Weighting Particle Swarm Optimization SIMO MC-CDMA Multiuser Detectors

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***Abstract*—This paper analyzes the performance of two heuristic approaches applied to a synchronous multicarrier multiuser detection (MUD) of multiple receive antennas code division multiple access (SIMO MC-CDMA) system. The particle swarm optimization (PSO) with weighting particle position based on combining multi-fitness functions (woPSO) is proposed and compared with the conventional PSO SIMO MC-CDMA. The woPSO strategy deal with the multi-objective dilemma imposed by the spatial diversity that results in independent likelihood function for each receive antenna. Additionally, the computational complexity of these algorithms was taken into account in order to show which one has the best trade-off in terms of performance and implementation complexity aspects.**

***Index Terms*—MC-CDMA, multiuser detection, particle swarm optimization, single/multiple-objective optimization.**

I. Introduction and System Model

Multiuser reception under AWGN and selective frequency single-input single-output (SISO) channels using genetic algorithm [1], local search with unitary Hamming distance (1-Opt LS) [2], and particle swarm optimization (PSO) [3], [4] based detectors have earlier been studied and shown to have excellent sub-optimum performance. Recently, heuristics algorithms have been applied to symbol detection in multiple-input multiple-output channels (MIMO) systems [5]. A survey on MIMO based-OFDMA systems, focused on MuD and estimation heuristics approaches is provided in [6].

Considering antenna-diversity-aided detection in synchronous single-input multiple-output (SIMO) 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. It poses a multi-objective optimization problem (MOOP) [7] due to the fact that while a specific signal estimation may be deemed optimum on the basis of one antenna LLF, the same estimation may not necessarily be deemed optimum in terms of another antenna LFF [8].

Various population-based approaches, such as evolutionary or genetic algorithms, were proposed in the last decade in order to solve MOOPs. Since PSO and evolutionary algorithms have some similarities, it is a natural extension apply PSO to MOOP; this combination has been denominated multi-objective PSO [9], [10].

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This work analyzes the performance-complexity trade-off of two heuristic multiuser detectors (HEUR-MUD) suitable for MC-CDMA systems under antenna-diversity-aided synchronous SIMO and flat fading channels: PSO and weighted multi-objective PSO version (woPSO) are compared.

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

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

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

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

where $c_{k,m}^{(n)}$ is the nth sequence chip with T_c duration and $p(t)$ is the rectangular pulse shape considered. Note that the total processing gain is NM. Additionally, it is assumed that the signature waveforms have normalized energy, $\int_0^{T_b} c_{k,m}^2(t)dt = \frac{1}{M},\ \forall k,\, m$. An equivalent independent Rayleigh flat channel is assumed in each subcarrier over all Q receive antenna. Hence, the channel impulse response of the mth subcarrier of the kth user in the qth receive antenna is given by $h_{q,k,m}^{(i)} = \beta_{q,k,m}^{(i)} \exp\left[\jmath \varphi_{q,k,m}^{(i)}\right]$, where the amplitude $\beta_{q,k,m}^{(i)}$ is a Rayleigh distributed random variable and the phase $\varphi_{q,k,m}^{(i)}$ is uniformly distributed in the $[0,\, 2\pi)$. In the following, we ignore the discrete-time index i over channel coefficients for simplicity. The received signal of the mth subcarrier, qth receive antenna, considering all K users is given by: $r_{q,m}(t) =$

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

where $\eta(t)$ is the additive white Gaussian noise (AWGN) term associated to the qth antenna and mth subcarrier, admitted identical average noise power in all Q receive antennas and M subcarriers, and bilateral power spectral density given by $N_0/2$.

For each receive antenna of multiple-antenna receiver, the signal is demodulated in each one of 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 a heuristic-assisted MUD, described in Section II. The channel state information (CSI) must be estimated at the receiver either by training or some blind methods. The received signal $r_{q,m}(t)$ can be more convenient expressed in matrix notation:

$$\mathbf{r}_{q,m}(t) = \mathbf{C}_m \mathbf{W}_{q,m} \mathbf{b} + \mathbf{n}_q, \quad (3)$$

with $\mathbf{C}_m = [\mathbf{c}_{1,m}(t), ..., \mathbf{c}_{K,m}(t)]$; $\mathbf{c}_{k,m}(t) = \left[c_{k,m}^{(0)}, ..., c_{k,m}^{(N-1)}\right]$; $\mathbf{W}_{q,m} = \text{diag}\left[A_1\beta_{q,1,m}\, e^{\jmath\varphi_{q,1,m}}, \ldots, A_K\beta_{q,K,m}e^{\jmath\varphi_{q,K,m}}\right]$; $\mathbf{b} = [b_1, b_2, ..., b_K]^\top$; $\mathbf{n}_q = [\eta_0, \eta_1, ..., \eta_{N-1}]^\top$, and $(\cdot)^\top$ representing the transpose operator and $\mathbf{n}$ is the filtered $N-$sampled AWGN. The MF output of the mth subcarrier can also be expressed in vector notation:

$$\mathbf{z}_{q,m} = [z_{q,1,m}, ..., z_{q,K,m}]^\top = \mathbf{R}_m \mathbf{W}_{q,m} \mathbf{b} + \mathbf{n}_{q,m} \quad (4)$$

where $\mathbf{n}_{q,m} = [\tilde{n}_{q,1,m}, \tilde{n}_{q,2,m}, \ldots, \tilde{n}_{q,K,m}]$ is the filtered noise vector with $\tilde{n}_{q,k,m} = \int_0^{T_b} \eta(t) \cdot c_{k,m}(t)\, dt$ and the correlation matrix

$$\mathbf{R}_m = \begin{bmatrix} \rho_{0,0}^{(m)} & \rho_{0,1}^{(m)} & \cdots & \rho_{0,K-1}^{(m)} \\ \rho_{1,0}^{(m)} & \rho_{1,1}^{(m)} & \cdots & \rho_{1,K-1}^{(m)} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{K-1,0}^{(m)} & \rho_{K-1,1}^{(m)} & \cdots & \rho_{K-1,K-1}^{(m)} \end{bmatrix}, \quad (5)$$

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 kth user' bit estimation, the conventional detector (CD) linearly combines decision variables overall M subcarriers and Q receive antennas:

$$b_k^{\text{cMFB}} = \text{ sign}\left(\sum_{q=1}^{Q}\sum_{m=0}^{M-1} z_{q,k,m}\widehat{h}_{q,k,m}^*\right), \; k = 1, \ldots, K, \quad (6)$$

with $\mathbf{b}^{\text{cMFB}} = \left[b_1^{\text{cMFB}}, \ldots, b_K^{\text{cMFB}}\right]^\top$, $\text{sign}(x) = x/\text{abs}(x)$ and * is the conjugate complex operator. The bit estimation on each receive antenna is given by: $\mathbf{b}^{\text{MFB},q} = \text{sign}\left(\sum_{m=0}^{M-1} \mathbf{z}_{q,m} \circ \widehat{\mathbf{h}}_{q,m}^*\right)$, $q = 1, 2, \ldots, Q$, where $\widehat{\mathbf{h}}_{q,m}^* = [\widehat{h}_{q,1,m}^*, \ldots, \widehat{h}_{q,K,m}^*]$ is an estimation channel vector, $\circ$ is the element wise multiplication operator, and the entire estimation is the vector composition: $\mathbf{b}^{\text{MFB}} = \left[\mathbf{b}^{\text{MFB},1}, \ldots, \mathbf{b}^{\text{MFB},Q}\right]$.

At the receiver, the maximum likelihood detector (MLD) jointly detects the data of all users and minimizes the effects of multiple access interference (MAI). The optimum multiuser detection (OMUD) considering each subcarrier m of the qth receive antenna maximizes the following objective function:

$$\Omega_{q,m}(\mathbf{b}) = 2\Re\left\{\mathbf{b}^\top \widehat{\mathbf{W}}_{q,m}^* \mathbf{z}_{q,m}\right\} - \mathbf{b}^\top \widehat{\mathbf{W}}_{q,m} \mathbf{R}_{q,m} \widehat{\mathbf{W}}_{q,m}^* \mathbf{b}, \quad (7)$$

where $\widehat{\mathbf{W}}_{q,m}$ is an estimate for the channel matrix. The OMUD [11] is based on the maximum likelihood criterion that choose $\mathbf{b}$ which maximizes the metric

$$\widehat{\mathbf{b}} = \arg\left\{\max_{\mathbf{b}\in\mathcal{A}^{\mathcal{M}K}} \left[\mathbf{f}\left(\Omega\left(\mathbf{b}\right)\right)\right]\right\}, \quad (8)$$

where $\mathbf{f}\left(\Omega\left(\mathbf{b}\right)\right)$ is a multi- or single-objective function that takes into account some combination rule considering $\Omega_{q,m}(\mathbf{b})$ functions, Q antennas and M subcarriers in (7); $\mathcal{M}$ is the message length and $\mathcal{A}$ is the symbol alphabet dimension; in the optimization context, $\mathbf{b}$ is the decision vector and $\mathcal{A}^{\mathcal{M}K}$ is a feasible region into the decision space. Here, it was adopted $\mathcal{M} = 1$.

In this work, it was considered two heuristic antenna-diversity-aided strategies: one based on linearly combining log-likelihood functions (LC-LLFs) and other is a *weighting multi-objective* approach (WO-LLFs). In the first heuristic strategy, each *particle* of length K (bits) on the mth subcarrier of the qth receive antenna is linearity combined considering all M subcarriers and Q receive antennas. The objective function is described in similar way of [8]:

$$\Omega\left(\mathbf{b}\right) = \frac{1}{Q}\sum_{q=1}^{Q}\sum_{m=0}^{M-1} \Omega_{q,m}\left(\mathbf{b}\right) \quad (9)$$

and the fitness value of the ith $K-$bits vector-candidate is:

$$f(\mathbf{b}_i) = [\Omega(\mathbf{b}_i)] \quad (10)$$

Since the channel fading associated with different receive antennas are independent, then $\Omega_q(\mathbf{b}) \neq \Omega_p(\mathbf{b})$ for $q \neq p$. Therefore, under deep fading condition in some antennas, the data estimation corresponding to different antennas may result different. Thus, the LLFs corresponding to different antennas combined according to (9) may not result in the best performance in terms of bit error rate (BER) minimization.

The second heuristic strategy based on weighting multi-fitness functions can be established according to:

$$\mathbf{f}(\mathbf{b}_i) = [\Omega_1(\mathbf{b}_i), \ldots, \Omega_Q(\mathbf{b}_i), \Omega(\mathbf{b}_i)] = [f_1(\mathbf{b}_i), \ldots, f_{Q+1}(\mathbf{b}_i)] \quad (11)$$

where $(Q+1)$ LLFs objective functions are separately applied to the ith $K-$bits particle-candidate $\mathbf{b}_i$; the first Q fitness values are the LLFs related to the Q receive antennas, given by $f_q(\mathbf{b}_i) = \sum_{m=0}^{M-1} \Omega_{q,m}(\mathbf{b}_i)$, and the $(Q+1)$th fitness value is the LC Q-LLFs, (9), i.e., $f_{Q+1}(\mathbf{b}_i) = \Omega(\mathbf{b}_i)$. Indeed, due to the independent fading of different receive antennas, in most cases, it's impossible to find a K-bits particle that results the best optimal for $\Omega_q(\mathbf{b})$, $\forall q$. Thus, the 2nd strategy consists to evaluate the K-bits particles for the next heuristic generation over $Q+1$ objective function, according to the rules described in Section II-B.

II. PSO MUD Algorithms for SIMO MC-CDMA

In the LC-LLFs strategy, the particle(s) selection for evolving is based on the the highest fitness values in (10), and decisions is based on a single entity by combining the subcarriers and antenna informations (9). On the other hand, in the WO-LLFs particle-selection strategy the LLF values information from Q receive antennas are used independently as well as in a combined way [last one LLF in (11)], in order to decide which K-particle will be selected for evolving.

A. LC-LLFs Selection PSO SIMO MC-CDMA

The ith PSO particle' position at instant t is represented by the $K \times 1$ vector:

$$\mathbf{b}_i[t] = [b_{i1}[t] \; b_{i2}[t] \; \ldots \; b_{iK}[t]]^\top \tag{12}$$

The interaction among particles is inserted in the calculation of particles' velocity. For the LC-LLF selection strategy, the ith particle's velocity, $\mathbf{v}_i[t]$, is given by:

$$\begin{aligned}\mathbf{v}_i[t+1] &= \omega \cdot \mathbf{v}_i[t] + \phi_1 \cdot \mathbf{U}_{i_1}[t](\mathbf{b}_i^{\text{best}}[t] - \mathbf{b}_i[t]) + \\ &\quad + \phi_2 \cdot \mathbf{U}_{i_2}[t](\mathbf{b}_g^{\text{best}}[t] - \mathbf{b}_i[t])\end{aligned} \tag{13}$$

where ω is the weight of the previous velocity in the present speed calculation; $\mathbf{U}_{i_1}[t]$ and $\mathbf{U}_{i_2}[t]$ are diagonal matrices with dimension K, and elements are r.v. with uniform distribution $\mathcal{U} \in [0,1]$, generated for the ith particle at instant t; $\mathbf{b}_g^{\text{best}}[t]$ and $\mathbf{b}_i^{\text{best}}[t]$ are the best global position and the best local positions found until the tth iteration, respectively; ϕ_1 and ϕ_2 are weight factors regarding the best particles and the best global positions' influences in the velocity update, respectively.

Note that the adoption of the conventional PSO implies in the selection of only one $\mathbf{b}_i^{\text{best}}[t]$ for each particle and only one $\mathbf{b}_g^{\text{best}}[t]$ for the entire population, obtained considering the linear combination signals over Q antennas.

In order to obtain fast convergence without losing a certain exploration and exploitation capabilities, ϕ_2 can be increased, being chosen from the range [3]: $\phi_2 \in [2; 10]$ (while $\phi_1 = 2$), witch results in an intensification search for the best global position.

For MuD optimization, each element $b_{ik}[t]$ in (13) just assumes the "0" or "1" values. This implies in a discrete mode for the position choice. That is carried out inserting in the algorithm a command of choice, dependent of the velocity. However, the velocity needs to be adjusted in a probabilistic mode. Several functions possess this characteristic, among those the sigmoid function: $S(v_{ik}[t]) = \{1 + e^{-v_{ik}[t]}\}^{-1}$ where $v_{ik}[t]$ is the kth element of the ith particle's velocity. This function is limited in the interval $[0,1]$. The selection of the future particle position is obtained through the statement:

$$b_{ik}[t+1] = 1, \;\; \text{if}\, \mathrm{u}_{ik}[t] < S(v_{ik}[t]); \quad b_{ik}[t+1] = 0, \;\text{otherwise} \tag{14}$$

where $\mathrm{u}_{ik}[t]$ is a r.v. with uniform distribution $\mathcal{U} \in [0,1]$.

In order to obtain larger diversification for the search universe, a factor ($V_{\max}$) is added to PSO model, which will be responsible for limiting the velocity in the range $[\pm V_{\max}]$. The insertion of this factor in the velocity calculation, makes possible the algorithm to escape from eventual local maximum. The bit chance is more probable every time that the particle velocity crosses the limits established by $[\pm V_{\max}]$, Table I.

After the conventional PSO's search finishes (G iterations), the estimation vector is proceed: $\widehat{\mathbf{b}} = \mathbf{b}_{\mathrm{g}}^{\text{best}}[G]$, which is associated with the particle's position that maximizes (10).

B. WO-LLF Selection PSO SIMO MC-CDMA

In each iteration the new particle' velocity is calculated weighting the contribution of the particle position associated to each receive antenna based on multi-objective function (11):

$$\begin{aligned}\mathbf{v}_i[t+1] = \;& \omega \cdot \mathbf{v}_i[t] + \sum_{q=1}^{Q+1} \Big[\phi_1^q \cdot \mathbf{U}_{i_1}^q[t] \left(\mathbf{b}_i^{\text{best},q}[t] - \mathbf{b}_i[t]\right) \\ &+ \phi_2^q \cdot \mathbf{U}_{i_2}^q[t] \left(\mathbf{b}_g^{\text{best},q}[t] - \mathbf{b}_i[t]\right)\Big]\end{aligned} \tag{15}$$

where all parameters are defined as explained previously, excepting ϕ_p^q and $\mathbf{U}_{ip}^q[t]$, $p = 1,2$ are defined for each q antenna and the positive acceleration coefficients satisfying $\sum_{q=1}^{Q+1} \phi_1^q + \phi_2^q = C$, a real constant number. In general, this constant is assumed equal 4 [12], but increasing ϕ_2^q the convergence is faster [3], due to the intensification of the best global position search.

TABLE I
MINIMUM BIT CHANCE PROBABILITY AS A FUNCTION OF $V_{\max}$.

$V_{\max}$	1	2	3	4	5
$1 - S(V_{\max})$	0.2690	0.1192	0.0474	0.0180	0.0067

Note that in (15), the $(Q+1)$th $\mathbf{b}_i^{\text{best},q}[t]$ and $(Q+1)$th $\mathbf{b}_g^{\text{best},q}[t]$ positions allow the exploration capability of the woPSO SIMO, while the others $\mathbf{b}_i^{\text{best},q}[t]$ and $\mathbf{b}_g^{\text{best},q}[t]$ positions bring additional exploitation capability. In order to balance the exploration and exploitation capabilities, we set: $\phi_1^{Q+1} = \phi_2^{Q+1} = \frac{1}{2}$ (exploration), and $\phi_1^q = \phi_2^q = \frac{1}{2Q}$, $1 \geq q \geq Q$ (exploitation).

The final estimation vector for the woPSO is determined by the vector $\widehat{\mathbf{b}} = \mathbf{b}_g^{\text{best},Q+1}[G]$, which is associated with the particle's position that maximizing $\Omega(\mathbf{b})$. For lack of space, detailed steps and explanations for the PSO and woPSO SIMO MC-CDMA algorithms are given in [13].

III. NUMERICAL RESULTS AND COMPARISONS

The main system and channel parameters used in Monte-Carlo simulations are summarized in Table II. It was adopted binary random generated sequences of length 32 (PN_{32}) or Walsh-Hadamard sequences (WH_{32}). In some performance plots its was included the single-user bound BER performance for SIMO synchronous MC-CDMA (SuB). In all simulated systems, the standard processing gain was $N = 8$, but the MC-CDMA equivalent processing gain is $NM = 32$, i.e., the adopted number of subcarrier is $M = 4$.

For simplicity, in this section we have assumed perfect CSI estimates, except for the Fig. 2, where errors in the channels estimates were modeled through the continuous uniform distributions $\mathcal{U}[1 \pm \epsilon]$ centralized on the true values of the coefficients, resulting:

$$\widehat{\beta}_{q,k,m} = \mathcal{U}[1 \pm \epsilon_\beta] \times \beta_{q,k,m}; \quad \widehat{\varphi}_{q,k,m} = \mathcal{U}[1 \pm \epsilon_\varphi] \times \varphi_{q,k,m}, \tag{16}$$

where ϵ_β and ϵ_φ are the maximum module and phase normalized errors for the channel coefficients, respectively.

A. Convergence and BER Performance

Fig. 1 and 2 show the PSO and woPSO SIMO MC-CDMA convergence for high loading system $L = \frac{K}{NM} = 1$, considering CSI perfectly estimated and with errors modeled by (16), respectively; in Fig. 2 it was used WH_{32} which propitiates smaller MAI than PN_{32}. The conventional detector is identified by CD. Under perfect CSI knowledge, both PSO algorithms reach the same BER performance after convergence, for $L = 1$ and other lower system loading conditions (not shown here). The product $\mathcal{P}G = 800$ is enough to guarantee convergence under high system loading, CSI errors, $E_b/N_0 \leq 12$ dB and $Q \leq 5$ Rx antennas. However, the woPSO taking advantage of a larger diversity strategy through $Q + 1$ fitness function evaluations in (11), reaches convergence somewhat faster than the conventional PSO. Under about 20% CSI error estimates even with high system loading, Fig. 2.c shows that for both PSO and woPSO the BER performance degradation (regard to near-perfect channel estimates, Fig. 2.a) is less than a half decade for $Q \leq 5$ and medium SNR scenario. Besides, woPSO shows an increasing speed convergence advantage over PSO as long as the number of Rx antennas increase.

TABLE II
SYSTEM, ALGORITHM AND CHANNEL PARAMETERS.

Parameter	Adopted Values
SIMO MC-CDMA System	
# Rx antennas	$Q = 1$ to 5
Spreading sequences	PN_{32} or WH_{32}
Processing gain	$N = 8$
Subcarriers	$M = 4$
Bit period, T_b	300 μs
# mobile users	$K = 5; 10; 15; 20; 25; 32$
Received SNR	$E_b/N_0 \in [0; 18]$ dB
Near-far ratio	$NFR = 0$ dB
PSO Algorithms Parameters	
Swarm pop. size	$\mathcal{P} = 10; 20; 28; 30$ individuals
# iterations	$G(K, Q) \in [10; 80]$
Veloc. bound factor	$V_{\max} = 4$
Veloc. weight factor	$\omega = 1$
Weight particle factor	$\phi_1 = 2$ (local); $\phi_2 = 10$ (global)
Rayleigh Channel	
Max. Doppler freq.	$f_{Dpl} = 100$ & 200 Hz
Per subcarrier	flat-frequency
Channel state info.	perfectly known at Rx and with errors

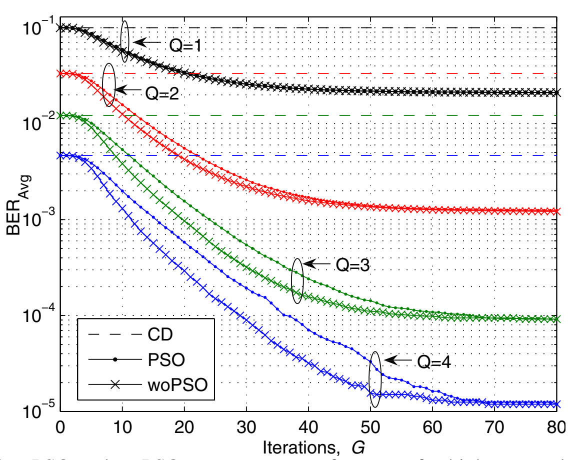

Fig. 1. PSO and woPSO convergence performance for high system loading ($K = 32$) and perfect CSI estimates. $E_b/N_0 = 12$dB and $\mathcal{P} = 10$.

Fig. 3 shows the same BER $\times E_b/N_0$ performance after convergence reached by PSO and woPSO MuD, denoted in legend by Heur-MuD, considering a system with $K = 20$ and $Q = 1$ to 5; a similar convergence behavior observed in the systems of Fig. 1 and 2 was obtained here. The product $\mathcal{P}\mathfrak{g}$ (where $\mathfrak{g}$: # iterations needs for convergence) decreases when the SNR increases and/or K decreases. Indeed, at $Q = 3$, $\mathcal{P}\mathfrak{g} \approx 680$ (Fig. 1) against $\approx 30 \times 13 = 390$ (Fig. 3).

Fig. 4 shows the behavior of the two Heur-MuD as a function of simultaneous users sharing the system, $K \in [5, 30]$. In spite of the increasing loading provokes a performance degradation, the BER is really superior to CD, including high system loading; this performance improvement grows as Q and/or SNR increases.

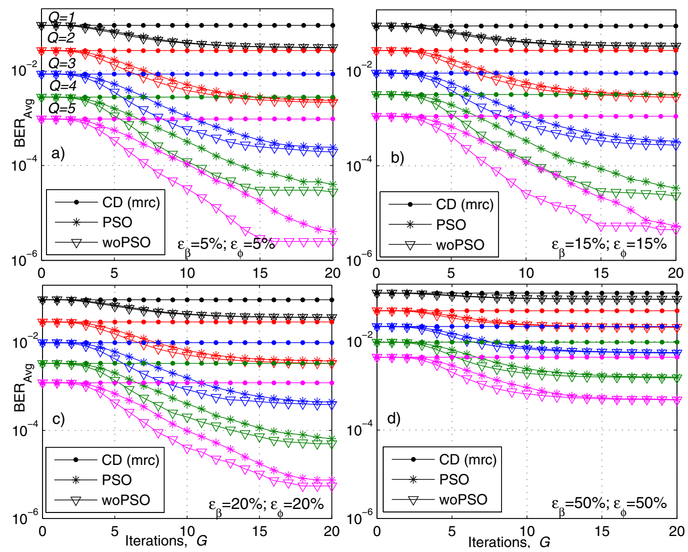

Fig. 2. Heur-MuD convergence under $K = 32$ users and channel error estimates: a) $\epsilon_{\beta,\varphi} = 5\%$; b) $\epsilon_{\beta,\varphi} = 15\%$; c) $\epsilon_{\beta,\varphi} = 20\%$; d) $\epsilon_{\beta,\varphi} = 50\%$. $Q = 1, ..., 5$, $E_b/N_0 = 8$dB, $\mathcal{P} = 28$, WH_{32} and $f_{Dpl} = 200$Hz.

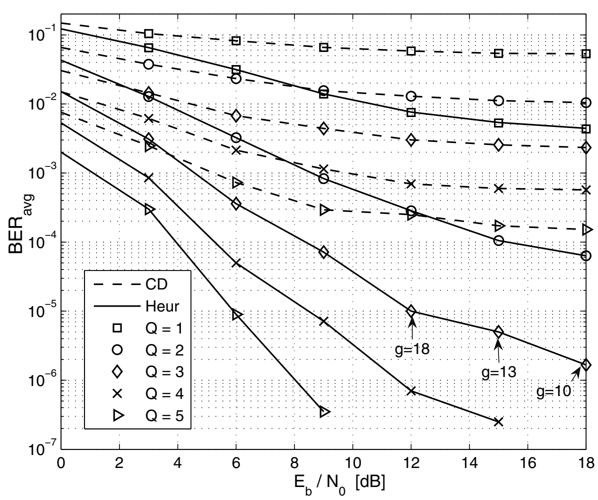

Fig. 3. BER performance for PSO and woPSO SIMO MC-CDMA. $Q = 1$ to 5 receive antennas, PN_{32}, $K = 20$ users, and $\mathcal{P} = 30$.

B. Computational Complexity

In spite of the two heuristic SIMO MC-CDMA multiuser detectors reach a similar performance, the number of operations can differ somewhat, depending on the degree of antenna diversity, the system and channel operation conditions, and if the convergence was reached or not. In order to accomplish a good efficiency measure for the Heur-MuD, it is taken into account the number of floating point operations needed for each one achieve the convergence. For sake of simplification, the analysis taken here considers that multiplication, transposition, comparison and random number generation operations all have the same computational cost. Thus, the complexity is expressed as a function of the number of users (K), receivers (Q), subcarriers (M), iterations for convergence ($\mathtt{g}$) and population size ($\mathcal{P}$).

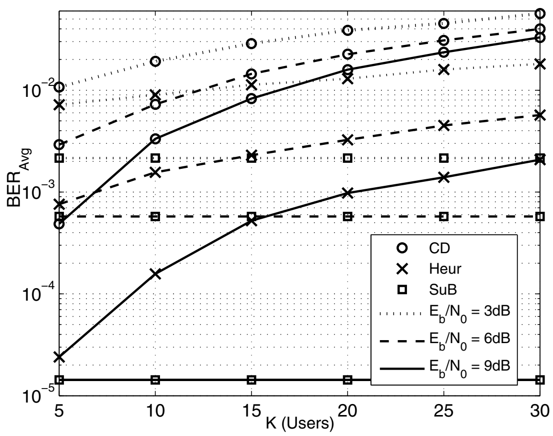

Fig. 4. BER performance for conventional PSO and woPSO SIMO MC-CDMA as a function of loading system. $Q = 2$ receive antennas and $\mathcal{P} = 20$

The cost function calculation (7) is the most significant factor in determining the MuD complexity. 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 detector 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 candidate-vector evaluation through cost function becomes $QM(K^2 + 2K)$.

For the PSO-MuD, it is accomplished $\mathcal{P}$ cost function evaluations in each iteration, being also necessary $3\mathtt{g}\mathcal{P}K + (\mathcal{P} - 1)K$ random number generations, $\mathtt{g}\,(3\mathcal{P}K + 2\mathcal{P} + 1)$ comparisons and $\mathtt{g}\,(3\mathcal{P}K + 1)$ multiplications. While for the woPSO-MuD, the additional steps in relation to PSO implies in a higher quantity of multiplications and random number generations in the velocity calculation. The total number of operations $\mathtt{C}$ is summarized in Table III.

TABLE III
COMPUTATIONAL COMPLEXITY $\mathtt{C}$ FOR THE HEUR-MUDS.

MUD	Operations
OMUD	$2^K QM\left(K^2 + 2K\right) + QM(4K^3 + K^2)$
PSO	$\mathtt{g}[QM\mathcal{P}(K^2 + 2K) + 9\mathcal{P}K + 2K + 2]$ $QM(4K^3 + K^2) + (\mathcal{P} - 1)K$
woPSO	$\mathtt{g}[QM\mathcal{P}(K^2 + 2K) + \mathcal{P}(4QK + 9K + 2Q + 2) + Q + 2]$ $QM(4K^3 + K^2) + (\mathcal{P} - 1)K$

Furthermore, Table IV shows the number of operations needed for the three algorithms reach the convergence under perfect CSI estimates conditions, Fig. 1, and with channel errors of $\epsilon_{\beta,\varphi} = 15\%$, Fig. 2.b. The complexity ratio $\mathtt{CR} = \mathtt{C}_{\text{woPSO}}/\mathtt{C}_{\text{PSO}}$ shows that the woPSO complexity gain grows when we have high antenna diversity, even under error channel estimates, Fig. 2.b.

TABLE IV
NUMBER OF OPERATIONS FOR THE CONVERGENCE, $\mathtt{C}$, AND CR.

SIMO, $K = 32$ **MC-CDMA MuD**	Fig.1 $Q = 1$	$Q = 2$	$Q = 3$	$Q = 4$	Fig. 2.b $Q = 5$
OMUD $[\times 10^{13}]$	1.87	3.74	5.61	7.48	9.35
PSO $[\times 10^{6}]$	2.76	6.46	10.7	14.5	16.2
woPSO $[\times 10^{6}]$	2.82	6.42	9.83	13.6	12.2
Complexity ratio, CR:	1.02	0.99	0.92	0.94	0.75

IV. CONCLUSIONS

Simulation results show that the proposed antenna-diversity-aided woPSO SIMO MC-CDMA detectors have capabilities to scape from local solutions, thanks to a balance between exploration and exploitation and presents somewhat advantage of convergence speed in relation to the conventional PSO, evidencing the potentiality of this technique in multiple-access wireless applications, specially in high system loading and increasing antenna diversity gain conditions.

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