems this feature makes such computational model very appealing in application domain where one has little or incomlete understanding of the problem to be solved but where training data readily available. ANN is capable of performing nonlinear mapping between the input and output space due to its large parallel interconnection between different layers and the nonlinear processing characteristcs. Thus they are ideally suited for the equalization of AWGN communication channel which are noisy as well as non-linear.

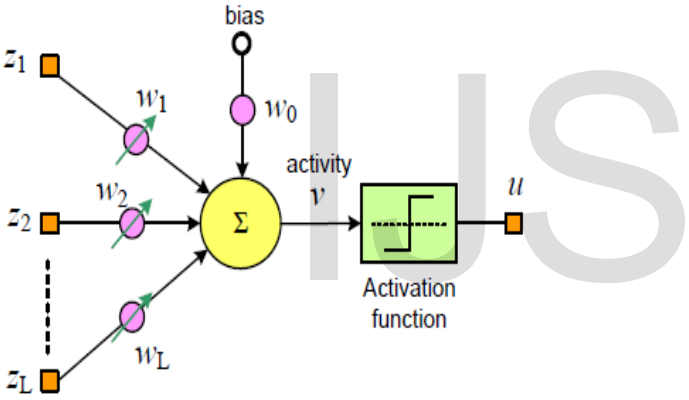


Fig:(2) Structure of a single Neuron

The terminology of ANNs has been developed from a biological model of the brain.A neural network consists of a set of connected cells :The neurons . The neurons receives input either from input cells or other neurons and performd some kind of transformation of the input & transmit the out come to other neurons or to output cells . The neural networks are built from layers of neurons connected so that one layer receives input from the preceeding layer of neurons and passes the output on the subsequent layers.

Each neuron is associated with three parameters whose learning can be adjusted;these are the connecting weights,the bias and the slope of nonlinear function.A feed forward structure with input,output,hidden layers and nonlinear sigmoid functions are used in this type of network.

The basic structure of an artificial neuron is presented in Fig.2.The operation in a neuron involves the computation of the weighted sum of the inputs and threhold.The resultant signal is then passed through a nonlinear activation function.This is also called a perceptron,which is built around a non linear neuron.

The output of the neuron may be represented as,

$$y(n) = \varphi[\sum_{j=1}^{N} w_j(n)x_j(n) + \alpha(n)] \quad \text{.....(1)[15]}$$

Where α(n) is the thershold/bias to the neurons at the first layer, $w_j(n)$ is the weight associated with the j^{th} inputs to the neuron and ϕ(.) is the nonlinear activation function. Different types of nonlinear activation functions are shown in fig(5).

1.1 Neural Network layers:-

The commonest type of ANN consists of three groups, or layers, of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units(Fig.3).The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units. The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

1.2 Neural Network Types:-

1.2.1.Feed-forward Network:-Feed-forward ANNs (Fig.3) allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same or preceding layer. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organisation is also referred to as bottom-up or top-down.

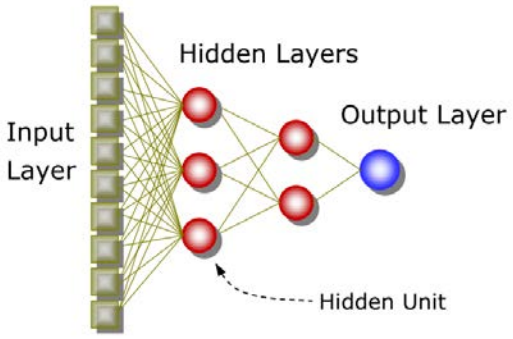
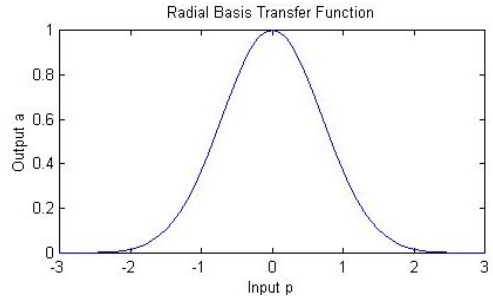


Fig:(3) A simplified multilayer feed forward neural network

1.2.2 Radial basis function Network:-

Radial Basis Function Networks (RBFN) consists of 3 layers; an input layer, a hidden layer & an output layer. The hidden units provide a set of functions that constitute an arbitrary basis for the input patterns. Hidden units are known as radial centers and represented by the vectors $c_1, c_2, c_3 \ldots\ldots\ldots c_h$. Transformation from input space to hidden unit space is nonlinear whereas transformation from hidden unit space to output space is linear. Dimension of each center for a p input network is [p*1].

Different types of radial basis functions could be used, but the most common is the Gaussian function:



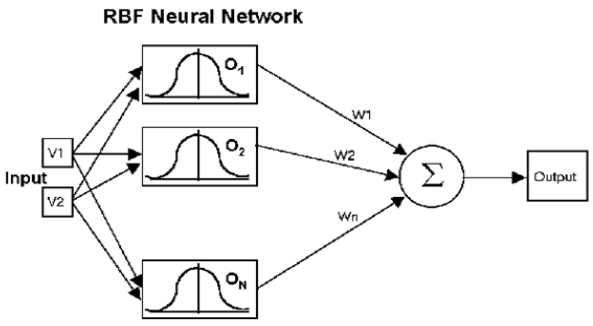


Fig:(4) Architecture of Radial Basis Function network

1.3Transfer function:-

The behaviour of an ANN depends on both the weights and the input-output function (transfer function) that is specified for the units. This function typically falls into one of three categories: linear (or ramp), threshold, sigmoid. For linear units, the output activity is proportional to the total weighted output.

-For threshold units[Fig.5(b)], the output are set at one of two levels, depending on whether the total input is greater than or less than some threshold value.

This function can be written like as

$$\varphi(v) = \begin{cases} 1, if\ v \geq 0 \\ 0, if\ v < 0 \end{cases} \ldots\ldots\ldots\ldots (2)[15]$$

-For sigmoid units[Fig.5(c)], the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurons than do linear or threshold units, but all three must be considered with rough approximations.

This function is s-shaped, is the most common form of the activation function used in artificial neural network. It is a function that exhibits a graceful balance between linear & nonlinear behavior. It is represented as:

$$\varphi(v) = \frac{1}{1 + e^{-av}} \ldots\ldots\ldots (3)[15]$$

Where v is the input to the sigmoid function and 'a' is the slope of the sigmoid function. For the steady convergence, a proper choice of 'a' is required.

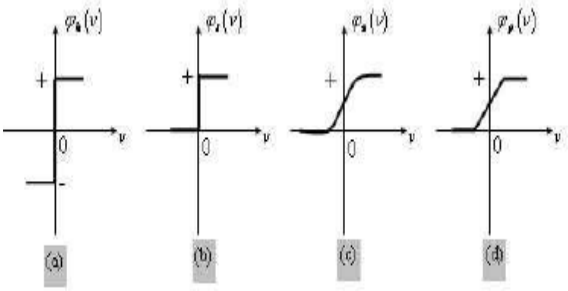


Fig:(5) Different type of non linear activation/transfer function[15]

1.4 Multilayer Neural Network(Multilayer Perceptron)

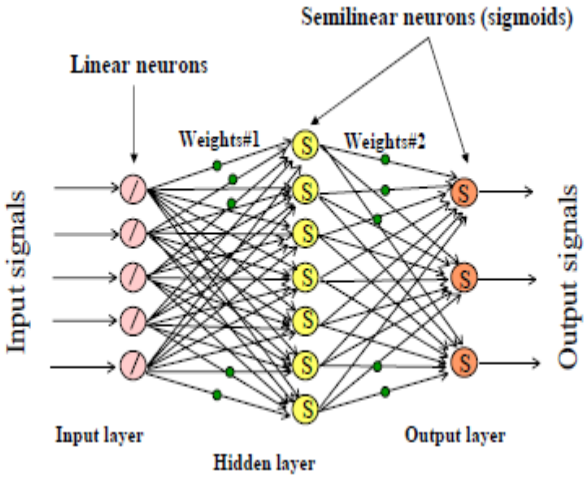


Fig:(6) A structure of multilayer perceptron

In the multilayer neural network or multilayer perceptron (MLP), the input signal propagates through the network in a forward direction,on a layer-by-layer basis.This network has been applied successfully to solve some difficult and diverse problemsby training in a supervised manner with a highly popular algorithm known as the error back-propagation algorithm.

The scheme of MLP using four layers is shown in below fig.6 represents the input to the network, f_j and f_k represent the output of the two hidden layers and $y_1(n)$ represents the output of the final layer of the neural network.The connecting weights between the input to the first hidden layer,first to second hidden layer and the second hidden layer to the output layers are represented w_{ij}, w_{jk} and w_{kl} by respeatively.

If P_1 is the number of neurons in the first layer,each element of the output vector may be calculated as,

$$f_j = \varphi_j \sum_{i=1}^{N} [w_{ij}x_i(n) + \alpha_j], j = 1,2,3 \ldots . P_1 \quad \text{.....(4)[15]}$$

where α_j is the threshold to the neurons at the first layer.N is the number of inputs and ϕ_j is the non linear activation function.The time index n has been dropped to make the equations simpler.Let P_2 be the number of neurons in the second layer. The output of this layer is represented as, f_k and may be written as

$$f_k = \varphi_k \sum_{j=1}^{P_1} [w_{jk}f_j + \alpha_k], j = 1,2,3 \ldots . P_2 \quad \text{.....(5)[15]}$$

Where, α_k is the thershold to the neurons in the second layer.The output of the final layer can be calculated as

$$y_l(n) = \varphi_l \sum_{k=1}^{P_2} [w_{kl}f_k + \alpha_l], j = 1,2,3 \ldots . P_3 \quad \text{.....(6)[15]}$$

Where,α_1 the thershold to the neuron at the final layer and P_3 is the number of neurons in the output layer. The output of the MLP may be expressed as

$$y_l(n) = \varphi_n[\sum_{k=1}^{P_2} w_{kl}\varphi_k[\sum_{j=1}^{P_1} w_{jk}\varphi_j[\sum_{i=1}^{N} w_{ij}x_i(n) + \alpha_j] + \alpha_k] + \alpha_l]$$

.....(7)[15]

II. METHODOLOGY

2.1 Adaptive Algorithms Used For Optimization

2.1.1 Back-propagation (BP) Algorithm

In BP algorithm, initially the weights and thresholds are initialized as very small random values.The intermediate and the final outputs of the MLP are calculated by using (4),(5) and (6).

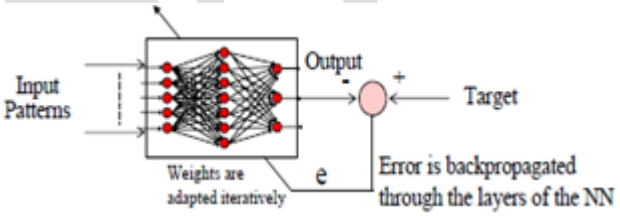


Fig:(7) A basic block diagram of feed forward neural nework equalizer training using back propagation algorithm

The final output y_1 (n) at the output of neuron 1,is compared with the desired output d(n) and the resulting error signal e_1 (n) is obtained as

$e_1(n) = d(n) - y_1(n)$.....(8)

The instantaneous value of the total error energy is obtained by summing all error signals over all neurons in the output layer,that is

$$\xi(n) = 1/2 \sum_{i=1}^{P3} e^2(n) \quad \text{.....(9)[15]}$$

where P3 is the number of neurons in the output layer

This error signal is used to update the weights and thresholds of the hidden layers as well as the output layer. For measuring degree of matching ,MSE(mean square error) performance criteria is taken into consideration

The updated weights are,

$w_{kl}(n+1) = w_{kl}(n) + \Delta w_{kl}(n)$……..(10)[15]

$w_{jk}(n+1) = w_{jk}(n) + \Delta w_{jk}(n)$……(11)[15]

$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n)$……(12)[15]

Where,$\Delta w_{kl}(n)$,, $\Delta w_{jk}(n)$, and $\Delta w_{ij}(n)$,are the change in weights of the output, hidden and input layer respectively.

The thresholds of each layer can be updated in a similar manner,that is

$\alpha_i(n+1) = \alpha_i(n) + \Delta\alpha_i(n)$…….(13)[15]

$\alpha_k(n+1) = \alpha_k(n) + \Delta\alpha_k(n)$……..(14)[15]

$\alpha_j(n+1) = \alpha_j(n) + \Delta\alpha_j(n)$…….. (15)[15]

Steps of the BP Algorithm:-

Step 1: obtain a set of training data

Step 2: set up neural network model

[Number of input neurons, Hidden neurons, and Output neurons, number of layers]

Step 3: Set learning rate η and momentum rate α

Step 4: initialize all connection weights w_{ij} , w_{jk}, w_{kl} and bias values α_j , α_k ,α_l

Step 5: set minimum error, E_{min}

Step 6: start training by applying input data and propagate through the layers then calculate total error.

Step 7: Back propagate error through output & hidden layer and adapt weights.

Step 8: Back propagate error through input & hidden layer and adapt weights.

Step 9: check it error is $< E_{min}$

If not ….repeat step 6-9,if yes….stop training.

2.2.2 LMS(standard LMS) algorithm:-

The least-mean square (LMS) algorithm updates the linear filter coefficients such that the mean square error (MSE) cost function is minimized

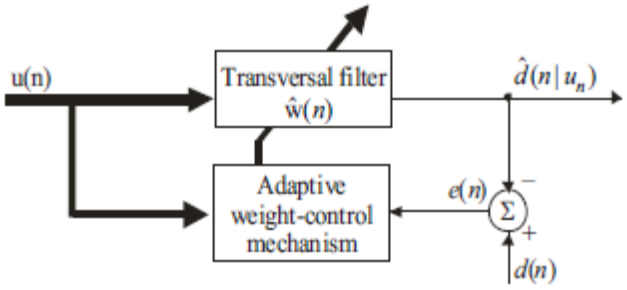


Fig:(9) Basic Block diagram of Adaptive Channel Equalizer Based on gradient decent algorithms [17]

LMS perform the following operation to update coefficients of the adaptive filter.
u (n)= Input signal

h (n) = system response

e (n) = Error signal

d (n)= desired signal.

$\hat{d}$(n)=Transversal FIR filter output

$\hat{w}(n)$ = weight vector of Transversal FIR filter

ξ (n) = E [e (n)] ……(16)[4]

The error estimation e (n) is

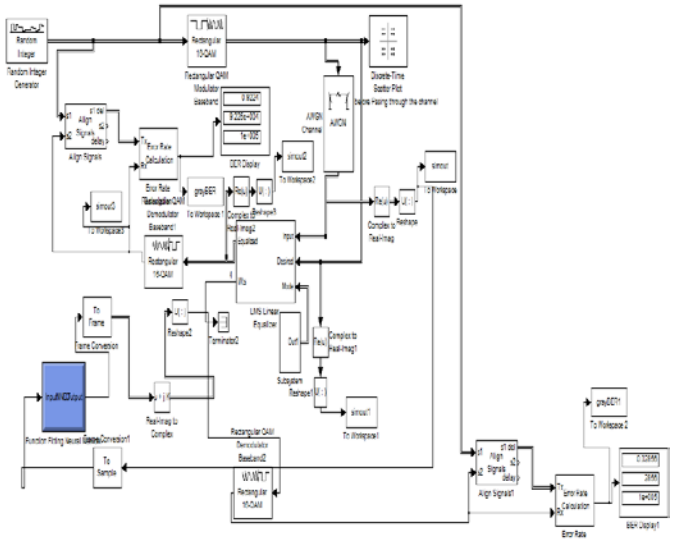
e (n) = d(n) – $\hat{d}$(n) ……(17)[4]

$\hat{d}$(n)=w (n)*u (n) ……..(18)[4]

Calculates the error signal $e(n)$ by using the equation(2). Coefficient updating equation is

w (n+1) = w(n) + μ u(n) e(n), …….(19)[4]

Where μ is the step size of the adaptive filter (n) is weight vector and u(n) is the input signal vector.



III. IMPLIMENTATION

3.1 Designing ANN models

Designing ANN models follows a number of systemic procedures. In general, there are five basics steps: (1) collecting data, (2) preprocessing data, (3) building the network, (4) train, and (5) test performance of model as shown in fig(10)

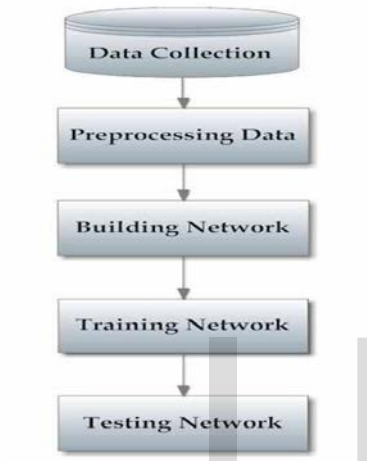


Fig. 10

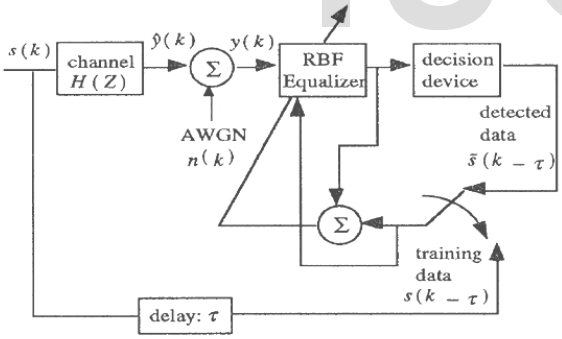


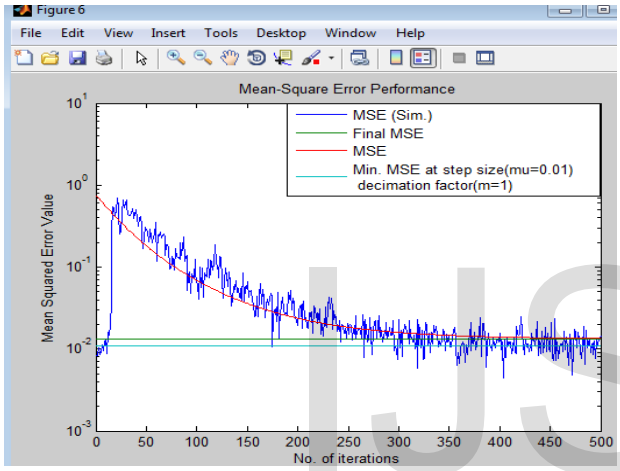
Fig:(11) A Block diagram of Radia Basis Function Neural Network Equalizer[18]

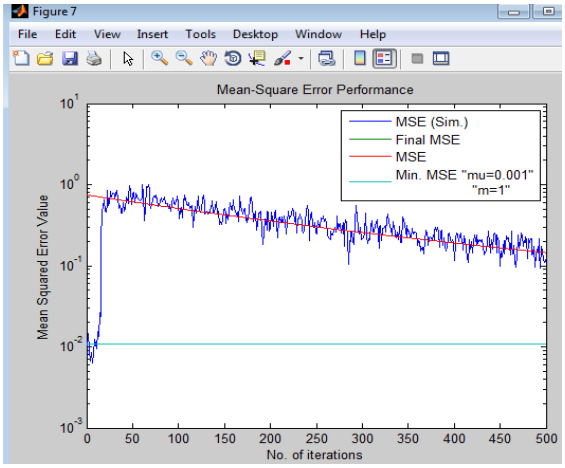
3.2 Set up for performance measurement:LMS,ANN based equalizer

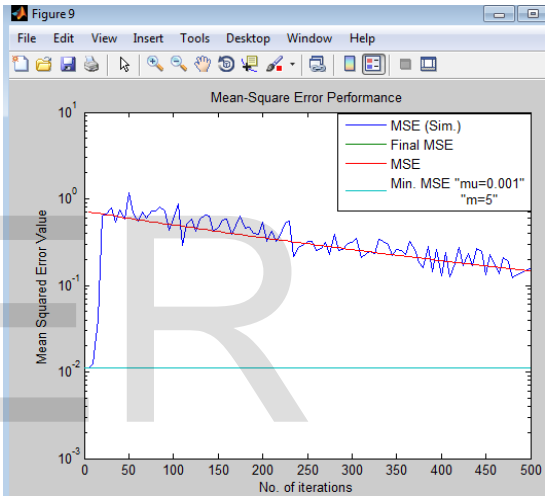
IV. SIMULATION RESULTS

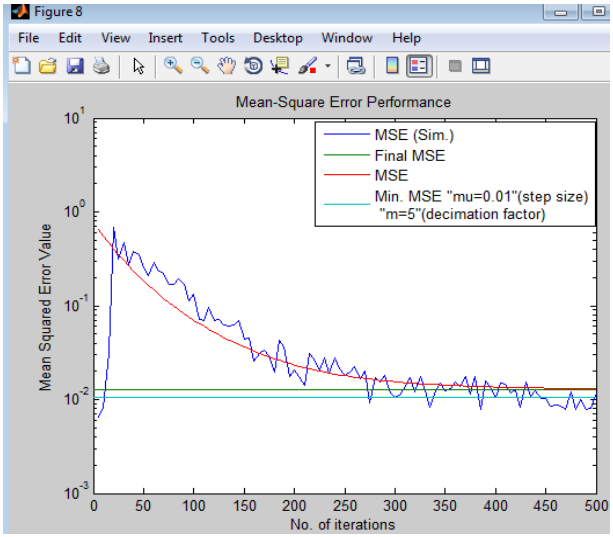
During simulation mean squared error (MSE) was used as performance criteria.This section presents the MSE performance of equalizer based on LMS for variety of parameters and neural network equalizer using back propagation algorithm to make a comparative analysis in terms of MSE performance criteria.The MSE versus Number of Iterations for AWGN Channel with Eb/No=1dB using QAM as modulation technique at reciever i/p was plotted for the performance analysis.

Simulation 1: Computer simulation of LMS based equalizer









Fig(12) LMS based Equalizer for different values of step size(μ), & decimation factor(m).

Simulation 2: Computer simulation of feed forward two layer neural network based Equalizer trained using Levenberg-Marquardt Back propagation algorithm(trainlm) by varying number of parameters like input & target data size, number of hidden neurons while selecting AWGN channel with (Eb/No=1dB) & maintaining percentage of validation & testing data as 15%.

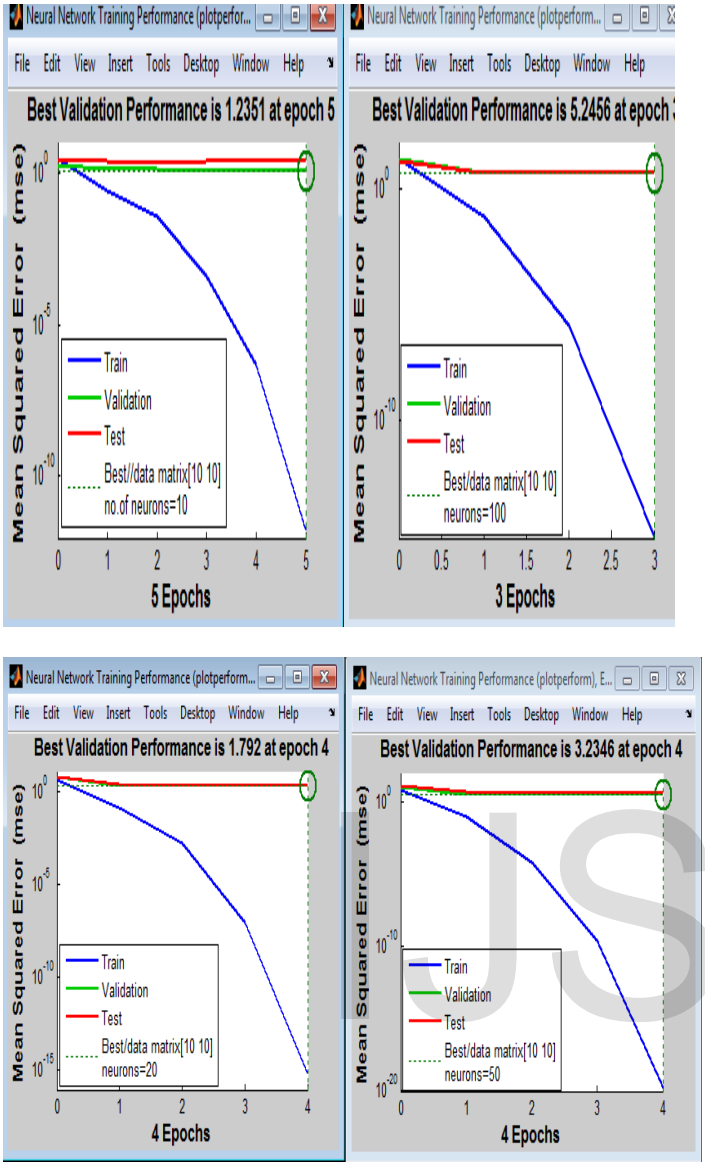


Fig.13 A MSE versus Number of Iterations (Epoches) curve for i/p & target data size [10 10],for different values of "hidden neurons"

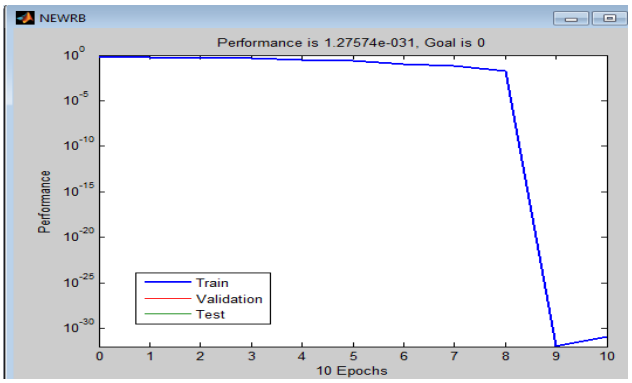


Fig. 14. A performance plot using "Radial Basis Function" as network type.

TABLE:1 **Parameters and specification of the system**

Data set size	[10 10]
SNR range	0-10 dB
Channel type	AWGN
Modulation type	QAM(quadrature amplitude modulation)

TABLE 2. **ANN parameters used for training**

ANN Type	Feed forward, Radial basis function
Number of layers	One input, one hidden, one output layer
Input layer	Equal to transmitted data sequence
SNR consideration	1 dB
Transfer function used	Tan-sigmoid, purelin
MSE minimization limit	-inf
Training type	LM-Back propagation

V. DISCUSSION

In the above section, computer simulations are carried out & plots are drawn between MSE & number of iterations for performance analysis. Here each learning curve is the result of ensemble averaging the instantaneous squared error "$e^2(t)$" [MSE] versus "number of iterations" .

In simulation of LMS based equalizer(fig.12) the results confirm that the rate of convergence of the adaptive equalizer based on LMS is highly dependent on the step-size parameter μ.For a large step-size parameter (μ=0.01), the equalizer converged to steady-state conditions in approximately 250 iterations(convergence faster). On the other hand, when μ was small (=0.001), the rate of convergence slowed down to 500 iterations. The result also shows that the mean square error

(MSE) has lower value of 10^{-2} at μ=0.01(larger step size) than MSE of $10^{-0.5}$ at μ=0.001(smaller step size).

Simulation results (Fig.13) relating to equalizer using feed forward two layer neural network presents a plot of MSE versus number of epochs(number of iterations), for data size [10 10], with different number of hidden neurons i.e.10,20,50&100.

In the plot of 10 hidden neurons by training a neural network, we got MSE of 10^{-12} within 5 epochs, in a plot of 20 neurons we got MSE value 10^{-15} in 4 epochs, & in a simulation of model with 50 hidden neurons MSE value achieved is 10^{-20} by taking 4 epochs only, and with 100 hidden neurons we got MSE 10^{-16}(approx.) in 3 epochs. From the study of simulations, it can be noticed that with the increase of number of hidden neurons (doubled) there is no very far reduction in MSE value, but computational complexity alongwith computation time increases upto a large extent..

Fig.14 depicts performance in terms of MSE versus number of iterations (epochs) of the equalizer based on ANN using RBF. It can be seen that we got MSE 10^{-32}(approx.) in 3 epochs only.

VI. CONCLUSION

Adaptive equalizer based on Artificial neural network employing network configuration such as Radial Basis function & feed forward using back propagation algorithm for different values of parameters such as data size, number of hidden neurons are simulated. In parallel to this gradient based LMS equalizer is also simulated & plots are obtained for different values of step size & decimation factor. On comparative analysis, we infer that a neural network model, as simulated above, yields a far reduction in mean squared error MSE with reduced convergence time compared to LMS based equalizer.

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