



Receiver Design Using Artificial Neural Network for Signal Detection in Multi Carrier – Code Division Multiple Access System

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Abstract: Multi carrier–code division multiple access (MC–CDMA) system is a promising wireless communication technology with high spectral efficiency and system performance. Though the multiple access techniques provide high spectral efficiency, these techniques were prone to multiple access interference (MAI). So, this paper mainly aims at the design of the 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. By contrast, being highly non-linear classifiers, the neural network (NN) receivers could be better alternative under such a case. The feasibility, efficiency and effectiveness of the proposed multilayer perceptron (MLP) NN based receiver are studied in detail for the MC–CDMA with non-linearistic degradations.

Keywords: OFDM, CDMA, MAI, MRC, EGC, MMSE, MLP, Maximum likelihood.

1. Introduction

OFDM is a broadband multicarrier modulation scheme that offers resistance from inter symbol interference (ISI) by splitting a serial data into numerous orthogonal narrow band streams [1, 2]. 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 [3, 4]. At the receiver, the multiple user's signals are distinguished from each other by using their unique user specific spreading codes. Thus, DS-CDMA can provide high spectral efficiency. Since both these techniques have their own merits, by integrating CDMA and OFDM, it is expected to get the combined benefits. The resulting technique can be formally called as MC–CDMA system [5, 6]. However, like any other multiple access technique, the MC–CDMA system 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 is necessary for detecting each user appropriately by mitigating MAI from other users [7, 8]. The MC–CDMA receiver detects information of all users using the available information at the receiver, such as the received signal, spreading codes of all users and estimated channel state information. Further, this detection process becomes more challenging as the number of users in the system increases due to increased amount of the MAI.

During the past decade, several designs and development of MC–CDMA receivers have been carried out. Among various linear receivers, the maximum ratio combining (MRC) receiver fails to correct channel induced phase distortions [9, 10]. The equal gain combining (EGC) receiver has the capability of correcting channel induced phase distortions, but fails to correct faded magnitudes of receiving signals [11]. On the other hand, several communications systems are 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, as a result it gives high residual error [12]. By contrast, the highly complex and nonlinear Maximum Likelihood (ML) detector is capable of achieving optimal performance through an exhaustive search; hence its use in practical systems is avoided [12]. The trade-off between complexity and the performance draws considerable research attention [13–16].

Most of the aforementioned classical detectors assume that the channel is perfectly known at the receiver’s end, whereas practical systems need estimation of the channel state information, which imposes an additional complexity. In addition to that, the process of signal detection in the MC–CDMA system with non-linearistic system distortion can be considered as a pattern classification problem, where the optimal decision boundary is highly nonlinear. Tacking these problems into consideration, the Artificial Neural Network (ANN) models can considered as a better alternative to signal detection problem because they highly nonlinear pattern classification capability [17–19]. The ANNs 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. Thus, in the recent past, ANNs are extensively utilized as multiuser detectors for space division multiple access–orthogonal frequency division multiplexing (SDMA–OFDM) system achieving better performance than conventional linear techniques [20–23]. Among various ANNs, the Multilayer Perceptron (MLP) is considered to be simple but powerful tools in the area of pattern classification, where the MLP classifies input pattern with arbitrarily shaped nonlinear decision boundaries [24]. So, Necmi Taspnar used this MLP model as a powerful tool for signal detection in MC–CDMA system [25]. However, the full capability of MLP receiver is not exploited. Hence, this paper tries to exploit the full capability of the MLP receiver.

The rest of the paper is organized as follows. The generalized MC–CDMA system model along with the mathematical representation of received signal is presented in Section 2. Section 3 describes some of the classical receivers for MC–CDMA. The Details of proposed MLP receiver for non-linear MC–CDMA system is discussed in Section 4. Simulation analysis with results is elaborated in Section 5. Finally, the conclusion is presented in Section 6.

2. MC–CDMA System Model

The schematic diagram of the MC–CDMA system along with its transmitter and receiver is shown in Fig. 1 [8]. 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, k^{th} 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.

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

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

Where

$$s_n^k = \sqrt{E_c} b^k c_n^k, \quad n = 1, 2, \dots, N \quad (2)$$

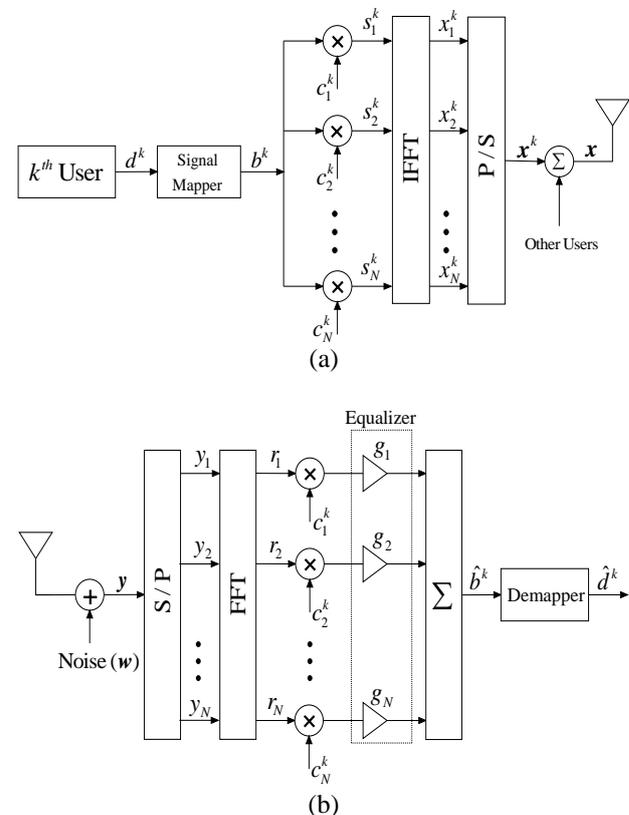


Figure. 1 A MC–CDMA system (a) Transmitter (b) Receiver

In Eq. (2), $b_k \in \{\pm 1\}$ is the data symbol of user k , $c_n^k \in \{\pm 1\}$ is the n^{th} chip of the k^{th} users 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 $\mathbf{x} = [x_1, x_2, \dots, x_N]^T$ is expressed as:

$$\mathbf{y} = \mathbf{h} \otimes \mathbf{x} + \mathbf{w} \quad (3)$$

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

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

The received signal given in Eq. (4) can be written in a matrix form as:

$$\begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_N \end{bmatrix} = \begin{bmatrix} H_1 & 0 & \dots & 0 \\ 0 & H_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & H_N \end{bmatrix} \begin{bmatrix} c_1^1 & c_1^2 & \dots & c_1^K \\ c_2^1 & c_2^2 & \dots & c_2^K \\ \vdots & \vdots & \ddots & \vdots \\ c_N^1 & c_N^2 & \dots & c_N^K \end{bmatrix} \begin{bmatrix} \sqrt{E_c} & 0 & \dots & 0 \\ 0 & \sqrt{E_c} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sqrt{E_c} \end{bmatrix} \begin{bmatrix} b^1 \\ b^2 \\ \vdots \\ b^K \end{bmatrix} + \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_N \end{bmatrix} \quad (5)$$

Where, $H_n, n = 1, 2, \dots, N$, is the n^{th} sub-carrier's frequency domain transfer factor of channel. For simplicity, the matrix representation shown in Eq. (5) can be written as:

$$\mathbf{r} = \mathbf{HCAb} + \mathbf{w} \quad (6)$$

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 Fig. 1(b). The estimate of k^{th} user's data symbol given as:

$$\hat{b}^k = \sum_{n=1}^N g_n c_n^k r_n, \quad k = 1, 2, \dots, K \quad (7)$$

Where g_n is a frequency domain equalization gain.

3.1 Maximal ratio combining 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:

$$g_n^{mrc} = H_n^*, \quad n = 1, 2, \dots, N \quad (8)$$

MRC equalizer gain given in Eq. (8), the $[K \times 1]$ estimated signal vector is obtained as follows:

$$\hat{\mathbf{b}} = (\mathbf{G}_{mrc} \mathbf{C})^T \mathbf{r} \quad (9)$$

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

3.2 Equal gain combining 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:

$$g_n = \frac{H_n^*}{|H_n|}, \quad n = 1, 2, \dots, N \quad (10)$$

Using EGC equalizer gain given in Eq. (10), the $[K \times 1]$ estimated signal vector is obtained as follows:

$$\hat{\mathbf{b}} = (\mathbf{G}_{egc} \mathbf{C})^T \mathbf{r} \quad (11)$$

where, $\mathbf{G}_{egc} = \text{diag} [g^{egc}]$ is a $[N \times N]$ diagonal equalizer matrix.

3.3 Minimum mean square error receiver

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

$$\hat{\mathbf{b}} = (\mathbf{G}_{mmse} \mathbf{C})^T \mathbf{r} \quad (12)$$

where, \mathbf{G}_{mmse} is a $[N \times N]$ diagonal equalizer matrix obtained by minimizing the $MSE = E[|\hat{\mathbf{b}} - \mathbf{b}|]$, so:

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

where, $(.)^H$ indicates Hermitian transpose and \mathbf{I}_N is N -dimensional identity matrix.

3.4 Maximum likelihood 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 \mathbf{B} be the $K \times 2^{mK}$ dimensional matrix containing i^{th} possible transmitting symbol vector in i^{th} column, where $i = 1, 2, \dots, 2^{mK}$, then the ML detector computes the Euclidean distance between actual received signal vector \mathbf{r} and expected received vector $\hat{\mathbf{r}} = \mathbf{HCAB}$ obtained from one of the possible transmitting vectors, that is $\mathbf{b} \in \mathbf{B}$. The possible transmitting vector, which gives minimum Euclidian distance, is assumed to be most possible transmitting vector as expressed here:

$$\hat{\mathbf{b}} = \arg \left\{ \min_{\mathbf{b} \in \mathbf{B}} \|\mathbf{r} - \mathbf{HCAB}\|^2 \right\} \quad (14)$$

The computational complexity of ML detector is very high due to this exhaustive search. Its complexity increases with the number of users and modulation order.

4. Multilayer Perceptron Neural Network Receiver

The configuration of an NN based receiver for MC-CDMA is shown in Fig. 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 Fig. 2, a $[N \times 1]$ dimensional known received sequence ' \mathbf{r} ' corresponding to the $[K \times 1]$ dimensional transmitting signal vector ' \mathbf{b} ' is given as an input to the NN model.

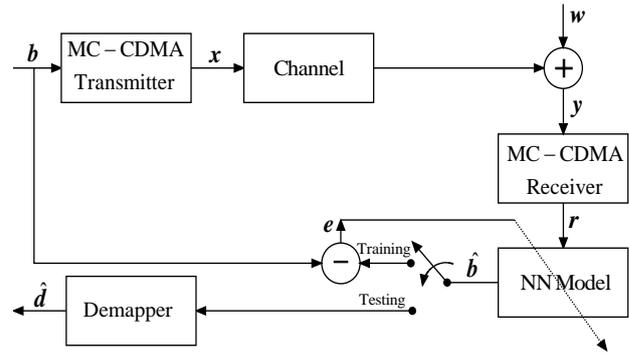


Figure. 2 NN based MC-CDMA receiver

The $[K \times 1]$ dimensional response vector $\hat{\mathbf{b}}$ of NN model is compared with desired response ' \mathbf{b} ' and error is computed. After the training, the well trained NN model is switched to the testing mode and it can be used as a signal detector. The NN response $\hat{\mathbf{b}}$ can be taken as estimate of transmitted signal. Among various NN models, the feed forward MLP model is considered as an effective model for the nonlinear signal classification [17, 18]. It consists of at least three layers of neurons such as an input layer, one or more hidden layers and an output layer. The hidden and output layers may have a non-linear activation function. The MLP network can be trained with the conventional Back Propagation (BP) algorithm, which is a supervised learning algorithm that uses two passes to calculate the change in network weights. In the forward pass, the weights are fixed and the input vector is propagated through the network to produce an output. An output error is calculated from the difference between actual output and the desired output. In the reverse pass, this error is then propagated backwards through the network, making changes to the weights as required.

The architecture of MLP model used for MC-CDMA receiver is shown in Fig. 3, which consists of an input layer of N units, one hidden layer of H_N neurons and an output layer of K neurons. Here, N and K are equal to chip length and number of users respectively. These layers have feed forward connections between neurons. Each neuron in the hidden has a summer along with a non-linear activation. Hence, the resultant output at h^{th} node in the hidden layer is expressed as:

$$z_h = \varphi \left(\sum_{n=1}^N U_{hn} r_n \right), \quad h = 1, 2, \dots, H_N \quad (15)$$

The output layer has a simple summation operator. Hence, the resultant output at k^{th} node in the output layer is expressed as:

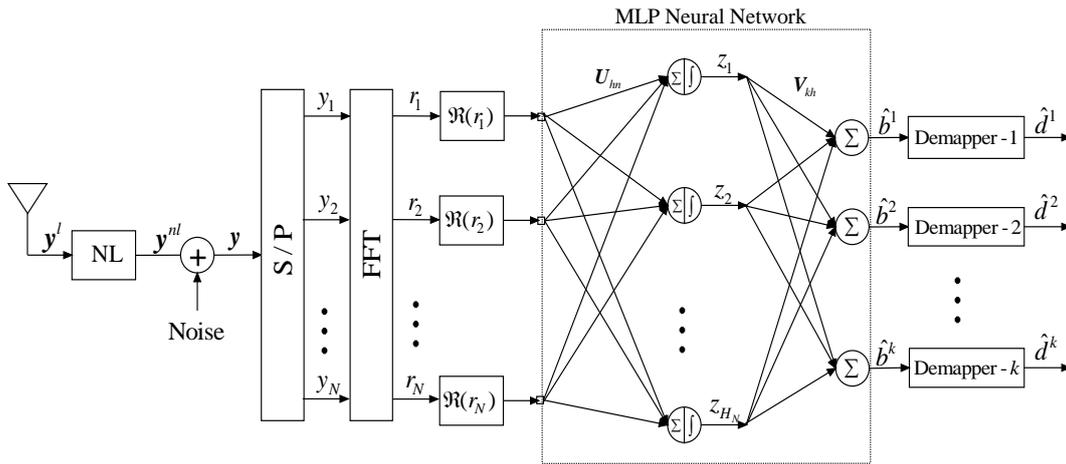


Figure. 3 MLP NN based MC-CDMA receiver

$$\hat{b}_k = \sum_{h=1}^{H_N} V_{kh} z_h, \quad k = 1, 2, \dots, K \quad (16)$$

Where U_{hn} denotes a weight associated between the hidden node h and input node n , V_{kh} denotes a weight associated between the output node k and hidden node h , $\varphi(t)$ denotes a nonlinear function such as bi-polar sigmoid, that is $\varphi(t) = \tanh(t)$, and $\varphi'(t)$ denote derivative of $\varphi(t)$, if $\varphi(t)$ is $\tanh(t)$, then, $\varphi'(t) = [1 - \tanh^2(t)]$.

In the MLP network training process, an iterative algorithm like the back propagation (BP) algorithm that minimizes an empirical error function can be used efficiently to update connection weights [19]. The BP algorithm computes error gradient δ at each layer using error term $e_k(i) = \hat{b}_k(i) - b_k(i)$, $k = 1, 2, \dots, K$ of each output node. Thus, the error gradient at k^{th} node of output layer and h^{th} node of hidden layer are given respectively [24]:

$$\delta_k = e_k \varphi'(\hat{b}_k), \quad k = 1, 2, \dots, K \quad (17)$$

$$\delta_h = \sum_{k=1}^K V_{kh} \delta_k \varphi'(z_h), \quad h = 1, 2, \dots, H_N \quad (18)$$

Using these error gradients, the network weights are updated in the $(i + 1)^{\text{th}}$ iteration as:

$$U_{hn}(i + 1) = U_{hn}(i) + \mu \delta_h(i) r_n(i) \quad (19)$$

$$V_{kh}(i + 1) = V_{kh}(i) + \mu \delta_k(i) z_h(i) \quad (20)$$

Where μ is the learning rate parameter, which should be chosen in between zero and one.

5. Simulation Analysis

In this section, the performance of MLP receiver for non-linear MC-CDMA system is examined under Rayleigh fading channel. Simulation results obtained by MLP receiver are compared to that of the conventional MRC, EGC, MMSE and ML receivers. Simulation results are provided for various receivers in terms of both bit error rate (BER) performance and complexity analysis. In the given simulation study, the BER is computed by averaging 1000 (N_F) data frames, where each data frame consists of 3000 (M) data symbols. Rest of the simulation parameters are given in Table 1.

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)	3000
Number of data frames (N_F)	1000
Modulation Type	BPSK
Channel	Rayleigh
Channel Non-linearity	$b(k) = a(k) + 0.2a^2(k) - 0.1a^3(k)$
MLP 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)	2000
Number of testing symbols	3000 (equal to M)

The average BER performance of four different users in a MC-CDMA system with both linear and nonlinear system distortion at different E_b/N_o values is shown in Fig. 4. This average BER is computed for MRC, EGC, MMSE, MLP and ML receivers [12]. From this figure it is observed that, the linear detectors like MRC, EGC and MMSE fail to mitigate the induced distortions in the received signals and leave residual interference, especially when the MC-CDMA system is exposed to non-linear distortion. Under such non-linearistic conditions, all the classical receivers have significant drop in BER performance. However, since the MLP NN has high non-linear classification ability, its performance even in non-linear system is not much deviating while comparing with the performance in linear system. In addition to that, its performance is close to the performance of optimal ML receiver. For example at 10^{-4} BER floor of a non-linear MC-CDMA system, the MLP receiver has 5 dB E_b/N_o gain while comparing with MMSE receiver and require just 1 dB additional signal power while comparing with ML receiver.

Robustness of MLP receiver is further analysed through performance evaluation of the MC-CDMA system while it is communicating different number of users as shown in Fig. 5. The MAI of any multiple access technique including MC-CDMA systems increases with number of users. So, the BER performance of all receiver of MC-CDMA degrades with increasing number of users as shown in Fig. 5. However, the MLP receiver has variable number of hidden node according to number of users, and hence it can be able form required decision boundaries for signal classification.

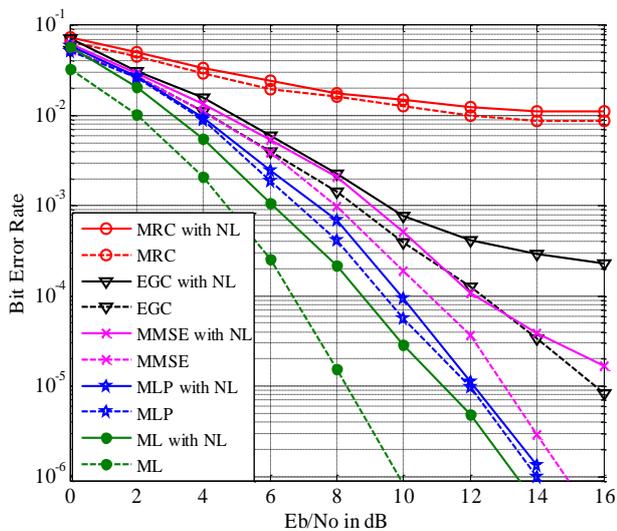


Figure. 4 Average BER of all users using various receivers in linear and non-linear MC-CDMA system

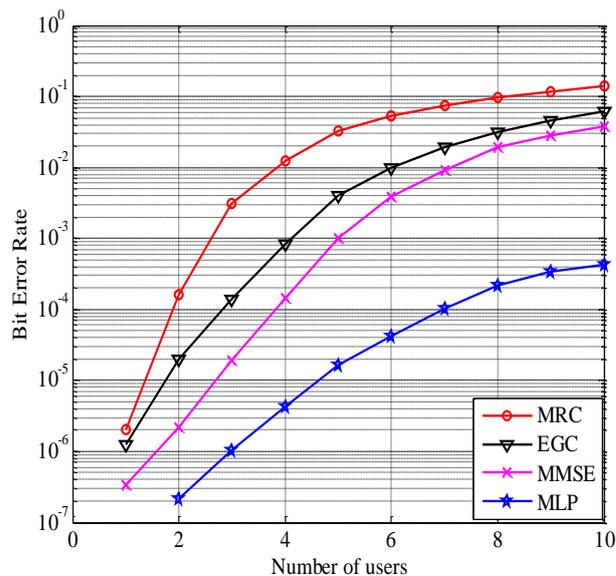


Figure. 5 BER of User 1 using various receivers at 10 dB E_b/N_o in a non-linear MC-CDMA system with different number of users

Further, the effect of non-linear distortion on estimated signal constellation using various receivers is shown in Fig. 6. In this figure, the constellation of User-1's estimated signals is plotted while User-1 is always transmitting '-1' in one complete data frame at 10 dB E_b/N_o and MC-CDMA system is communicating 4 users simultaneously. It is observed from this figure is that, as the classical receivers like MRC and EGC cannot correct the arbitrary amplitude and phase distortions of the output symbols, the resultant estimated symbols are widely dispersed over entire signal space diagram. However, though the MMSE is a linear receiver it assumes a priori knowledge of noise variance and channel covariance. Hence, some of its estimated symbols are closer to the BPSK decision boundary and even some of them cross the decision boundary entering in the wrong half plane.

By contrast, the adaptive MLP receiver use phase correction mechanism during the network training and hence these can continually correct the arbitrary amplitude phase distortions of output symbols. Thus, the estimated symbols form close clusters around the actual transmitted symbol. Thus, in this figure, the performance of MLP is slightly dropping while comparing with all other classical receivers. Thus, in this figure, the performance of MLP is slightly dropping while comparing with all other receivers. For example, when the MC-CDMA system is communicating 7 number of user, the MLP receiver has 10^{-4} BER, whereas the MRC, EGC and MMSE receivers have 0.08, 0.02 and 0.009 BERs respectively only.

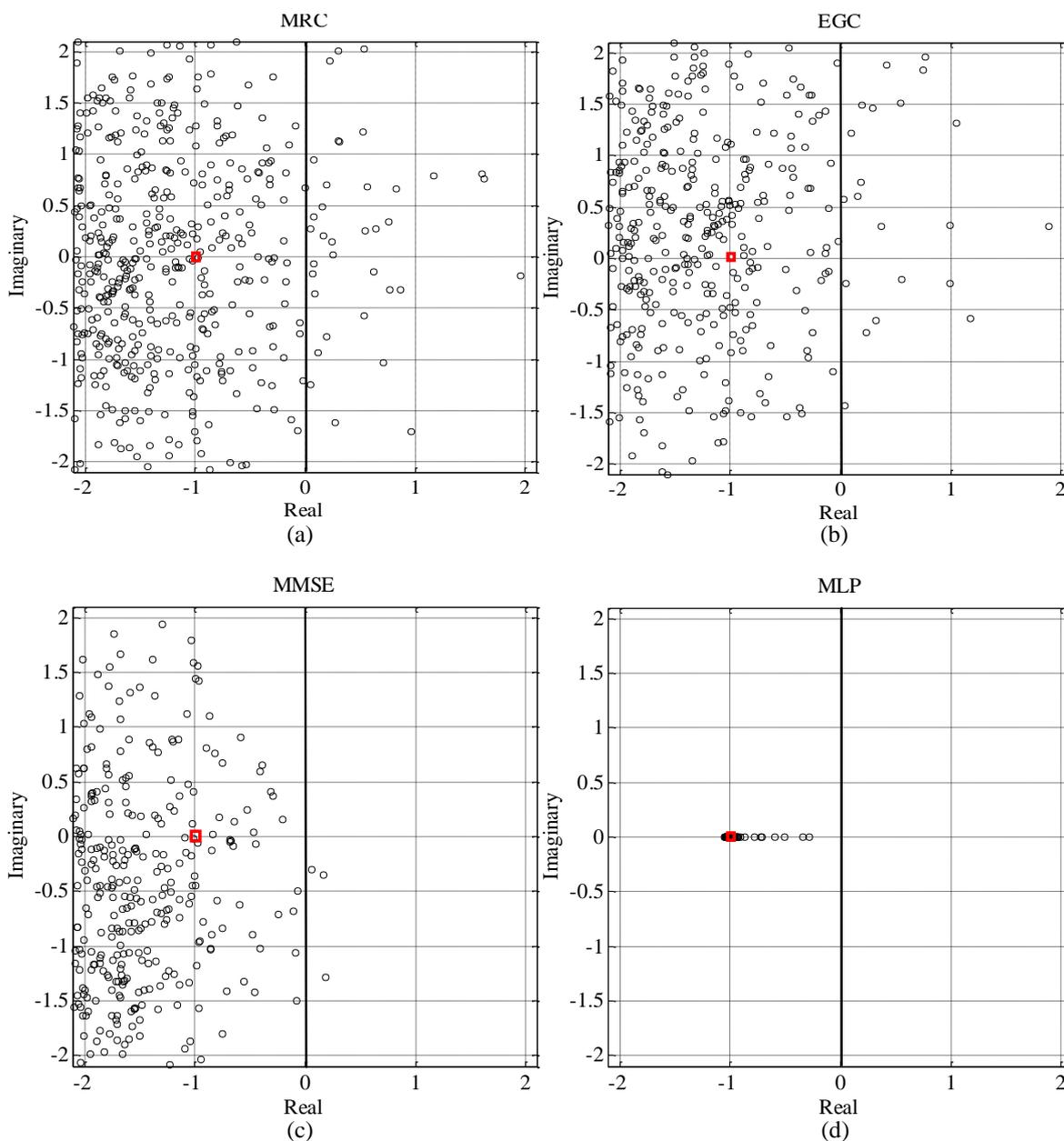


Figure. 6 Constellation plot of User 1’s detected signals in a non-linear MC–CDMA system at 10 dB E_b/N_o while User 1 is transmitting always ‘-1’ symbol using: (a) MRC receiver (b) EGC receiver (c) MMSE receiver (d) MLP receiver

Among various receivers of MC–CDMA system, though the ML receiver has an optimal performance, its computation complexity is very high. Especially, the computational complexity of ML receiver is increasing exponentially with a factor of 2^{mK} with number of users ‘ K ’ and modulation order ‘ m ’. Hence, the over-all complexity of the proposed MLP receiver and classical receivers is compared with the ML detector based on computational operations (both multiplication and addition) as given in Table 2.

The complexity of NNs mainly depends on the number of training samples (N_T) fed to the network model to reach the minimum MSE level and number

of data symbols per each data frame (M). Hence, the complexity of MLP is proportional to N_T and M . The complexity comparisons of various receivers are considered for a block-fading channel condition, where channel is assumed to be invariant for one complete data frame. In the given analysis, all parameters are chosen as given in Table 1. From the given complexity analysis, it is found that the complexity of MLP receiver is just a fraction of ML receiver and comparatively equal to all classical receivers. Hence the MLP receiver can be a better alternative to all classical receivers as it provide performance close to optimal ML receiver and has comparatively very low complexity.

Table 2. Complexity comparison of various MC-CDMA receivers

Receiver	Operation	Computational Complexity	Total	% of ML
MRC	multiplication	$N^2 \times (K + M)$	7.69×10^5	1.178
	Additions	$(N - 1) \times (K + M)$	4.51×10^4	0.979
EGC	multiplication	$N^2 \times (K + M + N)$	7.73×10^5	1.184
	Additions	$(N - 1) \times (K + M + N^2)$	4.89×10^4	1.062
MMSE	multiplication	$N^2 \times (K + M + 2N + 1)$	7.77×10^5	1.190
	Additions	$(N - 1) \times (K + M + N^2) + N^3$	5.29×10^4	1.149
MLP	multiplication	$[M \times H_N \times (N + K)] +$ $[N_T \times H_N \times (4N + 5K + 2H_N)]$	9.76×10^5	1.495
	Additions	$[M \times \{H_N \times (N + K - 1) - K\}] +$ $[N_T \times H_N \times (2N + 3K + H_N - 1)]$	5.92×10^5	1.286
	Tansig	$H_N \times (M + N_T)$	1.6×10^4	–
ML	multiplication	$M \times 2^{mK} \times N \times (N \times K + K^2 + K + 1)$	6.528×10^7	100
	Additions	$M \times 2^{mK} \times [N \times K \times (N + K - 1) - 1]$	4.6032×10^7	100

6. Conclusions

This paper investigates to develop an adaptive MLP receiver for MC-CDMA system with both linear and non-linear system distortions. The efficacy of MLP receiver along with its working model is discussed in detail. The performances of MLP receiver is compared with the linear MRC, EGC, MMSE and optimal ML receivers in terms of both BER performance and complexity analyses. From the extensive simulation study, it is found that, the classical receivers result high error floor as they cannot mitigate random amplitude and phase distortion from the received signal especially when the MC-CDMA system is subjected to the non-linearistic distortions. On the other hand, though the ML detector provides optimal performance, its complexity increases exponentially with number of users and modulation order. Hence, the MLP receiver comes out to be clear winner as it gives a BER performance close to the optimal ML and also it has great complexity gain over the exhaustive ML receiver. For example at 10^{-4} BER floor of a non-linear MC-CDMA system, the MLP receiver has 5 dB E_b/N_o gain while comparing with MMSE receiver and require just 1 dB additional signal power while comparing with ML receiver.

In this paper, the classical BP algorithm is used for training the MLP parameters, whereas this algorithm requires differentiable activation functions. Hence, selection of appropriate nonlinear activation

function of neuron node to suit the requirements in detection of high order modulated signals is a challenging task. So the free parameters of the MLP NN updating with metaheuristic optimization techniques based algorithms may be attempted and a new class of hybrid MUDs for MC-CDMA system can be developed.

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