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Performance Analysis of Communication Systems with Different Types of Neural Network

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Abstract**--**Neural networks are gaining more attention in wide variety of engineering systems. In communication system reduction in Bit Error Rate (BER) has always been the major criteria for performance improvement. Several techniques have been proposed and implemented for this in terms of modulation techniques, carrier offset compensation, equalizer techniques etc. This paper investigates the effect of neural network on the performance analysis of a communication system. Three different types of neural networks viz. back propagation (BP) neural network, nonlinear autoregressive (NAR) neural network and Radial bias function (RBF) neural network. The system is trained using these types of neural networks and the performance is measured for each. Results show that NAR gives the best performance as compared to the other two types.

Keywords**:** *Bit error rate, NAR, BP, RBF.*

I. INTRODUCTION

In new generation wireless communications - i.e. third generation (3G) standards such as WCDMA (Wideband Code Multiple Division Access) and UMTS (Universal Mobile Telecommunications System) towards which most of the current cellular networks will migrate - system component modeling has become a critical task inside the system design cycle, due to modern digital modulation schemes [1].

New standards may introduce changes in the behavior of the devices that are part of the system (e.g. mobile phones and their internal components) mainly due to the modulation schemes they use, generating nonlinearities in the behavior and memory effects (when an output signal depends on past values of an input signal). Memory effects in the time-domain cause the output of an electronic device to deviate from a linear output when the signal changes, resulting in the deterioration of the whole system performance since the device begins behaving nonlinearly. In this research work we are interested in modeling the different neural networks for performance analysis of communication system. Amplifiers are a major building block of modern RF digital wireless transmitters (i.e. cellular phones). Figure 1 shows a simplified block diagram of what a cellular phone communication would be. The voice coming from the phone speaker (analog signal) has to be digitalized to be transmitted through the wireless network, and this is the task of an Analog/Digital converter. The digitalized voice then has to be compressed to reduce bit rate and bandwidth. It is also codified, to format the data so the receiver can detect and minimize errors by expanding digitalized voice at receiver. The carrier signal and data signal are modulated by modulator at transmitter side. The modulated signal then transmitted from the cellular phone with enough strength to guarantee the communication. But the signal suffers from attenuation and needs amplification before that. Therefore, the final element of the chain is a power amplifier (PA) which amplifies the signal before it travels to the nearer antenna and to the receiver side of the communications chain.

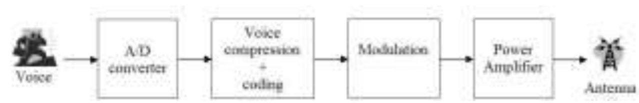

Fig. 1. Simplified block diagram of a digital wireless transmitter.

An amplifier works by increasing the magnitude of an applied signal. Amplifiers can be divided into two big groups: linear amplifiers, which produce an output signal directly proportional to the input signal, and power amplifiers which have the same function as the first ones, but their objective is to obtain maximum power at output. There are many classes in which power amplifier can works. : In Class A if it arrives at the limit of the linearity; and class B when it works in nonlinear regime. Moreover, in wireless communications, the transmitter itself introduces nonlinearities when operating near maximum output power [2].

Nonlinear behavior modeling has been object of increasing interest in the last years [3][4] since classical techniques that were traditionally applied for modeling are not suitable every time. This is the reason that new techniques and methodologies have been recently proposed, as for example neural network (NN) based modeling applied to PA modeling [5].

Neural networks, as a measurement-based technique, may provide a computationally efficient way to relate inputs and outputs, without the computational complexity of full circuit simulation or physics level knowledge [6], therefore significantly speeding up the analysis process. No knowledge of the internal structure is required and the modeling information is completely included in the device external response.

The application of Neural Network to dynamic systems modeling is a rather new research field.

In this paper we present a different NN model for modeling wireless communication system. In particular, this paper presents the results of the BER for a modulation system.

The organization of the paper is the following: in the next Section, NN-based modeling of different types is presented. Section 3 explains the various simulation results obtained by experimentation. Finally, the conclusions are reported in Section 4.

II. Neural network-based modeling

Neural network-based models are nowadays seen as a potential alternative for modeling electronics elements having medium-to-strong memory effects. Neural Networks are preferred because of their speed in implementation and accuracy. The model can be used during any stage of system design for a rapid evaluation of its performance and main characteristics. The model can be directly trained with measurements extracted from the real system, speeding up the design cycle. NN models can be more detailed and rapid than traditional equivalent models, and easier to develop when a new technology is introduced. By profiting from their potential to learn a device behavior based on simulated or measured records of its input and output signals, they were used in nonlinear modeling and design of many microwave circuits and systems [7].

Back Propagation (BP) Algorithm

One of the most popular NN algorithms is back propagation algorithm. Rojas [2005] claimed that BP algorithm could be broken down to four main steps:

i) Feed-forward computation.

ii) Feed-back computation to the output layer.

iii) Feed-back computation to the hidden layer.

iv) Weight updates

The Back Propagation algorithm is stopped when the value of the error function has become sufficiently small.

There are some modifications proposed by other scientist but Rojas definition seem to be quite accurate and easy to follow. The last step, weight updates is happening throughout the algorithm.

Feed-forward computation

Feed forward computation or forward pass is two step processes. First part is getting the values of the hidden layer nodes and second part is using those values from hidden layer to compute value or values of output layer.

Next step is to calculate error of node. Now errors have to be propagated from hidden layer down to the input layer. According to errors weights are updated.

Important thing is not to update any weights until all errors have been calculated. Here is quick second pass using new weights to see if error has decreased.

Non-linear Autoregressive Neural Network (NAR)

The first proposed network structure is the most straightforward network structure.There is two important issues for this model structure. The first issue is how many input variables we should adopt. This is the advantage of NAR because we can get a lot of historical variables from data. However, it is also the disadvantage of NAR because too many input variables make models become complicated and harm to learning efficiency. Fortunately, several fashions can be used to select input variables such as ACF introduced in section two. We also add two dummy variables to enhance the effect of vacations and national festivals. The second issue is how many samples we should adopt during model construction. Although it is good to include all available samples when training, however, it may not be suitable for short-term forecasting. It is because the change of passenger behavior is so fast that too many (far) samples may make the model misunderstand the trend [8].

Radial Basis Function Networks

Radial basis function (RBF) networks are feed-forward networks trained using a supervised training algorithm. They are typically configured with a single hidden layer of units whose activation function is selected from a class of functions called basis functions. While similar to back propagation in many respects, radial basis function networks have several advantages. They usually train much faster than back propagation networks. They are less susceptible to problems with non-stationary inputs because of the behavior of the radial basis function hidden units.

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Popularized by Moody and Darken (1989), RBF networks have proven to be useful neural network architecture. The major difference between RBF networks and back propagation networks (that is, multi layer perceptron trained by Back Propagation algorithm) is the behavior of the single hidden layer. Rather than using the sigmoid or S-shaped activation function as in back propagation, RBF networks use a Gaussian or some other basis Kernel function. In this network each hidden unit acts as a locally tuned processor that computes a score for the match between the input vector and its connection weights or centers. In effect, the basis units are highly specialized pattern detectors. The weights connecting the basis units to the outputs are used to take linear combinations of the hidden units to product the final classification or output.

III. SIMULATION RESULTS

As discussed about different artificial neural network, we design the digital modulation technique and carry out its performance analysis. The simulation is started by taking a random bit stream and modulating the same according to the involved technique. Noise is then added to this composite signal that acts like the characteristics of a typical channel. The received data is then demodulated to find the actual bits. A difference between the original and received bits give the figure of bit error rate calculated as the ratio of bits received in error and the total number of bits. The above procedure is carried out for varying signal to noise ratio. The plotted graph shows the effect of increasing SNR on SER. As shown in figure 3 the typical nature of the graph as when the signal to noise ratio increases and results in improved SER. Simulation of QPSK system with back propagation neural network is shown in same figure that shows less steep curve in high SNR region as compared to conventional QAM system. Figure 2 shows the convergence curve for back propagation algorithm.

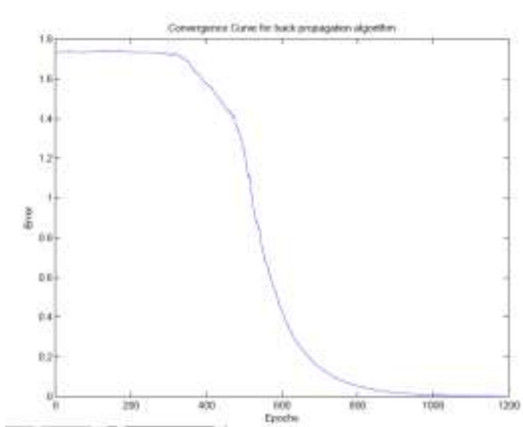

Fig. 2: Convergence curve for back propagation algorithm

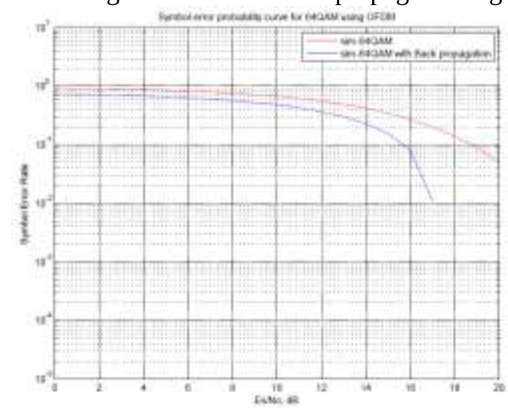

Fig. 3: Simulation for QAM with Back propagation neural network.

NAR Neural network is modeled in Matlab to carry out analysis of the communication system as before for the back propagation neural network. Figure 4 shows the graph for different stages of the neural network functionality where are figure 5 shows the results of the systems for with and without used of neural network and clearly demonstrates the improvement in BER with application of neural network.

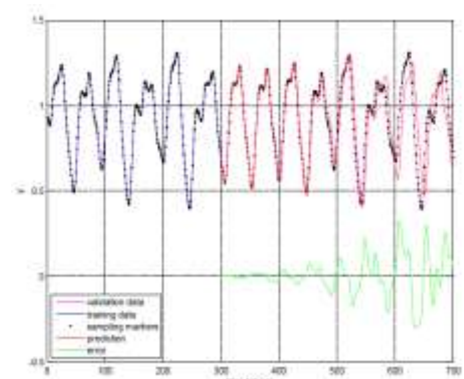

Fig. 4: NAR neural network stages.

In similar fashion the designing of neural network with RBF is achieved and analysis for BER is carried out resulting in graph shown in figure 7. The stages of RBF from training to validation along with the error are depicted in figure 6.

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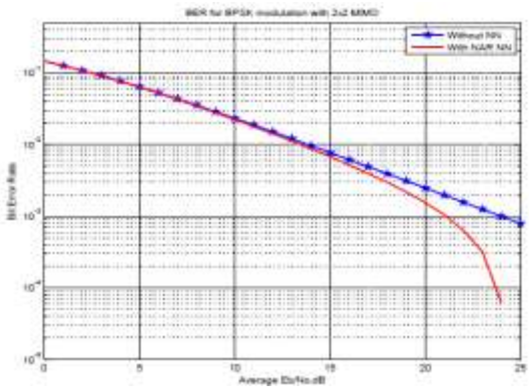

Fig. 5: Simulation for QAM with NAR neural network.

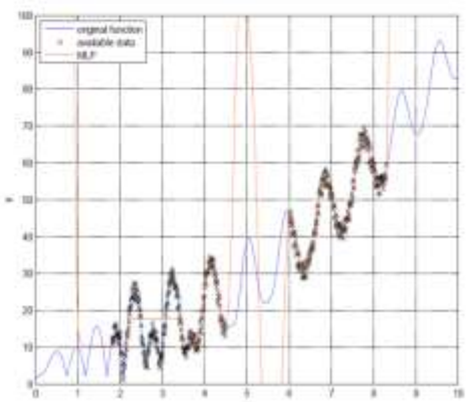

Fig. 6: RBF neural network stages.

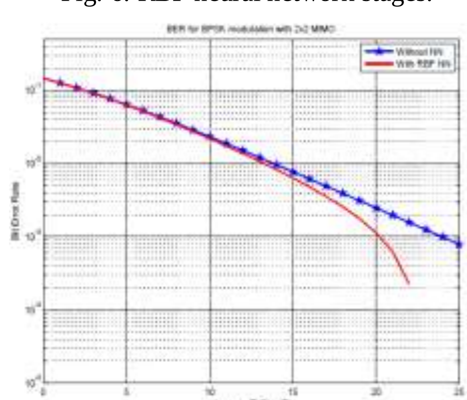

Fig. 7: Simulation for QAM with RBF neural network.

IV. CONCLUSION

Application of neural network surely finds its way in communication systems as they improve the performance of the system by giving results of better BER. However the computation time required in training the neural network shall be taken into account for communication system with stringent timing constraint. The performance shall again be analyzed with respect to other parameters. Our future work is dedicated to inclusion of other parameters like noise variance, attenuation, delay and carrier offset in the performance of communication system and further includes these parameters to provide training to neural network to expect better performance results.

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