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Use of Artificial Intelligence Based Models to Estimate the Use of a Spectral Band in Cognitive Radio

Danilo Lopez Sarmiento, Edwin Rivas Trujillo and Luis Fernando Pedraza
Faculty of Engineering, Distrital Francisco Jose de Caldas, Bogota, Colombia

Abstract: Currently one of the major challenges in wireless networks is the optimal use of the radio spectrum as most researcher agree that the licensed frequency band is not in use most of the time. There has been a large amount of research in this area that converges in the use of Cognitive Radio (CR) as an essential parameter so that the use of the available licensed spectrum is possible (by secondary users) well above the usage values that are currently detected; thus allowing the opportunistic use of the channel in the absence of Primary Users (PU). This study presents the results found when estimating or predicting the future use of a spectral transmission band (from the perspective of the PU) for a chaotic type channel arrival behavior. The time series prediction method (which the PU represents) used is ANFIS (Adaptive Neuro Fuzzy Inference System). The results obtained were compared to those delivered by the RNA (Artificial Neural Network) algorithm. The results show better performance in the characterization (modeling and prediction) with the ANFIS methodology.

Key words: ANFIS, cognitive radio, prediction primary user, RNA, licensed spectrum, optimal

INTRODUCTION

The use of licensed bands by Secondary Users (SUs) is conditioned to the inactivity of the channels or their non-use by PUs; since there is no guarantee that spectral frequency will be available throughout the transmission period of an SU, it is important to take into account how often PUs appear. Using the learning ability of cognitive radio, the history of spectrum usage is used to predict the future spectrum profile (Masonta *et al.*, 2013) through the characterization or modeling of PU and SU activity; in this way it is possible to administer and manage the appropriate spectrum, seeking to avoid collisions with the PUs in the decision making stage in CR. From the above, the future estimation of channel occupancy gives an indication to the SUs of the moments in which it will be possible to make use of the spectrum to transmit; a metric considered as sensitive and that will depend on how accurate the prediction model is based on usage history. In the characterization of the primaries (Mishra *et al.*, 2012) concludes that a significant number of existing approaches have a very high computational cost, making their implementation practically unviable in those nodes that base their useful life in the use of batteries (within rural areas) an approach that suggests that despite being an issue addressed by several researchers, several development challenges remain in the sense that it is necessary to propose methodologies that reduce computational cost and increase the success percentage when estimating future ones. The most representative techniques that study the dynamics of PUs are summarized in Fig. 1.

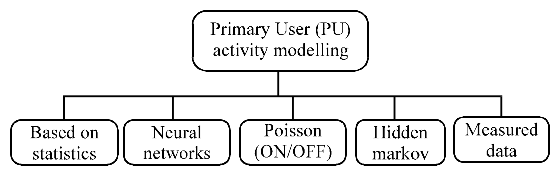

Fig. 1: Main paradigms used in PU activity

From Fig. 1, it can be observed that it is important to generate proposals that study the operation of methodologies such as ANFIS, SVMs (Support Vector Machine) among others in order to determine their modeling and prediction capacity which presents a PU in the transmission band of a wireless network. This premise validates the importance of studying the ANFIS Model in CR.

Literature review: Rehmani *et al.* (2013) a strategy for intelligent channel selection in multi-hop CR (SURF) is proposed; its operating principle benefits from continuous-time Markov chains to classify the available spectrum under the assumption of low PU activity and high number of cognitive nodes, causing each SU to dynamically migrate to the best channel. A cycle is included in the algorithm to learn from those estimates where the band selection was wrong, applying that

Corresponding Author: Danilo Lopez Sarmiento, Faculty of Engineering, Distrital Francisco Jose de Caldas, Bogota, Colombia

learning in future predictions. It is concluded that if the level of PU activity is high, the solution proposed is not adequate, a logical result since there is a deficiency of free spectral voids; when it is intermittent, the selection strategy works well by improving the system's performance through the control of collisions with PUs. An analytical study for a hybrid network based on the IEEE 802.11 standard is addressed by Khabazian *et al*. (2012). In order to preserve PU priority, it was assumed that SUs dispute their use when it is free of any primary activity over a period of time. They use queuing theory and model the variability of licensed nodes. In this case each PU is structured as a discrete queuing system M/G/1 with an arrival rate of λ packets/sec and service of 1/E [D] with E[D] as the medium access delay of PUs in the presence of Sus and its value shows the average of the time interval between the time of arrival of a packet to the main queue of a PU and the instant of time in which that PU accesses the channel to perform the transmission. The value of this variable associated with the queuing delay directly impinges on the average delay of packets $E[D_t]$ shown in Eq. 1:

$$E\,[D_t] = E\,[D] + \frac{\lambda E[D^2]}{2(1-\lambda E[D])} \quad (1)$$

Where:

E[D] = The denotes second moment of time it takes a
PU = Access the medium
λE [D] = The load on the queue

The analysis of the simulations argues that the performance of the primary network with a given packet arrival rate may be affected depending on the size of the useful packet load and the number of neighboring SU nodes.

The statistical approach based on binary time series by Yarkan and Arslan (2007) discloses the deterministic and non-deterministic behavior of channel use to predict future PU occupancy. The complexity of the analysis and the amount of storage memory required (of data) reduce it by assuming a sequence of binary states thus simplifying spectrum occupancy as well ("1" is empty, "0" is used). From the tests performed the short range prediction factor is quite satisfactory for the first two tests performed, however in the third sample the success of the prediction degrades strongly because the model is not updated and the data behavior is non-deterministic; a problem that could theoretically be solved by increasing its order at the expense of an exponential increase of the parameters to generate the prediction. From the deterministic perspective, the estimation is quite robust for the first four time slots according to the tests performed for three different bands in a GSM network during a capture with a duration of 17 msec from which 30 observations were obtained per channel once the model was applied.

Mishra *et al*. (2012) proposes a spectral decision-making system based on the quality of service for CR networks which guarantees the proper treatment of the packets by locating a band capable of satisfying the requirements of the SU where these can generate traffic with multiple priorities, dividing the flows to be processed in 4 different types with 8 available spectral bands also taking into account as system variables the availability of the channel, the fluctuation of the primary user with the assumption that the bandwidth is the same in each case (a condition that could be an advantage if the system is configured to operate like this). The availability of the channel is modeled as an ON/OFF source depending on the presence or absence of the PU (with a known behavior pattern) with a Markov two-state chain. Parameters a and β, represent the transition probability of the PU in the channel given an ON state (presence) to an OFF state (absence) and vice versa. The probability of availability of a void is given by Eq. 2:

$$\prod_i = \frac{\alpha_i}{\alpha_i + \beta_i}\ \forall i \in C' \quad (2)$$

Given that: C' = {1...C}. From the analysis of results it is found that when the number of channels increases, the appearance of false alarms decreases making the system work more properly.

The predictor based on the Static Neighbor Graph (SNG) (Xing *et al*., 2013) is designed to predict future locations of the PUs according to previous information collected from the mobility topology of the same licensed users. Initially, we construct a graph oriented to represent PU mobility history. To do this when a secondary user observes the passage of a PU from location i to j a directed edge (i, j) is added to the graph and the edge weight is set for $\omega_{ij} = 1$ if the edge (i, j) is not on the graph or 1 is added to the weight of the edge $\omega_{ij} = \omega_{ij}+1$ if the edge (i, j) is in the graph. Once the graph is obtained, a normalization procedure is performed on the edge weights such that $\forall i$, $\Sigma_j\ \omega_{ij} = 1$. Then, the mobility of the PUs is predicted as follows: If the current location of the UP is i and the cognitive user finds the place i on the graph, he returns a list (j, ω_{ij}) for all edges (i, j) and then predicts the future location of PU as j = a_{eg} max ω_{ij}. An interesting predictor of SNG-based PU is that additional valuable information can be obtained from the network structure.

Ghosh *et al.* (2010) a statistical model of time variation for spectrum occupancy is proposed using real frequency measurements. Using statistical characteristics extracted from real RF measurements, first and second order parameters are used in a statistical spectrum occupancy standard based on a combination of different density probability functions (Masonta *et al.*, 2013).

Although, most Cognitive Radio (CR) investigations focus on frequency bands above the upper limit of High Frequencies (HF) (Melian *et al.*, 2013) CR principles can also be applied to communications in the high bandwidth frequencies (HF) to make better use of the spectrum, based on regulatory and propagation restrictions. In this research, users are considered inherited from other frequencies such as the PUs that transmit without resorting to any intelligent procedure and the HFDVL architecture (voice and data transport in HF using 3 kHz bandwidths) is used as SUs. The objective of this study is to improve spectrum efficiency by detecting the future presence of PUs in channels (to avoid collisions) while transmitting information from SUs on different channels using the HFDVL transceiver. For this purpose a dynamic algorithm that monitors the activity of PUs (Wang *et al.*, 2011) is developed by estimating the short-term future predictions of the dwell time using the Hidden Markov Model (HMM). The system is trained for real values obtained in the amateur radio band on the 14 MHz frequency in three different situations: available channels, partially available and unavailable. The validation of results was based on predicting the activity in a channel during the next minute, reaching an average prediction error equal to 10.3% when the previous knowledge of the activity in the same is one minute long, being able to diminish its value to 5.8% when the previous analysis time is 8 min.

In CRNs, a static model such as that shown by Song and Zhang (2010) (where they use only a cycle for activity sensing and inactivity of PUs) fails to capture the dynamics of PUs behavior in the temporal domain. Researcher increase the number of measurements (to two cycles) to accurately estimate PU activity and thus to be able to improve the performance of the detection algorithms of free bands. The proposed method switches between two options; the first so-called fine sensing (which is used when the SU enters the primary network for the first time and therefore ignores the operation of the PU) and the second, normal sensing which based on a maximum likelihood estimator, learn to know the periods of PU activity and inactivity (in fine detection).

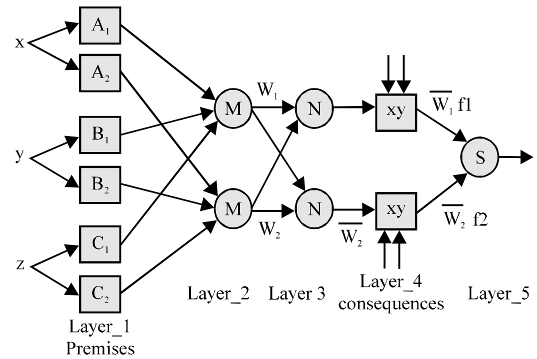

Fig. 2: Architecture proposed for the characterization of PUs with ANFIS

These occupancy patterns are used in normal detection where the Mean Square Error value (MSE) of ON-OFF periods is continuously monitored to ensure a sufficient accurate estimate. When its activity changes significantly (that is the value of the MSE is higher than a threshold), it forces the fine sensing to be executed again. The results in the simulation show that the method follows the dynamics of PU activity even at high fluctuation levels for PU.

From the state of the art, it can be concluded that most articles base the representation (modeling and prediction) of the activity of primary users in methodologies that do not possess the dynamic adaptation properties required by cognitive radio to make it a really intelligent and autoconfigurable system, rendering them unfeasible in a real implementation environment.

Adaptive neuronal inference system architecture: The architecture proposed for the development of the model is an adaptive network type in which its parameters are adjusted by a backpropagation algorithm, based on a set of data (input/output) that will allow the system to learn; due to faster training, the first-order systems for the diffuse Sugeno type are used. The system under consideration has three inputs x, y and z with a single output f. Therefore for a model of this type, a set of common rules are the fuzzy if-then rules represented Eq. 3:

$$\begin{aligned}&\text{Rule 1: if } x = A_1 \text{ and } y = B_1\text{, then } f_1 = p_1x+q_1y+r_1\\&\text{Rule 2: if } x = A_2 \text{ and } y = B_2\text{, then } f_2 = p_2x+q_2y+r_2\\&\text{Rule 3: if } x = A_3 \text{ and } y = B_3\text{, then } f_3 = p_3x+q_3y+r_3\end{aligned} \quad (3)$$

The system has a five-layer structure where the square nodes represent adaptive nodes and the circular fixed nodes as shown in Fig. 2.

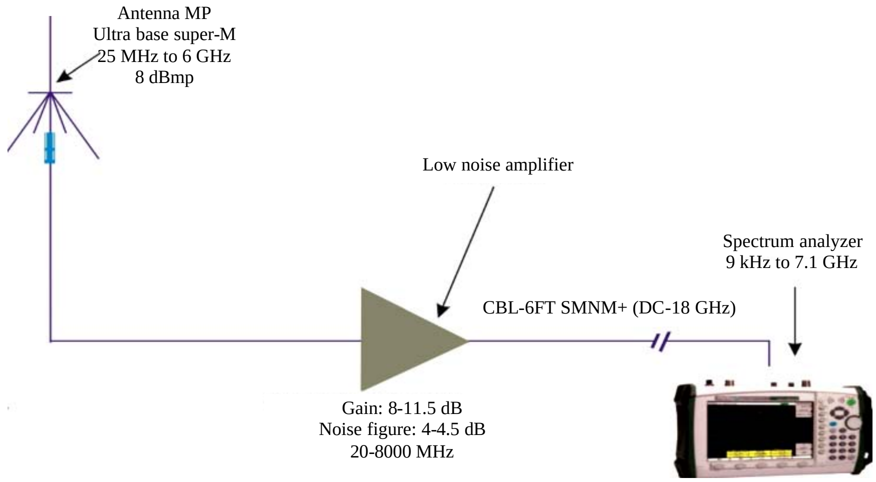

Fig. 3: Sampling power levels in the Wi-Fi band (Pedraza *et al*., 2014)

E1 = Average (A1:C1)

	A	B	C	D	E
1	-95,593338	-96,763824	-104,888016		-99,081726
2	-88,880859	-93,108475	-93,444763		-91,8113657
3	-93,393761	-94,169952	-105,450821		-97,6715113
4	-105,492752	-104,074631	-93,503723		-101,023702
5	-90,379135	-95,767059	-97,903625		-94,683273
6	-109,086472	-94,597824	-106,234016		-103,306104
7	-89,1763	-95,69886	-90,530212		-91,8017907
8	-95,15271	-95,850258	-94,270752		-95,09124
9	-103,740204	-92,53614	-99,580093		-98,6188123
10	-99,216263	-95,329651	-99,093506		-97,8798067
11	-98,256218	-97,161346	-100,749809		-98,7224577
12	-102,272583	-104,281631	-101,080544		-102,544919
13	-96,024277	-97,767433	-104,629845		-99,4738517
14	-97,75737	-100,156021	-91,52858		-96,480657

Fig. 4: Average Wi-Fi sample setting

PU signal processing: The measurements obtained by Pedraza *et al*. (2014) (Fig. 3) in the Wi-Fi band (2.4-2.48 GHz) were used for the evaluation of the neurofuzzy model of prediction of PU channel use (Garcia *et al*., 2016) where for the measurement ranges they took records of absolute power in multiple frequencies of a radio-electric channel in dBm obtained in intervals of 290 msec.

For practical purposes in the development of the tests, a total of 600 records have been used of which 300 were used in the training of the ANFIS network (modeling) and the remaining 300 were used to test the functioning of the neuro-adaptive system in the prediction of PU channel usage. A representative sample of the data sequence used can be observed in Fig. 4 in which the "columns" refer to the power levels in a channel while the "rows" indicate how many power samples were taken (every 290 msec). Because the data representing a Wifi channel consists of 40 columns (a condition that was established for simplicity) it was decided to average them in order to obtain a single level of power and to make good use of the data (Fig. 4).

Once the samples are obtained they are normalized to minimize the variation between the data for a range between 0 and 1, considering the maximum value and the minimum value that were obtained from all the records taken by the devices of Fig. 3. Finally, it ends with the treatment of the (chaotic) PU signal, applying a filtering in order to eliminate periodic trends that are considered as noise, obtaining a signal to estimate the modeling and prediction as shown in Fig. 5.

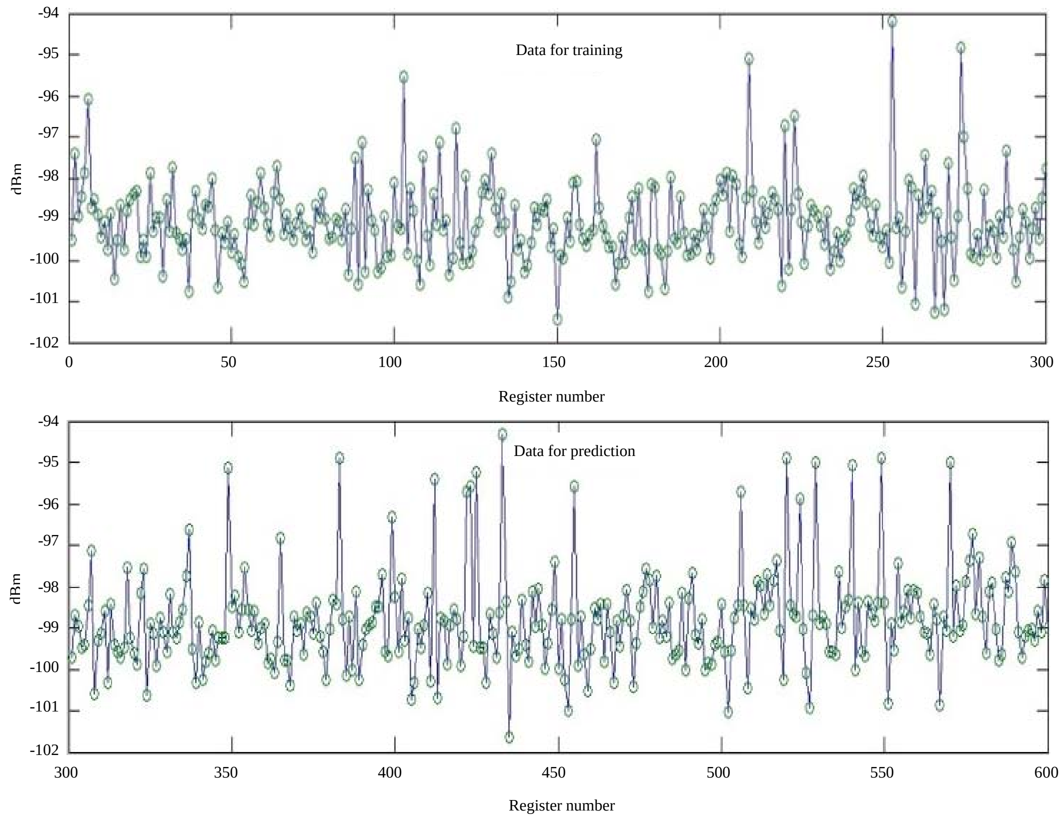

Fig. 5: Display of normalization and takagi-sugeno model

MATERIALS AND METHODS

Training and prediction of the pu characterization model with anfis: In the training of the neuro-diffuse model, three previous samples (y (k-1), y (k-2) and y (k-3)) of the signal to be predicted (y (k)) are used thus there are three input universes (y (k-1), y (k-2) and y (k-3)) in which each has two sigmoid sets (mf1 and mf2) and an output universe (u(k)) with 6 linear output sets (mf1, mf2, mf3, mf4, mf5 and mf6) as can be in Fig. 6.

To start the training of the network, a FIS structure is initially required which is responsible for specifying the system parameters for learning the ANFIS algorithm. In (Fig. 7), the first block complies with this through the generation of a fuzzy inference system that initializes the parameters of the membership function, generating a system with a single output using a grid partition in the data. If a value is not assigned for the number of membership functions the fuzzy matrix type takes a value that will be linear.

Then the algorithm establishes the dimensions that represent the information; For this case, the FIS data parameter assumes that the last column represents the response that must be obtained when the remaining columns are presented and the first one uses it to obtain the length of each column (proving that they have the same dimension thus preventing possible errors). Subsequently, a matrix of ones is created and is multiplied by the number of membership functions then checks that the type of output requested is a valid option then takes the matrix generated by the membership functions and performs a multiplication between the elements that it has in each row thus obtaining the number of rules to be generated.

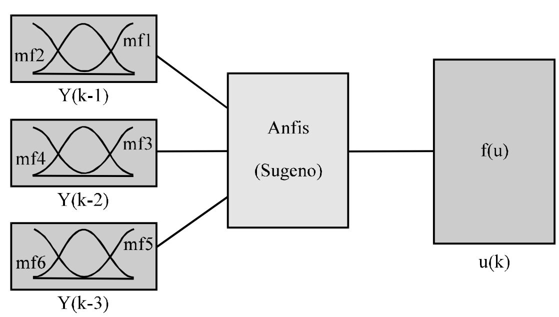

Fig. 6: ANFIS system based on the takagi-sugone model

Then, assigns the data to the FIS that is generated, taking into account that: the method to add "AND" logic rules is obtained by the product of the inputs; the method to add “OR” logic rules is generated with the sum of the inputs; the defuzzification method (which converts the results of fuzzy rules into numbers) is obtained using backpropagation.

Finally, the rules were built according to the type of entry (gaussmf, sigmf, etc.) keeping them in a list; it thenm minimizes the error value between the output desired and output delivered by the neuro fuzzy model. Part of the algorithm simulated in matlab for the characterization of a primary user can be observed in alorithm.

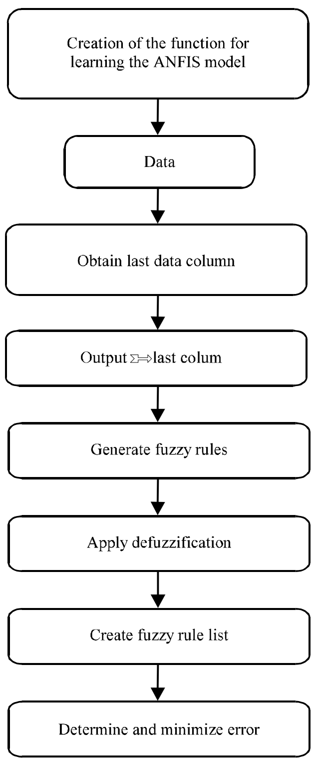

Fig. 7: Block diagram of the training and prediction model with ANFIS

Algoritham (Pseudocode of the training stage of the ANFIS: Train ANFIS with different input variables):

```
fprintf ('/nTrain %d ANFIS models, each with 3 input selected from 10 candidates.../n/n',...
anfis_n);
model = 1;
for d = 1: length (group 1),
  for e = d+1: length (group 2),
    for k = 1: length (group 3),
      in 1 = deblank (input_name (group1 (d), :));
      in 2 = deblank (input_name (group 2 (e), :));
      in 3 = deblank (input_name (group 3 (f), :));
      index (model, :) = [group 1(d) group 2 (e) group 3(f)];
      trn_data = data(1: trn_data_n [group 1(d) group 2 (e)
      group 3(f) size (dat, 2)]);
      chk_data = data(trn_data_n+1:trn_data_n+300,
      [group 1(d) group 2 (e) group 3(f) size (dat, 2)]);
      in_danilo = dals (trn_data (:, 1: end), 'sugeno', 150);
      [~, t_err, ~, ~, c_err] = ...
        anfis (trn_data, in_danilo, ...
        [epoch_n nan ss ss_dec_rate ss_inc_rate], ...
        [0 0 0 0], chk_data, 1);
    trn_error (model) = min (t_err);
    chk_error (model) = min (c_err);
      f print f ('ANFIS model = % d: %s %s %s', model, in 1, in 2, in 3);
    f print f ('--> trn = %, 4f, ', trn error (model);
```

RESULTS AND DISCUSSION

The sequence for training (modeling) and testing (estimation of accuracy in prediction) of the ANFIS model is shown in Fig. 8. Once simulating the neuro fuzzy system, the results of modeling and prediction shown in Fig. 9 were obtained. The results were validated comparing the neurofuzzy system with the response delivered by an artificial neural network; the results are presented in Fig. 10.

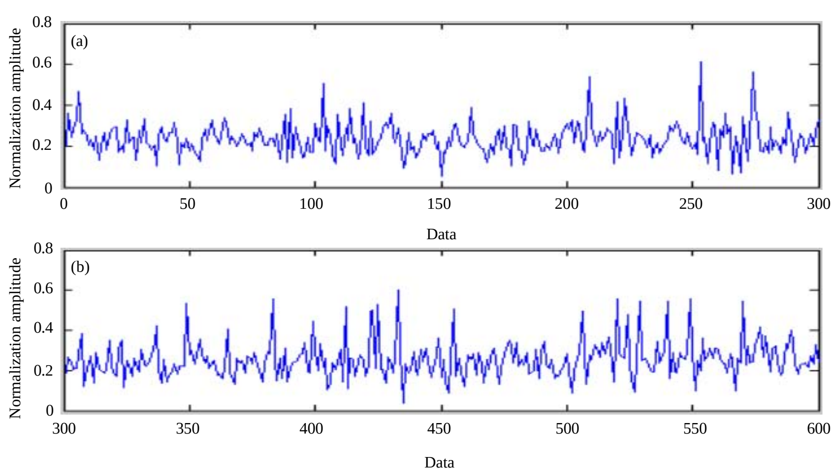

Fig. 8: Trace data of 300 values for training and prediction: a) Training data and b) Checking data

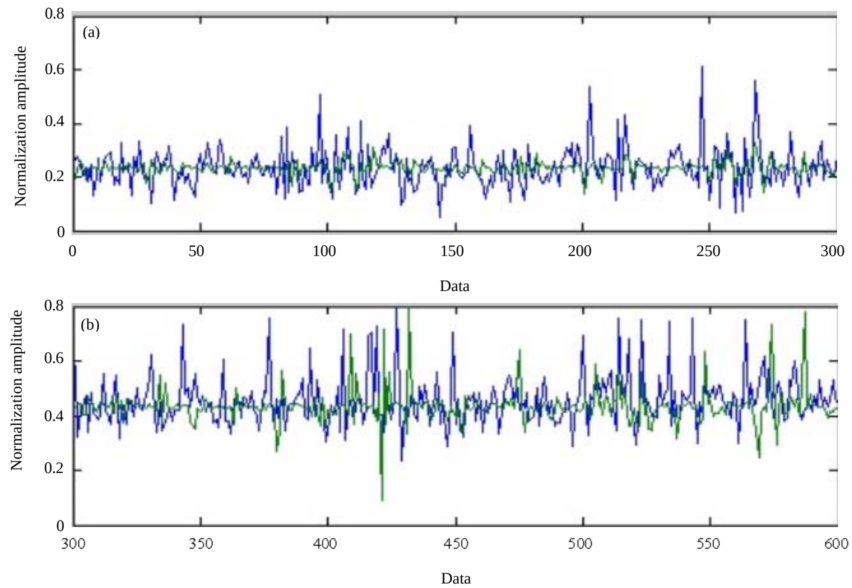

Fig. 9: Modeling and prediction with ANFIS: a) Training data and modeling with = 0.68902 and b) Checking data and anfis prediction with RMSE = 0.10799

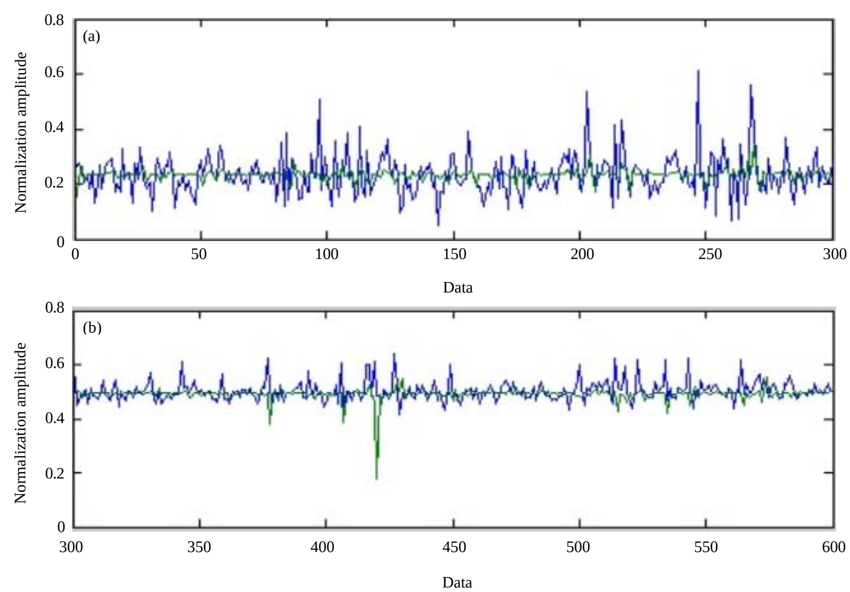

Fig. 10: Modeling and prediction with RNA: a) Training data RNS modeling with RMSE = 0.071257 and b) Checking data RNA prediction with RMSE = 0.10663

Table 1: RMSE values for ANFIS and RNA

Parameter	RMSE-ANFIS	RMSE-RNA
Modeling	0.68902	0.071257
Prediction	0.10799	0.106630

Table 1 shows a comparison between the two structures by evaluating the Mean Square Error (MSE) parameter of Eq. 4 which shows a better performance in the modeling and prediction of the arrival of PU to the channel for ANFIS than for RNA:

$$\text{MSE} = \left(\frac{1}{n}\right)\sum_{i=1}^{n}(y_i - \hat{y}_1)^2 \quad (4)$$

CONCLUSION

The great advantage of ANFIS neurofuzzy inference systems is their adaptability which makes them an excellent candidate to be used as a predictor in CRN while RNA is a structure with self-learning capability composed of multiple layers, applicable to the solution of problems that are not linearly separable which has been tested as an estimator of channel usage in CRN. The results of both methodologies, in principle, show relatively similar results (Fig. 9 and 10); although from the prediction variable, ANFIS is able to be more successful in monitoring sudden changes in the signal. This appreciation is clearly evident from the results obtained in the Result Mean Square Error (RMSE). A critical variable when using systems based on artificial intelligence is the processing time of the data in this sense a t = 4.5 min for RNA was obtained and a t = 4.2 min for ANFIS; values that can become raised in CRN. Nevertheless, ANFIS is susceptible to improvement due to its flexibility and the ability to use simple network topologies for sequences of chaotic input data in addition to offering the possibility of using clustering by extracting a set of rules that model the data.

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