Indonesian Journal of Electrical Engineering and Computer Science
Vol. 37, No. 2, February 2025, pp. 888~902
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v37.i2.pp888-902

Novel method for multi-user collaborative spectral decision in decentralized cognitive radio networks

Cesar Hernández, Diego Giral, Camila Salgado
Department of Electrical Engineering, Faculty of Technology, Universidad Distrital Francisco José de Caldas, Bogotá D. C., Colombia

Article Info

Article history:

Received Jul 23, 2024
Revised Sep 9, 2024
Accepted Sep 30, 2024

Keywords:

Cognitive radio networks
Collaborative strategy
Decentralized network
Decision making
Deep learning
Spectral decision
Spectral opportunity

ABSTRACT

Cognitive radio networks positively impact the performance of wireless communications and have proven to be an excellent alternative for efficient and effective use of the radio spectrum. However, few proposals collaboratively work on decision-making in decentralized cognitive radio networks. The present work refers to a novel method and device that reduces the rate of channel changes during secondary user communications in decentralized cognitive radio networks through a collaborative spectral decision between several secondary users while allowing multiple secondary users access to the network. This proposal consists of a multi-user unit that regulates the access of multiple secondary users (SUs) to the spectrum, a priority unit that guarantees timely access to the SUs according to their level of importance, and a prediction unit that forecasts the arrival time of the primary user (PU). This multichannel unit regulates the assignment of multiple spectral opportunities to the SU according to the type of application it is using and a unit of deep learning that determines which spectral opportunity(s) are most suitable for each SU and spectral allocation. The results obtained allow us to satisfactorily validate the proposal developed and corroborate the importance of collaborative work in decision-making to select spectral opportunities.

Corresponding Author:

Cesar Hernández
Department of Electrical Engineering, Faculty Technology, Universidad Distrital Francisco José de Caldas
Bogotá D. C., Colombia
Email: cahernandezs@udistrital.edu.co

1. INTRODUCTION

Most research work in cognitive radio is based on a centralized network, where all the information is organized in one place, and accessing it is easier and more beneficial for decision-making. However, although the observation and global knowledge of the network have advantages, for large-scale systems and applications in public safety networks, it is not the best option, the increase in measurement costs, the complexity of the system, the amount of information that must be controlled, added to the imbalance and potential chaos if the base station fails (vulnerability). This makes it a non-feasible architecture for all cognitive radio network (CRN) structures [1]. In the case of distributed networks, such as mobile ad-hoc networks or MANET (mobile ad-hoc network), they are characterized by their high mobility, autonomy, adaptation, and independence; their applications are found in scenarios involving land vehicles (VANET), unmanned aerial vehicles [2], urban surveillance and search or rescue missions [3]. However, the lack of infrastructure, dynamic topology, rapid deployment, and harsh application environments make MANET vulnerable to a wide range of security attacks [4]-[6]. In addition, the power consumption and delay is high [5], the bandwidth is low as well as its performance due to frequent link failures [3], [6], [7]. The above problem can be solved if the responsibility for the information is distributed among different control points, the basic criterion of the decentralized cognitive radio network (DCRN). Now, because DCRNs do not centralize the information and management of the network, the concept of collaboration between secondary user (SU) for decision-making is important [8]-[10].

The present invention relates to a device that reduces the rate of channel changes during SU communications in DCRNs. This through a collaborative spectral decision between several SUs while allowing multiple SUs access to the network. In addition, adequate spectral allocation improves the performance of spectral mobility in CRNs (smart wireless networks), positively affecting the quality-of-service parameters of decentralized mobile communications.

The method and device proposed for the collaborative spectral assignment of multiple users in DCRNs is composed of a global positioning system (GPS) that allows the exact location of the SU to be determined, a clock that allows to determine the date and time of each spectral detection, a spectral information storage unit/process that allows to save, order and analyze the spectral information detected by the SU and that exchanged with other SUs, three micro SD memories that allow spectral information to be stored, a spectral information exchange unit/process to regulate the method of information exchange between SUs, a multi-user collaborative spectral assignment unit/process, composed in turn off: a multi-user unit/process that regulates the access of multiple SUs to the spectrum, a priority unit/process that ensures timely access to SUs according to their level of importance, a prediction unit/process that forecasts the time of arrival of a PU to the spectral opportunity used by the SU, a multi-channel unit/process that regulates the allocation of multiple spectral opportunities to the SU according to the type of application you are using, a deep learning unit/process that determines which spectral opportunity(s) are most appropriate for each SU and spectral mapping. Currently, there is no similar solution in the current literature or in the state of the art at the patent level.

2. RELATED WORKS

In the search for works related to this proposal, only two works related to the topic of collaborative spectral assignment in CRNs were found, but without taking into account the aspect of multiple access and decentralization. The work done in [8] refers to a method for the intelligent selection of spectral opportunities in CRNs, which improves the performance of mobility in CRNs, modifying their behavior dynamically, according to the requirements and parameters of the user's communication. The proposed method is composed of a control unit coordination the selection process of the best spectral opportunity according to spectrum characteristics and user requirements. Through an adaptive selection unit, according to certain information parameters: type of application, supply-demand relationship, traffic pattern, and traffic level, the most appropriate available channel selection mechanism is chosen from three different ways: feedback, through the feedback allocation unit, multichannel, through the multichannel allocation unit, and prediction, through the unit of prediction. This is based on the following decision criteria: the probability of channel availability, estimated time of channel availability, the signal-to-noise ratio of the channel, and channel bandwidth.

By the above, Giral-Ramírez *et al.* [8] has some similarities with the present proposal, it differs in several important respects; first, in the present proposal, the spectral allocation method is collaborative, through the exchange of information between secondary users, and not centralized as in [8]; second, that this proposal allows access by multiple SUs and [8] does not have such a capability; third, that this proposal prioritizes the performance of some secondary users while [8] it doesn't; fourth, that the present invention works with a machine learning technique called deep learning, while [8] performs multi-criteria decision-making.

The work done in [9] describes allocating joint resources of cognitive cooperative networks based on utility optimization. According to the method, master and slave users of a CRN share spectrum resources and perform the transmission of information. Master users occupy the corresponding authorized frequency bands for communication, and slave users communicate through a direct transmission or cooperative transmission mode under the condition that they do not interfere with the communication of master users. A network resource scheduler receives service requests from slave users, models a slave user co-utility function, performs optimized sub-channel allocation, transmits power from slave users and optimized selection of cooperative relay modes based on the utility maximization rule. According to the invention, the resource sharing of the cognitive cooperative network spectrum can be done effectively, and the network's overall performance can be improved.

Accordingly, the present proposal differs in several important respects; first, the spectral allocation method is collaborative, through the exchange of information between SUs, in the present proposal, and not from the connections as in [9]; second, that this work solution it is not geared towards the spectral assignment and is not intended to reduce the rate of channel changes, whereas the present invention is; third, that the present invention allows access by multiple SUs and the [9] does not have such capability; fourth, that the present invention prioritizes the performance of some SUs while [9] does not; fifth, that the present invention works with a machine learning technique called deep learning, while the [9] use utility functions.

3. CONCEPTUAL FOUNDATIONS

3.1. Spectral opportunity

A spectral opportunity is a spectral resource available in a frequency band. Spectral opportunity is also called available frequency, channel, spectral resource, white space, or spectral gap [10]. The objective of this proposal is to be able to select the most appropriate spectral opportunity for the SU.

3.2. Cognitive radio networks

CRNs are the evolution of wireless networks [11]. The main characteristics of cognitive radio, which give it all its capabilities, are cognitive ability and reconfigurability [12]. However, CRNs pose challenges in spectrum management due to the fluctuating nature of the available spectrum and the quality of service (QoS) requirements of wireless applications [12]-[15].

CRNs can be classified into infrastructure or non-infrastructure architecture [11]. Infrastructure-based CRNs can be further classified into centralized or decentralized; infrastructure-free CRNs are referred to as distributed networks [11]. By the above, NRCs can operate with several approaches, each with advantages and disadvantages, and their use depends on the application. A hybrid model is DCRNs; this architecture is characterized by using the advantages of centralized and distributed networks together. Decentralized architectures have infrastructure and are easy to implement, among other advantages [11]. Because of the above, the decentralized approach is an efficient option for large networks.

3.3. Spectral decision

After performing the spectrum detection, the SU must decide the best spectral opportunity. This process must satisfy the QoS requirements and must also include the actions taken by other users as a parameterization criterion. Inadequate decision-making affects the QoS parameters such as latency, throughput, reliability, signaling, interference, energy efficiency, bandwidth, signal-to-noise plus interference ratio (SINR), and error rate.

Accordingly, spectral decision is a key function in NRCs [16], [17]. Decision-making is a process that seeks to select the best spectral alternative from a finite set of possibilities, allowing SUs to generate a sequence of actions that will lead to the achievement of their goals. Given the complexity of this process, solutions must be efficient due to the high volumes of information and the minimal requirements of each particular application [18], [19].

3.4. Spectral handoff

Spectrum mobility or spectral handoff can be defined as the process in which a cognitive radio user changes its operating frequency for one of several reasons [20]-[22]. According to recent research, spectral mobility significantly impacts CRN's performance and is highly dependent on the selection of the spectral opportunity that is made during the spectral decision process [23]-[25]. The goal of selecting the most appropriate spectral opportunity for the SU can significantly reduce the number of spectral handoffs.

4. PROPOSED DEVICE

According to Figure 1, the device for collaborative spectral assignment of multiple users in DCRNs is composed of a user detection unit (1), a GPS unit (3), a clock (4), an information storage unit (5), a spectral information exchange unit (12), and a spectral allocation unit (19). Where the storage unit (5) consists of a controller 1 (6), a micro SD1 memory (7), a micro SD2 memory (8), a micro SD3 memory (9), an arithmetic unit 1 (10), and a register 1 (11). The spectral information exchange unit (12) consists of a controller 2 (13), an arithmetic unit 2 (14), a comparator 1 (15), a comparator 2 (16), a register 2 (17), and a register 3 (18). And the multi-user collaborative spectral allocation unit (19) consists of a controller 3 (20), a memory 4 (21), an arithmetic unit 3 (22), a processor (23), a multi-user unit (24), a priority unit (25), a prediction unit (26), a multichannel unit (27), a deep learning unit (28), and finally, the spectral allocation (29). The operation of the proposed device is described in detail in the proposed method section.

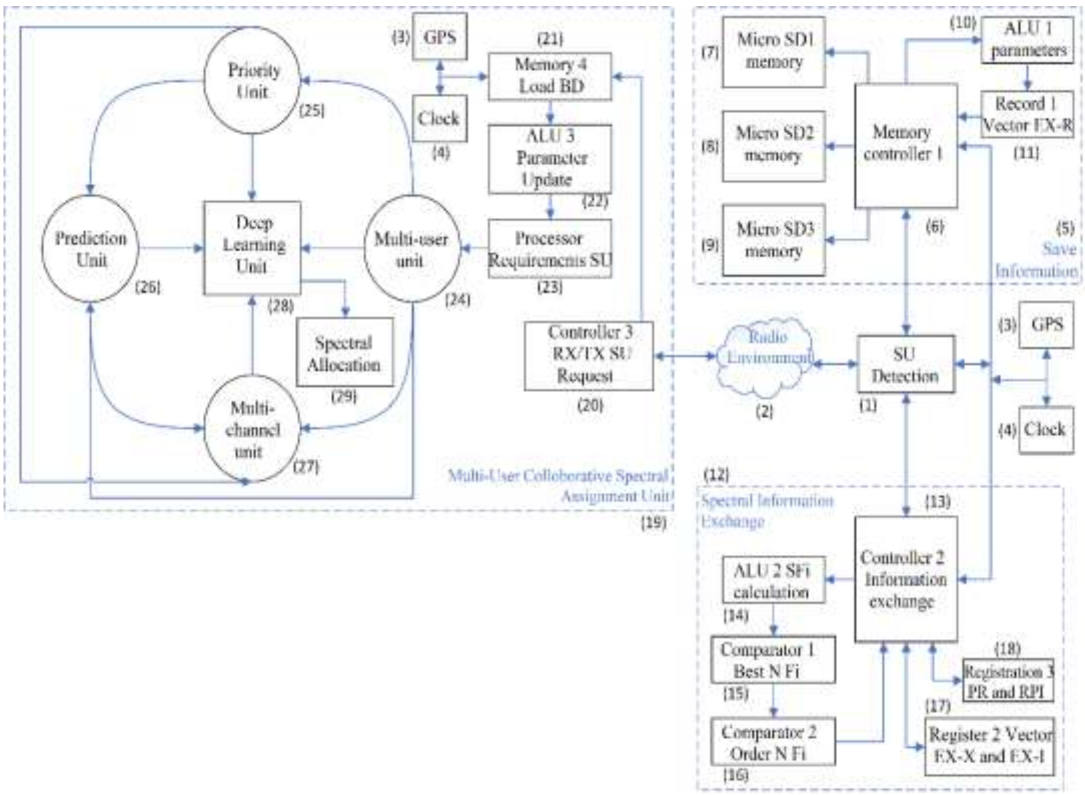

Figure 1. Functional block diagram of the appliance

5. PROPOSED METHOD

The proposed method is composed of a GPS that allows to determine the exact location of the SU, a clock that allows to determine the date and time of each spectral detection, a unit/process of storage of spectral information that allows to save, order and analyze the spectral information detected by the SU and that exchanged with other SUs, three micro SD memories that allow spectral information to be stored, a spectral information exchange unit/process to regulate the method of information exchange between SUs, a multi-user collaborative spectral allocation unit/process, which in turn consists of: a multi-user unit/process that regulates the access of multiple SUs to the spectrum, a priority unit/process that ensures timely access to SUs according to their level of importance, a prediction unit/process that forecasts the time of arrival of a PU at the spectral opportunity used by the SU, a multi-channel unit/process that regulates the assignment of multiple spectral opportunities to the SU according to the type of application it is using, a deep learning unit/process that determines which spectral opportunity or spectral opportunities are the most suitable for each SU and finally, spectral assignment. This method will be described in made from four phases: the collaborative phase, the spectral information storage phase, the spectral information exchange phase, the spectrum allocation phase, and the deep learning phase.

5.1. Collaborative phase

Figure 2 describes the collaborative phase of the proposed method, which comprises two procedures: an independent spectral detection performed by each SU, and an exchange of spectral information between different SUs. According to Figure 2, the proposed method starts (I) by setting a first timer to zero (II) to determine how long the first procedure should take. The first procedure begins with reading the GPS and the clock (III) to identify the area to which the information measured from the spectral detection (III) belongs and the corresponding date and time when said spectral detection is made. Once a Fi has been detected, it is checked if it has been previously detected during the same instant of time (IV) from the DBsenseFi list; if so, it is discarded, and a new one is searched. If the detected Fi is not in the DBsenseFi list, then its corresponding spectral information (V) is saved; this process is described in more detail in Figure 3. Once the spectral information of the newly detected Fi frequency is stored, it is added to the DBsenseFi (VI) list so that it is not detected again during the corresponding instant. Suppose the spectral detection cycle is performed for the first time and during the first week.

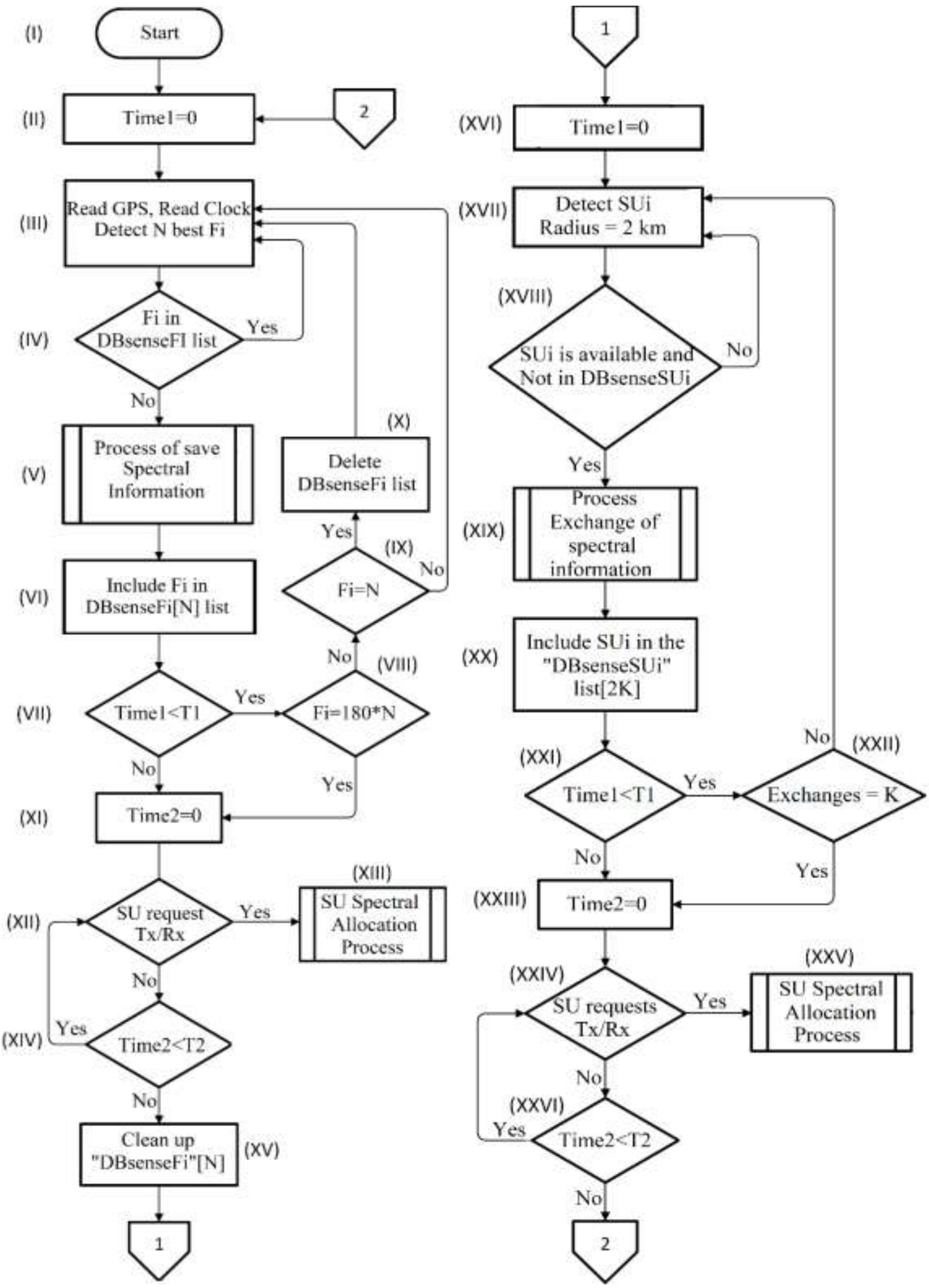

Figure 2. Collaborative phase diagram

In that case, the duration of the cycle will be approximately one hour, during which time it must detect for 180 consecutive instants of time, 423 GSM frequency channels (124 of GSM 850 and 299 of GSM 1900); but if the cycle is performed after the first week, an analysis of all the information stored during the first week is carried out and it is determined which are the best N (N can vary around 50) Fi frequencies. Only those N Fi are monitored, from the second week onwards, which would only take about 5 minutes. The next step is to check if the first timer reached the value of 60 minutes or 5 minutes (VII), depending on the week of execution of the method (first or second onwards). Suppose the first timer has not yet reached the time limit. In that case we proceed to check whether all the necessary spectral information (VIII) has already been stored, i.e., the 423 Fi for 180 instants of time; if it is the first week, or the N Fi for 180 instants of time if it is the second week onwards. If all the necessary spectral information has not yet been obtained, then check if all the Fi of interest (IX) have already been detected; if not, proceed to step (III); on the contrary, all the Fi of interest have already been detected, proceed to delete the DBsenseFi list (X) and return to step (III). Going back to step (VIII), if all the necessary spectral information has been stored, then the second timer (XI) is initialized to zero, the same step that would have to be executed if, in (VII), the first timer reaches the predetermined time limit. Once the second timer (XI) is restarted, the first procedure remains in a loop for one hour, waiting for a request to transmit information from the user (XII); if there is one, then the SU multi-user collaborative spectral assignment process (XIII) is carried out. This loop repeats until the second timer reaches 60 minutes (XIV). When this happens, the DBsenseFi (XV) list is cleaned up, and we start the second procedure, which corresponds to the exchange of information between SU.

In the second procedure, the first step is to reset the first meter (XVI) and detect some SU within a radius of 2 km (XVII); when one is detected it is determined if said SU is available (XVIII), if not, it is returned to step (XVII) to detect a new SU; if, on the other hand, the SU is available, the process of exchanging spectral information between the two SUs (XIX) is initiated, a process described in greater detail in Figure 4. Subsequently, the SU is included in a list called DBsenseSUi (XX), which has a capacity for 2K users. The next step is to check if the first timer reached the value of 5 minutes (XXI); if not, it is verified if the K spectral information exchanges (XXII) have been reached; K will be a parameter that will be dynamically adjusted according to the information obtained from the exchanges. If the K exchanges are still not reached, the second procedure goes to step (XVII). Otherwise, the second timer (XXIII) is restarted, the same step that would have to be executed if, being in (XXI), the first timer reaches the predetermined time limit. Once the second timer (XXIII) is restarted, the second procedure remains in a loop for one hour, waiting for a request to transmit information from the user (XXIV); if there is one, then the process of spectral assignment of the SU (XXV) is carried out, this process is described in greater detail in Figure 5. This loop repeats until the second timer reaches 60 minutes (XXVI). When this happens, everything starts over from step (II), restarting the first timer and returning to the first procedure.

5.2. Spectral information storage phase

Figure 3 describes the spectral information storage phase. According to Figure 3, this phase begins (XXVII) by reading the GPS and the clock and identifying the frequency and power of the detected Fi (XXVIII). Then the zone to which the spectral data belongs is verified; if it is in the area of residence, which corresponds to zone 1 (XXIX), it is stored in the micro SD1 memory (XXX); if, on the other hand, it is in the work zone, which corresponds to zone 2 (XXXI), it is stored in the micro SD2 memory (XXXII), and if it is not in either of the previous two, then it is saved in micro SD3 (XXXIII) memory. The capacity of the three micro SD memories is 182×424=78 kB, which corresponds to 78 kB×3=234 kB or higher; for our invention, a memory of 1 MB is selected. After selecting the micro SD memory corresponding to the spectral data measurement area, the position in the memory is located according to the time and frequency value of the spectral data (XXXIV), and the spectral data (XXXV) is saved. Subsequently, it is verified if the power database is full (XXXVI); if not, the process of storing the spectral information (XXXIX) is completed, and the return to step (VI) of the collaborative phase in Figure 2 is completed. If, on the other hand, the database is full, the parameters D (channel availability), I (channel interference), E (channel error rate), and CCD (contiguous channels available) (XXXVII) are calculated. Then, the C, I, E, and CCD parameters are normalized and loaded into the EX-R (XXXVIII) information exchange vector. Finally, the process of storing the spectral information (XXXIX) is finished.

There are four decision parameters: channel availability (D), channel interference (I), channel error rate (E), and number of contiguous channels available (CCD). These are measured from the signals of power, probability of error, and signal frequency. The Parameter D corresponds to the analysis of the normalized duty cycle of each power signal that are potential spectral opportunities. Parameter I is calculated from the power of adjacent channels during each instant of time and the channel changes made by SUs after the arrival of a primary user (PU). Parameter E is calculated from the percentage of failed packets and the number of retransmissions of packet, for each frequency channel. The CCD parameter is measured from the number of available contiguous channels that are tracked at both the top and bottom of the channel's center frequency to be analyzed.

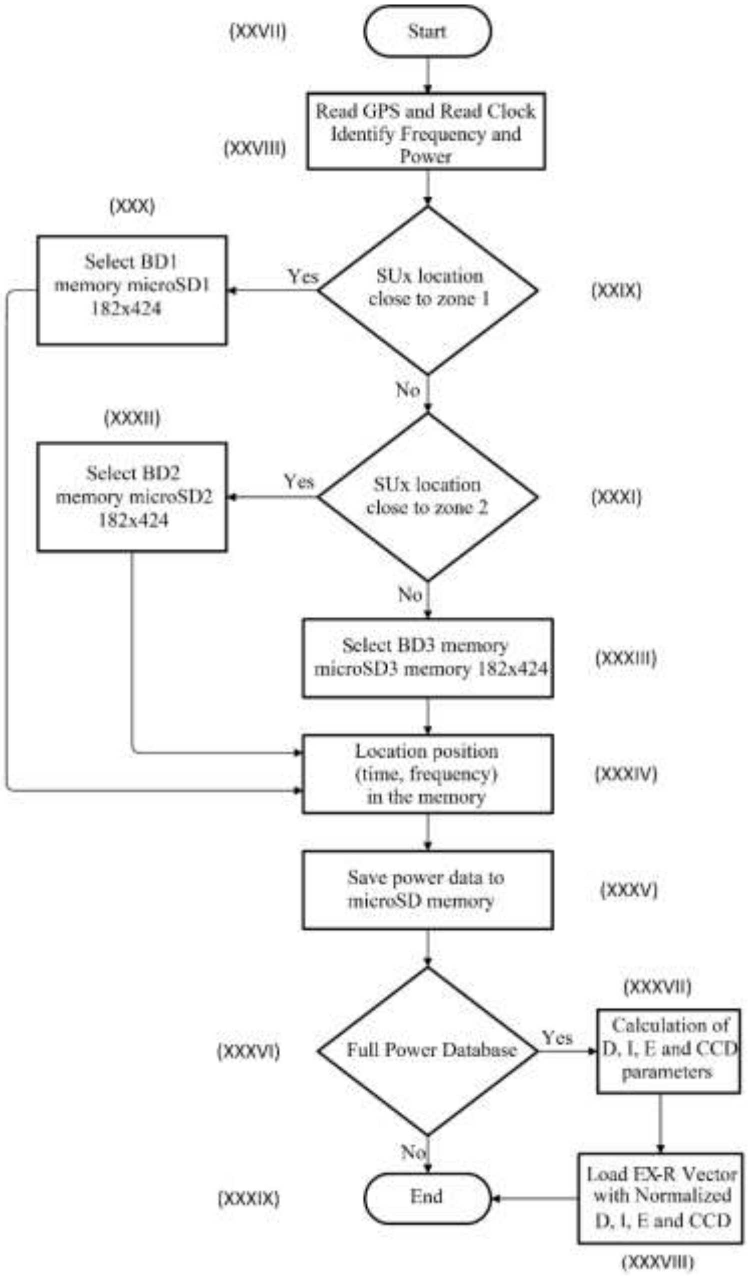

Figure 3. Spectral information storage diagram

5.3. Spectral information exchange phase

Figure 4 depicts the phase of spectral information exchange between SUs. According to Figure 4, this phase begins (XL) by reading the GPS and the clock (XLI). It is then verified if the exchange is significant (XLII), that is if the information to be exchanged for the date, time, place, and frequency is already in the database of both SUs. If the exchange is not significant, the exchange of information is terminated (XLIII), and the present phase (LIV) is terminated; but if, on the other hand, the exchange is significant, it is determined if it is the first exchange to be made by the SU (XLIV), if so, RP is initialized with one and the EX-X vector is loaded with the information of the vector EX-R (XLV). Then it is directed to step (XLVII). In case it is not the first exchange, the EX-X vector is loaded with the following information: [(EX-X vector)×RP+(EX-R vector)]/(RP+1) and incremented by one RP unit, and then directed to step (XLVII). In step (XLVII), the two secondary users exchange the EX-X and RP vectors. Then, the received vectors EX-X and RP are loaded into the vectors EX-I and RPI, respectively (XLVIII). Then, the EX-X vector is updated with the following information: [(EX-X vector)×RP+(EX-X vector)×RPI]/(RP+RPI) and RP is also updated with RP+RPI (XLIX).

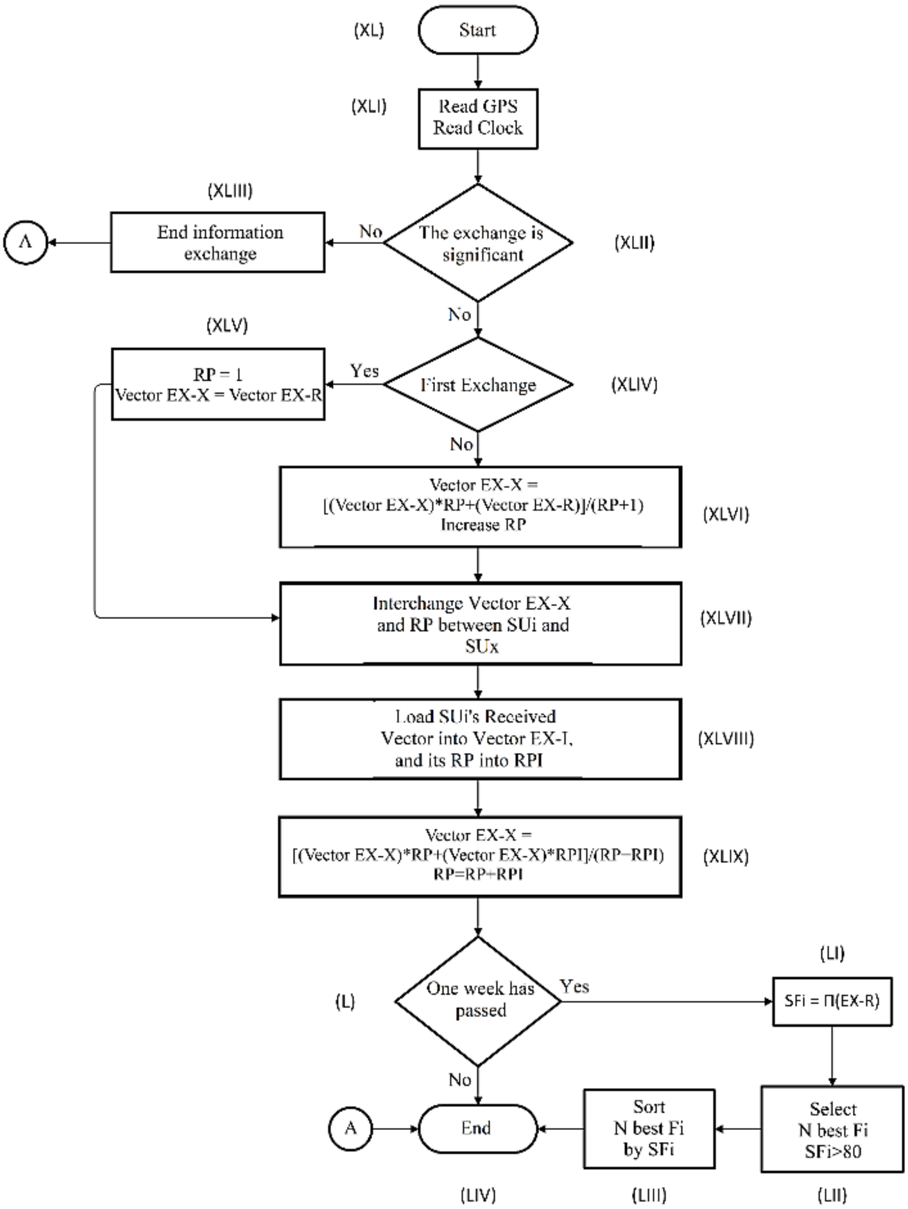

Figure 4. Spectral information exchange diagram

Next, it is determined if one week has elapsed since the start of storage of the spectral information (L). If not, the spectral information exchange phase (LIV) is terminated. However, if so, the score of each frequency or spectral opportunity in the database is evaluated from the following function: SFi=D×0.3+I×0.3+E×0.2+CCD×0.2 (LI), subsequently, the best N Fi (LII) are selected, which correspond to those Fi with an SFi value greater than 80 out of 100, and are ordered from highest to lowest SFi score (LIII), and finally, the spectral information exchange phase (LIV) is completed.

5.4. Spectral assignment phase

Figure 5 depicts the spectral allocation phase of SUs. According to Figure 5, this phase initiates (LV) by reading the GPS and the clock (LVI). The corresponding database (LVII) is then loaded based on the information from the GPS and the clock; the decision parameters (LVIII) are updated, i.e., D, I, E, and CCD, and the requirements of the SU (LIX) are read. According to the requirements of the SU, one or more relevant processes are executed to decide how many and which spectral opportunities to assign to each SU. The first thing is to check if there are multiple SUs (LX); if not, the method is directed to step (LXIII), but if not, the multi-user process (LXI) is executed, which will be described later, and how many and which SUs require priority (LXII) are analyzed. If no SU requires priority, the method is routed to step (LXIII), and if one or more

SUs require priority, then the priority process (LXIV) is executed, which will be described later; the output of this process goes to step (LXIII) and to the multichannel process (LXVII). Step (LXIII) evaluates whether any or some of the applications to be developed by SUs are delay-sensitive; if so, the prediction process (LXV) is executed, which will be described later, and it is evaluated whether multiple channels (LXVI) are required to develop such applications. If there is no delay-sensitive application, the method is directed to step (LXVI) to analyze the number of channels or spectral opportunities needed by each SU application. If more than one channel is required, the multichannel process is executed (LXVII), and it is verified that its result is equitable (LXVIII); if not, it is returned to step (LXVII) to re-assign the number of channels when equity is finally reached, the deep learning process (LXIX) is executed. The same runs if no more than one channel is required in the step (LXVI).

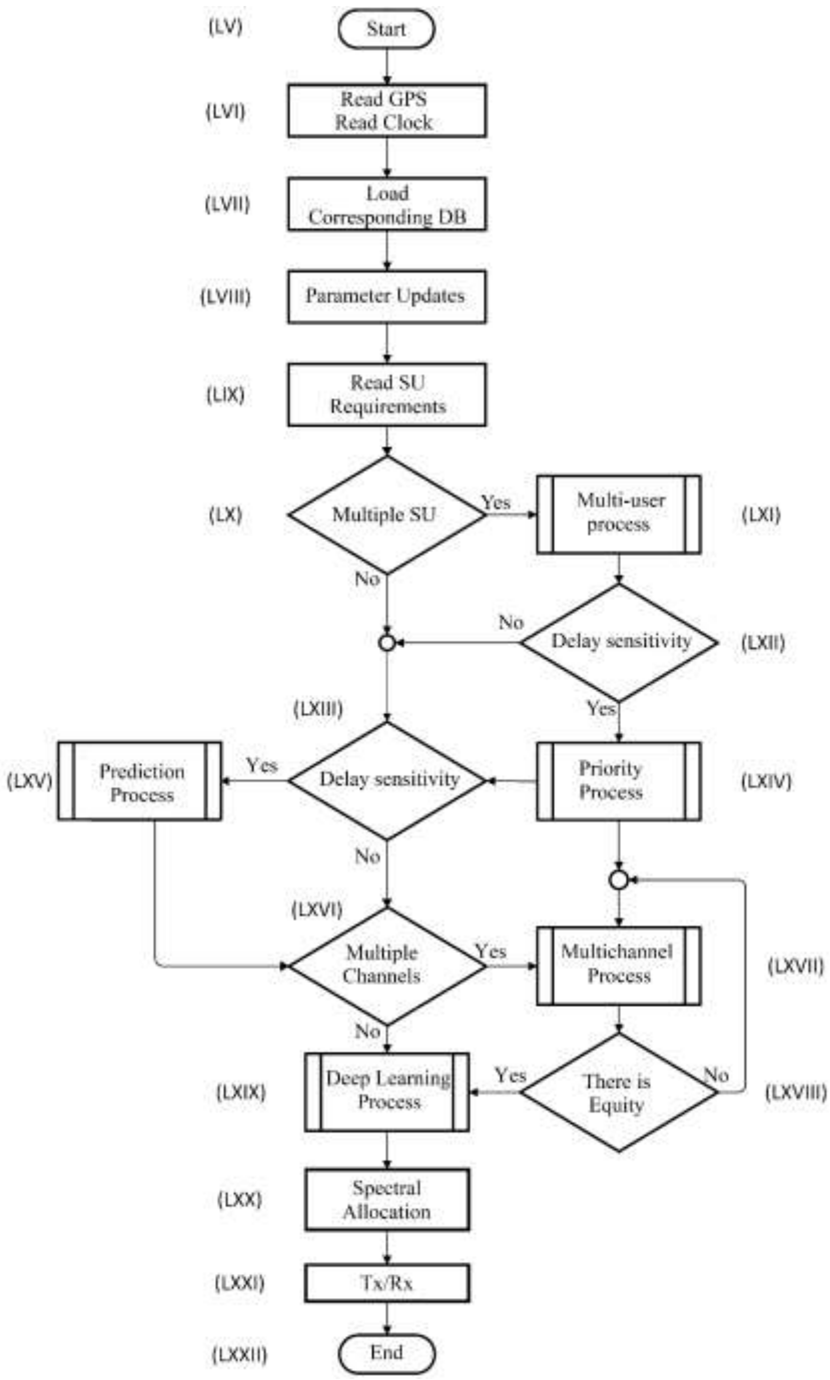

Figure 5. Spectral allocation diagram

The deep learning process is described in detail in Figure 6. The deep learning process selects the most appropriate channels or spectral opportunities according to the requirements of each SU. It sends that information to the next step to make the spectral assignment (LXX). After the corresponding channels are assigned to each SU that made the request, the spectral assignment phase of SU (LXXI) is completed.

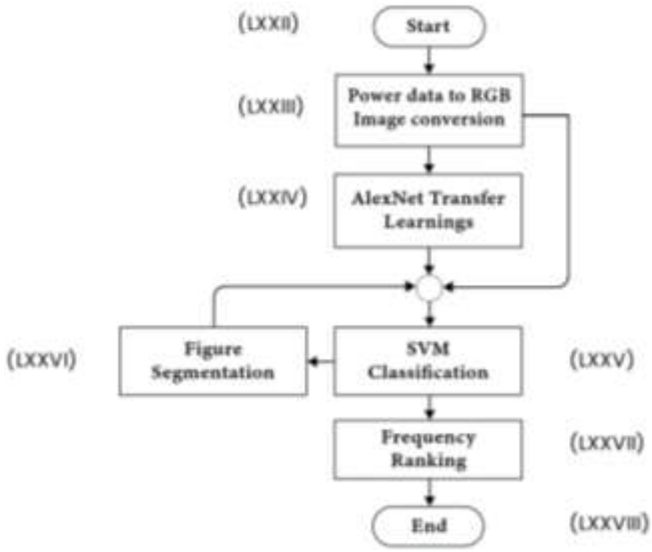

Figure 6. Deep learning diagram

5.4.1. Multi-user process stage

The multi-user process allows the possibility of transmission to several SUs simultaneously. To achieve this, the number of channels needed by each SUs is first determined according to the application they will run. The SUs are then sorted according to their priority level. At this point, it is analyzed if the number of spectral opportunities is less than the number of channels required, in which case if the difference is less than the number of SUs, then it is reduced by one or two channels to the SU with the highest bandwidth demand. If the difference exceeds the number of SU, you start by eliminating the SUs with the highest bandwidth requirements one by one until you find the balance between supply and demand. Suppose the number of spectral opportunities exceeds the required channels or equity between supply and demand is reached. In that case, the multi-user collaborative spectral allocation process is continued in the priority process.

5.4.2. Priority process stage

This process is performed when multiple SUs request to transmit information, and within them, one or more summarize a previously initiated communication. The process first identifies SUs that require priority and then initiates a sorting process to rank them from highest to lowest priority. To achieve this, a value of 10 is assigned to SUs running a highly delay-sensitive application, five if it is of low sensitivity, and 0 if it is not delay-sensitive. It then assigns a value of 10 to running high-importance applications such as telemedicine, 5 to medium-importance applications such as streaming, and 0 to low-importance applications such as emails. It then assigns a value of 10 to SUs that carry more than half of their transmitted information, 5 to those with more than 20%, and 0 to those with less than 20%. Finally, these values are averaged, and the SUs are organized from according to the highest to and lowest results. If two or more SUs reach the same average value, they are prioritized by important applications and transmitted information.

5.4.3. Prediction process stage

The prediction process is used for all SUs that are or will be running a delay-sensitive application, such as voice, streaming, or video conferencing. For each of the requests, it predicts the availability time of the channel or channels to be used through integrated autoregressive time series models of moving averages (ARIMA), integrated autoregressive models of seasonal moving averages (SARIMA), and integrated autoregressive models of fractional moving averages (FARIMA). It sticks with the result with the lowest correlation level between the lags of the predicted time series.

The main objective of developing predictive allocation is to reduce the level of interference between users. The task of prediction is to know when the channel change should be made and to which channel to make it. The prediction process models the time series of powers measured in each channel to achieve this. It then makes, the power forecast for the respective channel, for each instant of time and based on the decision threshold given by the false alarm probability equation, it predicts whether the channel will be occupied or available. The Box-Jenkins methodology was followed to develop the time series models. This methodology consists of building a time series model in four stages: identification, parameter estimation, model verification, and model forecasting.

5.4.4. Multi-channel process stage

Equity is an important factor in multichannel allocation, whereby an under-resourced wireless network tries to allocate resources equitably to users. To perform the multichannel allocation, the bandwidth demand of the users is analyzed, and the number of channels required is quantified according to the type of application each user is running. Channel demands can be single-channel (single) or multi-channel (multi-channel), depending on the type of service or application being developed. The present invention has the ability to handle four types of applications: voice services (demand one channel), Web services (demand 2 channels), streaming services (demand 4 channels), and videoconferencing or multimedia services (demand 10 channels).

Multichannel assignment begins by determining the number of channels required by each SU. Then multichannel band localization is performed, identifying contiguous available frequency channels and treating them as a single multichannel frequency band. The decision parameter information is read and stored in the corresponding EX-X vector after identifying all multi-channel and single-channel bands (when no adjacent channels are available). In order to evaluate all multichannel (XIV) and single-channel bands, the SFi is calculated for each channel and an SFj for each channel where $SFj=D\times 0.2+I\times 0.2+E\times 0.3+CCD\times 0.3$. Then, the P number of channels required to run applications with high delay sensitivity and the Q number of channels to run applications with low delay sensitivity are then determined. The first P channels from the SFi list are selected, and if any of them are in the SFj list, they are removed from it, and then the first Q channels from the modified SFj list are selected.

Once the multichannel allocation is completed, an equity assessment is carried out to determine the level of fairness of the allocation made. Next, it is determined whether or not there is equity; if the equity threshold is not met, the multichannel assignment is carried out again. Equity assessment is measured through the Jain Index, which identifies underutilized channels. The information is transferred to the deep learning process if there is equity.

5.5. Deep learning phase

Figure 6 describes the deep learning phase. According to Figure 6, this phase begins (LXXII) by converting power data to red, green, blue (RGB) image (LXXIII). The result of the step (LXXIII) feeds into the AlexNet transfer learning process (LXXIV) and the support vector machine (SVM) classification process (LXXV). Step (LXXIV) delivers its results to the SVM (LXXV) classification process. The SVM classification process (LXXV) delivers its results to the figure segmentation process (LXXVI), the results of which feed back into the SVM classification process (LXXV). This phase ends with the ranking of Fi frequencies (LXXVII) based on the results of the SVM classification process (LXXV).

The deep learning process uses the spectral information data to extract relevant features; there is no need to perform or implement methodologies for the manual extraction of features. During the training process, the correct set of features is identified automatically without the need to process the data. Deep learning is done hierarchically. The lower layers characterize basic structures, while the higher-level layers analyze more complex structures. In this invention transfer learning is used, which is a process that adjusts the model of previously trained neural networks, such as AlexNet; this strategy only requires adjusting the input data and then delivering new classes. An additional feature of this type of structure is the reduction in processing times. The deep learning method analyzes the data directly from the power array and the D, I, E, and CCD parameters. The process involves implementing a traffic classifier to determine high and low traffic levels.

Due to the high performance of deep neural networks in image recognition, the proposed model classifies a set of images associated with the power levels; the images are obtained from the conversion to RGB of the database. Figures with multiple variations are used to train the neural network. The first task of the model is to convert the power matrix to figures, subsequently, these figures and through the cross-validation criterion are taken for the training and validation of the strategy to be implemented; in addition to the figures obtained from the power matrix, another set of figures with other types of behaviors is randomly generated. This is to ensure a better training process. The figures taken for training are uploaded to the AlexNet network, and the activations of the deep network learning layers are calculated.

The features are extracted by activations, and taking into account the hierarchical structure of the layers, layer 20 of the network (fc7) is taken, higher-level layers analyze more complex structures. With the information from layer 20, a SVM is trained as a classification procedure. To verify the operation of the classifier, the test figures previously obtained in the cross-validation are used. Subsequently, the power matrix figure delivered by the collaborative simulator process will replace these test figures. The classifier will identify the figures with high and low traffic; these will be stored but will not be analyzed in the process to determine the final ranking. Finally, the information, including the traffic classification, will be delivered to the final phase of the model; this phase will take time and frequency data to establish the operation ranking.

5.5.1. Power data to RGB image conversion stage

This process is divided into two procedures; the first, called “Power–Data Base,” performs the conversion of the spectral power database to an RGB array. The conversion is carried out through a linear adjustment; the maximum and minimum power values of the conversion range are determined; these values are taken as the basis for an adjustment per unit of the other values, the origin is assumed as a turning point, and this value corresponds to the threshold adjusted by the user. Green is scaled for low traffic, and red is scaled for high traffic.

The second procedure is called “Power–Random”; it is responsible for generating other types of features for image processing over this procedure. The user has no control. However, it is essential to improve the characteristics that are extracted from the deep neural network. It is only necessary to set a threshold range; the procedure performs the linear and graphical adjustment. With the graphs obtained in “Power – Data Base” and “Power – Random,” the cross-validation methodology for training (train) and validation (train) is used.

5.5.2. SVM qualification stage

For the classification of the images. The SVM was used to classify the images because there are two types of classifiers (high and low traffic), and a multiclass SVM is required. The input parameters are the training and test images; the test images in the validation process correspond to the adjustment made through cross-validation. The outputs correspond to the confusion matrix, an indispensable tool for determining image classification performance. The feedback from this process is directly related to the traffic classification figures to obtain the information associated with the spaces with spectral opportunities. The figures with high traffic classification will be stored and discarded, and the information on the figures with low traffic will be delivered to the process associated with the final ranking.

5.5.3. Frequency ranking stage

The time and frequency information of the figures with low traffic is delivered to the ranking. The classification of the figures is made according to the range of frequencies and time, they are compared and finally, weights are assigned to the zones. The ranking corresponds to a row vector, where the channels with the best spectral opportunities are found descendingly.

6. RESULTS AND DISSCUSION

The results achieved through this proposed device and method for the collaborative spectral decision of multiple users in DCRNs, which reduces the rate of channel changes during SU communications, are shown in Figures 7 to 9. The method proposed in our work is represented by the level of collaboration between the SUs, the greater the number of SUs, the greater the collaboration between them and therefore the better the performance. The comparative evaluation was carried out with three decision-making algorithms: combinative distance-based assessment (CODAS), complex proportional assessment (COPRAS), and multiplicative exponential weighting (MEW). The main reason for selecting these algorithms was that most publications on spectral decision and spectral mobility present an excellent performance of these algorithms. Also, to make a fair comparison, we decided to implement a collaboration strategy for each.

The metric that was used to perform the comparative validation was the throughput level (see Figures 7 to 9), during a nine-minute information transmission between SUs. In Figures 7 to 9, the performance in the throughput metric for the CODAS, COPRAS, and MEW algorithms, respectively, is shown. Here, it can be observed that the best performance is obtained when the 8 SUs work collaboratively. However, the lowest performance is not always obtained with a single SU. This may be because the information shared between SUs was not yet sufficiently relevant, so it is proposed for future work to estimate the quality of the spectral information through some parameter before sharing it with other SUs.

Table 1 shows the relative performance of each selected algorithm. From there it is better appreciated how the performance increases as more SUs enter to collaborate with each other. Here too, as in the delay metric, the best performance is obtained by the CODAS algorithm.

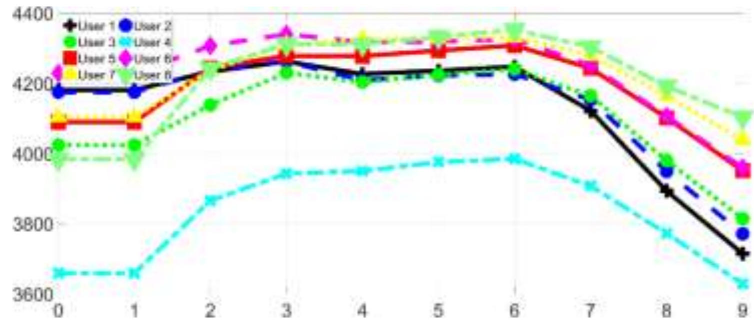

Figure 7. Throughput for CODAS

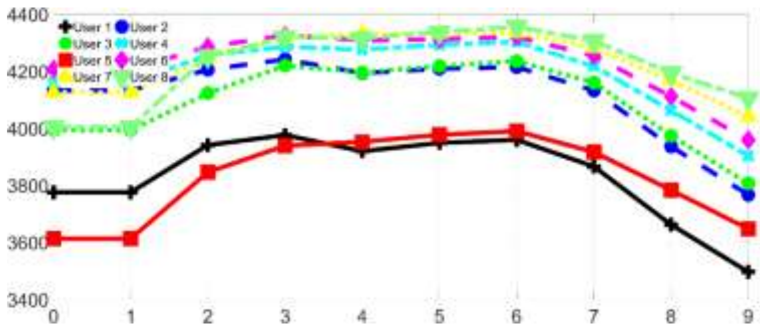

Figure 8. Throughput for COPRAS

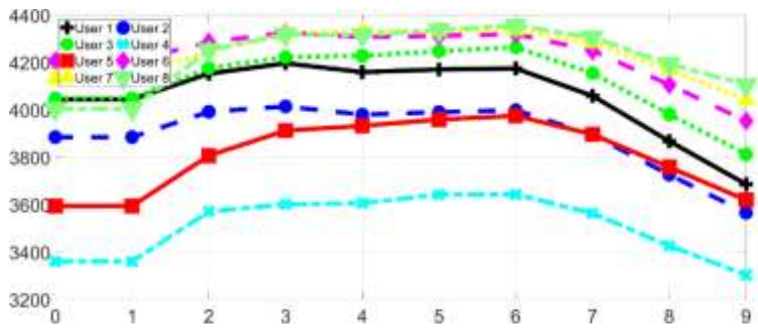

Figure 9. Throughput for MEW

Table 1. Comparative evaluation for throughput

Collaboration	CODAS	COPRAS	MEW
SU 1	90.73	85.37	89.27
SU 2	92.2	92.2	87.32
SU 3	93.17	92.68	92.93
SU 4	88.29	95.61	80.49
SU 5	96.34	88.78	88.29
SU 6	96.34	96.59	96.83
SU 7	98.54	98.9	98.78
SU 8	100	100	100
Score	94.45	93.77	91.74

7. CONCLUSION

The results achieved through this proposal of a device and method for the collaborative spectral decision of multiple users in DCRNs show that a reduction in the rate of channel changes during SU communications was achieved by approximately 59% about the CODAS algorithm and 32% about the COPRAS algorithm. This confirms that the collaborative strategy works adequately. The performance achieved by the proposed method shows the importance of carrying out an adequate collaboration strategy between SUs with sufficient quality of exchange information that does not affect the energy autonomy of the device but also provides significant information for the spectral decision. As well as the execution of prediction, multi-user, multichannel, and priority processes according to the requirements of the SU. However, despite the excellent results of the proposed method, it is necessary to carry out more tests in controlled environments to optimize the use of resources, time, and energy.

Reducing the number of handoffs or channel changes is a relevant aspect for the QoS of SU communications. This work achieves the reduction of the handoff rate through collaboration between SUs in a novel way. As a future work, it is proposed to optimize the amount of information exchanged and add parameters that allow evaluating whether said information is timely and relevant.

ACKNOWLEDGEMENTS

The authors would like to thank the Oficina de Investigaciones of Universidad Distrital Francisco Jose de Caldas for supporting this investigative project.

REFERENCES

[1] D. A. Pankratev, A. A. Samsonov, and A. D. Stotckaia, "Wireless data transfer technologies in a decentralized system," in *IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus)*, Jan. 2019, pp. 620–623, doi: 10.1109/EIConRus.2019.8656671.

[2] A. Bujari, C. T. Calafate, J.-C. Cano, P. Manzoni, C. E. Palazzi, and D. Ronzani, "Flying ad-hoc network application scenarios and mobility models," *International Journal of Distributed Sensor Networks*, vol. 13, no. 10, p. 155014771773819, Oct. 2017, doi: 10.1177/1550147717738192.

[3] S. Dhamodharavadhani, "A survey on clustering based routing protocols in mobile ad hoc networks," in *International Conference on Soft-Computing and Networks Security (ICSNS)*, Feb. 2015, pp. 1–6, doi: 10.1109/ICSNS.2015.7292426.

[4] A. A. A. Abass, N. B. Mandayam, and Z. Gajic, "An evolutionary game model for threat revocation in ephemeral networks," in *51st Annual Conference on Information Sciences and Systems (CISS)*, Mar. 2017, pp. 1–5, doi: 10.1109/CISS.2017.7926128.

[5] W. Kongsiriwattana and P. Gardner-Stephen, "Eliminating the high stand-by energy consumption of ad-hoc Wi-Fi," in *2017 IEEE Global Humanitarian Technology Conference (GHTC)*, Oct. 2017, pp. 1–7, doi: 10.1109/GHTC.2017.8239229.

[6] A. Vasudeva and M. Sood, "Survey on sybil attack defense mechanisms in wireless ad hoc networks," *Journal of Network and Computer Applications*, vol. 120, pp. 78–118, Oct. 2018, doi: 10.1016/j.jnca.2018.07.006.

[7] M. M. Goswami, "AODV based adaptive distributed hybrid multipath routing for mobile AdHoc network," in *International Conference on Inventive Communication and Computational Technologies (ICICCT)*, Mar. 2017, pp. 410–414, doi: 10.1109/ICICCT.2017.7975230.

[8] D. A. Giral-Ramírez, C. A. Hernández-Suarez, and I. P. P. Parra, "Novel methodological proposal for decision-making in decentralized cognitive radio networks based on information exchange between SU," *IEEE Access*, vol. 11, pp. 133993–134008, 2023, doi: 10.1109/ACCESS.2023.3333893.

[9] Q. Chen, X. Sun, R. Chai, and P. Wang, "Joint utility optimization resource allocation scheme for cognitive relay networks," in *Proceedings of the 2014 9th International Conference on Communications and Networking in China, CHINACOM 2014*, Aug. 2014, pp. 572–577, doi: 10.1109/CHINACOM.2014.7054361.

[10] S. Salehi and V. Solouk, "Channel assignment and users mobility influence on primary users QoE in cognitive radio network," *Ad Hoc Networks*, vol. 129, p. 102807, Apr. 2022, doi: 10.1016/j.adhoc.2022.102807.

[11] D. Giral, C. Hernández, and C. Salgado, "Spectral decision in cognitive radio networks based on deep learning," *Expert Systems with Applications*, vol. 180, pp. 115080, Oct. 2021, doi: 10.1016/j.eswa.2021.115080.

[12] A. Bdrany and S. B. Sadkhan, "Decision making approaches in cognitive radio-status, challenges and future trends," *3rd International Conference on Advanced Science and Engineering, ICOASE 2020*, pp. 195–198, 2020, doi: 10.1109/ICOASE51841.2020.9436597.

[13] S. J. Darak, H. Zhang, J. Palicot, and C. Moy, "Decision making policy for RF energy harvesting enabled cognitive radios in decentralized wireless networks," *Digital Signal Processing*, vol. 60, pp. 33–45, Jan. 2017, doi: 10.1016/j.dsp.2016.08.014.

[14] C. Hernandez, C. Salgado, H. López, and E. Rodriguez-Colina, "Multivariable algorithm for dynamic channel selection in cognitive radio networks," *EURASIP Journal on Wireless Communications and Networking*, vol. 2015, no. 1, p. 216, Dec. 2015, doi: 10.1186/s13638-015-0445-8.

[15] H. Reyes, S. Subramaniam, N. Kaabouch, and W. C. Hu, "A Bayesian inference method for estimating the channel occupancy," in *IEEE 7th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, Oct. 2016, pp. 1–6, doi: 10.1109/UEMCON.2016.7777865.

[16] D. M. Alias and Ragesh G. K, "Cognitive radio networks: a survey," in *International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, Mar. 2016, pp. 1981–1986, doi: 10.1109/WiSPNET.2016.7566489.

[17] A. A. Khan, M. H. Rehmani, and A. Rachedi, "When cognitive radio meets the internet of things?," in *International Wireless Communications and Mobile Computing Conference (IWCMC)*, Sep. 2016, pp. 469–474, doi: 10.1109/IWCMC.2016.7577103.

[18] L. R. M. Pinto and L. H. A. Correia, "Analysis of Machine learning algorithms for spectrum decision in cognitive radios," in *15th International Symposium on Wireless Communication Systems (ISWCS)*, Aug. 2018, pp. 1–6, doi: 10.1109/ISWCS.2018.8491060.

[19] M. E. Youssef, S. Nasim, S. Wasi, U. Khisal, and A. Khan, "Efficient cooperative spectrum detection in cognitive radio systems using wavelet fusion," in *International Conference on Computing, Electronic and Electrical Engineering (ICE Cube)*, Nov. 2018, pp. 1–6, doi: 10.1109/ICECUBE.2018.8610981.

[20] C. Hernandez, D. Giral, and C. Salgado, *Multiuser spectral allocation model for decentralized cognitive radio net*works *(in Spanish: Modelo de asignación espectral multiusuario para redes de radio cognitiva descentralizadas)*, Primera ed. Bogotá: Editorial UD, 2021.

[21] C. Hernandez, D. Giral, and F. Martínez, "Decision-making analysis in cooperative environments for decentralized cognitive radio networks," *Heliyon*, vol. 10, no. 4, 2024, doi: 10.1016/j.heliyon.2024.e25977.

[22] Y. Rizk, M. Awad, and E. W. Tunstel, "Decision making in multiagent systems: a survey," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 10, no. 3, pp. 514–529, Sep. 2018, doi: 10.1109/TCDS.2018.2840971.

[23] A. Roy, S. Midya, K. Majumder, S. Phadikar, and A. Dasgupta, "Optimized secondary user selection for quality of service enhancement of two-tier multi-user cognitive radio network: a game theoretic approach," *Computer Networks*, vol. 123, pp. 1–18, Aug. 2017, doi: 10.1016/j.comnet.2017.05.002.

[24] H. Taherdoost, "Machine learning algorithms: features and applications," in *Encyclopedia of Data Science and Machine Learning*, IGI Global, 2022, pp. 938–960.

[25] J. Shi, M. Jain, and G. Narasimhan, "Time series forecasting (TSF) using various deep learning models," *arXiv preprint arXiv:2204.11115*, 2022, doi: 10.48550/arXiv.2204.11115.

BIOGRAPHIES OF AUTHORS

Cesar Hernandez was born in Villavicencio, Colombia. He received bachelor's and master's degrees in electronic engineering and telecommunications from Universidad. Distrital Francisco José de Caldas, Colombia, and the Ph.D. degree in engineering from Universidad Nacional de Colombia. He is a Titular Professor of electrical engineering programs with Universidad Distrital Francisco José de Caldas. His research interests include mathematical optimization, cognitive radio networks, and intelligent systems. He can be contacted at email: cahernandezs@udistrital.edu.co.

Diego Giral was born in Bogotá, Colombia. He is master's graduate in Electric Engineering from Universidad de los Andes. He received bachelor's degrees in Electric Engineering from Universidad Distrital Francisco José de Caldas, Colombia. He is currently an associate professor at Universidad Distrital Francisco José de Caldas. His research interests include cognitive radio networks. He can be contacted at email: dagiralr@udistrital.edu.co.

Camila Salgado was born in San Luis de Gaceno, Colombia. She is master's graduate in Information and Communication Sciences from Universidad Distrital Francisco Jose de Caldas. She is currently a researcher of the Universidad Distrital Francisco José de Caldas. Her research interests include cognitive radio networks. She can be contacted at email: lcsalgadof@udistrital.edu.co.