Inter-Operator Spectrum Sharing for Celullar Networks using Game Theory

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***Abstract*—In this paper, we present a game theoretical framework for DSA (Dynamic Spectrum Access) in cellular networks. We model and analyze the interaction between cellular operators with packet services, in a spectrum sharing context. We present inter-operator DSA algorithms based on game theory. A two-players non-zero sum game is formulated, where the operators are the players. We define a utility function, for the operator that takes: (1) the users throughput, (2) the spectrum price, and (3) the blocking probability into consideration. We present two system models: a) a centralized model where a DSA algorithm, for the global welfare in terms of the operators rewards, is inspired by the Pareto optimality concept. b) a distributed model, where a DSA algorithm is based on Nash equilibria concept. The convergence to NE in the distributed model is analyzed. The rewards of the operators in the centralized DSA algorithm are compared with those in the FSA (Fixed Spectrum Access) situation. The obtained rewards using the centralized DSA algorithm significantly exceed the FSA rewards. The obtained blocking probabilities are shown not to exceed the target value.**

I. Introduction

Spectrum sharing and DSA techniques have been active research topics for the past decade due to the spectrum crowd situation. The existing spectrum allocation process, denoted as FSA, headed for static long-term exclusive rights of spectrum usage [1] and shown to be inflexible [2].

In the cellular context two main axis of resource management exist. The JRRM (Joint Radio Resource Management) axe, in which one operator manages jointly his networks (or Radio Access Technology) making benefit of his own licensed bands [3]. The second axe, which we call *operator sharing DSA* (or *Inter-operator DSA*), in which the competition and/or the cooperation aspects between different operators are explored. Competition aspects are referred to the costs and revenues partitioned among the operators as a result of spectrum sharing.

In this paper, we are interested in developing inter-operator DSA algorithms for cellular networks in a spectrum sharing context. DSA algorithms are being investigated as new promising techniques to overcome the inflexible FSA situation which has leaded to resources limitation problem. For instance, in [4], the authors propose a dynamic algorithm to allocate the spectrum to competing base stations. The base stations are sharing a common spectrum band controlled by a spectrum broker. The broker assigns the spectrum to the base stations to maximize its revenue, without violating the interference constraint.

As cellular operators pay high prices for the license, hence their main interest in sharing the spectrum lies behind the expected benefits [5]. The revenue maximization, under the interference constraint, in a spectrum auction framework has been studied in [6]. Reference [7] analyzes a network model where the service-providers base stations are sharing a common amount of spectrum. A distributed DSA algorithm is proposed where each user maximizes his utility (bit rate) minus the payment for the spectrum.

In this paper we present and analyze inter-operator DSA algorithms based on game theory, with cellular operators sharing a common pool of spectral resources. A two-players non-zero sum game is formulated where the operators are the players.

Game theory has been used to study several telecommunication problems and spectrum sharing techniques. Game theory equips us with various optimality criteria for the spectrum sharing problem [8]. In [9] the authors made use of game theory to analyze the power allocation problem of peer-to-peer systems in unlicensed bands. The authors in [10] also analyze peer-to-peer node conflicts. Each player (system) wants to determine the operating channel in a spectrum sharing game. A distributed channel allocation algorithm has been proposed in [11] for BFWA (Broadband Fixed Wireless Access) networks to replace the regular frequency planning method. The algorithm is based on a mixed strategy game.

Most of the research done for DSA using game theory has focused on decentralized networks (i.e. peer-to-peer systems) [9], [10], and [12] or on primary/secondary usage context [13]. However no research exists where game theory is used to study the conflicts between cellular operators.

Our main contributions are: modeling the interaction between the operators in the form of utility function, and proposing a DSA algorithm based on the Pareto optimality concept. We address the pricing and reward issue by defining a model for the operators reward that takes into consideration: (1) the spectrum price as a function of demand, (2) the end-user satisfaction as a function of the achieved throughput, and (3) the blocking probability.

In this paper we extend our work presented in [14] to more realistic scenarios. A SMDP (Semi Markov Decision Process) framework for DSA in cellular networks is proposed in [14].

The paper is organised as follows: Section II presents the network model in terms of system model, traffic model, and the principle of DSA operation. In section III, we illustrate the game theory framework, the Pareto optimality, and we give the utility function details. Section IV gives the numerical results. Conclusion is finaly given in section V.

II. Network model

A. System models

We intend to study DSA among cellular operators on the cell level. For the centralized model, we consider a *meta-operator* who owns and manages a common pool of spectral resources in a specific region. The authors in [2] refer to the common sepctrum pool notation as (Coordinated Access Band or CAB). In this paper, each operator operates one RAN (Radio Access Network) of packet services. The operators (RANs) do not own the spectrum but rather share the pool. According to the load variations of the RANs, the meta-operator dynamically attributes frequency blocks to the operators.

The cellular networks (RANs) are supposed to be homogeneous in propagation and in traffic, and the operators are assumed to deploy classical frequency reuse scheme (i.e. reuse 1 or reuse 3). Based on these assumptions, all cells of an operator statistically behave the same way, we can thus focus on a single cell per operator. Note that, the main difference among frequency reuse schemes lies on their impact on interference production and hence on the achievable throughput (section II-B).

The CAB is subdivided into m_{max} elementary spectrum bands (blocks) where a number of blocks m_i is allocated momentarily to operator (cell) i. The assigned blocks to the operators are non-overlapping blocks. Fig. 1 gives the general schema of our centralized system model. Parameters $n_i,\ i = 1,2$ are the number of active users in cell i, and λ_i is the arrival rate of cell i.

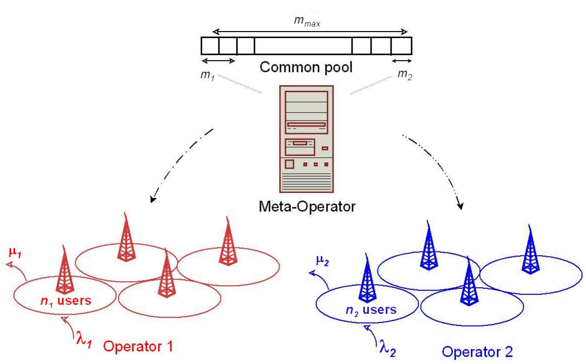

Fig. 1. Centralized model: two operators access to a common spectrum pool

Our model could be coherent with SOFDMA (Scalable Orthogonal Frequency Division Multiple Access) cellular networks (i.e. WiMAX, 3GPP-LTE), where the bandwidth of the system is scalable [17]. In these systems, the operator has indeed an additional flexibility in resource allocation through the possibility of scaling the bandwidth.

For the centralized model, we are presenting a DSA algorithm that assigns bandwidth to the operators based on Pareto optimality concept. The *meta-operator* is aware of the operators situations such as: number of users, maximum cell throughput, the arrival rates, etc... As for the distributed model, the central entity (i.e. the *meta-operator*) does not exist and the operators have direct, and simultaneous, access to the CAB. The DSA algorithm in the distributed model is based on Nash equilibrium, where each operator knows his own arrival rate value and does not know the opponent arrival rate.

B. Traffic

We consider a bursty packet traffic, such as web browsing or file downloading on the downlink: a user alternates between packet calls (several packets are transferred in a very short time) and reading times (there is no transfer). In this paper, we focus on the packet call level and so we neglect the details of the packet level. An illustration of the traffic model is shown in Fig. 2.

We assume Poisson arrivals of user downlink packet calls with rate λ_i in cell i. Traffic is supposed to be elastic: the packet call size is exponentially distributed with mean X_{ON} bits for all cells and so the service rate depends on the available cell throughput. We assume a fair share of resources between users of a given cell (for both operators). For cell i let D_i be the data rate (in bits/s) accessible with one spectrum block. Then the service rates can be written as:

$$\mu_i = \frac{m_i D_i}{X_{ON}}.$$

The average data rate accessible by users in a cell is proportional to the bandwidth allocated to the cell. We assume the cell throughput is equally divided among all users of the cell.

As the frequency reuse scheme mainly impacts the achieved throughput, and as all cells (within each operator) have the same throughput (because the reuse is regular and the networks are homogeneous), we can adapt the traffic model in order to take the effect of interference generated by the reuse scheme. We consider the results obtained in [15], and we make use of the average cell throughput obtained (i.e. D_i) for reuse 3 case.

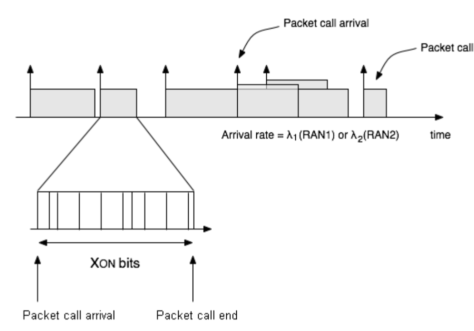

Fig. 2. Assumed traffic model.

The authors in [15] have presented an analytical evaluation of different frequency reuse schemes for OFDMA networks.

Based on the presented model, we can see that each cell behaves as M/M/1/n_i^{max} system, where n_i^{max} is the maximum number of users the cell accepts (according to the Connection Admission Control configuration).

III. Game Theory Framework

In this section we introduce our game theoretical framework, and we give the details of the players utility function. We formulate a two-players non-zero sum game, where the players are the operators. The game G is defined as, $G = (P, S, U)$, where P is the set of players (in this paper we have two players), S is the strategy (action) set for each player, and U is the payoff (utility) obtained by each player given the strategy S.

The strategy performed by each player (operator) represents the number of spectrum blocks m_i allocated to the player i, i.e. $m_1, m_2 \in S$. The utility obtained by player i is the mean (over the number of users) achieved reward given the number of allocated blocks to ***both*** operators (m_1, m_2), and the user arrival rates to both operators (λ_1, λ_2). More details about the operator utility will be given in section III-C.

For each couple of arrival rates (λ_1, λ_2), we formulate a strategic game (matrix game). By solving the game, NE (Nash Equilibrium) points as well as PO (Pareto Optimal) points are obtained.

A. Distributed model

Let $u_i(s_i, s_{-i})$ be the utility of player i given his strategy s_i, and the strategy s_{-i} of the opponent players. The strategy profile s^* is a strict NE strategy if, for each player i,

$$u_i(s_i^*, s_{-i}^*) > u_i(s_i, s_{-i}^*), \forall s_i \in S_i.$$

According to our network model the strategy s_i represents the number of assigned blocks m_i to the operator i.

In the distributed model, each operator plays his best-response strategy against the opponent player. The best-response function $br_i(s_i)$ of player i to the opponents' strategies s_{-i} is denoted by,

$$br_i(s_i) = \max u_i(s_i, s_{-i}), s_i \in S_i$$

Note that, the operator does not need to know the opponent arrival rate, however he knows the opponent strategy.

B. Centralized model

The strategy $s^{'}$ is a Pareto-superior to the strategy profile s if, for at least one player i,

$$u_i(s_i^{'}, s_{-i}^{'}) > u_i(s_i, s_{-i}), \forall s_i \in S_i,$$

without making another player worse off [16].

A strategy is a Pareto-Optimal (PO) when no Pareto improvements can be made. It is worth mentioning that, in the centralized model and from the *meta-operator* point of view, the PO points are more interesting to focus on for the sake of an efficient DSA algorithm. The NE points are not always efficient compared to PO points [8].

It is likely to have more than one PO point for the same game. In this case a selection criterion is needed in order to choose a unique PO point. We choose to maximize the sum of operators utilities (social welfare maximization) in case the game solution gives more than one PO point.

C. Utility function

The operator's utility represents the revenues (obtained through the connected end-users) as well as the costs in terms of spectrum price and blocked users. On one hand, revenue is assumed to be proportional to the satisfaction of the users. On the other hand, it is supposed that spectrum cost follows the 'law' of supply and demand.

The challenging issue in DSA techniques for the operator lies in the trade-off between the cost paid for the spectrum and the revenues obtained from the satisfied users: more spectrum means a higher cost for the operator but also means higher throughputs for the end-users. Based on this principle we define a utility function that takes into account: (1) the user throughput, (2) the blocking probability and (3) the spectrum price.

The higher the satisfaction of users, the higher the operator revenue. The revenue obtained from a given customer in cell i increases with its satisfaction:

$$\phi_i(n_i, m_i) = K_u(1 - \exp(-\mu_i/(n_i\mu_{com}))), \tag{1}$$

where K_u is a constant in euros per unit of satisfaction, μ_{com} is a constant called comfort service rate, and the satisfaction is an increasing function of the user data rate (without unit) [18]. Note that, the users satisfaction function considers only the admitted users to the system.

In order to consider the non-admitted users in the utility, the operator is penalized by susbtracting P_i^{bk} from the revenues due to the blocked users. The substracted value is supposed to be very low as long as the blocking probability is below a threshold value, and very high when the blocking probability approaches the threshold. The penality P_i^{bk} can be denoted as:

$$P_i^{bk} = \exp((\pi_i^{bk} - \delta\pi_{th})K_{bk}), \tag{2}$$

where π_i^{bk} is the blocking probability at the steady state of the Markov chain, π_{th} is the blocking probability threshold value, K_{bk} is a parameter which decides how fast the penality increases as a function of the blocking probability, and δ is a parameter that controls the increasing start point of the penality, $0 < \delta < 1$. The penality can also be seen as if the operator loses money due to the blocked users.

As the spectrum price depends on the market demand, the price increases when the amount of free spectrum decreases. The spectrum price paid by operator p can be given as:

$$P_i^{sp} = K_B m_i \exp\left(-\frac{m_{max} - m_1 - m_2}{m_{com}}\right), \tag{3}$$

where m_{com} is a constant that controls the variation of the price and K_B is a constant in euros per block. If m_{com} is high, the exponential function is close to 1 whatever the state. If m_{com} is small, there is a high discount when the CAB is free. Note that the price paid by the operator for a given elementary band varies with the occupation of the spectrum pool. As the pool size is limited and as spectrum cost increases with increasing demand, there is a strong interaction between the operators.

From equations 1, 2, and 3, the mean (over the number of users) obtained reward per cell for operator i can thus be written:

$$\bar{u}_i = \sum_{n_i=0}^{n_i^{max}} n_i \pi_{n_i} \phi_i(n_i, m_i) - P_i^{sp} - P_i^{bk},$$

where π_{n_i} is the steady state probability that the cell has n_i active users.

IV. Numerical results

A. Parameters

Hereafter we define the paremeters we used to illustrate the DSA algorithm. The spectrum pool is assumed to have a size of 2 MHz, the elementary band (m_p = 1 block) has a size of 100 KHz (that gives a total number of blocks equal to 20 blocks), and m_{com} = 1 MHz. For the sake of simplicity, we assume all cells have the same characteristics: X_{ON} = 2 Mbits, and $n_i^{max} = 8$ users for cell i. Based on the results in [15], the average cell data rates D_i is considered to be 2.6 Mb/s per MHz for reuse 3 case.

The pricing constants are fixed as follows: K_u = 100 euros/unit of satisfaction, K_B = 400 euros/MHz, K_{bk} = 40 euros, π_{th} = 20% and δ = 0.9. Parameter μ_{com} is set to 0.25 s^{-1}, which corresponds to a comfort throughput of 500 kb/s.

The FSA case is the case where the CAB is divided equally between the two operators no matter the values of their arrival rates.

B. Distributed model case

We analyze the distributed model in terms of convergence to NE. Each of the operators uses the best-response algorithm. For the considered parameters set, Fig. 3 shows the simultaneous plays of the operators in a game with $(\lambda_1, \lambda_2) = (0.7, 1.8)s^{-1}$. The figure shows two different cases where the players have different initial strategies for each case. Note that the game has two NE points: the number of blocks obtained by the operators at NE, $m(NE) = (6, 14)$ and $(5, 15)$. In one of the cases (on the left side of Fig. 3) the operators converge to one of the NE points. Though in the other case, they do not converge but they oscillate between a mix of the two NE strategies.

Simulations show that in 62% of the cases the operators converge to NE (they oscillate in 38% of the cases), depending on the initial strategy of both players.

For the games with a unique NE, the best-response algorithm converges in 100% of the cases. It is obvious that the best-response does not guarantee the convergence to NE when non of the NE points dominates the other.

C. Centralized model case

In this section we give the results for the centralized model case, based on the Pareto optimality concept. For the considered parameter set, Fig. 4 gives the obtained *per-cell* utilities for operator 1.

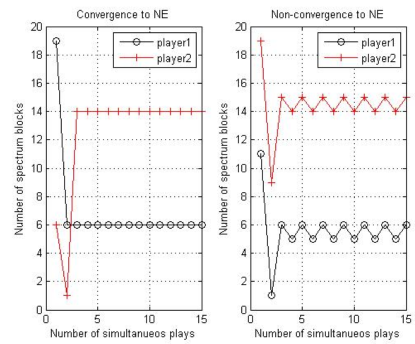

Fig. 3. Distributed model for a game with $(\lambda_1, \lambda_2) = (0.7, 1.8)s^{-1}$.

First of all, it is clear that in FSA situation, the utilities of operator i are dependant only on λ_i. The arrival rates in the opponant operator has no effect. However in DSA situation, the interaction between the operators are more visible especially for high arrival rates.

We can notice that the operators' utilities obtained using DSA algorithm (PO utilities) considerably exceed the utilities achieved with FSA.

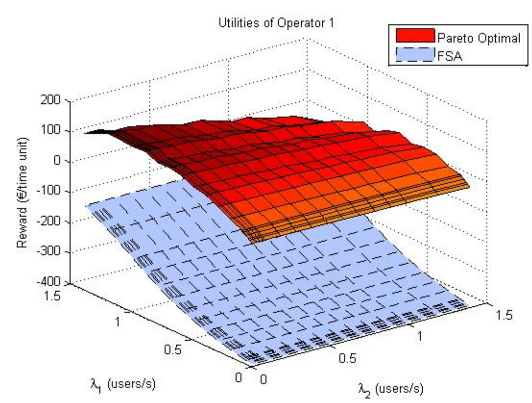

Fig. 4. Utilities obtained with FSA, and with Pareto Optimal DSA algorithm.

Fig. 5 gives the percentage of the CAB utilization for the DSA case. We can notice the algorithm gives more spectrum to the operators with the increase of the arrival rates. Note that in FSA case, the CAB is 100% used for all arrival rate values.

It is worth to mention that, the interaction between the operators becomes less remarkable as the spectrum price goes down. The gain of DSA over FSA in terms of rewards decreases.

The effect of the penality function (equation 2) on the obtained blocking probability is illustrated in Fig. 6. The figure gives the obtained blocking probability for operator 1 using centralized DSA (i.e. Pareto based DSA) as function of λ_1, for different values of π_{th}. The arrival rate of operator 2 λ_2 is set to $0.2s^{-1}$.

D. Distributed versus centralized

According to our analyses of several games with (λ_1, λ_2) ranging from $(0.05, 0.05)$ to $(2, 2)s^{-1}$, the obtained NE points

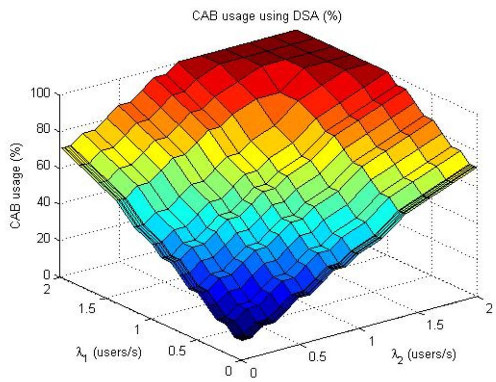

Fig. 5. CAB utilization using Pareto optimality concept.

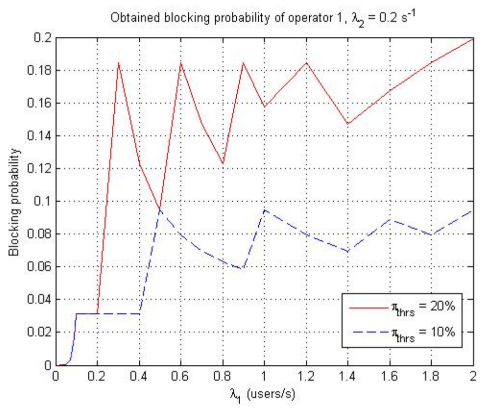

Fig. 6. Obtained blocking probability for operator 1. $\lambda_2 = 0.2s^{-1}$.

are shown to have a PoA (Price of Anarchy) equals to:

- 1 for all the games at $\pi_{th} = 10\%$,
- 0.97 for the game $(\lambda_1, \lambda_2) = (1.4, 1.4)$ at $\pi_{th} = 20\%$, and
- 1 for all the other games at $\pi_{th} = 20\%$.

Note that the PoA is the ratio of reward obtained at the NE point compared to the reward obtained at the PO point. The PoA analyses show that the NE points are as efficient as Pareto. In a practical situation the operators are supposed to stop executing the best-response algorithm after a certain number of plays whether they converge or not.

V. Conclusion

In this paper, we have presented DSA algorithm for cellular operators based on game theory. We have defined utility function for the operators that considers the users bit rate, the blocking probability and the spectrum price. We have presented a penality function for the blocking probability control. We have presented two system models: a distributed model based on Nash equilibria, and a cenralized model based on Pareto optimality. We have studied the distributed system in terms of convergence to NE. A convergence period is needed to reach the unique NE point, and there is a possibility of not converging to NE using the best-response algorithm. The studied Nash equilibrium points are shown to have a PoA of 1. The obtained operators' utilities using the centralized DSA algorithm are shown to considerably exceed the utilities achieved using FSA. The obtained blocking probabilities are shown not to exceed the target value, thanks to the introduction of the penality notion to the reward function.

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