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Proactive Spectral Handoff Based on Markov Chains

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Abstract

The growth of mobile services, allocation policies, the scarcity of the radio spectrum and underutilization have promoted the use of computer science strategies for cognitive radio. This paper proposes a prediction model for the spectral transfer based on Markov chains, the objective of the algorithm is to predict the spectral occupation from the present state of the system. Markov chains are a technique that simulates the prediction of the current condition of the previous states. To evaluate the strategy a Matlab program is developed in five stages, information of power, availability, and bandwidth are taken from the Spectrum Mobility Analytical Tool software. The number of channels is dynamic and can be adjusted through two selection techniques, the fuzzy multivariable feedback algorithm - FFAHP and a random model of normal distribution. Five evaluation metrics were used for the performance analysis: cumulative average number of failed handoffs, cumulative average number of carried-out handoffs, average bandwidth, cumulative average delay, and cumulative average performance. For prediction analysis, four indicators are used: exact prediction, good prediction, regular prediction and bad prediction. The results of the analysis show that the prediction of spectral handoff using Markov chains is efficient, the cumulative maximum number of failed handoffs was 69, the exact predictions are above 91%, no indicator of a poor prediction was presented, and the regular predictions do not exceed 0.5%.

Keywords: Markov Chain, Spectral Handoff, Prediction, Cognitive Radio, Mobile Networks

INTRODUCTION

Cognitive radio is the technology capable of performing a dynamic allocation of the radio spectrum. The concept was created by Joseph Mitola III in 1999 as "the point at which wireless Personal Digital Assistant (PDA) and related networks are, in computational terms, sufficiently intelligent with respect to radio resources and corresponding communications Computer to computer to detect the user's eventual communication needs as a function of the context of use and provide the most appropriate radio resources and wireless services at the same time. "According to the IEEE, "it is a type of radio that can autonomously detect and reason about its environment and adapt accordingly" [1]–[3].

Unlike traditional networks, in cognitive radio, there are two types of users, the user who pays to use a licensed frequency band called primary, and the secondary user who makes opportunistic use of the licensed spectrum while it is available, this user must release the spectral resource when the primary user requests it. The process by which the secondary user switches from one frequency channel to another is referred to as spectral handoff [4], [5].

The growth of mobile services, allocation policies, radio spectrum scarcity and underutilization have promoted the use of cognitive radio techniques, the majority of current techniques have as their central challenge to guarantee the optimization of space -time of the frequency spectrum, using strategies based on computer science [6].

Among computer science strategies, artificial intelligence and machine learning stand out. These areas have allowed us to extend solving techniques to fields such as gradient search, game theory, fuzzy logic, genetic algorithms, neural networks, swarm algorithms, probabilistic models such as Markov, vector support machines, k-means, among others.

During a spectral handoff it is inevitable that communication breaks temporarily, because it is required to carry out a search process of spectral availability; prediction techniques permit the secondary user to switch to a new spectral band with the minimal degradation, reducing latency [2], [7]–[9]. This paper proposes a spectral handoff prediction model based on Markov chains, the objective of the proposed algorithm is to predict the spectral occupation from the present state of the system.

Unlike related work, the performance assessment is carried out through a trace of real spectral occupancy data taken from the frequency band of the Global System for Mobile Communications (GSM) technology, which allows to include the actual behavior of the primary users within the performed simulations. To reduce simulation times, the study channels were reduced using two selection techniques, the fuzzy multivariable feedback algorithm - FFAHP [10] obtained by the Spectrum Mobility Analytical Tool software [11] and from a random selection based on a normal distribution model.

The article is made up of five sections including the introduction. The second section describes the generalized mathematical model of a Markov chain. In the third section the used methodology is presented, where the developed algorithm is described in detail. The fourth section presents the results and, finally, in the fifth section, the conclusions are drawn.

RELATED WORK

There are a large number of papers that analyze or compile strategies for the allocation of the spectrum dynamically. In [12] is carried out a detailed description of techniques based on artificial intelligence, heuristic, and metaheuristic optimization algorithms, Table 1 presents a comparative summary based on the advantages and limitations of different artificial intelligence techniques.

Table 1. Advantages and limitations of artificial intelligence techniques

Algorithm	Advantages	Limitations
Artificial neural network (ANN)	Ability to describe a multitude of conceptually scalable functions. Excellent for classification. It can identify new patterns.	Training can be slow depending on the size of the network. Possible need for more training or learning.
Metaheuristic algorithms	Excellent for optimization and learning parameters. It can use other learning techniques.	Formulation of difficult rule spaces when learning is not restricted to value parameters.
Hidden Markov Model (HMM)	Good classification. Easily scalable. It can predict based on experience.	It requires a good and complex computational training.
Rule-based system (RBS)	Simple implementation. Ability to establish future rules.	Rules of derivation of somewhat tedious processes. It requires knowledge or perfect mastery that is not always available.
Ontology (OBS)	Ability to deduce logically. Ability to understand the capacities of self and others.	It requires perfect mastery of ontological knowledge. Low efficiency for sophisticated processes.
Case-based system (CBS)	It can work in chaotic situations with many variables. Allows rapid acquisition of knowledge.	It is based solely on the previous case. Requires long memory availability. May include irrelevant patterns.

In [13] the techniques based on machine learning algorithms are oriented in accordance with the problem of cognitive radio to be solved. The hierarchical organization of learning algorithms and their dependence is shown in Figure 1, two main categories of problems are identified (decision-making and classification of characteristics) and learning algorithms are presented for each category.

In [14] is proposed a methodology based on a stochastic game theory for centralized and decentralized access systems, where wireless users (secondary users), over time compete for dynamically available transmission opportunities. The secondary users become selfish and autonomous agents, who interact strategically to acquire the available spectrum opportunities. The results show that the proposed solution allows secondary users to implement learning and communication algorithms to opportunistically and efficiently take advantage of spectrum resources.

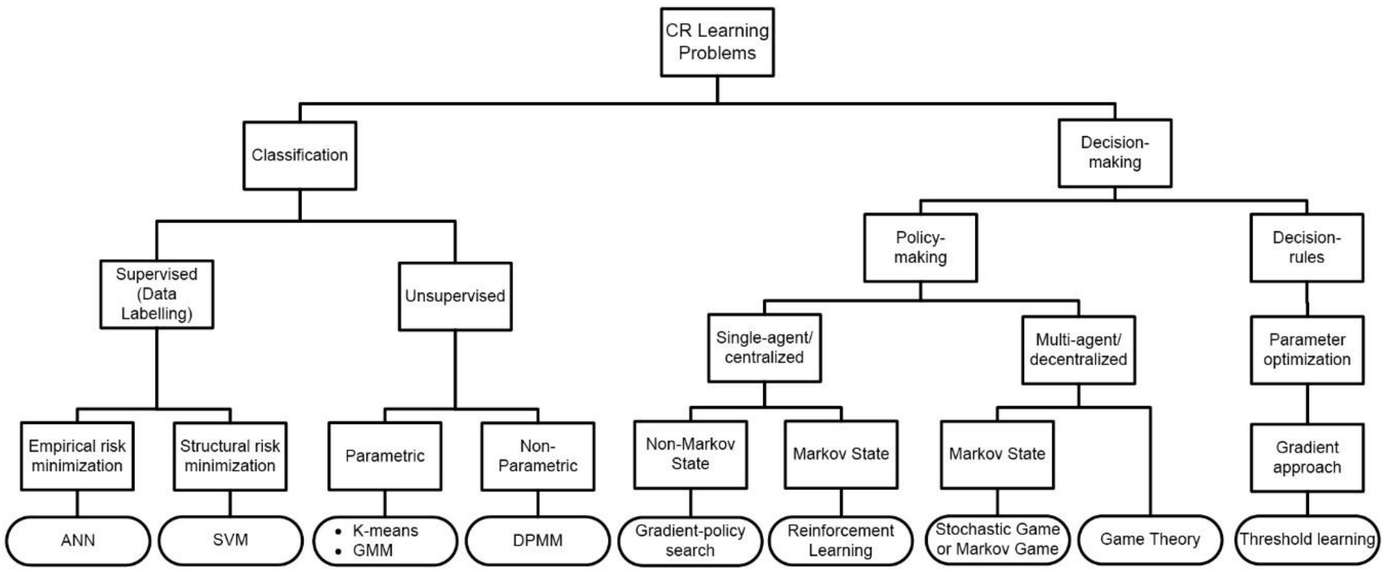

Figure 1. Typical problems in cognitive radio and its corresponding learning algorithms [13]

In [15] a proactive technique is proposed (the secondary user performs the spectrum detection and handoff, prior to the arrival of the primary user) for spectral handoff using coalition game theory, the model allows congestion to be taken into account. The proposal allows maximizing the utilization of the available resources and the fulfillment of the QoS requirements of the secondary user.

In [16] deterministic optimization techniques are used, from modifications in the algorithm of minimum paths or Dijkstra. The paper proposes a new method for decision making, which consists of the assignment of vertices or edges to the spectrum according to the criteria or parameters to be evaluated, these edges allow to create a matrix, from which an adjacent list is obtained, where its size is the available frequency bands of the spectrum to which an identifier is assigned that goes from zero to n, from the aforementioned assignment of a weight to each criterion or parameter, identifying the shortest path.

Among the statistical and probabilistic techniques, the hidden Markov models analyze the dynamic behavior of a random phenomenon as a process with observable and unobservable states [17]. Numerous applications of Markov algorithms in cognitive radio have been used to identify patterns, processes of cognitive motor observation and prediction [12].

MARKOV CHAIN

In order to define a Markov chain five elements are required to define, transition diagram, states and state spaces, transition, probability of transition, and representation.

Markov chains are a spherical technique that is based on the analysis of the internal dynamics of the system, simulating the prediction of the real state at a given time from the previous states. It is a random process with the property that gave the true value of the process Xt, the future values Xs for s>t are independent of the past values Xu for u<t.

The states are the characterization of a system at a given instant; formally it is a variable whose values can only belong to the set of states of the system. The state space is a sequence of random variables X = {Xn: n ≥ 0}, which take values in a finite or countable set ε, for all n and any states i0, i1,. . . , in, j in ε that satisfies the Markov condition (equation (1) and (2)).

$$P_{ij} = P\left(X_{n+1} = i_{n+1} \middle| X_0 = i_0, \ldots, X_n = i_n\right) \tag{1}$$

$$P_{i_n j_{n+1}} = P\left(X_{n+1} = i_{n+1} \middle| X_n = i_{nn}\right) \tag{2}$$

The probability that Xn+1 is in state j since Xn is in state i is the transition probability (equation (3)) in one step from i to j and is denoted as $Pi_n j_{n+1}$.

$$P_{i_n j_{n+1}} = P\left(X_{n+1} = j \middle| X_n = i\right) \tag{3}$$

The transition probabilities depend on the states and the instant at which the transition is made. When probabilities are independent of time (they are not a function of n) the chain has stationary transition probabilities and is known as a homogeneous chain in the time (equation (4) and (5)).

$$P_{i_n j_{n+1}} = P_{ij} \tag{4}$$

$$P\left(X_{n+1} = j \middle| X_n = i\right) = P\left(X_1 = j \middle| X_0 = i\right) \ \forall n \tag{5}$$

The Pij values are referred to as the transition probability and satisfy a probability distribution (equation (6)).

$$\sum_{j=1}^{m} P_{ij} = 1, \ \ \forall i > 0, \ P_{ij} > 0 \tag{6}$$

All values are combined and form the transition matrix T of size m x m (equation (7)).

$$T = [P_{ij}] = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix} \tag{7}$$

Markov chains are represented by a transition diagram (Figure 2). Usually, the states are represented by nodes (circles), the transition is presented as lines with direction labeled with respective probabilities.

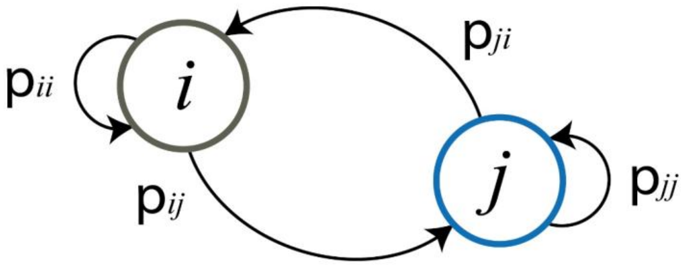

Figure 2. Representation of a Markov chain

METHODOLOGY

The algorithm elaborated for the evaluation of spectral handoff using Markov chains is divided into five stages

(Figure 3). The first stage corresponds to the selection of the input data; In the second, a selection of channels is carried out for the input matrix with two selection algorithms, the objective is to decrease the study channels to improve the simulation times; In the third stage the construction of the transition probabilities matrix is performed; In the fourth one, the transition matrix is evaluated; and finally, in the fifth, the results of the evaluation are processed, and the relevant indicators are shown graphically. The description of each stage is made from the implemented algorithms, by structure, the programming is developed using functions.

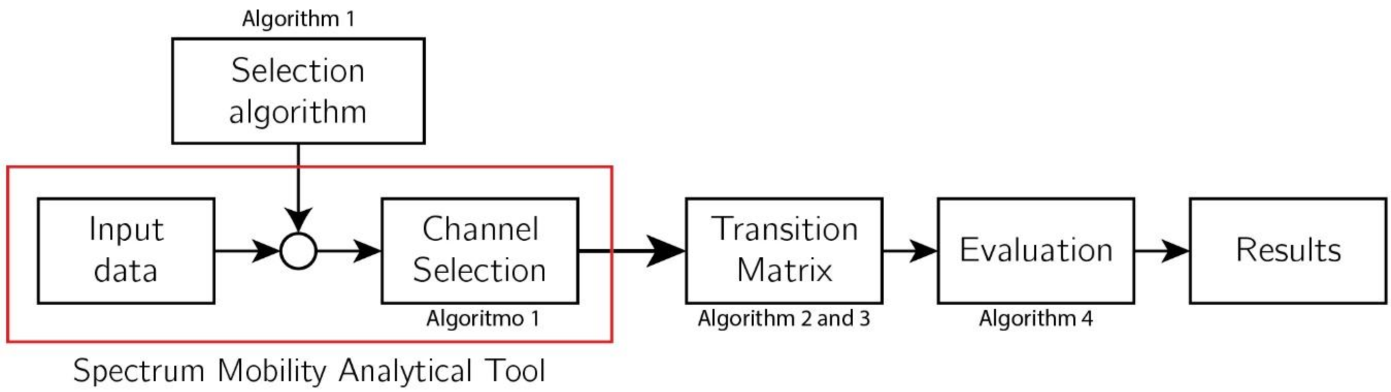

Figure 3. Stages of the algorithm

Input data

Figure 4 shows the input and output data; the input information belongs to the parameterization of the Spectrum Mobility Analytical Tool software, which requires defining the variables: threshold, noise floor, bandwidth, and multichannel [11].

The main spectral occupation database taken from the software corresponds to the high-traffic power information in a GSM network in the city of Bogota-Colombia. The handoff model used is FFAHP.

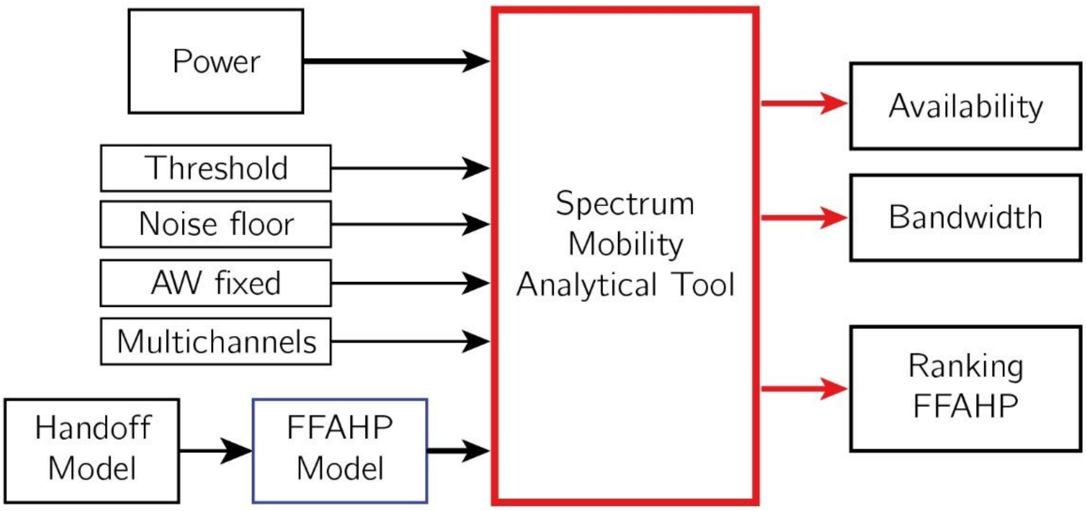

Figure 4. Input and Output data

From the Spectrum Mobility Analytical Tool software, the required information is taken for the evaluation of Markov chains as a prediction technique, such as availability matrix, bandwidth matrix (necessary to calculate the delay and throughput) and the channel ranking for FFAHP.

Training and validation matrix

The availability matrix has the necessary information to train and evaluate prediction algorithms. The time steps for the training and validation matrix of availability are adjusted according to the Spectrum Mobility Analytical Tool database using the Test-Validation technique, with an 83% -17% ratio. The amount of data used for training was 10800 and validation was 1800 [11].

Selection of study channels, validation and training matrix

Figure 5 shows the block diagram for the second stage, its main function is to select the study channels (columns), therefore, requires the availability matrix and bandwidth, parameterization variables corresponds to the number of channels (Between 1 and 550); As a selection strategy two techniques are used, the first uses the FFAHP Ranking previously obtained by the Spectrum Mobility Analytical Tool software and the second one based on a random selection based on a normal distribution model. The output data are the training matrix, validation matrix, and bandwidth matrix, adjusted to the number of parameterized channels.

In the block "Channel selection" is taken the availability matrix that counts with the information of training and validation, and is adjusted according to the number and the algorithm of selection channels; The bandwidth matrix is configured according to the validation data.

Algorithm Description: For stage 2 "channel selection" and "selection algorithm", the validation data (V) and training (E) according to the number and algorithm of channel selection are obtained from the programming of the function “Evaluación_Entrenamiento”, as input data are required the availability matrix (D), the FFAHP (R) ranking, the bandwidth matrix (N), the selection algorithm (A_S) and the number of channels (Channels).

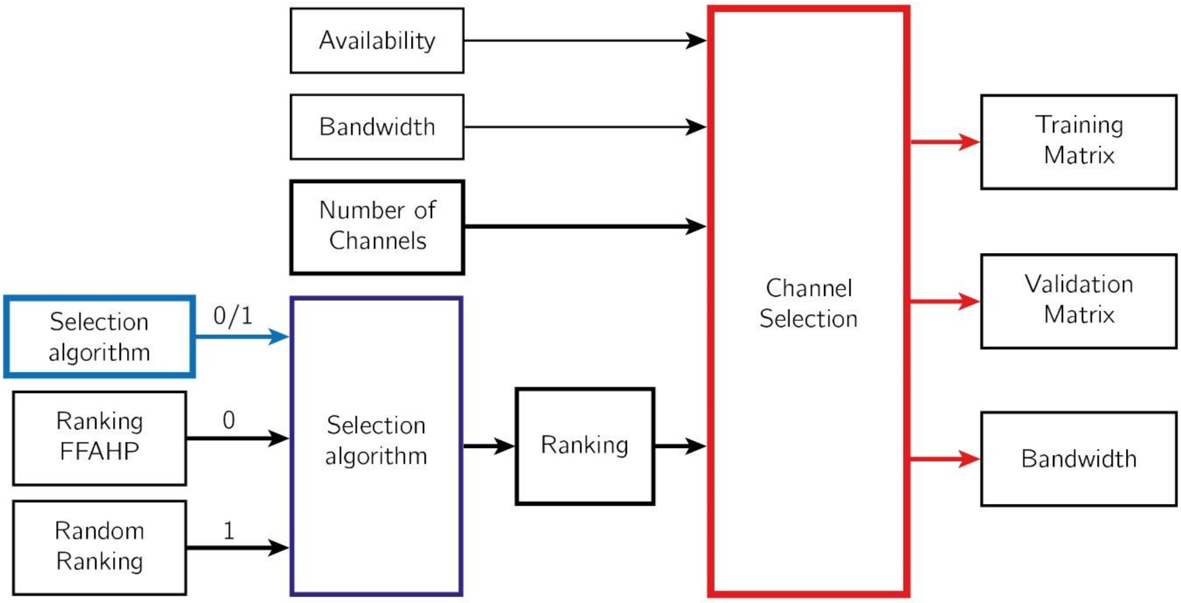

Figure 5. Selection of study channels, validation matrix and training matrix

The availability matrix, bandwidth and ranking using the FFAHP algorithm, are output variables of the Spectrum Mobility Analytical Tool; the number of channels is dynamic and can be adjusted as long as the available number (550). The technique of selection corresponds to 0 (zero) if you want to select under the FFAHP ranking, where you take channels with punctuation high, medium and low; if the selection technique corresponds to 1 (one), the channels will be select with the distribution of normal probability. Here, the general structure of the function is presented, omit the cycles that construct the respective matrices.

State probability

Figure 6 shows the block diagram for the third stage; the objective is to determine the transition probability matrix, the input data correspond to the training matrix, the number of channels and a state vector, the state vector indicates the present states of the training matrix.

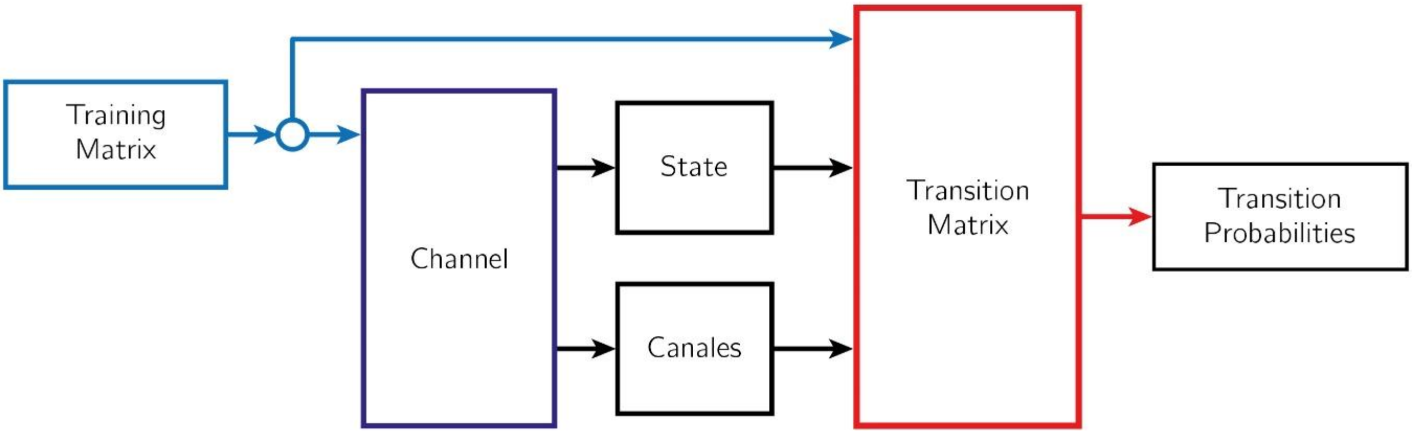

Figure 6. Transition matrix

The training transition matrix determines the current and future state probabilities that are required for the implementation of the chains; the training matrix probabilities will be used in the validation matrix to quantify the spectral handoffs. Markov establishes as a requirement to know the current and future state of the system; a future state is defined as time steps + 1.

The technique used for the current states is oriented to model each time steps through a positive integer number, to obtain this model, each row of the training availability matrix is represented as a binary number, where each bit corresponds to a channel, next the conversion of base 2 to base 10 is carried out.

For the future states, a sweep of the training matrix is performed according to the obtained set of current states; the highest and lowest occurrence states are defined by evaluating all the channels of the future time steps and later normalizing the results.

Description of the algorithm: In order to determine the current and future states, it is necessary to establish the possible binary representations of the time steps taking into consideration the number of available bits. Hence, it is necessary to construct a truth table where the size corresponds with the number of channels selected to identify the possible combinations or states.

The transition matrix utilizes two algorithms. The first Algorithm determines the possible states and the second Algorithm constructs the transition matrix from the current and future state probabilities.

The first Algorithm decides the size of the truth table or combinations of viable states through the size of the training matrix of stage 2, from the programming of the "States" function. As input data only the training matrix (M_E) is required, the aim is to measure the size of the matrix to establish the combinations of the truth table, the output information are the possible states and the number of channels, the variable Number of channels, although previously known, is part of the output of the function.

The second Algorithm calculates future state probabilities (Pb) from the programming of the "Probability_estate" function, as input data requires the training matrix (M_E) of stage 2, states (Estados) of the first Algorithm and the number of channels (Canales).

The algorithm takes the viable states and assesses them in the training matrix to determine which states are part of the system (current state), then determines the future states of greatest and least occurrence, evaluating all channels of the future time steps.

Spectral handoffs evaluation

Figure 7 displays the block diagram for the fourth stage, the purpose of this stage is to analyze the spectral handoffs by evaluating the transition probabilities on the validation matrix, the required information for the evaluation is the validation matrix of the second stage and the transition probability of the third stage.

The results are quantified at the output of the evaluation from the construction of the figures of bandwidth, handoffs, failed handoffs, delay, and throughput, also they are given indicators associated with the exact, good, regular and bad predictions.

The output figures are constructed using the Spectrum Mobility Analytical Tool software; the indicators are percentage values given in the assessment of the algorithm, Table 2 presents the indicators and the respective characteristics.

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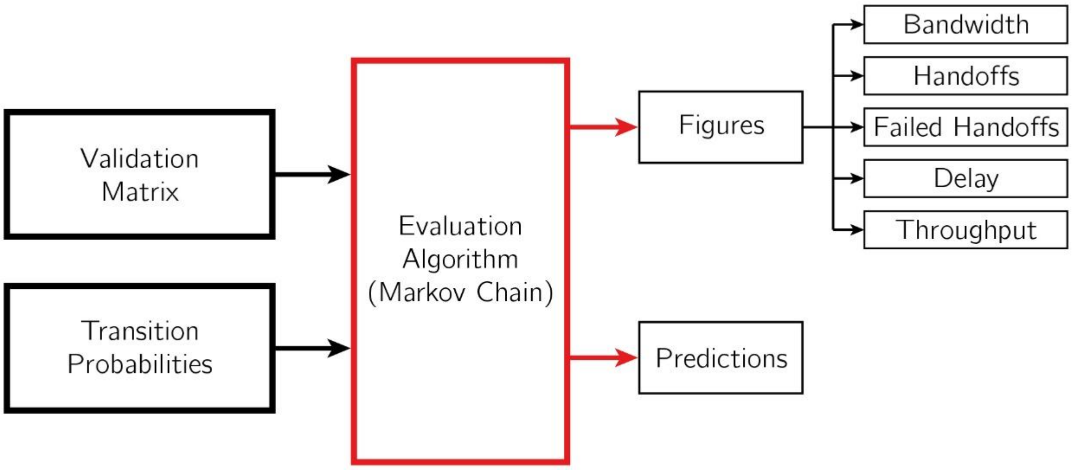

Figure 7. Evaluation algorithm

Table 2. Prediction indicators

Indicator	Characteristic
Exact prediction	It is defined as the condition where the prediction of the future is 100% accurate.
Good prediction	It is defined as the condition where the prediction of the future has a success greater than 70% and less than 100%.
Regular prediction	It is defined as the condition where the prediction of the future has a success greater than 30% and less than 70%.
Bad prediction	It is defined as the condition where the prediction of the future has a success less than 30%.

Description of the algorithm*:* This Algorithm presents a general structure of the code used for validation, due to the extensiveness, it is summarized in the way it uses the current and future states of the transition probability matrix. To evaluate the performance of the Markov chains it starts with the representation of each time step as an integer number, to achieve this goal the procedure consists of modeling each time step as a binary number (each bit represents a channel) and then obtaining its equivalent in decimal base, this decimal representation allows to quantify the current state and to recognize the future state through the transition matrix, to be able to predict the future is required of the current state; with the most probable prediction, the algorithm establishes the best channel, if the secondary user changes time step and finds that the prediction of the available channel is correct, it is said that the prediction was correct, if, on the contrary, it concludes there is a primary user , it performs a handoff to the channel with the next best probability of availability and quantifies handoff, failed handoffs and predictions.

RESULTS

The evaluation of the spectral handoff algorithm using the Markov chains for a high traffic GSM network is performed by means of five evaluation metrics: the cumulative number of failed handoffs, the cumulative number of total handoffs, the average bandwidth, the cumulative average delay and cumulative average throughput. The results achieved for each of the metrics are observed in Figure 8, Figure 9, Figure 10, Figure 11 and Figure 12.

Figure 8 presents the cumulative number of failed handoffs for a 10-minute transmission time, using the fuzzy multivariate feedback algorithm - FFAHP and the random distribution as channel selection techniques, for both strategies the number of failed handoffs is low, the difference between the two strategies is of 46 failed handoffs, being the random algorithm that obtains the smallest number.

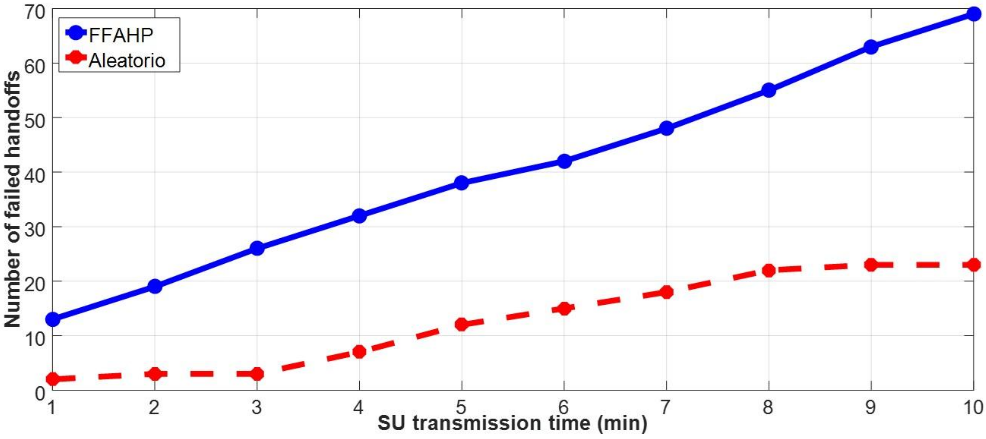

Figure 8. Cumulative number of failed handoffs for GSM network and high traffic.

Figure 9 presents the cumulative number of handoff, the first 3 minutes of transmission, the handoff number is higher for the FFAHP algorithm, maintaining a median of 13 handoffs in this time interval, the minute 4 is an intercept point, since this time instant the cumulative number of handoff is higher for the random distribution algorithm, the final difference is 36 handoffs.

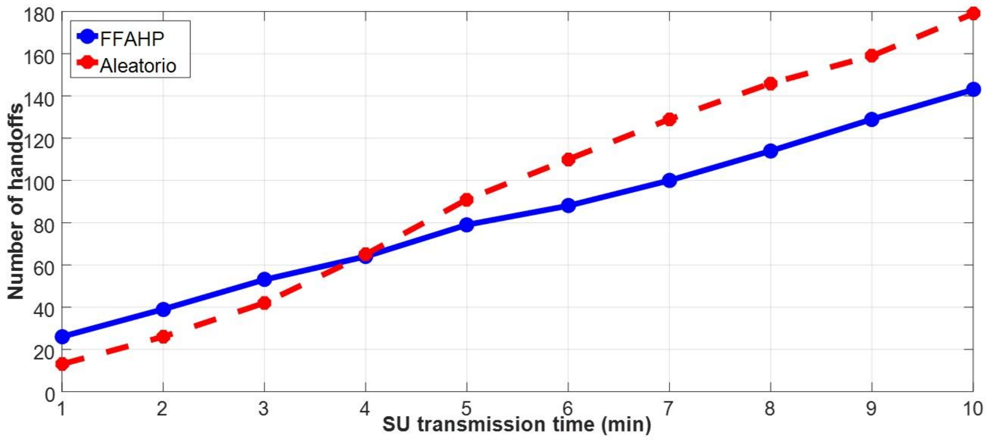

Figure 9. Cumulative number of total handoff for GSM network and high traffic.

Figure 10 describes the average bandwidth, the bandwidth variation for the random distribution is high compared to the FFAHP, the level of bandwidth for the random distribution on average is 1.5 times greater than FFAHP.

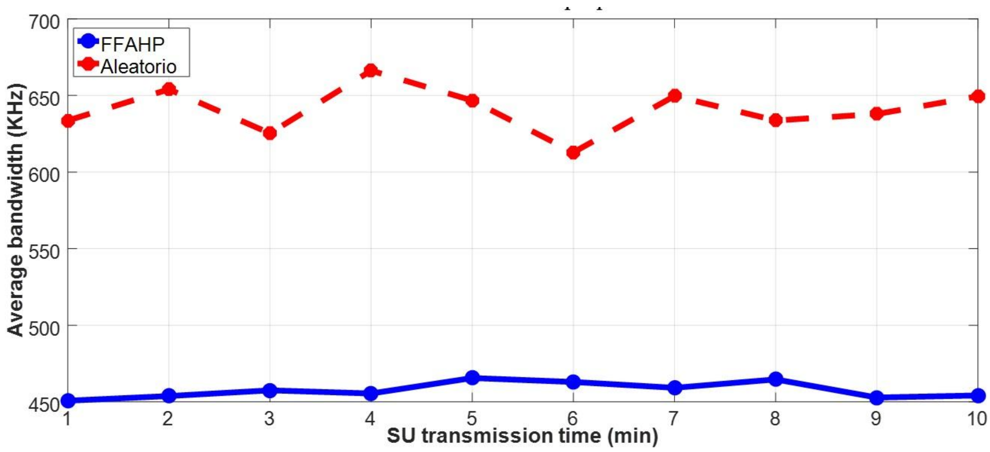

Figure 10. Average bandwidth for GSM network and high traffic.

Figure 11 shows the average delay that occurred in each algorithm during the 10 minutes of transmission; the delays correspond to the difference between the total and the failed handoff. In general, the two strategies perform well, with linear growth below 50s; The difference between the techniques does not exceed 5.2s, a value obtained for the last minute.

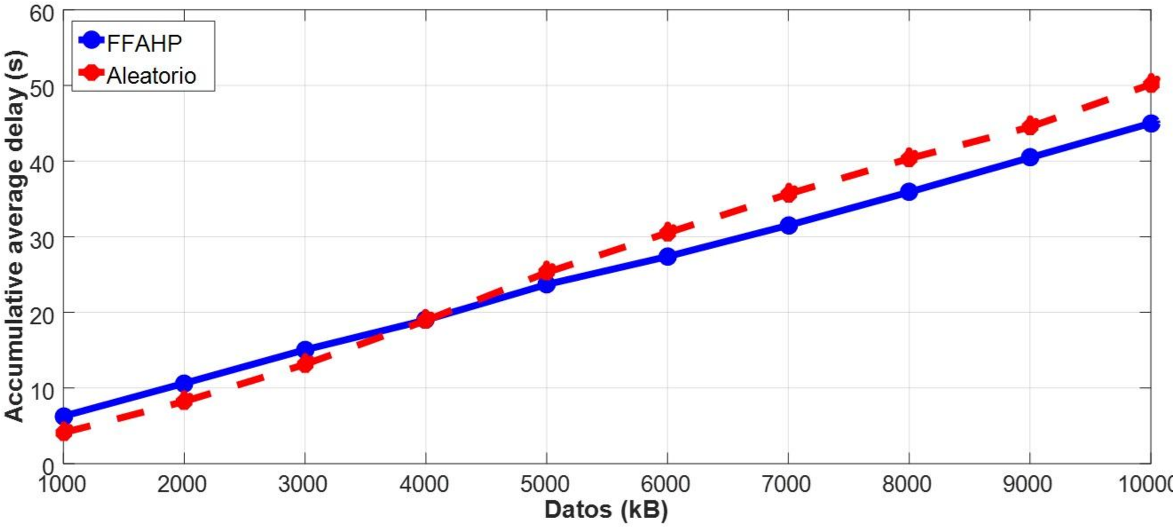

Figure 11. Cumulative average delay for GSM network and high traffic.

Figure 12 describes the average throughput with a standard 16QAM modulation; it is evident that the values are higher for the random distribution, with an average difference of 1406kbps.

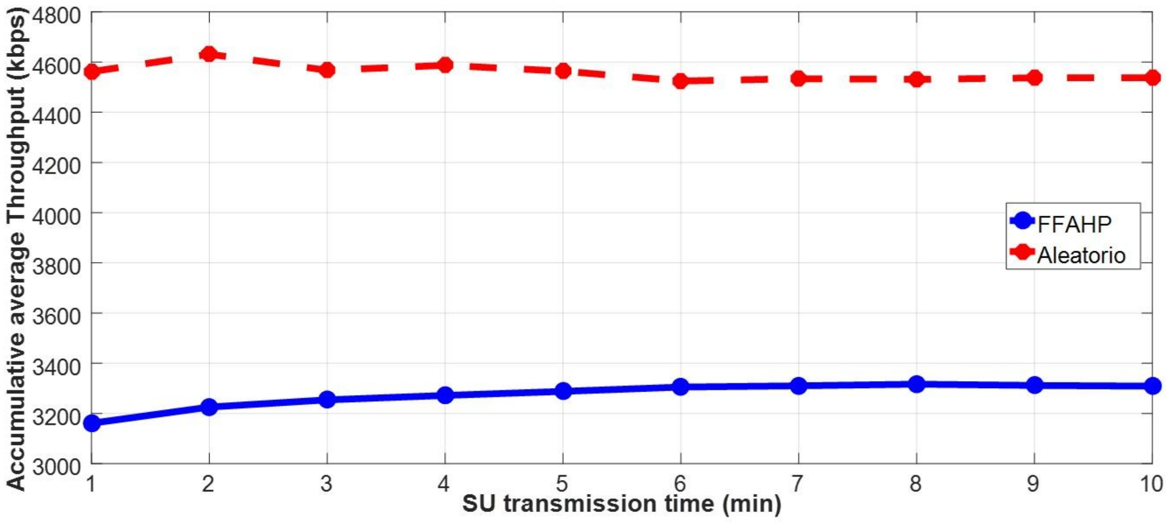

Figure 12. Cumulative average throughput for GSM network and high traffic.

Table 3 presents the results obtained for the two channel selection models using Markov chains, in terms of the five evaluation metrics.

Table 3. Evaluation metrics.

	Failed Handoffs	Total Handoff	Average bandwidth	Average delay	Average Throughput
FFAHP	69	143	457.68	45.01	3309
Random	23	179	640.92	50.15	

Table 4. Prediction indicators in quantity and percentage

	Exact	Good	Regular	Bad	Total time steps
FFAHP	1726	68	6	0	1800
	95,89%	3,78%	0,33%	0%	
Random	1644	153	3	0	
	91,33%	8,50%	0,17%	0%	

Table 4 present the results obtained in terms of the quantity and percentage prediction indicators for channel selection using the fuzzy multivariable feedback algorithm - FFAHP and the random distribution.

The results are favorably conclusive for both techniques using Markov chains, the lowest value of the "Exact" indicator was for the random distribution, in 1644 time steps the prediction was successful, the highest value of the "Regular" indicator was for FFAHP, In 6 time step it required jumping between 30% and 70% of the channels. In general, the exact predictions are above 90%, no indicator of a bad prediction was presented, and the regular predictions do not exceed 0.5%.

CONCLUSIONS

According to the results obtained through the simulations performed, from real spectral occupancy data for high traffic in a GSM network at a transmission time of 10 minutes, it is concluded that spectral handoff prediction using Markov chains is efficient. The results according to the metrics analyzed are favorably conclusive, the cumulative maximum number of failed handoffs was 69, and the cumulative maximum number of total handoffs was 179; The exact predictions are above 91%, no indicator of a poor prediction was presented, and the regular predictions do not exceed 0.5%.

The prediction of spectral handoff using Markov chains and the fuzzy multivariable feedback algorithm - FFAHP, presents positive results in the channel selection process, if random selection techniques are used, the metrics remain favorable, notwithstanding, unlike the Random strategy the FFAHP algorithm ensures the repeatability of the results.

In accordance with the obtained metrics through the simulations, the difference was 46 failed handoff, with the random algorithm being the one with the best behavior; The cumulative number of handoff is greater for the random distribution algorithm, with a final difference of 36 handoff, for the average delay time, a linear growth is obtained below 50s and a difference between techniques no higher than 5.2 S, the throughput presents higher values for the random distribution, with an average difference of 1406kbps.

Spectral prediction techniques based on computer science are tools that give strategies to solve the problem of the efficient use of the radio spectrum, each model provides, according to its nature adaptive characteristics that present excellent performance results with minimal degradation, reducing latency and ensuring the optimization of the spectrum space-time, which allows improving the communications of the secondary users without altering the primary users.

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