An Energy Efficient Distributed Power Control Algorithm and its Convergence

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***Abstract*— Game theory is a set of mathematical tools suitable to the modeling and optimization of problems involving agents with conflicting interests competing for limited resources. It applies well for a number of problems in wireless communication, including power control. In this work, some basic concepts on game theory are presented and the power control problem in wireless data systems is approached as a noncooperative game. Finally, a new distributed power control algorithm based on the game theory is developed and compared to the classical distributed power control.**

***Keywords*— Power control, noncooperative game theory, energy efficiency.**

I. INTRODUCTION

GAME theory is a tool for analyzing the interaction of decision makers with conflicting objectives and limited resources. Economists have long used it as a tool for examining the actions of economic agents such as firms in the market. In recent years, it has been applied to problems in wireless communication, mainly to the power control problem [1], [2], [3].

The basic unit of game theory is the game, which has three basic elements: a set of players, a set of possible actions for each player, and a set of cost functions mapping action profiles into real numbers. The set of possible actions for each player is called strategy space and the concept of cost function refers to the pay back of the player as a result of its actions. Utility functions take the place of cost functions when one refers to satisfaction measures of players instead of their pay back.

In power-controlled wireless communication systems, each transmitter usually tries to provide a determined signal-to-interference-plus-noise ratio (SINR) to its correspondent receiver. Determining the target SINR is usually a task of an outer loop power control, which is slower than the inner loop one. A fast outer loop power control might improve the energy efficiency of the system, hence the power could be appropriately allocated.

Most previous works relative to the power control problem formulated as a game consider a unique SINR level to be targeted by each transmitter/receiver pair. Furthermore, with respect to the utility functions, they fall in two classes: those dependent only on intrinsic properties of the channel (SINR, transmit power) [3] and those dependent also on lower layer decisions such as modulation and coding [1], [2].

In this work we also study the application of game theory to the decentralized power control problem in a wireless data system. We formulate the problem as a noncooperative game with the following basic elements: the transmitters constitute the set of players; the action of each player is to adjust its transmit power; and the cost function is the squared error between the target and the actual SINR values. In this game, each player adjusts its transmit power aiming to minimize its cost function. Therefore, the cost function is not dependent on system parameters.

After a brief introduction to noncooperative games, we show, in Section II, that the solution to the power control game whose cost function is the squared error between a fixed target SINR and the actual SINR corresponds to the well-known Distributed Power Control algorithm (DPC) [4]. In Section III we propose a new decentralized power control algorithm, which simultaneously performs the choice of the best target SINR value and minimizes the squared error between the target and the actual SINR. Convergence properties of the proposed algorithm are demonstrated. Simulation results are discussed in Section IV and the conclusions of this work are given in Section V.

II. DISTRIBUTED POWER CONTROL ALGORITHM

Noncooperative games are characterized by players that act based only on their own strategy space, without information about the strategy of the other players. However, in games with two or more stages, where players act more than once, their actions are also based on the current state of the game, which is provided by the previous actions of all players. Then, since time plays a role, these games are considered dynamic games.

A game where the gains of a player represent losses to the other players is called a zero-sum game. In zero-sum games, as the name suggests, the sum of the cost functions of all players is identically zero. Even if this sum is equal to a nonzero constant, the game can be treated within the framework of zero-sum games without any loss of generality. However, in other cases, the gains of a player do not correspond to losses to the other players, i.e., the sum of the cost functions of all players is not a constant. Such games are called nonzero-sum games. A detailed discussion about noncooperative games can be found in [5].

We denote $G_K = [N, \{P_j\}, \{c_j\}]$ the dynamic noncooperative nonzero-sum power control game with K stages, where each stage k corresponds to an actuation of the power control algorithm, which is discrete and has k as its discrete time index. The transmitters constitute the set of players, with $N = \{1, 2, ..., n\}$ as their index set; the continuous set of power values $P_j = [p_{min}, p_{max}]$ is the strategy set of player j; and c_j is the cost function of player

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j, $j \in N$. We emphasize that the j^{th} player has control only over its own power p_j, which is selected such that $p_j \in P_j$. The power vector $\mathbf{p}(k) = [p_1(k), ..., p_n(k)] \in P$ is the outcome of the stage k of the game in terms of the selected power levels of all the players, where $P = P_1 \times \cdots \times P_n$. The vector consisting of the elements of $\mathbf{p}(k)$ other than the j^{th} element is denoted by $\mathbf{p}_{-j}(k)$.

This game has a feedback information structure, since at each actuation of the power control, the players know exactly the current state of the game and this information is fed back into their strategies. Thus, we can define the game as follows:

$$\min_{p_j(k+1)\in P_j} c_j\left(p_j(k+1), \mathbf{p}_{-j}(k+1)\right) = |\gamma^t - \gamma_j(k+1)|^2 \tag{1}$$

where γ^t is a fixed target SINR and $\gamma_j(k+1)$ is the SINR of player j at the time instant $k+1$, expressed as:

$$\gamma_j(k+1) = \frac{p_j(k+1)g_j(k+1)}{I_j(k+1)} \tag{2}$$

where $g_j(k+1)$ is the channel gain and $I_j(k+1)$ is the interference-plus-noise perceived by the receiver j, that is:

$$I_j(k+1) = \sum_{i=1}^{n} (p_i(k+1)g_i(k+1)) + \sigma^2,\ i \neq j \tag{3}$$

where σ^2 is the average AWGN power.

Then, at the time instant k, each player has as objective to determine its own power level at the next time instant, in such a manner that the squared error between the target and the actual SINRs is minimized. Note that the channel gain and the interference-plus-noise power have positive and continuous values. Furthermore, the transmit power that optimizes individual cost function depends on the transmit powers of all other transmitters. Therefore, it is necessary to determine a set of powers where each player is satisfied with the cost that it has to pay, given the power selections of other players. Such an operating point is called an equilibrium.

A suitable solution to this problem is the Nash Equilibrium Point. The Nash Equilibrium concept offers a predictable, stable outcome of a game where multiple agents with conflicting interests compete through self-optimization and reach a point where no player wishes to deviate from. Formally, a power vector $\mathbf{p}^*(k) = [p_1^*(k), ..., p_n^*(k)]$ is a Nash Equilibrium Point of G_K if, for each $j \in N$, it holds:

$$c_j\left(p_j^*(k+1), \mathbf{p}_{-j}^*(k+1)\right) \leq c_j\left(p_j(k+1), \mathbf{p}_{-j}^*(k+1)\right) \tag{4}$$

Existence and Uniqueness of $\mathbf{G_K}$ Equilibrium

Necessary and sufficient conditions for the existence of a Nash Equilibrium Solution are given by Theorem 1.

Theorem 1: For each $j \in N$ let P_j be a closed, bounded and convex subset of a finite-dimensional Euclidian space, and the cost functional $c_j : P_1 \times \cdots \times P_n \longrightarrow \mathbb{R}$ be jointly continuous in all its arguments and strictly convex in p_j for every $p_i \in P_i$, $i \neq j$. Then, the associated nonzero-sum game admits a Nash Equilibrium.

A proof of the theorem can be found in [5]. The strategy set $P_j = [p_{min}, p_{max}]$ is a closed, bounded and convex subset of the Euclidian space $\mathbb{R}$, for all j. Thus, in order to prove the existence of a Nash Equilibrium Solution to the presented nonzero-sum game, it is necessary to verify the continuity of the cost function c_j with respect to all its arguments and if it is strictly convex in p_j for all $p_i \in P_i$, $i \in N$, $i \neq j$. Then, from (1) and (2), we have:

$$c_j = {\gamma^t}^2 - 2\gamma^t\left[\frac{g_j(k+1)}{I_j(k+1)}\right]p_j(k+1) + \left[\frac{g_j(k+1)}{I_j(k+1)}\right]^2 p_j^2(k+1) \tag{5}$$

We conclude from (3) and (5) that the cost function c_j is continuous with respect to all its arguments. The cost function strict convexity is considered in the following.

Nash Equilibrium Point of $\mathbf{G_K}$

The necessary optimality condition for a differentiable function is that its first-order derivative be equal to zero. The partial derivative of the cost function c_j with respect to p_j is given below:

$$\frac{\partial c_j}{\partial p_j(k+1)} = -2\gamma^t\left[\frac{g_j(k+1)}{I_j(k+1)}\right] + 2\left[\frac{g_j(k+1)}{I_j(k+1)}\right]^2 p_j(k+1) \tag{6}$$

$$\frac{\partial c_j}{\partial p_j(k+1)} = 0 \Longrightarrow p_j(k+1) = \gamma^t\frac{I_j(k+1)}{g_j(k+1)} \tag{7}$$

The sufficient optimality condition for a two-time differentiable function is that its second-order derivative be different from zero. The second-order partial derivative of c_j with respect to p_j is shown below to be strictly positive. Then, the strict convexity of c_j is formally guaranteed:

$$\frac{\partial^2 c_j}{\partial p_j^2(k+1)} = 2\left[\frac{g_j(k+1)}{I_j(k+1)}\right]^2 > 0 \tag{8}$$

Therefore, the presented game admits a unique Nash Equilibrium Solution, given by (7). Although, (8) guarantees that this solution minimizes the cost function c_j for all $j \in N$.

However, in practice, values of channel gain and interference-plus-noise power at time instant $k+1$ are not available at the time instant k. If we consider a high power control actuation frequency, we may have the following approximation:

$$\frac{g_j(k+1)}{I_j(k+1)} \approx \frac{g_j(k)}{I_j(k)} \tag{9}$$

Then, using (7) and (9), in logarithmic scale, we obtain:

$$p_j(k+1)_{dBm} = p_j(k)_{dBm} + \gamma_{dB}^t - \gamma_j(k)_{dB} \tag{10}$$

Therefore, the decentralized power control problem formulated as a noncooperative game, where each player has as objective to minimize the squared error between the target and the actual SINRs, presents as Nash Equilibrium Solution the well-known Distributed Power Control algorithm (10).

III. Proposed Power Control Algorithm

The classical DPC is originally a target SINR tracking power control algorithm which deals with all transmitters equally, i.e., it does not consider individual resources situation on determining the SINR to be achieved by each transmitter/receiver pair. It is an inner loop power control algorithm, where each transmitter tries to provide a unique SINR to its correspondent receiver. This approach may result in an inefficient power allocation, since there is not flexibility that would allow links in bad situation to aim at a lower SINR and links in favorable situation to reach a higher SINR, except if there is an outer loop.

We propose a new distributed power control algorithm which considers each link individually, providing to each one a suitable SINR to be targeted at each power control actuation. It is important to emphasize that the proposed algorithm requires exactly the same feedback information that the classical DPC does, thus not demanding any extra resource.

The decentralized power control problem is once more formulated as a dynamic noncooperative nonzero-sum power control game with K stages, now denoted $H_K = [N, \{P_j\}, \{c_j\}]$. However, it differs from the presented G_K on the target SINR, as follows:

$$\min_{p_j(k+1)\in P_j} c_j\left(p_j(k+1), \mathbf{p}_{-j}(k+1)\right) = |\gamma_j^t(k+1) - \gamma_j(k+1)|^2 \quad (11)$$

where $\gamma_j^t(k+1)$ is the target SINR and $\gamma_j(k+1)$, defined in (2), is the actual SINR of player j at the time instant $k+1$.

It is necessary a rule for the choice of the SINR to be targeted by each link. A good policy must consider the power level required to achieve such a SINR, as in [6]. In order to keep the power control system stable, we have considered the following simple and logical rule: the target SINR is a continuous linear function of the transmit power, both in logarithmic scale. Thus:

$$\gamma_j^t(k+1)_{dB} = A - Bp_j(k+1)_{dBm} \quad (12)$$

where A and B are positive parameters that can be defined using the extreme points of the straight line: $\left(p_{min}^{dBm}, {\gamma_{max}^t}^{dB}\right)$ and $\left(p_{max}^{dBm}, {\gamma_{min}^t}^{dB}\right)$. Fig. 1 illustrates the rule for the choice of the target SINR of each player j.

Thus, parameters A and B are expressed as:

$$A = {\gamma_{min}^t}^{dB} + \left(\frac{{\gamma_{max}^t}^{dB} - {\gamma_{min}^t}^{dB}}{1 - \frac{p_{min}^{dBm}}{p_{max}^{dBm}}}\right) \quad (13)$$

$$B = \frac{{\gamma_{max}^t}^{dB} - {\gamma_{min}^t}^{dB}}{p_{max}^{dBm} - p_{min}^{dBm}} \quad (14)$$

Then, at time instant k, each player has as objective to determine, simultaneously, its target SINR and its own power level for the next time instant, in such a manner that the squared error between the target and actual SINRs is minimized. This approach may provide a safe SINR evolution to all players, since the extreme possible values of the SINR to be targeted can be chosen higher than a threshold SINR, which corresponds to the minimum operating point required. We have chosen a linear function of transmit power as a rule for the target SINR for simplicity. Other kind of functions may be used and this is an interesting point for future works.

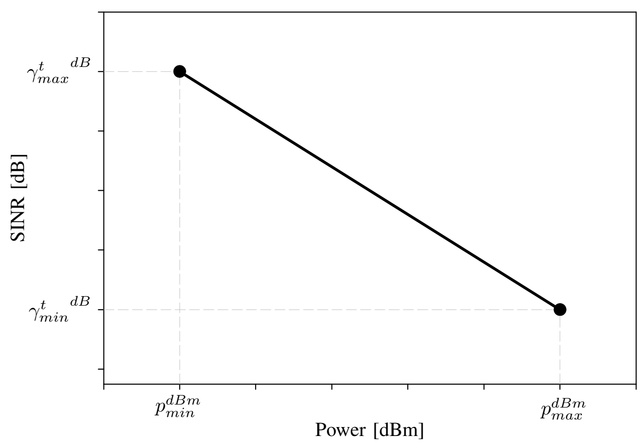

Fig. 1. Target SINR as a function of the transmit power.

The same assumptions considered in G_K relative to channel gain and interference-plus-noise power hold in H_K. Here, the Nash Equilibrium Point is also a suitable solution.

Existence and Uniqueness of $\mathrm{H_K}$ *Equilibrium*

Invoking Theorem 1, we have the necessary and sufficient conditions for the existence of a Nash Equilibrium Solution. As in G_K, the strategy set $P_j = [p_{min}, p_{max}]$ is a closed, bounded and convex subset of the Euclidian space $\mathbb{R}$, for all j. Thus, the existence of a unique Nash Equilibrium Point depends on the continuity of the cost function c_j with respect to all its arguments and on its strict convexity in p_j for all $p_i \in P_i$, $i \in N$, $i \neq j$.

In order to have the cost function expression of player j, $j \in N$, explicitly as a function of all power choices, we obtain from (12) the relation between the target SINR and the power level of player j in linear scale, and use it in (11):

$$\gamma_j^t(k+1) = \left(10^{A/10}\right) p_j^{-B}(k+1) \quad (15)$$

The cost function of player j becomes:

$$c_j = Xp_j^{-2B}(k+1) - Yp_j^{-B+1}(k+1) + Zp_j^2(k+1) \quad (16)$$

with:

$$X = 10^{2A/10}$$
$$Y = 2\left(10^{A/10}\right)\left[\frac{g_j(k+1)}{I_j(k+1)}\right] \quad (17)$$
$$Z = \left[\frac{g_j(k+1)}{I_j(k+1)}\right]^2$$

Note that X is constant and Y and Z are continuous. Then, analyzing (16) we guarantee that the cost function c_j is continuous with respect to all its arguments if, and only if $p_j(k+1) \neq 0$, $j \in N$. Then, by defining $p_{min} > 0$ the continuity of the cost function is assured. Moreover, negative power values are unfeasible. Conditions for cost function strict convexity are met in the following.

Nash Equilibrium Point of $\mathbf{H_K}$

The necessary optimality condition for a differentiable function is that its first-order derivative be equal to zero. The partial derivative of the cost function c_j with respect to p_j is given below:

$$\frac{\partial c_j}{\partial p_j(k+1)} = -2BXp_j^{-2B-1}(k+1) - Y(-B+1)\,p_j^{-B}(k+1) + 2Zp_j(k+1) = 0 \tag{18}$$

$$p_j(k+1)\{[-2BX]\,p_j^{-2(B+1)}(k+1) + [-Y(-B+1)]\,p_j^{-(B+1)}(k+1) + 2Z\} = 0 \tag{19}$$

where $p_j(k+1) = 0$ is not a feasible outcome, since continuity condition implies $p_{min} > 0$. Thus:

$$[-2BX]\,p_j^{-2(B+1)}(k+1) + [-Y(-B+1)]\,p_j^{-(B+1)}(k+1) + 2Z = 0 \tag{20}$$

We rewrite (20) as a quadratic function of the variable F, through the following change of variable:

$$p_j^{-(B+1)}(k+1) = F \tag{21}$$

$$[-2BX]\,F^2 + [-Y(-B+1)]\,F + 2Z = 0 \tag{22}$$

Solving (22) in F and returning to variable $p_j(k+1)$ by using (21), we obtain the Nash Equilibrium Point, since it holds $p_j(k+1) > 0$ for all $j \in N$. In logarithmic scale, it is expressed as follows:

$$p_j(k+1)_{dBm} = \frac{1}{B+1}\left[A + I_j(k+1)_{dBm} - g_j(k+1)_{dB}\right] \tag{23}$$

The sufficient optimality condition for a two-time differentiable function is that its second-order derivative be different from zero. The second-order partial derivative of c_j with respect to p_j is given below:

$$\frac{\partial^2 c_j}{\partial p_j^2(k+1)} = \left[4B^2X + 2BX\right] p_j^{-2(B+1)}(k+1) + [YB(1-B)]\,p_j^{-(B+1)}(k+1) + 2Z \tag{24}$$

where $X, Y, Z, B > 0$.

Using (21) once more, (24) can be rewritten as a quadratic function of the variable F:

$$\frac{\partial^2 c_j}{\partial p_j^2(k+1)} = \left[4B^2X + 2BX\right] F^2 + [YB(1-B)]\,F + 2Z \tag{25}$$

whose minimum value ϵ is given by:

$$\epsilon = -\frac{[YB(1-B)]^2 - 4\left[4B^2X + 2BX\right]2Z}{4\left[4B^2X + 2BX\right]} \tag{26}$$

Making $\epsilon > 0$ we guarantee that the second-order derivative of the cost function c_j is strictly positive, and obtain the following inequality:

$$B^3 < 2B^2 + 7B + 4 \Longrightarrow B < 4 \tag{27}$$

Then, the constraints $0 < B < 4$ assure the strict convexity of the cost function c_j defined in the subset $[p_{min}, p_{max}] \in \mathbb{R}$, with $p_{min} > 0$. Furthermore, they correspond to the following practical constraints:

$$0 < {\gamma_{max}^{t}}^{dB} - {\gamma_{min}^{t}}^{dB} < 4\left[p_{max}^{dBm} - p_{min}^{dBm}\right] \tag{28}$$

Therefore, the proposed game admits a unique Nash Equilibrium Solution given by (23). Minimization of the cost function c_j for all $j \in N$ is guaranteed if (28) holds.

However, as discussed in Section II, we assume a fast power control actuation (9). It means that (23) can be rewritten as:

$$p_j(k+1)_{dBm} = \frac{1}{B+1}\left[A + I_j(k)_{dBm} - g_j(k)_{dB}\right] \tag{29}$$

If $p_j(k)_{dBm}$ is added and subtracted on the right side of the last equation, we do not alter the equality and can finally present the proposed algorithm:

$$p_j(k+1)_{dBm} = \frac{1}{B+1}\left[A + p_j(k)_{dBm} - \gamma_j(k)_{dB}\right] \tag{30}$$

with A and B defined in (13) and (14), respectively.

It can be observed that if ${\gamma_{max}^{t}}^{dB}$ and ${\gamma_{min}^{t}}^{dB}$ tend to a unique value ${\gamma^t}_{dB}$, parameters A and B tend, respectively, to ${\gamma^t}_{dB}$ and 0. It means that if the flexibility on the SINR to be targeted decreases, the proposed algorithm tends to the classical DPC.

IV. RESULTS

In order to evaluate the proposed power control algorithm, we considered a set of co-channel base stations transmitting at the downlink.

We implemented a simulator consisting of trisectorized base stations arranged on a cellular grid according to a 1/3 reuse pattern. Base stations are located at the corner of the sectors. The sector antenna radiation pattern employed is ideal, with main-lobe gain of 0dBi and gain outside the sector of -200dBi. Mobile stations are uniformly distributed over the cell area.

A simplified path loss model is considered, $PL(d) = PL(d_0) + 10n log_{10}(d/d_0)$, with the loss exponent set to 4 and with a loss of 120 dB at the cell edge (1 kilometer of distance to the base station). Shadowing is modeled as a log-normal random variable with zero mean and 6 dB of standard deviation. Fast fading is implemented following the Jakes' model [7], with a Doppler shift of 18.5 Hz, due to the operation frequency of 2GHz and the mobile speed of 10 km/h.

In each snapshot, the power control actuation frequency is 1kHz and up to 600 iterations of the power control algorithm are performed. Other important simulation parameters are the thermal noise power, the maximum transmit power and the minimum transmit power, respectively assumed -110 dBm, 35 dBm and -70 dBm.

Fig. 2 shows a sample of the SINR evolution achieved by a given user in a typical snapshot for both algorithms. For DPC we set two target SINR values, 10 dB and 25 dB, while for the proposed algorithm we have two continuous sets of possible values for the target SINR, [8, 30] dB and [8, 60] dB. In this case, three mobile stations are placed in the cell grid and the same system configuration and fading realizations are used for all approaches.

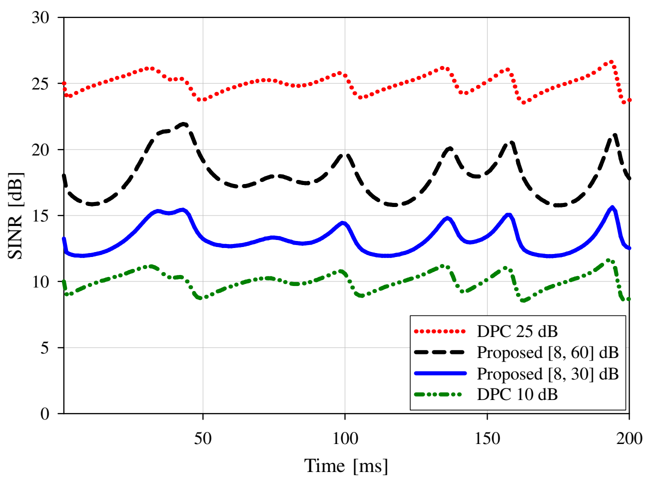

Fig. 2. Sample of SINR evolution for the evaluated power control algorithms.

It is clearly observable that the proposed algorithm achieves intermediate SINRs relative to those of DPC in both approaches. Achieving high SINRs requires high power levels, that means high energy consumption. However, the absolute power level, individually, is not a suitable performance parameter to power-controlled systems.

Energy efficiency has been one of the most important aspects in the power control research field. In order to evaluate the energy efficiency of the proposed algorithm compared to DPC, we adopt a simplified radio link quality to data rate model used in [8] for EGPRS systems. Such model maps the SINR into the data throughput as follows:

$$\bar{R} = 2\bar{\gamma} \tag{31}$$

where $\bar{R}$ is the average throughput and $\bar{\gamma}$ is the average SINR.

Table I shows the energy efficiency values for the user whose SINR evolution is shown in Fig. 2. The proposed algorithm presents higher efficiency than DPC for both approaches.

TABLE I
ENERGY EFFICIENCY OF THE APPROACHES SHOWN IN FIG. 2.

Algorithm	Energy Efficiency
DPC $\gamma^t = 25$ dB	2317 kbits/Joule
DPC $\gamma^t = 10$ dB	2317 kbits/Joule
Proposed $\gamma^t \in [8, 30]$ dB	2661 kbits/Joule
Proposed $\gamma^t \in [8, 60]$ dB	3048 kbits/Joule

In order to evaluate the system-level advantage of the proposed algorithm over the DPC, we simulated 10000 snapshots for all system loads. The target SINR for the DPC algorithm was set in such a manner that it provides approximately the same average throughput achieved by the proposed algorithm for each system load. The following two approaches were considered, as can be seen in Fig. 3.

Approach 1: $\gamma^t \in [8, 30]$ dB

Approach 2: $\gamma^t \in [8, 60]$ dB.

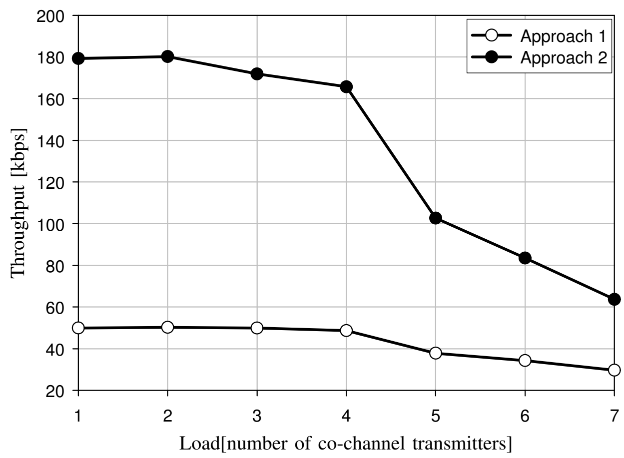

Fig. 3. Data throughput for all system loads.

The performance of the algorithms relative to energy efficiency is illustrated in Fig. 4. For both approaches, the proposed algorithm presents higher efficiency than DPC. As expected, lower flexibility on the SINR to be targeted implies in an approximation between the proposed and DPC algorithms. This can be clearly verified in the referred figure where the curves of both algorithms are nearer from each other in the Approach 1 than in the Approach 2.

It is important to observe the gain in the average data throughput provided by the proposed algorithm over the DPC. Fig. 5 shows that for high loads (4 or more transmitters), the DPC on Approach 1 and the proposed algorithm on Approach 2 operate with comparable average transmit power levels. However the proposed algorithm provides a considerably higher average throughput on Approach 2 than the DPC on Approach 1, as illustrated in Fig. 3.

Another interesting result we have obtained, which emphasizes the higher performance of the proposed algorithm relative to DPC refers to the ability of attaining an SINR equal or superior to the minimum radio link quality required. This ability is illustrated in Fig. 6.

In practical systems, there exists a threshold SINR, which corresponds to the minimum operating point required.

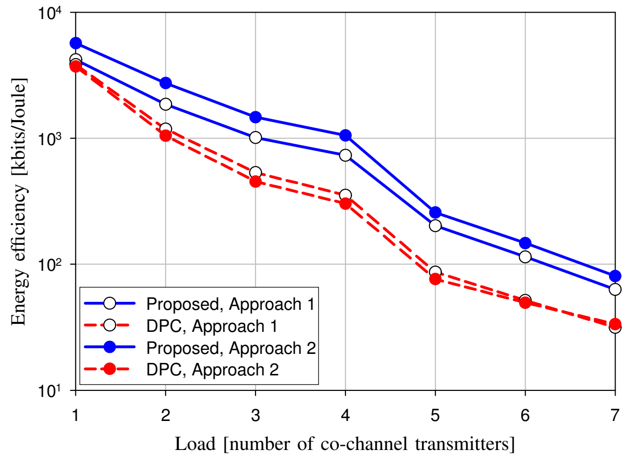

Fig. 4. Energy efficiency for both approaches.

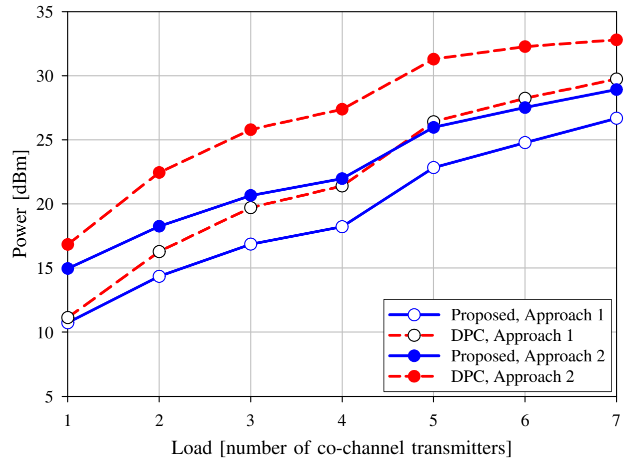

Fig. 5. Transmit power for both approaches.

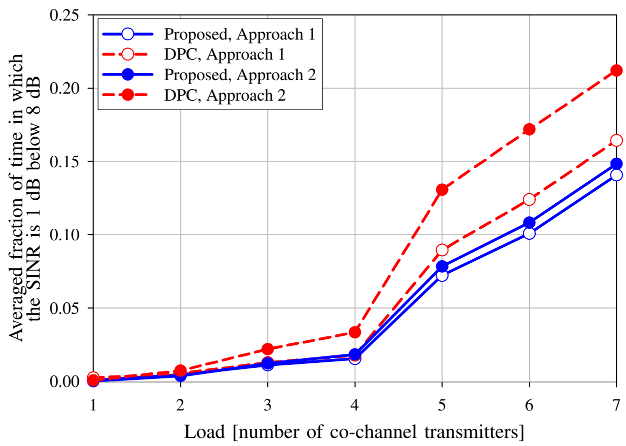

Fig. 6. Averaged fraction of time in which the SINR is 1 dB below the threshold SINR for both approaches.

Difficulties on keeping the SINR above the threshold value are common, specially for high system loads. Therefore, we assume a SINR margin below the threshold SINR at which the signal quality is still assumed acceptable. Then, we calculate the average fraction of time in which the SINR is 1 dB below the threshold, considered 8 dB. In other words, this 1 dB difference between the threshold and the minimum acceptable quality can be thought as a protection margin. In Fig. 6, the robustness of the proposed algorithm with respect to the guarantee of the minimum operational requirements for high system loads and increased average data throughputs can be observed.

Therefore, the proposed algorithm has been shown more efficient in terms of energy than the conventional DPC for all system loads and more robust against providing insufficient radio link quality, specially for high system loads and increased average data throughput requirements. Furthermore, it does not require, a priori, an outer loop algorithm to set up the target SINR values.

V. CONCLUSIONS

The formulation of the fixed target SINR power control problem as a dynamic noncooperative game was presented in this work. It was found as its Nash Equilibrium Solution the conventional Distributed Power Control algorithm.

A new energy efficient distributed power control algorithm was derived from the formulation of the power control problem as a dynamic noncooperative game with the target SINR defined as a linear function of the transmit power. Through the Nash Equilibrium Point, the proposed algorithm performs the choice of the best SINR to be targeted for each link and promotes its tracking simultaneously.

The new distributed power control algorithm was compared to the conventional DPC with respect to energy efficiency and guarantee of a minimum SINR through computational simulations and it has outperformed the DPC in both aspects.

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