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Departamento de Tecnologías de la Información y las Comunicaciones

Estudio teórico - práctico de los mecanismos de comercio automático de espectro radioeléctrico

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Resumen

El incremento de la demanda de comunicaciones inalámbricas frente a un estático espectro radioeléctrico con el que hacerle frente ha terminado con éste casi asignado por completo, que no ocupado: la solución pasa por utilizarlo de forma más eficiente y uno de los mecanismos planteados es el comercio automático de espectro: hacer posible que los operadores con licencia alquilen porciones a otros para satisfacer demandas de usuarios en tiempo real en un mercado secundario, que permitiría un uso mayor y más dinámico del espectro al tiempo que mantiene los incentivos de los operadores que ya poseen licencia. La casuística de este área se debe al hecho de ser una problemática reciente, así como lo es la herramienta más hábitual para su resolución, Teoría de Juegos; y al número de modelos económicos de comercio pre-existentes con que se puede estudiar, que además no pueden aplicarse directamente por las peculiaridades del bien con que se comercia así como de los agentes. Este trabajo busca exponer una visión general, ordenada y didáctica de las líneas de investigación existentes en este concepto. Se muestra como los distintos trabajos desglosan el comercio de espectro en diferentes subbproblemas y sus combinaciones, con aplicaciones reales todavía lejanas y cómo la Teoría de Juegos es la solución que se adapta de forma más natural al sentido del mismo.

Abstract

The increasing demand of wireless communications versus an static radio-electric spectrum to cope with it has led to an almost fully assigned but sparsely used spectrum. This work studies one of the mechanisms proposed to improve spectrum efficiency, automated spectrum trading: licensed operators would be able to lease unused bandwidth to unlicensed ones so as to satisfy real time demands from users in secondary markets, resulting in a higher and more dynamic usage of spectrum while having the advantage over any other resource allocation method that there is an incentive to those who got a license. The different case studies in the area exist due to the fact that it is a recent field of study and so it is the main tool used here: Game Theory; along with the number of economic models to study it, which can't be directly applied because of the particular characteristics of the trading good and agents. We are looking to give a general, organized and didactic view of the diverse research lines on the area, showing how different works break spectrum trading up into what sub-problems and their combinations, still far from real applications, and how Game Theory is the most common and natural approach to deal with them.

Contents

Chapter 1

Introduction

Wireless communications need of, among other resources, the radioelectric spectrum, which is finite (at least what can be used to transmit information because electromagnetic spectrum, that is to say, all possible radiations, is formally infinite). Government agencies such as the ECC in Europe, Ofcom in the UK and FCC in the United States, grant access to it through fixed, long term licenses on large geographical areas, traditionally on national lotteries, comparative hearings and later on auctions in what is called “command-and-control” management scheme. The ever-growing demand of spectrum due to the growth and popularization of mobile services has left these traditional policies obsolete as almost all the spectrum has already been assigned. However, reports like the 2002 one of the FCC Spectrum Policy Task Force [1] pointed out that most of the licensed spectrum showed very little use and it would be necessary to switch to a more flexible, market-oriented management [4] to improve efficiency. So, in 2003, the FCC started allowing license holders to lease their licenses under different constraints [11].

A dramatic improvement on spectrum usage efficiency could be possible thanks to the development of “cognitive radios”, term that appears for the first time by J. Mitola in [2], radios that are capable of gathering information about their surrounding radio environment (*cognitive capability*) and adapt their transmission parameters according to what they discovered (*reconfigurability*) [3]. In the most typical scenario, unlicensed users (also called “secondary users”) with this equipment would look for unused fragments of spectrum anywhere in time, space, frequency and/or power, known as “spectrum holes”, and use them for their transmissions under some harm constraints for the protection of licensed users (“primary users”).

This situation corresponds to the “Hierarchical Access Model”, one of the possible models under “Dynamic Spectrum Access” (DSA) [5], but there are more [6] as the “Exclusive Use Model” , which considers leasing or selling licenses, the “Spectrum Commons Model’ which considers open sharing with no categories of users. In fact, there is still a long debate on how the spectrum should be considered, either as a property (“property rights”) related to the exclusive use and hierarchical model or as a common good like a town river, see [7]for more on this. There is more on regulation issues on [11]

No matter which of these models is considered, an improvement on spectrum usage to deal with demands and new services can annoy already licensed operators, as these approaches mean some costs to them such as changes in their infrastructures, lowered QoS because of interferences, profit reduction due to increased competition... , apart from the fact that they already paid for their licenses. Among all mechanisms proposed to improve spectrum efficiency, automated spectrum trading has the advantage of providing economic (and/or any other) incentives to these already established operators, encouraging their cooperation and avoiding demotivation on their investments or future primary operators, being this the main issue addressed by most works on this area. At the same time, "pricing" is a tool to efficient resource allocation and prevents infra-utilization and may contribute to a auto-regulated system (if spectrum markets are created and full competition is achieved). Apart from this social/economic problems, cognitive networks also present a vast range of techonological challenges [9]

Previous works in Economy are not easily translated to spectrum trading because of big differences not only with the agents that take part on these transactions but also with peculiarities of the trading good. Regarding the agents, they are automatic agents (however, automatic transactions on Stock Exchange are starting to be used [49]); their supply and demand can vary in real time because their need to transmit depends on information generation, which may change fast; the fact that these agents may not have complete and/or reliable information about the market due to the complexity that it would involve, specially in ad-hoc networks (it would imply, for example, that all entities know all channel gains, among much more information). About the trading good, spectrum characteristics can also vary and the perception of them made by the agents, with regard to availability, quality (physical variatiopns on channel parameters). In addition, the same spectrum portion can be valued differently by different buyers, depending on the usage they make of it. There are more aspects to take into account, such that it is divisible, it can be shared simultaneously by users where their activity could harm each other , it can be reutilized geographically... All this adds to the previously announced technological and social/economic challenges.

Our main contribution is to serve as an introduction to the immense number of case stuides available in spectrum trading, trying to categorize the different sub-problems they tackle and techniques used, with a special attention on the most recent works and with a essentially didactic view which is directly translated into the structure of our work, dealing with these works in an increasing complexity order. In section 2 we breakdown the works with one buyer and one seller of spectrum. In section 3 we show monopolies. The most typical situations with competition among sellers and buyers are studied in section 4. We devote a special section to a very popular spectrum trading mechanism in section 5, auctions. We give some hints of future research lines and conclusions on section 6.

Finally, as an Appendix, we develop an spectrum trading model based on a single-sided auction using a Markov Decision Process where several secondary users try to access a system offering a price (from a finite set) and the operator decides to let them in or out depending on the tradeoff among blocking probability of primary users and profit from than accesing user.

Chapter 2

“When it takes two to tango”

The foundation of the spectrum trading house (and any trading in general) is the case where a transaction takes place between only two entities. Usually one of these entities, the ”seller", wants to supply unused spectrum opportunities it owns for as much monetary value as possible, whereas the ”buyer" is interested in that good but willing to pay as less as it can. [*] Although this situation can appear as simplistic, it is useful as more than as a starting point of understanding, it can resemble a real scenario when primary and secondary networks have a centralized structure so the transaction is negotiated between their base stations as in fig. 2.1

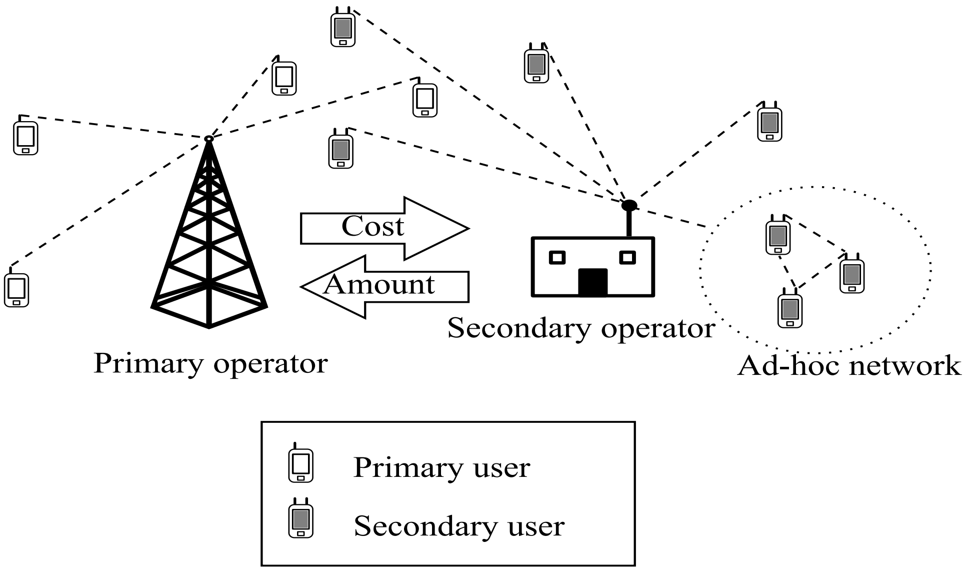

Figure 2.1: Basic spectrum trading

For the buyer, the compromise between its interest in what the seller offers and its cost is expressed in the utility function, which is a quantitative measure of the buyer’s

[*]There are variations on this: the buyer may not pay with money but with cooperation with the seller’s transmissions; the buyer may not be willing to pay less but to get the best possible quality; the transaction good could be bandwidth, data rate, successfully sent packets...

satisfaction degree. Derived from that function, the demand function can be obtained, which expresses how much of the trading good should be bought given a price in order to maximize its satisfaction. Similarly, the seller is also in a compromise between the revenue it obtains from the buyer and some costs associated with the sale: as it will have less remaining spectrum available, it may not be able to satisfy an increase of demand from primary users (higher blocking probability), interferences, apart from fixed costs because of the investment in infrastructure. This compromise is expressed in the profit function, and differentiating it with respect to the amount of good sold, the supply function is obtained, which shows how much of the trading good should be sold given a price in order to maximize its satisfaction.

One solution to this conflict of interests between the buyer and the seller is proposed by D.Niyato and E.Hossain in some of their works [13, 14, 15, 16, 17], and its based on the supply/demand model of Microeconomics theory (with some techniques being used to eliminate the constraint of perfect competition of the market), whose solution is the market-equilibrium price, a price that makes supply and demand equal and thus, maximizes satisfaction for both the seller and the buyer so that there is no incentive for any of them to deviate from it. Solving that equation in a centralized way may imply having an almost global knowledge of the network (i.e. the demand function could depend on the channels gains) which is a hard constraint to met in a real environment, so they proposed several distributed and iterative algorithms to reach the solution.

Chapter 3

Monopolies

Some works such as [23, 24, 20, 19, 22, 21, 25, 26, 30, 27, 31, 29, 28, 32] feature only one entity as seller while introducing several secondary users. Users take their own decisions independently, although they influence each other (i.e primary operators charge them as a function of their total demands). As we said in the introduction, the most studied issue is “pricing” to incentive licensed operators [23, 24, 22], while another important focus of this section is resource allocation [20, 19]. A model with several sellers and several buyers would be more natural and desirable due to the increased competition that would maximize the effects of spectrum trading. These works, however, use a monopoly model because of their interest to simplify the framework, getting rid of buyers competition, so they could focus on the above considering other aspects such as secondary users interactions, different system models i.e. random spectrum access [21],etc.

3.1 Techniques

The most common tool to model interactions among secondary users is Game Theory [23, 20, 19, 26, 27, 30, 31, 29, 28, 32, 25]. *Game Theory* is a mathematical study of situations involving individual rational decision makers with different (and often conflicting) objectives. . In the framework of Game Theory, the interaction among those individuals is a *game*. In that game, each of the them are *players*, whose actions *,moves* or *decisions*, bring an outcome to them (*payoff*) and they are mapped to the set of possible situations of the “world” a player can perceive in a *strategy*. Rationality refers to the players’ attitude to select what maximizes their satisfactions.

It is clear to see that it adapts to the spectrum trading scenario: each user has the goal of maximizing his satisfaction using a shared resource from an operator so their actions have an influence on each other. In this case, spectrum trading can be seen as a game, where users are the players, their moves would be the action of requesting spectrum opportunities from the operator and the payoff could be the variation on their net utilities.

Once the model is set out, what is interesting in spectrum trading is to find if the set of strategies of the players intersect so that the system is in equilibrium. There are different types of equilibria, being Nash equilibrium (NE) the most popular, system status where no player has motivation to unilaterally change his action because he would obtain a worse payoff. Nash equilibrium does not always exist as well as there can be infinite NE points and a NE does not necessarily entail optimality. There are several ways to understand the concept of “optimal” such as “Pareto optimal”, which states that a solution to the game is Pareto optimal if there is no other solution to increase any player payoff without worsening other. A more restricting solution would be “social optimal” similar to Pareto optimal but involving all the entities of the transaction. Apart from that, some other properties of the solutions may be studied, such as spectrum usage efficiency, fairness or stability of algorithms. The key of these works is how to configure the game parameters, such as utility functions, to model transactions in order to reach a convenient solution. To illustrate these concepts, see figure 3.1. Let’s imagine a simple game consisting of two players requesting bandwidth from an operator which will charge proportionally to their aggregate demand. Both players would buy less bandwidth if the other player buys more (as the cost will increase) but they have different utilities/demands/strategies which led to the best responses graph on the the figure. Those best responses intersect in two points: A and B, which are Nash equilibria: there each of the players is reacting to each other with its best possible action so they have no incentive to change their actions. However in this case (as usual), as it can be seen on the graph on the right, none of those points are optimal. The collection of Pareto optimal points form the users Pareto front. In addition, considering the operator’s profit, the social optimum may not be a point in that front* It is worth commenting that, as it is represented here, the points of Pareto front and social optimum of a particular game may not be equilibria so the efforts should be oriented to make the system stabilize on the most efficient NE or re-formulate the game.

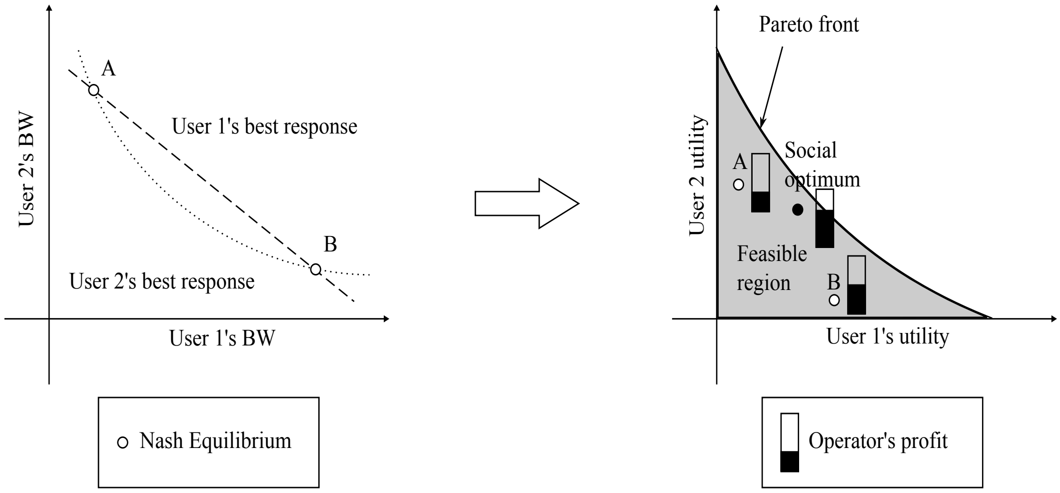

Figure 3.1: On the left: best response of each player to the other’s action. On the right, utility received by each user

There are several different games and possible classifications attending to various aspects of them. One of them worth commenting in spectrum trading is whether players perform their actions simultaneously [19, 20, 23, 25, 30, 31] or sequentially, so players have

*Users’ total utility versus operator’s profit can be represented in a similar graph with its own Pareto front where the social optimum lays information about actions performed by players that moved first as in a Stackelberg game ref:Simeone2008,ref:Zhang2009,ref:Yi2010,ref:Vazquez2010 and/or the game is played along rounds so they know about moves made in previous rounds, as in dynamic/repeated games [23]. In a Stackelberg game, at least one of the agents, the “leader”, makes its decision first and the rest of the players (“followers”) react to it. The leader assumes rationality, that is to say, as the followers can see its decision before making their own , they will choose their best possible responses, the ones that maximize their utilities function. The solution to this game is the Stackelberg equilibrium, which is different from Nash equilibrium, the leader receives a better payoff: it knows the followers’ best response and using backward induction it can optimize its strategy, and this is the catch of this model: the leader needs to know the followers’ true valuation of the trading good, which is an unrealistic assumption in a competitive environment. In a dynamic game, players interact, that is to say, execute an action, more than once which is based on previous moves by them and/or the others. The advantage offered over static games is that it does not require that each player knows a priori the strategy of the rest (as each strategy is the best response to the strategy of others, and NE is a point where those best responses intersect), players learn on each round by observing taken actions and payoffs and adapt theirs. However, these algorithms are hard to develop, convergence is slower and they may not reach the same solutions. But, at a cost of a growing complexity, they can reach more solutions in a dynamic environment if they take into account future utilities/payoffs and/or infinite horizons (infinite rounds), so they are continuosly adapting to variable situations (such as real variations on supply and demand).

Another important classification refers to players’ attitude: non-cooperative or cooperative games. Non-cooperative games are most common in spectrum trading, because of their simplicity and closeness to reality: each user is on a free-for-all share of resources trying to maximize its satisfaction on its own, with no communication or help from other users, which are competitors. However, most of the times this selfish behavior leads to inefficient outcomes and different techniques are used to drive players to other equilibria points. Cooperative games offer a way to avoid those situations mostly through communication between players, such as binding agreements enforced by a third party, “commitments” (a player takes a binding action on him and informs the others so he can persuade them to take convenient actions to him, like threads), bargaining [25]. In this sense, they are closely related to dynamic games, specially infinite horizon games, where cooperation is encouraged due to the long term relationship that could be established among players and the possibility to punish those who don’t respect agreements in future actions.

One of the Game Theory branches that is receiving special attention is the one that merged with a previous well-known trading model, auctions. As we will show later, an auction can be seen as a game with incomplete information as it happens in a dynamic game. Auctions will be discussed in a different section due to their high use and peculiarities.

Regarding the operator/seller behavior on a monopoly, there are three possible options. The most ordinary one, which gives them an incentive to grant access to users is optimization of pricing [19, 23], i.e. users play a game where their strategies are the amount of commodity they are going to request from the operator, given the price previously announced by him. That price will be set up by the operator as a result of optimization of his revenue under different constraints, taking into account the status of the environment and information from users as willingness to pay. On the opposite side of this idea, another case is when the operator literally plays the game, developing his own strategy, bargaining... as seen on the section “Seller on the game” There is also the possibility where the users also perform the optimization of price in a distributed manner as in [20].

Game Theory is not always used, there also many works where the trading process relay entirely on optimization i.e. [21, 24, 22]: finding the values of some parameters such that selected functions are maximized/minimized, subject to a number of constraints. In the context of spectrum trading, these parameters usually are price per commodity unit (often bandwidth or power), the constraints are related to degradation caps on primary users’ activity and the goal of the optimization can be diverse (which applies to the pricing optimization performed on games) and will be discussed later.

Depending on the form of the function to optimize and the constraints, different optimization techniques are used, while the efforts are often oriented to formulate the problem as a convex optimization problem (goals and constraints are all convex functions) or trying to reduce it to one, due to mathematical advantages to solve them.

It is interesting to know that the equivalent to dynamic/repeated games exist in optimization through the application of (stochastic) dynamic programming to solve Markov Decision Processes [24]: a model that considers different states of a system (which could be seen as each trading stage, i.e. time slots) in which one decision maker choose an action based on that state and the state changes randomly and the decision maker receives a payoff. The main difference with dynamic games are the fact that in optimization there is only one centralized decision maker compared to the distributed nature of game theory, however, there are techniques halfway between these two disciplines, such as considering Nature as a player on the game (Stochastic games) or multiple decision makers (competitive MDP).

3.2 Motivation

Going on to comment some of these works, H.Mutlu et al. [24] are focused on maximizing profit of a spectrum owner from SUs’ payment for accessing its call center, considering that charged price will vary as a function of the occupation of the system. That variation on the charged price will also influence the arrival rate of SUs (decreasing with price) and there is no associated cost to PU of sharing unused resources: damage to PUs is only reflected as a monetary value punishment to the spectrum owner if any PU entering the system is rejected because it is full. First they show an optimal pricing policy calculated with stochastic dynamic programming using a MDP and considering that this varying price makes cost less predictable to a SU and thus, reduces their demands, they obtain a suboptimal threshold single-price policy which does not depend on the form of SUs’ demand functions but only on their support.

H.Yu et al. [19] show spectrum trading in the context of power control in a CDMA system: focusing on a cell with a PU base station, PUs and SUs both trying to communicate with the BS, so the commodity in this market is uplink power. SUs play a non-cooperative game of power given the price set by a optimization process on the PU’s

BS. That optimization process contemplates the revenue obtained by charging some price-per-power unit to SUs and does not consider any cost of sharing unused resources but a fixed constraint on the power received from a SU, total power received from SUs and minimum SINR for a SU. A suboptimal algorithm (it is a non-convex problem) is presented so that the allocation is sub-maximices revenue of PU and it's efficient and fair among SUs, understanding "fair" as charging more to those with a better channel quality and bigger valuation of the power unit. However, it considers such private SU's information as known by the BS when, in fact, could be user in a malicious way by a SU to obtain lower prices.

Using a very similar scenario, [22] introduce "quality discrimination spectrum trading": a spectrum trading market where SUs are classified into multiple (discrete) categories according to their preference for a given spectrum quality when buying a channel, where "quality" stands in the example used as maximum allowable transmission power. All computation efforts are centered in the PU's BS, who has to derive the optimal set of qualities-prices and associate each SU consumer type one, so that PU's revenue is maximized while making this associations (called "contracts") incentive compatible to SUs, that means, each SU from a type would have to find his associated quality-price as the best option, even considering not to transfer at all. This solution improves PU incentive by losing some aggregate utility of the system compared to the maximum social surplus.

Again in the context of power control , [20] aims to improve social optimality of the resource sharing, considering that each CDMA channel is a multi-user interference channel, that is to say, multiple SUs can share the same channel, having to consider mutual interference. It uses a non-cooperative power game among SUs while price optimization is also performed by them in a decentralized manner using different variations of a "iterative water-filling" algorithm, depending on whether is preferred a faster convergence speed but with the need of having SUs syncronized and correctly estimating information about each other or a relaxed but slower version . In order to achieve that, the pricing function obtained by the SUs is user-dependent and no matter which algorithm flavor is used, it would require local information about SUs. They also develop a MAC protocol to implement the exchange of messages needed.

D. Niyato and E.Hossain not only worked on market-equilibrium. In [23] they apply a well known non-cooperative game to SUs, Cournot game, in which SUs compete for the amount of spectrum they want (to maximize their utility functions) given the price announced by the PU, taking into account that it charges them the same fixed price, proportional to their total demand. This work is focused on maximizing the profit of SUs at NE, but leaves the door open for the maximization of PU profit by stating that it could perform price optimization. The most important contribution of this paper is a dynamic game model formulation which frees SUs from the need to know the strategy adopted by each user and their payoffs and only relies on SUs' knowledge of the variation of the profit obtained from PU under their different actions.

3.3 Seller on the game

Although primary users/network always take part actively in the trading process, there are some works where they literally enter the game as players [26, 27, 28, 29, 30, 31, 25, 32], mainly acting as leaders in a Stackelberg game as in [26, 27, 28, 29].

This is the chosen method in some works where there is no bandwidth-for-money trading, but bandwidth-for-cooperation instead [26, 27, 28]. The premise is as simple as the usual trading: a primary user will lease some transmission opportunities if secondary users, in turn, help the primary user on its transmission by acting as relays, which makes the primary user to be able to increase its transmission rate.

In [26], time is divided into blocks where each block has three stages. On the first stage, the primary user communicates with its intended receiver via direct link and secondary users receive the information too (broadcast). On the second stage, some secondary users re-transmit the same info to the primary receiver. Finally, those secondary receivers can communicate with their intended secondary receivers. Before each of these transmission blocks, the primary users tries to optimize its utility function by selecting which secondary users it is willing to use as relays and how much time it will associate to each stage, based, as said before, on knowledge about their best responses depending on the system status (i.e. channel gains). After the primary user makes public its decision, the selected secondary users play a non-cooperative power control game where each secondary user tries to maximize its utility taking into account that they will use the same amount of power for cooperating with the primary user than for their own transmission. That election includes the possibility not to transmit at all in case the bandwidth offered by the primary user is not worth acting as relay. It is clear to see the Stackelberg model and its leader-follower scheme matches perfectly this kind of problems.

J.Zhang and Q.Zhang [27] add to the previous work the thought that a primary user has certain traffic demand and once it is satisfied, it will have no incentive in improving its transmission rate and therefore it won't be willing to permit secondary users access. In order to avoid that situation, [27] proposes that secondary users should also pay some monetary value to the primary. It also sets a different MAC of secondary users, TDMA, rather than power control, claiming that simultaneous transmission of all secondary users on an interference channel as [26] shows is unrealistic because an SNR constraint can not be met. In [27] cooperative SUs play a non-cooperative payment selection game: their actions are how much they are willing to pay and transmission time is divided among them proportional to the amount they paid.

Chapter 4

Spectrum sellers' competition

Until this section, only the relationship between one seller and a buyer or multiple buyers has been studied. This may not be a natural or most typical situation, as it is highly likely that more tan owner spectrum licensee (owner) on a region will be interested in selling, and furthermore, it is a desirable situation from the point of view of resource exploitation and users' welfare because of the competition. However, as competition grows, spectrum sellers' profit diminishes and several dangers arise, such as demotivation to provide their service and investments, aggressive market strategies to end up as a monopolist or forbid entrance to newcomers, etc. so regulation may be needed to encourage competition while keeping incentives for spectrum owners. For more on this see [12, 46]

This competition among sellers is introduced in most of these works on a three-layered market model as in figure 4.1 composed of primary spectrum operators which obtain spectrum through licenses from a regulatory entity (such as the FCC) and provide service to a set of primary users on long term subcriptions, and secondary spectrum operators which buy unused spectrum to the primary providers and sell it to secondary users in a typically shorter time basis (even real-time/on demand). That is to say, the first layer of the market would be the (i.e. auction) process where primary operators get spectrum licenses, the second layer market involves those operators selling portions of that spectrum to secondary operators in a larger time scale than secondary operators selling spectrum to users in the third layer [*]. However a market model can have more than three layers, by allowing secondary users to re-sell spectrum, establishing ternary, quaternary markets... Most works on this section focus on secondary operators, where previous commented works could be representing either the second stage market or the third one (depending on the time scale).

The reason of existence of these virtual [†] intermediaries to do the secondary trading is that they could focus on it, being near the end costumer and thus, crafting tailored plans and/or adding innovative services [40, 48]. In addition, it is a way to ease the entrance

[*] Not to be confused with the number of game stages modeling this markets: usually focus will be on the second and third layers, so games will have three stages: spectrum investment (secondary operators buying spectrum), spectrum pricing (secondary operators setting a price) and demand distribution (secondary users selecting secondary operator

[†] "Virtual" as they have no spectrum license and may not even have infrastructure as a Mobile Virtual Network Operator MVNO for cellphones (i.e "Ting", "Truphone" or"Straight Talk" in the USA)

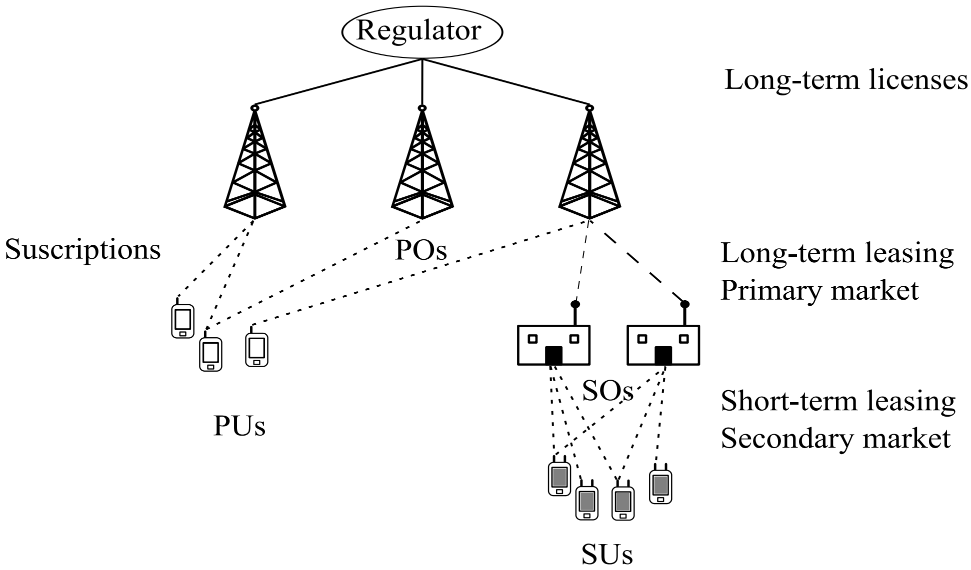

Figure 4.1: Three-layered market

to the market to a potentially new primary operator and so, improving users wellfare and spectrum utilization as well as providing incentives for existing primary operators since they'll have the ability of selling their bandwidth excess without having to worry about designing princing and/or marketing plans for secondary users to buy it.

As in previously cited works, pricing is still the most exhaustive issue studied but adding to it new dimensions brought by competition and focusing on this middle layer: spectrum differentiation/substitutability [34, 36, 35, 44], joint study of spectrum investment with pricing [36, 39, 40, 41, 42, 45] *. There are also works outside this three-layered market model [33, 34, 37, 47] even with a different relationship between primary and secondary operators [43]

Spectrum differentiation refers to the consideration of spectrum as an heterogeneous good instead of the common assumption of all portions being equal in characteristics. The "model" section of [34] explains it in more depth but basically lower frequency signals go better through obstacles and can travel further at the cost of less amount of information transmitted and less ability to directionalize the signal. Other reasons are that the spectrum holes may or may not be contiguous blocks which may be needed for some transmission technologies, different perceived QoS depending on the geographical distribution, number of users on that operator... All this leads to different valuations by users depending on their preferences and thus, different demands and services selection (even selection of more than one operator although typically no demand split is considered as it would make any analysis very complex) which enable more niche markets that should be taken into account in pricing.

Focusing on secondary operators, intermediary entities with no spectrum licenses

*L.Duan et al. works[39, 42] don't really study sellers' competition but they are closely related to its other works featured in this section showing the same structure and dealing with investment as if they were on a competitive environment ownership, makes possible to study the impact of spectrum purchase to owners on the final price charged to secondary users. There are several ares of concern around spectrum investment: some authors like J.Jia et al. on [36] assume that, no matter if the spectrum is bought to the regulator or to primary users, these are long-term transactions (i.e. for years) as legacy from the old command-and-control law framework, while secondary operators are looking to satisfy secondary users' needs almost on demand, so, they work trying to adapt secondary operators real time dynamic pricing strategies to those long-term investment decisions. Another point of interest is that competition can also take place at the investment stage among secondary operators either directly, where they are trying to get "best quality" spectrum, i.e. [45], and/or they are charged based on their aggregate demand [36] or indirectly, as the bandwidth amount offered by each operator to the secondary users and its aggregate total will influence prices and profits [40]. And while most of the works on spectrum trading only consider leasing as the way to obtain spectrum, some research on influence of spectrum sensing [39, 42] or sharing spectrum bands [37].

Regarding those works showing a different market structure, in [33] a variation of a private commons regime is modeled (the authors call it "mixed commons/property-rights) regulated and centralized in a Spectrum Policy Server per geographic domain. When each user enters the system, it connects to this broker which obtains its location and a function called "acceptance probability of services" related to its utility function. Then the SPS stars an iterative bidding process of service offers among operators where the winning bid is the one with the most acceptance probability, which is shown to the user and accepted with that probability. The objective of this framework is to maximize users' utilities but that doesn't mean optimizing bandwidth usage or SPS profit and this iterative bidding hurts operators' profit. An extension to a multiuser environment is also studied where the SPS would partition the available bandwidth among each bidding process looking to optimize its own revenue which is proven to be the same as optimizing bandwidth usage, however, each chunk is treated as before so there is a loss on resource allocation and operators' profit.

Y.Xing et al. [34] thought that a centralized controller didn't match the reality of a situation that is distributed by nature and proposed a model with only operators and users interacting directly, where users perceive spectrum as an heterogeneous good and with different valuations of it depending on their application and distance to the operators. Users also have different sensibilities to either "quality" (understood as any valuation that a user can make) or price (more interested in one versus the other) and a limited budget and QoS minimal requirements. Based on that, they sort operators and choose their preferred. Operators play a non-cooperative game to set their prices (given fixed qualities) assuming full information of this and a stochastic learning game when there is lack of it where they update their prices based on the profit they obtained. The authors also did a mini-study of cooperation among groups of providers showing that even non-cooperating ones benefit from it. One of the interesting results show that cost has a huge impact on profit and low-end sellers may end up gaining more. Price war phenomenon in also observed under some circumstances (where cycles among different equilibrium points take place) This work is one of the most complete in the area but it does not contemplate dynamics such as supply/demand variations with time.

With a different perspective, [37] investigates a duopoly of operators which have a fixed part of spectrum and share another band but they can only use it under congestion and proportionally to their excess traffic. Operators play a one shot non-cooperative game on price on each time slot, given fixed capacities of spectrum and a demand depending only on minimum price perceived, taking into account that users will choose the operator with lowest perceived price. This perceived price is a congestion price: users believe they are charged per successfully transmitted packet when in reality they are charged per submitted packet as announced price is the one obtained on the game multiplied by the average number of retries needed to transmit it (which can be estimated by each operator based on its received demand/capacity ratio). A numerical example of NE is provided where the interesting fact is that it is reached when both operators are saturated, however it does not provide insights on how to avoid trivial equilibrium (0,0) when total demand is less than total capacity, the effect of a possible usage cost of the unlicensed band and the extension to more than to operators. Regulation is suggested as a bigger shared band would benefit user welfare but decrease operators' profit.

S. Dixit et al. [47] are also interested in a different market model, without brokers or any centralized entity and no information sharing, as they consider that the cost of such that infrastructure would be high and operators would not be willing to share any information on a competitive environment. Instead, the authors propose that the primary base stations should be the ones to also serve secondary users selling directly their unused spectrum (strictly unused. No trade is considered of primary users' QoS for revenue from secondary users, although it considers a fixed cost for providing the service). In order to be completely decentralized, they set prices based on local info such as remaining bandwidth. This model is transformed when competition takes place to a static non-cooperative gane, where in order to avoid inefficiency of a Nash Equilibrium, service differentiation is proposed based on their distance from user, although it is not explained in detail. An extension to a dynamic pricing strategy (without calculating equilibrium on competition, which may be too complex) is proposed, where price charged to users increases for each accepted SU.

L. Guijarro et al. in [43] is close to the three-layered market model (it is a three-layered market indeed) and studies dynamic spectrum access but *á la Mobile Virtual Network Operator*, that is to say, when the virtual operator buys spectrum to the licensed one, it becomes its competitor for a common pool of users and play a non-cooperative game on price per subscription which is taken into account by both operators on the sale. The sale is the result of a bargaining game where price would depend on the bargaining power of the licensed operator (as an example, full power is assumed so licensed operator is looking to optimize its profit) but the bandwidth is not determined and only constrained. Bandwidth could be adjusted depending on the objective: maximize operators' profit, user welfare or social welfare (all entities benefit).

J. Jia and Q.Zhang. in [36] did the first joint study of spectrum investment and pricing and set the baseline framework for these studies, with a three stage non-cooperative game on spectrum investment, pricing and secondary users service selection, adding spectrum heterogeneity. This type of multi-stage games are solved using "backward induction": studying how users would react to prices (based on their utility functions), each secondary operator can analyze which would its best response on setting its price and knowing that each operator can set how much spectrum would it lease from the primary. The authors also propose a solution where secondary operators can only know their profit functions, breaking the game up into two dynamic games: first a short-term price adjustment game and then a long-term spectrum leasing adjustmente once the previous game is stabilized, with the disadvantage that it takes long time to reach equilibrium

L. Duan et al. works [40, 41] use this same structure but secondary operators don't directly compete in sepectrum investment (spectrum cost is fixed and the same for both, it does not depend on their aggregate demand), although they claim to be first on joint-studying spectrum leasing and pricing taking into account users heterogeneity, that is to say, different transmission conditions for them. They use different functions on the mathematical development which allow them to obtain threshold structures for the decisions of each stage, and a fair and predictable SNR for users. In addition, they prove that operators' profit gets reduced only by a 20% compared to a monopoly. In [39, 42] they do not consider operators competition but they keep using the same market structure with a very interesting variation: operators first try to get spectrum from the spectrum owner by sensing and then by leasing. So, these works study how much to invest on leasing (which is more expensive than sensing), taking into account the uncertainity in obtaining spectrum through sensing (although it is found free on sensing, it may be occupied at the moment of transmission so it can not be used). Under this scheme, operator's expected profit and users' utilites increase.

Chapter 5

A well-studied market mechanism: auctions

Auctions have been used along History to sell items and specially to sell limited common goods [55, 54] because of their notion of giving and item to the one that valuates it most and because the transaction can take place in public and remove suspicious about the government benefiting any buyer for a bribe.

An auction is controlled by an auctioneer, which in spectrum trading is usually the spectrum owner or an external regulator authority. In its most basic form, buyers submit "bids" according to their valuation of the item and the buyer with the highest bid and thus, the one who valuates the trading good most, gets the item and pays for it depending on its bid. By assigning the spectrum to the ones that valuate them most, social welfare could be maximized. However, focusing on that as a strict goal could lead to starvation to buyers with less "bid" power (less budget) , discourage them from competition and finally, end up worsening social welfare [56].

Game Theory is also used to study auctions, which can be seen as games where bidders are the players and the strategies are the bids. These games would be games of imperfect information and that is the strongest point of auctions related to spectrum trading: unlike most of the previously commented works, they don't assume the knowledge of the private valuations of the goods by the buyers and it is in the best interest of buyers to submit bids accordingly to their true valuations *. Indeed, the biggest concern of most works on spectrum trading auctions is to develop cheat-proof mechanisms such as second price auctions or VCG auctions while trying to reduce their computational complexities [50, 58, 57, 51], however, they are still vulnerable to collusion attacks.

As it happens with games, there are several types of auctions and the challenge is to properly design its rules to achieve different sub-objectives. However, it is unlikely that the seller would simply let the auction play by some rules and accept its result, without really getting involved in it (even if it is the auctioneer) and there are several mechanisms for it to intervene, such as setting a reserve price (it won't sell unless bids reached some value) or multi-unit double auctions, where sellers also bid with the price they are willing to sell [52, 53]

* In reality, that's not exactly true. The key is that they are more efficient under liars

Auctions may not achieve points as near to social optimum as market-equilibrium or optimization but they are simpler to implement and faster to converge, however, they are not as fast as some games and it is hardly suitable for real time markets. In addition, auctions usually need an auctioneer so they don't get along well with ad-hoc networks.

Chapter 6

Future research lines and conclusions

We have shown the variety of economic models used to study spectrum trading and the special characteristics of spectrum as a trading good and its agents. Apart from the tendency to unify more of these aspects on more and more complex models, there are the following open challenges:

- Communication overload: the cost associated to information exchange among agents is not usuall considered, understanding “cost” as the resources needed to do so (such as power) and/or delays that prevent real time trading.
- Protection against misconducts/nasty agents: most of the spectrum trading algorithms are based on the knowledge of agents private information and/or trusting that they would report their true valuations but in reality they have incentives to transmit wrong information so that they would gain more profit at a cost of unfairness, system disequilibrium... Other negative situations could be malicious cooperations among providers or users to rise/lower prices.
- Lack of rationality and incomplete information: in that sense, similar failures can occur in a system when that information gets lost or it is faulty. In addition, Game Theory assumes that players are rationals but does not offer protection against failures in their decisions due to decisions in these situations.
- Dyanmic programming/games: most works on spectrum trading consider a one-shot interaction among agents without taking into account future payoffs, priorities on trading due to previous agreements, that is to say, they do not take into account previous or future trading history, which could be used to maximize satisfaction in long-term. There are mathematical tools to implement this but it has not been used much due to the additional complexity they introduce.

This work tried to show a panoramic view of spectrum trading with the intention of being a starting point to enter on it. In this work it can be seen that spectrum trading is a relatively new field of study where there are several approches to implement it but these are far from real applications due to its complexities. Game Theory is one of the most used tools because of its natural adaptability to a decentralized and independent decision making on networks around spectrum trading.

Appendix A

An MDP Framework for Centralized Dynamic Spectrum Auction

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Abstract

Public administrations assign the spectrum bands to wireless operators by a license scheme. Generally, operators gain spectrum licenses by bidding for them in public auction processes (primary market). The increasing demand of spectrum and the existence of spectrum holes have revealed the inefficiency of this mechanism. One practical and economically feasible way to solve this inefficiency is to allow spectrum owners to sell their spectrum opportunities in a secondary market. In order to do this in real-time, a protocol is required to support negotiations on access price, channel holding time, etc, between the spectrum owner and secondary users. In this work, we consider the bid-auction model, in which secondary users bid for the spectrum of a single spectrum owner. We explore the possibilities of a formal design based on a Markov decision process (MDP) formulation which has to include the trade-off between the blocking probability of primary users and the expected revenue.

Introduction

Cognitive radio refers to a set of technologies aiming to increase the efficiency in the use of the radio frequency (RF) spectrum. Wireless communication systems are offering increasing bandwidth to their users, therefore the spectrum demand is becoming higher. However, RF spectrum is scarce and operators gain access to it by a licensing scheme in which public administrations assign a frequency band to each operator. Currently, this allocation is static in the sense that a licensed band can only be accessed by one operator and their clients (primary users or PUs). However, it is a known fact that while some RF bands are heavily used at some locations and at particular times, many other bands remain largely underused [1]. The consequence is that, while the spectrum scarcity problem hinders the development of new wireless applications, there are large portions of unoccupied spectrum (*spectrum opportunities*).

Cognitive radio provides the mechanisms allowing unlicensed (or secondary) users (SUs) to access licensed RF bands by exploiting spectrum opportunities. It is crucial for this opportunistic access to be performed with the least possible impact on the quality of service provided to licensed users. Dynamic spectrum access (DSA) refers to the mechanism that manages the spectrum use in response to system changes (e.g. available channels, unlicensed user requests) according to certain objectives (e.g. maximize spectrum usage) and subject to some constraints (e.g. minimum blocking probability for LUs). DSA can be implemented in a centralized or distributed fashion. In the former one, a central controller collects all the information required about spectrum usage and transmission requirements of secondary users in order to make the spectrum access decision, which is generally derived from the solution of some optimization problem.

MAC protocols for DSA can also include spectrum trading features. In situations of low spectrum usage, the licensed operator may decide to sell spectrum opportunities to unlicensed users in the *secondary spectrum market*. In order to do this in real-time, a protocol is required to support negotiations on access price, channel holding time, *etc*, between the spectrum owner and secondary users. There are several models for spectrum trading. In this work, we consider the bid-auction model, in which secondary users bid for the spectrum of a single spectrum owner.

This paper addresses the design of centralized DSA MAC protocols comprising dynamic spectrum auction. We explore the possibilities of a formal design based on a Markov decision process (MDP) formulation (Section A). We survey previous works on this issue (Section A) and propose, in Section A, a design framework to balance the grade-of-service (given by the blocking probability for LUs) of different user categories and the expected economic revenue . This trade-off can be managed in two ways. One consists of computing a single objective value by combining the expected values of the blocking probability and the revenue. The weights assigned to each objective determine the point in the Pareto front where the attained policy lies. The other approach, which is presented in Section A, is to set a constraint in one of the objectives and solve for the other one. This strategy results in a constrained MDP formulation (CMDP) and the policies obtained are not necessarily deterministic.

Related Work

In [62] the spectrum broker controls the access of secondary users based on a threshold rule computed by means of an MDP formulation with the objective of minimizing the blocking probability of secondary users. In order to cope with the non-stationarity of traffic conditions, the authors propose a finite horizon MDP instead of an infinite horizon one. The drawback is that the policy cannot be computed off-line, imposing a high computational overhead on the system.

Tang *et. al.* study in [63] several admission control schemes at a centralized spectrum manager. The objective is to meet the traffic demands of secondary users, increasing spectrum utilization efficiency while assuring a grade of service in terms of blocking probability to primary users. Among the schemes analyzed, the best performing one is based on a constrained Markov decision process (CMDP).

In [52], spectrum trading from LUs to SUs is modeled as a non-cooperative dynamic game, using a Markov chain to describe groups of SUs buying opportunities from LUs. Given its distributed implementation, the main goal of this approach is finding the system's equilibrium. The objective in [57] is maximizing the profit of primary users, with especial interest in assuring bidding truthfulness.

Our paper focuses on centralized dynamic trading of spectrum channels. The centralized framework allows us to explore the use of MDP and CMDP formulations to balance benefit and grade of service for LUs. Note the main advantages of this approach is that it assures operating at global optimum and reduces the computational effort at the SUs.

System model

The model includes a spectrum bidding procedure, in which secondary users offer a price, within a finite countable set of prices for mathematical tractability, for the use of a channel. Taking into account a trade-off between the blocking probability of licensed users and the expected benefit obtained from spectrum rental, secondary users can be accepted or rejected.

As explained in the introduction, public administrations assign the spectrum bands to wireless operators by a license scheme. Generally, operators gain spectrum licenses by bidding for them in public auction processes. We refer to this spectrum assignment framework as *primary market*. The increasing demand of spectrum and the existence of spectrum holes have revealed the inefficiency of this mechanism. One practical and economically feasible way to solve this inefficiency is to allow spectrum owners to sell their spectrum opportunities in a *secondary market*. In contrast to the primary market, the secondary operates in real-time. Secondary users, that may be operators without a spectrum license, submit their bids for spectrum opportunities to the spectrum owner, who determines the winner or winners by giving them access to the band and charging them the bidding price.

Incoming traffic is characterized by a classic Poisson model. Licensed users arrive with a rate of λ_L arrivals per unit of time. The arrival rate for unlicensed users is denoted by λ_U. The licensed spectrum managed by the central controller is assumed to be divided into channels (or bands) with equal bandwidth. Each user occupies a single channel. The average holding times for licensed and unlicensed users are given by $1/\mu_L$ and $1/\mu_U$ respectively, where μ_L and μ_U denote the departure rate for each class. Because a Poisson traffic model is considered, both the inter-arrival time and the channel holding times are exponentially distributed random variables for both user classes. The model can be easily extended including more user classes, the probability that a user occupies two or more channels, and so on. Essentially the procedure is the same, but the Markov chain would comprise more states as more features are considered in the model. In this model, the state of the Markov chain is determined by the number of channels k occupied by licensed users

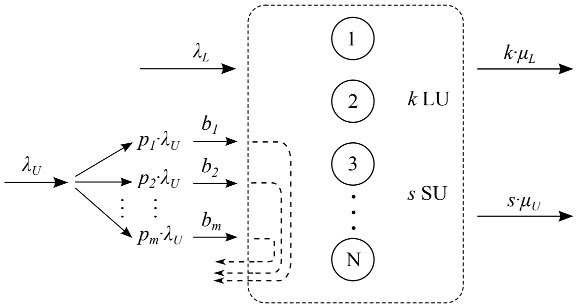


Figure A.1: Diagram of the auction based access model. Secondary users (SU) can offer up to m different bid prices. Each bid offer is assigned a probability. The access policy decides upon each offer according to the price offered and the system's state.

(LU), and the number of channels s occupied by secondary users (SU). Because spectrum is a limited resource, there is a finite number N of channels. Figure A.1 depicts a diagram of the model and its parameters. Note that we can map all the possible combinations of (k, s) for $0 \leq k \leq N$, $0 \leq s \leq N$ and $k + s \leq N$ to a single integer i such that

$$0 \leq i \leq \frac{N\,(N+1)}{2} + N + 1. \tag{A.1}$$

The number in the right hand side of A.1 is the total number of states. Let N_T denote this number.

For mathematic tractability, the bidding prices are classified into a finite set of values: $\mathbb{B} = \{b_1, b2, \ldots b_m\}$ given in money charged per unit of time. Each price on this set has a probability p_i, $i = 1 \ldots m$ to be offered by an incoming user. Obviously $\sum_{i=1}^{m} p_i = 1$. Figure A.1 depicts the model described.

The model described above consists of a continuous-time Markov chain.In this case, the objective of the MDP is to obtain the maximum economic profit with the minimum impact on the licensed users. In the framework of MDPs we have to define the actions and the costs of these actions. According to the objetive, the expected cost is obtained as a linear combination of the blocking probability of the primary users and the income benefit from secondary users. By adjusting the weighting factors we can compute a Pareto front for both elements. Let $g(i, u)$ denote the instantaneous cost of taking action u at state i. The control u at each stage determines the admitted and rejected bidding prices. Logically, the control should be defined as a threshold, *i.e.* when $u = i$ only bids equal or above p_i are admitted. For notation convenience, the control $u = m + 1$ indicates that no bid is accepted. The per-stage reward function $g(i, u)$ is given by the linear combination of $g_L(i, u)$, defined as:

$$g_L(i, u) = \begin{cases} 1, & \text{if } i \equiv (k, s) \text{ and } k + s = N \\ 0, & \text{otherwise} \end{cases} \tag{A.2}$$

where the symbol "$\equiv$" denotes equivalence, i.e. i maps a state (k, s) such that $k + s = N$; and $g_U(i, u)$ defined, in this model, as the expected benefit at stage i when decision u is made. Therefore $g(i, u)$ = $\alpha g_L(i, u)$ + $\beta g_U(i, u)$ where the scalars α and β are weighting factors. Note that $\beta < 0$ since the objective is to minimize the average expected cost given by $g(i,u)$. Let B_i denote the expected income when an unlicensed user whose bidding price is b_i is accepted. Since the average channel holding time for unlicensed users is $1/\mu_U$, then $B_i = b_i/\mu_U$. Given a control u, $P(r|u)$ denotes the conditional probability that the bidding price of the next accepted secondary user is b_r.

$$P(r|u) = \begin{cases} \frac{p_r}{\sum_{j=u}^{m} p_j}, & \text{if } r \geq u \\ 0, & \text{otherwise} \end{cases} \tag{A.3}$$

Let us define $\tilde{g}_U(i,u,j)$ as the average benefit associated to the transition from state i to state j. Its expression is

$$\tilde{g}_U(i,u,j) = \begin{cases} p_U \sum_{r=1}^{m} B_r P(r|u), & \text{if } j = i+1 \\ 0, & \text{otherwise} \end{cases} \tag{A.4}$$

where $p_U = \lambda_U/(\lambda_U + \lambda_L)$ denotes the probability that the next arrival corresponds to a secondary user. Therefore, the per-stage benefit $g_U(i,u)$ is given by

$$\begin{aligned} g_U(i,u) &= \textstyle\sum_{j=1}^{N_T} \tilde{g}_U(i,u,j) p_{i,j}(u) \\ &= p_{i,i+1}(u) p_U \textstyle\sum_{j=1}^{N_T} B_r P(r|u). \end{aligned} \tag{A.5}$$

We can formulate the auxiliary discrete-time average cost problem for the model described. The equation providing the optimum average cost λ is

$$\begin{aligned} \tilde{h}(i) = \ & \min_{u\in\{0,1\}} \Big[\alpha g_L(i,u) + \beta g_U(i,u) v_i(u) - \lambda + \\ & + \sum_{j=1}^{N_T} \tilde{p}_{ij}(u) \tilde{h}(j) \Big] \end{aligned} \tag{A.6}$$

for $i = 1, \ldots, n$, where $v_i(u)$ is the transition rate out of state i. The structure of this problem also anticipates a threshold-type solution. In this case, there will be a set of thresholds, one per bidding price. By properly adjusting the weighting factors α and β we can also compute a Pareto front allowing us to determine the maximum possible benefit for a given blocking objective for the licensed users.

Constrained MDP

So far, the approach to merge several objectives consisted on combining them into a single objective by means of a weighted sum and solving the problem as a conventional MDP. However, when several objectives concur in an MDP problem, the formulation strategy may consist on optimizing one of them subject to constraints on the other objectives. This strategy results in a CMDP formulation of the problem. Solving MDPs by iterative methods such as policy or value iteration allows us to find deterministic policies, *i.e.* policies that associate each system's state $i \in S$ to a single control $u \in U(i)$, where $U(i)$

is a subset of U containing the controls allowed in state i. However, these policies do not, in general, solve CMDP problems. Instead, the solution of CMDPs is a randomized policy, defined as a function that associates each state to a probability distribution defined over the elements in $U(i)$.

There are mainly two approaches to solve CMDPs, linear programming (LP) and Lagrangian relaxation of the Bellman's equation. This paper follows the former one. Each feasible LP formulation relies on the use of the *dual* variables $\phi(i,u)$, defined as the stationary probability that the system is in state i and chooses action u under a given randomized stationary policy. The problems addressed in this paper result, under every stationary policy, in a truncated birth-death process, since primary users are always accepted. In consequence, every resulting Markov chain is *irreducible*, in other words, it is recurrent and there are not transient states. Moreover, the state and action spaces are finite. Under these circumstances, as shown in [60], every feasible solution of the LP problem corresponds to some randomized stationary policy. Therefore, if the constrained problem is feasible, then there exists an optimal randomized stationary policy.

The LP approach consists of expressing the objective and the constraints in terms of $\phi(i,u)$. Once the problem is discretized, the average cost is defined as

$$\lambda = \lim_{K\to\infty} \frac{1}{K} E\left\{\sum_{k=0}^{K} g_U(x_k, u_k)\right\} \tag{A.7}$$

where k denotes the decision epoch of the process. The objective is to find the policy μ solving

$$\min_{\mu} \lambda \tag{A.8}$$

The constraints are defined similarly to the main objective: each constraint impose a bound on an average cost related to different per-stage cost. Each constraint has the following form:

$$c = \lim_{K\to\infty} \frac{1}{K} E\left\{\sum_{k=0}^{K} g_L(x_k, u_k)\right\} \leq \beta \tag{A.9}$$

where $g_L(x(t), u(t))$ is the real-valued function providing the per-stage cost associated to the constraint β. Therefore the constrained average reward MDP with one constraint is defined as

$$\begin{gathered} \min \lambda \\ \text{s.t.} \\ c \leq \beta \end{gathered} \tag{A.10}$$

Given the characteristics of the problem (finite state and action spaces and recurrent Markov chain under every policy), the limits in (A.7) and (A.9) exist and are equal to

$$\lambda = \sum_{i\in S} \sum_{u\in U(i)} g_U(i,u)\,\phi(i,u) \tag{A.11}$$

and

$$c = \sum_{i\in S} \sum_{u\in U(i)} g_L(i,u)\,\phi(i,u) \tag{A.12}$$

respectively. In addition, the following conditions must be hold by the *dual* variables:

$$\sum_{u \in U(j)} \phi(j,u) = \sum_{i \in S} \sum_{u \in U(i)} p_{i,j}(u) \phi(i,u) \tag{A.13}$$

for all $j \in S$, which is closely related to the balance equations of the Markov chain and

$$\sum_{i \in S} \sum_{u \in U(i)} \phi(i,u) = 1, \tag{A.14}$$

which, together with $\phi(j,u) \geq 1$ for $i \in S$ and $u \in U(i)$ correspond to the definition of $\phi(i,u)$ as a limiting average state action frequency. In consequence, the LP for the CMDP has the following formulation

$$\begin{gathered} \min_{\phi} \sum_{i \in S} \sum_{u \in U(i)} g_U(i,u) \phi(i,u) \\ \text{s.t.} \\ \sum_{i \in S} \sum_{u \in U(i)} g_L(i,u) \phi(i,u) \leq \beta \\ \sum_{u \in U(j)} \phi(j,u) - \sum_{i \in S} \sum_{u \in U(i)} p_{i,j}(u) \phi(i,u) = 0 \\ \sum_{i \in S} \sum_{u \in U(i)} \phi(i,u) = 1 \\ \phi(j,u) \geq 1 \end{gathered} \tag{A.15}$$

Assuming that the problem is feasible and ϕ^* is the optimal solution of the LP problem above, the stationary randomized optimal policy μ^* is generated by

$$q_{\mu^*(i)}(u) = \frac{\phi^*(i,u)}{\sum_{u' \in U(i)} \phi^*(i,u')} \tag{A.16}$$

for cases where the sum in the denominator is nonzero. Otherwise, the state is transitory and the control is irrelevant. Note that $q_{\mu^*(i)}(u)$ denotes the probability of choosing action u at state i under policy μ^*.

Numerical Results

We will consider three scenarios characterized by the asymmetry between the traffic intensity of licensed and unlicensed users. In every scenario, the average holding time is equal for every user, independently of their type. Therefore the service rate $\mu_L = \mu_U = 5$. Assuming that the time unit is an hour, this results in an average holding time of 12 minutes per connection. The total traffic ($\lambda = \lambda_L + \lambda_U$) is 40 calls/h, which results in a total incoming traffic of 8 Erlangs. In a wireless cell covering 2.5 km^2 of urban area (cell radius equal to 400 m), with 2000 people per km^2 and a 10% aggregate market penetration (licensed and unlicensed users), the number of covered users is around 500, and the resulting traffic intensity is 0.016 Erlangs per user. The number of available channels is set to $N = 10$, in order to evaluate the system in a relatively congested situation. With the assumed traffic intensity we can estimate the blocking probability of the system for the aggregate traffic by means of the well-known Erlang's B formula (see [64]):

$$E(n, \rho) = \frac{\frac{\rho^n}{n!}}{\sum_{j=0}^{j=n} \frac{\rho^j}{j!}} \tag{A.17}$$

where n is the number of channels and ρ denotes the utilization factor. In our case ρ=λ/μ_L = λ/μ_U. According to this formula, if the system accepted every incoming user, the total blocking probability would be $E(10, 8)$=0.12. As we will see, this probability is an upper bound for the blocking probability of the primary users, which are always accepted if the system has any available channel, and a lower bound for the secondary users.

The three scenarios are summarized in Table A.1.

parameter	**scenario 1**	**scenario 2**	**scenario 3**
λ_L (calls/h)	30	20	10
λ_U (calls/h)	10	20	30
μ_L=μ_U (calls/h)	5	5	5
N	10	10	10

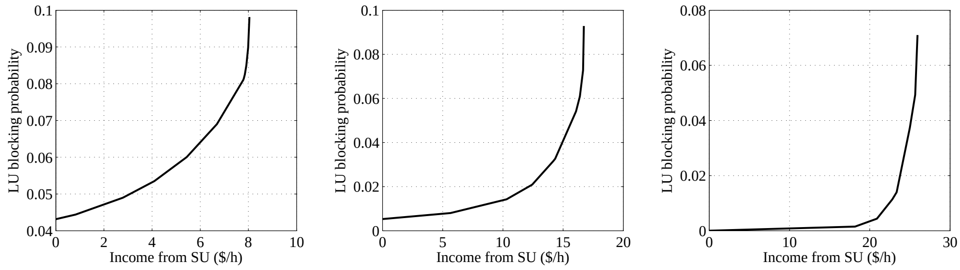
Table A.1: Parameters values at the three scenarios of the priority based access problem.

Additionally we define three classes of secondary users (SU), characterized by the price that they offer per minute of channel occupation. The bid offers per class are: class 1: 0.01 \$/m, class 2: 0.02 \$/m and class 3: 0.03 \$/m. We define the probability of an SU incoming call being of each class. The SU class probability distribution is: class 1 probability: 0.5, class 2 probability: 0.3 and class 3 probability: 0.2. We summarize SU class definition in Table A.2.

SU class	**class 1**	**class 2**	**class 3**
offered price (\$/m)	0.01	0.02	0.03
probability	0.5	0.3	0.2

Table A.2: Classification of SU in terms their bid offers and their probabilities.

Note that both the offered prices and their probability distributions are static, *i.e.* they do not change over time and are independent of the system occupation. It is not completely unrealistic taking into account typical tariff policies of wireless operators. In this environment the class structure and the probability distribution may be seen as types of contracts for secondary users and market penetration of each type of contract respectively. However, for a more dynamical auction process, where bidders are able to change their bid offers adaptively, the model should be revised. One possibility would be to define one probability distribution for each state. More detailed modeling strategies would increase the complexity of the MDP solving algorithm or even make them intractable. This is a classic problem of MDP formulation, known as the *curse of dimensionality* and is typically addressed by means of the heuristic approach of approximate dynamic programming.



(a) scenario 1 (b) scenario 2 (c) scenario 3

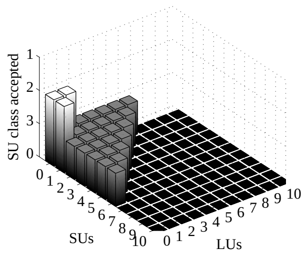
Figure A.2: Pareto fronts obtained for the auction-based access in scenario 1 (a), scenario 2 (b) and scenario 3 (c)

Figure A.2 shows the Pareto fronts for the auction-based system in the three scenarios. It can be observed that, for the same traffic intensity (the three scenarios receive 40 calls per unit of time) when the traffic share of the secondary users is higher (scenarios with higher number) the Pareto front moves away from the y-axis, *i.e.* the income obtained from secondary users increases and it also approaches the x-axis, *i.e.* the blocking probability of the licensed users diminishes. It is interesting to check that, especially in scenarios 2 and 3, a very small increment of the blocking probability of licensed users can multiply the benefit obtained from spectrum leasing by a factor of 2 or 3. On the other hand, these figures also indicate that once the income surpasses certain threshold, Pareto-optimal policies can only produce small increments of the income by dramatically rising the blocking probability.

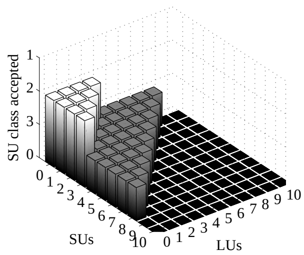
A graphical representation of the policies can be observed in Fig. A.3. Bars represents the lowest accepted class (bid offer) at each state. States where bar has zero height correspond to states where every secondary user is rejected, independently of its bid offer. As expected, as the traffic intensity of the primary users reduces respect that of the secondary users, there are more states where secondary users are admitted in the system, and lower bids are accepted. It is interesting that it is the total number of occupied channels what determines the policy (as the symmetry of the policy reveals) independently of the type of users in occupying them (primary or secondary).

Conclusions

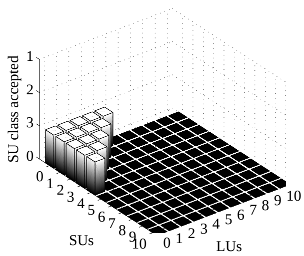
This paper proposes an MDP framework for centralized bid-auction access to the spectrum by SUs. The SUs are classified according to the price they are willing to pay for the use of the spectrum. The main issue of the problem addressed is that two contrary objectives coexist: to reduce blocking probability for licensed users and to increase the income received from spectrum leasing. For this problems there does not exist an *optimal* policy, but a set of *Pareto optimal* policies. We have shown how to compute policies at the Pareto front by weighting the objectives in a MDP problem or by reformulating the problem as a constrained MDP. Numerical solutions of the proposed equations shows the influence of traffic share on system's performance and on the structure of Pareto-optimal policies.



(a) scenario 1



(b) scenario 2



(c) scenario 3

Figure A.3: Graphical representation of the policies for the auction-based access in scenario 1 (a), scenario 2 (b) and scenario 3 (c)

Appendix B

Resumen en castellano

Introducción

Las comunicaciones inalámbricas necesitan, entre otros recursos, de espectro radioeléctrico, el cual es un recurso finito. Agencias gubernamentales como la ECC en Europa, Ofcom en Reino Unido y FCC en los Estados Unidos, proporcionan acceso al mismo a través de licencias fijas a largo plazo para grandes áreas geográficas. La cada vez más creciente demanda de espectro debido al crecimiento y popularización de los servicios móviles ha dejado a estas políticas obsoletas ya que casi todo el espectro ya ha sido asignado.

Una gran mejora en la eficiencia del uso del espectro podría ser posible gracias al desarrollo de las "radios cognitivas", [2], radios que son capaces de recabar información acerca de su entorno radio y adaptar su parámetros de transmisión de acuerdo con lo que han descubierto. En el escenario más típico, los operadores y/o usuarios sin licencia (también llamados *operadores/usuarios secundarios*) con éste equipo buscarían fragmentos de espectro sin utilizar en cualquier lugar del tiempo, espacio, frecuencia y/o potencia de transmisión, conocidos como "agujeros en el espectro", y usarlos para sus propias transmisiones bajo ciertas restricciones para la protección de los operadores y/o usuarios con licencia (*operadores/usuarios primarios*)

En cualquier caso, el mejor aprovechamiento del espectro para dar cobertura a la demanda y a nuevos servicios puede chocar con la reticencia de los operadores ya licenciados, pues cualquiera de estas aproximaciones incurre en ciertos costos a éstos, amén del hecho de que éstos ya hicieron un desembolso por la licencia: cambios en las infraestructuras ya establecidas, posibles perjuicios en su calidad de servicio por interferencias, reducción de beneficios por competencia incrementada... De los distintos mecanismos para mejorar la eficiencia en el uso del especto, el comercio automatizado del mismo ("Spectrum trading") tiene como ventaja el que provee incentivos económicos a estos operadores ya establecidos, de tal manera que se estimula su cooperación y no se desmotiva su inversión y la de posibles futuros operadores primarios. éste es el principal problema que abordan los trabajos en esta área. Al mismo tiempo, el introducir valor económico al espectro es una herramienta de asignación de recursos eficiente que previene su infrautilización , y que podría incluso ser autorregulada (si se opta por la creación de mercados de espectro sin intervención y se consigue un régimen de plena competencia). Aparte de esto, las redes cognitivas presentan un vasto rango de retos tecnológicos [9]

Trabajos previos en Economías no son fácilmente trasladables al comercio de espectro por grandes diferencias tanto en los agentes que forman parte de las transacciones como por peculiaridades del bien con el que se comercia. Respecto de los agentes, son agentes automáticos (aunque por ejemplo las transacciones automáticas en Bolsa están empezando a utilizarse [49]); su oferta y su demanda puede variar en tiempo real pues las necesidades de transmitir dependen de la generación de información, que puede cambiar rápidamente; y el hecho de que no suelen tener ni completa ni fideligna información del mercado debido a la complejidad en que incurriría especialmente en redes ad-hoc. En cuanto al espectro, a diferencia de otros bienes, también puede variar sus características y la percepción de las mismas por partes de las entidades de la transacción. Asimismo, una misma porción de espectro puede ser valorada de manera distinta entre compradores dependiendo de la aplicación que vayan a darle. Además, es un bien que puede ser reutilizado geográficamente, cuyo uso puede ser simultaneado por varios agentes, en el que la actividad de unos puede degradar la de otros en la misma banda o adyacentes...

Nuestra contribución en este campo es servir como introducción a la inmensa casuística en los trabajos de comercio automatizado de espectro intentando diferenciar los distintos sub-problemas que aborda y las diferentes técnicas que se usan, con especial atención a los trabajos más recientes, y con una visión esencialmente didáctica que se traslada directamente a la estructura de nuestra exposición, tratando los trabajos en orden creciente de complejidad de su estructura. En la sección 2 se presentan monopolios. En la sección 3 se estudian situaciones más típicas con varios vendedores. Por último en la sección 4 se muestran futuras líneas de estudio y conclusiones.

Cuando “es cosa de dos”

Las bases de cualquier transacción en general es el caso en el que tiene lugar entre sólo dos entidades. El caso más sencillo es en el que una de esas entidades, el “vendedor” quiere cambiar oportunidades de transmisión de su espectro que él no usa, por un valor económico, el más alto posible, mientras que la otra entidad, ‘el “comprador”, está interesado en ese bien pero quiere pagar tan poco como sea posible. Aunque esta situación pueda parecer simplista, es útil no ya sólo como marco base de comprensión, que también puede asemejarse a un escenario real cuando las redes primarias y secundarias tengan una estructura centralizada y por ende la transacción se negociara entre las estaciones bases. Ver 2.1.

Para el comprador, por tanto, existe un compromiso entre su interés por el bien ofrecido, la cantidad y el coste de su adquisición, que se expresa en la “función de utilidad”, que es una medida cuantitativa del grado de satisfacción que le produce al comprador dicho bien. De esa función puede obtenerse la función de demanda, que expresa cuánto de ese bien debería comprar dado un precio para maximizar su satisfacción. Por otro lado y de manera similar, el vendedor también tiene un compromiso entre el beneficio que obtiene de la venta de su espectro y el coste de vender ese espectro: al disponer de menor espectro sobrante puede no ser capaz de satisfacer un incremento en la demanda de los usuarios primarios, mayor interferencia, etc. aparte de costes fijos por la inversión en infraestructura. Este compromiso se expresa en la “función de beneficios” y derivándola respecto de la cantidad de bien que vender, se obtiene la función de oferta, que muestra cuánto del bien debería venderse dado un precio para maximizar su satisfacción.

Una solución a este conflicto de intereses entre vendedor y comprador es propuesto por D.Niyato y E.Hossain en varios de sus trabajos [13, 14, 15, 16, 17] y está basada en el modelo de oferta y demanda de Microeconomía, , donde el precio varía hasta que se equilibra en un punto de ambas se iguala, con ciertas ayudas en la formulación para poder eliminar la restricción de que el mercado tenga que estar en plena competencia.

Monopolios

Los siguientes trabajos: [23, 20, 24, 19, 22, 26, 27] todavía muestran una sola entidad como vendedor mientras que introducen varios usuarios/operadores secundarios. éstos toman sus propias decisiones independientes, si bien se influencian mutuamente. La mayoría de estos trabajos, tanto en esta sección como en general, se centran en la optimización del beneficio del operador primario [23, 24, 22], mientras que otro foco importante de esta sección corresponde a la utilización de dar valor económico al espectro como herramienta para reparto eficiente del mismo [20, 19].

La herramienta más común para modelar las interacciones entre los usuarios secundarios es *Teoría de Juegos*: [23, 20, 19, 26, 27]. Teoría de Juegos es el estudio matemático de situaciones que involucran a individuales racionales que toman decisiones sobre diferentes (y a menudo en conflicto) objetivos.

Hay un enorme rango de juegos diferentes. Un tipo de juego muy interesante son los juegos dinámicos/juegos con repetición como [23], en los que la interacción entre jugadores ocurre más de una vez y los movimientos pasados pueden observarse e influir en futuras acciones. La gran ventaja que ofrecen estos juegos frente a los estáticos es que no requieren el conocimiento de las estrategias de todos los jugadores. Frente a ello, en un juego dinámico los jugadores van aprendiendo en cada iteración si bien estos algoritmos son más difíciles de plantear/analizar, son más lentos y no tienen por qué converger exactamente a la misma solución. Por otra parte y a costa de crecer en complejidad, pueden conseguir mejores soluciones al considerar conceptos como utilidades/recompensas futuras y/o tener horizonte infinito y por ende, estar continuamente adaptándose a situaciones de variabilidad (i.e. de demanda, oferta...).

Una rama de la Teoría de Juegos que está recibiendo gran atención es la que se ha fusionado con un modelo económico muy trabajado anteriormente, las subastas. Las subastas pueden verse como un juego con información parcial, siendo éste su punto fuerte: se usa para vender ítems basándose en la valoración privada que cada comprador hace del mismo, sin asumir como en la mayoría de trabajos expuestos aquí que las funciones de utilidad de los jugadores son conocidas por todos (algo que sería improbable que ocurra en un escenario real: son entidades competitivas). Asignando los ítems a las entidades que más los valoran, maximizan el bienestar social. Su desventaja es, sin embargo, que son más lentas en su desarrollo y suelen requerir una entidad que centralice el desarrollo, lo que las hace poco apropiadas para el mercado de tiempo real. Los sub-ojetivos que se tratan en los trabajos con subastas son los mismos que en el resto, añadiéndose un especial interés por estar a prueba de trampas como [50] o cómo integrar a los vendedores de una forma más activa en el proceso, especialmente cuando hay más de uno [52].

No siempre se usa Teoría de Juegos, también hay un buen número de trabajos que se apoyan en la optimización para todo el modelo [24, 22]: encontrar los valores de algunos parámetros tales que unas funciones seleccionadas sean maximizadas o minimizadas, sujetas a una serie de restricciones. En el contexto del comercio de espectro, esos parámetros son usualmente el precio por unidad de espectro (ancho de banda, potencia, ...), las restricciones están relacionadas a la degradación en la calidad de los usuarios primarios y las funciones a optimizar, que es el beneficio de los operadores primarios, pueden ser muy diversas y seleccionarlas no es una tarea trivial. Dependiendo de la forma de la función a optimizar y las restricciones, diferentes técnicas pueden usarse, siendo que la mayoría de los esfuerzos están orientados a formularlas como un problema de optimización convexo (las funciones y las restricciones son todas funciones convexas en sentido matemático), más sencillos de resolver.

Pasando a desglosar algunos de estos trabajos, D.Niyato y E.Hossain en [23] aplican un conocido juego no cooperativo al comportamiento de los secundarios, juego de Cournot, en el que éstos escogen la cantidad de espectro que quieren dado el precio que anuncia el primario, teniendo en cuenta que les cargará un precio proporcional a la demanda total de todos los secundarios. La contribución más importante de este trabajo es una formulación de juego dinámico que permite que los secundarios sólo necesiten conocer la variación de su utilidad al tomar sus decisiones para acabar convergiendo al equilibrio.

H.Mutlu et al. [24] se centran en maximizar el beneficio de un propietario de espectro derivado del pago de los usuarios secundarios por acceder a su centro de llamadas, considerando que el precio variará en función de la ocupación del sistema. Esa variación en el precio que se carga influenciará la tasa de llegada de los secundarios. El coste que tiene el primario se refleja sólo por medio de un castigo monetario si un usuario primario llega al sistema y no puede acceder por estar lleno.

En el contexto de control de potencia, [22] introduce el comercio de espectro con “discriminación de calidad”: los usuarios secundarios son clasificados en multiples categorías de acuerdo a su preferencia por una determinada “calidad” de espectro, donde “calidad” se refiere a máxima potencia permitida en esa banda. Los esfuerzos de computación se centran en la estación base del primario, que deriva el set optimo de calidades que ofrecer y precios asociados, así como la asociación de cada uno de estos pares a un tipo consumidor de usuario secundario, de manera que se maximiza el beneficio del operador primario a la vez que estas asociaciones (llamadas “contratos”) tienen incentivo para los usuarios sencundarios, siendo así que cada usuario secundario de cada tipo decidirá precisamente que la mejor calidad-precio es la que el primario le asoció, incluso considerando la opción de no transmitir. Esta solución es peor que el óptimo social que podría conseguirse idealmente, a cambio de incrementar el incentivo en los primarios dramáticamente.

En escenario similar, [20] apunta a mejorar el bienestar social de la compartición de recursos considerando que cada canal CDMA es un canal multiusuario, esto es, múltiples usuarios secundarios comparten canal y han de considerar interferencias mutuas. Usa un juego no cooperativo sobre potencia en los usuarios secundarios, los cuales también realizan una optimización del precio a pagar de manera descentralizada, donde la función de precio es obtenida por cada uno de ellos y es distinto en cada uno, requiriendo sólo información local. También desarrolla un protocolo MAC para el intercambio de mensajes necesario.

El trabajo de O.Simeone et al. [26] introducen un campo interesante en el comercio de espectro y es pasar del intercambio espectro-por-dinero a espectro-por-cooperación. La premisa es tan simple como el comercio habitual: un usuario primario vende oportunidades de transmisión a los usuarios secundarios si, a cambio éstos primero le ayudan en su transmisión haciendo de "relays", lo que permite que el usuario primario incremente su tasa de .transmisión. J.Zhang y Q.Zhang [27] añade al trabajo previo la idea de que el usuario primario tiene cierta demanda de tráfico y una vez satisfecha, no tiene incentivo en continuar mejorando su tasa de transmisión y por tanto, dejaría de permitir el acceso a usuarios secundarios. Para evitarlo, los autores proponen que los usuarios secundarios deberían además pagar cierto valor monetario al primario.

Competición de vendedores

La competición entre vendedores se introduce en muchos de estos trabajos como un modelo de mercado en tres capas como 4.1 en el que en la primera capa los operadores primarios obtienen licencias de entidades reguladoras para largos plazos y dan servicio a usuarios primarios por medio de suscripciones; en la segunda capa éstos operadores venden porciones de ese espectro que poseen a operadores secundarios en una escala de tiempos menor; y en la tercera capa los operadores secundarios venden ese espectro a usuarios secundarios a escalas de tiempo muy pequeñas, casi tiempo real.

Como en trabajos citados previamente, el ajuste del precio sigue siendo el problema más exhaustivamente estudiado, pero añadiéndole nuevas dimensiones traídas por la competición de los vendedores y enfocarse en los operadores secundarios como capa intermedia: heterogeneidad del espectro [34, 36], estudio conjunto de inversión en espectro y precio de venta [36, 41, 42]. También hay trabajos fuera de este modelo de tres capas como [34, 37], incluso con una relación diferente entre operadores primario y secundarios [43]

Y.Xing et al. [34] proponen un modelo con operadores y usuarios interactuando directamente (sin categorías), donde los usuarios perciben el espectro como un bien heterogéneo del que hacen diferentes valoraciones dependiendo de su aplicación y distancia a los operadores. Los usuarios también tienen diferentes sensibilidades hacia bien la "calidad" (entendida como cualquier valoración que el usuario quiera hacer) o precio, así como un presupuesto limitado y mínimos requerimientos de QoS. Uno de sus resultados más interesantes es que el coste del espectro tiene gran impacto en el beneficio, de manera que los vendedores de perfil bajo (menor calidad) pueden acabar ganando más. Este trabajo es uno de los más completos del área pero no contempla dinamismo, como la variación de oferta y demanda con el tiempo.

J. Jia y Q.Zhang. en [36] realizó el primer estudio conjunto de la inversión en la compra de espectro y precio posterior a usuarios, fijando el marco de trabajo de partida para estos estudios, con un juego no cooperativo también en tres etapas: inversión en compra de espectro, fijación del precio de venta a secundarios, selección de los usuarios secundarios de su operador preferido, teniendo en cuenta heterogeneidad en el espectro. Este tipo de juegos multi-etapa suelen resolverse mediante “backward induction” (inducción hacia atrás). Los autores también proponen una solución cuando los operadores sólo puede conocer su función de beneficio, rompiendo el juego en dos juegos dinámicos: primero uno a corto plazo de ajuste del precio en una serie de iteraciones y luego otro más a largo plazo, cuando el anterior esta estabilizado, de ajuste del ancho de banda a alquilar de los primarios, con la desventaja de que para alcanzar el equilibrio del sistema se requiere cierto tiempo.

L.Duan et al. [41] trabajan esta misma estructura con la salvedad de que los operadores secundarios no compiten directamente en la etapa de compra de espectro (el coste del espectro es el mismo para ambos y fijo, no depende de su demanda total como en trabajo anterior), aunque claman ser los primeros en realizar el estudio conjunto de inversión en espectro y ajuste de precio considerando heterogeneidad en las condiciones de transmisión de los usuarios (diferentes condiciones de canal, potencia máxima). Utilizan distintas funciones en el desarrollo matemático, que les permiten obtener estructuras de tipo umbral para las decisiones de cada etapa y una SNR para los usuarios justo y predecible por ellos mismos. Además, anuncian que el beneficio que obtienen los operadores en competición es sólo un 20% menor que el caso monopolístico.

Posibles líneas de trabajo futuras y conclusiones

Además de la tendencia a unificar en un mismo modelo cada vez más sub-aspectos estudiados, existen como problemas abiertos la sobrecarga de comunicación (no se suele contemplar el coste que requiere el intercambio de mensajes asociado); la protección contra conductas maliciosas como mentir en la publicación de información privada o cooperación maliciosa entre proveedores o entre usuarios para subir/bajar precios respectivamente; y la falta de racionalidad e información completa pues fallos similares a los anteriores pueden ocurrir cuando simplemente esa información no aparece debido a fallas o incluso se transmite de forma errónea. Teoría de Juegos, además, asume que los jugadores son totalmente racionales pero no ofrece protección contra fallos en sus decisiones que hicieran que esa afirmación no sea totalmente cierta.

En este trabajo se ha presentado una visión panorámica del comercio automático de espectro que por su visión didáctica aspira a ser el punto de partida para aquellos que quieran introducirse en el mismo. Puede apreciarse en esta visión como es un campo relativamente nuevo con abundantes desarrollos teóricos pero cuyas soluciones siguen estando más o menos lejos de las aplicaciones reales ante la complejidad de las mismas, donde prima la utilización de la moderna Teoría de Juegos por su adaptabilidad natural a la estructura descentralizada e independiente de las redes que surgen en torno al comercio de espectro.

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