This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TMC.2014.2329835, IEEE Transactions on Mobile Computing

An Operations Research Game Approach for Resource and Power Allocation in Cooperative Femtocell Networks

Rami Langar, *Member IEEE*, Stefano Secci, *Member IEEE*, Raouf Boutaba, *Fellow IEEE*, Guy Pujolle, *Senior Member IEEE*

Abstract—Femtocells are emerging as a key technology to improve coverage and network capacity in indoor environments. When femtocells use different frequency bands than macrocells (i.e., split-spectrum approach), femto-to-femto interference remains the major issue. In particular, congestion cases in which femtocell demands exceed the available resources raise several challenging questions: how much a femtocell can demand? how much it can obtain? and how this shall depend on the interference with its neighbors? Strategic interference management between femtocells via power control and resource allocation mechanisms is needed to avoid performance degradation during congestion cases. In this paper, we model the resource and power allocation problem as an operations research game, where imputations are deduced from cooperative game theory, namely the Shapley value and the Nucleolus, using utility components results of partial optimizations. Based on these evaluations, users' demands are first rescaled to strategically justified values. Then, a power-level and throughput optimization using the rescaled demands is conducted. The performance of the developed solutions is analyzed and extensive simulation results are presented to illustrate their potential advantages. In particular, we show that the Shapley value solution with power control offers the overall best performance in terms of throughput, fairness, spectrum spatial reuse, and transmit power, with a slightly higher time complexity compared to alternative solutions.

Index Terms—Femtocell networks, resource allocation, power control, Nucleolus, Shapley value, Operations Research Game.

1 INTRODUCTION

FEMTOCELLS have recently emerged as a promising technology to enable broadband connectivity in mobile access networks. Instead of redimensioning macrocells at the base station level, the modular installation of low-cost and low-power user-deployed units can provide multiple benefits. Indeed, it is expected that femtocells will enhance coverage indoors, deliver higher throughputs and off-load traffic from existing macro-cellular networks [2]. However, the deployment of Femtocell Access Points (FAPs) raises several technical issues among which interference management remains the most challenging. Interferences can occur with the macrocells as well as with neighboring FAPs, especially in suburban and urban environments.

Under certain design choices, crosslayer interference with the macrocell is manageable (by adopting a split-spectrum approach as in [8]–[12], [16]–[19], [40], [41]), while co-layer interference among FAPs requires collaboration among neighboring cells. We can refer to this as collaborative femtocell networks since coordination or cooperation mechanisms are needed between independent femtocells to manage reciprocal interferences, power levels and resource allocation. The independence of FAPs resides in the fact that the installation of a FAP for residential or enterprise usage is expected to be subject to separate billing, while the opportunistic behavior can be motivated by the attempt of each FAP to satisfy its users, by acquiring the maximum number of resources with maximum power. Therefore, inter-femto resource and power allocation needs to be managed via collaborative approaches that have as motivation the performance improvement for all the participating FAPs. Instead of unilaterally competing to access the radio resources, dissipating energy to provide higher speed communication to users, FAPs can cooperate under binding agreements in order to reduce interferences in a strategically acceptable way.

This scenario raises a number of strategic questions: how much a femtocell can demand? how much it can obtain? and how this shall depend on the interference with its neighbors?

To answer these questions, we propose a game-theoretic approach for strategic resource and power allocation in collaborative femtocell networks. This is especially needed in urban environments, with a high density of FAPs, and where femtocells have different levels of interference and resource demands, and the overall demand exceeds the available bandwidth. We

- *Manuscript received March 25, 2013; revised April 4, 2014; accepted May 23, 2014; approved by IEEE Transactions on Mobile Computing.*
- *R. Langar, S. Secci and G. Pujolle are with the LIP6, University of Pierre and Marie Curie, Paris 75005, France (E-mails: rami.langar@lip6.fr; stefano.secci@lip6.fr; guy.pujolle@lip6.fr).*
- *R. Boutaba is with the School of Computer Science, University of Waterloo, ON, N2L3G1 Canada (E-mail: rboutaba@uwaterloo.ca).*
- *A preliminary version of this paper appeared in the proceedings of the 2013 IEEE International Conference on Communications (ICC 2013) [1].*

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TMC.2014.2329835, IEEE Transactions on Mobile Computing

formulate the problem as an operations research (OR) game in which the FAPs are modeled as players evaluating strategic coalitions between them, so as to find power levels that maximize users' throughput and control interference. Based on these evaluations, users' demands are rescaled to strategically justified values. Finally, a power-level and throughput optimization using the rescaled demands is conducted. We evaluate game imputations based on two possible cooperative game theory methods, the Shapley value [3] and the Nucleolus [4]. The performance of the developed solutions is analyzed and extensive simulation results are presented to illustrate their potential advantages. In particular, we show that the Shapley value solution with power control offers the overall best performance in terms of throughput, fairness, spectrum spatial reuse, and transmit power, with a slightly higher time complexity compared to alternative solutions.

In summary, our key contributions are the following:

- We formulate the resource and power allocation (RPA) problem in femtocell networks as a Mixed Integer Linear Program (MILP).
- We tackle the problem of co-tier interference using a cooperative game theoretic approach, by formulating a coalitional game in which FAPs are the players. According to existing literature [5], we refer to the game as an OR game because the worth $v(S)$ of a given coalition S is obtained by solving an Operation Research problem (i.e., the formulated MILP problem).
- We compare our approach with several existing solutions and discuss the associated gains.

The reminder of this paper is organized as follows. Section 2 presents an overview of related works. In Section 3, we describe the context of our work and formulate the problem as an OR game approach. Section 4 presents our proposed game-theoretic approach, followed by a discussion of simulation results in Section 5. Finally, Section 6 concludes this paper.

2 Related Work

Interference management using power control has been extensively studied in the literature. [6], [7] are seminal works in this field. The general objective is the computation of efficient resource and transmit power allocation, while accounting for wireless node interference. In the following, we discuss a selection of relevant approaches in femtocell networks: centralized ones, distributed ones, semi-centralized or hybrid ones and game theoretical ones.

2.1 Centralized, distributed and hybrid approaches

In the context of femtocell networks, some existing works [8]–[12] investigated the resource management using dynamic policies for frequency assignment. However, to achieve efficient resource allocation and spatial reuse, power control strategies need to be applied as well.

To this end, authors in [13] proposed a decentralized strategy to allocate Resource Blocks (RBs) and regulate femtocell's transmit powers depending on their distance from the underlying macrocell. In this case, distance information should be exchanged between femtocells and macrocells to calculate the minimum and maximum power allowed for transmission.

In [14], authors provide a link quality protection algorithm in two-tier femtocell networks. They progressively reduce the signal-to-interference-plus-noise ratio (SINR) targets at strong femtocell interferers when a cellular user is unable to meet its SINR target. First, the radio link quality for a cellular user is determined with a set of N transmitting femtocells having different SINR targets. Then, femtocell data rates are determined when users perform utility-based SINR adaptation; providing link quality protection to an active cellular user may necessitate femtocells to deliberately lower their SINR targets. The main problem here is that achieving higher SINR targets in one tier limits the highest SINRs obtainable in the other tier because of near-far effects caused by the asymmetric positions of interfering users with respect to nearby base stations.

Authors in [15] study the power loading and resource allocation problem. They propose a water filling algorithm to mitigate interference from femtocells toward macrocells, but give higher priority to macrocells, which may results in a fairness problem and a femto user service degradation, especially with the increasing number of indoor femtocell users and their high bandwidth demand.

Authors in [16] propose an inter-cell interference coordination scheme to alleviate and prevent excessive interference, especially for cell-edge users. The scheme consists of two separate algorithms; one is located at the FAP, the other at a central controller. In the first step, users send channel state information (CSI) to their serving FAP indicating information on the most dominant interference. Then, based on the channel condition and the users demand, the FAP prepares a utility matrix and iteratively applies the Hungarian algorithm to find RBs restriction requests for each of its interfering neighbors. This restriction request list is then forwarded to the central entity, which resolves the conflicting requests and sends back to each scheduler the list of RBs to be restricted. This process is reiterated each predefined time interval. This centralized approach can be counterproductive since it does not take into account independent and autonomous FAPs assumptions.

In [17], [18], authors propose a decentralized model for the allocation of a modulation and coding scheme (MCS), subchannels, and transmit power to femto users. The resolution algorithm is divided into two subproblems, where RBs are assigned so as to minimize the sum of transmit power using a network simplex algorithm on a chosen MCS. This approach provides a notable running time improvement over the centralized one. However, it comes at the expense of a loss in solution quality.

A hybrid centralized/distributed approach is proposed in [19], in which the authors exploit cooperation among neighboring femtocells and improve resource allocation and throughput satisfaction via power optimization. First, femtocells are grouped in a distributed fashion into disjoint clusters with respect to interference maps. Then, within each cluster, a joint resource and power allocation is centralized at a cluster-head that periodically optimizes the throughput satisfaction.

The above-described approaches do not take into account the assumption of independent and autonomous network nodes, which may lead to counter-productive results in the framework of our work.

2.2 Game-theoretic approaches

Recently, there has been significant interest in applying game theory to the analysis of collaborative communication networks, with the aim to identify rational strategic solutions for multiple decision-maker situations. As opposed to mono-decision maker problems, which can be solved with centralized approaches, game-theoretic solutions adopt a multi-agent approach to account for different objective functions and/or counter objections to rationally non justified solutions [20]. When the collaboration among network agents does not imply binding agreements and need just coordination, non-cooperative game theory can identify strategic solutions as a function of various types of game equilibria [21]. Some proposals in this direction are [22]–[26], where each user chooses its own transmit power level and attempts to maximize its utility function. The proposed games settle at a stable and predictable state, called the Nash equilibrium (NE), at which no user has any incentive to unilaterally change its power level. For femtocell networks, power control games are also formulated and analyzed in [27]–[31]. Although the achieved NE gives a steady operating point, it is not guaranteed to be Pareto-efficient. A number of pricing schemes are adopted in [32]–[36] to improve the efficiency of the NE.

When instead binding agreements are required to motivate cooperation, cooperative game theory allows solutions with the desirable properties of efficiency and rationality [37]. Specifically, authors in [38] show how node cooperation can improve system performance; in particular, they study the effectiveness of transmitter and receiver cooperation, in wireless networks, from a coalitional game theory perspective. Similarly, the authors in [39] study the spectrum sharing problem in wireless networks as a dynamic coalition formation game in which interferer wireless links self-organize to reach stable coalition structures. Our previous work in [40] presents a game theoretic approach for resource allocation in cooperative femtocell networks. In this approach, resource allocation is modeled as a Bankruptcy game between interferer femtocells. However, it does not take into account transmit power allocation on the selected RBs. Furthermore, authors in [41] model the femtocell spectrum sharing problem as a coalitional game in partition function form using an utility function that captures the costs in terms of transmit power. This approach enables femtocells to form partitions inside which co-tier interference is suppressed using interference alignment. However, it does not take into account users' cheating behavior (i.e., users demand more resources than what they really need) since FAPs could end up with higher allocations if they claim higher demand.

Adopting the same femtocell cooperation assumptions and requirements as in [40], in this paper, we model the OFDMA resource and power allocation problem in femtocell networks as a cooperative game. However, rather than partitioning the femtocell network topology in disjoint clusters as in [19] and [41], we allow femtocells to negotiate both resources and transmit powers in multiple femtocell groups, where groups are locally detected as function of interferer femtocell neighbors. Hence, we target a solution in which the joint resource and transmit power allocation is periodically pre-computed based on changing femtocell resource demands and interference maps. In particular, we consider dense environment situations in which the overall demands is quite often higher than the available resources. As detailed in the following, we investigate two solution concepts: the well-known Shapley value [3] (already adopted in a variety of situations in networking such as inter-domain routing [42] and network security [43]); and the less-known Nucleolus [4] (used, for instance, in strategic transmission computation [44] [45]).

3 Context and Problem Formulation

We consider an OFDMA (e.g., LTE) femtocell's network consisting of several FAPs representing residential or enterprise networks. In such system, the frame structure relies on time-frequency RBs, also called tiles[1]. In our study, we focus on co-layer interference mitigation as in [8]–[11], [16]–[19], [40], [41], and we study the case of downlink communications. Each FAP serves a number of users. User demands represent the required bandwidth (TP_u^{req}), then expressed in number of required tiles (d_u^n), as follows.

$$d_u^n = \lceil \frac{TP_u^{req}}{\psi \cdot eff_u} \rceil \quad (1)$$

Where $\psi = (SC_{ofdm} \cdot SY_{ofdm})/T_{subframe}$ is a fixed parameter that depends on the network configuration, SC_{ofdm} and SY_{ofdm} are the numbers of subcarriers and symbols per tile, respectively, and $T_{subframe}$ is the frame duration in time units. In LTE specification [46], $SC_{ofdm} = 12$, $SY_{ofdm} = 7$, and $T_{subframe} = 0.5\ ms$. The

1. A tile is the smallest unit of resource that can be assigned to a user and corresponds to 0.5 ms and 180 KHz frequency band.

parameter eff_u is the efficiency (bits/symbol) of the used modulation and coding scheme.

As already mentioned, in urban dense environment, we expect that the overall demand of femtocells is often higher than the available resources. Therefore, our objective is to find, for such congestion situations, a strategic resource and power allocation that satisfies throughput expectations while controlling the interference between femto-femto users. In the following, we first present notations used in our analysis, then we present the corresponding (mono decision-maker) optimization problem, and finally describe our Operations Research game modeling along with the possible imputation schemes in cooperative game theory.

3.1 Notations

- $\mathcal{F} = \{F_1, ..., F_N\}$ is the set of FAPs, where N is the total number of femtocells deployed in the network.
- $\mathcal{I}_n$ denotes the interference set of $F_n \in \mathcal{F}$, which corresponds to the set of femtocells composed of F_n and the femtocells causing interference to users attached to F_n. Note that interference is not symmetric since it depends on user positions.
- $\mathcal{U}_n$ is the set of users attached to the FAP F_n.
- d_u^n denotes the demand of user $u \in \mathcal{U}_n$.
- $D_n = \sum_{u \in \mathcal{U}_n} d_u^n$ denotes the demand of the FAP F_n.
- $\mathcal{K} = \{1, ..., K\}$ is the set of available tiles.
- $\Delta_{n,u}^k$ is the binary resource allocation variable for user $u \in \mathcal{U}_n$, which is set to 1 if the tile k is used, and 0 otherwise.
- $P_{n,u}^k$ is the transmit power allocated from FAP F_n to its user u on tile k, where $P_{n,u}^k \geq P_{min}$ if the tile k is used by user u, or $P_{n,u}^k = 0$ otherwise.
- P_{min} is the minimum required transmit power per tile for a successful transmission.
- P_{max} is the total power constraint per FAP.
- $\Gamma_{u,k}$ is the required SINR for user u on tile k.

3.2 Related Optimization Problem

For the sake of comparison with common resource and power allocation (RPA) approaches, between *non-independent* femtocell networks, let us first show how RPA could be formulated as a mono decision-maker optimization problem, i.e., a Mixed Integer Linear Program (MILP) as in the QP-FCRA approach [19] mentioned in Section 2.

If femtocells are not independent, a centralized node (i.e., the cluster-head in the case of QP-FCRA) may solve the RPA problem as shown in the following Problem 1.

In this problem, $pl(u,n)$ denotes the path loss between user u and its FAP F_n, $w_{u,k} = \sum_{m \neq n} P_{m,u'}^k / pl(u,m)$ represents the interference suffered by user u on the tile k, and σ is the noise density. Note that in our case, the path loss is modeled based on A1-type generalized path loss models in the frequency range 2−6 GHz developed in WINNER [47].

Problem 1 RPA problem formulation

$$\min \sum_{F_n \in \mathcal{F}} \sum_{u \in \mathcal{U}_n} \sum_{k=1}^{K} \alpha \ P_{n,u}^k - (1-\alpha)\Delta_{n,u}^k$$

subject to:

$$(a)\ \forall k,\ \forall F_n \in \mathcal{F},\ \forall u \in \mathcal{U}_n :$$
$$P_{n,u}^k \geq \Gamma_{u,k} \times pl(u,n) \times (\sum_{m \neq n} P_{m,u'}^k / pl(u,m) + \sigma^2)$$
$$-(1-\Delta_{n,u}^k) \times M \times P_{max}.$$
$$(b)\ \forall k,\ \forall F_n \in \mathcal{F},\ \forall\ u, v \in \mathcal{U}_n : \Delta_{n,u}^k + \Delta_{n,v}^k \leq 1$$
$$(c)\ \forall F_n \in \mathcal{F},\ \forall u \in \mathcal{U}_n :\ \sum_{k=1}^{K} \Delta_{n,u}^k \leq d_u^n$$
$$(d)\ \forall F_n \in \mathcal{F} :\ \sum_{u \in \mathcal{U}_n} \sum_{k=1}^{K} P_{n,u}^k \leq P_{max}$$
$$(e)\ \forall k,\ \forall F_n \in \mathcal{F},\ \forall u \in \mathcal{U}_n :\ P_{n,u}^k \geq \Delta_{n,u}^k \times P_{min}$$
$$(f)\ \forall k,\ \forall F_n \in \mathcal{F},\ \forall u \in \mathcal{U}_n :\ \Delta_{n,u}^k \in \{0,1\}$$

Condition (a) denotes that the transmit power on tile k should guarantee the required SINR. The second term on the right hand of the inequality ensures that $P_{n,u}^k = 0$ if $\Delta_{n,u}^k = 0$, where M is a carefully chosen very high value. If the tile is in use ($\Delta_{n,u}^k = 1$), then the second part of the inequality turns to zero and the $P_{n,u}^k$ gets the required value. Condition (b) ensures that two users attached to the same FAP cannot use the same tile. Condition (c) indicates that a user can not obtain more than what he demands. Conditions (d) and (e) refer to the power constraints, and finally condition (f) indicates that $\Delta_{n,u}^k$ is a binary variable.

Later, we compare our proposal to such semi-centralized QP-FCRA solution [19], and to a totally distributed approach, as in DRAPM [17], as well as to the legacy cooperative game without variable transmission power levels [40], arising the interest in developing strategic approaches to solve the RPA problem. It is worth noting that QP-FCRA is used as baseline for comparison since Problem 1 is NP-hard, hence a complete centralized solution is not possible.

3.3 Operations Research Game Modeling

As mentioned earlier, in urban environments, a dense deployment of femtocells is expected, so that situations in which the overall resource claim (i.e., sum of the demands) overcomes the amount of available tiles (K) in the shared spectrum. In such situations, we cannot ensure that the resource assignment (i.e., tiles as well as the corresponding transmit power allocation), while resolving the above RPA problem in a totally distributed fashion (as in [17], [18]), or in a centralized fashion (as in [19]), is strategically done, and that users are faithfully and equally treated. More clearly, distributed approaches exclude any form of coordination and would favor opportunistic and cheating behaviors that other FAPs can not control (e.g., femtocell claims higher demands than what is really needed). On the other hand, centralized approaches risk to generate enormous signaling for large interference sets (likely in dense environments).

This suggests to resolve the RPA problem via collaboration among neighboring femtocells, under an adequate binding agreement fixing common rules on shared information and allocation scheme.

Assuming that femtocells belonging to the same interference set, share information about respective demands, the interaction can be modeled as a cooperative game with transferable utility (TU). The choice of the game characteristic function, representing the profit attributed to each coalition of players in a canonical coalitional game, is important. We stay under the assumption that a coalition S of FAPs, within the same given interference set $\mathcal{I}_n$, group apart so as to decide among themselves how to share the spectrum in the worst-case scenario of cooperation. That is, they will be able to share all the available resources (tiles) while FAPs outside S (i.e., the FAPs in $\mathcal{I}_n \backslash S$) that do not cooperate use the maximum allowed power P_{max} to satisfy at maximum their users. This prevents the use of some resources within the given coalition S.

Hence, $\forall S \subseteq \mathcal{I}_n$, we define the worth $v(S)$ reflecting the available resources when FAPs form the coalition S, as follows.

$$v(S) = max\Big(0,\ |S| \times K - \sum_{F_n \in S} \sum_{u \in \mathcal{U}_n} x_u^n\Big) \qquad (2)$$

where the first term (i.e., $|S| \times K$) represents the available resources that can be reused within the coalition S in the most favorable case (interference-free scenario). The second term (i.e., $\sum x_u^n = \sum \left(d_u^n - \sum_{k=1}^{K} \Delta_{n,u}^k\right)$) indicates the resources that are not available for user u due to the use of the maximum transmit power of neighboring FAPs outside the coalition S (i.e., worst-case scenario of cooperation).

Our aim is thus to maximize the worth $v(S)$, which corresponds to minimize the unavailable resources (i.e., $\sum x_u^n$). This is achieved by resolving the above-mentioned RPA optimization problem (Problem 1), where $\mathcal{F} \equiv S$.

Since the proposed utility function $v(S)$ is obtained by resolving an Operation Research problem (i.e., RPA optimization problem), we call this game as *Operations Research (OR) Game*.

It is worth noting that classical utility function, such as the one used in our previous work in [40], is not suitable in this context since it does not take into account the transmit power allocation on the allotted resources nor users' cheating behavior (i.e., users demand more resources than what they really need), as will be shown in Section 4.

Proposition 3.1. *The utility function $v(S)$ in (2) is convex, and thus satisfies the supermodularity property [3], [48], stronger than the superadditivity one, which means that the marginal contribution of a player to a coalition is larger than its marginal contribution to another smaller coalition:*

$$\forall S \subset T \subset \mathcal{I}_n \backslash \{i\}, \quad v(T \cup \{i\}) - v(T) \geq v(S \cup \{i\}) - v(S) \qquad (3)$$

Proof: First, let us use the following variables: $X(S) = \sum_{F_n \in S} \sum_{u \in \mathcal{U}_n} x_u^n$ and $r_u^n = \sum_{k=1}^{K} \Delta_{n,u}^k$. The latter represents the total resources allocated to user $u \in \mathcal{U}_n$ after resolving the RPA optimization problem. Let us also use (*) and (**) notations when the RPA optimization problem is executed within a coalition S and $S \cup \{i\}$, respectively. $v(S \cup \{i\}) - v(S)$ can be thus written as:

$$\begin{aligned} & v(S \cup \{i\}) - v(S) \\ &= K + X(S) - X(S \cup \{i\}) \\ &= K + \sum_{F_n \in S, u \in \mathcal{U}_n} r_u^{n^{**}} - \sum_{F_n \in S, u \in \mathcal{U}_n} r_u^{n^{*}} + \\ &\quad + \sum_{u \in \mathcal{U}_i} \left(d_u^i - r_u^{i^{**}}\right) \end{aligned}$$

Hence, $v(T \cup \{i\}) - v(T) - \Big(v(S \cup \{i\}) - v(S)\Big)$

$$= \sum_{F_n \in T \backslash S, u \in \mathcal{U}_n} \left(r_u^{n^{**}} - r_u^{n^{*}}\right)$$

Note that our aim is to minimize the unavailable resources within a coalition S (i.e., X(S)), which corresponds to maximize the allocated resources (i.e., r_u^n). As the (*) optimization is more constrained than the (**) optimization, it must hold that $r_u^{n^{**}} \geq r_u^{n^{*}}$. Indeed, $r_u^{n^{*}}$ is obtained after resolving the RPA optimization problem within the coalition S, assuming all non-cooperative femtocells (i.e., FAPs outside S including the player {i}) use their maximum transmit power. Removing the player {i} from the set of constraints and adding it in the RPA optimization process aims at reducing its harmful transmit power (from P_{max} to an optimal computed value P^*), and hence improve the overall resource allocation vectors. This concludes the convexity proof. □

3.4 Possible imputation schemes

Solutions to cooperative games are essentially qualified with respect to the satisfaction of rationality constraints, desirable properties and existence conditions. Namely, the Core of a game [49] is the set of imputations that satisfies individual and collective rationality (one or a coalition gets at least what it would get without cooperating), and efficiency (all the resources are allocated).

As our game is convex, the Core is not empty [3], [48] and may contain singleton solution that shows interesting properties. Among them, the Shapley value shows desirable properties in terms of null player, symmetry, individual fairness, and additivity [3]. It is defined as:

$$\Phi_i(v) = \sum_{S \subseteq \mathcal{I}_n \setminus \{i\}} \frac{|S|!(|\mathcal{I}_n| - |S| - 1)!}{|\mathcal{I}_n|!} [v(S \cup \{i\}) - v(S)] \tag{4}$$

i.e., computed by averaging the marginal contributions of each FAP in the interference set $\mathcal{I}_n$ in each strategic situation i.e., (players' permutation).

Another appealing solution concept, the Nucleolus [4], which is the imputation that minimizes the worst inequity. It is computed by minimizing the largest excess $e(x, S)$, expressed as:

$$e(x, S) = v(S) - \sum_{j \in S} x_j \ \ , \forall S \subseteq \mathcal{I}_n \tag{5}$$

The excess $e(x, S)$ measures the amount by which the coalition S falls short of its potential $v(S)$ in the resource allocation x; the Nucleolus corresponds to the lexicographic minimum imputation of all possible excess vectors.

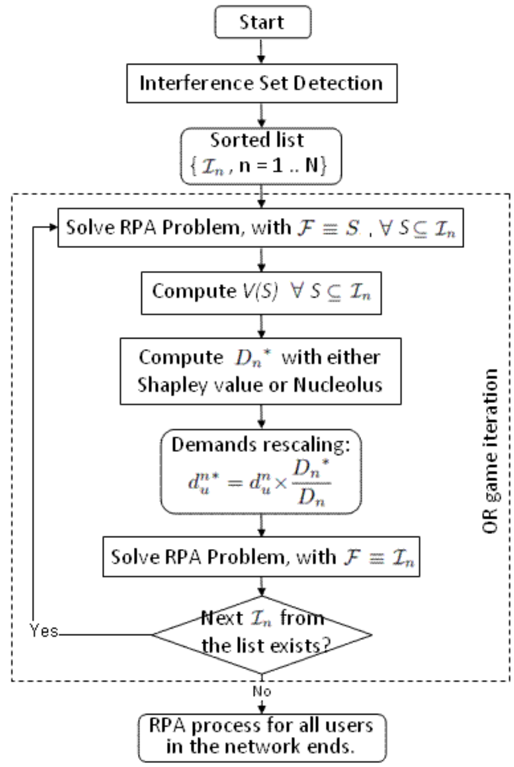


Fig. 1. Flowchart of the proposed game theoretic approach

4 Proposed Game Theoretic Approach

The game-theoretic approach we propose is composed of two main phases: an Interference Set Detection phase, and an OR Game Iteration phase, as shown in the flowchart of Fig. 1. Formally, it represents a binding agreement between cooperating femtocell subscribers.

4.1 Interference Set Detection

Upon each significant change in demands or in network topology, each femtocell F_n determines the set of interferer femtocells (denoted by $\mathcal{I}_n$) that cause interference to its users based on the minimum required SINR[2]. Indeed, each user within the F_n boundary calculates the ratio of the received signal from F_n to the signals received from all surrounding/neighboring femtocells. If this ratio is lower than the minimum required SINR, then the corresponding neighboring femtocells will be considered as interferers for F_n, and will belong to $\mathcal{I}_n$. FAPs are able to share their interference set with other FAPs in the network using a common interface such as the wired backhaul [51][3] or a dedicated wireless link [41], [52]. Then, the list of interference sets are sorted, first according to cardinality, and then according to the overall demand, both in a decreasing manner (i.e., first the largest sets with highest overall demand).

It is worth mentioning that the interference set detection phase is performed before the game execution and is based, as stated earlier, on the channel state information sent from active users. Note that only FAPs within the same interference set are able to cooperate. The cost of cooperation captured by the utility function $v(S)$ in (2) does not include the cost of information exchange needed to construct the interference sets since this operation is common for all studied approaches (semi-centralized [19], distributed [17], as well as the legacy cooperative game without variable transmission power levels [40]) and updated only at each significant change in demand or in network topology.

4.2 OR Game Iteration

In the second phase, resources as well as transmit powers are eventually allocated, proceeding with solving the OR game model presented in Section 3.3 for each interference set, and following the order in the sorted list from the first phase. The rationale behind such an agreement is that we first solve the most critical situations. Strategically, in this way we do not penalize FAPs that interfere less compared to FAPs that interfere more, as well as FAPs that claim little resources compared to FAPs that claim a lot.

As shown in Fig. 1, within each interference set, the OR game start by rescaling the demands of each player in order to avoid users' cheating behavior, followed by a global optimization for both tiles and transmit power assignment. In the following, we detail these two steps.

2. In LTE networks, user feedback reports can include interferer femtocell identifiers (Physical Cell Identity) [50].

3. In LTE networks, this can be aggregated at, or relayed by, Home-enhanced Node B (i.e., femtocell) gateways (i.e., HeNB-GW) [51].

4.2.1 Demands Rescaling

First, within an interference set $\mathcal{I}_n$, demands of each FAP are rescaled in order to allocate rational resources to each player (i.e., the FAPs in $\mathcal{I}_n$) without exceeding the available resources and avoid cheating behavior. Indeed, FAPs could end up with higher allocations if they claim higher demand. While in non-cooperative game theory, cheating behaviors are difficult to be *realistically* taken into account in the decision-making modeling, we can manage this problem in our approach by a binding agreement that fixes the rules of the cooperation.

To do so, the game starts by performing local optimizations within each coalition $S \subseteq \mathcal{I}_n$ using Problem 1 defined above with $\mathcal{F} \equiv S$, and computes the worth $v(S)$ defined in equation (2). As our game is convex, the "grand coalition" with all FAPs in $\mathcal{I}_n$ eventually forms. The sub-coalitions $S \subseteq \mathcal{I}_n$ are thus used to compute how much they are strategically important within the "grand coalition", as a function of position and interference, and thus to compute the imputation. Next, the Shapley value [3] and the Nucleolus [4] are applied to divide the grand coalition's payoff among its members. The outcome (denoted by ${D_n}^*$) corresponds to the strategic resources that each player (i.e., FAP) should have. Each FAP $F_n \in \mathcal{I}_n$ then updates its demands according to the new computed value: demands are thus rescaled with values that are strategically justified and rationally acceptable by all competing femtocells, since they have been computed while accounting for all possible strategic situations (the sub-coalitions).

It is worth noting that the intermediate transmit power values obtained after solving the local optimizations for each coalition S are not the final ones since an agreement on the allocated resources need to be first determined.

Finally, using the rescaled demands, a global optimization within the whole interference set $\mathcal{I}_n$ will be performed to assign resources (i.e., tiles) as well as the final transmit power on each tile to users. This is the aim of the second step.

4.2.2 Tiles and Transmit Power Assignment

Knowing now the exact amount of resources that each FAP within the given interference set should have (i.e., ${D_n}^*$), a global optimization within $\mathcal{I}_n$ is performed to assign, for each FAP within $\mathcal{I}_n$, the dedicated resources along with the final corresponding transmit power. To this end, Problem 1 defined above is solved again such that $\mathcal{F} \equiv \mathcal{I}_n$ in this case, and taking as input the rescaled demands computed in the previous step (i.e., $d_u^{n*} = d_u^n \times \frac{{D_n}^*}{D_n}$, $\forall u \in \mathcal{U}_n$ and $\forall F_n \in \mathcal{I}_n$).

It is worth noting that the above two steps are repeated for all interference sets following the order in the sorted list from the first phase. Since a FAP can belong to many interfering sets, if it has already participated to a game in a previous game iteration, it is excluded from the next game iteration in which it appears. However, we note that its corresponding resources and transmit powers (computed from the previous game iteration) are taken into account as potential interferers in the constraint (a) of Problem 1, which will be solved in the next game iteration. That is, in Problem 1, $P^k_{m,u'}$, which corresponds to the transmit power of interferer femtocells, is either equal to P_{max} if $F_m \in \mathcal{I}_n \backslash S$ and has not yet participated in a previous game iteration or adjusted to its already computed value, otherwise.

Note also that the number of possible steps of our game theoretic approach is finite and bounded by the number of interference sets detected in the network (i.e., size of the sorted list $\mathcal{L} = \{\mathcal{I}_n, n = 1..N\}$. Hence our approach converges to a stable allocation strategy with a complexity of polynomial order.

TABLE 1
Simulation parameters

Carrier frequency	2 GHz	N	200
d_u^n	$1 \sim 25$ tiles	K	100
σ^2	$-121.45\ dBm$	P_{max}	20 mW
α	10^{-3}	P_{min}	0.1 mW

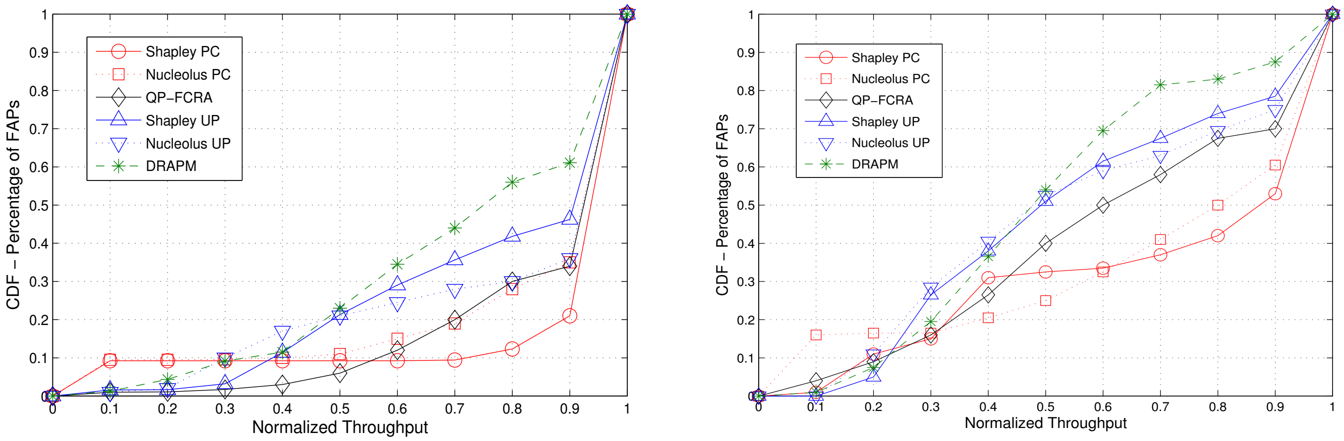
5 Performance Evaluation

In this section, we evaluate the performance of the proposed OR game approach using two game-theoretic imputation solutions for demands rescaling, i.e., the Shapley value and Nucleolus. We compare the benefits of our approaches with respect to the legacy cooperative game without variable transmission power levels (i.e., Shapley value and Nucleolus with uniformly distributed power, as in our previous work [40]), as well as the semi-centralized optimization approach, as in QP-FCRA [19] and the distributed approach described in DRAPM [17]. Note that the corresponding optimization problems are solved using the solver "IBM ilog cplex" [53].

We simulated several scenarios with a dense network size of 200 FAPs where, for each simulation, FAPs are randomly distributed in a 2-D 400 m $\times$ 400 m area. We considered two interference level scenarios, a low-level one and a high-level one, based on two SINR thresholds, 10 and 25 dB, to show the impact of the interference level on the performance metrics. Based on the SINR, the path loss model of WINNER [47], and with static user positions; each FAP determines the set of its interferer femtocells. Users are uniformly distributed within the FAPs with a maximum number of four users per FAP. Each user uniformly generates its traffic demand that can be directly translated to a certain number of tiles, using the equation (1), with a maximum required bandwidth ${TP_u^{req}}_{max} = 10\ Mbps$, corresponding to a maximum value of 25 tiles per user[4]. As in [17], [19], the analysis

4. In our simulations, the 16 QAM modulation with a coding rate of $3/4$ is adopted, allowing a bit rate per tile equals to $432\ Kbps$.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TMC.2014.2329835, IEEE Transactions on Mobile Computing



(a) SINR = 10 dB.

(b) SINR = 25 dB.

Fig. 2. Throughput Cumulative Distribution Function (CDF).

is achieved using a typical OFDMA frame (downlink LTE frame) consisting of $K = 100$ tiles. This corresponds to a channel bandwidth of 10 MHz, which is the most commonly used in practice (i.e., 50 tiles in the frequency domain) and one subframe of $1\ ms$ in length (i.e., 2 time slots)[5]. The simulation parameters are reported in Table 1. We focus on the comparison among the different strategies based on the offered normalized throughput, the allocation fairness, the spectrum spatial reuse, as well as the transmit power and the computation time.

5.1 Throughput analysis

Fig. 2 reports the mean normalized throughput (i.e., mean ratio of the number of allocated tiles to the total initial demands; in the following referred to as throughput) for the two interference level scenarios. We can observe that the game-theoretic approaches with power control (referred to as Shapley PC and Nucleolus PC in the figure) outperform the other schemes, especially in high interference level [see Fig. 2(b)]. In particular, we can observe that:

- The median throughput is always higher for the Shapley PC in both interference levels. This is clearly shown in the high interference case, where it is equal to 0.87 for the Shapley PC, meaning that 50% of femtocells have a throughput of 0.87 or more, compared to 0.8 for Nucleolus PC, 0.6 for QP-FCRA, 0.47 for DRAPM, and 0.5 for both Shapley and Nucleolus with uniformly distributed power (referred to as Shapley UP and Nucleolus UP in the figure).
- At high throughputs, our game-theoretic approaches with power control outperforms the remaining schemes; e.g., in the high interference case, Shapley PC allows 48% of FAPs with throughput greater than 0.9, compared to 40% for Nucleolus PC, 30% for QP-FCRA, 25% for Nucleolus UP, 20% for Shapley UP, and only 12% of FAPs for DRAPM.
- Among the game-theoretic approaches, the Shapley value persistently outperforms the Nucleolus, with relevant differences at high throughputs.
- At low throughput and low interference level [see Fig. 2(a)], QP-FCRA, game-theoretic approaches with uniformly distributed power, and DRAPM offer good performance as they ensure that only 2% of FAPs obtain a throughput less than 0.1, compared to 10% of FAPs in the case of game-theoretic solutions with power control.

The latter point can be explained by the fact that, our approaches strategically allocate low transmit powers for users, even if they are located at the cell edge, to control interference. In low interference scenario, this results in lower throughput compared to the other schemes, which use higher transmit power. However, such agreement between FAPs aims at maximizing the throughput for the majority of femtocells, as shown in Fig. 2(a), where Shapley PC allows 80% of femtocells with throughput greater than 0.9, compared to 65%, 52%, and 40% of femtocells for both Nucleolus PC/UP and QP-FCRA, Shapley UP, and DRAPM, respectively.

All in all, the Shapley PC seems the most appropriate approach with respect to the offered throughput, especially in high interference scenario, as in urban environments with a dense deployment of femtocells.

5.2 Fairness analysis

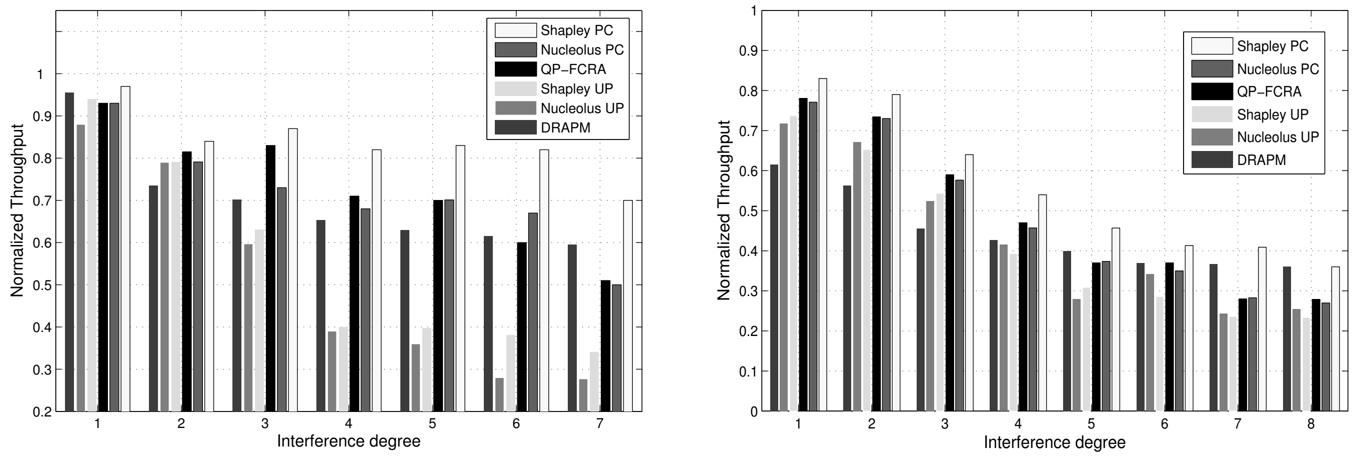
We evaluate the fairness of the solutions using three aspects.

(i) The Jain's fairness index [54], defined as:

$$FI = \left(\sum_{n=1}^{N} \sum_{u \in \mathcal{U}_n} (\beta_u^n / d_u^n) \right)^2 / \left(N \times \sum_{n=1}^{N} \sum_{u \in \mathcal{U}_n} \left(\beta_u^n / d_u^n \right)^2 \right) \quad (6)$$

5. According to the LTE specification [46], scheduling is done on a subframe basis for both the downlink and uplink. Each subframe consists of two equally sized slots of $0.5\ ms$ in length.

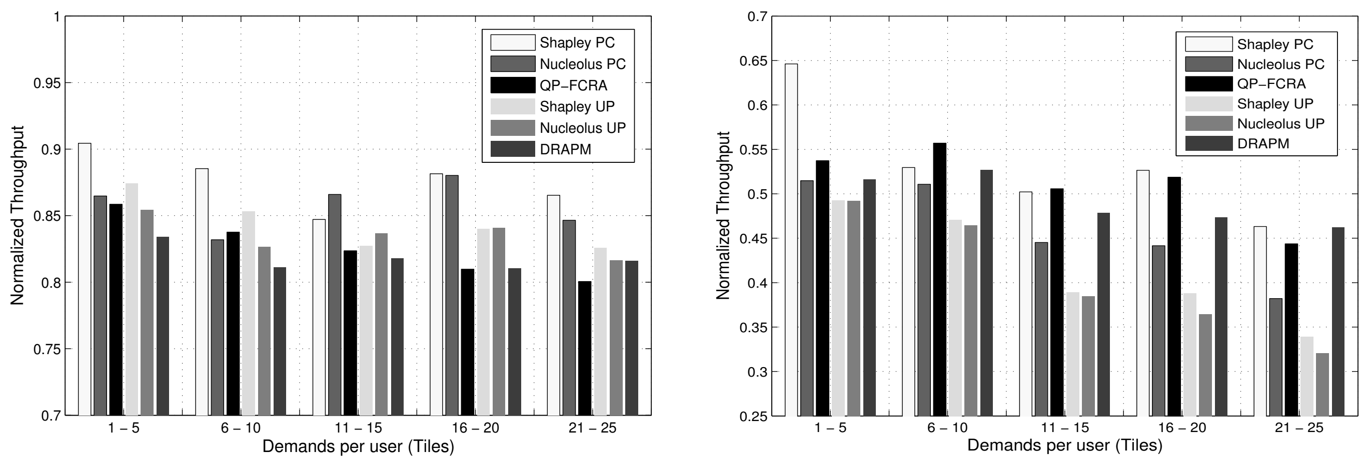
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TMC.2014.2329835, IEEE Transactions on Mobile Computing



(a) SINR = 10 dB.

(b) SINR = 25 dB.

Fig. 3. Throughput distribution as a function of the interference degree.



(a) SINR = 10 dB.

(b) SINR = 25 dB.

Fig. 4. Throughput distribution as a function of user demands.

TABLE 2
Mean Fairness Indexes

SINR	Nucle. PC	Shap. PC	Nucle. UP	Shap. UP	QP-FCRA	DRAPM
10 dB	0.9129	0.9318	0.6927	0.7201	0.9167	0.9018
25 dB	0.7609	0.7891	0.5852	0.6239	0.7742	0.7601

where $\beta_u^n = \sum_{k=1}^{K} \Delta_{n,u}^k$ indicates the allocated resources to user u. The fairness indexes are reported in Table 2. We can notice that the Shapley value with power control gives the highest fairness, thanks to the strategic constraints that avoid penalizing femtocells presenting high interference degree and those with lower demands (as will be shown in Figs. 3 and 4). On the other hand, the performance of Nucleolus PC is slightly lower than the QP-FCRA approach, but remains far better than the case with uniformly distributed power as well as DRAPM.

(ii) Fig. 3 further investigates how femtocell interference degree is taken into account, illustrating the mean normalized throughput as a function of the interference degree (that corresponds to the cardinality of its interference set) for both interference levels. This is interesting to determine if high interfering femtocells are penalized with respect to low interfering ones. We can observe that:

- Globally, the legacy cooperative game without variable transmission power levels (i.e., Shapley UP and Nucleolus UP) appear as the less performant solutions.
- The Nucleolus PC behaves similarly to QP-FCRA, especially in the 25 dB SINR threshold case, since their objective is almost the same: to minimize the worst case scenario.
- The Shapley PC persistently outperforms the other methods, with relevant differences at high interference degrees. Indeed, it shows a throughput increase of approximately 22% and 12% than QP-FCRA in low and high interference level, respectively. Compared to DRAPM, these gains are reduced to 20% and 5%, respectively.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TMC.2014.2329835, IEEE Transactions on Mobile Computing

TABLE 3
Mean Spectrum Spatial Reuse

SINR	Nucle. PC	Shap. PC	Nucle. UP	Shap. UP	QP-FCRA	DRAPM
10 dB	0.4492	0.4828	0.4147	0.4100	0.4610	0.44
25 dB	0.401	0.4533	0.2836	0.2801	0.4107	0.3901

It is appropriate to conclude that the interference degree is taken into account in a significantly different way with Shapley PC, showing an interesting fairness performance, especially desirable for urban dense environments.

(iii) In order to assess how the allocated resources are affected by the demand volume, Fig. 4 plots the throughput as a function of user demands. Globally, DRAPM shows a roughly constant behavior, which implies that its resource allocation is done irrespectively of the user demands. On the other hand, game-theoretic approaches decrease with growing demands. This is more clearly shown in the high interference case [see Fig. 4(b)]. In particular, the Shapley PC favors low demands significantly more than the Nucleolus PC. This may be interpreted as unfair to high demands. However, from a network management standpoint, it is a positive behavior as the Shapley PC can discourage too greedy demands at the benefit of lower "normal" demands.

5.3 Spectrum Spatial Reuse analysis

Table 3 reports the spectrum spatial reuse (SSR) of all approaches. Note that SSR denotes the average portion of FAPs using the same tile within the network, and can be expressed as follows:

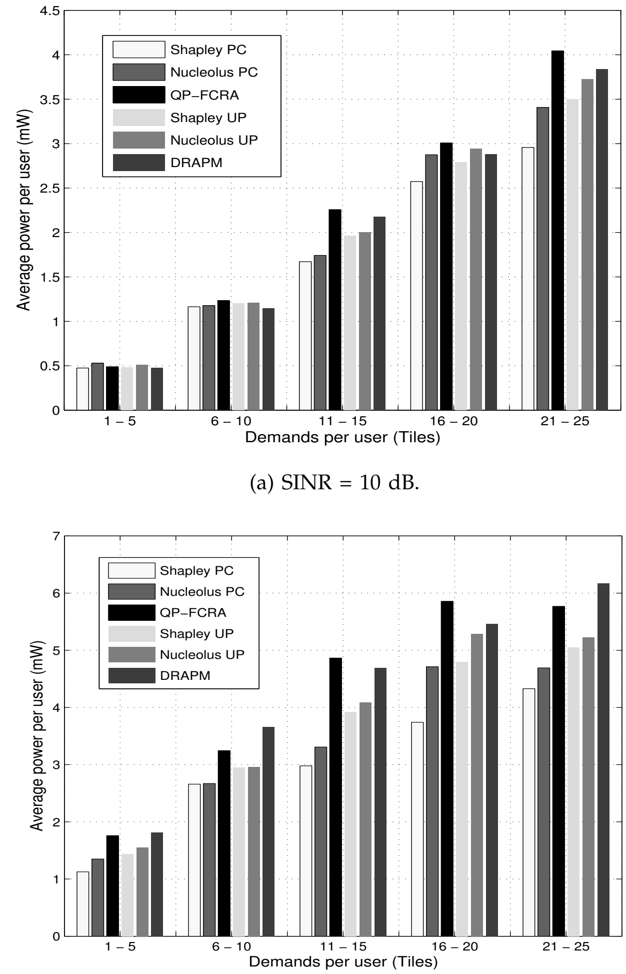
$$SSR = \frac{1}{N \times K} \sum_{k=1}^{K} \sum_{u \in U_n} \sum_{F_n \in \mathcal{F}} \Delta_{n,u}^{k} \tag{7}$$

The more a tile is reused, the better is the performance. This is clearly shown in Table 3, where Shapley PC enhances the tiles reuse by a factor of 1.104, 1.162, and 1.618, compared to QP-FCRA, DRAPM, and game theoretic approaches with uniformly distributed power, respectively, in the 25 dB SINR threshold case. These factors decrease down to 1.048, 1.098, and 1.177, respectively, in low interference level. These results confirm our previous observations.

5.4 Transmit Power analysis

Figs. 5 and 6 respectively show the transmit power per user as a function of user demands and the distance to the served FAP in both SINR threshold cases. We can here appreciate how much the strategic constraints in game-theoretic approaches with power control contribute to reducing the allocated transmit power, while achieving higher throughputs, as shown in previous figures. In particular, we can observe that:

- At low demands and low interference level [see Fig. 5(a)], almost all schemes use the same average transmit power.



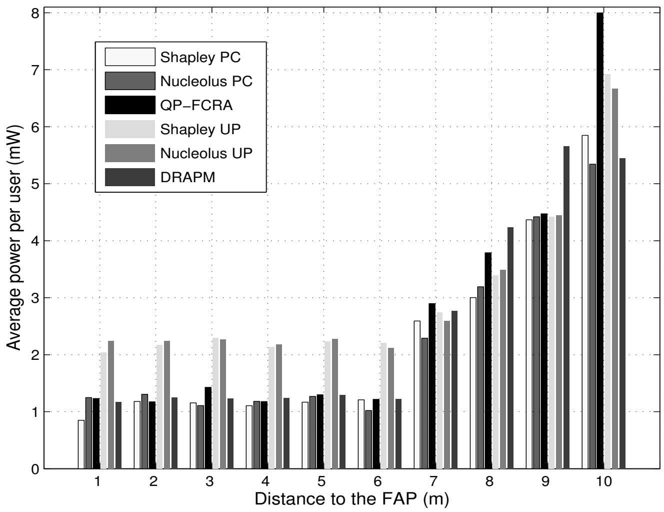
(a) SINR = 10 dB.

(b) SINR = 25 dB.

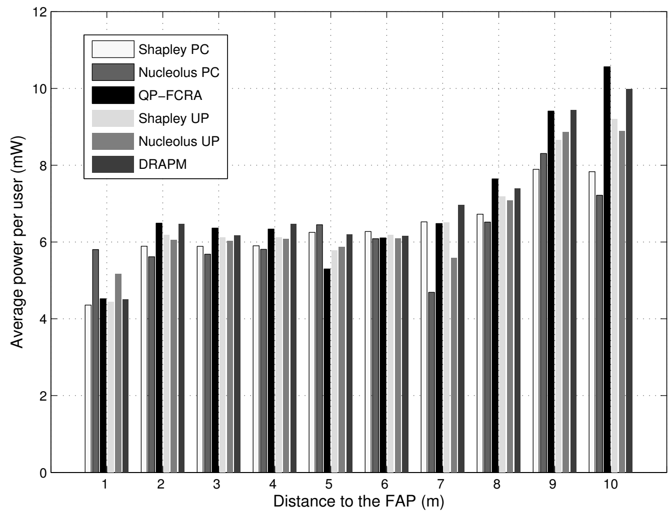
Fig. 5. Transmit power per user as a function of user demands.

- The gain of both Shapley PC and Nucleolus PC over the other schemes is more significant in higher demands.
- Globally, the transmit power increases with the user' demands as well as with the distance to the served FAP for all schemes. This is simply because users far away from their FAP need more power to reach them, and users with higher demands need more resources to satisfy them, so that more transmit power is needed.
- From Fig. 6, two zones within the FAP coverage can be defined: an *inner zone*, where the distance between a user and its served FAP is lower than 7 meters, and an *outer zone*, where the distance to the served FAP is greater than 7 meters. In the *inner zone*, the transmit power for all schemes is almost constant and the benefit of femtocells cooperation is not significant, since interference effect from neighboring FAPs appears to be negligible in that zone. On the other hand, in the *outer zone*

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TMC.2014.2329835, IEEE Transactions on Mobile Computing

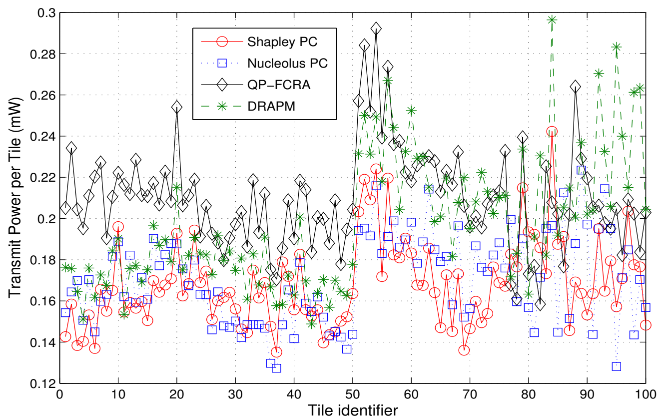


(a) SINR = 10 dB.

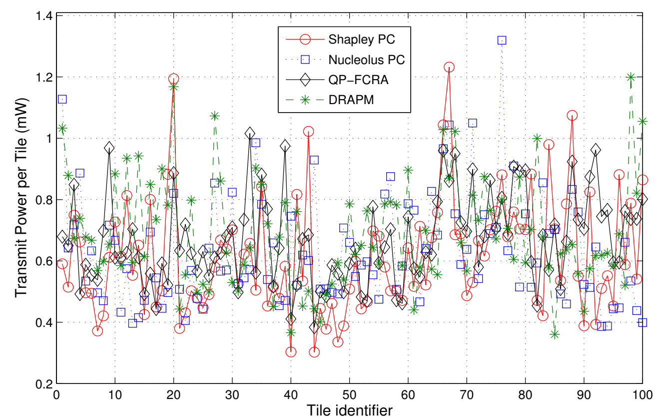


(b) SINR = 25 dB.

Fig. 6. Transmit power per user as a function of the distance.



(a) SINR = 10 dB.



(b) SINR = 25 dB.

Fig. 7. Transmit power per tile.

(i.e., femtocell border), game-theoretic approaches with power control (i.e., the Shapley PC and the Nucleolus PC) clearly contribute to reducing the allocated transmit power to avoid interference with the neighboring FAPs.

It seems appropriate to conclude that the benefit of femtocells cooperation for resource and power allocation is more significant for users with higher throughput demands and located in the *outer zone* (i.e., femtocell border).

To further show the benefit of our game theoretic approaches, we plot in Fig. 7 the transmit power per tile in both interference levels. The Shapley UP and Nucleolus UP are omitted from this figure, since their transmit powers are constant over the 100 available tiles. We can observe that both Shapley PC and Nucleolus PC almost use the minimum transmit power per tile. This is more clearly shown on Fig. 7(a), where the transmit power per tile lies between 0.14 and 0.18 mW most of the cases in low interference level, compared to the semi-centralized and distributed approaches, which often use a transmit power per tile higher than 0.2 mW.

5.5 Computation time analysis

Finally, Table 4 reports the computation time of all schemes. We can observe that, our game-theoretic approaches with power control need a little bit more time to assign strategically resources and transmit power to users, compared to the other schemes. In particular, the Nucleolus shows lower time complexity compared to the Shapley value. In addition, a stronger dependence on the interference level (higher for the high interference level) appears especially for the Shapley value, which is not surprising since the number of marginal contribution is the factorial of the interfering set size. In turn, the

TABLE 4
Average Computation Time (in Seconds)

SINR	Nucle. PC	Shap. PC	Nucle. UP	Shap. UP	QP-FCRA	DRAPM
10 dB	1.9401	2.147	0.62	1.08	1.204	1.20
25 dB	2.6486	2.718	0.8600	2.320	2.549	2.1

Nucleolus and more precisely the Nucleolus UP does not show any important dependence on the interference level, with an average computation time of less than $1s$ in both low and high interference cases.

6 CONCLUSION

In this paper, we have presented a novel approach based on cooperative game theory to address the problem of interference mitigation in femtocell networks. Specifically, we presented a game-theoretic approach for strategic resource and power allocation in cooperative femtocell OFDMA networks. Upon detection of interference maps, the proposed approach iterates operations research games from the largest interference set with highest demand to the lower sets. Within each iteration, femtocells' demands are first rescaled by performing local optimizations within the formed strategic coalitions, then a global optimization problem using the rescaled demands as input is solved to assign resources as well as transmit power to femto users. We adopted solutions from coalitional game theory, the Nucleolus and the Shapley value, and analyzed the performance of the developed schemes. Compared to three alternative solutions, one based on legacy cooperative game without variable transmission power levels, and two others based respectively on semi-centralized and distributed computations, our proposed approach achieves better performance. In particular, the Shapley value solution with power control is strictly superior to all the others in terms of throughput, fairness, spectrum spatial reuse, and transmit power. However, it comes at the expense of a slightly higher time complexity. In addition, we showed that the benefit of such cooperation is more significant for users with higher throughput demands and located in the *outer zone* (i.e., femtocell border). This approach represents therefore a promising solution for resource and power allocation in future femtocell network deployments.

ACKNOWLEDGMENTS

This work was supported in part by the ABCD project funded by the French National Research Agency under grant agreement no. ANR-13-INFR-005, and in part by the FERRARI project funded by CNRS under grant agreement no. 05948. The authors would like to thank Sahar Hoteit for her preliminary formulation of the problem in [40] and Mouna Hkimi for providing the simulation code which we extended and used in this work.

REFERENCES

[1] M. Hkimi, R. Langar, S. Secci, R. Boutaba, and G. Pujolle, "Demands Rescaling for Resource and Power Allocation in Cooperative Femtocell Networks", in Proc. of *IEEE ICC 2013*.
[2] D. Lopez-Perez , A. Valcarce, G. de la Roche, and J. Zhang, "OFDMA Femtocells: A Roadmap on Interference Avoidance", *IEEE Comm. Mag.*, vol. 47, no. 9, pp. 41-48, Sep. 2009.
[3] L. Shapley, "A value for n-person games", *Contributions to the Theory of Games*, Annals of Mathematics Studies, 28, 307-317. Princeton U Press., 1953.
[4] D. Schmeidler, "The Nucleolus of a Characteristic Function Game", *SIAM Journal on Applied Mathematics*, vol. 17, no. 6, 1969.
[5] P. Borm, H. Hamers and R. Hendrickx, "Operations research games: A survey", *Springer-Verlag TOP Journal*, vol. 9, no. 2, pp. 139-199, 2001.
[6] G. J. Foschini and Z. Miljanic, "A Simple Distributed Autonomous Power Control Algorithm and its Convergence", *IEEE Trans. Veh. Tech.*, vol. 42, no. 4, pp. 641-646, Nov. 1993.
[7] R. Yates, and C. Y. Huang, "Integrated power control and base station assignment", *IEEE Trans. Veh. Tech.*, vol. 44, no. 3, pp. 638-644, Aug. 1995.
[8] K. Sundaresan and S. Rangarajan, "Efficient Resource Management in OFDMA Femtocells", in Proc. of *ACM MobiHoc 2009*.
[9] V. Chandrasekhar and J. Andrews, "Spectrum Allocation in Tiered Cellular Networks", *IEEE Trans. Commun.*, vol. 57, no. 10, pp. 3059-3068, Oct. 2009.
[10] Y. Arslan, J. Yoon, K. Sundaresan, V. Krishnamurthy, and S. Banerjee, "A Femtocell Resource Management System for Interference Mitigation in OFDMA Networks", in Proc. of *ACM MobiCom 2011*.
[11] Y. Liang, W. Chung, G. Ni, I. Chen, H. Zhang, and S. Kuo, "Resource Allocation with Interference Ovoidance in OFDMA Femtocell Networks", *IEEE Trans. Veh. Tech.*, vol. 61, no. 5, pp. 2243-2255, Jun. 2012.
[12] A. Hatoum, R. Langar, N. Aitsaadi, R. Boutaba, and G. Pujolle, "Cluster-based Resource Management in OFDMA Femtocell Networks with QoS Guarantees", *IEEE Trans. Veh. Tech.*, (in press), Nov. 2013.
[13] X. Chu, Y. Wu, D. Lopez-Perez, and X. Tao, "On Providing Downlink Services in Collocated Spectrum-sharing Macro and Femto Networks", *IEEE Trans. Wireless Commun.*, vol. 10, no. 12, pp. 4306-4315, Dec. 2011.
[14] V. Chandrasekhar and J. Andrews, "Power Control in Two-Tier Femtocell Networks", *IEEE Trans. Wireless Commun.*, vol. 8, no. 8, pp. 4316-4328, Aug. 2009.
[15] F. Cao and Z. Fan, "Power Loading and Resources Allocation for Femtocells", in Proc. of *IEEE VTC Spring 2011*.
[16] M. Rahman and H. Yanikomeroglu, "Enhancing Cell-edge Performance: a Downlink Dynamic Interference Avoidance Scheme with Inter-cell Coordination", *IEEE Trans. Wireless Commun.*, vol. 9, no. 4, pp. 1414-1425, Apr. 2010.
[17] A. Ladanyi, D. Lopez-Perez , A. Juttner, X. Chu, J. Zhang, "Distributed Resource Allocation for Femtocell Interference Coordination Via Power Minimisation", in Proc. of *IEEE GLOBECOM 2011*.
[18] D. Lopez-Perez, A. Ladanyi, A. Juttner, H. Rivano, and J. Zhang, "Optimization Method for the Joint Allocation of Modulation Schemes, Coding Rates, Resource Blocks and Power in Self-Organizing LTE Networks", in Proc. of *IEEE INFOCOM 2011*.
[19] A. Hatoum, R. Langar, N. Aitsaadi, R. Boutaba, and G. Pujolle, "QP-FCRA: QoP-based Power Control and Resource Allocation in OFDMA Femtocell Networks", in Proc. of *IEEE GLOBECOM 2012*.
[20] G. Owen, "Game Theory", *3rd ed. London, U.K.:Academic*, Oct.1995.
[21] T. Basar, G. J. Olsder, "Dynamic Noncooperative Game Theory", *SIAM Classics in Applied Mathematics*, 1999.
[22] N. Feng, S. Mau, and N. Mandayam, "Joint Network-Centric and User-Centric Radio Resource Management in a Multicell System", *IEEE Trans. Commun.*, vol. 53, no. 7, pp. 1114-1118, Jul. 2005.
[23] Z. Han and K. J. R. Liu, "Noncooperative Power Control Game and Throughput Game over Wireless Networks", *IEEE Trans. Commun.*, vol. 53, no. 10, pp. 1625-1629, Oct. 2005.
[24] M. Cesana, I. Malanchini, A. Capone, "Modelling Network Selection and Resource Allocation in Wireless Access Networks with Noncooperative Games", in Proc. of *IEEE MASS 2008*.

[25] Y. Wu, and D. Tsang, "Distributed Power Allocation Algorithm for Spectrum Sharing Cognitive Radio Networks with QoS guarantee", in Proc. of *IEEE INFOCOM 2009*.

[26] F. Meshkati, V. Poor, S. Schwartz, and R. Balan, "Energy-Efficient Resource Allocation in Wireless Networks with Quality-of-Service Constraints", *IEEE Trans. Commun.*, vol. 57, no. 11, pp. 3406-3414, Nov. 2009.

[27] E. J. Hong, S. Y. Yun, and D.-H. Cho, "Decentralized power control scheme in femtocell networks: a game theoretic approach", in Proc. of *IEEE PIMRC 2009*.

[28] C.-H. Ko and H.-Y. Wei, "On-demand resource-sharing mechanism design in two-tier OFDMA femtocell networks", *IEEE Trans. Veh. Tech.*, vol. 60, no. 3, pp. 1059-1071, Mar. 2011.

[29] S. Lien, Y. Lin, and K. Chen, "Cognitive and game-theoretical radio resource management for autonomous femtocells with QoS guarantees", *IEEE Trans. Wireless Commun.*, vol. 10, no. 7, pp. 2196-2206, Jul. 2011.

[30] D. T.Ngo,L. Bao Le, Tho Le-Ngoc, E. Hossain, D. In Kim, "Distributed Interference Management in Two-Tier CDMA Femtocell Networks", in *IEEE Trans. Wireless Commun.*,vol. 11, no. 3, pp. 979-989, Mar. 2012.

[31] Duy. T.Ngo , Long B. Le, Tho . Le-Ngoc. "Distributed Pareto-Optimal Power Control for utility Maximizationin Femtocell Networks", in *IEEE Trans. Wireless Commun.*,vol. 11, no. 10, pp. 3434-3446, Oct. 2012.

[32] C. Saraydar, N. Mandayam, and D. Goodman, "Pricing and Power Control in a Multicell Wireless Data Network", *IEEE J. Sel. Areas Commun.*, vol. 19, no. 10, pp. 1883-1892, Oct. 2001.

[33] P. Marbach, and R. Berry, "Downlink Resource Allocation and Pricing for Wireless Networks", in Proc. of *IEEE INFOCOM 2002*.

[34] M. Xiao, N. B. Shroff, and E. K. P. Chong, "A utility-based power control scheme in wireless cellular systems", *IEEE/ACM Trans. Networking*, vol. 11, no. 2, pp. 210-221, Apr. 2003.

[35] F. Wang, M. Krunz, and S. Cui, "Price-based Spectrum Management in Cognitive Radio Networks", *IEEE J. Sel. Topics Signal Proc.*, vol. 2, no. 1, pp. 74-87, Feb. 2008.

[36] M. Rasti, A. R. Sharafat, and B. Seyfe, "Pareto-efficient and goal-driven power control in wireless networks: A game-theoretic approach with a novel pricing scheme", *IEEE/ACM Trans. Networking*, vol. 17, no. 2, pp. 556-569, Apr. 2009.

[37] R. B. Myerson, "Game Theory, Analysis of Conflict", *Cambridge, Harvard Univ.Press*, 1991.

[38] S. Mathur, L. Sankar, and N. B. Mandayam, "Coalitions in Cooperative Wireless Networks", *IEEE J. Sel. Areas Commun.*, vol. 26, no. 7, pp. 1104-1115, Sept. 2008.

[39] Z. Khan, S. Glisic, L. DaSilva, and J. Lehtomaki, "Modeling the Dynamics of Coalition Formation Games for Cooperative Spectrum Sharing in an Interference Channel", *IEEE Trans. Computational Intelligence and AI in Games*, vol. 3, no. 1, pp. 17-30, Mar. 2011.

[40] S. Hoteit, S. Secci, R. Langar, G. Pujolle, and R. Boutaba, "A Bankruptcy Game Approach for Resource Allocation in Cooperative Femtocell Networks", in Proc. of *IEEE GLOBECOM 2012*.

[41] F. Pantisano, M. Bennis, W. Saad, M. Debbah, and M. Latva-aho, "Interference Alignment for Cooperative Femtocell Networks: A Game-Theoretic Approach", *IEEE Trans. Mobile Computing*, vol. 12, no. 11, pp. 2233-2246, Nov. 2013.

[42] M. Mycek et al., "Cooperative Multi-Provider Routing Optimization and Income Distribution", in Proc. of *DRCN 2009*.

[43] T. Alpcan, and T. Basar, "A Game Theoretic Approach to Decision and Analysis in Network Intrusion Detection", in Proc. of *CDC 2003*.

[44] Z. Han, and V. Poor, "Coalition Games with Cooperative Transmission: A Cure for the Curse of Boundary Nodes in Selfish Packet-Forwarding Wireless Networks", *IEEE Trans. Commun.*, vol. 57, no. 1, pp. 203-213, Jan. 2009.

[45] W. Saad, Z. Han, M. Debbah, A. Hjrungnes, and T. Basar, "Coalitional Game Theory in Wireless and Communications Networks", *IEEE Signal Processing Mag.*, vol. 26, no. 5, pp. 77-97, Sept. 2009.

[46] 3GPP Tech. Spec. TS 36.300 v10.5.0, evolved universal terrestrial radio access (E-UTRA) and evolved universal terrestrial radio access network (E-UTRAN); overall description; stage 2, Oct. 2011.

[47] D. Winner II, "Winner II channel models part I- channel models", *Tech.Rep*, Sep. 2007.

[48] T. Driessen, "Cooperative Games, Solutions and Applications", *Kluwer Academic Publishers*, 1988.

[49] Lioyd S. Shapley "On balanced sets and cores", *Naval Research Logistics Quarterly*, vol. 14, no. 4, 1967.

[50] 3GPP TS 32.500 V10.0.0 (2010-06) specification.

[51] 3GPP TS 32.781 V9.1.0 (2010-03) specification.

[52] R. Madan, A. Sampath, N. Bhushan, A. Khandekar, J. Borran, and T. Ji, "Impact of Coordination Delay on Distributed Scheduling in LTE-A Femtocell NetWorks", in Proc. of *IEEE GLOBECOM 2010*.

[53] http://www-01.ibm.com/software/integration/optimization/cplex-optimizer/

[54] R. Jain, W. Hawe, D. Chiu, "A Quantitative Measure of Fairness and Discrimination for Resource Allocation in Shared Computer Systems", *DEC Research Report TR-301*, 1984.

Rami Langar is currently an Associate Professor at the LIP6, University of Pierre and Marie Curie, Paris, France. He received the M.Sc. degree in network and computer science from the University of Pierre and Marie Curie in 2002; and the Ph.D. degree in network and computer science from Telecom ParisTech, Paris, France, in 2006. In 2007 and 2008, he was with the School of Computer Science, University of Waterloo, Waterloo, ON, Canada, as a Post-Doctoral Research Fellow. His research interests include mobility and resource management in wireless mesh, vehicular ad-hoc and femtocell networks, green networking, cloud radio access networks, performance evaluation, and quality-of-service support.

Stefano Secci is currently an Associate Professor at the LIP6, University of Pierre and Marie Curie, Paris, France. He received the M.Sc. and Ph.D. degrees in communications engineering from Politecnico di Milano, Milan, Italy, and the Ph.D. degree in computer science and networks from Telecom ParisTech, Paris, France. He worked as network engineer with Fastweb, Milan, Italy, and as Post-Doctoral Fellow with Telecom ParisTech, NTNU, Norway, and George Mason University, USA. His current research interests are about future Internet routing resiliency, mobility, cloud networking and policy.

Raouf Boutaba is currently a Full Professor of Computer Science at the University of Waterloo, Waterloo, ON, Canada. He received the M.Sc. and Ph.D. Degrees in Computer Science from the University Pierre and Marie Curie, Paris, France, in 1990 and 1994, respectively. His research interests include network, resource and service management in wired and wireless networks. He has received several best paper awards and other recognitions such as the Premiers Research Excellence Award, the IEEE Hal Sobol Award in 2007, the Fred W. Ellersick Prize in 2008, the Joe LociCero and the Dan Stokesbury awards in 2009, and the Salah Aidarous Award in 2012. He is a fellow of the IEEE and the Engineering Institute of Canada.

Guy Pujolle is currently a Full Professor at the LIP6, University of Pierre and Marie Curie, Paris, France, and a member of The Royal Physiographical Academy of Lund, Sweden. He is the French representative at the Technical Committee on Networking at IFIP. Guy Pujolle is a pioneer in high-speed networking having led the development of the first Gbit/s network to be tested in 1980. He was participating in several important patents like DPI (Deep Packet Inspection), virtual networks or virtual access points. He is the cofounder of QoSMOS (www.qosmos.fr), Ucopia Communications (www.ucopia.com), EtherTrust (www.ethertrust.com), Virtuor (www.VirtuOR.fr), and Green Communications (www.greencommunications.fr).