Energy Efficiency Optimization in MPG DS/CDMA

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Abstract— **In this contribution, the heuristic continuous ant colony optimization (ACO) algorithm is deployed to solve the energy-efficiency (EE) optimization problem in multirate multi-processing gain (MPG) DS/CDMA network. The EE design deal with quasi-concave energy efficiency function, allowing the system to operate in the maximal energy efficiency point. Numerical results considering realistic wireless mobile channels and system operation conditions have been shown the applicability of the ACO heuristic approach in order to solve hard problems (in many cases non-convex optimization problems) with practical interest in obtaining energy-efficient design, which is of great interest to establish the next wireless generation green communication networks. The performance and complexity of the proposed ACO-heuristic approach are compared with other two procedures, a heuristic approach based on particle swarm optimization (PSO) and the disciplined convex optimization approach (CvX) tools.**

Keywords— **Resource allocation; energy-efficient design; ant colony optimization; CDMA; particle swarm optimization.**

I. Introduction

Answer: The problem solved in this paper is the overall Energy Efficiency Optimization in a DS/CDMA network. The network allows multirate users through Multiple Processing Gains (MPG), and the optimization algorithm is based on the Ant Colony Optimization (ACO) metaheuristic. On the other hand, reference [9] deals with three problems via ACO: The Power Control aiming to maximize the battery lifetime and the Weighted Throughput Maximization, both on MPG-DS/CDMA networks; The third problem solved is the anomaly detection in computer networks. Hence, the paper 1569767843 discuss a new application of the ACO algorithm, which is considerably different from reference [9]. Besides, all the sentences of the work where rewritten. The similarity can be due to the fact that the same algorithm was deployed in both works.

Resource optimization (RO) techniques, primarily power/energy consumption minimization, are becoming increasingly important in wireless systems and networks design, since battery technology evolution has not followed the explosive demand of mobile devices. RO in wireless networks aim to maximize the sum of utilities of link rates for best-effort traffic. The usual approach consists in considering the problem jointly, i.e., optimizing the joint power control and link scheduling, which is known to be notoriously difficult to solve, even in a centralized manner.

One of the most interesting ways of dealing with the power allocation problem is the energy-efficiency (EE) approach [1], [2], which aims to maximize the transmitted data per energy unit. The energy-efficient approach on CDMA system-based networks can include the joint strategies of spreading-code and receiver optimization [3], as well as the balancing of two important conflicting metrics, energy efficiency *versus* spectral efficiency [4]. Hence, from a wider approach, the power control problem in a multiple access system-based networks could be formulated aiming to optimize the deployment of two main resources scarcely available, i.e., spectrum and energy.

Game theory, which has its roots in the economy field, has been broadly applied in wireless communications for random access and power control optimization problems. From the analysis of two conflicting metrics, namely throughput maximization and power consumption minimization, the distributed energy efficiency cost function can be formulated as a (non)-cooperative game [4], [5]. As a consequence, although the sum-rate increases with the number of active users, the generated level of interference induced by the new users sharing the same bandwidth increases too. Hence, by one side the total network power consumption enlarges in order to achieve the optimum SINR, while, on the other hand, the EE is reduced. As a solution, the best achievable EE-SE trade-off when each node allocates exactly the power necessary to attain the best SINR value, which guarantees the maximal EE while SE is determined by the attainable rate in each node given by Shannon capacity equation. Besides, the energy efficiency is normally reduced by the efficiency function, coding factor and by the circuit power consumption as well. In this work, we deal with heuristic optimization methods applied to EE maximization of CDMA systems.

II. System Model and Problem Formulation

Let consider a downlink (DL) multirate MPG-DS/CDMA network, in which the bit error rate (BER) is used as a QoS metric, since it is directly related to the signal to noise plus interference ratio (SNIR). Thus, the SNIR is associated to the carrier to interference ratio as follows:

$$\gamma_i = F_i \times \Gamma_i, \qquad i = 1, \dots, U \tag{1}$$

where $i \in U$ is the user's indexer, γ_i is the SNIR, $F_i = \frac{r_c}{r_{i,\min}}$ is the processing gain, r_c is the chip rate, $r_{i,\min}$ is the base information rate, and Γ_i is the CIR, defined as [6], [7]:

$$\Gamma_i = \frac{p_i |g_{ii}|^2}{\sum_{j=1, i\neq j}^{U} p_j |g_{ii}|^2 + \sigma^2}, i = 1, ..., U \tag{2}$$

where p_i is the transmit power bounded by $p_{\max}$, $|g_{ii}|$ the amplitude channel gain (considering the effects of path loss, shadowing and multipath fading) and σ_i^2 the additive white Gaussian noise (AWGN) at the i-th receiver's input.

The achievable information rate for spread spectrum systems in AWGN channel considering the gap between theoretical bound and the real information rate is defined based on Shannon channel capacity [8] as:

$$r_i = \frac{\mathtt{W}}{m_i F_i} \log_2(1 + \theta_i \gamma_i) \qquad \left[\frac{\text{bits}}{\text{sec}}\right] \tag{3}$$

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where r_i is the achievable information rate, $m_i = \log_2 M_i$ with M_i being the modulation order, θ_i is the inverse of the gap between the theoretical bound and the real information rate, $\frac{\mathtt{w}}{F_i}$ the user's non spread signal bandwidth and $\mathtt{w} \approx r_c$ is the total system bandwidth. Usually, θ_i can be defined as [9]:

$$\theta_i = -\frac{1.5}{\ln(5\text{BER}_i^{\max})} \tag{4}$$

where $\text{BER}_i^{\max}$ is the maximum tolerable bit error rate.

In order to enable the users to have minimum QoS warranty, the minimum information rate can be mapped into SNIR through the Shannon's capacity model using the gap introduced in (4). Note that for minimum SNIR γ_i^*, eq. (3) uses the minimum information rate ($r_{i,\min}$) established to the ith user belonging to service or user class SERV. This way, it is possible to obtain the condition needed for the minimum SNIR to be satisfied given a minimum information rate:

$$\gamma_i^* = -\frac{2}{3}\ln\left(5 \cdot \text{BER}_{\text{serv}}^{\max}\right)\left(2^{m_i} - 1\right) \tag{5}$$

A. Energy-Efficient Design (EED)

The energy-efficient MPG-DS/CDMA design can be formulated as an optimization problem that aims to maximize the ratio between the overall information rate (or equivalently the system throughput) $\mathcal{S}$ and the total power consumption P_{T}, including the fixed circuitry power P_{C}:

$$\begin{aligned} \underset{\mathbf{p}\in\wp}{\text{maximize}} \quad & \eta_{\text{E}} = \frac{\mathcal{S}}{P_{\text{T}}} = \frac{\sum_{i=1}^{U} \frac{\mathtt{w}}{m_i F_i} \cdot \log_2\left(1 + \theta_i \gamma_i\right)}{\iota \cdot \sum_{i}^{U} p_i + P_{\text{C}}} \\ \text{s.t.} \quad & (\text{C.1}) \quad 0 \le p_i \le p_{\max} \\ & (\text{C.2}) \quad \gamma_i \ge \gamma_i^*, \ \ \forall i \end{aligned} \tag{6}$$

where the parameter $\iota > 1$ is related to the drain inefficiency of the RF power amplifier.

The EE optimization problem consists in finding the appropriate transmitted power for each user belonging to different user's multimedia classes, with different QoS requirements mapped into SNIR, in such a way that the overall system energy efficiency is maximized. Moreover, the objective function in (6) is a special case of nonlinear fractional program [10], [11]. Since that the numerator of η_{E} is concave regarding $\mathbf{p} = [p_1, \ldots, p_U]$, $\forall i$ (a non-negative sum of multiple concave functions), and the denominator is affine, i.e., convex as well as concave, the objective function (6) is quasi-concave [12].

1) Dinkelbach's Method: Deploying the iterative *Dinkelbach's method* [10], [11] it is possible to solve the quasi-concave EED problem in a *parameterized concave form.*

The original fractional program in (6) can be associated with the following parametric concave program [10], [12]:

$$\underset{x\in\mathcal{X}}{\text{maximize}} \quad f(x) - \lambda\, z(x),$$

where $\lambda \in \mathbb{R}$ is treated as a parameter. For the sake of notational simplicity, we define $\mathcal{X} \supset \{\wp\}$ as the set of feasible solutions of the optimization problem in (6), and $\wp$ is a compact and connected set. The optimal objective function in the parametric problem, denoted by $\mathcal{F}(\lambda)$, is a convex and continuous function that is strictly decreasing. Besides, without loss of generality, we define the *maximum energy efficiency* λ^* of the considered system as:

$$\lambda^* = \frac{\mathcal{C}(\mathbf{p}^*)}{\mathcal{U}(\mathbf{p}^*)} = \underset{\mathbf{p}\in\wp}{\text{maximize}} \quad \frac{\mathcal{C}(\mathbf{p})}{\mathcal{U}(\mathbf{p})} \tag{7}$$

which is equivalent to find the root of the nonlinear equation $\mathcal{F}(\lambda) = 0$. Dinkelbach's method is in fact the application of Newton's method to a nonlinear fractional program [13]. As a result, the sequence converges to the optimal point with a superlinear convergence rate [11]. In summary, Dinkelbach [10] proposes an iterative method to find increasing values of feasible λ by solving the parameterized problem:

$$\mathcal{F}(\lambda_n) = \max_{\mathbf{p}\in\wp} \ \left\{\mathcal{C}(\mathbf{p}) - \lambda_n\, \mathcal{U}(\mathbf{p})\right\} \ \ @n\text{th iteration.} \tag{8}$$

The iterative process continues until the absolute difference value $|\mathcal{F}(\lambda_n)|$ becomes as small as a pre-specified ϵ.

Algorithm 1 Dinkelbach's Method

```
Input:       λ0 satisfying F(λ0) ≥ 0;    tolerance ε
Initialize:  n ← 0,
repeat
    Solve problem (8) with λ = λn to obtain p*_n
    λ_{n+1} ← C(p*_n) / U(p*_n);
    n ← n + 1
until |F(λn)| ≤ ε;
Output: λn; p*_n
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In order to demonstrate the DM effectiveness, illustrative EE optimization results are discussed with the inner-loop of Algorithm 1 firstly performed by CVX optimization tool, a package for specifying and solving convex programs [14]; secondly by deploying $\text{ACO}_{\mathbb{R}}$ metaheuristic method, which is reviewed in the following.

III. $\text{ACO}_{\mathbb{R}}$ Metaheuristic

The $\text{ACO}_{\mathbb{R}}$ is a metaheuristic based on the ants behavior when looking for food. Firstly proposed for combinatorial optimization problems, the ants walk through the points of the input set, and deposit pheromone on its edges. Given a set of points next to an ant, the probability of each point to be chosen forms a probability mass function (PMF). The main idea of $\text{ACO}_{\mathbb{R}}$ is the change of this PMF to a *probability density function* (PDF); hence, ants sample continuous PDFs instead of choosing a point next to it, since the continuous domain has infinite points to be chosen. The $\text{ACO}_{\mathbb{R}}$ uses a Gaussian kernel PDFs (weighted sum of Gaussians) method to sample each dimension of the problem [15]:

$$G^i(x) = \sum_{l=1}^{F_s} \omega_l g_l^i(x) = \sum_{l=1}^{F_s} \omega_l \frac{1}{\sigma_l^i \sqrt{2\pi}} e^{-\frac{(x-\mu_l^i)^2}{2{\sigma_l^i}^2}}, \tag{9}$$

where $i = 1, \ldots, U$ is the indexer, with U being the number of dimensions of the problem; $\boldsymbol{\omega} = [\omega_1, \omega_2, \ldots, \omega_{F_s}]$ is the weight vector associated to each Gaussian in the kernel; $\boldsymbol{\mu}^i = [\mu_1^i, \mu_2^i, \ldots, \mu_{F_s}^i]$ is the vector of means and $\boldsymbol{\sigma}^i = [\sigma_1^i, \sigma_2^i, \ldots, \sigma_{F_s}^i]$ is the vector of standard deviations. Hence, the cardinality of both vectors is equal to the number of Gaussians in the set, $|\boldsymbol{\omega}| = |\boldsymbol{\mu}^i| = |\boldsymbol{\sigma}^i| = F_s$.

The pheromone information is kept in a solutions file, where the l-th solution s_l, $\forall l = 1, 2, \ldots, F_s$, in the i-th dimension,

$\forall i = 1, \ldots, U$, is kept at the n-th iteration, as well as the respective cost function values $J(s_l)$. Thus, the file stores F_s solutions, which are used to generate PDFs dynamically through (9). Note that the size of the file is equal to the number of Gaussian PDFs in the kernel (G^i); hence, the kernel is sampling the solutions file indeed. Besides, for each G^i, the values of the i-th variable of all solutions becomes the elements of the mean vector, $\boldsymbol{\mu}^i = [\mu_1^i, \ldots, \mu_{F_s}^i] = [s_1^i, \ldots, s_{F_s}^i]$, that is, the l-th value of dimension i is the mean of the l-th gaussian of G^i.

The number of ants m is another input parameter to be adjusted. The ants are responsible for the sampling of G^i, and thus, for the algorithm evolution as well. In each iteration, each ant chooses one solution of the file with probabilities given by:

$$\omega_l = \frac{1}{qF_s\sqrt{2\pi}} \exp\left[-\left(\frac{l-1}{\sqrt{2}qF_s}\right)^2\right], \quad l = 1, \ldots, F_s \qquad (10)$$

where q is the diversification parameter of the ACO algorithm. Here, the weight of the l-th solution can be seen as the probability of a solution to be chosen and sampled by an ant. Hence, l which is the solution's rank in the file, is also the input parameter in Eq. (10), which is a Gaussian PDF with mean 1 and standard deviation $q \cdot F_s$. So, eq. (10) gives rise to an important equilibrium between q and F_s parameters, making their individual calibration sensitive to each one, in order to achieve a good trade-off among robustness and convergence velocity for each specific optimization problem.

In order to perform the sampling, the standard deviations vector σ^i must be defined for the i-th variable of the file:

$$\sigma_l^i = \xi \sum_{e=1}^{F_s} \frac{|s_e^i - s_l^i|}{F_s - 1} \qquad (11)$$

where ξ can be thought as the inverse of the pheromone evaporation rate [15]. Thus, σ_l^i can be though as the mean distance between the l-th solution to the others at dimension i. Once the sample process is done, the solutions file is sorted based on the value entries in the cost function matrix. After sorting, a number of solutions equal to the number of sampled solutions is discarded, so the size of the file is constant throughout the optimization process. A summary of $\text{ACO}_{\mathbb{R}}$ is showed in Algorithm 2.

The *algorithm robustness* $\mathcal{R}$ can be thought as the ratio between the number of convergence success $\texttt{cS}$ to the total number of realizations $\mathcal{T}$ after N iterations taken in each realization:

$$\mathcal{R} = 100 \cdot \texttt{cS}/\mathcal{T} \qquad [\%], \qquad @N \quad \text{iterations} \qquad (12)$$

and the *algorithm speed* as the average number of iterations needed to the algorithm achieves convergence in terms of the maximum tolerable mean square error (MSE) in $\mathcal{T}$ trials for a given problem.

A. The DM-$\text{ACO}_{\mathbb{R}}$ Adaptation

The $\text{ACO}_{\mathbb{R}}$ algorithm was adapted in order to fit the Dinkelback's method inner loop. It is well known that the initial guess leads to the quality of solution for every metaheuristic. Besides, in the Algorithm 1, a new input $\mathbf{p}_{n-1}^*$ is supplied for the inner-loop algorithm on each outer-loop iteration. Since each input cannot be forgotten, each $\text{ACO}_{\mathbb{R}}$ instance must populate its solution' file in a way that it does not lose the achievement of the previous outer-loop iterations. Thus, the volatility coefficient α has been adopted, aiming to control the generation of new instances for the $\text{ACO}_{\mathbb{R}}$ solutions. The random generation of a solution' file in the n-th outer-loop iteration is given by:

$$s_l \sim \mathcal{U}\left[\mathbf{p}_{n-1}^* - \Psi;\ \mathbf{p}_{n-1}^* + \Psi\right], \ l = 1, 2, \ldots, F_s \qquad (13)$$

where $\mathbf{p}_{n-1}^*$ is the best power vector found in the previous outer-loop iteration, and $\Psi = e^{-\alpha \cdot n}$ is the sample interval limit. Therefore, the solutions generation process is always a perturbation in the previous outer-loop best solution, which becomes tighter as the DM evolves, since Ψ is a bivariate negative exponential function.

Algorithm 2 $\text{ACO}_{\mathbb{R}}$

```
Input: q, ξ, F_s, m, U
Initialize Solutions File: F ~ U(F_s, U)
while The end conditions aren't met do
    Choose each ant's solution through ω
    while The last ant doesn't finishes its sample do
        for Each dimension i of the File F do
            Generate σ^i vector through eq. (11)
            Sample the Gaussian Kernel G^i, eq. (9)
        end for
    end while
    Sort F and drop its m worst solutions
end while
```

IV. Numerical Results

The DS/CDMA resource allocation simulations were carried out within the MatLab 7.0 platform; the main scenario parameters are presented in Table I. We assumed a rectangular cell with one base station in the center and users uniformly spread across all the cell extension. We considered that all mobile terminals experience slow fading channels, i.e. $T_{\text{slot}} < (\Delta t)_c$, where $T_{\text{slot}} = R_{\text{slot}}^{-1}$ is the time slot duration, R_{slot} is the updating rate for the RA parameters, such as transmitted power vector and user symbol information. $(\Delta t)_c$ is the channel coherence time. As part of the SNIR estimation process, the channel is assumed constant in each optimization window, herein admitted $T_{\text{slot}} = 667\mu s$. Thus, the EE maximization (EEM) algorithms must converge to the solution within T_{slot} interval. Numerical results are obtained by Monte-Carlo simulation (MCS) procedure over $\mathcal{T} = 1000$ realizations.

For comparison purpose, particle swarm optimization (PSO) results have been included. Both meta-heuristics' input parameters where obtained in a non-exhaustive fashion. Numerical results in this subsection include: **a**) comparison using Dinkelbach's method (DM) in the outer-loop, with inner-loop in the Algorithm 1 performed by ACO algorithm (DM-ACO), CvX (DM-CVX) and PSO algorithm (DM-PSO), considering power, rate and energy efficiency figures of merit; **b**) convergence analysis of these three approaches for different number of multirate users in the range $U \in [2; 30]$, including the associated evolution of EE $\times N_{\text{DM}}$ iterations, as well as the EE-ACO and EE-PSO robustness analysis; **c**) computational complexity of the DM-ACO, DM-CVX and DM-PSO approaches in solving the EE optimization problem, eq. (6).

In all results, the same initial power-vector and static channel amplitudes configuration based on Rayleigh distribution have been adopted for the three EED approaches. Typically, the static channel power losses in dB for a system with U users results in a relative power loss matrix of the interfering signals ranging from $[8; 40]$ dB, representing a high interference regarding the direct ones, due to the adopted high cross-correlation among the spreading sequences.

TABLE I

ADOPTED SYSTEM AND QOS PARAMETERS FOR THE EED PROBLEM

CDMA Bandwidth	$w = 5$ MHz
Max. power per user MT	$p_{\max} = 3$ [W]
PA inefficiency MT	$\iota = 2.7$
Power circuitry	$P_C = 0.32 \cdot U$ [W]
Modulation order	$m_i = 2,\ (QPSK)\ \forall i$
# Users per Class	$\{U^{\text{VOICE}};\ U^{\text{VIDEO}};\ U^{\text{DATA}}\}$
$U = [12, 20, 30]$:	$[\{6;\ 4;\ 2\}, \{9;\ 6;\ 5\}, \{16;\ 9;\ 5\}]$
User Rates $(\frac{r_c}{F})$ $\left[\frac{\text{bit}}{s}\right]$	$r_{i,\min}^{\text{serv}} = r_c \cdot \left[\frac{1}{256};\ \frac{1}{16};\ \frac{1}{8}\right]$
$\text{BER}^*_{i,\text{serv}}$	$[5 \cdot 10^{-3};\ 2 \cdot 10^{-5};\ 1 \cdot 10^{-6}]$
$\text{ACO}_{\mathbb{R}}$ Input Parameters	
Population Size	$m = U$;
File Size	$F_s \in [4, 6]$;
Diversity Factor	$q = 0.3$;
Pheromone Evapor. Rate	$\xi = 1.3$;
Volatility Factor	$\alpha = 0.7$;
Average σ tolerance	$\epsilon_{\text{aco}} = 1 \times 10^{-6}$;
Max. # iterations	$N = 1000$;
PSO Input Parameters	
Population Size	$m = 10 \cdot U$;
Inertia Weight	$\omega = 0.3$;
Local acceleration coeff.	$\phi_1 = 2$;
Global acceleration coeff.	$\phi_2 = 2$;
Volatility Factor	$\alpha \in [0.1, 0.5]$;
Max. # iterations	$N = 1000$;

Illustrative EE optimization results are depicted in Figs. 1 and 2. Figs. 1-a and 1-b depicts the total energy efficiency as a function of the transmission power allocation of the first and last user, p_1 and p_{30}, while the others users hold individually their best power allocation given by DM computed at the end of the optimization process, i.e., $N_{DM}^{\text{aco,cvx}} = 6$, $N_{DM}^{\text{pso}} = 40$. For DM-ACO and DM-CVX it is clear that after 3 or 4 iterations, the all users achieve their individual near-optimum EE; as a consequence, the maximal $\sum$EE holds. On the other hand, DM-PSO evolves slowly through smaller steps, and is able to achieve total convergence only after $N_{\text{DM}} = 40$ iterations.

Fig. 2 shows the achieved rates relative to the minimum QoS given by $\text{BER}^*_{i,\text{serv}}$ after the respective N_{DM} iterations for both analytical CvX and heuristic ACO, PSO approaches. Thus, all the $U = 30$ users operate under maximum $\sum$EE configuration satisfying their respective QoS; it is found that the problem is feasible regarding C.1 and C.2 constraints. Besides, one can conclude that all algorithms achieve the same individual rates.

The normalized mean square error (NMSE) regarding the analytical optimization approach (DM-CVX) is evaluated in order to check the quality of solution achieved by both metaheuristics, given by:

$$\text{NMSE}[n] = \frac{1}{\mathcal{T}} \cdot \sum_{t=1}^{\mathcal{T}} \frac{||\mathbf{p}_t[n] - \mathbf{p}^*||^2}{||\mathbf{p}^*||^2} \qquad (14)$$

where $||\cdot||^2$ denotes the squared Euclidean distance between vector $\mathbf{p}_t$ at the t-th realization and the optimum solution vector $\mathbf{p}^*$ given by the DM-CVX solution; $\mathcal{T}$ is the number of realizations, assumed herein $\mathcal{T} = 300$. Fig. 3.a) shows the NMSE evolution for both metaheuristcs As reference, the maximal eligible $\text{NMSE}^{\text{th}} = 10^{-2}$ has been considered for both metaheuristics achieve a 99.999% of $\sum EE^*$. After five outer-loop DM iterations, the DM-ACO is able to reach a NMSE $< 10^{-2}$ for all considered system loadings, and in one more iteration, it is able to achieve a NMSE $\approx 10^{-5}$. Moreover, NMSE keeps improving further, showing that the $\text{ACO}_{\mathbb{R}}$ algorithm is powerful enough to perform DM inner-loop optimization. On the other hand, it is clear that DM-PSO needs almost six times the number of outer-loop iterations than DM-ACO to achieve a NMSE $\leq \text{NMSE}^{\text{th}}$ when $U > 12$, which turns the DM-PSO in an expensive approach regarding DM-ACO in terms of computational complexity.

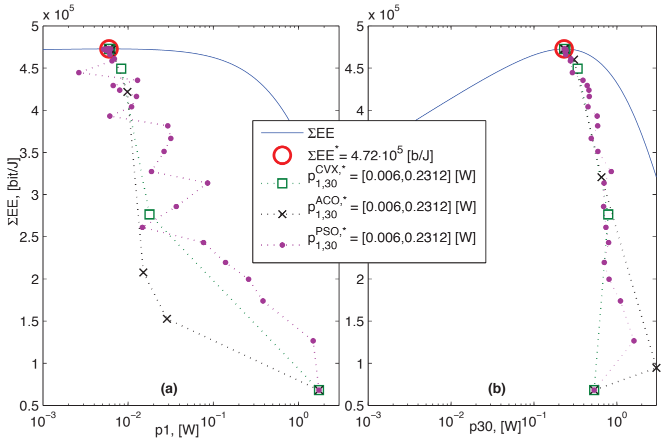

Fig. 1. Sum EE behaviour for the optimal power vector $\mathbf{p}^*$, except to a) p_1 and b) p_{30} user. $U = 30$. Number of iterations in DM: $N_{\text{DM-CVX}} = 6$; $N_{\text{DM-ACO}} = 6$ achieving $\epsilon = 10^{-5}$, and $N_{\text{DM-PSO}} = 40$ achieving $\epsilon = 10^{-3}$.

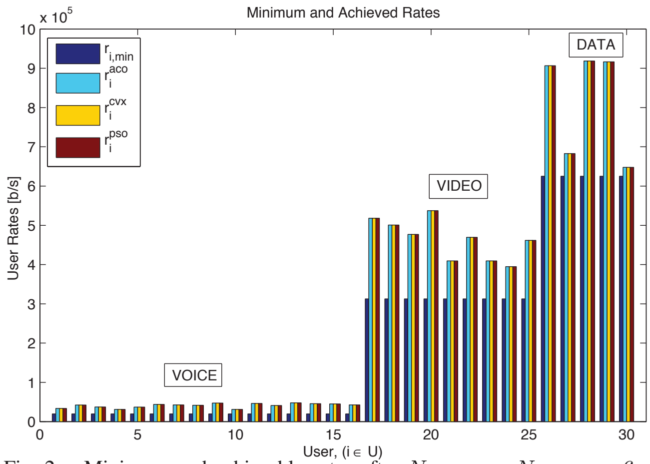

Fig. 2. Minimum and achievable rates after $N_{\text{DM-CVX}} = N_{\text{DM-ACO}} = 6$ and $N_{\text{DM-PSO}} = 40$ iterations.

Figs. 4.a and Fig. 4.b show the $\sum$EE and the corresponding $\sum$Power evolution through the three EEM algorithms outer-loop iterations. For both DM-ACO and DM-CVX, one can note a similar evolution, due to the equal initial power vectors and the same static channel assumed, aside the powerful converge feature of the $\text{ACO}_{\mathbb{R}}$ algorithm.

Once DM-ACO deploys the same number of outer iterations as DM-CVX, it concludes that $\text{ACO}_{\mathbb{R}}$ is a powerful heuristic when maximizing the Dinkelbach's parametric function method. On the other hand, DM-PSO method suffers from insufficient diversity strategy to scape from local optima. Hence, when the dimension of the problem increases ($U > 30$), the PSO algorithm is not able to achieve full inner-loop convergence and the $\sum$EE evolution is slower. Indeed to illustrate the slow convergence of PSO, typical inner-loop evolution for both heuristic algorithms is depicted in Fig 3.b). For the CVX [14], we have assumed a linear convergence, since the instantaneous values of its internal variables are not available.

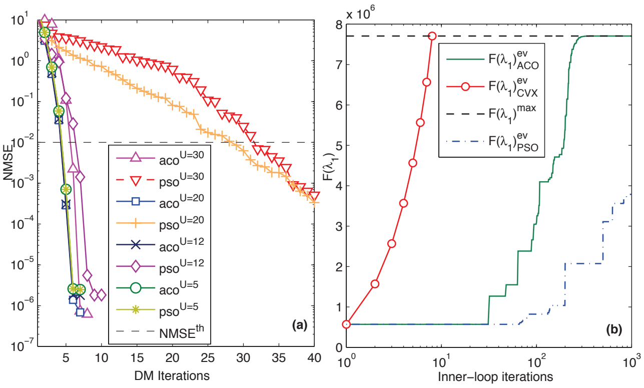

Fig. 3. **a**) DM-ACO and DM-PSO NMSE evolution for $U = [5; 12; 20; 30]$ users; **b**) $\text{ACO}_{\mathbb{R}}$, CVX and PSO inner-loop evolutions during the first DM iteration in the Algorithm 1; $U = 30$ users.

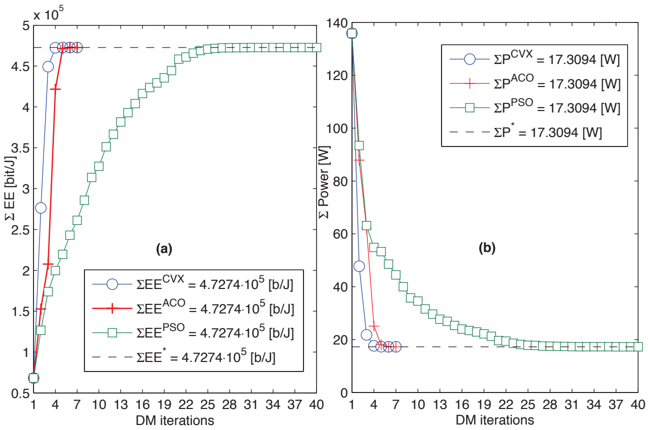

Fig. 4. DM-ACO, DM-CVX and DM-PSO $\sum EE$ and $\sum P$ evolution for $U = 30$ users.

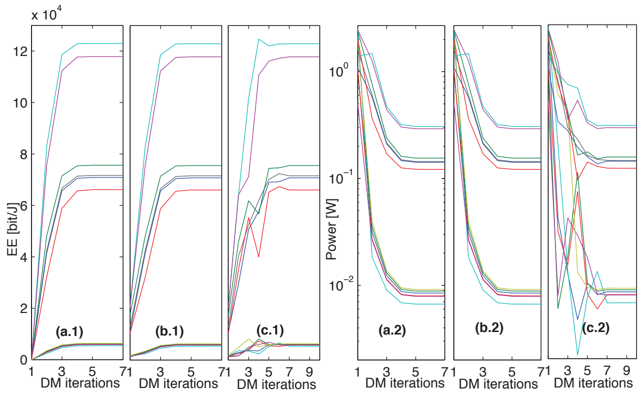

Fig. 5. Individual energy efficiency (1) and power evolution (2) for: a) DM-ACO; b) DM-CVX; c) DM-PSO. $U = 12$ users.

Figs 5 shows the individual EE and power evolution; both evolutions are not monotonic due to the fact that the aim of the single-objective optimization posed by the EED problem is to maximize the total energy efficiency of the system. Furthermore, the outer-loop similarity among the DM-ACO and DM-CVX evolutions becomes evident here.

Finally, Table II summarizes the achieved $\sum$EE for different system loading through DM-CVX, and the respective robustness attainable by DM-ACO and DM-PSO algorithms. The total energy efficiency decreases as the system loading increases due to the increasing level of the multiple access interference. Besides, both metaheuristic approaches achieve 100% of robustness, considering convergence success when NMSE $< 10^{-2}$, which is clear in Fig. 3.a).

TABLE II

ACHIEVED PERFORMANCE METRICS FOR THE EEM PROBLEM.

Users	$\sum$EE [b/J]	Robustness [%]	
U	DM-CVX	DM-ACO	DM-PSO
2	$6.51 \cdot 10^5$	100%	100%
12	$6.05 \cdot 10^5$	100%	100%
20	$5.43 \cdot 10^5$	100%	100%
30	$4.72 \cdot 10^5$	100%	100%
40	$3.77 \cdot 10^5$	100%	96%

V. CONCLUSIONS

$\text{ACO}_{\mathbb{R}}$ algorithm has been successfully applied to the EED optimization problem in a MPG-DS/CDMA network under realistic wireless mobile channels and system operation conditions. Numerical results demonstrated the superiority of the $\text{ACO}_{\mathbb{R}}$ approach regarding PSO. Besides, the heuristic DM-ACO method has demonstrated be very competitive regarding the analytical DM-CVX approach in terms of both suitable performance metrics and reduced complexity. More importantly, the developed optimization design demonstrated to be useful in order to obtain energy-efficient systems for the next wireless generation green communication networks.

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