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.

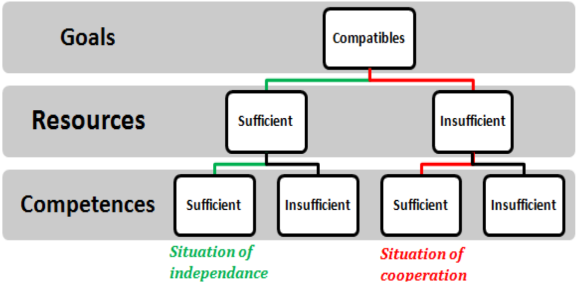

Figure 1: Binary tree modeling the interactions between agents in the case of CR

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.

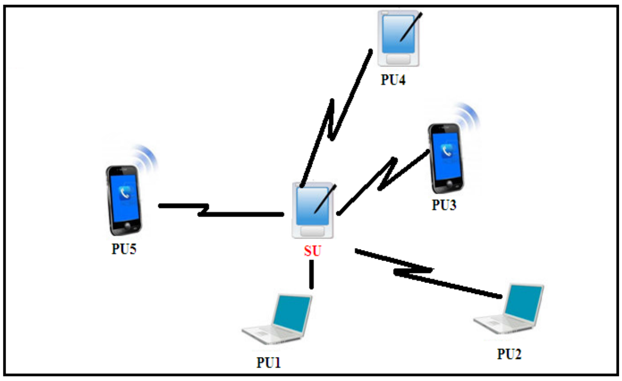

Figure 2: Ad hoc topology

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).

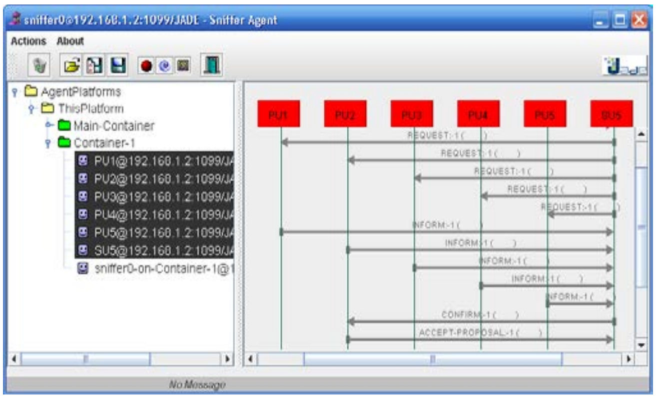

Figure 3: Sniffer with 1 required channel

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

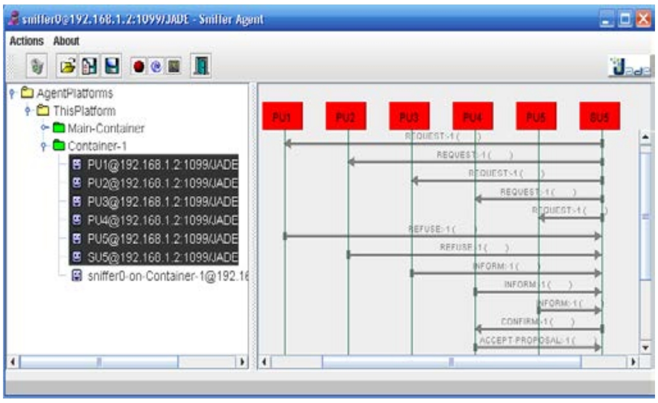

Figure 4: Sniffer with 3 required channels

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

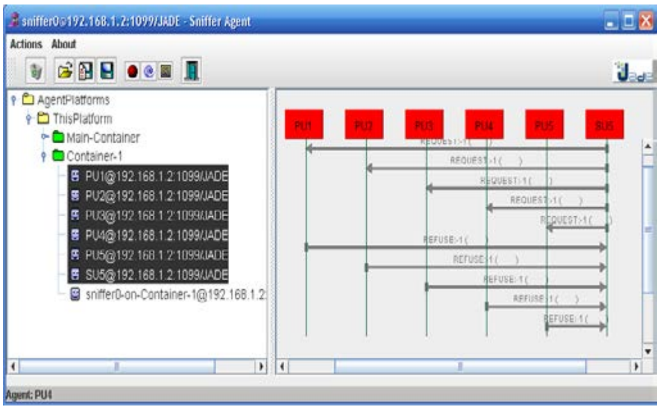

Figure 5: Sniffer with 5 required channels

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.

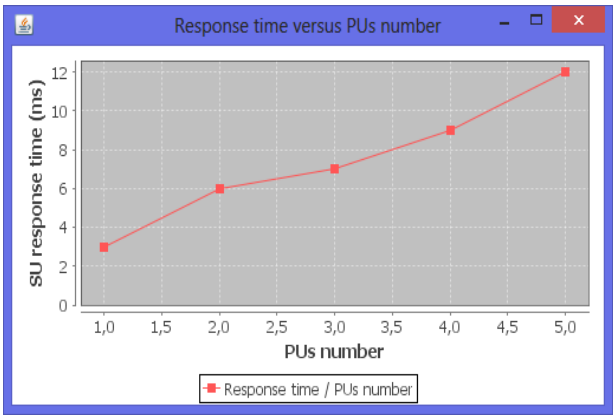

Figure 6: Impact of PU number on the SU response time (ms)

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.

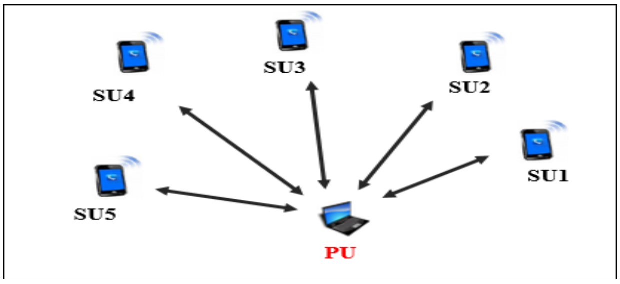

Figure 7: network topology

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 $\boldsymbol{\sum_{i=0}^{nb-1} W[i] \leq m}$.

- 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.