Spectral Handoff in Cooperative Cognitive Radio Networks

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***Abstract* - Depending on the targeted wireless application, a collaborative spectrum allocation strategy may offer additional advantages over a non-collaborative strategy. The challenge lies in combining the information received from users organized in a collaborative manner. The purpose of the present article is to propose a collaborative spectrum allocation model for a decentralized cognitive radio network. In this sense, the cognitive radio user shares his information with other neighboring network users. The shared information is characterized through five levels of collaboration (10%, 20%, 50%, 80% and 100%) where each one represents the percentage of information that is to be shared for training and subsequent model validation. The comparative assessment is carried out with the decision-making multi-criteria algorithms SAW and TOPSIS. The results reveal that the SAW algorithm outperforms the alternatives under different scenarios and collaboration levels in terms of the handoff metric.**

Keywords - Cognitive Radio Networks; Cooperative; GSM; Handoff; SAW; TOPSIS.

I. INTRODUCTION

The increasing use of wireless applications poses new challenges in the future of communication systems. Cisco states that the traffic from mobile data has grown 18 times over the past 5 years and it is expected that the total traffic of mobile data reaches 49 exabytes per month in 2021 [1]–[6]. This particular scenario and given that current allocation policies are fixed and regulated by the state [7], have led to overall scarcity in the radio-electric spectrum. However, the results show that certain bands between 50 and 700 MHz, are being underused since their duty cycles are practically non-existent. In these bands, spectral usage times remain below 10% [8], in contrast with other bands which are normally saturated and allocated to cellphone networks.

Cognitive Radio (CR) is defined by the International Telecommunications Union (ITU) as “a radio or system that is aware and detects its surroundings and that can be adjusted dynamically and autonomously according to its radio operation parameters”. Its solution consists on Dynamic Spectrum Access (DSA), achieving an opportunistic and intelligent use of the frequency spectrum. Hence, an unlicensed cognitive radio user (Secondary User – SU) can take over an available licensed band, yet he must release said channel and seek another one whenever: 1. a primary user (PU) needs to occupy the same channel, 2. when the quality of the channel is downgraded by the SU or 3. when the mobility of the SU leaves him outside of the coverage area. Seeking a new channel or spectral opportunity (often called white space or spectral hole) in order to proceed with transmission is known as spectral handoff (SH) [9]–[13]. This gives CR the capacity to provide large bandwidth (BW) share to the SU, through heterogeneous wireless architectures.

Centralized networks are architectures with an infrastructure controlled by a central coordinator. The information visualized by each SU feeds the central base, so it can make decisions to maximize communication parameters. However, this may not be the best option for large scale systems and public safety network applications. The increase in measuring costs, the complexity of the system, as well as the unbalance and potential chaos derived from possible failures (vulnerability) in the base station, turn this architecture into an unfeasible option for all CRN structures [14]. The problem can be solved by distributing the responsibility of the information among different control points, which are a crucial criterion in decentralized cognitive radio networks (DCRN).

The focus of this research consists on establishing the decision-making process for a DCRN, by giving the nodes the capacity to learn from the environment and propose new strategies that enable SU to exchange information in a collaborative manner. The above is achieved from the analysis of the history of the spectral occupation data and the behavior of decision criteria such as the probability of availability, the average time of availability, the signal to noise ratio and the bandwidth of each frequency channel.

Collaborative strategies have delivered new models to support the efficient use of radio resources and the decision-making process in CRN. In collaborative decision-making, users communicate between each other by exchanging availability and interference measurements, among other information retrieved locally. Seeking to harness spatial diversity, unlicensed users share their information with neighboring users [15]. The information shared is characterized with the definition of five collaboration levels (10%, 20%, 50%, 80% y 100%), where each one represents the percentage of information that is to be shared for training and subsequent model validation. The collaborative approach offers additional advantages over its non-collaborative counterpart. One of the challenges in spectrum allocation relates to how to combine the information from users organized in a collaborative manner while maintaining transmission [16].

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This article presents a comparative assessment of Simple Additive Weighting (SAW) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) which are two multi-criteria decision-making algorithms most used in a Global System for Mobile communications (GSM) DCRN [17]–[22]. Both algorithms are assessed and compared in terms of the average number of handoffs generated during a 9-minute of data transmission using the same amount of data. The comparison is carried out in four different scenarios, depending on the type of service (real time and better effort) and the traffic level (low and high): real time (RT) with high traffic (HT), better effort (BE) with low traffic (LT), RT with LT and BE with HT. The main contribution of the present work is to include different collaboration levels (10%, 20%, 50%, 80% and 100%) between secondary users who share space-time data regarding the spectral occupation that ultimately feeds the database of the decision-making algorithms.

The rest of the document is structured as follows. Section II shows a description of the simulation environment.. Section III presents the results obtained in the comparative analysis of the performance evaluation for the proposed algorithms. Finally, conclusions are drawn in Section V.

II. Methodology

For the comparative assessment of multi-criteria decision-making strategies, a simulator was developed based on information retrieved from 551 channels. The test-validation technique is used for training and validation with an 83% - 17% proportion, which corresponds to 10800 training data and 1800 validation data, equivalent to 1 hour for training and 10 minutes for assessment. The information corresponds to real data captured in a metering campaign in the GSM frequency band.

The spectral occupancy data corresponds to a week of observation captured at Bogota City in Colombia. The energy detection technique was used to determine the occupation or availability of the analyzed GSM band, with a decision threshold for the power of 5 dBm above the noise power. To determine whether a frequency channel is busy or not, the proposed decision threshold is based on the average noise floor for the frequency band used. Thus, the average noise floor is -113 dBm and the decision threshold is set to -113 + 5 = -108 dBm.

Figure 1 presents the general structure of the implemented model. The simulator is comprised of four processing blocks. The first block is called the “collaborative block” which segments the power matrix into five collaboration levels and distributes it among SU. The second block known as “MCDM” includes all the mathematical models needed in the decision-making process for SAW and TOPSIS algorithms. The third block is the “Search Algorithm” which is a structure in charge of simulating and quantifying throughput characteristics. The block “Figure” builds the respective charts.

A. *Functions of the collaborative block*

For the specific description of the collaborative algorithm, the three functions must be analyzed that can segment the matrix. Figure 2 presents the specific block diagram of the collaborative model. The blocks where the input and output signals converge correspond to the functions of the algorithm. The first function is called “User Division” and is in charge of dividing the matrix according to the adjustments of the number of users (Number of user and User Full). The second block is comprised of two functions: User Zone Continuous and User Zone Random. These functions are in charge of selecting the block of users. The selection method is parameterized by the “Segmentation” variable. If the continuous selection method is chosen, the function “User Zone Continuous” will be in charge of the selection. If the random method is chosen, then the “User Zone Random” function performs the selection. The following sections describe the characteristics and adjustments of each input and output variable of the implemented collaborative model.

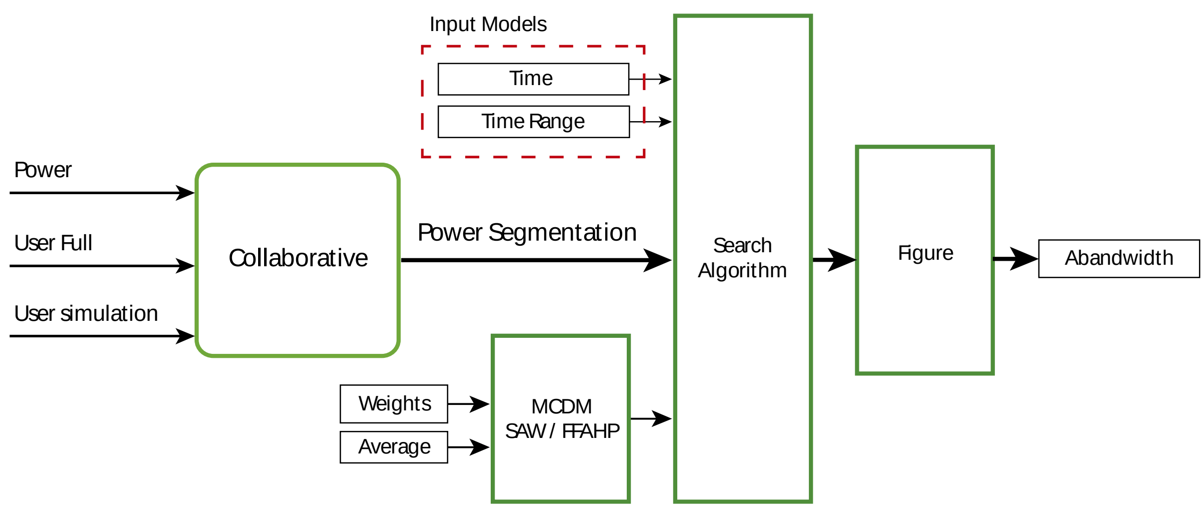

Figure 1. General structure of the model

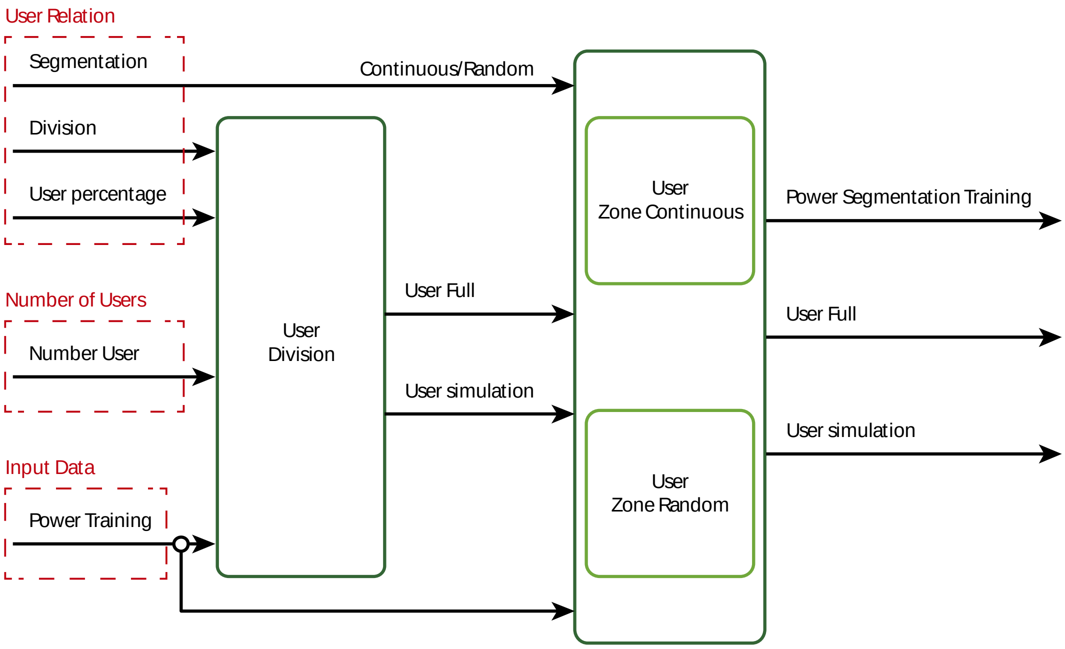

Figure 2. Functions of the collaborative block.

B. TOPSIS

This algorithm is based on two parts: the solution which cannot be accepted under any situation and the ideal solution of the system. The decision matrix X is initially built and normalized using the square root method discussed in (1) [17][23][24].

$$\tilde{X} = \begin{pmatrix} \tilde{\chi}_{11} & \cdots & \tilde{\chi}_{1M} \\ \vdots & \ddots & \vdots \\ \tilde{\chi}_{N1} & \cdots & \tilde{\chi}_{NM} \end{pmatrix} = \begin{pmatrix} \omega_1 \tilde{\chi}_{11} & \cdots & \omega_M \tilde{\chi}_{1M} \\ \vdots & \ddots & \vdots \\ \omega_1 \tilde{\chi}_{N1} & \cdots & \omega_M \tilde{\chi}_{NM} \end{pmatrix} \quad (1)$$

where ωi is the weight allocated to criterion i, and the sum of all weights must be equal to 1.

Afterwards, the ideal solution and the worst solution are defined as described in (2) and (3).

$$A^{+} = \left\{ \left(\max \tilde{\chi}_{ij} | j \in X^{+} \right), \left(\min \tilde{\chi}_{ij} | j \in X^{-} \right) \right\} = \left\{ \tilde{\chi}_{1}^{+}, \ldots, \tilde{\chi}_{M}^{+} \right\} \quad (2)$$

$$A^{-} = \left\{ \left(\min \tilde{\chi}_{ij} | j \in X^{+} \right), \left(\max \tilde{\chi}_{ij} | j \in X^{-} \right) \right\} = \left\{ \tilde{\chi}_{1}^{-}, \ldots, \tilde{\chi}_{M}^{-} \right\} \quad (3)$$

where i = 1…M, y X+ y X- are the set of benefits and costs, respectively.

Then, the Euclidian distance D is computed for each alternative as seen in (4) and (5).

$$D_{i}^{+} = \sqrt{\sum_{j=1}^{M} \left(\tilde{\chi}_{ij} - \tilde{\chi}_{j}^{+} \right)^{2}} \qquad i = 1, \ldots, N \quad (4)$$

$$D_{i}^{-} = \sqrt{\sum_{j=1}^{M} \left(\tilde{\chi}_{ij} - \tilde{\chi}_{j}^{-} \right)^{2}} \qquad i = 1, \ldots, N \quad (5)$$

Finally, the alternatives are organized in descending order based on the preference index given by (6).

$$C_{i}^{+} = \frac{D_{i}^{-}}{D_{i}^{+} + D_{i}^{-}}, \qquad i = 1, \ldots, N. \quad (6)$$

C. SAW

This algorithm builds a decision matrix comprised of criteria and alternatives. The algorithm assigns a weight to each intersection of the matrix based on the criterion set by the designer. This establishes a score for each assessed spectral opportunity (SO) and determines a ranking that includes all alternatives. The SO with the highest score is ultimately chosen [17][23][24]. In (7), $r_{i,j}$ belongs to the matrix and the sum of weights is equal to 1.

$$u_i = \sum_{j=1}^{M} \omega_i r_{i,j} \qquad \forall i \in 1, \ldots, N \quad (7)$$

The steps used to develop this algorithm were: (1) identifying the objectives and alternatives; (2) assess the alternatives; (3) determine the weights of each combination; (4) add the aggregated values based on preferences; and (5) analyze sensitivity [17].

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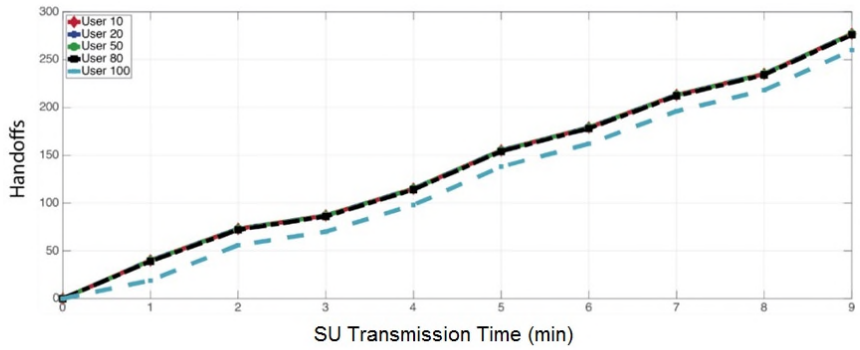
III. RESULTS

Two applications were considered during performance assessment: Real Time (RT) and Better Effort (BE) as well as two traffic levels: High Traffic (HT) and Low Traffic (LT), to create four types of scenarios: GSM RT HT, GSM RT LT, GMS BE HT and GSM BE LT. They were analyzed in terms of the average accumulative handoff (AAH) both for the SAW (Figure 3) and the TOPSIS algorithms (Figure 4).

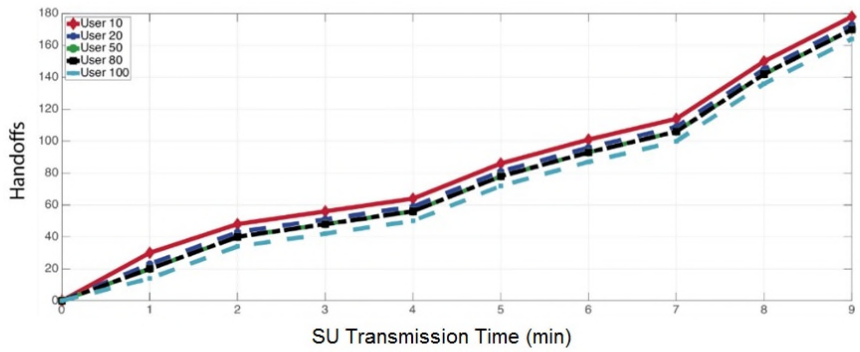
Figure 3 and Figure 4 show that there is a stronger variation of handoffs in LT than in HT. Another interesting finding is that the number of handoffs is fairly similar between BE and RT for the same traffic level, which undermines the importance of this variable within a spectral allocation model. It could also lead to redefining the operation of the chosen algorithm.

In the case of the SAW algorithm, the collaboration level of 100% reaches a reduction of 4.5% for RT-HT, 9.5% for RT-LT, 2.3% for BE-HT, and 16.3% for BE-LT.

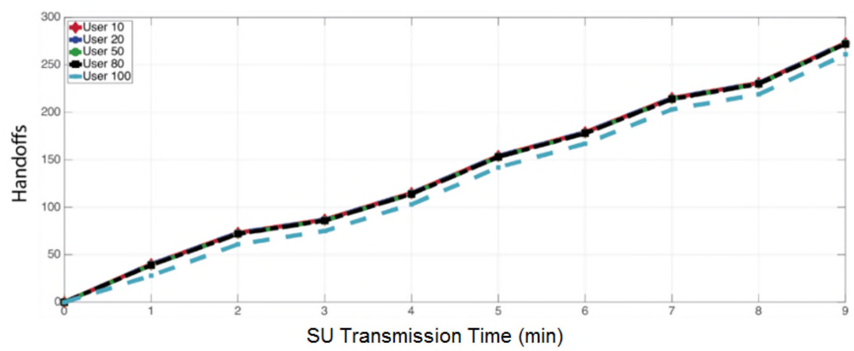
In the case of the TOPSIS algorithm, the collaboration level of 100% reaches a reduction of 2.1% for RT-HT, 3.9% for RT-LT, 6.4% for BE-HT, and 15.4% for BE-LT.



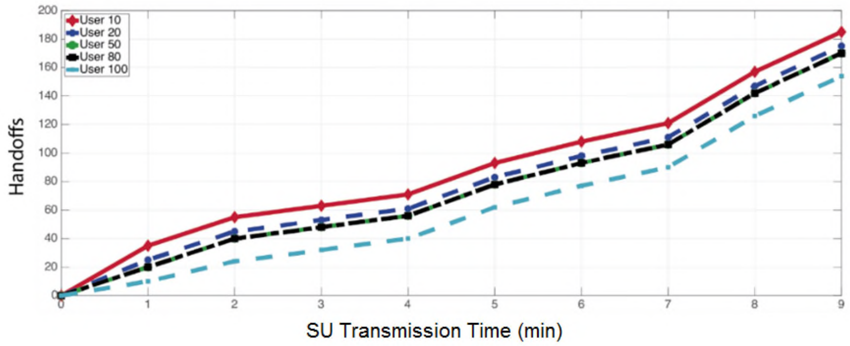
a. GSM RT HT



b. GSM RT LT

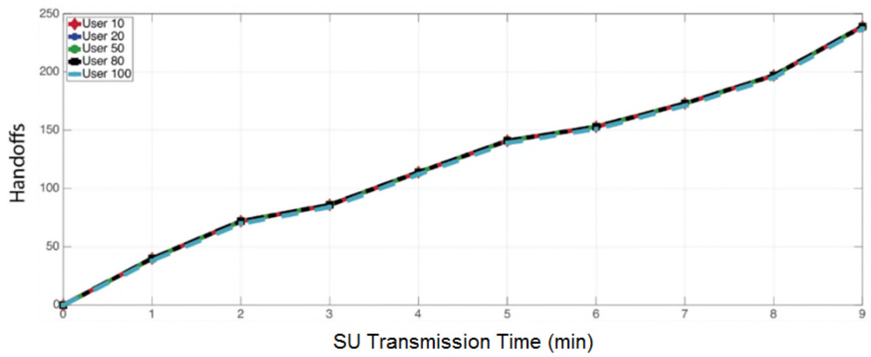


c. GSM BE HT

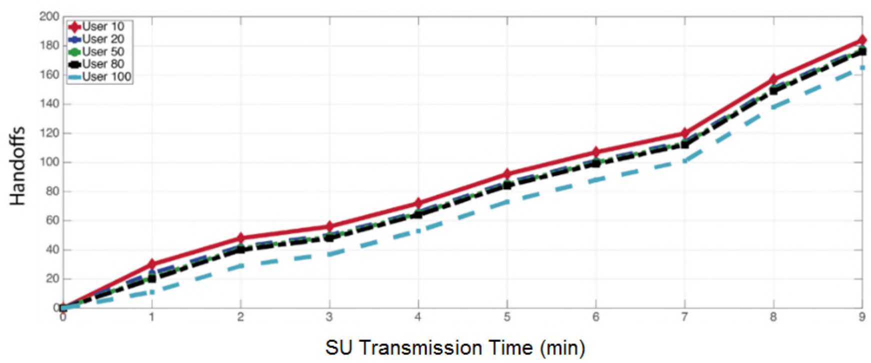


d. GSM BE LT

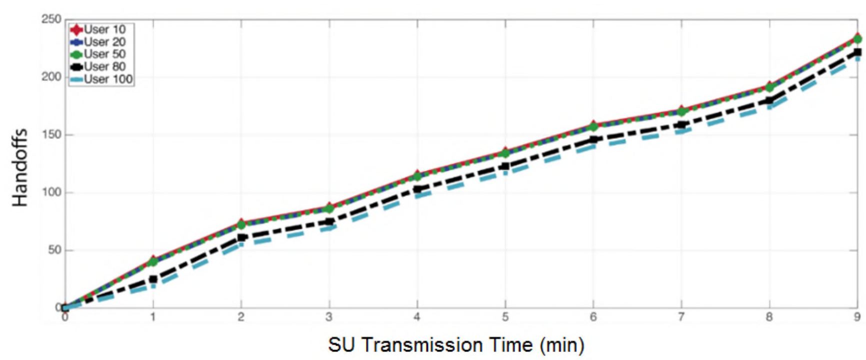
Figure 3. AAH in GSM for SAW algorithm



a. GSM RT HT



b. GSM RT LT



c. GSM BE HT

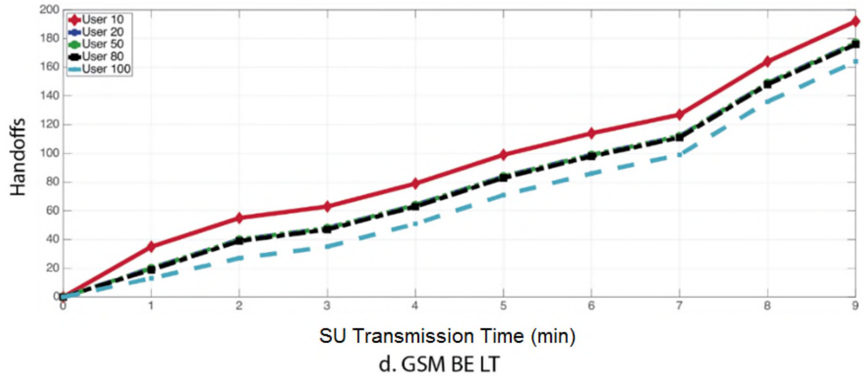


Figure 4. AAH in GSM for TOPSIS algorithm

The behavior of the handoffs and the failed handoffs are similar in the corresponding evaluation scenarios, with RT-HT presenting the least variation of handoffs at different levels of collaboration, in contrast to the BE-LT scenario, which experiences the greater variation. In general, low traffic scenarios experience a high variation, around 20%, compared to high traffic, whose variation is low, around 7%. It is also noted that collaboration has a greater impact on the TOPSIS algorithm compared to the SAW algorithm.

IV. CONCLUSIONS

A collaborative spectral assignment model was developed through the exchange of information between secondary users for two multi-criteria decision-making algorithms, SAW and TOPSIS. The comparative evaluation of these two techniques was carried out through the number of handoffs made during a 9-minute transmission.

The spectral decision-making algorithm affects the results obtained in terms of handoff. However, the differences are not significant compared to the ones obtained with the variation of the cooperation level. The cooperation level between secondary users has a higher incidence in better effort and low traffic applications.

When the secondary user chooses to access a channel, he should not only consider the quality of the channel, but also factor in the decisions to access channels incoming from other users.

As future work we propose the implementation of machine learning techniques and consider multi-user access to the spectrum.

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