

# Design of MC-CDMA receiver using radial basis function network to mitigate multiple access interference and nonlinear distortion

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**Abstract** Multicarrier code division multiple access (MC-CDMA) is a novel wireless communication technology with high spectral efficiency and system performance. However, all multiple access techniques including MC-CDMA were most likely to have multiple access interference (MAI). So, this paper mainly aims at designing a suitable receiver for MC-CDMA system to mitigate such MAI. The classical receivers like maximal-ratio combining and minimum mean square error fail to cancel MAI when the MC-CDMA is subjected to nonlinear distortions, which may occur due to saturated power amplifiers or arbitrary channel conditions. Being highly nonlinear structures, the neural network (NN) receivers such as multilayer perceptron and radial basis function networks could be better alternative for such a case. The possibility NN receiver for a MC-CDMA system under different nonlinear conditions has been studied with respect to both performance and complexity analysis.

**Keywords** OFDM · CDMA · MAI · MRC · MMSE · MLP · RBF · Maximum likelihood

## 1 Introduction

The direct sequence code division multiple access (DS-CDMA) is a communication system that can support multiple users to transmit data within the same spectral

band using their unique user-specific spreading codes [1, 2]. At the receiver, the multiple user's signals are distinguished from each other using the same codes. Thus, DS-CDMA can provide high spectral efficiency. At the same time, since it spreads spectrum, it may lead to frequency selective fading in the channel. So, the orthogonal frequency division multiplexing (OFDM), which is a broadband multicarrier modulation scheme that offers resistance from intersymbol interference (ISI) by splitting a serial data into numerous orthogonal narrowband streams, can be integrated to DS-CDMA to make frequency fading channel into flat fading channel [3, 4]. The resultant technique can be formally called as MC-CDMA system [5, 6]. 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 is necessary for detecting each user appropriately by mitigating MAI from other users [7, 8]. This MAI increases with increased number of users, and in such a case detection process becomes more challenging. The MC-CDMA receiver detects information of all users using the received signal, user-specific spreading codes and estimated channel state information.

In recent years, design of MC-CDMA receiver has become an attractive research area. 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 capability of correcting channel-induced phase distortions, but fails to correct faded magnitudes of received signals [11]. On the other hand, several communicational systems are prone to nonlinear distortions due to saturated power amplifiers and faded radio environments. Though the minimum mean square error (MMSE) receiver detects

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transmitted signal by considering noise variance and channel covariance, it cannot mitigate nonlinearistic distortion in the channel; as a result, it also gives high residual error [12, 13]. By contrast, the highly complex and nonlinear maximum likelihood (ML) receiver provides the optimal performance with an exhaustive search strategy. Hence, its implementation in real-time systems is restricted [12, 13]. So, research attention paid towards MC-CDMA receiver design considering the performance and complexity trade-off [14–16].

Majority of the abovementioned receivers detect signals with known channel state information, whereas practical systems require channel estimation. This may impose additional complexity. In addition to that, the process of signal detection in MC-CDMA system with nonlinear system distortion is viewed as a pattern classification issue with highly nonlinear decision boundaries. Considering these problems, the artificial neural network (ANN) or simply neural network (NN) models can interpret as a better alternative to signal detection issue because of their highly nonlinear pattern classification capability [17–19]. ANNs are highly nonlinear and parallel models with neurons as interconnection elements. ANNs can simultaneously process data and can adopt itself from past information. During signal detection process, NNs can offer robustness, limited memory and nonlinear classification ability. Thus, in 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 [20–25]. In the family of NNs, the multilayer perceptron (MLP) is a simple and powerful model used to classify input signals by randomly shaped nonlinear decision boundaries. So, Necmi Taspnar [26] used this MLP model as a powerful tool for signal detection in MC-CDMA system. However, in this paper, the full capability of MLP receiver is not exploited because the nonlinear distortion in the MC-CDMA system is not considered. Further, compared to MLP, the RBF has much improved performance during signal detection because RBF with Gaussian activation function may better approximate Gaussian noise than MLP [27, 28]. Hence, this paper tries to exploit full capability of MLP and RBF receivers by detecting transmitted signals of MC-CDMA system in nonlinear environment.

Organization of this paper is as follows. The generalized MC-CDMA system model with its mathematical notations is given in Sect. 2. The classical receivers for MC-CDMA system are discussed in Sect. 3. Section 4 describes the details of proposed neural network-based receiver for nonlinear MC-CDMA. Section 5 presents simulation analyses, and conclusion is given in Sect. 6.

### 2 MC-CDMA system model

The schematic block diagram of MC-CDMA system along with transmitter and receiver is presented in Fig. 1 [8]. The MC-CDMA system considered here allows  $K$  number of simultaneous users, and information symbol of each user is spread with a unique spreading code of length  $N$ . So,  $k$ th user’s data are multiplied by a spreading code, and then inverse fast Fourier transform (IFFT) is applied. The parallel output of IFFT is then converted into serial and added with remaining  $K - 1$  user’s data stream. This serial data signal is then passed through channel where nonlinear distortions and noise are added. These distorted serial data are converted to parallel, and fast Fourier transform (FFT) is applied. Then, the signal detection is performed. The discrete baseband transmitted signal vector in a time slot  $m$  is represented as:

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

where

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

In the above equation,  $b^k \in \{\pm 1\}$  is the data symbol of user  $k$ ,  $c_n^k \in \{\pm 1\}$  is the  $n$ th chip of the  $k$ th 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.

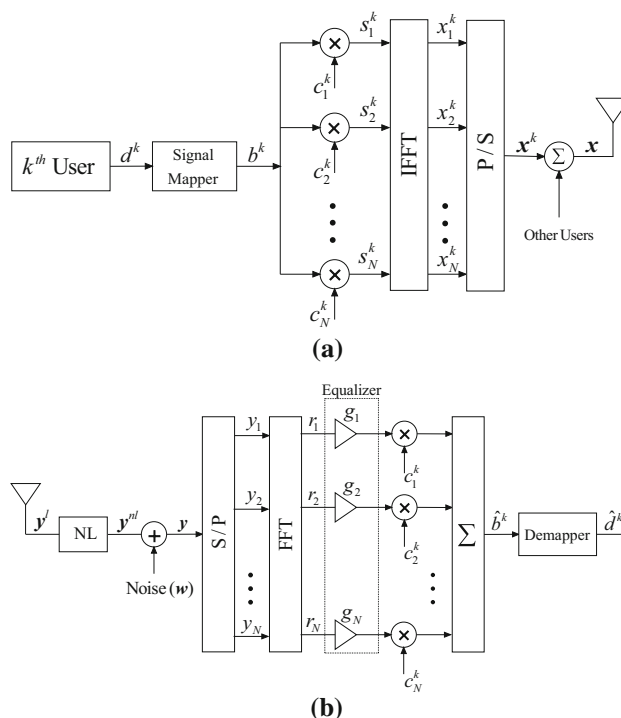


Fig. 1 A MC-CDMA system a transmitter, b receiver

So, discrete baseband received signal vector from the transmitted signal vector  $\mathbf{x} = [x_1, x_2, \dots, x_N]^T$  is expressed as:

$$\mathbf{y} = \text{NL}(\mathbf{h} \otimes \mathbf{x}) + \mathbf{w}, \tag{3}$$

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

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

Matrix form of the received signal given in Eq. (4) is denoted 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  $H_n, n = 1, 2, \dots, N$ , is the  $n$ th subcarrier’s frequency-domain transfer factor of channel. For simplicity, the matrix representation shown in Eq. (5) can be written as:

$$\mathbf{r} = \text{NL}(\mathbf{HCA}\mathbf{b}) + \mathbf{w}. \tag{6}$$

### 3 Classical MC-CDMA receivers

At the receiving end, data symbol of each user is detected using its unique user-specific spreading code  $c_n^k$  and frequency-domain equalization gain factor  $g_n$  as shown in Fig. 1b. Thus, the estimate of  $k$ th user’s data symbol  $\hat{b}^k$  is given as:

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

#### 3.1 Maximal-ratio combining (MRC) receiver

In maximal-ratio combining (MRC) receiver, 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 equalization gain,  $g_n$ , is given as:

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

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

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

where  $\mathbf{G}_{\text{mrc}} = \text{diag}[\mathbf{g}^{\text{mrc}}]$  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 Minimum mean square error (MMSE) receiver

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

$$\hat{\mathbf{b}} = (\mathbf{G}_{\text{mmse}}\mathbf{C})^T \mathbf{r}. \tag{10}$$

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

$$\mathbf{G}_{\text{mmse}} = (\mathbf{H}^H \mathbf{H} + 2\sigma_n^2 \mathbf{I}_N)^{-1} \mathbf{H}^H, \tag{11}$$

where  $(\cdot)^H$  denotes Hermitian transpose and  $\mathbf{I}_N$  is identity matrix of dimension  $N$ .

#### 3.3 Maximum likelihood (ML) receiver

The ML receiver works on the maximum a posteriori (MAP) criterion to detect signal vector of all users, while all users transmit data with equal probability [12]. However, the ML receiver requires  $2^{mK}$  number of metric computations to estimate actual transmitting signal vector, where  $m$  and  $K$  denote the modulation order and number of users, respectively. 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 receiver calculates the Euclidean distance between actual receiving signal vector  $\mathbf{r}$  and possible receiving signal vector  $\hat{\mathbf{r}} = \mathbf{HCA}\mathbf{b}$  found from one of the probable transmitting vectors, that is  $\mathbf{b} \in \mathbf{B}$ . The probable signal vector, which gives least Euclidean distance, is expected to be most likely to transmit as denoted here:

$$\hat{\mathbf{b}} = \arg \left\{ \min_{\mathbf{b} \in \mathbf{B}} \|\mathbf{r} - \mathbf{HCA}\mathbf{b}\|^2 \right\}. \tag{12}$$

Thus, ML detector requires an exhaustive search to determine the actual solution. Unfortunately, the corresponding

computational complexity increased extremely as the number of users and modulation order increase. Due to this exhaustive search, ML can be feasible in lower-order systems only.

#### 4 Neural network-based receivers for MC-CDMA system

The NN-based receiver for MC-CDMA is illustrated in Fig. 2. In the first stage, NN-based receiver is designed as per the MC-CDMA configuration and then the designed model is trained using training symbols. During training phase, an adaptive algorithm has to be used iteratively to adjust the network weights based on the error computed between desired output and actual network response. This network training is continued till minimum error 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 taken as an input of NN model. The  $[K \times 1]$ -dimensional response vector  $\hat{\mathbf{b}}$  of NN model is compared with desired response ' $\mathbf{b}$ ,' and error is calculated. Now, this well-trained network is used as signal detector in testing phase. The trained NN response  $\hat{\mathbf{b}}$  can be taken as estimate of transmitted signal.

##### 4.1 Multilayer perceptron (MLP) neural network receiver

In recent past, the MLP structure is treated as an efficient model for classification of nonlinear signals [17, 18]. It has minimum three layers such as an input layer, one or more hidden layers and an output layer. The hidden and output layers may have a nonlinear activation function. The MLP network mostly trained with the supervised back-propagation (BP) algorithm [17]. In the BP algorithm, firstly the weights are fixed and the input signal vector is transmitted through the network to yield an output vector. The output vector is used to compute an error while comparing with

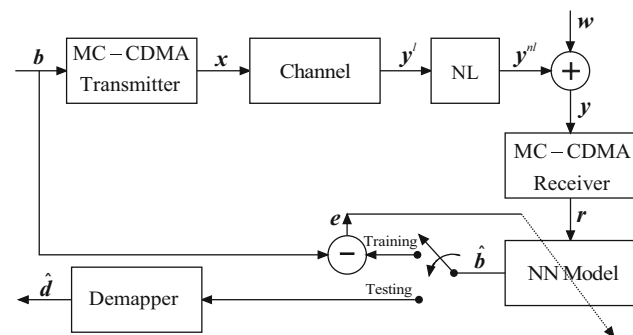


Fig. 2 NN-based MC-CDMA receiver

the desired signals. This error is then reverted back through the network to modify the network weights.

The structure of MLP receiver for MC-CDMA contains an input layer of  $N$  units, one hidden layer of  $H_N$  neurons and an output layer of  $K$  neurons as shown in Fig. 3. Here,  $N$  and  $K$  are corresponding to chip length and number of users, respectively. Feed-forward connections have been established among these layers. Each hidden neuron is modelled with a summer and a nonlinear activation. So, the resultant output of  $h$ th hidden neuron is denoted as:

$$z_h = \varphi \left( \sum_{n=1}^N U_{hn} \Re(r_n) \right), \quad h = 1, 2, \dots, H_N, \quad (13)$$

where  $\Re$  denotes real part. The output nodes are simple summers, and hence, the resultant output of  $k$ th output node is denoted as:

$$\hat{b}_k = \sum_{h=1}^{H_N} V_{kh} z_h, \quad k = 1, 2, \dots, K, \quad (14)$$

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

In the MLP network training process, BP algorithm can be used as follows [17]. Initially, the BP algorithm calculates error gradient  $\delta$  of each layer using the obtained error term  $e_k(i) = \hat{b}_k(i) - b_k(i)$ ,  $k = 1, 2, \dots, K$ . So, the error gradients at  $k$ th output node and  $h$ th hidden neuron are given, respectively, as:

$$\delta_k = e_k \varphi'(\hat{b}_k), \quad k = 1, 2, \dots, K \quad (15)$$

and

$$\delta_h = \sum_{k=1}^K V_{kh} \delta_k \varphi'(z_h), \quad h = 1, 2, \dots, H_N. \quad (16)$$

These error gradients are used to modify the network weights in the  $(i + 1)$ th iteration as:

$$U_{hn}(i + 1) = U_{hn}(i) + \mu \delta_h(i) \Re(r_n(i)) \quad (17)$$

$$V_{kh}(i + 1) = V_{kh}(i) + \mu \delta_k(i) z_h(i). \quad (18)$$

Here, the rate learning parameter  $\mu$  is to be chosen carefully between zero and one.

##### 4.2 Radial basis function (RBF) receiver

In NN domain, similar to MLP, the RBF model is also became popular in several classification problems for its close relation with Bayesian estimators [27, 28]. RBF

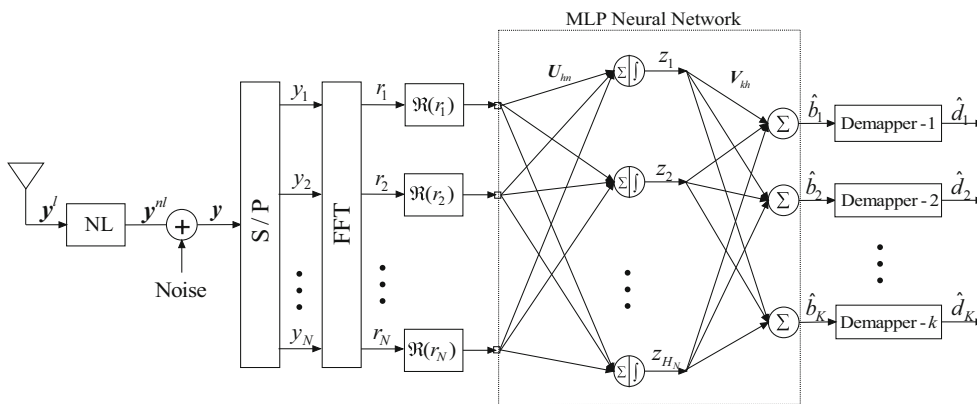


Fig. 3 MLP NN-based MC-CDMA receiver

network models form clusters such as hyperspheres around the similar group of input signals to classify them. Compared to MLP, the RBF configuration has better approximation capability for nonlinear classification problems due to its Gaussian activation function, which better approximates the Gaussian noise. This activation depends on the distance between the input vector and the centre. By properly selecting the number of hidden neurons, approximately  $2^K$ , where  $K$  is the number of users in the MC-CDMA system and by training all free parameters accurately, the RBF is able to detect users appropriately.

The architecture of RBF model is a three-layer feed-forward network, which consists of an input layer of  $N$  number of input units, an output layer of  $K$  number of neurons and the hidden layer with  $H_N$  number of neurons existing between input and output layers as shown in Fig. 4. The values of  $N$  and  $K$  are corresponding to chip length and number of users of the MC-CDMA system, respectively. The interconnection between input layer and hidden layer forms hypothetical connection and between the hidden and output layer forms weighted connections. In general, the RBF network incorporates Gaussian activation

functions; hence, the output of each neuron in the hidden layer is expressed as:

$$z_h = \exp\left(-\frac{\|\Re(\mathbf{r}) - \mathbf{C}_h\|^2}{2\sigma_h^2}\right), \quad h = 1, 2, \dots, H_N, \quad (19)$$

where  $\mathbf{C}_h$  is the  $(N \times 1)$ -dimensional centre and  $\sigma_h$  is the spread parameter of the  $h$ th hidden neuron. The neurons in the output layer are simple summing elements. Hence, the output of each output neuron is calculated as:

$$\hat{\mathbf{b}}_k = \sum_{h=1}^{H_N} W_{kh} z_h, \quad k = 1, 2, \dots, K. \quad (20)$$

In the RBF network training process, an iterative algorithm like GD that minimizes an empirical error function can be used to update free parameters of the network [29]. The procedure of this algorithm is summarized below.

Gradient descent algorithm for RBF network training:

- (a) Initialize randomly all the network parameters such as  $W_{kh}(i)$ ,  $\mathbf{C}_h(i)$  and  $\sigma_h(i)$  at iteration  $i$  ( $=1$ ). The network centres can be initialized by  $k$ -means clustering algorithm [20].

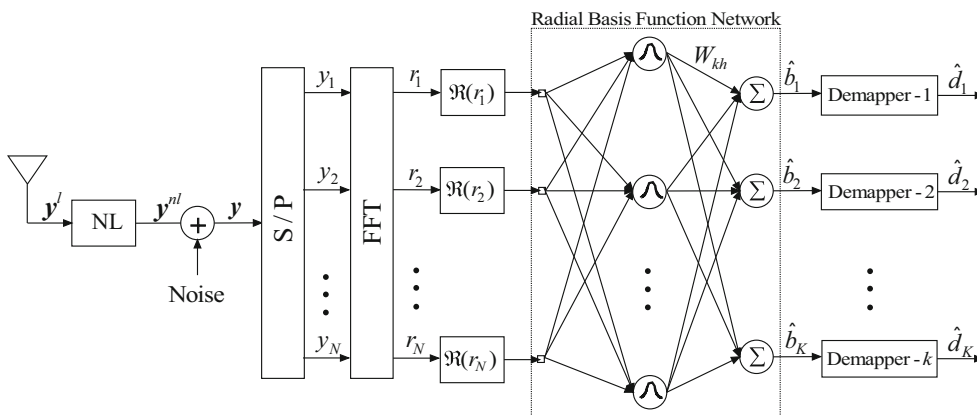


Fig. 4 RBF NN-based MC-CDMA receiver

**Table 1** Simulation parameters

Parameter	Description
Spreading code type	Hadamard
Number of users ( $K$ )	4
Chip length ( $N$ )	16
Number of subcarriers	16
Number of data symbols per frame ( $M$ )	3000
Number of data frames ( $N_F$ )	1000
Modulation type	BPSK
Channel	Rayleigh
<i>NN parameters</i>	
Number of input element in MLP	16 (equal to $N$ )
Number of hidden neurons in MLP	16 (equal to $2^K$ )
Number of output element in MLP	4 (equal to $K$ )
Number of input element in RBF	16 (equal to $N$ )
Number of hidden neurons in RBF	16 (equal to $2^K$ )
Number of output neurons in RBF	4 (equal to $K$ )
Learning rate parameter of MLP ( $\mu$ )	0.08
Learning rate parameters of RBF ( $\mu_w, \mu_c, \mu_s$ )	[0.08, 0.2, 0.12]
Number of training symbols ( $N_T$ )	1000
Number of testing symbols	3000 (equal to $M$ )
<i>The IEEE 802.11n WLAN channel parameters</i>	
Delay in nsec.	[0, 10, 20, 30, 40, 50, 60, 70, 80]
Average path gain (dB)	[0, -2.5, -5.4, -5.9, -9.2, -12.6, -15.6, -18.7, -21.8]
Maximum Doppler spread (Hz)	3

(b) Compute the hidden vector  $z(i)$  and output vector  $b(i)$ , respectively, from Eqs. (19) and (20).

(c) Compute the error term  $e_k(i)$  of each output node as:

$$e_k(i) = \hat{b}_k(i) - b_k(i), \quad k = 1, 2, \dots, K. \quad (21)$$

(d) Update the weights, centres and spreads according to:

$$W_{kh}(i+1) = W_{kh}(i) + \mu_w e_k(i) z_h(i), \quad (22)$$

$$C_h(i+1) = C_h(i) + \mu_c z_h(i) \frac{e^T(i) W_{kh}(i)}{\sigma_h^2(i)} \left( \sum_{n=1}^N \Re(r_n(i)) - C_h(i) \right), \quad (23)$$

$$\sigma_h(i+1) = \sigma_h(i) + \mu_s z_h(i) e^T(i) W_{kh}(i) \frac{\|\Re(r(i)) - C_h(i)\|^2}{\sigma_h^3(i)}, \quad (24)$$

where  $\mu_w$ ,  $\mu_c$  and  $\mu_s$  are the weight, centre and spread learning parameters, respectively, and  $(\cdot)^T$  indicates transpose operation.

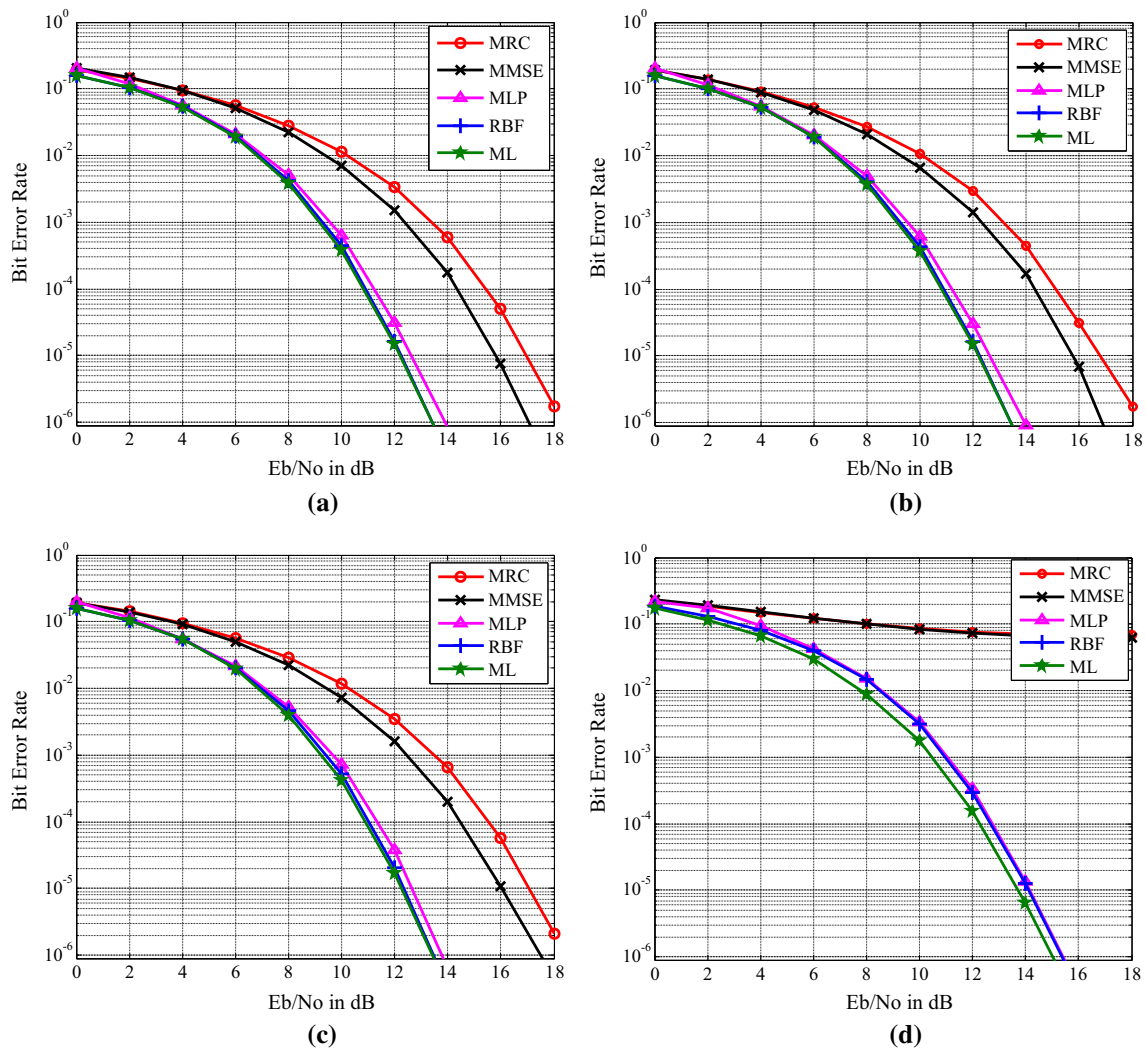
Compute the total error  $\|\hat{b}_k(i) - b_k(i)\|^2$  and proceed for the computation to the next iteration ( $i+1$ ) from Step b until this error is less than a defined value or specific convergence criteria is met.

## 5 Simulation analysis

In this section, the outcomes of the proposed NN-based receivers for nonlinear MC-CDMA system have been examined under IEEE 802.11n indoor wireless local area networks (WLAN) channel conditions. Simulation results obtained by NN receiver are compared with MRC, MMSE and ML receivers. Simulation results are provided for various receivers with respect to 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 for MC-CDMA system and NN receiver are summarized in Table 1. The parameters of WLAN channel model are also given in Table 1 [29].

Three different nonlinear characteristics between channel input 'a' and channel output 'b' can be introduced from [30]:





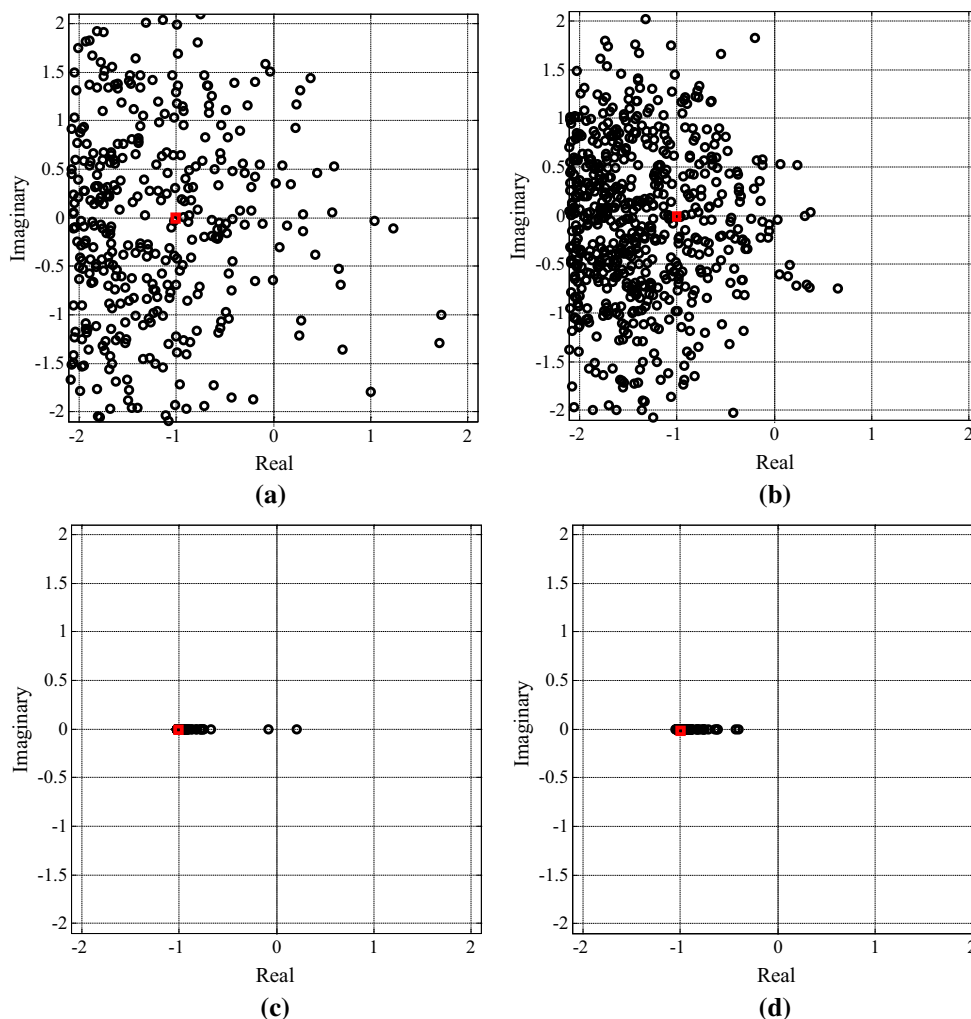
**Fig. 5** Average BER of all users using various receivers in a MC-CDMA system with different nonlinear conditions: **a** NL-0, **b** NL-1, **c** NL-2, **d** NL-3

$$\begin{aligned}
 \text{NL} = 0 & : b = a; \\
 \text{NL} = 1 & : b = \tan h(a); \\
 \text{NL} = 2 & : b = a + 0.2a^2 - 0.1a^3; \\
 \text{NL} = 3 & : b = a + 0.2a^2 - 0.1a^3 + 0.5 \cos(\pi a).
 \end{aligned}
 \tag{25}$$

Here, NL = 0 is regarding with a linear MC-CDMA model and NL = 1 represents a nonlinear model that may occur due to saturated power amplifiers in the system. NL = 2 and NL = 3 are corresponding to arbitrary nonlinear models.

The average BER of four different users in a MC-CDMA system with different nonlinear distortions while varying  $E_b/N_o$  values is shown in Fig. 5. This average BER for MRC, MMSE, MLP and RBF receivers is computed and compared with the performance of optimal ML receivers. From this figure, it is observed that, the linear detectors like MRC 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 severe nonlinear distortion. Hence, though the performance of the linear receivers is good enough in linear and mild nonlinear systems like NL-0, NL-1, NL-2 models, they result significant performance drop in severe nonlinear model (NL-3). However, being highly nonlinear classifiers, the NN-based receivers provide decent performance even in such a severe NL condition and close to the performance of ML receiver. Further, while comparing with MLP receiver the RBF receiver performs little better as it uses feedback of its own past output signals and result inherently dynamic architecture. For example, at  $10^{-5}$  BER floor, the MLP and RBF receivers require just 2 and 1.5 dB additional signal power while comparing with the optimal ML receiver.



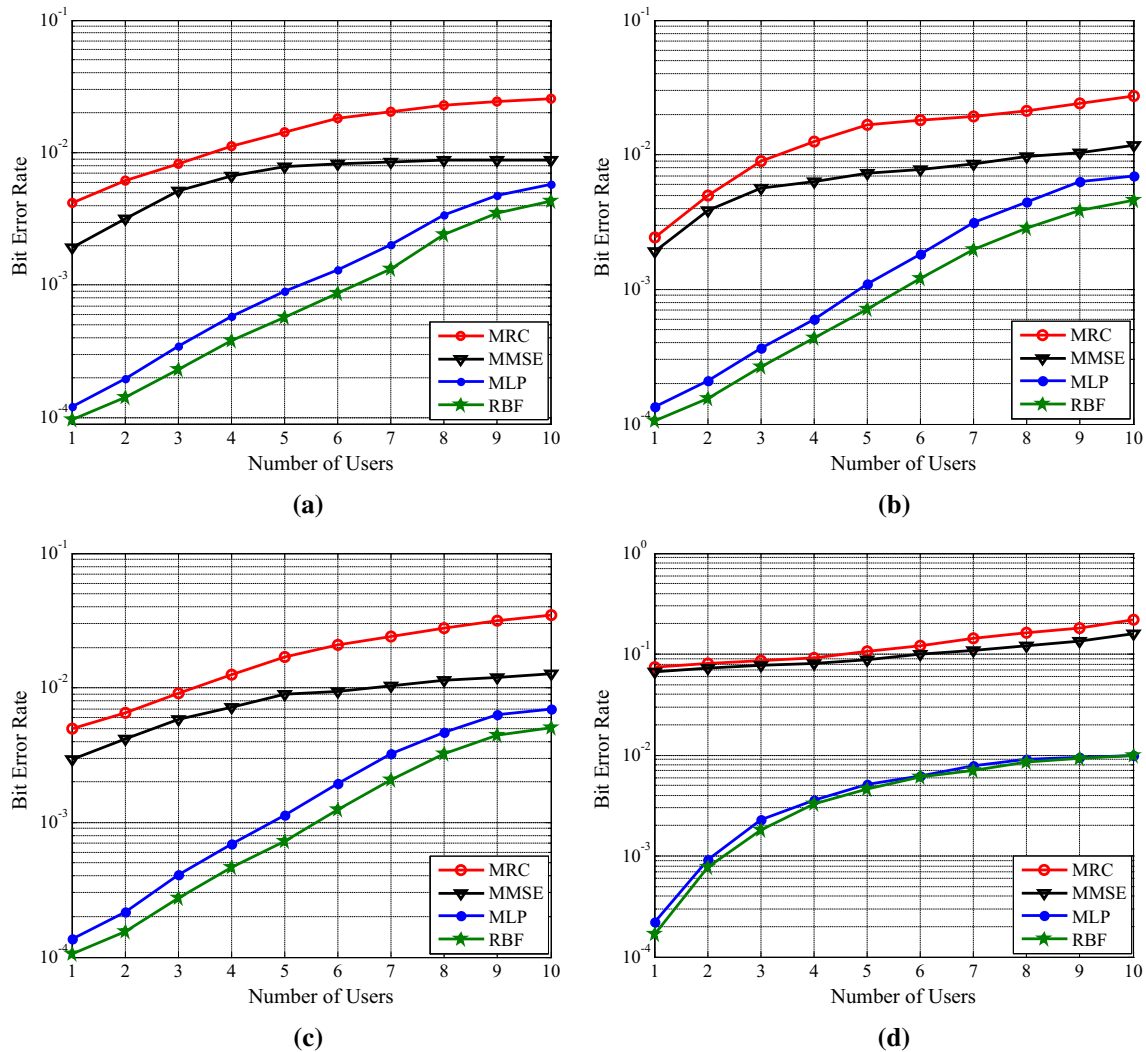
**Fig. 6** Constellation plot for detected signals of User 1 in a MC-CDMA system with NL-3 at 10 dB  $E_b/N_0$  while User 1 is always transmitting ‘-1’ symbol using various receivers: **a** MRC receiver, **b** MMSE receiver, **c** MLP receiver, **d** RBF receiver

Next, the effect of severe nonlinear distortion (NL-3) on estimated signals using linear and nonlinear receivers is shown through the constellation plots as given in Fig. 6. In this figure, the constellation of User - 1’s estimated signals is depicted while User - 1 is always transmitting ‘-1’ in one complete data frame at 10 dB  $E_b/N_0$  while the MC-CDMA system communicating four users simultaneously. This figure illustrates that the resultant estimated symbols of MRC receiver are widely dispersed over entire signal space diagram because it cannot mitigate the arbitrary amplitude and phase distortions resulted in the output symbols automatically. However, though the MMSE is a linear receiver, it detects signals with the knowledge of channel covariance and noise variance. Hence, some of its estimated symbols are nearer to the BPSK decision region and some of them arrived in wrong decision region. By contrast, the adaptive NN receivers can automatically correct the random amplitude and phase distortion of the received signals during the

training process. Thus, the detected symbols of the NN receivers, especially the RBF receiver, form clusters close to the actual transmitted symbol.

Robustness of NN receivers is further analysed through performance evaluation of the MC-CDMA system while it is communicating different number of users as shown in Fig. 7. In this figure, BER of User 1 is always evaluated at 10 dB  $E_b/N_0$  in a MC-CDMA with different NL models as given in Eq. (25). The MAI of any multiple access technique including MC-CDMA systems increases with number of users. So, the BER of all receivers degrades with increasing number of users as shown in Fig. 7. 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. Similarly, the RBF receiver has an inherent capability of highly nonlinear classification ability. Thus, in this figure, the performances of NN receivers are slightly falling while





**Fig. 7** BER of User 1 using various receivers at 10 dB  $E_b/N_o$  while varying number of users in a MC-CDMA system with different nonlinear conditions: **a** NL-0, **b** NL-1, **c** NL-2, **d** NL-3

comparing with the linear receivers. For example, when the MC-CDMA system with NL-3 is communicating seven users, the NN receivers have around 0.006 BER approximately, whereas the MRC and MMSE receivers have 0.12 and 0.1 BERs, respectively, only.

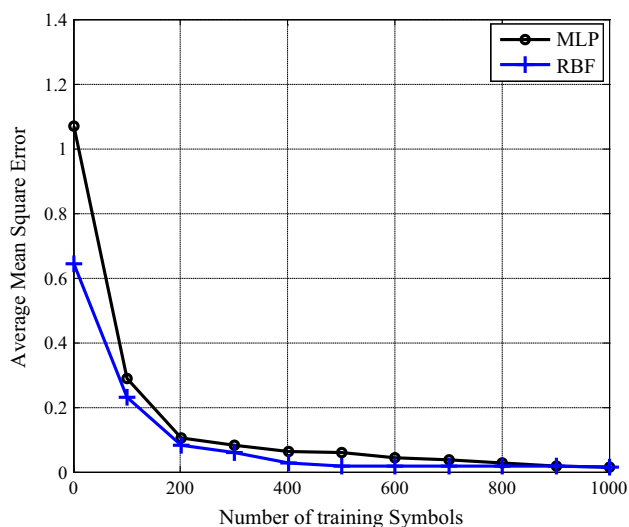
Among various receivers of MC-CDMA system, the ML receiver has an optimal performance, but its computation complexity is very high. Particularly, the computational complexity of ML receiver is increasing exponentially with a factor of  $2^{mK}$  with number of users ‘ $K$ ’ and modulation order ‘ $m$ .’ Hence, to justify the use of NN receivers, the complexity of the proposed NN receivers is compared with the ML detector based on number of computational operations (in terms of both multiplication and addition) given in Table 2. The NN receiver’s complexity mostly depends on the number of training samples ( $N_T$ ) set to the network model to achieve the minimum MSE level and number of data symbols per each data frame ( $M$ ). Hence, the

complexity of NN receivers is proportional to  $N_T$  and  $M$ . The complexity analysis of various receivers is considered for a block-fading channel condition, where channel is remained to be constant 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 NN receivers is just a fraction of ML receiver and close to all classical receivers. Being inherently of low-complexity structures, complexity of the RBF receiver is further less compared to the MLP receiver.

During training process, the NN adjusts the network weights between input and output units. So, this NN training process should be as fast as possible in order to operate in a real-time situation. The tracking error by means of mean square error (MSE) can be used to analyse convergence speed of the neural network models as shown in Fig. 8. In this figure, the MSEs of MLP and RBF models are computed at 10 dB  $E_b/N_o$ . It is shown that, the RBF

**Table 2** Complexity comparison of various MC-CDMA receivers

Receiver	Operation	Computational complexity	Total	% of ML
MRC	Multiplications	$N^2 \times (K + M)$	$7.69 \times 10^5$	1.178
	Additions	$(N - 1) \times (K + M)$	$4.51 \times 10^4$	0.979
MMSE	Multiplications	$N^2 \times (K + M + 2N + 1)$	$7.77 \times 10^5$	1.190
	Additions	$(N - 1) \times (K + M + N^2) + N^3$	$5.29 \times 10^4$	1.149
MLP	Multiplications	$[N_T \times \{4H_N \times (N + K) + K^2\}] + [M \times H_N \times (N + K)]$	$2.26 \times 10^6$	3.462
	Additions	$[N_T \times H_N \times (2N + 3K + 2H_N - 2)] + [M \times \{H_N \times (N + K - 1) - K\}]$	$2.25 \times 10^6$	4.894
	Tansig	$H_N \times (M + N_T)$	$1.6 \times 10^4$	–
RBF	Multiplications	$[N_T \times \{H_N \times (7 + 3K) + N + 1\}] + [M \times \{H_N \times (2N + K + 1)\}]$	$2.09 \times 10^6$	3.213
	Additions	$[N_T \times \{3H_N + 2N + 2K\}] + [M \times \{H_N \times (2N + 1) - 1\}]$	$1.67 \times 10^6$	3.626
	Exponential	$H_N \times (M + N_T)$	$1.6 \times 10^4$	–
ML	Multiplications	$M \times 2^{mK} \times N \times (N \times K + K^2 + K + 1)$	$6.528 \times 10^7$	100
	Additions	$M \times 2^{mK} \times [N \times K \times (N + K - 1) - 1]$	$4.6032 \times 10^7$	100

**Fig. 8** Convergence speed comparison of NN models at 10 dB  $E_b/N_0$ 

model is more rapid than that of MLP model in correcting the network weights since the gradient descent algorithm used for RBF can simultaneously adopt weights, centres and spreads at a time algorithm. Due to such faster tracking ability, the RBF reaches the minimum MSE level with less count of training symbols compared to that of MLP network and the network parameters are updated accordingly.

Hence, the RBF receiver can be a better alternative to all given receivers as it provides performance close to optimal ML receiver, comparatively very low complexity and faster convergence.

## 6 Conclusions

This paper aims to develop adaptive NN receiver for MC-CDMA system with nonlinear system distortions. The efficacy of NN receivers along with their working

model discoursed in detail. The NN receivers are compared with the linear MRC, MMSE and optimal ML receivers with respect to both bit error rate and complexity analyses. From extensive simulation study, it is found that, the linear 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 severe nonlinear distortions. On the other hand, though the ML receiver is an optimal one, its complexity increases exponentially with number of users and modulation order. Hence, the NN receivers can be viewed as better alternatives as they provide a BER close to BER of ML receiver and as they also have rich complexity gain over the extensive ML receiver. In addition to that, irrespective of any given nonlinear distortions in the MC-CDMA system, the NN receivers perform almost same due to their highly nonlinear classification ability. Further, in NN domain, the RBF receiver has been considered even more suitable because of a reduced network structure and its better performance.

### Compliance with ethical standards

**Conflict of interest** We declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere. So we have no conflict of interest.

## References

- Viterbi AJ (1995) CDMA: principles of spread spectrum communication. Addison-Wesley, Boston
- Miller L, Lee J (1998) CDMA systems engineering handbook. Artech House, London
- Weinstein SB, Ebert PM (1971) Data transmission by frequency-division multiplexing using the discrete Fourier transform. IEEE Trans Commun 19(5):628–634

4. Prasad R (2004) OFDM for wireless communications systems. Artech House, London
5. Prasad R, Hara S (1997) Overview of multicarrier CDMA. *IEEE Commun Mag* 35(12):126–133
6. McCormick AC, Al-Susa EA (2002) Multicarrier CDMA for future generation mobile communication. *Electron Commun Eng J* 14(2):52–60
7. Fettweis G, Bahai AS, Anvari K (1994) On multi-carrier code division multiple access (MC-CDMA) modem design. *Proc IEEE Veh Technol Conf*. doi:[10.1109/VETEC.1994.345380](https://doi.org/10.1109/VETEC.1994.345380)
8. Hanzo L, Keller T (2006) OFDM and MC-CDMA: a primer. Wiley, West Sussex
9. Nathan Y, Jean-Paul MGL, Gerhard F (1994) Multi-carrier CDMA in Indoor Wireless Radio Networks. *IEICE Trans Commun* 77(7):900–904
10. Proakis JG (1995) Digital communications. Mc-Graw Hill, New York
11. Steele R, Hanzo L (1999) Mobile radio communications. Wiley, New York
12. Verdu S (1998) Multiuser detection. Cambridge University Press, Cambridge
13. Seyman MN, Taşpınar N (2013) Symbol detection using the differential evolution algorithm in MIMO-OFDM systems. *Turk J Electr Eng Comput Sci* 21:373–380
14. Silva A, Teodoro S, Dinis R, Gameiro A (2014) Iterative frequency-domain detection for IA-precoded MC-CDMA system. *IEEE Trans Commun* 62(4):1240–1248
15. Yan Y, Ma M (2015) Novel frequency-domain oversampling receiver for CP MC-CDMA systems. *IEEE Commun Lett* 19(4):661–664
16. Sung WL, Chang YK, Ueng FB, Shen YS (2015) A new SAGE-based receiver for MC-CDMA communication systems. *Wirel Pers Commun* 85(3):1617–1634
17. Hornik K (1991) Approximation capabilities of multilayer feed-forward networks. *Neural Netw* 4(2):251–257
18. Seyman MN, Taspınar N (2013) Radial basis function neural networks for channel estimation in MIMO-OFDM systems. *Arab J Sci Eng* 38(8):2173–2178
19. Seyman MN, Taşpınar N (2013) Channel estimation based on neural network in space time block coded MIMO-OFDM system. *Digit Signal Proc* 23:275–280
20. Bagadi KP, Das S (2013) Efficient complex radial basis function model for multiuser detection in a space division multiple access/multiple-input multiple-output-orthogonal frequency division multiplexing system. *IET Commun* 7(13):1394–1404
21. Bagadi KP, Das S (2013) Neural network-based multiuser detection for SDMA-OFDM system over IEEE 802.11 n indoor wireless local area network channel models. *Int J Electron* 100(10):1332–1347
22. Bagadi KP, Das S (2013) Neural network-based adaptive multiuser detection schemes in SDMA-OFDM system for wireless application. *Neural Comput Appl* 23(3):1071–1082
23. Bagadi KP, Das S (2014) Multiuser detection in SDMA-OFDM wireless communication system using complex multilayer perceptron neural network. *Wirel Pers Commun* 77(1):21–39
24. Bagadi KP, Das S (2014) Minimum symbol error rate multiuser detection using an effective invasive weed optimization for MIMO/SDMA-OFDM system. *Int J Commun Syst* 27(12):3837–3854
25. Bagadi KP, Annepu V, Das S (2016) Recent trends in multiuser detection techniques for SDMA-OFDM communication system. *Phys Commun* 20:93–108
26. Taspınar N, Cicek M (2013) Neural network based receiver for multiuser detection in MC-CDMA systems. *Wirel Pers Commun* 68(2):463–472
27. Widrow B, Lehr MA (1990) 30 years of adaptive neural networks: perceptron, madaline, and backpropagation. *Proc IEEE* 78(9):1415–1442
28. Ko KB, Choi S, Kang C, Daesik H (2001) RBF multiuser detector with channel estimation capability in a synchronous MC-CDMA system. *IEEE Trans Neural Netw* 12(6):1536–1539
29. Schumacher L, Pedersen KI, Mogensen PE (2002) From antenna spacings to theoretical capacities-guidelines for simulating MIMO systems. In: The 13th IEEE international symposium on personal, indoor and mobile radio communications, pp 587–592
30. Patra JC, Meher PK, Goutam C (2009) Nonlinear channel equalization for wireless communication systems using Legendre neural networks. *Signal Process* 89:2251–2262