

Performance analysis of neural network based time domain adaptive equalization for OFDM

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Abstract - This paper investigate time domain neural network based LMS adaptive equalizer for broadband fixed wireless access system. The simulation result shows improvement in the BER, flatter spectral response, it also shows improvement in the convergence rate of the LMS algorithms which results the fast reconfigurability required for Software Radio. The investigation is made in the multipath fading environment and using different mapping techniques.

Index Terms- OFDM, ISI, ICI, Fading, LMS, Neural Network.

I. INTRODUCTION

In the rapidly growing world of wireless telecommunications, a number of trends are gaining widespread popularity. Among these is the explosion of interest in multi-carrier communications, and its application to wireless multiple-access. Wireless communication systems are currently designed to provide high data rates at high terminals speeds [1]. In particular, there has been a great deal of research and development of late in areas of OFDM (orthogonal frequency division multiplexing). High data rate give rise to intersymbol interference (ISI) due to multipath fading channels, such channel is called frequency selective channel. The time variant channel causes Doppler spread and the Doppler spread in conjunction with ISI gives rise to so called doubly selective channel.

In doubly selective channels, the time variation of the channel over an OFDM block destroys the orthogonality between subcarriers and so induces intercarrier interference (ICI). In addition to this, interblock interference (IBI) arises when the channel delay spread is larger than the cyclic prefix (CP), which to restore the orthogonality and so to eliminate ICI/IBI. In this paper, we propose time-domain neural network equalization techniques to combat these channel effects [2].

An emerging application that uses OFDM as a transmission technique is digital video broadcasting. Digital video broadcasting encounters long-delay multipath channels. Using a CP of length equal to the channel order, results in a significant decrease in throughput. On the other hand, applying digital video broadcasting over mobile channels for high speed terminals (motor way speeds) induces ICI which has been shown to decrease performance significantly. The

motivation of this paper is to combat these channel effects for such applications.

II. SYSTEM MODEL

The single input single output system is assumed for analysis, as shown in figure 1; it can be extended to single input multiple output (SIMO) or MIMO system. At the transmitter, incoming binary sequence is applied RS encoder, then to M-PSK modulator where M=4, 8, 16 are used for analysis. The channel is considered is multipath fading, the received sequence can be written as

$$y(n) = \sum_{\theta=-\infty}^{\infty} h(n, \theta)x(n - \theta) + \eta(n) \quad (1)$$

Where $x(n)$ is transmitted time domain sequence, $\eta(n)$ is AWGN, and $h(n, \theta)$ is multipath fading channel such as Rayleigh and Ricean channel are used for performance investigation[1]. The transmitted time domain sequence $x(n)$ can be written as

$$x(n) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} S^{(k)} [i] e^{j \frac{2\pi nk}{N}} \quad (2)$$

where $i = [n/(N+v)]$, and $m = n - i(N+v) - v$ this includes the transmission of cyclic prefix (CP) of length v .

III. TIME DOMAIN EQUALIZATION WITH NEURAL NETWORK

All the simulation and analysis in this paper are done in complex base band domain. Channel shortening with the use of a time domain equalizer as shown in figure 2, the objective is to shorten the channel impulse response to effective channel impulse response having significant length with the use of neural network based time domain equalizer. A Bayesian estimator can be used for channel equalization [6-8]. The Bayesian estimation rule is given by the following equation:

$$s'(k) = \sum_{i=1}^M s_i p(s_i) \quad (3)$$

where s_i denotes the i -th possible transmitted symbol, belonging in the set of M possible complex symbols and $p(s_i)$ is the the probability density function of occurrence of s_i .

This estimator type may be implemented using neural networks. In the presence of AWGN, the probability density function $p(s_i)$ is chosen to be a Gaussian function[5]. The Gaussian-shaped radial basis function ϕ_i may be described as follows:

$$\phi_i(\mathbf{r}) = (2\pi\sigma^2)^{-d/2} \exp\left(-\frac{\|\mathbf{r} - \mathbf{c}_i\|^2}{2\sigma^2}\right) \quad (4)$$

where d is the dimensionality of the observation space, $\phi_i(\mathbf{r})$ is the radial basis function output of the i -th neuron to the n dimensional input vector \mathbf{r} , \mathbf{c}_i is the center of the i -th neuron and σ denotes the standard deviation of the AWGN. The radius of the radial basis functions in this case equals $2\sigma^2$.

Assuming that Gaussian-shaped radial basis functions are used, equation (3) is modified as follows:

$$\mathbf{s}'(k) = \sum_{i=1}^N w_i \phi_i(k) \quad (5)$$

Since the received signal has been corrupted by AWGN, an update algorithm (e.g. the complex LMS algorithm) has to be used for correct symbol detection. In OFDM systems the channel is divided into K subchannels. Thus, the proposed neural network channel equalizer may be divided into K neural "subnetworks" (Fig. 2). Each neural subnetwork is used for the equalization of a single subchannel.

The α -LMS algorithm applied to single adaptive linear neuron shown in figure 3 embodies the minimal disturbance principle, in accordance with which it incorporates new information into the weight vector while changing embedded information based on past

learning to minimal extent[3],[4]. The α -LMS algorithm has recursive update equation

$$W_{k+1} = W_k + \mu \epsilon_k \frac{X_k}{|X_k|^2} \quad (6)$$

Here the weight vector W_k is modified by the product of the scaled error and normalized input vector

$$\Delta W_k = \frac{\mu \epsilon_k X_k}{|X_k|^2} = \frac{\mu}{|X_k|} \epsilon_k X_k^T = \mu'_k \epsilon_k X_k^T \quad (7)$$

where X_k is a unit vector in the direction of X_k , μ is the learning rate, and μ'_k is a pattern-normalized learning rate. Note that the change in error for the pattern X_k depends on the extent of change in the weight vector, W_k . This can be seen as follows

$$\Delta \epsilon_k = (d_k - X_k^T W_{k+1}) - (d_k - X_k^T W_k) \quad (8)$$

$$= -X_k^T \Delta W_k \quad (9)$$

However,

$$\Delta W_k = W_{k+1} - W_k = \frac{\mu \epsilon_k X_k}{|X_k|^2} \quad (10)$$

and therefore

$$\Delta \epsilon_k = -X_k^T \left(\frac{\mu \epsilon_k X_k}{|X_k|^2} \right) = -\frac{\mu \epsilon_k X_k^T X_k}{|X_k|^2} = -\mu \epsilon_k \quad (11)$$

The error correction is proportional to the error itself, and each iteration reduces the error by factor of μ . The choice of μ controls the stability and speed of convergence. In general, stability is ensured if $0 < \mu < 2$.

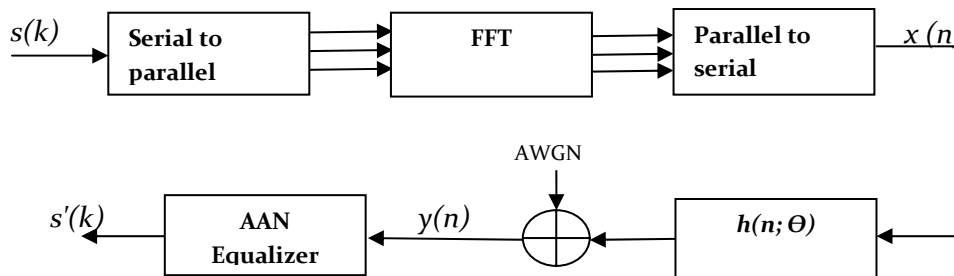


Figure 1. System model

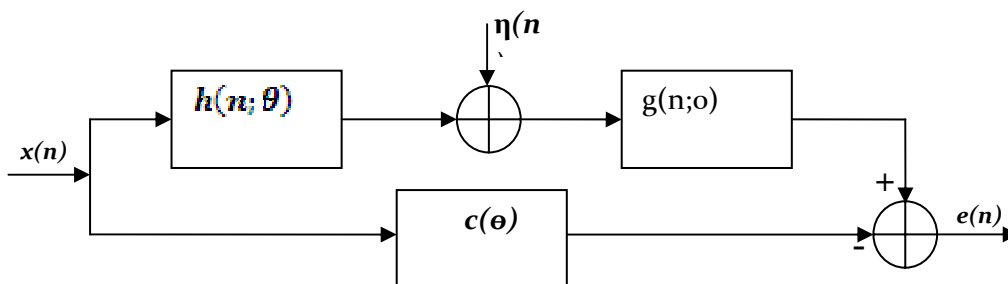


Figure 2. Time domain equalizer.

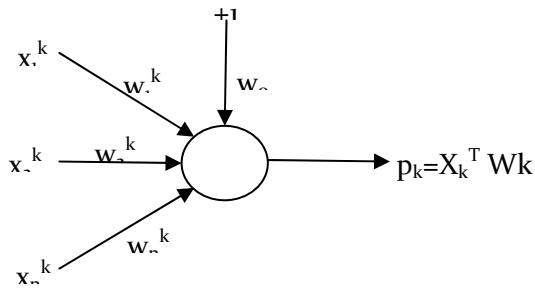


Figure 3. An adaptive linear neuron

IV. SIMULATION RESULTS

In this section, shown some simulation results for the proposed ISI/ICI mitigation techniques. The considered system for experiment was a SISO system with multipath fading channel. The figure 4. shows the SIMULINK implemented block diagram for LMS algorithm, the performance of OFDM system is analysed using different mapping techniques such as QPSK, 8-PSK, QAM and CPM, different channel environments such as Rayleigh fading and Ricean fading with AWGN.

As Shown in Figure 5(a) performance of system is analyzed for complex LMS algorithm without neural network, the BER performance of OFDM system is slightly improved as shown in figure 5(b) for neural network LMS algorithm with learning rate $\mu=0.01$. The BER performance is also investigated for various learning rates $\mu = 0.05, 0.1, 0.5, 1.0, 1.25$ as shown in figures 6, 7, 8 respectively, as learning rate increases the BER performance is improved significantly. The convergence rate is slower for less learning rate as learning rate increases the convergence rate is also increased considerably. The increase in convergence rate causes the fast reconfigurability of software radios.

V. CONCLUSION

This paper investigate the performance of OFDM system under multipath environment such as Rayleigh fading & Ricean fading with AWGN. Compared to conventional channel equalizer structures the proposed

neural network equalizer offers superior BER performance and better overall properties. Considering the fact that it offers practical advantages, it could be considered as a better alternative to the existing equalization methods for OFDM systems and thus as an excellent tool for software defined radios and cognitive radios where fast reconfigurability is required, wireless modem and future communication systems.

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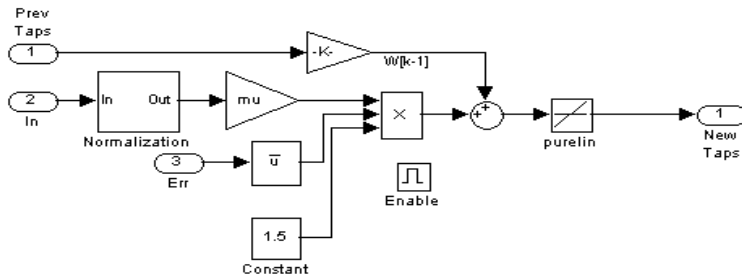


Figure 4. LMS Update Coefficient Block Diagram.

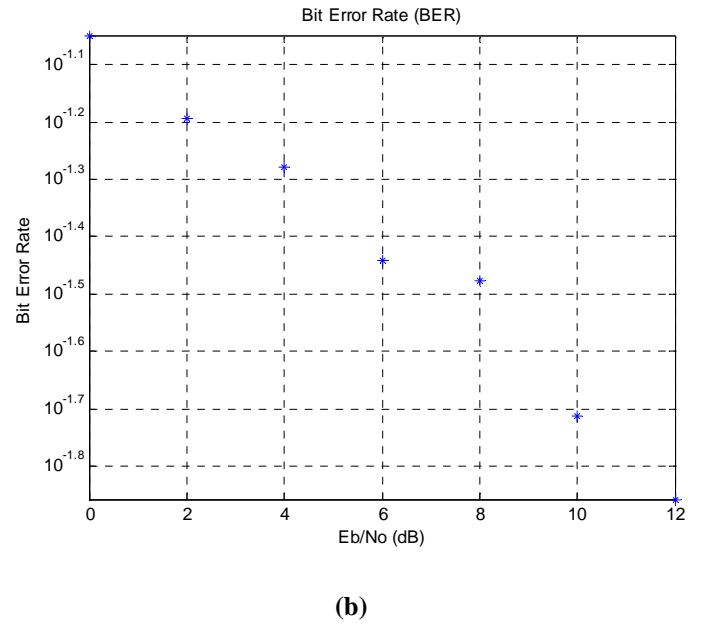
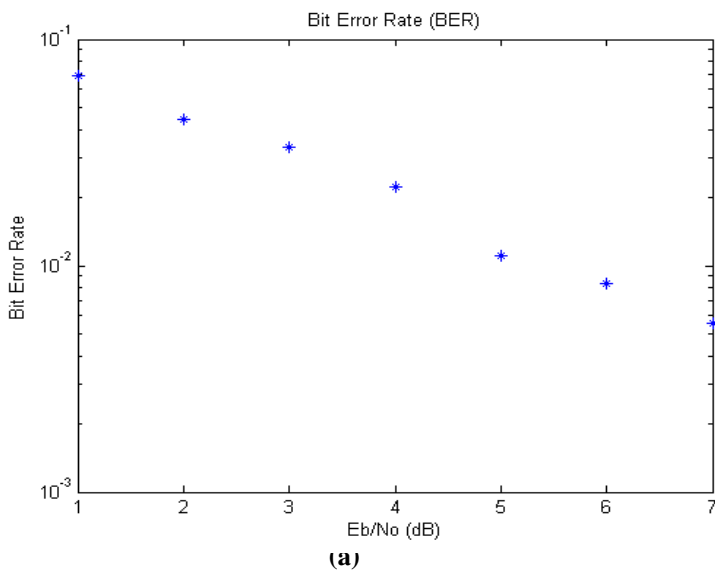


Figure 5. (a) BER performance Without NN Equalizer, (b) BER performances of the considered NN-equalizer

$\mu = 0.01$

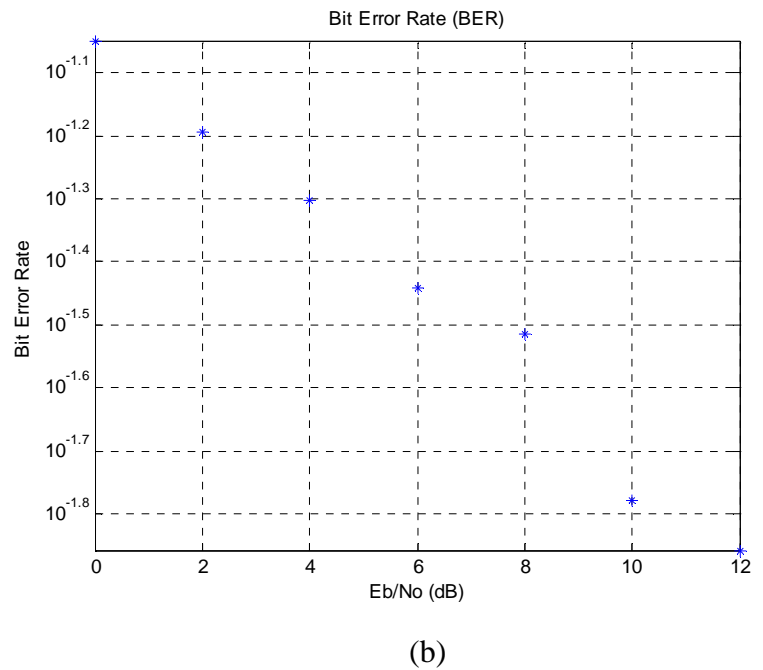
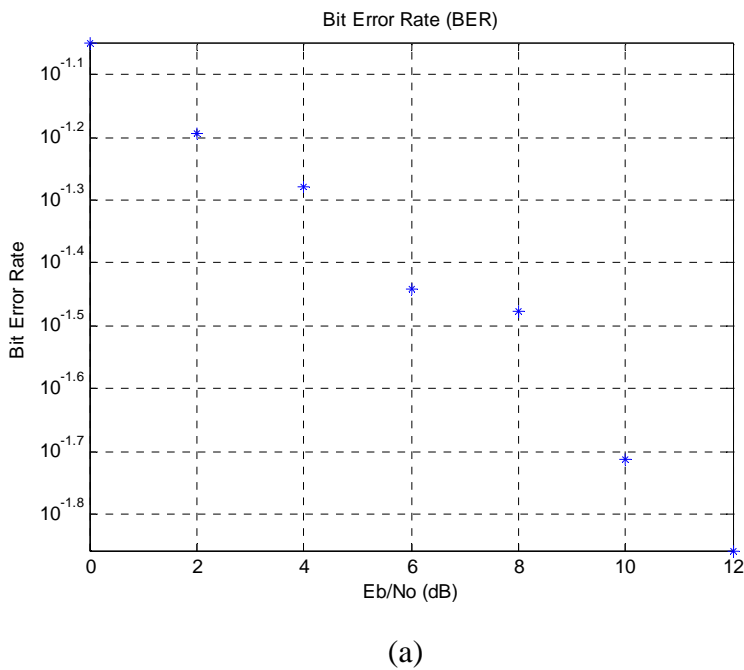


Figure 6. BER performances of the considered NN-equalizer(a) $\mu = 0.05$,(b) $\mu = 0.1$

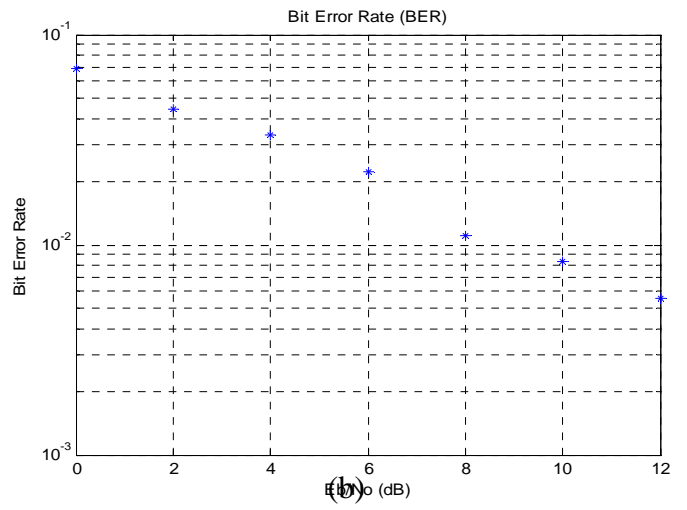
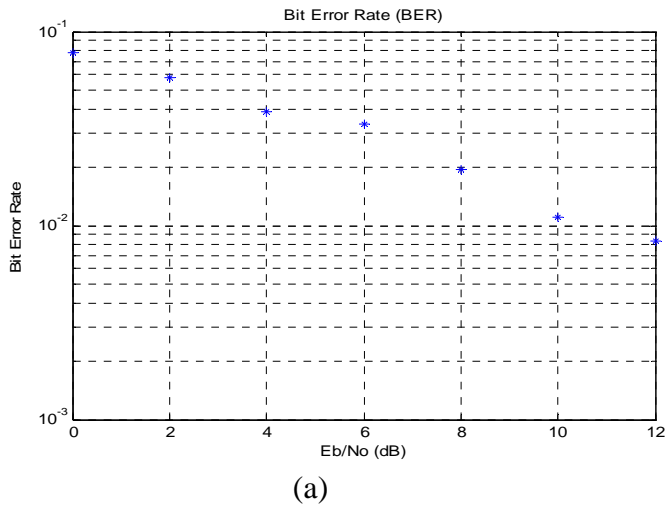


Figure 7. BER performances of the considered NN-equalizer (a) $\mu = 0.5$, (b) $\mu = 1.0$

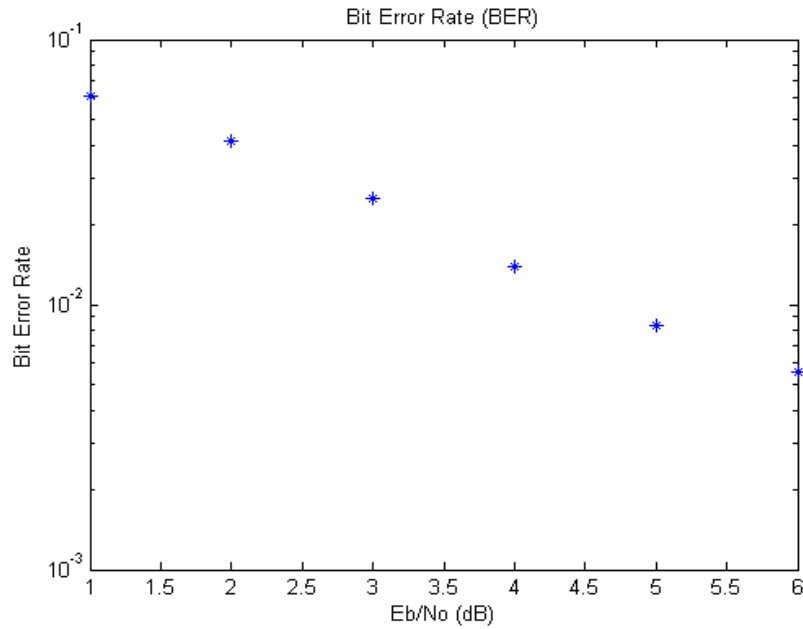


Figure 8. BER performances of the considered NN-equalizer $\mu = 1.5$.