COMPARISON OF DIFFERENT NEURAL NETWORK BASED MULTI-USER DETECTORS

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ABSTRACT

This paper is concerned with multi-user detection (MUD) in mobile communication systems. Its purpose is to give an insight to the problems of Code Division Multiple Access (CDMA) and to propose novel algorithms for multi-user detection. MUD has gained much attention due to the poor performance of traditional (Rake) receiver techniques of code division multiple access systems. CDMA is standardized as the modulation scheme for third generation UMTS (Universal Mobile Telecommunication Standard), as a consequence it is essential to deal with the problem of detection. In this article neural network based multi-user detection algorithms are proposed, which seem to have superior performance. These algorithms are compared through simulations in various environments.

1 INTRODUCTION

Traditionally, existing code division multiple access systems like IS-95 does not apply multi-user detection. These systems can be described as low bit-rate communication capabilities employing lumpish and resource wasting synchronization procedures to provide proper background for single-user detection based on Rake receiver. The systems of the future like UMTS is planed to provide a high speed (up to 2 Mbps) communication, where perfect synchronization cannot be assured. On the other hand the better utilization of radio resources has become more and more important which opts against using such wasting mechanisms. It seems that traditional single-user detection should not be applied any more in future systems.

Multi-user detection has received considerable interest in recent years, due to the sharp increase of code division mutliple access mobile communication and its successful commercialization. Nevertheless, transmitting information reliably over a radio channel proved to be a major challenge, owing to multipath fading and other factors which can deteriorate the performance. Thus, the task of performing optimal detection is of great importance, which is still one of the central issues of the corresponding research. Traditional methods which carry out the simple matched filter detection [1] yield poor performance in the case of numerous or differing power users. On the other hand, to implement the optimal Bayesian decision meets severe combinatorial limits. Some authors proposed the use of neural architectures, like Hopfield network, to overcome these difficulties [2], [3], [4] in order to provide an alternative method for optimization. Unfortunately, the Hopfield model can get easily stuck into a local minimum, therefore it may not yield the optimal detection, although its performance is good enough. The authors have developed a brand new detection scheme, named as Stochastic Hopfield Network (SHN [9]), where a noise term is added to the Hopfield recursion, which helps to escape from local optimum thus improving the performance.

The paper is organized as follows: In *Section 2* the multi-user detection problem is formulated and the basic notation is introduced. In *Section 3.2* the applicability of Hopfield neural network is highlighted. In *Section 3.3* the new stochastic neural network is introduced. In *Section 4* the performance of the proposed detection algorithms is analyzed by extensive simulations.

2 CHANNEL MODEL

One of the major attributes of CDMA systems is the multiple usage of the same frequency band and time slot. Despite the interference caused by this multiple access property, the users can be distinguished by their codes. Let us investigate a DS-CDMA system, where the ith symbol of the kth user is denoted by $b_k(i)$. Applying BPSK modulation, the output signal of the kth user, denoted by $q_k(t)$, is given as

$$q_k(t) = \sqrt{E_k} \sum_{i=-M}^{M} b_k(i) s_k\left(t - iT\right), \tag{1}$$

where $s_k(t)$ is the continous signature signal associated to the kth user, T is the time period of one symbol and $(2M+1)$ is the size of a block. E_k refers to the energy of the kth user. For the sake of generality we assume multipath propagation channel, so the channel distortion $h_k(t)$ for the kth user is modeled by a sum of simple attenuators and phase shifters:

$$h_k(t) = \sum_{l=1}^{L_k} \alpha_{kl} \delta(t - \tau_{kl}), \tag{2}$$

where α_{kl} is a complex value representing attenuation and phase shifting on the lth path, τ_{kl} is a delaying factor on the lth path, L_k is the number of paths of user k.

The received signal can be written as follows:

$$r(t) = \sum_{k=1}^{K} h_k(t) * q_k(t) + n(t). \quad (3)$$

Substituting (1) and (2) in (3) we get

$$r(t) = \sum_{k=1}^{K} \sum_{i=-M}^{M} \sum_{l=1}^{L_k} \sqrt{E_k}\alpha_{kl} b_k(i) s_k\left(t - iT - \tau_{kl}\right) + n(t),$$

where K is the number of users using the same band, $n(t)$ is a white Gaussian noise with a constant N_0 spectral density. Assuming that the users' codes, the signal energies and channel attenuation factors and delays are perfectly known (coherent detection), the conventional Rake receiver (channel matched filter) generates the following output for the kth user and ith symbol

$$\tilde{b}_k(i) = \sqrt{E_k} \sum_{l=1}^{L_k} \alpha_{kl} \int_{-\infty}^{\infty} r(t + iT + \tau_{kl}) s_k(t) \mathrm{d}t. \quad (4)$$

The traditional single-user detector (SUD) works in the same manner as in sole-user channel and therefore it simply calculates the sign of expression (4) yielding $\hat{b}_k^{\mathrm{SUD}} = \mathrm{sign}\{\tilde{b}_k\}$. This, however, will severely deteriorate the detector's performance, which can be seen from the following formula:

$$\tilde{b}_k(i) = \overbrace{b_k(i)\rho_{kk}(0)}^{\text{Useful signal}} + \overbrace{\sum_{j=-M,\, j\neq i}^{M} b_k(j)\rho_{kk}(i-j)}^{\text{Inter symbol interference}} +$$

$$+ \overbrace{\sum_{m=1,\, m\neq k}^{K} \sum_{j=-M}^{M} b_m(j)\rho_{km}(i-j)}^{\text{Interference caused by others}} + \overbrace{n_k(i),}^{\text{Colored noise}} \quad (5)$$

where ρ_{km} is defined as follows:

$$\rho_{km}(i) = \sqrt{E_k}\sqrt{E_m} \sum_{l=1}^{L_k} \sum_{n=1}^{L_m} \alpha_{kl}\alpha_{mn} \cdot$$

$$\cdot \int_{-\infty}^{\infty} s_k(t) s_m(t + iT - \tau_{mn} + \tau_{kl}) \mathrm{d}t \quad (6)$$

and

$$n_k(i) = \sqrt{E_k} \sum_{l=1}^{L_k} \alpha_{kl} \int_{-\infty}^{\infty} n(t + iT + \tau_{kl}) s_k(t) \mathrm{d}t$$

being still a zero mean white Gaussian noise due to linear transformation.

In (5), the effect of the second term can be cancelled by well known techniques e.g. channel equalization. Unfortunately if the system load - defined as the number of users in the system per processing gain - tends to be hundred percent, the third term related to the first one in (5) becomes so significant that it can absolutely deteriorate the performance of the SUD, namely it cannot be assured better bit error ratios as ten percent. The same degradation happens when the so called near-far effect arises. In this case one or more users with higher power may jam the others' signal. As a consequence, for making proper detection we have to deal with the interference terms in the output of the matched filter.

3 MULTI-USER DETECTION

We have seen that traditional detection fails to achieve reliable performance since it ignores the presence of other users in the same cell. Hence we need a more sophisticated approach to handle the task of detection in multi-user environment.

3.1 Optimal Multi-user Detection

Optimal Multi-user detection is based on Bayesian decision. In this section we elaborate on the optimal solution in a more detailed manner since it helps to understand how it works, and why the sub-optimal solutions shows worse performance. Using the output of the channel matched filter all operations will be processed on the vector of discrete received values ($\underline{\tilde{\mathbf{b}}} = [\tilde{b}_k(i)]$). To obtain optimal solution based on the Bayesian decision for the data sequence $\underline{\hat{\mathbf{b}}} = [\hat{b}_l(i)]$ one wants to chose the maximal probability binary sequence conditioned by received data series. This probability is described in the following expression ([1]):

$$\underline{\hat{\mathbf{b}}}^{\mathrm{opt}} = \arg \max_{\underline{\mathbf{y}}\in\{-1,+1\}^N} \left[\Pr\left\{\underline{\mathbf{y}}\middle|\underline{\tilde{\mathbf{b}}}\right\}\right] =$$

$$= \arg \max_{\underline{\mathbf{y}}\in\{-1,+1\}^N} \left[\frac{\Pr\left\{\underline{\mathbf{y}} \cap \underline{\tilde{\mathbf{b}}}\right\}}{\Pr\left\{\underline{\tilde{\mathbf{b}}}\right\}}\right],$$

assuming uniformly distributed binary source we get

$$\underline{\hat{\mathbf{b}}}^{\mathrm{opt}} = \arg \max_{\underline{\mathbf{y}}\in\{-1,+1\}^N} \left[\frac{\Pr\left\{\underline{\mathbf{y}} \cap \underline{\tilde{\mathbf{b}}}\right\}}{\Pr\left\{\underline{\mathbf{y}}\right\}}\right] =$$

$$\arg \max_{\underline{\mathbf{y}}\in\{-1,+1\}^N} \left[\Pr\left\{\underline{\tilde{\mathbf{b}}}\middle|\underline{\mathbf{y}}\right\}\right]. \quad (7)$$

In our model the $\underline{\tilde{\mathbf{b}}}$ is Gaussian (4, 5), which entails that

$$f\left(\underline{\tilde{\mathbf{b}}}\middle|\underline{\mathbf{y}}\right) = \frac{1}{\left(\sqrt{2\pi}\sigma\right)^N} \exp\left\{-\frac{(\underline{\tilde{\mathbf{b}}} - \underline{\underline{\mathbf{R}}}\,\underline{\mathbf{y}})^H(\underline{\tilde{\mathbf{b}}} - \underline{\underline{\mathbf{R}}}\,\underline{\mathbf{y}})}{2\sigma^2}\right\}$$

where $\underline{\underline{\mathbf{R}}} = [R_{kl}]$ is a symmetric quadratic dominated matrix generated by $\rho_{km}(i)$ in a proper manner. Since the optimization variable $\underline{\mathbf{y}}$ can be found only in the exponent and all other values are constant we only deal with the numerator in the exponent. Leaving out the constant terms the expression reduces to

$$\underline{\hat{\mathbf{b}}}^{\mathrm{opt}} = \arg \min_{\underline{\mathbf{y}}\in\{-1,+1\}^K} \left[-2\underline{\mathbf{y}}^H\underline{\tilde{\mathbf{b}}} + \underline{\mathbf{y}}^H\underline{\underline{\mathbf{R}}}\,\underline{\mathbf{y}}\right]. \quad (8)$$

To put it in words the task of optimal multi-user detector is to find - e.g. with exhaustive search - the optimal binary sequence ($\underline{\mathbf{y}}$) which maximizes the quadratic form of (8). The advantage of this solution is simply its perfection, however, unfortunately, the search for the global optimum of (8) usually proves to be rather tiresome, which prevents real time detection (its complexity by exhaustive search is $\sim O(2^K)$). Therefore, our objective is to develop powerful novel optimization techniques which paves the way toward real time multi-user detection.

3.2 MUD by Hopfield Net

The Hopfield net is a system applying strong feedback mechanisms, which yields a desired dynamic behaviour governed by the connection matrix. Its state transition rule is given by the following formula:

$$Y_l(k+1) = \operatorname{sign}\left\{\sum_{j=1}^{K} W_{lj} Y_j(k) - V_l\right\} \tag{9}$$

where $Y_j(k)$ is the output of the jth neuron at the kth time instant. V_l denotes the decision threshold related to the lth neuron and W_{lj} is the connection strength between the output of the jth neuron and the input of the lth neuron. The state vector is updated in a sequential manner, based on the rule $l = k \bmod K$. Then the Hopfield net will maximize the following quadratic form (often referred to as Lyapunov function):

$$J(\underline{\mathbf{Y}}(k)) = \underline{\mathbf{Y}}^T(k)\,\underline{\underline{\mathbf{W}}}\,\underline{\mathbf{Y}}(k) - 2\,\underline{\mathbf{V}}^T\,\underline{\mathbf{Y}}(k). \tag{10}$$

This optimization process can get stuck in one of the local optima, though. One must note the visible similarity between (8) and (10). To use the Hopfield net for multi-user detection we have to observe the similarity between those equations and chose the parameters in (9) in the following manner:

$$\begin{aligned} W_{lj} &= -\rho_{lj} \\ W_{ii} &= 0 \\ V_k &= -\tilde{b}_k \\ \hat{b}_k^{\mathrm{HNN}} &= \lim_{i\to\infty} Y_k(i) \end{aligned} \tag{11}$$

To avoid local minima, we develop a Stochastic Hopfield Net (SHN) which will be introduced in the next section.

3.3 The Stochastic Hopfield Net

The idea of SHN is to add some noise to each state transition in order to escape from the local minima [9]. Therefore, the original state transition rule of Hopfield net (9) is modified as follows:

$$Y_l(k+1) = \operatorname{sign}\left\{\sum_{j=1}^{K} W_{lj} Y_j(k) - V_l + \nu(k)\right\}. \tag{12}$$

Here $\nu(k)$-s are independently distributed random variables with zero mean and $F(x,k)$ distributions. Furthermore, we assume that $F(x,k) = 1 - F(-x,k)$ is symmetric and $\lim_{k\to\infty} \sigma(k) = 0$, where $\sigma(k) := \mathbf{E}\left\{\nu(k) - \mathbf{E}\left\{\nu(k)\right\}\right\}^2$, which means that the variance of this random variable is cooled down with k. One should note, that SHN has a stochastic state transition rule because of the noise term.

Theorem 1. *With the above mentioned conditions to $\nu(k)$ the operation of the stochastic neural network asymptotically coincides with the state transition of the Hopfield net.*

Proof. The probability that the SHN will follow the operation of the normal HN can be calculated as follows:

$$\begin{aligned} &\Pr\{\text{normal operation}|k\} = \\ &= \Pr\{\nu(k) < -X_l | X_l < 0\}\Pr\{X_l < 0\} + \\ &+ \Pr\{\nu(k) > -X_l | X_l \geq 0\}\Pr\{X_l \geq 0\}, \end{aligned}$$

where $X_l = \sum_{j=1}^{K} W_{lj} Y_j(k) - V_l$ is the term determining the operation of the normal Hopfield net. Taking into account the symmetry of the underlying density function one can obtain:

$$\begin{aligned} \Pr\{\text{normal operation}|k\} &= \Pr\{\nu(k) < |X_l|\} = \\ &= F\left(|X_l|, k\right), \end{aligned}$$

it is clear that $\lim_{k\to\infty} F(|X_l|, k) = 1$, so the SHN will approximate the operation of the normal Hopfield net if $\sigma(k)$ tends to be zero. □

Our objective is, however, that the stationary state of this random state transition rule will yield the global optimum. In [10] the authors have succeeded in proving that if one uses

$$F(x) = \frac{1}{1 + e^{-\alpha x}} \tag{13}$$

distribution to generate values of $\nu(k)$, then the global optimum has the maximal stationary probability [10]. Although it is still a question how to decrease the variance of the noise elements in neurons which depends on the value of α. There has not yet been any analytical proof, but it is clear that the greater α is, the smaller the variance of x becomes.

4 SIMULATION

We have compared the performance of three different detection schemes, such as the single-user Rake receiver, Hopfield neural network implementation, and the stochastic neural network by extensive simulations. Unfortunately we were unable to simulate the performance of the optimal detector (the global minima of the associated quadratic form) due to its computational complexity. That is the reason why the theoretical BPSK performance is depicted on the figures that is expected to be very close to the one of the optimal detector [4]. In our complex baseband equivalent model the bit error ratio of BPSK Additive White Gaussian Noise (AWGN) can be calculated as

$$BER = Q\left(-\sqrt{\frac{E_b}{N_0/2}}\right) = \int_{-\infty}^{-\sqrt{\frac{2E_b}{N_0}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \mathrm{d}x.$$

We used a five path propagation Rayleigh fading influenced radio environment for simulations which means that in (2) for all k $L_k = 5$ and the amplitude of α_{kl} follows Rayleigh distribution, and its phase is uniformly distributed. The delays of different paths (τ_{kl}) were uniformly randomly chosen within the range of [0...30]. On the channel, we applied power control that means the power of different users were set to be exactly equivalent (or nearly equivalent, see Figure 3 and the corresponding explanation). All users transmit 51 bit long packets ($M = 25$).

We applied the Gold code set with length of 31, while 31 users were transmitting on the same channel (see Table 1). It means that the radio channel was fully loaded. Since there are 33 possible codes with this length for the sake of interest we simulated the case of 33 users as well [10]. It involves overloaded channel where neural network based solutions still show outstanding performance.

1110100110101100101111000110001
1011100000011101111100111001111
0000101110100000110111001110110
1011000011100001101100100001001
1110011001000111100010011001111
1001011001001001101001110111011
0111001001110101100000000001101
10100000010000010101101100110110
0001001000011000101010101000110
1110111101111110000101010000111
0011011011111110110110001100110
1011011010001111101011111000101
0111011110010000001001111011101
0101001000001111001111000001001
0000111001000101011110110100110
0001111111100011101000100010111
1110001010000101000111011010110
1100110000110011101001111100101
0010111011011101001010011100101
1011100001000011101010011110010
0010101100111000100011100110101
00100110001000001011010000100011
0110101111001101111101100111101
1101001011000010111111111010000
1011011110101000100111000001100
1010011011101100101010111111010
0010010100010110011001101000101
00000001111100000000101001100101
0000111101100010010010001101111
0101101010101101001001111110010
110001101000000011000000010110001
0010111101000110101011101010110
00100010000000001000100101111101

Table 1: The Gold code set of length 31

According to previously stated limitations we cannot determine yet which annealing schedule fits best to the stochastic neural network based multi-user detector (i.e. how we have to increase the value of α in (13)). We used the simplest function $\alpha(k) = Ak$, where k refers to the iteration instance and A is the initial value. Based on several simulations we found that $A = 1.5$ results the best performance, so we used this value and function in all of the simulations.

On Figure 1 the performance of different detection schemes are compared. On the horizontal axis the bit energy per noise variance ratio is depicted from 6 to 11 dB, on the vertical one the bit error ratio is shown. It is very spectacular that the Rake receiver cannot be used for detection in this heavily loaded environment, since it cannot reach the widely applied 10^{-3} bound. The Hopfield neural network (signed as HN-MUD) works much better; it needs about 10 dB to provide sufficient (10^{-3}) bit error ratio. The stochastic neural network implementation (signed as SHN-MUD) outperforms the original Hopfield realization by 1.5-2 dB, what is more its curve seems to be very close to the BPSK theoretical bound (signed as BPSK AWGN) which refers to almost similar performance as the optimal detector has.

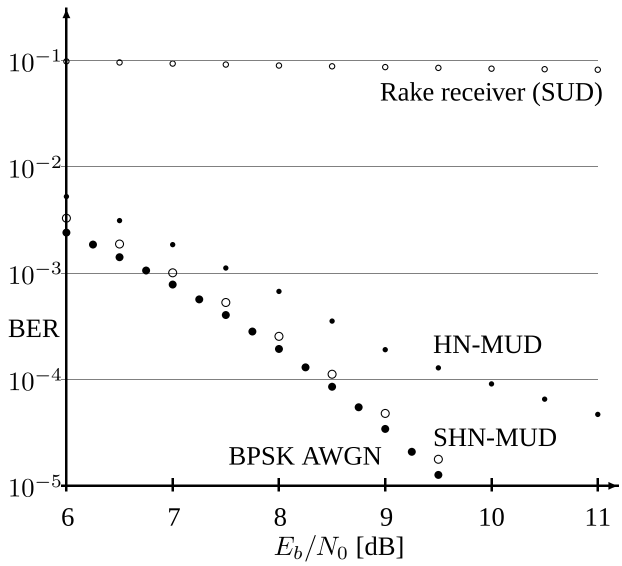

Figure 1: Comparison of detector schemes

Although we have seen that stochastic realization outperforms the original Hopfield neural network, but it is still a question how much additional iteration is needed in exchange for better performance. We have to state once again that we have not yet found the best annealing scheme, so our comparison refers to the one that we have randomly chosen. The average number of iterations needed by the Hopfield net is detailed in Table 2.

On Figure 2 the performance of the stochastic neural network based multi-user detector is depicted as the function of processed iteration according to different E_b/N_0 scenarios. Due to small number of simulations these curves become more rugged as the bit error ratio trends to zero. Comparing Figures 1 and 2 we can conclude that the stochastic neural network implementation reaches the performance of the original in 9-10 iterations. Taking a look at Table 2 it

E_b/N_0 [dB]	Average Iterations
6	4.759
7	4.359
8	3.970
9	3.694
10	3.466
11	3.364

Table 2: Number of iterations needed by Hopfield net

means that the stochastic implementation requires only 1-2 times more computation in comparison to the Hopfield net. In practice it amounts to saying that installing 2 times faster hardware one can assure the same detection properties, and under some circumstances (less users, less computation) we can gain 2 dB enhancement in performance.

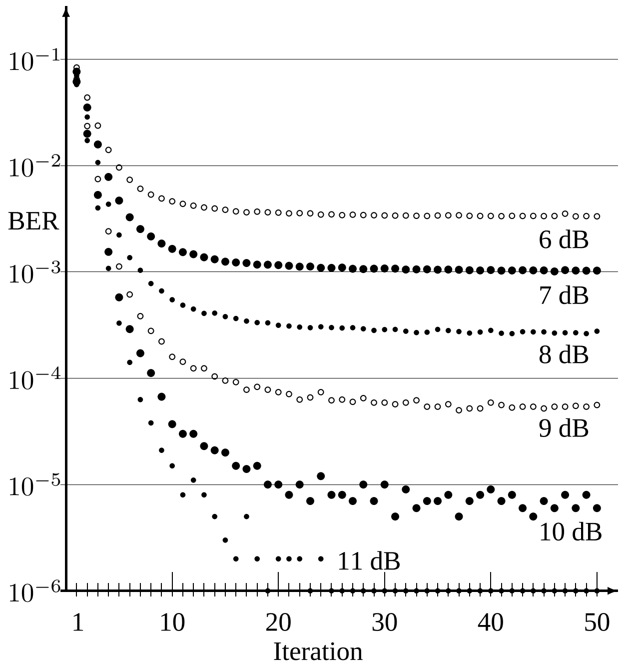

Figure 2: Performance vs. iterations

For further analysis we investigated the power control fault tolerance of the neural network based multi-user detectors, the so called near-far effect resistance analysis. Traditional methods examine the performance as the function of relative energy (E_1/E_k) with respect to one single user. We applied normally distributed power for each user, where the mean was equal to the nominal value, namely $\mathbf{E}\{E_k\} = 1$, the deviation was set to be $\mathbf{E}\{E_k\}^2 - \mathbf{E}\{E_k^2\} = 0.1$, we changed the noise variance (N_0), and we measured the bit error ratio of all users. In this way, we generated more sophisticated simulation of faulty power control. The results can be seen on Figure 3. On the horizontal axis the bit energy per noise variance ratio is depicted from 6 to 16, the vertical one refers to the bit error ratio. As it has already been proven [1] Rake receiver suffers significant performance degradation, which is not very striking in the figure due to small values close to ten percent. The Hopfield implementation shows outstanding efficiency under these circumstances, but it turned out that stochastic implementation cannot follow its rival. What is the reason for this kind of behaviour? The explanation is twofold: in this heavily distorted "power uncontrolled" environment the strong feedback mechanism produces cumulated errors. This effect deteriorates both neural network based detectors performance. On the other hand due to (6) the weight matrix deteriorated not to be diagonal dominated, which yields rough state space including many local minima. The stochastic neural network gets out from local extreme values, and gets into other ones, but it can still wander away from the global minimum, due to the cooling schedule and it can stuck in a worse state. Although it seems that stochastic neural network implementation is not applicable in this situation, according to our inappropriate annealing scheme these results only prove the inapplicability of the cooling schedule, but not the algorithm itself. The proper sceduling scheme is still the case of investigation.

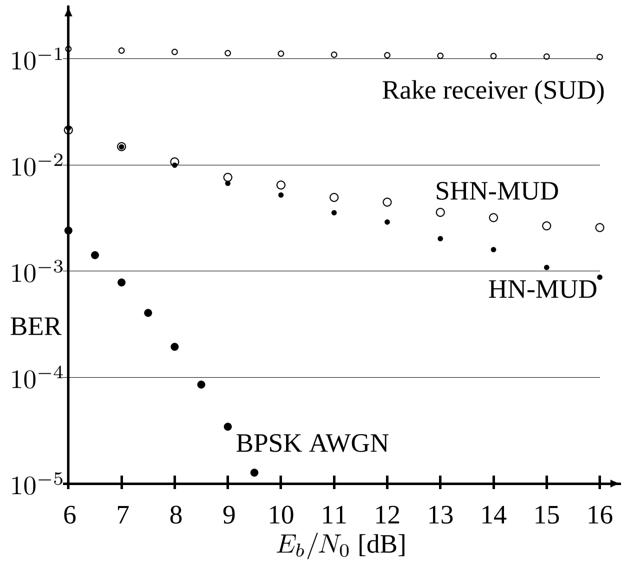

Figure 3: Performance under faulty power control

It seemed to be very interesting to examine the situation of 31 users on the same channel, while the receiver detects only 29 of them. Something similar occurs when two mobile phones which are not recognized yet try to establish connection with the base station, while 29 users are already connected and communicating. In this way the data flood of the connection building users can be regarded as jamming interference to the others. On Figure 4 the simulation results of the proposed situation is depicted. The power of all users are set to be equivalent. On the horizontal axis the bit energy per noise variance is shown from 6 to 11, on the vertical one the bit error ratio is plotted as in Figure 1. The Rake receiver yields the same performance as on Figure 1, which is not astonishing. The two neural network based multi-user detectors suffer remarkable performance degradation due to interference of unrecognized users. Here stochastic neural network outperforms its emulant as well with about 1 dB.

Finally we investigated the effect of the noise term initial value A in an overloaded system, where the number of users was 33 using 31 long Gold codes, the results can be

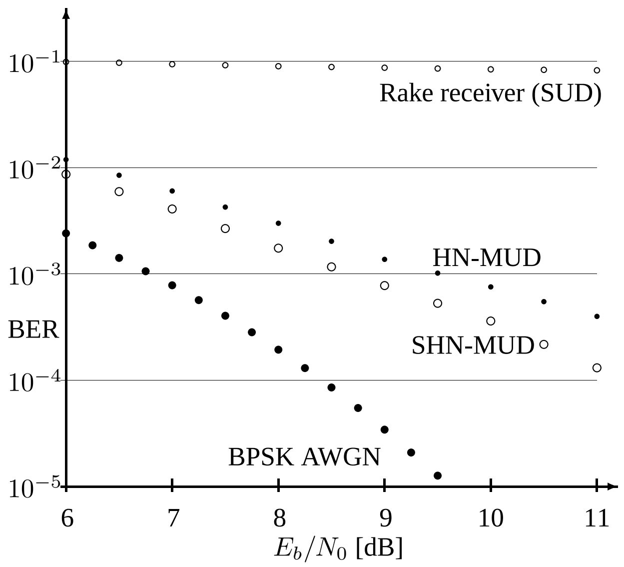

Figure 4: Performance in case of 2 unrecognized users

seen on Figure 5. All users communicate at power level of $E_b/N_0 = 8$ dB. On the horizontal axis the number of iterations, on the vertical the bit error ratio is depicted. As one can see, the best performance can be achieved at $A = 1.5$. Here the best bit error ratio is achieved providing fast convergence at the same time. According to full load we can compare the results to the 31 user case. The final value of the stochastic network's performance is approximately 0.000262 which is very close to the one obtained by simulating 31 users (0.000252).

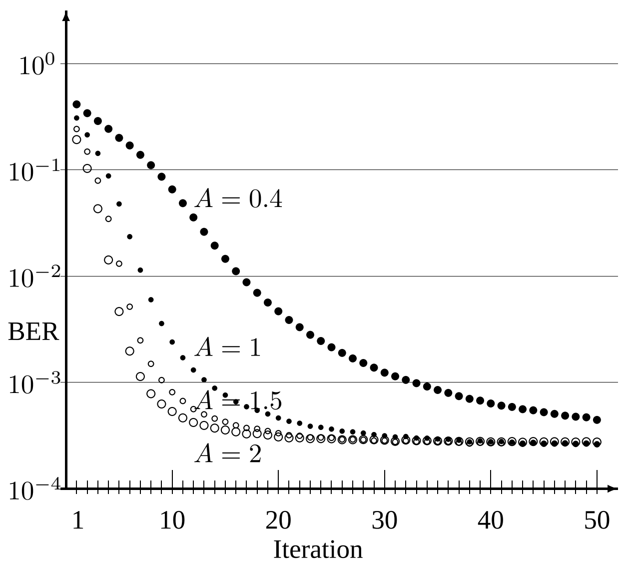

Figure 5: Performance vs. iterations and initial value

5 CONCLUSIONS

In this paper we have proposed a complex baseband equivalent model for UMTS CDMA mobile communication environment. We have demonstrated the problems of single-user detection. We analytically proved that for the optimal multi-user detection solution, a corresponding quadratic form should be minimized. After defining neural network based solution and proving its applicability, we have introduced a new multi-user detection scheme based on a stochastic neural network. By extensive simulations we have highlighted that our stochastic neural network based solution can outperform the original one, although we were unable to determine perfect cooling schedule for the noise variance in the neurons. In perfect coherent channel the performance of stochastic neural network based detector stay close to theoretical BPSK AWGN bound which entails that it is close to the optimal multi-user detector. For further work we would like to describe the annealing schedule analytically, and apply our stochastic realization for complex valued multi-state modulation schemes.

ACKNOWLEDGEMENTS

The authors would like to thank the support of ETIK (Inter University Centre of Telecommunications and Informatics, consist of Ericsson, KFKI computer group, MATÁV, Sun Microsystem Hungary, Westel ltd.) and the assistance of COST 262 project.

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