ON USING MULTI AGENT SYSTEMS IN COGNITIVE RADIO NETWORKS: A SURVEY

Emna Trigui, Moez Esseghir and Leila Merghem_Boulahia

Autonomic Networking Environment, ICD/ERA, CNRS UMR STMR 6279
University of Technology of Troyes, 12, rue Marie Curie, 10010 Troyes Cedex, France
{emna.trigui, moez.esseghir, leila.merghem_boulahia}@utt.fr

ABSTRACT

In the last decade, cognitive radio technology received a lot of consideration for spectrum optimization. This issue creates huge opportunities for interesting research and development in a wide range of applications. This paper presents a state of the art on cognitive radio researches especially works using multi-agent systems. We propose among others a classification of cognitive radio proposals based on multi-agent concept and point out the pros and cons for each of the described approach.

KEYWORDS

Cognitive radio, multi-agent systems, radio spectrum management, wireless network

1. INTRODUCTION

Wireless networks have shown an impressive progression these past few years. Their fast evolution arise a much larger need for spectrum resources. Consequently, new efficient approaches for spectrum resources allocation must be implemented. Cognitive radio (CR) technology has been introduced as a key concept of dynamic spectrum resources allocation. CR was conceived to operate across different spectrum bands and heterogeneous radio access technologies (RAT). To achieve cognitive radio goal, which consists in improving spectrum allocation, recent works investigate different methods and protocols such us game theory, medium access control (MAC) protocols and multi-agent systems (MAS). As each approach is related to a specific protocol layer (MAC, network or application layers) and handles a particular CR management function (sensing, sharing, etc), we end up with a large variety of solutions [1].

Using multi-agent systems (MAS) seems to be one of the approaches that suits well to the cognitive radio specifications. First, it guarantees the autonomy of users as embedded agents can manage their own spectrum need in a dynamic and decentralized manner. Second, agents can perceive their environment and communicate with each other, which is mandatory for a CR terminal. Third, the intelligent property of an agent leads to smart MAS and so to an efficient Cognitive Radio Network (CRN).

Various multi-agent system based approaches were proposed to sense the spectrum holes on the one hand, and to allow information sharing and decision distribution among multiple CR terminals, on the other hand. The underlying key idea of using MAS in CRN is to manage fairly and in a decentralized way the shared radio resources between multiple cognitive radio users, in order to enhance the overall spectrum efficiency.

DOI : 10.5121/ijwmn.2012.4601

2. COGNITIVE RADIO OVERVIEW

Cognitive radio concept has been recently introduced in order to enhance the efficiency of the radio spectrum usage in next generations of wireless and mobile computing systems. Basically, the cognitive radio offers new opportunities for resolving static spectrum sharing problem by allowing CR nodes to sense unused spectrum bands and dynamically access them. In the following subsection, we provide a brief introduction to cognitive radio concept. Then, we focus on CR functions and we explain how relevant they are to spectrum management.

2.1. Cognitive Radio Concept

Cognitive radio concept was firstly introduced in 1998 by Joseph Mitola III [2] as *"a radio that employs model-based reasoning to achieve a specified level of competence in radio-related domains"*. A cognitive radio changes its transmission or reception parameters in such a way to avoid interferences between users and to enhance the entire wireless communication network's efficiency. A CR terminal interacts with its radio environment, senses and detects free spectrum bands and then uses them opportunistically. Accordingly, it has enough capabilities to effectively manage radio resources.

In cognitive radio networks, there are two types of users: licensed or primary users (PUs), and unlicensed or secondary users (SUs). PUs can access the wireless network resources according to their license while SUs are equipped with cognitive radio capabilities to opportunistically access the spectrum. Cognitive radio capability allows SUs to temporarily access the PUs' under-utilized licensed channels. To improve spectrum usage efficiency, cognitive radio must combine with intelligent management methods. In the following subsection, we first describe CR primary functions and then, we detail proposed solutions to improve dynamic spectrum access.

2.2. Spectrum Management

Cognitive radio system requires four major functions [3] that enable it to opportunistically use the spectrum. These functions consist in the CR terminal's main steps for spectrum management. They are: spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility. Each function is defined as follows.

1) Spectrum Sensing: It is the key enabling technology for cognitive radio networks. Its main objective is to detect the unused channels and to provide more spectrum access opportunities to CR nodes without interfering with PUs.
2) Spectrum Decision: This function is needed to select the best channel detected through the sensing phase, according to specific cognitive radio user's requirements (such as usage time, quality of service, width of spectrum band).
3) Spectrum Sharing: It is the allocation of the selected spectrum band amongst coexisting primary and secondary users while avoiding interferences between them.
4) Spectrum Handoff or Mobility: When an agreement with PU for spectrum sharing comes to end, CR terminal has to switch towards another band. It performs a spectrum handoff.

Throughout this paper, the expressions CR node (or CR terminal) and secondary user (or SU) will be used interchangeably for the rest of the document. Likely, the words access, allocation and sharing will also be used interchangeably.

Figure 1 illustrates the four main spectrum management functions of the cognitive radio cycle as well as the possible transitions between them. After performing spectrum sensing, CR node has to choose the most appropriate channel among detected free ones according to its application's requirements: it is spectrum decision. Next, CR terminal starts spectrum sharing process. Here, two transitions are possible: going back to sensing at the end of a sharing agreement or switching immediately to another band (spectrum mobility) in case a PU begins to use the same current channel for example. Spectrum mobility can happen proactively or reactively. In the first case, CR node predicts periodically the target band. In the other one, it initiates sensing when handoff is needed.

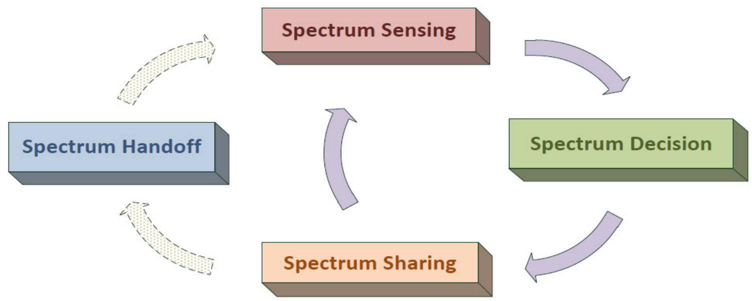

Figure 1. Spectrum management functionalities

Different approaches are proposed in the literature to provide effective solutions for each spectrum management function described above.

For example, regarding the spectrum sensing issues, some studies have proposed radio frequency energy detection [4, 5] which goal is to detect the presence of PU based on the signals that CR node can detect. Few other studies have investigated the hypothesis that empty spectrum portions are a combination of PU's signals, the additive white Gaussian noise and the signal gain [6, 7]. Other researchers have drawn their focus towards matched filter detection [8, 9]. In this technique, PU's signals are previously known and the corresponding match filter generates a high value of gain, which maximizes the received signal-to-noise ratio (SNR).

Another category of studies have focused on game theory [10] to achieve efficient spectrum sensing and spectrum sharing tasks, respectively. In those approaches [11-14], SUs form coalitions and sense cooperatively the spectrum in order to identify and access fairly free channels. Each user has a payoff calculated according to its participation in the coalition's tasks.

Medium Access Control (MAC) based solutions have been recently developed for dynamic spectrum access [15, 16] to improve overall spectrum efficiency. MAC protocols act on spectrum sensing, sharing and mobility. Some of them, referred as cognitive sensing, exploit sensing stimuli to build up a map of the spectrum opportunities that CR terminals can use. Other MAC protocols are concerned with spectrum sharing. They can help to schedule available resources, and distribute them upon CR users. The main goal of other MAC protocols is spectrum mobility. They aim to allow cognitive users to vacate selected channels when their quality becomes unacceptable.

MAS based approaches [36-57] are also increasingly used to insure dynamic spectrum access in CRN. MAS solutions have been proposed mostly in order to address the issues of spectrum sensing and spectrum sharing. These proposals will be discussed in section IV.

Spectrum handoff is relatively a new area of research and only a few investigation efforts have been done in the recent past. In those studies, two main spectrum handoff schemes were proposed: reactive and proactive. Through reactive approaches [17, 18], SUs perform spectrum switching after detecting the arrival of a PU in the band, the target channel is then selected instantaneously. However, through proactive spectrum handoff approaches [19-23], SUs predict the channel availability status and perform spectrum switching before a PU occupies the channel. This prediction is based on previous channel usage statistics. As an example, in [22] is proposed a predictive model for dynamic spectrum access based on the past channel history.

Compared to the reactive spectrum handoff, the proactive approach may be able to reduce handoff delay because the channel is preselected. Nevertheless, it can face a big challenge in case where the preselected target channel is no longer available when the spectrum handoff procedure is started.

In this paper, we will focus on using MAS for the spectrum management in CRN since the application of this technique in such a domain is increasingly occurring. Researchers use MAS in cognitive radio context as it offers a distributed, interactive and intelligent system added to the large range of autonomous and intelligent mechanisms that are already provided. Moreover, the high similarity between an agent in MAS and a cognitive radio node in CRN, as shown in table 1, can be considered as an important factor that makes MAS very suitable to resolve cognitive radio issues. Before discussing the utilization of MAS in CRN (section IV), we will first introduce multi-agent concept in the following section.

Table 1. Comparison between an agent and a cognitive radio node

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.

3. Multi-Agent Systems Review

Since its introduction in 1956, the artificial intelligence (AI) was a branch of computer science that focuses on machine intelligence. The objective is to produce a system simulating human reasoning, considering only one actor to solve problems.

The idea of Distributed Artificial Intelligence (DAI) is to move from individual to collective behavior in order to address the limitations of traditional AI 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.

In this paper, we focus on MAS and their application in cognitive radio networks as a solution for a more efficient spectrum management and radio resource allocation. The next sub-section describes main issues of multi-agent systems.

3.1. Concept and Definitions

An MAS [24] consists in multiple interacting computing elements, known as agents. Agents are programs that can decide for themselves what they need to do in order to satisfy their design objectives. Besides, they are capable of interacting with other agents by engaging in analogous social activity types such *cooperation*, *coordination* and *negotiation* [24]. Ferber [25] gives a definition of an agent and an MAS. According to him, an agent can be defined as a physical or virtual entity that can act, perceive its environment and communicate with others; it is autonomous and has skills to achieve its goals. Besides, an MAS is a set of agents interacting in a common environment [25].

To be intelligent, an agent must have some properties such as reactivity, proactivity and social ability [26]. We detail these capabilities in the following sub-section.

3.2. Agent's properties

Three main features are required to make an agent intelligent [24, 26], which are:

1) Reactivity: Intelligent agents are able to perceive their environment and respond in a timely fashion to changes that occur in it in order to satisfy their objectives.
2) Proactivity: Intelligent agents are able to exhibit goal-directed behaviour by taking the initiative to reach their goal.
3) Social ability: Intelligent agents are capable of interacting with other agents (and possibly humans) in order to reach their aims.

Each agent may face difficulties to solve complex problems alone. Consequently, the intelligence is distributed among various components, which can communicate and cooperate with each other to realize their goals. This is the origin of MAS idea.

As we have mentioned, one of the main characteristics of an MAS is its social ability, i.e., its capacity of interaction and communication between agents existing in the same environment. Therefore, we discuss, next, different techniques of agent's interaction.

3.3. Agent's interaction mechanisms

Interaction and communication are often confused in the literature. In fact, communication is the transmission of information between agents while interaction contains two elements: communication and the actions resulting from the information exchange. Two types of communication can be distinguished: direct communication that consists in message exchange between agents and indirect communication that consists in signals or indicators transmitted through the environment as pheromones, for instance. We propose to classify agent's interaction into three categories: *coordination*, *cooperation* and *negotiation*. This classification is inspired from [24] and [27]. In Figure 2, we give different mechanisms and communication types related to each interaction class. In the following paragraph, we describe briefly these three types of agent's interaction.

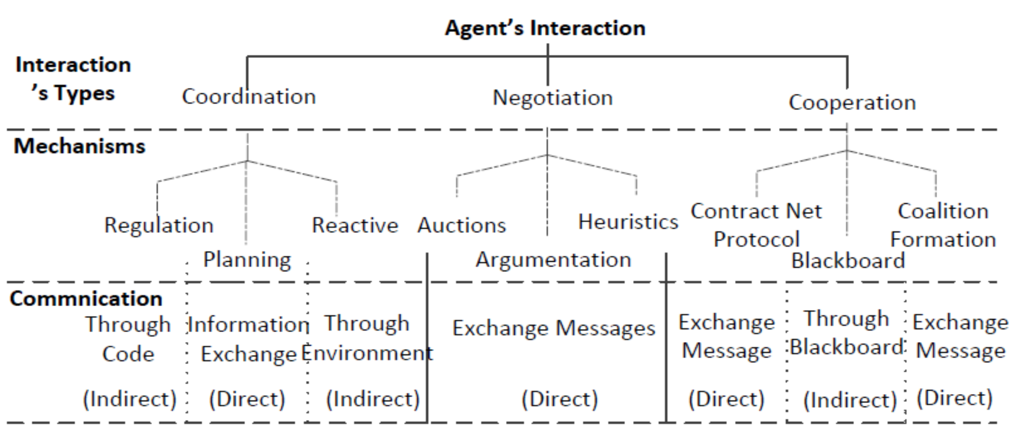

Figure. 2 Agents' interaction types

1) *Coordination:* It is a mechanism for ensuring that agent's activities preserve some desired relationships such as sequence and complementarity. The most popular coordination mechanisms are regulation, planning and reactive cooperation such as the one providing by the subsumption architecture [28]. The subsumption architecture is mainly used for ensuring reactive robot behavior. It is a way of decomposing complicated intelligent behavior into

many simple behavior modules, which are in turn organized into layers. Each layer implements a particular goal of the agent. The communication between agents in such architecture is indirect and can be made through the environment. The coordination by regulation is done through a communication based on a set of defined rules, for example by the use of code, law or social conventions. On the other hand, planning coordination defines a set of goals and plans and ensures the synchronization of agents' actions. This type of coordination can be centralized or distributed. In centralized coordination, a central agent prepares plans and distributes them to agents, solving synchronization and resource allocation problems. In distributed coordination, agents that can be planners and executors communicate their partial plans until goals are satisfied.

2) *Cooperation:* Cooperative agents work together to maximize theirs utilities and reach a common goal. In general, an agent cooperates with the others when it is not able to accomplish alone its task or if others are more efficient than it. As examples of cooperative approach, we can cite Blackboard [29], Contract Net Protocol (CNP) [30] and Coalition Formation [31]. The communication between agents in Blackboard technique is done via a shared blackboard where agents post their information. However, the Coalition Formation and the CNP are based on exchanging messages between agents.
3) *Negotiation:* It is a process that enables agents to reach agreement about the provision of a service by an agent for another one. Agents exchange messages in order to discuss their respective points of view. Negotiation can be used to resolve conflicts between agents. Different negotiation methods are proposed in the literature such as auctions [32], argumentation [33] and heuristics [34].

Many researchers mix coordination and cooperation mechanisms in a same category. That is why we can find CNP, blackboard and Coalition Formation defined as coordination mechanisms. Generally, reactive coordination is not highly efficient and planning and regulation mechanisms are very complex to implement. Therefore, planning, regulation and reactive coordination are rarely applied in cognitive radio networks. In the rest of the paper, we will focus on the most popular works using cooperation and negotiation mechanisms. Therefore, in the following two subsections, we will describe in detail multi agents' cooperation and negotiation protocols.

3.4. Cooperation Based Protocols

We will detail in this subsection Blackboard system, Contract Net protocol and Coalition Formation as cooperative MAS protocols.

3.4.1 Blackboard

The problem to solve is drawn up on a centralized blackboard and each participating agent contributes with its own knowledge until a sufficient solution is reached. Basically, a blackboard system [29] consists of three parts: (1) Knowledge Sources (KS) that provide the specific expertise needed by the application; (2) a blackboard, which contains the information of partial solutions; (3) and a control shell to maintain the coherence between various knowledge sources. All these parts work together to solve the assigned problems. This separation between knowledge (agents), space solution (blackboard) and knowledge management (control) gives the system a very high modularity and an easy access to knowledge. Besides, Blackboard technique provides a control mechanism that try at every resolution step to choose the best knowledge source. However, even if the control is providing an efficiency gain, it burdens the processing which results in a lack of flexibility. In addition, the blackboard is a centralised approach that depends highly on the central blackboard.

3.4.2 Contract Net Protocol

The contract net protocol (CNP) [30] is a MAS task-sharing protocol, consisting in a collection of software agents that forms the *'contract network'*. Each node of the network can, at different times or for different tasks, be a manager or a contractor based on its requirements. The manager is responsible for initiating the task and then monitoring its execution by exchanging a series of messages with the contractors while the contractor executes the assigned tasks. The CNP provides the advantage of real-time information and messages exchange making it suitable for situations where control and resources are distributed. CNP is fast and flexible. It is also used for task decomposition. However, when task is very complex and cannot be further decomposed into subtasks, CNP cannot be used.

3.4.3 Coalition Formation

Many tasks must be completed by more than one agent as its realization needs resources and capabilities that are beyond those of an agent alone. Very often, even if a task may be completed by a single agent, its performance can be too low to be acceptable. In such a situation agents may form groups to solve the problem by cooperation. Cooperative agents work together on a given task. Initially agents are independent and do not cooperate. When they cannot complete their tasks individually, agents may exchange information and try to form coalitions, which give them best efficiency [31]. Generally, in MAS Coalition Formation, the agents work in order to maximize the utility of the whole system, and after a successful completion of the assigned task the gained profit will be distributed equally or according to each agent contribution. Moreover, Coalition Formation makes possible the resolution of complex problem without task decomposition. However, this protocol is relatively slow due to the overhead resulting from the construction of coalitions.

3.5 Negotiation Based Protocols

In this subsection, we will detail the most popular negotiation based MAS mechanisms: auctions, argumentation and heuristics.

3.5.1 Auctions

An auction [32] takes place between an agent known as the auctioneer and a collection of agents known as bidders. The goal of auction is for the auctioneer to allocate the good to one of the bidders. Traditionally, four types of auctions are used: First-price sealed-bid auction (FPSB), Second-price sealed-bid auctions (Vickrey), Open Ascending-bid auctions (English auctions) and Open Descending-bid auctions (Dutch auctions).

In FPSB auction, bidders place their bid in a sealed envelope and simultaneously submit to the auctioneer. The envelopes are opened and the individual with the highest bid wins, paying a price equal to the exact amount bided. Vickrey auction is like FPSB auction but the winner pays a price equal to the second highest bid.

In English auctions, the price is steadily raised by the auctioneer with bidders dropping out once the price becomes too high. This continues until there remains only one bidder who wins the auction at the current price.

In Dutch auctions, the price starts at a level sufficiently high and is progressively lowered until a bidder indicates that he is prepared to buy at the current price. The winner pays the price at which he proposes.

We can find an hybrid form of auction called double auctions where participants are buyers and sellers in the same time and trade on the same product.

In almost all traditional settings except Vickrey, the auctioneer desires to maximize the price at which the good is allocated, while bidders desire to minimize the price. Auctions can be an effective solution to resolve conflicts between agents. Nevertheless, the major problems of auctions are the fraud and when the correct winner cannot be determined.

3.5.2 Argumentation

Argumentation [33] is the process of attempting to agree about what to believe by supporting arguments. It provides principles and techniques for resolving inconsistency or at least sensible rules for deciding what to believe in the face of inconsistency. Argumentation takes into account the bounded resources nature of real agents, by providing the possibility of acting before the completion of the reasoning process on the basis of provisional conclusions. However, this mechanism is very complex and need knowledge about past actions and agents' arguments.

3.5.3 Heuristics

Heuristics [34, 35] are mathematical and learning based solutions. For example, in a competitive market, the buyer agents can exchange false bids to increase their payoffs. Using heuristics, the seller agents can learn from the previous bids and information exchanges of malicious buyers and hence, they can decide to avoid any future trades with the malicious buyers. From simple negotiation, agents can accept or refuse proposals from other agents that can make the negotiation very long and inefficient especially when agents do not understand the cause of reject. Heuristics can also improve negotiation efficiency since agents can provide more useful feedbacks about the received proposals. These reactions may take the form of critique or cons/modified proposal. The difficulty in this technique is the choice of the more efficient heuristic.

In the next section, we will present the utilization of some of these different MAS protocols for the resolution of cognitive radio spectrum management issues.

4. MULTI-AGENT SYSTEMS APPLICATION IN COGNITIVE RADIO NETWORKS

MAS are relatively a new, yet, one of the most popular concepts in the research community. It is widely applied in the telecommunications and network domains. The involvement of MAS in the new research area of cognitive radio is notably present.

Agent's intelligence and cognition are important features in a cognitive radio network as it can help to perceive the environment and react properly. In addition, agent's interaction protocols such as negotiation and cooperation can provide more effective communication between network entities and can lead to a better exploitation of unused spectrum portions.

Recently, a large range of studies have used MAS to ensure efficient utilization of available spectrum resources in CRN. We propose to classify the existing works that apply MAS mechanisms for the resolution of cognitive radio problems into three main categories: negotiation, learning and cooperative based approaches, as shown in Figure 3.

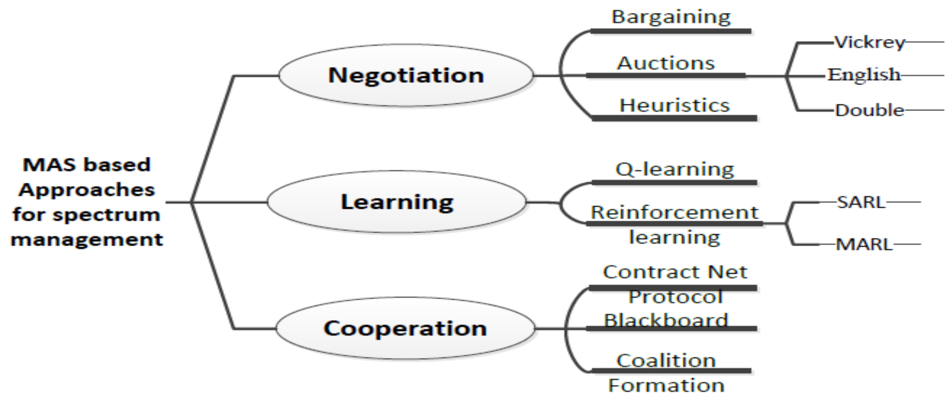

Figure. 3 Three main categories of MAS based approaches for spectrum management in CRN

4.1. Negotiation Based Approaches

Negotiation based approaches are largely used to address spectrum allocation issue in cognitive radio network especially auctions based ones. Agents' negotiation is a way to maximize user's utility since PUs and SUs negotiate in order to reach an agreement that best suits their needs. Cognitive radio solutions using multi-agent negotiation can be classified into three classes according to the adopted negotiation protocol: bargaining, heuristics and auctions.

Bargaining is a type of negotiation mechanism based on selling and buying concepts. Bargaining has been used in CRN to solve sensing issue [37] or to provide fair spectrum allocation [38, 39]. In [37], bargaining based pairwise cooperative spectrum sensing scheme is proposed. According to their locations regarding the PU, SUs are grouped into pairs. In the cooperative sensing pairs, the nearest SU to the PU senses the band and relays the detected information to the other CR users. In each pair, rational SUs can bargain with each other over the sensing time division, and thus save the sensing time for data transmission. Results show that this proposal improves the sensing accuracy. However, the distance between CR users and the PU is considered as the only factor affecting the bargaining results. In addition, users are assumed to be identical and their movement is simplified.

A distributed spectrum allocation solution via local bargaining is presented in [39] where SUs self-organize into small bargaining groups. The group formation process starts by sending a group formation request for a subset of spectrum portions from an initiator SU to the neighboring SUs. The interested SUs answer the request and a bargaining group is formed. Once the group is formed, users adapt their spectrum assignment to approximate a new optimal assignment. The group is later dismissed at the arrival of a PU or after completely utilizing the channels for the agreed time period. In such solution, network nodes are supposed to be collaborative but in the real system they can be selfish so that a pricing based bargaining would be more realistic.

Besides, ***heuristics*** based solutions in cognitive radio context are provided to solve complex problems in spectrum allocation issue. For example in [40], the problem of allocating the channels among cognitive radio nodes is handled. The proposal uses graph theoretic techniques to find an optimal and valid allocation when channels are limited. As the problem is an *NP* problem, authors have used novel distributed heuristic that relies on a local Common Control Channel. It is proved that this heuristic outperforms those existing in the literature and it can be easily implemented. Yet, heuristics techniques are rarely used in CRN because they are complex to define.

Moreover, ***auctions*** are popular negotiation processes used in CRN in order to solve and optimize spectrum utilization task. In such solutions [41-46], all users submit their bids to a centralized manager. Auctioneer allocates the resources in a way that maximizes its utility. The utility function changes according to auctions type (English, Vickrey, etc.).

In [41], a spectrum management policy based on the Vickrey auction (*multi- unit sealed bid*) is proposed. Cognitive radio mobile stations can compete for the utilization of the available PUs spectrum bands. SUs (bidders) submit bids without knowing bids of the other SUs in the auction, and the highest bidder wins, but the price paid is the second-highest one (Vickrey auction). A pricing and billing based solution is proposed in [42] presenting an auction sequence mechanism, which allow users to express their urgency, needs, purchase power and preferences. Vikrey auction [41] seems to be more suitable to execute in a given time when compared to English auction used in [42].

Double auction based spectrum trading scheme [44] has been proposed to resolve the spectrum access between PUs and SUs. Two different utility functions for PUs and SUs are designed based on a supply and demand relationship between them. Buyers (PUs) submit their bids and potential sellers (SUs) simultaneously submit their prices. Different from the traditional spectrum sharing approaches, in [43] proposal's, the SUs are allowed to make decision simultaneously and independently and make bid decisions based on self-interested considerations. Simulation results show the effectiveness of this spectrum trading methodology.

Another auction based approach is proposed in [47] by considering a cognitive radio network consisting of one PU and multiple SUs sharing the same spectrum. Each SU makes a bid for the amount of spectrum it requires and the PU may assign the spectrum band to the SU that do not degreed the PU's quality of service (QoS).

The spectrum trading model proposed in [48] uses agent as an additional part in the trading process that is different from secondary and primary users. The proposed trading model maximizes the payoff of the agent as well as it enhances the satisfaction of cognitive radio users. This model is flexible and easy to implement on the existing infrastructures. Authors give the example of an IEEE 802.22 network where agents are built on base stations that sense the VHF/UHF TV bands and serve all their associated clients without harmful interference to TV receivers.

4.2 Learning Based Approaches

Learning methods have been recently used to solve multiple issues in CRN. As examples, we can mention [49-51] for spectrum sensing, [52, 53] for spectrum sharing and [54] for spectrum access and control. We can distinguish two types of learning algorithms generally used in this context: reinforcement learning and Q-learning.

Reinforcement learning (RL) allows agents to learn from their past states (sharing pattern, neighborhood movement, etc.) in order to better perform their following actions and moves. In [49], authors propose a multi-agent learning approach, where each SU senses its nearby spectrum, perceives its current transmission parameters and takes necessary actions when PU appears. Several penalty values are enforced when the SU agents try to interfere with each other or with the PUs. This approach proves that allowing secondary users learning via interaction can improve the overall spectrum usage especially for the SUs' transmissions and channels switching capabilities. Two types of RL approaches are discussed in [56], namely Single Agent Reinforcement Learning (SARL) and Multi-Agent Reinforcement Learning (MARL). SARL has been applied in an operating environment with a single agent such as the base station in a centralized network, while MARL has been applied in an operating environment with multiple agents, such as all the SUs in a dynamic cognitive radio network. In MARL solution, agents learn and take their own respective actions, in a cooperative and distributed manner, as part of the joint action that maximizes the overall network performance. The difference between SARL and MARL is the Payoff Message Exchange (PME) that is an additional feature in MARL. The PME is the mean of communication for the learning engine embedded in each agent. SARL does not implement PME because it is a single-agent approach. In general, as proved in [56], RL provides high network-wide performance with respect to dynamic channels selection. However, they are mostly difficult to realize. For this reason, a recent form of RL that makes agent learning process easier has emerged, known as Q-learning.

Q-learning is an out part of reinforcement learning method that does not need a model of its environment. Q-learning algorithm is increasingly used for spectrum access because it allows agents to learn easily how to act optimally. For example, in [54], each SU senses channels and then chooses an unused frequency channel to transmit data unless other SUs exist. If two or more secondary users choose the same channel for data transmission, collision occurs. Such a scheme is similar to Aloha protocol where no explicit collision avoidance is applied. However, the SUs can try to learn collision avoidance, as well as channel qualities, according to their experience. Q-learning is exploited in [55] to ensure channels selection in CRNs. In [55], SUs periodically share the relative traffic information on the sensed channels with their neighbors. Based on this information exchange, the SUs dynamically tune their transmission powers on selected channels and avoid interferences. However, getting precise information in such learning schema can become more difficult if users have weak information about their neighbors' spectrum usages.

Learning methods show interesting efficiency in the resolution of cognitive radio tasks. They are increasingly used in the literature and still studied in order to provide more enhancements in the performance of cognitive radio systems. However, they are still faced to the high cost of learning and the uncertainty of its outcomes (i.e., the accuracy of what is learned is not guaranteed).

4.3 Cooperative Based Approaches

Some researchers have used specified MAS cooperation methods such as CNP, Coalition Formation and Blackboard to ensure efficient spectrum resource allocation.

A ***Contract Net Protocol*** based approach for spectrum sharing in CRN is proposed in [57]. This approach relies on Call for Proposal (CFP) concept. PU agent is considered as a "manager" and SUs are considered as "contractors". Each SU sends a CFP to PUs who are interested to share their spectrum bands. Based on a defined function, the SU characterizes each received proposal. Once the deadline to receive proposals expires, the SU sends an accept message to the PU that gives the best proposal and sends a reject message to all others. This cooperative framework enables cognitive radio devices to work cooperatively with their neighboring licensed devices in order to utilize efficiently the available spectrum dynamically. This technique enhances the overall spectrum allocation and ensures users satisfaction. However, this method is provided to solve the problem of allocation only between PUs and SUs and not consider spectrum sharing problem between SUs when no PU is occupying the band.

Coalition Formation is also used in [58] for sharing unlicensed spectrum bands. The band is assumed to be occupied by only secondary users. SUs are equipped with agents and interact with their neighbors to form several coalitions over the unlicensed bands. These types of coalitions can provide a less-conflicted spectrum access as the agents cooperatively agree for spectrum sharing. Another goal of using multi-agent coalition formation is to create cohesive groups that benefit from agents' participation in terms of their mutual successful access.

Recently, a new architecture for cognitive spectrum management based on cooperative agents has been proposed in [59]. In this approach, intelligent agents that are embedded in the radio devices coordinate their operations to exploit network's resources and avoid interference with PUs. Agents carry a set of modules to gather information about the terminal status and the radio environment and act according to the constraints of the user's application. Cognitive radio nodes that wish to transmit data will rely on their neighborhood agents' information to determine the status of the spectrum occupation. Coalition Formation is mainly used to reduce computational efforts on the cognitive radio terminal when collecting its environmental information.

Blackboard based system is adopted in [60] to present a cross-layer architecture for cognitive radio networks. The goal of this new architecture is to ensure efficient spectrum allocation and to improve overall quality of service. Each cognitive node generates parameters related to the current network state and deposes it on the blackboard in order to optimize bandwidth utilization. This blackboard approach helps to solve some related network problems such as intrusion detection and jamming.

As previously described, most of the studies based on multi-agent concept in cognitive radio networks focuses on spectrum sensing and allocation. However, no much MAS based research is made on the topic of spectrum mobility in CRN. Very few works have used cognitive radio and MAS concepts to improve mobility management in traditional cellular networks. For example, the proposed approach in [61] enables modification in base stations' parameters to meet new services requirements. These changes are performed using agents that manage cells via negotiation, learning and reasoning strategies. In [61], author's main goal was to reduce interference, handoff delay and blocking probability.

In [62], a proposal to solve the problems of spectrum mobility, sharing and handoff in CRN using MAS is presented. A mobile cognitive radio network is considered where each terminal is managed by an agent. Authors propose an algorithm that should be executed by a mobile cognitive radio terminal when moving from one geographical zone to another one. When the mobile cognitive radio user comes close to a new zone, it tries to collect information about its new environment in order to anticipate a possible handover. According to the recorded information, the CR user updates its knowledge base with, among others, spectrum conditions and PUs preferences such as price and use duration for the potentially allocated band. A possible negotiation process may be activated between the SU and the PU having the channel that best suits the user's requirements.

From the above discussion, we can confirm that multi-agent systems, which are variously and largely used for spectrum management in CR networks, can provide very efficient solutions to many cognitive radio issues. Using MAS in cognitive radio networks is promising and presents and open research area that can be more explored.

5. CONCLUSIONS

Cognitive radio is a promising technology that plays an important role in the exploitation of the existing spectrum resources. It seriously participates in enhancing the spectrum utilization by allowing opportunistic access to spectrum holes.

In this survey, we provided first a presentation of cognitive radio paradigm. Then, we gave an overview of multi-agent systems concept and their application in cognitive radio networks. We classify MAS based researches within CRN in three categories: negotiation mechanisms, learning methods and cooperative approaches. For each category, we explained the fundamental concepts and we provided examples from the literature.

In addition to existing game theory based approaches to solve CRN issues, most contributions using MAS in CRNs are based on auctions mechanisms. Learning methods have been recently used and they are evolving. However, cooperative approaches are not widely applied and still represent an open research topic in cognitive radio domain that may require more studies and investigation of novel proposals.

ACKNOWLEDGEMENTS

This work is partly supported by the Ministry of Higher Education and Research of France.

REFERENCES

[1] P. Ren, Y. Wang, Q. Du and J. Xu (2012), "A survey on dynamic spectrum access protocols for distributed cognitive wireless networks", *EURASIP Journal on Wireless Communications and Networking.*

[2] J. Mitola (2006), "*Cognitive radio architecture : The Engineering Foundations of Radio XML Link*", John Wiley and Sons.

[3] 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.

[4] D.C Oh, Y-H. Lee (2009), "Energy Detection Based Spectrum Sensing for Sensing Error Minimization in Cognitive Radio Networks", International Journal of Communication Networks and Information Security, vol. 1, no. 1, pp. 1-5.

[5] Z. Yaqin, L. Shuying, Z. Nan and W. Zhilu (2010), "A Novel Energy Detection Algorithm for Spectrum Sensing in Cognitive Radio", *Information Technology Journal*, vol 9*, pp.* 1659-1664.

[6] A. Ghasemi, and E.S. Sousa (2005), "Collaborative spectrum sensing for opportunistic access in fading environment", *IEEE Symposia on New Frontiers in Dynamic Spectrum Access Network*, pp.131- 136.

[7] M. E. Sahin, I. Guvenc and, H. Arslan (2010), "Uplink user signal separation for OFDMA-based cognitive radios" *EURASIP, Journal on Wireless Communications and Networking*.

[8] A. Bouzegzi, P. Ciblat and P. Jallon (2008), "Matched Filter Based Algorithm for Blind Recognition of OFDM Systems", *IEEE VTC-Fall*, pp. 1-5.

[9] S. Kapoor, S.V.R.K. Rao, and, G.Singh (2011), "Opportunisitic Spectrum Sensing by Employing Matched Filter in Cognitive Radio Network", *CSNT*, pp. 580-583.

[10] B. Wang, Y. Wu and K. J. R. Liu (2010), "Game theory for cognitive radio networks: An overview", *Computer Networking*, vol. 54, n°14, pp. 2537-2561.

[11] J. Rajasekharan, J. Eriksson, V. Koivunen (2010), "Cooperative game-theoretic modeling for spectrum sensing in cognitive radios", *Conference Record of the Forty Fourth Asilomar Conference on Signals, Systems and Computers*, pp. 165-169.

[12] W. Saad, H. Zhu, T. Basar, M. Debbah, A. Hjorungnes (2011), "Coalition Formation Games for Collaborative Spectrum Sensing", *IEEE Transaction on Vehicular Technology*, pp.276-297.

[13] J. Rajasekharan, J. Eriksson, V. Koivunen (2011), "Cooperative Game-Theoretic Approach to Spectrum Sharing in Cognitive Radios", *Computer Science and Game Theory*.

[14] M. Liang, Z. Qi (2011), "An Improved Game-theoretic Spectrum Sharing in Cognitive Radio Systems",*3rd International Conference on Communications and Mobile Computing*, pp. 270-273.

[15] A. De Domenico, E. Calvanese Strinati, M.G Di Benedetto (*2012*), "A Survey on MAC Strategies for Cognitive Radio Networks", *IEEE Communications Surveys & Tutorials*, vol. 14, n°1, pp.21-44.

[16] X. Zhang, S. Hang (2011), "CREAM-MAC: Cognitive Radio-EnAbled Multi-Channel MAC Protocol Over Dynamic Spectrum Access Networks", *IEEE Journal of Selected Topics in Signal Processing*, vol. 5, n°1, pp.110-123.

[17] C.-W. Wang and L.-C. Wang (2012), "Analysis of Reactive Spectrum Handoff in cognitive radio networks", *IEEE Journal on Selected Areas in Communication,* vol.30, n°10, pp. 2016-2028.

[18] C. W. Wang, L-C. Wang, F. Adachi (2010), "Modeling and Analysis for Reactive-decision Spectrum Handoff in Cognitive Radio Networks", *IEEE Globecom*, pp.1-6.

[19] C. W. Wang, L-C. Wang (2009) , "Modeling and Analysis for Proactive-decision Spectrum Handoff in Cognitive Radio Networks", *IEEE International Conference on Communication (ICC), June*, pp. 1-6.

[20] Y. Song and J. Xie (2010),"Common Hopping based Proactive Spectrum Handoff in Cognitive radio Ad Hoc Networks, *IEEE Globcom*, pp. 1-5.

[21] J. Duan, Y. Li (2011), "An optimal Spectrum Handoff scheme for Cognitive radio mobile Adhoc Networks", *Advances in Electrical and Computer Engineering Journal*, vol. 11, n°3, pp. 11-16.

[22] L. Wang, L. Cao and H. Zheng (2008), "Proactive channel access in dynamic spectrum networks", *Physical Communication*, vol. 1, n°2, pp. 103-111.

[23] Y. Song, J. Xie (2012), "ProSpect: A Proactive Spectrum Handoff Framework for Cognitive Radio Ad Hoc Networks without Common Control Channel", *IEEE Transactions On Mobile Computing,* vol. 11, n°7, pp. 1127-1139.

[24] Michael Wooldridge (2002),"*An Introduction to Multi-Agent Systems*", Wiley and Sons Editor, West Sussex, England.

[25] J. Ferber (1999), "*Multi-Agent System: An Introduction to Distributed Artificial Intelligence*", Addison Wesley Longman.

[26] G. Weiss (2000), "*A modern approach to distributed artificial intelligence*", MIT press, USA.

[27] B. Espinasse, S. Fournier, F. L. Gonçalves de Freitas (2008), "Agent and ontology based information gathering on restricted web domains with AGATHE", *ACM symposium on Applied Computing*.

[28] M. Ahmed, V. Kolar, M. Petrova, P. Mahonen, S. Hailes (2009), "A component-based architecture for cognitive radio ressource management", *International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CRWNCOM'09),* pp. 1-6.

[29] F. Jurado, M-A. Redondo, M. Ortega (2012), "Blackboard architecture to integrate components and agents in heterogeneous distributed eLearning systems: An application for learning to program", *Journal of Systels and Software,* vol. 85, n°7, pp. 1621-1636.

[30] U. Mir, S. Aknine, L. Merghem-Boulahia, and D. Gaïti (2010), "Agents' Coordination in Ad-hoc Networks," *8th ACS/IEEE International Conference on Computer Systems and Applications (AICCSA'10)*, Tunisia pp. 1-8.

[31] W. Gruszczyk, H. Kwasnicka (2008), "Coalition Formation in multi-agent systems- an evolutionary aproach", *International Multiconference on Computer Science and Information Technology (IMCSIT)*, pp. 125-130.

[32] G. Adomavicius and A. Gupta (2005), "Toward comprehensive real-time bidder support in iterative combinational auctions", *Information Systems Research*, vol. 16, n°2 .

[33] I. Rahwan, S.D Ramchurn and N.R Jennings (2003), "Argumentation-based negotiation", *The Knowledge Engineering Review*, vol. 18, pp.343-375.

[34] A. Amanna, D. Ali, D. Gonzalez Fitch, J. H. Reed (2012), "Hybrid Experiential-Heuristic Cognitive Radio Engine Architecture and Implementation". *Journal of Computer Networks and Communications,* 15 pages.

[35] D. Hu, S. Mao (2012), "Cooperative relay interference alignment for video over cognitive radio networks", *IEEE INFOCOM*, pp. 2014-2022.

[36] J. Xie, I. Howitt and A. Raja (2007), “Cognitive radio resource management using multi-agent systems”, *Consumer Communications and Networking Conference (CCNC)*, pp.1123-1127.

[37] M. Pan, Y. Fang (2008), “Bargaining based pairwise cooperative spectrum sensing for Cognitive Radio networks”, *IEEE Military Communications Conference*, pp. 1-7 .

[38] H. Liu, A.B MacKenzie, B. Krishnamachari (2009), “Bargaining to Improve Channel Sharing between Selfish Cognitive Radios”, *IEEE Globecom*, pp. 1-7.

[39] L. Cao and H. Zheng (2005), “Distributed spectrum allocation via local bargaining”, *IEEE Communications Society Conference on Sensor and Ad Hoc Communications and Networks*, pp. 475-486.

[40] S. Vijay, R. Rao, V. Prasad, C. Yadati, and I.G Niemegeers (2010), “Distributed heuristics for allocating spectrum in CR ad hoc networks”, *IEEE Globecom*, pp. 1-6.

[41] H.-B. Chang and K.-C. Chen (2010), “Auction-based spectrum management of cognitive radio networks,” *IEEE Transactions on Vehicular Technology*, vol. 59, n°4, pp. 1923-1935.

[42] C. Kloeck, H. Jaekel, F. K. Jondral (2006), “Multi agent wireless System for Dynamic and Local Combined Pricing, allocation and Billing”, *Journal of communication*, vol. 1, n°1, pp. 48-59.

[43] D. Niyato and E. Hossain (2008), “Competitive pricing for spectrum sharing in cognitive radio networks: Dynamic game, inefficiency of Nash equilibrium and collusion” *IEEE Journal on Selected Areas in Communication*, vol. 26, n°1, pp. 192-202.

[44] Y. Teng, Y. Zhang, C. Dai, F. Yang and M. Song (2011), “ Dynamic spectrum sharing through double auction mechanism in cognitive radio network”, *IEEE Wireless Communication and Networking Conference (WCNC)*, pp. 90-95.

[45] H. S Mohammadian, B. Abolhassan (2010), “Auction-based Spectrum Sharing for Multiple Primary and Secondary Users in Cognitive Radio Networks”, *IEEE Sarnoff Symposium*, pp. 1-6.

[46] G.S Kasbekar, S. Sarkar (2010), “Spectrum auction framework for access allocation in cognitive radio networks”, *IEEE/ACM Transactions on Networking*,vol. 18, n°6, pp. 1841-1854.

[47] X. Wang, Z. Li, P. Xu, Y.Xu, X. Gao, and H. Chen (2010), “Spectrum sharing in cognitive Radio Networks- An Auction based Approach”, *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics - Special issue on game theory*, vol. 40, n°3, pp. 587-596.

[48] L. Qian, F. Ye, L. Gao, X. Gan, T. Chu, X. Tian, X. Wang, M. Guizani (2011), “Spectrum Trading in Cognitive Radio Networks: An Agent-Based Model under Demand Uncertainty”, *IEEE Transactions on Communications*, vol. 59, n°11, pp. 3192-3203.

[49] C. Wu, K. Chowdhury, and M. D. Felice (2010), “Spectrum management of cognitive radio using multi-agent reinforcement learning,” *International Conference on Autonomous Agents and Multiagent Systems*.

[50] J. Lunden, V. Koivunen, S.R Kulkarni, H.V Poor (2011), “Reinforcement learning based distributed multiagent sensing policy for cognitive radio networks”, *IEEE DySPAN*, pp. 642-646.

[51] Ch. Zhe, R.C. Qiu (2011), “Cooperative spectrum sensing using Q-learning with experimental validation”, *IEEE Southeastcon*, pp. 405-408.

[52] F. Fu and M. van der Schaar (2008), “Dynamic Spectrum Sharing Using Learning for Delay-Sensitive Applications”, *International Conference on Communication (ICC)*.

[53] P. Venkatraman,B. Hamdaoui, B., and M. Guizani (2010), “Opportunistic bandwidth sharing through reinforcement Learning”, *IEEE Transactions on Vehicular Technology*, vol. 59, n°6, pp. 3148- 3153.

[54] H. Li (2010), “*Multiagent Q -Learning for Aloha-Like Spectrum Access in Cognitive Radio Systems*”, *EURASIP, Journal on Wireless Communications and Networking*.

[55] H. Li (2009), “Multi-agent Q-Learning of Channel Selection in Multi-user Cognitive Radio Systems: A Two by Two Case”, *IEEE Conference on System, Management and Cybernetics*, pp. 1893-1898.

[56] K-L-A Yau, P. Komisarczuk, and P.D. Teal (2010), "Enhancing Network Performance in Distributed Cognitive Radio Networks using Single-agent and Multiagent Reinforcement Learning", *IEEE Local Computer Networks (LCN)*, pp. 152-159.

[57] U. Mir, L. Merghem-Boulahia, and D. Gaïti (2010), "COMAS: A Cooperative Multiagent Architecture for Spectrum Sharing," *EURASIP, Journal on Wireless Communications and Networking*, 15 pages.

[58] U. Mir (2011), "Utilization of Cooperative Multi-agent Systems for Spectrum Sharing in Cognitive Radio Networks", Phd dissertation, University of technology of troyes.

[59] A. Ahmed, O. Sohaib, W. Hussain (2011), "An Agent Based Architecture for Cognitive Spectrum Management", *Australian Journal of Basic and Applied Sciences*.

[60] Y.B Reddy, C. Bullmaster (2008),"Cross-Layer Design in Wireless Cognitive Networks", *International Conference on Parallel and Distributed Computing, Applications and Technologies (PDCAT)*, pp. 462-467.

[61] J. Raiyn (2008), "Toward cognitive radio handover management", *IEEE 19th PIMRC*, p. 1-5.

[62] E. Trigui, M. Esseghir L. Merghem boulahia (2011), "Spectrum Access during Cognitive Radio Mobiles' Handoff", *International Conference on Wireless and Mobile Communications*, pp 221-224.

Authors

Emna Trigui received her engineering degree in Computer Engineering and her M.S. degree in Protocols, Networks and Multimedia Systems from the National School of Computer Science (ENSI, Tunisia). She is currently a PhD student at the University of Technology of Troyes (UTT, France) . Her research interests include computer networks, wireless communication, mobile ad hoc networking and cognitive radio networks.

Moez Esseghir received the National Engineer Diploma in computer sciences from Ecole Nationale des Sciences Informatique (ENSI), Tunis, Tunisia in 2002, the M.S. degree in networks from the University of Paris VI, Paris, France in 2003, the M.S. degree in computer sciences from ENSI, in 2004 and the Ph.D. degree in computer sciences from University of Paris VI in 2007. In 2008, he was with the North Carolina State University, Raleigh, USA, as Postdoctoral Fellow. Since September 2008, he is an associate professor in the Technology University of Troyes (UTT), France. His research interests include wireless sensor networks, vehicular communications and spectrum sharing in cognitive radio networks.

Leila Merghem Boulahia received an engineering degree in computer science from the University of Sétif, Algeria, in 1998, an M.S. degree in artificial intelligence and a Ph.D. in computer science from the University of Paris 6, France, in 2000 and 2003, respectively. She is an associate professor at the University of Technology of Troyes (UTT) in France still 2005. She received the best paper award of the IFIP WMNC'2009. Her main research topics include multi-agent systems, quality of service management, autonomic networks, cognitive and sensor networks and smart-grids. Dr. Merghem-Boulahia authored or co-authored five book chapters, thirteen peer-reviewed international journal articles and more than 40 peer-reviewed conference papers. She also acted or still acts as TPC member of the following conferences and workshops (IEEE ICC, IEEE Globecom, IEEE GIIS, ACM/IEEE ICCVE, IFIP Autonomic Networking, IFIP NetCon…). She is a Member of IEEE.

.