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Neuro-Fuzzy Network for Equalization of Different Channel Models

Amira A. Elbibas[1], Issmail M. Ellabib[2], Yousef Hwegy[3]
[1,2,3]*Department of Computer Engineering, University of Tripoli, Tripoli, Libya*

***Abstract*—the rapidly increasing need for information communication requires higher speed and efficient data transmission over communication channels. The rate of data transmissions over these channels is limited due to the effects of inter-symbol interference and additive noise. The conventional techniques used to reduce the effect of channel distortion are based on linear equalizer. However, these techniques are proved to perform poorly owing to non-stationary characteristics of the communication channel. Due to non-stationary characteristics of the channels, this paper addresses equalization problem by adapting the structure of Neuro-Fuzzy network to solve the equalization problem and explores its performance on different channel models.**

The proposed equalizer is compared with conventional equalizer and neural network equalizer in terms of performance and computation time. Both linear and nonlinear with time-varying and time-invariant channel models are considered with different coefficient. The performance is evaluated in terms of bit-error rate (BER) for different noise powers in the channels.

The results obtained demonstrated a significant improvement of the proposed equalizer in terms of both the performance and the computation time compared with LMS and RBF.

***Keywords*—ANFIS, Channel equalizer, digital communication, inter-symbols interference.**

I. INTRODUCTION

Due to the increasing demand for high speed data transmission in communication systems, communications channels are often impaired by the channel inter-symbol interference (ISI), the additive white Gaussian noise (AWGN), and co-channel interference (CCI). All these effects are complex problems. The process of recovery of a signal convolved with the impulse response of a communication channel, or a recording medium, is known as equalization.

The conventional techniques to equalization are based on linear adaptive equalizer. The linear adaptive equalizers are cheap in implementation and easy to train but they have poor performance in nonlinear distortion [2,3,5].

Particularly, an adaptive equalizer is subjected to a significant growth and development which contributes directly to the digital communication techniques revolution [7]. Adaptive equalizer is a programmable filter that automatically adjusts its own parameters so as to optimize its performance. The wireless and mobile channels are extremely random and time-variant. It is well known that the wireless multi-path channel causes arbitrary time dispersion, and attenuation is known as inter-symbol interference. Linear adaptive equalizers cannot reconstruct the transmitted signal when channels are nonlinear.

The problem of equalization is treated in two different ways. Firstly, it may be interpreted as an inverse filtering problem. Secondly, the problem of equalization may be considered as a classification problem, where the equalizer attempts to classify the input vector into a number of transmitted symbols. The traditional equalizers such as Linear and Decision-feedback are based on finding the inverse of the channel and compensating the channel's influence using inverse filter technique. The equalization techniques based on Neural Networks are considered the equalization problem as classification problem. The capabilities of neural networks for equalization of simple channels are described by Gibson, Siu and Cowan [8]. Multi-layer perceptron (MLP) equalizers are superior to conventional linear and decision feedback equalizers in terms of probability of error [3], but their practical applications are severely restricted due to difficulties such as very long training time. Radial basis function network (RBFN) equalizer has received a great deal of attention because of its structural simplicity and more efficient learning compared to MLP [5,7]. However, the structure of RBFN equalizer requires a large number of centers in the hidden layer, which increases the computational complexity.

Recognizing the broad relevance of this problem in many applications, this work aims to address the channel equalization problem. The main drawback of many existing equalization techniques to provide significant performance is the computational complexity and the time of training.

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An effective way to overcome this drawback is the use of hybridization techniques. Recently, soft-computing techniques such as hybridization between Fuzzy logic and Neural Networks have been applied successfully to different nonlinear distortion problems [6]. The main concern in this work is to develop hybridization approach based on Fuzzy logic and Neural Network techniques for the equalization problem. These techniques have many features that make them a particularly appealing and promising approach. Neural networks, which model the low-level structure of the human brain, can learn from experience and easily adapt to changing environments. Fuzzy logic, which reproduce the approximate reasoning process of the human mind by representing knowledge via linguistic if-then rules, allow for precise output inference starting from imprecise input.

This work focuses on the design of an approach based on the Neuro-Fuzzy Inference System (ANFIS) for the channel equalization. The proposed approach adapts the structure of ANFIS to solve the equalization problem and explores its performance to different channel models. The performance is evaluated in terms of bit-error rate (BER) for different noise powers in the channel. Both linear as well as non-linear channels will be considered for performance evaluation. The BER of the proposed equalizer will be compared with conventional and neural network equalizers.

This paper is organized as follows. In Section II we describe the channel equalization model. Section III describes the general procedure of Adaptive Neuro-Fuzzy Inference System (ANFIS) and the adaptation of the ANFIS for the channel equalization. Experimental results are presented in Section IV along with a comparative performance analysis involving other existing techniques. Finally, Section V provides some concluding remarks.

II. CHANNEL EQUALIZATION

The two principal causes of distortion in a digital communication channels are Inter Symbol Interference (ISI) and the additive noise. The ISI can be characterized by a Finite Impulse Response (FIR). The noise can be internal or external to the system. Hence at the receiver the distortion must be compensated in order to reconstruct the transmitted symbols. The equalization process must be adaptive because it is very difficult to predict the effect of the changing environment.

The mechanism of the adaptation includes two phases. Firstly the equalizer needs to be trained with some known samples in the presence of some desired response (i.e., supervised learning).

After training the weights and various parameters associated with the equalizer structure are determined and applied. The typical digital communication system block diagram is shown in Figure 1. The transmitted data *x(k)* is assumed an independent sequence taking values of either *+1* or *-1* symbols with equal probability. The digital data sequence *x(k)* is passed through FIR filter. The observed sequence y*(k)* is formed by adding white Gaussian noise *η(k)* with zero mean and a variance of *σ2 η* .

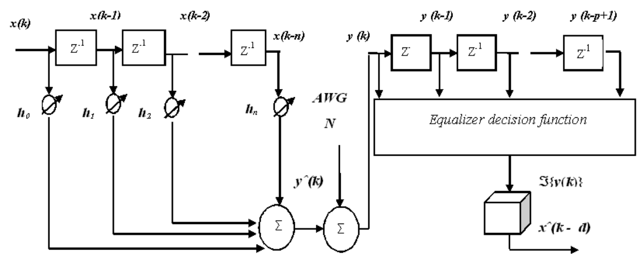

Fig.1: The Block Diagram of a Typical Digital Communication System.

The equalizer uses an input vector *y(k)*. The term *p* is the equalizer order (i.e., number of taps in equalizer) and the channel order is *n* (*n+1* taps). The equalizer provides decision function $\mathfrak{I}\{y(k)\}$ based on the input vector which is then passed through a decision device to provide the estimate of transmitted signal $x\hat{}(k-d)$ where *d* is the delay associated with equalizer decision. Hence, the channel can be modeled by a FIR filter with the following transfer function:

$$\mathrm{H(z)} = \sum_{\mathrm{i=0}}^{\mathrm{n_h}-1} \mathrm{h_i\,z^{-i}} \qquad (1)$$

Where h_i is the channel impulse response.

Different channel models with different coefficients will be applied and investigated in order to evaluate the performance of the proposed approach. Equation 2 represents the channel model of Linear Time-invariant and Time-varying channels. Equation 3 represents the channel model of nonlinear Time-invariant and Time-varying channels.

$$y\hat{}(k) = a_1(k)x(k) + a_2(k)x(k-1) \qquad (2)$$

$$y\hat{}(k) = a_1(k)x(k) + a_2(k)x^2(k) + a_3(k)x^3(k) \qquad (3)$$

III. ADAPTATION OF NEURO-FUZZY FOR CHANNEL EQUALIZATION

To illustrate the procedure of the Adaptive Neuro-Fuzzy Inference System (ANFIS), for simplicity, it is assumed that the system includes two inputs, *x* and *y*, and one output, *z*.

Suppose that the rule base contains three fuzzy if-then rules. For the first-order Sugeno FIS: the three rules can be expressed as:

Rule1: If x is A_1 and y is B_1, then $z_1 = p_1x+q_1y + r_1$.

Rule2: If x is A_2 and y is B_2, then $z_2 = p_2x+q_2y + r_2$.

Rule3: If x is A_3 and y is B_3, then $z_3 = p_3x+q_3y + r_3$.

Where, *pi*, *qi* and *ri* (i = 1, 2, 3) are the linear parameters in the consequent part of the Sugeno fuzzy model [6]. The architecture of ANFIS is shown in Figure 2, and a brief introduction of the model is as follows.

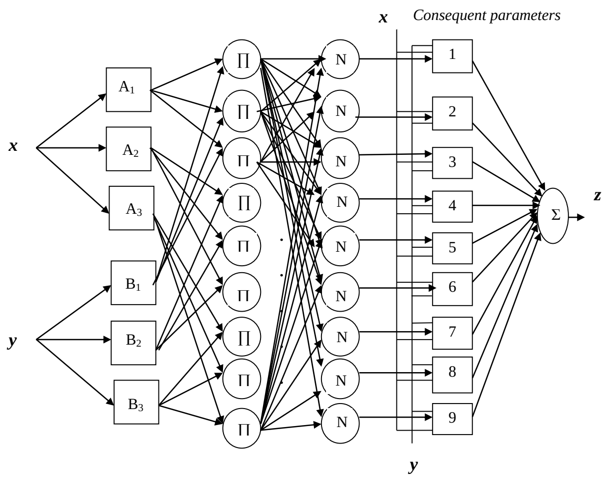

Fig. 2: The ANFIS architecture.

Layer 1 (Input nodes): Each node in this layer generates membership grades of the crisp inputs and each node's output $O_{1,i}$ is calculated by

$$O_{1,i} = \mu_{A_i}(x) \qquad \textit{for } i = 1,2,3 \qquad (4)$$

$$O_{1,i} = \mu_{B_{i-3}}(y) \qquad \textit{for } i = 4,5,6 \qquad (5)$$

Where, x and y are the crisp inputs to the node i , A_i and B_i are the linguistic labels characterized by appropriate membership functions μ_{A_i} and μ_{B_i}, respectively. The following Gaussian membership function is used in this study.

$$\mu_{A_i}(x) = e^{-\frac{(x-b_i)^2}{2a_i^2}} \qquad (6)$$

$$\mu_{B_i}(y) = e^{-\frac{(y-b_i)^2}{2a_i^2}} \qquad (7)$$

Where, a_i, b_i are parameters to be learnt. Parameters in this layer are referred to as the premise parameters.

Layer 2 (Rule nodes): The outputs of this layer, called firing strengths $O_{2,i}$, are the products of the corresponding degrees obtained from the layer 1.

$$O_{2,i} = w_i = \mu_{A_i}(x).\mu_{B_i}(y) \qquad \text{for } i=1,2,3 \qquad (8)$$

Layer 3 (Average nodes): The main objective of this layer is to calculate the ratio of each i^{th} rule's firing strength to the sum of all rules' firing strength. Consequently, $\overline{w_i}$ is taken as the normalized firing strength.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{\sum_i w_i} \qquad \text{for } i=1,2,3 \qquad (9)$$

Layer 4: The output of each node is

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \quad i=1,2,3 \qquad (10)$$

Where p_i, q_i, r_i are the parameters set of this node. These are referred to as consequent parameters.

Layer 5: There is a single node that computes the overall output

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (11)$$

The block diagram of the simulation system for the equalizer is shown in Figure 3. Random binary input signals *x(k)* are transmitted through the communication channel. Channel output signals are corrupted by additive white Gaussian noise *η(k).* The current output signals of the equalizer are compared with the desired signals transmitted through the channel. In case of the presence of error, the learning of the equalizer starts learning to adjust the parameters values of the equalizer. Learning is continued until the value of the error would be an acceptable minimum value.

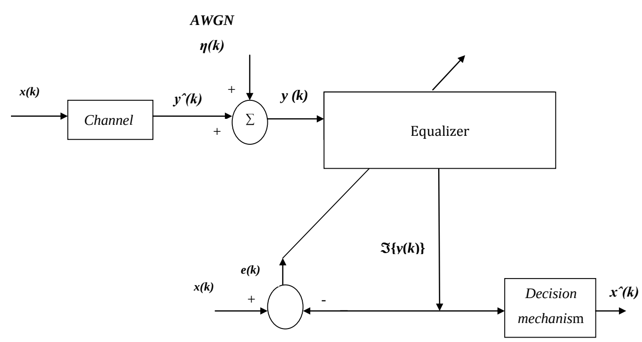

Fig. 3: The block diagram of the equalizer simulation system.

A correct decision of the equalizer occurs when the channel input *x(k)* is equal the equalizer decision output.

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Based on the values of the transmitted signal *x(k)* ={±1}, the channel states can be partitioned into two classes as follows.

$$\hat{x}(k) = Sgn(\Im\{y(k)\}) = \begin{cases} +1, & \Im\{y(k)\} \geq 0 \\ -1, & \Im\{y(k)\}x < 0 \end{cases} \qquad (12)$$

Where $\hat{x}(k)$ is the decision device output and $\Im\{y(k)\}$ is the equalizer output (decision device input).

IV. EXPERIMENTAL WORK

The performance of the proposed approach (ANFIS) is evaluated and compared with LMS and RBF approaches for the equalization of several types of channels. In this work, both linear and nonlinear with time-varying and time-invariant channel models are considered with different coefficients.

The approach is implemented using MATLAB. The criteria that is used to determine the performance of the equalizer is the Bit Error Rate (BER) versus Signal-Noise Ratio (SNR). The amount of noise that is added to the transmitted signal can be given as follows.

$$SNR = 20log_{10}\{\sigma_r/\sigma_e\} \qquad (13)$$

Where, σ_r and σ_e are the standard deviations of the signal and noise, respectively.

The BER is calculated as follows

$$BER = log_{10}(\textstyle\sum_{i=1}^{n} e_i/n)\ dB \qquad (14)$$

Where ,e_i is the error value, and n is the number of samples.

The BER is plotted against the SNR for all channel models with different coefficients in order to evaluate and compare the performance. The input signal of the channel is assumed to be an independent sequence taking values {-1,+1} with equal probability. The output of the channel (received signal), which is combination of the signal and the additive white Gaussian noise, is a random waveform. The settings of the experiments (for best results) are 5, 8, 9, and 10 hidden neurons for the RBF, and 5 rules (hidden neurons) for the ANFIS. The results are obtained after 20 epoch and using 4096 training data. Figure 4 to Figure 11 illustrate the performance comparison between LMS, RBF, and ANFIS based approaches in terms of BER versus SNR on different channel models.

The results, as shown, demonstrate the significant improvement on the performance of ANFIS compared with LMS and RBF for all the channels.

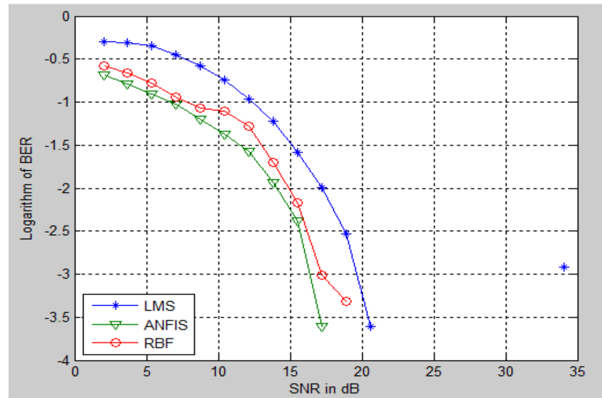

Fig. 4: Performance comparison between LMS, RBF, and ANFIS on channel *$y_1\hat{}(k)$ =0.7x(k) +0.3x(k-1).*

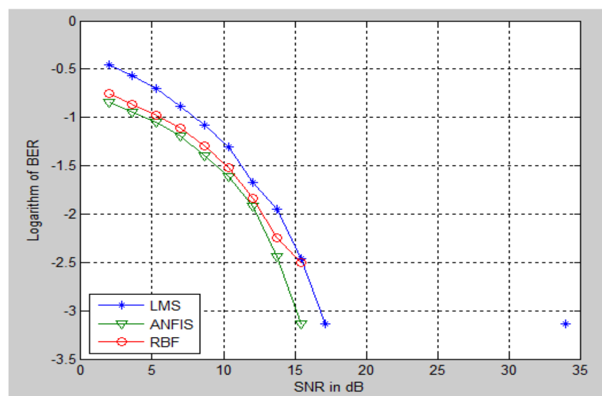

Fig. 5: Performance comparison between LMS, RBF, and ANFIS on channel *$y_2\hat{}(k)$ =x(k) +0.5x(k-1).*

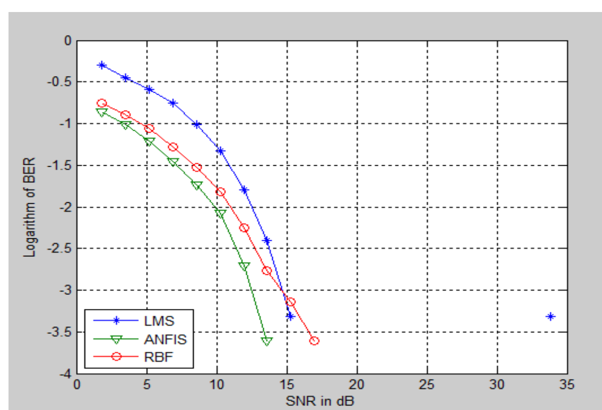

Fig. 6: Performance comparison between LMS, RBF, and ANFIS on channel *$y_3\hat{}(k)$ =0.93x(k) +0.26x(k-1).*

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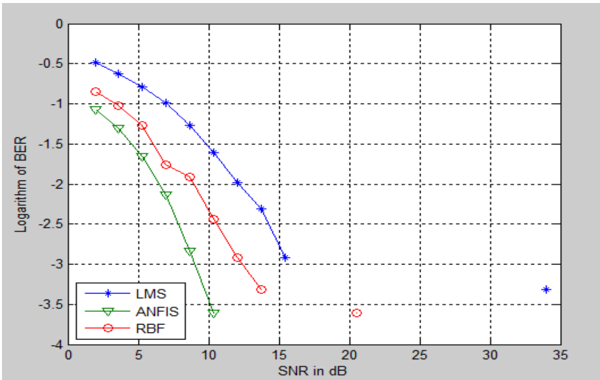

Fig. 7: Performance comparison between LMS, RBF, and ANFIS on channel $y_4\hat{}(k) = x(k) - 0.2x^2(k) + 0.1x^3(k)$.

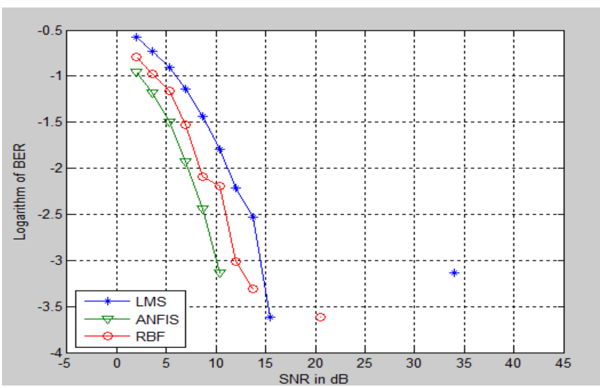

Fig. 8: Performance comparison between LMS, RBF, and ANFIS on channel ***for*** $y_5\hat{}(k) = x(k) + 0.5x^2(k)$.

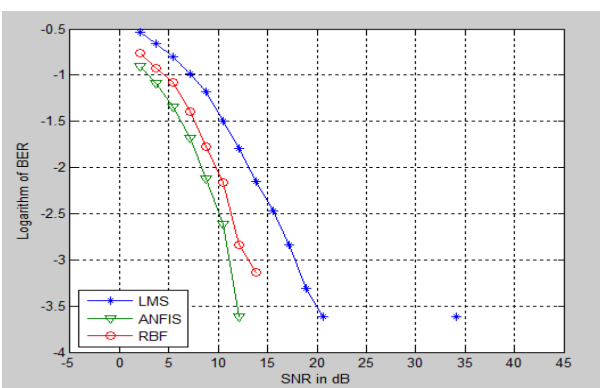

Fig. 9: Performance comparison between LMS, RBF, and ANFIS on channel $y_6\hat{}(k) = x(k) + 0.3x_2(k) - 0.1x^3(k)$.

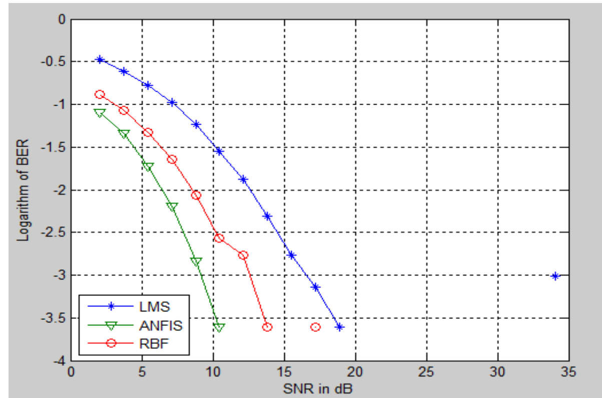

Fig. 10: Performance comparison between LMS, RBF, and ANFIS on channel $y_7\hat{}(k) = x(k) - 0.2x^2(k) + 0.1x^3(k)$.

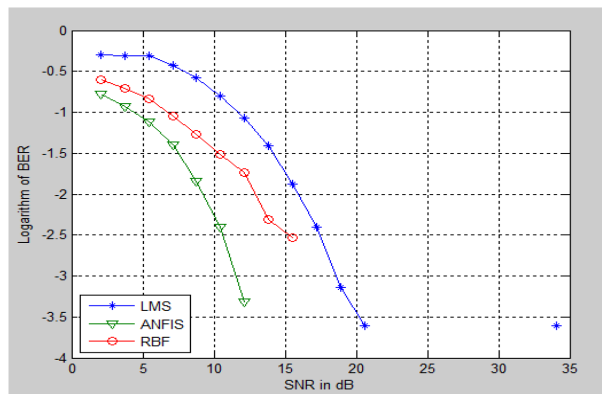

Fig. 11: Performance comparison between LMS, RBF, and ANFIS on channel $y_8\hat{}(k) = x(k) - 0.2x^3(k)$.

Figure 12 illustrates the simulation times of the LMS, RBF, and ANFIS for 20 epochs and 4096 training data for different channel models. It can be concluded from this figure that LMS has very low simulation time for the channels, but it has very poor performance compared with RBF and ANFIS as illustrated above. Moreover, ANFIS has a significant improvement in terms of both the performance and the computation time compared with RBF.

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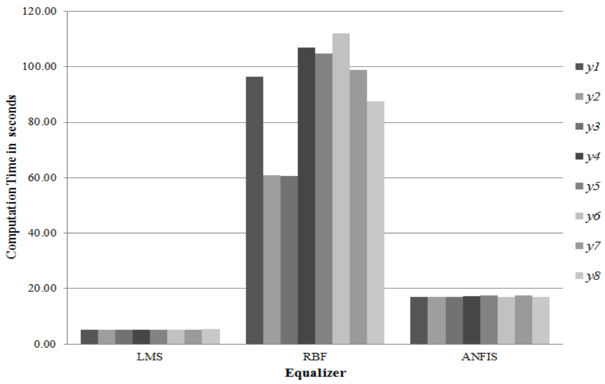

Fig. 12: Simulation Time of LMS, RBF and ANFIS equalizers for different channel models.

V. CONCLUSION

In this paper, an approach based on the integration of artificial neural network with fuzzy logic is introduced in order to improve the performance of the equalization system. The ANFIS structure is adapted for the channel equalization. The performance criteria used for the performance comparisons between the approaches is the BER versus SNR. The experimental work demonstrated that the proposed equalizer gives superior performance compared to other equalizer such as LMS and RBF equalizers for different channel models. It is also demonstrated that the proposed equalizer reduces the structural complexity of the neural network. The significant of the proposed equalizer is its computational simplicity, due to the small size of the network, which can achieve better performance and efficient extraction of information from a small number of training samples.

However, extension of this work to include more general systems is an interesting topic for further research. Other possible direction for research is investigating the proposed equalizer with less possible number of fuzzy rules in order to reduce the computation time.

REFERENCES

[1] Abiyev, R.H., Alshanableh, T.,"Neuro-fuzzy network for adaptive channel equalization," 5th Mexican International Conference on Artificial Intelligence. IEEE CS .MICAI 2006 . A Pizaco ,Mexico, November 13-17, 2006.

[2] Abiyev, R., Mamedov, F., Alshanableh, T.," Equalization of channel distortions by using nonlinear neuro-fuzzy network "ISNN(2), Lecture Notes in Computer Science , Vol . 4492 ,pp.241-250, Springer, 2007.

[3] S. Chen, G J Gibson, C F N Cowan, and P.M. Grant "Adaptive equalization of finite non-linear channels using multi-layer perceptron", IEEE Trans. Signal Processing, Vol. 20, No. 2, pp. 107-20, Jun 1990.

[4] H Qureshi, "Adaptive equalization", Proceedings IEEE, Vol. 73, pp. 1349-87, Sep 1985.

[5] I S Chen, B Mulgrew, and P Grant, "A clustering technique for digital communication channel equalization using RBFN", IEEE Trans. Neural Networks, Vol. 4, pp. 570-9, Jul 1 1993.

[6] R J Jhy-Shing, "ANFIS: Adaptive-Network-Based Fuzzy Inference System", IEEE Transaction on Systems, Man, and Cybernetics, Vol. 23, May 1993.

[7] Devi Rani Guha, Sarat Kumar Patra,"Channel Equalization for ISI channels using Wilcoxon Generalized RBF Network", IEEE (978-1-4244-4837-1), ICIIS-09 University of Peradeniya, Srilanka, December 2009.

[8] G.J. Gibson, S. Siu, S. Chen, C.F.N. Cowan and P.M. Grant, "The Application of Nonlinear Architectures to Adaptive Channel Equalization", IEEE International Conference on Communications,ICC'90 (Atlanta, USA), vol. 2, pp. 649-653, 16-19 April 1990.