Journal of Engineering Science and Technology
Vol. 15, No. 4 (2020) 2624 - 2638

DYNAMIC MULTICHANNEL TRANSMISSION IN COGNITIVE RADIO NETWORKS

HANS MARQUEZ, DIEGO GIRAL, CESAR HERNANDEZ*

Technological Faculty, Universidad Distrital Francisco José de Caldas,
Street 68D Bis A South # 49F - 70, Bogotá, Colombia
*Corresponding Author: cahernandezs@udistrital.edu.co

Abstract

In cognitive radio networks, the secondary users run different types of wireless applications and, therefore, require different levels of bandwidth. A possible solution to said requirement from secondary users is the multichannel spectrum allocation with equity. The present research has the purpose to assess the performance of multichannel algorithms with the MFA and K-means algorithms through bandwidth and equity metrics, under different assessment scenarios. A simulation tool was developed with the parameters of interest of a cognitive radio with multi-user approach. The results show a satisfying performance of the K-means algorithm with a 2% margin compared to MFA. The Jain indicator in all four assessment scenarios surpassed 94%. One of the main contributions of the present work lies is the fact that it considers multiple SU which dynamically vary at the same time throughout transmission as well as the performance assessment.

Keywords: Cognitive radio, Fairness, K-Means, MFA, Multichannel, Multiuser.

1. Introduction

The inefficient and sporadic use of the spectrum, along with the increase in its use related to the demand of wireless applications have led to the downgrade of the quality of service [1-4]. The previous situation has prompted the development of research projects that have defined dynamic spectrum allocation (DSA) as a possible solution to the matter, materialized through cognitive radio (CR) [5-9]. This gives CR the capacity to significantly increase spectral efficiency since it allows the primary user (PU) to share the spectrum with one or several secondary users (SU) in an opportunistic manner [6,10]. CR is a technology that can improve spectral resources, while offering the possibility of solving problems in different Engineering areas [1, 11, 12].

To model the network with real parameters, it is important to mention that not all SU run the same applications and, hence, require different bandwidth (BW) [13]. Hence, it is interesting to allow SU to perform multi-channel transmissions for real time (RT) applications [14], and simple channel transmissions for delay-tolerant applications or low BW demand [15]. However, when several channels are assigned to a single SU, the equity criterion could be significantly affected for other SUs interested in using these resources to transmit their own information. Hence, it becomes necessary to include a Fairness criterion that can control this aspect.

The present research seeks to assess the performance of two multichannel algorithms, that can harness the spectral opportunities (SO) for SU, even though a multichannel approach as long as the number of SO and SU enables it. The proposed methodology can assign several frequency channels for transmission to secondary users that require larger BW. Nonetheless, this is only possible if the number of SU that require the spectral resource is lower than the number of SO. To assess the scenario, the chosen algorithms include a fairness criterion to guarantee an equitable allocation of spectral opportunities among SU.

The review of previous research projects allowed some that included multichannel models without the fairness criterion [16] and fairness criterion without multichannel models [17]. The number of publications is reduced if the multichannel models apply the fairness criterion. Furthermore, the number of articles is dismal when the structure is dynamic. In [18], some of these approaches are linked and the authors analyse multiuser and multichannel scenarios for dynamic access. The proposed learning model based on the Dirichlet process predicts the traffic profile in the channel and creates an optimal dynamic access scheme as non-linear programming problem. However, although a multichannel, multiuser and dynamic structure is proposed, the channel allocation is not characterized in terms of the type of service, the multichannel spectrum allocation is not based on an equity model and cases of under-allocation and over-allocation are not contemplated. In [19], the authors analyse two problems: spectrum detection and spectrum exchange where channels have different characteristics and the detection performance of SUs varies. Game theory and crossed entropy are used, the dynamic model corresponds to access and not to the variation of SU over time as seen in this article. The equity model is not contemplated.

The development of the present research, centered in dynamic multichannel allocation, considered diverse parameters and scenarios for their corresponding validation and assessment such as selection of multichannel algorithms, SU dynamics, decision criteria, demand of spectral resources, traffic level, transmission time and assessment metrics. The chosen multichannel allocation algorithms were MFA [20] and K-means [13, 21-23] due to their performance in related work [22-24]. The SU dynamics were established based on the constant variation of SU that enter to ask for spectral resources and those who leave when their data transmission is over. The decision-making criteria used were the availability probability (AP), estimated time of availability (ETA), signal plus interference noise ratio and bandwidth (BW), which were calculated for each SO. The demand of spectral resources was included in four types of SU that require different BW due to the application required. These were classified according to the number of channels necessary for the transmission of SU1 (1 channel required), SU2 (2 channels required), SU4 (4 channels required) and SU10 (10 channels required). Additionally, two scenarios were considered where the number of SU with types 1, 2, 4 and 10 was different, leading to high and low levels of SO available. These scenarios were classified as strong overallocation demand and strong under-allocation demand. Two traffic levels were also defined: high and low. The transmission time is a parameter ranging from 1 to 10 minutes. Finally, the assessment metrics were bandwidth and fairness.

2. Experimentation Procedure

The experiments were carried out based on a simulation tool which was designed and developed to simulate a cognitive radio network. The software was developed using the Guide Matlab environment which allows users to work in a friendly and parameterizable environment without the need for a Matlab license. Given that it is a portable file it does not include the source codes and can be used, copied and distributed non-profit, as long as the Universidad Distrital Francisco José de Caldas is credited. The graphical interface of the simulator can be visualized in Fig. 1.

The software operates with a database that contains information on spectral occupancy. In contrast to the related work, this database corresponds to the real information of licensed users. The information trace was measured in the frequency band of the Global System technology for Mobile Communications (GSM). However, the software is designed to adapt to other types of technologies while only requiring to load a new spectral occupancy matrix.

The spectral occupancy data corresponds to a one week of observation, captured within the metering campaign in the city of Bogotá, Colombia. To determine the occupancy or availability of each channel, the energy detection technique was used, setting a decision threshold of 5 dBm over the noise floor power of the spectrum analyser and through the equation of the false alarm probability. The equipment for spectral measurement was comprised of a Discone Antenna in a frequency range between 25 MHz and 6 GHz, a low-noise amplifier (LNA) in the operation range between 20 MHz and 8 GHz and finally, a spectrum analyser in the operation range between 9 kHz and 7.1 GHz. The main technical parameters were set as follows: bandwidth resolution at 100 kHz, span at 50 MHz and sweep time at 290 ms.

The volume of information of PU spectral occupancy was generated by two matrices classified into high and low traffic. Hence, there is an input in the simulator called Traffic Level which chooses the type of traffic for simulation. Furthermore, there are other inputs parameterizable by users such as Criteria Time, Fixed AB, Threshold and Noise Floor, that will directly affect channel availability and how the fairness-based algorithms have to equitably assign resources for users. Figure 2 describes the software structure which basically consists of five functions and a main core.

The first function of the diagram called input_data seeks to pre-process the spectral occupancy data retrieved in the GSM frequency band, which are given in power levels. After the pre-processing stage, the input_data function delivers the values of each decision criteria: AP, ETA, SINR and BW. The previous variables serve as input parameters for the criteria_values function with the purpose of calculating the average value of each decision criteria, based on the configuration set by the user in the graphical environment. The handoff models function classifies the available frequencies in the licensed band from best to worst, according to the model logic. This classification groups multiple channels which are called multichannel bands with the purpose of being allocated to users requesting multiple channels.

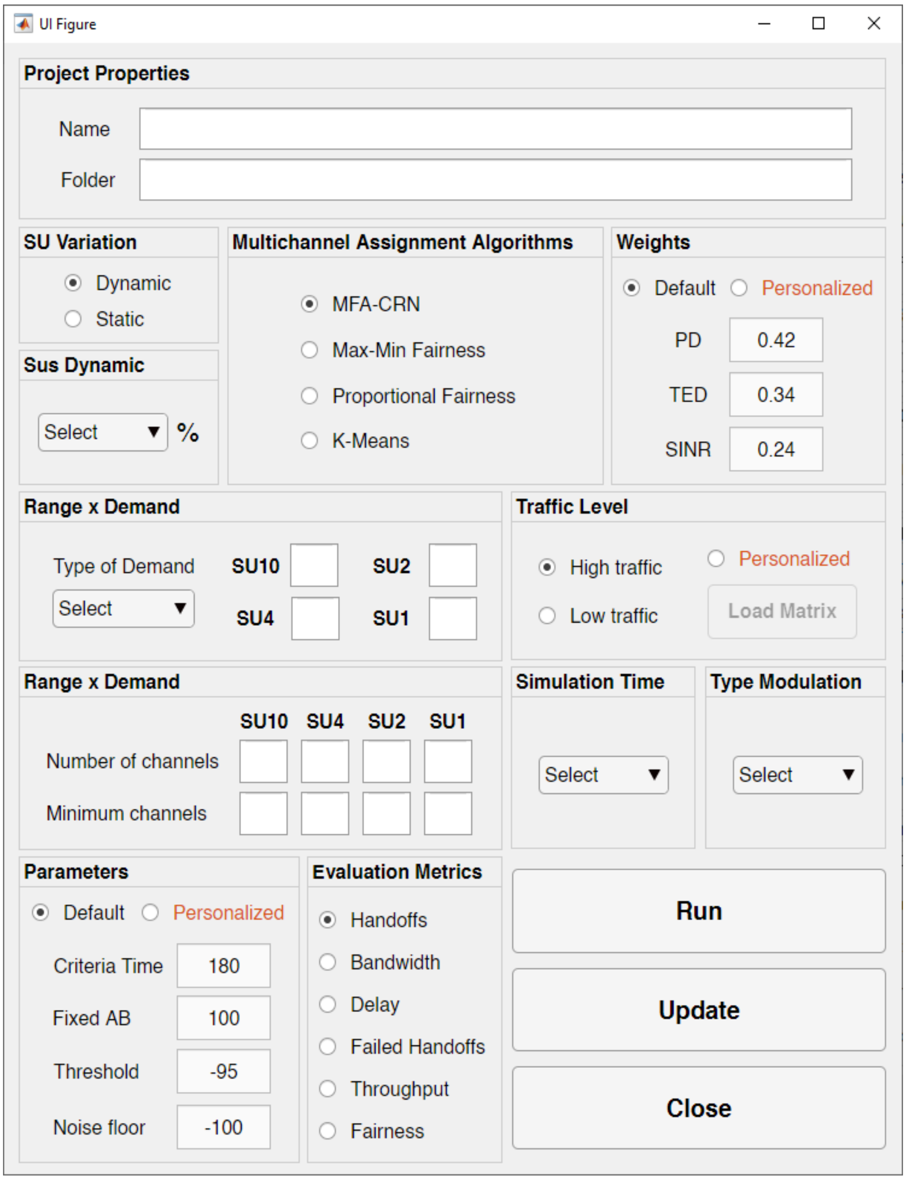

Fig. 1. User interface for simulation.

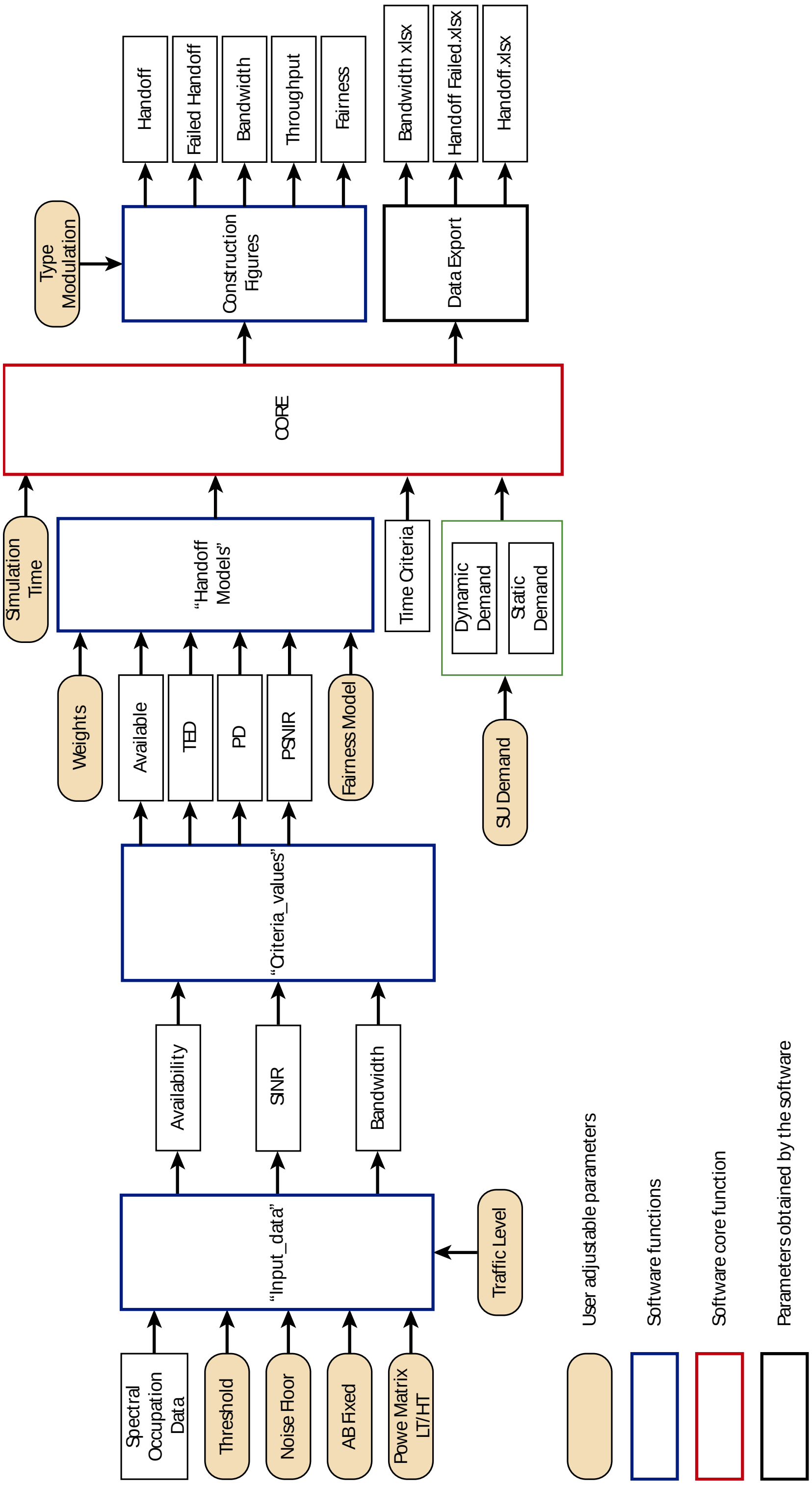

Fig. 2. Block diagram of the simulation software.

The core function performs a step-by-step assessment of the chosen model during the transmission time set by the user and assesses the decisions made by the model in terms of real spectral occupancy data. However, the core function considers how users will behave during transmission, i.e. whether the behaviour is static or dynamic. The Construction Figures function based on the results stored by the core function creates five output figures: Handoffs, Failed Handoffs, Bandwidth, Throughput and Fairness. The present article analyses two out of these five assessment metrics (Bandwidth and Fairness). Finally, the data export function exports the quantitative data of the entire process in a .xlsx (Excel) file.

The developed simulator allows to assign multiple channels with the equity criterion. However, this multiple allocation offers the possibility to vary the number of secondary users (SU) during the simulation process or leave it as static if required. Hence, the simulator can interact with multiple SU instead of just a single user.

The input called SU demand refers to different types of demand incoming from SU. Such type of demand is classified into two scenarios: Demand A (Strong Overallocation) and Demand D (Strong Under-allocation). This leads to assess the performance of the resource allocation process in different radio environments. However, this input has two subcomponents that establish the behaviour of SU during the simulation time: static demand and dynamic demand.

Static demand*:* The users established in Demands A and D remain invariant over the simulation time set by the user.

Dynamic demand: The users established in Demands A and D vary throughout the simulation time set by the user. This variation of users is given by the number of dropouts and additions of SU during the simulation time. The variation is predefined by the user within a range from 1 to 25% based on a statistical analysis. Hence, for a dynamic variation of 10%, the number of dropouts cannot surpass a certain percentage and the number of new user additions cannot exceed twice of this percentage.

The variation is controlled through a random function with a minimum variation set by default as zero (0) and a maximum variation set by the user (see Eq. (1)).

$$0 \leq \textit{funcion random} \leq \textit{variacion max definida por usuario} \tag{1}$$

Therefore, users that dropout cannot exceed the value established by the user. It is noteworthy to mention that the dropouts take place each time that one minute of simulation has passed. Additionally, a user addition policy is applied that is controlled through a random function that decides the number of users to be added in simulation and the number of requested channels. These additions have a variation interval between zero (0) and up to twice the variation interval set by the user (see Eq. (2)). This assures that users that dropout cannot exceed the value established by the user. Additions take place after each minute of simulation.

$$0 \leq \textit{funcion random} \leq 2 * \textit{variacion max definida por usuario} \tag{2}$$

The *core* function of the simulator carries out the processes required to search for the available channels and their subsequent allocation in an equitable manner to all users available in simulation. These allocations of resources generate the metrics of bandwidth (BW) and fairness. These metrics are progressively stored during the time of simulation. Once the simulation time has been concluded, the Construction Figures block receives as input variables the matrices containing the metric data, the simulation time and the modulation time used for simulation. This block builds the charts for each metric where the SU classes are discriminated according to the preestablished demand of channels. Thus, a database is generated for each metric and stored in the (.xlsx) format for subsequent analysis.

2.1. K-means algorithm

The unsupervised learning algorithm k-means is used for the selection of channels. It classifies data into *k* groups and its purpose consists on defining a number of *k* centroids for each group. Then, the data is taken and associated to the closest center. This procedure is carried out iteratively for a number of *n* times which means that the centroids will vary in each iteration until they reach stability (Vassilvitskii, 2007). Finally, this algorithm has the goal to minimize the target function known as the mean square error given by Eq. (3).

$$J(V) = \sum^{c}\sum^{ci}\left(\left\|x_i - v_j\right\|\right)^2 \quad (3)$$

where $\| x_i - v_j \|$ is the Euclidian dynamic, x_i, v_j, c_i is the number of data in the jth group and c is the number of centroids.

Figure 3 describes the proposed k-means algorithm. The first block called BD Spectral Occupation contains real spectral occupancy data corresponding to the GSM band. These data correspond to the input matrix of the *Spectral Information* Processing block, which has the task to determine the occupation or availability of each channel in the GSM band, based on the false alarm probability. The block called BW User Demand contains information on the number of users requesting 10 channels, 4 channels, 2 channels and 1 channel.

The rectangular dotted area in Fig. 3 corresponds to the proposed k-means algorithm comprised of three blocks. The block called Band Location Algorithm receives the channel demands made by SU, both for a single channel or multiple channels for transmission and locates the multichannel bands. Then, the K-means clustering algorithm performs 15 iterations of grouping seeking to assemble the channels into two clusters with the best channels according to the AP, ETA and SINR criteria. Finally, the Multichannel Fairness Allocation block allocates the channels while trying to satisfy the demands in fair manner.

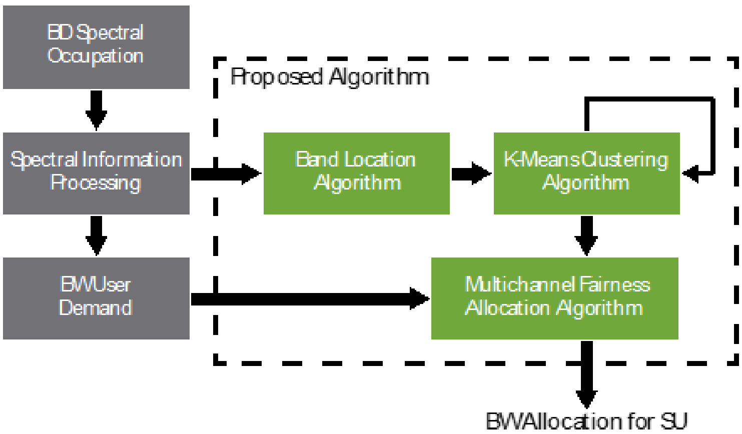

Fig. 3. K-means algorithm [13, 21].

2.2. MFA algorithm

An equitable allocation algorithm considers the fairness or equity criterion for which a wireless network with insufficient resources can become an excellent alternative when allocating resources to users. Figure 4 describes the Multichannel Fairness Algorithm (MFA) whose operation is similar to the k-means algorithm. The rectangular area corresponds to the proposed algorithm comprised of three blocks: Band Location Algorithm, Multichannel Ranking Algorithm and Multichannel Fairness Allocation Algorithm. The first block is in charge of organizing the available channels into multichannel frequency bands. The second one is in charge of ranking the multichannel bands in terms of the chosen decision criteria. The third block determines how many and which channels are assigned to each SU according to their requests and the offer available. The allocation is carried out in a fair manner for all users.

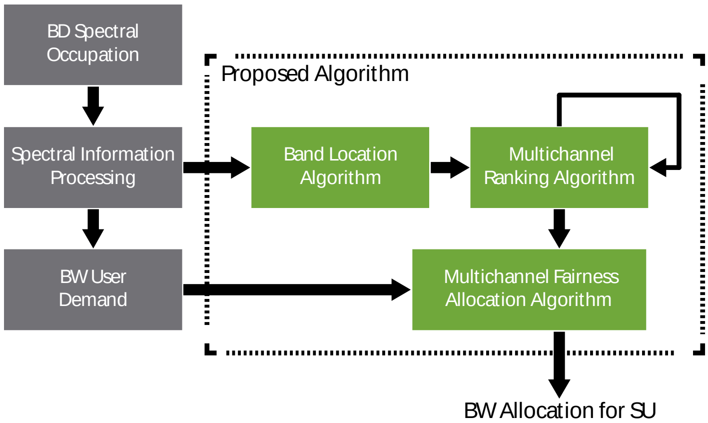

Fig. 4. General structure of the proposed MFA-CRN algorithm [13, 24].

Algorithm multichannel ranking

The algorithm creates an ordered list of the bands and unique channels based on a score. This process uses the decision-making criteria of the input vectors related to the Availability Probability (AP), the Average Availability Time (AAT), the Average SINR (ASINR) and the Bandwidth (BW) for each channel (Fig. 2). The multichannel algorithm uses these vectors to assign a score to each unique band and channel. Finally, the score of each one is order from highest to lowest, creating a multichannel ranking vector.

At this point, the spectral opportunities are ranked based on the current information of the decision criteria. An additional feedback process is implemented to improve the selection of opportunities. This process receives the current assessments (PS) for each spectral opportunity and ponders them with the value of the recent assessment (LS) and average of the assessments (AS) carried out over the past hour. This ponderation leads to the definitive ranking of the spectral opportunities which is then delivered as an input to the MFA (Eq. (4)) [25].

$$Final\_Score_i = \alpha \times PS + \beta \times LS + (1 - \alpha - \beta) \times AS \quad (4)$$

where α=*0.62* and β=*0.58*. The values obtained from multiple self-regressive experiments with different combinations of α and β with an experimental precision of 87% [25].

2.3. Fairness metric

The fairness metric is a special property of resource allocation algorithms. If a wireless network has the resources to satisfy the demand then it can share the resources equitably to the network users. Fairness can be defined as the equality of resources among users based on a pre-established agreement [26, 27].

The fairness metric can be measured through the Jain index which identifies underused channels as described in Eq. (5) [26, 27].

$$J = \frac{\left(\sum_{i=1}^{n} X_i\right)^2}{n\sum_{i=1}^{n} X_i^2} \tag{5}$$

where n is the number of users and X_i is the performance of the i^{th} connection.

3. Results and Discussion

To assess the performance of the MFA and k-means algorithms, a complete analysis was carried out that included the following parameters: (1) Dynamic SU with 10% variation; (2) two types of demands; strong overallocation (A) and strong under-allocation (D); (3) four types of services (voice, web, videoconferences, streaming and multimedia) that identify four types of SU - 10 channels (SU10), 4 channels (SU4), 2 channels (SU2) and 1 channel (SU1); (4) two types of traffic labelled as low and high; (5) a transmission time of 10 minutes; and (6) two assessment metrics which are bandwidth and fairness.

According to the previous statements, four assessment scenarios were defined:

- Scenario 1 - SUB-LT corresponds to a strong under-allocation (SUB) demand with low traffic (LT).
- Scenario 2 - SUB-HT corresponds to a strong under-allocation (SUB) demand with high traffic (HT).
- Scenario 3 - SOB-LT corresponds to a strong overallocation (SOB) with low traffic (LT).
- Scenario 4 - SOB-HT corresponds to a strong overallocation (SOB) with high traffic (HT).

Under-allocation refers to the allocation of a number of channels lower than the ones required and overallocation refers to the allocation of more channels than needed. Four figures were built for these four scenarios. Figure 5 describes scenarios 1 and 2 meanwhile Fig. 6 describes scenarios 3 and 4, for the assessment metric of BW. Figure 7 describes scenarios 1 and 2, Fig. 8 describes scenarios 3 and 4 for the fairness assessment metric.

As shown in Fig. 5, the average variation of bandwidth for both algorithms and the two types of traffic are grouped in terms of the SU types. The highest values are obtained for k-means and MFA with 10 channels (SU10) with proportional behaviours, for LT at minute 4. K-means shows an increase of 86 kHz compared to MFA. In HT, k-means outperforms MFA over the 10 minutes of transmission with an increase that does not exceed 37 kHz obtained for minutes 6 and 7.

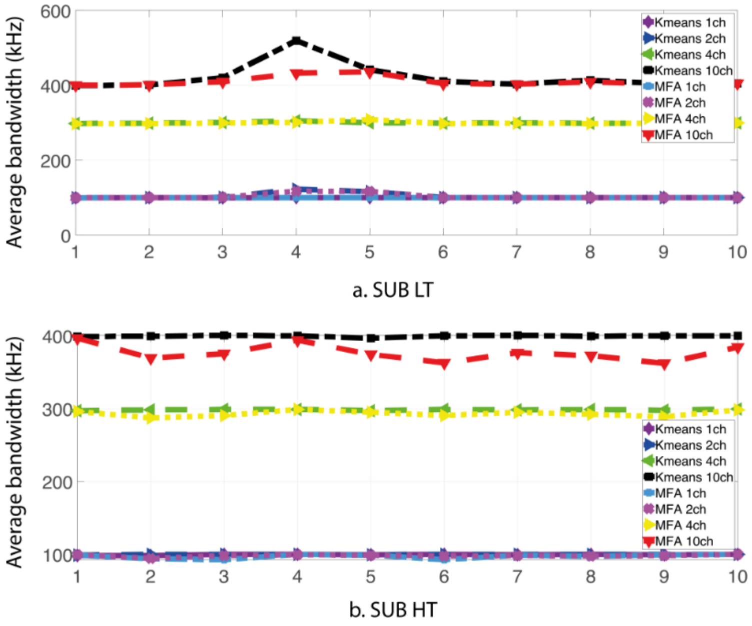

Fig. 5. Bandwidth under-allocation.

As shown in Fig. 6, the average variations of bandwidth for both algorithms and both traffic types are grouped in terms of the SU. In LT, no variations are identified over the 10 minutes of transmission and, in HT, some changes are detected in minutes 4 and 6 with variations under 70 kHz.

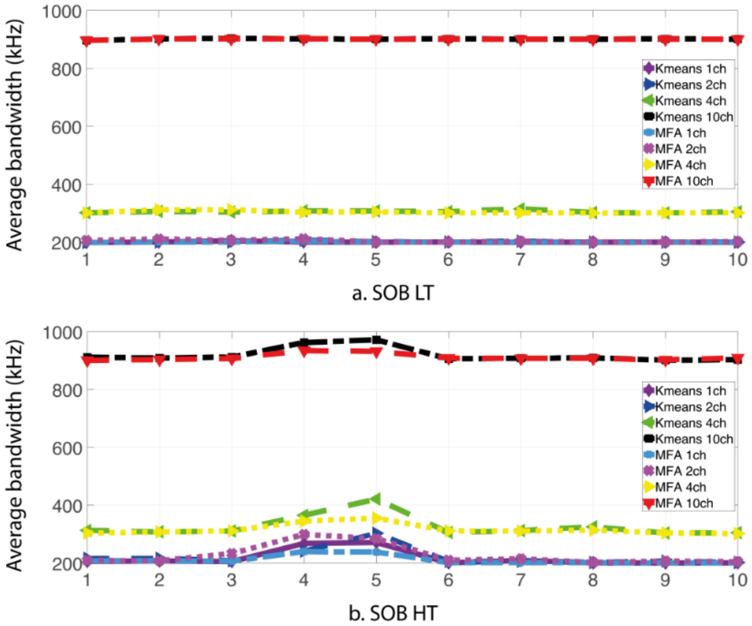

Fig. 6. Bandwidth overallocation.

Figures 7 and 8 represent the Jain index in the form of a bar diagram. This metric measured to characterized the Fairness criterion can determine whether users are receiving a fair portion of the system resources. The scale for each figure is fitted so that variations can be observed. However, Fig. 7 and 8 reveal that the values are close to 1 in all cases with the lowest one corresponding to an under-allocation in high traffic of 0.945. These values of the Jain index over 94% evidence a high performance in the equitable resource allocation processes in terms of bandwidth for both multichannel allocation algorithms.

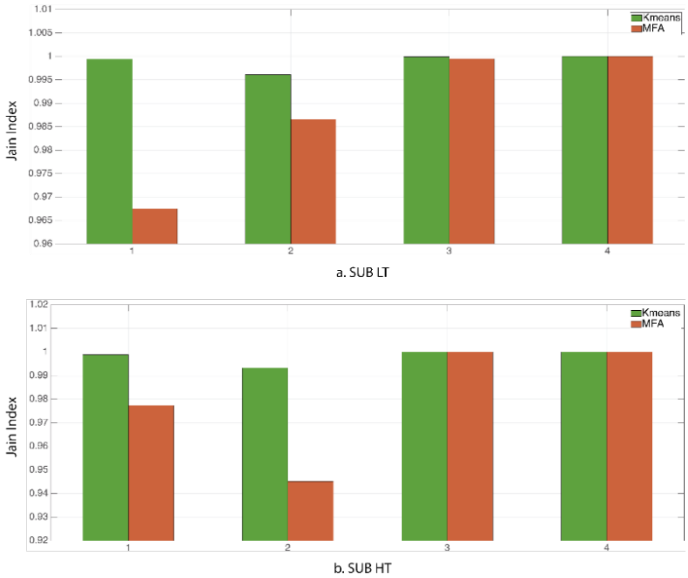

Fig. 7. Fairness under-allocation.

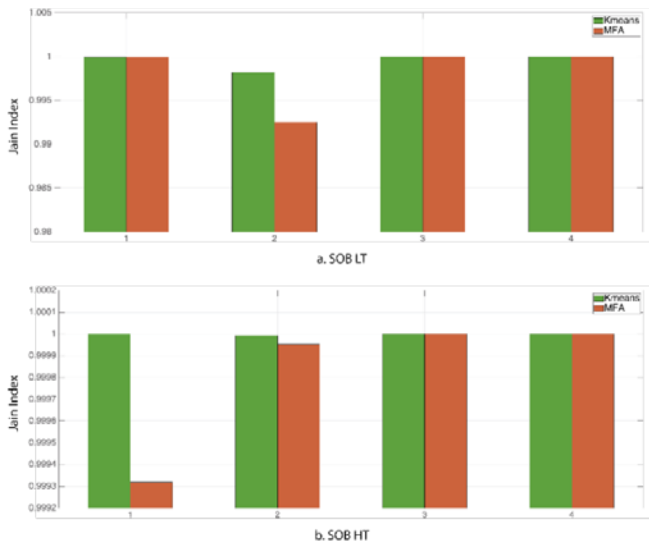

Fig. 8. Fairness overallocation.

Comparative assessment

In Tables 1 and 2, the comparative percentages of the performance of each algorithm are presented for each metric, type of SU and demand scenario. The k-means algorithm has the best performance with a 2% margin compared to MFA.

Table 1. Comparative assessment per metric for different SU types.

BW Metric	SU1		SU2		SU4		SU10	
	MFA	K-means	MFA	K-means	MFA	K-means	MFA	K-means
SUB-LT	99,89	99,89	103,39	103,83	299,67	299,78	410,28	421,67
SUB-HT	97,28	99,50	98,28	99,83	293,28	298,39	376,89	399,56
SOB-LT	200,28	200,50	204,06	201,22	303,89	305,61	900,72	901,17
SOB-LT	210,33	216,72	227,00	220,56	316,33	326,89	911,06	919,06
Average	151,94	154,15	158,18	156,36	303,29	307,66	649,73	660,36

Table 2. Comparative assessment of fairness for each metric and user type.

Fairness Metric	SU1		SU2		SU4		SU10	
	MFA	K-means	MFA	K-means	MFA	K-means	MFA	K-means
SUB-LT	0,9675	0,9994	0,9865	0,9960	0,9995	0,9999	1	1
SUB-HT	0,9772	0,9987	0,9451	0,9932	1	1	1	1
SOB-LT	0,9999	0,9999	0,9925	0,9982	1	1	1	1
SOB-HT	0,9993	1,0000	0,9999	0,9999	1	1	1	1
Average	0,9860	0,9995	0,9810	0,9968	0,9998	0,9999	1	1

Based on the bandwidth allocation analysis, in strong under-allocation with low traffic (LT), the highest variation between MFA and k-means takes place for 10 channels (SU10) with 11.39 kHz, where k-means has the best performance for 2 and 4 MFA channels with the corresponding low variations at 044 kHz and 0.11 kHz. For 1 channel (SU1), both algorithms are tied. For a strong under-allocation with high traffic (HT), K-means has the best performance in all four types of SU. The highest variation is 22.67 kHz with 10 channels (SU10) and the lowest variation is 1.55 kHz in 2 channels (SU2).

For strong overallocation with low traffic (LT), k-means offers the best results with the highest variation at 2.84 kHz for SU2 and the lowest variation at 0.45 kHz for SU10. In strong overallocation with high traffic (HT), the result is equivalent to low traffic. K-means has the best performance in SU1, SU4 and SU10 while MFA excels for the SU2 type.

According to the fairness analysis, all scenarios delivered results with high performance in the bandwidth allocation processes and the Jain indicator for all cases surpassed 94%.

4. Conclusions

The dynamic allocation of multichannel spectrum is a feasible proposal with satisfying results for both secondary and primary users. This allows a much more efficient use of the radioelectric spectrum.

None of the implemented strategies had the best performance overall in all parameters. The selection of the algorithm must be determined in terms of the scenario and the type of traffic. The allocation of bandwidth revealed that k-means offered the best performance in all four scenarios with SU10 and SU1. For SU2 and SU4, the result is based on the type of demand. In overallocation, k-means and MFA offered the best results respectively. In under-allocation, the traffic type must also be analysed. For low traffic, MFA has the best performance while k-means takes first place in high traffic. In terms of fairness, the Jain indicator surpassed 94% for all cases thus meaning that the bandwidth allocation processes showed a high performance in all the proposed scenarios.

5. Future Work

Regarding future work, it is required to implement a scenario that can analyse decentralized and distributed structures. Furthermore, to make the model more realistic, additional features must be included to the multiuser models that can quantify network externality. Since none of the strategies delivered the best performance for all parameters, hybridize the techniques could improve performance.

Acknowledgements

The authors wish to thank the Center for Research and Scientific Development of the Universidad Distrital Francisco José de Caldas (Bogotá, Colombia) for the support of this research.

References

1. Tuberquia, D.L.; López, H.; and Hernández, C. (2019). *Multifractal model for cognitive radio networks* (1th Ed.). Bogotá: UD Editorial.
2. Bernal, C.; and Hernández, C. (2019). *Modelo de decisión espectral para redes de radio cognitiva* (1th Ed.). Bogotá: UD Editorial.
3. Tahir, M.; Hadi, H.M.; and Islam, M.R. (2017). Novel distributed algorithm for coalition formation for enhanced spectrum sensing in cognitive radio networks. *AEU - International Journal Electronics and Communications*, 77, 139-148.
4. Hernández, C.; Márquez, H.; and Giral, D. (2017). Comparative evaluation of prediction models for forecasting spectral opportunities. *International Journal Engineering Technology,* 9(5), 3775-3782.
5. Pedraza, L.F.; Hernández, C.; and Salgado, C. (2018*). Modelo de predicción de la ocupación espectral para el análisis y diseño de redes de radio cognitiva* (1th Ed.). Bogotá: Editorial UD.
6. Akyildiz, I.F.; Lee, W.Y.; Vuran, M.C.; and Mohanty, S.A. (2008). Survey on spectrum management in cognitive radio networks. *IEEE Communication Magazine*, 46(4), 40-48.
7. Federal Communications Commission. (2003). Notice of proposed rulemaking and order, Federal Communications Commission, Washington D.C.
8. IEEE Community Society. (2008). IEEE standard definitions and concepts for dynamic spectrum access: Terminology relating to emerging wireless networks, system functionality, and spectrum management. IEEE Standard 1900.1-2019.

9. Hoven, N.; Tandra, R.; and Sahai, A. (2005). *Some fundamental limits on cognitive radio* (1th Ed.). Berkeley: Wireless Foundations EECS.
10. Ozger, M.; and Akan, O.B. (2016). On the utilization of spectrum opportunity in cognitive radio networks. *IEEE Communication Letters*, 20(1), 157-160.
11. Gómez, V.; Hernández, C.; and Rivas, E. (2018). *Desarrollo, políticas y futuro de las microredes inteligentes* (1th Ed.). Bogotá: UD Editorial.
12. Rizk, Y.; Awad, M.; and Tunstel, E.W. (2018). Decision Making in multiagent systems: A survey. *IEEE Transactions on Cognitive and Development Systems*, 10(3), 514-529.
13. Hernández, C.; Márquez, H.; and Pedraza, L.F. (2017). *Modelo de asignación multicanal con equidad para la movilidad espectral en redes de radio cognitiva* (1th Ed.). Bogotá: UD Editorial.
14. Hernández, C.; Giral, D.; and Martínez, F. (2018). Benchmarking of algorithms to forecast spectrum occupancy by primary users in wireless networks. *International Journal Engineering Technology*, 10(6), 1611-1620.
15. Kwon, Y.M.; and Park, H.K. (2016). Distributed channel allocation for ad-hoc multichannel cognitive radio networks. *International Journal Control Automation. KoreaTech*, 9(6), 173-180.
16. Li, X.; Song, Q.; Wang, J.; Tao, H.; and Zhang, J. (2013). Improved idle channel utilization in distributed multi-channel cognitive radio systems. *Proceedings of the IEEE Vehicular Technology Conference*. Dresden, Germany, 1-6.
17. Huang, P.; Wang, C.; and Xiao, L. (2015). RC-MAC: A receiver-centric MAC Protocol for event-driven wireless sensor networks. *IEEE Transactions on Computers*, 64(4), 1149-1161.
18. Huang, X.; Tang, X.; and Hu, F. (2019). Dynamic spectrum access for multimedia transmission over multi-user, multi-channel cognitive radio Networks. *IEEE Transactions on Multimedia*, 22(1), 201-214.
19. Zhang, N.; Liang, H.; Cheng, N.; Tang, Y.; Mark, J.W.; and Shen, X.S. (2014). Dynamic spectrum access in multi-channel cognitive radio networks. *IEEE Journal on Selected Areas in Communications*, 32(11), 2053-2064.
20. Hernández, C.; Márquez, H.; and Pedraza, L. (2016). Multichannel allocation spectrum model with fairness criterion for cognitive radio networks. *Contemporary Engineering Science*, 9(29), 1503-1524.
21. Márquez, H.R.; Salgado, C.; and Hernández, C. (2017). Asignación multicanal usando K-means en redes de radio cognitiva. *Tecnura*, 21(52), 68-78.
22. Lei, K.; Tan, Y.; Yang, X.; and Wang, H. (2018). A K-means clustering based blind multiband spectrum sensing algorithm for cognitive radio. *Journal Central South University*, 25, 2451-2461.
23. Liu, X.; Jia, M.; and Ding, H. (2020). Uplink resource allocation for multicarrier grouping cognitive internet of things based on K-means Learning. *Ad Hoc Networks*, 96, 1-9.
24. Márquez, H.R; Hernández, C.; and Páez, I. (2015). Multichannel scheme under max-min fairness environment for cognitive radio networks. *World Academy Science Engineering Technology Institute Journal Electrical Computer Energy Electron Communication Engineering*, 9(10), 1178-1182.

25. Hernández, C.; Pedraza, L.F.; and Rodríguez-Colina, E. (2016). Fuzzy feedback algorithm for the spectral handoff in cognitive radio networks. *Revista Facultad de Ingeniería de La Universidad de Antioquia*., 2016(80), 47-62.
26. Jain, K.R.; Dah-Ming, W.C.; and Hawe, W.R. (1984). A Quantitative measure of fairness and discrimination for resource allocation in shared computer system. Retrieved May 1, 2019, from http://www.cs.wustl.edu/~jain/papers/ftp/fairness.pdf.
27. Lertsinsrubtavee, A.; and Malouch, N. (2016). Hybrid spectrum sharing through adaptive spectrum handoff and selection. Retrieved May 1, 2019, from: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=7381671.