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Recurrent Neural Network Based Bit Error Rate Prediction for 802.11 Wireless Local Area Network

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Abstract: *Bit Error Rate (BER) will specify the status of the channel or Channel State Information (CSI) in wireless network. Precise and timely assessment of CSI will help in providing desired Quality of Service (QoS) to the network users in the farm of judicial admission control, inter and intra network handoff. Here, BER of time varying 802.11 wireless channel is predicted by neural network system. The wireless channel is modeled as time varying nonlinear system. The neural network systems are the appropriate paradigm to predict and analyze the behaviors of time varying nonlinear system. In this framework BER of 802.11 wireless channel is predicted by two recurrent neural network architecture such as Recurrent Radial Basis Function Network (RRBFN) and Echo State Network (ESN). The Prediction accuracy RRBFN and ESN are in the range of 83.6 % to 98 % and 86.1% to 99.6 % respectively.*

Keywords: *Bit Error Rate, Channel Sate Information, Quality of Service, Admission Control, Network Handoff, Prediction and Recurrent Neural Network*

1. INTRODUCTION

In the recent past due to the technological breakthrough in the field of wireless system it has enabled the pervasive acceptance and deployment of wireless network, but still wireless system is not a preferred choice to the wired counterpart. The reason for preferring wired network to a wireless network is due to the capricious behavior of the wireless network and it is increasingly becoming important to know the CSI of the network well in advance so that corrective measures can be taken in terms of admission control and intra or inter network handovers [1]. These remedial measures in turn improve the QoS of a wireless network and make the wireless network more reliable. The CSI can be determined by BER. In this paper, BER of a time varying fading channel with modulation technique like Binary Phase Shift Keying (BPSK), Quadrature Phase Shift Keying (QPSK) and 16-Quadrature Amplitude Modulation (QAM) with pedestrian mobility to vehicular mobility were predicted using artificial neural network approach

The nucleus of any prediction mechanism is to monitor the past and present behavior of the system and to establish statistical relationship between set of input to the set of output over a given time scale. This relationship is either linear or nonlinear and time invariant (static) or time variant (dynamic). The wireless channel is a nonlinear dynamic system, where the nonlinearity and dynamism is due to the effect of noise, multipath fading and channel modulation technique. The noise and modulation technique will induce nonlinearity in wireless channel. The reflection, diffraction and scattering effect will intern delay certain amount of transmitted signals, which will reach the receiver. These delayed signals will reach the receiver some times in phase with the direct signal or some times out of phase with the direct signal. These effects will in turn make the behavior of the channel dynamic. These phenomenons affect the quality of signal which in turn varies in an unpredictable way. Such time variant and nonlinear system is difficult to model and analyze its behavior. Neural networks are the efficient methods to model, evaluate and predict the behavior of such systems. In our work, we predict the behavior of 802.11 wireless channels with the two recurrent neural networks namely ESN and RRBFN.

The rest of the paper is organized as follows. In section 2, review of related work in the field of BER prediction and its estimations are presented. In section 3, the system is modeled from wireless channel, prediction and neural network viewpoint. In section 4, the system model is validated with a set of simulation trails. Finally, paper is concluded in section 5.

2. RELATED WORKS

There are several research works on channel prediction or estimation. Sometimes channel prediction in a wireless network is studied under channel equalization problem.

These works are either on statistical approach or on soft computing approach. The major works on statistical approach are Maximum Likelihood (ML) estimator [2] and Minimum Mean Square Error (MMSE) estimator [3]. In soft computing approach it is either a neural network or pattern classification method. Some of the major works on pattern classification are Nonlinear Recursive Least Square (NRLS) algorithm and it is used for any standard classification problem and the same is used in channel equalization [4].Pattern classification method is combined with statistical ray tracing model which is used to obtain accurate field prediction model [5]. However this model will illustrate the channel characteristics as time invariant parameter. Using neural network for adaptive equalization to combat Inter Symbol Interference (ISI) is not a new concept. Some of the major works in the equalization are on nonlinear adaptive channel equalization [6][7][8]. Multi-Layer Perceptron (MLP) is used for power prediction and power control in CDMA receivers[9].Fully connected recurrent neural network is used for narrow band channel prediction, but this is restricted to evaluating the performance of training algorithm for nonlinear channel prediction [10]. Recently recurrent neural network is used for estimating quality of wireless network from MAC layer viewpoint, by estimating the Available Band-Width (ABW) [11]. Here the wireless channel model is compared with linear and nonlinear model and it is also shown how nonlinear model will suite the behavior of realistic wireless channel. In the above works, the communication channel is modeled as a nonlinear system but not as a nonlinear time varying system. In our work the wireless channel is modeled as nonlinear time varying system to predict the BER of the channel.

3. SYSTEM MODEL

3.1 Channel Model

BER of wireless link can be determined by link quality, modulation and coding scheme [1]. Average theoretical BER for M-ary Phase shift Keying under Rayleigh fading is given by [12] and average BER for M-QAM is [13].

$$BER = \frac{2^{m-1}}{M-1}\left(1-\sqrt{\frac{\sin^2(\frac{\pi}{m})m\gamma_f}{\left(1+\sin^2(\frac{\pi}{m})m\gamma_f\right)}}\right) \quad (1)$$

$$BER = \frac{M}{5}\left(\exp\left(-\frac{3\gamma_f}{2(2^m-1)}\right)\right)$$

Where $M = 2^m$ and γ_f is effective signal to noise ratio under fading channel and is summation of instantaneous signal to noise ratio over an interval N

$$\gamma_f = \frac{1}{N}\sum_{K=1}^{N}\frac{E_b}{N_0}(kt)\varphi(kt) \quad (2)$$

Where E_b is the transmitted bit energy, N_0 is amplitude of the one sided power spectral density of Additive White Gaussian Noise (AWGN) and φ is average value of α^2, when fading characteristics α is Rayleigh distribution α^2 is chi–square probability distribution with two degree of freedom [14]. In an 802.11 fading channel the instantaneous BER is a parameter of $\frac{E_b}{N_0}$ and α is given by

$$BER(t) = f\left(\frac{E_b}{N_0}(t), \alpha(t)\right) \quad (3)$$

The BER (t) is a nonlinear function $f(.)$ of parameter $\frac{E_b}{N_0}$ and α, this is due to the channel modulation scheme [8][15]. The parameters of $f(.)$ also depends on time hence instantaneous BER is a nonlinear dynamic system. Average BER can be calculated by averaging N iteration instantaneous BER [7].

$$BER = \frac{1}{N}\sum_{K=1}^{N} BER(kt) \quad (4)$$

BER of a wireless channel can be modeled as nonlinear time varying system

3.2 Prediction Model

The regression analysis is the commonly used method for prediction model. In regression analysis the relationship between dependent variables and predicted variable need to be specified and the relationship can be a linear or nonlinear. Here equation.3 is a nonlinear function. In a statistical method, the nonlinear regression is the problem of inferences

$$\hat{y}_{t+1} = f\left(y_t, \ldots, y_{t-k+1}\right) \quad (5)$$

$$Y = [y_t, \ldots, y_{t-k+1}]$$

Where $\hat{y}_{t+1}$ is the predicted value of the predictor at time t + 1, Y is regressor at time t and $f(.)$ is a model used for prediction. In the K step prediction the equation 5 becomes,

$$\left[\hat{y}_{t+k}, \hat{y}_{t+k-1}, \ldots, \hat{y}_{t+1}\right] = f\left(y_t, \ldots, y_{t-k+1}\right) \quad (6)$$

The success of the prediction model will depend on how accurately it predicts the K- step value $\hat{y}$, ε prediction error. This error is the difference between predicted value and actual value i.e., $\varepsilon = \hat{y} - y$. Accuracy of the predictor is verified by statistical approaches like Mean Square Error

(MSE) and Maximum Likelihood Estimation (MLE) [14][15]. Some of the general nonlinear predictors are Unscented Kalman Filter (UKF), differential algebra, Bayesian and neural network [16][17][18]. In order to incorporate temporal behavior to these nonlinear predictors, which in an explicit manner[19][20] or by implicit manner is to build all together a new predictor that has both nonlinearity as well as temporal behavior [21] [22]. The statistical quality of such nonlinear temporal predictors is determined by Lyapunov exponents [23].

3.2 Neural Network Model

Feedforward neural network has the ability to map any nonlinear function to an arbitrary degree of accuracy [8]. One such popular feedforword network is Radial Basis Function Network(RBFN). It is a single hidden layer feedforword network. Each node in the hidden layer has a parameter vector called as center. These centers are used to compare with network input and produce radically symmetrical response. These responses are scaled by connection weights of the output layer and then produce network output, where Gaussian basis function is used and which is given by,

$$\hat{y} = \sum_{i=1}^{n} w_i \exp\left(-\frac{\|y-\mu_i\|}{2\sigma_i}\right) \tag{7}$$

Where σ_i is the dimension of the influence field of the hidden layer neuron, y and μ_i are input and prototype vector respectively. Radial Basis Function (RBF) has achieved considerable success in nonlinear function prediction but the performance of RBF is less satisfactory for the nonlinear dynamic function prediction [24]. The RRBFN considers the time as an internal representation and the dynamic aspect of nonlinear function can be obtained by having self-connection on the input neuron of sigmoidal firing function and the recurrent weights are in the range [-1 , +1], with normal distribution. This is a special case of locally recurrent, globally feedforward neural network [14]. The RRBFN output for Gaussian basis function is

$$\hat{y}(t) = \sum_{i=1}^{n} w_i \exp\left(-\frac{\sum_{j=1}^{m}\left(y^j-\mu_i^j\right)^2}{\sigma_i}\right) \tag{8}$$

Where j is the number of neurons in the input layer of RRBFN, the described RRBFN model is shown in Fig. 1

Recurrent neural network with standard gradient decent algorithms will provide better function approximation for a short time step. For the longer temporal dependencies the gradient vanishes as the error signal is propagated back through time so that network weights are never adjusted correctly and the system will fail to predict for longer and complex time series steps. To deal with this an echo state network was proposed [25]. It consists of two parts such as a dynamical system with a rich set of dynamics followed by a memoryless output readout function shown in Figure 2.

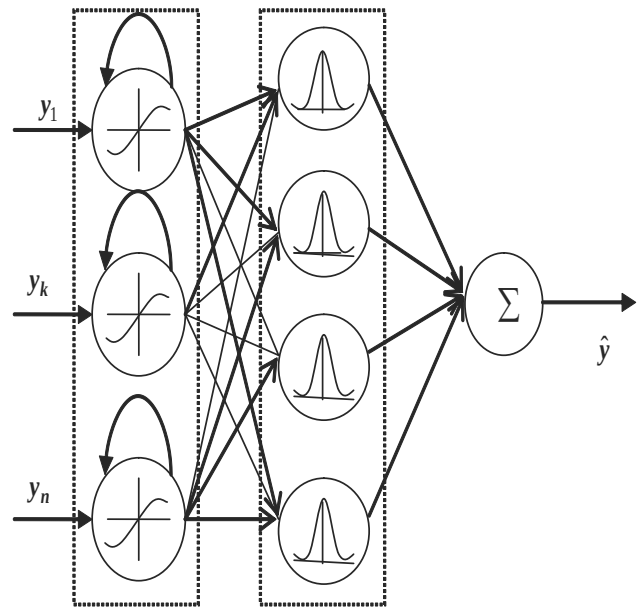

Figure 1: Recurrent Radial Basis Function Network.

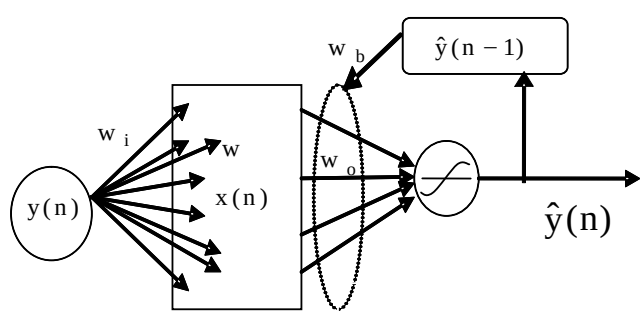

Figure 2: Echo State Network

The dynamical system consists of large number of neurons that are randomly interconnected and selfconnected and these connections are fixed. This dynamical system is also called as reservoir and the optimal connections of neurons inside the reservoir will always require a number of trails. During the training process only weights of memoryless output function is changed through offline linear regression process or by online methods like Recursive Least Square(RLS)[17].The general state of reservoir is given by,

$$x(n) = \varphi(w_i y(n) + wx(n-1) + w_b \hat{y}(n-1) \tag{9}$$

Where φ is the sigmoidal activation function, $y(n)$ is current input vector, $x(n-1)$ is the internal state of reservoir at time step $n-1$, $\hat{y}(n-1)$ is the output of ESN at previous time step. w_i, w and w_b are the input, reservoir and feedback weight

vectors respectively. The output of ESN at time step n is given by,

$$\hat{y}(n) = \varphi_o(w_o x(n)) \quad (10)$$

Where φ_o is activation function of the output neuron and this can be a linear or sigmoidal. w_o is output weight vector and x(n) is current state of the reservoir

4. SIMULATION RESULTS AND DISCUSSION

In order to compare the prediction accuracy of RRBFN and ESN model, simulation method is used. The simulation is of two phases. In the first phase, generation of time varying parameters of the wireless channel such as fading, Additive White Gaussian Noise (AWGN), signal strength, mobile speed and nonlinear parameters such as modulation and coding scheme are simulated. The simulation setup and its parameters for BPSK, QPSK and 16-QAM modulation is given in Table 1. For all these channels multipath fading signals are generated using modified jakes technique and the data rate is varied from 2 to 4 Mbps

Table 1
Simulation Parameters

Modulation	*Doppler Frequency*
BPSK	75 Hz
QPSK	50 Hz
16-QAM	30 Hz

The second phase of simulation is training and testing of the RRBFN and ESN predictor. Here the fading signal samples collected in first phase is used for training and testing of the predictors. The training and testing samples are randomly picked from the sample size of 6000. The RRBFN network has three layers: input, hidden and output. Here 500 neurons in the input layer with sigmoidal activation function and with the recurrent connections, the range of recurrent weights are –1 to +1. The hidden RBF layer has 375 neurons with RBF activation and output layer has single neuron with linear activation. The ESN network has 450 neurons in the reservoir with 75% of recurrent connection in the range of weights between –1 to +1. Input weights are in the range of –0.40 to +0.40 and recurrent weights are in the range of –0.6 to +0.6. Spectral radius is set to 0 and all the layer neurons have sigmoidal activation function.

The instantaneous bit error of BPSK modulation from simulation, output of RRBFN and ESN network are shown in Figure 3.

Average BER and instantaneous BER i.e. BER(t) is listed in Table 2

From the Table 2, it is apparent that Average BER of simulation, RRBFN and ESN network will closely resemble, but instantaneous BER of each system will differ at various time intervals. From this, one can conclude that both RRBFN and ESN are excellent predictors but not good reconstructors [26].

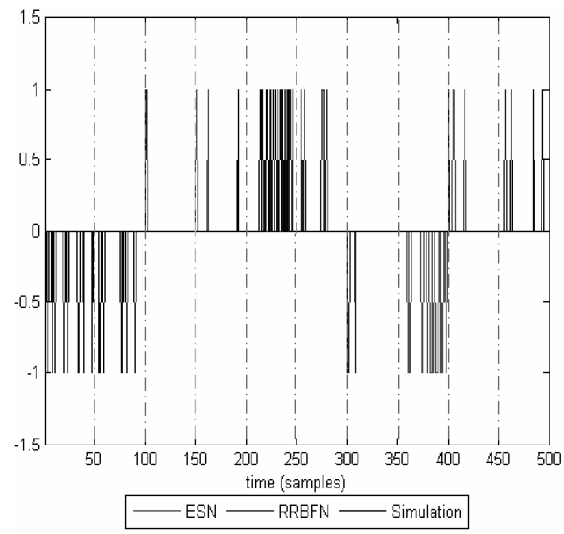

Figure 3: Instantaneous BER of ESN, RRBFN and Simulation

Table 2
Simulation Parameters

Time Interval	*RRBF*	*ESN*	*Simulation*
1-50	0.16	0.12	0
51-100	0.12	0	0.16
101-150	0.04	0.04	0.04
151- 200	0.02	0.02	0.04
201-250	0.2	0.16	0.02
251-300	0.02	0.06	0.06
301-350	0	0.06	0
351-400	0	0.08	0.2
401-450	0	0.02	0.06
451-500	0.06	0.04	0.04
Average	0.064	0.060	0.062

MSE of prediction of ESN model and RRBFN model for BPSK modulation is shown in Fig 4.

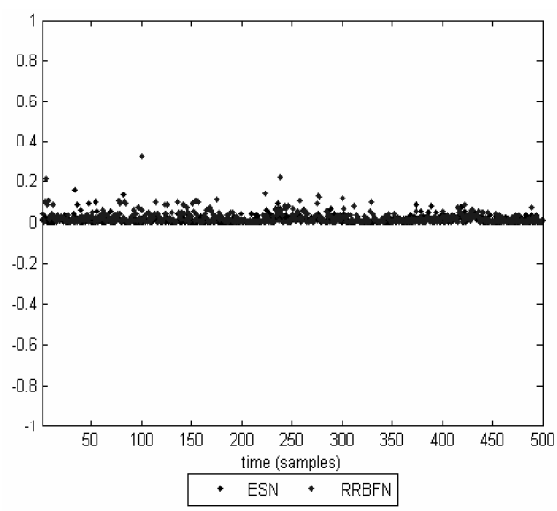

Figure 4: MSE of ESN and RRBFN

Predicted fading samples of RRBFN and ESN along with the transmitted bit pattern is shown in Figure 5.

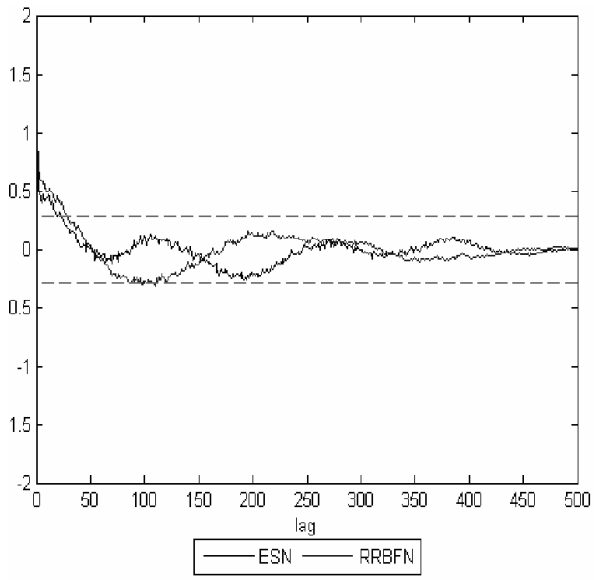

Figure 5: Fading Samples of ESN and RRBFN

Auto-Correlation Function (ACF) of predicted error at 95 % confidence interval for BPSK modulation is shown in Fig 6.

From Fig. 6 it is evident that accurate prediction of fading samples for BPSK modulation from ESN network is approximately 135 steps and from RRBFN network it is roughly 100 steps.

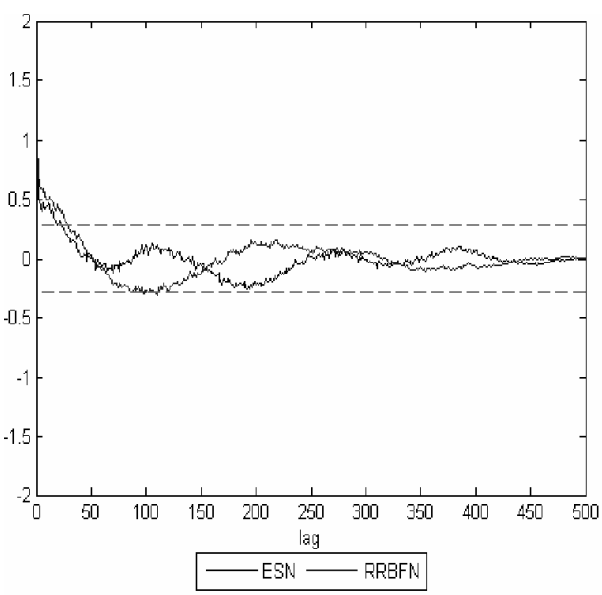

Figure 6: ACF of Prediction Error of ESN and RRBFN

Average BER of simulation, RRBF and ESN network under BPSK modulation is shown in Fig 7.

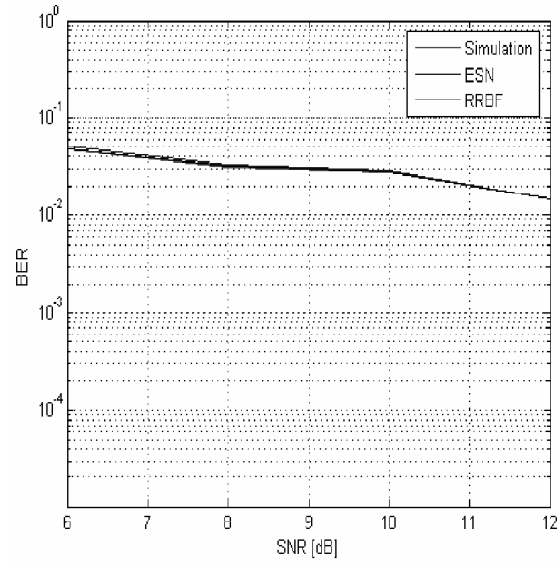

Figure 7: Average BER V/s SNR of BPSK Modulation

The average BER of Simulation and Prediction of ESN and RRBFN closely resembles each other. Average BER of simulation, RRBFN and ESN network with 50 step prediction under QPSK modulation is shown in Figure 8.

Average BER of Simulation, RRBFN and ESN network with 50 step prediction under 16-QAM modulation is shown in Figure 9.

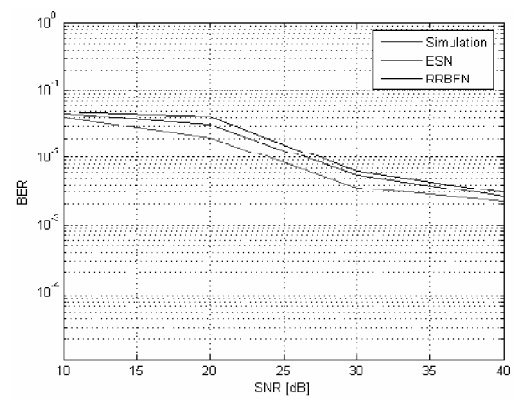

Figure 8: Average BER V/s SNR of QPSK Modulation

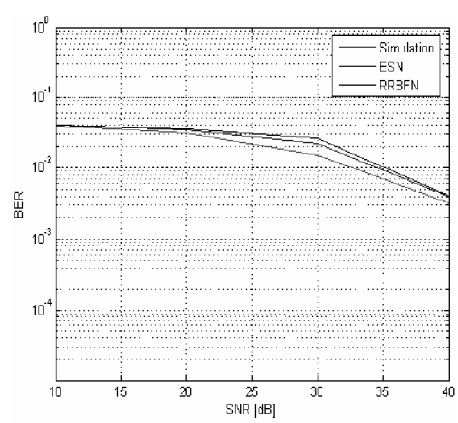

Figure 9: Average BER V/s SNR of 16-QAM Modulation

The Minimum and Maximum MSE for ESN and RRBFN network for different modulation scheme is listed in Table 3.

Table 3
Minimum and Maximum MSE

Modulation	*Network*	*Maximum MSE*	*Minimum MSE*
BPSK	RRBFN	0.000023	0.0000031
QPSK	RRBFN	0.00042	0.000085
16-QAM	RRBFN	0.0013	0.00019
BPSK	ESN	0.000018	0.0000025
QPSK	ESN	0.00026	0.000074
16-QAM	ESN	0.0024	0.00057

From Table 3, it is evident that ESN network perform slightly better than RRBFN network. Variation of maximum and minimum prediction error is slightly less in ESN network

5. CONCLUSION

In this paper BER prediction of 802.11 wireless channel is demonstrated with two recurrent neural network architectures such as ESN and RRBFN. For BPSK modulation the prediction accuracy is superior compared to QPSK and 16-QAM modulation. Both in QPSK and 16-QAM system the predicted value is higher than simulated value and this is due to chaos introduced in the system due to multipath fading and modulation. From the study ESN based predictor is slightly better in terms of prediction accuracy. But ESN network takes more training samples and longer training time compared to RRBFN. During the training phase the training MSE for ESN and RRBFN are 0.01254 and 0.0162 respectively. The prediction accuracy of ESN and RRBFN is 99.6% and 98% respectively for BPSK modulation. For QPSK and 16-QAM modulation the prediction accuracy of ESN is 86.1 and for RRBFN it is 83.6. Both RRBFN and ESN network performance are within the satisfactory limit

Future work includes applying Neural Network(NN) models for predicting BER for 802.16e Mobile WirlessMAN network. Furthermore, the NN based predictors will be used for both long term and short term traffic prediction[27] and also for the purpose of inter/intra network handovers in heterogeneous wireless networks the NN based Multi Attribute Decision Making(MADM) or Multi Criteria Decision Making (MCDM) technique will be applied.

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REFERENCES

[1] W. Xiucho and A. L. Ananda, "Link Characteristics Estimation for 802.11 DCF Based WLAN", in *29th Annual IEEE International Conference on Local Computer Network*, 2004, 302-309.

[2] G., Yu, H. Wang and D. Sheng, "Advanced K-step Forward Prediction Algorithm", in *International Conference on Communication, Circuits and System*, 2004, 271-281.

[3] A. Wiesel., J. Goldberg. and H. Messer-Yaran, "SNR Estimation in Time Varying Fading Channel", *IEEE Transaction on Communications*, **54**(5), 2006, 841-848.

[4] E. Soria-olivas, G. Camps-Valls and D. Jose, "Non-linear RLS-based Algorithm for Pattern Classification", *Signal Processing*, **86**, 2006, 1104-1108.

[5] V. Degli-Esposti, A. De'Marsi and F. Fuschini, "A Field Prediction Model for Urban Environment Based on Pattern Recognition and Statistical Ray Tracing", in *53rd Vehicular Technology Conference*, 2001, **1**, 428-432.

[6] Al-Mashouq and I. S. Reed., "The Use of Neural Nets to Combine Qualization with Decoding for Severe Intersymbol Interference Channels", *IEEE Transactions on Neural Networks*, **5**(6), 1994, 982-988.

[7] P. R. Chang. and B. C. Wang, "Adaptive Decision Feedback Equalization for Digital Channel using Multilayer Neural networks", *IEEE Journal on Selected Areas in Communication*, **13**(2), 1995, 316-324.

[8] M. Li., G. Huang and P. Saratchandran, "Performance Evaluation of GAP-RBF Network in Channel Equalization", *Neural Processing Letters*, **22**, 2005, 223-233.

[9] X. M. Gao., X. Z. Gao and M. Jarno, "Power Prediction in Mobile Communication Systems Using an Optimal Neural-Network Structure", *IEEE Transaction on Neural Networks*, **8**(6), 1997, 1446-1455.

[10] W. Liu, L. Yang and L. Hanzo, "Recurrent Neural Network Based Narrowband Channel Prediction", in *63rd Vehicular Technology Conference*, 2006, **5**, 2173-2177.

[11] J. Zahang and E. Marsic, "Link Quality and Signal-to-Noise Ratio in 802.11 WLAN with Fading: A Time-Series Analysis", in Proceedings of the 64th Vehicular Technology Conference, 2006, **5**, 1-5.

[12] K. Pahlvan. and P. Krishnamurthy, *Principles of Wireless Networks-A Unified Approach*, Prentice-Hall, Inc., 2002.

[13] Y. Chang, F. Chien and K. J. Kuo, "Performance Comparison of OFDM-TDMA and OFDMA with Cross–layer Consideration", in *64th Vehicular Technology Conference*, 2006, 1-5.

[14] S. Chen., B. Mulgrew. and P. M. Grant, "A Clustering Technique for Digital Communication using Radial Basis Function Network", *IEEE Transactions on Neural Networks*, **4**(4), 1993, 570-579.

[15] H. Harpham. and C. W. Dawson., "The Effect of Different Basis Function on Radial Basis Function Network for Time Series Prediction: A Comparative Study", *Journal of Neurocomputing*, **69**, 2006, 2161-2170.

[16] R. M. Guerra and J. D. Morales, "Nonlinear Estimator: Differential Algebraic Approach", *Applied Mathematics Letter*, **9**(4), 1996, 21-25.

[17] A. R. Nix. and J. P. McGeehan, "High Speed Bit Error Rate Estimation in Frequency Selective Time-varying Channels", in *IEEE Singapore International Conference on Communication Systems*, 1994, 677–681.

[18] E. A. Wan and R. D. V. Merve, "The Unscented Kalman Filter for Nonlinear Estimation", in *IEEE Symposium on Adaptive Systems for Signal Processing, Communication and Control*, 2000, 153-158.

[19] M. R. Berthold, "A Time Delay Radial Basis Function Network for Phoneme Recognition". in *The International Conference on Neural Networks*, 1994, **7**, 4470-4473.

[20] A. Waibel, T. Hanzawa and G. Hinton, "Phoneme Recognition using Time Delay Neural Network", *IEEE Transactions on Acoustics, Speech and Signal Processing*, **37**(3), 1989, 328-339.

[21] H. Jaeger, "Harnessing Nonlinearity: Predicting Chaotic Systems and Saving Energy in Wireless Communication", *Journal of Sciences*, 304, 2004, 78-80.

[22] R. Zemouri, D. Racoceanu and N. Zerhouni, "Recurrent Radial basis Function Network for Time Series Prediction", *Engineering Applications of Artificial Intelligence*, **16**, 2003, 453-463.

[23] S. Haykin, *Neural Networks: A Comprehensive Foundation*, Person Education Inc., 1999.

[24] Y. Y. Kim and S. Q. Li, "Modeling Multipath Fading Channel Dynamics for Packet Data Performance Analysis", *Wireless Networks*, **6**, 2000, 481-492.

[25] Y. Xue, L. Yang and S. Haykin, "Decoupled Echo State Network with Lateral Inhabitation", *Neural Networks*, Article in press, 2007.

[26] S. V. Dudul, "Prediction of a Lorenz Chaotic Attractor using Two-layer Perceptron Neural Network", *Applied Soft Computing*, **5**, 2005, 333-355.

[27] P. Konstantina, T. Nina and Z. Zhang, "Long-term Forecasting of Internet Backbone Traffic", *IEEE Transaction on Neural Networks*, **16**(5), 2005, 1110-1124.