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# Neural Network Based Receiver for Multiuser Detection in MC-CDMA Systems

**Necmi Taşpınar · Metin Çiçek**

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**Abstract** In this paper, we present a multiuser detection technique based on artificial neural network (NN) for synchronous multicarrier code division multiple access systems over Rayleigh fading channels. To test the robustness of the proposed receiver, also the effect of power control problem is studied with a comparative manner. Bit error rate (BER) performance of the NN based receiver is compared with the single user bound and conventional receivers. Although the BER performance of the conventional receiver degrades as the number of the users and power level differences among the users increase, as a decision structure, neural network based receiver gives closer BER performance to the single user bound.

**Keywords** MC-CDMA · Multiuser detection · Neural networks · Mobile cellular communication systems

## 1 Introduction

Among the future wireless communication systems, two important techniques have been receiving interest for the same applications. One of them is code division multiple access (CDMA) which provides better capacity for voice and data communications than other multiple access techniques. The other is orthogonal frequency-division multiplexing (OFDM) technique which provides high data rate transmission with a number of lower rate subcarriers. With this technique, these subcarriers make the system robust to cope with multipath fading and intersymbol interference (ISI). Two techniques can be combined under multicarrier code-division multiple access (MC-CDMA) modulation which is among the most promising candidate for the physical layer of fourth generation mobile cellular communication systems

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[1–3]. But this system suffers from two problems: multiple access interference (MAI) and near-far rate (NFR).

In a MC-CDMA system, several users simultaneously transmit information over a common channel using pre-assigned orthogonal codes for all users and each of them achieves an interference-free single user performance. But at the receiver, there is a loss of orthogonality among users due to the increase of the number of the active users and the channel effect. This is known as MAI which causes performance degradation over the system [4]. The second problem is NFR which occurs when the relative received power of interfering signals becomes larger. To overcome these problems, some optimal and sub-optimal multiuser detections (MUDs) have been proposed for MC-CDMA systems [4–6].

Neural network approach is one of the nonlinear suboptimal multiuser detection techniques. There are some studies on multiuser detection using neural networks for CDMA and MC-CDMA systems in the literature [7–12]. The neural network receiver was made first by Aazhang, Paris and Orsak [7]. They demonstrated by applying a complicated training method called assisted back propagation, where the number of the neurons increases exponentially with the number of the nodes and the performance of multilayer perceptron is close to that of the optimum receiver. The receiver proposed in [8] uses a radial basis function (RBF) neural network that becomes too complex under the multipath environment. In [9], neural network based receiver for multiuser detection without power control in a MC-CDMA system was proposed. In [10], parallel interference cancellation in CDMA was performed with two different structures by using neural network to get better bit error rate performance. In [11], multiuser detection in CDMA was realized with an adaptive neuro-fuzzy inference system and the bit error rate performance was compared with the performances of the matched filter and a neural network receiver. In [12], multiuser detection in CDMA was performed using neural network and parallel interference cancellation (PIC) to get better bit error rate performance for asynchronous the additive white Gaussian noise (AWGN) and Rayleigh fading channels. In the literature, there are also studies using neural networks for the solution of some communication problems [13–18]. In [13], artificial neural network based equalizer with soft decision decoding was proposed as an alternative tool to mitigate the multipath-induced intersymbol interference equalization for indoor optical wireless links. In [14], an alternative approach for signal detection and equalization using the continuous wavelet transform and the artificial neural network in diffuse indoor optical wireless links was proposed. In [15], a receiver structure based on the discrete wavelet transform and artificial neural network was introduced for effective removal of the artificial light interference and multipath induced intersymbol interference in indoor optical wireless links. In [16], a new receiver based on the discrete wavelet transform and artificial neural network is proposed and studied for the digital pulse interval modulation system in diffuse indoor optical wireless channel subjected to artificial light interference. In [17], an adaptive neuro-fuzzy inference system for channel estimation in orthogonal frequency division multiplexing systems was proposed. In [18], a new channel estimator based on neural network with feedback for multiple input-multiple output orthogonal frequency division multiplexing communication systems was proposed.

In this paper multiuser detection in multicarrier code division multiple access was performed using neural network to get better BER performance for synchronous Rayleigh fading channels. In the receiver, neural network is used after the conventional maximal ratio combining (MRC) process that have much better BER performance than the MRC and equal gain combining (EGC) techniques. During the training process of the neural network, the outputs of the MRC are used as training data and correct user data is used as target. In the paper, near-far resistance performances to the power control problem of the receivers are also examined. The rest of this paper is organized as follows: in Sect. 2, the system model of MC-CDMA is described. In Sect. 3, the multilayered perceptrons (MLPs) and its training are described briefly. In Sect. 4, neural network based receiver model is described. In Sect. 5, computer simulation results are given. Finally, Sect. 6 contains conclusions.

## 2 System Model

In this paper, the description of MC-CDMA system focuses on the uplink system. We consider a synchronous MC-CDMA system with binary phase shift keying (BPSK) modulation in a Rayleigh fading channel as shown in Fig. 1. In Fig. 1, users bits are multiplied by a spreading code and then inverse fast Fourier transform (IFFT) is performed. The signal is sent through Rayleigh fading channel. At the receiver, fast Fourier transform (FFT) is performed and then the signal is fed into detection scheme.

The received signal at the output of the channel is given by [19]

$$\mathrm{r}\,(\mathrm{t}) = \sum_{\mathrm{k}=1}^{\mathrm{K}} \sum_{\mathrm{n}=1}^{\mathrm{N}} \mathrm{A_k b_k S_{kn} h_{kn} e^{jw_n t}} + \mathrm{n(t)}, \quad \mathrm{t} \in [0, \mathrm{T_s}] \tag{1}$$

where $\mathrm{b_k}$ is the input bit of the kth user, $\mathrm{b_k} \in \{1, -1\}$, $\mathrm{A_k}$ is the received amplitude of the kth user, $\mathrm{T_s}$ is the symbol interval and $\mathrm{w_n} = 2\pi \mathrm{n}/\mathrm{T_s}$. $\mathrm{s_{kn}}$ denotes the nth component of the kth user's spreading code. The spreading code length is the same size of the IFFT length ($\mathrm{N} = 32$). The Rayleigh fading channel is assumed frequency-flat fading for each subcarrier of all users and denoted by $\mathrm{h_{kn}}$ complex coefficients. n(t) denotes the additive white Gaussian noise (AWGN) with independent real and imaginary components, each of which has zero mean and variance $\sigma^2$. After the fast Fourier transform (FFT) operation, the received signal for the nth subcarrier is given by [19]

$$\mathrm{r_n} = \sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{A_k b_k S_{kn} h_{kn}} + \eta_{\mathrm{n}} \tag{2}$$

where $\eta_{\mathrm{n}}$ is a complex Gaussian random variable with zero mean and variance $2\sigma^2/\mathrm{T_s}$. Equation (2) can be written in matrix form as:

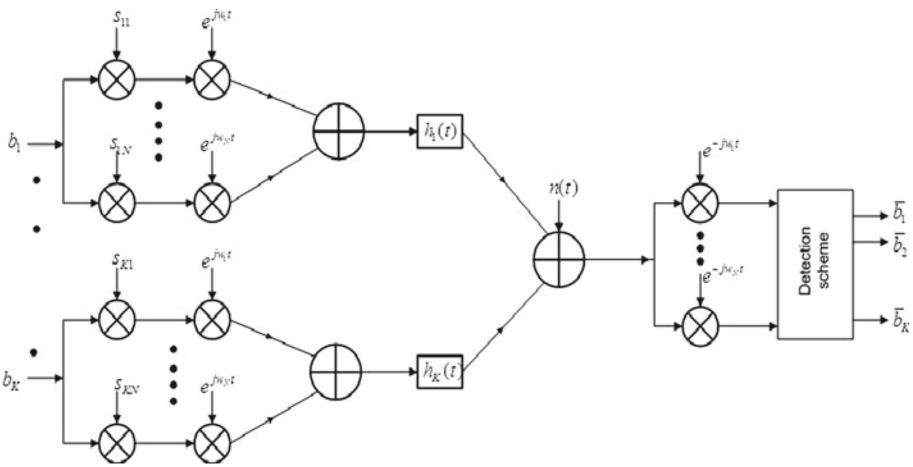


**Fig. 1** MC-CDMA system model

$$\begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_N \end{bmatrix} = \begin{bmatrix} s_{11}h_{11} & s_{21}h_{21} & \ldots & s_{K1}h_{K1} \\ s_{12}h_{12} & s_{22}h_{22} & \ldots & s_{K2}h_{K2} \\ \vdots & \vdots & \ddots & \vdots \\ s_{1N}h_{1N} & s_{2N}h_{2N} & \ldots & s_{KN}h_{KN} \end{bmatrix} \begin{bmatrix} A_1 & 0 & \ldots & 0 \\ 0 & A_2 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & A_K \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_K \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_K \end{bmatrix} \tag{3}$$

Equation (3) can be shown in matrix notation such as [19]:

$$r = CAb + n \tag{4}$$

where [19]

$$C = \begin{bmatrix} s_{11}h_{11} & s_{21}h_{21} & \ldots & s_{K1}h_{K1} \\ s_{12}h_{12} & s_{22}h_{22} & \ldots & s_{K2}h_{K2} \\ \vdots & \vdots & \ddots & \vdots \\ s_{1N}h_{1N} & s_{2N}h_{2N} & \ldots & s_{KN}h_{KN} \end{bmatrix} \tag{5}$$

In Eq. (4), A is the amplitude matrix which consist of amplitude values of each user, b is the original message matrix that consist of bits of each user's message and n is noise matrix. In the conventional MRC receiver, the N paralel channel outputs of the FFT process are despread by the despreading codes of each user and weight coefficients [20]:

$$Z_k\,(i) = R\left\{\sum_{n=0}^{N-1} r_n(i) s_{kn}\beta_{kn}\right\} \tag{6}$$

where $\beta_{kn} = [h_{kn}]^*$ for MRC receiver which is based on correcting the phase and the amplitude of each subcarrier and $\beta_{kn} = h_{kn}^*/|h_{kn}|$ for EGC receiver which is based on correcting only the phase. $h_{kn}$ is the coefficient obtained by channel estimation about nth subcarrier of the kth user, $[]^*$denotes the conjugate operation and $R\{.\}$ denotes the real operation. At the end of the receiver $i$th bit of the kth user can be estimated by [20]

$$b_k\,(i) = Z_k(i)/\,|Z_k(i)| \tag{7}$$

## 3 Artificial Neural Networks (ANNs)

Artificial neural networks basically consist of nonlinear functional blocks called neurons that are connected to each other by parallel synaptic weights. Neural networks have learning ability which means that synaptic weights are adjusted with the learning algorithm so that the neural network reacts on a given input by a desired output. One of the commonly used type of neural networks is feed forward multilayered perceptron (MLP) [21]. The MLPs consist of the input, the hidden and the output layers and they have feedforward connections between neurons. The neurons in the input layer only act as buffers to distribute the input signals to the neurons in the hidden layer. There are various activation functions that are used in the neurons. The weights are changed with the various learning algorithm to get a proper output. A typical MLP structure is shown in Fig. 2. In this study, the Levenberg-Marquardt algorithm is used as the learning algorithm for the MLPs.

### 3.1 The Levenberg-Marquardt algorithm

The Levenberg Marquardth (LM) algorithm is basically Hessian-based algorithm for nonlinear least square optimization. In LM training, to adjust synaptic weights of input to hidden

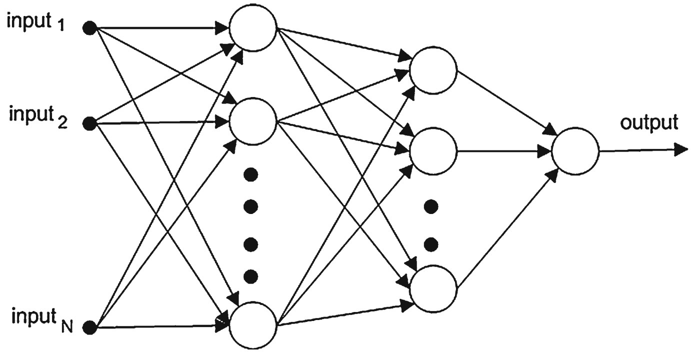


**Fig. 2** Multilayer network model

layer and hidden to output layer the objective function E(w) that will be minimized is given as [21]:

$$\mathrm{E}\,(\mathrm{w}) = \frac{1}{2}\sum_{\mathrm{k}=1}^{\mathrm{c}} (\mathrm{d_k} - \mathrm{o_k})^2 \tag{8}$$

where $\mathrm{d_k}$ is the kth desired output, $\mathrm{o_k}$ is the kth actual output and c is the number of output points. The Levenberg-Marquardt algorithm uses the update formula [21]:

$$\Delta\omega = -\left(J^T J + \mu I\right)^{-1} \mathrm{J^T.E} \tag{9}$$

where J is the Jacobian matrix which contains first derivatives of the network errors with respect to the weights and biases and μ is the learning rate which determines by how much the weights $w$ can be changed at each steps. When higher learning rate (max of 1.0) is used the network is trained faster. Although larger values of μ accelerate the training process they may induce oscillations that may slow down the convergence so the algorithm diverges. On the contrary, if the smaller learning rate ( min of 0.0) is used the algorithm will take a long time to converge.

The training steps are illustrated as:

Step 1. Initialize the weight and learning rate.
Step 2. Compute objective function that is sum of squared errors between desired and actual outputs using Eq. (8).
Step 3. Solve weights using update formula Eq. (9).
Step 4. Recompute squared error using $w + \Delta w$. If error is smaller than computed one in step 2 then reduce the learning rate ($\mu$) 0.1 times, if error is not reduced increase learning rate ($\mu$) 10 times and go to step 3.
Step 5. Finish the training when error is less than the predetermined value.

## 4 Neural Networks (NN) Based Receiver

The proposed NN based receiver is shown in Fig. 3. In this figure, S is one of the input set of MRC which is a matrix size of K × N and denotes the N length spreading codes for all users. Another input $\bar{\mathrm{H}}$ which is the same size of S and consists of $\mathrm{h}^*_{\mathrm{kn}}$ parameters belonging to all subcarriers and users is given as

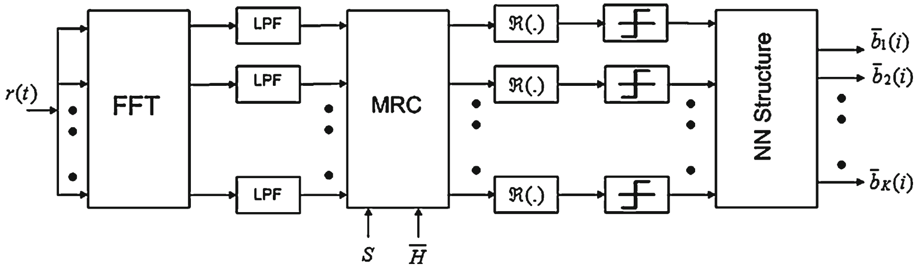


**Fig. 3** A NN based MC-CDMA receiver

$$\bar{\mathrm{H}} = \begin{bmatrix} \mathrm{h}_{11}^{*} & \cdots & \mathrm{h}_{\mathrm{K}1}^{*} \\ \vdots & \ddots & \vdots \\ \mathrm{h}_{1\mathrm{N}}^{*} & \cdots & \mathrm{h}_{\mathrm{KN}}^{*} \end{bmatrix} \tag{10}$$

As it is seen from Fig. 3, the outputs of the MRC receiver are taken as input for the proposed receiver. The number of the input nodes, hidden layer nodes and output nodes of the NN is equal to the number of the users. It is a feed forward network and it is trained by Levenberg-Marquardt algorithm. In the hidden layer a tangent sigmoid activation function was used and in the output layer a pure linear activation function was used. During the training, the signal to noise ratio is assumed as 10 dB and training data of 500 bits were used.

## 5 Simulation Results

Simulations were performed in three different ways: the BER of the desired user versus the signal to noise ratio (SNR), the BER of the desired user versus the near-far rate (NFR) and the BER of the desired user versus the number of active users. In all of them, a synchronous Rayleigh fading channel was considered and a perfect channel estimation was assumed. Simulations have been carried out through the transmitter to the receiver in all of the MC-CDMA system. The simulation parameters are given in Table 1.

**Table 1** MC-CDMA simulation parameters

| Parameter | Value |
|---|---|
| Number of subcarrier | 32 |
| Spreading code size | 32 |
| Spreading code | Hadamard |
| Modulation type | BPSK |
| Channel type | Rayleigh fading |
| Input number of NN | K, user number |
| Output number of NN | 1 |
| Number of neural hidden layers | 1 |
| Number of neurons in hidden layer | K, user number |
| NN activation function | Tangent sigmoid |
| NN training algorithm | Levenberg-Marquardt |
| Training length | 500 bits for each user |

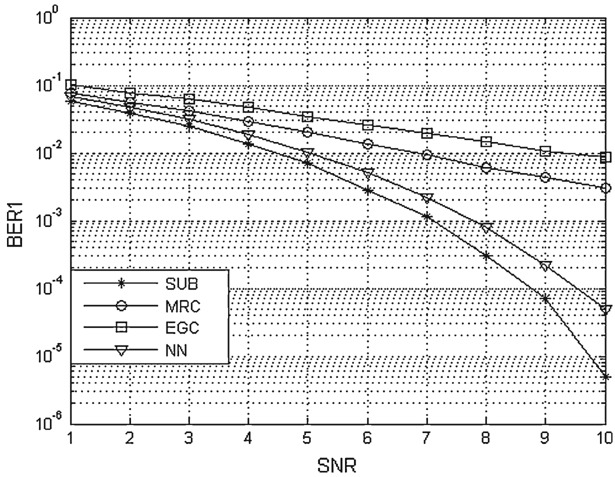


**Fig. 4** The BER versus the signal to noise ratio of the desired user in a five users synchronous Rayleigh fading channel with $NFR_2 = NFR_3 = NFR_4 = NFR_5 = 1$

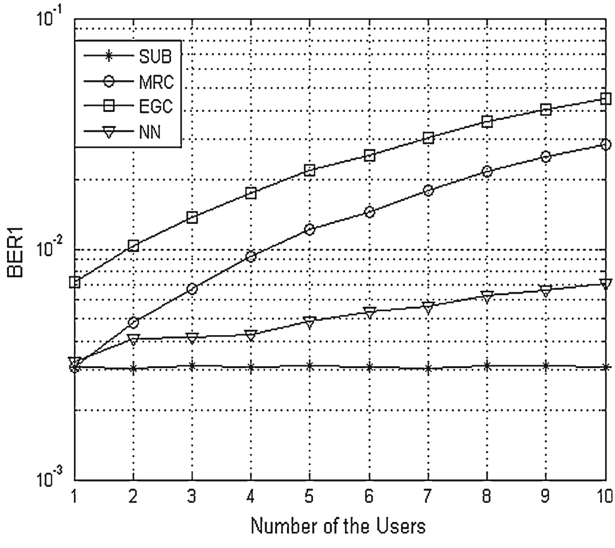


**Fig. 5** BER of desired user versus the number of the active users for the receivers with perfect power control

The NFR of user k are defined such as:

$$NFR_k = \frac{\text{user k power}}{\text{user 1 power}} = \frac{A_k^2}{A_1^2} \tag{11}$$

The BER versus the signal to noise ratio of the desired user in a Rayleigh fading channel with five users is shown in Fig. 4. As it is seen in this figure, the NN based receiver has a much better performance than the others and its BER performance is closer to the single user bound.

The BER performances of the desired user versus the number of the active users are shown in Fig. 5. The SNR value of the channel is 6 dB and the amplitudes of the all users are assumed

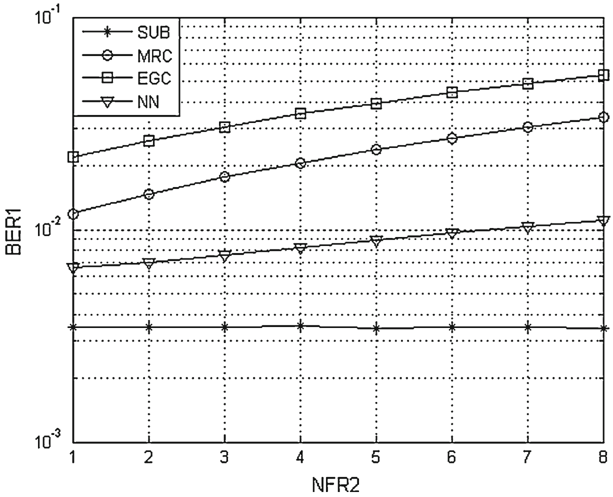


**Fig. 6** The BER of the desired user versus the near-far rate between the second user and the desired user ($NFR_2$) in a five users synchronous Rayleigh fading channel with SNR = 6 dB, $NFR_3 = NFR_4 = NFR_5 = 1$

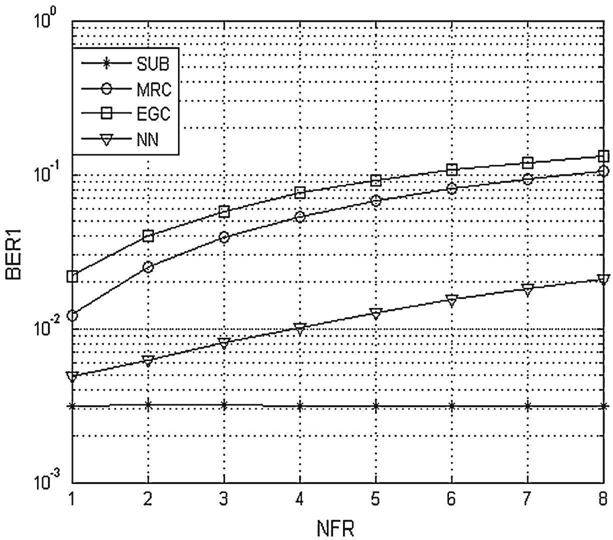


**Fig. 7** The BER of the desired user versus the near-far rate between the desired user and other users in a five users synchronous Rayleigh fading channel with SNR = 6 dB, $NFR = NFR_2 = NFR_3 = NFR_4 = NFR_5$

as equal. Although it can be observed from the Fig. 5 that the NN based receiver has a much better BER performance than the others, the BER performance of the NN receiver that uses the outputs of the MRC receiver degrades for the bigger number of the users due to degrading performance of the MRC receiver for the bigger number of the users.

The near-far resistance of the MC-CDMA receivers are investigated in Figs. 6 and 7. Figure 6 shows the BER performance of the desired user versus the near-far rate between the second user and the desired user ($NFR_2$). For the five users system, the SNR of the channel is assumed as 6 dB and the amplitudes of the desired user and other users beyond the second user are assumed equal ($NFR_3 = NFR_4 = NFR_5 = 1$). From Fig. 6, it is observed that the performance of NN based receiver is the most robust among all receivers. The near-far resistance of the receivers are shown in Fig. 7 in a different way: the amplitude of the desired user is constant and the other user's amplitudes are assumed equal and varying ($NFR = NFR_2 = NFR_3 = NFR_4 = NFR_5$). As it is seen from both figures which the NFR value at the training is assumed as 1, NN based receiver is the closer one to the single user bound and the most resistant to the near-far problem.

## 6 Conclusion

In this paper, we present a neural network based receiver for multiuser detection in synchronous MC-CDMA. The BER performances versus signal to noise ratio (SNR), number of the users and near-far rate are investigated by computer simulations for Rayleigh fading channels and the simulation results are compared with the conventional receiver scheme (MRC). Simulation results show that the proposed neural network based receiver gives closer BER performance to the single user bound (SUB) and achieves significant performance improvement compared with the conventional MRC receiver.

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