

Ant Colony Input Parameters Optimization for Multiuser Detection in DS/CDMA Systems

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Abstract

In this work a simple and efficient methodology for tuning the input parameters applied to the ant colony optimization multiuser detection (ACO-MuD) in direct sequence code division multiple access (DS-CDMA) is proposed. The motivation in using a heuristic approach is due to the nature of the NP complexity posed by the wireless multiuser detection optimization problem. The challenge is to obtain suitable data detection performance in solving the associated hard complexity problem in a polynomial time. Previous results indicated that the application of heuristic search algorithms in several wireless optimization problems have been achieved excellent performance-complexity tradeoffs. Regarding different system operation and channels scenarios, a complete input parameters optimization procedure for the ACO-MuD is provided herein, which represents the major contribution of this work. The performance of the ACO-MuD is analyzed via Monte-Carlo simulations. Simulation results show that, after convergence, the performance reached by the ACO-MuD is much better than the conventional detector, and somewhat close to the single user bound (SuB). Flat Rayleigh channels is initially considered, but the input parameter optimization methodology is straightforward applied to selective fading channels scenarios, as well as to joint time-spatial wireless channels diversities.

Keywords: Ant colony intelligence, multiuser detection, input parameters optimization, computational complexity, multiple access communication networks, DS-CDMA.

1. Introduction

In the direct sequence/code division multiple access (DS/CDMA) technology, all the users share the entire frequency band available at the same time. This is possible due the spreading sequence with short chip period, which is used in order to spread the user information along all the available bandwidth spectrum, as well as serves as an identification code for each user, providing some level of multiple access interference (MAI) immunity. The application of sequences with low cross correlation allows to support a considerably number of users simultaneously, as well as the possibility of operation in the asynchronous configuration mode, meeting the requirements of wireless mobile communication uplink.

However, as the system loading¹ increases, the utilization of sophisticated detectors become necessary, such as multi user detection (MuD) Verdú (1998), in such a way to obtain a reasonable separation among the several user' signals, each one under an intense multiple access interference level generated by $K - 1$ interfering users. The best performance is achieved by the optimum multiuser Detector (OMuD) or maximum likelihood (ML) detector, which complexity grows exponentially with the number of users, $O(2^K)$ Verdú (1998).

After the Verdú's revolutionary work, a wide number of suboptimal MuD approaches have been proposed in an attempt to get high performance multiuser receivers with low complexity. Among the suboptimal MuDs, the linear multiuser detectors, such as Decorrelator Verdú (1986) and MMSE (*Minimum Mean Square Error*) Poor and Verdu (1997), as well as the nonlinear MuDs, such as interference cancelers Patel and Holtzman (1994), *zero-forcing* Duel-Hallen (1995), among

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¹The number of users by the processing gain ratio, $L = K/N$.

others have been widely discussed in literature in the past two decades. More recently, a new class of multiuser detection approach has been successfully proposed with increasing gain in complexity-performance trade-off: the heuristic-based multiuser detectors Ergun and Hacıoglu (2000); Lim and Venkatesh (2003); Hijazi and Natarajan (2004); Ciriaco et al. (2006).

In the last decade, proposals based on heuristic methods have been reported to solve the MuD problem, getting performance close to the ML performance with polynomial computational complexity Ergun and Hacıoglu (2000); Abrão et al. (2009). The use of heuristic search algorithms is motivated by the fact that optimization problems related to wireless communication systems results in non-polynomial (NP-hard) problems, e.g. MuD optimization problem Verdú (1989). So, from a practical point-of-view, the challenge is to obtain satisfactory results for these high computational complexity problems in a polynomial time. This requirement comes from the fact that detection stage must be provided in a short time under a limited computational resources in order to met the real time wireless communication applications and services. Meeting this requirement the wireless communication system is able to be implemented on modern digital signal processors platforms.

Furthermore, the input parameters optimization of the heuristic-based algorithms is of paramount importance in order to obtain reliable results. Specifically on MuD optimization problem, in Abrão et al. (2010) a detailed study about the input parameters of the particle swarm heuristic algorithm applied to DS/CDMA multiuser detection problem has been conducted. Hence, present work aims to develop an input parameters analysis for the ant colony optimization (ACO) heuristic-based algorithm applied to DS/CDMA multiuser detection problem.

Previous results shows the heuristic based algorithms application in several wireless communications optimization problems has achieved great success in the performance-complexity tradeoff. In the multiuser detection context, the heuristic based algorithms (Heur-MuD) most commonly used includes the evolutionary programming (EP) based algorithms, specially the genetic algorithms (GA) Ergun and Hacıoglu (2000); Ciriaco et al. (2006), particle swarm optimization (PSO) Zhao et al. (2006); de Oliveira et al. (2006), ant colony optimization (ACO) Xu et al. (2007) and the local search method (LS) Lim and Venkatesh (2003); Oliveira et al. (2009).

The first algorithm using the ACO heuristic approximation was proposed in 1991 by Colorni Colorni et al.

(1991), and since that many variant algorithms were described in the literature. The ACO intelligence has achieved great success in solving combinatorial optimization problems that had arisen in many areas. For example in power electronics field, variants of this heuristic method, such as elitist ant system (EAS), rank-based ant system (AS_{rank}) and max-min ant system (MMAS) just to name a few, have been deployed, for instance, in reactive power controls Abbasy and Hosseini (2007). Recently, this ant behavior-based technique has been widely applied to multiple access multiuser detection Hijazi and Natarajan (2004); Lai and Lain (2005); Xu et al. (2007); Zhao et al. (2010).

The computational complexity of DS/CDMA ACO multiuser detection was analyzed in Hijazi and Natarajan (2004), noting that with a few iterations the ACO-MuD algorithm was able to reach the near-optimal performance spending only a small fraction ($\approx 5\%$) of computational effort necessary to perform an exhaustive search. In Hijazi and Natarajan (2005), a similar performance is reached considering different received powers for the users. Also, the lower computational complexity for the ACO algorithm regarding to genetic algorithm has been evidenced. Besides, under the same channel and system operation conditions the authors have been shows the the worse performance of the GA-MuD regarding that obtained with ACO-MuD.

In a more complex system and environment, Hijazi and Natarajan, Lain and Lai (2007) have explored the joint receiver diversity and ACO multiuser detection techniques. In that work, authors have been shown the near-far robustness effect achieved by ACO algorithm, differently from GA algorithm, which performance is degraded under severe NFR condition. Furthermore, Xu et al. (2007) analyzes the ACO-MuD applied to multi carrier DS/CDMA systems (MC-DS/CDMA). ACO-MuD in this context is able to reach the optimal performance, regardless the adopted number of carriers. Under this promising performance, the authors have carried out complexity analysis and verified that the ACO-MuD complexity seems the conventional detector, even under a system loading of 100%.

An heuristic ACO-based multiuser detector for space-time block coding (STBC) systems with receiver diversity was proposed in Hongwu (2009). This STBC ACO-MuD applies the Pareto-optimally (PO) concept in the pheromone updating step, selecting only the ants with the best results in that iteration. Numerical results have indicated a very close performance to the optimal one; importantly, authors have demonstrated a very low computational complexity for the STBC ACO-MuD. Furthermore, the proposed ACO-MuD presented a per-

formance much better than GA-MuD at the same operation system and channel conditions; also, the STBC ACO-MuD does not present the bit error rate saturation (BER-floor), a degradation performance effect that occurring at high SNR region.

This work is divided in seven parts. Besides this introductory section, the adopted system model is described in Section 2. In section 3, the ACO-based heuristic algorithm applied to MuD detection is minutely exploited, while in section 4, an input parameters optimization methodology was proposed for the algorithm, considering different channel conditions. An analysis on the number of iterations Golub and Loan (1996) computed by the ACO-MuD algorithm is carried out in Section 5. The numerical results for the performance of ACO-MuD detector are presented in section 6. Finally, the main conclusions of this work are offered in section 7.

2. System Model

In a DS/CDMA system, deploying BPSK modulation under non-line-of-sight (NLOS) fading channels, the time continuous baseband signal that arrives at the receiver can be described as:

$$r(t) = \sum_{k=1}^K A_k b_k s_k(t - \tau_k) * h_k(t) + \chi(t) \quad (1)$$

where K is the number of active users in the system; $t \in [0, T_b]$ and T_b is the bit period²; A_k is the transmitted signal amplitude of the k th user, given by $A_k = \sqrt{\frac{E_k}{T_b}}$, where E_k is the bit energy and P_k the power of the signal received by the k th user; $b_k \in \{\pm 1\}$ is the k -th user's transmitted bit information, assumed independent and equiprobable distributed; $h_k(t)$ is the channel impulse response for the k th user, and $\chi(t)$ is the time continuous additive white Gaussian noise (AWGN), representing the thermal noise and other noise sources uncorrelated to the transmitted signals, with bilateral power density $N_0/2$. The spreading sequence, s_k , assigned to the k -th user is represented by:

$$s_k(t) = \sum_{i=0}^{N-1} z_k^{(i)} p_{\square}(t - iT_c) \quad (2)$$

where \mathbf{z}_k is the chip vector with elements $z_k^{(i)} \in \{\pm 1\}$ and chip period T_c ; $p_{\square}(\cdot)$ represents the rectangular pulse with unitary amplitude in $[0, T_c)$ interval.

²Adopted without loss of generality as normalized.

For a synchronous system ($\tau_k = 0$) and NLOS non-selective frequency channel, the channel coefficients can be described as:

$$h_k(t) = c_k(t)\delta(t) = \beta_k e^{j\phi_k} \delta(t) \quad (3)$$

where $c_k(t)$ is the time continuous channel complex coefficients for the k th user; $\beta_k(t)$ is the module of c_k with a Rayleigh stochastic distribution and $\phi_k(t)$ the phase of c_k with an Uniform distribution in the interval $[0, 2\pi)$.

Multiplying the received signal by the spreading sequence of the interest user (matched filter to this sequence), the conventional detector (CD) provides the information de-spreading. In this way and using matrix notation, the output of the matched filter bank (MFB) is given by:

$$\mathbf{y} = \mathbf{RCAb} + \boldsymbol{\chi}, \quad (4)$$

where \mathbf{y} is the $K \times 1$ output vector, \mathbf{R} is the $K \times K$ correlation matrix, $\mathbf{C} = \text{diag}(c_1, c_2, \dots, c_k)$ the $K \times K$ channel coefficients diagonal matrix, \mathbf{A} is the diagonal matrix of received amplitudes, and \mathbf{b} is the $K \times 1$ vector containing one information bit for each user. $\boldsymbol{\chi}$ is the sampled AWGN $K \times 1$ vector with bilateral power spectral density $N_0/2$.

At the MFB output follows the hard decisor which takes decision according to the signal polarity:

$$\mathbf{b}_{\text{cd}} = \text{sgn}(\mathbf{y}) \quad (5)$$

where the modified signum function $\text{sgn}(\cdot)$ given by:

$$\text{sgn}(x) = \begin{cases} -1 & \text{if } x < 0, \\ +1 & \text{if } x \geq 0. \end{cases}$$

The conventional detector for DS/CDMA uplink receiver (MFB) considers the MAI as a additional background noise, being not able to separate multiple access interference (MAI) from the interest signal. On the other hand, the multiuser detectors (MuD) takes advantage of MAI as a way to takes its performance closer to the optimal. In Verdú (1998), it was shown that the optimal multiuser detector (OMuD), or maximum likelihood (ML) detector, calculates the cost function of all the possible candidate-solutions, and return as the optimal solution the argument of the higher value found. The cost function can be expressed as:

$$f(\boldsymbol{\theta}) = \Re\{2\mathbf{y}^T \mathbf{C}^H \mathbf{A} \boldsymbol{\theta} - \boldsymbol{\theta}^T \mathbf{C} \mathbf{A} \mathbf{R} \mathbf{A}^H \boldsymbol{\theta}\} \quad (6)$$

where $\Re(\cdot)$ is the real operator and $\boldsymbol{\theta}$ the $K \times 1$ information bits candidate vector. Consequently, the estimated transmitted bit vector for the K users is defined as:

$$\widehat{\mathbf{b}}_{\text{opt}} = \arg \max_{\boldsymbol{\theta} \in \{\pm 1\}^K} f(\boldsymbol{\theta}) \quad (7)$$

Since the optimal detector (ML) calculates the cost function for all the possible solutions, it is immediate that its performance grows exponentially with the users number K , because the number of possible combinations is given by 2^K .

From the computational complexity viewpoint, a remarkable reduction in the number of computed operations can be obtained calculating previously $\mathcal{F}_1 = 2\mathbf{y}^T \mathbf{C}^H \mathbf{A}$, and $\mathcal{F}_2 = \mathbf{C} \mathbf{A} \mathbf{R} \mathbf{C}^H$ in (6), since these terms stay fixed along the algorithm iterations, and there isn't reason to be re-calculated at each iteration. This way, an efficient-running cost function can be deployed:

$$f(\boldsymbol{\theta}) = \Re\{\mathcal{F}_1 \boldsymbol{\theta} - \boldsymbol{\theta}^T \mathcal{F}_2 \boldsymbol{\theta}\} \quad (8)$$

3. Heuristic ACO-MuD

Heuristic algorithms are iterative guided search methods in subspaces that presents fast convergence to global optimum, even that convergence in 100% of cases is not guaranteed, Hijazi and Natarajan (2004). They are very efficient in obtaining almost optimum performances, but with a computational cost very lower than exhaustive search methods. In MuD context, the optimal solution (OMuD) is reached with the maximum likelihood (ML) approach, which performs an exhaustive search among all the candidate vectors in (7).

The ant colony optimization is based on the foraging behavior of the ant colony in nature. In search of food, the ants of a colony are scattered randomly in their neighborhood. When an ant is successful in its search for food, it comes back to the nest and leaves pheromones in the way. This pheromone will induce the other ants to take this same way in the search for food, further strengthening the pheromone trail. If the food at the end of a certain way runs out and the ants stop taking it, this pheromone will be evaporated.

For BPSK signaling, uplink receiver side and just one antenna at the base-station (BS) receiver and each of K users' transmitter, i.e., from the interest user receiver viewpoint at BS, we have a single-input-single output (SISO) communication system, with $K - 1$ interfering users. So, the multiuser detection problem at the BS receiver side is constituted by 2^K possible candidate solutions in (7). These solutions are seen by the algorithm as all the possible vector-candidates (or trails) that the ants can travel. The quality of each trail is evaluated by the cost function, defined in eq. (6). The algorithm steps aiming to find a solution that maximizes (6), or analogously, find the fastest trail for the ants until the food.

The MFB outputs serve as initial information to the ants. So, from (4) the log-likelihood function (LLF) for the k th user can be defined:

$$\mathcal{L}_k(\pm 1) = 2\Re\{\pm \mathcal{A}(k)\mathbf{y}(k)\} - \mathcal{A}(k)^2 \mathbf{R}(k, k) \quad (9)$$

where $\mathcal{A}(k) = \mathbf{A}(k, k)\mathbf{C}(k, k)$ is the k th signal received amplitude, including the channel effects (fading, path loss and shadowing).

The desirability function is defined using the LLF function:

$$\mathcal{D}_k(\pm 1) = 1 + e^{-\mathcal{L}_k(\pm 1)} \quad (10)$$

From the desirability function, the intrinsic affinity function is defined, which influences the trail decision of each ant along the algorithm iterations:

$$\eta_k(\pm 1) = \frac{\mathcal{D}_k(+1) + \mathcal{D}_k(-1)}{\mathcal{D}_k(\pm 1)} \quad (11)$$

The signals at the matched filter bank output are assumed as initial information. It is then necessary to take into consideration that the decision taken by the ants be influenced by the paths taken previously, which resulted in better results. This way, the solution found by the algorithm will evolve along the iterations.

In order to quantify this evolution, the $2 \times K$ pheromone table \mathcal{P} is created, in which the first row refers to the probability of positive bits, and the second row refers to the probability of the negative bits. Its elements are initialized with probability λ . Along the iterations, this table is being filled according to the quality of the paths taken by each ant and a tendency, measured in terms of increasing probability of that specific bit be 1 (positive bit) or 0 (negative bit).

The first way to update this table takes into account the paths chosen by each ant in that iteration, and how successful these choices were (measured by the cost function evaluation). A pheromone amount which is equivalent to the cost function value regarding the path taken by the ant is multiplied by the γ coefficient, and incrementally accumulated at the respective positions in the \mathcal{P} matrix:

$$\mathcal{P} = \mathcal{P} + \gamma \cdot f(\text{trail}(m)) \cdot \mathcal{T}(\text{trail}(m)) \quad (12)$$

where $\text{trail}(m)$ is the path taken by the m th ant in a given iteration and $\mathcal{T}(\text{trail}(m))$ is a $2 \times K$ filled with 1 in the positions related to the path taken by the ant and 0 in the others.

The second way to update this table takes into account the best path found by the ACO-MuD algorithm until that moment, named herein $\boldsymbol{\theta}_{\text{best}}$. Similar to the adopted procedure in the first update stage, now, a

pheromone amount which is equivalent to the cost function of $\boldsymbol{\theta}_{\text{best}}$ is multiplied by a coefficient σ and deposited at the respective positions of \mathcal{P} :

$$\mathcal{P} = \mathcal{P} + \sigma \cdot f(\boldsymbol{\theta}_{\text{best}}) \cdot \mathcal{T}(\boldsymbol{\theta}_{\text{best}}) \quad (13)$$

Aiming to scape from possibles local optima (maxima), at each new iteration i , the pheromone table is multiplied by a coefficient $(1 - \varepsilon)$, being ε the pheromone evaporation rate:

$$\mathcal{P}_{i+1} = (1 - \varepsilon) \cdot \mathcal{P}_i \quad (14)$$

Hence, an excessive amount of pheromone is avoided to be accumulated over any possible trail.

Once factors, which influence the path choice of the ants along the iterations, have been defined, it is possible to define the bit choice probability:

$$P_k(\pm 1) = \frac{[\mathcal{P}_k(\pm 1)]^\alpha [\eta_k(\pm 1)]^\beta}{[\mathcal{P}_k(+1)]^\alpha [\eta_k(+1)]^\beta + [\mathcal{P}_k(-1)]^\alpha [\eta_k(-1)]^\beta} \quad (15)$$

where α and β parameters provide more or less importance (weighting factors) to the pheromone amount and the initial information, respectively. Note that α is related to the algorithm convergence speed, while β is related to the reliability that can be assigned to the MFB output, which must be set a low value in hostile conditions of channel and/or system loading ($L > 0.5$).

At each iteration, the choice of a certain bit related to each ant trail will be taken from the probability defined in (15). If some trail is more successfully than $\boldsymbol{\theta}_{\text{best}}$, the best-candidate solution is updated.

After the algorithm performs a specified number of iterations N_{iter} , the solution found by the algorithm is returned by the vector $\boldsymbol{\theta}_{\text{best}}$. The ACO-MuD pseudo-code is described in Algorithm 1.

4. ACO-MuD Input Parameters Optimization

Essentially, there are four input parameters in the ACO-MuD algorithm, $\alpha, \beta, \gamma \in \sigma$; the values assigned to these parameters can dramatically affect algorithm's performance.

The parameter α is related to the weight given to the information registered in the pheromone table during the probability calculation. As α grows, more and more ants choose to take the better path identified in the table (higher probability value). Thus, the algorithm's convergence speed is improved, because the ants tend to choose the same way quickly. This affects the convergence time and, as a consequence, the algorithm's complexity.

The parameter β is related to the *a priori* information during the probability calculation. β increasing implies in more ants following the initial solution trend, i.e., choosing the solution given by the MFB outputs \mathbf{y} , in the MuD context. However, if the initial information is not reliable, i.e., in multiuser scenarios which SNR is low and/or system loading is high ($L \geq 0.7$), high values of β could induce the ants to choose a mistaken path, increasing the system's BER.

Algorithm 1 ACO-MuD

1. Initialization: $N_{\text{iter}}, \mathbf{b}_{\text{cd}}, \mathcal{P} = \lambda, \text{dim. } 2 \times K$.
 2. Calculate terms \mathcal{F}_1 e \mathcal{F}_2
 3. Initial Solution:
 - $\boldsymbol{\theta}_{\text{best}} = \mathbf{b}_{\text{cd}}; \quad \bullet f_{\text{best}} = f(\boldsymbol{\theta}_{\text{best}})$
 4. "A priori" information mapping:
 - $\mathcal{L}_k(\pm 1) = 2\Re\{\pm \mathbf{A}(k)\mathbf{y}(k)\} - \mathbf{A}(k)^2 \mathbf{R}(k, k)$
 - $\mathcal{D}_k(\pm 1) = 1 + e^{-\mathcal{L}_k(\pm 1)}$
 - $\eta_k(\pm 1) = \frac{\mathcal{D}_k(+1) + \mathcal{D}_k(-1)}{\mathcal{D}_k(\pm 1)}$
 5. For $i = 1, \dots, N_{\text{iter}}$:
 - Calculate probabilities $P_k(\pm 1)$ according to (15);
 - Paths taken by each ant, $m = 1, \dots, M$:
 - path taken $trail(m)$ is chosen according to the probabilities calculated above.
 - The path chosen by each ant $f(trail(m))$ is measured by (8).
 - If any path is better than $\mathbf{f}_{\text{best}}, \boldsymbol{\theta}_{\text{best}}$ and \mathbf{f}_{best} are updated,
 - Pheromone Table update.
 - Pheromone accumulation is done according to the path chosen by each ant ("massive incremental"):
$$\mathcal{P} = \mathcal{P} + \gamma \cdot f(trail(m)) \cdot \mathcal{T}(trail(m))$$
 - Pheromone accumulation is done according to the best path found, $\boldsymbol{\theta}_{\text{best}}$:
$$\mathcal{P} = \mathcal{P} + \sigma \cdot f(\boldsymbol{\theta}_{\text{best}}) \cdot \mathcal{T}(\boldsymbol{\theta}_{\text{best}})$$
 - Pheromone evaporation rate:
$$\mathcal{P} = (1 - \varepsilon) \cdot \mathcal{P}$$
 6. When N_{iter} is completed, the algorithm returns $\boldsymbol{\theta}_{\text{best}}$.
-

On other hand, the parameters γ and σ are related to the pheromone accumulation according to the quality of paths taken by each ant and the best path found so far $\boldsymbol{\theta}_{\text{best}}$, respectively. According the study about the ACO algorithm parameters applied to the traveling salesman problem done in Dorigo et al. (1996), the ACO algorithm performance is not affected by the values assigned to γ and σ parameters. Indeed, our simulation results

described in the next subsections, related to these two input parameters optimization applied to the MuD problem, offer support to the conclusions found in Dorigo et al. (1996).

The evaporation rate ε parameter is responsible to avoid an excessive pheromone accumulation over a specific path, avoiding a mistaken convergence of the algorithm over some local optima. Hence, this parameter optimization also is quite relevant in order to achieve high successful convergence rate performances, mainly when the objective function presents many local optima, such as the ACO-MuD function, eq. (6), and specially under specific system operation situations, i.e., high loading and hostile channel conditions. However, in the current study the parameter ε assumes value 0.5, and its importance related to the algorithm's performance improvement will be analyzed in the next work.

Next, it is carried out a complete analysis optimization on the four input parameters of ACO algorithm, specifically applied to the MuD problem considering the reverse link of DS/CDMA systems under flat frequency fading channels and different mobility conditions for the mobile terminals. Monte-Carlo simulation method is deployed in order to determine the optimum values of the ACO-MuD input parameters. A 20dB SNR, Gold spreading sequences with length (processing gain) 31 and system loading $L_{\%} = 100 \cdot \frac{K}{N} = 100\%$ have been adopted. For the others ACO-MuD parameters, the following values have been assumed: initial pheromone probability, $\lambda = 0.01$; population = 30 ants, and $N_{\text{iter}} = 20$ iterations. Table 1 presents the values of the system and channel parameters deployed in the ACO-MuD input parameter optimization analysis.

Note that the performances reached by the ACO-MuD, in terms of bit error rate (BER), were compared to the performance reached when there are only one active user in the system, namely SuB (*single-user-bound*), since due to the full system loading ($K = 31$) the optimum multiuser detector (OMuD) performance calculation becomes computationally impossible.

The optimization is made starting from presetting initial values for the four main parameters, for instance, $\alpha = 1, \beta = 1, \sigma = 8$ e $\gamma = 1$. Keeping three parameters fixed and ranging the fourth, a first set of curves for the ACO-MuD input parameter optimization could be obtained. Then, the four optimized parameters at this first step of optimization are updated. Hence, a second set of curves for the optimized input parameters could be obtained, now in a narrower values range, being the optimized values of the first step the middle of the values range. The values obtained at this second optimization step are then assumed as optima for the ACO-MuD al-

Table 1: System and channel parameters used in the ACO-MuD analysis.

Parameter	Adopted Values
<i>DS/CDMA system</i>	
Processing Gain	$N = 31$
Spreading Sequence	Gold 31
Modulation	BPSK
Number of users	$K = 31$
Signal-Noise Ratio	SNR $\in [5; 30]$ dB
System Loading	$L = \frac{K}{N} = 1$
Near-Far Effect	$NFR = 0$ dB
Mobility	$\sim \mathcal{U}[0; V_{\text{max}}]$ [km/h] $V_{\text{max}} = [60; 120; 240]$
<i>Channel</i>	
Fading channel	Flat Rayleigh
<i>ACO-MuD Algorithm</i>	
Pheromone Initial Prob.	$\lambda = 0.01$
Evaporation Rate	$\varepsilon = 0, 5$
Population	$M = 30$ ants
Iterations Number	$N_{\text{iter}} = 20$
<i>Input Parameters Optimization – ACO-MuD</i>	
Pheromone amount	$\alpha \in [0; 3]$
Initial Information	$\beta \in [0; 15]$
Pheromone acc. due θ_{best}	$\sigma \in [1; 13]$
Pheromone acc. due <i>trails</i>	$\gamma \in [1; 7]$

gorithm at that channel condition and system operation point.

4.1. ACO-MuD Performance under Low Speed Vehicular Channels

Figure 1.a shows the first performance analysis ranging the parameters according the methodology described above. For the parameters α and β , it could be observed an optimum value trend, given by: $\alpha = 0.6, \beta = 6$. For the parameters σ and γ , one can see that there were not performance degradation throughout their respective range values. Hence, intermediate values have been assumed given by $\sigma = 5$ and $\gamma = 3$. Then, this set values has been deployed as the basis for the second optimization step for the parameters α and β . Results in Figure 1.b is taken considering a narrower range centered on the respective optimum value obtained from the first optimization step.

Finally, the optimum input parameter values for the ACO-MuD operating on non-selective fading channels with mobile units moving with uniformly distributed speeds in the range $v \sim \mathcal{U}[0, 60]$ km/h and system loading of $L_{\%} = 100\%$ were obtained, as shown at the first line of Table 2 ($V_{\text{max}} = 60$ km/h).

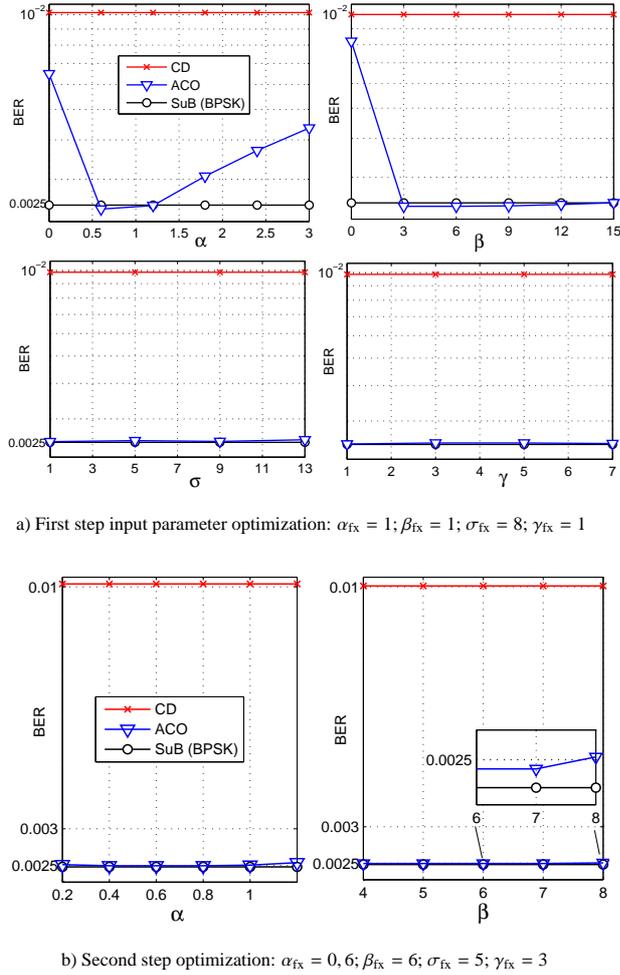


Figure 1: ACO-MuD input parameters optimization: $V_{\text{max}} = 60\text{km/h}$ and $\text{SNR} = 20\text{ dB}$

Table 2: Optimized values for the ACO-MuD input parameters considering different system's mobility conditions.

Parameters	α	β	σ	γ
$V_{\text{max}} = 60\text{ km/h}$	0.6	7	5	3
$V_{\text{max}} = 120\text{ km/h}$	0.4	7	5	3
$V_{\text{max}} = 240\text{ km/h}$	0.6	4	5	3

4.2. ACO-MuD Performance under High and Ultra-High Speed Vehicular Channels

Figure 2 put in perspective the final results for the input parameter values optimization under high ($V_{\text{max}} = 120\text{ km/h}$) and ultra-high ($V_{\text{max}} = 240\text{ km/h}$) speed vehicular non-selective Rayleigh channels.

Under higher mobility, and at same system loading $L = 1$, one can see from Figure 2 the similar results regarding the optimal input parameters values obtained by

the two-step optimization procedure for the low-speed vehicular channels, as described in the section 4.1.

According to the methodology described above, under high mobility the optimal values for the α e β parameters in the first optimization step were changed to $\alpha = 0.6$ and $\beta = 7.5$. Similarly to the low mobility case, for σ and γ parameters it was assumed $\sigma = 5$ and $\gamma = 3$. This set was used in the second optimization stage of the parameters, considering a narrower ranges centered in each optimum value found in the first step.

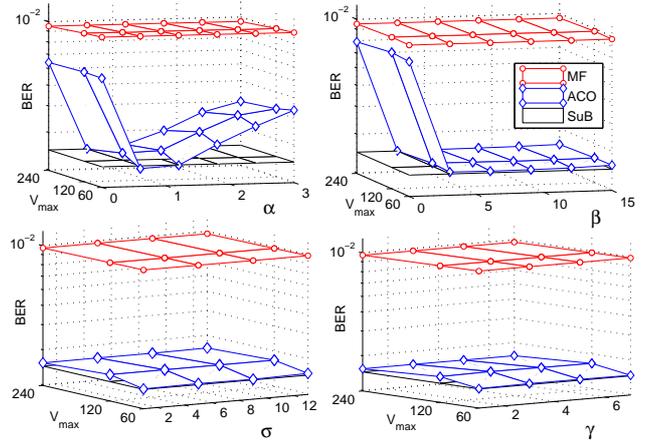


Figure 2: ACO-MuD input parameters optimization. $\text{SNR} = 20\text{ dB}$.

The second line of table 2 summarizes the optimum ACO-MuD input parameters values set for mobile units moving with uniformly distributed speeds in the range $v \sim \mathcal{U}[0; 120]\text{ km/h}$ under flat frequency fading channels and system loading of 100%.

Furthermore, Figure 2 shows too the final ACO input parameters optimization values for ultra-high speed vehicular channels. Again, it was observed significant performance changes only for the parameters α and β . After obtained the first set of optimized values for these parameters, $\alpha = 0.6$, $\beta = 3$ and assuming fixed values for $\sigma = 5$ and $\gamma = 3$, this set serves as the basis for the second step optimization for α e β , but in a narrower range centered respectively in each one of the optimum values obtained at the first step.

Last line of Table 2 shows the optimum values set for the ACO-MuD input parameters under flat frequency fading channels with mobile units velocities uniformly distributed in the range $v \sim \mathcal{U}[0, 240]\text{ km/h}$.

Analyzing the optimized values on different mobility situations, one can conclude from Figure 2 that there were not significant differences for distinct channel mobility conditions, from low to ultra-high speed vehicular channels. The parameters α and β , which are related

to the convergence speed and the *a priori* information reliability, respectively, are more influential to the algorithm's performance (convergence), while the parameters σ and γ proved to be less sensible, corroborating the analysis carried out in Dorigo et al. (1996) for a general purpose discrete ACO algorithm.

Furthermore, the input parameters optimization procedure developed herein has indicated the ACO-MuD efficiency in achieving the quasi-optimum BER performance with no necessity of a significant adjustments in the algorithm's input parameters values, i.e. the algorithm is able to achieve the near-optimum BER performance under a relatively wide ranges for the four input parameters. Besides, the ACO-MuD input parameter optimization results have revealed that the parameters σ and γ are virtually immune to the multiple access channel mobility, also indicating that the algorithm is able to operate robustly under different Rayleigh channels mobility conditions and full system loading.

5. Computational Complexity

In this section, the computational complexity of the conventional (CD), ACO-MuD, and OMuD DS/CDMA detectors have been compared. In this analysis the number of necessary number of operation for each detector is presented. In order to obtain the number of operation in each algorithm, the respective pseudo-code has been analyzed, counting the number of sums and multiplications Golub and Loan (1996) performed. For the ACO-MuD algorithm, the number of operations is calculated considering the total number of iterations until the convergence, N_{iter} . In order to simplify and compare the algorithms, only the number of multiplications and divisions were considered, since the sum and subtraction operations has computational time negligible. The table 3 summarizes the number of operations for each algorithm.

Table 3: Number of Operations necessary for each DS/CDMA detector.

Detector	Number of Operations
CD	KN
ACO-MuD	$\left[3K(K^2 + K + 5) + KN(2K + 1) \right] + N_{iter} \left[M(K^2 + 4K + 1) + 24K + 1 \right]$
OMuD	$K(3K^2 + 2K + 1) + KN(2K + 1) + 2^K(K^2 + 2K)$

6. Numeric Results for MuD problem with Optimized ACO Input Parameters

In order to prove the ACO-MuD algorithm robustness and efficiency, in this section the performance of the heuristic detector with and without optimized input parameters is compared, regarding the number of iterations (convergence speed) and signal-to-noise ratio (SNR). Figure 3 shows the converge velocity of the ACO-MuD under $SNR = 20dB$, $V_{max} = 120$ km/h and with and without optimized input parameters. One can see that with optimized input parameters values found in Section 4, the optimized ACO-MuD with parameters $\alpha = 0.4$, $\beta = 4$, $\sigma = 5$ and $\gamma = 3$ achieves the BER performance bound (maximum likelihood optimum detector, i.e., performance very close to SuB) after five iterations. Thus, for the optimized ACO-MuD, $N_{iter} = 5$ iterations are enough for the complete convergence under non-selective Rayleigh SISO DS/CDMA channels and full system loading ($L = 100\%$) condition.

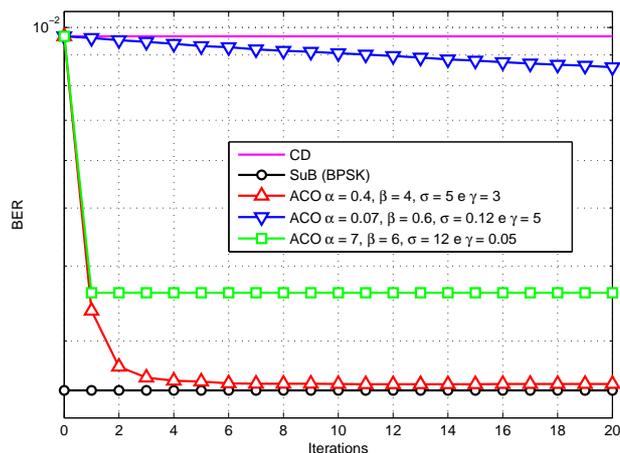


Figure 3: ACO-MuD Convergence performance under $SNR = 20$ dB, flat Rayleigh channel, $L = 100\%$ and $V_{max} = 120$ km/h.

In order to confirm the convergence performances related to ACO-MuD input parameters values, as found in Fig. 3, Fig. 4 presents the ACO-MuD BER performance for a wide range of $SNR \in [0; 25]$. As one can immediately conclude, the best ACO-MuD performance (curve with marker $-\Delta-$) is achievable under optimized input parameters; besides, under with the optimized input parameters values, the ACO-MuD is able to achieve the OMuD performance for all SNR values ranging $[0; 25]$ dB.

Note that, for this scenario, while the OMuD needs 2^{31} cost function calculations (cfc), resulting in over 2 billions of cost function calculations, on the other hand

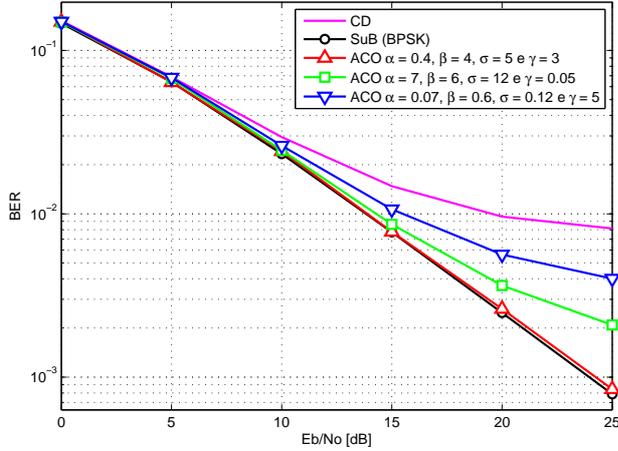


Figure 4: BER performance for ACO-MuD under Flat Rayleigh channels, $L = 100\%$ loading, $V_{\max} = 120$ km/h, considering different values for the input parameters.

the ACO-MuD with optimized parameters evaluates a number of cfc given by the product of the ants population M and the algorithm iterations N_{iter} . With the values assumed in the simulations, this complexity is of the order of $C = M \cdot N_{\text{iter}} = 150$ [cfc]. Hence, the optimized ACO-MuD is able to find solutions very close to those obtained by the OMuD, but with only a fraction of the cfc, i.e. $\approx 1.4 \cdot 10^7$ times lower than the number needed by OMuD.

The complexity in terms of number of operations needs for ACO-MuD (with optimized input parameters) convergence is explored in Figure 5, indicating the marginal increasing in the necessary number of operation as a function of the increasing number of active users. Besides, for comparison purpose, the CD and OMuD complexity were considered. The figure pinpoints the exponential complexity behavior of the OMuD with the number of users, which becomes unfeasible for a high number of users, while the ACO-MuD complexity keeps itself close to the conventional detector with polynomial complexity order $O(K^3)$, as shown in Table 3.

Comparing the ACO-MuD complexity according to the expressions shown in Table 3 with the previously adopted M , N , K and N_{iter} values, the number of operation needs by ACO-MuD results $\approx 6.8 \cdot 10^6$ times lower than OMuD. This difference in the complexity ratio between the detectors, when comparing with the previous result taking into account only cfc, is justified by the number of operations analysis adopted here, which takes into account all the pre-processing performed by the ACO-MuD algorithm beyond the cost function cal-

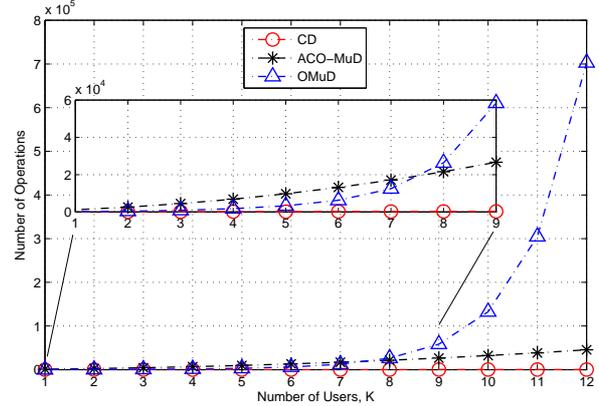


Figure 5: Number of operation as a function of increasing K .

ulation, while for OMuD the overall processing complexity is almost entirely dominated by the cfc step.

Deploying the same values for the input parameters used in Fig. 3, the excellent achievable ACO-MuD BER performance in terms of convergence speed is put into perspective in Fig. 6, considering a wide range of system SNR operation and full system loading $L_{\%} = 100\%$. The number of iterations to achieve total convergence increases with SNR values; e.g. for SNR=10 dB, $N_{\text{iter}} = 2$, while for SNR=20 dB, $N_{\text{iter}} = 5$ and for SNR=30 dB, $N_{\text{iter}} = 9$. However, it is worth noting that the necessary number of iteration for total convergence remains small, proven the high efficiency of the ACO-MuD with optimized input parameters in finding the global optimum under a high multiple access interference and a wide range of SNR.

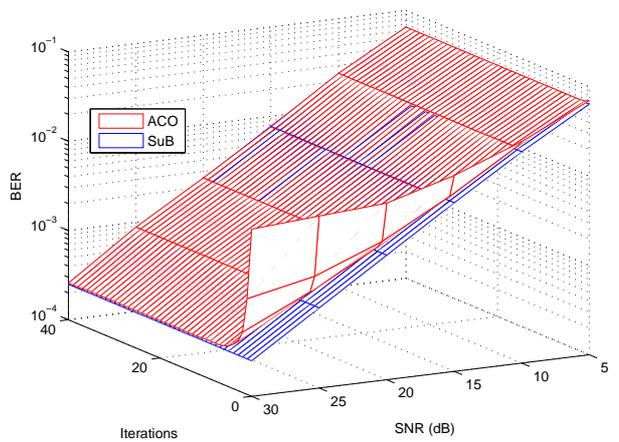


Figure 6: ACO-MuD Convergence performance under SNR $\in [5; 30]$ dB, flat Rayleigh, $L_{\%} = 100\%$, $V_{\max} = 120$ km/h; $\alpha = 0.4$; $\beta = 7$; $\sigma = 5$; $\gamma = 3$.

The robustness to the near-far effect for the three MuD's is compared in Fig. 7, which evaluates the BER performance degradation as a function of increasing system loading and NFR. Here, half of the users was considered as the interest performance evaluation and the another half as interfering users. It is clear that the ACO-MuD performance degradation is solely affected by the near-far effect, been robust to the system loading increasing. However, under not so strong near-far effect, the ACO-MuD is relatively robust in the range $NFR \in [-10; 10]$ dB for small system loadings, becoming a little less robust under high system loadings approaching one in this NFR range. To be more specific, in the range of $NFR \in [-10; 5]$ dB, the ACO-MuD performance is very close to the theoretic OMuD bound, and just marginally degraded in the range $NFR \in [5; 10]$ dB.

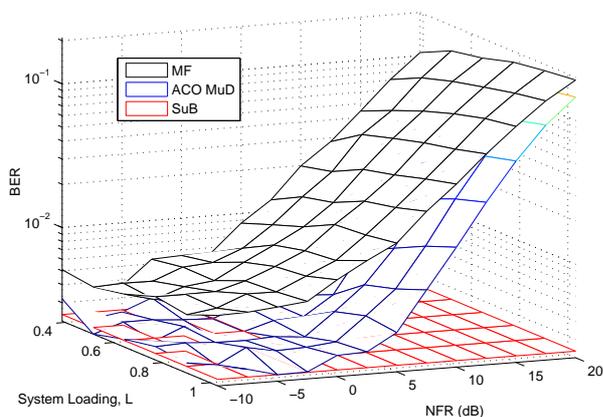


Figure 7: ACO-MuD Performance under $NFR \in [-10; 20]$ dB, flat Rayleigh, $L_{\%} \in [40; 100]$ %, $V_{\max} = 120$ km/h, $SNR = 20$ dB; $\alpha = 0.4$; $\beta = 7$; $\sigma = 5$; $\gamma = 3$.

7. Conclusions

A heuristic multiuser detector based in an ant colony optimization (ACO-MuD) suitable to perform in BPSK DS/CDMA systems under flat Rayleigh fading channels was proposed and successfully characterized. An input parameters optimization methodology for the ACO-MuD was carried out, in order to achieve the best possible performance with a fixed number of iterations. The optimized values proved to be robust enough, such a way to ensure a near-optimum performance for different system and channel operations scenarios, as well as different power control situations, without the need of significant changes in the algorithm.

Indeed, the input parameters optimization for the ACO-MuD shows that the parameters σ and γ are virtually immune to the channel mobility and loading system variation, indicating that the algorithm is able to operate robustly under different mobile channel coherence times; in practice, only the α and β parameters needs to be slightly adjusted when drastic changes in both system operation conditions and multiple access channel occur.

The computational complexity for the proposed ACO-MuD deploying optimized input parameters, was analyzed by both the number of cost function calculations, as well as by the number of operations. ACO-MuD complexity results very low, resulting in a very small fraction of the OMuD computational complexity ($\approx 10^{-7}$) under full system loading condition, wide range of NFR and channel mobility, but with very similar performances.

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