Cognitive Radio Resource Management Using Multi-Agent Systems, Auctions and Game Theory

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Abstract:
In the last few years, we have attested an impressive growth in wireless communication due to the popularity of smart phones and other mobile devices. Due to the emergence of application domains, such as sensor networks, smart grid control, medical wearable and embedded wireless devices, we are seeing increasing demand for unlicensed bandwidth. There has been also increasing interest from the wireless community in the use of game theory and multi-agent systems. Our aims in this article are to summarize the different uses of game theory in wireless networks and we focused on its use in cognitive radio networks, then to discuss how multi-agent systems can be applied to solve the problem of radio resource management, and finally give the results of our simulations when combining auctions theory with multi-agent systems for the negotiation between agents.

Key-Words: Game theory; Wireless Networks; Cognitive radio network; Multi-agent systems; Auctions theory.

1 Introduction

A wireless network is identified by a distributed, dynamic, self-organizing architecture. Each node in the network is capable of independently adapting its operation based on the current environment according to predetermined algorithms and protocols.

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.

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 using auctions, game theory and multi-agent systems (MAS).

Game theory is a set of tools developed to model interactions between agents with conflicting interests [1]. It is a field of applied mathematics that defines and evaluates interactive decision situations. It provides analytical tools to predict the outcome of complicated interactions between rational entities, where rationality demands strict adherence to a strategy based on observed or measured results [2]. Originally developed to model problems in the field of economics, game theory has recently been applied to network problems, in most cases to solve the resource allocation problems in a competitive environment. The reason that game theory is an adapted choice for studying cooperative communications is various. Nodes in the network are independent agents, making decisions only for their own interests. Game theory provides us sufficient theoretical tools to analyze the network users' behaviors and actions. Game theory, also primarily deals with distributed optimization, which often requires local information only. Thus it enables us to design distributed algorithms. [3]

MAS are particularly suitable for reactive and robust solutions to complex problem for which there is no centralized control [4] [5]. Indeed, the MAS is a group of agents where each agent has one or more basic skills. The goal is to make work together agents to solve a problem or perform a specific task. Somehow, we distribute intelligence; each autonomous agent has only a local vision of the problem or an elementary task of a job.

The interest of the agent-based solutions lies in the complete absence of central entity governing the operation of agents, which ensures high strength and high reliability (because if an agent fails, the system continues to function).

This article surveys the literature on game theory as they apply to wireless networks. We identified five areas of application of game theory in wireless networks; therefore, we discuss related work to game theory in communication networks [6], wireless sensor networks, resource allocation, power control and cognitive radio (CR) networks. After that, we discuss the use of multi-agent systems in cognitive radio networks. First, we choose auction theory as protocol for negotiation between agents and then study two different scenarios (the first uses only one secondary user and multiple primary users; the second uses one primary user and multiple secondary users). In the last case, we have also study the use of different methods of auction theory and compare between them.

2 Game theory in wireless network

A game is a set of three fundamental components: a set of players, a set of strategies, and a set of payoffs. Players or nodes are the decision takers in the game. The strategies are the different choices available to nodes. Finally, a utility function (payoffs) decides the all possible outcomes for each player. Table 1 shows typical components of a wireless networking game.

Components of a game	**Elements of a wireless network**
Players	Nodes in the wireless network
A set of strategies	A modulation scheme, Coding rate, transmit power level, etc.
A set of payoffs	Performance metrics (e.g. Throughput, Delay, SNR, etc.)

Table 1: Components of wireless networking game

Game theory has emerged in divers recent works related to power control, resource allocation, wireless sensor networks, communication networks and cognitive radio networks.

2.1. Game theory and power control

MacKenzie and al. [7] have presented applications of game theory to problems in random access and power control. In the case of random access, the authors examine the behavior of selfish users in a simplified Aloha system; surprisingly, rational selfish users do not implement the “always transmit” strategy that one might expect. In the case of power control, they show that game theoretic techniques can yield an optimal operating point without the intervention of an external controller.

Lin and al. [19] have addressed the crucial issue of how to design efficient MAC protocols in autonomous wireless networks with selfish users. They model the wireless medium access control problem as a non-cooperative game in which the MAC protocol can be regarded as distributed strategy update scheme approaching the equilibrium point.

Niyato and al. [15] have proposed an adaptive bandwidth allocation and admission control mechanism based on game theory for IEEE 802.16 broadband wireless networks. A non-cooperative two-person non-zero-sum game is formulated where the base station and a new connection are the players of this game. The solution of the game formulation provides not only the decision on accepting or rejecting a connection, but also the amount of bandwidth allocated to a new connection. A queueing model considering adaptive modulation and coding in the physical layer is used to analyze quality of service (QoS) performances, namely, the delay performance for real-time and the throughput performance for non-real-time polling services and best effort service.

2.2. Game theory and resource allocation

In Bacci and al. [16], the authors focused their study on the particular issue of allocating power resources to optimize the receiver performance in terms of spreading code acquisition. The problem of initial signal acquisition is formulated as a non-cooperative game in which each transmitter-receiver pair in the network seeks to maximize a specifically chosen utility function.

Emmanouil and al. [17] have proposed a novel way of maximization of the network throughput and the provision of fairness which are key challenges in IEEE WLANs, using game theory. The authors examine two types of power control games, namely the non-cooperative and the cooperative power control game. In the case of non-cooperative power control game they find the Nash equilibrium in a distributed way. In the case of cooperative power control game they expect that there exists a central entity called coordinator which announces the calculated Nash bargaining solution to the access points.

Srivastava and al. [49] have described how various interactions in wireless ad hoc networks can be modeled as a game. This allows the analysis of existing protocols and resource management schemes, as well as the design of equilibrium-inducing mechanisms that provide incentives for individual users to behave in socially-constructive ways.

Zhou and al. [11] have developed a novel approach to encourage efficient behavior in solving the interaction between InPs (Infrastructure Providers) and SPs (Service Providers) by introducing economic incentives, in the form of game theory. Based on the non-cooperative game model, a bandwidth allocation scheme in the network virtualization environment is established, using the concept of the Nash Equilibrium. Then, the authors propose an iterative algorithm to find the Nash Equilibrium and solve the bandwidth allocation problem.

2.3. Game theory and wireless sensor networks

Shen and al. [13] have presented a survey of security approaches based on game theory in wireless sensor networks (WSNs). According to different applications, a taxonomy is proposed in the paper, which divides current existing typical game-theoretic approaches for WSNs security into four categories: preventing Denial of Services (DoS) attacks, intrusion detection, strengthening security, and coexistence with malicious sensor nodes. The main ideas of each approach are overviewed while advantages and disadvantages of various approaches are discussed. Then, the authors overviews related work and highlights the difference from other surveys, and points out some future research areas for ensuring WSNs security based on game theory, including Base Station (BS) credibility, Intrusion Detection System (IDS) efficiency, WSNs mobility, WSNs Quality of Service (QoS), real-world applicability, energy consumption and sensor nodes learning.

Guan and al. [21] have introduced a novel routing algorithm to solve the obstacle problem in wireless sensor networks based on a game-theory model. Their algorithm forms a concave region that cannot forward packets to achieve the aim of improving the transmission success rate and decreasing packet transmission delays. Zheng [20] has also proposed a reliable routing model against selfish nodes in wireless sensor networks. Game theory is used in his model to find the balance between the reliability and resource limitation.

2.4. Game theory and communication networks

Saad and al. [8] have provided a comprehensive overview of coalitional game theory, and its usage in wireless and communication networks. For this purpose, they introduced a novel classification of coalitional games by grouping the sparse literature into three distinct classes of games: canonical coalitional games, coalition formation games, and coalitional graph games. For each class, they explained in details the fundamental properties, discussed the main solution concepts, and provided an in-depth analysis of the methodologies and approaches for using these games in both game theory and communication applications.

Xiao and al. [9] have proposed a game model to interpret the IEEE 802.11 distributed coordination function mechanism. In addition, by designing a simple Nash equilibrium backoff strategy, the authors have presented a fairness game model.

Charilas and al. [10] have presented a collects applications of game theory in wireless networking and presents them in a layered perspective, emphasizing on which fields game theory could be effectively applied. Several games are modeled in this paper and their key features are exposed.

Khan and al. [12] have presented the user-centric network selection decision mechanism, where negotiation between users and network operators is carried out using game-theoretic approach. They model the utility functions of users and network operators in terms of offered prices and service quality. The proposed approach builds on IEEE 802.21 standard. Session Initiation Protocol (SIP) and Mobile Internet Protocol (MIPv6).

The game model proposed in [30] leads to acquire more advantage results. At Nash equilibrium, network throughput is maximized and all nodes are satisfied, without the need to change their strategies, which makes the network stable and more efficient.

Sundararaj and al. [22] have explored the theoretical approach to improve existing delay and disruption tolerant networking routing algorithms using game theory.

2.5. Game theory and cognitive radio networks

Almost all optimization problems in cognitive radio can be mapped into games. The following table shows the mapping cognitive applications into game models [29].

Application	Model
Dynamic Spectrum Allocation	Exact potential game
Distributed Power Control	Super-modular game
OFDM Channel Filling	Exact potential game

Table 2: Mapping cognitive applications into game models

Neel and al. [18] have defined how the components of the cognition cycle map into normal form game model and describe standard game theory techniques for investigating four important issues that game theory should address: steady state existence, steady state identification, convergence and steady state optimality. The authors defined also, three game models that can aid the analyst in addressing these issues and conclude with a discussion of additional ways in which the use of game models aids the analysis and development of cognitive and adaptive radios.

Nie and al. [23] have proposed a game theoretic framework to analyze the behavior of cognitive radios for distributed adaptive channel allocation. The authors have defined two different objective functions for the spectrum sharing games, which capture the utility of selfish users and cooperative users, respectively. Based on the utility definition for cooperative users, the authors show that the channel allocation problem can be formulated as a potential game, and thus converges to a deterministic channel allocation Nash equilibrium point.

Neel and .al [24] have addressed how the insertion of cognitive radio technology into a network will impact performance and demonstrates how techniques from game theory can be used to analyze the network as a first step of shaping the decisions of the radios to achieve optimal network performance.

Scutari and .al [28] have proposed and analyze a totally decentralized approach, based on game theory, to design cognitive MIMO transceivers, which compete with each other to maximize their information rate. The formulation incorporates constraints on the transmit power as well as null and/or soft shaping constraints on the transmit covariance matrix, so that the interference generated by secondary users be confined within the temperature-interference limit required by the primary users. The authors provide a unified set of conditions that guarantee the uniqueness and global asymptotic stability of the Nash equilibrium of all the proposed games through totally distributed and asynchronous algorithms.

Bloem and .al [25] have suggested a game theoretical approach that allows master-slave cognitive radio pairs to update their transmission powers and frequencies simultaneously. This is shown to lead to an exact potential game, for which it is known that a particular update scheme converges to a Nash Equilibrium (NE). A Stackelberg game model is also presented for frequency bands where a licensed user has priority over opportunistic cognitive radios.

Xia and .al [26] have studied the power control of the transmitter in basic cognitive cycle and game theory is applied for modeling. Non-cooperative power control game which is created by D. Goodman is used; however, they authors introduce a new sigmoid efficiency function only related to user's SIR.

Ji and al. [27] have provided a game theoretical overview of dynamic spectrum sharing from diver’s aspects: analysis of network users' behaviors, efficient dynamic distributed design, and optimality analysis.

Game theory offers a suite of tools that may be used effectively in modeling the interaction between independent nodes in wireless network. Because of these numerous benefits, adopting analytic approach that emphasizes the use of game theory over wireless networks is preferable for analyzing the users’ needs in such networks. However, game theory focuses on solving the Nash equilibrium and analyzing its properties and not to consider how players should interact to reach this equilibrium. On contrary, multi agent systems seem to be a way to overcome this problem [14].

3 Multi-agent systems in Cognitive Radio Networks

A multi-agent system is a dynamic federation of agents connected by the shared environments, goals or plans, and which cooperate and coordinate their actions [31]. It is this capacity to communicate, to coordinate and to cooperate which makes interesting the use of agents in cognitive radio networks. The association of MAS and the CR can provide a great future for the optimal management of frequencies (in comparison with the rigid control techniques proposed by the telecommunications operators).

In the case of use of unlicensed bands, the CR terminals have to coordinate and cooperate to best use the spectrum without causing interference. In [32], the authors propose an architecture based on agents where each CR terminal is equipped with an intelligent agent, there are modules to collect information about the radio environment and of course the information collected will be stored in a shared knowledge base that will be accessed by all agents. The proposed approach is based on cooperative MAS (the agents have common interests). They work by sharing their knowledge to increase their collective and individual gain. Agents are deployed on the PUs and SUs terminals and cooperate with each other in the works proposed in [33] [34] [35].

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.

To make the CR systems practical, it requires that several CR networks coexist with each other. However, this can cause interference. The authors of [36] 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 [37] [38], 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 [39] [40]. In [39] 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 [41] 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 in a decentralized environment, this by using MAS. For this, they propose an approach based on MAS for sharing information and decisions distribution among multiple WLANs in a distributed manner.

Interference from the acquisition of the channels in a cellular system during Handovers can be reduced according to [42] [43] using a CR to manage the handover. 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 handover.

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 [44], the authors described a new approach based on multi-agent reinforcement learning which is used in CR networks with ad hoc decentralized control. In other words, they set up several CR scenarios and affect each case a reward or penalty. The results of this approach have shown that with this method, the network can converge to a fair spectrum sharing and of course it reduces interferences with PUs.

The authors in [45] have developed a cooperative framework for spectrum allocation that can generate highly effective behavior in dynamic environments and achieve better utility of the participating devices. The proposed approach is based on multi-agent system cooperation and implemented by deploying agents on cognitive radio and primary user devices. Experimental evaluations confirm the efficiency of the algorithms proposed by the authors for distributed and decentralized environments.

3.1 Interactions between agents

One of the main properties of the agent in MAS is interacting with the other agents. These interactions are generally defined as any form of executed action in the system and which causes changing the behavior of another agent.

An interaction is a dynamic linking of two or more agents through a set of reciprocal actions. The interactions are expressed from a series of actions whose consequences exert in return an influence on the future behavior of agents [46].

Common types of interaction include cooperation (working together to solve a common goal), coordination (organizing problem solving so that harmful interactions are avoided or beneficial interactions are exploited); and negotiation (reaching an agreement acceptable to all parties involved).

In the case of CR, SUs seek to satisfy their application by seeking a free channel and PUs have the opportunity to share their spectrum too. So, we can say that the goals are compatibles because there is no contradiction between PUs and SUs goals.

When we speak about resources, we mean the number of available channels (free parts of the spectrum).

In the scenarios we will process, we assume that SUs have sufficient competences, which means that each agent can make the sensing alone (no need to other agents). Based on the Ferber classification [4] of interaction situations, we modeled the scenario that will be encountered in the context of CR through a binary tree in Figure 1.

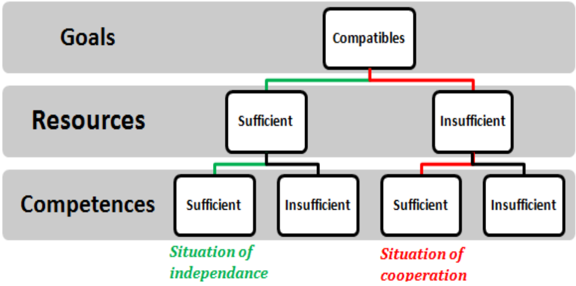

Figure 1: Binary tree modeling the interactions between agents in the case of CR

In the situation of independence, there is no problem to solve regarding to the interaction of agents because resources and competences are sufficient. This is why we are particularly interested by the situation of cooperation. The goal of researches carried out in the field of cooperation and negotiation between agents is to achieve an overall state of MAS by promoting agents synergy. Thus the objective may be to achieve a better state, to improve the overall result while satisfying all the local results.

When the resources used by the agents are limited and they are in a situation of congestion, we use most often:

- **The law of the strongest** (define a priority according to the strength of the agent), but in the case of CR, SUs have the same goal and want to satisfy their need in spectrum. So setting priorities in this case, returns to favor some types of applications.

- **Techniques of negotiation**, i.e. compromises will be established between the agents. Indeed, it is interesting to use this method because the installation of these mechanisms would make it possible to lead to acceptance by an agent to cooperate with other agents. In the case of CR, we must only verify whether the PU is ready to cooperate or not.

Subsequently, we will use this method (negotiation) to solve the problem of congestion between SUs.

3.2 Protocol choice

To solve the problem of congestion caused by the lack of resources, and well model the negotiation, a protocol must be selected. We chose a protocol based on auctions theory because we believe that this is an ingenious approach to allocate resources to a set of agents. It should be understood that the allocation is a difficult problem to the extent that resources are limited compared to the number of requests.

Since an auction restricts negotiating variables to a reduced number of parameters essentially price, this makes it easier for programmers. Finally, an auction leads to a mutually acceptable solution for the seller and buyers (in our case the PUs and SUs), markets forces being the only referee of the outcome of the negotiation.

3.3 Auctions and Cognitive Radio

Generally, an auction consists of several stakeholders; Table 3 describes the difference between traditional auctions and what corresponds to each speaker when applying this method to the negotiation in CR networks.

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

Table 3: Difference between classical auctions and auctions in CR networks

Multiple secondary users can cooperate to increase the reliability of spectrum sensing in cognitive radio networks. In [48], a new approach is proposed to optimize the trade-off between sensing reliability and power efficiency in cooperative cognitive radio networks over fading channels. The proposed approach is based on discarding the secondary users which are in deeply faded channels. Two different schemes were proposed to discard the secondary users. In the first scheme, the secondary users are randomly discarded. While the second scheme selecting the secondary users with the highest signal strength to keep tracking the activity of the PU and discarding the users with the lowest signal strength.

The proposed approach in [47] has proven that 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.

In the literature, most of the disadvantages and problems are related to the auction controller (initiator), it can have misleading behavior, it can also use false participants to increase the evaluation of the object. To avoid such problems, we use a cooperative multi-agent system architecture in this paper for managing radio resources, it is a network architecture without infrastructure "ad hoc network", we consider that all our agents are fixed because they work locally, each in its own site and communicate with each other directly.

3.4 Simulations

3.4.1 Scenario 1

In this scenario, we assume the existence of a single SU and multiple PUs. SU has an application need expressed in terms of channels and each PU has a number of free channels to share with the SU.

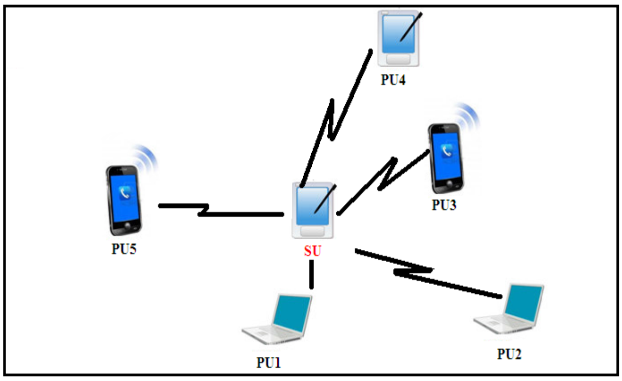

Figure 2: Ad hoc topology

To solve the problem of spectrum congestion, we use negotiation in a multi-agent system. To do this, we deployed an agent for each PU and SU. To get an idea on how agents communicate with each other, we used the JADE platform [50]. JADE (Java Agent DEvelopment framework) is developed in Java, runs on all operating systems and has a very specific architecture for building agents.

We have done many tests keeping the same set of data but changing the number of channels required by the SU every time.

	Number of free channels	Price
PU1	1	270
PU2	2	230
PU3	3	320
PU4	4	250
PU5	3	340

	Number of required channels
Simulation 1	1
Simulation 2	3
Simulation 3	5

Table 4: Set of data

In Simulation 1, all PUs can satisfy the SU but the best offer is listed by PU2 because it offers the cheapest price. The figure below shows the result of the simulation 1, indeed it is an interaction between agents diagram (sniffer).

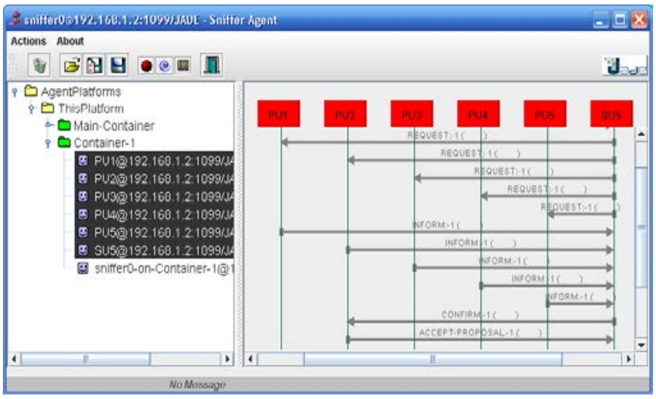

Figure 3: Sniffer with 1 required channel

In simulation 2, PU1 and PU2 can't satisfy the SU, the best offer is listed by PU4. The sniffer is as follows:

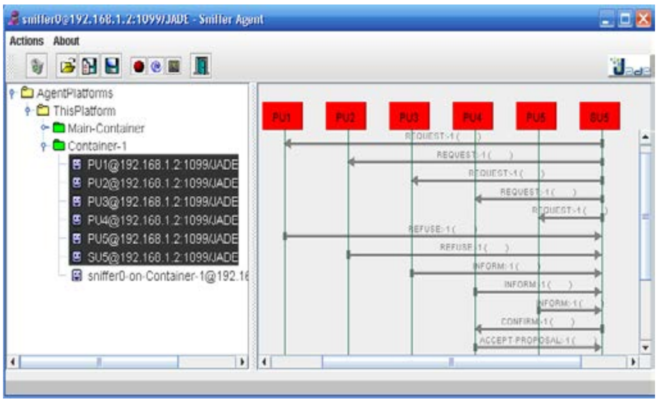

Figure 4: Sniffer with 3 required channels

In the third simulation, there is no PU to satisfy the SU. The sniffer is as follows:

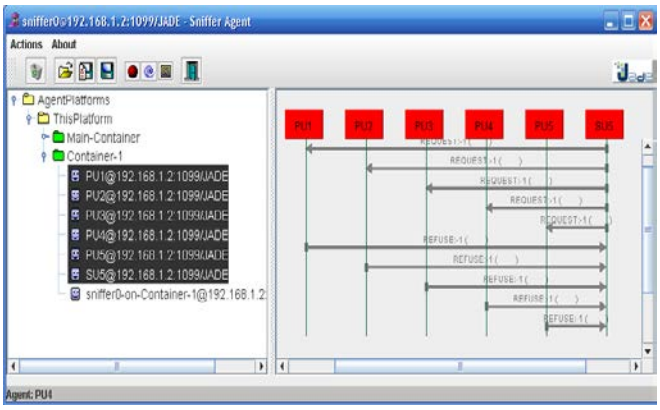

Figure 5: Sniffer with 5 required channels

To see the impact of the number of PUs on the response time of SU, we set the number of SU channels to 3 and used the same set of data presented previously. We noticed that the negotiation time increases for SU by negotiating with more PU. This is logical since there is no longer response to be treated. The following graph shows the result.

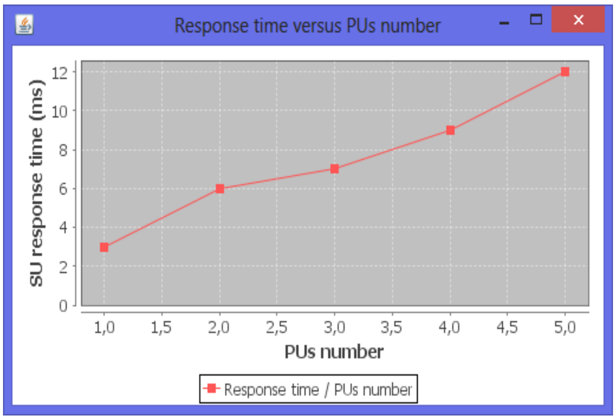

Figure 6: Impact of PU number on the SU response time (ms)

We then evaluated the importance of negotiation in relation to the price paid by the SU. Negotiation takes more time to be implemented, especially in the case of several PUs, but it is always interesting to SU because it allows it to find the best offer unlike the case where there is no negotiation.

3.4.2 Scenario 2

This scenario deals with the case where there is a single PU and several SUs connected in "ad hoc" mode using a particular type of negotiation " many to one " as the PU agent negotiates with SU agents who need free channels to maximize the dynamic spectrum access . PU and SUs negotiate agreement on the basis of certain criteria such as price and number of channels.

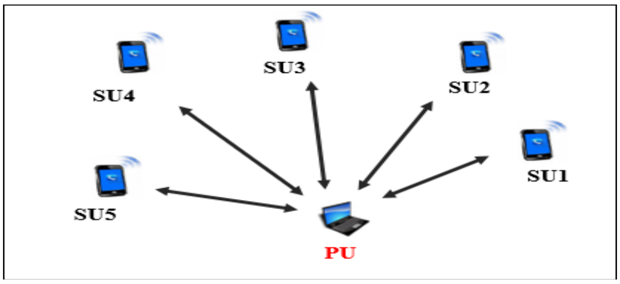

Figure 7: network topology

This scenario closely resembles the Knapsack problem and to solve these problems, computer scientists have often used the dynamic programming or greedy algorithms. In fact, the greedy algorithm does not always give the optimal solution but has lower complexity than the dynamic programming and generally allows obtaining a correct solution to various problems.

In this scenario, we opted for a particular type of trading ie First-price sealed-bid auctions which occur in a single round. We have implemented the auction using the greedy algorithms at first and then using dynamic programming. We then compared the results of simulations obtained with those of the FIFO' method (FIFO without blocking unmet demand).

In what follows, we note:

- nb : the number of SUs.
- m : the number of free channels at PU.
- W : array of size nb, W[i] is the number of requested channels by SU_i.
- C : array of size nb, C [i] is the proposed price for W [i] by SU_i.
- The increasing monotonic function to be optimized is: $\text{Max} \sum_{i=0}^{nb-1} C[i]$.

For simulations, we have used the same set of data in the three methods (First-price sealed-bid auctions using dynamic programming/greedy algorithm and FIFO') in order to compare the obtained results.

The used set of data is: nb=4, m=4, C = {300, 354.35, 212.6, 141.7, 141.68} and W = {6, 5, 3, 2, 2}.

A. *Simulation of First-price sealed-bid auctions using greedy algorithm:*

The initiator starts the auction and each participant submits a bid in an envelope or electronically in a single round (turn), without knowing the bids of the others. The participant who made the biggest bid wins the object and pays the amount of its offer.

Figure 8 shows the interactions between SU agents and PU agent using the sealed-bid auctions. The principle of this agent is to wait for the receipt of all application and meet the demand of SU offering a price for all channels such as price (C [i] / W [i]) is higher than other SU and the number of required channels is less than that available $\sum_{i=0}^{nb-1} W[i] \leq m$.

- The SU agents send to the PU_EnvSc agent INFORM messages to inform the proposed price and the number of channels they need.
- The PU_EnvSc agent sends a confirmation message to the agent SU3 which satisfies its request.

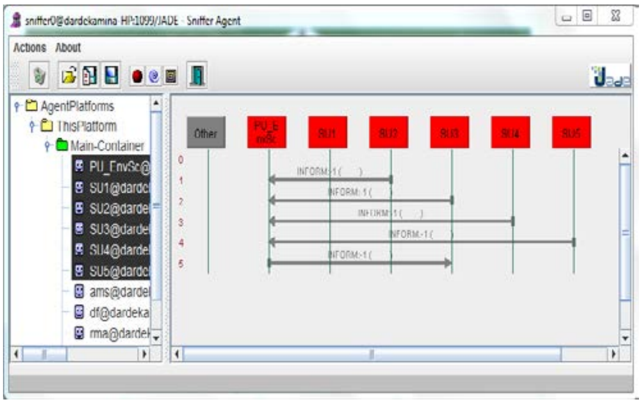

Figure 8: Agent sniffer for sealed-bid auctions

B. *Simulation of sealed-bid auctions using dynamic programming*

To solve the spectrum allocation problem, we propose to use dynamic programming which is an algorithmic technique to optimize the amounts of monotonically increasing functions under constraint. This technique applies to optimization problems whose objective function is described as "the sum of monotonically increasing functions of resources."

The increasing monotonic function to be optimized is: Max $\sum_{i=0}^{nb-1} C[i]$.

The constraint is: $\sum_{i=0}^{nb-1} W[i] \leq m$.

The proposed algorithm in [47] for the dynamic programming is as follows:

```
function COUT(W, C, m)
    n ← C.length
  for j = 0 to m do
      tab[0][j] ← 0
  end for
  for i = 1 to nb do
      for j = 0 to m do
         if j ≤ W[i − 1] then
            tab[i][j] ← tab[i − 1][j]
         else
            tab[i][j] ← max(tab[i − 1][j], C[i − 1] + tab[i − 1][j − W[i − 1]
         end if
      end for
  end for
  return tab[nb][m]
end function
```

Figure 9: Sealed-bid auction algorithm with dynamic programming

Figure 10 shows the interactions between SU agents and PU agent which use auction with dynamic programming. The principle of this agent is to wait for the receipt of all applications and meet the demand of SU offering a price for all channels such that this price is higher than other SU and the number of required channels is less than that available $\sum_{i=0}^{nb-1} \boldsymbol{W[i]} \leq \boldsymbol{m}$.

- SU agents send to the PU_Dynamique agent INFORM messages to inform the number of required channels and the proposed price for all of these channels.
- The PU_Dynamique agent sends a confirmation message to SU4 and SU5 agents.

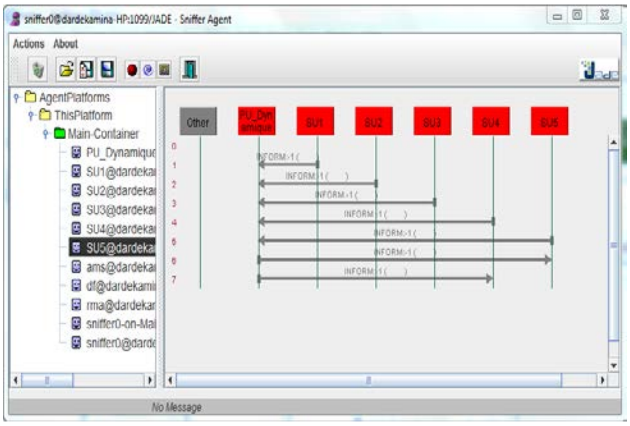

Figure 10: Sniffer agent for the auction using dynamic programming

C. *Simulation FIFO'*

Figure 11 describes the interactions between SU agents and PU agent that uses FIFO' technique which satisfy the first application received by the PU with the constraint $\sum_{i=0}^{nb-1} \boldsymbol{W[i]} \leq \boldsymbol{m}$.

- SU agents send to PU_FIFO agent INFORM messages which contains proposed prices and the number of required channels.
- PU_FIFO agent sends a confirmation message to SU3.
- SU4 and SU5 agents send INFORM messages to PU_FIFO agent. These messages contain proposed prices and the number of required channels.

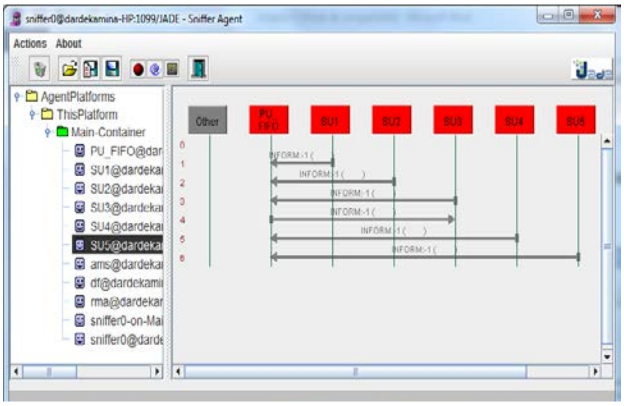

Figure 11: Agent sniffer for FIFO' technique

D. Comparative study

We have implemented the sealed-bid auction algorithm with and without dynamic programming and then compared the results with those of FIFO' method.

i. Comparison in terms of efficiency

When we speak about efficiency, we mean the number of satisfied SU. For this, we have compared the three methods previously used.

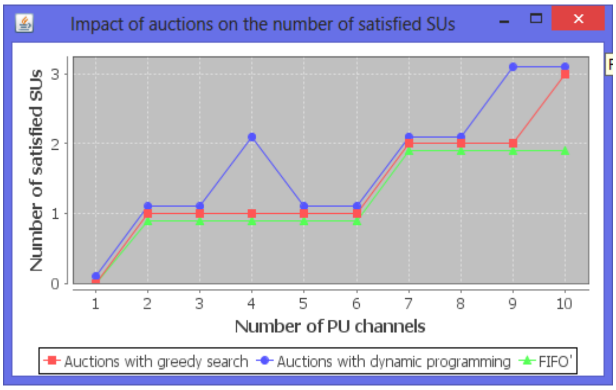

Figure 12: Impact of auctions on the number of satisfied SUs

From Figure 12, we note that the number of satisfied SUs with the auction using dynamic programming is higher compared to that obtained with FIFO' and the sealed-bid auction using greedy algorithm.

ii. Comparison in terms of PU gain

In this section, we will show the impact of auctions on the obtained gain by the PU. The results obtained are shown in Figure 13.

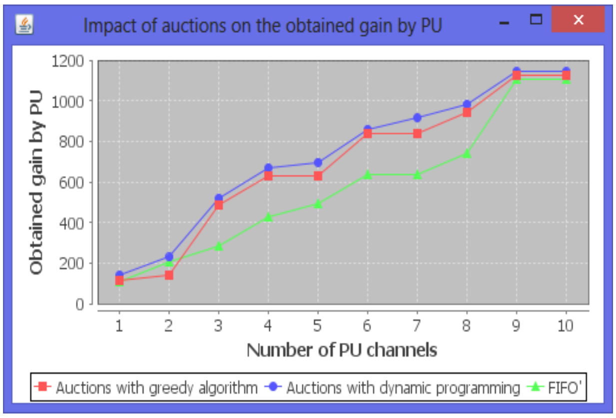

Figure 13: Impact of auctions on obtained gain by PU

We note that the use of auctions with dynamic programming is more beneficial for the PU because earnings are much higher compared to the use of auctions with greedy algorithm or using the FIFO' method.

iii. Comparison in terms of required time

To obtain the PU processing time (in millisecond "ms"), we made a comparison between the use of the two types of auctions with the FIFO' method.

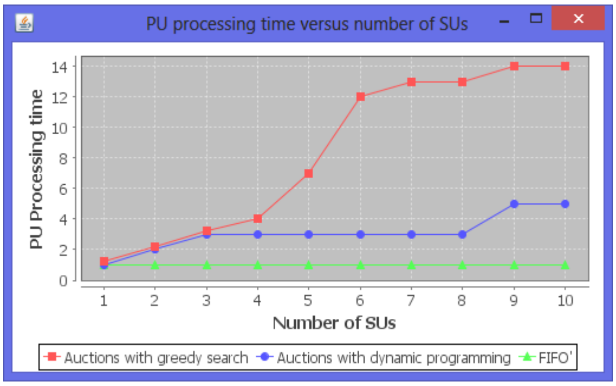

Figure 14: PU processing time/number of SU

As shown in Figure 14, with the two types of auctions, the PU processing time increases with increasing the number of SU. This is clear because with more available SUs, PU takes more time to select the best offer. But the use of auctions with dynamic programming are better than auctions with greedy algorithm in terms of required time because the auctions in this case needs a lot of time to sort the received requests.

iv. Comparison in terms of SU response time

Figure 15 shows the impact of the arrival rate of SU on the response time side SU.

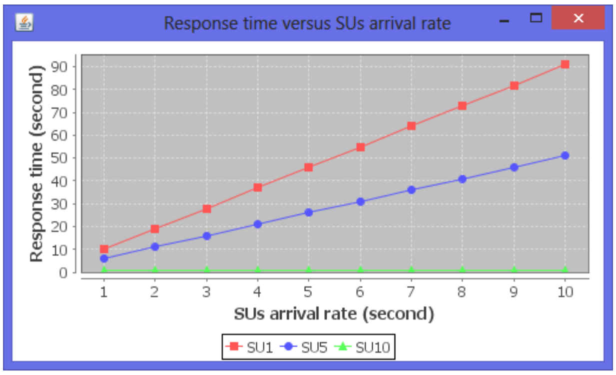

Figure 15: response time/SU arrival rate

It should be noted here that the SU response time corresponds to the expected time for a response from the PU, as the auction must wait until the arrival of the last SU and the launch of PU. (The cost of treatment in ms side PU is still negligible).

This graph shows that the response time for a given SU increases with the SU arrival rate except the last SU arrival will always wait for a second; time to start the PU. We also note that over the arrival of a SU is close to that of the last SU over its response time is reduced. And the arrival of a SU is far from that of the last SU arrival plus the response time is increased. To be more precise, if X is the SU arrival rate:

- SU1 will wait for 9*X+1 because 9 SUs arrive behind every X second, the PU is started 1s after SU10 (red curve).

- SU5 will wait 5*X+1 because 5 SUs arrive behind every X second, the PU is started 1s after SU10 (Blue curve).

- SU10 comes last so it will always wait 1s, time to start the PU (green curve).

4 Conclusion

This paper gives a detailed insight in applications of games theory in wireless networks. We have presented recent works related to game theory in power control, resource allocation, wireless sensor networks, communication networks and cognitive radio networks.

The results obtained through our simulations show that negotiation based on multi-agent systems is interesting for SU because it allows it to find the best deal available despite negotiation time which increases according to the number of PU.

We have also shown that regardless of the number of required channels, the use of auctions with dynamic programming is better than the use of greedy algorithm and FIFO' because the procedure is faster and has many advantages in terms of number of satisfied SU, PU obtained gains, PU processing time and finally SU response time.

So we have shown through this paper the utility of using game theory, multi-agent systems and auctions for resource management in the context of cognitive radio networks.

In our future work and in order to improve simulation results, we will focus on the use of coalitions of PUs and SUs.

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