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An AHP-TOPSIS Integrated Model for QoS-Aware Energy Efficiency in Green Cognitive Radio Networks

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ABSTRACT

The selection of the best spectrum band available to meet the quality of service requirements of secondary users without interfering with the transmission of the primary users is considered as a challenge in cognitive radio networks. On the other side, green network is a recent concept that refers to the processes used to optimize a network in order to make it more energy efficient. In this paper, we propose a new algorithm ensuring the selection of the best available spectrum satisfying the demands of the secondary users based on TOPSIS and AHP in OFDM-based cognitive radio networks. We will assess the need for the secondary users in terms of quality of service and energy efficiency, by analyzing the characteristics of the available channels and taking into account the interference generated with the presence of the primary user. It efficiently manages energy because it allows a significant reduction of the transmission power used by the secondary user and therefore presents an effective solution in green networking.

1. INTRODUCTION

A novel concept of green network (GN) has started its functions due to the need of better energy efficiency (EE) of cognitive radio systems. This is a new design that involves devices used to improve a network to make it more energy efficient, which will result a reduction in the amount of CO emitted by telecommunications infrastructures participating in the greenhouse effect.

The spectrum in cognitive radio (CR) is divided between primary users (PU) and secondary users (SU) that will optimize its use [1]. It can be said that the CR enables intelligent communication by adapting its transmission parameters according to the variations of the environment in which it operates. this provides good quality of service (QoS) and better energy efficiency.

OFDM (Orthogonal Frequency Division Multiplexing) is defined as an inviting modulation and transmission technique for CR because of its flexibility in spectrum shaping, its good spectrum management and its ability to better analyze the spectral activities [2]. OFDM is widely used in the literature. However, these studies have been limited to optimizing the transmission rate of SUs, limiting the interference introduced in PUs to predefined thresholds [2, 3].

Recently, research has increased on optimizing EE. Wang et al. [4] have improved the EE of the CR system by relying on OFDM exposed to the interference requirements of PUs and the distinct data rates of SUs. an algorithm was formulated by the authors to improve the EE of OFDM-based CR communication systems with sub-channel inconsistencies [5]. This optimization led them to certify a minimum required throughput and a specific power budget for the SU. Thangaraj and Aruna [6] have worked on energy-efficient resource allocation for an OFDM-based heterogeneous cognitive radio network (HCRN) in an imperfect spectrum sensing scenario with excellent QoS.

On the other hand, other research has focused on the optimization of QoS with multi-objective. Saoucha and Benmammar [7] have exploited firefly, bat, and cuckoo search algorithms to optimize the communication quality of the SU. Benmammar et al. [8] suggested applying to cognitive radio a parallel dynamic programming algorithm for multi-objective Pareto optimum maximization. The approach is used to choose the most compromising solution of the Pareto front. which makes the cognitive engine able to achieve perfect feedback results, compared to using metaheuristics and maximizing Qos. The reliability as well as the efficiency of artificial intelligence (AI) techniques is known to optimize the performance of a cognitive radio network (CRN) [9-11].

To allow a wireless multiple access channel Ostovar [12] propose a function to establish the presence of the main user and optimize the energy efficiency of cognitive radio systems for the calculation of the mathematical structure. The average throughput to average power consumption ratio was established to evaluate the network performance under detection constraints. the authors' objective is to minimize energy consumption and maintain detection accuracy by maximizing detection time by managing the constraints of transmission power and throughput.

Wang et al. [13] have treated the problem of average EE maximization for difficult decisions using hybrid spectrum sharing, in contrast a problem could arise, that of the average formulation of the maximum EE generated by the iterative optimization of the detection time and the number of cooperative SUs. This optimization is based on the following elements: the average transmission power of SUs, the peak transmission power, the data rate constraints and the average interference power constraint of PUs.

To manage energy efficiency, Mili et al. [14] have suggested decreasing the power of the secondary transmitter for location and spectrum sharing in fading moments. However, the additional channel state information (CSI) affecting the secondary antenna has also been studied in the context of spectrum sharing through closed form expressions for the relevant transmission power. It should be noted that there was a discussion about imperfect cross CSI containing a licensed band split between these primary and secondary links. Therefore, the distribution of power over the perfect and imperfect measure was minimized.

Khaled et al. [15] have addressed energy and security in a CR-based communication approach. Furthermore, user and network related factors are reconsidered such as the user's battery level and the type of user data as well as the number of unused bands and the level of vulnerability. Given the time complexity of the optimal solution, the authors have also provided a heuristic solution

In this context, we have already proposed an AI-based solution more precisely on reinforcement learning, which consists in using the Q-learning algorithm which will help cognitive users to find the optimal channel which has low power emission to reduce the energy consumption of these infrastructures and thus satisfy GN [16]. However, this work two limits; on the one hand the complexity of learning algorithms can affect energy consumption. On the other hand, learning poses a scalability problem with a fairly high number of channels.

Our contribution in this paper is to help the SU to select the most appropriate channel for opportunistic use according to the type of application data used during transmission while saving the consumed energy and avoiding interference with PU based on the information received from the spectrum sensing function. To achieve our goal, we proposed an algorithm based on TOPSIS (technique for order preference by similarity to ideal solution) due to its simplicity with moderate complexity/execution time. To optimize TOPSIS and determine the weighting criteria for each objective, analytic hierarchy process (AHP) method was used to assign the weight of each criterion.

The rest of this paper is organized as follows. In part 2, the OFDM-based cognitive radio environment is presented. Part 3 gives a description on our proposed algorithm whose objective is the QoS-aware energy efficiency optimization in OFDM-cognitive radio networks. In part 4, we present the results of the simulation. Finally, section 5 discusses final remarks and suggestions for future work.

2. SYSTEM MODEL

2.1 System description

In this paper, we are based on the same system used in [7], which consider that the PU and the SU share adjacent frequency bands as illustrated in Figure 1, where the PU occupies the central frequency band, while the free frequency bands detected by the SU are divided into N subcarriers whose two halves are on either side of the band used by the PU. We consider that the SU regularly scans the PUs spectrum for vacant bands for its transmission. The modulation scheme used by cognitive radios is OFDM.

Each subcarrier is characterized by its bit rate, transmission power, interference level and error rate. The choice of these parameters depends either on the capacity of the channel, or on the quality of service and energy efficiency. A channel can be selected for the transmission according to the type of application used by the SU during the transmission; we used 4 types of applications: voice, videoconference, email, transaction. Each application presents a need for either a high or minimal rate of the cited characteristics of the subcarriers, which will be evaluated using the TOPSIS method to ensure the selection of the best subcarrier available for the SU.

Figure 1 illustrates a coexistence model that will lead to the generation of mutual interference between the PU and the SU.

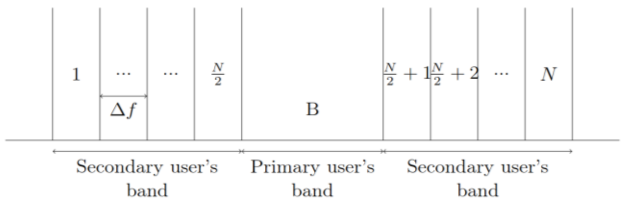

Figure 1. Example of spectrum sharing between PU's and SU's in a multi-carrier communication system [7]

2.2 Interference generated by the SU

The system used with OFDM allows us to calculate the interference generated by the SU at the ith subcarrier as follows:

$$I_i(d_i, P_i) = \int_{d_i-\beta/2}^{d_i+\beta/2} |g_i|^2 \, \emptyset_i(f) df \qquad (1)$$

where, d_i represents the spectral distance between the center frequency of the PU band and the ith subcarrier. β is the PU bandwidth. P_i is the transmit power of the SU, g_i is the gain of the ith subcarrier channel from the base station to the PU. df is the bandwidth of each secondary user subcarrier. $\emptyset_i(f)$ is the power density spectrum of the ith SU subcarrier, which is defined below:

$$\emptyset_i(f) = P_i T_s \left(\frac{\sin \pi f T_s}{\pi f T_s}\right)^2 \qquad (2)$$

where, T_s is the symbol duration. f represents the subcarrier frequency.

2.3 Error rate

There are different types of functions to measure the error rate ($\overline{P_{be}}$) on the channels, these functions are specific for each type of modulation used: Phase Shift Keying (PSK) or Quadrature Amplitude Modulation (QAM) [17]:

$$\overline{P_{be}}(BPSK) = Q\left(\sqrt{\frac{P_i}{N}}\right) \qquad (3)$$

$$\overline{P_{be}}(M-ary\ PSK) = \frac{2}{log_2(M)} Q\left(\sqrt{2 * log_2(M) * \frac{P_i}{N}} * sin\frac{\pi}{M}\right) \qquad (4)$$

$$\overline{P_{be}}(M-ary\ QAM) = \frac{4}{log_2(M)}(1-\frac{1}{\sqrt{M}})\, Q\left(\sqrt{\frac{3*log_2(M)}{M-1}\frac{P_i}{N}}\right) \qquad (5)$$

The three functions shown use the function $Q(x)$, which represents the Gauss error function, the estimation of this function represents [18]:

$$Q(x) = \frac{e^{\frac{-x^2}{2}}}{1{,}64x + \sqrt{0{,}76x^2+4}} \quad (6)$$

where, $\overline{P_{be}}$ is the average error rate for each subcarrier. P_i is the signal strength on the subcarrier i. M is the modulation index. N is the attenuation index.

2.4 Application data types used during transmission

Inspired by the work presented in [19] which introduces the concept of association of application specific requirements employed with the network dynamics of the frequency spectrum is driven to follow a QoS methodology. This was made possible by a new paradigm, Data Centric Prioritization (DCP), the enhancement of the unique union between the type of application data being transmitted and a “true best fit” cognitive radio frequency decision in a cognitive radio community cluster. We chose 4 types of applications to use in our study when a SU wishes to transmit: video conference, voices, transaction and email. The transmission of each type of application data depends on one or more evaluation criteria of a channel (bit rate, interference, transmission power, error rate).

2.5 Radio frequency environment

Transmission through the channel requires three parameters: power, modulation type and attenuation.

Power: The values of the transmission power have been chosen in compliance with the rules of the FCC (Federal Communications Commission) is given the obligation to always respect a certain limit, even for the PU. The range of emission power taken differs between 0.1 mW and 2.4808 mW with a step of 0.025 mW giving 94 power values. The maximum power value of 2.4808 mW was chosen as a contribution to the maximum permissible power value for the U-NII (Unlicenced-National Information Infrastructure) band: 5.15 GHz - 5.25 GHz, set to 2.5 mW [20].

Modulation: Among the parameters that a CR must be capable of reconfiguring dynamically is modulation as the bandwidth necessary to carry a signal depends on the type of the used modulation. In our simulation, we used one types of modulation: QAM modulation, with a modulation index (number of bits per symbol) that varies between 0 and 10 ($2^i, i \in [0{,}10]$).

Attenuation: To simulate a dynamic multi-channel environment, a random attenuation value between [0.1] dB was assigned for each channel.

3. OUR PROPOSED ALGORITHM FOR QOS-AWARE ENERGY EFFICIENCY OPTIMIZATION

TOPSIS was developed by Yoon and Hwang [21], defined as a multi-criteria analysis method for decision support. The multi-criteria decision-making method (MCDM) is the multi-objective optimization technique used to measure alternatives; the primary idea of this method is to elect an action having:

• The smallest distance to the called “ideal” action (positive-ideal solution).

·The greatest distance to the called "anti-ideal" action.

Recent research has proven the effectiveness of the TOPSIS method in many various fields of communication. Loganathan et al. [22] proposed a novel multi-criteria channel decision model is developed by using the Enhanced TOPSIS (E-TOPSIS) which achieves certain desirable characteristics that allow channel decision makers to construct complex decision-making problems. It takes into account several factors of each channel and node, hence the allocation and sharing of channels effectively. In order to access an integrated weighting network in a heterogeneous multi-cognitive wireless network coexistence area, a selection algorithm based on AHP-TOPSIS has been outlined [23].

The different steps of TOPSIS can be expressed as follows [24]:

Step 1: Calculate the normalized decision matrix.

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}} \quad (7)$$

Step 2: Calculate the weighted normalized decision matrix.

$$v_{ij} = w_i * n_{ij}, j = 1 \ldots\ldots m, i = 1 \ldots\ldots n \quad (8)$$

where, w_i is the weight of the ith attribute or criterion, and $\sum_{i=1}^{n} = 1$.

Step 3: Determine the positive ideal and negative ideal solution.

$$A^+ = \{v_1^+, \ldots. v_n^+\} = \{(max_j * v_{ij} | i \in I), (min_j * v_{ij} | i \in I),\} \quad (9)$$

$$A^- = \{v_1^-, \ldots. v_n^-\} = \{(max_j * v_{ij} | i \in I), (min_j * v_{ij} | i \in I),\} \quad (10)$$

Step 4: Calculate the separation measure from the ideal solution.

$$d_j^+ = \sqrt{\{\sum_{i=1}^{n}(v_{ij} - v_i^+)\}}, j=1\ldots\ldots.m \quad (11)$$

$$d_j^- = \sqrt{\{\sum_{i=1}^{n}(v_{ij} - v_i^-)\}}, j=1\ldots\ldots.m \quad (12)$$

Step 5: Calculate the relative closeness to the ideal solution.

$$R_j = d_j^- / (d_j^+ + d_j^-), j=1, \ldots\ldots.m \quad (13)$$

Since $d_j^- \geq 0$ and $d_j^+ \geq 0$, then clearly $R_j \in [0{,}1]$.

TOPSIS remains dependent on an adequate approach to delineate the weighting of criterion for each type of application data used. However, this concept retains its reliability and certainty in the treatment and evaluation of several attributes and the quantity of alternatives. To assign the weights to the criteria we used the AHP method.

Based on a mathematical concept, AHP is an organized, reliable technique that supports our decisions and deconstructs a complex problem into a multi-level hierarchical constitution of objectives, criteria, sub-criteria and alternatives [25]. AHP can be used to make many complex and unstructured choices containing many attributes [26].

In this section we detail our QoS and EE optimization algorithms based on AHP-TOPSIS method for OFDM-based cognitive radio system.

Algorithm 1: OFFLINE AHP-Calculating weight of criteria

1. **Function** Calculate_weight()
2. Get the user application data type.
3. Determine Alternatives.
4. Pairwise Comparison (criteria and alternatives).
5. Weight Calculation for each application data type.
6. **return** Weighting Vectors W_i[w1, w2, w3, w4].
7. **End function**

Algorithm 2: Sensing and parameters initialisation

1. **Function** Sensing_init()
2 Get the parameters sensed by the CR:
3. Power_max, Interference_max, N, modulation type, Mod_max,
4. Get the user running application data type.
5. Choose the adequate Weighting Vector W_i [w1, w2, w3, w4].
6. Create a matrix Q to fill the available subcarriers with the characteristics of each subcarrier initially, such as all subcarriers are free.
7. **for (i=0; i<N; i++) do**
8. Calculate interference, which is the interference introduced by the ith subcarrier into the PU's band, respect as in (1)
9. Calculate error rate, respect as in (5).
10. Calculate Power_cur, Bit_rate_cur.
11. Insert((i, Bit_rate_cur, Interf_cur, Power_cur, Erro_rate_cur,Occup),Q)
12. **End for**
13. **End function**

Algorithm 3: Pseudo code of AHP-TOPSIS algorithm adaptation for CR-OFDM system

1. W=Calculate_weight()
2 Sensing_init()
3. Create a vector V to store solutions returned by TOPSIS
4. V=**TOPSIS** (Q, W).
5. SBest = **MAX** (V) Get the maximum V value
6. **While** ((subcarrier(SBest) is occupied) **or** (subcarrier->power>Power_max)
or (subcarrier->power>Power_max)) **do**
7. SBest = **MAX** (V) Get the next less maximum V value
8. **end while**
9. Occup=Occup+1
10. **Transmit** through this subcarrier (SBest)
11. Occup=Occup-1

Our proposal to improve QoS and EE consists first of all of a function (Calculate_weight ()) illustrated by Algorithm 1 and executed offline to optimize the execution time. This function detects the types of data application used and using the AHP method, for each data type and according to its need it makes a comparison between the criteria and calculates the weight of each criterion while trying in all cases to save the transmission power. Therefore, we have for each type of application a vector with the associated weights of each criterion according to its importance.

The second function (Sensing_init ()) presented by Algorithm 2, loads the parameters necessary for the SU to transmit, i.e., the maximum power and the interferences authorized that a SU can transmit (Power_max, Interference_max), the subcarriers number (N), the modulation types and its maximum value. Thereafter, it chooses the vector of the weights used by TOPSIS after having detected the type of the used application; more over it creates a matrix containing the list of subcarriers with all the necessary parameters calculated: the bit rate (Bit_rate_cur), the interference, the error rate present on the subcarriers (Interf_cur, Error_rate_cur) and also the transmit power (Power_cur).

In Algorithm 3 and in line 4, we call the TOPSIS algorithm by passing it as parameters the matrix Q and the vector of the weights, so the algorithm will choose an alternative, among the set of alternatives present in the matrix Q, which has firstly, the shortest distance to the ideal alternative (the best alternative on all criteria), and, which has the greatest distance to the ideal negative alternative (the one which degrades all the criteria) according to the vector of the weights introduced, so that at the end we obtain a vector (V) with values obtained from the evaluation of each subcarrier.

To choose the best solution, the SU will just take the maximum value of the vector V (Algorithm 3 , line 5).

Note that we must test before transmitting if the subcarrier is free and if the transmission power does not exceed the maximum threshold and also if the interference generated on the subcarrier does not also exceed the maximum threshold. In the event that one of the conditions previously presented is not respected, we must choose another solution and this time we will choose a value lower than that chosen before. In the case where all the conditions are respected, the SU can transmit on this subcarrier by putting its state in occupied.

4. SIMULATIONS AND RESULTS

In our simulations, we assume that primary and secondary users coexist according to the model illustrated in Figure 1. The SU has a bandwidth distributed over 16 subcarriers with 8 subcarriers on each side of the PU bandwidth. We assume also that a Rayleigh fading channel with an average of 1, in other words we consider that all the paths are independent and of comparable attenuations. In addition, the OFDM symbol duration is Ts = 100 s and the maximum transmission power of the secondary user is 2.5 mW, as well as the maximum interference tolerated by the PU is 0.01 [7]. Our approach is programmed with JAVA Environment and JADE multi-agent system [27].

The four types of application data used by the CR user are characterized by the variation of the weights calculated by the AHP algorithm which are presented in Table 1.

Table 1. Weighting application data types

Application data types	Bit rate	Interference	Transmission power	Error rate
Voice	0.12	0.38	0.3	0.2
Videoconference	0.6	0.2	0.08	0.12
Transaction	0.14	0.22	0.08	0.56
Email	0.08	0.27	0.53	0.12

4.1 TOPSIS execution time

Figure 2 represents the execution time of the algorithm using TOPSIS according to the number of subcarriers, we notice that between 16 and 128 subcarriers, the time is almost the same and does not exceed 5 ms, but certainly by increasing the number to 256 and 512 or even 1024 subcarriers the time will increase. So, the increase in the number of sub-careers increases the execution time but it remains reasonable in an environment like CR (real-time). We remind here that the AHP algorithm is executed offline and does not affect this execution time.

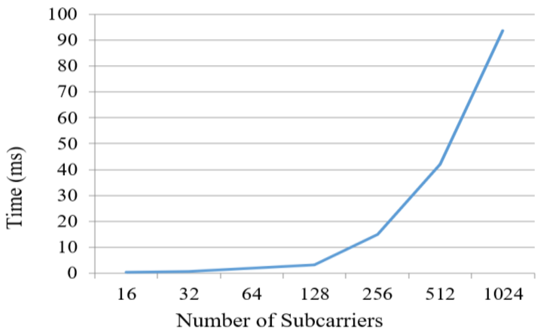

Figure 2. TOPSIS execution time according to the number of subcarriers

To validate our approach, we will make a comparison between a transmission mode in a basic CR environment and another transmission mode in a CR environment with the use of the AHP-TOPSIS algorithm for the choice of a subcarrier for the transmission.

The results below are presented with an average of ten simulations.

4.2 Impact on the transmission power and energy efficiency

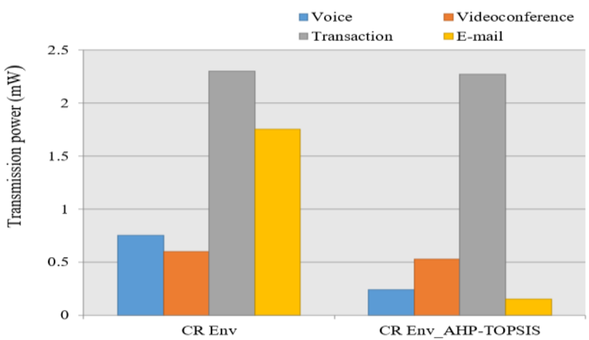

Figure 3. Average of the transmission power values used in CR Environment and CR Environment with AHP-TOPSIS

Figure 3 shows the average transmission power values used in a basic CR environment and in a CR environment using our proposed algorithm. The use of TOPSIS combined with AHP allows defining the optimal configuration for the transmission of each type of data application. Figure 3 shows that the transmission power has been reduced in all types of application given compared to the classic use of CR. Although sometimes it is almost equal values; the case where we use "Transaction" which is due to the fact that we assign a low weight to the minimization of power since it is an application which does not support the errors which implies a strong power of emission. Our approach based on TOPSIS and AHP shows its effectiveness in order to reduce the transmission power and therefore efficient energy management; an interesting result in green networking.

4.3 Impact on interference and error rate

In Figures 4 and 5, we present the impact of the use of TOPSIS on generated interferences and error rate respectively. With basic CR sensing, the SU makes spectrum handoff to channels that satisfy its transmission but not necessarily minimizing interference and / or error rate. In the case of using CR with AHP-TOPSIS, the SU executes the TOPSIS algorithm during the detection. This step allows us to have a classification of the available channels according to the application used and the degree of importance of each evaluation criterion to decide which channel to choose for the transmission. Figures 4 and 5 clearly show that the interference values generated and error rate when using TOPSIS are much lower than that generated in the basic CR. Therefore, the use of TOPSIS has really proven to be effective in optimal channel selection term and therefore an optimized QoS management.

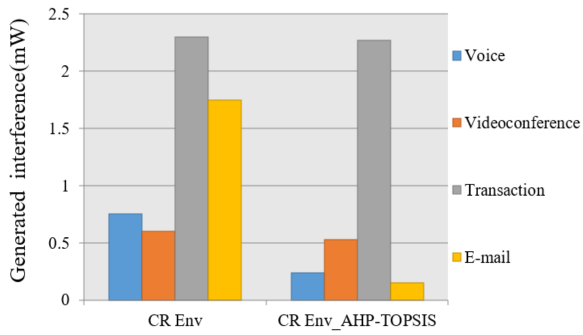

Figure 4. Impact of AHP-TOPSIS on generated interferences

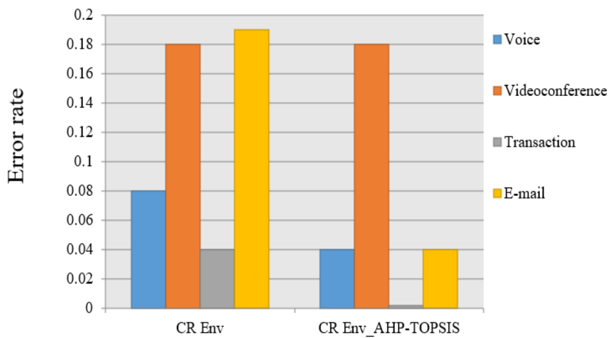

Figure 5. Impact of AHP-TOPSIS on error rate

4.4 Reduction rate of the different criteria

In the following, we calculate the reduction rate of the transmission power, interference and error rate to show the gain obtained using the AHP-TOPSIS algorithm in each type of data application as follows: (CR (J) – CR_AHP-TOPSIS(J)) / CR(J).

Figure 6 shows the results obtained. Our proposed algorithm reduced the transmission power by 68% when using VOICE application, by 11% when using VIDEOCONFERENCE and by 90% when using EMAIL application. As the most important weight is allocated to the minimization of the transmission power, the EMAIL application is the one that gives the most satisfaction. On the other hand, our algorithm could not reduce the transmission power for the TRANSACTION application because minimizing the error rate is more important than minimizing the transmission power.

For the reduction rate concerning interference and error rate, it is really significant. For example, when using a VOICE application, the interference reduction rate is 80% and when using a TRANSACTION application, the error rate is reduced by 95%.

We can therefore conclude that our proposed algorithm has significantly reduced the different criteria studied regardless of the application used by the SU and therefore our proposal has allowed the SU to choose an optimal channel for its transmission.

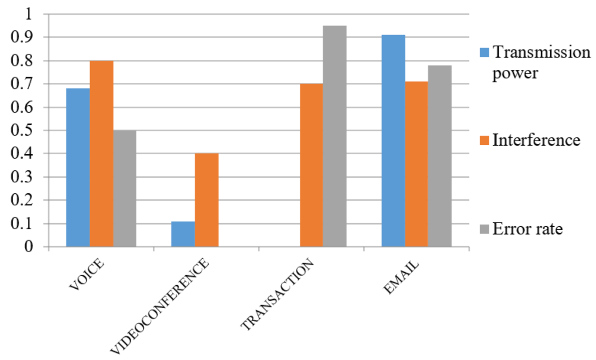

Figure 6. Reduction rate

5. CONCLUSIONS

In this paper, we have proposed a new spectrum selection algorithm based on AHP-TOPSIS in OFDM-based cognitive radio networks. The essential objective is to select the best available subcarrier by evaluating its characteristics according to the needs of secondary users according to the type of its used application. The algorithm exposed in this work allows to include several criteria with the TOPSIS method to migrate towards a flexible and inclusive use of data for the spectrum selection decision. In the present work, we have been able to obtain a significant gain in terms of transmission power, which will lead to a reduction in the energy consumed and better energy efficiency. The results of our simulations clearly show that the reduction rate of interference and error rate is considerable and therefore the optimization of QoS is ensured in this type of environment due to the use of our proposed algorithm. So, we can say that the approach proposed in this paper is very significant in the context of green networking where managing energy consumption is seen as the big challenge in order to reduce the amount of CO emitted by telecommunications infrastructures participating in the greenhouse effect. As perspectives of our current work, we target a comparison of the performances obtained from AHP-TOPSIS with those of metaheuristics such as: Gray Wolf Optimizer (GWO), Flower Pollination Algorithm (FPA) and Shuffled Frog Leaping Algorithm (SFLA). Indeed, our optimization problem has an exponential complexity with the increase of the number of subcarriers. It is classified as an NP-hard problem and therefore the use of approximate methods or metaheuristics is essential to solve it.

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