Neural Network Based BER Prediction for 802.16e Channel

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Abstract: **The prediction of Bit Error Rate (BER) in IEEE 802.16e Mobile WirlessMAN network is investigated here. The state of the channel is estimated on symbol by symbol basis on a realistic fading environment. The state of a channel is modeled as nonlinear and temporal system. Neural network method is the best system to predict and analyze the behaviors of such nonlinear and temporal system. In this context, BER prediction by k symbol ahead is investigated by two different recurrent neural network architectures such as Recurrent Radial Basis Function (RRBF) Network and Echo State Network (ESN). The Predicted BER will match very well with the simulation results.**

1. INTRODUCTION

Recently, orthogonal frequency division multiplexing (OFDM) has received considerable importance in the field of wireless broadband technologies due to its inherent advantages such as achieving high data rate in transmission of data and ability to convert frequency selective fading channel in to several nearly flat fading channels[1]. The Orthogonal Frequency Division Multiple Access (OFDMA) is a multi-user version of OFDM system, in which set of carriers are assigned an individual user based on user request, there by multiple access scheme is achieved. In 802.16e wireless network the channel is an OFDMA Channel. Knowing the state of the channel in advance it will improve the performance of the wireless system by a set of schemes such as rate adaptation, power control, admission control, intra or inter handoff. These days knowing state of the channel or Channel State Information (CSI) in advance is becoming increasingly important in wireless network to guarantee the Quality of Service (QoS) to the network users. Many studies have confirmed that there is a nonlinear time varying distortion of the signal, where in, when a signal is propagating through the wireless channel [1], this nonlinear and time varying distortion is due to noise, Doppler shift and multipath fading [2]. The commonly used method in determining the quality of wireless link is BER, the BER conveys the CSI effectively [3].

The core work of any prediction approach is to observe the past and current behavior of the system and to establish statistical relationship between set of input to the set of output over a given time scale. In a linear prediction system the relationship is a linear function. This linear function may be time variant or time invariant. In a nonlinear system the relationship between input and output is nonlinear function and this can be time variant or time invariant. The time variant system is also called as temporal system. The behaviors of nonlinear temporal system can be efficiently predicted and combat through the neural network [4]. In our work we predict the K step ahead BER of 802.11e OFDMA channel with the RRBF and ESN network and the results of both the neural networks are compared.

The rest of the paper is organized as follows. In section 2, review of set of related work in the field of BER prediction and estimation. In section 3, system is modeled from OFDMA channel model, prediction and neural network perspective. In section 4, the system model is validated with set of simulation experiments. Finally, paper is concluded in section 5

2. RELATED WORK

There are several research works on OFDM channel prediction or estimation and most of these work are either frequency synchronization or on combating Inter Symbol Interference (ISI) due to channel impairment. OFDM system are sensitive to the frequency references, a small carrier offset in turn causes the loss of orthogonality among the subcarriers and will introduce Inter Channel Interference (ICI).This will degrade the system performance [2] and hence frequency synchronization is of at most important in OFDM communication. In OFDM system the synchronization is achieved either by inserting pilot subcarriers in regular frequency and space interval or by non-pilot or blind method. The advantage of pilot based estimators are its reliability and accuracy [2][5].In a blind estimation technique the estimator makes use of Maximum Likelihood(ML) technique in predicting Cyclic Prefix(CP)[6] or by frequency synchronization scheme using OFDM symbols with identical halves[7]. In order to mitigate the effect of ISI predictors either use statistical approach like Least Square (LS) or minimum mean square Error (MMSE)[8][9] or by neural network approach like Radial Basis Function (RBF) network or Self Organizing Map(SOM) network [10][11].

3. SYSTEM MODEL

3.1 Channel model

In OFDMA system, in order to achieve multiuser diversity among a set of overlapping but orthogonal subcarriers, the N subcarriers are divided among L traffic channel and each with M subcarriers, these subcarriers are divided in to C cluster having M_c subcarriers as shown in Figure 1[2]. The OFDMA system with L traffic channel each with M subcarriers under Rayleigh fading environment with χ uncorrelated paths to the receiver and the normalized delays are $\tau_0, \tau_1, ...\tau_{\chi-1}$ respectively. Path gain for χ number of path is independent complex Gaussian random variable and is given by.

$$\alpha = \left[\alpha_0, \alpha_1, ..., \alpha_{\chi-1}\right]^T \quad (1).$$

Where (α_j) have independent real and imaginary parts with zero mean and variance $\frac{\sigma_j}{2}, j = 0,1,...\chi-1$. The channel frequency response is given by [2].

$$\mathrm{h} = \left[\mathrm{h}_0, \mathrm{h}_1, ...\mathrm{h}_{M-1}\right]^T$$
$$\mathrm{h}_n = \sum_{i=0}^{\chi-1} \alpha_i e^{-j\frac{2\pi\tau_i n}{M}}, n = 0,1,...M-1 \quad (2).$$

The x_m is the transmitted symbol and y_m is the received symbol on m^{th} subcarrier of the l^{th} traffic channel, the length of the CP is greater than channel response and in order to mitigate ISI, the received symbol y_m is given by[12].

$$y_m = h_m x_m + v_m, m = 0,1,...M-1 \quad (3).$$

Where v_m is the Additive White Gaussian Noise (AWGN) with variance N_0. on the traffic channel l , the channel frequency response is given by

$$h_l = \left[h_{l1}, h_{l2}, ..., h_{lM}\right]^T \quad (4).$$

For the k^{th} user in lth channel the channel response is h_l^k ,the Average Signal to Noise Ratio (SNR) for the k^{th} user and l^{th} channel is given by[2] .

$$\mathrm{SNR}_l^k = \frac{\left\|h_l^k\right\|}{MN_0} \quad (5).$$

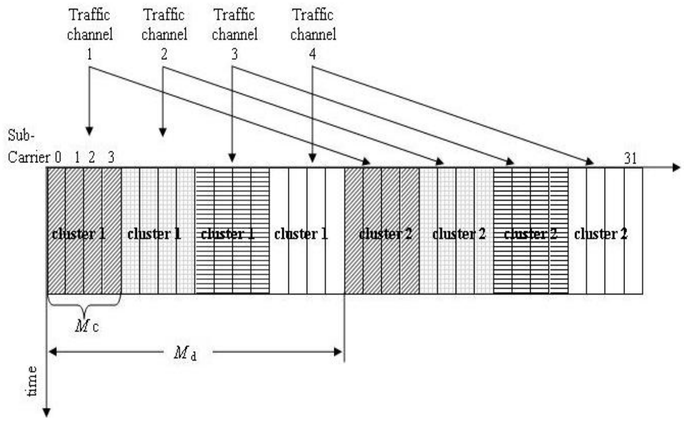

Figure 1 - OFDMA Traffic Channel Configuration

The Average BER of the l^{th} channel for the k^{th} user with M-ary QAM modulation is given by [13].

$$\mathrm{BER}_l^k = \frac{M}{5}\left(\exp\left(-\frac{3\mathrm{SNR}_l^k}{2(2^r-1}\right)\right) \quad (6)$$

Where r is the Number of bits per constellation $M = 2^r$ and M is the number of subcarriers per Channel. If the modulation scheme is MPSK system, then BER of the k^{th} user on l^{th} channel is given by [8].

$$\mathrm{BER}_l^k = \frac{1}{2}\left(1 - \sqrt{\frac{\mathrm{SNR}_l^k}{1+\mathrm{SNR}_l^k}}\right) \quad (7)$$

Assuming fading is an ergodic process on all traffic channels, the average BER of the entire system is given by.

$$\mathrm{BER} = \sum_{i=1}^{L}\sum_{j=1}^{K} \mathrm{BER}_i^j \quad (9)$$

3.2 Prediction model

The regression analysis is commonly used method for prediction model. In regression analysis the relationship between dependent variables and predicted variable need to specify, 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.

$$\hat{y}_{t+1} = f\left(y_t, ..., y_{t-k+1}\right)$$
$$Y = \left[y_t, ..., y_{t-k+1}\right] \quad (10)$$

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

$$[\hat{y}_{t+k}, \hat{y}_{t+k-1}, ..., \hat{y}_{t+1}] = f(y_t, ..., y_{t-k+1}) \quad (11)$$

The success of the prediction model will depends on how accurately we predict the K step value $\hat{y}$, ε prediction 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 Likely hood Estimation (MLE) [14][15]. Some of the general non linear predictors are Unscented Kalman Filter (UKF), differential algebra, Bayesian and neural network [16][17]. To implement temporal behavior to the nonlinear neural network predictor either in an explicit manner [18][19] or by implicit manner by build all together new predictor that has both nonlinearity as well as temporal behavior [20][21].

3.3 Neural network model

Feedforward neural network has ability to map any nonlinear function to an arbitrary degree of accuracy [1].One such popular feedforword network is radial basis function network. It is single hidden layer feedforword network where 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, this response are scaled by connection weights of the output layer and then produces network output when Gaussian basis function is used and is given by.

$$\hat{y} = \sum_{i=1}^{n} w_i \exp\left(-\frac{\|y-\mu_i\|}{2\sigma_i}\right) \quad (12)$$

Here σ_i is the dimension of the influence field of the hidden layer neuron, y and μ_i are input and prototype vector respectively. RBF has achieved considerable success in nonlinear function prediction but the performance of RBF is less satisfactory for nonlinear dynamic function prediction [21]. The Recurrent Radial basis function network considers the time as an internal representation, dynamic aspect of nonlinear function can be obtained by having self-connection on the input neuron of sigmoidal firing function and recurrent weights are the range [-1 , +1] with normal distribution, this is a special case of locally recurrent globally feedforward neural network[21]. The RRBFN output for Gaussian basis function is

$$\hat{y}(t) = \sum_{i=1}^{n} w_i \exp\left(-\frac{\sum_{j=1}^{m}\left(y^j - \mu_i^j\right)^2}{\sigma_i}\right) \quad (13)$$

Where j is the number of neurons in the input layer of RRBFN, the described RRBFN model is shown in Figure 2.

Recurrent neural network with standard gradient decent algorithms will provide better function approximation for short time steps. For the longer time steps due to the back propagation architecture, the error signal will propagate back and will vanish the gradient. Due to this phenomenon network weights will never be adjusted correctly and system will fail to predict for longer and complex time series steps. In order to deal with it echo state network [20] was proposed. Echo state network consists of two parts such as dynamical system with rich of dynamics followed by a memoryless output readout function shown in Figure 3.

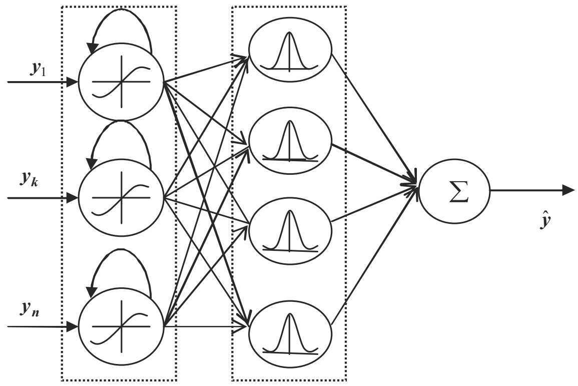

Figure 2-Recurrent radial Basis function network.

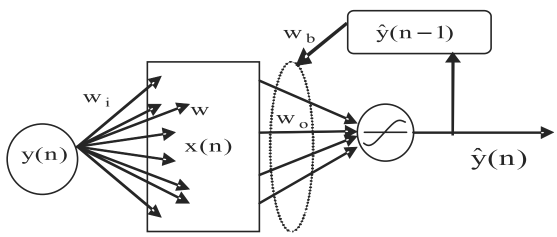

Figure 3 - Echo State network

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. The optimal connections neurons inside the reservoir will always require the number of trails. During the training process only weights of memoryless output function is changed through offline linear regression process or by online methods, such as Recursive Least Square (RLS). The general state of reservoir is given by.

$$x(n) = \varphi(w_i y(n) + wx(n-1) + w_b \hat{y}(n-1)) \qquad (14)$$

Where φ is the sigmoidal activation function, y(n) is current input vector, x(n-1) in 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.

$$\hat{y}(n) = \varphi_o(w_o x(n)) \qquad (15)$$

Where φ_o is activation function of output neuron, this can be 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 RRBFN and ESN model for BER prediction 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, AWGN, Signal strength and mobile speed and nonlinear parameter such as modulation and coding scheme is simulated. The simulation setup and its parameters are: jakes wireless channel with Doppler frequency of 75 Hz, additive white noise with the power spectrum N_o, QPSK modulation with ½ coding rate or 16-QAM modulation with ½ coding rate, FFT size is 128, Channel bandwidth is 1.25 MHz and 5 GHz Carrier Frequency. In order to achieve channel diversity, Fully Used Subchannelization (FUSC) technique is used[22]. Total number of guard subcarriers are 22 ,data subcarriers are 96, pilot subcarriers are 9, total number of traffic channels are 2, the number of clusters in each traffic channel is 2, traffic channel configuration is {(48, 24)} and the clusters spacing is 48 subcarriers. The output of the first phase is received fading signal of all subcarriers for the Signal to Noise Ratio (SNR) ranging from 5 to 35 dB and 10 to 40 dB for QPSK and 16-QAM respectively.

The second phase of simulation is training and testing of the RRBF and ESN predictor, here the fading signal samples collected in first phase is used for training and testing of predictors, the training and testing samples are randomly picked from the sample size of 6000. The RRBF network has three layers input, hidden and output, here 500 neurons in input layer with sigmiodal activation function with recurrent connection 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 with range of weights between -1 to +1. Input weights are in the range of -0.40 to +0.40, 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 output of RRBF and ESN network for QPSK modulation for 5 and 15 symbols prediction is shown in Figure 4. The 16-QAM modulation for 5 to 15 symbol prediction is shown in Figure 5. The minimum and maximum Mean Square Error (MSE) for both QPSK and 16-QAM is listed in Table 1.

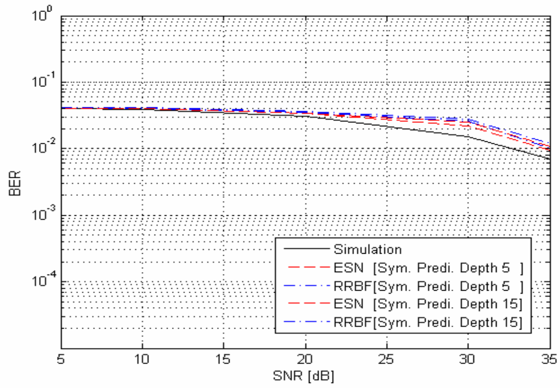

Figure 4- QPSK Modulation with Rayleigh Fading

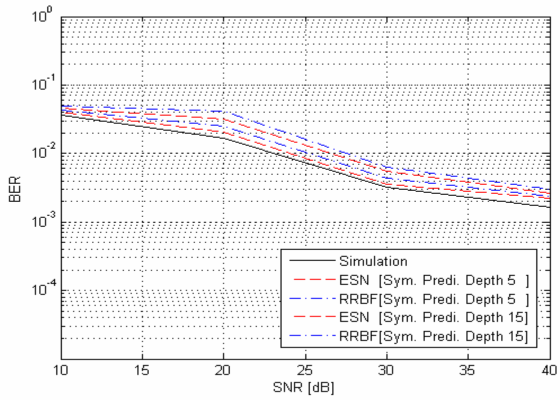

Figure 5- 16-QAM with Rayleigh Fading

Table. 1-Min. and Max.MSE for QPSK AND 16-QAM

Modulation	Symbol Depth	Network	Maximum MSE	Minimum MSE
QPSK	5	E.S.N	0.000023	0.0000031
QPSK	5	R.R.B.F.N	0.000032	0.0000059
QPSK	15	E.S.N	0.0013	0.00019
QPSK	15	R.R.B.F.N	0.0024	0.00057
16-QAM	5	E.S.N	0.052	0.0045
16-QAM	5	R.R.B.F.N	0.083	0.0074
16-QAM	15	E.S.N	0.092	0.021
16-QAM	15	R.R.B.F.N	0.135	0.028

5. CONCLUSION

In this paper, BER prediction of 802.16e OFDMA channel is demonstrated with two recurrent neural networks such as ESN and RRBFN. Simulation results shows that ESN based Predictor is superior in terms of prediction accuracy, but ESN network takes more training samples and longer training time compare to RRBFN. The prediction accuracy of ESN and RRBFN for 5 step prediction is 96.75% and 96.69% respectively. The prediction accuracy for 15 symbols ahead for ESN is 94.31% and RRBFN is 92.92%.. The performance of both ESN and RRBFN are with in the acceptable limit for both 5 and 15 symbol prediction for QPSK modulation as well as 16-QAM.

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