Joint User Association, Scheduling and Power control in Multi-Cell Networks

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***Abstract*—The emphasis of this paper is put on 5G multi-cell networks which are composed of dense and mutually interfering evolved NodeBs (eNBs) sharing the scarce radio resources. Consequently, greater focus is given to resource management techniques that take Inter-Cell Interference (ICI) into account, in particular to power control. Beside power control, this paper tackles also user association and scheduling. Despite the relevance of the addressed problem, it has remained largely unsolved, mainly due to its non-convex and combinatorial nature. We address this multifaceted challenge in a distributed fashion for reduced complexity.**

Keywords-ICIC; Game Theory; 5G.

I. INTRODUCTION

Orthogonal Frequency Division Multiple Access (OFDMA) allows assigning frequency sub-carriers to mobile users, in the downlink, within each cell in an orthogonal manner. However, when the same Resource Block (RB) is used in neighboring cells, interference may occur and degrade the channel quality perceived by the User Equipment (UE), especially those UEs at the cell edge as shown in Fig. 1.

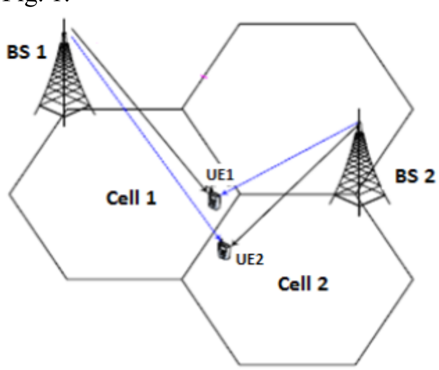


Figure 1. Cell-Edge Inter_Cell Interference.

Hence, efficient Inter-Cell Interference Coordination (ICIC) techniques [1] are considered among the key building blocks of 5G networks. In particular, ICIC through power control is an essential component to manage co-channel interference. Intelligent UE association, resource allocation, and interference management schemes are necessary to realize good performances and the interactions between these schemes have to be studied carefully because of their mutual dependence. In this paper, we propose a framework to study the joint UE association, scheduling and power allocation in a distributed fashion.

A. Related Work

In current OFDMA networks, several articles have tackled the issue of joint power control and UE association ([2]-[4]).The work in [2] formulates the joint serving cell selection and power allocation problem as an optimization task whose purpose is to maximize either the minimum user throughput or the multi-cell sum throughput. Heuristic solution approaches are proposed to solve these non-polynomial problems. In [3], a primal-dual infeasible interior point method has been applied to solve the problem of sum-rate maximization for the uplink. The original problem is solved in a two stage formulation by separating the UE association and power control variables and also by a single stage formulation where all variables are solved simultaneously. In [4], the authors propose algorithms based on local measurements and do not require coordination among the wireless devices. They focus on the optimization of transmit power and of user association. The method is applicable to both joint and separate optimizations. The global utility minimized is linked to potential delay fairness. The distributed algorithm adaptively updates the system parameters and achieves global optimality by measuring SINR and interference. The work in [5] investigates the problem of Cell selection and resource allocation in heterogeneous wireless networks, by proposing a distributed cell selection and resource allocation mechanism, in which this processes are performed by UE independently. The problem is formulated as a two-tier game named as inter-cell game and intra-cell game, respectively. In the first tier, UEs select the best cell according to an optimal cell selection strategy derived from the expected payoff. In the second tier, UEs choose the proper radio resource in the serving cell to achieve maximum payoff.

B. Our Contribution

In our work, we assume that proportional fairness among UEs boils down to time fairness as shown in section II and we solve the joint UE association and power control in a distributed fashion. Accordingly, the UE association and power control schemes are portrayed as non-cooperative games that can lead to a substantial complexity reduction. In our case, eNBs and UEs optimize their local parameters by making use of signaling messages already present in the networks. Notably, a fully distributed algorithm for the UE association scheme based on reinforcement learning will be applied by UEs to attain the Nash Equilibriums (NE) of the game. Decentralized schemes can adapt to fast changes of network state at the cost of reduced efficiency.

The rest of the paper is organized as follows. The network model is presented in Section II. Our approach is put forward in Section III. Our approach is detailed in Section IV where the decentralized power control allocation is given in Section IV-A, and the distributed UE association algorithm is highlighted in Section IV-B. Extensive simulations displayed in Section V prove the relevance of our devised schemes. Conclusion is given in Section VI.

II. THE NETWORK MODEL

We consider a cellular network covering a set of eNBs denoted by $J = \{1, \dots, |J|\}$ and a set of UEs denoted by $I = \{1, \dots, |I|\}$. In this paper, we limit our attention to the downlink channel with OFDMA. The time and frequency radio resources are grouped into time-frequency Resource Blocks (RBs) whose set is denoted by K. In particular, we denote by $K(j)$ the set of RBs used by eNB j.

We consider a saturation mode where each eNB has persistent traffic towards its UEs. Further, we assume that all RBs are assigned at each scheduling period to a given UE.

A. The Radio Model

The Signal-to-interference-plus-noise-ration (SINR) of UE i associated to eNB j and allocated RB k is given by:

$$\rho_{ijk} = \frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j' \neq j} \pi_{j'k} G_{ij'k}}. \tag{1}$$

Where π_{jk} is the downlink power devoted by eNB j to RB k, G_{ijk} is the channel power gain of UE i on RB k associated to eNB j, and N_0 is the noise power.

We assume that there is a mapping function *f( )* that maps ρ_{ijk} to its corresponding bit rate r_{ijk} (bit/s) realized by UE i associated with eNB j served on RB k, i.e., $r_{ijk}=f(\rho_{ijk})$.

B. The Utility Function Model

This paper considers the network utility maximization problem under proportional fairness, i.e., log-utility objective for the downlink of a wireless cellular network [6].

In view of that, we maximize $\sum_{i \in I} \log(r_i)$ where r_i is the mean bit rate of any UE i given by:

$$r_i = \sum_{j \in J} \theta_{ij} \alpha_{ij} \sum_{k \in K(j)} f(\rho_{ijk}), \tag{2}$$

with α_{ij} being the proportion of time that UE i is scheduled on the downlink by eNB j and θ_{ij} is the association variable given by what follows:

$$\theta_{ij} = \begin{cases} 1 \; if \; UE \; i \; is \; associated \; with \; eNB \; j \\ 0 \; otherwise. \end{cases} \tag{3}$$

We assume, in this paper, that the proportional fairness among UEs boils down to time fairness by assuming that the percentage of time UE i is served in eNB l is $\alpha_{il} = \frac{1}{|I(l)|}$, where *I(l)* is the set of UEs associated to eNB *l*.

Hence, the joint proportional fair scheduling, UE association and power control problem is as follows:

$$\underset{\theta,\pi}{\text{maximize}} \sum_{i \in I} \log(r_i) \tag{4a}$$

$$= \sum_{i \in I} log\left(\sum_{j \in J} \theta_{ij} \frac{1}{|I(j)|} \sum_{k \in K(j)} f(\rho_{ijk})\right)$$

subject to:

$$\sum_{j \in J} \theta_{ij} = 1, \forall i \in I, \tag{4b}$$

$$\sum_{k \in K(j)} \pi_{jk} \leq P_j^{max}, \forall j \in J, \tag{4c}$$

$$\theta_{ij} \in \{0,1\}, \forall i \in I, \forall j \in J, \tag{4d}$$

$$\pi_{jk} \geq P_j^{min}, \forall j \in J, \forall k \in K(j). \tag{4e}$$

Constraints (4c) guarantee that the total power does not surpass a given limit, and constraints (4e) give the minimum power allocated per RB.

Note that the utility function in (4a) can be re-written as:

$$U = \sum_{i \in I} log\left(\sum_{j \in J} \theta_{ij} \frac{1}{|I(j)|} \sum_{k \in K(j)} f(\rho_{ijk})\right) \tag{5a}$$

$$= \sum_{i \in I} \sum_{j \in J} \theta_{ij} \log\left(\frac{1}{|I(j)|} \sum_{k \in K(j)} f(\rho_{ijk})\right) \tag{5b}$$

$$= \sum_{i \in I} \sum_{j \in J} \theta_{ij} \log\left(\frac{1}{|I(j)|}\right) + \sum_{i \in I} \sum_{j \in J} \theta_{ij} \log(r_{ij}) \tag{5c}$$

Where $r_{ij} = \sum_{k \in K(j)} f(\rho_{ijk})$ is the mean bit rate obtained by UE i connected to eNB j.

In this paper, we consider that the function *f( )* is the identity function. Accordingly, the utility formulation is technology-agnostic: the mapping between the SINR and the throughput of each UE can be derived in respect to the appropriate modulation and coding scheme in wireless networks. Hence, optimizing the devised network utility leads inevitably to augmenting the UE throughput.

III. PROBLEM FORMULATION

The ensuing joint UE association and power control problem will be presented by what follows.
As $\alpha_{ij} = \frac{1}{|I(j)|} = \frac{1}{\sum_{i \in I(j)} \theta_{ij}}, \forall j \in J$, the utility function in (5) can be re-written such as:

$$U = \sum_{i \in I} \log\left(\sum_{j \in J} \frac{\theta_{ij}}{\sum_{i \in I(j)} \theta_{i'j}} \sum_{k \in K(j)} \rho_{ijk}\right) \quad (6)$$

As the θ_{ij} variables are binary and $\sum_{j \in J} \theta_{ij} = 1$ for all UEs, there exists only one eNB j for which $\theta_{ij} = 1$ ($\theta_{ij'} = 0, \forall j' \neq j \in J$). Hence, the utility function in (6) can be re-casted as:

$$U = \sum_{i \in I} \sum_{j \in J} \theta_{ij} \log\left(\frac{\sum_{k \in K(j)} \rho_{ijk}}{1 + \sum_{i' \neq i} \theta_{i'j}}\right) \quad (7)$$

Given Jensen's inequality and the concavity of the log function, we have:

$$\log\left(\frac{\sum_{k \in K(j)} \frac{\rho_{ijk}}{1+\sum_{i' \neq i} \theta_{i'j}}}{|K(j)|}\right) \geq \frac{\sum_{k \in K(j)} \log\left(\frac{\rho_{ijk}}{1+\sum_{i' \neq i} \theta_{i'j}}\right)}{|K(j)|}$$

Thus, the utility function can be re-casted as follows:

$$U = \sum_{i \in I} \sum_{j \in J} \theta_{ij} \log\left(\sum_{k \in K(j)} \frac{\rho_{ijk}}{1 + \sum_{i' \neq i} \theta_{i'j}}\right) \quad (8)$$
$$\geq \sum_{i \in I} \sum_{j \in J} \sum_{k \in K(j)} \log\left(\frac{\rho_{ijk}}{1 + \sum_{i' \neq i} \theta_{i'j}}\right)$$

We consider the upper bound on the utility function, denoted by $\overline{U}$:

$$\overline{U} = \sum_{i \in I} \sum_{j \in J} \sum_{k \in K(j)} \log\left(\frac{\rho_{ijk}}{1 + \sum_{i' \neq i} \theta_{i'j}}\right) \quad (9)$$

Henceforward, we adopt this newly defined utility function $\overline{U}$. The ensuing joint UE association and power control will be solved according to a fully distributed approach in section IV.

IV. DISTRIBUTED POWER CONTROL AND UE ASSOCIATION

We resort to a distributed power control scheme presented in Section IV-A and to a distributed UE association scheme presented in Section IV-B. In particular, in the distributed UE association scheme, a fully distributed algorithm based on reinforcement learning will be run by UEs.

A. Distributed Power Control

For the distributed power control scheme, eNBs are the decision makers of the game. We define a multi-player game G_{PC} between the $|J|$ eNBs. The eNBs are assumed to make their decisions without knowing the decisions of each other. The formulation of this non-cooperative game $G_{PC} = \langle J, S, U^{PC} \rangle$ can be described as follows:

- A finite set of eNBs $J=\{1,...,|J|\}$.
- For each eNB j, the space of pure strategies S_j is:
  $S_j = \left\{ \begin{array}{c} \vec{\pi}_j \in \mathbb{R}^{|K|} \text{such as} p_j^{min} \leq \pi_{jk} \\ \text{and} \sum_{k \in K(j)} \pi_{jk} \leq p_j^{max} \end{array} \right\}.$
  An action of an eNB j is the amount of power π_{jk} sent on RB k. The strategy chosen by eNB j is then $\vec{\pi}_j = (\pi_{j1}, \dots, \pi_{jk})$. 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 :
  $$U^{PC} = \left(U_1^{PC}(\pi), U_2^{PC}(\pi), \dots, U_{|J|}^{PC}(\pi)\right)$$
  that quantify players' utility for a given strategy profile π where the utility function of any eNB j is given by:

$$U_j^{PC} = \sum_{k \in K(j), i \in I(j)} \log\left(\frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j' \neq j} \pi_{j'k} G_{ij'k}}\right) \quad (10)$$
$$= |I(j)| \sum_{k \in K(j)} \log(\pi_{jk}) + \sum_{k \in K(j), i \in I(j)} \log\left(\frac{G_{ijk}}{N_0 + \sum_{j' \neq j} \pi_{j'k} G_{ij'k}}\right)$$

For every j, U_j^{PC} is concave w.r.t. π_j and continuous w.r.t. $\pi_l, l \neq j$. Hence, a NE exists [7].
Note that we are only interested in the first part of the utility function that we call $U_j^{\overline{PC}}$ (the second part being independent of π_j) and given by what follows:

$$U_j^{\overline{PC}} = |I(j)| \sum_{k \in K(j)} \log(\pi_{jk}) = |I(j)| \log \prod_{k \in K(j)} \pi_{jk}$$

Consequently, the NE is the solution of the following optimization problem:

$$\underset{\theta}{\text{maximize}}\ U_j^{\overline{PC}}(\pi_j) = \log \prod_{k \in K(j)} \pi_{jk} \quad (11a)$$

$$\text{subject to:} \quad \sum_{k \in K(j)} \pi_{jk} \leq P_j^{max}, \quad (11b)$$

$$\pi_{jk} \geq P_j^{min}, \forall k \in K(j). \quad (11c)$$

As the utility function is strictly increasing, constraint (11 b) boils down to $\sum_{k\in K(j)} \pi_{jk} = P_j^{max}$. Since we need to maximize a product of variables whose sum is constant, the highest possible value for these variables π_{jk} is attained when they get the same value and hence $K \times \pi_{jk} = P_j^{max}$. Finally, owing to constraints (11c), the optimal power allocation is:

$$\pi_{jk} = \max\left(\frac{P_j^{max}}{K}, P_j^{min}\right), \forall k \in K(j)$$

B. Distributed UE Association

We also propose to solve the distributed UE association problem by having recourse to non-cooperative game theory. Non-Cooperative game theory models the interactions between players competing for a common resource. Hence, it is well adapted to model the eNB selection by selfish UEs. We define a multiplayer game G_{UA} between the $|I|$ UEs, assumed to make their decisions without knowing the decisions of each other.

The formulation of this non-cooperative game G_{UA} $=\langle I, S, U^{UA}\rangle$ can be described as follows:

- A finite set of UEs $I=\{1,...,|I|\}$.
- The space of pure strategies S formed by the Cartesian product of each set of pure strategies $S = S_1 \times S_2 \times ... \times S_{|I|}$, where the strategy space of any UE i is $S_i = \left\{eNB_j^i, eNB_{j'}^i\right\}$ with $j, j' \in J$.
  - If the UE i is finally associated with eNB_j^i (this is an outcome of the pure strategies played by UE i), then $\theta_{ij} = 1$, else $\theta_{ij'} = 1$.
  - We denote by $a_i \in S_i$ the action taken by UE i.
- A set of utility functions
  $$U^{UA} = \left(U_1^{UA}(\theta), U_2^{UA}(\theta), ..., U_{|I|}^{UA}(\theta)\right)$$
  That quantify UEs' utility for a given strategy profile θ, where the utility function of any UE i is given by:

$$U^{\mathrm{UA}} = \sum_{j\in J}\sum_{k\in K} \theta_{ij} \log\left(\frac{\rho_{ijk}}{1+\sum_{i'\neq i}\theta_{i'j}}\right) \quad (12)$$

  Note that interestingly, the utility depends of the outcome implied by the action taken by each individual UE. Then, we have $U_i(\boldsymbol{a})$, where $\boldsymbol{a} = (a_1, ..., a_I)$ is the action vector of all UEs.

The game G_{UA} is an unweighted crowding game as it is a normal-form game in which the UEs share a common set of actions and the payoff a particular UE i receives for choosing a particular action (selecting one of the available eNBs) is player specific and a non-increasing function of the total number of UEs choosing that same action. Unweighted crowding games have PNE (Pure NE).

Furthermore, when players have only two strategies (choosing between eNB_j^i and $eNB_{j'}^i$ for any UE i), the game has the Finite Improvement Path (FIP[1]) Property.

1) *Sub-strategic congestion games:* we consider a game with $|I| = n$ players that share a common set of R strategies. This game is very specific as for each strategy $r \in R$ there exists a set of sub-strategies $J(r)$. Each player determines a strategy $r \in R$ but its payoff depends on the sub-strategies of all players. The sub-strategy of player i, which is the action taken by each player, is a result of a mapping $a_i(r) \in \{1, ..., J(r)\}$from the common strategy set R to the sub-strategies set $J(r)$ for a given strategy r. In our context, the strategy is the choice of the two best detected eNBs and the sub strategy is the specific eNB to be associated with. Then, the mapping function is the best eNB decision process. A vector of strategy $\sigma = (\sigma_1, ..., \sigma_n)$ is a Nash Equilibrium if for all player i and strategy r:

$$U_{i\sigma_i}\left(n_{a_i(\sigma_i)}\right) \geq U_{ir}\left(n_{a_i(r)}+1\right),$$

where for all strategy r, for all sub-strategy $j \in J(r)$ we have:$n_j = |\{1 \leq i \leq n | a_i(\sigma_i) = j\}|$ is the number of players that take the sub-strategy j.

2) The Learning-based algorithm: we demote by P_i the mixed strategy which gives the probability that UE i selects eNB_j^i , i.e. $p_i = \mathbb{P}(a_i = eNB_j^i)$. We describe a Reinforcement Learning (RL) algorithm [10] in algorithm 1 that convergence of the algorithm is ensured by the existence of a potential function as the game possesses the FIP property [8].We present in Fig.2 the flowchart of the RL algorithm.

Algorithm 1 RL algorithm for UE Association

1) Initialization: set t=0 and each UE i defines a probability $p_i^j(0)$.
2) Each UE determines an initial action $a_i(t)$. Then, we get the action vector $\boldsymbol{a}(t) = \left(a_1(t), ..., a_{|I|}(t)\right)$.
3) Each UE i determines its eNB j depending on its own action $a_i(t)$and receives its utility $U_i(t) = U_i(\boldsymbol{a}(t))$.
4) Each UE i normalizes its utility as $\overline{U}_i(t) \coloneqq \frac{U_i(t)}{U_i^{max}}$, where U_i^{max} is the maximal utility realized by UE i.
5) Each UE i updates its decision probability as:
$$p_i^j(t+1) = p_i^j(t) + \frac{1}{t}\left(\mathbb{1}_{a_i(t)=eNB_j^i} - p_i^j(t)\right)\widetilde{U}_i(t).$$
6) Set $t \leftarrow t+1$ and go to step 2 (until satisfying termination criterion).

[1]A path is any sequence of strategy profiles in which each strategy profile differs from the preceding one in only one coordinate. When the unique player that deviates in each step strictly decreases its cost, the path is called an improvement path. Hence, an improvement path is generated by myopic players. A finite congestion game has the finite improvement path property (FIP) if every improvement path is finite [9].

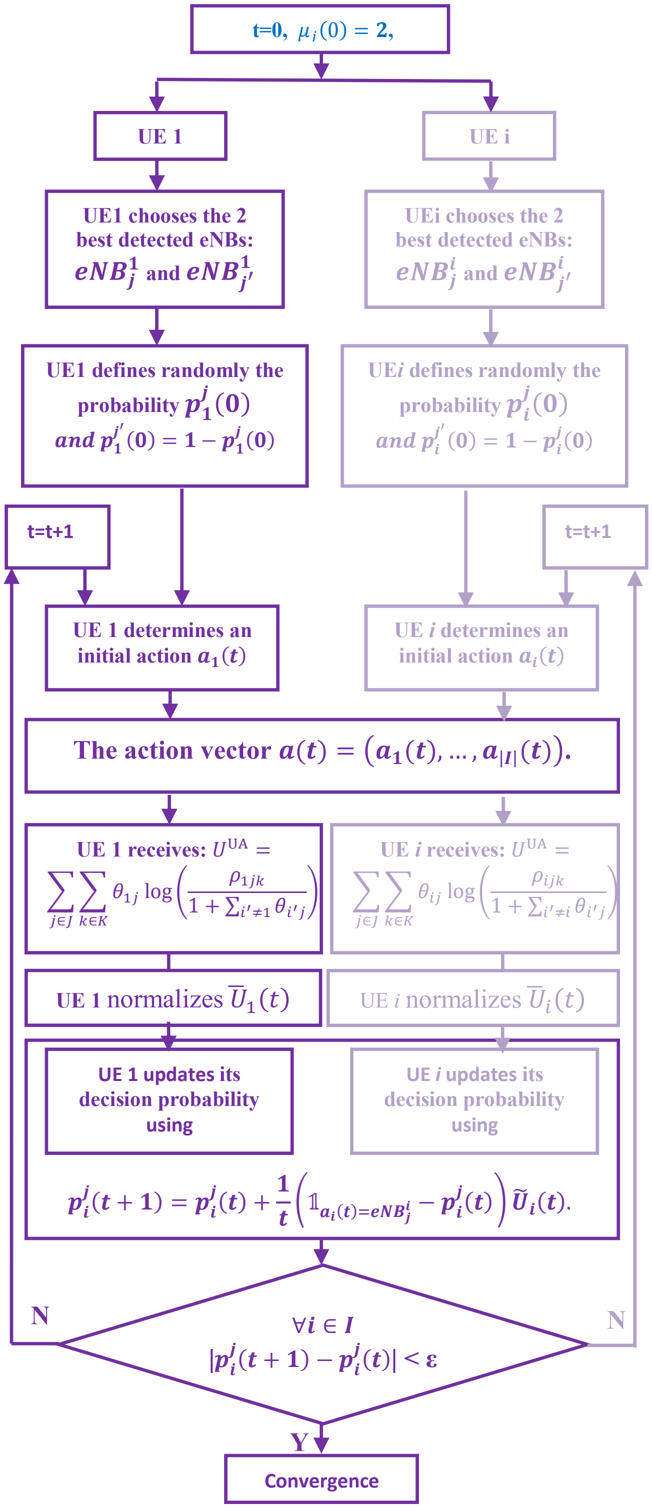


Figure 2. Flowchart of the RL algorithm.

3) The semi-distributed association algorithm: furthermore, we use the work in [11] as a reliable comparison for our work. In fact, the work in [11] turns to the Lagrangian dual decomposition method whereby a Lagrange multiplier μ is introduced to solve the UE association problem. The resolution gives a compound algorithm, described in algorithm 2, operated on both UE and BSs and necessitating weighty signaling among them. We deem the latter scheme semi-distributed UE Association and use it as a benchmark for the distributed UE Association. We present in Fig.3 the flowchart of the Semi-distributed algorithm.

Algorithm 2 Semi-distributed UE Association

Initialization: set t=0 and $\mu_j(0), \forall j\in J$ equals to some non negative value.

1) Each UE $i\in I$ determines eNB j^* which satisfies what follows:

$$j^* = \arg\max_j\left(\sum_{k\in K(j)}\log(\rho_{ijk})-\mu_j(t)\right)$$

2) Each eNB updates the value of n_j and μ_j and announces the latter to the system, according to the following steps:

a) The value of n_j is updated as follows:

$$n_j(t+1)=\exp\mu_j(t)-1$$

b) The Lagrange prices are updated as follows:

$$\mu_j(t+1)=\mu_j(t)-\delta(t).\left(n_j(t)-\sum_{i\in I}\theta_{ij}\right)$$

Where $\delta(t)$ is a suitably small step size

3) set $t\leftarrow t+1$ and go to step 1 (until satisfying termination criterion).

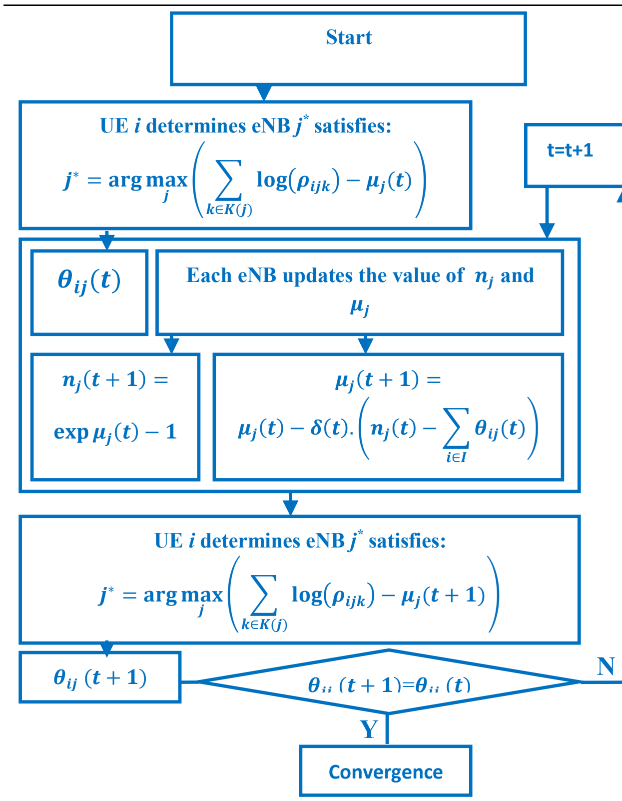


Figure 3. Flowchart of the Semi-distributed algorithm.

V. PERFORMANCE EVALUATION

We consider a bandwidth of 5 MHz with 25 RBs in a network of 9 hexagonal cells and a number of UE ranging from 4 to 14 per eNB uniformly distributed in any cell. Further, we consider the following parameters listed in the 3GPP technical specifications TS 36.942: the mean antenna gain in urban zones is 12 dBi (900 MHz). Transmission power is 43 dBm (according to TS 36.814) which corresponds to 20 Watts (on the downlink). The eNBs have a frequency reuse of 1, with W = 180 KHz. As for noise, we consider the following: user noise figure 7.0 dB, thermal noise -104.5 dBm which gives a receiver noise floor of P_N =-97.5 dBm.

We begin by comparing the global performance of our distributed association scheme and the semi-distributed association scheme given in Section IV-B and the one-shot distributed power control scheme given in section IV-A. We run 25 simulations for each scenario and we portray in Fig.4 the total rate using the Shannon capacity:

$$\sum_{i\in I}\sum_{j\in J}\sum_{k\in K(j)}\frac{\theta_{ij}}{1+\sum_{i'\neq i}\theta_{i'j}}W|K|\,log_2\left(1+\rho_{ijk}\right)$$

We can see in Fig.4 the low discrepancy between the total mean rate realized by the semi-distributed UE association and the distributed UE association, running according to the reinforcement algorithm 1. Hence, to distinguish the performance of these two UE Association schemes, we need to assess the complexity of the both algorithms.

The dual algorithm of the semi-distributed UE association provides sub-optimal performances with relatively high complexity: at each iteration, each eNB j broadcasts its μ_j, and each UE reports its association to the selected eNB. Hence, the amount of information to be exchanged is s.(|J|+|I|), where s is the mean number of iteration displayed in Fig.5. This amounts to approximately 120 messages exchanged for a dozen of UEs per eNB.

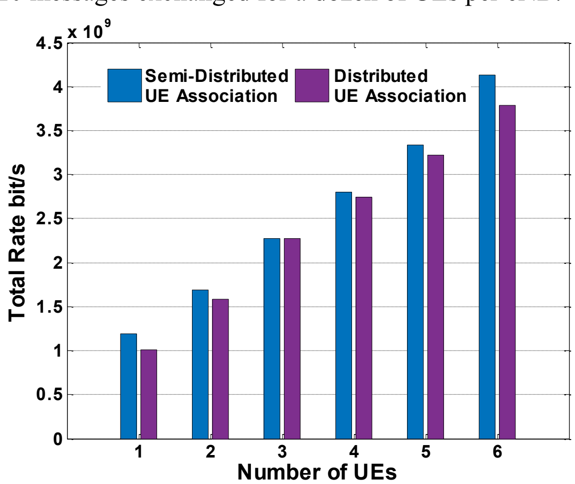


Figure 4. Performance evaluation of Distributed UE Association scheme vs Semi-distributed UE Association scheme

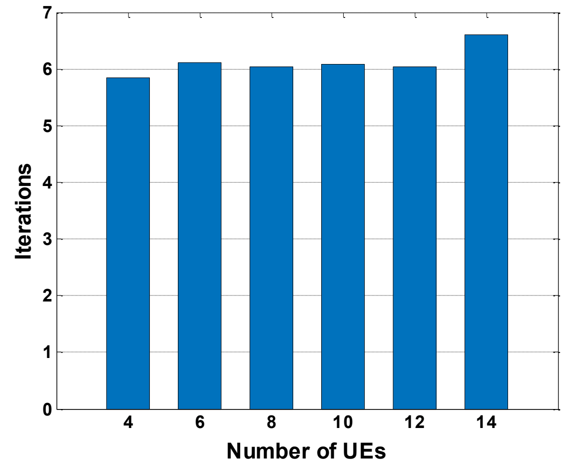


Figure 5. Convergence time of Semi-distributed UE Association scheme

In Fig.6, we display the convergence time to NE for the *distributed UE Association* algorithm. Even though the mean number of iterations until convergence for the distributed scheme is relatively high in comparison with the semi-distributed scheme, it remains reasonably low as shown in Fig.6 (a).

Furthermore, we depict in Fig.6 (b), the probabilities (pi, 1 − pi) for $i \in I$as a function of the number of iterations for 5 UEs chosen randomly among the 10 UEs attached to a given eNB (eNB 3 in the considered scenario). We can see that the UEs strategies converge to either 0 or 1 opting for one single BS among the 2 best received eNBs.

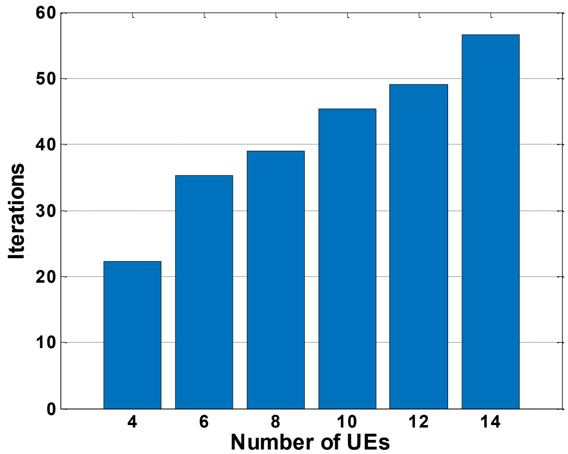
More importantly, we see that the convergence is relatively fast at the beginning of the algorithm but slows after a dozen of iterations.

Hence, the eNB that will be ultimately selected by any UE is clearly designated (around 3 iterations in the displayed results and after a mean of 5 iterations for the considered scenario) much earlier before convergence (a mean of 43 iterations). We recorded this behavior through the extensive simulations we performed.

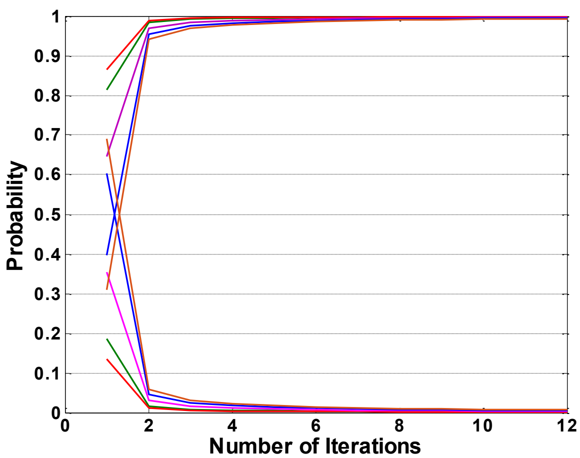
Thus, the performances of both UE association schemes are equivalent in terms of convergence time and mean rate which is a definite argument in favor of the *distributed UE Association* algorithm. The latter relies only on signaling already present in wireless networks. In fact, a serviced UE measures its channel quality based on pilots, i.e. Cell Specific Reference Signals (CRS) that are spread across the whole band and enables the UE to infer its SINR on each attributed RBs.In the semi-distributed scheme, the SINR values (actually the CQI (Channel Quality Indicator) values) need to be sent repeatedly from UEs to eNBs which incurs delays and erroneous estimations.

VI. CONCLUSION

The resource and power allocation problem is a challenging problem for present and future wireless networks.



(a) Mean Convergence Time



(b) Strategy Updates

Figure 6. Convergence time of Distributed UE Association scheme

Several papers tackle this arduous task but rarely in a multi-cell network that accounts for the harmful impact of interference. In this work, we formulate the joint multi-cell scheduling, UE association and power allocation problem for OFDMA-based networks, where the objective is to maximize system throughput while guaranteeing fairness among UEs. The joint problem is then decomposed and addressed in a distributed fashion by means of non-cooperative game theory. Extensive simulation results prove the significance of the devised scheme. In particular, we note that the distributed schemes combine a low degree of system complexity and good performances.

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