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GENETIC ALGORITHM-ASSISTED SEMI-ADAPTIVE MMSE MULTI-USER DETECTION FOR MC-CDMA MOBILE COMMUNICATION SYSTEMS

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A GENETIC ALGORITHM-ASSISTED SEMI-ADAPTIVE MMSE MULTI-USER DETECTION FOR MC-CDMA MOBILE COMMUNICATION SYSTEMS

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SUMMARY

ABSTRACT

In this work, a novel Minimum-Mean Squared-Error (MMSE) multi-user detector is proposed for MC-CDMA transmission systems working over mobile radio channels characterized by time-varying multipath fading. The proposed MUD algorithm is based on a Genetic Algorithm (GA)-assisted per-carrier MMSE criterion. The GA block works in two successive steps: a training-aided step aimed at computing the optimal receiver weights using a very short training sequence, and a decision-directed step aimed at dynamically updating the weights vector during a channel coherence period. Numerical results evidenced BER performances almost coincident with ones yielded by ideal MMSE-MUD based on the perfect knowledge of channel impulse response. The proposed GA-assisted MMSE-MUD clearly outperforms state-of-the-art adaptive MMSE receivers based on deterministic gradient algorithms, especially for high number of transmitting users.

I. INTRODUCTION

Multicarrier Code-Division Multiple Access (MC-CDMA) transmission techniques [1] raised a considerable interest in these last years, as they can jointly exploit the advantages of multicarrier Orthogonal Frequency Division Multiplexing (OFDM) and single-carrier Spread Spectrum DS/CDMA techniques. A relevant problem for MC-CDMA transmissions is represented by multi-user interference (MUI). For this reason, it is necessary to study efficient and computationally affordable multi-user detection (MUD) techniques. The basic MUD techniques for MC-CDMA systems are: Maximum Likelihood multi-user detection (ML-MUD), and Minimum Mean Squared Error multi-user detection (MMSE-MUD) [1]. ML-MUD computes the optimum symbol vector that maximizes the ML metric [1]. MMSE-MUD computes the optimal receiver gains that minimize the mean squared error between the transmitted symbol and the weighted output of the MC-CDMA receiver [1].

Examples of near-optimum ML-MUD algorithms implemented by means of unconventional mathematical tools like e.g.: genetic algorithms, neural networks and lattice decoding have been presented in [2-4]. The claimed aim of such kind of approaches is to reduce the dimension of the ML search space that grows exponentially with the number of active users. MMSE-MUD is often preferred in practical MC-CDMA applications for its reduced computational load (polynomially increasing with users number) and because it can easily support adaptive implementations [5]. In [6] and [7] some different adaptive MMSE-MUD implementations for MC-CDMA are shown that are based on Least-Mean-Square (LMS), Recursive-Least-Squared (RLS), and Normalized-Least-Mean-Square (NLMS) algorithms respectively. All these approaches are based on the deterministic gradient algorithm [5] and are very efficient from a computational point of view. Unfortunately, their performances and convergence rates are strongly influenced by the choice of the LMS/RLS updating parameters. These weakpoints can hinder the employment of adaptive MMSE multi-user detection in time-varying fading channels, making them more suitable for static channels, as shown in [6] and [7]. A first alternative solution has been proposed in [6], consisting in an explicit estimation of the channel matrix performed by means of LMS/RLS methodologies. The estimated channel coefficients are then used to compute the receiver weights deriving from the explicit solution of the MMSE equation. Such an approach performs better than fully adaptive MMSE solutions, but, on the other hand, it can suffer from the same drawbacks of deterministic gradient-based algorithms. To improve the reliability of MMSE-MUD in the presence of uncertainties about channel estimation and equalization, Li, Juntti and Latva-Aho proposed in [8] the use of a genetic algorithm (GA)-

based supplementary MUD stage, put in cascade with a MC-CDMA MMSE-MUD stage driven by a blind channel identification algorithm. Another interesting idea has been shown in [9], where a new pilot-based channel estimation scheme has been proposed. The estimated channel coefficients are then used as input to a parallel interference cancellation stage with MMSE filtering.

In this paper, we are going to discuss a GA-assisted approach for semi-adaptive per-carrier MMSE-MUD applied to MC-CDMA communication systems working over time-varying wireless channels. As mentioned in [10], GAs are mathematical tools for dynamic programming and optimisation whose funding concept relies on the natural biological evolution. The proposed GA-based MMSE-MUD approach relies on a trained step, obtained by periodically transmitting a short training sequence. During this working step, the GA-based MMSE receiver is parameterised (in terms of generation number, population size, crossover and mutation probabilities) in order to guarantee a robust convergence of the algorithm to near-optimum receiver gains. Then, the GA-based MMSE-MUD switches to the decision-directed updating step. In this last modality, the receiver gains are dynamically updated by the GA within the coherence period of the channel. The parameterisation of the GA optimisation procedure is changed when the switch from the trained step to the decision-directed step is performed.

The report is structured as follows: Section III is devoted at describing the MC-CDMA received signal model. Section IV will detail the GA-assisted MMSE-MUD algorithm proposed. Section V will present some selected simulation results. Finally, paper conclusions are drawn in Section VI.

II. MC-CDMA SIGNAL MODEL

Let's consider a synchronous downlink MC-CDMA transmission. The baseband equivalent of the transmitted multi-user signal is given by:

$$x(t) = A\sum_{i=-\infty}^{+\infty}\sum_{m=0}^{M-1}\sum_{k=1}^{K} c_m^k a_i^k e^{j\left(\frac{2\pi mt}{T}\right)}\Pi(t-iT) \qquad (1)$$

where: M is the number of subcarriers, K is the number of active users, c_m^k is the m-th chip of the k-th spreading code (Hadamard-Walsh sequences of length M has been employed for synchronous MC-SS spreading [1]), a_i^k is the complex symbol transmitted by the k-th user during the i-th signalling period of duration T, A is the transmitted signal amplitude, and, finally, $\Pi(t)$ is the waveform employed to carry the transmitted symbols. In the present dealing, we are supposing to employ BPSK modulation with rectangular NRZ waveforms. In such a way, the transmitted symbol is actually a single bit. The MC-CDMA signal is transmitted over a Rayleigh multipath-fading channel, characterized by a delay spread T_m and a Doppler spread B_d. The transmission data rate is chosen in order to cope with the basic working condition of a MC-CDMA system, i.e.: the channel must exhibit flat fading over each single subcarrier [1]. Under such hypothesis, the received MC-CDMA signal can be expressed as follows:

$$y(t) = \sum_{i=-\infty}^{+\infty} \sum_{m=0}^{M-1} \sum_{k=1}^{K} g_m(t) c_m^k a_i^k e^{j\left(\frac{2\pi m t}{T}\right)} \Pi(t - iT) + n(t) \qquad (2)$$

where: $g_m(t)$ is the channel gain related to the m-th subcarrier, and *n(t)* is the additive white Gaussian noise. $g_m(t)$ is a complex Gaussian process with Rayleigh-distributed envelope and uniformly-distributed phase [1]. The received signal is then processed by a coherent FFT-based OFDM demux block [1], low-pass filtered by a bank of integrators, and finally sampled at sampling rate equal to *1/T*. The sample of the received signal during the i-th signalling interval is given by:

$$y(i) \hat{=} \sum_{m=0}^{M-1} y_m(i) = \sum_{m=0}^{M-1} \sum_{k=1}^{K} g_m(i) c_m^k a_i^k + \eta_m(i), i = 0,1,2,.. \qquad (3)$$

In eq.3, $\eta_m(i)$ is the i-th sample of filtered AWGN noise affecting the m-th subcarrier (all these samples are independent and identically-distributed in Gaussian way [1]). One can note that the index *i* related to the signalling period appears also in the channel gain of eq.3. This means that we are considering a time-varying channel. Technical issues concerning the dynamic adaptation of the GA-assisted MMSE-MUD algorithm considered in this paper will be dealt in details in the following section.

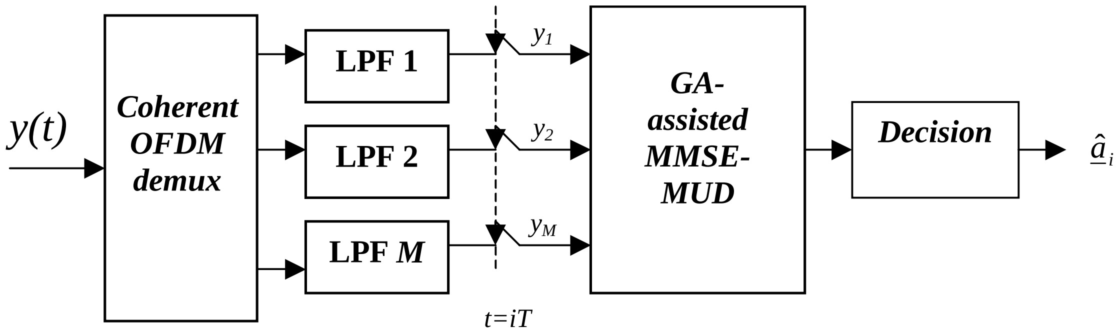

Fig.1. *Block diagram of the semi-adaptive MMSE-MUD receiver*

III. The proposed GA-assisted MMSE-MUD algorithm

Let us consider a per-carrier MMSE multi-user detector [6]. The optimisation criterion is to find an M-element weight vector $\underline{q}^{O}(i)=\left[q_{o}^{O},\ldots,q_{M-1}^{O}\right]$ such that:

$$q_m^O(i)=\arg\min_{q_m(i)} E\left\{\left|\left(\sum_{k=1}^{K} c_m^k a_i^k\right)-q_m(i)y_m(i)\right|^2\right\} \qquad (4)$$

The explicit solution of eq.4 is given as follows [1][6]:

$$q_m^O(i)=\frac{g_m^*(i)}{\left|g_m(i)\right|^2+2\sigma_\eta^2 \big/ KE_c} \qquad (5)$$

being E_c the energy per chip, the superscript operator * the complex conjugate operation, and σ_η^2 the variance of the noise samples $\eta_m(i)$. It must be noted that the computation of MMSE solution requires the exact knowledge of the M-element channel vector $\underline{g}(i)=\left[g_0(i),\ldots,g_{M-1}(i)\right]$. If the channel vector is unknown, the MMSE solution of eq.5 could be computed by replacing $g_m(i)$ with its estimation $\hat{g}_m(i)$. Reliable channel estimation is often computationally intensive. In [6] a Kalman-filter based blind channel estimation is proposed as effective, but computationally intensive solution. As alternative, LMS-based and RLS-based channel estimation methodologies with pilot symbols are considered in [6] as less effective, but computationally affordable solutions. In [8] singular-value decomposition (SVD) semi-blind channel estimation is employed. Such an algorithm is not computationally light and requires pilot symbols in order to avoid phase ambiguity in the computation of the channel coefficients. In [9], pilot-aided channel estimation is employed using pseudo-random training sequences. The estimation of the channel coefficients is substantially performed by means of a big pseudo-inverse matrix of the training sequences that could be computationally expensive. Full-adaptive MMSE implementations (based on LMS and RLS gradient descent criteria) are considered in [6] and [7]. These solutions are very attractive from a computational point of view. Nevertheless, they can work well only over static channels, provided a "bootstrap" of the algorithm obtained by means of an initial training-aided working step [7]. It is shown in [6] that fully adaptive MMSE solutions generally provide very poor performances in time-varying channels. Considering all critical aspects drawn by state-of-the-art contributions, we are proposing here a semi-adaptive MMSE-MUD algorithm for MC-CDMA systems. Standard GA implementations [10] represent feasible solutions as a set of individuals (called *population*). At each iteration (namely: *generation*), the genetic operators of crossover and mutation are applied on selected chromosomes with probability

α, and γ respectively, in order to generate new solutions belonging to the search space. The population generation terminates when a satisfactory solution has been produced or when a fixed number of generations have been completed. Genetic algorithms are widely employed in communication applications due to some basic features [10]:

1) The convergence to the optimal solution is theoretically guaranteed (provided that a proper parameterisation of the GA procedure is set in terms of number of generation and population size), avoiding that solution be trapped in local minima;

2) The GA-based procedure can dynamically adapt itself to time-varying system conditions, because a new population of individuals is computed at each new generation.

Our problem is to optimise MC-CDMA multi-user reception with respect to the per-carrier MMSE criterion, considering a transmission over a time-varying multipath fading channel. In order to make MUD reception robust and adaptive with respect to channel variations, we adopted a GA-assisted MMSE strategy articulated into two different steps:

1) *Training-aided step*. During this step, a B bit-length binary training sequence $\underline{\tilde{a}}^k = \left[\tilde{a}_1^k,...,\tilde{a}_B^k\right]$ is transmitted in form of header for each user k. The training step is repeated with a period approximately equal to the coherence time of the channel. The GA works with a selected parameterisation in terms of generation number G_{Tr}, population size P_{Tr}, crossover and mutation probabilities α_{Tr} and γ_{Tr} respectively. The footer *Tr* means that the GA parameterisation is related to the training step. The task of GA is to compute the weight matrix $\left\{\hat{q}_m^O, m = 0,.., M-1\right\}$ that minimizes the following metric:

$$\Lambda\left(\hat{q}_m\right) = \frac{1}{B}\sum_{i=1}^{B}\left|\left(\sum_{k=1}^{K} c_m^k \tilde{a}_i^k\right) - \hat{q}_m(i) y_m(i)\right|^2 \qquad (6)$$

The GA-based computation of the optimal weights is performed after having buffered B samples of the received signal $y_m(i)$. Note that the ensemble average of eq.4 has been replaced by the sample average of eq.6, made on the entire duration of the training sequence. If we don't perform such an average operation, the GA convergence will be seriously affected by noise effects, particularly at low SNR. It is possible to demonstrate by means of matrix calculations that if we use for training B-length binary vectors obtained from Hadamard-Walsh matrices, the elements of the optimal weight vector $\underline{\hat{q}}^O$ are exactly equal to the sample average of the theoretical optimum receiver weights of eq.5, i.e.: $\underline{\hat{q}}^O = 1/B \sum_{i=1}^{B} \underline{q}^O(i)$. We omitted such a demonstration for sake of brevity.

2) *Decision-directed adaptive step*. The output of the training step is the gain vector $\underline{\hat{q}}^{O}$ obtained by a GA-based optimiser parameterised in such a way to “learn” the channel in reliable way. During a coherence time period, the stochastic values of the channel coefficients acting over each subcarrier are strongly correlated [11]. This doesn’t mean that channel coefficients are time-invariant during a coherence time period, just that time variations of the channel impulse response are reasonably small. By this, a decision-directed adaptive updating step should be reasonably forecast. This is done by the adaptive LMS and RLS MMSE-MUD algorithms proposed in [6] and [7].

In the present dealing, the decision-directed updating step is performed by the GA, working with a different parameterisation and a different fitness function. The GA-based updating procedure is carried on symbol after symbol and it is initialised by the solution computed during the training-aided step, i.e.: $\underline{\hat{q}}^{O}$. During a symbol period a single iteration is performed by the GA and a single generation of individuals is produced. Among the new population, the individual $\underline{\hat{q}}^{U}(i)$ is chosen that minimises the following metric:

$$\Omega\left(\hat{q}_m^U(i)\right)=\left|\left(\sum_{k=1}^{K} c_m^k \hat{a}_i^k\right)-\hat{q}_m^U(i)\,y_m(i)\right|^2 \qquad (7)$$

In such a step, crossover and mutation operators don’t work, because only a GA generation runs. Note that the value $\hat{a}_i^k$ is related here to the estimated data symbol. This updating procedure is “light”, but this is reasonable because only small variations of the channel amplitude and phase are to be tracked during the coherence period. Moreover, in such a way, the effects of possible symbol errors on weight estimation are conveniently reduced.

In order to make clearer to reader our approach, we can summarize as follows the whole GA-based MMSE-MUD procedure:

i) At time t=0 the GA-based procedure is initialised by a random population.

ii) The training-aided step begins. The B-bit known training sequence is transmitted, B samples of the received signal are stored, and the weights vector $\underline{\hat{q}}^{O}$ is computed by minimizing the per-carrier cost function of eq.6. The GA parameterisation is chosen as: generation number = G_{Tr}, population size = P_{Tr}, crossover probability = α_{Tr} and mutation probability= γ_{Tr}. Numerical values assigned to G_{Tr}, P_{Tr}, α_{Tr} and γ_{Tr} will be discussed in the experimental results section.

iii) The training-aided step ends with the computation of the receiver weights at the time t=BT+εT (ε is the execution time of the GA-based optimisation procedure expressed in number of bit periods). Now, the GA switches to the decision-directed adaptive modality. At the beginning of the adaptive step, the GA is initialised with the receiver weights computed at the end of ii), i.e.: $\underline{\hat{q}}^{O}$, and the GA parameters are reassigned as follows: generation number G_D=1, population size P_D, crossover probability α_D=0 and mutation probability γ_D=0. The footer *D* means that the GA parameterisation is related now to the decision-directed adaptive step. The GA procedure produces a population of individuals that are very close to the one chosen during the previous signalling interval, i.e.: $\hat{q}_m^U(i-1)$ (a small variance is set to generate such kind of population). The choice of the best individual is made by minimising the cost function of eq.7.

iv) The decision-directed updating step ends at the time $t=BT+\varepsilon T+W_{coh}T$, where W_{coh} is the coherence time-window of the channel. The GA is re-initialised with the weights computed at the end of the coherence time-window, i.e.: $\underline{\hat{q}}^{U}(W_{coh})$ and re-parameterised in order to start again with the training-aided step of ii).

IV. Experimental results

The semi-adaptive GA-assisted per-carrier MMSE-MUD algorithm has been tested by means of intensive simulations, considering the following fixed parameters: number of subcarriers *M*=32, transmission data rate r_b=1024Kb/s, coherence bandwidth of the channel 2MHz, Doppler spread of the channel 100Hz.

A preliminary series of simulation results has been obtained in order to provide an efficient parameterisation of the GA-assisted MMSE-MUD procedure in terms of generation numbers, population size, crossover and mutation probabilities, and training sequence length. After reiterated simulation trials, we derived the following parameterisation that seems to satisfy the tradeoffs in terms of algorithmic efficiency and computational sustainability:

- *Training-aided step*: generation number G_{Tr}=10 population size, P_{Tr}=10, crossover probability α_{Tr} =0.9, mutation probability γ_{Tr}=0.01;
- Decision-directed step: population size P_D=10;
- Training sequence length *B*=16 bit;
- Coherence window length W_{coh}=1700 bit (computed on the basis of the Jake's model [11] for Rayleigh fading channels).

In order to compare the proposed MMSE-MUD algorithm with other MMSE-MUD state-of-the-art algorithms, we considered a LMS per-carrier MMSE-MUD like the one shown in [6]. The weight-updating rule of the LMS receiver is given as follows:

$$\hat{q}_m^{LMS}(i+1) = \hat{q}_m^{LMS}(i) + \mu\left\{\sum_{k=1}^{K} c_m^k a_i^k - \hat{q}_m^{LMS}(i) y_m(i)\right\}\left(y_m(i)\right)^* \quad (8)$$

In eq.8, μ is the *step size* parameter [6]. We modified the LMS algorithm to make it working in semi-adaptive modality, with the periodic transmission of a *B*-bit length training sequence. The training-aided step for the LMS algorithm is designed in order to force a fast convergence to the optimum weights. On the other hand, during the decision-directed step, the LMS step size is reduced with respect to the one used during the training-aided step. This is done in order to reduce the impact of symbol errors in the updating process. The ideal MMSE-MUD with optimum solution computed as in eq.5 has been employed as basic touchstone in order to have a "lower bound" of the achievable performance.

Simulation results in terms of measured bit-error-rate are shown in Figure 2 and 3. In Fig. 2, BER results are plotted versus signal-to-noise ratio (SNR) for a fixed number of users (*K*=9). One can note that the BER curve related to the proposed GA-assisted MMSE-MUD algorithm is almost coincident with the curve related to ideal MMSE-MUD (requiring perfect knowledge of channel gains) for all SNR values. On the other hand, BER performances of LMS MMSE are strongly influenced by the choice of the step size μ (the step size is referred here to the training-aided modality. In the decision-directed modality, the step size has been reduced to a magnitude order less). Two curves related to the LMS are drawn with different step sizes. The second curve with step size equal to 0.01 is the best one. In any case, LMS performs worse than GA when SNR is high and the impact on system performances of MUI is dominant. Another series of results is shown in Fig.3, where BER vs. user number is drawn for *SNR*=15dB. We can see that the BER curve provided by the GA-assisted MMSE-MUD is always very close to the ideal MMSE BER curve, also for a number of users close to the maximum allowable (*K*=30). On the other hand, LMS performances degrade very much with respect to ideal MMSE as the number of user increases.

To conclude this section, we report some brief insights about the computational complexity of the proposed algorithm. As pointed in [10], GA requires a number of elementary operations to derive a solution that is equal to $\upsilon_{op} = (\alpha + \gamma)GP$. Thus, the computational burden required during the training-aided step is of the order of $K \cdot M \cdot G_{Tr} \cdot P_{Tr}$ elementary operations to be executed during an execution time window εT, where ε>1. The value assigned to ε mainly depends on the computational power of the signal-processing device employed. During the decision-directed adaptive step, the computational requirement of the GA is reduced to $K \cdot M \cdot P_D$ elementary operations to be executed during a signaling period *T*. The computational complexity of LMS is obviously lighter (the number of elementary operations required is proportional to $K \cdot M$), but LMS is generally less performing than GA-based MMSE-MUD and is strongly influenced by the step-size parameter setting. Simulation results, not reported here, evidenced that a very slight displacement of μ from its best setting can increase BER values up to three magnitude orders.

V. CONCLUSION

In this paper we proposed a novel semi-adaptive GA-based approach for MMSE-MUD in MC-CDMA systems transmitting information over time-varying multipath fading channels. The proposed algorithm evidenced some advantages with respect to state-of-the-art contributions. First of all, it doesn't require any channel estimation. It is only required a short training sequence periodically transmitted in order to perform a GA-assisted MMSE training-aided step aimed at "learning" time variations of the channel impulse response outside the coherence time. After the training-aided step, the computed weights are dynamically updated by the GA-based optimisation procedure that is properly re-parameterised. Numerical results in terms of BER evidenced near-optimum behaviour of the proposed algorithm, outperforming LMS-based MMSE approaches especially when the impact of MUI becomes predominant in limiting transmission capacity.

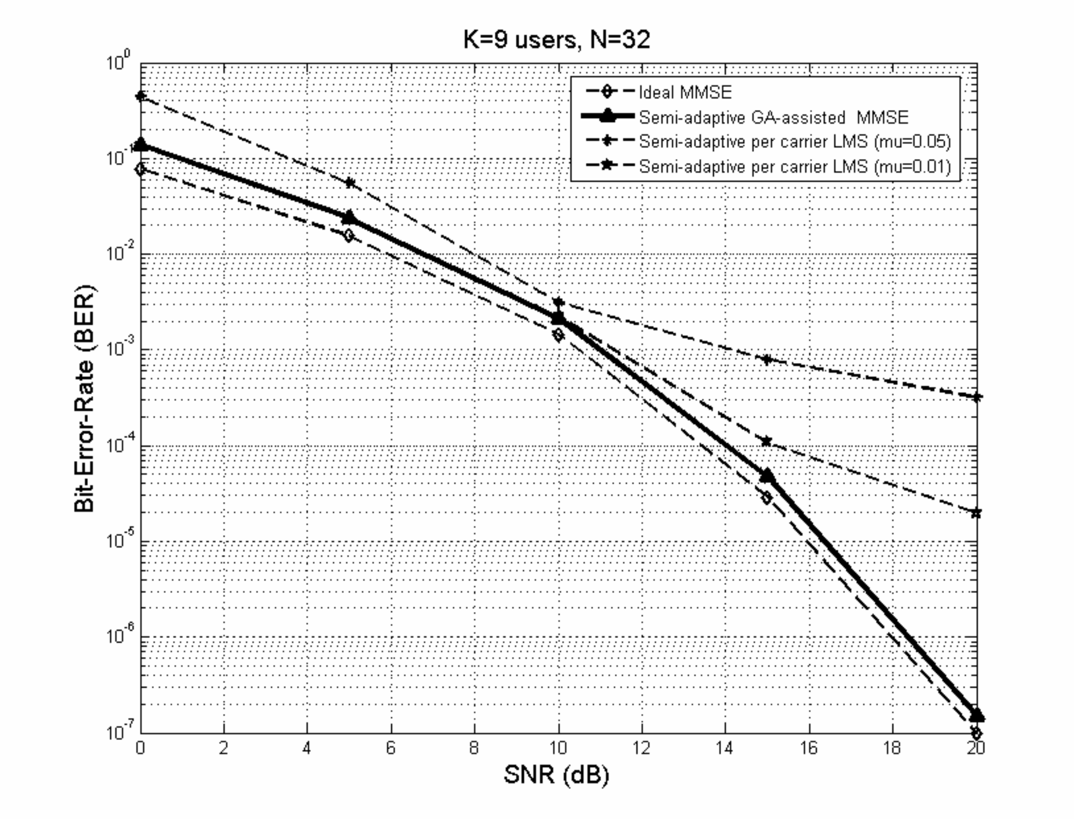

Fig.2. *BER vs.SNR for a fixed number of users (K=9)*

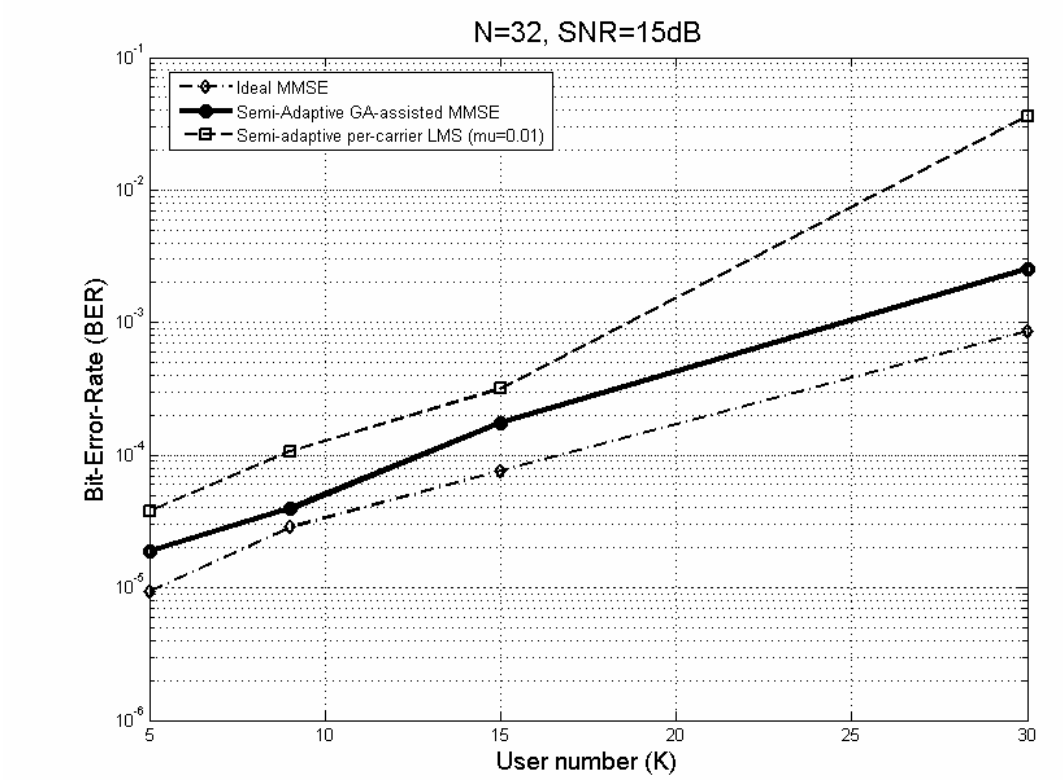

Fig.3. *BER vs. user number for a fixed signal-to-noise ratio (SNR=15dNB)*

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