Achieving Power and Energy Efficiency in Self-Organizing Networks

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***Abstract*—The target of this paper is to propose a practical low-complexity power allocation algorithm that strikes a good balance between Spectral Efficiency (SE) and power saving for the downlink of interference-limited cellular networks. Because abundant interference usually results from dense frequency reuse and high power transmission, power optimization schemes are critical to interference management in wireless systems. Powerful power optimization schemes can be efficiently implemented in the framework of Self-Organizing Network (SON). In this context, we resort to non-cooperative game theory to devise two distributed power allocation schemes. By only considering SE, our first Power Control Game (PCG) algorithm, deemed *SE-PCG*, provides high SE but push autonomous eNBs into consuming all available power. To address this shortcoming and enhance Energy Efficiency (EE), we put forward another PCG algorithm, deemed *EE-PCG,* which inflicts a penalty on power consumption. The originality of our scheme lies in deriving the power penalty through a signaling-free heuristic. We have analyzed the proposed algorithms through extensive numerical simulations and compared them with the state-of-the-art approaches. The results have shown that our algorithms outperform the latter.**

Keywords—SON, ICIC, Power Control allocation, non-cooperative game theory, OFDMA.

I. Introduction

Energy consumption in mobile communication systems has shown continuous growth during the last decade. In [1], it was reported that 3% of the world-wide energy is consumed by the information and communication technology infrastructures. In addition, energy costs represent 50% of operators' operating expenses [2]. Hence, operators have to use approaches that reduce power consumption while keeping Spectrum Efficiency (SE) at high levels. In order to do so, radio resource management techniques should be designed astutely to reduce energy consumption and inter-cell interference (ICI). This paper addresses the problem of Inter-Cell Interference Coordination (ICIC) through power control in the downlink of cellular OFDMA-based systems. The power level selection process of resource blocks (RBs) is learned as a non-cooperative game. The latter is suitable for the decentralized context of Self Organizing Networks (SON) [3], where network elements dynamically allocate radio resources in a distributed fashion based on measurements.

In LTE [4] and LTE-A [5] systems, Fractional Frequency Reuse (FFR) [6] and Soft Frequency Reuse (SFR) [7] were introduced to avoid the detrimental impact of ICI on system performance, by applying static rules on RB and power allocation among neighboring cells. However, static ICIC fails to cope with realistic scenarios where traffic is variable throughout the network. Therefore, in this work, we favor dynamic ICIC and stress on fully distributed schemes suitable for SON. For that, we formulate two distributed ICIC power allocation algorithms in order to maximize system throughput. In addition, we prove that the model at hand is a super-modular game [8] for both algorithms. Such games have always a Nash Equilibrium (NE) that can be suitably attained using best response dynamics.

In the first algorithm, deemed *SE-PCG*, each eNB optimizes its own performance locally. However, the available power will be unduly wasted due to the selfishness of eNBs. The second scheme, deemed *EE-PCG*, is a fully distributed power allocation method, where each eNB optimizes its performance while accounting for power consumption. For that, UEs send a power cost metric to their servicing eNB, so that they can set the appropriate transmission power. The existence of a power cost in the utility function diminishes the greediness of eNBs that are no longer tempted to transmit at full power on all RBs. In addition to power economy, the EE-PCG algorithm operates without any inter-cell signaling.

The rest of this paper is organized as follows. Section II describes the related works, which is followed by section III, where the system model and the problem formulation are presented. Section IV presents the power allocation as a non-cooperative game. In section V, we present the SE-PCG algorithm*,* while we explain the heuristic-based EE-PCG algorithm in section VI. Subsequently, the performance of the proposed approaches, as well as the comparison with some of the state-of-the art approaches, are presented in section VII. Finally, we conclude in section VIII.

II. RELATED WORK

Power allocation has been widely used to maximize UE capacity and to minimize inter-cell interference. In [9], the proposed meta-heuristic-based downlink power allocation for LTE/LTE-A provides the required QoS by tuning the transmit power at each cell and minimizing the average inter-cell interference level. In [10], a semi-distributed neighboring gradient information based algorithm and a fully distributed heuristic based algorithm were proposed to automatically create soft FFR patterns in OFDMA based systems. The goal of the proposed algorithms is to adjust the transmit power of the different RBs by maximizing the overall network utility. The authors in [11] proposed a distributed heuristic power control algorithm that aims at minimizing the total downlink power of an LTE system, where the impact of the power control algorithm on ICI and system performance is evaluated. The study in [12] is based on a relay node reference signal power control and multi-agent reinforcement learning algorithm. The relay node is modeled as an agent that learns an optimal policy of reference signal power control. The learning is achieved through interaction with the environment. The main goal of this method is to balance the load distribution of the SON network through dynamically changing its coverage area. In [13], the authors proposed a distributed power control method for LTE uplink networks via a cooperative game to solve the energy efficiency problem. They used the Lagrange multipliers and presented an iterative algorithm to reach Nash equilibriums. The study in [14] presented a power allocation algorithm for adjusting the transmit power in each sub-band. The algorithm creates an efficient and dynamic SFR pattern for enhancing the performance of OFDMA downlink. Finally the work in [15] provided a probabilistic model that randomizes the spectrum allocation problem for SON Network.

Our work originally combines non-cooperative game theory and a simple, yet efficient, heuristic to derive a fast and inter-cell signaling-free algorithm. Signaling reduction and the good performance of our algorithm in comparison to the state-of-the-art techniques like frequency reuse-3, FFR and SFR, makes our fully distributed *EE-PCG* algorithm very robust and suitable for the SON context.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

Consider the downlink of a Single Input Single Output (SISO) LTE network. In this OFDMA network, the radio Resource Block (RB) is the smallest radio resource unit [16] that can be scheduled to a mobile user. Each RB has seven OFDM symbols with normal cyclic prefix in the time domain [17] (or six OFDM symbols with extended cyclic prefix) and twelve consecutive subcarriers in the frequency domain.

We assume that each cell is served by one eNB and we denote the set of all eNBs as J. Let $I(j)$ denotes a fixed assignment of users associated to eNB $j \in J$, and G_{ijk} be the channel gain between eNB $j \in J$ and user $i \in I(j)$ on subchannel $k \in K$, where k is the set of RBs. Symbols, variables and parameters used within this paper are defined in Table 1.

TABLE I. SYMBOLS, VARIABLES AND PARAMETERS IN THE DOCUMENT.

J	Set of eNBs.
I	Set of all UEs.
$I(j)$	Set of users associated to eNB j.
K	Set of RBs.
G_{ijk}	Channel power gain between UE i on RB k and eNB j.
ρ_{ijk}	SINR of user i associated to eNB j served on RB k.
β_{jk}	Interference impact of all eNBs on UEs served by eNB j on *RB k*.
N_0	Noise power.
π_{jk}	Transmit power of eNB j on RB k.
p_j^{max}	Maximum downlink transmission power per eNB.
p^{min}	Minimum downlink transmission power per RB.

Each UE i is connected to the eNB with the highest received signal power. We adopt the widely used Proportional Fair (PF) scheduler for serving active users and we assume that all RBs are assigned on the downlink at each scheduling epoch. In order to evaluate the maximum system performance, a permanent downlink traffic scenario is considered. In this scenario, each eNB has persistent traffic towards its users.

B. Problem Formulation

The transmit power π_{jk} of each eNB j is allocated to resource block k serving the users in the network. The total transmit power of eNB j is the sum of the transmit power on each RB $k \in K$:

$$\pi_j = \sum_{k \in K} \pi_{jk}. \tag{1}$$

In addition to the transmit power π_j of eNB $j \in J$, each eNB consumes power p_j^0 due to site cooling and signal processing. Therefore, the average power consumption $p_j$of eNB $j \in J$ is modeled as a linear function [18] of the average transmit power per site π_j as:

$$p_j = p_j^1 \pi_j + p_j^0. \tag{2}$$

The coefficient p_j^1 accounts for the power consumption that scales with the transmit power due to radio frequency amplifier and feeder losses. Using (1), the power consumption by eNB j becomes by:

$$p_j = p_j^1 \sum_{k \in K} \pi_{jk} + p_j^0. \tag{3}$$

The transmit power π_{jk} is directly related to the signal-to-interference-plus-noise-ratio (SINR) of user i associated with eNB j:

$$\rho_{ijk} = \frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j' \neq j} \pi_{j'k} G_{ij'k}}. \tag{4}$$

where N_0 is the noise power, which is, without loss of generality, assumed to be the same for the all users on all RBs. Assuming a proportional fairness service by each eNB on each resource block, the system utility function is given by [19]:

$$U(\pi) = \sum_{j\in J}\sum_{i\in I(j)}\frac{g(|I(j)|)}{|I(j)|}\sum_{k\in K}\log(\rho_{ijk}) \tag{5}$$

$$= \sum_{j\in J}\sum_{i\in I(j)}\sum_{k\in K}\frac{g(|I(j)|)}{|I(j)|}\log\left(\frac{\pi_{jk}G_{ijk}}{N_0+\sum_{j'\neq j}\pi_{j'k}G_{ij'k}}\right).$$

where $|I(j)|$ is the cardinality of set $I(j)$, $g(|I(j)|)$=$\sum_{s=1}^{|I(j)|}1/s$, as we consider the PF scheduler with a fast varying fading channel (Rayleigh fading) [20].

In the following sections, we will provide two algorithms maximizing the above mentioned utility function based on distributed approaches.

IV. Non-Cooperative game for Power Allocation

Central power allocation is complex and requires the presence of a central control unit (like in CoMP [21]) to harvest signaling information from eNBs and allocate power optimally. Therefore, we adopt here distributed schemes to reduce system complexity in the framework of SON.

A. Game Formulation

Non-Cooperative game theory models the interaction between players competing for a common resource. Hence, it is well adapted to power allocation modeling. Here, eNBs are the decision makers or players of the game.

We define a multi-player game G between the eNBs. The eNBs are assumed to make their decisions without knowing the decisions of each other in order to eliminate the need of exchanged information.

The formulation of this non-cooperative game $G=\langle J,S,U\rangle$ can be described as follows:

- A finite set of eNBs $J = (1, ..., |J|)$ and a finite set of RBs $K = (1, ..., |K|)$.
- For each eNB j, the space of pure strategies S_j is as follows:

$$S_j = \left\{\begin{matrix}\pi_j \in R^{|K|} such\ as\ \pi_{jk} \geq p_j^{min} and \\ \sum_{k\in K}\pi_{jk} \leq p_j^{max}, \forall k\in K\end{matrix}\right\}.$$

- An action of an eNB j is the amount of power $\pi_{j,k}$ sent on RB k. The strategy chosen by eNB j is then $\pi_j = (\pi_{j,1},\dots,\pi_{j,k})$. A strategy profile $\pi = (\pi_1,\dots,\pi_{|J|})$ specifies the strategies of all players and $S = S_1 \times \dots \times S_{|J|}$ is the set of all strategies.
- A set of utility functions $U=(U_1(\pi), U_2(\pi),\dots, U_{|J|}(\pi))$ that quantify player's utilities for a given strategy profile π.

B. The Nash Equilibrium

In a non-cooperative game, an efficient solution is obtained when all players adhere to a Nash Equilibrium (NE) [22]. A NE is a profile of strategies in which no player will profit from deviating its strategy unilaterally. Hence, it is a strategy profile where each player's strategy is an optimal response to other players' strategies.

$$U_j(\pi_j,\pi_{-j}) \leq U_j(\pi_j^{'},\pi_{-j}), \forall i\in N, \forall\, \pi_j^{'} \in S_j. \tag{6}$$

where π_{-j} denotes the vector of strategies played by all other eNBs except eNB j.

C. Super-Modular Games

According to [8], a game is super-modular if for any eNB$\in J$:

- The strategy space S_j is a compact sub-lattice of $\mathbb{R}^k$.
- The objective function U_j is super-modular, i.e., if $\forall l \in J-\{j\}\ and\ \forall\pi_j \in S_j$, $\frac{\partial U_j}{\partial\pi_l\partial\pi_j} \geq 0$.

In [8], it was proven that, in super-modular game, if we start with a feasible policy, the sequence of best responses monotonically converges to an NE; it monotonically increases in all components in the case of maximization in a super-modular game.

V. SE Power Control Game

For our first power Control game, *SE-PCG*, every eNB $j\in J$ strives to improve selfishly its own utility function:

$$U_j(\pi_j,\pi_{-j}) = \frac{g(|I(j)|)}{|I(j)|}\sum_{i\in I(j)}\sum_{k\in K}\log\left(\frac{\pi_{jk}G_{ijk}}{N_0+\sum_{j'\neq j}\pi_{j'k}G_{ij'k}}\right).$$

For every j, U_j is concave w.r.t.$\pi_j$and continuous w.r.t. $\pi_l, l\neq j$. Hence, a NE exists. Furthermore, the game is super-modular. In fact, the strategy space S_j is a compact convex set of $\mathbb{R}^k$, while the objective function of any eNB j is super-modular:

$$\frac{\partial U_j}{\partial\pi_l\partial\pi_j} = 0, \forall l \in J-\{j\}.$$

As we are in presence of a super-modular game, we know that Best Response algorithm permits attaining the NEs [8]. Accordingly, at each iteration t, eNB j strives to find, in parallel for all RBs $k\in K$, the following optimal power level as a response to $\pi_{-j}(t-1)$:

$$U_j(\pi_j,\pi_{-j}) \leq U_j(\pi_j^{'},\pi_{-j}), \forall i\in N, \forall\, \pi_j^{'} \in S_j \tag{7}$$

which can be computed by solving the following optimization problem:

$$\max_{\pi_j} U_j(\pi_j,\pi_{-j}). \tag{8a}$$

Subject to:

$$\sum_{k\in K}\pi_{jk} \leq p_j^{max}, \tag{8b}$$

$$\pi_{jk} \geq p^{min}, \forall k\in K. \tag{8c}$$

A. The Power Expression at Equilibrium

The optimum power π^* of the convex problem (8) must satisfy the Karush-Kuhn-Trucker (KKT) conditions, i.e., there exists a unique Lagrange multiplier $\beta \geq 0$ such that:

$$\nabla_{\pi_{jk}}(U_j) + \beta . \nabla_{\pi_{jk}}\left(f_j(\pi_j)\right) = 0, \forall k \in K, \quad (9a)$$

$$\beta . f_j(\pi_j) = 0, \quad (9b)$$

$$p^{min} \leq \pi_{jk}, \forall k \in K. \quad (9c)$$

where $f_j(\pi_j) = p_j^{max} - \sum_{k\in K} \pi_{jk}$. Thus, according to (9a), the power allocation is given by:

$$\pi_{j,k} = \sqrt{\frac{g(|I(j)|)}{\beta}}, \forall k \in K. \quad (10)$$

Note that all power levels for a given eNB j are equal at equilibrium. Finally, to obtain the power levels that are sought for, we have recourse to (9b): as $\beta > 0$, we have that $\sum_{k\in K} \pi_{jk} = p_j^{max}$ at optimality and hence, by virtue of the equality among the power components, we have $\pi_{jk} = \frac{p_j^{max}}{k}$, $\forall k \in K$. Hence, we deduce the following:

$$\pi_{jk} = \max\left(p^{min}, \frac{p_j^{max}}{K}\right), \forall k \in K, \forall j \in J. \quad (11)$$

VI. EE Power Control Game

We have proposed in Section IV a game theory-based power allocation method, but the proposed algorithm suffers from some shortcomings. In fact, it drives eNBs to consume all available power as shown in (11). In this section, we introduce a penalty on power consumption proportional to the interference harm inflicted by eNB j on its neighboring eNBs. Accordingly, we propose a simple heuristic to evaluate such a penalty that we deem β_{jk} and we formulate a non-cooperative game $G^{"} = \langle J, S, W\rangle$, where:

$$W_j(\pi_j, \pi_{-j}) = \sum_{k\in K}\left(U_{jk} - \beta_{jk}\pi_{jk}\right), \forall j \in J.$$

For every j, W_j is concave w.r.t. π_j and continuous w.r.t.π_l, $l \neq j$. Hence, a NE exists [22]. Furthermore, the game is super-modular. In fact, the strategy space S_j is a compact convex set of $\mathbb{R}^k$, while the objective function of any eNB j is super-modular:

$$\frac{\partial W_j}{\partial \pi_l \partial \pi_j} = 0, \forall l \in J - \{j\}.$$

Thus, we know that a Best Response algorithm permits attaining the NEs. Accordingly, at each iteration t, eNB j strives to find, in parallel for all RBs $k \in K$, the following optimal power level as a response to $\pi_{-j}(t-1)$:

$$\pi_j^*(t) = arg \max_{\pi_j} W_j(\pi_j, \pi_{-j}), s.t. \pi_j^* \in S_j. \quad (12)$$

which corresponds to the following optimization problem:

$$\max_{\pi_j} W_j(\pi_j, \pi_{-j}) = \sum_{k\in K}\left(U_{jk} - \beta_{jk}\pi_{jk}\right), \quad (13a)$$

Subject to: $\sum_{k\in K} \pi_{jk} \leq p_j^{max}$, $\forall k \in K, \forall j \in J$, (13b)

$$\pi_{jk} \geq p^{min}, \forall k \in K. \quad (13c)$$

A. The Power Expression at Equilibrium

Let us write the Lagrangian of problem (13) as follows:

$$L(\pi_j, \gamma) = \sum_{=k\in K}\sum_{i\in I(j)} \frac{g(|I(j)|)}{|I(j)|} log\left(\frac{\pi_{jk}G_{ijk}}{N_0 + \sum_{j'\neq j} \pi_{j'k}G_{ij'k}}\right)$$

$$- \sum_{k\in K} \pi_{jk}\beta_{jk} + \gamma\left(p_j^{max} - \sum_{k\in K} \pi_{jk}(t)\right). \quad (14)$$

where$\gamma \geq 0$ is the Lagrangian multiplier. The dual problem in (14) may be expressed as follows:

$$min_{\gamma\geq 0} h(\gamma) = min_{\gamma\geq 0} max_{\pi_j} L(\pi_j, \gamma) \quad (15)$$

As $L(\pi_j, \gamma)$ is a standard concave function, each eNB j derives the optimal power levels by seeking zero points of the derivatives of $L(\pi_j, \gamma)$. Accordingly, we obtain:

$$\pi_{jk}(t) = \frac{g(|I(j)|)}{\gamma(t) + \beta(t)}, \forall k \in K \quad (16)$$

Recall that $\beta_{jk}$is a constant evaluated according to a simple heuristic that will be explained in the next subsection. Note that the higher the interference harm $\beta_{jk}$is, the lower the power allocated on that particular RB k will be.

Finally, to obtain the power level that is sought for, we use a gradient method to update the dual variable γ since h(γ)is differentiable:

$$\frac{\partial h(\gamma)}{\partial \gamma} = p_j^{max} - \sum_{k\in K} \pi_{jk}(t) \quad (17)$$

Hence, γ is updated as follows:

$$max\left(0, \gamma(t-1) - \delta_t\left(p_j^{max} - \sum_{k\in K} \pi_{jk}(t-1)\right)\right) \quad (18)$$

whereδ_t is a suitably small step size.

B. Heuristic to assess power penalty

Our proposed power penalty is based on an inter-cell signaling-free heuristic. In our proposed *EE-PCG* algorithm, we consider that at each iteration, any eNB j decides to optimize the power allocation using equation (13). We assume that the power penalty β_{jk}existing in equation (13) will be the average interference impact of eNB j on other eNBs and it is reflected by the interference impact of all other neighboring eNB to eNB j. Accordingly, the value of the power penalty cost β_{jk} is given by:

$$\beta_{jk} = \frac{1}{|K|.|J|.|I(j)|}\frac{g(|I(j)|)}{|I(j)|}\sum_{i\in I(j)}\sum_{\substack{l\in J\\ l\neq j}} S_{ilk}. \quad (19)$$

We assume that S_{ilk} reflects the interference level inflected by eNB j on a given neighboring cell served by eNB l. This S_{ilk} represents the SINR received by user $i, i \in I(j)$, from neighboring eNB l, $l \in J, l \neq j$. Note that the power penalty is computed per RB, per eNB, and per UE and reflects the proportional fairness gain. The value of S_{ilk} is given by:

$$S_{ilk} = \frac{G_{ilk}\pi_{lk}}{\left(\sum_{\substack{l' \in J \\ l' \neq l}} \pi_{l'k} G_{il'k} + N_0\right)} \tag{20}$$

S_{ilk} is practically measured in a real environment by any UE and used, for instance, for the handover process. All UEs served by eNB j transmit the value of S_{ilk} periodically to eNB j. When an eNB receives a new value of S_{ilk} from the served UEs, it starts the *EE-PCG* algorithm. First of all, eNB j computes β_{jk} using (19), and starts optimization using the current π_{jk} as initial power value.

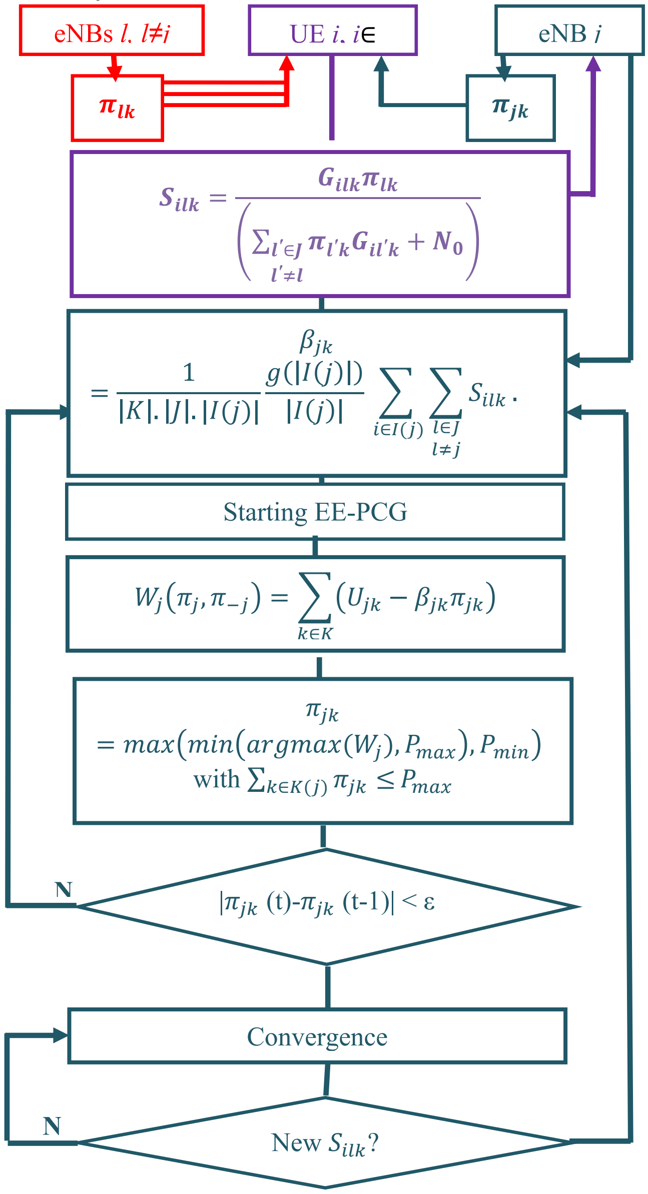


Fig. 1. Flowchart for EE-PCG algorithm.

Each eNB adapts the signal transmission in the downlink without any Inter-cell signaling. The eNB repeats this adaptation process at each iteration until convergence. The Flowchart, illustrated in Fig.1, represents the *EE-PCG* algorithm process.

VII. Simulation Results

We consider an LTE system with 9 hexagonal cells served by 9 eNBs at their centers. Each cell has a band of 5 MHz divided into 25 RBs. The number of UEs in each cell ranges from 4 to 14 and they are uniformly distributed inside the cells. Furthermore, we consider the following parameters listed in 3GPP TS 36.942 [23]: the mean antenna gain in urban zones is 12 dBi (900 MHz). eNodeB total Transmit power is 43 dBm. As for noise, we consider the following parameters: user noise figure 7.0 dB, thermal noise −104.5 dBm which gives a receiver noise floor of N_0= −97.5 dBm.

For each algorithm, 25 snapshots were run. In each cell a predefined number of users is selected. For each simulation instance, the same pool of RBs, UE and pathloss matrix are given for all algorithms.

In Fig.2, we illustrate the significant power saving of the *EE-PCG* algorithm in comparison with the *SE-PCG* algorithm. We can see that the relative power saving percentage, for all eNBs, vary from 89%to 93%, which is a very significant power economy. In fact, the existence of the power penalty cost $-\sum_{k \in K} \pi_{jk}\beta_{jk}$ in the utility function (13) diminishes the selfishness of eNBs in comparison with the *SE-PCG* algorithm.

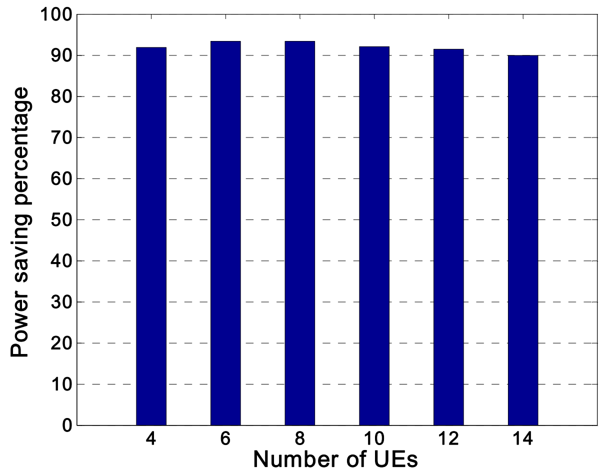


Fig. 2. Relative power savingpercentage of the EE-PCG algorithm compared to SE-PCG algorithmas function of number UEs.

This power saving is obtained while maintaining good performance as portrayed in Fig. 3, where the total Throughput is depicted as a function of the number of UEs for the EE-PCG and the SE-PCG algorithms.

In Fig. 4, we report the mean convergence time per eNB of the EE-PCG algorithm for various scenarios. We note that each eNB attains the NE within 64 to 72 iterations as shown in Figure 4. At each iteration, all eNBs try to maximize their payoff function given in (13). Note that convergence is faster when increasing the number of UEs because the power penalty cost estimation is more accurate. This fast convergence time and the fully distributed power penalty cost estimation are well adapted to the SON context.

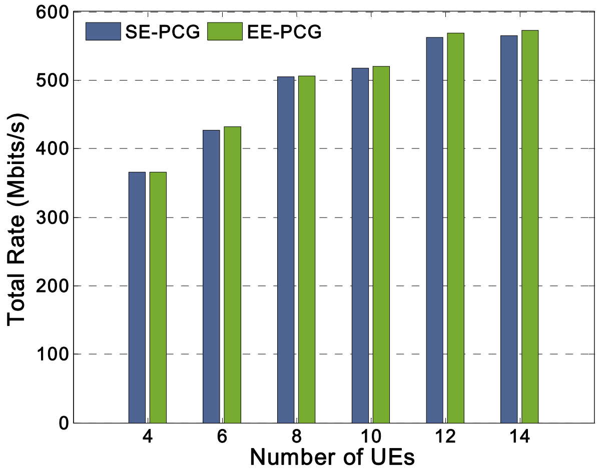


Fig. 3. Total Throughput of the EE-PCG and SE-PCG algorithms as function of number UEs.

Moreover, we noted during the extensive simulations conducted, that the power levels attain 90% of the values reached at convergence in less than 20 iterations, which is relatively fast.

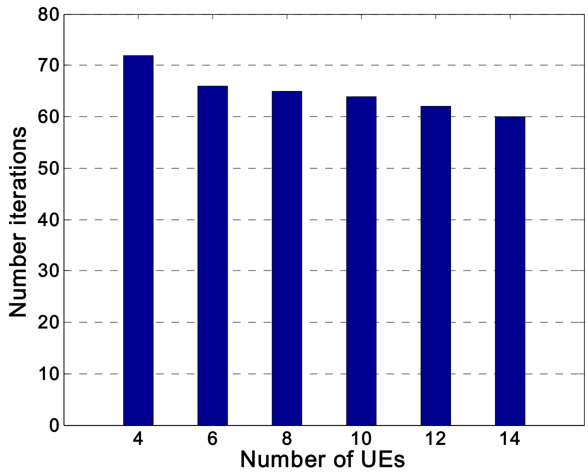


Fig 4. Total convergence time by eNB as function of the number of UEfor EE-PCGalgorithm.

We represent in Fig. 5 the power distribution on the 25 RBs for an eNB selected randomly and for which convergence time was equal to 64 iterations. At t=0, we set the power value $\frac{P_j^{max}}{K}$ for each RBs. The latter high power level will increase the power penalty due to the resulting high level of interference. This increase of β_{jk} forces the eNBs to decrement drastically, at the first iteration, their power values to P^{min}. Lowering the power allocation will decrease the power penalty, which will drive again eNBs to increase back their power level, as seen in Fig. 5. This behavior is reproduced by increasing and decreasing β_{jk} alternately, until we reach a stable power allocation.

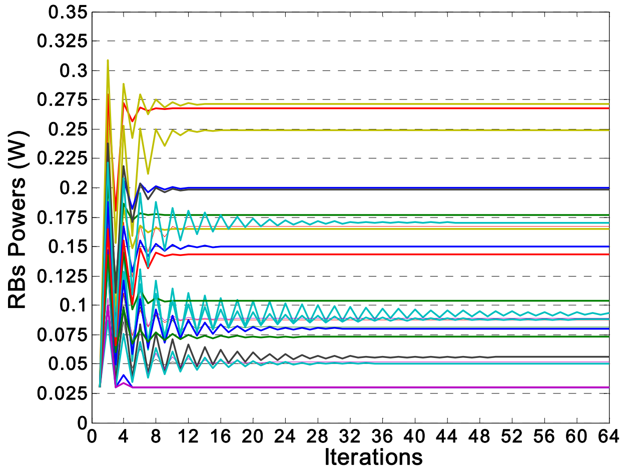


Fig 5. Power distribution by RBs before reaching convergence for EE-PCG algorithm.

The low convergence time in conjunction with high performance is an undeniable asset for the SON context. As it can be seen from the results, the EE-PCG can provide better efficiency than the SE-PCG algorithm with much reduced consumed power.

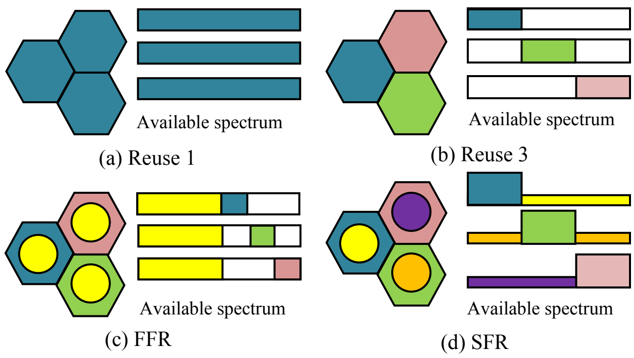
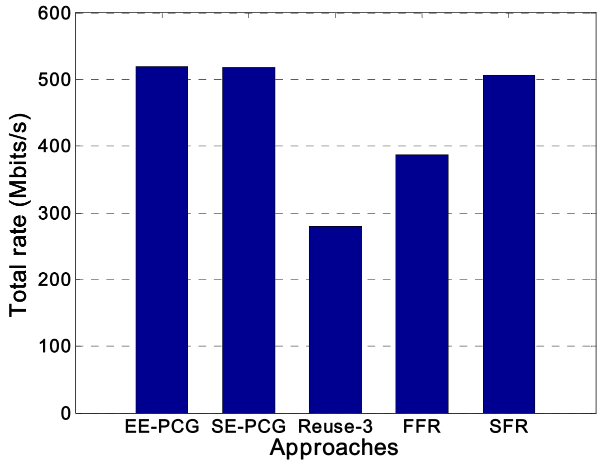


Fig 6. State-of-the-art frequency allocation techniques.

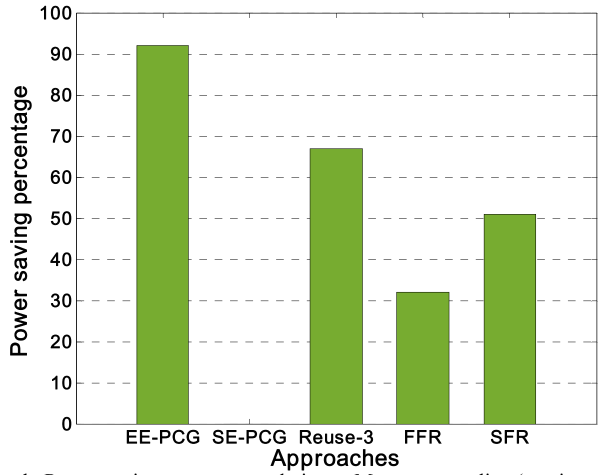
However, we still need to assess the performance of our devised schemes with state-of-the-art approaches such as the frequency reuse-3 model, FFR, and SFR techniques:

- In the frequency reuse-3 model Fig. 6(b), one third of the available spectrum is used in each cell in a cluster of three adjacent cells. Interference issues are removed at the cost of lower spectral efficiency.
- The FFR, Fig. 6(c) and SFR Fig. 6(d) techniques divide each cell into two zones for cell-center UEs and cell-edge UEs with restrictions on frequency resource usage and power allocation per zone.

Accordingly, we display in Fig. 7.a the total rate of our SE-PCG and EE-PCG algorithms in addition to the above mentioned standard techniques. We can clearly see from the portrayed results that our dynamic ICIC schemes provide higher rates than the state-of-the-art ICIC techniques. In particular, the EE-PCG satisfies UEs needs better than static ICIC with quantified transmission power levels and static resource allocation. This performance of the EE-PCG is obtained while maintaining a high power saving performances in comparison with SE-PCG and state-of-the-art approaches as portrayed in Fig. 7.b



a. Total rate (Mbits/s): scenario of 10 UEs/eNB



b. Power saving percentage relative to Max power policy (serving all RBs with maximum power)

Fig 7.Comparison with state-of-the-art approaches

VIII. Conclusion

In this paper, we proposed two distributed ICIC power control games for the downlink of a SON OFDMA-based network. We demonstrated that both algorithms provide a significant performance in comparison with the state-of-the art approaches. The first algorithm provides high spectral efficiency, but push autonomous eNBs into consuming all available power. The second algorithm reduces power wastage without degrading system performance owing to a power penalty cost. The latter is estimated via an inter-cell signaling free heuristic that enables our energy efficient algorithm to astutely adjust the downlink transmission power according to UE feedbacks.

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