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Performance Analysis of Adaptive Channel Equalizer Using LMS, Various Architecture of ANN and GA

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Abstract

The adaptive channel equalizer based on gradient decent least mean square (LMS) algorithm, artificial neural network and genetic algorithm aim to minimize the inter symbol interference(ISI) present in the linear dispersive communication channel. There are gradient decent learning algorithms such as least mean square, which have a possibility that during training mode of the channel equalizer, its weights do not achieve optimum values hence mean square error (MSE) falls to local minimum. In this section, we propose a new adaptive channel equalizer, simulated using artificial neural network with various architectures and derivative free optimization technique such as genetic algorithm(GA).The performance of proposed equalizer is measured and analyzed in terms of mean square error and convergence rate. It is observed that adaptive equalizer based on GA yield better performance compared to its LMS counterpart. It is found that simulated results are true for both linear and nonlinear channels.

Keywords: LMS, MSE, Gradient Decent, GA, ANN, Channel Equalizer, ISI

INTRODUCTION

Many digital communication systems employ adaptive equalizers to combat the distortion effects of changing channel conditions. The adaptive equalization process estimates the transfer function of the channel and applies the inverse of the transfer function to the received signal so as to minimize the distortion effects. The adaptive channel equalizers typically employs filters but amplitude and phase distortions arises due to various types of fading effects. Equalization is basically used to reduce inter symbol interference in baseband signals. ISI causes the value of a given symbol to be corrupted by the values of preceding and following symbols. A channel equalizer is essentially a digital filter with an adaptive response to compensate for inter symbol interference which arises due to channel distortions. Several well-known highly efficient algorithms are developed for adapting the filter coefficients to make filter response to converge the channel equalizer. In the process of converging the equalizer coefficients, large step sizes are typically used to allow the coefficients to converge faster during an initial adaptation stage, while small step size changes are used at other times to prevent the coefficient values from changing rapidly. The present invention is directed to a process that supports the efficient use of such step size changes. Adaptive equalization techniques are used in a wide range of applications such as to minimize interference, noise cancellation, echo cancellation. Adaptive equalizers are used generally for non-stationary signals and environmental conditions. Its major applications includes adaptive noise cancellation, which is used to eliminate noise or interference from noisy signal in real life applications. Adaptive equalizer is an alternative approach of estimating signals corrupted by additive white noise or interference.

System Design

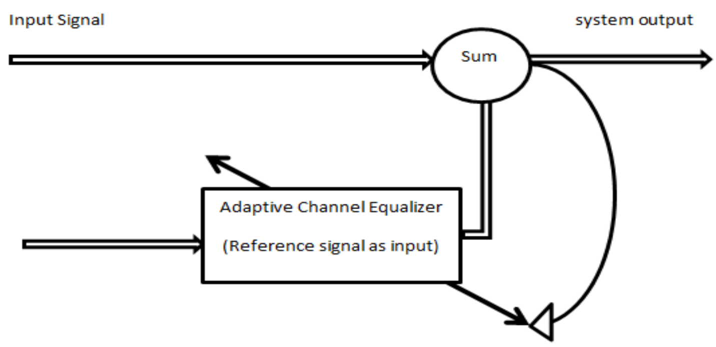


Figure 1: Basic block diagram of adaptive channel equalizer

As shown in fig 1, an adaptive filter consists of two parts: a linear filter and an adaptive algorithm. You can use linear filters can be of various types such as finite impulse response (FIR) and infinite impulse response (IIR) filters. Where u(n) is applied as a input to a linear adaptive filter, y(n) is the corresponding output signal, d(n) is another input to the filter

,e(n) denotes the error which is difference between d(n) and y(n), W_i(n) are weights also known as the filter coefficients whereas 'i' subscript is an integer with a value range of [0, N–1] where N represent the length of the adaptive filter. The adaptive algorithm adjusts W_i(n) iteratively to minimize the mean square error ξ(n).

ξ (n) = E [e (n)] …….(1)

The error estimation e(n) is

e (n) = d(n) –y(n) …….(2)

y(n)=w(n)*u(n) …….(3)

where u(n) is an input signal vector

The rest of the paper is organized as follows:

Various adaptive algorithms which are used as optimization techniques are described in section 2.In section 3, methodology of simulation is discussed in detail. Section 4 gives performance analysis by simulation results of LMS, ANN and GA based equalizers for various parameters. The simulation results are summarized & discussed in section 5, from detailed discussion of simulation results conclusion & future aspects has been given in section 6.

Adaptive Algorithms Used As Optimization Techniques

In this section various adaptive algorithms which are used as optimization techniques are discussed in detail.

Least Mean Square Algorithm: The least-mean square (LMS) algorithm updates the linear filter coefficients such that the mean square error (MSE) cost function is minimized .It performs the following operation to update coefficients of the adaptive filter. Calculates the error signal *e*(*n*) by using equation(2).

Coefficient updating equation is

w (n+1) = w(n) + μ u(n) e(n), …….(4)

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

Normalized LMS:

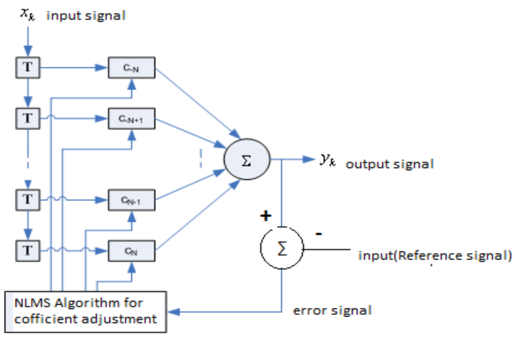


Figure 2: Linear transversal filter with Normalized LMS

The normalized LMS (NLMS) algorithm is a modified form of the standard LMS algorithm. The NLMS algorithm updates the coefficients of an adaptive filter by using the following equation:

$w(n+1) = w$(n)+μe(n).$\frac{\overleftrightarrow{u(n)}}{\|u(n)\|^2}$ …….(5)

This equation can be rewritten as :

$w(n+1) = w$(n)+μ(n).e(n).$u(n)$ …….(6)

Where $\mu(n) = \frac{\mu}{\|u(n)\|^2}$

The NLMS algorithm has a time-varying step size *μ*(*n*),which improves the convergence speed of the adaptive filter.

Artificial Neural Network: Artificial neural network (ANN) takes the name from the network of nerve cells in the brain.Recently,ANN 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.Moreover all gradient based algorithms such as LMS, are often characterized by slow convergence. In this paper, a novel approach to adaptive channel equalization is being introduced feed forward neural network based on back propagation algorithm, linear layer(train),layer recurrent & NARX network type that exploits the principle of discriminative learning, by minimizing an error function are being explored. The performance of proposed methods can also be compared with adaptive equalizer based on LMS algorithm. A LMS equalizer using feed-forward neural network based on back propagation algorithm & compared its performance with adaptive equalizer based on neural network. The main feature of back propagation algorithm is high speed of convergence w.r.t. gradient-based approaches. Computer simulation regarding the equalization of QAM signals in AWGN transmission channel is described, which demonstrate the effectiveness of the proposed technique.

Layer Recurrent: A recurrent neural network (RNN) is a modification to the feed forward multilayer neural network architecture which allow the temporal classification, as shown in Figure(3).In recurrent neural network architecture one more layer known as ``context" layer is inserted to the structure, which store the information between various observations. At each time step, new inputs are given to the RNN structure. The previous contents of the hidden layer are passed into the context layer, then fed back into the hidden layer in the next time. A well known algorithm named as back propagation through time (BPTT) which is similar to the back propagation algorithm, used to set the weights of hidden layers and context layers.

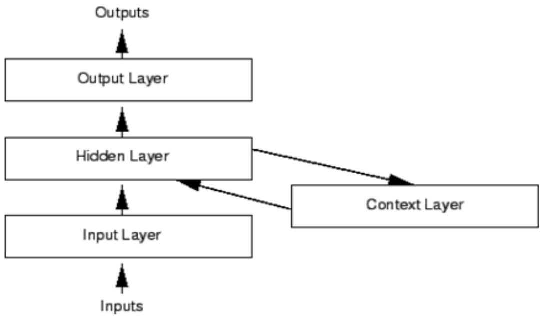


Figure 3: Recurrent neural network architecture

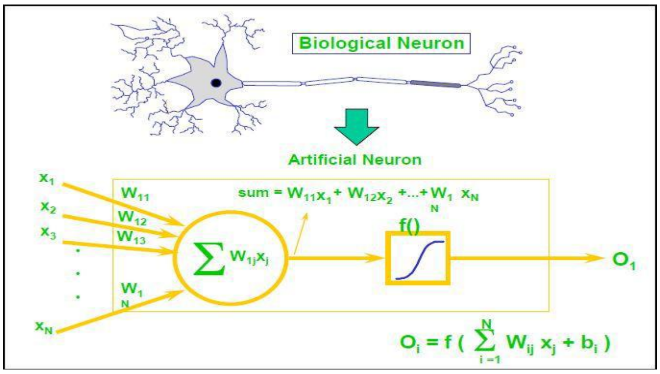
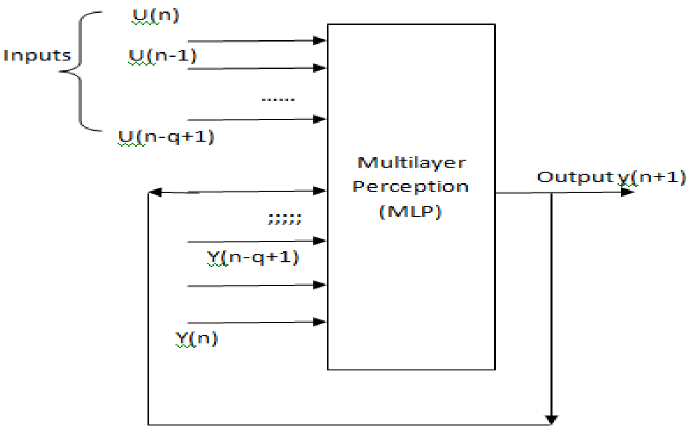


Figure. 5: A basic perceptron architecture

NARX: More complex forms of recurrent networks are possible. This can be done by extending MLP as a basic building block. Typical paradigms of complex recurrent models are:Nonlinear Autoregressive with Exogenous Inputs Network (NARX) The structure of the NARX model includes: A MLP static network. A current input u(n) and its delayed versions up to a time q. A time delayed version of the current output y(n) which feeds back to the input layer. The output is calculated as:

y(n+1)=F(y(n),…,y(n-p+1),u(n),…,u(n-q+1)) .... (7)

A schematic of NARX model as follow:



NARX network has many applications, it can be used as a predictor, to estimate the next value of the input signal, also can be used for nonlinear filtering problems, in which the target output is a noise-free version of the input signal. The use of the NARX network is known in another well known application such as the modeling of nonlinear dynamic systems

*Perceptron Learning Process:*Every neural network posses knowledge which is contained in the values of the connections weights. Modifying the knowledge stored in the network as a function of experience implies a learning rule for changing the values of the weights which is stored in the weight matrix. Learning rule is the process of determining the values of the weights. All learning methods used for adaptive neural networks can be classified into two major categories: Supervised learning which uses external training, so that each output unit knows what its desired response to input signals ought to be, an important issue regarding supervised learning is the problem of error convergence or the minimization of mean square error (MSE). So here the objective is to determine a set of weights which minimizes the MSE.

Multilayer Perceptron

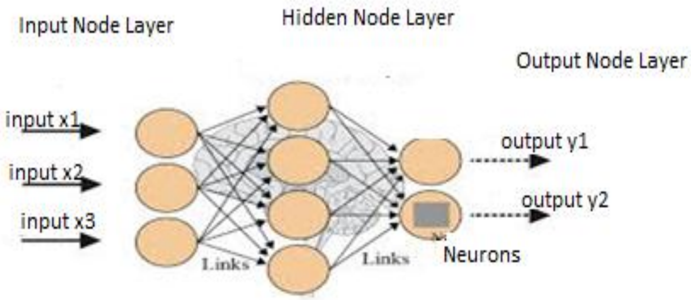


Figure 6: A Multi Layer Perceptron Architecture

In the multilayer perceptron (MLP), the input signal propagates through the network on a layer-by-layer basis in a forward direction. It has been successfullyapplied to solve some diverse problems by training it in a supervised manner with a most popular algorithm known as the error back-propagation.

How to draw a optimization plot for neural network based equalizer: Optimization plot is based on the updated weight estimates at each iteration of the iterative grip search routine, and drawn using valid data. When the new weights are only incrementally different from those of the preceding iteration. When the misclassification rate reaches a required threshold When the limit on the number of runs is reached

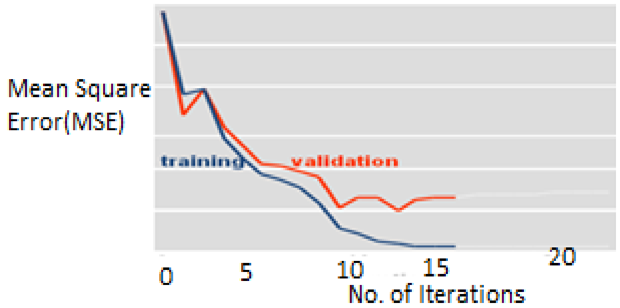


Figure. 7: A general plot of MSE versus Iterations

Where, during simulation total data is divided into three parts:Training data,validation data & testing data.

The Genetic Algorithm: GAs are evolutionary techniques which uses a Darwinian criterion of population evolution generally called stochastic search mechanism.This process of natural selection, is utilised to increase the effectiveness of a group of possible solutions to obtain an environmental optimum. The most common algorithm is Gradient-descent training used in signal processing today because they have a solid mathematical foundation however gradient-descent training have few limitations:

- Derivative based algorithm so there are chances that the parameters may fall to local minima during training.
- Do not perform satisfactorily under high noise conditions and for non linear channels
- In certain cases they do not perform satisfactorily if the order of the channel increases
- LMS algorithm at times exhibits slower convergenceThese limitations can be removed by using evolutionary algorithms such as genetic algorithms.Genetic algorithms uses the process of natural selection and does not involve error gradient statistics.A GA is able to find a global error minima for any given problem.

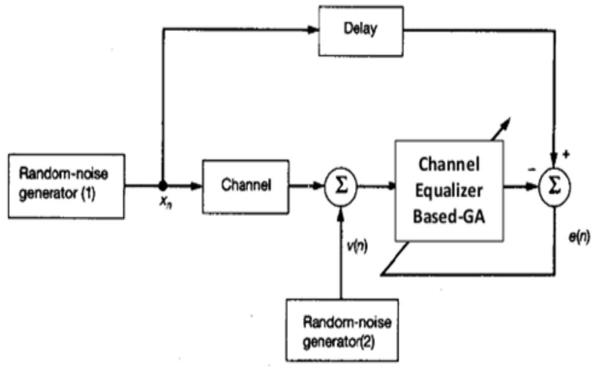


Figure 8: A schetamic model of adaptive channel equalizer based GA[17]

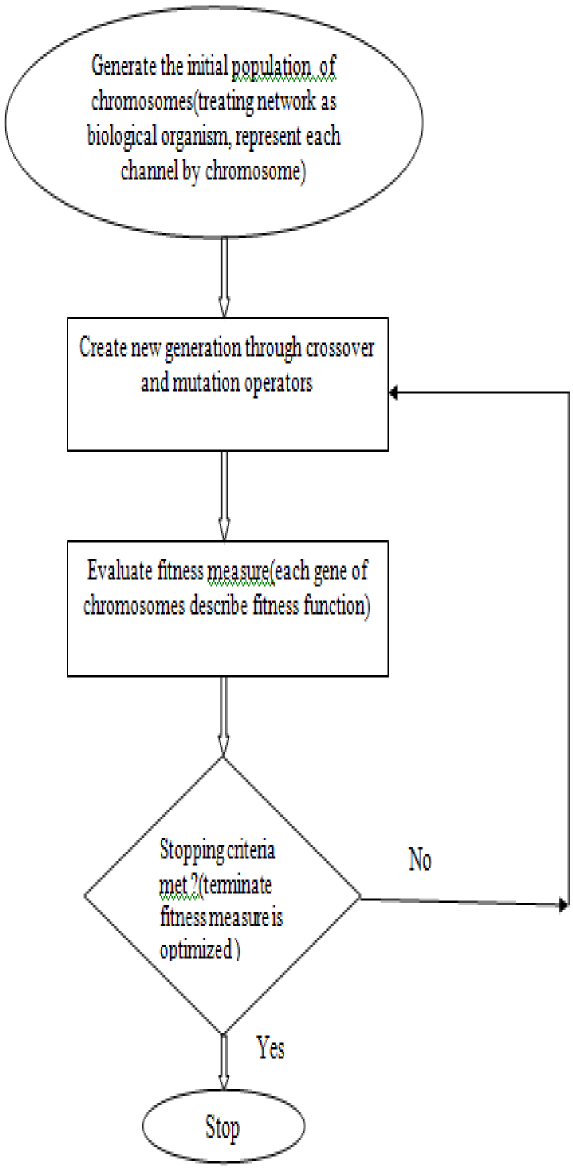


Figure 9: Flow chart of genetic based adaptive algorithm for channel equalizers

$E_i(n) = \frac{1}{M}\sum_{j=1}^{M} e_{ji}^{\,2}(n)$……………………….. (8)

The solution cost value – of the f chromosome in the population is calculated from a training-block of M training signals in equation (8)and from this cost an associated fitness is assigned :

$f_i(n) = \frac{1}{(1+E_i(n))}$ …………………………… (9)

The fitness can be related to be the inverse of the cost as seen in the fitness function in eq(9).

Here fitness of each chromosome in the population is computed and two pools are created which are a survival pool and a mating pool.

The chromosomes selected from the mating pool will be utilised to generate a new set of chromosomes through the evolutional processes of natural selection and the survival of fittest.This process allow a number of chromosomes to pass onto the next generation.The chromosomes which are selected randomly for the two pools but selection as more biased towards the survival of fittest. In this process each chromosome may be choosen more than once, fitness function value of the chromosomes will decide which one is more likely to be selected, so that next generation of solutions can be generated more effectively.

METHODOLOGY OF SIMULATION

In this section plots have been drawn between MSE & number of iterations for performance analysis. Each learning curve is the result of ensemble averaging the instantaneous squared error "$e^2(t)$" versus "number of iterations" curve.

Least Mean Square algorithm: LMS based equalizer has been simulated with AWGN channel by varying various parameters such as step size and decimation factor.

Neural network: A Computer simulation of feed forward two layer neural network based Equalizer was trained using Levenberg-Marquardt Back propagation algorithm by varying number of parameters like input & target data size, number of hidden neurons for AWGN Channel

(Eb/No=1dB). The percentage of validation & testing data has been maintained as 15% for all the measurements.

In addition, neural network simulation was carried out by using different network types such as Feed forward, Radial Basis Functions, NARX, linear layer (train)& layer recurrent.

Genetic algorithm: Computer simulation has been carried out for GA based adaptive channel equalizer using GA optimization toolbox by writing a proper objective function for a problem.

Set up for Performance Measurement: implementation of LMS (fixed step size) Neural Network based equalizer

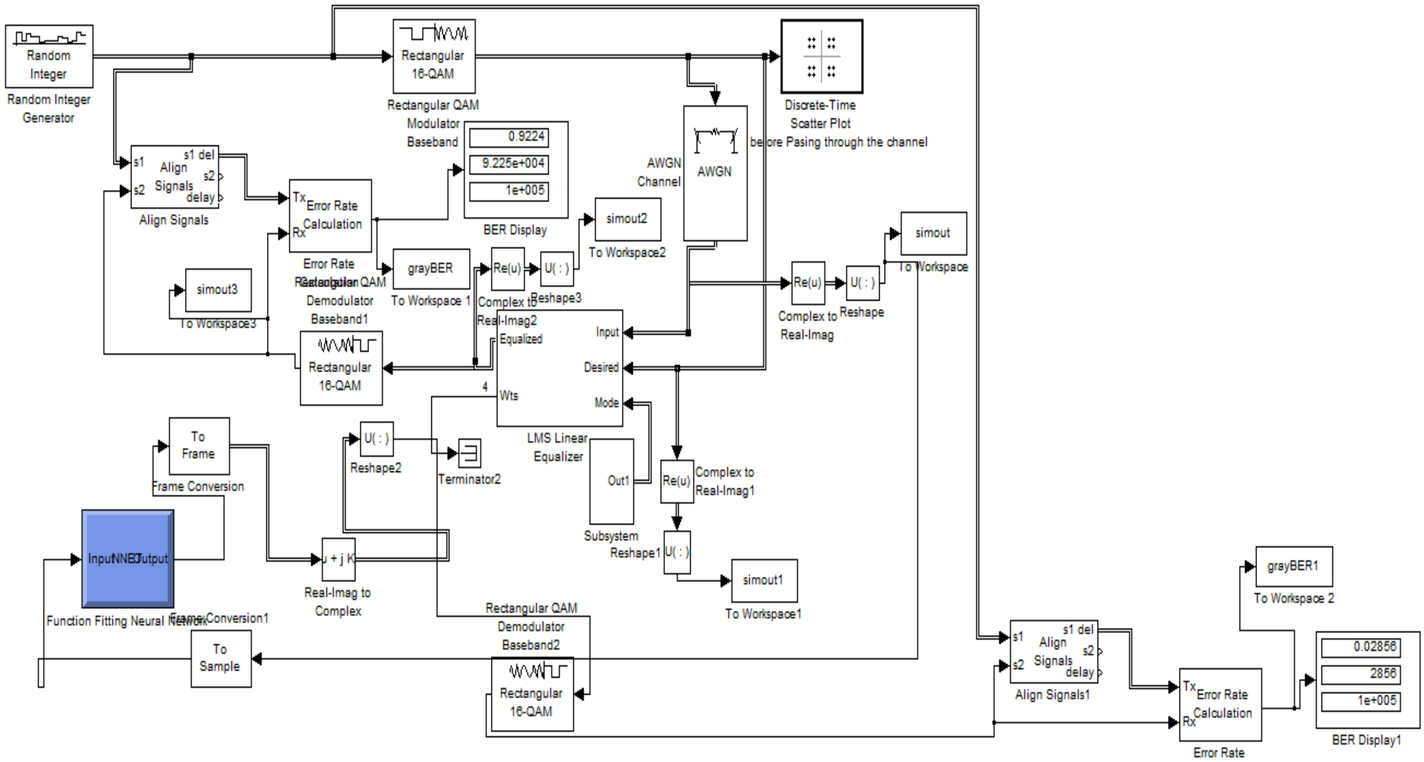


Figure. 10: Neural network based Equalizer using Back Propagation Algorithm LMS with AWGN channel: Simulink model

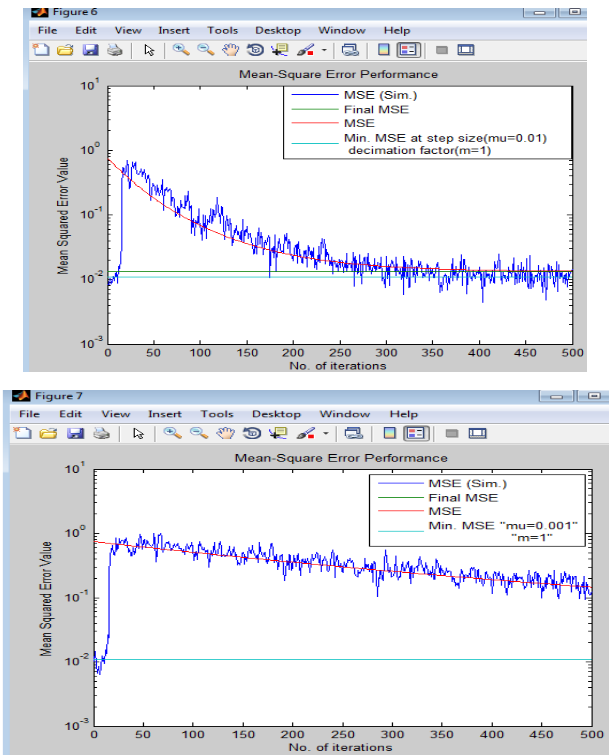
SIMULATION RESULTS

In the previous sections LMS, ANN and GA based equalizers and their structures were described followed by it's training.The actual performance of the equalizers was evaluated by computer simulation.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 and some other architectures of ANN to make a comparative analysis in terms of MSE performance criteria.The simulation results of GA based adaptive equalizer is presented in terms of fitness function value(MSE) as a cost function, minimization of objective function value is the main target, which is achieved by choosing genetic algorithm in optimization toolbox. To do so first a fitness function was written in MATLAB script, in which problem is defined.

The performance of the proposed channel equalizer is evaluated in terms of mean square error (MSE) and convergence rate and is compared with its LMS counter parts.

The MSE versus number of iterations for AWGN Channel with E_b/N_o=1dB using QAM as modulation technique at reciever input was plotted for the performance analysis.

*Simulation-1:*Computer simulation of LMS based equalizer



Figuire 11: LMS based Equalizer was simulated by changing value of step size(μ)

Simulation-2: Computer simulation of feed forward two layer neural network based Equalizer It is trained using Back Propagation algorithm(trainlm) by varying number of parameters like input & target data size, number of hidden neurons. Where (E_b/N_o=10 dB) for AWGN Channel, percentage of validation & testing data is 20%.

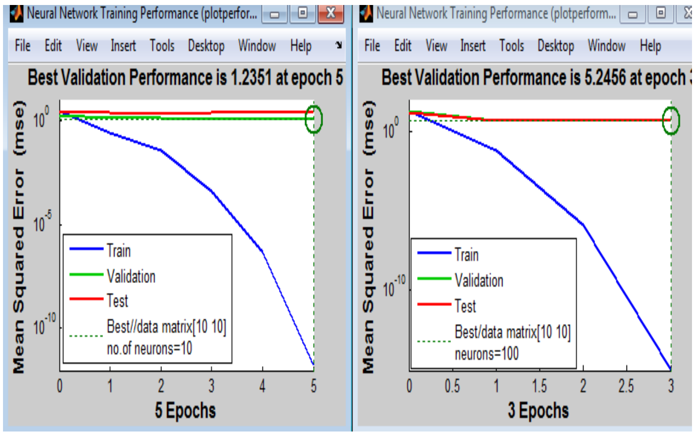


Figure 12: A MSE versus Epoch curve for input & target data size is[10 10],for "hidden neurons=10 & 100"

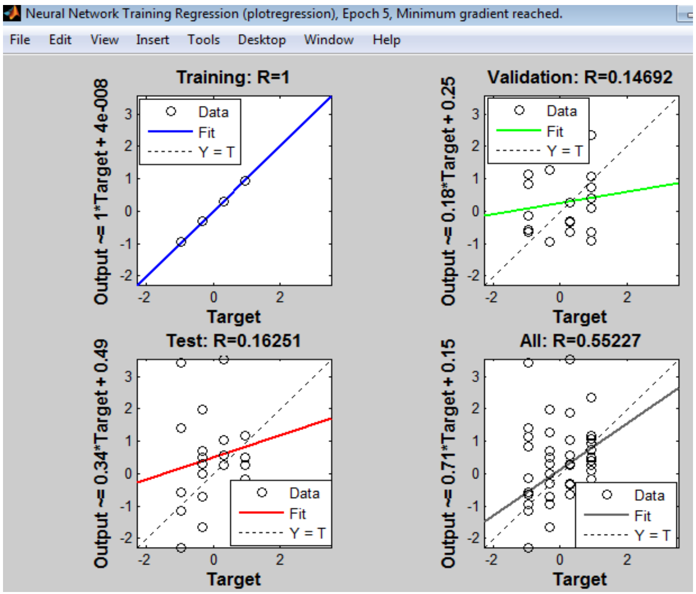


Figure 13: A Regression plot of neural based equalizer for input & target data size is[10 10],number of hidden neurons=10.

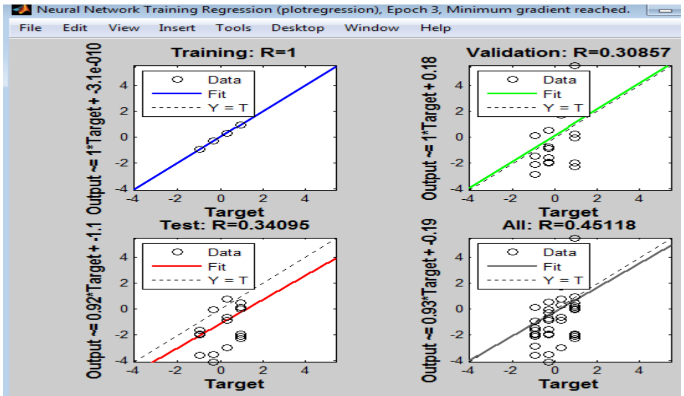


Figure 14: A Regression plot for input & target data size is[10 10],number of hidden neurons=100.

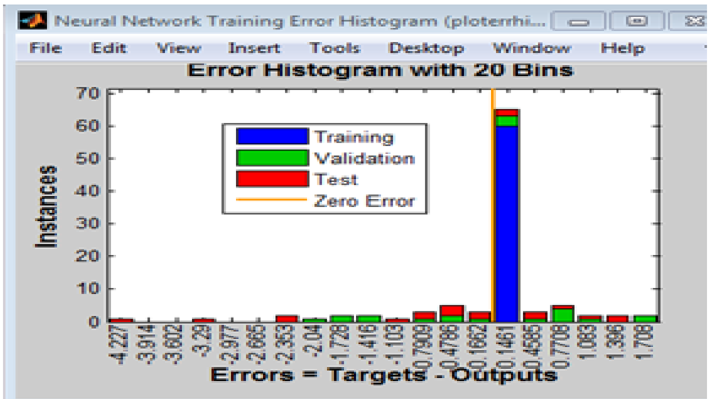


Figure 15: Plot of train state & error histogram for data matrix[10 10] number of neurons=10

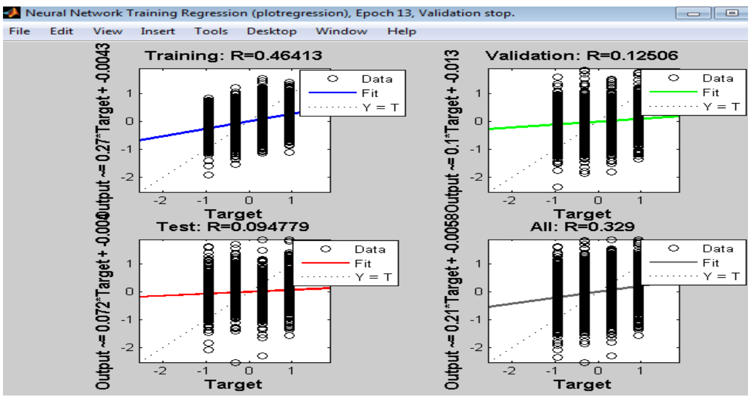


Figure 16: A Regression plot for data size [100 100], number of hidden neurons=10

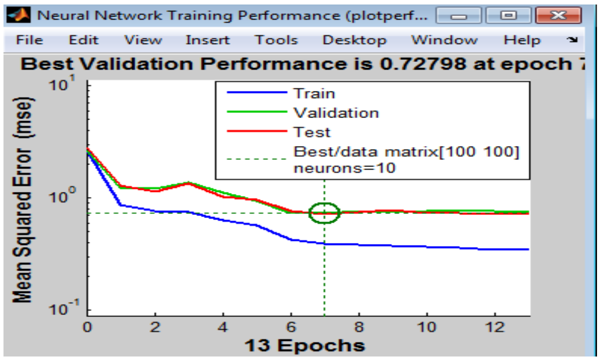


Figure 17: A MSE versus Epochs curve for[100 100]data matrix, number of hidden neurons=10

Simulation-3: A Computer simulation of LMS based Neural Network Equalizer & Neural Network Equalizer for different parameters: A Comparison

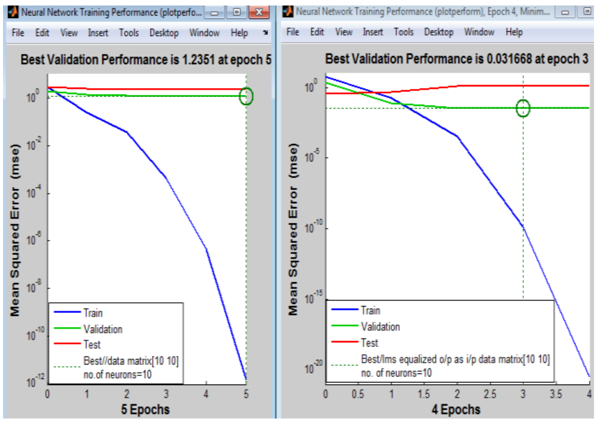


Figure 18 (a,b): A plot of MSE versus no. of epochs in fig(a)

shows neural network equalizer performance curve & fig(b) shows LMS based neural network equalizer MSE plot for data size[10 10],number of hidden neurons=10.

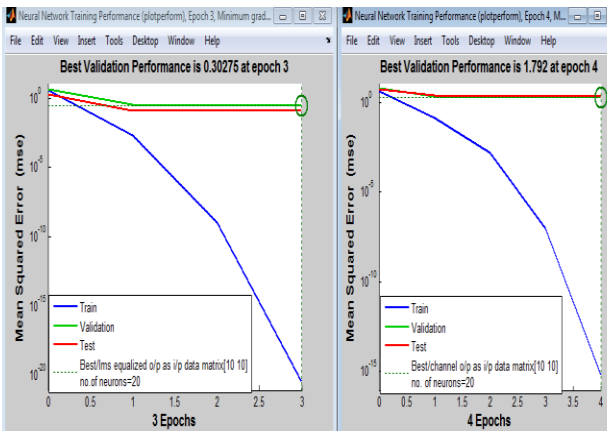


Figure 19(a,b): A plot of MSE versus number of epochs in

fig(a) shows LMS based neural network equalizer MSE plot & fig(b) shows neural network equalizer performance curve for data size[10 10],number of hidden neurons=20.

Simulation-4: Comparison of neural network based equalizer performance in terms of MSE versus no. of iterations (epochs) by using different network types

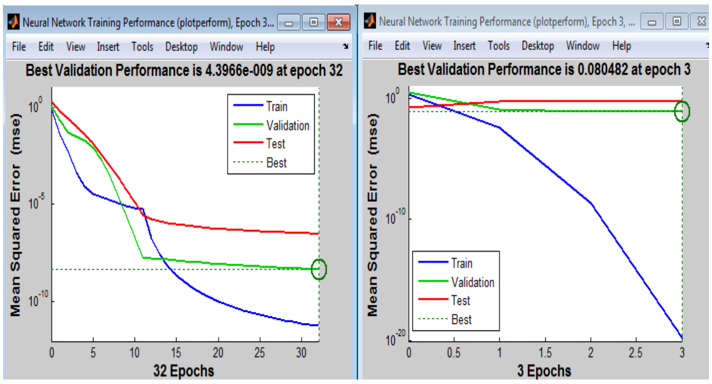


Figure 20(a,b). A performance plot by using feed forward network type fig(a) by using transfer function "tansig" fig(b) shows for transfer function "purelin"

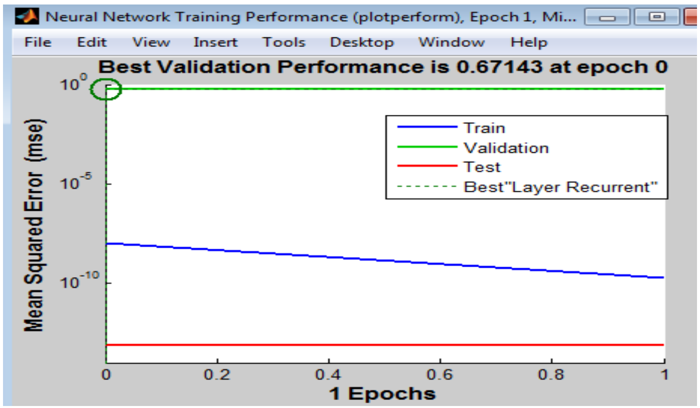


Figure 21: A MSE curve drawn by simulating layer recurrent network type

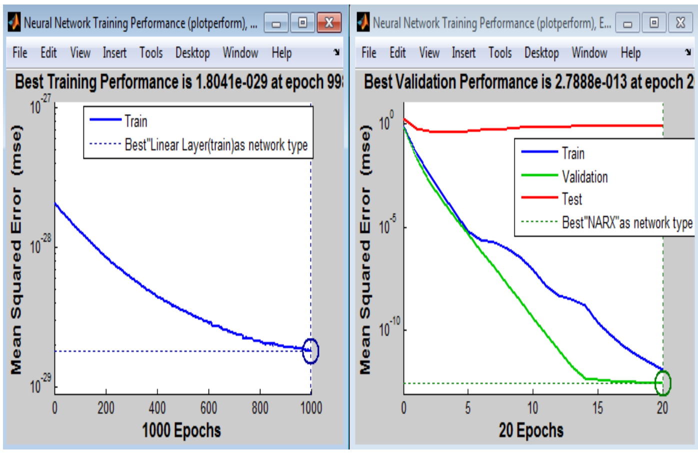


Figure 22(a,b): A performance plot shown in fig(a)by using "Linear Layer(train)" & fig(b) by using "NARX" as network type.

Simulation-5: Results Of GA Optimization Tool are shown in Fig.23

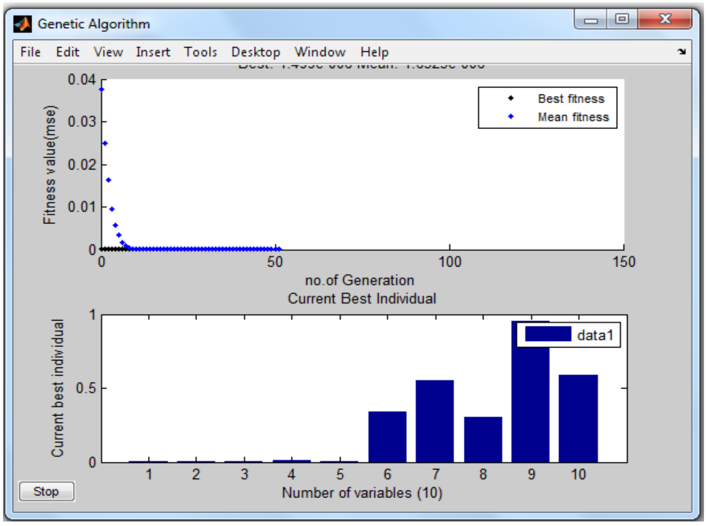


Figure 23: Plot of function value versus generations (best curve), current best (individuals) versus number of variables in GA.

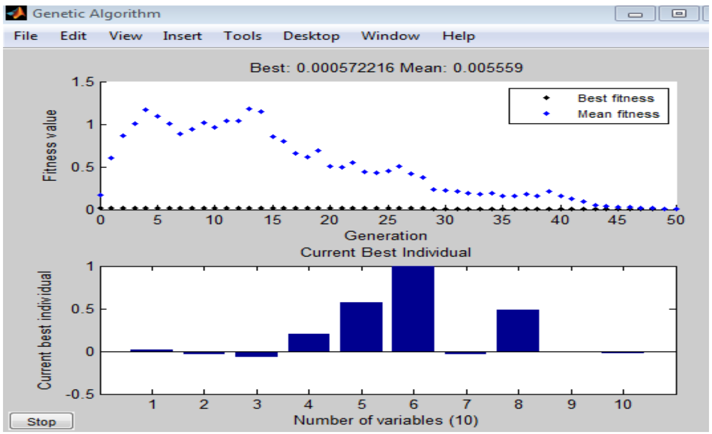


Figure 24 Plot of function value versus generations (worst curve), current best (individuals) versus number of variables in GA

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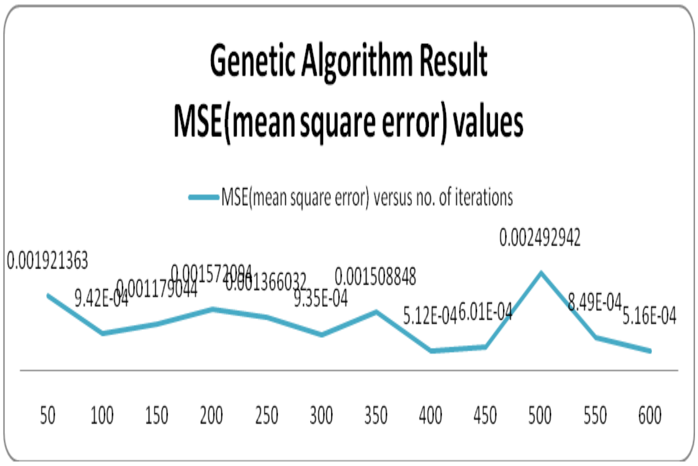

Figure 25; A plot of MSE versus number of Iterations (drawn in excel file) using GA

TABLE 1: Optimized Results of GA in Tabular Form

MSE Values	0.00191	9.42E-04	0.001179	0.001572	0.001366	9.35 E-04	0.001509	5.12E-04	6.01E-04	0.002493
No. Of Iterations	50	100	150	200	250	300	350	400	450	500

DISCUSSION

Results are summarized as below:

In simulation-1: LMS based equalizer results are shown In fig.11. 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).

*In simulation-2:*From the simulation results of Multi layer perceptron using back propagation algorithm it is observed that by training a neural network based equalizer with 10 hidden neurons we got MSE of 10^{-12} is obtained within 5 epochs, whereas with 100 hidden neurons we found MSE 10^{-14}(approx.) by taking 3 epochs. So in this simulation study we have seen that with the increase of number of hidden neurons there is not much reduction in MSE value, but computational complexity along with computation time increases to a large extent .

From the simulated results of above neural network equalizer model for [100 100] data size, number of hidden neurons=10,as seen from fig.17,it provide very poor results as compare to a model of data size [10 10], with hidden neurons=10.

In simulation-3: Comparison between LMS based Neural Network Equalizer & Neural Network Equalizer for different parameters is done. A Comparative study is made by taking data size [10 10], number of hidden neurons=10,it can be from fig.18,19 LMS based feed forward neural network equalizer provides MSE of 10^{-20} within 4 epochs, whereas feed forward neural network equalizer gives 10^{-12} in 5 epochs. By taking number of hidden neurons=20, we got MSE of LMS based neural equalizer obtained as low as 10^{-22} in 3 epochs is obtained, whereas with same neurons, neural equalizer provided MSE of 10^{-15} in 4 epochs. It clearly shows that performance of LMS based neural equalizer is better than neural network based equalizer.

*In simulation-4:*Comparative analysis of neural network based equalizer performance in terms of MSE versus number of iterations(epochs) by using different network types such as feed forward, layer recurrent, linear layer(train), NARX.

it has been observed that in a feed forward network [equalizer is simulated for transfer function "tansig" & "purelin" as shown in fig.20],we obtained a MSE of 10^{-12} in 32 epochs for "tansig" is obtained and MSE value of 10^{-20} is achieved in 3 epochs with "purelin" as transfer function. Similarly for linear layer (train) network type as shown in fig.21, MSE of 10^{-29} is obtained in 1000 iterations whereas in NARX network type in fig.22 we got MSE=10^{-13} in 20 epochs is obtained.

*In simulation-5:*The performance of the GA-based channel equalizer is obtained and compared with standard adaptive algorithms. As we have seen from above simulation results curves as in fig.23, 24, and 25 & tabular form GA based equalizer provided very low value of MSE(~10^{-2}) as compared to LMS based Equalizer(which is ~10^{-1}) and faster convergence rate here GA based equalizer takes only 50 iterations to converge, whereas LMS based equalizer takes more than 100 iterations.

CONCLUSION AND FUTURE ASPECTS

From the above discussion it can be concluded that standard adaptive algorithms such as LMS is associated with local minima problem when they are used to train the weights of the equalizers. The use of these algorithms in the design of adaptive equalizer at times fails to provide satisfactory performance. To alleviate these limitations, and to optimize performance of the system further have been simulated ANN based equalizer and LMS based neural network equalizer also a derivative free evolutionary technique such as GA based equalizer has been used. The performance of LMS based equalizers is compared with equalizers based on neural network for number of parameters. From our results , it is observed that neural network based equalizer provides low MSE & converges faster than LMS based equalizers. it is clearly shown that LMS based neural network equalizer perform better than ANN based equalizer. Through the computer simulation it is shown that GA based equalizers yield superior performance compared to its LMS counterpart, which is true for both linear and nonlinear channels. A model of GA based Neural Network equalizer has been simulated to further optimize the simulation results obtained so far in this paper. There are many other derivative free evolutionary techniques available for optimization such as PSO (particle swarm optimization),Ant Colony optimization and ANFIS etc. which can also be tried for this problem.

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