Performance Analysis Of Linear Multiuser Detectors And Neural Network Detector In Non-Gaussian Noise Channel

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***Abstract* - In multiuser detection techniques, the maximum likelihood multiuser detector provides the best performance in DS-CDMA systems with impulsive ambient noise. But the high complexity makes it impractical. And therefore, effective sup-optimal detectors in non-Gaussian noise are needed. In this paper, we present two-layer perceptron neural network with back propagation training algorithm as a multiuser detector of synchronous DS-CDMA system with non-Gaussian ambient noise. We provide some simulation examples to analyze and compare the performance of the neural network detector with the decorrelator and MMSE (linear multiuser detectors) against MAI, Gaussian and non-Gaussian additive noise. Simulation results show that the performance of the examined detectors degrades in the presence of non-Gaussian noise than in AWGN. However, the neural network detector performs better than the linear multiuser detectors.**

Keywords—DS – CDMA, Multiuser detection, impulsive noise, Decorrelating detector, MMSE detector, neural network detector.

I. INTRODUCTION

DS-CDMA system is attractive for cellular mobile communications because it offers attractive features such as soft capacity, soft handoff, and frequency reuse [1]. But, the capacity of DS-CDMA systems is significantly limited by multiple access interference (MAI), that produced by the other co-channel users [2]. Multiuser Detection (MUD) improves the capacity of DS-CDMA systems by minimizing the impacts of the MAI and mitigating the near-far effect inherent in single-user detection [2-8]. But, the problem with MUD techniques lies in the implementation of a detector that optimally demodulates each user signal [3]. Traditional approaches which use simple matched filter detection affected by MAI and near-far problems and yield poor performance in the presence of multiple or different energy users [4].

Although the optimal multiuser detector [2], proposed by Verdú, has shown significant superior performance over the conventional detector; its computational complexity which increases exponentially with the number of active users in the given system makes it impractical to be used in DS-CDMA systems. As a result, suboptimal multiuser detectors with near optimum performance and less complexity have received great attention. Suboptimal detectors can be classified into two categories, linear detectors and non-linear detectors [7]. The most common linear detectors are the decorrelating detector and MMSE detector. The computational complexity of linear detectors is linearly in proportion to the number of active users.

In non-linear suboptimal multiuser detectors, interferences are estimated and then removed from the received signal. Interference cancellation and neural network (NN) detector are examples of non-linear multiuser detectors. The first NN detector was proposed by Aazhang et al [9]. They proposed detection technique based on multilayer feed forward neural network (MLFFNN) .They prove that the performance of MLFFNN is close to that of the optimum detector, by applying a complex training method, where the number of the neurons increases exponentially with the number of active users [9]. In the present paper, we propose two layers FFNN detector, which will be trained using back propagation learning algorithm. Our main task is to develop a NN detector that provides near-optimal performance without significant increase in the computational complexity and overcomes the drawbacks of the suboptimal detectors whereas the performance based on the previous knowledge of different parameters such as received amplitude, cross-correlation characteristics of signature codes [1].

The key assumption of both optimal and suboptimal detectors synthesizing and analysis has been the use of the Gaussian model for the ambient noise [10]. However, in fact, this assumption is not true in all physical communication channels. Particularly, impulsive noise can occur due to the impulsive nature of man-made electromagnetic interferences such as car ignition, fluorescent lighting and industrial machines close to the signal receivers [10]. Moreover, natural noise such as, lightning in the atmosphere and ice cracking in the Antarctic region, which results in non-Gaussian impulsive noise [8]. So, in our paper, the problem of data stream detection in DS-CDMA systems under the condition of communication channels with impulsive non-Gaussian additive noise will be considered.

In this paper, we will investigate and compare the performances of decorrelator, MMSE, and NN detectors, under the condition of impulsive noise channels, and the, of course, the presence of the MAI. The impulsive noise is modeled by a two-term Gaussian mixture distribution model that is known as Ɛ- contaminated Gaussian mixture model.

The paper is organized as follows: In Section 2, the system model is explained and Section 3 introduces an impulsive noise model. In Section 4, the linear MUDs and the NN detector are presented. Simulation results are presented in Section 5 and conclusions are presented in Section 6.

II. SYSTEM MODEL

We consider synchronous DS-CDMA system with Binary Phase Shift Keying (BPSK) modulation in an impulsive noise channel. The received signal in the base station is given by [11, 12]:

$$\mathrm{r(t) = y(t) + n(t)}, \quad -\infty < t < \infty \tag{1}$$

Where $y(t)$ and $n(t)$ represent the useful signal and the ambient channel noise, respectively. The ambient noise is assumed to be non-Gaussian. The useful signal is comprised of the data signals of k active users in the system and can be expressed as:

$$\mathrm{y(t)} = \sum_{\mathrm{k=0}}^{\mathrm{k}} \mathrm{A_k} \sum_{\mathrm{i=0}}^{\mathrm{M-1}} \mathrm{b_k(i)\, s_k(t - iT - \tau_k)} \tag{2}$$

Where M is the number of data bits per user, T is the bit period time, and where A_k is the received amplitude of the kth user, b_k is the bit sequence of the kth user, b_k ∈ (+1,-1), τ_k is the kth users' time delay and $s_k(t)$ is the spreading waveform of duration T for the kth user. $S_k(t)$ Is defined for N length of signature sequence and BPSK modulation as: $\mathrm{A_k} \sum_{\mathrm{i=0}}^{\mathrm{M-1}} \mathrm{b_k(i)\, s_k(t - iT - \tau_k)}$

$$s_k(t) = \sum_{\mathrm{n=0}}^{\mathrm{N-1}} \mathrm{a_n^k p(t - nT_c)}, \quad \mathrm{t\epsilon[0, T]} \tag{3}$$

Where N is the spreading gain, a_n^k is a spreading sequence of $\pm 1's$ assigned to the kth user and $p(t)$ is the rectangular waveform of duration T_c, where$NT_c = T$. In the case of a synchronous system $\tau_{1=}\tau_{2=} \dots \dots \tau_{k=0}$. The block diagram of synchronous DS- CDMA system transmitter model is shown in Figure 1.The received signal at the receiver is given by:

$$\mathrm{r(t)} = \sum_{\mathrm{k=0}}^{\mathrm{k}} \mathrm{A_k b_k(i) s_k(t - iT) + n(t)} \quad \mathrm{t\epsilon[iT, (i + 1)T]} \tag{4}$$

At the receiver side, the received signal is processed by matched filter (MF); commonly the first stage in the baseband signal detection [13], the output of the MF is given by:

$$\mathrm{y_k} = \int_0^{\mathrm{T}} \mathrm{r(t) S_k(t) dt} \tag{5}$$

Then

$$y_k = \int_0^T \{\sum_{j=1}^k A_j b_j S_j(t) + n(t)\} S_k(t) d(t) \tag{6}$$

$$\mathrm{y_k = A_k b_k} + \sum_{\mathrm{j \neq k}}^{\mathrm{k}} \mathrm{A_j b_j} \int_0^{\mathrm{T}} \mathrm{S_k(t) S_j(t) dt} + \int_0^{\mathrm{T}} \mathrm{S_k(t) n(t)} \tag{7}$$

In form of a matrix the soft output of the MF can act as [13]:

$$Y = RAb + n \tag{8}$$

Where R is the normalized cross correlation matrix whose diagonal elements are equal to 1 and whose (I, j) elements is equal to the cross-correlation ρ_{ij}, A=dig $\{\mathrm{A_1, A_2, \dots \dots \dots \dots . A_k}\}$, Y= $[y_1, y_2, \dots \dots \dots \dots \dots y_k]^T$, b= $[b_1, b_2, \dots \dots \dots \dots \dots b_k]^T$and n is a non-Gaussian random vector.

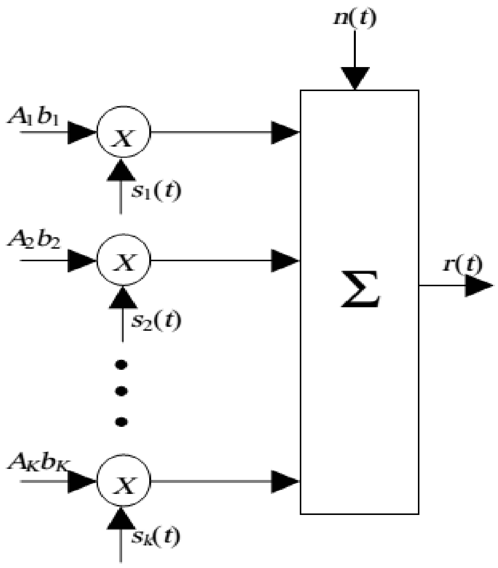

Fig. 1. Synchronous DS – CDMA system transmitter model

III. IMPULSIVE NOISE MODEL

The most commonly used practical model the mixture ε – contaminated Gaussian mixture model. The model is a composite of two Gaussian parts [11]:

$$f_{(x)} = (1 - \varepsilon) f_n(0, v^2) + \varepsilon f_I(0, \kappa v^2) \tag{9}$$

Where the term $f_n(0, v^2)$ is the Gaussian pdf with the main μ and variance v^2 represents the background Gaussian noise and the term $f_I(0, \kappa v^2)$ represents the non-Gaussian impulsive noise with main μ and varianceκv^2. The variance of the second term is much larger than that of the nominal first term and therefore, leads to impulsive behavior. Where ε representing the probability that impulses occur ε ∈ [0,1] , $v > 0, and\ \kappa \geq 1$ .We will study the effect of changes in the shape of the noise distribution on the performance of the system by changing the parameters ε and κ with fixed total noise variance.

$$\sigma^2 = (1 - \varepsilon) v^2 + \varepsilon v^2 \tag{10}$$

The mathematical tractability of this model allows for used widely to model physical noise arising in radio and acoustic channels [11]. Because of the model flexibility, many various naturally occurring noise distribution shapes can be approximated using this model [12]. This method has been used to model non-Gaussian measurement channels in narrowband interference elimination, a problem of considerable engineering interest.

IV. DECORRELATOR DETECTOR

The most cited linear multiuser detector is the decorrelating detector that applied the inverse of the correlation matrix R^{-1} to the output of the MF to separate the users' data [3]. The decision for the Kth user is made based on:

$$\hat{b} = \mathrm{sgn}\left(R^{-1}(RAb + n)\right) \quad (11)$$

$$\hat{b} = \mathrm{sgn}(Ab + R^{-1}n) \quad (12)$$

Although the decorrelator detector fully removes the MAI, the decision is affected because of the noise [4]. In a noiseless case ($N_0 = 0$), the decorrelator detector achieves ideal demodulation as [13]:

$$\hat{b} = \mathrm{sgn}(Ab) \quad (13)$$

The structure of the decorrelator detector is presented in figure 2 and the decorrelator algorithm flow chart is represented in Figure 3[7]. The decorrelator detector has some attractive characteristics [4, 8]:

- Provides substantial capacity gain over the MF detector.
- Eliminate the impact of the MAI.
- It does not need estimate the received amplitude, so it is near-far resistance.
- Computational complexity is much less than the optimum detector.

The decorrelator detector suffers from some drawbacks:

- The inverse of cross correlation matrix (R^{-1}) increases the computational complexity as the number of active users increases.
- Enhances noise.

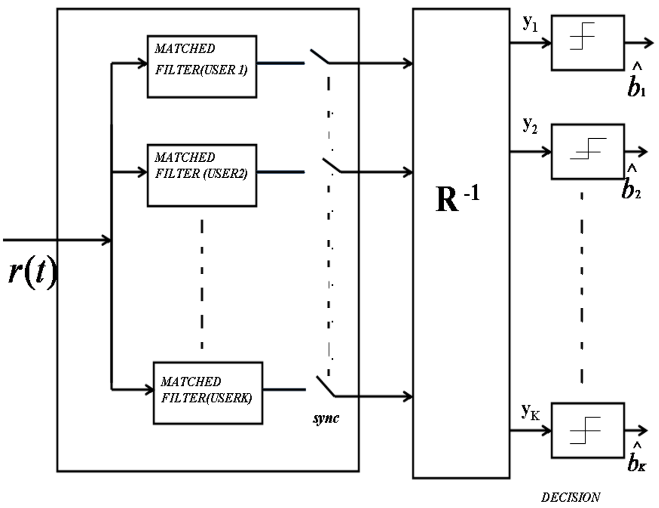

Fig. 2. Decorrelating linear detector

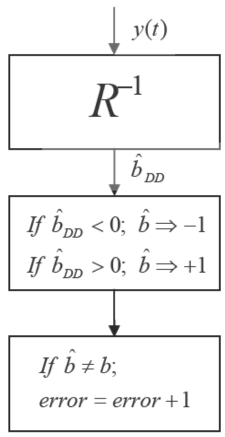

Figure 3. Algorithm for the decorrelating detector

V. MMSE DETECTOR

The MMSE detector is another kind of linear multiuser detectors [5]. The MMSE detector performs a linear mapping L_{MMSE} which minimizes the mean squared error (MSE) $E(|b_k - Ly|)^2$ between the actual data and the soft output of the MF detector. The MMSE as shown in Figure 4 applies modified inverse of the correlation matrix $[R + \left(\frac{N0}{2}\right) A^{-2}]^{-1}$ to the MF bank outputs. So the decision for the Kth user is made based on:

$$\hat{b}_k = \mathrm{sgn}\left(\left((R + N_0 A^{-2})^{-1} y\right)_k\right) \quad (14)$$

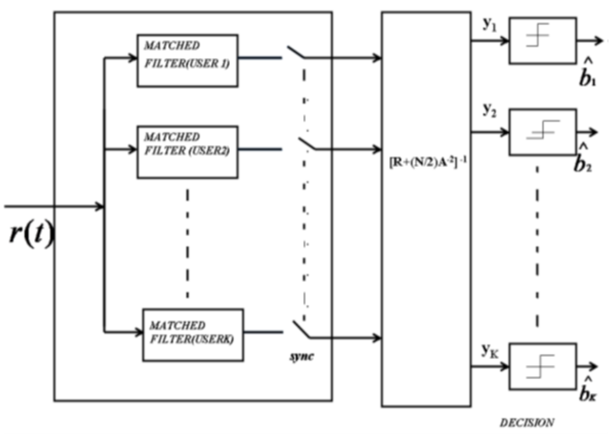

Fig. 4. MMSE linear detector

$$\hat{b}_k = \mathrm{sgn}\left(\left((R + N_0 A^{-2})^{-1}(RAb + n)\right)_k\right) \quad (15)$$

The MMSE algorithm flow chart is represented in Figure 5[7]. The MMSE linear detector seeks to achieve a balance between eliminating the MAI and not enhancing the noise [8]. The MMSE detector, in general, performs better than decorrelating detector because it takes the background noise into account. But the MMSE detector is the same as the decorrelating detector in the absence of noise. Moreover, The MMSE detector requires the knowledge of the received amplitudes. Also, it is influenced by the near-far problem [6].

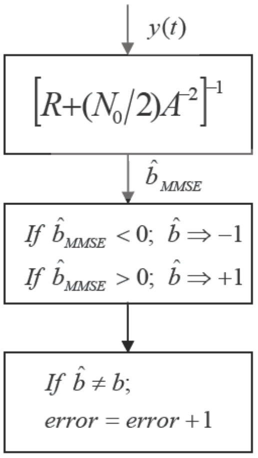

Fig. 5. Algorithm for the Minimum Mean-Squared Error(MMSE) detector

VI. NEURAL NETWORK DETECTOR

The NN detector is a kind of non-linear multiuser detectors [9]. The proposed NN detector is the multilayer feed forward neural network. The configuration of the NN- based detector is presented in Figure 6[13]. As we can see from Figure 6, NN detector consists of a conventional MFs bank followed by the NN detector. The soft outputs of the MF are used to train the NN (training phase). Then, the NN detects the users' bits from the MF output (detection phase). The considered NN detector is a two layer feed forward network (hidden layer) and (output layer), which commonly known as Multi-Layer Perceptron (MLP).

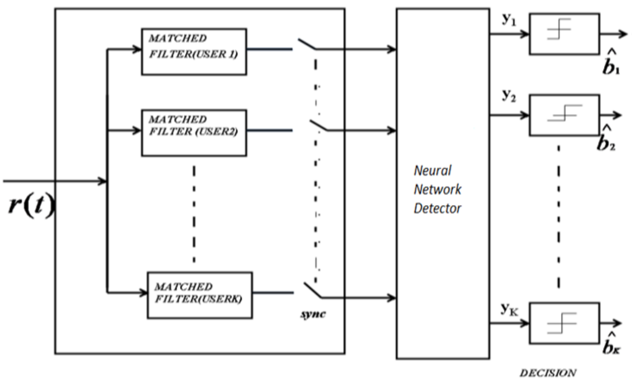

Fig. 6. Neural network detector

In our paper, the conjugate gradient backpropagation with Fletcher-Reeves updates algorithm is used as the learning algorithm for the MLPs. In the hidden layer, a tangent sigmoid (tansig) activation function was used, while in the output layer a pure linear (purelin) activation function was used, and training data of 1000 bits were used.

The NN detector depends on parallel computing in each layer this means fixed demodulation time complexity in proportion to the number of users. Unlike the decorrelator and MMSE which depends on the inverse of correlation matrix which means variable demodulation time in proportion to the number of users [14]. Moreover, the computational complexity of the NN detector is much less than that of the optimum detector. Furthermore, the NN detector has near-optimal performance, near-far resistance, and adaptivity [15]

VII. SIMULATION RESULTES

The investigated detectors are decorrelator, MMSE, and NN detector. The simulations were conducted in three different ways:

We first compare the performance of the examined detectors under the condition of impulsive noise channel at a various probability of impulses occurrence ($\mathcal{E} = 0, 0.01, and\ 0.1$, and $\kappa = 100$). Then, we compare the performance of the examined detectors against the MAI. Finally, provide a comparison of the performance of the examined detectors.

The simulations were performed in a synchronous non-Gaussian channel with K=5, 15 and 30 active users and with the assumption that all active users have equal power. Gold sequence of length (N=31) was used as spreading code, and bit error rate (BER) was considered as the performance index. Ɛ-mixture impulsive noise model was used in terms of an uncertain ambient noise.

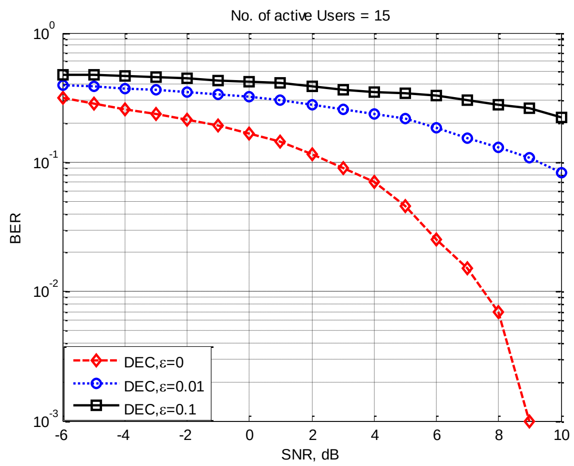

Fig. 7. BER versus SNR of the decorrelator detector in a synchronous CDMA channel with different ε –mixture impulsive ambient noise probability.

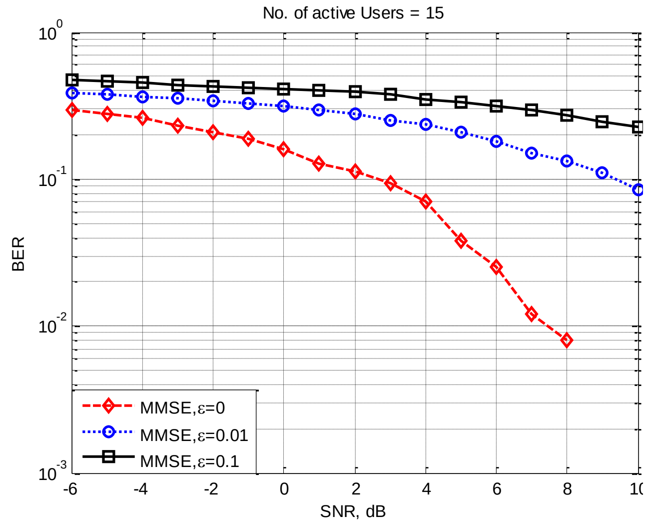

Fig. 8. BER versus SNR of the MMSE detector in a synchronous CDMA channel with different ε –mixture impulsive ambient noise probability.

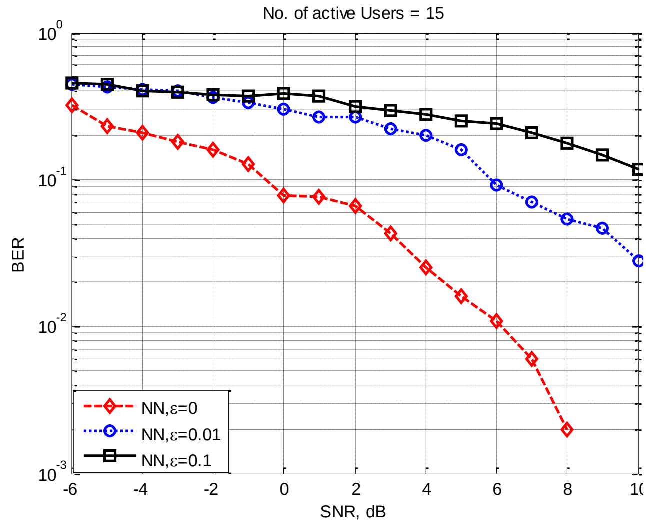

Fig. 9. BER versus SNR of the NN detector in a synchronous CDMA channel with different ε –mixture impulsive ambient noise probability.

In the case of the presence of 15 active users in the system, it is clear from figure 7 - figure 9 that, as the probability of impulsive noise increases, the performance of the examined detectors degrade. (More noise leads to more performance degradation).

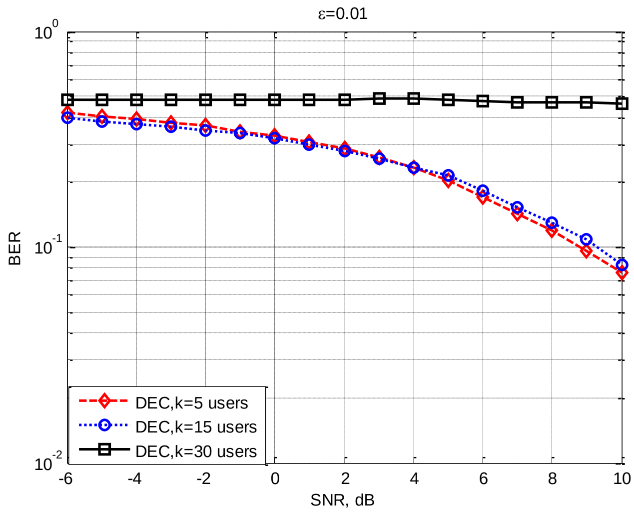

Fig. 10. BER versus SNR of the decorrelator detector in a synchronous CDMA channel with ε –mixture impulsive ambient noise at probability Ɛ = 0.01 for different numbers of active users K=5, 15 and 30.

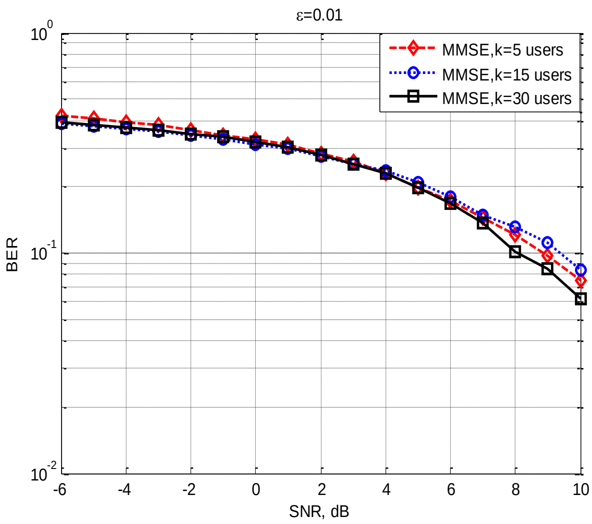

Fig. 11. BER versus SNR of the MMSE detector in a synchronous CDMA channel with ε –mixture impulsive ambient noise at probability Ɛ = 0.01 for different numbers of active users K=5, 15 and 30.

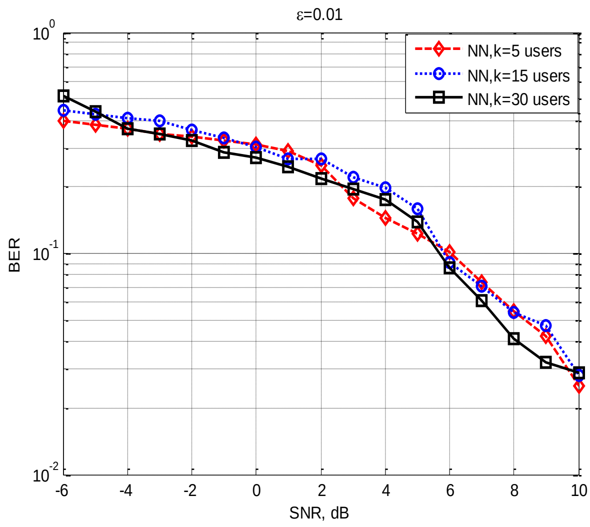

Fig. 12. BER versus SNR of the NN detector in a synchronous CDMA channel with ε –mixture impulsive ambient noise at probability Ɛ = 0.01 for different numbers of active users K=5, 15 and 30.

In the case of the probability of impulsive noise ε=0.01, and the presence of 5, or 15, or 30 active users in the system. It is clear from figure 10 – figure 12, that at K=5, and 15, the performance of the examined detectors degrade. This degradation is due to the impact of the MAI, which results from the presence of multi users in the system. It is well known that as the number of active users increases, the bad impact of MAI increases. At K=30, the DEC detector approximately losses its workability, while both MMSE and NN detectors provide reasonable performances. Also, it is clear from figure 11, that the MMSE provides competitive BER performances at K=5, 15, and 30 active users.

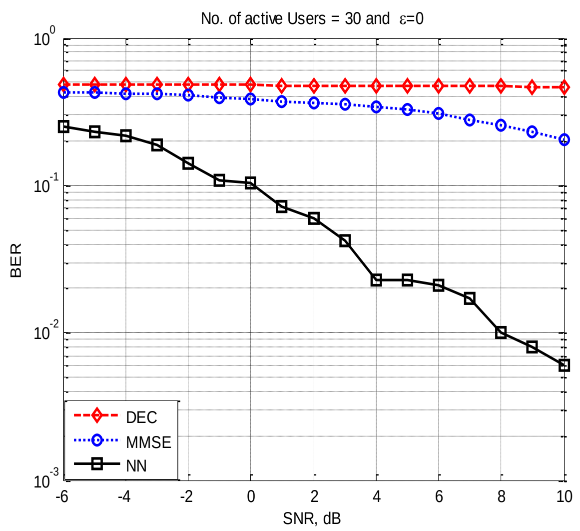

Fig. 13. BER versus SNR of the examined detectors in a synchronous CDMA channel with ε –mixture impulsive ambient noise at probability Ɛ = 0 for number of active users K= 30.

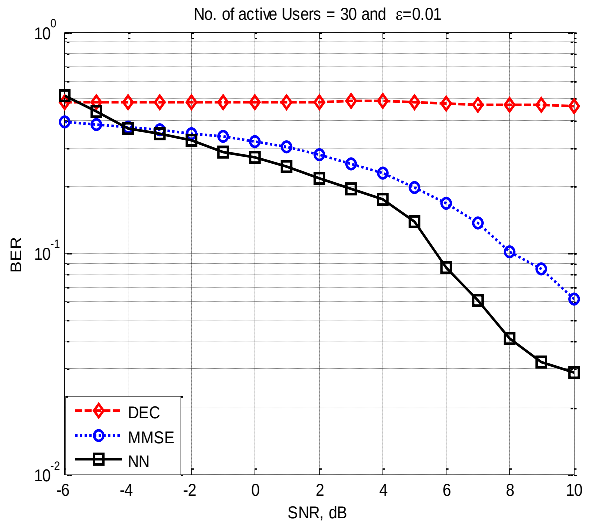

Fig. 14. BER versus SNR of the examined detectors in a synchronous CDMA channel with ε –mixture impulsive ambient noise at probability Ɛ = 0.01 for number of active users K= 30.

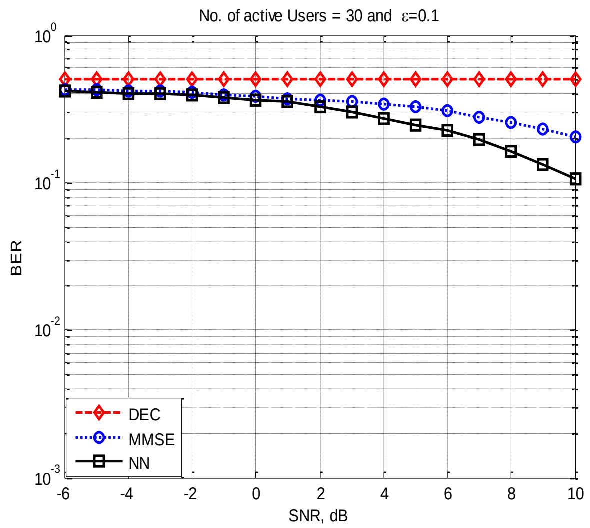

Fig. 15. BER versus SNR of the examined detectors in a synchronous CDMA channel with ε –mixture impulsive ambient noise at probability Ɛ = 0.1 for number of active users K= 30.

In the case of the presence of 30 active users in the system, it is clear from figure 13 – figure15 that, the proposed NN detector provides superior performance over the linear multiuser detectors in the case of Gaussian ε=0, and non-Gaussian additive noise ε=0.01, and 0.1. On the other hand, the MMSE detector outperforms the decorrelator detector.

VIII. CONCLUSION

In multiuser detection techniques, the maximum likelihood multiuser detector provides the best performance in DS-CDMA systems with impulsive ambient noise. But the high complexity makes it impractical. And therefore, effective sup-optimal detectors in non-Gaussian noise are needed. In this paper, we present two-layer perceptron neural network with back propagation training algorithm as a multiuser detector of synchronous DS-CDMA system. We provided some simulation examples to demonstrate the performance of the neural network detector, decorrelator and MMSE against MAI, Gaussian and non-Gaussian additive noise. Simulation results show that the performance of the examined detectors degrades in the presence of non-Gaussian noise than in AWGN. However, the neural network detector performs better than the linear multiuser detectors. We also observed that MMSE detector performs better than the decorrelator detector and this because it takes the background noise into account. As well, the increase in the number of interfering users leads to increase MAI.

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