Energy and Spectral Efficiencies Trade-off in Multiple Access Interference-Aware Networks

Álvaro R. C. Souza, Taufik Abrão, Fábio R. Durand, Lucas H. Sampaio, Paul Jean E. Jeszensky

***Abstract*— This work analyzes the power allocation problem in DS/CDMA systems under the energy efficiency (EE) metric, maximizing the transmitted information per energy unit. As the spectral efficiency (SE) is one of the most important performance metrics and is maximized with infinite power, the trade-off between these two metrics (EE-SE trade-off) are investigated and characterized in relation to multiple-access interference (MAI) power level, resulting that the optimum operating point is the max-EE point and the EE limitation imposed by MAI. To corroborate these results, we develop two algorithms for power allocation based on distributed instantaneous SINR level.**

***Keywords*— Energy efficiency, spectral efficiency, DS/CDMA, distributed power control.**

I. Introduction

Due to the explosive demand of mobile services worldwide and to battery lifetime limitations, resource allocation techniques in wireless networks had become a great concern and a challenge to many researchers in the last decades. In general, the problems aims to maximize system throughput given the maximum power or minimize power consumption given a minimum rate criterium. Besides this scenario, the increasing importance of rational use of scarce resources (specially energy), core of Green Communications approach, brings the metric of Energy Efficiency (EE), which aim to maximize the number of transmitted bits per energy unit, measured in bits per Joule.

The problem of maximizing EE is mainly investigated in wireless systems for code-division multiple access (CDMA) [1], multi-carrier direct sequence CDMA (MC-DS-CDMA) [2] and orthogonal frequency-division multiple access (OFDMA) [3], [4]. The strategy presented in those papers is that all users transmit at the maximum achievable EE, constrained by the maximum power available. As a consequence, some users can allocate the maximum power without transmitting at the optimum EE, increasing the generated interference. As CDMA systems are limited by interference, specially when using single-user detections techniques, putting some of these non-optimum users in outage can result in interference reduction and greater EE. On the other hand, since rate and spectral efficiency (SE) remain as fundamental metrics for modern wireless systems, it becomes necessary to investigate the gap between energy and spectral efficiencies-based allocation processes, determining the trade-off among these two metrics and the optimum operating point. This issue is an important opened topic in Green Communications area [5]. Previously, the EE-SE trade-off has been investigated in [6] considering OFDMA systems and some simplifications in the system model, given the difficulty in the analytical characterization.

This work proposes to analyze the existing EE-SE trade-off for DS-CDMA systems under matched-filter (MF) detection, determining the optimum EE-SE trade-off, as well as to the impact of multiple-access interference (MAI) on this trade-off. In order to corroborate the conclusions of this analysis, we develop two algorithms for power allocation using game theory (specially non-cooperative games), since the overall network EE depends on the behavior of all users.

II. Network System Model

For analysis simplicity, we have assumed an uplink direct sequence code division multiple access (DS/CDMA) network. However, the extension for multi-cell multi-carrier multiple access systems is straightforward. The received signal by the base station can be described as

$$\mathbf{y} = \sum_{k=1}^{K} \sqrt{p_k} h_k b_k \mathbf{s}_k + \boldsymbol{\eta} \ , \tag{1}$$

where p_k is the transmitted power for the kth user, h_k is the channel gain between the kth user and the base station, constant during the chip period, $\mathbf{s_k}$ is the kth user spreading code, b_k is the modulated symbol and $\boldsymbol{\eta}$ is the thermal noise vector, assumed to be AWGN, zero-mean and covariance matrix given by $\sigma^2 \mathbf{I}_N$, where N is the processing gain.

The uplink $1 \times K$ channel gain vector, considering path loss, shadowing and fading effects, between users and the base station, is given by $\mathbf{h} = [h_1, \cdots, h_K]$, with $h_i = |h_i| e^{\angle h_i}$ and assumed to be static over the optimization window.

The signal-to-interference-plus-noise ratio (SINR) is defined by the received signal power to the sum of interfering power plus background noise, measured after demodulation. Adopting a matched filter (MF) receiver and random spreading sequence, the SINR output for kth user is given by:

$$\gamma_k = \frac{p_k |h_k|^2}{\sum\limits_{\substack{j \neq k \\ j=1}}^{K} p_j |h_j|^2 \mathbf{s}_j \mathbf{s}_k^T + \sigma_k^2} = \frac{p_k |h_k|^2}{I_k + \sigma_k^2}, \tag{2}$$

where I_k represents the MAI power level and $\mathbf{s}_k \mathbf{s}_k^T = 1$.

A. QoS Requirements

In order to guarantee the quality of service (QoS), a minimum data rate $R_{k,\min}$ must be provided for each user by the system network service, being an important requirement to be warranted. So, in general, data rate for the kth user is assumed to be a function of SINR γ_k. To model it, we use a modified version of Shannon capacity equation: [7], given by:

$$r_k = \mathcal{C}_k^{\text{gap}} = \mathtt{w} \log_2(1 + \theta_k \cdot \gamma_k), \qquad \forall k \qquad [\text{bit/s}], \tag{3}$$

Álvaro R. C. Souza and Taufik Abrão, Dept. of Electrical Engineering and Computer Science. State University of Londrina, Londrina-PR, Brazil. Fábio R. Durand, Dept. of Electrical Engineering, UTFPR - Campo Mourão-PR. Lucas H. Sampaio and Paul Jean E. Jeszensky, Dept. of Telecomm. and Control Engineering, Escola Politécnica of the University of São Paulo. São Paulo-SP, Brazil. E-mails: {alvarorcsouza, lucas.dias.sampaio}@gmail.com, taufik@uel.br, fabiodurand@utfpr.edu.br, pjj@lcs.poli.usp.br

where w is the system bandwidth and θ_k is the gap describing the limitations and imperfections in real communication systems, approaching to real data rates [8], given by

$$\theta_k = -\frac{1.5}{\log(5\,\mathrm{BER}_k)}, \qquad \text{with} \quad \theta_k \in]0;1], \tag{4}$$

where BER_k is the maximum tolerable bit error rate by the kth user [9]. So, the SE is readily obtained from (3):

$$\zeta_k = \log_2(1+\theta_k \cdot \gamma_k), \qquad \forall k \qquad [\mathrm{bit/(s \cdot Hz)}]. \tag{5}$$

From (3), the minimum data rate for the kth link, $R_{k,\min}$, which is able to guarantee the QoS, can be easily mapped into the minimum SINR

$$\gamma_{k,\min} \quad = \quad \frac{2^{\frac{R_{k,\min}}{r_c}}-1}{\theta_k}, \qquad \forall k = 1,\ldots,K. \tag{6}$$

III. Problem Formulation

In a MAI limited communication system, the kth user selfishly (non cooperative approach) allocates his own transmit power p_k in order to maximize his own energy efficiency function, given by [10]:

$$\xi_k = r_k \frac{L}{M}\frac{f(\gamma_k)}{p_k+p_c} \qquad \left[\frac{\mathrm{bit}}{\mathrm{Joule}}\right], \qquad \forall k = 1,\ldots,K \tag{7}$$

where M is the number of bits in each transmitted data packet; L is the number of information bits contained in each data packet, p_c is the circuit power consumption, and $f(\gamma_k)$ is the efficiency function, which approximates the probability of error-free packet reception. Given a non-coded communication, it can be approximated by [11]

$$f(\gamma_k) = (1-e^{-\gamma_k})^M, \tag{8}$$

which is widely accepted for BPSK and QPSK modulation.

It is worth noting that both transmission power and circuit power consumptions are very important factors for energy-efficient communications. While p_k is used for reliable data transmission, circuit power represents average energy consumption of device electronics [4]. Besides, note that ξ_k is measured in $\left[\frac{\mathrm{bit}}{\mathrm{Joule}}\right]$, which represents the number of successful bit transmissions that can be made for each energy-unit drained from the battery and effectively used for transmission.

In a more general context, we can define the global energy efficiency function as the ratio of the total achievable capacity over the total power transmission consumption:

$$\bar{\xi} = \frac{\sum_{k=1}^{K}\ell_k r_k f(\gamma_k)}{P_{\mathrm{Tot}}} \qquad \left[\frac{\mathrm{bit}}{\mathrm{Joule}}\right], \tag{9}$$

where $P_{\mathrm{Tot}} = \sum_{k=1}^{K}(p_k+p_c)$, and $\ell_k = \left(\frac{L}{M}\right)_k$

A. Distributed Non-cooperative EE Power Optimization Game

The network energy efficiency depends on the behavior of all users; so, the power control can be properly modeled as a non-cooperative game [12]. In this context the non-cooperative power control game is defined as

$$\mathcal{G} = [\mathcal{K}, \{\mathcal{A}_k\}, \{u_k\}], \tag{10}$$

where $\mathcal{K} = \{1,2,\ldots,K\}$ is the set of players (users), $\{\mathcal{A}_k\} = [0, P_{\max}]$ is the strategy set for the kth user, with $P_{\max}$ being the maximum allowed power for transmission, and the utility function $\{u_k\}$ is performed by (7).

Consider the power allocation for the kth user, p_k, and denote the respective power vector of other users as

$$\mathbf{p}_{-k} = [p_1, p_2, \ldots, p_{k-1}, p_{k+1}, \ldots, p_K]. \tag{11}$$

Hence, given the power allocation of all interfering users, $\mathbf{p}_{-k}$, the **best-response** of the power allocation for the kth user can be expressed as

$$p_k^{\mathrm{best}} = f_k(\mathbf{p}_{-k}) = \arg\max_{p_k} \; u_k(p_k, \mathbf{p}_{-k}), \tag{12}$$

where $f_k(\mathbf{p}_{-k})$ is the kth best-response function. Finally, the distributed energy-efficiency problem with power constraint under non-cooperative game perspective may be posed by:

$$\begin{aligned} \arg\max_{p_k} \xi_k \quad &= \quad \arg\max_{p_k} \; \ell_k r_k \frac{f(\gamma_k)}{p_k+p_c} \\ s.t. \quad & \quad 0 \le p_k \le P_{\max} \end{aligned} \tag{13}$$

which solution consists in adopting the best-response strategy for user k. Indeed, the best-response strategy consists in obtain the best user utility function (EE) individually for each user, as posed by (12).

B. Best SINR Response

Since the EE utility function (7) depends on p_k and γ_k and both of them are related, we can define p_k as a function of γ_k using (2), obtaining

$$p_k = \gamma_k \frac{I_k + \sigma_k^2}{|h_k|^2} = \gamma_k \widetilde{I}_k, \tag{14}$$

where $\widetilde{I}_k$ is the multiple access interference plus noise normalized by the channel gain. Applying (14) into (7) and taking it's first derivative ($\frac{\partial \xi_k}{\partial \gamma_k} = 0$), we can determine the point(s) γ_k^* that maximizes the kth user's EE. So, after some simplifications, the solution of $\frac{\partial \xi_k}{\partial \gamma_k} = 0$ for a fixed value of $\widetilde{I}_k$ is given by

$$\begin{aligned} M e^{-\gamma_k} \log_2(1+\theta_k\gamma_k) + \frac{\theta_k(1-e^{-\gamma_k})}{(1+\theta_k\gamma_k)\ln 2} = \\ \widetilde{I}_k(1-e^{-\gamma_k}) \cdot (\gamma_k \widetilde{I}_k + p_c)^{-1} \cdot \log_2(1+\theta_k\gamma_k). \end{aligned} \tag{15}$$

In order to guarantee that (15) has only one maximizer, we introduce the concept of strict quasiconcavity, defined as [13]:

Definition 1 (Strict quasiconcavity): A function z, that maps a convex set of n-dimensional vectors $\mathcal{D}$ into a real number is strict quasiconcave if for any $\mathbf{x}_1, \mathbf{x}_2 \in \mathcal{D}, \mathbf{x}_1 \neq \mathbf{x}_2$,

$$z(\lambda\mathbf{x}_1 + (1-\lambda)\mathbf{x}_2) > \min\{z(\mathbf{x}_1), z(\mathbf{x}_2)\}, \quad \lambda \in [0,1]. \tag{16}$$

With this definition, the strict quasiconcavity of u_k is summarized by Lemma 1:

Lemma 1 (Strict quasiconcavity of u_k): The utility function $u_k(p_k, \mathbf{p}_{-k})$ is strict quasiconcave in p_k

This result is very important in the proof of existence and uniqueness of the system equilibrium. However, due to space limitation all proofs are not developed herein.

IV. Increasing Interference Effect and Nash Equilibrium on EE-SE Trade-off

In this section we present the trade-off between non-cooperative energy-efficient and spectral-efficient power control schemes. This trade-off is determined by the MAI level, which is responsible by the *gap* among the maximal EE and the optimum SE (only attainable with infinity power allocation). In realistic interference-aware systems the increasing number of active users brings to an increment on system capacity; therefore, the SE of the system grows accordingly. We define the *gap* between the max-EE and the opt-SE as

$$\Lambda = \zeta(\gamma^*_{k,\text{SE}}) - \zeta(\gamma^*_{k,\text{EE}}), \qquad [\text{bit}/(\text{s}\cdot\text{Hz})] \qquad (17)$$

and then characterized its reduction when the interference level increases. To quantify this effect, we have defined the coupling network parameter

$$\beta_k = \langle|h_k|^2\rangle \,/\, \langle|h_j|^2\rangle, \quad k: \text{interest}; \; j \neq k: \text{interfering users},$$

where $\langle\cdot\rangle$ is the operator temporal average. We consider a ring cell geometry, where the kth interest user is located at the interior radius (d) and the interfering ($K-1$) users are located at the exterior radius (d_{interf}), varying the number of interfering users and exterior radius size (to affect the β_k factor). Hence, in Fig. 1, the max-EE and the opt-SE are presented and parameterized in terms of the system loading and $d_{\text{interf}}^{-i}, i \geq 2$. It is clear the *gap* reduction between the max-EE and the asymptotic-SE when the interference level increases. Even increasing the maximum power (increasing the maximum SE achievable), we observe the same behavior, besides the EE reduction given the MAI level increasing (approximately two magnitude orders). Table I shows the system parameters used in this hypothetic simulation scenario.

Given the fact that in real communication DS/CDMA systems the interest is in high system loading which implies in higher MAI, we observe that the optimal SINR for the EE-SE trade-off is the SINR that maximizes EE ($\gamma^*_{k,\text{EE}}$). As we can see from Fig. 1, when the number of users is increased, the gap between the SE at the max-EE point and opt-SE is reduced and even become null. We can see from Fig. 1.d, in some cases the MAI power level is so high that makes impossible to some users achieve the max-EE point without using a higher power than the maximum power allowed. In that cases, these users allocate maximum power to achieve the bigger EE they can, since the utility function is strictly increasing in the interval $[0, p^*_k]$. This approach increases the MAI power level, which could reduce system's EE; however, if some of these non-optimal users are put in outage, we can increase the energy efficiency as a consequence of the MAI level reduction.

When circuit power consumption is much smaller than the transmitted power ($p_c << p_k$), an interesting result emerges: the optimum SINR obtained from the EE optimization problem in (15) is the same for any MAI level, while the asymptotic SINR necessary to the SE maximization still related to the interference power level, $\bar{I}_k$. Hence, under this hypothesis, the best SINR for max-EE criterium depends only on the system parameters, such as max-BER (QoS), modulation level, coding and packet coding size. It is worth noting that when the MAI

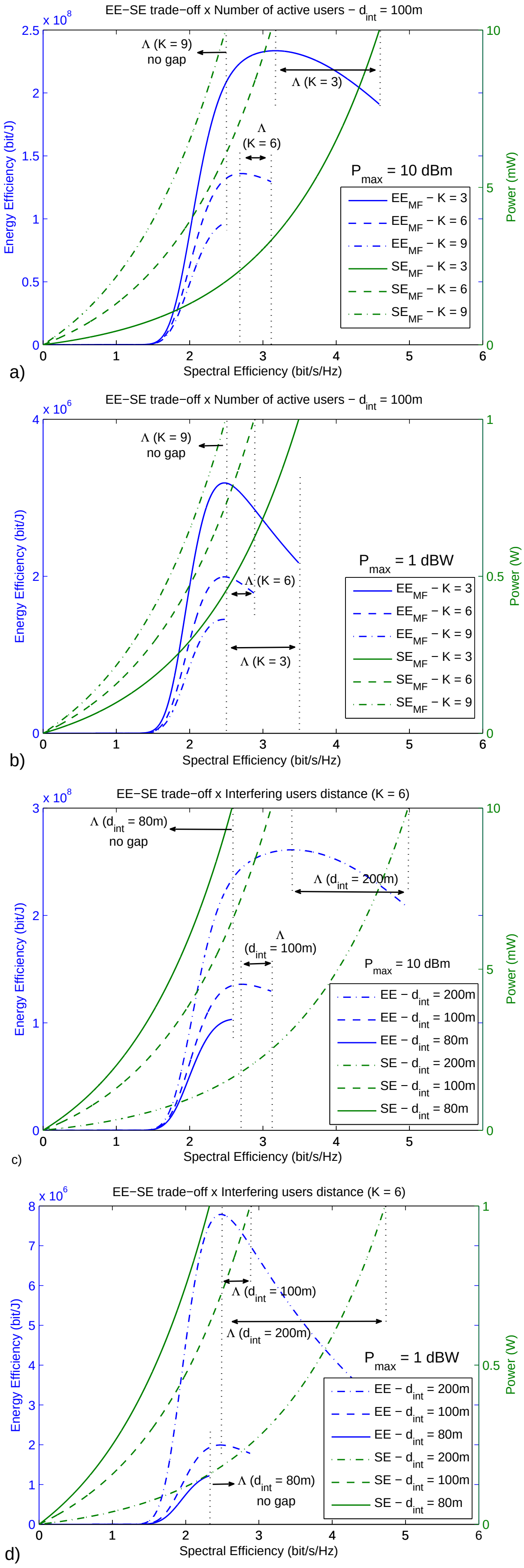

Fig. 1. EE-SE trade-offs considering different interfering scenarios and maximum power. a) and b) Fixed $d_{\text{interf}} = 100$m, $\beta_k = 0.50$, $K \in [3, 6, 9]$; c) and d) Fixed $K = 6$, $d_{\text{interf}} \in [200, 100, 80]$m, $\beta_k \in [0.25, 0.50, 0.63]$.

increases, the transmitted power becomes higher and indeed the condition $p_c << p_k$ holds, and the optimum SINR value tends to converge.

TABLE I
EE-SE TRADE-OFF ANALYSIS

Parameters	**Adopted Values**
DS/CDMA	
Noise Power	$P_n = -90$ [dBm]
Processing Gain	$N = 15$
Max. power per user	$P_{\max} = 10$ [dBm], 1 [dBW]
Interest user distance	$d = 50$ [m]
Interfering users distance	$d_{\text{interf}} = [80, 100, 200]$ [m]
Packet size	$M = 80$ [bits]
Data bits	$L = 50$ [bits]
Maximum BER	$\text{BER}_k = 10^{-3}$
Circuit Power	$p_c = 7$ [dBm]
Bandwidth	$\mathtt{w} = 10^6$ [Hz]
Channel Gain	
Path loss	$\propto d^{-2}$
Fading coefficients	Rayleigh distribution, mean over 5000 samples
Verhulst PCA	
Convergence factor	$\alpha = 0.5$
Number of iterations	$N_{\text{it}} = 500$

V. PROPOSED EE-SE ALGORITHM

The proposed algorithm to implement the optimal EE-SE trade-off solution is described in Algorithm 2 and is based on Verhulst power control algorithm [14]. On the other hand, in order to avoid users' outage, in which users are not able to achieve the optimal SINR in terms of EE (due to $P_{\max}$ constraint), but are able to maintain the minimum data rate, $R_{k,\min}$, an alternative algorithm is proposed in Algorithm 3. Both algorithms uses the same structure, that corresponds to the basic algorithm defined in the literature [11], [1], [5] and presented in Algorithm 1.

Algorithm 1 Basic EE Power Allocation Algorithm [1], [11]

Initialization: $i \leftarrow 1$, N_{it}, $p_k[0] = \sigma_k^2, \forall k$
  for $i = 1 : N_{\text{it}}$
    for $k = 1 : K$:
      Evaluate $\widetilde{I}_k$ (via SINR_k measurement);
      Find γ_k^*, by solving (15);
      Find p_k^* iteratively using Verhulst Algorithm [14].
    end
  end
Output: p_k^* $\forall k$

Algorithm 2 EE-SE with Verhulst Optimum Power Allocation

Initialization: $K_{\text{out}} = \{\}$
  Execute Algorithm 1, obtaining $\mathbf{p}^*$;
  Compute achieved SINR and optimum SINR (γ_k^*) for each user;
  Compute K_{out}, where $k \in K_{out}$ if $\gamma_k < \gamma_k^*$;
  if $\{K_{out}\} \neq \emptyset$
    choose user with worst channel gain in K_{out} (j-th user);
    set $\gamma_j^* = 0$;
    Restart.
  end
Output: p_k^* $\forall k$ (EE-SE trade-off solution with max-EE)

Existence and uniqueness of the achieved equilibriums. Given that the equilibrium is defined by $\mathbf{p}^* = (p_1^*, \ldots, p_k^*, \ldots, p_K^*)$, the Nash equilibrium can be defined as:

Definition 2 (Nash Equilibrium): An equilibrium is said to be a Nash equilibrium if and only if any user cannot improve their response by changing unilaterally the optimum value achieved [12]. In the context of the energy-efficiency problem:

$$u_k(p_k^*, \mathbf{p}_{-k}) \geq u_k(p_k, \mathbf{p}_{-k}), \qquad \forall p_k \neq p_k^*. \tag{18}$$

Algorithm 3 EE-SE–$R_{k,\min}$ and Verhulst Power Allocation

Initialization: $K_{\text{out}} = \{\}$
  Execute Algorithm 1, obtaining $\mathbf{p}^*$;
  Compute achieved SINR (γ_k) and rate (R_k) for each user;
  Compute the optimum SINR (γ_k^*) for each user;
  Compute K_{out}, where $k \in K_{out}$ if $\gamma_k < \gamma_k^*$ and $R_k < R_{k,min}$;
  if $\{K_{out}\} \neq \emptyset$
    Choose user with worst channel gain in K_{out} (j-th user);
    Set $\gamma_j^* = 0$;
    Restart.
  end
Output: p_k^* $\forall k$ (EE-SE trade-off solution with $R_{k,\min}$)

The conditions for the existence of the Nash equilibrium in the EE–SE trade-off non-cooperative game, implicit in Algorithms 2 and 3, are summarized by Theorems 1 and 2:

Theorem 1: The system achieves at least one equilibrium $\mathbf{p}^*$ for Algorithm 2, and $p_1^*, \ldots, p_k^*, \ldots, p_K^* \in \mathbf{p}^*$ are defined by the following conditions:

1) If $p_k \leq P_{\max}$ and $\frac{\partial(u_k(p_k, \mathbf{p}_{-k}^*))}{\partial p_k} = 0$, then $p_k^* = p_k$
2) Else, $p_k^* = 0$

Theorem 2: The system achieves at least one equilibrium $\mathbf{p}^*$ for Algorithm 2, with $p_k^* \in \mathbf{p}^*$ obeying the conditions:

1) If $p_k \leq P_{\max}$ and $\frac{\partial(u_k(p_k, \mathbf{p}_{-k}^*))}{\partial p_k} = 0$, then $p_k^* = p_k$
2) If $p_k = P_{\max}$, $\frac{\partial(u_k(p_k, \mathbf{p}_{-k}^*))}{\partial p_k} \neq 0$ and $R_k \geq R_{k,min}$, then $p_k^* = P_{\max}$
3) Else, $p_k^* = 0$

The first condition in the Theorem 1 occurs when the user has sufficient power to achieve the optimum SINR point; the second one occurs when the user cannot achieve the optimum point (the outage scenario). The first condition in the Theorem 2 is the same condition of the first condition of Theorem 1; however, when the user cannot achieve the maximum efficiency but is able to achieve a minimum rate criterion, in the second condition, kth user set his transmit power to the maximum available. Finally, when the two criteria fails, the user must set his Tx power to zero.

The uniqueness of the Nash equilibrium for both non-cooperative games is summarized in Lemma 2.

Lemma 2: When the equilibrium $\mathbf{p}^*$ is achieved without removing any user, this Nash equilibrium is unique. When is needed to remove any user, multiple equilibriums could exist, but for our adopted criterion, the equilibrium is also unique.

VI. NUMERICAL RESULTS

In this section, some changes are introduced in the system parameters in Table I. Analysis hereafter assumes a ring geometry, with internal radius $r_{\text{int}} = 50$m and external radius $r_{\text{ext}} = 200$m, with K mobile users uniformly distributed on $\sim \mathcal{U}[r_{\text{int}}, r_{\text{ext}}]$, and the base station in the center of the ring. The processing gain was assumed $N = 63$; maximal transmitted power per user was $P_{\max} = 10$ dBm, while circuit power was fixed $p_c = 7$ dBm per user; number of mobile terminals $K \in \{2;\, 15\}$. For all users, same QoS have been adopted, i.e., maximal $\mathrm{BER}_k = 10^{-3}$ and $R_{\min} = 500$ [kbps]. Fading is modeled as Rayleigh distribution (module), simulated by a complex Gaussian random process, with zero mean and variance given by d_j^2. In order to analyze the average network behavior, the average results have been taken over 2000 realizations with random positions, channel and spreading sequences. We assume that the mobile transmitter has perfect channel state information (CSI) available, but the measurement of other mobile users' CSI can only be made through the quantized bits transmitted by the base station.

Figs. 2 and 3 present four metrics to analyze the two proposed algorithms: sum of rates of all users, $\sum R$, sum of power consumption, including the circuit power, $\sum P$, overall energy efficiency and the outage probability. The first three metrics also bring the comparison with the classical approach [1]. From Fig. 2 one can conclude that the Algorithm 3 obtains the best result for sum rate maximization, mainly when the system loading increases, since only a user is dropped when the rate achieved by this user is lower than the minimum rate $R_{\min}$. As a consequence, the power consumption (right-side axis) is increased, because any user that doesn't achieve the optimum SINR tries to achieve it using maximum power allowed, increasing remarkably the interference level.

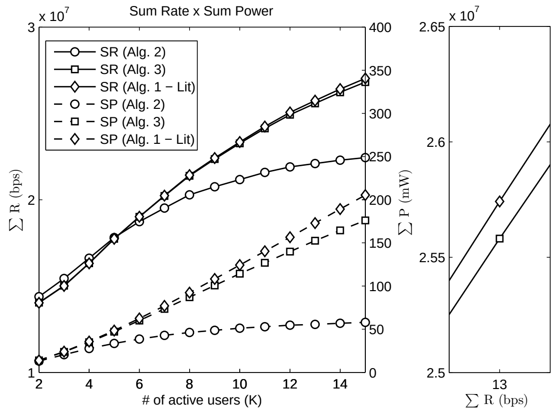

Fig. 2. Sum rate versus Sum Power for the proposed algorithms.

Fig. 3.a indicates that the rate improvement obtained by the Algorithm 3 and literature's approach reduces the system's energy efficiency, once that there are users transmitting with non-optimal powers. The best-response in terms of energy efficiency is achieved by Algorithm 2, but incurs in more users in outage (Fig. 3.b). Although there is a marginal power-rate trade-off difference among the two proposed algorithms, both are more energy-efficient than the common literature approach.

VII. Conclusions

In this work we have analyzed the distributed energy efficiency (EE) cost function taking in perspective the two conflicting metrics, throughput maximization and the power consumption minimization. We have found that SINR on the max-EE equilibrium depends on the MAI power level when considering circuit power, mainly when MAI level is low. As the interference increases, the EE-SE trade-off *gap* is reduced; the optimum SINR is that maximizes EE. Finally, we have shown that removing non-optimal EE users allows better energy-efficiency, at the cost of higher outage probability.

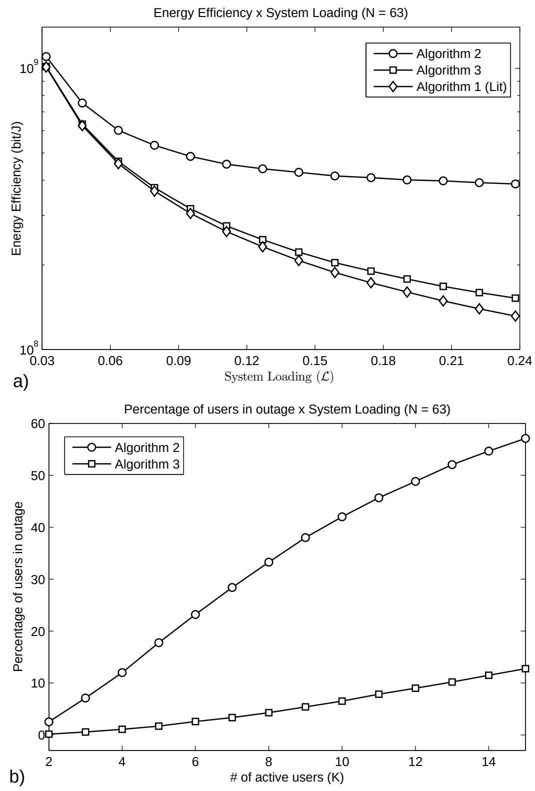

Fig. 3. a) Energy Efficiency and b) outage probability.

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