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SIGNAL DETECTION IN MC-CDMA SYSTEM USING ELM RECEIVER TO MITIGATE MULTIPLE ACCESS INTERFERENCE AND NON-LINEAR DISTORTION

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ABSTRACT

Multi-carrier code-division multiple access system supports multiple users at the same time over the same frequency band. It is a multiple access scheme used in OFDM-based telecommunication systems. Though it is a promising wireless communication technology with high spectral efficiency and system performance, it is prone to multiple access interference (MAI). So, this paper mainly aims to design a MC–CDMA receiver to mitigate MAI. The classical receivers like maximal ratio combining (MRC), equal gain combining (EGC), and minimum mean square error (MMSE) fails to cancel MAI when the MC– CDMA is subjected to non-linearistic degradations. In this case, the neural network (NN) receivers could be a better alternative. The efficiency and effectiveness of the proposed ELM (Extreme Learning Machine) Algorithm-based receiver is studied thoroughly and explained in detail for the MC–CDMA with non-linearistic degradations.

Keywords: OFDM, CDMA, MAI, MRC, EGC, MMSE, ELM, maximum likelihood.

1. INTRODUCTION

OFDM is a frequency-division multiplexing (FDM) scheme used as a multi-carrier modulation method. It offers resistance from inter-symbol interference (ISI) by splitting a serial data into numerous orthogonal narrow-band streams. On the other hand, the direct sequence code division multiple access (DS-CDMA) is a spread spectrum communication technique that can support multiple users to transmit data within the same bandwidth. The multiple users' signals at the receiver are distinguished by using respective unique user specific spreading codes. Thus, it can provide high spectral efficiency and by integrating CDMA and OFDM, desired system can be obtained. However, like any other multiple access technique, the MC-CDMA system is also prone to multiple access interference (MAI), when one user comes under vicinity of another user in the same cell. Thus, in order to overcome this problem, an efficient receiver has to be designed in order to mitigate MAI from other users. The detection process becomes more challenging as the number of users in the system increases due to increased amount of the MAI. There are several designs and developments on MC-CDMA receivers. The maximum ratio combining (MRC) receiver which is among linear receivers fails to correct the channel induced phase distortions. The equal gain combining (EGC) receiver has the capability of correcting this, but fails to correct the faded magnitudes of the receiving signals. And, several communications systems are also prone to non-linearistic system distortions due to power amplifiers and faded radio environments. Though the minimum mean square error (MMSE) receiver detects transmitted signal by considering noise variance and channel co-variance, it cannot mitigate non-linearistic distortion in the channel, and gives high residual error. The trade-off between complexity and the performance draws considerable research attention. The practical systems need estimation of the channel state information, which imposes an additional complexity, whereas most of the classical detectors assume that the channel is perfectly known at the receiver's end. Besides this, MC-CDMA system signal detection process with non–linearistic system distortion can be considered as the pattern classification problem, where the decision boundary is highly nonlinear.

The Artificial Neural Network (ANN) models can be considered as a better alternative to signal detection problem because of their highly nonlinear pattern classification capability. They are parallel distributed structures in which many simple interconnected elements (neurons) simultaneously process information and adapt themselves to learn from past patterns. Attractive properties of NNs relevant of the signal detection problem are robustness, finite memory and nonlinear classification ability. Among various ANNs extreme learning machine (ELM) is a good choice. Recently, the extreme learning machine is getting an increasingly significant and efficient research topic for machine learning and AI due to its unique characteristics, i.e., extremely fast training, good generalization, and universal approximation/ classification capability. Unlike the other traditional learning algorithms, e.g., back propagation (BP)-based neural networks (NNs), or support vector machine (SVM), the parameters of latent layers of ELM are randomly generated and need not to be tuned, thus the hidden nodes could be established before the training samples are acquired.

The remaining paper is organized as such. The MC-CDMA system model along with its mathematical representation of the received signal is presented in the next section. The third section describes some of the classical receivers for MC–CDMA. The Details of proposed ELM Algorithm receiver for non-linear MC-CDMA system is discussed in the next one. Simulation analysis with results is elaborated in Section 5. Then the conclusion of this is presented in the last section.

2. MC-CDMA SYSTEM MODEL

The schematic diagram of the MC-CDMA system along with its transmitter and receiver is shown in Figure-1. The MC–CDMA system considered here allows K number of simultaneous users, and each user's data symbol is spread with a spreading code of length N. So, kth user's data is multiplied by a spreading code and then inverse fast Fourier transform (IFFT) is performed. The parallel output of IFFT is then converted into serial and added with remaining K–1 user's data stream. This signal is then sent through channel. At the receiver, the serial data is exposed to non-linearistic distortion and noise. This distorted serial data is converted to parallel, and fast Fourier transform (FFT) is performed. Then, the signal is fed to signal detector.

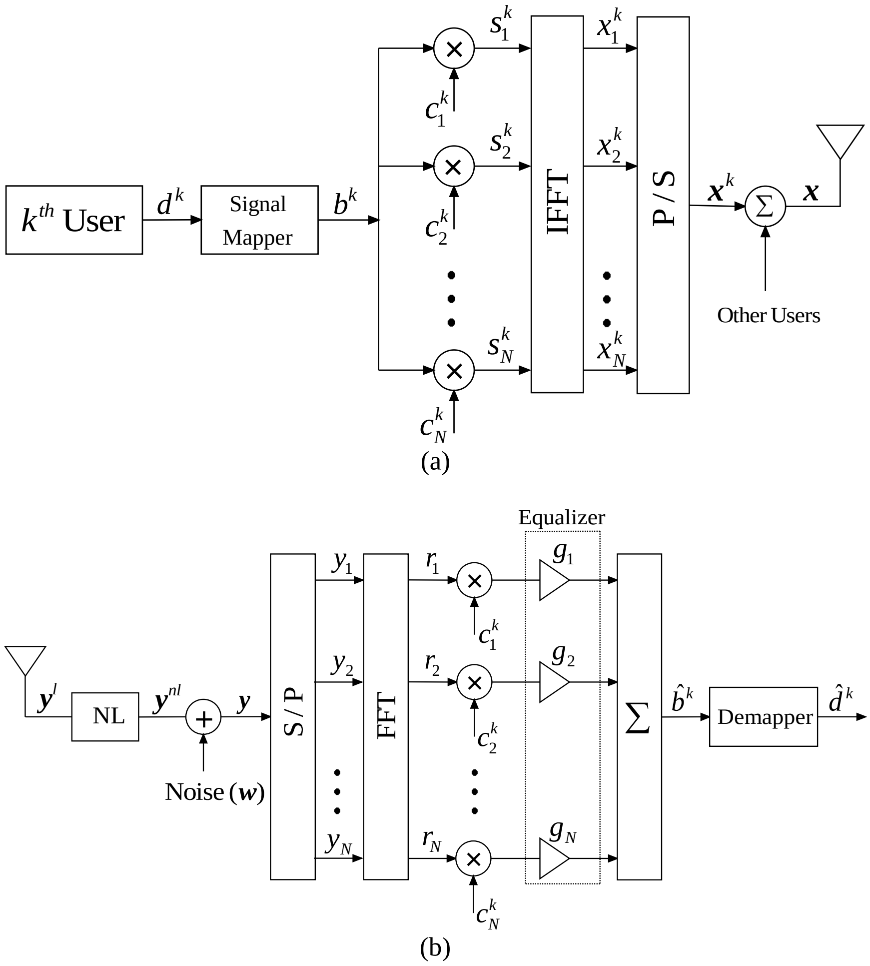

Figure-1. A MC-CDMA system (a) Transmitter (b) Receiver.

The discrete baseband representation of the transmitted signal vector in a time slot m can be written as:

$$x_m = \sum_{k=1}^{K}\sum_{n=1}^{N} s_n^k \exp\left(\frac{j2\pi nm}{N}\right), \qquad m = 1,2,...,N \tag{1}$$

where

$$s_n^k = \sqrt{E_c}\, b^k c_n^k, \qquad n = 1,2,...,N \tag{2}$$

In the above equation,
$b^k \in \{\pm1\}$ is the data symbol of user k,
$c_n^k \in \{\pm1\}$ is the n^{th} chip of the k^{th} user's spreading sequence,
E_c is the energy per subcarrier, or chip, and

$E_c = E_b/N$, where E_b is the energy per bit before spreading. This E_c is assumed to be same for all users.

So, discrete base band received signal vector from the transmitted signal vector $x = [x_1, x_2,\ldots,x_N]^T$ is expressed as:

$$\boldsymbol{y} = \mathrm{NL}\left(\boldsymbol{h}\otimes\boldsymbol{x}\right) + \boldsymbol{w} \tag{3}$$

where, $\boldsymbol{h}$ denotes channel impulse response, $\otimes$ denotes convolution operation, $\boldsymbol{w}$ denotes additive white Gaussian noise (AWGN)process having zero mean and a one-sided power spectral density of $N_0$and NL(.) denote non-linear function. Thus, the received symbol r_n of n^{th} sub-carrier can be expressed as:

$$r_n = \sum_{m=1}^{N} y_m \exp\left(\frac{-j2\pi nm}{N}\right), \quad n = 1, 2, ..., N \tag{4}$$

The received signal given in Eq. (04) can be written in a matrix form as:

$$\begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_N \end{bmatrix} = \text{NL}\left[\begin{bmatrix} H_1 & 0 & \cdots & 0 \\ 0 & H_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & H_N \end{bmatrix}\begin{bmatrix} c_1^1 & c_1^2 & \cdots & c_1^K \\ c_2^1 & c_2^2 & \cdots & c_2^K \\ \vdots & \vdots & \ddots & \vdots \\ c_N^1 & c_N^2 & \cdots & c_N^K \end{bmatrix}\begin{bmatrix} \sqrt{E_c} & 0 & \cdots & 0 \\ 0 & \sqrt{E_c} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sqrt{E_c} \end{bmatrix}\begin{bmatrix} b^1 \\ b^2 \\ \vdots \\ b^K \end{bmatrix}\right] + \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_N \end{bmatrix} \tag{5}$$

Where, H_n, n = 1, 2,…,N, is the n^{th} sub-carrier's frequency domain transfer factor of channel. For simplicity, the matrix representation shown in Eq. (05) can be written as:

$$\boldsymbol{r} = \text{NL}\left(\boldsymbol{HCAb}\right) + \boldsymbol{w} \tag{6}$$

3. CLASSICAL MC–CDMA RECEIVERS

At the receiver, each user's data symbol is detected using their unique user specific spreading code as shown in Figure 1(b). The estimate of k^{th} user's data symbol $\hat{b}^k$ given as:

$$\hat{b}^k = \sum_{n=1}^{N} g_n c_n^k r_n, \qquad k = 1, 2, ..., K \tag{7}$$

Where g_n is a frequency domain equalization gain factor.

3.1 Maximal Ratio Combining (MRC) Receiver

In Maximal Ratio Combining (MRC) scheme, the diversity combiner assigns a higher weight to stronger signal than a weaker signal, because a stronger signal provides a more reliable communication [8, 9]. The corresponding equalisation gain, g_n, is given as:

$$g_n^{mrc} = H_n^*, \quad n = 1, 2, ..., N \tag{8}$$

Using MRC equalizer gain given in eq. (08), the [K × 1] estimated signal vector $\hat{\boldsymbol{b}}$ is obtained as follows:

$$\hat{\boldsymbol{b}} = \left(\boldsymbol{G}_{mrc}\boldsymbol{C}\right)^T \boldsymbol{r} \tag{9}$$

where, $\boldsymbol{G}_{mrc} = diag\left[\boldsymbol{g}^{mrc}\right]$ is a [N × N] diagonal equalizer matrix, $\boldsymbol{C}$ is a [N × K] chip code matrix, and $\boldsymbol{r}$ is a [N × 1] receiver signal vector.

3.2 Equal Gain Combining (EGC) Receiver

The performance of MC-CDMA receiver is decent until there is a good degree of orthogonality among different user's spreading codes. However, the orthogonality of spreading codes may be demolished by multipath propagation in the medium. Although the MRC scheme optimally combines the multi-path components to maximise the SNR, it may further impair the orthogonality of the codes. In order to avoid this problem, Equal Gain Combining (EGC) detector can be used because it can correct phase distortions of the signal introduced in the channel [8, 11]. Thus, the equalisation gain of EGC detector g_n, is given by:

$$g_n = \frac{H_n^*}{|H_n|}, \quad n = 1, 2, ..., N \tag{10}$$

Using EGC equalizer gain given in eq. (10), the [K × 1] estimated signal vector $\hat{\boldsymbol{b}}$ is obtained as follows:

$$\hat{\boldsymbol{b}} = \left(\boldsymbol{G}_{egc}\boldsymbol{C}\right)^T \boldsymbol{r} \tag{11}$$

where, $\boldsymbol{G}_{egc} = diag\left[\boldsymbol{g}^{egc}\right]$ is a [N × N] diagonal equalizer matrix.

3.3 Minimum Mean Square Error (MMSE) Receiver

Let, b be the transmitting signal vector of K number of users, then estimate of it, that is $\hat{\boldsymbol{b}}$, is obtained by linearly combining the received signals r with the aid of the array weight matrix G_{mmse} and chip code matrix C, resulting in [12]:

$$\hat{\boldsymbol{b}} = \left(\boldsymbol{G}_{mmse}\boldsymbol{C}\right)^T \boldsymbol{r} \tag{12}$$

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where, G_{mmse} is a $[N \times N]$ diagonal equalizer matrix obtained by minimizing the $\mathrm{MSE} = E\left[\left|\hat{\boldsymbol{b}} - \boldsymbol{b}\right|^2\right]$, so:

$$\boldsymbol{G}_{mmse} = (\boldsymbol{H}^H \boldsymbol{H} + 2\sigma_n^2 \boldsymbol{I}_N)^{-1} \boldsymbol{H}^H \tag{13}$$

where $(.)^H$ indicates Hermitian transpose and I_N is N-dimensional identity matrix.

3.4 Maximum Likelihood (ML) Receiver

The ML detector uses the Maximum a Posteriori (MAP) criterion when all the users are equally likely to transmit [12]. The ML detector supporting K simultaneous transmitting users invokes a total of 2^{mK} metric evaluations in order to detect the actual transmitting symbol vector, where m denotes the modulation order of signal mapper. Let B be the $K \times 2^{mK}$ dimensional matrix containing i^{th} possible transmitting symbol vector in i^{th} column, where $i = 1, 2,\ldots, 2^{mK}$, then the ML detector computes the Euclidean distance between actual received signal vector r and expected received vector $\hat{\boldsymbol{r}} = \boldsymbol{HCAb}$ obtained from one of the possible transmitting vectors, that is $b \in B$. The possible transmitting vector, which gives minimum Euclidian distance, is assumed to be most possible transmitting vector as expressed here:

$$\hat{\boldsymbol{b}} = \arg\left\{\min_{\boldsymbol{b}\in\boldsymbol{B}} \left\|\boldsymbol{r} - \boldsymbol{HCAb}\right\|^2\right\} \tag{14}$$

Thus ML detector requires an exhaustive search to determine the actual solution. Unfortunately, the corresponding computational complexity grows exponentially with the number of users and modulation order. Due to this exhaustive search, ML can be feasible in lower order systems only.

4. MULTILAYER EXTREME LEARNING MACHINE ALGORITHM BASED RECEIVER

The configuration of an NN based receiver for MC–CDMA is shown in Figure-2. Firstly, the NN based receiver is designed according to the MC–CDMA structure and then the corresponding model is trained using training symbols. During network training, an adaptive algorithm has to be applied recursively to update the free parameters of the network based on the error obtained. The process of training a NN involves the adjustment of the weights between each pair of the individual neurons until a close approximation of the desired output is achieved. In Figure-2, a $[N \times 1]$ dimensional known received sequence '$\boldsymbol{r}$' corresponding to the $[K \times 1]$ dimensional transmitting signal vector '$\boldsymbol{b}$' is given as an input to the NN model.

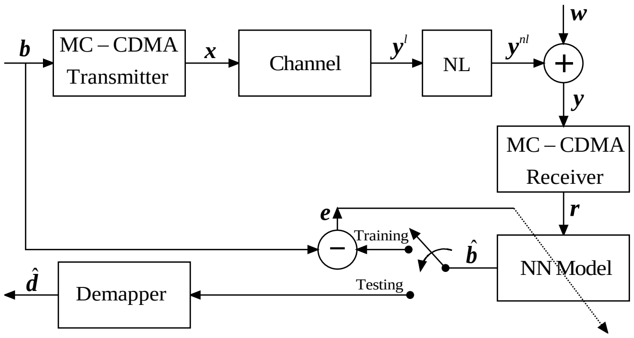

Figure-2. NN based MC–CDMA receiver.

The [K × 1] dimensional reaction vector bˆof NN demonstrate is contrasted and required (desired) reaction 'b' and blunder is processed. After the preparation (training), NN model which is all well prepared is changed to the testing mode and it will be utilized as a signal detector. The NN reaction bˆ will be considered as transmitted signal estimation. Among different pool of NN models, the ELM which is an SLFN is considered as a successful model for the nonlinear signal classification.

Extreme learning machine is one of the learning algorithms for the single hidden layer feedforward neural networks (SLFNs) used in classification and regression. It is easy to use and effective algorithm for single hidden layer feedforward neural network. The ELM used for single hidden layer feedforward neural network training can adaptively and randomly set the hidden layer node number and randomly assign the input weights and hidden layer biases, the output layer weights obtained by the least square method(LSM), the whole learning process completed through only one mathematical change without much iterations. If we compare the training speed with the traditional BP algorithm, then ELM has been significantly improved (usually 10 times or more).

ELM has the exact structure as SLFN as shown in Figure-3.

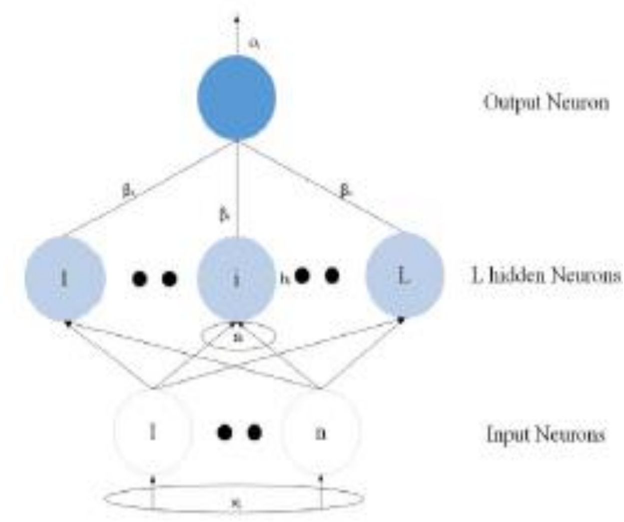

Figure-3. ELM based MC–CDMA receiver.

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Suppose *aij* be the random connection weight between the *ith* input neuron and the *jth* hidden neuron, *bj* is the bias of *jth* hidden neuron, activation function of hidden layer is *g*, which gives a training set {*xi*, *ti*| *xi*∈*Rd*, *ti*∈*Rm*, *i*=*1*,...,*N*}, where *xi* be the training data vector, *ti* representing the label or say target output of corresponding training simple, *N* donates the length of the training set. After then we can calculate the output matrix *H* of the hidden layer

$$H = \begin{bmatrix} h(x_1) \\ \vdots \\ h(x_N) \end{bmatrix}^T = \begin{bmatrix} h_1(x_1) & \cdots & h_1(x_N) \\ \vdots & \ddots & \vdots \\ h_L(x_1) & \cdots & h_L(x_N) \end{bmatrix} \tag{15}$$

Where

$$h_j(x_n) = g\left(\sum_i x_n(i) \cdot a_{i,j} + b_j\right) \tag{16}$$

The output weights vector should satisfy the equation

$$T = \beta \cdot H$$

Then we can calculate

$$\beta = T \cdot H^{\perp}$$

Then the output function of ELM is given as

$$f(x) = \beta \cdot h(x) = TH^T\left(HH^T\right)^{-1} \cdot h(x) \tag{17}$$

The ELM Algorithm can be summarized as follows:

a) Randomly generating or manually setting the latent(hidden layer parameters)i.e., the input weights (*aij*, *i*=*1*,...,*d* and *j*=*1*,...,*L*)and the biases (*bj*, *i*=*1*,...,*d* and *j*=*1*,...,*L*)for the additive latent nodes.

b) Calculation of the output (hidden layer) matrix *H* of hidden layer.

c) Calculation of the output weights according to the given equations.

5. SIMULATION ANALYSIS

Table-1. Simulation parameters.

Parameter	Description
Number of Users (K)	4
Chip Length (N)	16
Number of sub-carriers	16
Number of data symbols per frame (M)	1000
Number of data frames (N_F)	50
Modulation Type	BPSK
Channel	Rayleigh
Channel Non-linearity	$b(k) = a(k) + 0.2a^2(k) - 0.1a^3(k)$ [26]
ELM NN Parameters	
Number of input element	16 (equal to N)
Number of hidden neurons	4 (equal to K)
Number of output element	1
MLP training algorithm	Back Propagation
Learning rate parameter (μ)	0.08
Number of training symbols (N_T)	200
Number of testing symbols	500 (equal to M)

The performance of the ELM Algorithm based receiver for non-linear MC-CDMA system has been examined under Rayleigh fading channel. The simulation results obtained by the receiver has been compared to that of the conventional MRC, EGC and MMSE receivers. The results are provided for various receivers in terms of bit

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error rate (BER) performance. In this given simulation study, the BER is computed by averaging 50 (*NF*) data frames, where each of the data frames consists of 1000(*M*) data symbols and rest of the simulation parameters are given in Table-1.

The average bit error rate (BER) of the four different users in the system with the both nonlinear and linear system distortion at various *Eb*/*No* values can be seen in the given fig. The average BER has been calculated for MRC, EGC, MMSE and ELM receivers. It can be declared that the linear detectors MRC, EGC and MMSE has failed to decrease (mitigate) the distortions which are induced in the signals received. In case of such nonlinear conditions, all the normal receivers have a drop in the BER performance. However, as the ELM based receiver has high classification ability under nonlinear conditions also, its performance is better when compared to that of the remaining.

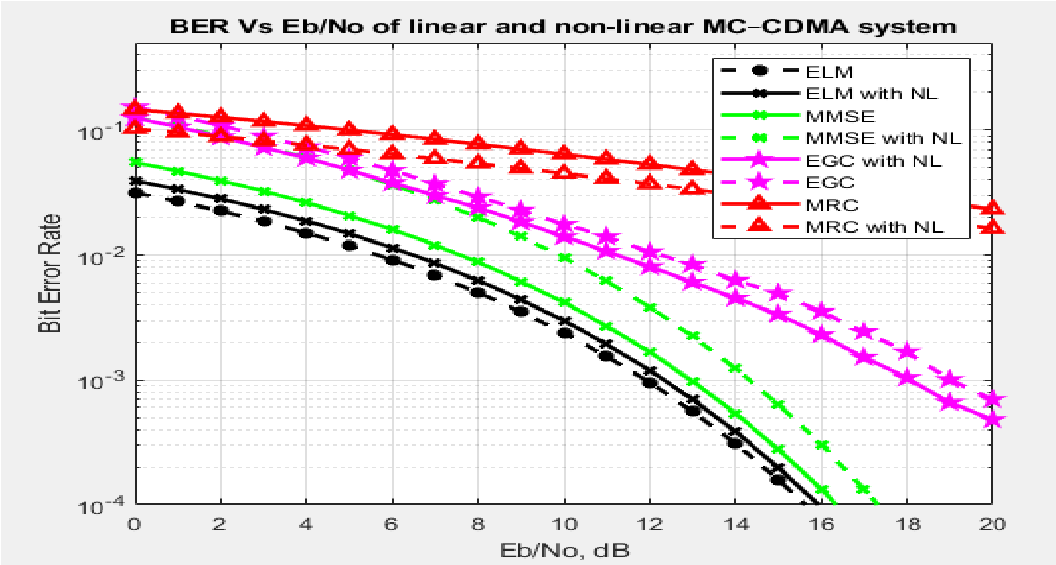

Figure-4. Average BER of all users using various receivers in linear and non-linear MC–CDMA system.

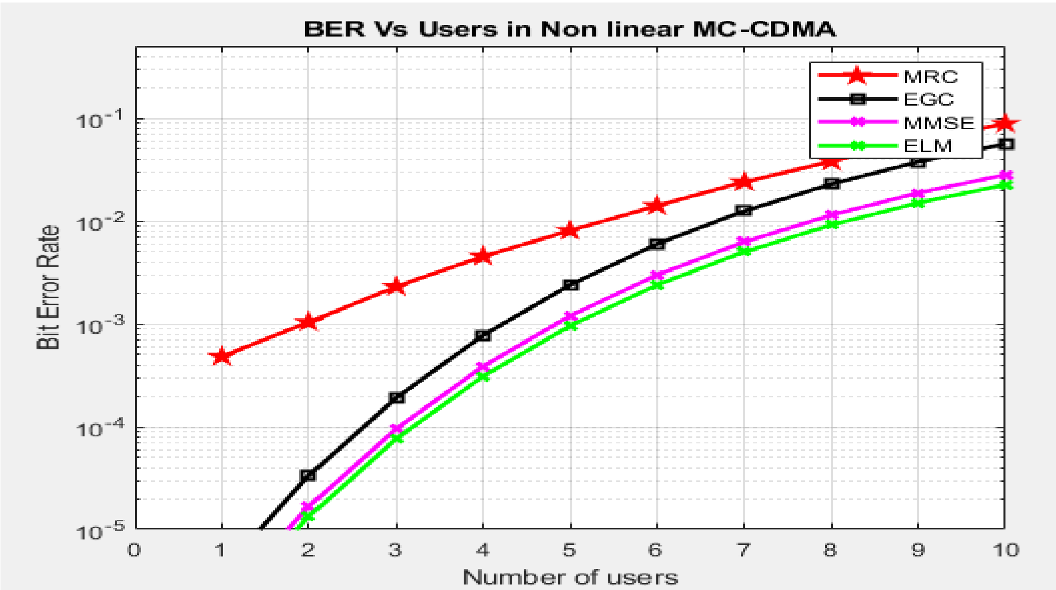

Figure-5. BER of User 1 using various receivers at 10 dB E_b/N_o in a non-linear MC-CDMA system with different number of users.

The performance and robustness of the ELM receiver is also analysed through the evaluation of the system while it is communicating with the different number of users as shown in the figure. The MAI (multiple access interference) of any system increases with the increase in the number of users which can be seen in the figure.

Also the effect of the non-linear distortions on the estimated signal constellation from the various receivers is shown in Figure-6. In this, the constellation of first user's estimated signals has been plotted while the first user is always transmitting '-1' in one complete data frame at 10 dB *Eb*/*No* and the MC-CDMA system is communicating four users simultaneously. It can be seen from the figure that, as the conventional receivers like MRC and EGC could not correct the amplitude and phase distortions (arbitrary) of the output symbols, the resultant symbols were widely dispersed over the entire signal space diagram. But, the MMSE which is a linear receiver assumes a priority of noise variance and channel covariance. So, some of the estimated symbols of it are closer and nearer to the BPSK decision boundary. However, the ELM receiver uses the phase correction mechanism during the network training and so these could continually correct the amplitude and phase distortions of the output symbols. Therefore, the estimated symbols are closer and from closer clusters around the transmitted symbol. Therefore, it can be declared from the simulations that the ELM receiver is a better alternative for the classical conventional receivers as it provides much better performance.

6. CONCLUSIONS

This paper intimates the development of an adaptive ELM receiver for MC–CDMA system which has both nonlinear and linear system distortions and the efficiency is described in detail. The performances of the classical receivers like MRC, EGC and MMSE have been compared with the desired ELM receiver on part of the BER and other performances. From the simulation analysis, the normal receivers resulted high errors and could not mitigate the amplitude and phase distortions when they are prone to non linearistic conditions. the ELM receiver can be the best among all the four on part of BER and overall performances.

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