Multiuser Detection with Neural Network MAI Detector in CDMA Systems for AWGN and Rayleigh Fading Asynchronous Channels

Necmi Taspinar[1] and Yalcin Isik[2]
[1]Department of Electrical and Electronics Engineering, Erciyes University, Turkey
[2]Silifke-Tasucu Vocational School, Selcuk University, Turkey

Abstract: *In this study, the performance of the proposed receiver with the neural network Multiple Access Interference (MAI) detector is compared with the matched filter bank (classical receiver), neural network that detects user's signal and single user bound for Additive White Gaussian Noise (AWGN) and Rayleigh fading asynchronous channels by computer simulations. There are a lot of study in the literature that compare the neural network receiver and other methods. These neural network receivers detect the user bits after the matched filter. In this study, MAI is detected after the matched filter with the proposed neural network receiver and then user bits are obtained by subtracting MAI from the matched filter output. The proposed receiver with the neural network MAI detector has got better Bit Error Rate (BER) performance than the neural network that detects user`s signal in AWGN and Rayleigh fading asynchronous channels for Signal Noise Ratio (SNR) simulations, and in AWGN asynchronous channels for the number of users simulations, although both have the same complexity. However, both have almost same BER performance in AWGN and Rayleigh fading asynchronous channels for Near Far Ratio (NFR) simulations, and in Rayleigh fading asynchronous channels for the number of users simulations.*

Keywords: *CDMA, multi-user detection, neural network, MAI detector.*

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1. Introduction

In a Code Division Multiple Access (CDMA) system, all users share the same transmission medium in the same frequency and time. Each user transmits information over the common transmission medium by multiplying information signal and its own spreading code. All signals of the users are added in the channel. In the receiver, user data is obtained by multiplying the received channel signal with the spreading code of the user and integrating over one bit period. In this system when the signal powers of the users are different, information of the user that has weak signal is obtained with much errors, this situation is called as the near-far problem. To overcome this problem, power control system that makes all signal levels the same in the input of the base station is used. Although, the power control, as the number of the active users in the system increases, information of the users is obtained with more errors. This situation is called as the Multiple Access Interference (MAI). The solution of this problem is to use orthogonal codes. But, in asynchronous transmission the orthogonality is degraded due to the different transmission delays of the users. A potential solution of these problems is the optimum multiuser detector that consists of a bank of Matched Filters (MF) followed by a viterbi Maximum Likelihood (ML) detector [20]. However, the computational complexity of this detector increases exponentially with the number of users, and the method is extremely complex to implement for a realistic number of users. Therefore, there has been considerable research into suboptimal detectors. Two types of linear detectors have also been suggested. These are the decorrelating detector [13] and the Minimum Mean Squared Error (MMSE) detector [21]. Complexity of these receivers is linear in the number of users.

In non-linear multiuser detection, which is also called subtractive detection, the interference estimates are generated and then removed from the received signal before detection. One of the nonlinear multiuser detection techniques is Neural Network (NN) approach [1, 2, 3, 4, 5, 12, 14, 15, 16, 17, 18, 22]. The NN receiver was made first by Aazhang *et al.* [1]. They demonstrated that the performance of multilayer perceptron is close to that of the optimum receiver, by applying a complicated training method called the assisted back propagation, where the number of the neurons increases exponentially with the number of the nodes. The receiver proposed in [14] uses Radial Basis Function (RBF) NN that becomes too complex under the multipath environment. The energy function of Hopfield Neural Network (HNN) is identical to the likelihood function encountered in the multiuser detection. Therefore, some researchers have used the

HNN for multiuser detection [12, 16, 18], and also in [15] Hopfield network was used as adaptively. A NN based decision feedback scheme for interference suppression was investigated in [4]. Compact NN [2], annealed NN [22] and a modified Kennedy-Chua NN which is based on the Hopfield model [5] were used for multiuser detection. Robust version of the linear decorrelating detector with three layers recurrent NN was proposed in [3]. Shayesteh and Amindavar [17] analyzed the performance of two-layer perceptron NN using back propagation training algorithm as multiuser detector of CDMA signals in Additive White Gaussian Noise (AWGN) and fading channels. They compared the performance of decision based NN, fuzzy decision NN and discriminative learning NN with the back propagation net in AWGN channel. In [1, 2, 3, 4, 5, 12, 14, 15, 16, 17, 18, 22], the NN is trained to get users' data. Isik and Taspinar [8] trained the NN to get MAI and they improved BER performance of the receiver without increasing the complexity of the NN. They used the NN to get MAI, and then obtained the users' data by subtracting MAI from the output of the MF in the AWGN synchronous channel. Isik and Taspinar [9] also used NN and PIC method in cascade in the AWGN and Rayleigh fading asynchronous channels. In another study, Isik and Taspinar [10] used Adaptive Neuro-Fuzzy Inference System (ANFIS) for multiuser detection in CDMA systems. Jieling *et al.* [11] used the particle swarm optimization to improve the performance of the adaline NN for multiuser detection in CDMA systems. Taspinar and Cicek [19] used artificial NN for multiuser detection in Multicarrier Code Division Multiple Access (MC-CDMA) systems using Rayleigh fading channels.

AWGN synchronous channel is simple than the Rayleigh fading asynchronous channel. Rayleigh fading channel conditions are harder than AWGN channel conditions due to random amplitude changes. Also, data bit estimation in asynchronous channel is harder than the in synchronous channel. In this study, the NN is used to get MAI instead of users' signals in the AWGN and Rayleigh fading asynchronous channels. In this receiver, the outputs of the MF bank are used as the training data, but the MAI for these outputs is used as target data. So, the network is trained as MAI detector instead of classical multi user NN receiver. In the detection process, the network is used as MAI detector and its outputs are subtracted from the outputs of the MF. In this way, the network behaviour becomes more flexible and it can be generalized better.

The paper is organized as follows: In section 2, the background information in regard to the CDMA system is presented. In section 3, the Multilayered Perceptrons (MLPs) and its learning algorithm (Levenberg-Marquardt) used in the training are described briefly. In section 4, the structure of the receiver with the Neural Network MAI (NNMAI) detector is introduced. In section 5, computer simulation results are given. Finally, section 6 contains conclusions.

2. System Model

We consider the asynchronous CDMA system with Binary Phase Shift Keying (BPSK) modulation in an AWGN and Rayleigh fading channels. Data for each user as random series in forms of *+1*, *-1* is generated and multiplied with its spreading code to obtain CDMA signal. CDMA signals of all users and AWGN are added in the channel. CDMA signal in the asynchronous AWGN channel for K users, also received signal in the base station is given by:

$$r(t)=\sum_{k=1}^{K}\sum_{i=-M}^{M}A_k b_k(i)S_k(t-iT-\tau_k)+n(t) \qquad (1)$$

where b_k is the data bit of the kth user, $b_k \in \{1,-1\}$, A_k is the received amplitude of the kth user, τ_k is the kth user`s time delay which is in the interval $[0,T)$, $2M+1$ is the number of transmitted bits (packet length) in each transmission, $n(t)$ is AWGN and $S_k(t)$ is the signature waveform of duration T for the kth user. $S_k(t)$ is defined for N length of signature sequence and BPSK modulation as:

$$S_k(t)=\sum_{n=0}^{N-1}a_n^k\,p(t-nT_c) \qquad (2)$$

where $a_n^k \in(-1,1)$ is the normalized spreading sequence, T_c is the chip interval (the bit period of the spreading code), $p(t)$ is the rectangular waveform of duration T_c, T is the bit period where $T=NT_c$.

The cross-correlation of the signature sequences are defined as:

$$\rho_{jk}(i)=\int_{-\infty}^{+\infty}s_j(t-\tau_j)s_k(t+iT-\tau_k)dt,\quad i=0,\pm 1 \qquad (3)$$

At the receiver side, received CDMA signal $r(t)$ that is given in equation 1 is multiplied kth user's signature waveform $S_k(t)$ and integrated in one bit period to find kth output of the MF and it is given by:

$$y_k=\int_{\tau_k}^{T+\tau_k}r(t)S_k(t-\tau_k)dt \qquad (4)$$

Substituting equations 1 and 2 in equation 4, the output of the MF for kth user is obtained like that:

$$\begin{aligned}y_k(i)&=A_k b_k(i)+\sum_{j<k}A_j b_j(i+1)\rho_{kj}+\sum_{j<k}A_j b_j(i)\rho_{jk}\\&+\sum_{j>k}A_j b_j(i)\rho_{kj}+\sum_{j>k}A_j b_j(i-1)\rho_{jk}+n_k(i)\end{aligned} \qquad (5)$$

In the MF receiver, to decide a bit as $+1$ or -1, zero threshold circuit is used as the decision device. ith bit of kth user, $\hat{b}_k(i)$ is given by:

$$\hat{b}_k(i)=sgn\,[y_k(i)] \qquad (6)$$

For Rayleigh fading channel, received signal given in equation 1 is defined as:

$$r(t)=\sum_{k=1}^{K}\sum_{i=-M}^{M}A_k b_k(i)S_k(t-iT-\tau_k)*h_k(t)+n(t) \tag{7}$$

where

$$h_k(t)=C_k e^{-j\varphi k}\delta(t-t_k) \tag{8}$$

where C_k is amplitude of the kth user that has Rayleigh distribution, φ_k is the phase in the range $[0, 2\pi)$ and t_k is the delay in the range $[0, T)$.

3. Artificial Neural Networks (ANNs)

The NNs are constructed with the neurons that are connected to the each other. Each connection has a weight factor and these weights are adjusted in a training process. There are many types of NNs for various applications in the literature. A common used one of these is the MLPs.

3.1. Multilayered Perceptrons (MLPs)

The MLPs [6, 7] are the simplest and therefore most commonly used NN architectures. NN consists of neurons that are connected to each other with weights and works parallel. Function of the network is determined by connections between neurons. The network can do some certain functions by adjusted weight factors between neurons. Adjusting the weight factors is called as training. During the training, weights are changed until the certain outputs are obtained for the defined inputs. After the training, NN processes the inputs to get desired outputs. MLPs consist of input, hidden and output layers and they have feed forward connections between neurons. Neurons in the input layer only act as buffers for distributing the input signals to neurons in the hidden layer. There are various activation functions that are used in neurons. Weights are changed with various learning algorithm for getting proper output. A typical MLP structure is shown in Figure 1. In this structure, P inputs are applied to the first layer by multiplying W_1 weight matrix. The outputs of the first layer are obtained by using activation function and bias as it is seen in equation 9. The outputs of the first layer are applied to the second layer by multiplying W_2 weight matrix. The outputs of the second layer are obtained by equation 10. Finally, the outputs of the second layer are applied to the third layer (output layer) by multiplying W_3 weight matrix. The outputs of the output layer are obtained by equation 11. In this study, the Levenberg-Marquardt algorithm is used as learning algorithm for MLPs.

$$a_1=f_1(W_1p+b_1), \tag{9}$$

$$a_2=f_2(W_2a_1+b_2) \tag{10}$$

$$a_3=f_3(W_3a_2+b_3)=f_3(W_3f_2(W_2f_1(W_1p+b_1)+b_2)+b_3) \tag{11}$$

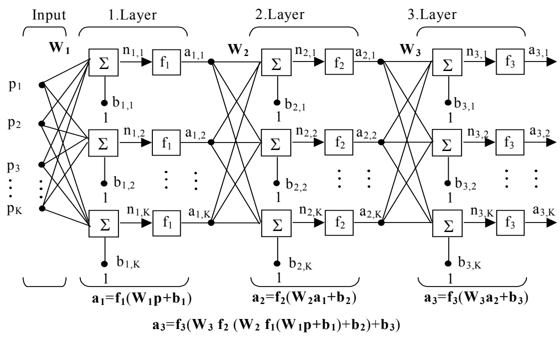

Figure 1. Multi layer network model [7].

3.2. Levenberg-Marquardt Algorithm

The levenberg-marquardt algorithm [7] was designed to approach second-order training speed without having to compute the Hessian matrix. Levenberg-Marquardt uses the update formula:

$$\Delta W=-(J^TJ+\mu I)^{-1}J^Te \tag{12}$$

where J is the Jacobian matrix, which contains first derivatives of the network errors with respect to the weights and biases, e is a vector of network errors, and μ is the control parameter. The first term in equation 12 represents the linearized assumption and the second term represents a gradient-descent step. The control parameter μ governs the relative influence of these two approaches. Each time Levenberg-Marquardt succeeds in lowering the error, it decreases the control parameter by a factor of 10, thus strengthening the linear assumption and attempting to jump directly to the minimum. Each time it fails to lower the error, it increases the control parameter by a factor of 10, giving more influence to the gradient descent step, and also making the step size smaller. This is guaranteed to make downhill progress at some point.

4. The Receiver with the Neural Network MAI Detector

There are a lot of studies in the literature that use the NNs. In these studies, the outputs of the MFs are used for the training and the NN is trained to get the bits of the users. Also, we used the outputs of the MFs for the training, but we trained the NN to get MAI instead of the bits of the users. For this reason during the training, MAI is obtained from the outputs of the MFs, and then the NN is trained for this MAI. After training process, the NN is used as MAI detector. MAI which is detected by NNMAI receiver for the desired user is subtracted from the MFs output of this user and result is applied to the zero threshold circuit to get any bit of the desired user. The up-link transmission is considered and the number of the outputs of the NNs was chosen as the number of active users. MAI can be obtained from the training data during the training with Parallel Interference Canceller (PIC) approach. MAI can be calculated as:

$$(MAI)_k(i) = \sum_{\substack{j=1 \\ j \neq k}}^{K} A_j \rho_{jk} b_j(i) \tag{13}$$

However, we used a different method to obtain MAI with lower computational complexity. The output of the MF for *k*th user for the training can be produced without noise as:

$$y_k = A_k b_k + (MAI)_k \tag{14}$$

During the training, MAI can be obtained easily by subtracting known training user data from the produced output of the MF for this known training user data by using equation 14.

Two layer NNs are used in MAI detector and signal detector. Both NNs that are used at the detectors are exactly the same. The number of hidden and output neurons was chosen as the number of the users, whereas the number of input nodes was chosen as three times of the number of the users. In the training of the network, the Levenberg-Marquardt algorithm is used. In the hidden layer tangent sigmoid activation function was used and in the output layer pure linear activation function was used. The receiver with the NN that is trained for signals of users is shown in Figure 2 and the receiver with the NN that is trained for MAI is shown in Figure 3 in the asynchronous channel.

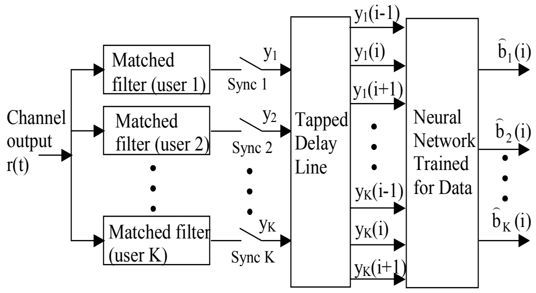

Figure 2. Multiuser receiver with NN trained for signals of users in asynchronous channel.

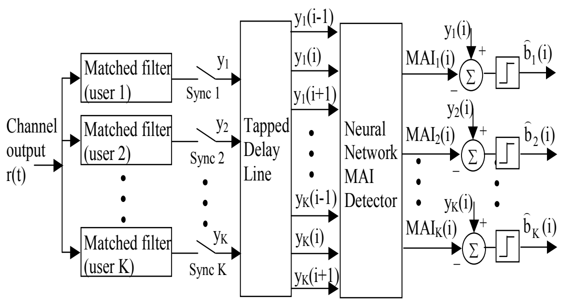

Figure 3. Multiuser receiver with the NN trained for MAI in asynchronous channel.

5. Simulation Results

Simulations were performed in AWGN and Rayleigh fading asynchronous channels for 31 bits spreading codes and 10 users. Simulations have been carried out in three different ways: BER of desired user versus Signal to Noise Ratio (SNR), BER of desired user versus Near-Far Rate (NFR) and BER of desired user versus the number of active users. SNR of the first user and NFR of user k are defined such as:

$$SNR_1 = \frac{signal\ power}{noise\ power} = \frac{A_1^2}{2\sigma^2} \tag{15}$$

$$NFR_k = \frac{user\ k\ power}{user\ 1\ power} = \frac{A_k^2}{A_1^2} \tag{16}$$

where σ^2 is the variance of the noise with the zero mean value, A_1 is the amplitude of the first user and A_k is the amplitude of user k signal. With the simulation results, the performance of proposed receiver which is the receiver with the NNMAI detector are compared with the MF bank, NN receiver and Single User Bound (SUB).

In the 10 user's asynchronous AWGN channel, BER values of the first user versus SNR_1 for various multi-user receivers are shown in Figure 4. In the asynchronous channel simulations, NNs consider three successive bits of all users ($y_k[i-1]$, $y_k[i]$, $y_k[i+1]$) to obtain results for one bit of all users ($b_k[i]$). 3000 bits training data set was used and 10dB SNR value was assumed during the training. Training data is randomly produced for each simulation and it is assumed that it is known by the receiver. After training procedure, receiver gets hundreds packets of data including noise and fading. The NFR values are taken as 2 for all users during the training and simulations. As it is seen in Figure 4, receiver with MAI detector has superior performance than the MF and better performance than the NN receiver that detects user's signal. The receiver with MAI detector has reached to the 10^{-5} value of BER with almost 10dB value of SNR, while the NN receiver that detects user's signal has reached to the same BER value with 12dB value of SNR, with 2dB differences.

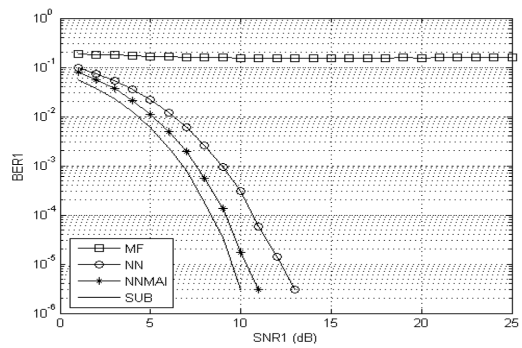

Figure 4. BER values of the first user versus SNR_1 for various multiuser receivers. (AWGN asynchronous channel, NFR_k=2, k=2,3,….,10).

The number of the bits in data set that is used during the training affects the performance of the receiver. The performance comparison of the 15 users NN and NNMAI receivers for the 500bits and 6000bits training set is shown in Figure 5. As it is seen in Figure 5, length of the training set effects the performance of the

NNMAI receiver more than the NN receiver. As it is seen in Figure 5, increasing the number of the bits in the training set improves the performance of the receivers. On the other hand, increasing the number of the bits in the training set increases the training time. For this reason, the length of the training set is selected as depends on the problem. In our simulations, 3000bits and 1000bits training sets were chosen to get results good enough with the acceptable training time.

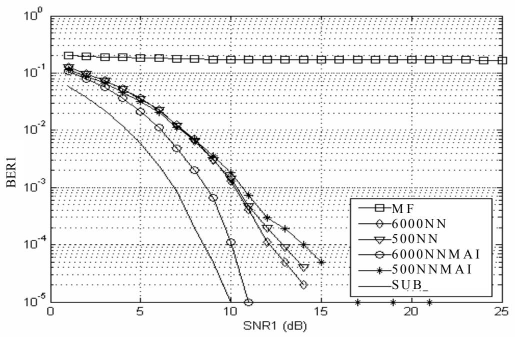

Figure 5. BER values of the first user versus SNR_1 for various multiuser receivers in different length of the training set. (AWGN asynchronous channel, NFR_k=2, k=2,3,….,15).

BER values of the first user versus NFR are shown in Figure 6. Channel conditions are the same with previous simulation. SNR value of the first user is 5dB and amplitudes of the each user are equal except first user. The NNs were trained for three different NFR values as 1, 2 and 4 with 1000bits training set for each NFR value. As it is seen in Figure 6, BER performance of the receiver with MAI detector is a little better than the NN receiver that detects user's signal. But BER performance of the receiver with MAI detector has superior performance than the MF.

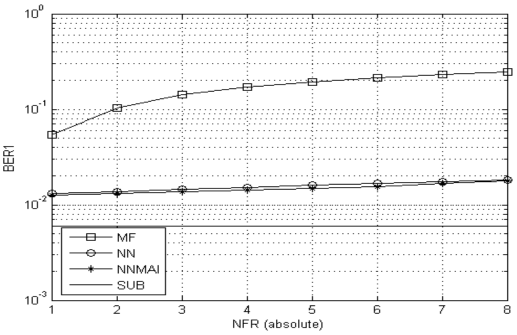

Figure 6. BER values of the first user versus NFR for various multiuser receivers. (AWGN asynchronous channel, SNR value of the first user is 5dB).

BER values of the first user versus the number of the users are shown in Figure 7. SNR value of the first user is 5dB and perfect power control is assumed. BER performance of the receiver with MAI detector is better than the NN receiver that detects user's signal and the MF. The receiver with MAI detector has reached to the 10^{-2} value of BER with 10 users, while the other NN receiver has reached to the same BER value with 8 users, with 2 users differences.

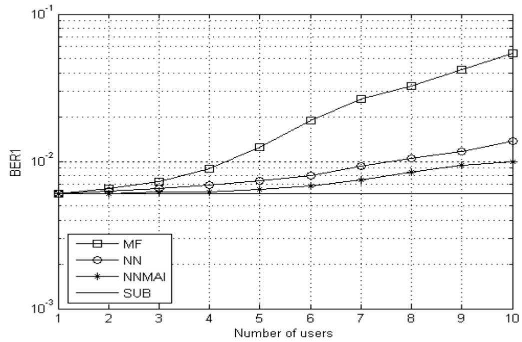

Figure 7. BER values of the first user versus the number of the users for AWGN asynchronous channel. (SNR value of the first user is 5dB and perfect power control is assumed).

In the 10 users asynchronous Rayleigh fading channel, BER values of the first user versus SNR_1 for various multi-user receivers are shown in Figure 8. 3000bits training data set was used and 10dB SNR value was assumed during the training. The NFR values are taken as 2 for all users during the training and simulations. As it is seen in Figure 8, the receiver with MAI detector has superior performance than the MF and better performance than the other NN receiver. The receiver with MAI detector has reached to the 10^{-2} value of BER with almost 16dB value of SNR, while the other NN receiver has reached to the same BER value with 19dB value of SNR, with 3dB differences.

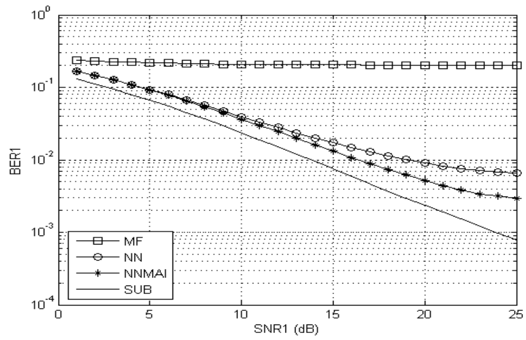

Figure 8. BER values of the first user versus SNR_1 for various multiuser receivers. (Rayleigh fading asynchronous channel, NFR_k=2, k=2,3,….,10).

BER values of the first user versus NFR are shown in Figure 9. Channel conditions are the same with previous simulation. SNR value of the first user is 5dB and amplitudes of the each user are equal except first user. The NNs were trained for three different NFR values as 1, 2 and 4 with 1000bits training set for each NFR value. BER values of the first user versus the number of the users are shown in Figure 10. SNR value of the first user is 5dB and perfect power control is assumed. As it is seen in Figures 9 and 10, BER performance of the receiver with MAI detector is almost same with the other NN receiver for both simulations. But BER performance of the receiver with MAI has better performance than the MF.

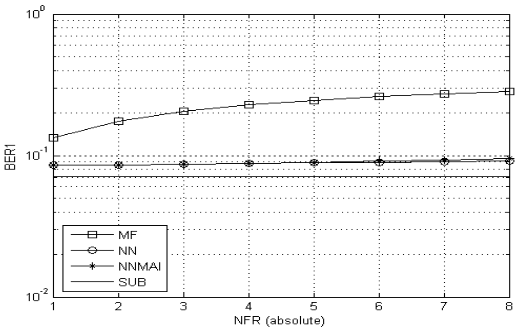

Figure 9. BER values of the first user versus NFR. (Rayleigh fading asynchronous channel, SNR value of the first user is 5dB).

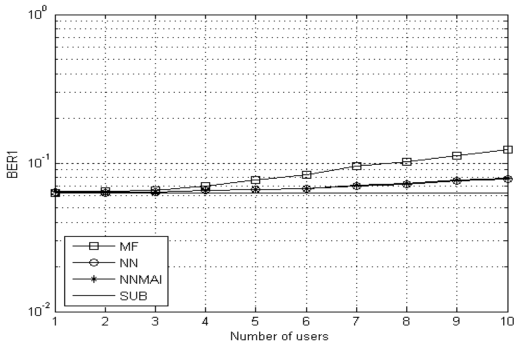

Figure 10. BER values of the first user versus the number of the users for Rayleigh fading asynchronous channel. (SNR value of the first user is 5dB and perfect power control is assumed).

6. Conclusions

In this study, the NN is used to detect MAI instead of user`s signal as usual to make multiuser detection. The receiver with the NNMAI detector has got better BER performance than the neural network that detects user`s signal in AWGN and Rayleigh fading asynchronous channels for SNR simulations, and in AWGN asynchronous channels for the number of users simulations, although both have same complexity. However, both of them have almost same BER performance in AWGN and Rayleigh fading asynchronous channels for NFR simulations, and in rayleigh fading asynchronous channels for the number of user simulations.

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Necmi Taspinar received his BSc degree in electronic engineering from Erciyes University, Kayseri, Turkey in 1983, MS degree in electronic and telecommunications engineering from the Technical University of Istanbul, Turkey in 1988, and PhD degree in electronic engineering from Erciyes University, Turkey in 1991. From 1984 to 1992 he was a research assistant, during 1992-1996 he was an assistant professor, during 1996-2002 he was an associate professor, and since 2002 he has been full professor in the Department of Electrical and Electronic Engineering, Erciyes University, Turkey. His research interests include theory and applications of error-control coding, multi-user detection, channel estimation, equalization, synchronization, CDMA and spread-spectrum systems, OFDM systems, MIMO systems and applications of neural networks, fuzzy logic, adaptive neuro-fuzzy inference system and heuristic approaches to communications problems.

Yalcin Isik received his BSc degree in electronics engineering from Gazi University, MS Degree in electronics engineering from Hacettepe University and PhD degree electronics engineering of Erciyes University, Turkey in 1985, 1988 and 2006 respectively. He is now an instructor at Endustrial Electronic Program of Vocational High School at Selcuk University of Turkey. His current research interest includes multiuser detection in CDMA, neural networks and fuzzy systems.