

Modeling and Prediction Primary Nodes in Wireless Networks of Cognitive Radio Using Recurrent Neural Networks

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Abstract

The cognitive radio is a methodology that proposes the management of the radio spectrum dynamically, by integrating the stages of sensing, decision making, sharing and spectral mobility. The spectral decision-making phase is in charge of deciding which is the best available channel to transmit the data of Secondary Users (SUs) in an opportunistic manner, and its success depends on how efficient is the Primary User characterization model (PUs). The use of Recurrent Neural Networks (RNNs) is proposed as a model to reduce the prediction error that is presented in the future estimation of channels in the frequency band of 2.4 GHz. The findings found that the RNNs have the necessary self-management to improve the forecast channels' use by PUs in the WiFi spectral band and with better levels of success than those delivered by the Multilayer Perceptron Neural Networks (MLPNN).

Keywords: Cognitive radio; Modeling; Primary User; prediction, WiFi

1 Introduction

Just as land becomes more expensive and scarce in urban areas due to they are densely populated in respect of the quality of life offered at those sites, the range of operation of the radio spectrum is more useful in certain frequency bands than in others for wireless networks because they facilitate the interconnection of devices decreasing the probability of errors. At present, wireless systems have been characterized by a policy of fixed spectral assignment and regulated by the Government of each Country; which presents several problems related to the use of spectrum within which are: 1) A significant amount of unused spectrum, as seen in Figure 1 where the typical figures of spectral occupancy in the 30 MHz band to 3 GHz band are shown; 2) The use of the spectrum is mainly concentrated in the portions ranging from 88 to 216 MHz and from 470 to 902 MHz [1], a problem that is exacerbated by the large spatial and temporal variations in the spectral occupation [2] [3] [4]. The consequence of the underutilization of the spectrum is that today there is a scarcity of this resource causing a significant degradation in the quality of the service offered by the telecommunications companies (example: cellular band); aspect that has motivated researchers from different branches to propose possible solutions to optimize their use. Dynamic Spectrum Access (DSA) appears as a solution and with it the concept of Cognitive Radio (CR), where its main objective is to identify spectral holes not used by licensed users (PUs) so that they can be exploited in an opportunistic manner by unlicensed users. (SUs).

The CR can be defined as a system controlled by a cognitive process capable of perceiving and processing the existing conditions in the environment, to be later used by a learning technique able to optimize the performance of the network. Carrying out this task involves the use of highly intelligent algorithms capable of making decisions under diverse conditions in different radio environments, in addition to another series of challenges that need to be resolved [5] [6] [7].

Additionally, the dynamic spectrum management in CR includes four main stages [8] [9] [10], where the spectral decision (which is in charge of selecting the best available channel based on the quality of service requirements requested by the SU and reconfiguring the radio) is of relevant importance as it is one of the phases that has been least investigated [11], and that will depend fundamentally on the characterization of the channel and the statistical behavior of the use of the channel by the PU.

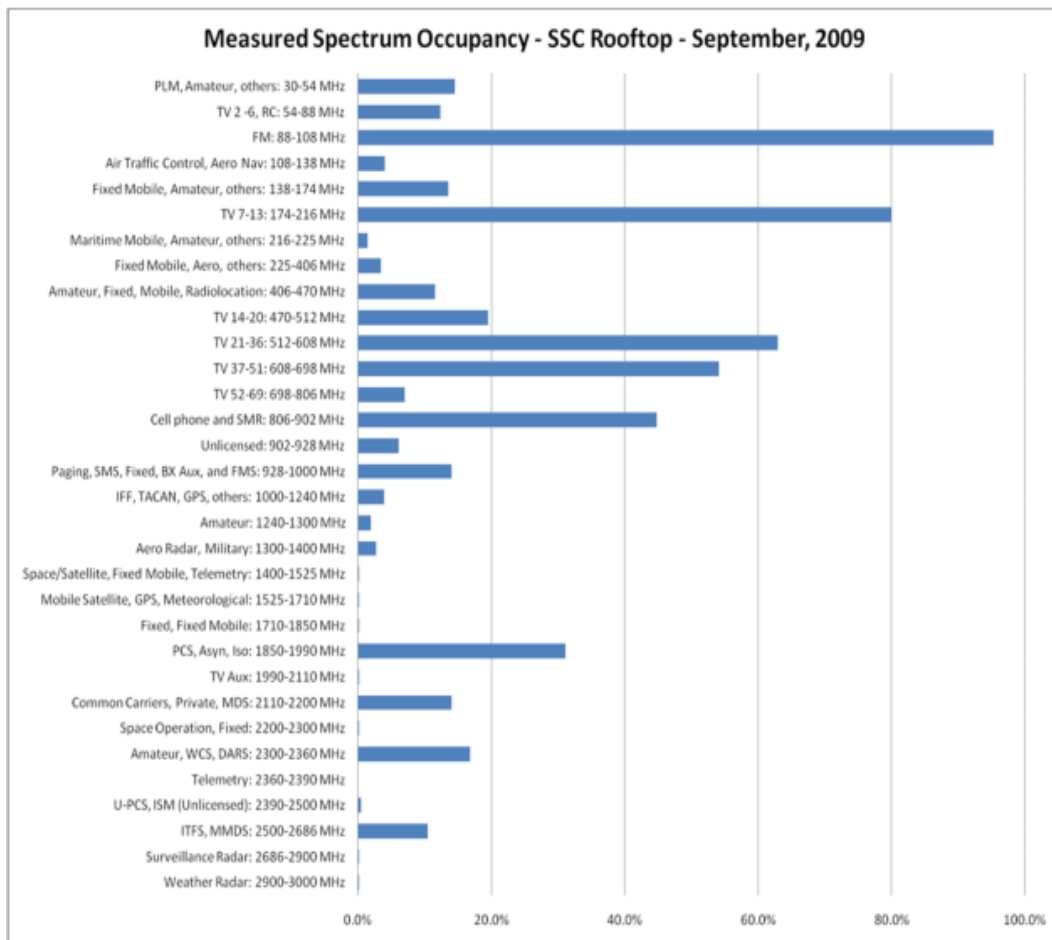


Figure 1. Spectrum occupation in the 30 MHz to 3 GHz range [1].

In this sense, one of the variables on which will depend success on the selection of channels, is related to how good is the prediction model that is being used to represent the dynamics of the PU; if the prediction is not so good, it is likely that an inappropriate channel will be selected and the SU will generate an interference that is unacceptable for the PU (Figure 2). In spite of the existence of several proposals for the modeling of the primary user activity, it is important to continue investigating it in order to minimize the prediction error and at the same time optimizing the phase of decision making in CR [11], and it is there where this article focuses; for this initially in section 2 a succinct state of art of the most representative models in the characterization of PUs is presented, in section 3 the proposed model is included for the implementation (by simulation) of a recurrent neuronal system that allows the characterization of PUs in the WiFi spectral band, in sections 4 and 5 the results found are presented, the respective validation of the system when its efficiency in the prediction is compared with that found with Bayesian Networks; finally, the respective conclusions, acknowledgments and bibliographical references are generated.

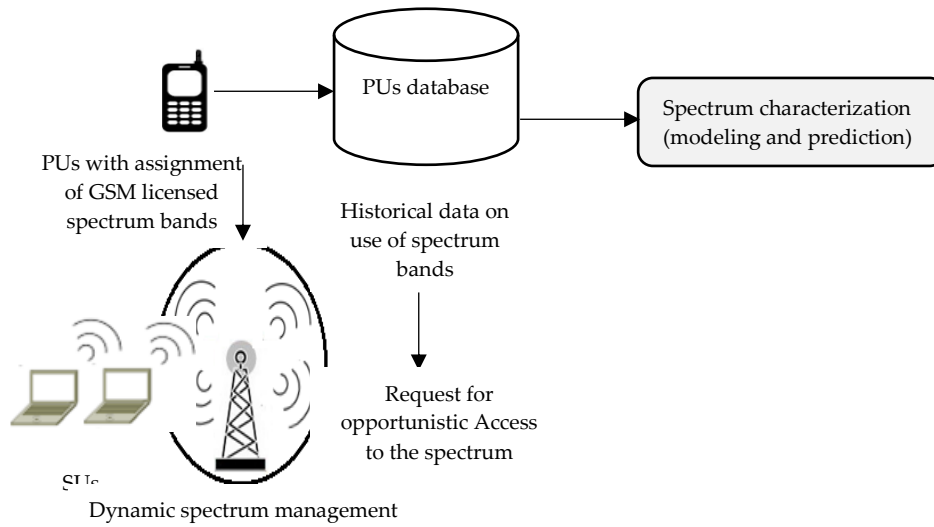


Figure 2. Contextualization of the characterization in the spectral decision stage in wireless cognitive radio networks.

2 Scientific Review

The future estimation of the occupation of the channels by the PUs gives an indication to the SUs of the moments in which the spectrum can be used to transmit; metric considered as sensitive and that will depend on how accurate the prediction model is based on its historical use [11]. In the characterization of PUs, [12] concludes that a significant number of existing approaches have a very high computational cost, making their implementation practically unfeasible in those nodes that base their useful life on the use of batteries (within rural areas); This approach allows us to conclude that there are still several development challenges in the sense that is necessary the construction of proposals that reduce the computational cost when estimating future predictions.

Within the most representative methodologies that study the dynamics of PUs in the spectral bands are mainly those shown in Figure 3, which are presented discriminated according to the type of paradigm that allows their implementation and / or simulation.

From Figure 2, it is generally observed that the scientific literature bases the representation of the activity of the primary users with methodologies that have an important computational cost such as [13], [14], [15], [16] among others, being unviable in applications of open field when the conservation of energy is important [11]. An alternative, which could solve these shortcomings by increasing efficiency, are models based on self-learning that provide feedback from their own mistakes to enhance future performance, as is the case with RNNs.

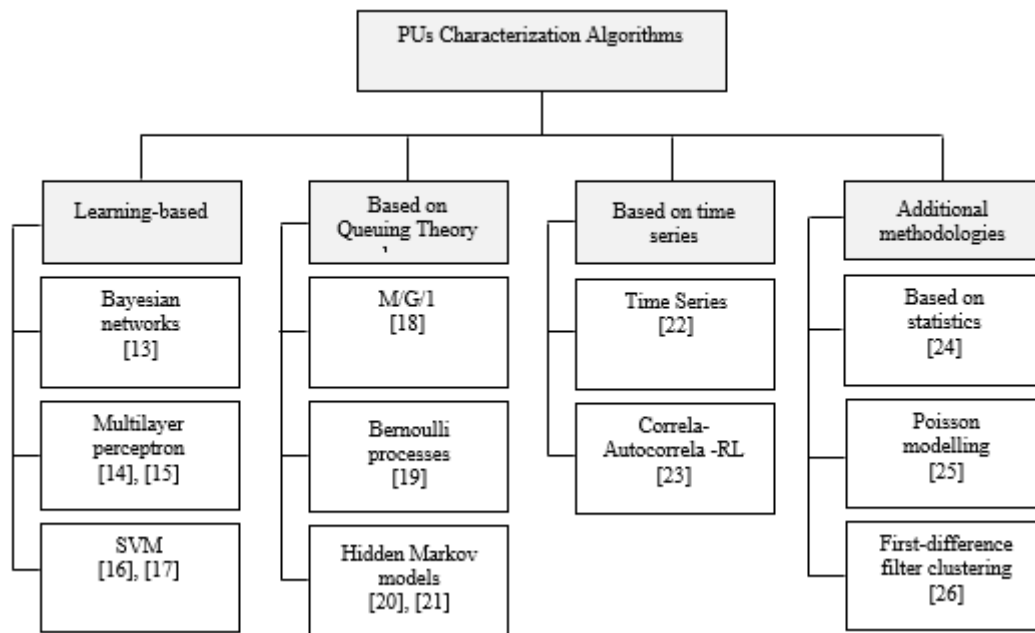


Figure 3. Existing models in the state of the art for the characterization of PUs in wireless cognitive radio networks.

3 Characterization of PUs with RNNs in WiFi networks

3.1 Design criteria

The algorithm aims to characterize the occupation of the channels based on the behavior of the PUs. Variables such as bandwidth and channel capacity are not relevant for the development of it since they are directly related to the characteristics of the transmission means.

Within the area of artificial intelligence, recurrent neural networks are ideal for identifying patterns; In this sense, the algorithm must be able to adapt to new patterns of behavior (if they exist), different from those exposed in training historical data.

The algorithm must characterize the behavior of a channel based on an occupation historical, in case you want to model and predict several frequency bands, it must be replicated. In other words, a neural network must be built for each channel that is intended to be characterized.

3.2 Mathematical modeling of the RNN system

Recurrent neural networks allow one or more of the neurons that conform it to provide feedback (graphically, you can see cycles) each other; the above suggests that a RNN can in principle send the "history" of previous inputs to each output [27]. For the modeling of the PUs characterization system, was used an RNN with a single hidden layer auto-connected as shown in figure 4, and starting from the fact that the network structure would be fed only by the use behavior of the channel

WiFi historical by a PU to generate the characterization; however, the algorithm has the ability to be dynamic, which implies variation in the number of entries of the RNN and increase in the number of hidden layers depending on the size of the data they enter.

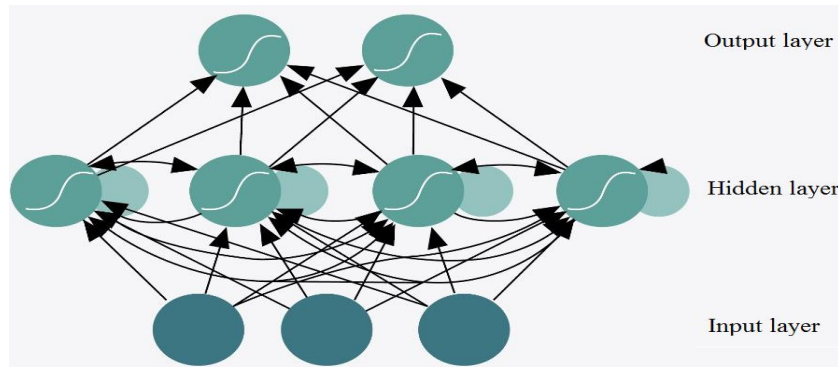


Figure 4. Structure of an RNN [1].

The key idea of the design is based on the fact that the recurrent connections allow a "memory" of the previous inputs that, remaining in the internal state of the neuron, optimizes its output or response (that is, it has the capacity to maintain over time patterns identified in the data that feed the network "to be used later in new estimates). For this reason, it is possible to apply, for learning and / or training cognitive RNN, a similar method to that used in a Multilayer Perceptron Neural Network (MLPNN) in which the activation functions are maintained, but these activations must arrive to the hidden layer from two places: the input layer and the hidden layer itself (see figure 5).

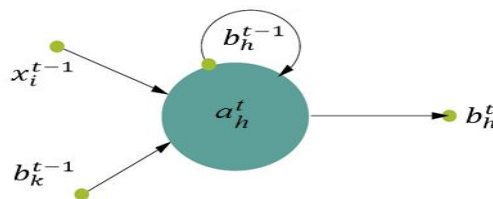


Figure 5. Inputs and output of the h-th neuron of the hidden layer for a fixed time t.

The mathematical development of the RNN is based on the notation shown in Table 1 [27].

Additionally, it must be taken into account that: the subscript t refers to time; $b_h^{(0)} = 0$; and that the weights between the neurons are denoted as w_{ij}

Starting from the previous description (Table 2) and taking as reference the described in figures 2, 4 and 5, equations 1, 2 and 3 are obtained.

Table 1. Mathematical nomenclature of the RNN network.

	Input layer	Hidden layer	Output layer
Subscript	i	h	k
Input	x_i	$a_h^{(l)}$	a_k
Output	x_i	$b_h^{(l)}$	y_k
Number of units	I	H_l	K

$$a_h^t = \sum_{i=1}^I x_i^t w_{ih} + \sum_{j=1}^H b_j^{t-1} w_{jh} \quad (1)$$

$$b_h^t = \sigma(a_h^t) \quad (2)$$

$$a_h^t = \sum_{k=1}^H b_k^t w_{hk} \quad (3)$$

Once the behavior of the hidden layer in the RNN is known, the algorithm Backpropagation Through Time - BPTT is used to stimulate or train the RNN; for this, the chain rule is applied repeatedly, taking into account that the loss function depends on the activation of the hidden layer. Therefore, for the h -th hidden neuron, equation 4 is obtained [27].

$$\delta_h^t = \frac{\partial E}{\partial b_h^{(t)}} = \frac{\partial E}{\partial b_h^{(t)}} \frac{\partial b_h^{(t)}}{\partial a_h^{(t)}}$$

$$\delta_h^t = \frac{\partial E}{\partial a_h^t} = \frac{\partial E}{\partial b_h^t} \frac{\partial b_h^t}{\partial a_h^t} \left(\sum_{k=1}^K \frac{\partial E}{\partial a_k^t} \frac{\partial a_k^t}{\partial b_h^t} + \sum_{j=1}^H \frac{\partial E}{\partial a_j^{t+1}} \frac{\partial a_j^{t+1}}{\partial b_h^t} \right)$$

$$\delta_h^t = b_h^t (1 - b_h^t) \left(\sum_{k=1}^K \delta_k^t w_{hk} + \sum_{j=1}^H \delta_j^{t+1} w_{hj} \right) \quad (4)$$

Assuming that the same weights are used in each time step, the sum up must be applied over all the considered time to obtain the derivatives with respect to the weights of the recurrent network and obtain the result or response of prediction of primary users in CRNs, described in equation 5 [27].

$$\frac{\partial E}{\partial w_{ij}} = \sum_{t=1}^T \frac{\partial E}{\partial a_j^t} \frac{\partial a_j^t}{\partial w_{ij}} = \sum_{t=1}^T \delta_j^t b_i^t \quad (5)$$

From the previous equation it is important to highlight that the output or response found by the characterization model (using RNNs), will allow to adjust and improve its accuracy in the estimation of the PUs behavior as it is executed (autonomously) the process of training or learning.

3.3 Flow diagram of the RNN algorithm

Figure 6 describes in a general way the main elements that make up the software application that was implemented in Java in order to validate the performance of the RNN (from the perspective of its predictive capacity).

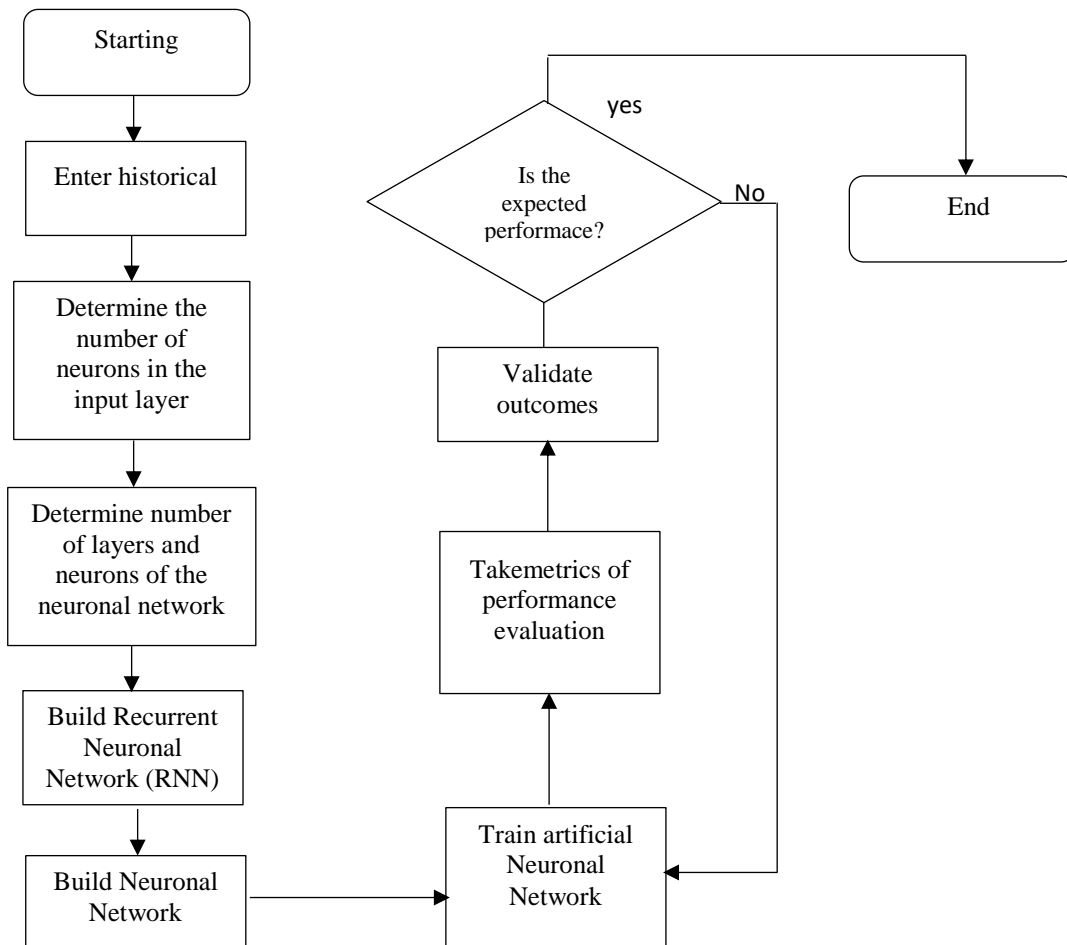


Figure 6. Descriptive diagram of the RNN

Although it is not discriminated in figure 6, the traces of data or database (of historical use behavior) that enters the prediction system come from a spectral database, which underwent a digital treatment for its conversion to discrete sequences as described in [28].

4 Analysis of Results

This section presents the results obtained by simulating the PUs characterization algorithm, with real data sequences (WiFi traces), taking as a reference the fact that from 100% of the traces that feed the RNN, 70% is used in the training or learning of the RNN and the other 30% in the validation (or estimation of the prediction).

4.1 Results found with the RNN prediction algorithm

As a qualitative description, the results found by the RNN algorithm are presented both in the training or learning stage of the model and in the validation or output response phase (see figures 8, 9, 10) when modeling and estimating the behavior of a PU in a WiFi spectral channel, for a sequence of user data described as shown in Figure 7.

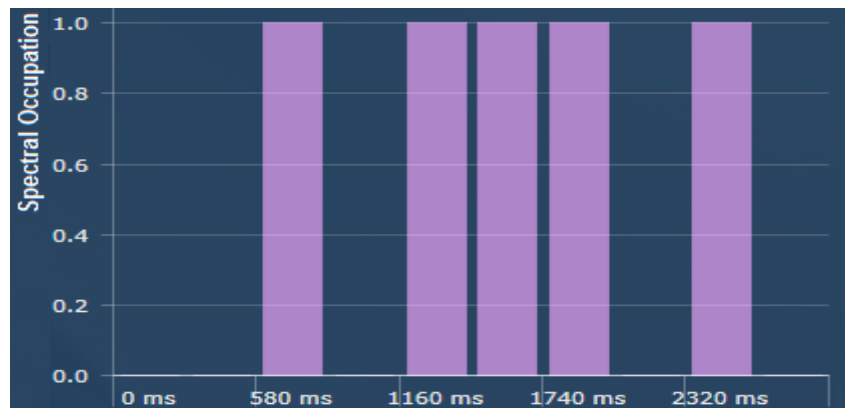


Figure 7. History of the use behavior of the channel by the PU.

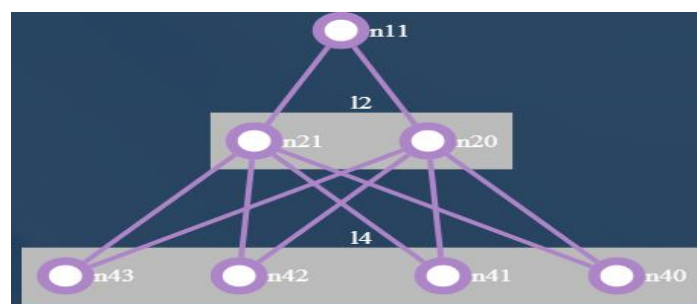


Figure 8. Generation of the neural network from the sequence that enter the neurons entering the RNN.

Particularly figure 8 describes the neural network that constructs the algorithm from the historical sequence of use of the channel by the PU; the structure that is shown has the property of being dynamic, that is, it varies its structure according to the quantity and types of data used to train the neural network based on artificial intelligence.

Figure 9, details the level of learning reached by the RNN network over the time variable; It is observed that the PU occupation pattern of the channel was perfectly detected and assimilated, reaching a modeling percentage of 100% (compare the instants of time in which the PU uses the channel (purple color), compared to the correct one in the learning that the recurrent network had (see light blue lines)).

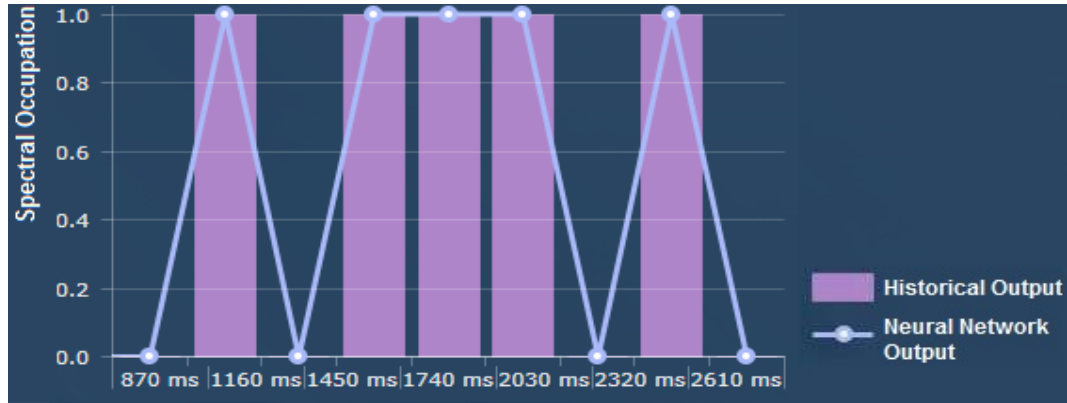


Figure 9. Training outcomes of the recurrent neural network.

The correct behavior in the prediction is 83.4% (see figure 10) for this particular data pattern, being able to obtain more optimal values in the estimation, if the learning sequence of the RNN has a highest rate of length, although this would increase the simulation time of the system.

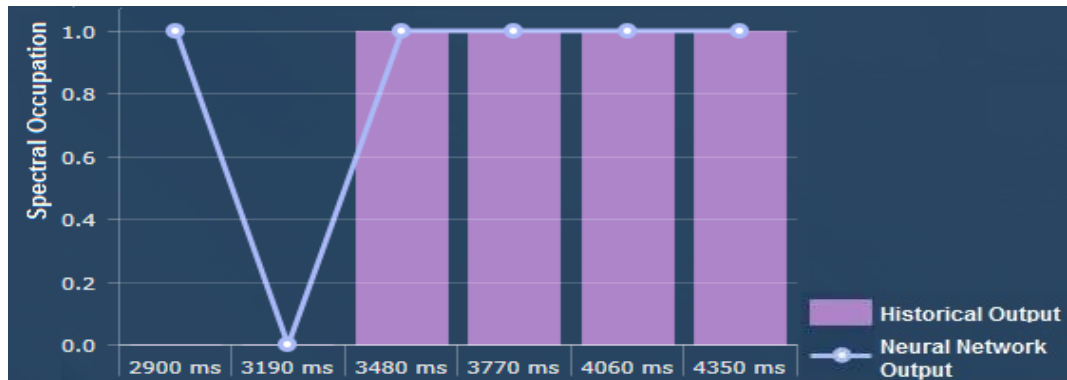


Figure 10. Results of the validation stage of the RNN.

4.2 Performance evaluation of the intelligent model of prediction RNN

To validate the structure, the performance of the design and simulation of the RNN was compared quantitatively (for reasons of space in the publication of the paper), with that delivered by a multilayer perceptron neural network; the data found are summarized in tables 2 and 3 for different evaluation metrics.

When performing a thorough analysis for two completely different input samples (high and low channel occupancy index by the PU) to that of section 4.1, it can be highlighted that there is a better performance in RNN reaching percentages of success in the prediction that oscillate between 63.3% and 85.45%, values that improve to those delivered by the MLPNN structure.

On the other hand, if the efficiency of the variable "processing time" is analyzed, it is concluded that the MLPNN model is more optimal. The two previous assessments allow us to conclude that the implementation of RNN or MLPNN as predictors in wireless cognitive Radio Networks (CRNs) will depend on the type of network on which we wish to execute: RNN is more efficient in environments where the processing capacity is more generous (as is the case of infrastructure-based cognitive radio networks) while MLPNN could work better in distributed environments (where the percentage of processing is vital for the functioning of cognitive nodes).

Table 2. Results found with the RNN and MLPNN algorithms

Metric	RNN		MLPNN	
	High index	Low index	High index	Low index
Number of iterations	4.000	4.000	4.000	4.000
Training error	0.7333	0.3401	0.7439	0.3777
Processing time (msec)	1477282	1530911	1200787	1149090
Validation error (%)	28.99	11.44	29.94	12.74
Prediction error (%)	36.87	14.55	38.22	15.36

Table 3. Percentage of success in the estimation of occupation of a channel by a PU in the 2.4 GHz band.

Evaluation algorithm	WiFi			
	RNN		MLPNN	
	High index	Low index	High index	Low index
Estimation accuracy percentage (%)	63.13	85.45	61.78	84.64

5 Conclusions

Taking as reference the results found throughout the validation of the primary user characterization algorithm in a WiFi channel of the 2.4 GHz spectral band, it can be concluded that recurrent neural networks (RNNs) could become a very good pattern of prediction in real CRNs, since the results were better than those found with the multilayer perceptron network (MLPNN).

An important characteristic of the research work done, is the fact that the PUs characterization algorithm using RNNs was tested, evaluated and contrasted using real data traces, which were obtained by making measurements in Bogotá (Colombia) with an analyzer of spectra; aspect that is relevant since from what is found in the state of the art, most of the proposed models are valued from data generated by simulation, which is far from reality.

The choice to evaluate the performance of our RNN model against MLPNN is due to the fact that there are published proposals that suggest the possibility of solving the problem of characterization of PUs in spectral bands with conventional neural networks; however, it has been demonstrated from the results found and summarized in Table 3 that the level of estimation is more accurate when using recurrent neural networks owing to their feedback capacity.

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