Inter-Cell Interference Coordination based on Power Control for self-organized 4G Systems

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Abstract—Orthogonal Frequency Division Multiplexing (OFDMA) accepted as the multiple access scheme for the 4G Systems provides resistance to inter-symbol and intra-cell interference. However inter-cell interference, when dense frequency reutilization is used, can deteriorate the performance of users with bad channel quality, in particular at cell-edge. Inter-Cell Interference Coordination (ICIC) [1] is a promising mechanism to enhance system performance of 4G. This paper addresses the problem of ICIC in the LTE downlink where the power level selection of resource blocks (RBs) is portrayed as a sub-modular game in the context of self-organizing networks. The existence of Nash equilibriums (NEs) for that type of games shows that stable power allocations can be reached by selfish eNodeBs. To attain these NEs, we propose a semi-distributed algorithm based on a best response algorithm. Based on local knowledge exchanged through the X2 interface in 4G networks [2], each eNodeB will first select a pool of low interference RBs. Then, each eNodeB - to save energy - will make its best to fix the power level on these RBs achieving comparable performances in comparison with a policy serving active users with full power (MAX Power Policy). In order to evaluate our proposal, we compare the obtained results to an optimal global CoMP (Coordinated Multi-Point) solution where a central controller is the decision maker [3].

***Keywords*—ICIC, 4G, Game Theory, OFDMA, CoMP, SON.**

I. INTRODUCTION

4G networks are designed to achieve high spectral efficiency by reusing the same frequency resource in each cell. However, this approach increases the inter-Cell Interference (ICI) and may degrade the channel quality especially for cell-edge users. In this work, we propose a method for Inter-Cell Interference Coordination (ICIC) to reduce ICI through efficient distributed power control. Power control does not only reduce the impact of interfering signals by lowering their power level (signals usually belonging to cell- center users), but it can increase the power level on resource blocks that suffer from bad radio conditions (usually RB allotted for cell-edge users).

Several works have been proposed and studied power control algorithms in OFDMA-based systems. In [4], a hybrid algorithm combined power control with adaptive modulation. It permits using high order modulation schemes at low Signal to Noise Ratio values without degrading the system performance. In [5], authors proposed an adaptive power control scheme to reduce inter-cell interference by applying a "Fair SINR" strategy, where power allocation is distributed among users in a way to obtain the same Signal-to-Interference and Noise Ratio (SINR) at the receiver. In [6], a distributed power control algorithm is proposed where each cell aims independently at minimizing its own power consumption under user's rate constraints. The power allocation scheme takes into account the inter-cell interference. It is performed iteratively according to the proposed "Bit Allocation Algorithm" until the allocated power levels remain invariant after two consecutive iterations. In [7], a semi-distributed neighboring gradient information based algorithm and one fully distributed non-trivial heuristic based algorithm are proposed to automatically create soft Fractional Frequency Reuse (FFR) patterns in OFDMA based systems. The goal of the proposed algorithms is to adjust the transmit power of the different RBs by maximization of the overall network utility. The work in ([8], [9]) build upon the work in [7]. The work in [8] extends the proposed algorithms for multi antenna OFDMA-based systems with space division multiple access. The work in [9] differs mainly by of power control spatial granularity, where the power is set on a per-beam basis. Finally in [10], the author addressed the problem of interference with a decentralized eICIC algorithm, they used Almost Blank sub-frame (ABSF) and Cell Selection Bias (CSB) to manage the interference between cells.

Our work belongs to the category of decentralized ICIC. Resorting to non-cooperative game theory is suitable to model the way eNodeBs compete in a distributed manner for limited resources. Devising an optimal power level selection scheme depends on the existence of Nash equilibriums (NE) for the present game. In this paper, we prove that the model at hand is a sub-modular game (see [14], [13]). Such games have always a NE and it can be attained using a greedy best response type algorithm (called algorithm I in both references). A comparison is made with a centralized CoMP system to assess the price of anarchy.

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The paper is organized as follows. The system model is introduced in Section II. In section III the power level selection scheme is presented as a non-cooperative sub-modular game as well as a semi distributed learning algorithm based on a best response algorithm. Section IV presents the simulations results. The optimal CoMP approach is given in V with a comparison with our decentralized scheme. We conclude in Section VI.

II. System Model

We consider a Single Input Single Output (SISO) LTE network comprising a set $M=\{1,...,m\}$ of omnidirectional eNodeBs serving hexagonal cells. Each eNodeB can communicate with its neighboring eNodeBs using X2 interface. We focus on the OFDMA downlink scenario in this paper. The time and frequency radio resources are grouped into Resource Blocks (RBs). RB is the smallest radio resource block that can be scheduled to a UE. Each RB consists of 7 OFDMA symbols in the time dimension and *12* sub-carriers in the frequency dimension. The total number of RBs is denoted by n and $N=\{1,...,n\}$ represents the set of RBs.

A. Downlink Data Rate

The SINR observed at eNodeB i on RB k allocated to user u can be expressed as:

$$SINR_{i,k,u} = \frac{G_i . P_{i,k} . \left(\frac{1}{d_{u,i}^i}\right)^\beta}{\sum_{\substack{j\in M,\\ j\neq i}} G_j . P_{j,k} . \left(\frac{1}{d_{u.j}^i}\right)^\beta + P_N} \quad (1)$$

where Gi represents the antenna gain of eNodeB i, Pi,k is the power transmitted by eNodeB i on RB k with $Pi,k \in [P_{min}, P_{max}]$, $d^i_{u,j}$ is the distance between eNodeB j and user u served by eNodeB i, P_N represents the thermal noise power per RB and β is the path-loss factor varying between 3 and 6. It should be noted that $P_{min}\neq 0$ and our algorithm focuses on RBs already selected by the eNodeB.

We denote by $D_{i,k,u}$ the data rate achieved by user u on RB k in eNodeB i given by what follows:

$$D_{i,k,u} = \frac{W}{E_b/N_o} . SINR_{i,k,u}$$

where W is the bandwidth per RB. Given a target error probability, it is necessary that $E_b/N_0 \geq \gamma$, for some threshold γ which is user specific.

Each cell will be logically divided into N_z concentric discs of radii R_z, $z=1,...,N_z$, and the area between two adjacent circles of radii R_{z-1} and R_z is called zone z, $z=1,...,N_z$. We denote by ρ_z the density of uniformly distributed mobile users in zone z. This users have the same radio conditions leading to the same γ_z and the same mean rate per zone $D_{i,k,z}$ according to what follows:

$$D_{i,k,z} = \frac{\frac{W}{\gamma_z} \int_{R_{z-1}}^{R_z} \frac{\rho_z . 2rdr}{r^\beta} . G_i . P_{i,k}}{\sum_{\substack{j\in M,\\ j\neq i}} G_j . P_{j,k} . \frac{1}{\left(d_{i,j}^i\right)^\beta} + P_N}$$

$$= \frac{\left(\frac{2.W.\rho_z}{(2-\beta)} \frac{R_z^{2-\beta} - R_{z-1}^{2-\beta}}{\gamma_z}\right) . G_i . P_{i.k}}{\sum_{\substack{j\in M,\\ j\neq i}} P_{j,k} . \frac{G_j}{\left(\delta_{i,j}^z . R_{cell}\right)^\beta} + P_N} \quad (2)$$

Where R_{cell} is the cell radius. As for interference, we consider mainly for simplification the impact of eNodeB j on eNodeB i by replacing $d^i_{u,j}$ by $d^i_{z,j}=\delta^z_{i,j}.R_{cell}$ the distance between eNodeB i and eNodeB j (the value of $\delta^z_{i,j}$ depends on how far is eNodeB j from zone z of eNodeB i).

B. Cost Function

We denote by $T_{i,k,z}$ the data unit transmission time for users in zone z through RB k in eNodeB i. In fact, the latter is the inverse of the data rate perceived by the user:

$$T_{i,k,z} = \frac{I_{i,k,z}}{P_{i,k}} \quad (3)$$

where $I_{i,k,z}$ is given by:

$$I_{i,k,z} = \frac{\sum_{\substack{j\in M,\\ j\neq i}} P_{j,k} . H_{i,j}^z + P_N}{H_{i,z}} \quad (4)$$

While $H_{i,z} = \left(\frac{2.W.\rho_z}{(\beta-2)} \frac{R_{z-1}^{2-\beta} - R_z^{2-\beta}}{\gamma_z}\right) . G_i$ captures distance dependent attenuation of power inside zone z and $H_{i,j}^z = \frac{G_j}{\left(\delta_{i,j}^z . R_{cell}\right)^\beta}$ is the distance dependent attenuation of power between eNodeB i, j.

We denote by N^i_z the pool of RBs used by users in zone z. eNodeB i will pay an amount α_z per power unit for the use of a given RB $k \in N^i_z$. This power unitary cost can decrease with the zone index to further protect users that are far away from the antenna; or it can increase to favor cell-center users in order to enhance overall performances. Furthermore, the price for the amount of allocated power depends on the traffic load per cell L_i to favor a group of cells in comparison with its neighbors if they experience momentarily peak of traffic (for a short time due to a sudden incident or for a long time due to an organized event). Lowering the price paid for the power budget for such eNodeBs can enable them to increase relatively their transmitted power to better service their congested cells. Accordingly, the goal of the power control scheme proposed in this paper is to minimize the following cost function in eNodeB i for RB k allotted to a user in zone z:

$c_{i,k,z} = \kappa . T_{i,k,z} + \alpha_z . (1-L_i) . P_{i,k}$, If RB k is used in zone z (5)

$=0$, If RB k is not used in zone z (6)

where κ is a normalization factor.

III. Non-Coorperative Game For power Control

Non-Coorperative game theory models the interactions between players competing for a common resource. Hence, it is well adapted to power control. We define a multi-player game G between the m eNodeBs players. The eNodeBs are assumed to make their decisions without knowing the decision of each other.

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

- A finite set of players $M=(1,...,m)$ and a finite set of RBs $N=(1,...,n)$.
- For each eNodeB i, the space of strategies S_i is formed by the Cartesian product of each set of strategies $S_i=S_{i,1}\times...\times S_{i,n}$. An action of a eNodeB i is the amount of power $P_{i,k}$ sent on RB k and $S_{i,k}=[P_{min},P_{max}]$. A strategy profile $P=(P_1,...,P_m)$ specifies the strategies of all players and $S=S_1\times...\times S_m$ is the set of all strategies.
- A set of cost functions $C=(C_1(P),C_2(P), ... , C_m(P))$ that quantify players costs for a given strategy profile P where $C_i=(c_{i,1,z},c_{i,2,z},...,c_{i,n,z})$ in the cost of eNodeB i.

  As the frequencies allocated to different RBs are orthogonal, minimization of cost $c_{i,k,z}$ given in (5) on RB k is done independently of other RBs. Hence, we demote by $P_{-i,k}$ the strategies played by all eNodeBs on the RB k except eNodeB i.

A. The Nash Equilibrium

In a non-cooperative game, an efficient solution is obtained when all players adhere to a Nash Equilibrium (NE). 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.

$$c_{i,k,z}(P_{i,k},P_{-i,k}) \le c_{i,k,z}(P'_{i,k},P_{-i,k}) \tag{7}$$

$\forall\ i\in M,\ \forall\ z\in N_z,\ \forall\ k\in N^i_z,\ \forall\ P'_{i,k}\in S_{i,k}$

For every $i \in M$, in any zone and for all $k\in N^i_z$, $c_{i,k,z}$ is convex w.r.t. $P_{i,k}$ and continuous w.r.t. $P_{j,k} j\neq i$. Hence, a Nash equilibrium exists [11].

Proposition 3.1: The Nash equilibrium is either the solution of the following system of m equations:

$$P_{i,k} = \sqrt{\kappa.\frac{\sum_{j\in M, j\neq i} P_{j,k}.H^z_{i,j} + P_N}{\alpha_z.(1-L_i).H_{i,z}}} \tag{8}$$

$\forall\ i\in M,\ \forall\ z\in N_z,\ \forall\ k\in N^i_z$

or at the boundaries of the strategy space.

Proof: Since the cost functions are convex, at the Nash equilibrium, the optimal power levels are obtained by computing the partial derivative of the cost function of each *eNodeB i* on any of the used RB k in respect to its strategy $P_{i,k}$ and by equating the result to zero:

$$\frac{\partial c_{i,k,z}}{\partial P_{i,k}} = -\kappa\frac{\sum_{j\in M, j\neq i} P_{j,k}.H^z_{i,j} + P_N}{P^2_{i,k}.H_{i,z}} + \alpha_z.(1-L_i) = 0$$

$\forall\ i\in M,\ \forall\ z\in N_z,\ \forall\ k\in N^i_z$

We obtain a system of m equations with m unknowns given in (8). Unfortunately, the solution of the above system is not always feasible (not between P_{min} and P_{max}) as the set of actions is bounded. Furthermore, we need a distributed algorithm to attain the new NEs as the system evolves in time. In fact, a decentralized approach is adaptable to the system changes in dynamic scenarios while maintaining a low degree of system complexity. We turn to sub-modularity theory to obtain an algorithm that can attain Nash equilibriums.

B. Sub-modular Game

S-modularity was introduced into the game theory literature by [14] in 1979. S-modular games are of particular interest since they have Nash equilibriums, and there exists an upper and a lower bound on Nash strategies of each user [15]. More importantly, these equilibriums can be attained by using a greedy best response type algorithm ([14],[13]).

Definition 3.2: consider a game $G=\langle N,S,C\rangle$ with strategy spaces $S_i \subset \mathbb{R}^m$ for all $i \in M$ and for all $z \in N_z$, $k \in N^i_z$, G is sub-modular if for each i and k, $S_{i,k}$ is a sublattice[1] of $\mathbb{R}^m$, and $c_{i,k,z}(P_{i,k},P_{-i,k})$ is sub-modular in $P_{i,k}$.

Since $S_{i,k}$ is a single dimensional set, sub-modularity in $P_{i,k}$ is guaranteed. Also, in our work, since $\mathbb{R}^m = \mathbb{R}$ and $S_{i,k}=[P_{min},P_{max}]$ is a convex and compact subset, $S_{i,k}$ is a sublattice of $\mathbb{R}$.

Definition 3.3: If the utility function $c_{i,k,z}$ is twice differentiable, it is sub-modular if: $\frac{\partial c_{i,k,z}(P_{i,k},P_{-i,k})}{\partial P_{i,k}\partial P_{l,k}} \le 0$ for all $l \neq i \in M$, for all $k \in Nzi$, for any zone z and for any feasible strategy. We need only to check whether the utility function ci,k,z is sub-modular for every eNodeB i and every selected RB k which is straightforward as the following derivative is non-positive $\forall P\in S,\ i\neq j$;

$$\frac{\partial c_{i,k,z}(P_{i,k},P_{-i,k})}{\partial P_{i,k}\partial P_{l,k}} = -\frac{H^z_{i,l}}{P^2_{i,k}H_{i,z}}$$

Therefore, our game is indeed sub-modular.

C. Attaining the Nash Equilibrium

1) The Best Power Response: The Best response strategy of player i is the one that minimizes its cost given other players strategies. A best power response scheme consists of a sequence of rounds, each player i chooses the best response to the other players strategies in the previous round. In the first round, the choice of each player is the best response based on its arbitrary belief about what the other player will choose. In some games, the sequence of strategies generated by best power response converges to a NE, regardless of the players' initial strategies. S-modular games are part of those games.

To reach the NE, the work in [12] proposes the following greedy best response algorithm built on an algorithm called algorithm I in [14], [13]: there are T infinite increasing sequences T^i_t for $t \in T$ and $i=1,...,m$. Player i uses at time T^i_k the best response policy (a feasible one) to the policies used by all other players just before T^i_k. This scheme includes in particular parallel updates (when T^i_t does not depend on t). Once this user updates its strategy, the strategies of one or more other users need not be feasible anymore.

Any eNodeB i strives to find, for the pool of selected RBs in any zone z, the following optimal power level:

$$P^*_{i,k} = \arg min_{P_{i,k}} c_{i,k,z}(P_{i,k},P_{-i,k})$$

for $P_{i,k} \in [P_{min}, P_{max}]$. By definition $P^*_{i,k}$ is a best response of

[1] A is sublattice of $\mathbb{R}^m$ if $a \in A$ and $a' \in A$ imply $a\wedge a' \in A$ and $a\vee a' \in A$.

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eNodeB *i* to the other eNodeBs strategies on RB *k*.

2) Distributed Learning of NE: In a real environment, a best response type algorithm as the one proposed in ([13],[14]) cannot be practically applied as every eNodeB I needs to know the policy of all other eNodeBs $P_{-i,k}$ on every used RB *k*, which necessitates expensive signaling. Fortunately, we can easily render our algorithm distributed by making use of signaling information already present in the downlink of an LTE system. In fact, $P_{-i,k}$ (or equivalently $P_{j,k}$ $\forall$ $j \neq i$) only intervene in the total interference $I_{i,k,z}$ endured on RB *k* in zone *z* of eNodeB *i* in equation (4). In practice mobile users sent every TTI, for the attributed RB *k*, the CQI (Channel Quality Indicator) indicating the channel quality and interference. This CQI is calculated based on pilots CRS (Cell specific Reference Signals) that are transmitted in every downlink sub-frame and in every RBs across the entire cell bandwidth independently of the individual UE allocation. However, the eNodeBs should update their transmission powers on selected RBs sequentially in a predefined round robin fashion that need to be set once and for all.

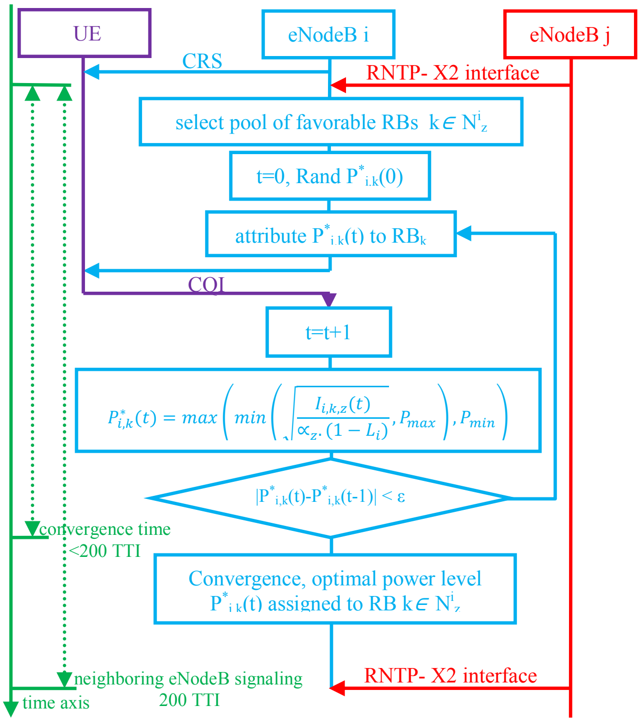

Fig. 1. Flowchart for BPR Power Control Algorithm

We present in figure 1 the flowchart of the BR Algorithm deemed BPR, which is a power control scheme under the distributed best-response algorithm. In LTE, the RNTP (Relative Narrow-band Transmit Power) indicator (received every 200*TTI through the X2 interface) advertises on which RBs a neighboring eNodeB will use full power. This information is necessary for the ICIC mechanism to lower the impact of inter-cell interference by avoiding an eNodeB i from allocating some RBs and selecting properly the pool of favorable RBs deemed N^i_z. Hence, it is fundamental that our BPR algorithm converges before the exchange of new RNTP messages. At the system start, any eNodeB i allocates in parallel all selected RB k∈N^i_z with an initial random power $P_{i,k}(0)$ to a given mobile user in zone z ∈ N_z as advocated by the scheduler.

IV. Simulation Results

We consider 9 hexagonal cells where each cell is surrounded with 6 others. The physical layer parameters are based in the 3GPP technical specifications TS 36.942. These parameters are shown in table 1:

TABLE I. PHYSICAL LAYER PARAMETERS

Channel bandwidth	10 Mhz	***Number of RBs***	50
User Noise Figure	7.0 dB	***Time subframe***	1 ms
Sub-channel bandwidth	180 Khz	***Thermal noise***	-104.5 dBm
Mean antenna gain[a]	12 dBi	***P_0***	10 W
Receiver noise floor PN	-97.5 dBm	***Transmission power***[b]	43 dBm
Antenna configuration	1-transmit, 1-receive SISO (Single Input Single Output)		

a. urban zones (900 Mhz)

b. *according to TS 36.814 corresponding to 20 Watts*

We set $x_{i,k}$ for any eNodeB *i* on RB *k* belongs to *{0.1,0.2,0.35,0.5,0.6,0.7,0.85,1} and* $L_i=0$. We conducted in this paper preliminary simulations in a Matlab simulator where only two zones with same area size are taken into account: cell-center zone located at a distance smaller than $R_1=0.7$ *Km* and cell-edge zone located between R_1 *and* $R_2=R_{cell}=1$ *Km*, We assume that 64-QAM and 16-QAM are respectively used as cell-center and cell-edge users modulation. Various power unitary costs *(α1,α2)* were tested. For each scenario, 400 simulations were run where in each cell a random number of users is chosen in each zone corresponding to a snapshot of the network rate. For each simulation instance, the same pool of RBs per zone is given for the three policies: our devised BPR algorithm, Max Power policy where full power P_0 is used on all RBs and Random policy where power levels are set at random. For every simulation, 100 runs of Random policy were made.

In figure 2, we depict the total transfer time per zone $T_z = \sum_{i=1}^{m}\sum_{k=1}^{n} T_{i,k,z}$ for cell-center and cell-edge users as a function of various power unitary costs *(α1,α2)* for BPR and Max Power Policy. In most scenarios, we aimed at favoring cell-edge users by lowering the power unitary cost in comparison to that of cell-center users. We notice as expected that the improvement in one zone as compared to the Max Power policy is obtained at the expense of performance degradation of the other zone. This fact is highlighted in the lowest sub-figure where the relative deviation $100*(T_z^{BPR} - T_z^{MaxPower}/T_z^{BPR})$ is displayed. Further, we see that the improvement in one zone does not strictly depend on how low its power unitary cost is but on how low it is relatively to the other zone: despite the fact that no power unitary cost is inflected on cell-edge users in scenario (10,0), the total transfer time is greater than that for scenarios (20,2), (30,2) or (40,2).

In figure 3, we depict the system transfer time: $T = \sum_{z=1}^{2}\sum_{i=1}^{n}\sum_{k=1}^{m} T_{i,k,z}$ as a function of power unitary cost for BPR, Max power policy and random policy. Except for (2,30) and (40,2) where there is a large discrepancy between the power unitary cost of one zone in comparison with the other,

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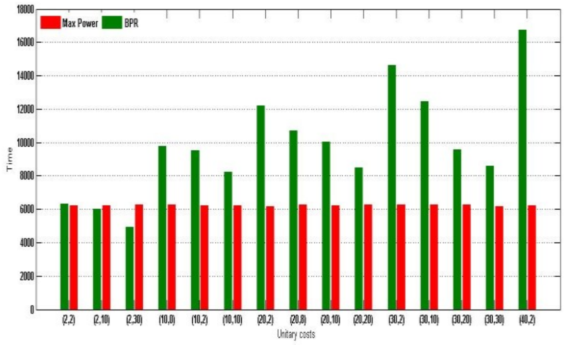
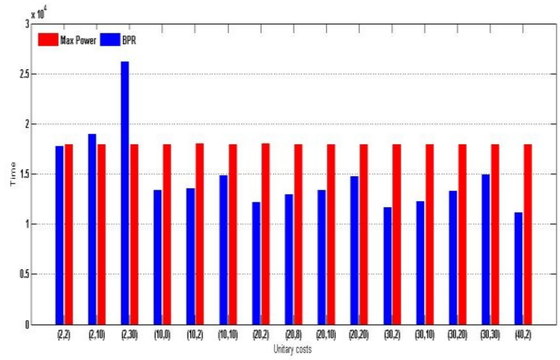
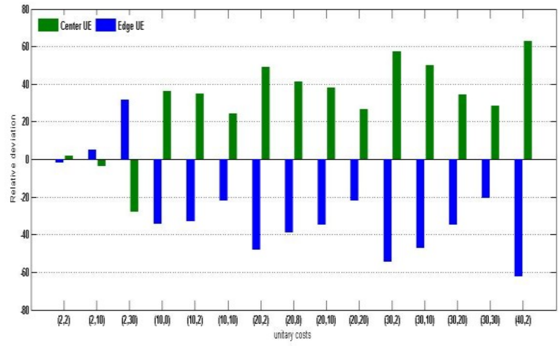
the performances of BPR and Max Power policy are equivalent for all other scenarios.



(a) Cell-center Users



(b) Cell-edge Users



(c) Relative Deviation

Fig. 2. Transfer Time per zone as function of power unitary cost for BPR vs. Max Power Policy

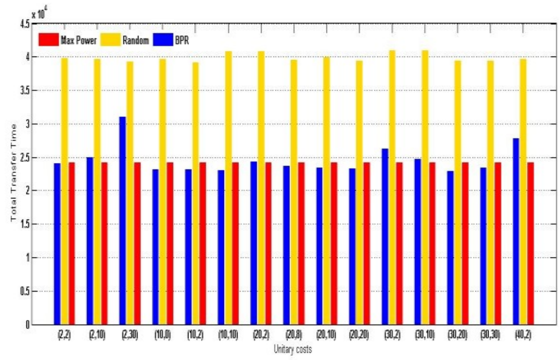


Fig. 3. Total Transfer Time as a function of power unitary cost for BPR vs. Max power policy and Random Policy

However, BPR permits a considerable power economy in comparison with Max Power policy as we can see in figure 4 where the relative deviation between the total power in BPR and the Max Power policy is displayed as a function of power unitary cost. We can see that the best performances are reached when the same (high) power unitary cost is assigned for both zones in scenarios (20,20) and (30,30) where power economy vary from 72% till 82% while the total transfer time is slightly lower than that in the Max Power policy. In figure 5, we report the mean convergence time as a function of power unitary cost. We note that BPR attains NE faster than 120 TTI and hence before the exchange of new RNTP messages.

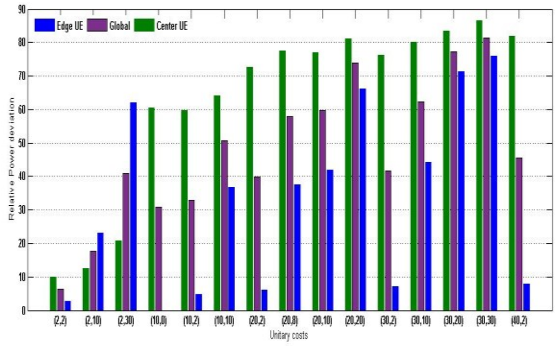


Fig. 4. Power Economy

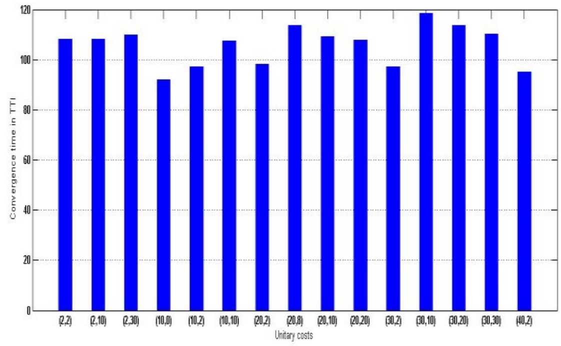


Fig. 5. Convergence Time

V. CoMP Optimization

In this section, we quantify the loss in efficiency suffered when a distributed scheme is adopted rather than a centralized CoMP optimization.

A. Optimal Centralized Approach

Unlike the distributed SON (Self Organizing Networks) approach where precedence is given to the interests of each individual eNodeB, power control may be performed in a way that favors the overall system performance. We do so by introducing a centralized CoMP approach, where a central controller assigns the power levels of each eNodeB in order to minimize the total network cost. The obtained optimizations problem is a non-linear convex problem subject to $0 \leq x_{i,k} \leq 1$

$$minimize: \sum_{i,z} \left(\frac{I_{i,k,z}}{x_{i,k}} + \alpha_z . P_0 . x_{i,k} \right)$$

B. *Simulation Results*

In figure 6, we illustrate the mean time necessary to send a data unit for all users as a function of the system load for the optimal policy, our algorithm based on Best Power Response and Max Power policy. We see that the performances of BPR and the Optimal policy are equivalent while we notice an expected improvement in comparison with the Max Power approach that resorts to full power.

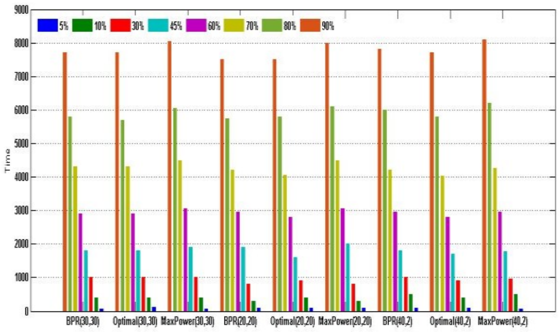
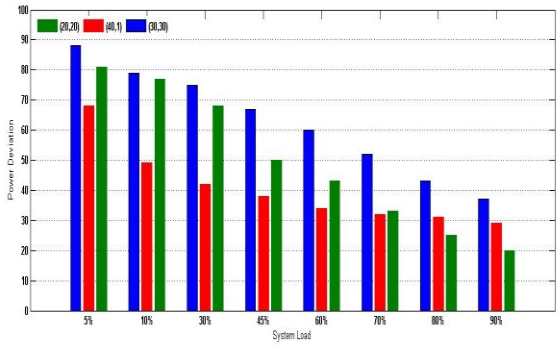
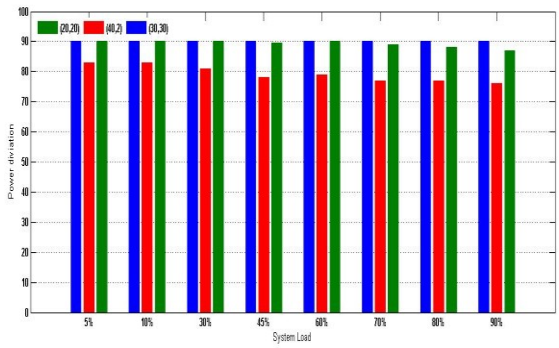


Fig. 6. Global Transfer Time as a function of power unitary cost for BPR, Max Power and Optimal policies



(a) BPR policy



(b) Optimal Policy

Fig. 7. Power Economy as a function of power unitary cost for BPR and Optimal policies

However, the power economy made in the optimal approach as compared to BPR tempers its benefits as we can see from figure 7, where the relative deviation between the total power in BPR (respectively in the Optimal policy) and the MAX Power policy is displayed as a function of power unitary cost. It is obvious that the optimal policy saves up much more power than the decentralized approach even in high load whereas the power economy in BPR withers slowly as load increases. Nevertheless, the slight discrepancy between the global transfer time in BPR and the Optimal policy which is the primary goal sought for and the low degree of system complexity of the decentralized approach makes it still an attractive solution.

VI. CONCLUSION

In this paper, the power levels are astutely set as part of the LTE Inter cell Interference coordination process. We proposed a game based on a semi distributed algorithm based on best power response to reach NEs in a time coherent with the RNTP signaling time. Numerical simulations assessed the good performances of the proposed approach in comparison with a policy that services active users with full power. More importantly, considerable power economy can be realized.

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