Research Article

Resource Allocation with MAC Layer Node Cooperation in Cognitive Radio Networks

Andreas Merentitis and Dionysia Triantafyllopoulou

Department of Informatics and Telecommunications, University of Athens, Panepistimiopolis, Ilissia, 15784 Athens, Greece

Correspondence should be addressed to Dionysia Triantafyllopoulou, siarina@di.uoa.gr

Received 1 November 2009; Revised 29 January 2010; Accepted 21 February 2010

Academic Editor: Hamid Sadjadpour

Copyright © 2010 A. Merentitis and D. Triantafyllopoulou. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

An algorithm for cooperative Dynamic Spectrum Access in Cognitive Radio networks is presented. The proposed algorithm utilizes Medium Access Control layer mechanisms for message exchange between secondary nodes that operate in license exempt spectrum bands, in order to achieve interference mitigation. A fuzzy logic reasoner is utilized in order to take into account the effect of the coexistence of a large number of users in the interference as well as to cope for uncertainties in the message exchange, caused by the nodes' mobility and the large delays in the updating of the necessary information. The proposed algorithm is applied in Filter Bank Multicarrier, as well as Orthogonal Frequency Division Multiplexing systems, and its performance is evaluated through extensive simulations that cover a wide range of typical scenarios. Experimental results indicate improved behaviour compared to previous schemes, especially in the case of uncertainties that cause underestimation of the interference levels.

1. Introduction

The proliferation of mobile devices, coupled with the ever-increasing demand for higher data rates' support, constitutes static frequency allocation schemes suboptimal, as they frequently result in spectrum underutilization. Cognitive Radios (CRs) supporting Opportunistic Spectrum Access (OSA) [1] emerged as a new paradigm that offers an effective solution to the problem of spectrum scarcity. However, the increased variance in spectrum availability combined with the end users' diverse characteristics and Quality of Service (QoS) requirements poses a number of challenges that need to be addressed.

More specifically, for Cognitive Radio systems operating in licensed spectrum bands with coexistence of both primary and secondary users, the operations of spectrum sensing, defined as the identification of the spectrum bands that are available for transmission, and spectrum mobility, that is, the vacation of the wireless channel when a primary user is detected, are of key importance. On the other hand, Cognitive Radio systems operating in license exempt spectrum

bands, where different operators coexist, require efficient spectrum decision and spectrum sharing algorithms as well as power control mechanisms for interference mitigation. For example, if all users transmit at the maximum valid power level, then every user is causing significant interference to all the others, a fact that can result in reduced total utility from the network perspective and, finally, poor QoS for the end users.

In this scope, algorithms that employ cooperative spectrum sharing in order to maximize the overall system performance are required. These algorithms need to be *distributed*, in order to be applied efficiently in ad hoc networks operating in unlicensed spectrum bands where synchronization is necessary only for users of the same operator. Such algorithms should also be able to employ *efficient message exchange* schemes in order to maximize the overall system utility (therefore, the related systems are classified as cooperative CR systems); however, uncertainties in message exchange should also be considered. Furthermore, they should be able to *converge* to an optimal solution within a finite number of iterations to be applicable to real systems.

In order to address some of the previous challenges, the authors in [2] propose a price-based iterative water-filling algorithm which allows users to converge to the Nash Equilibrium. This algorithm can be implemented in a distributed manner with CRs negotiating their best transmission powers and spectrum. In [3], a Dynamic Open Spectrum Sharing Medium Access Control (MAC) protocol for wireless ad hoc networks is proposed. This protocol performs real-time dynamic spectrum allocation by allowing nodes to adaptively select an arbitrary spectrum for the incipient communication subject to spectrum availability. In [4], a distributed approach to spectrum allocation that starts from the previous spectrum assignment and performs a limited number of computations to adapt to recent topology changes is considered. According to the proposed local bargaining approach, the users affected by a mobility event self-organize into bargaining groups and adapt their spectrum assignment to approximate a new optimal conflict-free assignment. The authors in [5] propose a graph-theoretic model for efficient and fair access in open spectrum systems. Three policy-driven utility functions that combine efficient spectrum utilization and fairness are described, and a vertex labeling mechanism is used to build both centralized and distributed approximation algorithms. In [6], a group-based coordination scheme, and distributed group setup and maintenance algorithms where users select coordination channels adaptively are proposed. In [7], an algorithm that allows for transmission power and transmission frequencies to be chosen simultaneously by Cognitive Radios competing to communicate over a frequency spectrum is proposed. Finally, in [8], an algorithm in which each user selects a single channel along with its transmission power by taking into account information concerning the interference caused to other users in the network is introduced.

In this paper, an algorithm based on the spectrum sharing scheme of [8] for distributed interference compensation in Cognitive Radios that operate in license exempt spectrum bands is proposed. The proposed algorithm refines the utility function used in [8] to improve the system scalability in the case of a large number of user pairs and to take into account uncertainties that may be the result of user mobility and large delays in the update of the interference prices. More specifically, a fuzzy logic reasoner is utilized in order to take into account the effect of a large number of users and the related interference as well as to cope for uncertainties in the message exchange process. The performance of the proposed algorithm is evaluated through simulations. In this direction, the overall utility value of the algorithm is compared to the utility of a simple “always select the maximum valid power” policy. The proposed algorithm is also applied in both Filter Bank Multicarrier (FBMC) and Orthogonal Frequency Division Multiplexing (OFDM) systems in order to show its flexibility and capability of transparently exploiting an improved Physical layer, without any further modifications. Moreover, comparison with the distributed algorithm of [8] is used to validate the improvement in terms of the overall utility level under uncertainties that cause 25% underestimation of the interference. Finally, in order to quantify the improvement

using conventional network metrics and to show the relation between a higher overall utility value and parameters that directly affect the user experience, comparison with the algorithm of [8] in terms of Signal-to-Interference-plus-Noise Ratio (SINR) is also performed. Experimental results indicate that SINR is consistently improved with the use of the proposed algorithm.

The rest of the paper is organized as follows. Section 2 describes in detail the proposed algorithm. Fuzzy Inference for defining the algorithm parameters is outlined in Section 3. In Section 4, the performance of the proposed algorithm is evaluated through simulations. Finally, Section 5 contains conclusions and plans for future work.

2. Algorithm Outline

The main idea of the proposed algorithm is that users exchange information concerning their interference levels, using explicit MAC layer message exchange mechanisms. A transmitter sets its power level by considering not only its own SINR information, but also the negative impact in utility for other users caused from the greater interference that will come as a side effect of the increase in transmission power of that particular user. This functions as a counter-motive that prevents users from always increasing their transmission power towards the maximum valid level.

Assuming a system with a total of L user pairs in a spectrum band with K available channels, the SINR of the i th user pair, $i \in \{1, 2, \dots, L\}$ in the k th channel, $k \in \{1, 2, \dots, K\}$, is given by the following equation [8]:

$$\gamma_i(p_i^k) = \frac{p_i^k \cdot h_{ii}}{n_0 + \sum_{j \neq i} p_j^k \cdot h_{ji}}, \quad (1)$$

where p_i^k is the transmission power for user i on channel k , h_{ii} is the link gain between the i th receiver and the i th transmitter, $n_0 = 10^{-2}$ is the noise level, p_j^k , $j \in \{1, 2, \dots, L\}$, $j \neq i$, is the transmission power for all other users on channel k , and h_{ji} is the link gain between the i th receiver and the j th transmitter. It should be noted that $h_{ij} \neq h_{ji}$, since the first expresses the gain between the i th transmitter and the j th receiver and the latter expresses the gain between the j th transmitter and the i th receiver.

In the general case, the carrier frequency of a signal is varied; therefore the magnitude of the change in amplitude will also vary. The coherence bandwidth measures the separation in frequency after which two signals will experience uncorrelated fading. More specifically, in the case of frequency-selective fading, the coherence bandwidth of the channel is smaller than the bandwidth of the signal. Thus, different frequency components of the signal experience decorrelated fading. On the other hand, in the case of flat fading, the coherence bandwidth of the channel is larger than the bandwidth of the signal. Therefore, all frequency components of the signal will experience the same magnitude of fading. In the following analysis, a flat-faded channel without shadowing effects is assumed. For a flat-faded channel, there are no delay spread and no frequency selectivity, as mentioned previously. Thus, a single coefficient

is used for channel attenuation. Since the described channel is static, that is, the coefficient is fixed, the only attenuation present is the path loss. Therefore, in this particular case, h is strictly the channel attenuation or channel gain. In this paper, the environment is assumed to cause average-to-high loss (path loss exponent equals three, a value typical for indoor urban environments), thus the channel gain is $h_{ji} = d_{ji}^{-3}$, where d is the distance between the j th transmitter and the i th receiver.

In order to model the impact on utility for user i caused by the transmission of all other users, the notion of interference price is adopted from [8]. Interference price is defined as

$$\pi_i^k = \frac{\partial u_i(\gamma_i(p_i^k))}{\partial (\sum_{j \neq i} p_j^k \cdot h_{ji})}, \quad (2)$$

where $u_i(\gamma_i(p_i^k)) = \theta_i \log(\gamma_i(p_i^k))$ is the logarithmic utility function and θ_i is a user-dependent parameter. As shown, the interference price expresses the marginal utility degradation due to a marginal increase in sustained interference. Interference prices are exchanged between the users in a completely asynchronous fashion, while every user is able to update its own price and power level at different times. Each user selects an appropriate transmission power level in order to maximize the difference between the increase in its own utility minus the utility degradation for others, caused by the increased interference as expressed by the interference price. Specifically, the mathematical formula that [8] attempts to maximize is

$$u_i(\gamma_i(p_i^k)) - p_i^k \sum_{j \neq i} \pi_j^k \cdot h_{ji}. \quad (3)$$

The first part of this equation is closely related to the Shannon capacity for user i (the constant term is excluded in order to have a form that can be proved to converge in all cases [8]). Increasing that part is directly related to an increase in the maximum bit rate. However, since the transmission of every user is considered as noise by the other users, the second term expresses the utility loss of the other users if user i increases its transmission power level.

The algorithm is comprised by the following steps.

- (1) *Initialization*: For every user $i \in \{1, 2, \dots, L\}$ transmitting in channel k , select a valid transmission power level p_i^k and a positive value for the interference price π_i^k .
- (2) *Power Update*: For every user i at a time interval $t_{ai} \in T_i$, where T_i is a set of positive time instances in which the user i will update its transmission power level and $t_{a1} \neq t_{a2} \neq \dots \neq t_{ai}$, set p_i^k to maximize (3).
- (3) *Interference Price Update*: For every user i at a time interval $t_{bi} \in T'_i$, where T'_i is a set of positive time instances in which the user i will update its interference price and $t_{b1} \neq t_{b2} \neq \dots \neq t_{bi}$, calculate and announce the updated interference price π_i^k and notify the other users for the updated value.

Steps (2) and (3) are repeated asynchronously for all users until the algorithm reaches its final steady state. In order to perform the power update of step (2), users select p_i^k from the set TP of the allowable transmission power levels, so that the surplus of (3) is maximized. Provided that the allowable power levels are equidistant values with each one being derived from its previous by adding a constant increment, then it can be proved that the algorithm converges, as long as the increment is sufficiently small. Moreover, if the problem is partitioned so that there is a single available spectrum area, or the algorithm is executed only for subgroups selecting the same spectrum area M , then it converges to a global maximum under arbitrary asynchronous updates [8].

In order to execute the algorithm, every user in the network needs to know its own SINR value and channel gain as well as the channel gains and the interference prices announced by other users. The SINR and the channel gain between a user pair can be calculated at the receiver and forwarded back to the transmitter. The channel gains between users can be calculated if receivers periodically broadcast a beacon [9] (h_{ii} message between Receiver i and Transmitter i in Figure 1). This information can also be provided on demand through a specially defined message sent from the receiver. Thus, in case the transmitter requires channel gain information before the reception of the next scheduled beacon, it can request this information from the receiver who will respond with the relative measurements. Finally, interference price values can be also conveyed in the same manner (message π_{ij} from Receiver i to Transmitter j in Figure 1). Every user announces a single interference price, therefore the delay that is introduced by the algorithm scales linearly with the number of users. This also implies that, given the fact that the updates are distributed in an asynchronous manner, the complexity of the algorithm is polynomial to the number of users and available power levels (that depend on the size of the increment in the Power Update step).

In the original version of the algorithm of [8], an underestimation of the interference prices is likely to occur in some cases. This can be caused by problems in message exchange, for example, due to users' mobility or increased update time intervals for the interference prices, considering that updates are asynchronous for all users. The effect of this underestimation is the convergence of the algorithm to a nonoptimal solution. Moreover, as the number of user pairs increases, the highest allowable transmission power level is more likely to be chosen, since the previous problems escalate. This is not desirable, since it will often result in increased interference to a potentially large number of neighboring users, especially in the case that the interference is underestimated for the reasons mentioned above.

Therefore, in this work, a coefficient " α " is introduced in order to improve the scalability of the algorithm in case a large number of users are sharing the same spectrum band and to cope with uncertainties, such as large update intervals and problems in the message exchange mechanism. In both cases, there is a danger that the impact of the interference on other users due to the increase in transmission power

FIGURE 1: An example network topology with four transmitter-receiver pairs.

will be underestimated as explained above. Thus, factor α needs to avert this scenario by increasing the weight of the second term of (3), which expresses the utility loss other users will experience from a transmission power increase. In such cases, it will compensate for the underestimation of interference, by increasing the value of the second term and, therefore, it can result in a system that approximates the case of “perfect” message exchange (without long delays, reduced message range, etc. that reduce the second term in (3)).

If coefficient α is included as a weight multiplied with the subtracted interference term, then the following equation is derived, that is the objective to be maximized:

$$u_i(p_i^k) - \alpha \cdot p_i^k \sum_{j \neq i} \pi_j^k \cdot h_{ji}. \quad (4)$$

In a “real” protocol implementation, parameters such as the storage requirements and scalability of the message exchange mechanism should be addressed. Moreover, the overhead and delays introduced by message exchange should be taken into consideration together with parameters such as timeliness and path optimality (for increased reliability in message transmission). However, the performance of the original version of the algorithm in [8] was shown not to degrade sharply in case the message exchange is imperfect (e.g., if the nodes can only exchange messages with their closest neighbors up to a specific range, or if some messages are lost). This characteristic is the outcome of the fact that,

in the case of imperfect message exchange, the algorithm gracefully degrades towards the “worst case” scenario of unregulated transmission with the maximum allowable power level, as the value of the subtracted term is gradually underestimated in (3). The term “graceful degradation” refers to that fact that when a certain number of messages are lost, the performance of the system does not drop sharply towards the worst case. This characteristic is greatly desirable for systems that operate in faulty or unreliable environments (e.g., [10]). In this work, the previous property is further improved with the introduction of coefficient α that provides the capability to handle uncertainties.

3. Fuzzy Inference

Fuzzy logic is well suited for the purpose of defining the value of factor α since it can address vague and unclear requirements efficiently and the system can be easily fine-tuned to exhibit the desirable behavior. Fuzzy logic is based on fuzzy set theory, in which every object has a grade of membership in various sets. Inputs are mapped to membership functions or sets (fuzzification process). Knowledge of a restricted domain is captured in the form of linguistic rules. Relationships between two goals are defined using fuzzy inclusion and noninclusion between the support and hindering sets of the corresponding goals [11]. As a last step, the required output is defuzzified (to numerical) from the “THEN” part of the rules in order to produce the consequent.

An important advantage of fuzzy logic is that it can be applied transparently in combination with other well-known decision methods, such as multiobjective genetic algorithms [12] and game theoretic approaches [13]. Moreover, proper definition of the linguistic rules can be used to reduce signaling overhead by avoiding the ping-pong phenomenon, that is, when decisions or selections are made and the input variables are not constant but temporarily present regressive behavior. Network-related decision making and resource allocation based on fuzzy logic approaches have been proposed in various works, such as [14], with promising results.

For the previous reasons, but mainly due to its effectiveness in dealing with uncertainties and vague requirements, fuzzy logic was selected for defining the value of coefficient α , that is, the weight of the subtracted interference-related term in (4). Specifically, α is defined as:

$$\alpha = \frac{1}{\beta} \cdot IW + \gamma, \quad (5)$$

Where IW is the Interference Weight derived after defuzzification. IW takes values in the range $(\beta_{\min} - \beta_{\max})$ in order to provide adequate resolution capabilities for the fuzzy reasoner, also according to the specific ranges of the membership functions. Parameter β has the value of $\beta_{\max}$, while γ equals 1. This implies that α cannot be greater than two, meaning that the underestimation of the interference is not expected to be greater than 100%. Beyond that point, message exchange is not considered very reliable and the algorithm degrades towards the “always transmit with the maximum power” case (although a portion of the underestimation is still alleviated). On the other hand, if uncertainties are very low, the first term of the sum is converging to zero and the value of the equation is approximately equal to that of the original algorithm. For all other cases the first term is a nonzero value in the (0,1) interval that compensates for a typical underestimation of the interference due to imperfect message exchange.

The fuzzy reasoner used for deriving α is of type “Mamdani”, because it is intuitive, well suited for human input, flexible, and widely accepted. It receives three inputs (number of users, mobility level, and update time interval for the interference prices) and generates one output (the Interference Weight). The input membership functions are triangular (selected mainly for simplicity in calculations) and three membership functions per input variable are defined, therefore the number of fuzzy rules is $3^3 = 27$.

The membership functions for the output variable “Interference Weight” are five and the output value is set in the range (0–500), in order to achieve a greater degree of resolution and flexibility for the output of the fuzzy reasoner. The membership functions mf1–mf5 are given the labels “very low”, “low”, “moderate”, “high” and “very high”, respectively, in Table 1.

As can be seen, the number of users is selected to be the dominant factor, which has the greatest effect in the final outcome. This is a result of the fact that if the number of users is large, even a small increase in the transmission power of a user has the potential to cause increased interference

TABLE 1: Rules of the fuzzy reasoner.

Rule number	Users	Update interval	Mobility level	Consequent
1	Low	Low	Low	Very low
2	Low	Low	Moderate	Very low
3	Low	Low	High	Low
4	Low	Moderate	Low	Low
5	Low	Moderate	Moderate	Low
6	Low	Moderate	High	Low
7	Low	High	Low	Low
8	Low	High	Moderate	Low
9	Low	High	High	Moderate
10	Moderate	Low	Low	Low
11	Moderate	Low	Moderate	Low
12	Moderate	Low	High	Moderate
13	Moderate	Moderate	Low	Moderate
14	Moderate	Moderate	Moderate	Moderate
15	Moderate	Moderate	High	High
16	Moderate	High	Low	Moderate
17	Moderate	High	Moderate	High
18	Moderate	High	High	High
19	High	Low	Low	Moderate
20	High	Low	Moderate	High
21	High	Low	High	High
22	High	Moderate	Low	High
23	High	Moderate	Moderate	High
24	High	Moderate	High	Very high
25	High	High	Low	High
26	High	High	Moderate	Very high
27	High	High	High	Very high

and reduce the QoS to a large number of users if its effect is underestimated due to uncertainties in message exchange. The update time interval and the mobility level have similar weights but different behaviors. The first has a uniform effect over the entire valid range of update times; while the latter starts to affect the outcome only after a relatively high level, but after which it increases sharply, as only after a relatively high level of mobility is reached, users are likely to underestimate the interference they will cause to others (due to problems in message exchange, etc.).

The Defuzzification method used for generating the final crisp value is “Centroid”, also known as “Center of Gravity (COG)”. This method determines the center of the area below the combined membership function; therefore the final output u_{COG} is given from (6), where u_i are the centers of the membership functions $\mu_F(u)$:

$$u_{\text{COG}} = \frac{\sum_{i=1}^{27} u_i \cdot \mu_F(u_i) du}{\sum_{i=1}^{27} \mu_F(u_i) du}. \quad (6)$$

The defuzzification method takes into account the area as a whole, counting overlapping regions only once.

FIGURE 2: Interference weight as a function of the update interval and the mobility level.

FIGURE 3: Interference weight as a function of the update interval and the number of users.

The three-dimensional (3D) representation of the Interference Weight (crisp value in the range (0–500)) as a function of the interference price update time interval and the mobility level is presented in Figure 2.

The coefficient increases with the update time interval as it is more likely that transmitters do not have the updated interference price information for other users. The increase is approximately uniform for the entire valid update time range. On the other hand, the coefficient also increases as the level of mobility increases. However, in this case the increase is not uniform but begins after a relatively high mobility level is reached and then rises quickly. The exhibited behavior is the outcome of the fuzzy rules defined in Table 1.

The 3D representation of the Interference Weight derived from the specified rule base and defuzzification method as a function of the interference price update time interval (defined as up to 100 seconds but normalized in the (0–1) range) and the number of users (up to 20 user pairs) is presented in Figure 3.

For the update time interval, the behavior is similar to that in the previous case. On the other hand, the coefficient also increases with the number of users. The increase is rather sharp (as determined by the rules in Table 1) and the value of the coefficient is rising quickly even for a relatively small

FIGURE 4: Interference weight as a function of the mobility level and the number of users.

number of users. This is necessary because, as mentioned previously, when the number of user pairs is large, even a small increase in interference has the potential to affect many users and significantly decrease the overall utility of the network.

The 3D representation of the Interference Weight as a function of the number of users and the mobility level, depicted in Figure 4, is presenting for both parameters the behavior explained above. The overall form of the figure resembles the previous; however the mobility level is starting to affect the outcome only after a threshold is crossed, as expected according to the selected set of fuzzy rules.

The overall methodology for the derivation of the optimal transmission power of every user pair is depicted in Figure 5. Initially, the number of user pairs is defined, together with the mobility level and the update time interval for the interference prices. As a next step, fuzzification of the values takes place in order to prepare them for elaboration in a fuzzy logic context. Following the fuzzification process, fuzzy reasoning based on a set of predefined rules (Table 1) is applied. These rules describe the desired behaviour of the system and define the impact of the input parameters (number of users, mobility level, and update time interval) in the value of the Interference Weight. After fuzzy reasoning is completed, the result is defuzzified to numerical, giving the crisp value of the Interference Weight. The topology characteristics are used to initialize the simulator and every user selects a valid initial value for the transmission power level p_i^k and the interference price π_i^k . Finally, the users proceed to update their transmission power levels and interference prices asynchronously in order to maximize (4). The process is completed when the system reaches a steady point in which no user is requesting to modify its transmission level.

4. Performance Evaluation

The performance of the proposed algorithm is evaluated through extensive MATLAB simulations. In this direction, the overall utility value of the algorithm is initially compared to the utility of a simple “always select the maximum

FIGURE 5: Overall methodology for deriving the transmission power levels.

valid power” policy as well as the utility of the original algorithm. The proposed algorithm is also applied in both FBMC and OFDM systems in order to validate its flexibility and capability of transparently exploiting an improved Physical layer, without any further modifications. Moreover, a scenario of long update time intervals in which some of the messages are delayed causing other nodes to not have the latest interference price information is considered, in order to study the performance of both algorithms in a specific case of nonideal message exchange. Finally, in order

to quantify the improvement using conventional network metrics and to show the relation between a higher overall utility value and parameters that directly affect the user experience, comparison with the algorithm of [8] in terms of SINR is also performed.

As explained previously, users set their power level so as to maximize (4). The total “useful” utility for the network is the sum of the utilities for every user pair. The distance between users that constitute a pair is a random number in the (1–20) meters range, while the distance between users

FIGURE 6: Utility values for the proposed algorithm, the always transmit with the maximum valid power scenario and the original algorithm without coefficient α for (a) 10 and (b) 20 user pairs.

that are not a pair is a random value in the [5, 50] meters range. This is a more common and more practically significant scenario than using entirely random values, (e.g., it is often encountered in a conference room as well as an airport or train station, where coworkers are initiating a point-to-point ad hoc communication). The value of β in (5) is set to 500, since the Interference Weight takes values in the range (0–500), in order to provide adequate resolution capabilities. For all cases we assume the presence of uncertainties due to imperfect message exchange (one in every four messages is lost) that cause 25% underestimation of the interference. If such uncertainties are not present, then the algorithm behaves similarly to the algorithm of [8]. In the presence of uncertainties, parameter α compensates for the underestimation of interference and helps the system converge near its optimal point, as described in the previous sections.

The improvement in the total utility of the network if the proposed algorithm is utilized over the scenario in which every user transmits using the maximum allowable power level as well as over the original version of the algorithm that does not include the coefficient α , is depicted in Figure 6. The vertical axis depicts the achieved useful utility while the horizontal axis represents the corresponding topology instance. The considerable range over which the distance values are selected, coupled with the randomness of the relative positions between nodes and the presence of uncertainties that cause underestimation of the interference in ways that are not necessarily uniform (e.g., only some messages may be delayed), causes the final value of the utility function to vary significantly between different experiments both for the original and the proposed algorithm. Thus, the final utility of each topology instance is the average utility of ten experiments for the same instance. Finally, in order to study the effect of the number of users on the system, a scenario of 10 user pairs and 20 user pairs was simulated.

The utility for the scenario in which the users transmit always using the maximum power level defines the lower bound for the behaviour of the system. The proposed algorithm outperforms the original one, for the majority of times, with a more significant improvement for the lower utility values. This property is very important since it can improve the Bit Error Rate (BER) and raise QoS from poor to acceptable levels. Furthermore; the proposed algorithm always outperforms the always maximum power scenario, while the original algorithm in some cases results in similar performance. The reason for this is that the existence of the coefficient α in the proposed algorithm does not allow the system to reach the worst case of completely unregulated transmission since it always compensates for at least a portion of the underestimated interference. Another interesting point is that as the number of users increases, the average utility of the system decreases although extreme values are not affected significantly. This is justified by the fact that the interference exhibits a cumulative behavior that affects all other user pairs, therefore reducing the average utility. However, extreme values are mainly the outcome of the topology and the relative distance of the user pairs, thus, are less sensitive to the number of users.

The next step is to compare the results of the proposed algorithm using OFDM and FBMC systems. However, a short outline of the FBMC technique is required. According to the principle of transmission based on filter banks, the transmitter incorporates a Synthesis Filter Bank (SFB) while the receiver incorporates an Analysis Filter Bank (AFB). In the structure, the Fast Fourier Transform (FFT) is present as in OFDM [15]. It is however augmented, to complete a filter bank, by the Polyphase Network (PPN) which is comprised of a set of digital filters, whose coefficients globally form the impulse response of the so-called prototype low-pass filter. FBMC systems have somewhat increased hardware

FIGURE 7: Utility function for the proposed algorithm with FBMC and OFDM.

complexity compared to the classical OFDM approach but compensate for this with a number of advantages. Among others, they do not require guard time and cycle prefix, while the use of Offset QAM (OQAM) implies that the full capacity of the transmission bandwidth is achieved. The improvement in the total utility of a network consisting of ten user pairs if the proposed algorithm is used with FBMC over OFDM is depicted in Figure 7.

This improvement stems from the fact that FBMC uses lower transmission power for the same bandwidth compared to OFDM [16] and therefore causes reduced interference. The proposed algorithm is able to transparently exploit this improvement and translate it in increased utility values.

To evaluate the resilience of the algorithm in the presence of long update time intervals we perform simulations with the assumption that some of the messages are delayed and, consequently, other nodes do not have the latest interference price information that has been announced. Thus, the definition of “long update times” that we consider in this work is to be at least equal to twice the average update time (so that other nodes have updated the announced interference price in this interval). Since it is already established that transmitting with the maximum power is the lower bound of performance for both the original and the proposed algorithm, in this scenario, we evaluate the behaviour of the original and the proposed algorithm with both FBMC and OFDM in order to study the effect of increased delays on each of these cases.

The first point that is noteworthy is the fact that the improved Physical layer of FBMC in this scenario provides a significant advantage that even surpasses the advantage offered by the proposed algorithm. Therefore, using FBMC with the original algorithm is better for this case than using OFDM with the proposed algorithm. The best option is to use the proposed algorithm with FBMC, combining the advantage of improved Physical layer capabilities

FIGURE 8: Utility values for the original and the proposed algorithm with both FBMC and OFDM, under the assumption of long message delays (10 user pairs).

and improved upper-layer functions. Regarding the latter point, the proposed algorithm consistently outperforms the original one when both use the same Physical layer (FBMC) under the assumption of long delays. Furthermore, if we juxtapose Figure 8 with Figure 6 we can derive some additional conclusions. Specifically, although the average utility values are reduced for all algorithms, the proposed algorithm is not affected as much as the original from the increased delays, thus the property of “graceful degradation” is indeed enhanced. Since real systems usually have to cope with nonideal conditions, this property is highly desirable.

Finally, it is very important to quantify the performance improvement in terms of conventional network metrics to show the relation between a higher overall utility value and parameters that directly affect the user experience. Since the main comparison is between the original algorithm and the proposed one, their behaviour in terms of SINR is compared in Figure 9. SINR is chosen as the most appropriate metric for comparison as it reflects directly on the QoS and the final user experience and can also be compared without considering external parameters, such as modulation and coding schemes that will impact for example the final BER of the system. The two graphs are following a similar pattern but the proposed algorithm consistently outperforms the original when the interference is underestimated, as it compensates for the interference underestimation and raises SINR to acceptable levels, especially for the lower values.

Regarding the overall simulation time and scalability properties of the algorithm, for all cases, the number of iterations for convergence is comparable to the number of user pairs. More specifically, for 10–30 user pairs usually less than thirty and up to fifty iterations are required for reaching the final steady state. Furthermore, the average execution time on a Core2 Quad Q9400 CPU operating at 2.66 GHz is less than two minutes for up to 20 user pairs and approximately five minutes for up to 30 user pairs.

FIGURE 9: SINR for the original and the proposed algorithm under 25% underestimation of interference.

5. Conclusion

In this paper, an improved algorithm, based on the algorithm of [8], was presented for cooperative DSA in unlicensed bands, utilizing MAC layer mechanisms for message exchange (interference prices) between the secondary nodes in order to achieve interference mitigation. The main improvement in this work compared to [8] is the introduction of a coefficient α that is serving as the weight of the interference term, increasing its impact in cases of imperfect message exchange, long update time intervals for interference prices, as well as increased number of users. In such cases, the interference that is caused to other user pairs by an increase in the transmission power of a user is often underestimated, resulting in a convergence of the algorithm to a nonoptimal solution. In the presence of such uncertainties, if this underestimation is compensated by a properly defined weight parameter, the system approximates its optimal behavior as in the case of “perfect” message exchange.

The value of the weight parameter was derived from a fuzzy logic reasoner. Fuzzy logic was selected because it is particularly effective in dealing with uncertainties and vague requirements. Moreover, the outcome of the proposed algorithm has been compared to the original algorithm in terms of the overall utility level (defined as the sum of the user utilities) under uncertainties that cause 25% underestimation of interference. Furthermore, comparison was also made between the proposed algorithm in FBMC and OFDM systems. In this case, using FBMC increased the achieved utility. The improvement stems from the fact that FBMC uses lower transmission power for the same bandwidth compared to OFDM and therefore causes reduced interference. Additionally, a scenario of long update time intervals in which some of the messages are delayed causing other nodes to not have the latest interference price information was considered, and the performance of both

algorithms in a case of nonideal message exchange was evaluated. Results indicate that the algorithm consistently outperforms previous schemes in terms of SINR under uncertainties and can transparently exploit the improved Physical layer offered by FBMC.

Acknowledgments

This work was performed in Project PHYDYAS which has received research funding from the Community’s Seventh Framework program. This paper reflects only the authors’ views and the Community is not liable for any use that may be made of the information contained therein. The contributions of colleagues from PHYDYAS consortium are hereby acknowledged.

References

- [1] P. Pawelczak, S. Pollin, H.-S. W. So, A. Bahai, R. Prasad, and R. Hekmat, “Quality of service assessment of opportunistic spectrum access: a medium access control approach,” *IEEE Wireless Communications*, vol. 15, no. 5, pp. 20–29, 2008.
- [2] F. Wang, M. Krunz, and S. Cui, “Price-based spectrum management in cognitive radio networks,” in *Proceedings of the 2nd International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CrownCom ’07)*, pp. 70–78, August 2007.
- [3] L. Ma, X. Han, and C.-C. Shen, “Dynamic open spectrum sharing MAC protocol for wireless ad hoc networks,” in *Proceedings of the 1st IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN ’05)*, pp. 203–213, November 2005.
- [4] L. Cao and H. Zheng, “Distributed spectrum allocation via local bargaining,” in *Proceedings of the 2nd Annual IEEE Communications Society Conference on Sensor and Ad Hoc Communications and Networks (SECON ’05)*, pp. 475–486, September 2005.
- [5] C. Peng, H. Zheng, and B. Y. Zhao, “Utilization and fairness in spectrum assignment for opportunistic spectrum access,” *Mobile Networks and Applications*, vol. 11, no. 4, pp. 555–576, 2006.
- [6] J. Zhao, H. Zheng, and G.-H. Yang, “Distributed coordination in dynamic spectrum allocation networks,” in *Proceedings of the 1st IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN ’05)*, pp. 259–268, November 2005.
- [7] M. Bloem, T. Alpcan, and T. Basar, “A stackelberg game for power control and channel allocation in cognitive radio networks,” in *Proceedings of the 2nd International Conference on Performance Evaluation Methodologies and Tools*, Nantes, France, October 2007.
- [8] J. Huang, R. A. Berry, and M. L. Honig, “Spectrum sharing with distributed interference compensation,” in *Proceedings of the 1st IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN ’05)*, pp. 88–93, November 2005.
- [9] J. Huang, R. A. Berry, and M. L. Honig, “Distributed interference compensation for wireless networks,” *IEEE Journal on Selected Areas in Communications*, vol. 24, no. 5, pp. 1074–1084, 2006.
- [10] O. A. Rawashdeh, “Towards decentralized management of graceful degradation in distributed embedded systems,” in

Proceedings of IEEE Dependable Systems and Networks Conference (DSN '08), Anchorage, Alaska, USA, June 2008.

- [11] C. Carlsson and R. Fullér, "Fuzzy multiple criteria decision making: recent developments," *Fuzzy Sets and Systems*, vol. 78, no. 2, pp. 139–153, 1996.
- [12] S. Buljore, M. Muck, P. Martigne, et al., "Introduction to IEEE P1900.4 activities," *IEICE Transactions on Communications*, vol. E91-B, no. 1, pp. 2–9, 2008.
- [13] W. Wei and M.-J. Wang, "Fuzzy-MOGA-based traffic signal control at intersection," in *Proceedings of the International Conference on Machine Learning and Cybernetics*, vol. 1, pp. 639–644, November 2003.
- [14] A. Merentitis, E. Patouni, N. Alonistioti, and M. Doubrava, "To reconfigure or not to reconfigure: cognitive mechanisms for mobile devices decision making," in *Proceeding of the 68th IEEE Vehicular Technology Conference (VTC '08)*, pp. 1–5, September 2008.
- [15] H. Zhang, D. Le Ruyet, and M. Terre, "Spectral efficiency comparison between OFDM/OQAM- and OFDM-based CR networks," *Wireless Communications and Mobile Computing*, vol. 9, no. 11, pp. 1487–1501, 2009.
- [16] D. S. Waldhauser, L. G. Baltar, and J. A. Nossek, "Filter bank based multicarrier systems," in *Proceedings of Techniken, Algorithmen und Konzepte für Zukünftige COFDM Systeme (TakeOFDM '08)*, 2008.