A decentralized approach for self-coexistence among heterogeneous networks in TVWS

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***Abstract*— This paper focuses on coexistence and self-coexistence challenges between secondary heterogeneous wireless networks/users sharing TV Whitespace spectrum. The coexistence problems arise from having several primary and secondary networks of different technologies cohabiting the same licensed spectrum simultaneously. The self- coexistence problems arise from many secondary systems /users coexisting at the same place while using identical or different technologies. In particular, fair distribution of available spectrum becomes a serious issue. In this work we use a game theoretic approach to model the self-coexistence problem as a competitive game between secondary networks. We show that our game belongs to the class of congestion-averse games which are known to posses pure Nash Equilibria. This leads us to a decentralized approach for spectrum sharing among systems with different PHY/MAC characteristics. We show that our proposal outperforms other centralized algorithms in terms of user fairness and per-user theoretical data rates.**

***Index Terms*—cognitive radio, self-coexistence, congestion-averse games**

I. Introduction

With the and almost universal deployment of 'handheld' IT technology the need for continuous wireless internet access has become a necessity, almost everywhere in the world. This creates severe congestion in the frequency spectrum, especially in urban areas where the number of users is already high. The optimal solution is to develop cognitive radios which will behave as secondary users and use the spectrum whenever it is not being used by primary users. A *cognitive radio* is a radio that can change its transmission parameters based on interaction with the environment in which it operates [1]. In 2009 US and UK regulatory bodies have approved the use of cognitive radios in TV White Spaces because with the advent of analog to digital transition in TV broadcasting, a substantial amount of spectrum has become available in TV bands. The digital transition was completed in US in 2009 and UK in 2012 [2].The unused TV spectrum that has become available for use after digital transition in TV broadcasting is called *TV White Space (TVWS)* and its capacity is considerably high. According to Ofcom [3] research, there is more than 150MHz of interleaved spectrum in over 50% of locations and 100MHZ of interleaved spectrum in 90% of locations in UK. Most available (unused or vacant) channels can be found in less densely populated areas, such as in developing countries or rural areas [4]. Frequency bands corresponding to TVWS spectrum are: VHF 30-300 MHz and UHF 300-1000 MHz except for the channels reserved for emergency transmissions and wireless microphones [5]. The TV White Spaces are convenient for two main reasons: the first one is their superior propagation characteristics for wireless communication which enable larger coverage, and the second one is that infrastructure requirements needed are comparably lower than higher spectra which makes it ideal for rural and underdeveloped areas where connection through optical fiber is very difficult [6].

Because cognitive radios might be used for different purposes and operate with different technologies, coexistence and self-coexistence problems arise. Coexistence is the situation that arises when primary users and cognitive radio devices (secondary users) exists/operate in the same time and location, whereas self-coexistence is the existence in time and space among many cognitive radio users or networks which can be of the same or different type. To overcome these problems the devices will have to continuously sense the channel to detect primary and secondary user transmissions and ensure that primary users are protected at all times. In case that the secondary user is using the spectrum and a primary user starts operating, then the secondary user is obliged to immediately vacate the channel in order to avoid causing interference to the primary user. To ensure this, the UK regulator, Ofcom and Federal Communication Commission (FCC) in the United States, have proposed three methods to be used by secondary users: beacons, sensing and geo-location with database [7]. When beacons are used as a controlling method, secondary users will only start transmitting if they have already received a beacon signal recognizing the vacant channel. The drawback of this method is that it requires the infrastructure of beacons to be implemented and maintained [8]. With sensing, the secondary users will sense the spectrum and try to detect the presence of primary users based on the

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amount of energy received. Secondary users may operate when they do not detect any primary signals. However, in the case of cognitive devices, this is not a straightforward task as it involves detecting other signal characteristics such as modulation and bandwidth, thus increasing device complexity and cost [9]. The third technique uses geo-location and databases [10]. Secondary users have to send a query to a database which has all the information regarding the spectrum usage in the vicinity during the specific time period. Then the database will respond with the list of available frequencies including all transmission parameters that need to be followed for the secondary transmission to start. Secondary users, however, must have geo-location capability, while the database must be kept updated at all times, which incurs additional overhead. An additional challenge on using geo-location and database access is when secondary users are indoors where GPS connectivity may not be available due to the signal disruption from buildings, walls, etc. [11] .

Following the decision by US and UK to allow opportunistic use of TVWS several standards were developed to facilitate its practical implementation such as: ECMA-392, IEEE 802.11af, IEEE 802.16h, IEEE 802.22. Because cognitive radios might be used for different purposes and operate with different technologies, coexistence and self-coexistence problems arise. The main challenge arises when the various systems using the same spectrum have different operating parameters (transmit power, bandwidth, MAC/PHY layer, etc.) and also because the different networks tend to selfishly occupy the spectrum to satisfy their own needs without considering the need of other networks that are cohabiting the same spectrum.

To this end, IEEE 802.19.1 standard was introduced to be used for coexistence of networks of different types, in particular for coexistence between 802.22 and non 802.22 networks [12]. The main limitation of this standard is that it tackles the problem of coexistence based on a centralized system architecture. In this coexistence enabling system, the coexistence decisions are made at coexistence manager which is responsible for making the operating decisions.

A. Contributions of this paper

In this paper, we propose an autonomous decentralized algorithm based on congestion-averse games for self-coexistence decision making in TVWS. In congestion-averse games players strategically choose from a set of resources and derive utilities that depend on the congestion on each resource. This algorithm addresses the challenges of self-coexistence in terms of fairness and efficiency of resource allocation.

In summary, our approach and key contributions are as follows:

A realistic model for the self-coexistence problem in TVWS is provided which captures both the relationship between the different networks as well as the relationship between a network and its users. Moreover the model does not consider only specific types of networks, but can be easily extended to cover as many types of various technologies as necessary.

The self-coexistence problem, modeled as an optimization problem is then transformed into a competitive game between networks using game theory concepts. The utility and cost functions are defined for each network, capturing the different interactions between the different networks. We prove that the game we model belongs to the class of congestion-averse games, which are known to possess some desirable qualities such as pure Nash Equilibrium.

Finally, a decentralized algorithm, known to reach the Nash equilibrium in congestion-averse game in polynomial time is applied to solve the self coexistence problem. The algorithm was adapted and rewritten in the context of the self-coexistence problem.

Using numerical evaluations we show that the proposed approach easily outperforms centralized algorithms proposed in literature in terms of bandwidth demand, fairness, and achieved theoretical user rates. We also show that the decentralized application of our algorithm performs almost as good as a centralized application of the same algorithm, used as a benchmark for evaluating the decentralized algorithm.

The reminder of the paper is organized as follows. Section II summarizes the related work on cognitive radio networks and we present our network model in section III. In section IV we formulate our game approach while in section V we evaluate our approach using simulation results. Finally we conclude the paper in section VI.

II. Related Work

While research on coexistence of heterogeneous networks in TVWS spectrum bands has been widely investigated, very little work has been done to tackle the problem of self-coexistence. Coexistence and self-coexistence of heterogeneous wireless networks in TVWS has been shown to be a major problem. Without the use of coexistence mechanisms, the utilization of TVWS spectrum will be significantly reduced. It was shown in [13] that without the use of coexistence mechanisms, 92% of available spectrum is overlapped by neighboring networks. Based on the proposed architecture in [14], the coexistence mechanisms are classified into three groups: centralized, coordinated and autonomous mechanisms. The difference among these coexistence mechanisms relies on where the coexistence decision is made:

1) *Centralized mechanisms* - use a database in which all coexistence information is collected and stored centrally and information to users is passed through internetwork coordination channels. However, this solution is costly and also ineffective when there are many coexisting devices or even networks that do not want to be part of a centralized control system. In addition scalability can also be an issue.

2) *Distributed mechanisms* - All the decisions regarding interference mitigation are made individually by each network or device and then the information is passed to others through control channels. This solution also incurs communication overhead and depends on the willingness of the networks to exchange information. Furthermore, it relies on the existence of a common control channel and assumes that all coexisting networks use the same access technology in order to be able to decode each other's messages. Again, in this case scalability

problems may arise.

3) *Decentralized mechanisms* -All the decisions for channel selection and interference mitigation are done only by individual observations. Internetworking between different technologies and scalability, in this case, should not be a problem.

Few algorithms have been proposed in the relevant literature that deal directly with the coexistence and self-coexistence problems at heterogeneous cognitive radio networks at PHY or MAC layer. Most of such algorithms are centralized or assume some form of coordination between participating networks.

The authors in [15] came up with a hybrid scheme for resource allocation. While in centralized scenarios the decision on the network users are imposed by network manager, in decentralized scenarios the authors used a game theory approach, namely Stackelberg games, in which the networks broadcast the load information to all network users. The main drawback of this proposed scheme is that the decentralized solution does not use completely autonomous mechanisms.

The authors in [16] proposed a hybrid scheme for heterogeneous networks looking specifically at the coexistence problem between 802.22 and 802.11af networks. The proposed solution, targets the problem of hidden terminals. However, the authors assume the presence of a 802.19.1 controller to manage the coexistence thus its performance relies heavily on centralized exchange of information.

In [17] the authors proposed an autonomous scheme for enabling coexistence between IEEE 802.11af and 802.22 networks. The basic idea is to use the sensing antenna available at the 802.22 receiver to send out a busy tone in order to protect its communications from hidden 802.11af terminals. The proposed algorithm is tailored to the problem of coexistence only between 802.11af and 802.22 networks and completely ignores the general problem of self-coexistence within secondary networks as well as any lack of fairness achieved during channel access.

A framework for modeling spectrum sharing as a congestion game is provided in [18]. Congestion games [19] is a game theoretic modeling for resources competition settings in which the associated payoff (cost) of the players is a function of the level of congestion (i.e., the number of users using the corresponding recourse). In [18] the authors propose to expand the notion of the resource so that the resource allocation problem satisfies the congestion game model. They proceed to define the game for different scenarios; however they focus on the classical resource allocation problem and do not consider the specificities of the self-coexistence problem in cognitive networks.

A recent work dealing with the problem of coexistence in heterogeneous wireless systems [20] proposes a centralized algorithm that deals with the problem of spectrum sharing among secondary networks and compares the results to other Coexistence Decision Making (CDM) algorithms that are specified on IEEE 802.19.1 standard. Nonetheless, this is a centralized algorithm which imposes a considerable amount of communication overhead and complexity.

In addition, there are also a few autonomous approaches available in the literature. The self-coexistence problem between wireless regional area networks was presented in [21]. The channel assignment problem was formulated as a non-cooperative potential game with utility functions aiming at maximizing the spatial reuse and minimizing the interference. Even though the main objective of this paper is the self-coexistence, the main drawback is that they look at the self-coexistence within secondary users only for WRANs (Wireless Regional Area Networks).

In [22] authors also proposed a game theoretic approach for solving the coexistence problem between cognitive radio networks. The problem is formulated as an uplink channel allocation problem in a non-cooperative game. However, the authors address the coexistence problem only in the uplink. Furthermore they do not consider the presence of heterogeneous networks but rather assume that all secondary networks are of the same type, but belonging to different operators.

In our proposed approach we also apply game theory to address the problem of self-coexistence in TVWS, between secondary networks of different types. We consider the usage of independent mechanisms where there is no central manager for decision making, no database for information queries and storage and no common physical communication channel between networks of the same and different type for information exchange. The self-coexistence and interference mitigation are ensured only based on the individual observations, which means that there is no need to synchronize and coordinate between networks to reach a fair solution, i.e., a decentralized mechanism, as defined earlier.

III. System Scenario and Problem Statement

We consider a scenario where different types of secondary networks compete to gain access to a pre-determined set of TVWS channels, which we assume, are already vacated by their primary users. Each secondary network serves a number of secondary users and is controlled by a central unit (base station or access point). One such scenario is shown in Fig. 1.

We denote the set of competing networks as N, and the set of available TVWS channels as C. Individual networks are denoted by lower case n, while individual channels by c. Each network may have different transmitting parameters, i.e., transmit power P_n, and may operate at different bandwidths ω_n. Each network may have a certain demand, in terms of spectrum which we denote by d_n and which is expressed in number of channels demanded. We assume that all channels in the set C have equal bandwidth such that it satisfies the most demanding network.

Each secondary network serves a number of secondary devices that are located within the operating range of the associated network. We denote the set of users associated to network n as U_n and individual users by u. In these kinds of scenarios a self-coexistence decision making mechanism

(SCDM) is used to ensure the best use of TVWS resources in terms of throughout and fairness, among the different cognitive networks.

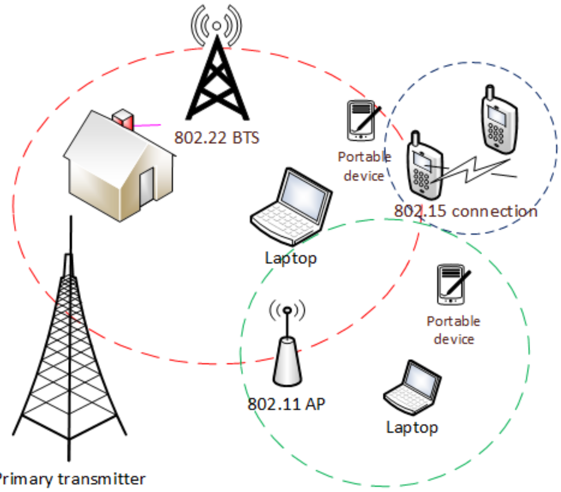


Fig. 1. System scenario

In this paper we assume a decentralized configuration in which secondary networks make coexistence decisions on their own, using individual sensing information, as well as information received by the secondary devices under their coverage. Therefore we do not assume the existence of an additional central entity or communicating channel between the secondary networks.

The task of the SCDM is to decide which available channels, which are free of incumbent users, should be allocated to which secondary network in a way that i) enables coexistence between the different networks, ii) meets the bandwidth/data rate demands of each network and iii) ensures fair allocation among the different networks.

In general, each network may choose any subset of channels, thus allowing for more than one network to be allocated on the same channel simultaneously.

Close attention in such cases must be paid to the interference between the different networks, which tends to be heavily asymmetric due to the varying transmit powers. Interference is caused when two or more networks operate in the same channel, and the users of each network receive harmful transmission from the other base stations in addition to the useful transmissions coming from their own base station.

The interference caused at the final secondary users determines the signal to noise and interference ratio (SINR) which proportionally affects the channel capacity and hence influences the quality of the service each network is able to provide to its users.

The SINR, denoted by $\gamma_{u,c}$, at a receiving user u of network n on channel c is given by:

$$\gamma_{u,c} = \frac{a_{n,u,c} P_n \sigma_{n,c}}{N_0 + \sum_{m \in N \wedge m \neq n} a_{m,u,c} P_m \sigma_{m,c}} \quad (1)$$

where P_n, P_m represent the transmit powers of network n, and m which are transmitting simultaneously on channel c. Attenuation experienced by the signal transmitted by the base station of network n when reaching user u is denoted by $a_{n,u,c}$, and similarly $a_{m,u,c}$ is the attenuation from network m. The signal attenuation depends on many factors, such as distance, line of sight, shadowing and multipath. For the purposes of this work, we have considered the free-space path loss model for the attenuation values, however more realistic and complex models can also be used. Hence, the value for the attenuation $a_{n,u,c}$ is given by the expression:

$$a_{n,u,c} = \left(\frac{4\pi d_{n,u}}{\lambda_c}\right) \quad (2)$$

where $d_{n,u}$ is the distance between the base station/access point of network n and user u, and λ_c is the signal wavelength (inversely proportional to the signal frequency).

We use a binary variable $\sigma_{n,c}$ to indicate whether channel c has been selected by a specific network, i.e., $\sigma_{n,c} = 1$ if $c \in s_n$. The noise level is denoted by N_0. To summarize, the expression in the numerator represents the useful power received by user u from network n, while the expression in the denominator represent the noise (expressed by a constant) plus the interference coming from other networks transmitting simultaneously on the same channel, i.e., the total harmful power received by user u from all other networks other than n.

It is in the interest of every secondary network, therefore, to maximize the SINR obtained by the users it serves on the channels it selects. Globally however, it is important to maximize the SINR obtained by all users in all the networks. Consider for example the following global non-linear optimization problem:

$$\max_{\sigma_{n,c}} \sum_{n \in N} \sum_{u \in U_n} \sum_{c \in C} \frac{a_{n,u,c} P_n \sigma_{n,c}}{N_0 + \sum_{m \in N \wedge m \neq n} a_{m,u,c} P_m \sigma_{m,c}} \quad (3)$$

$$\text{s.t. } \sigma_{n,c} \in \{0,1\} \quad (3a)$$

$$\sum_{c \in C} \sigma_{n,c} \leq d_n \quad (3b)$$

Note that the first constraint (3a) is related to the binary nature of the allocation variables σ, indicating whether a network has selected a certain channel or not. The second constraint (3b) limits the number of channels selected by a network n so as not to exceed the network's demand, d_n.

Due to the nature of the $\sigma_{n,c}$ variables, the global optimization problem is a nonlinear integer programming problem which is known to be NP-hard; since the linear integer programming problem is a special case of it and the latter is known to be NP-hard [23]. It should be noted, that such a formulation does not account for fairness in the system, therefore it is clear, that due to the complexity of the task, a different approach, preferably less complex and decentralized is required.

To this end, we use game theory concepts to reframe our problem. We model the problem of selecting the channels as a non-cooperative game, in which the players are the secondary networks competing for the vacated TVWS spectrum. Each network executes an algorithm in order to make a SCDM decision, that is, adopts a strategy that eventually leads to a Nash equilibrium (NE). A NE is a game solution, in which no player can gain anything by unilaterally changing his own strategy. This ensures that once a NE is reached, no network has an interest in changing the channels it has selected. This equilibrium may be disturbed when a change in the environment is noticed, such as the appearance of primary user transmission or the discovery of an additional secondary network. It is clear, however, that a game-theoretic approach does not ensure that an optimal solution is reached. Nevertheless, in Section V we show that the channel allocation strategy through our game-theoretic approach performs better than existing centralized solutions especially in terms of fairness.

IV. Formulating Self-Coexistence As a Congestion Game

We address the coexistence problem using game theory which is an appropriate mathematical tool to obtain a multi-objective distributed solution in a scenario where entities, i.e., secondary networks, share the same pool of resources, i.e., TVWS channels.

A. The congestion-averse game

We formulate the problem of SCDM as a competitive congestion-averse game between *secondary networks* where each network wants to maximize its own utility. Classical congestion games were originally defined by Rosenthal in the seminal paper [19]. Congestion games are of particular interest to us since they were proven to admit at least one pure-strategy NE.

These games are characterized by a set of players N and a set of elementary resources *C*. Each player can choose as its strategy any subset of elementary resources. The utility that can be obtained at each resource depends strictly on the number of players selecting the same resource. The logic follows that the higher the number of players selecting the same resource the higher is the congestion, therefore the lower is the utility derived by a player selecting that resource. The final utility of each player is then calculated as the sum of the utilities obtained at each selected elementary resource.

Formally we define a congestion game by the 4-tuple :

$$G = \{N, C, (S_i)_{i\in N}, (\pi_c)_{c\in C}\} \tag{4}$$

where *N* is the set of players corresponding to the secondary networks; *C* is the set of elementary resources (channels); $S_i \subset 2^C$ is the strategy set of player *i* and π_c:$\mathbf{N} \rightarrow \mathbf{Z}$ is the payoff associated with channel *c*. The payoff π_c is a function of the total number of users using channel *c* and is assumed to be non-increasing. A player in this game aims to maximize its total payoff which is the sum total of payoff over all channels its strategy involves.

Denote $\boldsymbol{s} = (s_1, s_2, \dots, N)$ the strategy profile of the game G, where $s_i \in S_i$, then user *i*'s total payoff is given by

$$\pi^i(\boldsymbol{s}) = \sum_{c\in s_i} \pi_c(\eta_c(\boldsymbol{s})) \tag{5}$$

where $\eta_c(\boldsymbol{s})$ is the total number of users using resource *c* in profile $\boldsymbol{s}$.

We argue that channel allocation process in the context of SCDM can be formulated as a congestion game, with *N* being the number of secondary networks competing for resources and *C* the set of TVWS channels available for allocation. Clearly, if we express the utility of each network as a function proportional to the signal-to-noise-and-interference ratio (SINR) obtained by its end users, it will depend on the number of other networks simultaneously selecting the same channel, albeit not directly.

We note from SINR expression in (1) that the SINR itself does not depend only on the number of networks selecting the same channel but also on their identity, i.e. their individual effect on other networks. Therefore, we define a utility function that is similar to the SINR expression, but that depends strictly on the number of the networks η_C selecting a specific resource *c:*

$$\pi_{n,c} = \frac{\alpha_{n,c} P_n}{N + \beta_{n,c}\eta_C} \tag{6}$$

We now proceed to define parameters $\alpha_{n,c}$ and $\beta_{n,c}$:

$$\alpha_{n,c} = \frac{1}{|U_n|}\sum_{u\in U_n} a_{n,u,c} \tag{7}$$

$$\beta_{n,c} = \frac{\bar{p}}{|U_n|(|N|-1)}\sum_{m\in N\wedge m\neq n}\sum_{u\in U_n} a_{m,u,c} \tag{8}$$

where we define $\bar{p} = \min(P_n)$. Note that both parameters α and β represent averages of the attenuation values that were present in the SINR expression. Equation (6) is an approximation of the average SINR experienced by the users of a secondary network. It is equivalent to assuming that instead of multiple users, each network serves only one user whose SINR represents the average experienced by the actual users. To this end, we calculate $\alpha_{n,c}$ which represents the average of the channel gains of the users of the network and $\beta_{n,c}$ which is the average of all the attenuation factors from the interfering networks to the users of the secondary network under consideration. The last equation is another simplification: instead of considering multiple interfering networks, we simplify the expression to consider only one interfering network, whose interfering effect we assume to be the average of all the interfering networks. Consequently, in order to adhere to a strict definition of a congestion game, we lose some of the realism in our utility function, i.e., we are not able to fully capture how the networks affect each other. However, by making a slight modification to η_c, we manage to take into account the different transmit powers of the different network types. This modification allows certain players to be counted as multiple players when counting the number of players selecting a specific resource *c*. Namely, if a network with a high transmit power chooses resource *c* we increment the η_c value by a number higher than 1. Only for the network with the lowest transmit power, we increment the η_c value by 1 and then for every other network type with stronger transmit power we increment by an integer value proportional to the transmit power. We proceed to define an integer weight parameter for each player $w_n \sim P_n/\min(P_n)$. Finally we define *the weighted number of players* $\tilde{\eta}_c$, given by the following expression

$$\tilde{\eta}_c = \sum_{n\in N} w_n \sigma_{n,c} \tag{9}$$

Although $\tilde{\eta}_c$ is no longer strictly the number of players selecting resource c, it is still a valid congestion value and it is universally known to all the players. From the perspective of a single player, this implies no change in the game structure, because one player transmitting at higher power is equivalent to multiple players transmitting at lower powers, if the interference caused is equivalent. Note, that users in each network can sense the interference they receive from other networks, and can report this information to their base station or access point. Furthermore, we assume that networks can identify what kind of other networks are also in the area, while the weights can be predetermined for each type of network and known in advance by all the players.

However it must be noted that in the classic congestion game the utility function is identical for all the players. Since parameters α and β are network specific, it means that our game is not a straightforward congestion game but rather a *game with congestion-averse utilities (CAG),* as defined in [24]. In CAGs, in contrast with classic congestion game, utility functions can indeed depend on player identities.

A strategic game is said to be congestion-averse if its utility function satisfies the following three conditions:

i. monotonically decreases as congestion increases,
ii. is submodular in that the "better" collection of resources a player uses — the less incentive he has to add new resources, and
iii. is independent of irrelevant alternatives, i.e., a player's preference between two resources depends only on congestion on the resources in question, and is independent of the congestion level on the other resources.

Definition 1

Let us define a game

$$\Gamma = \{N, C, \{S_n\}, \pi_n(\eta_C)\} \tag{10}$$

where *N,* the set of secondary networks is the set of players*;* C, the set of available TVWS channels, is the set of elementary resources*;* $\{S_n\}$ is the set of possible pure strategies of player *n;* strategy $s_n \in S_n$ can be any possible combination of channels *c* from the set C. π_n is the utility of player *n* when selecting strategy $s_n \in S_n$:

$$\pi_n(s_n, \boldsymbol{s_{-n}}) = \sum_{c\in s_n} \pi_{n,c}(\eta_C) - \rho_n \sum_{c\in s_n} \sigma_{n,c} \tag{11}$$

where $\boldsymbol{s_{-n}}$ denotes the strategies chosen by all players other than *n*. We recall that η_C depends also on the strategies of other players.

Note that we have introduced an additional component to our utility expression, which we call the cost component. Here ρ_n is the price paid per resource selected. This additional component is necessary to transform the game into a CAG as discussed below, and also to ensure a degree of fairness among networks. From a practical point of view, it is also reasonable to expect networks to pay a certain price for each resource used; indeed whenever a network decides to use additional resources, it does so at a specific expense, especially in terms of consumed energy, which in some types of networks can be a significant limitation.

It can easily now follow from the above discussion that:

Proposition 1.
The game given by definition 2 is a CAG game, given $\rho_n > 0$.

Proof. Note that the utility of each network will be a sum over the utilities obtained at each resource:

$$\pi_n = \sum_{c\in s_n} \pi_{n,c}(\eta_c) \tag{12}$$

The utility provided in (6) directly satisfies condition (i) due to the definition we have provided for $\pi_{n,c}$, which is monotonically decreasing in η_C. Because we assume independence between the TVWS channels available, we also satisfy condition (iii), since the utility at each resource *c,* is not affected by the congestion level at other resources. If we keep the utility expression without the cost component, i.e., $\pi_n = \sum_{c\in s_n} \pi_{n,c}(\eta_c)$, condition (ii) is not satisfied. Indeed, because the overall utility is the sum of utilities over all selected resources, the best strategy will always include the selection of all available resources. This happens because regardless of the congestion value, the utility value at each resource is always positive, leading to a situation where even a heavily congested resource will contribute positively to the final utility value. It is therefore necessary to introduce a cost component to the utility to demotivate networks to select resources that bring about marginal contributions.

We introduce a simple linear cost component which imposes a specific price to be paid for each resource selection. Imposing $\rho_n > 0$, we satisfy condition (ii) since now clearly we have a mechanism which enables the networks to discard those heavily congested resources whose marginal contribution to the final utility does not justify the cost that needs to be paid. That means that once a good selection is reached, the network has no incentive to pay an additional cost to include additional resources which payback little in terms of utility. Therefore, we conclude that the game defined in Definition 2 is a CAG game.■

CAG was used to model the problem of choosing recharging stations for Electrical Vehicles in [25]. Here we introduced a game and showed that it is a CAG game, for the context of SCDM. In [24] it has been proven that these CAG games also possess pure Nash Equilibria (NE), which can moreover be reached in polynomial time.

B. *Reaching the Nash Equilibrium*

CAG games are known to possess the *single profitable move property* (SPMP). The SPMP implies that once the players choose a strategy profile from which there is no profitable *elementary* move, then the strategy is in fact a pure Nash Equilibrium.

There are three types of elementary moves in the context of CAGs: 1) *additions*, instances of including a new channel to the strategy; 2) *drops*, instances of excluding a channel from a strategy and 3) *switches,* which consist in dropping a selected channel by replacing it with another.

The authors in [24] prove that CAGs indeed possess the SPMP property and further provide an algorithm which reaches the NE in polynomial time.

Specifically, the authors use two types of sequences of elementary moves to construct their algorithm. First they define a *drop ladder* which is a sequence defined by one drop in the beginning, followed by several switches. Next, they also define a *swap ladder*, which is a drop ladder concluded by an addition. Moreover, the authors argue that it is not necessary to consider all possible combinations of such elementary moves, but only those that result in maximum gain, i.e., maximally profitable moves. Consequently the drop and swap ladders become sequences of maximally profitable moves, rather than ordinary moves.

The logic of the algorithm is rather straightforward: if the game is started from a strategy which is stable both against additions or switches (AS-stable profile), then if the players proceed by building maximal drop ladders, which may terminate as swap ladders, the game will eventually reach a NE. This relies mainly on the fact that there can only be a limited number of swap ladders consecutively [24]. The authors show that the algorithm requires $O(N^2R^2)$ elementary changes.

Here, we present the same algorithm adapted to our particular self-coexistence problem. Note that the algorithm must be initiated from a strategy profile, $\boldsymbol{s}$, which has no profitable additions or switches left., i.e., AS-stable A strategy profile is the set of channels chosen by individual networks. One such strategy profile is when all networks select all available channels.

Algorithm 1 is applied iteratively until none of the networks have any single profitable moves left. Note that the individual networks independently perform step 2 - 34,, and since this is a decentralized scheme, the networks don't interact with each other. Each network can decide to change their strategy, i.e., initiate the algorithm, based on their own sensing information, or feedback they receive from their users. The different network operators will update their strategies whenever they sense a new network is transmitting (interference level increases), or when they notice a drop in the interference level due to one of the networks leaving or changing their strategy.

Input to the algorithm are the network-specific parameters we defined in the previous section, $\alpha_{n,c}$ and $\beta_{n,c}$, as well as the price parameters ρ. As suggested previously in this paper, we start from the AS-stable strategy, $\boldsymbol{s}$, in which all networks choose all available channels. The procedure described next is performed by each network independently. In lines 3-5, the network calculates the gain in utility for each possible drop, $D_{n,c}$. In lines 9-10, the network chooses the channel with the highest $D_{n,c}$ value (provided that it is positive), and drops the selected channel from its strategy, initiating a drop ladder sequence. Then it proceeds to calculate the gains in utility for every possible switch, $S_{n,c,c'}$, between two channels c and c', in lines 13-15. Again, it chooses the duplet of channels (c,c') which maximize the value of $S_{n,c,c'}$, and performs the switch (lines 18-21).

Algorithm 1: Reaching a NE

Input: α, β, ρ, **s**
1: **for all** $n \in N$
2: Calculate π_n given $s_n \in \boldsymbol{s}$
3: **for all** $c \in s_n$
4: $s_n^{temp} \leftarrow s_n - c$
5: Calculate π_n^{temp} given s_n^{temp}
6: $D_{n,c} = \pi_n^{temp} - \pi_n$
7: **end for**
8: **if** max $D_{n,c} > 0$
9: $c_d \leftarrow \max_c D_{n,c}$
10: $s_n^* \leftarrow s_n - c_d$
11: Calculate π_n^* given s_n^*
12: **for all** $c \in s_n^*$ **and** $c' \notin s_n^*$
13: $s_n^{temp} \leftarrow s_n - c + c'$
14: Calculate π_n^{temp} given s_n^{temp}
15: $S_{n,c,c'} \leftarrow \pi_n^{temp} - \pi_n^*$
16: **end for**
17: **if** max $S_{n,c,c'} > 0$
18: $c_d \leftarrow \max_c S_{n,c,c'}$
19: $c_a \leftarrow \max_{c'} S_{n,c,c'}$
20: $s_n^* \leftarrow s_n^* - c_d + c_a$
21: Calculate π_n^* given s_n^*
22: **for all** $c \notin s_n^*$
23 $s_n^{temp} \leftarrow s_n^* + c$
24: Calculate π_n^{temp} given s_n^{temp}
25: $A_{n,c} \leftarrow \pi_n^{temp} - \pi_n^*$
26: **end for**
27: **if** max $A_{n,c} > 0$
28: $c \leftarrow \max_c A_{n,c}$
29: $s_n^* \leftarrow s_n^* + c$
30: Calculate π_n^* given s_n^*
31: Go to step 3.
32: **else**
33: Repeat steps 12-31
34: **end if**
35: **end if**
36: **end if**
37: **end for**

Once a switch is performed, the network checks whether there is a channel among the unselected channels which would bring about a profit in utility (lines 23-25). If there is, the network adds the channel with the highest gain (lines 28-29). This, completes a swap ladder, therefore the player starts building the new drop/swap ladder, going back to line 3. While there are no profitable additions, the network continues switching channels until there are profitable switches left, thus building consecutive drop ladders. The algorithm terminates, when there are no more drop/swap ladders left.

V. Simulation Results

We apply the algorithm for reaching NE in CAG-s, both in a centralized (for comparative purposes) and decentralized manner, and compare it to the centralized algorithm (FACT) proposed in [20] which models the channel allocation problem in SCDM as an energy-minimization problem. The algorithm, is used as a comparison benchmark for the decentralized solution we propose.

We simulate a scenario with N=20 secondary networks, spread randomly over an area of 1km square. The secondary networks can be of three types 1) IEEE 802.22, 2) IEE 802.11af and 3) IEEE 802.15. Each type of network has different configurations, different transmit powers and different operating ranges. We assume a central frequency $f_0 = 700\ MHz$. All antennas are considered omnidirectional. The price parameter ρ is fixed for all networks at $\rho = 5$.

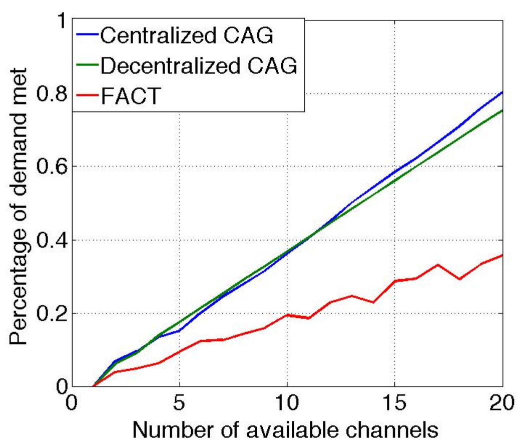


Fig. 2 Meeting the bandwidth demand

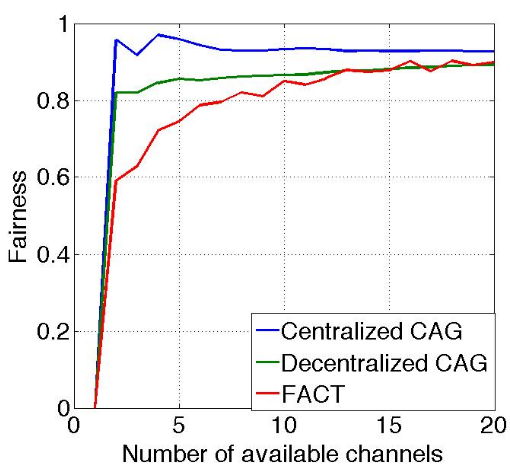


Fig. 3 Fairness

We simulate, using MATLAB software, a number of users for each network, randomly dropped within their operating range. The number of available TVWS channels is varied from 1 to 20, and we consider they have fixed 8 MHz bandwidth. The output of each SCDM algorithm is a strategy which identifies which channels are allocated to which network. Once the strategies are obtained, we calculate the SINR and the rate each user can obtain at the selected channel using the Shannon capacity formula:

$$r_n = \sum_{u \in U_n} \sum_{c \epsilon C} \omega_n \log_2(1 + \gamma_{u,c}) \tag{13}$$

where W is the channel bandwidth. Note that the individual attenuation values between transmitters and receivers are calculated using the free-space path loss model.

The utility of each network is also calculated using the formulas provided in the previous section. When the game is solved centrally, we assume the presence of a controller with global knowledge, who applies Algorithm 1 on behalf of the networks. Furthermore, the profitability of the moves is calculated with respect to global utility rather than the individual network utilities. We assume that each network demands a certain number of channels and this demand is generated randomly between 15 and 25.

Firstly we compare the two algorithms in their ability to satisfy the demands of the networks, which is calculated as the ratio between the number of channels allocated and channels requested (demand). This is shown in Fig. 2. Note that demand is evaluated only in terms of number of channels allocated, and not on the quality obtained at each specific channel. We observe that as expected, the centralized CAG algorithm significantly outperforms the FACT algorithm, which is also a centralized algorithm. While the performance of the decentralized CAG algorithm is poorer, it still performs better than FACT.

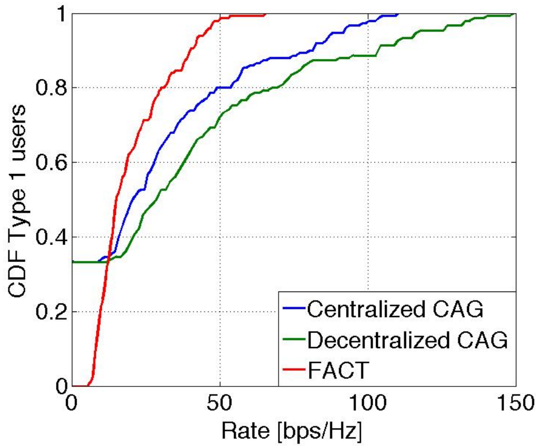
Secondly, we evaluate the fairness of each algorithm by using the Jain Fairness index defined as:

$$\Im(x_1, x_2, \ldots, x_n) = \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n \sum_{i=1}^{n} x_i^2} \tag{14}$$

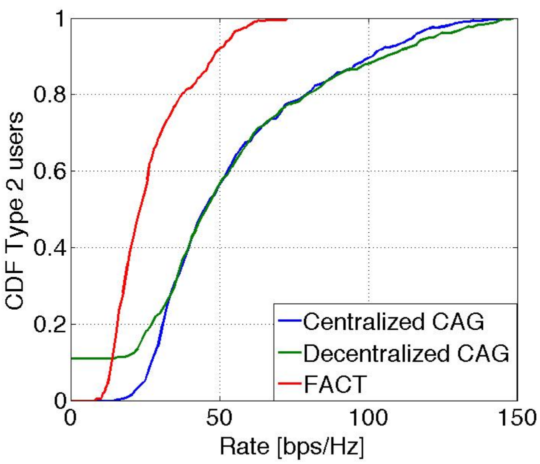
where x_i represents the average user rate of network i. As shown in Fig. 3 the CAG game solved centrally performs best in terms of fairness. FACT improves steadily as the number of available channels increases, but does not outperform the decentralized CAG although FACT itself is a centralized algorithm. This is a significant result, implying that even when networks independently make decisions according to Algorithm 1, they are able to reach a good level of fairness.

It should be noted that one of the objectives of the FACT algorithm is indeed ensuring fairness, however fairness is only considered with respect to number of channels allocated to each network, and not the quality of the channels allocated, which is what is highlighted in these results.

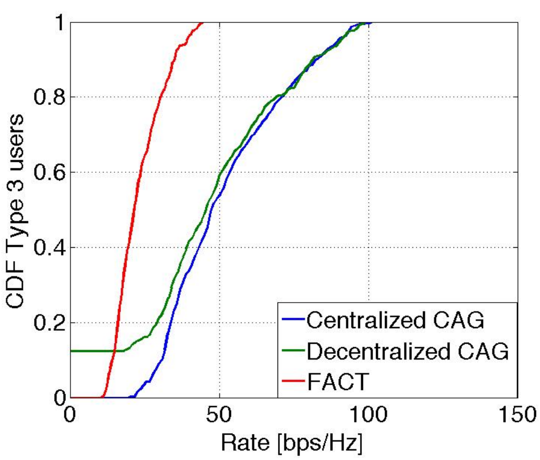
Moreover, we also look at the theoretical rates obtained by each individual user. We fix the number of available channels to C=20 and plot the CDF of the per-user rates for each type of network in Fig. 4. We observe that in general the rates obtained with CAG are much higher than those obtained with FACT for all types of users.



a)



b)



c)

Fig. 4 CDF of average user rates for users of a) Type 1 networks; b) Type 2 networks and c) Type 3 networks

Again, this is due to the fact that the FACT algorithm does not take into account the quality obtained at each allocated channel. Note how the per-user rate for type 2 and 3 networks, which transmit at much lower transmit power than type 1, is much higher with CAG central game than the FACT algorithm. The decentralized implementation indeed performs almost as good as the centralized algorithm which is remarkable considering that the decentralized implementation does not require overhead or global knowledge.

Finally, we also compare the performance of the CAG algorithm to the optimal solution with respect to the global utility. Due to the difficulty of finding the optimal solution at the global level, we compare the algorithm performance in a small-scale scenario, involving $N=3$ networks and $C=4$ available channels.

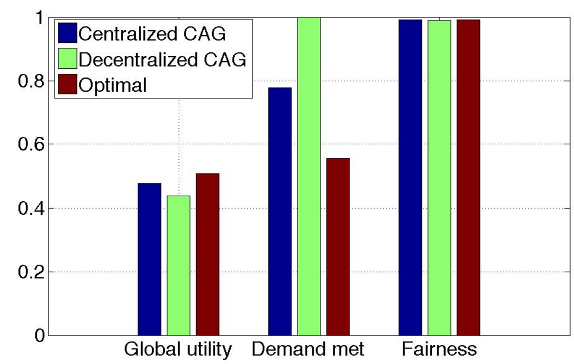


Fig. 5 Performance of the CAG algorithm compared to the optimal solution in three key metrics: global utility, percentage of demand met and fairness.

In Fig. 5 we show how both implementation of the CAG algorithm fare when compared to the optimal solution. It is clear that in terms of global utility, the centralized implementation performs almost as well as the optimal solution, but the decentralized solution performs almost as well. In terms of demand met, the decentralized solution is able to meet all the demands of the different networks, which is due to the fact that since the networks do not have a global perspective, they tend to act more selfishly. In terms of fairness, all three approaches perform quite well.

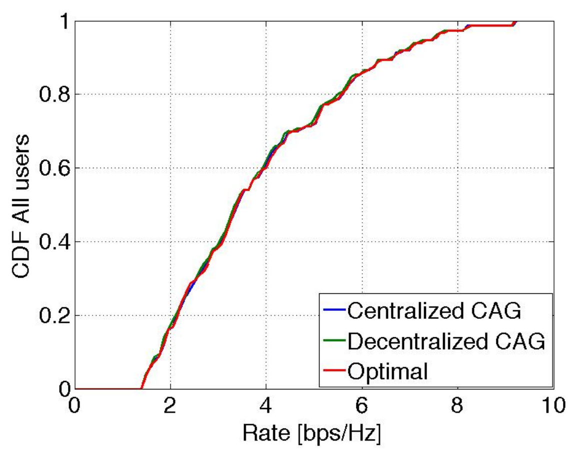


Fig. 6 CDF of average user rates

In Fig. 6 we also show the CDF of the average user rates obtained when applying the CAG algorithm and the optimal solution. It is quite evident that in terms of this metric, the performance of the CAG algorithm is indistinguishable from the optimal solution. Therefore, in terms of practical uses of the CAG algorithm, we can conclude that the performance is *near optimal.*

We note however, that the algorithm we propose may result in outcomes in which some networks are not allocated any channels at all. Such is the case in our simulation results for some of the Type 1 networks, which have the highest transmit powers. However, we note that by calibrating the price value for each network individually, such outcomes can be avoided, however, such moves may result in degraded performance in terms of fairness, a trade-off we plan to explore in future works.

VI. Conclusions

In this paper we address the problem of self-coexistence in between secondary networks in a cognitive radio environment. The task of sharing the common set of available channels in the TVWS, accessible to secondary users, is an important issue that needs to be tackled to ensure efficient use of the limited resources. We propose a decentralized scheme for this important self-coexistence task, based on a game theoretic approach. Decentralization is a desirable feature in these kinds of scenarios, where we have different types of secondary networks, operating with different technologies. We model the SCDM problem as a non-cooperative game between heterogeneous secondary networks, and verify that the game belongs to the class of games with congestion-averse utilities (CAG), which are known to have at least one pure Nash Equilibrium. Taking advantage of properties of such games we propose to use the framework provided in [26] to build an algorithm which can be applied by coexisting secondary networks independently.

A decentralized and centralized (for comparative purposes) implementation of the algorithm have been developed. Extensive experimental simulations show that the implementation of the proposed algorithm (centralized and decentralized) outperforms existing centralized FACT algorithm proposed in [20] in terms of bandwidth demand, fairness and achieved theoretical user rates.

In the future we plan to enhance our model by including realistic channel models to account for propagation losses. Also, another aspect which we plan to consider is the inclusion of channels with different characteristics in terms of bandwidth and quality of service requirements.

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