

# GA, SA, and TS Near-Optimum Multiuser Detectors for S/MIMO MC-CDMA Systems

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**Abstract**—This paper analyzes the performance and complexity of four heuristic approaches applied to a synchronous multicarrier multiuser detection (MuD) of single/multiple transmit antennas and multiple receive antennas code division multiple access (S/MIMO MC-CDMA) system. The genetic algorithm (GA), simulation annealing (SA) and Tabu search (TS) heuristic algorithms (HA) in a single-objective optimization form were considered. Monte-Carlo simulations showed that the performances, after convergence, achieved by the four near-optimum HA-MuD S/MIMO MC-CDMA are identical. However, their computational complexities differ depending on the operation system conditions. Therefore, the HA-MuD complexities were carefully analyzed in order to determine which one has the best trade-off between bit error rate (BER) performance and implementation complexity aspects.

**Index Terms**—MC-CDMA detection, SIMO, MIMO, genetic algorithm, simulating annealing, Tabu search, single-objective optimization.

## I. INTRODUCTION

Multicarrier CDMA emerged from the combination of Direct Sequence Code Division Multiple Access (DS-CDMA) and Orthogonal Frequency Division Multiplexing (OFDM) technologies [1]. Instead of DS-CDMA where the spreading spectrum takes place in the time domain, the spreading in the classic MC-CDMA is done in the frequency domain. Hence, the detector has the capacity of achieving frequency diversity at the cost of a reduced spreading factor.

Multiuser reception under additive white Gaussian noise (AWGN) and selective frequency single-input single-output (SISO) channels using genetic algorithm based detectors has been studied earlier [2], [3] and showed to have excellent sub-optimum performance. Recently, heuristic algorithms have been applied to symbol detection in multiple-input multiple-output channels (MIMO) systems [4]. A survey on MIMO based-OFDMA systems, focused on multiuser detection and estimation heuristics approaches is provided in [5].

This work analyzes heuristic multiuser detectors (HA-MuDs), specifically genetic, simulation annealing and Tabu search algorithms, with a single-objective antenna-diversity-aided optimization criterion, applied to a synchronous single/multiple-input multiple-output MC-CDMA systems. The antennas are assumed to be sufficiently separated such that the received signals at each element are faded independently,

resulting in an independent log-likelihood function (LLF) for each antenna.

## II. SYSTEM MODEL

We consider the uplink of a synchronous MC-CDMA system with  $Q$  receive antennas at the base station and  $K$  mobile users equipped with single antenna terminals. The system can be seen as a MIMO system with  $K$  transmitter antennas and  $Q$  receive antennas. The transmitter employs both time- and frequency-domain spreading, as depicted in Figure 1. The information bit of the  $k$ th user with duration  $T_b$  is spread in  $M$  parallel subcarriers. In each subcarrier, the resultant signal is time-domain spread by a sequence  $c_{k,m}(t)$ ,  $m = 0, \dots, M-1$ , with  $N$  chips with duration  $T_c$ , such that  $N = T_b/T_c$ . The transmitted signal of the  $k$ th user has the form:

$$s_k(t) = A_k \sum_{i=-\infty}^{\infty} \sum_{m=0}^{M-1} c_{k,m}(t) b_k^{(i)} e^{j\omega_m t}, \quad (1)$$

where  $A_k = \sqrt{\frac{E_{bk}}{M}}$ ,  $E_{bk}$  is the  $k$ th signal energy per bit and  $b_k^{(i)} \in [-1, 1]$  is the  $i$ th transmitted bit related to the  $k$ th user. The spreading sequence signed to the  $m$ th subcarrier of the  $k$ th user can be expressed as

$$c_{k,m}(t) = \sum_{n=0}^{N-1} c_{k,m}^{(n)} p(t - nT_c), \quad (2)$$

where  $p(t)$  is the rectangular pulse shape considered. Since the signature waveform  $c_{k,m}(t)$  is used for spreading the data bits to  $N$  chips in the time-domain, and mapping them to a total of  $M$  subcarriers in the frequency-domain for all the  $K$  users, then the total processing gain is  $NM$ . Additionally, it is assumed that the signature waveforms have normalized energy,  $\int_0^{T_b} c_{k,m}^2(t) dt = 1/M$ ,  $\forall k, m$ .

An equivalent independent Rayleigh flat channel is assumed in each subcarrier over all  $Q$  receive antenna. Hence, the channel impulse response of the  $m$ th subcarrier in the  $q$ th receive antenna of the  $k$ th user is given by  $h_{q,k,m} = \beta_{q,k,m} e^{j\varphi_{q,k,m}}$ , where the amplitude  $\beta_{q,k,m}$  is a Rayleigh distributed random variable and the phase  $\varphi_{q,k,m}$  is uniformly distributed in the  $[0, 2\pi)$ . The received signal on the  $m$ th subcarrier,  $q$ th receive antenna, and all  $K$  users is given by:

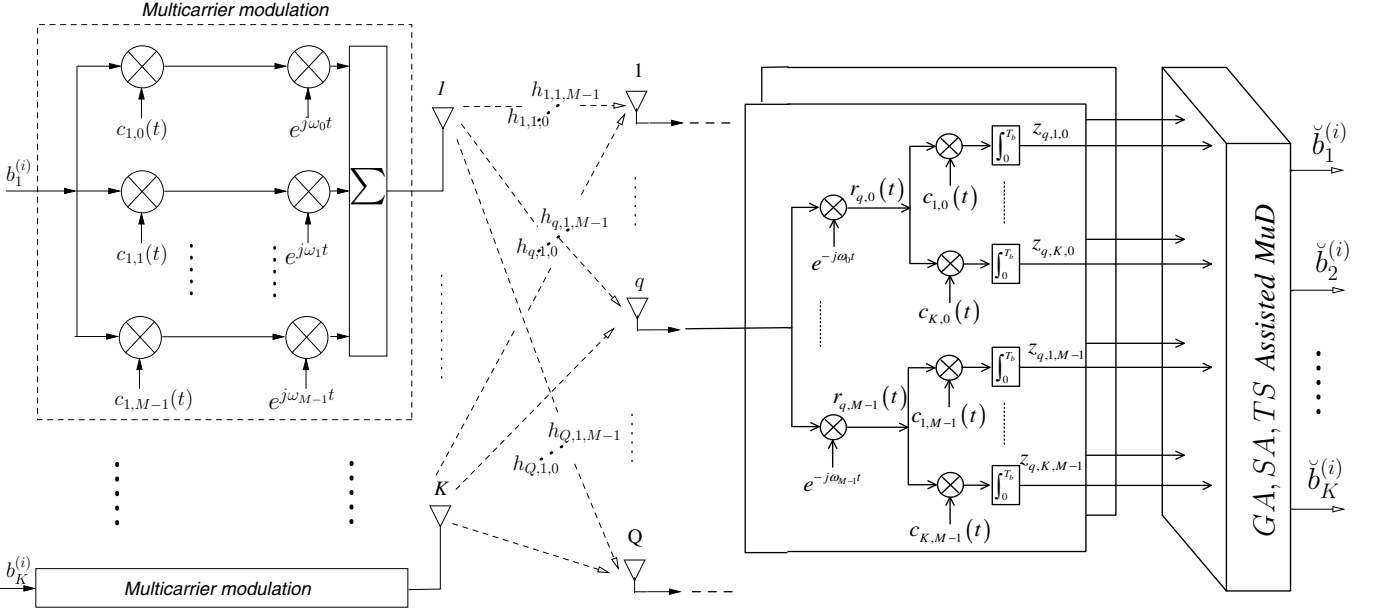


Fig. 1. Equivalent S/MIMO MC-CDMA system with transmitter and receiver schemes. The receiver has two stages: matched filter for each subcarrier followed by a heuristic multiuser detector.

$$r_{q,m}(t) = \sum_{i=-\infty}^{\infty} \sum_{k=1}^K A_k b_k^{(i)} c_{k,m}(t - iT_b) \beta_{q,k,m} e^{j(\omega_m t + \varphi_{q,k,m})} + \eta(t), \quad (3)$$

where  $\eta(t)$  is the AWGN term associated to the  $m$ th subcarrier bandwidth of  $q$ th antenna and with bilateral power spectral density given by  $N_0/2$ .

For each receive antenna of multiple-antenna receiver, the signal is demodulated in all the  $M$  subcarriers and passed through a matched filter (MF) for each of the  $K$  users, generating  $z_{q,k,m}$ . The resulting signal is submitted to the heuristic-assisted MuD described in Section III. The channel state information (CSI) has to be estimated at the receiver either by training or some blind methods. In this work we have assumed perfect CSI estimates.

The equivalent baseband representation of the received signal on the  $m$ th subcarrier of the  $q$ th antenna,  $r_{q,m}(t)$ , can be expressed in matrix notation as [6]:

$$\mathbf{r}_{q,m}(t) = \mathbf{C}_m \mathbf{W}_{q,m} \mathbf{b} + \mathbf{n}_{q,m}, \quad (4)$$

with  $\mathbf{C}_m = [\mathbf{c}_{1,m} \dots \mathbf{c}_{k,m} \dots \mathbf{c}_{K,m}]$ ;  $\mathbf{c}_{k,m} = [c_{k,m}^{(0)} \dots c_{k,m}^{(N-1)}]^\top$ ;  $\mathbf{W}_{q,m} = \text{diag}[A_1 h_{q,1,m} \dots A_k h_{q,k,m} \dots A_K h_{q,K,m}]$ ;  $\mathbf{b} = [b_1 \dots b_k \dots b_K]^\top$ ;  $\mathbf{n}_{q,m}$  is the  $N$ -sampled AWGN vector on the  $q$ th antenna,  $m$ th subcarrier. The MF output of the  $m$ th subcarrier from  $q$ th antenna can also be expressed in vector notation:

$$\mathbf{z}_{q,m} = [z_{q,1,m}, z_{q,2,m}, \dots, z_{q,K,m}]^\top = \mathbf{R}_m \mathbf{W}_{q,m} \mathbf{b} + \tilde{\mathbf{n}}_{q,m} \quad (5)$$

where  $\tilde{\mathbf{n}}_{q,m} = [\tilde{n}_{q,1,m}, \dots, \tilde{n}_{q,k,m}, \dots, \tilde{n}_{q,K,m}]$  is the filtered sampled noise vector after matched filter, and the correlation matrix is given by:

$$\mathbf{R}_m = \begin{bmatrix} \rho_{1,1}^{(m)} & \rho_{1,2}^{(m)} & \dots & \rho_{1,K}^{(m)} \\ \rho_{2,1}^{(m)} & \rho_{2,2}^{(m)} & \dots & \rho_{2,K}^{(m)} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{K,1}^{(m)} & \rho_{K,2}^{(m)} & \dots & \rho_{K,K}^{(m)} \end{bmatrix}, \quad (6)$$

with the auto- and cross-correlation of the spreading code represented as  $\rho_{i,j}^{(m)} = \int_0^{T_b} c_{i,m}(t) \cdot c_{j,m}(t) dt$ .

For  $k$ th user' symbol estimation, the conventional detector (CD) linearly combines decision variables overall  $M$  subcarriers and  $Q$  receive antennas:

$$\hat{b}_k^{\text{CD}} = \text{sign}(y_k) \quad (7)$$

with  $y_k$  being the linearly combined decision variable, defined as:

$$y_k = \sum_{q=1}^Q \sum_{m=0}^{M-1} z_{q,k,m} \cdot \hat{h}_{q,k,m}^* \quad (8)$$

with  $\hat{h}_{q,k,m}$  being the estimated complex channel coefficient on the  $m$ th subcarrier,  $q$ th antenna,  $k$ th user. Therefore, the entire estimation from all users is the vector composition:

$$\hat{\mathbf{b}}^{\text{CD}} = [\hat{b}_1^{\text{CD}} \dots \hat{b}_k^{\text{CD}} \dots \hat{b}_K^{\text{CD}}] \quad (9)$$

At the receiver, the maximum likelihood (ML) detection detects the data of all users and jointly minimizes the effects of multiple access interference (MAI). The optimum multiuser

detection considering each subcarrier  $m$  on the  $q$ th receive antenna must maximize the following objective function [7]:

$$\Omega_{q,m}(\mathbf{b}_i) = 2\Re \left\{ \mathbf{b}_i^\top \widehat{\mathbf{W}}_{q,m}^* \mathbf{z}_{q,m} \right\} - \mathbf{b}_i^\top \widehat{\mathbf{W}}_{q,m} \mathbf{R}_{q,m} \widehat{\mathbf{W}}_{q,m}^* \mathbf{b}_i, \quad (10)$$

where  $\mathbf{b}_i$  is a vector-candidate and  $\widehat{\mathbf{W}}_{q,m}$  is an estimate for  $\mathbf{W}_{q,m}$ . The optimum MuD (OMuD) is based on the maximum likelihood criterion that chooses  $\mathbf{b}_i$  which maximizes the metric:

$$\mathbf{b}^{opt} = \arg \left\{ \max_{\mathbf{b}_i \in \mathcal{A}^{\mathcal{MK}}} [\Omega(\mathbf{b}_i)] \right\} \quad (11)$$

where  $\Omega(\mathbf{b}_i)$  is a multi or single-objective function that takes into account some combination rule considering  $\Omega_{q,m}(\mathbf{b}_i)$  functions, for  $Q$  antennas and  $M$  subcarriers in (10),  $\mathcal{M} = 1$  is the message length and  $\mathcal{A} = 2$  is the symbol alphabet dimension; in the optimization context, and  $\mathcal{A}^{\mathcal{MK}}$  is the feasible region in the decision space.

In this paper, it was considered the linear combined Q-LLFs antenna-diversity-aided strategy (LC Q-LLFs). Hence, the objective function is described as:

$$\Omega(\mathbf{b}_i) = \frac{1}{Q} \sum_{q=1}^Q \sum_{m=0}^{M-1} \Omega_{q,m}(\mathbf{b}_i) \quad (12)$$

Equation (11) is a combinatorial optimization problem, which requires an exhaustive search in  $J = \mathcal{A}^{\mathcal{MK}}$  possibilities of  $\mathbf{b}_i$ . Therefore, the ML detector complexity increases exponentially with the number of users.

### III. HA-MUDS FOR S/MIMO MC-CDMA

In the LC Q-LLFs individual-selection strategy, the selection of individual(s)<sup>1</sup> for evolving is based on the highest fitness values of (12) and decisions are based on a single-objective optimization procedure, i.e., by combining the subcarriers and antenna-specific performance measures.

Several HA-MuDs algorithms have been analyzed. Details of the GA, SA, STTS and RTS S/MIMO MC-CDMA MuD algorithms, as well as their pseudo codes, can be found in [8].

#### A. GA S/MIMO MC-CDMA

Genetic algorithms are based on selection mechanism and natural evolution, following the theory of species evolution of Darwin which explains the life history by the action of physical processes and genetic operators in populations or species. These processes are known as reproduction, perturbation, competition and selection, being responsible for an efficient search of the global solution.

In order to improve the convergence chances of heuristic algorithms, the population size is determined in the GA initialization stage and maintained constant in all generations as [2]:

$$\mathcal{P} = 10 \left\lceil 0.3454 \left( \sqrt{\pi(\mathcal{MK} - 1)} + 2 \right) \right\rceil, \quad (13)$$

<sup>1</sup>In this section we use GA nomenclature. For SA and TS context we have “vector-candidate”.

where the operator  $\lfloor x \rfloor$  returns the greatest integer not larger than  $x$ .

In the GA-MuD context, the aptitude is measured through the LLF function (10) and it is directly responsible for the death or survival of individuals. In the LC Q-LLFs selection strategy, the fitness evaluation for each individual is obtained by linearly combining each LLF function associated to each one of the  $Q$  receive antennas and  $M$  subcarriers in (12).

The  $i$ th symbols estimates from the MF outputs over the  $Q$  receive antennas are adopted as initial GA's individual. The other  $(\mathcal{P} - Q)$  members of the first population are obtained from the initial individual with convenient perturbations [2].

The selection process chooses the best  $T$  individuals from the population  $\mathcal{P}$  as the parents for the next generation. The mating pool size  $T$ , with the constraint  $2 \leq T < \mathcal{P}$ , should be selected in order to guarantee the convergence velocity and the final solution quality [9]. For the S/MIMO MC-CDMA MuD problem a fixed mating pool size  $T = 0.1\mathcal{P}$  was adopted.

For the genetic operators, it was adopted the uniform crossover [9] with crossover probability  $p_c$  and the mutation based on noise:  $\text{new}_{\text{indiv}} = \text{sign}[\text{indiv} + \mathcal{N}(0, \sigma^2)]$ , where  $\mathcal{N}(0, \sigma^2)$  represents a Gaussian distribution with expectation zero and standard deviation  $\sigma$  strongly related with the mutation probability  $p_m$  [2].

The GA S/MIMO MC-CDMA uses a replacement strategy called global elitism [9], where only the best  $\mathcal{P}$  individuals from the joint population of parents and offspring are maintained for the next generation. Finally, the optimization process finishes after a fixed number of generations ( $G$ ).

#### B. SA S/MIMO MC-CDMA

The simulation annealing (SA) algorithm concept stems from thermal annealing mechanism which aims to obtain perfect crystallizations by a slow enough temperature reduction, giving the atoms sufficient time to attain the lowest energy state [10]. In order to escape from a local maximum, the SA algorithm uses an acceptance probability function, proportional to the temperature, that allows even so to accept a particular solution that possesses a higher value (a state of higher energy). This enables the algorithm to leave a local maximum area and seeks for the global maximum in other areas. Classically, the acceptance probability function is inspired in the Boltzman distribution:

$$P(\Delta E) = \exp(\Delta E/T_k) \quad (14)$$

where  $\Delta E = \Omega(\mathbf{b}_i') - \Omega(\mathbf{b}_i)$ ,  $\mathbf{b}_i'$  is a set of possible received bits that differs from  $\mathbf{b}_i$  by only one chip, i. e., unitary Hamming distance from  $\mathbf{b}_i$ , and  $T_k$  is the temperature in the current iteration, defined by:

$$T_k = \delta^k T_0 \quad (15)$$

where  $T_0$  is initial temperature of the process, and  $\delta$  is the cooling rate. Eq. (15) is not the only way to describe the cooling process, but one usual method found in the literature [10]. The initial temperature of the process has a high value,

$T_0 \gg 0$  and the temperature is reduced after a fixed number of iterations  $It$ .

Besides the initial set of received bits  $\hat{\mathbf{b}}^{\text{CD}}$ , the SA algorithm is initialized with more three parameters:  $T_0$ ,  $\delta$ , and  $It$ . These last three parameters were empirically adjusted through a non-exhaustive attempt procedure.

### C. Tabu Search S/MIMO MC-CDMA

The *short term Tabu search* (STTS) algorithm is based on the deterministic operation way of a memory. The memory is implemented by recording displacement characteristics of the previously visited solutions [11], [12] avoiding cycling. This is described by the Tabu list (TL), which is formed by the recent past of search, being called effect of short term memory. These displacement characteristics are forbidden for the Tabu list for a certain number of iterations, avoiding returns to local solutions, promoting a diversification in the search.

The *reactive Tabu search* (RTS) algorithm combines the effect of short term with other memory effect to avoid returns to local maxima and to guarantee an efficient search. This effect is known as long term memory, which alternates between intensification and diversification phases [12], [13].

The Tabu list of the STTS algorithm is implemented using the effects of short term. However, it does not assure escaping from local maxima returns. Additionally, the choice of a fixed prohibition period ( $P_{TL}$ ) for each problem becomes a difficult task, because a small period is insufficient to avoid returns to local maxima and a huge period reduces the amount of possible displacements, resulting in an inefficient search.

The memory of long term of RTS is constituted by the effect of short term memory of the STTS algorithm adapting the prohibition period during the search, being admitted that this period assumes different values at each iteration ( $P_{TL}^g$ ). The prohibition period is initialized with a small value,  $P_{TL}^0$ , being adapted in the occurrence of repetitions. When a repetition is found, the diversification is encouraged by the increment of the period  $P_{TL}^g$ . For that diversification not to assume very high values after some iterations, the period  $P_{TL}^g$  is reduced when  $|f(\mathbf{b}_i) - f_{\text{best}}^g| < x f_{\text{best}}^g$ ,  $\forall i$  and  $0 < x < 1$ ; the best solution (cost function or energy value) until the  $g$ th iteration is expressed by  $f_{\text{best}}^g$ . A robust value for the constant that controls the reduction of the period  $P_{TL}^g$  was obtained in [12], being found  $x = 0.3$  for the AWGN MuD detection problem.

## IV. NUMERICAL RESULTS AND COMPARISONS

The main system and channel parameters used in Monte-Carlo simulations are summarized in Table I. Binary random sequences of length 32 was adopted, and the single-user bound BER performance for S/MIMO MC-CDMA (SuB) was included in Figure 5. In all simulated systems, the equivalent processing gain is  $NM = 32$ , with  $M = 4$  subcarriers and  $N = 8$ . Perfect power control is assumed among users sharing the system.

### A. Convergence and BER Performance

Monte-Carlo simulations (MCS) results indicate that the GA, SA, RTS and STTS S/MIMO MC-CDMA algorithms almost reach the same performance after convergence, although with different computational complexity, as discussed in Section IV-B. The main reason is that the SA, STTS and RTS algorithms use the same 1-optimum search strategy to select their potential solutions inside the search space. To corroborate this assertion, Figure 2 shows that all HA-MuDs almost reach the same BER performance after convergence, in spite of their different starting points. The small performance differences appear due to the MCS method. Therefore, under equal initial solutions, the four HA-MuDs reach similar performance after convergence, as showed in Figure 3, which presents HA-MuD convergence for two loading sceneries and signal-noise ratio (SNR). Besides, in Figure 3, it is observed a performance degradation when the loading increases. This loss can be compensated with the SNR and/or number of receive (Rx) antennas increasing. In both sceneries the performance of the heuristic detectors are clearly superior when compared to CD. Indeed, the performance gain of the HA-MuD over the CD when the number of receive antennas increases is emphasized in Figure 4. For medium (Figure 4.a) and full loading (Figure 4.b), the system is capable to reach a small BER ( $\text{BER} < 10^{-3}$ ) for a small number of receive antennas and SNR.

TABLE I  
SYSTEM, ALGORITHM AND CHANNEL PARAMETERS.

Parameter	Adopted Values
<i>S/MIMO MC-CDMA System</i>	
# Rx antennas	$Q = 1$ to 5
Code Sequences	Random with length 32
Processing gain	$N = 8$
Subcarriers	$M = 4$
Bit period, $T_b$	300 $\mu\text{s}$
# mobile users	$K = 5; 10; 15; 20; 25; 32$
Received SNR	$E_b/N_0 \in [0; 18]$ dB
<i>GA Algorithm Parameters</i>	
mutation probability	$p_m \approx 5\%$
crossover probability	$p_c = 50\%$
mating pool size	$T = 0.1P$
<i>SA Algorithm Parameters</i>	
# iterations @ $T_k$	$It = 2$
Initial Temperature	$T_0 = 0.3K$
Cooling rate	$\delta = 0.9$
<i>STTS Algorithm Parameters</i>	
Tabu list length	$P_{TL} = 3$
<i>RTS Algorithm Parameters</i>	
Tabu list initial length	$P_{TL}^0 = 1$
Reduction control	$x = 0.3$
<i>Rayleigh Channel</i>	
Max. Doppler freq.	$f_{\text{Dpl}} = 100$ Hz (slow channel)
Per subcarrier	flat-frequency
Channel state info. (CSI)	perfectly known at Rx
# iterations (GA, SA & TS)	$G(K, Q) \in [25; 40]$

### B. Computational Complexity

In spite of the HA-MuDs reach a similar performance, the number of operations varies for each of the different strategies. In order to obtain a fair comparison for the efficiency, it is

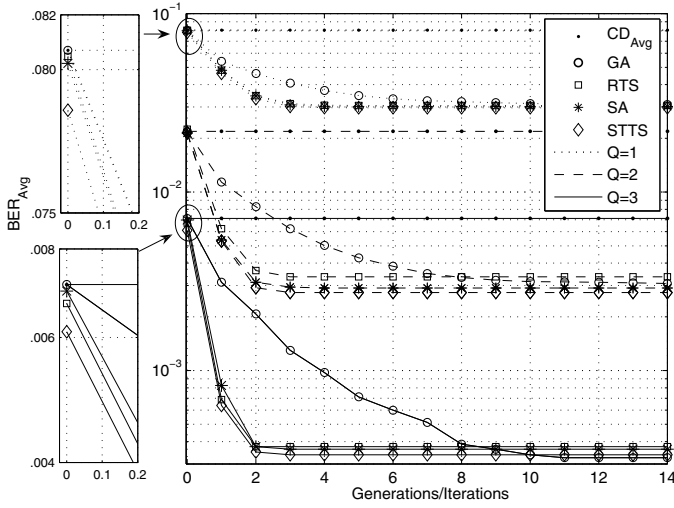


Fig. 2. Convergence performance for CD, GA, SA, RTS and STTS S/MIMO MC-CDMA considering distinct initial solutions for  $E_b/N_0 = 6\text{dB}$ ,  $K = 20$ ,  $\mathcal{P} = 30$ .

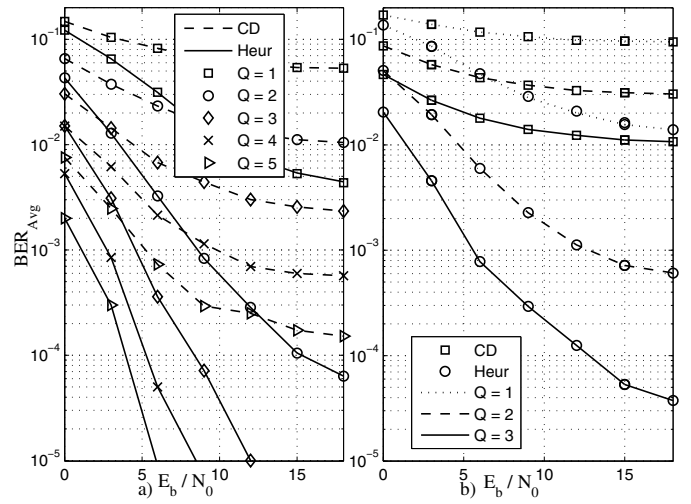


Fig. 4. BER performance for HA-MuD S/MIMO MC-CDMA. a)  $K = 20$ ,  $\mathcal{P} = 30$  and  $G = 25$ ; b)  $K = 32$ ,  $\mathcal{P} = 40$  and  $G = 25$ .

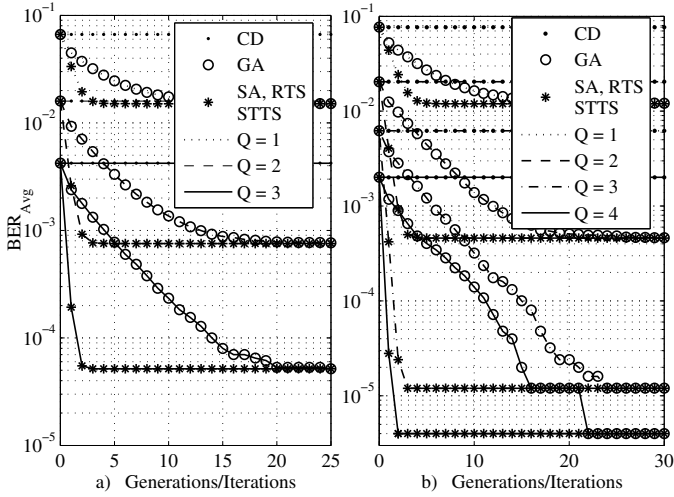


Fig. 3. Convergence performance for HA-MuD S/MIMO MC-CDMA. a)  $E_b/N_0 = 9\text{dB}$ ,  $K = 20$ ,  $\mathcal{P} = 30$ ; b)  $E_b/N_0 = 12\text{dB}$ ,  $K = 25$ ,  $\mathcal{P} = 30$ .

taken into account the number of floating point operations needed for each HA-MuD achieve the convergence, defined herein as computational complexity. The considered operations are multiplication, comparison and random number generation. This analysis is limited by the fact that operations with distinct computational complexity are considered with the same cost. The complexity is expressed as a function of the number of users ( $K$ ), received antennas ( $Q$ ), subcarriers ( $M$ ), number of iterations for convergence ( $\mathcal{G} \leq G$ ) and population size ( $\mathcal{P}$ ).

The cost function calculation (10) is the most significant factor in determining the complexity of the detectors. The terms  $\widehat{\mathbf{W}}_{q,m}^* \mathbf{z}_{q,m}$  and  $\widehat{\mathbf{W}}_{q,m} \mathbf{R}_{q,m} \widehat{\mathbf{W}}_{q,m}^*$  are evaluated outside the iterations loop and adopted constant during the detection search. It is accomplished  $4K^3 + K^2$  operations in these two terms, being this calculation evaluated  $QM$  times (for each subcarrier and each antenna). Inside the iterations loop,

the number of operations needed for each vector-candidate evaluation through cost function becomes  $QM(K^2 + 2K)$ .

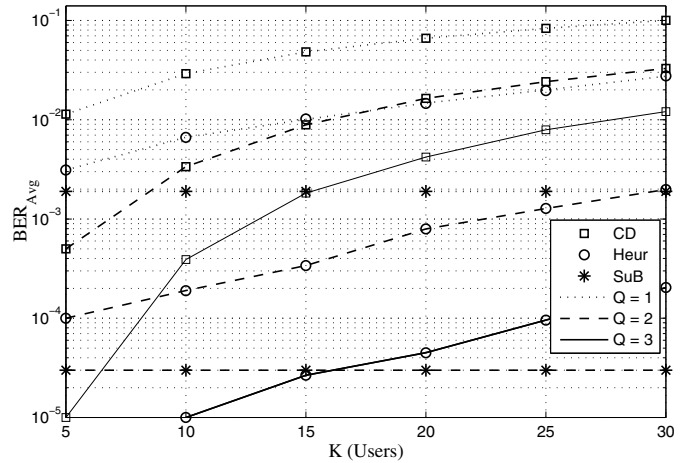


Fig. 5.  $\text{BER} \times K$ .  $E_b/N_0 = 9\text{dB}$ ,  $\mathcal{P} = 30$  and  $G = 25$ .

Table II expresses in literal form and Table III numerically, under simulated system conditions, the HA-MuDs and OMuD computational complexities. HA-MuDs provide an enormous reduction in the number of operations when compared with the OMuD. The complexity of the SA, RTS and STTS algorithms are very close amongst themselves and smaller than the complexity of GA under all analyzed system loading condition. However, when the number of users in the system substantially increases, the complexity of the SA, STTS and RTS algorithms approaches the GA, according to Figure 6. Around  $K = 690$  users, the SA, STTS and RTS complexities become slightly superior to the GA. Indeed, for practical values of active users in the system, SA algorithm accomplishes the best performance-complexity trade-off among the strategies considered here.

TABLE II  
COMPUTATIONAL COMPLEXITY FOR THE HEURISTIC MuD.

MuD	Operations
OMuD	$\approx QM2^K (K^2 + 4K)$
GA	$QM [K^2 (4K + 1) + (PK)(G + 1)(K + 2)] +$ $+P [K(8.5G + 2) + (M + 4)(G + 1)] - (K + 3P)$
SA	$QM [K^3 (G + 5) + 2K^2 (G + 1)] + KG (M + 4 + \frac{7}{K} + \frac{M}{G})$
STTS	$QM [K^3 (G + 5) + 2K^2 (G + 1)] +$ $+KG (M + 5 + 2K + P_{TL} + \frac{9}{K} + \frac{M}{G})$
RTS	$QM [K^3 (G + 5) + 2K^2 (G + 1)] +$ $+KG (M + 5 + 2K + P_{TL}^g + \frac{13}{K} + \frac{M}{G})$

## V. CONCLUSIONS

The proposed single-objective heuristic antenna-diversity-aided MC-CDMA MuDs show capabilities to escape from local maxima, making possible to reach excellent system performance at moderate complexity cost, evidencing the potentiality of this technique in wireless applications that demand increasing throughputs.

In spite of the four heuristic S/MIMO multiuser detectors reaching the same performance after convergence, for practical operation system conditions, the complexities of SA and TS are quite similar and smaller in relation to GA approach. Complexity analysis and simulation results showed that, among the considered strategies, the SA S/MIMO MC-CDMA presented the smallest computational complexity and accomplished the best performance-complexity trade-off under practical system scenarios.

TABLE III  
NUMBER OF OPERATIONS ( $\times 10^5$ ) NEEDED FOR CONVERGENCE,  $Q = 3$ .

Fig.	OMuD	GA	SA	STTS	RTS
2	60390	23.5	9.127	9.163	9.161
3a	60390	38.23	8.07	8.096	8.095
3b	2919235	86.09	18.11	18.13	18.13
4b	593736278	154.5	124.4	125	125

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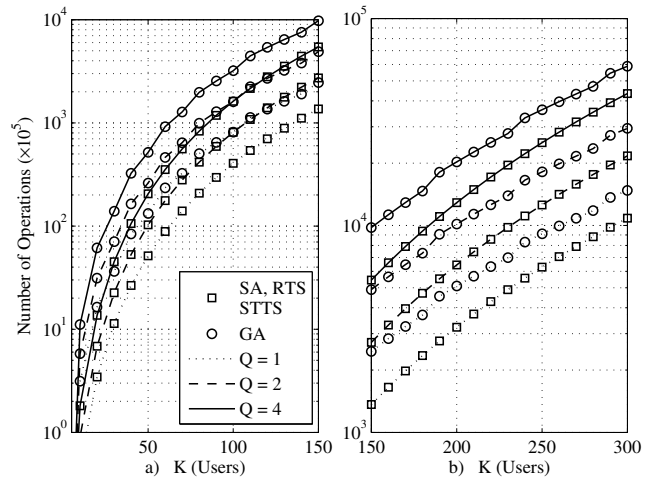


Fig. 6. Number of operations for all HA S/MIMO MC-CDMA.  $G = 25$  for GA and  $G = 5$  for SA, STTS and RTS. a)  $K = [0, 150]$ ; b)  $K = [150, 300]$ .

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