HAL
open science

A Survey on Dynamic Spectrum Access Techniques in Cognitive Radio Networks

Badr Benmammar, Asma Amraoui, Francine Krief

To cite this version:

Badr Benmammar, Asma Amraoui, Francine Krief. A Survey on Dynamic Spectrum Access Techniques in Cognitive Radio Networks. International Journal of Communication Networks and Information Security (IJCNIS), 2013, 5 (2), pp.68-79. hal-00842583v2

HAL Id: hal-00842583

https://inria.hal.science/hal-00842583v2

Submitted on 5 Apr 2014

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

A Survey on Dynamic Spectrum Access Techniques in Cognitive Radio Networks

Badr Benmammar[1], Asma Amraoui[1], Francine Krief[2]

[1] LTT Laboratory of Telecommunication Tlemcen, UABT Tlemcen, Algerie
[2] LaBRI Laboratory Bordeaux 1 University, Talence, France
{badr.benmammar, amraoui.asma}@gmail.com, krief@labri.fr

***Abstract*:** The idea of Cognitive Radio (CR) is to share the spectrum between a user called primary, and a user called secondary. Dynamic Spectrum Access (DSA) is a new spectrum sharing paradigm in cognitive radio that allows secondary users to access the abundant spectrum holes in the licensed spectrum bands. DSA is an auspicious technology to alleviate the spectrum scarcity problem and increase spectrum utilization. While DSA has attracted many research efforts recently, in this paper, a survey of spectrum access techniques using cooperation and competition to solve the problem of spectrum allocation in cognitive radio networks is presented.

***Keywords*:** Cognitive Radio, Dynamic Spectrum Access, Auction, Game Theory, Markov Models, Multi Agent Systems.

1. Introduction

In the past five years, we have attested an impressive growth in wireless communication due to the popularity of smart phones and other mobile devices. Due to the emergence of application domains, such as sensor networks, smart grid control, medical wearable and embedded wireless devices, we are seeing increasing demand for unlicensed bandwidth. A study carried out by the Federal Communications Commission (FCC) has shown that some frequency bands are overloaded at the rush hours. However, the use of the frequency spectrum is not uniform: according to the hours of day and to the geographical position; a frequency band can be overloaded while another remains unused. The idea to develop tools to better use the spectrum has naturally emerged.

With spectrum becoming an ever deficient resource, it is fastidious that new systems utilize all available frequency bands as efficiently as possible. Dynamic spectrum access allocates spectrum more dynamically and it is an active area of research. DSA requires not only advances in technology but also new policy and economic models for spectrum use.

Cognitive radios are widely viewed as the disruptive technology that can radically ameliorate both spectrum efficiency and utilization. Cognitive radios are fully programmable wireless devices that can sense their environment and dynamically adjust their transmission waveform, channel access method, spectrum use, and networking protocols as needed for good network and application performance.

The research community has made important progress in addressing the many research challenges combined with cognitive radio and DSA. However, there is a big gap between individual research results and the large-scale deployment of cognitive radio networks that dynamically optimize spectrum use. Recent developments such LTE-A (Long Term Evolution-Advanced) which relies on flexible spectrum use, offer colossal opportunities to demonstrate the promising value of cognitive radio and DSA.

The revolutionary technology presented in this survey will be at the cutting edge of future wireless communications. Dynamic spectrum access and cognitive radio networks will be supplied with an all-inclusive introduction to this emerging technology, outlining the fundamentals of cognitive radio networks and dynamic spectrum access.

In this survey, first, we define cognitive radio and its main functions i.e. spectrum sensing, spectrum decision, spectrum sharing and spectrum mobility. Then DSA methods are discussed, we classify these techniques in four areas, those based on auction, on game theory, on Markov chains and on Multi Agent Systems (MAS).

2. Cognitive Radio

The idea of Cognitive Radio was officially presented by Joseph Mitola in a seminar at the Royal Institute of Technology in Stockholm in 1998, later published in an article by Mitola and Gerald Q. Maguire, Jr. in 1999 [32].

The term Cognitive Radio is used to describe a system with the ability to sense and recognize its context of use, in order to enable it to adjust its radio operating parameters dynamically and autonomously and learn the results of its actions and its environmental setting operation.

CR is a form of wireless communication in which a transmitter/receiver can detect intelligently communication channels which are in use and those who are not, and can move to unused channels. This optimizes the use of available spectrum radio frequency while minimizing interference with other users.

The principle of CR, included in the IEEE 802.22 and IEEE 802.16h [14], requires an alternative spectrum management that is: a user called secondary (SU) may at any time access to frequency bands that are free, that is i.e., not occupied by primary user (PU) of the licensed band. The SU will assign the service once completed, or once a PU has shown an inclination connection.

Cognitive radio system requires four major functions that enable it to opportunistically use the spectrum [17]. These functions consist in the CR terminal's main steps for spectrum management. They are: spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility.

2.1. Spectrum Sensing

This is the basic functionality; it consists on sensing unused spectrum and sharing it without interference with the other users. One of the goals of the spectrum sensing, especially for the interference sensing, is to obtain the spectrum status (free/busy), so that the spectrum can be accessed by a SU under stress of interference. The challenge is that of measuring the interference at the receiver caused by the primary transmissions of SUs.

2.2. Spectrum Decision

A decision model is required for spectrum access. The complexity of this model depends on the parameters considered in the analysis of the spectrum.

The decision model becomes more complex when a SU has multiple objectives. For example, a SU may intend to maximize performance while minimizing disturbance caused to the primary user. Stochastic optimization methods will be an interesting tool to model and solve the problem of spectrum access in a CR.

When multiple users (both primary and secondary) are in the system, preference will influence the decision of the spectrum access. These users can be cooperative or uncooperative in access to spectrum.

In a non-cooperative environment, each user has its own purpose, while in a cooperative one, all users can work together to achieve one goal. For example, many SUs may compete with each other to access the radio spectrum (eg, O1, O2, O3, O4 in Figure 1 below) so that their individual throughput is maximized. During the competition between SUs, all ensure that the interference caused to PUs is maintained below the temperature limit corresponding interference.

In a cooperative environment, CRs cooperate with each other to make a decision for accessing the spectrum and maximizing the objective function taking into account the common constraints. In such a scenario, a central controller can coordinate the spectrum management.

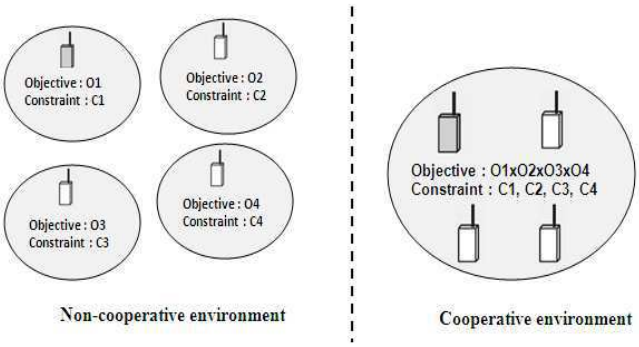

Figure 1. Cooperative and non-cooperative spectrum Access

In a distributed multi-user environment, access to non-cooperative spectrum, each user can achieve an optimal decision independently by observing the behaviour of other users (historical/action). Therefore, a distributed algorithm is required for the SU to make the decision to access to spectrum independently.

2.3. Spectrum Analysis or Sharing

The sensing spectrum results are analyzed to estimate the spectrum quality. One issue here is how to measure the spectrum quality which can be accessed by a SU. This quality can be characterized by the Signal/Noise Ratio (SNR), the average correlation and the availability of white spaces. Information on the available spectrum quality for a CR user can be imprecise and noisy. Learning algorithms of Artificial Intelligence techniques can be used by CR users for spectrum analysis.

2.4. Spectrum Mobility or Handoff

Spectrum mobility is the process that allows the CR user to change its operating frequency. CR networks are trying to use the spectrum dynamically allowing radio terminals to operate in the best available frequency band, to maintain transparent communication requirement during the transition to a better frequency.

Figure 2 illustrates the four main spectrum management functions of the cognitive radio cycle as well as the possible transitions between them.

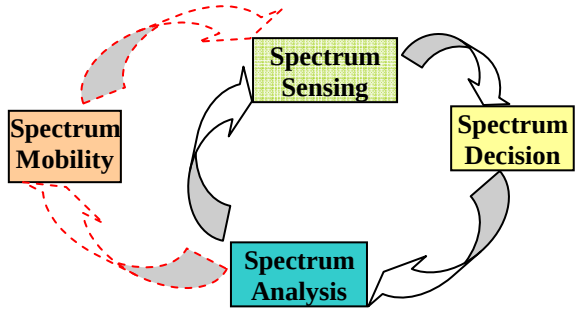

Figure 2. Spectrum management functionality' s

3. Dynamic Spectrum Access

The explosive growth in wireless services over the past several years illustrates the huge and growing demand of the consumers for communications, thus the spectrum becomes more congested. We know that static spectrum allocation is a major problem in recent wireless network domains. Generally, these allocations lead to inefficient usage creating empty spectrum holes or white spaces. To solve the problem of spectrum congestion, CR networks use Dynamic Spectrum Accessing.

Cooperative communication is known as a way to overcome the limitation of wireless systems [22]. However, since users generally have a limited knowledge about their environment, we claim that cooperative behavior can provide them the necessary information to solve the global issues.

Basically, a SU does not own a license for its spectrum usage and it can access the spectrum either opportunistically or by coexisting with the neighboring licensed users. This kind of access is called "license sharing" and a rather large number of solutions already exist in the literature [42,31,25].

We have found a lot of proposed schemes related to spectrum access, those using auctions, a large number of approaches used Game theory, and a little less works used Markov approaches for dynamic spectrum access. But few researches have been done in this topic using Multi Agent Systems.

3.1. Spectrum Access using Auctions

Auctions are based on the concept of selling and buying goods or services. The main goal of using auctions in CR networks is to provide a motivation for the SUs to maximize their spectrum usage. In order to fully utilize the spectrum,

the dynamic spectrum allocation using auctions has become a promising approach that allows SUs to lease unused bands by the PUs.
Generally, an auction consists of several stakeholders; Table 1 describes the difference between traditional auctions and what corresponds to each speaker when applying this method to the negotiation in CR networks.

Table 1. Difference between classical auctions and auctions in CR Networks

Traditional auctions	Auctions in CR networks
Objects to sell	Free channels
Bidder	Secondary User (SU)
Seller	Primary User (PU)
Auctioneer	Regulator

Auctions often are classified as one of the following auction types [62], listed in Figure 3:

First-price sealed-bid auction (FPSB**):** winner pays his bid. In this case, one should bid below one's value an amount that depends on how many other bidders there are. The more bidders, the closer to one's value that one should bid. There is a tradeoff between profit and the frequency of winning.

Second-price sealed-bid auction (Vickrey**):** winner pays highest losing bid. In this type of auction, the optimal strategy is to bid one's value.

English auction (Open Ascending-bid auctions**):** auctioneer begins with a low price. Bidders raise their bids until nobody is willing to bid higher. The optimal strategy in an English auction is to bid up to one's value, staying in the auction until the bids exceed one's value.

Dutch auction (Open Descending-bid auctions**):** auctioneer calls out prices beginning with a very high value and gradually reduces it. The first bidder to accept an offered price wins. The Dutch auction gets its name because of its use in the flower markets in Holland.

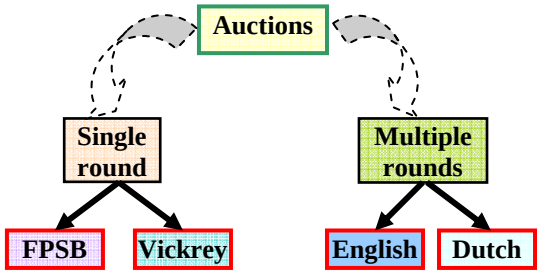

Figure 3. Organigram showing types of auctions

We can find hybrid form of auction called double auctions where participants are buyers and sellers in the same time and trade on the same product.
In auction-based solutions, each channel is assigned to only one network, i.e. that there is no concept of PU and SU in the same channel. In the literature, two possibilities are offered [7].

- The regulator allocates channels to the PUs; these users allocate independently the unused portions of their channel to SUs.
- The regulator allocates the right to be Primary or SU in the channel.

A framework for spectrum allocation in the CR is proposed in [12] using auctions where the regulator can simultaneously allocate the rights to be primary or SU in the channel.
Another way of using auctions is proposed in [44], where the authors proved that on certain scenarios the spectrum is efficiently used when multiple SUs win access to a single channel; this is what distinguishes their method with the traditional auctions where only one user can win.
In these solutions, the users' behaviors are untruthful, so the centralized manager can't optimize the global utility function of the network [30].
A scenario where secondary users can opportunistically access unused spectrum vacated by idle primaries was considered in [49]. The authors introduce two metrics to protect primary performance, namely collision probability and overlapping time. They present three spectrum access schemes using different sensing, back-off, and transmission mechanisms and show that they achieve indistinguishable secondary performance under given primary constraints. The authors provide closed form analysis on secondary user performance, present a tight capacity upper bound, and reveal the impact of various design options, such as sensing, packet length distribution, back-off time, packet overhead, and grouping.
The authors in [43] have considered the problem of spectrum sharing among primary users (PUs) and secondary users (SUs). They formulate the problem based on bandwidth auction, in which each SU makes a bid for the amount of spectrum and each PU may assign the spectrum among the SUs by itself according to the information from the SUs without degrading its own performance. The authors show that the auction is a noncooperative game and that Nash equilibrium (NE) can be its solution.
A primary radio network (PRN) consisting of a primary system base station (PS-BS) and multiple primary system mobile stations (PS-MSs) was considered in [50]. The authors construct a CR network (CRN) consisting of a PRN with multiple CR-MSs and propose a spectrum-management policy framework based on the Vickrey auction such that CR-MSs can compete for utilization of the PRN spectrum bands available for opportunistic transmission of CR-MSs. PRN users are granted incentives at a discounting factor to access spectrum bands and are being compensated for possible operating interference from CR-MSs, whereas the interference is constrained under a tolerance level without losing satisfaction for the PS-MSs.
In [51], the authors have presented a secondary spectrum market where a primary license holder can sell access to its unused or under-used spectrum resources in the form of certain fine-grained spectrum-space-time unit. Secondary wireless service providers can purchase such contracts to deploy new service, enhance their existing service, or deploy ad hoc service to meet flash crowds demand. Within the context of this market, the authors investigate how to use auction mechanisms to allocate and price spectrum resources so that the primary license holder's revenue is maximized.

The authors begin by classifying a number of alternative auction formats in terms of spectrum demand and then study a specific auction format where secondary wireless service providers have demands for fixed locations (cells). They propose an optimal auction based on the concept of virtual valuation. Assuming the knowledge of valuation distributions, the optimal auction uses the Vickrey-Clarke-Groves (VCG) mechanism (generalization of a Vickrey auction for multiple items) to maximize the expected revenue while enforcing truthfulness. To reduce the computational complexity, they further design a truthful suboptimal auction with polynomial time complexity. It uses a monotone allocation and critical value payment to enforce truthfulness. Simulation results show that this suboptimal auction can generate stable expected revenue.

The authors in [15] consider a cognitive radio network which contains one PU and many SUs. They use a technique based on auctions for dynamic spectrum access. The authors have suggested using a single round auction especially if we seek to satisfy applications that require an immediate response, because the use of multiple rounds auctions can make us lose a few seconds since the procedure is slightly longer and slower. To maximize the gains of the PU, the use of multiple round auctions is better. But, if we are interested in the number of satisfied SU, it is better to use a single round auction because the procedure is faster. The method proposed by the authors has also proven that to solve the problem of spectrum congestion, we should use one of dynamic spectrum access techniques (single or multiple rounds) rather than using nothing and satisfy the first received request.

Figure 4 illustrates the impact of auctions on the obtained gains by the PU.

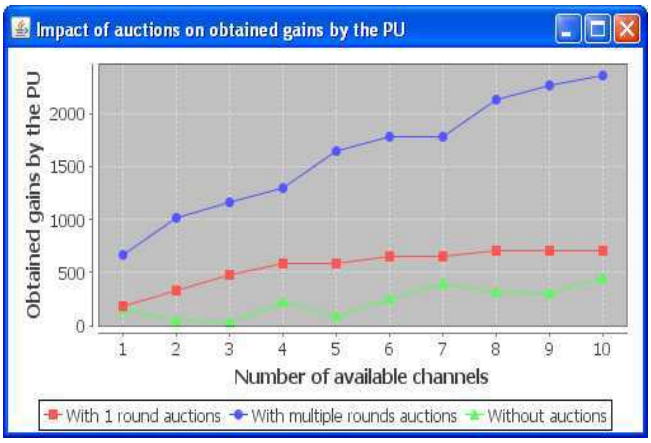

Figure 4. Impact of auctions on the obtained gains by the PU

Auction is often modeled as a competitive mode; in this case, cognitive radio can function only at a non-cooperative way. On contrary, MAS or game theory seems to be a way to overcome this limit; in fact, cooperative way may be implemented in this case. Thus, cognitive radio can function at both cooperative and competitive modes.

3.2. Spectrum Access using Game Theory

Game Theory can be defined as a mathematical framework which consists of models and techniques that use to analyze the iterative decisions behavior of individuals concerned about their own benefit. These games are generally divided into two types [10], cooperative games and competitive games.

- **Cooperative (coalition) Games**: all players are concerned about all the overall benefits and they are not very worried about their own personal benefit. Some few recent works in CR [42] [45] consider the use of cooperative game theory to reduce transmission power of SUs in order to avoid generating interference to PU transmissions.
- **Competitive Games**: every user is mainly concerned about his personal payoff and therefore all its decisions are made competitively and moreover selfishly. In the existing literature, we found that game theoretical concepts have been extensively used for spectrum allocations in CR networks [31] [37] [35], where the PU and SU participating in a game, behave rationally to choose strategies that maximize their individual payoffs.

The most known property of game-theoretical approaches is called Nash Equilibrium (NE). In NE, each player is assumed to know the equilibrium strategies of the other players, and no player has anything to gain by changing his or her own strategy.

Pareto efficiency is another important concept of game theory. This term is named after Vilfredo Pareto, an Italian economist, who used this concept in his studies and defined it as; “A situation is said to be Pareto efficient if there is no way to rearrange things to make at least one person better off without making anyone worse off” [48].

In any game, someone will find pure and mixed strategies. A pure strategy has a probability of one, and will be always played. On the other hand, a mixed strategy has multiple purse strategies with probabilities connected to them [65]. Pure strategy selects a single action and plays it, each row or column of a payoff matrix represents both an action and a pure strategy. Mixed strategy randomize over the set of available actions according to some probability distribution.

Let A_i = {all possible actions for agent i}, and a_i be any action in A_i.

S_i (a_j) = probability that action a_j will be played under mixed strategy s_i.

The support of s_i is support (s_i) = {actions in A_i that have probability > 0 under s_i}.

A pure strategy is a special case of a mixed strategy; the support consists of a single action.

In fully mixed strategy, every action has probability > 0. i.e., support $(s_i) = A_i$.

In a game without a pure strategy Nash Equilibrium, a mixed strategy may result in a Nash Equilibrium.

Some of the existing works using game theory for the dynamic spectrum access are mentioned here. For example, in [16], the authors assume that the PUs are aware of their environment and of the SUs existence. PUs adopt the roles of leaders by selecting a subset of SUs and grating them spectrum access. Whereas in [19], a framework using game theory where the PU do not have the knowledge about their neighborhood, so they are unaware of the presence of SUs, and the SUs are only allowed to access the spectrum opportunistically (users are modeled as rational, selfish and think only to maximize their profits).

An interesting game is proposed in [21] where the PU first determines the spectrum price based on the quality of spectrum and then, the SU decides how much spectrum to buy by observing the price.

In the bargaining games, the individual players have the opportunity to cooperate in order to reach a mutual agreement. At the same time, these players can have conflicts of interest and no agreement can be made with any individual player without its approval. For CR networks, the bargaining games are applied to allocate spectrum bands in centralized and decentralized network settings; the author in [8] proposes to design secured autonomous networks where terminals and base stations interact and self-adapt in an intelligent manner without needing a central controller or a regulator. The network design is done at the equilibrium state.

Mention that even cooperative and competitive games focus on solving the NE and analyzing its properties, they do not provide any details about the players' interaction to reach this equilibrium [37].

The authors in [47] consider the problem of spectrum sharing among a PU and multiple SUs. They formulate this problem as an oligopoly market competition and use a noncooperative game to obtain the spectrum allocation for secondary users. Nash equilibrium is considered as the solution of this game.

In [2], the authors have developed a framework for resource allocation in a secondary spectrum access scenario, where a group of cognitive radios accesses the resources of a primary system. They assume the primary system is a cellular OFDM-based network operating in uplink. The authors have developed an optimum resource allocation strategy, using cooperative game theory, which guarantees the primary's required QoS and allocates an achievable rate at a given bit error rate for the secondary, when possible. The proposed cognitive radio game (CRG) is a network-assisted resource management method, where users (both primary and secondary) inform the primary system's BS of their channel state information and power limitation and the base station calculates the optimum sub-channel and power allocation for all users.

The authors in [5] have considered dynamic spectrum access among cognitive radios from an adaptive, game theoretic learning perspective. Spectrum-agile cognitive radios compete for channels temporarily vacated by licensed primary users in order to satisfy their own demands while minimizing interference. For both slowly varying primary user activity and slowly varying statistics of "fast" primary user activity, the authors apply an adaptive regret based learning procedure which tracks the set of correlated equilibria of the game, treated as a distributed stochastic approximation.

The authors in [64] investigates the impact of the tradeoff between spectrum sensing and spectrum access on the cooperative strategies of a network of SUs that seek to cooperate in order to improve their view of the spectrum (sensing), reduce the possibility of interference among each other, and improve their transmission capacity (access). The authors have modeled the problem as a coalitional game in partition form and an algorithm for coalition formation is proposed. Using the proposed algorithm, the SUs can make individual distributed decisions to join or leave a coalition while maximizing their utilities which capture the average time spent for sensing as well as the capacity achieved while accessing the spectrum. The authors show that, by using the proposed algorithm, the SUs can self-organize into a network partition composed of disjoint coalitions, with the members of each coalition cooperating to jointly optimize their sensing and access performance.

Simulation results show the performance improvement that the proposed algorithm yields with respect to the non-cooperative case.

Figure 5 demonstrates that, as the amount of time α dedicated for sensing a single channel increases, the time that can be allotted for spectrum access is reduced, and, thus, the average payoff per SU per slot for both cooperative and non-cooperative spectrum sensing and access decreases. In this figure, we can see that, at all α, the proposed joint spectrum sensing and access through coalition formation exhibits a performance gain over the non-cooperative case. This advantage decreases with α, but it does not go below an improvement of 54.7% relative to the non-cooperative scheme at α = 0.5, i.e., when half of the slot is used for sensing a single channel.

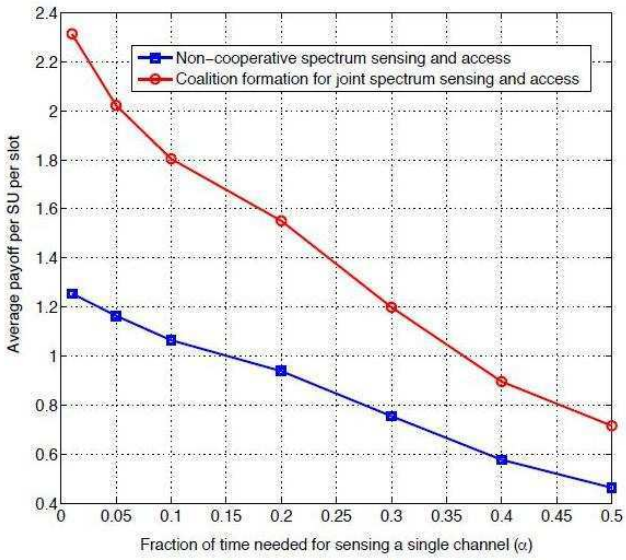

Figure 5. Average payoff achieved per SU per slot for a network with N = 10 SUs and K = 14 channels as the fraction of time needed for sensing a single channel α varies.

Game theory gives insight into several less-known aspects, which arise in situations of conflicting interests. It develops a framework for analyzing decision making in such situations where interdependence of agents is considered like the problem of spectrum access between SUs in cognitive radio networks. But, all the competitive problems cannot be analyzed with the help of game theory, also, the assumption that players have the knowledge about their own pay-offs and pay-offs of others is not practical and the techniques of solving games involving mixed strategies particularly in case of large pay-off matrix is very complicated.

3.3. Spectrum Access using Markov Approaches

Game theoretical approaches do not model the interaction between the SUs and the PUs for spectrum access. This modeling can efficiently be performed using Markov chains [30].

Few research have been done in this field, for example, In [40], a Markov model is presented, where each SU randomly selects its own channel rather than exchanging control messages with the neighboring SUs. A very interesting approach using Markov models is developed by the authors in [1] to analyze the different policies proposed for spectrum sharing.

Some works used the CTMC (Continious Time Markov Chains) model because it achieves good statistical tradeoffs between fairness and efficiency. Presented works in [1] [46] [41] used CTMC to capture the interaction between primary and SUs. Both queuing and without queuing models are analyzed and the throughput degradation due to SUs interference is compensated.

In [57], a Markov chain analysis for spectrum access in licensed bands for cognitive radios is presented and forced termination probability, blocking probability and traffic throughput are derived. In addition, a channel reservation scheme for cognitive radio spectrum handoff is proposed. This scheme allows the tradeoff between forced termination and blocking according to QoS requirements. Numerical results show that the proposed scheme can greatly reduce forced termination probability at a slight increase in blocking probability.

A decentralized cognitive MAC protocols that allow secondary users to independently search for spectrum opportunities without a central coordinator or a dedicated communication channel is proposed in [58]. Recognizing hardware and energy constraints, the authors assume that a secondary user may not be able to perform full-spectrum sensing or may not be willing to monitor the spectrum when it has no data to transmit. The authors develop an analytical framework for opportunistic spectrum access based on the theory of partially observable Markov decision process (POMDP). This decision-theoretic approach integrates the design of spectrum access protocols at the MAC layer with spectrum sensing at the physical layer and traffic statistics determined by the application layer of the primary network. It also allows easy incorporation of spectrum sensing error and constraint on the probability of colliding with the primary users. Under this POMDP framework, the authors propose cognitive MAC protocols that optimize the performance of secondary users while limiting the interference perceived by primary users. A suboptimal strategy with reduced complexity yet comparable performance is developed. Without additional control message exchange between the secondary transmitter and receiver, the proposed decentralized protocols ensure synchronous hopping in the spectrum between the transmitter and the receiver in the presence of collisions and spectrum sensing errors.

The authors in [59] propose and analyze a dynamic spectrum access schemes in the absence or presence of buffering mechanism for the cognitive secondary subscriber (SU). They develop a Markov approach to analyze the proposed spectrum sharing policies with generalized bandwidth size in both primary system and secondary system. Performance metrics for SU are developed with respect to blocking probability, interrupted probability, forced termination probability, non-completion probability and waiting time. Numerical examples are presented to explore the impact of key systems parameters like the traffic load on the performance metrics. Comparison results indicate that the buffer is able to significantly reduce the SU blocking probability and non-completion probability with very minor increased forced termination probability. The analytic model has been verified by extensive simulation.

The authors in [60] use hidden Markov models (HMMs) to model and predict the spectrum occupancy of licensed radio bands. They proposed a technique that can dynamically select different licensed bands for its own use with significantly less interference from and to the licensed users. It is found that by predicting the duration of spectrum holes of primary users, the CR can utilize them more efficiently by leaving the band, that it currently occupies, before the start of traffic from the primary user of that band. The authors propose a simple algorithm, called the Markov-based channel prediction algorithm (MCPA), for dynamic spectrum allocation in cognitive radio networks. They present the performance of the proposed dynamic spectrum allocation algorithm when the channel state occupancy of primary users are assumed to be Poisson distributed. The impact of CR transmission on the licensed users is also presented. It is shown that significant SIR improvements can be achieved using HMM based dynamic spectrum allocation as compared to the traditional CSMA based approach.

A queuing analytic framework to study important performance measures experienced by SUs in a CR network was developed in [61]. The authors studied queuing delay and buffer statistics of SUs' packets by modeling PUs' activity as a two state Markov chain and SUs' channel quality variation as a finite state Markov chain (FSMC). In order to allocate available channels among the SUs, an opportunistic channel allocation scheme is considered. The proposed framework facilitates to design an admission controller for SUs' network in order to maintain a given quality service (QoS) requirement which is specified in the form of statistical delay guarantee.

The authors in [63] have proposed an approach to dynamic spectrum access in which the occupancy state of each frequency band at each time instant is estimated, and available bands are allocated accordingly. Estimation is performed from power spectral density measurements which are assumed to obey a hidden Markov process (HMP). The value of the hidden state represents the status of a given frequency band which could be free or occupied. The authors have trained the system using real spectrum measurements, and tested it on simulated data for which the occupancy state of each frequency band at each time instant is known.

Table 2. HMP-Based Spectrum sensing performance

SNR (dB)	P_{fa}	P_d	P_{pe}
6	4.000e-3	0.7158	0.0403
8	7.986e-4	0.9018	0.0395
10	1.495e-4	0.9849	0.0382
12	1.495e-4	0.9849	0.0382
14	0	1	0.0381

P_{fa} = False alarm probability, P_d = Detection probability and P_{pe} = Prediction error probability.

Table 2 shows the values of P_{fa}, Pd and P_{pe} respectively, for various SNR values. For this channel, the probability of false alarm P_{fa} is very small for all values of SNR and decreases as

the SNR increases. The probability P_d increases as the SNR increases. P_{fa} and P_d approach to 0 and 1, respectively, when SNR is greater than 14 dB. Unlike P_{fa} and P_d which have either increase or decrease trend, the probability of prediction error P_{pe} has negligible fluctuation around 0.038 for all SNR values.

The probability of prediction error is computed as follows: $Ppe = P_{pe/off}\ P_{off} + P_{pe/on}\ P_{on}$. Where $P_{pe/off}$ and $P_{pe/on}$ are the conditional probabilities of prediction error given channel off state and channel on state; P_{off} and P_{on} are the probabilities of off state and on state, respectively.

Markov modelling easily handles the computation of the probability of an event resulting from a sequence of sub-events. This type of problem does not lend itself well to classical techniques. The Markov models are simple to generate although they do require a more complicated mathematical approach. So, there are several problems with these models, for example, they make the Markovian assumption that the emission and the transition probabilities depend only on the current state, the number of parameters that need to be set in a Markov models is huge and as a result of the above, the amount of data that is required to train a Markov models very large.

3.4. Spectrum Access using Multi Agent Systems

The idea of Distributed Artificial Intelligence (DAI) is to move from individual to collective behavior in order to address the limitations of traditional artificial intelligence when solving complex problems requiring the distribution of intelligence over several entities. The DAI includes three basic research areas which are: distributed problem solving, parallel artificial intelligence and multi-agent systems [52].

We can find several definitions concerning the agent which are different only in the type of application for which the agent is designed. The authors in [53] gave the following definition: "an agent is a piece of software that can achieve a specific task in an autonomous way (for the sake of the user or the application)".

All the agents have the possibility of coordinating, communicating and co-operating with the system or with other agents. A common approach consists in defining the agent by its properties, such as autonomy, intelligence, mobility, etc...

Two principal types of agent, mobile agents and intelligent agents are identified [54].

The principal attributes of a mobile agent are the mobility of the code, the data and the state (state of a process, a machine or a protocol). This makes it possible for software entities to move in an autonomous way through the network to achieve specific task, thereby taking advantage of proximity [53].

An intelligent agent is a software entity which carries out operations for the account of the user (or for another program) with some degree of freedom and autonomy and which exploits knowledge or representations of the desires and the objectives of the user [55]. The authors in [53] give the following definition: Intelligent agents are software entities that are able to perform delegated tasks based on internal knowledge and reasoning, where aspects such as inter agent communication and negotiation are fundamental. Usually mobility is not considered as an issue. Another definition was given in [55]: "an intelligent agent is an information processing system, located in some environment, which is able to carry out flexible and autonomous actions in order to meet its aims of design".

A multi-agent system is a dynamic federation of agents connected by the shared environments, goals or plans, and which cooperate and coordinate their actions [56]. It is this capacity to communicate, to coordinate and to cooperate which makes interesting the use of agents in cognitive radio networks.

The association of MAS and the CR can provide a great future for the optimal management of frequencies (in comparison with the rigid control techniques proposed by the telecommunications operators). In the case of use of unlicensed bands, the CR terminals have to coordinate and cooperate to best use the spectrum without causing interference.

In [39], the authors propose an architecture based on agents where each CR terminal is equipped with an intelligent agent, there are modules to collect information about the radio environment and of course the information collected will be stored in a shared knowledge base that will be accessed by all agents. The proposed approach is based on cooperative MAS (the agents have common interests). They work by sharing their knowledge to increase their collective and individual gain.

Agents are deployed on the PUs and SUs terminals and cooperate with each other in the works proposed in [36] [24] [25]. By cooperative MAS, we mean that PU agents exchanged t-uples of messages in order to improve themselves and the neighbourhood of SU agents. They propose that the SUs should make their decision based on the amount of available spectrum when they find a suitable offer (without waiting for response from all PUs). In other words, the SU agent should send messages to the appropriate neighbour PU agent and of course the concerned PU must respond to these agents to an agreement on sharing the spectrum. After the end of the spectrum use, the SU must pay the PU.

A comparison is made in [24] between an agent and a CR. Basically, both of them are aware of their surrounding environments through interactions, sensing, monitoring and they have autonomy and control over their actions and states. They can solve the assigned tasks independently based on their individual capabilities or can work with their neighbors by having frequent information exchanges.

Table 3. Comparison between an agent and a Cognitive Radio

Agent	Cognitive radio node
An agent is a virtual entity that can perceive its environment, act and communicate with other agents.	A cognitive radio terminal interacts with its radio environment, detects the free frequencies and then exploits them.
Agent is autonomous and has skills to achieve its goal.	The cognitive radio node has enough capabilities allowing it to manage the radio resources.

To make the CR systems practical, it requires that several CR networks coexist with each other. However, this can cause interference. The authors of [22] think that to remedy this

problem, the SU can cooperate to sense the spectrum as well as to share it without causing interference to the PU. For this, they propose schemes to protect the PU from interferences by controlling the transmission power of the cognitive terminal.

In [29] [23], the authors propose cooperation between PUs and SUs and between SUs only. Agents are deployed on the user's terminals to cooperate and result in contracts governing spectrum allocation. SU agents coexist and cooperate with the PU agents in an Ad hoc CR environment using messages and mechanisms for decision making. Since the internal behaviours of agents are cooperative and selfless, it enables them to maximize the utility function of other agents without adding costs result in terms of exchanged messages.

However, the allocation of resources is an important issue in CR systems. It can be done by making the negotiation among SUs [34] [38]. In [34] the authors propose a model based on agents for the spectrum trading in a CR network. But instead of negotiating spectrum directly with the PU and SU, a broker agent is included. This means that the equipment of PU or SU does not require much intelligence as it does not need to perform the spectrum sensing. The objective of this trading is to maximize the benefits and profits of agents to satisfy the SU. The authors proposed two situations, the first uses a single agent who will exploit and dominate the network, in either case there will be several competing agents.

The authors in [20] study the use of CR in wireless LANs and the possibility of introducing the technology of agents, in other words they try to solve the problem of radio resources allocation by combining resources management WLAN in a decentralized environment, this by using MAS. For this, they propose an approach based on MAS for sharing information and decisions distribution among multiple WLANs in a distributed manner.

Interference from the acquisition of the channels in a cellular system during Handovers can be reduced according to [13] [4] using a CR to manage the handover. Indeed, the mobility of the device imposes a different behaviour when changing zones. The terminal must ensure service continuity of applications and the effective spectrum management. The authors propose an approach that uses negotiation, learning, reasoning and prediction to know the needs of new services in modern wireless networks. They propose an algorithm to be executed by the mobile terminal during the cognitive phase of handover.

The MAS contains several intelligent agents interact with each other. Each agent can sense and learn. The agent can select behaviours based on local information and attempt to maximize overall system performance. In [7], the authors described a new approach based on multi-agent reinforcement learning which is used in CR networks with ad hoc decentralized control. In other words, they set up several CR scenarios and affect each case a reward or penalty. The results of this approach have shown that with this method, the network can converge to a fair spectrum sharing and of course it reduces interferences with PUs.

The authors in [26] have developed a cooperative framework for spectrum allocation that can generate highly effective behavior in dynamic environments and achieve better utility of the participating devices. The proposed approach is based on multi-agent system cooperation and implemented by deploying agents on cognitive radio and primary user devices. Experimental evaluations confirm the efficiency of the algorithms proposed by the authors for distributed and decentralized environments.

For the simulation, the authors assumed two different fixed values of times (such as T1 and T2), where T1 represents the short-term case and T2 is the longer period. When T1 is considered, the SU agents can ask for an amount of spectrum within one hour limit ($0 \leq T1 \leq 60$ Minutes) and similarly this limit is within two hours, as in case of T2 ($0 \leq T2 \leq 120$ Minutes).

The number of cooperation messages transmitted and received in the entire system with the success rate (in percentage) is shown in Table 4. According to this table, the values of exchanged messages are almost leveled off for the middle periods (from 30 to 70 agents). Further, Table 4 depicts that the average number of messages (per agent) remains between 4 and 5 even with the increased number of agents. The authors assume also that the approach is linear in terms of messages and success rate. Particularly when time limit is T2 (around 90 to 120 agents), the performance of the approach substantially degrades (reaching below 80%), but nevertheless it remains steady.

Table 4. Success rate and number of messages at T1 and T2

No of agents	Number of messages		Success rate (in %)	
	T1	**T2**	**T1**	**T2**
10	45	41	100	98.7
20	81	72	90	85
30	117	115	88.23	84
40	159	161	87.31	82
50	185	176	86	82
60	253	261	85	80
70	271	262	84.41	79.3
80	325	366	82	80
90	388	392	82	78.53
100	416	434	81	77.26
110	475	483	80.5	78.77
120	503	516	80	77.42

The results show that the proposed approach can absorb the high spectrum sharing demands by introducing the cooperation between primary and secondary user devices. Furthermore, the proposed approach improves the overall utility and minimizes the spectrum loss with a minimum communication cost. The spectrum allocation success rate is almost 80% even with large number of agents.

In [11], a learning mechanism is available for each agent. This learning provides a reward for each agent so that it can make the right decision and choose the best action. They modeled each SU node as a learning agent because the transmitter and receiver share a common result of learning or knowledge. The authors presented a function of reinforcement learning in MAS to achieve optimality in the cooperation between agents in a distributed CR network.

A channel selection scheme without negotiation is considered for multi-user and multi-channel in [38]. To avoid collision incurred by non-coordination, each SU learns

to select channels based in their experiences. In such a scheme, each SU senses channels and then selects a slowed frequency channel to transmit the data, as if no other SU exists. If two SUs choose the same channel for data transmission, they will collide with each other and the data packets cannot be decoded by the receiver. However, the SUs can try to learn how to avoid each other.

The authors in [18] are interested to the use of IEEE 802.22, and proposed an algorithm called "Decentralized Q-learning" based on the multi-agent learning theory to deal with the interference problem caused to PUs. They modeled the secondary network using MAS where the different agents are base stations of the IEEE 802.22 WRAN. They proved that the proposed MAS is able to automatically learn the optimal policy to maintain protection for PU against interference. The authors of [33] and [27] used the MAS to design a new cognition cycle with complex interaction between PU, SU and wireless environments and they used the hidden Markov chains to model the interactions between users and the environment. The results of this approach have shown that the algorithm can guarantee fairness among users.

What could make the use of MAS in the CR interesting and more concrete is the existence of a simulation framework to test the proposed works and approaches. This is precisely what the authors propose in [9]. Their platform allows studying the emerging aspect, the behaviors of heterogeneous CR networks.

As shown above, using MAS seems to be the approaches that suits well to the spectrum access in cognitive radio networks because it guarantees the autonomy of users as embedded agents can manage their own spectrum need in a dynamic and decentralized manner. But, in cognitive radio networks, we often consider multiple secondary users competing in a non-cooperative way for a limited set of frequencies left available by primary users. As a consequence, game theory is the natural framework to study the interactions among such users. It should be noted that auction is often modeled as a competitive game, so, the hybridization of game theory and auction seem promising for spectrum access, and so, cognitive radio can function at both cooperative and competitive modes. However, game theory focuses on solving the Nash equilibrium and analyzing its properties and not to consider how players should interact to reach this equilibrium. On contrary, MAS seems to be a way to overcome this problem. We also note that, the results obtained using Markov models are very promising and these models can offer a new paradigm for predicting channel behavior in cognitive radio networks, an area that has been of much research interest lately. Table 5 makes a comparison between the four techniques used for dynamic spectrum access.

Table 5. Comparison between the four techniques used for dynamic spectrum access

Techniques used for DSA	Strengths	Weaknesses
Auction	- Well adapted to competitive environment.	- Not well adapted to cooperative environment. - Not well adapted to modeling the interaction between users.
Game theory	- Well adapted to both competitive and cooperative environment.	- Focuses on solving the Nash equilibrium and analyzing its properties and not to consider how players should interact to reach this equilibrium.
Markov models	- Well adapted to modeling the predicting channel behavior.	- Not well adapted to modeling the interaction between users.
SMA	- Well adapted to modeling the interaction between users. - Guarantees the autonomy of users.	- Have to use the other techniques (Auction, Game theory and Markov models) to perform more complex processing.

So, to summarize our survey, we can say that the four techniques used for dynamic spectrum access in the context of cognitive radio networks (auction, game theory, Markov models and SMA) are completely complementary.

Researchers in CR have been more interested in spectrum sensing, decision and sharing than spectrum mobility. Nevertheless, terminal mobility still arises as a major issue. DSA will take into account nodes mobility. Future directions of research must use multi-agent systems negotiation that enables mobile CR terminals to switch to the best available spectrum band giving their applications requirements. The four techniques used for DSA in the context of CR networks must take into account nodes mobility.

4. Conclusion

In this survey, we have presented various techniques of dynamic spectrum access in cognitive radio networks, starting by auctions where the utility function of the network is not optimized each time because it depends on user behavior and then passing by game theory which is widely used in this area because it can achieve equilibrium between users that provides efficient spectrum management. Then, we cited some works that used Markov models, which in addition to the above methods provides a model of the interaction between PUs and SUs. Finally, we focused on the use of multi-agent systems in dynamic spectrum access.

However, this last method has been exploited by a minority of researchers (compared to game theory) to solve the problem of spectrum allocation. Different approaches using the MAS in the CR are studied, those offering cooperation between SUs only, others offer a cooperation between primary and SUs and those proposing to include a broker agent to negotiate the spectrum, knowing that the most works studied are using reinforcement learning.

Our paper explains in detail cognitive radio and its main functions (spectrum sensing, spectrum decision, spectrum sharing and spectrum mobility) including different methods designing dynamic spectrum access. We think that this survey is a perfect introduction for graduate students and researchers, as well as a useful self-study guide for practitioners. The influence of the main functions of cognitive radio on the performance of the upper layer

protocols such as routing and transport are not investigated in this survey, the open research issues in these areas are not outlined.

However, we think that our survey is a good complement to literature review related to routing in cogntive radio networks [66, 67] and to transport protocol for cognitive radio [68, 69].

In our future work, we think we can improve the wireless links reliability and ensure good quality of service to CR mobile terminals [3] [4] [6] by integrating multi-agent systems. We intend to work on multi-agent systems negotiation [70] that enables CR mobile terminals to switch to the best available spectrum band giving their applications requirements (Spectrum Mobility). We will deploy agents on both PUs and SUs to negotiate in order to have a better use of the spectrum. The use of game theory and auction in this context is also possible [15].

References

[1] S. Khan, K-k. Loo, "Real time cross layer flood detection mechanism," Elsevier Journal of Network Security, Vol. 16, No. 5, pp. 2-12, 2009.

[2] Attar, A., Nakhai, M. R. and Aghvami, A. H. "Cognitive radio game for secondary spectrum access problem. Wireless Communications", IEEE Transactions on, 8(4), 2121-2131, 2009.

[3] Amraoui A, Baghli W, Benmammar B, "Improving video conferencing application quality for a mobile terminal through cognitive radio", 14th IEEE International Conference on Communication Technology (ICCT 2012). Chengdu, China, November 9th-11th, 2012.

[4] Amraoui, A., Benidris, F.Z., Benmammar, B., Krief, F., Bendimerad, F.T. "Toward cognitive radio resource management based on multi-agent systems for improvement of real-time application performance". In: 5th IFIP International Conference on New Technologies, Mobility and Security, NTMS 2012, Istanbul, Turkey (2012).

[5] Maskery, M., Krishnamurthy, V. and Zhao, Q. "Decentralized dynamic spectrum access for cognitive radios: cooperative design of a non-cooperative game. Communications", IEEE Transactions on, 57(2), 459-469, 2009.

[6] B. Benmammar and F. Krief. "MQoS NSLP: a mobility profile management based approach for advance resource reservation in a mobile environment". Proceedings of the 7th IFIP IEEE International Conference on Mobile and Wireless Communications Networks (MWCN 2005). Marrakech, Morocco. September 19-21, 2005.

[7] Chen Bin, Hoang, A.T., Ying-Chang Liang, "Cognitive Radio Channel Allocation Using Auction Mechanisms", Vehicular Technology Conference VTC Spring 2008.

[8] Chu Tian et al, "Spectrum Trading in Cognitive Radio Networks An Agent-based Model under Demand Uncertainty", Global Telecommunications Conference, 2010.

[9] Debbah M, "Mobile flexible networks: The challenges ahead", Proceedings of International Conference on Advanced Technologies for Communications, invited paper, pp. 3-7, 2008.

[10] Dzikowski Jacek, Cynthia Hood, "An Agent-Based Simulation Framework For Cognitive Radio Studies", Simutools '09 Proceedings of the 2nd International Conference on Simulation Tools and Techniques, 2009.

[11] Gafar Mohamed, Elnourani Ahmed, "Cognitive Radio and Game Theory: Overview and Simulation". Blekinge Institute of Technology, 2008.

[12] Galindo-Serrano Ana, Lorenza Giupponi, "Aggregated Interference Control for Cognitive Radio Networks Based on Multi-agent Learning". Proceedings of the 4th International Conference On CROWNCOM, 2009.

[13] Gaurav S, Kasbekar, Sarkar S, "Spectrum auction framework for access allocation in cognitive radio networks". IEEE.ACM Transactions on Networking, vol. 18, pp. 1841 – 1854, 2010.

[14] Gaurav S, Kasbekar, Sarkar S, "Spectrum auction framework for access allocation in cognitive radio networks", IEEE.ACM Transactions on Networking, vol. 18, pp. 1841 – 1854, 2010.

[15] A. Amraoui, B. Benmammar, F. Krief, FT. Bendimerad. "Auction-based Agent Negotiation in Cognitive Radio Ad Hoc Networks", (Book Chapter), Fourth International ICST Conference, ADHOCNETS 2012, Paris, France, October 16-17, 2012, Revised Selected Papers Series: Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, Vol. 111. pp. 119-134, Springer Edition, 2013.

[16] Haykin Simon, "Cognitive Radio: Brain-Empowered Wireless Communications", IEEE Journal On Selected Areas In Communications, Vol. 23, No. 2, 2005.

[17] I.F. Akyildiz, W. Y. Lee, and K. R. Chowdhury (2009), "CRAHNs: Cognitive Radio Ad Hoc Networks," Ad Hoc Networks, vol.7, pp.810-836.

[18] Hossain E, Niyan D, Zhu Han, "Dynamic Spectrum Access and management in cognitive radio networks", Cambridge University Press 2009.

[19] Jiandong Li, Chungang Yang, "A Markovian Game-Theoretical Power Control Approach In Cognitive Radio Networks: A Multi-Agent Learning Perspective", Wireless Communications and Signal Processing (WCSP), 2010.

[20] Lai L, El Gamal H, "The water-filling game in fading multiple-access channels". IEEE Transactions on Information Theory, vol. 54, pp. 2110–2122, 2008.

[21] Letaief Ben, K., Wei Zhang, "Cooperative Communications for Cognitive Radio Networks", Proceedings of the IEEE, 2009.

[22] Li Y, Wang X, Guizani M, "Resource pricing with primary service guarantees in cognitive radio networks: A Stackelberg game approach", Proceedings of IEEE Globecom 2009, pp. 1-5, 2009.

[23] Li H, "Multi-agent Q-Learning of Channel Selection in Multi-user Cognitive Radio Systems: A Two by Two Case", Systems, Man and Cybernetics, 2009.

[24] Lim Kok et al, "Achieving Context Awareness and Intelligence in Distributed Cognitive Radio Networks: A Payoff Propagation Approach", Workshops of International Conference on Advanced Information Networking and Applications, 2011.

[25] Mir Usama, Leila Merghem-Boulahia, Dominique Gaïti, “A Cooperative Multiagent Based Spectrum Sharing”, Sixth Advanced International Conference on Telecommunications, 2010.

[26] Mir Usama, Leila Merghem-Boulahia, Dominique Gaïti, “Dynamic Spectrum Sharing in Cognitive Radio Networks: a Solution based on Multiagent Systems”. International Journal on Advances in Telecommunications, vol 3 no 3 & 4, 2010.

[27] Usama Mir, LeilaMerghem-Boulahia, Dominique Gaïti. (2010). “COMAS: A CooperativeMultiagent Architecture for Spectrum Sharing”. EURASIP Journal onWireless Communications and Networking, Volume 2010, Article ID 987691.

[28] Mir Usama, Leila Merghem-Boulahia, Dominique Gaïti, “Utilization of a Cooperative Multiagent System in the Context of Cognitive Radio Networks”. © Springer-Verlag Berlin Heidelberg 2009, LNCS 5844, pp. 100–104, 2009.

[29] Mir Usama et al, “A Continuous Time Markov Model for Unlicensed Spectrum Access”, IEEE 7th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), 2011.

[30] Mir Usama, Leila Merghem-Boulahia, Dominique Gaïti, “Multiagent Based Spectrum Sharing Using Petri Nets”. Y. Demazeau et al. (Eds.): Trends in PAAMS, AISC 71, pp. 537–546. springerlink.com © Springer-Verlag Berlin Heidelberg 2010.

[31] Mir Usama, “Utilization of Cooperative Multiagent Systems for Spectrum Sharing in Cognitive Radio Networks”, PHD theses, Sep 2011.

[32] Mitola J, Maguire G, “Cognitive radio: Making software radios more personal’’, IEEE Personal Communications, 1999.

[33] Niyato D, Hossain E, “Competitive pricing for spectrum sharing in cognitive radio networks: dynamic game, inefficiency of Nash equilibrium, and collusion”. IEEE Transactions on Selected Areas in Communications, vol.308, pp. 192-202, 2008.

[34] Qi Zhao, Qin shi, Wu Zhijie, “Self-Organize Network Architecture for Multi-Agent Cognitive Radio Systems”, International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery, 2011.

[35] Raiyn J, “Toward cognitive radio handover management based on social agent technology for spectrum efficiency performance improvement of cellular systems Personal”, IEEE 19th International Symposium

[36] Tan Yi, Sengupta S, Subbalakshmi K. P, “Competitive spectrum trading in dynamic spectrum access markets: A price war”. Proceedings of IEEE GLOBECOM, pp. 1-5, 2010.

[37] Trigui Emna, Moez Esseghir, Leila Merghem Boulahia, “Gestion dynamique du spectre entre terminaux radio cognitive mobiles”, CFIP 2011 - Colloque Francophone sur l Ingénierie des Protocoles, 2011.

[38] Wang B, Wu Y, Liu K. J. R, “Game theory for cognitive radio networks: An overview”. Elsevier Computer Networks, vol. 54, pp. 2537–2561, 2010.

[39] Wu Cheng et al, “Spectrum management of cognitive radio using multi-agent reinforcement learning”, AAMAS ‘10 Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems, 2010.

[40] Xie Jiang, Howitt Ivan, Raja Anita, “Cognitive Radio Resource Management Using Multi Agent Systems”, Consumer Communications and Networking Conference, 2007.

[41] Xin C et al, “On random dynamic spectrum access for cognitive radio networks”, Proceedings of IEEE GLOBECOM, 2010.

[42] Xing Y et al, “Dynamic spectrum access in open spectrum wireless networks”, IEEE Journal on Selected Areas on Communications, vol. 24, pp. 626-637, 2006.

[43] Wang, X., Li, Z., Xu, P., Xu, Y., Gao, X. and Chen, H. H. “Spectrum sharing in cognitive radio networks—an auction-based approach. Systems”, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 40(3), 587-596, 2010.

[44] Yau K L.A et al, “Enhancing Network Performance in Distributed Cognitive Radio Networks using Single-Agent and Multi-Agent Reinforcement Learning”. Local Computer Networks (LCN), 2010.

[45] Yongle W et al, “Collusion-resistant multi-winner spectrum auction for cognitive radio networks”, Proceedings of IEEE GLOBECOM, pp. 1-5, 2008.

[46] Zhang J, Zhang, Q, “Stackelberg game for utility-based cooperative cognitive radio networks”, Proceedings of ACM MOBIHOC, pp. 23-32, 2009.

[47] Niyato, D., Hossain, E. “Competitive spectrum sharing in cognitive radio networks: a dynamic game approach”. Wireless Communications, IEEE Transactions on, 7(7), 2651-2660, 2008.

[48] D. Fudenberg and J. Tirole, “Game Theory”, MIT Press, 1983.

[49] Huang, Senhua, Xin Liu, and Zhi Ding. "Opportunistic spectrum access in cognitive radio networks." INFOCOM 2008. The 27th Conference on Computer Communications. IEEE. IEEE, 2008.

[50] Chang, Hung-Bin, and Kwang-Cheng Chen. “Auction-based spectrum management of cognitive radio networks”, Vehicular Technology, IEEE Transactions on 59.4 (2010): 1923-1935.

[51] Jia, Juncheng, et al. “Revenue generation for truthful spectrum auction in dynamic spectrum access”. Proceedings of the tenth ACM international symposium on Mobile ad hoc networking and computing. ACM, 2009.

[52] E. Trigui, M. Esseghir and L. Merghem Boulahia, “ON USING MULTI AGENT SYSTEMS IN COGNITIVE RADIO NETWORKS: A SURVEY”, International Journal of Wireless & Mobile Networks (IJWMN) Vol. 4, No. 6, December 2012.

[53] H. Jens, G. Carmelita and F. Peyman. “Agent technology for the UMTS VHE concept”. ACM/IEEE MobiCom’98, Workshop on Wireless Mobile Multimedia, Dallas, USA, October 1998.

[54] T. Magedanz and R. Popescu-Zeletin. “Towards Intelligence on Demand” – On the Impacts of Intelligent Agents on IN. 4th International Conference on Intelligence in Networks, Bordeaux, France, November 1996.

[55] N.R. Jennings, K. Sycara and M.J. Wooldridge. "A Roadmap of Agent Research and Development". Autonomous Agents and Multi-Agent Systems, 1(1):7-38, 1998.
[56] M.N. Huhns. "Multi-agent Systems". Tutorial at the European Agent Systems Summer School, (EASSS'99), 1999.
[57] Zhu, Xiaorong, Lianfeng Shen, and T-SP Yum. "Analysis of cognitive radio spectrum access with optimal channel reservation", Communications Letters, IEEE 11.4 (2007): 304-306.
[58] Zhao, Qing, et al. "Decentralized cognitive MAC for opportunistic spectrum access in ad hoc networks: A POMDP framework", Selected Areas in Communications, IEEE Journal on 25.3 (2007): 589-600.
[59] Zhang, Yan. "Dynamic spectrum access in cognitive radio wireless networks", Communications, 2008. ICC'08. IEEE International Conference on. IEEE, 2008.
[60] Akbar, Ihsan A., and Willium H. Tranter. "Dynamic spectrum allocation in cognitive radio using hidden Markov models: Poisson distributed case", SoutheastCon, 2007. Proceedings. IEEE. IEEE, 2007.
[61] Rashid, Mohammad M., et al. "Opportunistic spectrum access in cognitive radio networks: A queueing analytic model and admission controller design", Global Telecommunications Conference, 2007. GLOBECOM'07. IEEE. IEEE, 2007.
[62] R. JR. Cassady. "Auctions and Auctioneering". University of California Press, Berkley and Los Angeles, California, (1967).
[63] Nguyeny, Thao, Brian L. Mark, and Yariv Ephraim. "Hidden Markov process based dynamic spectrum access for cognitive radio", Information Sciences and Systems (CISS), 2011 45th Annual Conference on. IEEE, 2011.
[64] Saad, Walid, et al. "Coalitional games in partition form for joint spectrum sensing and access in cognitive radio networks", Selected Topics in Signal Processing, IEEE Journal of 6.2 (2012): 195-209.
[65] [3] Raoof, O., and Al-Raweshidy, H. "Theory of Games: An Introduction". SCIYO. COM, 1, 2010.
[66] Al-Rawi, Hasan AA, and Kok-Lim Alvin Yau. "Routing in distributed cognitive radio networks: A survey", Wireless Personal Communications (2012): 1-38.
[67] Cesana, Matteo, Francesca Cuomo, and Eylem Ekici. "Routing in cognitive radio networks: Challenges and solutions", Ad Hoc Networks 9.3 (2011): 228-248.
[68] Chowdhury, Kaushik R., Marco Di Felice, and Ian F. Akyildiz. "TP-CRAHN: A transport protocol for cognitive radio ad-hoc networks", INFOCOM 2009, IEEE. IEEE, 2009.
[69] Sarkar, Dilip, and Harendra Narayan. "Transport layer protocols for cognitive networks", INFOCOM IEEE Conference on Computer Communications Workshops, 2010. IEEE, 2010.
[70] Jrad, Z. F., Benmammar, B., Corréa, J., Krief, F., and Mbarek, N. "A user assistant for QoS negotiation in a dynamic environment using agent technology". In Wireless and Optical Communications Networks, 2005. WOCN 2005. Second IFIP International Conference on (pp. 270-274). IEEE.