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Weighting Particle Swarm, Simulation Annealing and Local Search Optimization for S/MIMO MC-CDMA Systems

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***Abstract*—This paper analyzes the complexity-performance trade-off of three heuristic approaches applied to synchronous multicarrier multiuser detection (MUD) of single/multiple transmit antennas and multiple receive antennas code division multiple access (S/MIMO MC-CDMA) systems. Weighting particle swarm optimization (WOPSO) and unitary Hamming distance search-based strategies, specifically 1-opt local search (1-LS) and simulation annealing (SA) multiuser detection algorithms, were analyzed in details using a single-objective antenna-diversity-aided optimization approach. Monte-Carlo simulations show that, after convergence, the performances reached by the three heuristic MUD (HEUR-MUD) S/MIMO MC-CDMA algorithms are identical, with computational complexities remarkably smaller than the optimum multiuser detector (OMUD). However, the computational complexities could differ substantially depending on the operation system conditions. The complexities of the HEUR-MUDs were carefully analyzed in order to demonstrate that 1-LS scheme provides the best trade-off between implementation complexity aspects and bit error rate (BER) performance when applied to multiuser detection of S/MIMO MC-CDMA systems with low order modulation.**

***Index Terms*—MC-CDMA, multiuser detection, particle swarm optimization, simulating annealing, single-objective optimization, unitary Hamming distance search.**

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, in the classic MC-CDMA, the spreading is done in the frequency domain.

Multiuser reception under additive white Gaussian noise (AWGN) and/or selective frequency single-input single-output (SISO) channels using 1-LS, PSO and SA algorithms based detectors has been studied earlier [2]–[5] and shown to have excellent near-optimum performance at low to moderate complexity. Recently, heuristic algorithms have been applied to symbol detection in non-spreading multiple-input multiple-output (MIMO) systems [6], [7]. PSO heuristic based-methods have been applied to non-spreading MIMO multiuser detection on 16- and 64-quadrature-amplitude (16- and 64-QAM) modulation [8], [9]. On the other hand, there are few works applying heuristic sub-optimal multiuser detection approaches to S/MIMO MC-CDMA systems. In [10] a large[1] S/MIMO MC-CDMA system with sub-optimal near-exponential diversity performance and low-complexity, based on a kind of directional search, was proposed. Essentially, the algorithm searches out a sequence of bit vectors on a monotonic likelihood ascent, and converges to a fixed point, within a finite number of steps [10]. A survey on MIMO based-orthogonal frequency division multiple access systems, focused on multiuser detection and estimation heuristics approaches is provided in [11].

PSO and weighting multi-fitness PSO SIMO MC-CDMA multiuser detectors were recently compared in [12], pointing out the huge complexity reduction of these techniques, with little performance degradation, in comparison to optimum multi-user detector. For the same bit error rate performance, the numerical results have been indicated a slight advantage of WOPSO over standard PSO SIMO MC-CDMA MUD in terms of convergence rate and computational complexity, when the number of receive antennas and/or the system loading increase. Based on this, the present work considers a weighting PSO version for analysis.

This work analyzes heuristic multiuser detectors, specifically focused on the BER performance and computational complexity of 1-LS, SA and WOPSO algorithms in a single-objective antenna-diversity-aided optimization synchronous single/multiple-input multiple-output MC-CDMA systems. The adopted system model for the MC-CDMA scheme is based on the one presented in [13]. In this sense, the relevance of the paper for the field of swarm intelligence can be identified as: a) the paper offers a performance $\times$ computational complexity tradeoff comparison between PSO and other two heuristic optimization methods, in a given application; b) it provides an example of particle swarm optimization applied to a practical and complex engineering problem; c) it might provide practical guidelines for swarm intelligence (SI) applications that use multiple access[2] radio communication under realistic channels.

The system model and the adopted single-objective optimization metric are discussed in Section II. Further insight into multi-objective optimization criterion applied to the S/MIMO MC-CDMA multiuser detection problem is provided in that

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[1] Number of transmit and receive antennas of the order of tens to hundreds.
[2] Two or more senders sharing the same radio spectrum.

Section. A detailed description of the three heuristic S/MIMO MC-CDMA MuD algorithms, addressing input parameters choices, is given in Section III. Section IV analyzes the computational complexity for each HEUR-MUD to achieve convergence. Numerical results, including BER performance and the evaluation of different complexity indexes, are discussed in Section V. The main conclusions are pointed out in Section VI.

II. SYSTEM MODEL

Let us assume K mobile users equipped with single-antenna terminals in a synchronous MC-CDMA communication system with Q receive antennas at the base station, characterizing a SIMO channel. Equivalently, the model could describe a MIMO MC-CDMA communication system for a single-user equipped with K transmit and Q receive antennas. In the antenna-diversity-aided systems, all 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. A model extension for asynchronous MC-CDMA systems is straightforward and can be found in [14].

The transmitter of Figure 1 employs both time- and frequency-domain spreading and is based on [13]. The information symbol of the kth user with duration T_b is spread into M parallel subcarriers. In each subcarrier, the resultant signal is time-domain spread by a sequence $c_{k,m}(t),\ m = 0, ..., M-1$, with N chips with duration T_c, such that $N = T_b/T_c$. The transmitted signal of the kth user has the form:

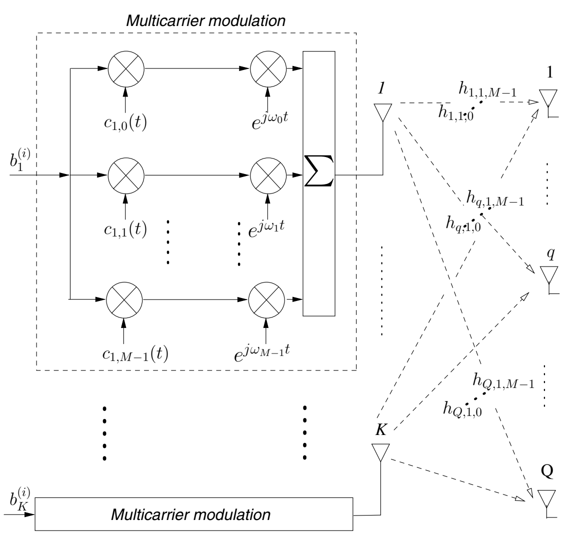

Fig. 1. Equivalent S/MIMO MC-CDMA transmitter scheme.

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

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

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

where $p(t)$ is the rectangular pulse shape considered. Note that once 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 on each subcarrier over all Q receive antennas. Hence, the channel impulse response of the mth subcarrier, kth user, and qth receive antenna is given by $h_{q,k,m}(t) = \beta_{q,k,m}(t)\, e^{\jmath\varphi_{q,k,m}(t)}$, where the amplitude $\beta_{q,k,m}(t)$ is a Rayleigh distributed random variable and the phase $\varphi_{q,k,m}(t)$ is uniformly distributed in the $[0,\ 2\pi)$. Assuming a slowly fading channel (time), the received signal on the mth subcarrier, qth receive antenna, and all K users can be written as:

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

where $\eta(t)$ is the AWGN term associated to the qth antenna and mth subcarrier, with bilateral power spectral density[3] given by $N_0/2$.

For each receive antenna of each of the K users, the signal is demodulated in all the M subcarriers and passed through a matched filter (MF), generating $z_{q,k,m}$. After channel phase compensations, the signal $z_{q,k,m}$ is submitted to a 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. Equation (3) can be more conveniently expressed in the matrix and vector notations; for the sake of simplicity, hereafter, the superscript index $^{(i)}$ was dropped out.

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

$$\begin{aligned}
\text{where:}\quad \mathbf{C}_m &= [\mathbf{c}_{1,m}(t),\, \mathbf{c}_{2,m}(t),\, ...,\, \mathbf{c}_{K,m}(t)]\,, \\
\mathbf{c}_{k,m}(t) &= \left[c_{k,m}^{(0)}, c_{k,m}^{(1)}, ..., c_{k,m}^{(N-1)}\right], \\
\mathbf{W}_{q,m} &= \mathrm{diag}\,[A_1 \cdot \beta_{q,1,m}\, e^{\jmath\varphi_{q,1,m}},\, A_2 \cdot \beta_{q,2,m} \cdot \\
&\quad e^{\jmath\varphi_{q,2,m}}, ..., A_K \cdot \beta_{q,K,m}\, e^{\jmath\varphi_{q,K,m}}]\,, \\
\mathbf{b} &= [b_1,\, b_2,\, ...,\, b_K]^\top, \\
\mathbf{n}_{q,m} &= [\eta_0,\, \eta_1,\, ...,\, \eta_{N-1}]^\top,
\end{aligned}$$

is the N-sampled AWG noise, and $(\cdot)^\top$ represents the transpose operator. The mth subcarrier MF output can also be expressed in vector notation:

$$\mathbf{z}_{q,m} = [z_{q,1,m},\, ...,\, z_{q,K,m}]^\top = \mathbf{R}_m \mathbf{W}_{q,m} \mathbf{b} + \tilde{\mathbf{n}}_{q,m}, \tag{5}$$

[3]This assumption implies identical average noise power in all Q antennas and M subcarriers.

where $\tilde{\mathbf{n}}_{q,m} = [\tilde{n}_{q,1,m}, \tilde{n}_{q,2,m}, \ldots, \tilde{n}_{q,K,m}]$ 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

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

with the auto- and cross-correlation of the spreading code defined as $\rho_{i,j}^{(m)} = \int_0^{T_b} c_{i,m}(t) \cdot c_{j,m}(t)\, dt$. For each receive antenna the decision variables are obtained from (5):

$$\breve{\mathbf{z}}_{q,m} = \left[\breve{z}_{q,1,m},\, \breve{z}_{q,2,m},\, \ldots,\, \breve{z}_{q,K,m}\right]^\top = \mathbf{R}_m \breve{\mathbf{W}}_{q,m} \mathbf{b} + \breve{\mathbf{n}}_{q,m}, \qquad (7)$$

which $\breve{\mathbf{W}}_{q,m} = \operatorname{diag}\left[A_1 h_{q,1,m} g_{q,1,m}, \ldots, A_K h_{q,K,m} g_{q,K,m}\right]$, $g_{q,k,m} = \widehat{h}^*_{q,k,m}/\mathrm{w}_{q,k,m}$, where $\widehat{h}_{q,k,m} = \widehat{\beta}_{q,k,m}\, e^{\jmath\widehat{\varphi}_{q,k,m}}$, is a channel coefficient estimate, * represents the conjugate complex operator, and the normalization factors of the weights are defined by the maximum ratio combining rule, i.e., $\mathrm{w}_{q,k,m} = 1$.

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

$$b_k^{\text{cMFB}} = \operatorname{sign}\left[\Re\left(\sum_{q=1}^{Q}\sum_{m=0}^{M-1} \breve{z}_{q,k,m}\right)\right],\ k = 1, \ldots, K, \quad (8)$$

with $\mathbf{b}^{\text{cMFB}} = \left[b_1^{\text{cMFB}}, \ldots, b_K^{\text{cMFB}}\right]^\top$, $\Re(\cdot)$ is the operator that extracts the real part of a complex number, and $\operatorname{sign}(\cdot)$ representing the signum function. The bit estimation by each receive antenna is simply:

$$\mathbf{b}^{\text{MFB},q} = \operatorname{sign}\left[\Re\left(\sum_{m=0}^{M-1} \breve{\mathbf{z}}_{q,m}\right)\right],\ q = 1, 2, \ldots, Q,$$

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, Figure 2, the maximum likelihood detection (MLD) 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 qth receive antenna must maximize the following objective function [15]:

$$\Omega_{q,m}(\mathbf{b}) = 2\Re\left\{\mathbf{b}^\top \widehat{\mathbf{W}}^*_{q,m} \mathbf{z}_{q,m}\right\} - \mathbf{b}^\top \widehat{\mathbf{W}}_{q,m} \mathbf{R}_{q,m} \widehat{\mathbf{W}}^*_{q,m} \mathbf{b}, \qquad (9)$$

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

$$\widehat{\mathbf{b}} = \arg\left\{\max_{\mathbf{b}\in\mathcal{A}^{\mathcal{M}K}} \left[\mathbf{f}\left(\Omega\left(\mathbf{b}\right)\right)\right]\right\}, \qquad (10)$$

where $\mathbf{f}(\Omega(\mathbf{b}))$ 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 (9). $\mathcal{M}$ 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 the feasible region in the decision space. The evaluation of the cost function can be done either considering the whole message, where all symbols of the transmitted vector from all K users are jointly detected (vector ML approach), or considering the optimal single symbol detection of all K multiuser signals, vector $\mathbf{b}_i$ (symbol ML approach). This work considers only symbol ML detection approach, $\mathcal{M} = 1$.

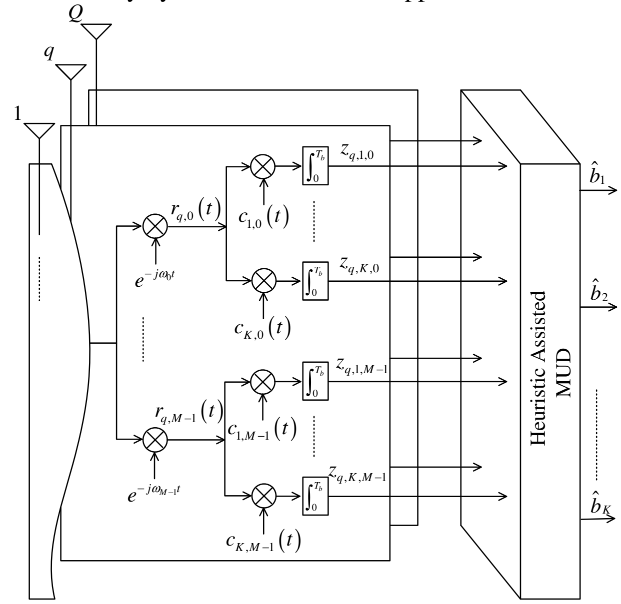

Fig. 2. MC-CDMA receiver structure considering Q receive antennas.

Equation (10) is a combinatorial optimization problem, which requires an exhaustive search in $J = \mathcal{A}^{\mathcal{M}\mathcal{K}}$ possibilities of $\mathbf{b}$. Therefore, the MLD has a complexity that increases exponentially with the number of users. Then, in this paper, two types of objective function were considered for the heuristic approach. The first one is the linearity combined Q-LLFs antenna-diversity-aided strategy (LC Q-LLFs), in which each of K-bits vector-candidates on the mth subcarrier of the qth receive antenna is linearity combined considering all the M subcarriers and Q receive antennas. Thus, the fitness value of the ith K-bits vector-candidate and objective function can be described as in [16]:

$$f(\mathbf{b}_i) = \left[\Omega(\mathbf{b}_i)\right], \qquad \Omega(\mathbf{b}_i) = \frac{1}{Q}\sum_{q=1}^{Q}\sum_{m=0}^{M-1} \Omega_{q,m}(\mathbf{b}_i). \quad (11)$$

Since the channel fading associated with different receive antennas are independent, then $\Omega_q(\mathbf{b}) = \sum_{m=0}^{M-1}\Omega_{q,m}(\mathbf{b}) \neq \Omega_p(\mathbf{b}) = \sum_{m=0}^{M-1}\Omega_{p,m}(\mathbf{b})$, for $q \neq p$. Under deep fading condition in some antennas, the data estimation corresponding to different antennas may not result equal.

The second heuristic objective function is a weighting multi-objective (WO) version, suggested in [12], which takes into account independent and combined log-likelihood functions, such that:

$$\begin{aligned} \mathbf{f}(\mathbf{b}_i) &= \left[\Omega_1(\mathbf{b}_i), \ldots, \Omega_Q(\mathbf{b}_i), \Omega(\mathbf{b}_i)\right] \qquad (12) \\ &= \left[f_1(\mathbf{b}_i), \ldots, f_{Q+1}(\mathbf{b}_i)\right], \end{aligned}$$

where $(Q+1)$ log-likelihood objective functions are separately applied to the ith $K-$bits vector-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, (11), i.e., $f_{Q+1}(\mathbf{b}_i) = \Omega(\mathbf{b}_i)$. Indeed, due to the independent fading on different receive antennas, in most cases, it is impossible to find a K-bits particle that results the best optimal for $\Omega_q(\mathbf{b})$, $\forall q$. Thus, with these $Q+1$ objective functions, the K-bits vector-candidates will be explored by the PSO search, according to the rules described in Section III-C.

III. HEUR-MUD ALGORITHMS FOR S/MIMO MC-CDMA

In the LC Q-LLFs vector-candidate-selection strategy, the selection of vector-candidate(s) for evolving is based on the highest fitness values of (11) and decisions are based on a single-objective optimization procedure, i.e., by combining the subcarriers and antenna-specific performance measures. SA and 1-LS MUD algorithms described below follow this strategy, while WOPSO MUD is based on the multi-objective LLFs defined by (12).

Details of the implemented SA, 1-LS and WOPSO S/MIMO MC-CDMA MUD algorithms (and other related algorithms), as well as their pseudo-codes, can be found in [17].

A. SA S/MIMO MC-CDMA

The simulation annealing algorithm concept stems from thermal annealing mechanism which aims to obtain perfect crystallizations by a slow enough temperature reduction to give atoms the time to attain the lowest energy state [18]. In order to escape from a local minimum, the SA algorithm uses an acceptance probability function, proportional to the temperature, which can even allow to accept a particular solution that possesses a higher value (a state of higher energy). This makes possible that the algorithm leaves a local minimum area and seeks for the global minimum in other areas. Classically, the acceptance probability function is derived from the Boltzmann distribution:

$$P\left(\Delta E\right) = \exp\left(\Delta E / T_k\right), \tag{13}$$

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

$$T_k = \delta^k T_0, \tag{14}$$

where T_0 is initial temperature of the process, and δ is the cooling rate. Eq. (14) is not the only way to describe the cooling process, but one usual method found in the literature [18]. The initial temperature of the process has a high value, $T_0 >> 0$ and the temperature is reduced after a fixed number of iterations It.

Besides the initial set of received bits $\mathbf{b}^{\text{MFB}}$, the SA algorithm must be initialized with three more parameters: T_0, δ, and It. These three parameters were empirically adjusted through a non-exhaustive attempt procedure [19].

B. 1-LS S/MIMO MC-CDMA

The local search is an optimization method that consists of searches in a previously established neighborhood [20]. For the local search algorithm it is important to restrict the neighborhood and to choose a good start vector-candidate in order to find a valid solution with low complexity. In this work it is adopted the 1-optimum local search, which consists of searching the solution within a space with unitary Hamming distance from the current vector-solution, i.e., the search is done over all vectors that differ in only one bit from the current solution; and the vector of the matched filter bank output, $\mathbf{b}^{\text{MFB}}$, is taken as the best initial solution [2].

In each new local search iteration, all the K vectors with unitary Hamming distance from the current best solution (previous iterations) are evaluated through the cost function computation, Eq. (11). The vector-candidate that results in the largest value for the cost function is compared to the current best solution. If there is improvement, the best solution is updated and a new iteration takes place. Otherwise, the search is concluded. The stop criterion can be seen as the absence of improvement in one iteration.

Basically, three advantages make the LS algorithm a good choice for solving the MUD problem: a) absence of input parameters; b) simple stop criterion, avoiding a priori calculation; c) simple strategy: possibility of additional simplifications.

C. WO-LLF Selection PSO S/MIMO MC-CDMA

The particle selection for evolving in LC, as well as WO, Q-LLFs strategies is based on the highest fitness values obtained through (11) or (12), respectively, and decisions are based on a single entity by combining the subcarriers and antenna informations. So, for evaluating (11) or, alternatively, (12) over all particle-candidates, it is necessary to calculate the particle velocity and its respective position. The ith PSO particle position at instant t is represented by the $K \times 1$ vector:

$$\mathbf{b}_i[t] = \left[b_{i1}[t]\ b_{i2}[t]\ \ldots\ b_{iK}[t]\right]^\top. \tag{15}$$

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 (12):

$$\begin{aligned}\mathbf{v}_i[t+1] = \;& \omega \cdot \mathbf{v}_i[t] + \sum_{q=1}^{Q+1} \Big[\phi_1^q \cdot \mathbf{U}_{i_1}^q[t] \left(\mathbf{b}_i^{\text{best},q}[t] - \mathbf{b}_i[t]\right) \\ & + \phi_2^q \cdot \mathbf{U}_{i_2}^q[t] \left(\mathbf{b}_g^{\text{best},q}[t] - \mathbf{b}_i[t]\right)\Big],\end{aligned} \tag{16}$$

where ω is the weight of the previous velocity in the present velocity calculation; $\mathbf{U}_{ip}^q[t]$, $p = 1, 2$, are diagonal matrices with dimension K, defined for each q antenna, whose elements are a random variable with uniform distribution $\mathcal{U} \in [0, 1]$, generated for the ith particle at instant t; $\mathbf{b}_g^{\text{best},q}[t]$ and $\mathbf{b}_i^{\text{best},q}[t]$ are the best global and the best local positions, respectively, found in the qth antenna ($q = 1, \ldots, Q$), as well as considering all combined antennas ($q = Q+1$), until the tth iteration; ϕ_p^q, $p = 1, 2, \quad q = 1, 2, \ldots, Q+1$, are weighting factors regarding the best particles ($p = 1$) and the best global ($p = 2$) positions influences in the velocity update. The positive acceleration coefficients satisfy $\sum_{q=1}^{Q+1} \phi_1^q + \phi_2^q = C$, where C is a real constant, generally assumed equal to 4 [4].

In order to obtain fast convergence without losing a certain exploration and exploitation capabilities, ϕ_2 could be increased, being chosen for the single-carrier DS/CDMA multiuser detection problem [3] from the range: $\phi_2 \in [2; 10]$

(while $\phi_1 = 2$), resulting in an intensification search for the best global position. So, the same procedure was adopted herein for the multi-carrier S/MIMO DS/CDMA MUD problem: due to the intensification of the best global position search, the higher the factor ϕ_2^q, the faster the convergence rate.

Although (12) is a multi-objective fitness function, this work considers the selection of simply $Q+1$ best position for each particle evolving, based on (16). Note that neither Pareto optimality nor non-dominant individual concepts were adopted herein. A comparative study considering combined multi-fitness functions particle swarm optimization (WOPSO) and standard PSO S/MIMO MC-CDMA MUD, both under single-objective optimization approach, was carried out in [12]. Simulation results show the capabilities of both schemes to scape from local solutions, thanks to a balance between exploration and exploitation. Furthermore, compared to the standard PSO, the WOPSO presents advantages of convergence speed and computational complexity reduction.

For MUD optimization with binary modulation, each element $b_{ik}[t]$ in (15) just assumes "0" or "1" values. This implies in a discrete mode for the position choice. Hence, it is carried out a decision step based on threshold, depending on the velocity. However, the velocity needs to be adjusted in a probabilistic mode. Several functions show 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 velocity. This function is limited by the interval $[0, 1]$. The selection of the future particle position is obtained through the statement:

$$b_{ik}[t+1] = 1 \text{ if } \mathrm{u}_{ik}[t] < S(v_{ik}[t]); \qquad 0 \text{ otherwise}, \quad (17)$$

where $\mathrm{u}_{ik}[t]$ is a random variable 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 WOPSO model, which will be responsible for limiting the velocity in the range $[\pm V_{\max}]$. This factor makes possible the algorithm to escape from eventual local maximum. The change of the bit is more probable every time that the particle velocity crosses the limits established by $[\pm V_{\max}]$, Table I.

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 (16), 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 S/MIMO, 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 those 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).

Indeed, for each iteration of the WOPSO S/MIMO algorithm, there is a set containing $(Q+1)$ best particle positions, $\mathbf{b}_i^{\text{best},q}[t]$, where the first Q positions can be associated to the Q end-points of visited Pareto front [21] $\mathcal{F}_{\text{i}}^*$, and the $(Q+1)$th one is the position in $\mathcal{F}_{\text{i}}^*$ that maximizes $\Omega(\mathbf{b})$. There is another set containing $(Q+1)$ best global positions, $\mathbf{b}_g^{\text{best},q}[t]$, where the first Q positions are Q end-points of $\mathcal{F}_{\text{g}}^*$, and the $(Q+1)$th one is the position in $\mathcal{F}_{\text{g}}^*$ that maximizes $\Omega(\mathbf{b})$.

However, in order to maintain the WOPSO optimization process as simple as possible[4], specially in scenarios where the number of receive antennas (Q) increase or, mainly when both system loading $\left(\frac{K}{MN}\right)$ and Q are large, just the $Q+1$ best particles obtained evaluating directly (12) is considered to evolve for the next iteration. After the WOPSO iterations terminate, the final estimation vector is determined by the vector $\widehat{\mathbf{b}} = \mathbf{b}_g^{\text{best},Q+1}[G]$, which is associated with the particle position that maximizes $\Omega(\mathbf{b})$.

IV. COMPUTATIONAL COMPLEXITY

In spite of the fact that all heuristic-based MUDs achieve a similar performance, the computational complexity (number of operations) varies for the different strategies. In order to accomplish a good efficiency measure of the considered algorithms, it is taken into account the number of floating point operations needed for each one to achieve the convergence, defined here 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), receivers (Q), subcarriers (M), iterations needed for convergence ($\mathcal{G} \leq G$) and population size ($\mathcal{P}$).

The cost function calculation in (11) 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 detector search. $4K^3 + K^2$ operations are needed for these two terms, and this calculation is done QM times (one for each subcarrier on each antenna). Inside the iterations loop, the number of operations needed for each vector-candidate evaluation through cost function becomes $QM(K^2 + 2K)$. Thus, for reference, the complexity to calculate one cost function (one-CFC) was included in Table II.

TABLE II
COMPUTATIONAL COMPLEXITY C FOR THE HEUR-MUDS.

MUD	Operations
OMUD	$2^K QM\left(K^2 + 2K\right) + QM(4K^3 + K^2)$
1-LS	$\mathcal{G}[QMK(K^2 + 2K) + 2K + 2] + QM(4K^3 + 2K^2 + 2K) + 1$
SA	$QM\left[K^3(\mathcal{G}+5) + 2K^2(\mathcal{G}+1)\right] + K\mathcal{G}\left(M + 4 + \frac{7}{K} + \frac{M}{\mathcal{G}}\right)$
WOPSO	$\mathcal{G}[QM\mathcal{P}(K^2 + 2K) + \mathcal{P}(4QK + 9K + 2Q + 2) + Q + 2]$ $QM(4K^3 + K^2) + (\mathcal{P} - 1)K$
one-CFC	$2QMK(2K^2 + K + 1)$

Essentially, the computational complexity of the HEUR-MUDs is mainly determined by the generation of new vector-candidates (search step), accomplished inside of the cost function calculation in (11). For the 1-LS MUD, the cost function is evaluated K times in each iteration and there are

[4]Note that the algorithm has to be implemented in real time using digital signal processing platforms.

also $\mathcal{G}(K+1)$ multiplications and $\mathcal{G}(K+1)+1$ comparisons. The WOPSO-MUD evaluates the cost function $\mathcal{P}$ times in each iteration, generates $\mathcal{GP}K(2Q+3)+(\mathcal{P}-1)K$ random numbers, executes $\mathcal{G}[3\mathcal{P}K+(Q+1)(2\mathcal{P}+1)]$ comparisons and $\mathcal{G}\left[\mathcal{P}K(2Q+3)+1\right]$ multiplications. In each SA-MUD iteration, the cost function is evaluated K times; there are also $\mathcal{G}[K(M+3)+1]$ multiplications, $\mathcal{G}(K+5)$ comparisons and $\mathcal{G}$ random number generations. The total number of operations $\mathtt{C}$ is summarized in Table II.

V. Numerical Results and Discussion

The main system and channel parameters used in this section are summarized in Table III. In all simulated scenarios, random generated sequences of length 32 (PN_{32}), processing gain $N=8$, and a number of subcarrier $M=4$ were adopted. Hence, the MC-CDMA equivalent processing gain results in $NM=32$.

TABLE III
System, algorithm and channel parameters.

Parameter	Adopted Values
S/MIMO MC-CDMA System	
# Rx antennas	$Q = 1$ to 5
Code Sequences	PN_{32}
Processing gain	$N = 8$
Subcarriers	$M = 4$
Bit period, T_b	300 μs
# mobile users	$K = 20;\ 25;\ 32$
Received SNR	$E_b/N_0 \in [0;\ 18]$ dB
SA Parameters:	
# iterations @T_k	$It = 2$
Initial Temperature	$T_0 = 0.3K$
Cooling rate	$\delta = 0.9$
WO*PSO Parameters:*	
Swarm pop. size	$\mathcal{P} = 10;\ 20;\ 30;\ 40$ vector-candidates
Veloc. bound factor	$V_{\max} = 4$
Veloc. weight factor	$\omega = 1$
Weight particle factors	$\phi_1^q = \phi_2^q = \frac{1}{2Q},\ 1 \le q \le Q$ $\phi_1^{Q+1} = \phi_2^{Q+1} = 0.5$
1-LS Parameters:	none
Rayleigh Channel	
Max. Doppler freq.	$f_{\text{Dpl}} = 100$ Hz (slow channel)
Per subcarrier	flat-frequency
Channel state info. (CSI)	perfectly known at Rx
# iterations (LS, SA, WOPSO)	$G(K, Q) \in [10;\ 80]$

All Monte-Carlo simulations (MCS) results indicate that, taking into account a specific number of receive antennas (Q), the SA, WOPSO and 1-LS MUDs reach the same BER performance after convergence, but with different computational complexity, as discussed in Section IV. This performance, as a function of E_b/N_0 (or equivalently, signal-to-noise ratio, SNR), and different number of receive antenna elements ($Q = 1, ..., 5$), is indicated in Fig. 3 by the label "Heur", while "CD" indicates conventional detector performance. For medium loading (Fig. 3.a), the system equipped with LS, WOPSO or SA multiuser detector reaches a BER $\approx 10^{-5}$ with $Q \ge 3$ at low-medium SNR. Even for full system loading (Fig. 3.b), a good BER performance can be achieved when $3 \le Q \le 5$ at moderate SNR.

Note that the SA and 1-LS MUDs use the same unitary Hamming distance search strategy to select their potentials solutions inside of the search space.

In order to corroborate the assertion that, after convergence, the three HEUR-MUDs reach the same BER performance for a fixed number of antennas, Fig. 4 and Table IV show a convergence speed comparison of the three schemes for medium and medium-high system loading. Combining these information, one can conclude that, for the unitary Hamming distance search strategies, the number of iterations necessary for convergence decreases with an increase in the number of receive antennas. On the other hand, for the WOPSO-MUD the opposite occurs.

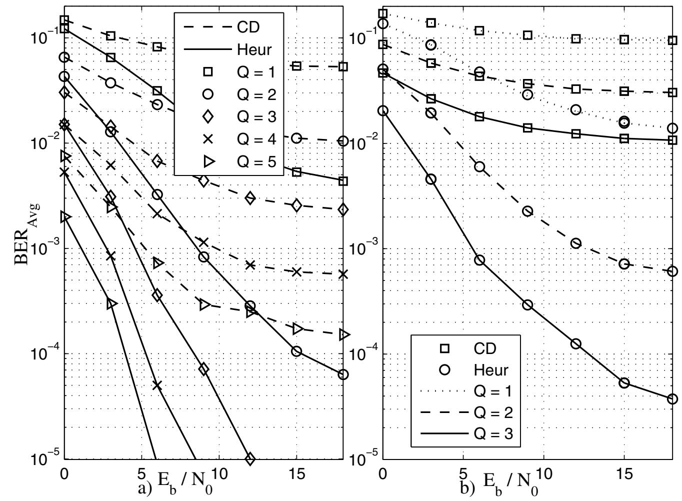

Fig. 3. BER performance for HEUR-MUD S/MIMO MC-CDMA. a) $K = 20$, $\mathcal{P} = 30$ and $G = 25$; b) $K = 32$, $\mathcal{P} = 40$ and $G = 25$.

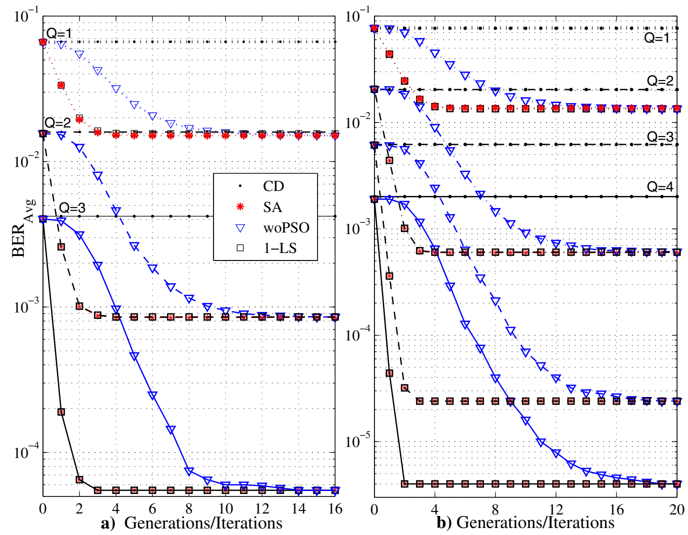

Fig. 4. Convergence performance for HEUR-MUD S/MIMO MC-CDMA. a) $E_b/N_0 = 9$dB, $K = 20$, $\mathcal{P} = 30$; b) $E_b/N_0 = 12$dB, $K = 25$, $\mathcal{P} = 30$.

TABLE IV
Iterations for convergence under different conditions.

$Q \in [1\,2\,3\,4]$	**Sys. I** (20 us.)	**Sys. II** (25 us.)	**Sys. III** (32 us.)
$\mathcal{G}_{\text{1-LS}}$	[4 3 3 −]	[5 4 3 2]	[5 4 3 3]
$\mathcal{G}_{\text{SA}}$	[4 3 3 −]	[5 4 3 2]	[5 4 3 3]
$\mathcal{G}_{\text{wOPSO}}$	[10 11 12 −]	[13 15 17 19]	[48 55 60 68]
E_b/N_0	9 dB	12 dB	12 dB
Obs	Fig. 4.a	Fig. 4.b	$\mathcal{P} = 10$

The complexities of the HEUR-MUD algorithms are analyzed in more details considering the complexity factor (CF) and complexity reduction (CR) indexes:

$$\mathrm{CF_{Heur}} = \frac{\mathrm{C_{Heur}}}{\text{one-CFC}}, \quad \text{and} \quad \mathrm{CR_{Heur}} = \frac{\mathrm{C_{Heur}}}{\mathrm{C_{OMUD}}}. \tag{18}$$

Fig. 5 puts into perspective the three complexity figures of merit needed for each HEUR-MUD algorithm to reach the convergence under perfect channel estimates and system conditions described in Table IV.

The CF factor decreases slightly with an increase in the number of antennas for 1-LS and SA MUDs under Syst. I, II and III, and results very close to the one-CFC cost complexity for both algorithms, while for WOPSO-MUD, the CF grows with Q, indicating that the latter needs some extra fine adjustment on the input parameters ($V_{\max}$, ω, ϕ_1, ϕ_2) when the number of receive antennas, SNR, and/or loading system change. Besides, Fig. 5.c shows the average (over Q antennas) complexity reduction indexes for the three system operation conditions. All the three HEUR-MUDs analyzed have a considerable complexity reduction compared to OMUD.

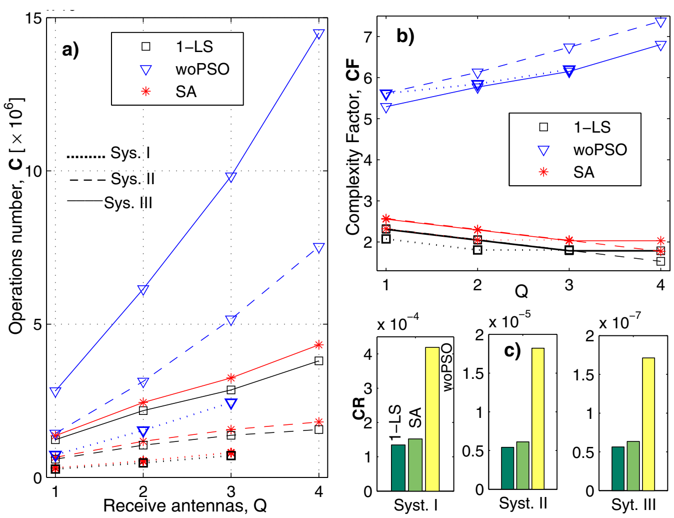

Fig. 5. a) operations C, b) complexity factor CF, and c) complexity reduction CR for HEUR-MUDs convergence.

VI. CONCLUSIONS

The unitary Hamming distance local search strategies (1-LS and SA) show a complex reduction factor at least three times smaller than the particle swarm optimization approach, which represents an implementation advantage, especially when high spatial diversities[5] are demanded. One can see that, under low-order modulation (BPSK), the 1-LS S/MIMO MC-CDMA MUD results in the best complexity-performance trade-off, besides the inherent absence of input parameters and the simple stop criterion advantages.

Future works include the use of multi-objective optimization with Pareto optimality selection (non-dominated individuals could be selected, once Q received signals are statistically independents), combined with direct search, genetic algorithm or swarm intelligence approaches applied to S/MIMO MC-CDMA multiuser detection and channel estimation problems under high order modulation formats and fading channels.

[5] Large number of receive antennas.

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