Dynamic Spectrum Access Techniques State of the art

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Chapter 3

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ABSTRACT

It is now widely recognized that wireless communications systems don't exploit the whole available frequency band. The idea has naturally emerged to develop tools to better use the spectrum. Cognitive Radio (CR) is the concept that meets this challenge.

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

CRs must have the ability to learn and adapt their wireless transmission according to the ambient radio environment. The application of Artificial Intelligence (AI) approaches in the CR is very promising because they are essential for the implementation of CR networks architecture. They must be able to coexist to make CR systems practical, which may cause interference to other users. To solve the problem of congestion, CR networks use Dynamic Spectrum Access (DSA).

In order to deal with this problem, the idea of cooperation between users to detect and share spectrum without causing interferences is introduced.

We found a large number of suggested works relating to spectrum access, those using Auctions, a large number of approaches use the Game theory, but those using Markov chains are fewer. However, some researches have been done in this area using Multi Agent Systems (MAS).

INTRODUCTION

We currently attend the multiplication of telecommunication standards considering recent progress in this area. The increasing number of standards broadens the range of offers and available services for each user; however, most available radio frequencies have already been allocated.

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.

Cognitive Radio is the concept that meets this challenge; better use the spectrum.

The context of our work is an alliance between wireless networks and intelligent methods. The application of AI approaches in the CR is very promising; indeed it is used in the implementation of CR networks architecture. Users must be able to coexist to make CR systems practical, which may cause interferences to other users. In order to deal with this problem, the idea of cooperation between the users to detect and share spectrum without causing interference is introduced. 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.

The main objective of our research is to intelligently manage radio resources in the context of a CR network. We think that the association of DSA techniques and the CR can provide a great future for the optimal management of frequencies. Thus, different machine learning techniques are considered, negotiation and cooperation algorithms are also needed to ensure a better and efficient spectrum allocation.

In this chapter, we explain the different existing approaches for dynamic spectrum allocation. For simplicity, we give a short definition about CR and its functions; we speak about the use of AI techniques in the CR and finally, we speak about DSA and the different methods used for it such as Auction theory, Game theory, Markov models or Multi Agent Systems.

COGNITIVE RADIO

The idea of CR was officially presented by Joseph Mitola in a seminar at KTH, the Royal Institute of Technology in 1998, later published in an article by Mitola and Gerald Q. Maguire, Jr. in 1999 (Mitola J, 1999).

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 (transceiver) can detect intelligently communication channels which are in use and those which 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 (Grandblaise, 2006), requires an alternative spectrum management i.e.: a mobile called secondary may at any time access to frequency bands that are free, i.e., not occupied by primary user (PU) of the licensed band. The secondary user (SU) will assign the service once completed, or once a PU has shown an inclination connection.

Functions of Cognitive Radio

The main functions of CR are (Hossain E, 2009):

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. Spectrum Management

Pick the best available frequencies to respond to the communication needs of users. CRs should decide on the best frequency band to respond Quality of Service (QoS) on all available frequency bands, so the spectrum management functions are needed for CRs. These management functions can be classified as follows:

a. Spectrum analysis

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 AI can be used by CR users for spectrum analysis.

b. 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 PU. 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 non-cooperative 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 so that their individual throughput is maximized.

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.

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

3. *Spectrum mobility*

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.

ARTIFICIAL INTELLIGENCE AND COGNITIVE RADIO

The techniques of AI for learning and decision making can be applied to the design of efficient CR. The concept of machine learning can be applied to CR for maximizing the capabilities of dynamic spectrum access. The proposed system architecture is shown in Figure 1.

Figure 1: Architecture of cognitive radio and machine learning

We notice that the architecture is similar to expert systems architecture. The interface refers to a transceiver which detects new data; the knowledge base keeps the system states and actions available. The reasoning engine uses the knowledge base to select the best action. The learning engine performs the manipulation of knowledge based on the observed information.

Different AI techniques can be used for CR reasoning. For certain wireless conditions, some AI techniques are more suitable than others for addressing specific problems. The chosen technique should minimize both complexity and processing time. The author in (S.Shatila, 2012) thinks that AI techniques such as neural networks and hidden Markov models are applicable techniques for reasoning and decision-making in the cognitive engine.

CRs must have the ability to learn and adapt their wireless transmission according to the ambient radio environment. The intelligent algorithms such as those based on machine learning, genetic algorithms and fuzzy logic are essential for the implementation of CR technology. In general, these algorithms are used to observe the state of the wireless environment and to build knowledge on it.

This knowledge is used by a CR to adapt its decision on spectrum access. For example, SUs can observe the activity of PUs transmission on different channels. This allows the CR to develop knowledge of primary user activity on each channel. This knowledge is then used by the CR to decide which path to choose so that the desired performance objectives can be achieved (eg, throughput is maximized while the interference or collisions caused to PUs are maintained below the target level).

Neural networks could be used and have a high ability for training and adaptation but also a high processing time to train the weights and a sensitivity to the quality of the training data. Similarly, the hidden Markov model can yield good decisions but faces basic problems in decoding, recognition, training and learning (Rabiner, 1989).

Neural networks

The artificial neural networks are made up of interconnected artificial neurons with each other to form a structure that mimics the behavior of biological neurons. They can be used in any phase of the cognition cycle of the CR (A Katidiotis, 2010).

The neural network model provides a black box for the nonlinear relationship between inputs (such as network settings) and outputs (network performance). This model of neural network can learn from training data that is available online in a way where the measurement data in real time are available. Although learning a neural network model requires a large amount of computational resources, the calculation of the output is much simpler and it only incurs a small overhead.

Therefore, this model is appropriate for a CR network for which a rapid response to changing radio environment is required for a SU. For example, the SU must interrupt transmission whenever the user activity on the primary channel is detected.

The neural network model shown in the Figure 2 consists of an input layer, hidden layers and an output layer.

Figure 2: Artificial neural network

When learning of the neural network model, all measured inputs are used to adjust the weight and to minimize the error with respect to known outputs. This adjustment is repeated until the error is below a certain threshold.

A study was done in (Aimilia Bantouna, 2012) on the different machine learning methods applied in cognitive systems. Among these methods, neural networks have been adopted in the spectrum sensing and adapting radio parameters in CR (A. Fehske, 2005) (Reed, 2005).

In (A Katidiotis, 2010), the authors propose learning programs that are based on artificial neural networks where the data rate is studied in relation to the link quality and signal strength of the wireless terminal.

The prediction of performance and capacity of CR network can be made using multilayer neural networks (N Baldo, 2009) or by using the Kohonen maps (P Demestichas, 2009).

In (Asma Amraoui, 2012) (B. Benmammar, 2012), authors perform a comparison between neural networks with supervised learning, C4.5 decision tree algorithm and KNN algorithm and prove that CR is an efficient tool to improve real-time application performance related to only one Cognitive Radio Mobile Terminal.

Fuzzy logic

Fuzzy logic provides a simple way to get the solution to a problem based on inaccurate, noisy, and incomplete information.

Instead of using complicated mathematical formulation, fuzzy logic uses a set of fuzzy membership functions and inference rules to obtain the solution that meets the desired objectives.

Generally, there are three important components in a system of control of fuzzy logic: fuzzifier, fuzzy logic processor and the defuzzifier. While the fuzzifier is used to plot the actual inputs by making them fuzzy, the fuzzy logic processor implements an inference engine to obtain the solution based on sets of predefined rules, whereas the defuzzifier is applied to transform the solution to real output. The Figure 3 shows the structure of a fuzzy controller.

Figure 3: Fuzzy controller

Today, the AI techniques are used to solve some problems in the field of Telecommunications. For example fuzzy logic was proposed as a solution to the handoff in cellular networks by the authors of (Pérez-Neira, 2008) (H.Maturino-Lozoya, 2000) (O'Brien, 2006).

In the literature, fuzzy logic is often used when dealing with cross-layer optimization (A.Merentitis, 2008) (A.Yang, 2007) in CR systems. This technique is also used for channels selection (A. Al-Fuqaha, 2008) or for the selection of the most appropriate SU to access the spectrum taking into account the efficiency, mobility and distance from the PU (Ly, 2008).

The use of fuzzy logic in the cooperative spectrum sensing can provide additional flexibility to existing combinations of methods has been proven in (Marja Matinmikko, 2009).

Fuzzy logic is often combined with neural networks in CR networks as mentioned by authors in (K.-R. Lo, 2003) (L.Giupponi, 2008). It is also used as an approach for multi-hop routing (A.El Masri, 2011) or for malicious users sensing in CR networks (Abolhassani, 2011).

Genetic algorithms

Genetic algorithms (GA) are a part of evolutionary computing, which is a rapidly growing area of AI. A genetic algorithm is a biologically inspired heuristic search technique that mimics the process of natural evolution; it is an adapted solution for optimization problems.

GAs are generally used to develop a biologically inspired model for a cognitive engine (A Katidiotis, 2010), they are also used in CR to solve multi objective optimization problem and to configure CR parameters when the wireless environment change (T. W. Rondeau, 2004) (T. R. Newman, 2007).

The authors of (Rieser, 2004) think that GAs are suitable for CR problems because they offer a significant amount of power and flexibility since that CRs are likely to face dynamic environments and situations as well as radio upgrades due to advancing technology.
In (Petri Mähönen, 2006), authors use GA for CR and propose a cognitive resource manager to select an algorithm from a toolbox to solve problems.

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 (Li, 2009). 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 (Mir Usama, 2010) (Niyato D, 2008) (Yang C, 2010).

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.

Spectrum Access using Auctions

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.

Table1. 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 are based on the concept of sale and purchase of goods or services. The main purpose of the use of auctions in CR networks is to provide motivation for SUs to maximize their use of spectrum. To fully utilize the spectrum, dynamic spectrum allocation using auctions has become a promising approach that allows users to rent unused channels by PUs.

In general, the proposed solutions by the different authors working on auctions theory for dynamic spectrum access are based on architecture with infrastructure (H Chang, 2010).

In (Zhu Han, 2009), the authors propose a mechanism for an efficient and equitable sharing of spectrum resources where we need a coordinator to manage the operation and model spectrum access in CR networks such repeated auction.

In solutions based on auctions, each channel is assigned to a single network, i.e. there is no notion of SU and PU in the same channel. In the literature, two possibilities are offered:

- Either the regulator allocates channels to PU; they independently allocate unused portions of their channel for SUs (Z Ji, 2006).
- Either the regulator allocates the right to be SU or PU in the channel (Gaurav S. Kasbekar, 2009).

The method of payment is often a major problem when we want to apply auctions in telecommunications networks; this is why some researchers are trying to find adequate solutions. For example the authors in (Bin Chen, 2008) use second price auctions to solve the problem of spectrum allocation and develop an approach which introduces the concept of fictive money for the payment in real time. Another interesting approach is proposed in (Guangen Wu, 2011) where the authors think that there is no concept of money for the auction but the price to pay is the waiting time.

However, some researches has been done by (Lin Chen, 2010) and offer a traditional approach based on auctions, and then they do an extension of their approach to a scenario that assumes that there are free unused channels. i.e. the SU will have the choice between paying a good QoS or access to an unused channel for free and encounter risk of interference with the users (if several SU operate simultaneously on these bands).

Another way to use auctions is proposed in (Yongle, 2008), where the authors have shown that in some scenarios the spectrum is used efficiently when multiple SU gain access to a single channel, this is what distinguish their method with the traditional auctions where only one user can win.

In these solutions, user behaviors can be false, so the centralized manager can't maximize the utility function of the overall network (Usama, 2011).

Spectrum Access using Game Theoretical Approaches

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 (Gafar Mohamed, 2008), cooperative games and competitive games.

- **Cooperative 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 (Yang C, 2010) (Zhang J,

2009) 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 (Niyato D, 2008) (Wang B, 2010) (Tan Yi, 2010), 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.

Some of the existing works using game theory for the DSA are mentioned here. For example, in (Xiuli He, 2007), the authors assume that 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 (Lai L, 2008), a framework using game theory where PUs don't have the knowledge about their neighborhood, so they are unaware of the presence of SUs, and 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 (Li Y, 2009) 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 (Debbah, 2008) 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 don't provide any details about the players' interaction to reach this equilibrium (Wang B, 2010).

Spectrum Access using Markov Approaches

Game theoretical approaches don't model the interaction between SUs and PUs for spectrum access. This modeling can efficiently be performed using Markov chains (Usama, 2011).

Few research have been done in this field, for example, In (Chunsheng Xin, 2010), 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 (Ahmed W, 2009) to analyze the different policies proposed for spectrum sharing.
Markov models can be used in the behavior prediction of open spectrum access in licensed bands (Capar F., 2002) and in unlicensed bands (Y. Xing, 2006).

The Hidden Markov Model (HMM) is a mathematically tractable statistical model to describe and analyze the dynamic behavior of a complex random phenomenon (Rabiner, 1989). The HMM generates sequences of observation symbols by making transitions from state to state. However, the states are hidden, and only the output is observable (F Z Benidris, 2012).

HMM are used for example by the signal classifier using pattern recognition (Xinying He, 2009) and for spectrum sensing duration scheduling (Jeon Wha Sook, 2010) (K. Kim, 2007) or to predict the interference temperature of the channel (Sharma, 2008) and for the spectrum occupancy prediction (Akbar I.A., 2007).

Some works used the Continuous Time Markov Chains (CTMC) model because it achieves good statistical tradeoffs between fairness and efficiency. Presented works in (Ahmed W, 2009) (Zhang, 2008) (Y. Xing, 2006) 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.

The authors in (Xiaorong Zhu, 2007) modified the Markov model proposed in (Tang P.K., 2006) and included spectrum handoff capability. In this system, PUs are prioritized as well as the secondary users are having spectrum handoff. SUs capacity in the presence of unrestricted PUs is modeled using three dimensional Markov chains.
It is shown through the analysis done in (Xiaorong Zhu, 2007) that the non-random channel assignment gives a better result compared to the random channel assignment.

In (S W Shon, 2010), a HMM-based channel prediction and selection algorithm is constructed based on a frequency-hopping algorithm to solve the interference problem. The proposed achieves the goal of reducing the interference time and increasing the throughput.

Spectrum Access using Multi Agent Systems

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 telecommunications operators). In the case of use of unlicensed bands, CR terminals have to coordinate and cooperate to best use the spectrum without causing interference.

In (Xie Jiang, 2007), 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 PUs and SUs terminals and cooperate with each other in the works proposed in (Trigui Emna, 2011) (Mir Usama a, 2010) (Mir Usama, 2010). By cooperative MAS, we mean that PU agents exchanged t-uples of messages in order to improve themselves and the neighborhood 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 neighbor 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 (Mir Usama, 2010) between an agent and a CR and shown in Table 2. 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 2: Comparison between an agent and a Cognitive Radio

Agent	Cognitive Radio
Environment awareness via past observations	Sensing empty spectrum portions and PU signals
Acting through actuators	Deciding the bands/channels to be selected
Interaction via cooperation	Interaction via beaconing
Autonomy	Autonomy
Working together to achieve shared goals	Working together for efficient spectrum sharing
Contains a knowledge base with local and neighboring agents' information	Maintains certain models of neighboring PU's spectrum usage

To make the CR systems practical, it requires that several CR networks coexist with each other. However, this can cause interference. The authors of (Li, 2009) 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 (Mir Usama b, 2010) (Yau K.-L.A., 2011), 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 behaviors 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 (Raiyn, 2008) (Cheng Wu, 2010). In (Raiyn, 2008) 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 (Letaief Ben, 2009) 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 Handoffs can be reduced according to (Gaurav S. Kasbekar, 2009) (Atiq Ahmed, 2011) using a CR to manage the handoff. Indeed, the mobility of the device imposes a different behavior 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 handoff.

The MAS contains several intelligent agents interact with each other. Each agent can sense and learn. The agent can select behaviors based on local information and attempt to maximize overall system performance. In (Tian Chu, 2010), they 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.

A very interesting approach is proposed in (Usama Mir c, 2010) where the authors have applied reinforcement learning RL on single-agent (SARL) and Multi-Agent (MARL) to achieve the sensitivity and the intelligence. They show in their results that the SARL and MARL perform a joint action that gives better performance across the network. They finally said reinforcement learning algorithm is adapted to be applied in most application schemas.

In the solution proposed in (Galindo-Serrano Ana, 2009), a learning mechanism as the local MARL is available for each agent. The local 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 the LCPP (Locally Confined Payoff Propagation) which is an important 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 (Cheng Wu, 2010). To avoid collision incurred by non-coordination, each SU learns to select channels based in their experiences. The MARL is applied in the context of Q-learning by considering the SUs as part of environment. 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 (Jiandong Li, 2010) 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 in (Qi Zhao, 2011) used the MAS to design a new cognition cycle with complex interaction between PUs, SUs 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 (Dzikowski Jacek, 2009). Their platform allows studying the emerging aspect, the behaviors of heterogeneous CR networks.

ADVANTAGES AND LIMITATIONS OF SPECTRUM ACCESS METHODS

The cooperative learning enables distributed learning and reduces network cost, so different AI techniques can be used for CR reasoning. We have seen the use of neural network, fuzzy logic and genetic algorithm. We have study other dynamic spectrum access techniques such as auction theory, Game theory, Markov models and Multi Agent Systems.

For certain wireless conditions, some AI techniques are more suitable than others for addressing specific problems, Table 3 summarizes the strengths and limitations of all the techniques studied in this chapter in order to select the most appropriate method for our problem.

Table3: Advantages and disadvantages of dynamic spectrum access techniques in CR.

Method	**Advantages**	**Disadvantages**
Neural networks	- Need few memory - Quick - Easily scalable - Excellent for classification	- Complex - Training required
Fuzzy logic	- Application to systems that are difficult to model - Simple implementation and interpretation - Good for device control with unclear quality boundaries	- Stability, accuracy and optimality of the system are not guaranteed - Performance is measured a posteriori - Settings are made by trials/errors
Genetic algorithms	- Parallel processing - Simple calculations because they use just the values of the function to optimize	- Slow - Choice of parameters and operators is difficult
Auctions theory	- Simplicity - Equitables and transparents	- Licence fees high
Game theory	- Easy reading of the outcomes strategies - Models agent's behavior in situations of choice	- High cost - Does not make rational choices
Markov models	- Modeling complicated processes. - Prediction from experience - Well for classification	- Don't take into account the hidden states - Cannot deal with a large number of states
Multi Agent Systems	- Modularity - Quick - Reliability and flexibility	- High cost - Lack of software support - Lack of methods

CONCLUSION

For an efficient license allocation, spectrum utilization must be efficient too. It is within this context that we have provided the advantages and limitations of each method of spectrum access we have presented previously. To solve the problem of spectrum congestion, we should use one of dynamic spectrum access techniques rather than using nothing and satisfy the first received request.

Auctions theory known by its simplicity facilitates rare resources allocation. The auctions-based systems rely on simple, transparent and well defined rules which are applied to all users in the same way.

Currently, there are several auction protocols, those done in a single round such as First-price sealed-bid auctions and those done in multiple rounds such as English auctions. It is preferable to use 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.

Game theory can predict and determine the most relevant auctions procedure. It has been widely used for spectrum sharing and remains an interesting field of research for spectrum management in the context of CR. Game theory is the most appropriate technique to obtain the equilibrium solution to the problem of the spectrum in such a scenario.

A Markov chain is a sequence of random variables which allow modeling the dynamic evolution of a random system. The fundamental property of Markov chains is that its future evolution depends on the past only through its current value. Otherwise, in the case of CR, this method allows to model the interaction between users (PU and SU).
MAS are scalable and adaptive which allow adding or removing agents from the system without causing problems. In the wireless networks, CR nodes can be modeled as agents where each time they switch to another area (handoff) the MAS changes. MAS are known by their speed because the agents can work in parallel for solving problems.

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.

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KEY TERMS & DEFINITIONS

In this section, you will find the most important keywords related to this chapter and their definitions:

Wireless networks: they are systems where there is no physical wired connection between sender and receiver, but rather the network is connected by radio waves to maintain communications.

Cognitive Radio: It is a promising technology that can alleviate the spectrum shortage problem by enabling to a transceiver to detect intelligently which communication channels are in use and which are not , and instantly move into vacant channels while avoiding occupied ones and causing no interference to incumbent communications.

Dynamic Spectrum Access: It includes novel approaches and technologies enabling more efficient use of the radio spectrum. It can help to solve the problem of spectrum congestion and to minimize white spaces caused by the static spectrum access. These new approaches are from different fields such are Artificial Intelligence, machine learning etc.

Artificial Intelligence: It is the computational simulation of human intelligence. In other words, we can say that AI is the ability of a machine to perform those activities that are normally thought to require intelligence. AI algorithms are used for pattern recognition, learning, planning and problem solving.

Machine learning: It is a branch of AI which focuses on the development of computer programs that can teach themselves to grow and change when exposed to new data. It allows computers to handle new situations via analysis, self-training, observation and experience.

Game theory: It is a method of using mathematical analysis in a competitive situation to select the optimum strategy in the face of an opponent who has a strategy of his own.

Multi Agent System: It is a group of agents where each one has one or more basic skills. The goal is to bring together agents to solve a problem or perform a specific task. Somehow, we distribute intelligence on agents.

APPENDIX - REVIEWQ QUESTIONS

In this section, you will find some review questions that you can answer based on the material presented in this chapter or by reading the references.

1. In a CR, learning comes in which step? Is it necessary?
2. What should we do to benefit from the advantages that offer the CR? In other words, how to efficiently to utilize a CR?
3. What is the most widely used method for spectrum sharing to obtain equilibrium?
4. What does the use of Markov model bring more than the other techniques?
5. Why is it recommended to use AI algorithms to solve the problem of spectrum congestion?
6. What is the difference between cooperation and competition?

7. If the auction theory is the simplest method to solve the problem of spectrum congestion, would it be better by combining it with the other techniques?
8. Are existing Dynamic Spectrum Access techniques nowadays sufficient to optimize the use of spectrum? Should we look for other solutions?
9. Which type of learning machine is often combined when using MAS?
10. Prediction algorithms are very used nowadays for the classification of behaviors in CR, is it a good idea?
11. In a non cooperative environment, what is the best technique to use?