Spectrum Sharing Models in Cognitive Radio Networks

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***Abstract*—Spectrum scarcity demands thinking new ways to manage the distribution of radio frequency bands so that its use is more effective. The emerging technology that can enable this paradigm shift is the cognitive radio. Different models for organizing and managing cognitive radios have emerged, all with specific strategic purposes. In this article we review the allocation spectrum patterns of cognitive radio networks and analyse which are the common basis of each model. We expose the vulnerabilities and open challenges that still threaten the adoption and exploitation of cognitive radios for open civil networks.**

I. Introduction

The huge number of wireless services available nowadays has significantly increased the demand of radio spectrum resources. This has given rise to a worrying shortage of spectrum. Moreover, the Federal Communications Commission (FCC) has reported that most of the spectrum allocated to licensed users is largely under-utilized [1], and spectrum utilization is discontinuous across time and space.

In order to increase the efficiency in spectrum utilization, a solution has been proposed which is based on opportunistic spectrum sharing. In this approach, unlicensed users, which are referred to as secondary users, are allowed to opportunistically access spectrum as long as they do not cause harmful interference with licensed users. Licensed users are referred to as primary users, and they always have usage priority.

Cognitive Radio (CR) [2] is the technology that has been proposed to implement opportunistic sharing. A cognitive radio is a system capable of sensing several spectrum bands, determine if there are unused portions, and adapt to operate in the vacant bands. The spectrum sensing mechanisms implemented by CRs should reliably detect the presence and absence of primary signals in real time. Once cognitive radios detect the presence of a primary user in their operating band, they must vacate the band immediately. Hence, accurate spectrum sensing is an essential feature of CR systems.

Beyond sensing the spectrum, another important issue of CRs is that users need to share the available spectrum between them in order to better exploit it. Dynamic Spectrum Sharing (DSS) techniques are the key technology for managing the spectrum among secondary users. DSS requires that secondary users' devices are cognitive (they can learn and make intelligent decisions on spectrum usage) and most important, 1 that they can achieve high levels of cooperation in order to maximize the overall network utility.

Since 2005, solutions for DSS have been proposed. Many approaches have been designed to perform in different scenarios and subject to different purposes. In consequence, proposed techniques should be classified and analysed to obtain open challenges not considered up to now, one of the most important: the security.

In section II we present a taxonomy of DSS techniques. We analyse different management models and classify them setting the points influencing to the performance. The main division is done regarding the network structure, which can be centralized or distributed, and the business model. Next, in section III we present a review of nowadays main proposals and classify the approaches regarding different features to obtain open challenges for next considerations as well. The aim of the analysis is to set possible issues to improve and make dynamic spectrum sharing techniques more fair, robust and secure. A comparative description of each approach is exposed. Finally, in Section IV we show the conclusions and the open challenges of current DSS techniques.

II. Taxonomy

The main requirement of cognitive radio systems is not interfering with primary users. Being able to work in the same frequency range of primary users without being noticed or causing channel degradation is not an easy task. If all the secondary users of an area try to sense and access the holes of the spectrum individually and in an indiscriminate way, they would collide ones with the others making impossible to transmit and producing bad side effects to the nearby (in space or frequency) users. So, cognitive radio requires some kind of coordination between the secondary users, or between the secondaries and the primaries, in order to effectively and transparently perform the spectrum sharing.

Spectrum allocation mechanisms can be classified into two different categories based on the nature of users' cooperation and organization. On the one hand, they can be distinguished according to their architecture: centralized or distributed. On the other hand, they can be sorted based on the business relations between primary users and secondary users: secondary market strategy (there is a trading), and self-organized strategy (no contact between primary and secondary users exist).

Next, we review the main characteristics of these groups.

A. Classification based on the network architecture

Approaches to regulate spectrum allocation can assume two different strategies: a centralized or a distributed approach. The first option is a scenario where there is an entity responsible for assigning and allocating spectrum referred as spectrum manager. The second option refers to a scenario in which there is not a main entity that gathers the information about the needs and capacities of the users of the network, but this information is distributed among all users and the spectrum allocation is carried out individually with local agreements.

In centralized approaches the spectrum manager collects users' information in order to have a global view of the characteristics of network links and prioritize users' demands and needs. It can perform an optimal allocation that maximizes the global efficiency taking the best profit of constrained resources. So, centralized solutions can provide good results, and are fairly simple and easy to manage. However, they face the problem that a single entity concentrates the management information and decision power of the network. The spectrum manager concentrates the data and decision power of the network, and it is a single point of failure. If it gets compromised, the information received from the users can be sold and exploited by third entities (so putting in risk the privacy of network members) and the decisions taken by the manager are not longer right nor fair.

In contrast, distributed solutions do not depend on a single entity. There is no central point in the network that has more information and takes decisions, but this power is distributed. These mean that all users need to acquire enough information of their neighbourhood to be able to take coherent decisions within their group and, in general, this implies that all nodes in the network must exchange their local observations and the process is costly and resource consuming.

B. Classification based on the business relations

The primary servers of a network can be aware of the existence of secondary users, and can try to deal with them to take some profit. Or, simply, they offer services to primary clients and do not involve themselves with the strategies and requests of the secondary users.

The first scenario is what is called a secondary market. Spectrum owners or operators lease the spectrum to secondary users, and help them to find right vacant spaces. Primary servers aim to maximize their profit under QoS constraint while secondary users wish to purchase a local, short-term data service. Under this situation, pricing strategies may be adopted to sell radio spectrum resources and to offer spectrum access to secondary services. Therefore, competition among spectrum owners is required to adjust the price which maximizes both their own profits and the users' satisfaction. The price is an indicative of the value of spectrum to both seller and users.

The strong point of secondary market schemes is the collaboration between primary servers and secondary users. Both groups are interested in using the spectrum without interferences and so, primary servers are usually involved in the process of sensing and detecting spectrum holes. This provides better detection probability rates and a major quality of service throughout the network.

The risk of a secondary market model is the spectrum over control of primary servers. If primary servers collide and are free to set spectrum prices, the usage of the unoccupied spectrum bands is no longer flexible nor accessible.

The second scenario in which we classify the allocation spectrum schemes regarding the business relation of primary and secondary users is refereed as self-organized. The resources in these networks are self-managed only by secondary users. Secondary users usually sense the spectrum cooperatively, find spectrum holes, and dynamically access free licensed bands. They continuously scan the spectrum to detect changes and adapt their transmission parameters or reallocated some channels. Primary users do not know the presence of secondary users and do not take part on the allocation process. Secondary users use mechanisms to share and allocate the resources which guarantee a good exploitation of the spectrum, and fairness among users.

Self-organized schemes are more difficult to deploy than the trading ones based on a secondary market because there is a tangible risk that these secondary networks can decrease the quality of service of primary networks. Since secondary users can access the licensed spectrum without a real time acceptance from the primaries, a miss-using of the network can pose very negative consequences for the network.

III. Spectrum Sharing Models

We can turn to review some of the main spectrum allocation proposals, classifying them within the two categories (architecture and business relations) we have defined. This revision wants to clarify the strategies used for each type of scenario, and points out which are the weak points or the open challenges yet to be resolved.

A. Centralized self-organized network

In self-organized scenarios, the resources are assumed to be managed by a cognitive radio base station that periodically collects all the topology, spectrum measurements and interference information from the secondary users of an area, and distributes the available spectrum channels among them. The central base station of the secondary network, i.e. the clusterhead, can be an entity such as the spectrum manager defined in 802.22 [3], but it is an independent server that is not related or controlled by the primary servers. Figure 1 depicts a scheme of the network architecture.

The spectrum manager has a global knowledge of the network cluster it controls. So, it can coordinate the activity of the wireless links in order to maximize the spectrum usage and minimize interference problems. Since the total spectrum bands available for secondary use are limited, the problem is how to fairly divide it between the users and, in the meantime, meet their demand not degrading primary transmissions. The centralized self-organized algorithms aim to solve the optimization problem, and for this, they basically use graph constructions.

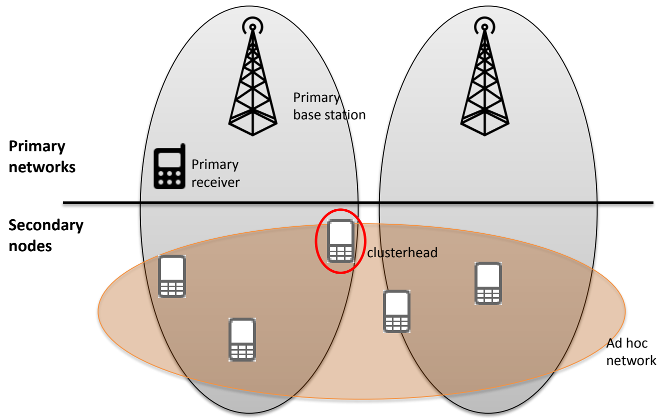

Fig. 1. Architecture of a centralized self-organized network

In [4] authors deal with the allocation and fairness problem assuming a static environment where there is a central server that calculates an allocation assignment based on global knowledge, and they focus on per snapshot optimization. They introduce the notion of heterogeneity in how the available channels are partitioned, and the rewards or utility that users obtain from occupying different bands. They apply these concepts to construct a label-based progressive minimum neighbour first (PMNF) graph colouring approach for utility-based channel allocation for both collaborative and noncollaborative users. Experimental results show that collaboration rules can induce 50% of improvement in the network.

Similar to [4], in [5] it is proposed a graph colouring and fairness mechanism for dynamic and changing environments. The algorithm can apply max-min and proportional fairness. Max-min fairness works in a way that the spectrum demand of the users is satisfied in order, from users with the smallest demands to the higher ones. Thus, the utility of the user with the minimum demands is maximized and each user obtains no more bandwidth than what it asks for. In contrast, proportional fairness involves the amount of bandwidth a user is allocated is proportional to the anticipated resource consumption required by the user. Thus, users that have worse wireless receptions will have a higher consumption cost and greater spectrum shares. The authors propose to solve the graph colouring problem of the scheme using an heuristic based on the degree of saturation (DSATUR). Their results show good performances and scaling capacities.

Another fairness approach is introduced in [6]. Authors propose a near-fair user scheduling scheme in a downlink single cognitive network based on the principals of proportional fairness. The system can give each user near equal opportunity to be served at the expense of some loss of sum-rate. Authors assume that each user has multiple antennas, and they apply an heuristic model based on the zero-forcing beamforming principle in order to limit the interference between different secondary users. Zero-forcing beamforming is a strategy in which a transmitter sends independent information to multiple receivers simultaneously with the condition to avoid interference among user streams.

Authors adapt the beamforming process to the cognitive radio networks environment and use a proportional fair scheduling so that all users can receive part of the bandwidth. Results encompass their objectives for small networks, although the scalability of the algorithm for larger network has not been proved.

In [7], a layered spectrum allocation process to adapt to the constantly changing topology of mobile networks is presented. Based on the conflict graph systems introduced in [4], [8], the authors introduce a solution that does not need to create a new graph structure each time the network topology changes but it compensates small variations. They propose a local bargaining-based spectrum allocation in which secondary users self-organize into clusters and adapt their spectrum assignment within each cluster to improve local system utility. Authors assume that users are willing to collaborate and share the spectrum with other members of the cluster if they require it. The coordinator of each cluster performs the bargaining request and computations with the neighbouring clusters. Then, the allocated channels are distributed inside the cluster.

Local bargaining starts from a random allocation and gradually improve the system utility. The approach converges quickly and it performs only slightly worse than static graph colouring approaches, and yet, can significantly reduce communication overhead. In order to adapt the approach for very resource-constrained networks such as sensor networks, the authors propose to modify the system in order to avoid the explicit coordination messages that the system requires. They introduce a rule-based spectrum management [9] in which users access the spectrum independently according to both local observation and predetermined rules.

In [10] the authors present a broker based system that schedules the use of the spectrum based on the trade-off between fairness (maximize the common rate among the links) and throughput (maximize the sum rate of the network). They model the system using a graph and employ linear programming to find the optimal spectrum distribution. The broker obtains and centralizes the link gains of network members and so, schedules the activity periods of the nodes depending on the fairness policies that have been agreed.

B. *Distributed self-organized network*

In an distributed cognitive radio network, the cognitive radios do not have global knowledge of the entire network. Therefore, distributed cognitive radio networks allow each user to acquire its neighbourhood information e.g. via a control channel. The amount of information available influences the outcomes of the algorithm. There is a trade-off between the acquired information and the complexity because in some cases information is limited and more computation is required to obtain user's strategies.

Similar to centralized approaches, the goals of distributed dynamic spectrum sharing are the maximization of network utilization and fairness. Generally, the improvement on the overall network performance leads on an increase in the algorithm complexity and a reduction on the control data exchange. Therefore is important to take in consideration the trade-off between algorithm complexity and information overhead, and try to optimize it.

Figure 2 shows the architecture of a distributed self-organized network. There is no coordinator, neither among the secondary users nor the primary ones.

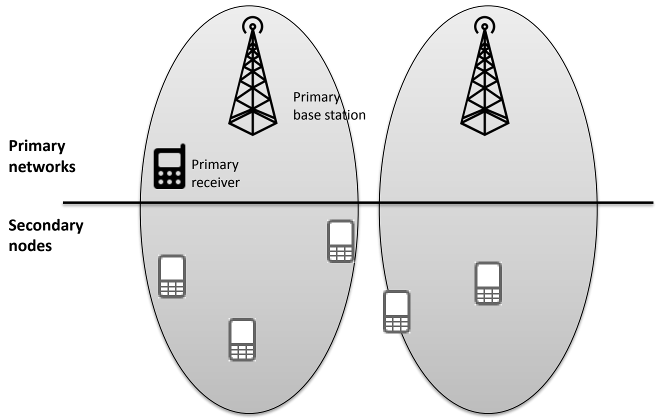

Fig. 2. Architecture of a distributed self-organized network

Distributed self-organized algorithms must develop a mechanism that can adaptively and efficiently allocate transmission powers and spectrum resources among cognitive radios according to the surrounding environment. Generally, the optimization problem is solved using game theory because it can provide defined equilibrium criteria to measure the optimization of spectrum usage.

Game theory involves a set of mathematical tools which models the player interactions in a decision processes [11]. The players, their set of actions or decisions, and the set of preferences associated with every action, are the components of a game. Each player in a game faces a choice among two or more possible strategies. A strategy tells the player what action to take in response to every possible strategy other players might take. The preferences of a player are described by means of the utility function. A game is the situation in which at least one player can only act to maximize his utility through anticipating the responses to his actions by one or more other players. Game theory attempts to predict the outcome of players' interactions and identify optimal strategies for the players. In equilibrium, each player of the game has adopted a strategy that he is unlikely to change.

As game theory studies conflict and cooperation among intelligent rational decision makers, the network users' behaviours and interactions can be analysed as games theoretical approaches. The distributed self-organized algorithms model the allocation problem as an outcome of a game where the players in the game are the secondary users of the network. The strategy space includes which licensed channels they will use, what transmission parameters to apply, which is the quality of service, etc. Network users can be cooperative, selfish and even malicious. The utility functions represent the various interests considering different users' behaviours.

Nie and Comaniciu [12] propose a game theoretic framework to distributely and adaptively control the channel allocation of a secondary network. They design two algorithms, for cooperative and non-cooperative scenarios.

In non-cooperative scenarios users are selfish and only look for their own benefit. The utility function of the game is based on the level of interference that a user perceives on that particular channel. Users learn how to choose the frequency channels which maximize their rewards through repeated playing of the game. The protocol is very light, it requires only a minimal amount of information exchange.

In the cooperative proposal each secondary user to measure both the interference that other nodes create in a desired channel, and the interference he estimates it would produce on his neighbours if he transmitted on that channel. In this model, secondary nodes must exchange status information on the interference created to other users as well as maintain an information table of all frequencies. An equilibrium is reached very fast if a best response dynamic is followed, i.e. secondary users continually improve their solutions based on their best response to the current situation. However, the scheme requires a significant knowledge about neighbouring users and substantial coordination overhead. Both cooperative and non-cooperative models converge to a channel allocation equilibrium, but only the cooperative model leads to a pure strategy Nash equilibrium channel allocation.

Apart from maximizing the utility of the spectrum, channel allocation protocols must also deal with the issue of fairness. In [8] the authors extend their colouring graph theoretical model for broker-based networks [4], to a totally distributed scheme where devices collaborate to negotiate local channel assignments towards global optimization.

In the proposed distributed approach devices collaborate to negotiate local channel assignments towards global optimization. Secondary users use only locally available information to determine its own spectrum assignment. First, a cognitive user detects the presence of primary users to determine its own channel availability and transmission constraints. Second, each secondary user coordinates with nearby neighbours to determine channel assignment in an iterative fashion. Therefore, for each iteration, each secondary user labels itself according to the labelling rules and broadcasts the label to its neighbourhood. Then, each secondary user collects neighbours' labels and the user with the maximum label within the group of neighbours selects the associated channel and broadcast the selection. Finally, secondary users update their list of available channels and recalculate their labels.

Authors compare the system using different labelling rules: non-collaborative, collaborative (rules that consider the impact of interference on neighbours), and fair rules that consider both the interference impact on neighbours and the last chance of the nodes to get a free channel. They compare the performance of centralized and distributed algorithms, and conclude that distributed algorithms that use collaborative rules can generate allocation assignments of similar quality than the centralized algorithm using global knowledge, while incurring substantially less computational complexity in the process. Besides, using fair rules gives the opportunity to nodes that are not in perfect signalling locations, to get access to the bandwidth.

The issue of fairness is also treated and analysed in the Fair Opportunistic Spectrum Access (FOSA) Scheme [13]. The authors introduce a simple algorithm in which secondary users that first find a channel unoccupied, can use it. Fairness with other users is achieved due to the dynamism of primary users, who appear and disappear of the network periodically. When the presence of a primary user is detected in the network, the occupant secondary user has to vacate the channel. If after a time the channel is available again, all the secondary users have the same opportunity to occupy this idle channel. So, at the end, all users have the same opportunities to access the network.

In [14] it is designed some spectrum sharing rules which lead the system to a Nash equilibrium that is fair and efficient. The authors model the scenario as a repeated instance of a Gaussian Interference Game (GIG) performed in multiple rounds. At the end of each stage, all the players can observe the outcome of the stage-game. They remember the past experience and they use it to decide on the actions of the next round.

The system has different equilibrium points. The authors state that if a system determines a strategy to be used within the system (i.e. a rule), the players that do not follow the rule have to be punished. They show that in most cases, the system can automatically and effectively detect dishonest behaviours and so, punish them. Having a rule for the system has the advantage of not requiring a central authority that verifies compliance to the protocol, and so, the system is self-enforcing. By adding punishment to the parameter measurement process the system spurs the players to behave truthfully.

The authors show that the rates obtained by this punishment model are nearly the best possible ones for a non-cooperative game, so the punishments are not really damaging the system.

C. Centralized trading

In the centralized trading approach, primary servers lease the spectrum that they do not use to the secondary users. The price of spectrum in each market depends on the spectrum supply from the primary service and the demand from the secondary users.

Figure 3 shows the architecture of a centralized network for a secondary market scheme. There is a broker (the Primary agent in the figure) that represents the primary server and who is responsible to deal with the secondary network.

In spectrum trading, an equilibrium price that balances the spectrum supply and demand is required to satisfy all of the entities in the market. In the presence of multiple primary or secondary users, the spectrum price depends on the selling strategies. Following the definition of trading pricing models given by [15], we classify spectrum sharing for a secondary market depending on the objectives of the sellers as follows:

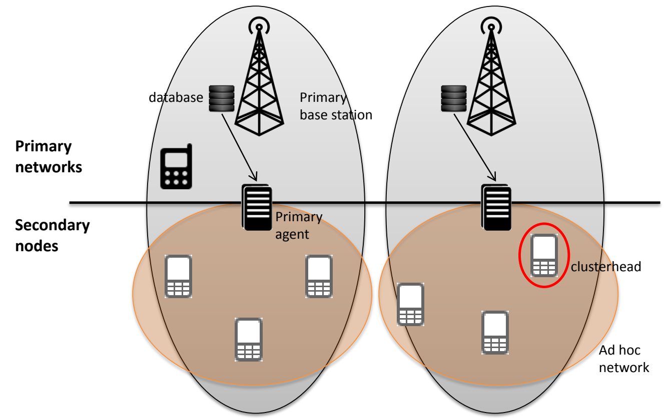

Fig. 3. Architecture of a centralized trading model

- Market equilibrium pricing model: tries to satisfy the spectrum demand, each primary server is unaware of the presence or price of other servers.
- Competitive pricing: aims to maximise the individual profit of the vendors.
- Cooperative pricing: aims to maximise the total profit.

Market equilibrium pricing solutions can be used in a centralized trading (a broker is responsible to sell the spectrum from a group of primary servers), or in a distributed scheme (each primary server sells its own spectrum). Proposals can be used in both scenarios. However, since a broker based architecture is simpler from the point of view of the users and so that is the one that can be more surely deployed, we analyse market equilibrium pricing solutions in this subsection of centralized schemes.

Moreover, cooperative pricing models are also a form of centralized trading. Available spectrum bands are merged in common to allow secondary radio networks to access the licensed bands. All the vendors agree on certain policies, and they let a broker sell the spectrum for themselves.

Finally, competitive pricing models are a form of distributed trading. Each vendor is selfish and looks for his own benefit. We will review these models into the next subsection.

In centralized secondary markets, the spectrum manager offers portions of the available resources (spectrum or power) to a group of secondary users. The secondary users must be connected to the manager who collects users' specific information such as location, path losses or demand functions. Next, the spectrum manager mediates a bidding process between the spectrum owners or operators to determine the one that could offer service to the user. When a user accepts an offer, the spectrum server manages the resource allocation and governs the transmission.

Different mechanisms are used to make the trading and spectrum allocation, for instance, auctions or game theory. The result is an optimal schedule that maximizes system's throughput (average rate, interference, fairness). Optimization problem is formulated regarding strategies of users and subject to system's constraints.

For example, authors in [16] analyse a competitive pricing model formulating it as a game that models an oligopoly market with a few firms competing to gain the highest profit. They demonstrate that in a distributed environment in which for any primary service, the profit functions of the other primary services are not available, the Nash equilibrium pricing can not provide a maximum profit. Primary services can get the maximum profit if they make an agreement to establish a collusion. Thus, they propose a centralized solution in which a manager knows the profit functions of all the primary servers and, with this global knowledge, can compute the optimal pricing strategy. Nevertheless, even in this model any primary service can deviate to gain higher profit. They demonstrated that if all of the primary services are aware of the punishment due to the deviation, by properly weighting the profit in the future, a collusion can be maintained in the long-term so that all of the primary services gain higher profit compared with that at the Nash equilibrium.

Market equilibrium pricing solutions are mainly based on auction mechanisms, that were introduced in the context of spectrum sharing by Huang et al. [17]. They analyse the well-known Vickrey-Clarke-Groves (VCG) auction scheme, which can maximize the total utility of a system. However, VCG requires the manager or seller knows the utility functions of the users, and in CR networks this information is only known by each user himself, who has to explicitly broadcast it to make it public. Thus, VCG is considered unsuitable for CRs due to the high information exchange and computations that the system requires.

In contrast, they propose two auction mechanisms (SINR and power based) in which users only need to submit bids. Contrary to traditional auction-based systems, bids are not the payment that users offer for a particular resource, but the user's willingness to pay. The manager can therefore allocate the spectrum in proportion to the bids and taking in consideration the interferences temperature that the allocation will provoke, using a non-cooperative game. Finally the users pay an amount proportional to the bandwidth they receive. Users set their bids according to the best response in the last auction, and authors present a distributed bid updating algorithm that after some iterations can reach socially optimal solutions that maximize the utility per user. The system assumes that the users and channels are static.

In a similar way than [17], authors in [18] propose an auction based system in which each secondary user makes a bid for an amount of the spectrum and each primary server assigns the spectrum to the best user according to the information he has from them. The contribution of the proposal is that they introduce the concept of fairness among secondary users in the bidding process, and they also consider that the performance of the primary service is never degraded due to irruption of secondary users. They assume that secondary users are, in general, selfish, and they model the auction as a non-cooperative game in which each secondary user rationally behaves to maximize its own profit.

In [19] authors study a sequential auction for sharing a wireless resource (bandwidth or power) among competing secondary users. The protocol is based on the sequential second-price auction, which assumes that a spectrum manager divides the available bandwidth in different units, and sells the units sequentially one after the other. In each round of the protocol, the buyers submit a bid for the resource that the manager is offering. The manager allocates this unit to the buyer with the largest bid but charges him with not his bid but the second largest one.

This system has been proved to have an efficient dominant equilibrium when the resource that it is being sold is unique and indivisible. However, this is not the case of the spectrum. They show that the proposed model has a pure strategy equilibrium, but this may not be unique and so some coordination of the users may be needed to decide on a particular outcome.

A scheme named iterative water-filling (IWF) is proposed in [20]. The system is a noncoopertive game that tries to maximize the sum-rate of the secondary network through individual optimization rate of each user. However, the system is unable to reach good overall performances since each user only seeks its own benefit.

In [21] authors extend the above IWF scheme applying price factors in the utility functions of the noncooperative game, and create the so-called PIWF system. Pricing models the transmission costs of a device, and prevents a user from using an indiscriminate large transmission power on a particular channel. PIWF maintains the distributed approach of the original algorithm, and it uses a user-dependent linear function that determines the prices by allowing network users to exchange neighbourhood information (transmission power, channel gain, and measured interference power) through MAC control packets. The procedure can iterate sequentially or in parallel. Simulations in [21] indicate that for large networks the parallel version converges faster and it achieves a good bandwidth efficiency in the form of a high sum-rate.

D. Distributed trading

In the distributed secondary market case, many secondary users purchase channels from many primary users which would charge for access. The objective is to optimally allocate the spectrum among secondary users and maximize providers' profit. Many providers compete for potential spectrum buyers. The dynamic spectrum market benefits the secondary users because they can fulfil their quality demands by switching among multiple service providers.

In Figure 4 we show the architecture of a distributed network for a secondary market scheme. Secondary users can contact the primary services directly by themselves, or can form a cooperative group and contact the seller through a manager. Cooperation would enable a more efficient dynamic spectrum sharing scheme, gives a better system performance and increases the profit for the secondary users. Note that, in this case, the server manager is a broker working for the secondary network, but it is not responsible of the allocation and distribution of the spectrum (as it is in centralized self-organized architectures).

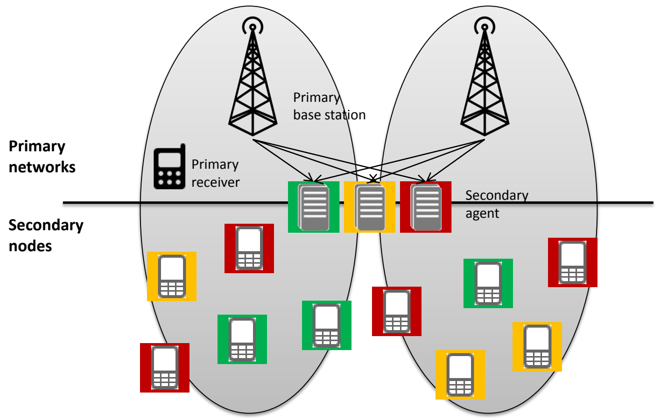

Fig. 4. Architecture of a distributed trading model

The distributed secondary-market system is based on the operator's competition. The sellers offer a price and quality for available spectrum bands with the goal to maximize its own profit. Then buyers evaluate different providers. Each secondary user has a utility function which takes into account the price and the quality. The buyer will make a selection of the seller for which utility is maximized. The utility function will be different depending on the buyers' interest, some of them will be more price sensitive and others will be more quality sensitive.

A seller may modify its price and/or quality searching the objective to maximize its profit. Therefore, an equilibrium case should be found in which primary providers obtain maximum profit and spectrum is optimally allocated. A specific algorithm is applied to discover the optimal operating price. The algorithm employed will depend on the nature and accuracy of information available. Primary users may have limited information about competitors' strategies and consumers' preferences; in these cases more computational capacity is required.

Game theory has been used to model the competition among spectrum sellers. Unlike game theory proposals in self-organized systems, here the players of the game are the primary servers, not the secondary users.

One of the proposals that adopt a game theoretical model to arrange the distributed trading is [22]. Here, the profit of primary brokers can be expressed as a function of the revenue and cost of a transmission. The primary users are flat rate charged. The cost given to the primary service is computed as the product of the spectral efficiency and allocated bandwidth(i.e. the loss of the total transmission rate).

Authors adopt a different selling strategy for each pricing model. For the market equilibrium pricing model they propose a Bertrand competition equilibrium in each primary user independently sets a price for selling part of its spectrum. In contrast, for the competitive pricing model they take a Stackelberg scheme. In the Stackelberg model, the first seller announces its price and then, the second updates its price to maximize its profit. There is an optimal competitive pricing strategy. Finally, in the cooperative pricing model, all primary users know each other and they cooperate to maximize the total profit by selling spectrum to the secondary users. Using this scheme, some primary users may receive lower individual revenue compared to the one obtained through Bertrand game. Therefore, to maintain cooperation, a fair N-person coalition game in which all of them make coalition and share the benefit from cooperation is considered.

Comparing the three strategies, cooperation achieves the highest total profit because of global optimization. Stackelberg competitive pricing is higher than Bertrand.

In [23], the authors also analyse a competitive market with multiple spectrum providers operating with different technologies and costs. They introduce the notion that two kind of secondary users exist, quality-sensitive and price-sensitive, and they examine the price strategies of the market when all the providers want to sell some part of their spectrum. In a competitive and distributed network, the primary users do not have global information of which are the sell prices of other servers or which is the consumer population. The authors propose a probabilistic pricing strategy using structured stochastic learning that allows sellers to determine the price of their spectrum by considering the history of the play. They model the system from game theoretical perspective and proof that it converges to a Nash equilibrium point whenever this exists. Moreover, if sellers cooperate, they can improve their profit.

The secondary users, have a utility function based on the price and estimated quality of the offered links. The buyer chose the seller for which the utility is maximized. The system is vulnerable to the free ride problem when two sellers cooperates (one with higher operating costs than the other), and the buyer population is quality sensitive. Then, the higher cost seller may free ride on the lower cost seller.

In [24], it is described a framework for competition under the regulation of a spectrum policy server. Operators compete with each other to ensure the user accepts their service offer with the highest probability. That paper formulates the operator competition as a non-cooperative game with many users simultaneously in parallel and proposes a spectrum policy server based iterative bidding scheme that achieves a Nash equilibrium of the operator game. Each user has an acceptance probability which is a function of the offered rate and price. The spectrum policy server collects user specific information. During the bidding process only the spectrum policy server and operators are involved. The spectrum policy server sets limits on bandwidth usage for each user-operator session. These limits are obtained form the optimization problem of the expected revenue which is the sum of the expected payments of the operators for their spectrum utilization. This scheme improves the user acceptance probabilities and the bandwidth utilization compared with that one where the bandwidth is equally shared.

IV. Conclusions

After analysing the current allocation spectrum schemes, we summarize the traditional solutions for each one of the analysed scenarios in Table I.

TABLE I
Allocation spectrum models

	Secondary market	**Self-organized network**
Central.	Auctions	Graph theoretical models
Distrib.	Game theoretical models (players: primary servers)	Game theoretical models (players: secondary users)
		Graph theoretical models (simplified versions)

A lot of research has been conducted in the area of spectrum allocation. One of the main reasons why there is not a winning solution for each exposed scenario is due to the low scalability of the presented solutions. Both centralized and distributed solutions require that the spectrum allocator has knowledge about the attributes of the network resources and entities, and given a mobile network whose environmental conditions continuously change, this means exchanging quite a lot of information. It is preferred to have sub-optimal but efficient solutions than schemes introducing a noticeable network overhead and taking the maximum profit of the spectrum. Note that, at the end, the network overhead due to the control information also reduces the available bandwidth of the network.

Beyond performance reasons, open challenges in spectrum sharing are related to security. Security issues are hardly considered in current schemes. If malicious users act with false identity or obtaining resources unfairly, then the performance of the system will be mitigated. A malicious user could be a user that makes selfish use of the network or wants to affect negatively the network. Two kind of malicious activities have to be prevented and punished if they are detected: users that during the allocation process (bidding, game theory actions, etc.) send false information of the environment to distort the outcome of the allocation function, and users that play with multiple false identities in order to get more bandwidth or payments than the one that could fairly obtain.

Besides, most game theoretical proposals assume that network players are rational. More analysis should be done in order to check the consequences of irrational players that just want to break the network. Due to the licensed nature of the spectrum cognitive radio networks are dealing with, avoiding any security risk is of utmost importance.

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