Contemporary Engineering Sciences, Vol. 10, 2017, no. 15, 721 - 738
HIKARI Ltd, www.m-hikari.com
https://doi.org/10.12988/ces.2017.7877

Intelligent Decision-Making Model for Spectrum in Cognitive Wireless Networks

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Abstract

This document proposes the design of a dynamic decision-making model in cognitive wireless networks that allows secondary users to opportunely harness the spectrum and use channels without affecting the traffic of primary users. The implemented model includes an initial decision-making algorithm with multiple criteria that classifies the best channels according to the spectrum characterization and a final algorithm for spectral occupancy prediction that allows the secondary user to change channels when the current channel is requested by a primary user. This algorithm was chosen after evaluating three prediction techniques. This work manages to integrate two decision methods that contribute to reducing the amount of channel changes that the secondary user must perform. The analysis of the results from prediction techniques indicate that the Grey Rational Analysis (GRA) algorithm in combination with the Support Vector Machine (SVM) algorithm presents the best performance in terms of choosing an available channel, reducing the primary user's interference and diminishing the rate of necessary handoffs.

Keywords: multicriteria decision-making, spectral decision, spectrum characterization, spectrum occupancy prediction

1 Introduction

In the past few years, wireless networks have gained great interest as a research topic due to the growth of the technologies that use the spectrum to communicate. The demand on behalf of users and the evolution of technologies indirectly generate scarcity in the frequency bands which complicates spectrum assignment [1].

The opportunistic access to the spectrum aims at harnessing those licensed frequency bands that are not efficiently used in order to use them without having negative impacts in the licensed users. This imposes a challenge in the study of efficient use of the spectrum.

Therefore, cognitive radio rises as a new generation network that can change its transmission parameters in terms of its interaction with the radio environment to give place to the active negotiation or communication with other users of the spectrum [2]. To achieve this, cognitive radio offers an intelligent system divided into cycles that describe the cognitive process which allows better resources management and network performance; the cognitive cycle is capable of detecting users in the spectrum, making decisions, moving onto other frequency channels and sharing the spectrum with other users [3].

One of the main functions that enables secondary users (SU) to opportunistically harness the spectrum is making decisions in different situations that do not affect the traffic of primary users (PU) and use efficiently the available channels [4]. The SU performs a detection process that is in charge of analyzing the RF environment and identifying the spectral occupancy of each channel. This process also detects possible PU interventions in the channels to be used [5]. When the SU establishes communication in a channel, it must keep monitoring the radio-frequency (RF) environment to identify future moments where a PU intervenes. At that moment, the SU needs to choose the next channel where it can keep and finish communication. Based on these situations, the SU needs to establish communication in various channels to reach the receiver and make decisions for an adequate transmission.

For the previously mentioned reasons, the main purpose of this work is to design a spectrum decision-making model that allows the SU to choose the best channel to transmit during the longest time and predicting possible interventions of the PU that force the SU to change to an appropriate and opportune channel. The model proposed initially includes a classification stage that organizes the least used channels by priority and defines the adequate channel to be used by the SU. Afterwards, the model implements prediction techniques to identify moments when the channel can be intervened by a PU and then choose another channel to maintain communication for the transmission of a specific service.

The present article is organized as follows: section 2 presents the work related to this article; section 3 describes the proposed model; section 4 presents the GRA multicriteria decision-making algorithm; section 5 describes the used prediction algorithms, section 6 presents the obtained results; and finally, section 7 states a set of conclusions.

2. Related Work

In literature, the adopted methods give solution to decision-making problems to choose the adequate network in different wireless network technologies, as is the case of the work performed in [6] where 8 MADM algorithms are evaluated such as GRA which ranks among the first techniques that guarantee the best continuity of the services delivered in these networks.

In [7], the best interface is chosen according to the network attributes such as delay, bandwidth and cost with the purpose of reducing handoff and improving customer satisfaction. The FAHP algorithm is notably used to compute the weights of the criteria and GRA classifies the candidate networks. The work in [8] adopts GRA in order to classify networks over different scenarios such as UMTS, WLAN and WIMAX based on multiple criteria of costs and package traffic. GRA offers an acceptable performance in the classification of different types of traffic.

Regarding prediction algorithms, in [9] the probability of a PU's appearance in the channel is predicted through neural networks that can learn the previous behavior of the PU. If that probability is high, the SU is forced to change channel. This model is well-adjusted with the average mean square error (MSE).

In [10], a neural network is used to predict the states of the cannel through Sigma-IF and MLP (Multilayer Perceptron). The results show that Sigma-IF presents a better prediction and reduces the detection time. In [11], SVM is used to predict the moment where the SU must move on to another channel before the channel is busy thereby reducing handoff time. In the article of [12], four different artificial intelligence techniques that involve neural networks and SVM are used where SVM behaves consistently and precisely.

3. Proposed Model

The proposed spectral decision-making model is shown in Figure 1. In the first part, data processing is performed over the measurements of the 824 MHz – 879 MHz frequency band and the parameters that characterize the spectrum occupancy, power index and signal-to-noise ratio (SNR). After registering the results, the best transmission channels are classified through the GRA (Grey Rational Analysis) multicriteria decision-making algorithm. Afterwards, the model organizes the best channels and initiates a prediction process for each one by using the capture channels. The model is trained using three artificial intelligence techniques: neural networks, SVM (support vector machines) and KNN (K-Nearest Neighbors).

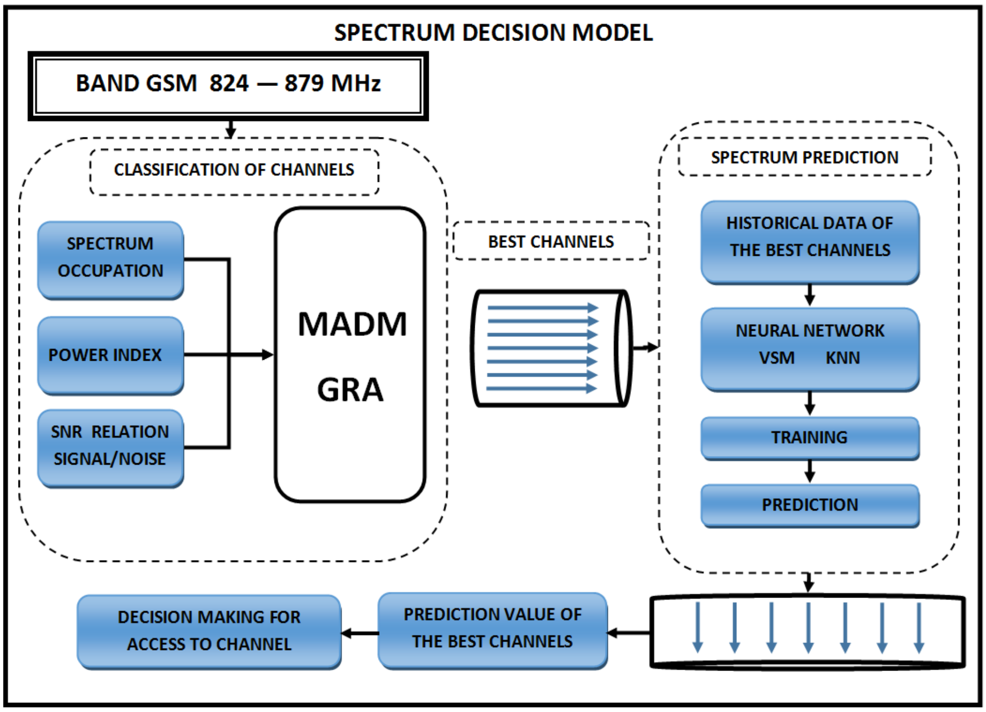

Figure 1. Proposed decision-making model in spectrum

In the first module, the calculation of parameters is presented. Those parameters will be the input of the classification. In the following stage, the best channels are organized according to their low spectrum occupancy, low index power and low SNR characteristics. After defining the best channels, the next module predicts the possible appearances of the PU for each channel while following the classification order.

3.1 Data processing

To develop the model, the spectral occupancy data were used. The data was captured in a spectral measurement of the Universidad Distrital Francisco José de Caldas. The configuration parameters are presented in Table 1.

In the registered measurements, power levels of low and high traffic for each frequency channel during an estimated time of 70 minutes divided into two stages: the first 60 minutes will be used for a training stage equivalent to 10800 time steps and the remaining 10 minutes correspond to an evaluation stage equivalent to 1800 time steps.

Table 1. Technical parameters for spectrum measurement

Parameters	Value
Frequency band	824 MHz - 879 MHz
Communication technology	GSM
Number of channels	500
Sweep time	290 ms
BW resolution	100 KHz

To determine whether the users are present in a channel or not, a decision threshold is defined as -95 dBm depending on the level of noise floor of the selected frequency band. If the data in the respective channel is under the threshold a logical ‘0’ is assigned indicating that the channel is unoccupied at that time instant. In contrast, if the data surpasses the threshold then a logical ‘1’ is assigned indicating an occupied channel.

3.2 Spectrum characterization

The spectrum characterization allows SU to identify the behavior and use of channels in a frequency band. It is required that the SU keep an observation on the channel’s availability in time instants due to the activity of each primary user [2].

Among the spectrum characterization parameters of this model, the following were evaluated: spectrum occupancy, power index and SNR.

3.2.1 Spectrum occupancy

Spectral occupancy allows the observation of the temporal evolution of each frequency channel. This occupancy can be assessed under the work cycle parameter which indicates the relation between time and active state of the channels.

Duty cycle: The work cycle is the time percentage in which a cannel is being used by a PU which is calculated in equation (1).

$$\%\ Ocupancy = \frac{T_{on}}{Total\ time} \tag{1}$$

Where T_{on} represents the time that the channel was occupied during the total measured time that is the training time in this case.

Another way to represent the spectrum occupancy is through the spectrum’s intensity which is calculated with equation (2) [12].

$$Intensity = \frac{T_{on}}{T_{on} + T_{off}} \quad (2)$$

In figure 2, the percentage of occupancy for each channel can be observed. It is registered over 52 minutes in the 824 MHz - 879 MHz frequency interval. The occupation focuses on the 854 MHz – 879 MHz section.

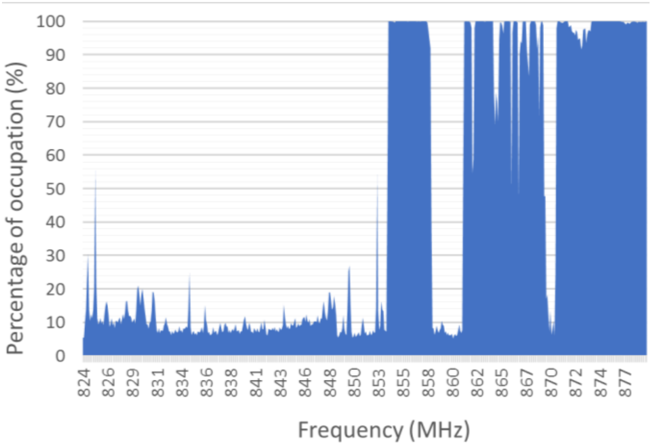

Figure 2. Work cycle for the GSM band.

3.2.2 Power index

It is the variable that indicates the relationship between the maximum $P_{\max k}$ and the minimum$P_{\min k}$ power levels of each selected frequency channel k (see equation (3)) [13].

$$Pi_k = \frac{P_{\min k}}{P_{\max k}} \quad (3)$$

Figure 3 shows the relationship between the power levels of each channel which allows inferring how high the PU signal can be when reaching for a channel. This calculation will indicate the most adequate index power when there is a low signal after defining the channels where the PU's intervention is low.

3.2.3 SNR

In this section, the signal to noise ratio is calculated as the difference between the measured reception level P_k in dBm and the level of noise floor P_N obtained with the spectrum analyzer as described in equation (4). The obtained result is in dBm.

$$SNR_k = P_k - P_N \quad (4)$$

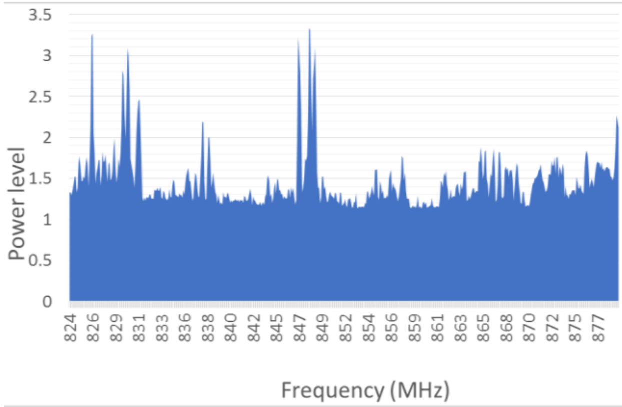

Figure 3. Power index for each channel in the GSM band

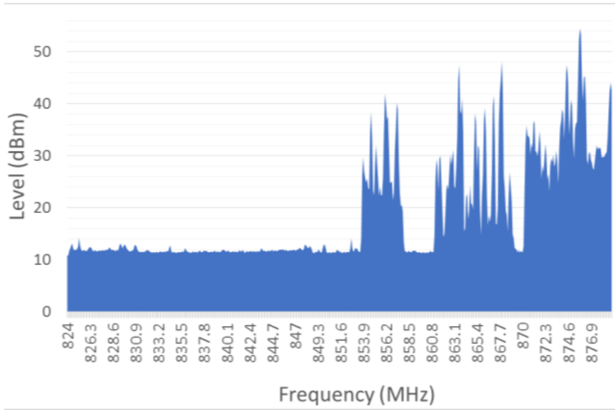

Figure 4. Signal-to-noise ratio for the 824 MHz - 879 MHz band

4. GRA Algorithm

GRA (Grey Rational Analysis) is an effective ponderation technique of attributes of MADM that analyzes the best alternative with the highest value of the grey relationship coefficient or GRC [14].

According to [15], the GRA algorithm followed the steps that will be now described:

Step 1: Build a decision matrix K for a model of k attributes and N data where k defines each parameter obtained in the data processing stage as an attribute and N represents the number of channels to be analyzed (see equation (5)).

$$K = \begin{Bmatrix} k_{1\,1} & k_{1\,2} \\ k_{2\,1} & k_{2\,2} \\ k_{N\,1} & k_{N\,2} \end{Bmatrix} \tag{5}$$

Step 2: Normalize the decision matrix K with the parameters obtained from the spectrum characterization to generate the normalized matrix S with equation (6). These data are the benefit parameters that will define the least occupied channels.

$$S_{ij} = \frac{max_{i\in N}k_{ij} - k_{ij}}{max_{i\in N}k_{ij} - min_{i\in N}k_{ij}} \tag{6}$$

Step 3: Define the weights for each attribute. On various occasions, the designer defines a weight for each attribute depending on his criterion and giving priorities to certain variables that may be important when it comes to making decisions. To calculate the weights of each attribute, two attributes are compared based on a table of absolute numeric values. In our case, the weights of each attribute are defined based on the Delphi method which consisted on consulting a set of experts on the importance and hierarchy of the three chosen parameters. Evaluators are consulted due to their experience and knowledge in the area. Table 2 defines the assigned criteria and weights.

Table 2. Criterion to establish weights in the GRA method

Criterios	**Ocupación de espectro**	**Índice de potencia**	**SNR**
Ocupación de espectro	1	5	7
Índice de potencia	1/5	1	3
SNR	1/7	1/3	1

Step 4: For each criterion, the geometric average is calculated (see equation (7)) and the result is normalized to obtain weights between 0 and 1. The weight obtained for the spectrum occupancy criterion was 0.7235. The resulting weight for the index power was 0.1932 and 0.083 for the SNR.

$$w_i = \sqrt[n]{\prod_{j=1}^{n} a_{ij}} \tag{7}$$

Step 5: Build the normalized pondered matrix. This matrix is the result of the weights obtained multiplied by each element in matrix S (see equation (8)).

$$v_i = w_j * S_{ij} \tag{8}$$

Step 6: Obtain the maximum value for each benefit criterion. In our case, the channel with the maximum value of each criterion is chosen (see equation (9)).

$$x_j = max\, \{v_{i,}\, j = 1, \dots, N\} \tag{9}$$

Step 7: The calculation of the position of the alternatives given the GRC value is performed with equation (10).

$$GRC_i = \frac{1}{N}\sum_{J=1}^{N} \frac{\Delta_{min} + \Delta_{max}}{\Delta_i + \Delta_{max}} \tag{10}$$

Where $\Delta_{i=|x_j - v_{ij}|}$ is the grey correlated distance, $\Delta_{max}= \; max\,(\Delta_i)_{i \in k}$ and $\Delta_{min}= \; min(\Delta_i)_{i \in k}$ are its maximum and minimum.

Table 3 shows the result of the weights calculated for the GRA algorithm that describe the degree of importance of each criterion when the best channel needs to be chosen.

Table 3. Normalized weight of criteria

Criteria	**Spectrum occupancy**	**Power index**	**SNR**
Normalized weight	0.7235	0.1932	0.083

5. Prediction Algorithms

Once the classification by priority of the best channel to be used is finished, a prediction process is started with the statistics taken from the measurements on low and high traffic. For the SU, this prediction will lead him to identify the instants of time where a PU can arrive to the channel and make adequate decisions to change to the second best channel depending on its classification [16].

For this model, three supervised learning algorithms are used: NAR (non-lineal autoregressive) neural networks, SVM and KNN which will be tested. The most consistent and pragmatic one will be chosen. In each algorithm, training data is used as the model's input as well as evaluation data to measure the efficiency of the prediction. The database is divided so that the first 60 minutes will be for training purposes and the final 10 minutes will be for evaluation purposes. The performance is tested on all three alternatives so that the most adequate is chosen in terms of prediction and change of channel.

5.1 Neural networks

With the Matlab tool, the prediction is implemented with artificial neural networks. As a first step, the data is normalized and the network is trained with each channel's input data. Finally, the resulting network is the prediction for each channel.

The neural network used is seen in Figure 5. This neural network is based on the NAR model which consists of the entry layer, the hidden layer (with 10 neurons) and the exit network with one neuron. Tests are carried out with less than 10 neurons in the hidden layer and the smallest error is achieved with 10 neurons. Each data input corresponds to a vector that will be the first chosen channel in the classification. The vector has a size of 1 channel per 10800 time steps which leads to 500 × 10800 input data.

Before entering the training data, it is necessary to adjust the inputs to a specific range which is [-1, 1]. Afterwards, the network is trained with the Levenberg-Marquadt algorithm. This method was chosen because it is the fastest one; it optimizes training and reduces the computational level in the execution of the model in comparison to other algorithms since the size of the data input is considerably big.

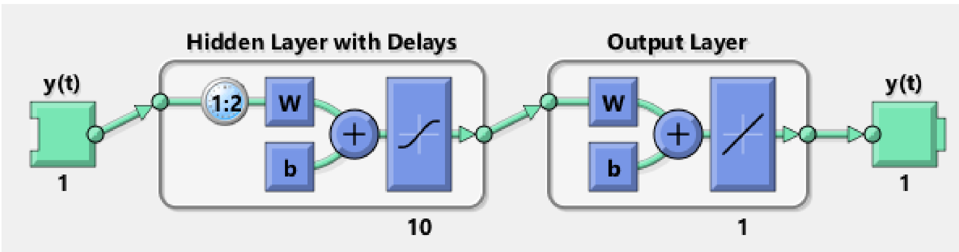

Figure 5. Non-lineal autoregressive system in neural networks

After obtaining the resulting network for each channel, the data conversion process to get the real prediction values. The mathematical formulation is shown in equation (11) where *y(t)* will be the next value of the previous data and *d* is the amount of previous delays.

$$y(t) = f\big(y(t-1)\,,\ldots y(t-d)\big) \tag{11}$$

5.2 SVM and KNN

For SVM and KNN, a procedure similar is carried out in both techniques. In the first part, the data processing is performed to obtain normalized data between -1 and 1 for SVM where -1 indicates that the channel is unoccupied during that time step and 1 indicates that the channel is occupied. For KNN, logical data between 0 and 1 are obtained where 0 indicates 'unoccupied' and 1 indicates 'occupied'.

In these prediction models, two classes are defined which will become the inputs for classification: class 1 describes the normalized data between [-1, 1] for SVM and [0, 1] for KNN and class 2 corresponds to the power levels of each channel. Afterwards, the classification process begins and the algorithm is trained to obtain a final vector for each channel and with the same size as the input data times. The input data are vectors of 1 channel × 10800 time steps for a total of 500 × 10800 values.

Mathematical model:

$$\hat{y} = \arg \min_{y=1:K} \sum_{K=1}^{K} \hat{P}(k|x)\, C\,(y|k) \tag{12}$$

Where $\hat{y}$ is the result of the prediction, K is the number of classes, $\hat{P}(k|x)$ is the a posteriori probability of the number classes for observation x and $C(y|k)$ is the cost of classifying an observation as y when its real key is K.

Figure 6. Prediction process for SVM and KNN

6. Results

The results obtained in the prediction stage are evaluated over two phases that measure the performance of the three prediction techniques that were implemented. In the first phase, the percent relative error is computed for low and high traffic scenarios using the evaluation data versus the prediction results. In the second phase, the number of channel changes (or handoffs) is computed by creating an algorithm that estimates the total handoffs, failed handoffs, perfect handoffs, anticipated handoffs, handoffs with interference and handoffs without interference.

6.1 Percent relative error

The relative error is calculated as seen in equation (13) where X_i represents the result obtained for each channel in a time instant and is the data from the evaluation stage. Since the resulting values are in the -1 to 1 range, they are normalized before using equation (13).

$$error = \frac{1}{n} \sum \left(\frac{|X_{v-} X_i|}{|X_v|} * 100 \right) \tag{13}$$

The result of the average relative error through prediction error is seen in Table 4.

Table 4. Average relative error for high and low traffic

High traffic		
Neural network	**SVM**	**KNN**
16.44 %	14.49%	14.41 %
Low traffic		
Neural network	**SVM**	**KNN**
18.42 %	19.05 %	19.07 %

6.2 Handoff calculation

For the calculation of handoff, an algorithm was designed that can measure the amount of jumps that the SU must perform in a 10-minute transmission. The algorithm determines this measurement based on the prediction results from the three techniques. It compares the data obtained in the prediction in each time step with the real evaluation data by calculating six handoff metrics: total handoffs, anticipated handoffs, handoffs with interference, handoff without interference, perfect handoffs and failed handoffs.

The total handoffs describes the number of jumps carried out by the SU during the 10 minutes of transmission; the failed handoffs indicate the number of jumps whose target channel is being occupied by a PU; the handoffs with interference show the number of jumps made after the PU's arrival; the handoffs without interference indicate the number of jumps made before the PU's arrival; the anticipated handoffs are the handoffs without interference that were made way before the PU's arrival; finally, the perfect handoffs are the handoffs without interference that were made very close to the PU's arrival. Figure 7, shows the handoff results for low and high traffic.

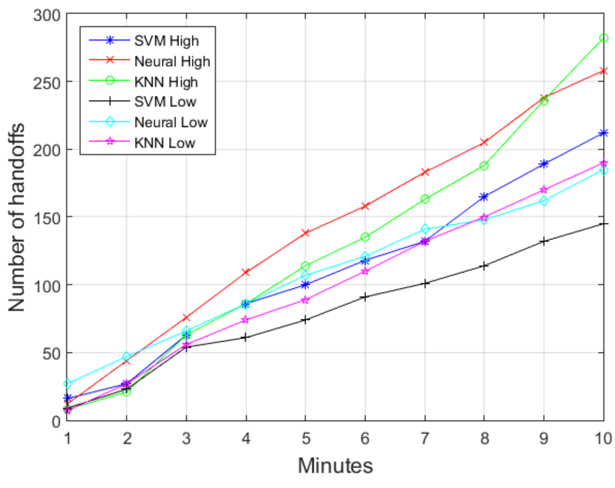

Figure 7. Calculation of total handoffs for high and low traffic

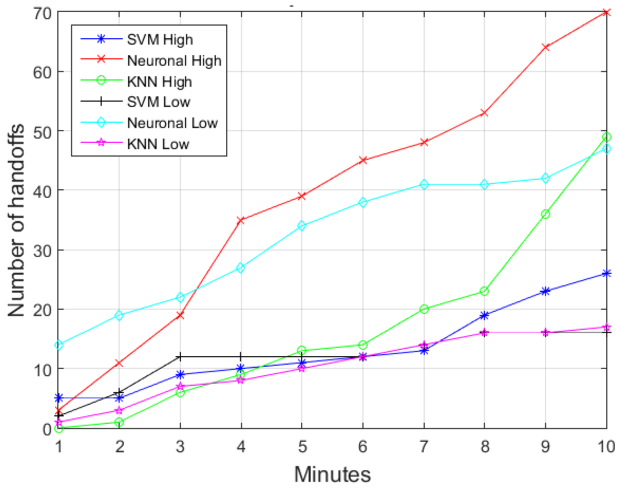

Figure 8. Calculation of anticipated handoffs for high and low traffic

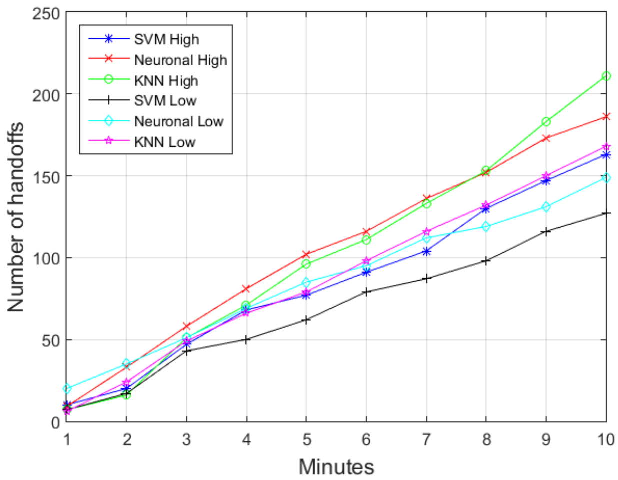

Figure 9. Calculation of handoffs without interference for high and low traffic

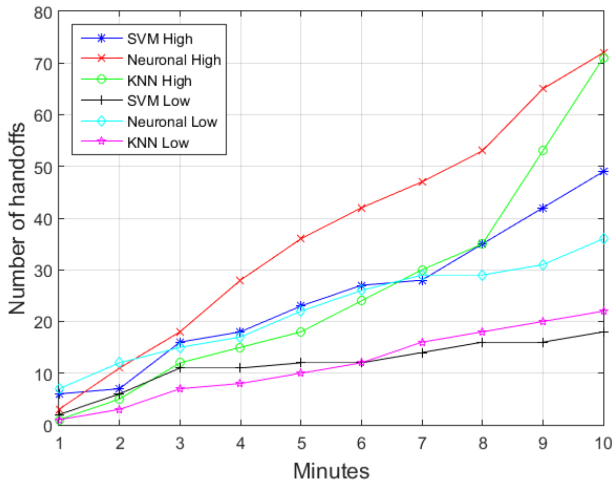

Figure 10. Calculation of handoffs with interference for high and low traffic.

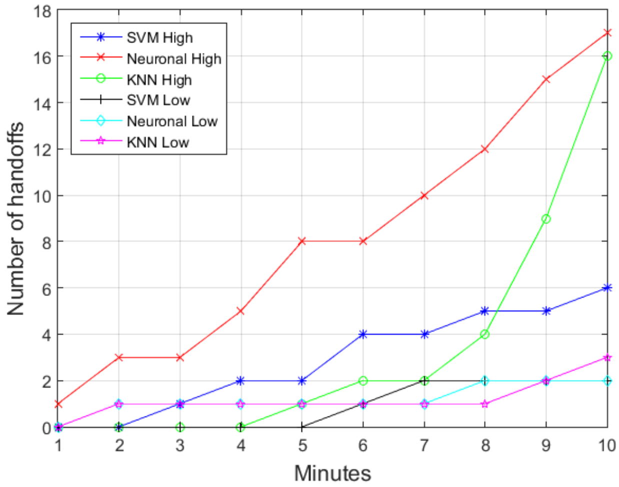

Figure 11. Calculation of perfect handoffs for high and low traffic.

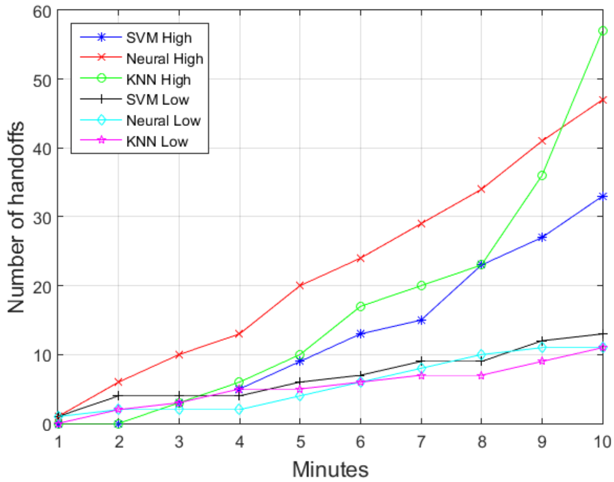

Figure 12. Calculation of falied handoffs for high and low traffic

The quantified data of the number of performed handoffs for high and low traffic are shown in tables 5 and 6.

Table 5. Comparative percent of handoffs in high traffic

High traffic	**Neural network (%)**	**SVM (%)**	**KNN (%)**
Total number of handoffs	82.17	100	75.18
Failed handoffs	85.45	100	77.01
Handoffs with interference	82.82	100	91.8
Handoff without interference	93.77	100	97.32
Perfect handoffs	100	42.95	86.11
Anticipated handoff	45.2	100	70.58
Total ponderation	81.57	**90.49**	83

Table 6. Comparative percent of handoffs in low traffic

Low traffic	Neural network (%)	SVM (%)	KNN (%)
Total number of handoffs	78.38	100	76.32
Failed handoffs	91.49	63.61	100
Handoffs with interference	55.91	91.88	100
Handoff without interference	96.4	100	99.45
Perfect handoffs	72.87	88.68	100
Anticipated handoff	33.09	79.88	100
Total ponderation	71.36	87.34	**95.96**

7. Analysis of Results

During the first analysis of measured percent relative error, it is evidenced in table 4 that the SVM and KNN algorithms have an 85.5% probability of giving a correct prediction in contrast to the neural network which has an 83.5% probability for high traffic. For low traffic, the behavior is similar in the three algorithms with a reduced prediction probability of 80%. The SVM and KNN techniques may present better stability, coherence in results and improve performance in terms of decision-making.

With tables 5 and 6, the handoff calculation results can be analyzed in the three evaluated algorithms for high and low traffic. For high traffic, the neural network algorithm and KNN are the techniques with the highest number of handoffs in comparison to SVM during the evaluation stage as seen in Figure 7. Neural networks and KNN are less efficient and less consistent since they generate more interference forcing the SU to change channels inadequately, so they are the techniques that anticipate the PU’s arrival the most and fail more in handoffs. This result can be seen in Figures 8 and 12.

When observing the comparative percent of handoff for high traffic, neural networks have a lower percentage with 81.57% and KNN with 83% making them less convenient for the implementation in this scenario compared to SVM which had a 90.49% as seen in Table 5. SVM offers better results in the handoff calculation even if it asserts in perfect handoffs with a 42.95% in comparison to neural networks and KNN. SVM does anticipate the change of channel with a 100% and reduces the interference with 100% compared to the other techniques as seen in Figures 8 and 9 respectively.

For low traffic, a different behavior is seen where KNN has better results obtaining a 95.96% compared to SVM that attained 87.34% and neural networks that attained 71.36%. For this scenario, KNN has the best performance and carries out the highest number of handoffs with 76.32% but is still convenient in handoffs that are anticipated, with interference, perfect and failed as seen in Figure 8, 10, 11 and 12 respectively. SVM presents deficiencies in failed handoffs reaching

63.61% in comparison to the other techniques as shown in Figure 12 but is still the algorithm with the lowest interference with 100%. The neural network method presents a low performance in all measurements since it is the algorithm that anticipates the most with a 33.09% and generates more interference reaching only 55.91%.

SVM and KNN are the techniques with the best performance for high and low traffic. On one hand, SVM is the algorithm with the lowest number of handoffs and generates less interference in the two scenarios maintaining 90.40% and 87.34% in comparison to the other algorithms. On the other hand, KNN is notorious for its performance in low traffic with 95.96% but lowers its performance in high traffic with 83%.

8. Conclusions

When organizing channels by priority, the SU can choose which channels are the least used allowing him to use the channel with the lowest probability of generating interference and staying in it for the longest time. The importance of classifying channels reduces the number of required handoffs for the SU to transmit its information diminishing the interference that it can cause on primary users.

The multicriteria decision-making GRA algorithm offers an effective result which is computationally fast for the calculation of the parameters that vary in time, allowing the model to adapt easily. The SVM and KNN methods are the most adequate techniques in this simulation since they can predict the nest state of a specific channel by a factor of 86% for high traffic and 81% for low traffic in SVM and 85% in high traffic and 81% in low traffic for KNN. Furthermore, SVM shows the best behavior in the change of channels since it reduces the interference with the lowest number of handoffs and changes more between channels without affecting the PU traffic in both scenarios. KNN can show a better performance in low traffic and be more accurate in perfect handoffs but it behaves irregularly for high traffic. In computational terms, the KNN and neural network methods are more efficient compared to SVM leading to the conclusion that there is no perfect prediction method for all types of simulation.

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Received: August 20, 2017; Published: September 26, 2017