Estimation of Future Occupation of Spectral Channels by Licensed Users in Cognitive Radio Networks Applying Neuro-Fuzzy Models

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Abstract

Cognitive radio is a paradigm that proposes the dynamic management of the radio spectrum, through the integration of sensing, decision making, sharing and spectral mobility. The decision-making phase is in charge of deciding the best channel available to transmit secondary user data (SUs) opportunistically; Its success depends on how efficient the characterization (modeling and estimation) model of primary users (PUs) in spectral bands is. A combination of prediction methodologies based on the ANFIS-GRID Neuro-Fuzzy Inference System (which divides the input data sequence into rectangular sub-spaces) and ANFIS-FCM (based on the use of the Fuzzy C- Means Clustering method) is proposed to reduce the forecast error in spectrum usage behavior by PUs in wireless cognitive radio networks. The results show that the proposed algorithm has the robustness necessary
to improve the prediction percentage far above that obtained against methodologies such as Long Short-Term Memory (LSTM) yielding a success percentage greater than 90% in the GSM frequency band. In conclusion, although the proposed ANFIS presents a better performance in the generation of forecasts for time series that represent the dynamics of the PUs, the computational complexity is higher, thus making its implementation in cognitive radio systems based on centralized network topologies feasible.

Keywords: ANFIS-GRID; ANFIS-FCM, Cognitive radio; GSM, Primary User, prediction

1 Introduction

In the same manner as land is more costly and scarce in urban areas due to the fact that they're densely populated (because of the quality of life they offer), the operating range of the radio electric spectrum is more useful in certain frequency bands than others because they facilitate the interconnection of devices and reduce the probability of errors. Wireless systems are currently characterized by a spectrum allocation policy that is established and regulated by the government of each country. This presents spectrum distribution issues (Figure 1) [1] because spectrum use is deficient due to large spatial and temporal variations in spectrum occupation [2]-[4]. A consequence of underutilization is a current spectrum shortage, which causes a significant degradation in the quality of service offered by telecommunications companies (for example, wireless band), an aspect that has motivated researchers from different fields to formulate possible solutions for optimizing spectrum use. Dynamic spectrum access (DSA) is a solution, along with the cognitive radio (CR) concept, the main purpose of which is to identify spectrum holes not used by PUs so that they can be used opportunistically by SUs. CR can be defined as a system that is controlled by a cognitive process capable of perceiving and processing existing environmental conditions. CR can subsequently be used by a learning technique capable of optimizing network performance. The above task implies the use of highly intelligent algorithms that are capable of making decisions under different conditions in different radio environments, as well as other challenges that need to be resolved [5]-[7].

Dynamic spectrum management in CR includes four main stages [8]-[10], one of which is spectrum decision (in charge of selecting the best channel available based on the SU's service quality requirements), which is important and relevant because it's one of the least explored stages [11], and essentially depends on the characterization and statistical behavior of channel use by the PU. In this regard, one of the variables on which the success of band selection depends is related to the quality of the prediction model used to represent PU dynamics; if the prediction is not very good, an inadequate channel will probably be selected, and the SU will generate an interference that is unacceptable for the PU. In spite of the existence of several proposals for modeling primary user activity, it's important to continue
conducting research in order to minimize the prediction error percentage as well as optimize the spectrum decision-making stage in CR; that is the focus of this research article which is comprised of the following: Section 2, the state of the art in regards to PU characterization in CR; Section 3, includes the neural structure of the ANFIS model for the characterization or future estimation of PUs in CR; Section 4 describes the methodology used in the research developed and the structure of the implemented algorithm; Section 5, analyzes the response given by the system in the future forecast of channel usage by the primary user; Finally, the ANFIS is validated by evaluating its performance against the recurrent neural network LSTM algorithm.

![Figure 1. Spectrum occupation in the 30 MHz to 3 GHz range [1].](image)

### 2 Scientific Review

Future estimation of channel occupation from the perspective of PUs gives SUs an indication of the times when they can make use of the spectrum; such a metric is considered sensitive to and highly dependent on the prediction model. In a characterization, [12] concludes that a significant number of existing approaches have a very high computing cost, which makes implementation practically impossible in nodes in which useful life is based on battery use (in rural areas). This conclusion suggests there are still several development challenges including the need to propose methodologies that reduce computing cost (especially for ad-hoc topologies) when estimating future predictions based on existing data [11], as well as the imperious need for the lowest possible prediction error when estimating future behaviors.

The article in [13] proposes three prediction mechanisms based on correlation, linear correlation and regression, and self -correlation, based on previous decisions, to predict future spectrum status as well as decision making regarding PU occupation.
The prediction-based correlation scheme uses the Pearson Correlation Coefficient which is measured from historical samples of windows; if the coefficient is above a certain threshold, the prediction window is filled with the latest sample. Linear regression prediction based on the Pearson Coefficient establishes the correlation between the spectrum detection status and the index vector. This coefficient is determined by a threshold value similar to the previous approximation, and there will be a correlation and regression if a linear relationship exists. If a relationship exists, it's used for spectrum prediction. Simulations show the proposed prediction scheme exhibits better results in diverse simulation settings. Furthermore, in order to obtain a more realistic evaluation, it's necessary to take into account the values of the utility system along with the PU’s disturbance relationship values.

In [14], the characterization problem is described in terms of the lack of a priori knowledge of traffic characteristics, and a predictor is designed based on the neural network model of an unsupervised multilayer perceptron (MLP), where there will be a desired value and its estimation; the difference between the two will be the error. The training algorithm acts at that point with the purpose of minimizing the error rate as much as possible by creating a correspondence function between the input vector and the desired value. The parameters are updated repeatedly until reaching the minimum mean squared error or, otherwise, the maximum number of iterations; once the training is finalized, the predictor is tested by means of random observations of subsequent predictions. The conclusion reached through simulations is that the calculation of erroneous predictions can be improved if each interval of the MLP predictor has a short duration, spectrum utilization improvement is more than 60%, and the energy reduction percentage for traffic intensity detection is 50% less than the reduction observed without the use of the MLP predictor.

In [15], an artificial neural network (ANN) model is used to predict channel status in a television band; in order to meet the goal, parameters such as the channel spectrum efficiency and the distance (d) between the primary base station and the secondary station are taken into account. The proposed ANN model predicts channel status as "1" for a busy channel and "0" for an available channel. The exploration system analyzes the licensed channels, taking into account that network variables such as the signal noise ratio (SNR), the bandwidth efficiency, the channel capacity, and the distance are provided as inputs to the ANN. All the parameters that are provided as inputs are indices for identifying blank spaces. Thus, it is concluded that the designed ANN model can identify spectrum holes for an SNR of up to -20dB. The neural network model that is trained and optimized the first time does not need to be trained further, and the optimized weights can be continuously stored for subsequent predictions, making this specific technique the most appropriate for detecting the spectrum and assigning it in the primary television station's coverage area.
In the state of the art discussion in [16], the authors stress the importance of autonomous learning in CR, taking into account that said learning implies that current and future characterizations and actions are obtained from past observations and behaviors, without confusing this with the reasoning posture (consisting of observing the current state of the environment and making decisions without necessarily taking the past into account), which is why the development of learning is essential for optimizing processes in CR; this learning may be supervised or unsupervised. Supervised learning is characterized by its use in known settings and the use of techniques such as: artificial neural networks (that can be used for spectrum modeling, characterization and decision at runtime, thus achieving a certain degree of learning), Support Vector Machine (SVM) (used as a signal classifier in CR settings) [17]; it’s important to point out it’s used by agents that learn autonomously without supervision, where said agents will base the learning process on their interactions with the environment using dynamic programming or time difference, or the trial-and-error method. On the other hand, unsupervised learning is useful if CR has no knowledge of certain environmental parameters and tries to learn an optimal action policy that leads to better system performance. Although most of the research on cognitive radio focuses on frequency bands above the upper limit of high frequency (HF) [18], CR principles can also be applied to HF band communications in order to use the spectrum more appropriately based on regulatory and propagation restrictions. Reference [18] considers that users inherited from other frequencies are PUs who transmit without resorting to any intelligent procedure. The HFDVL architecture (HF voice and data transport using 3 KHz bandwidths) is used for SUs. The goal of the study is to improve spectrum use efficiency by detecting the future presence of PUs in channels (to avoid collisions), while the information from SUs is transmitted through different channels using the transceiver. To that end, a dynamic algorithm that monitors the activity of the PUs [19] was developed, and estimates short term future predictions for presence time using the Hidden Markov Model (HMM). The system is trained for real values obtained in the amateur radio band in the 14 MHz frequency in three different scenarios: available, partially available, and unavailable channels. The validation of results was based on predicting activity on a channel during the next minute, reaching an average prediction error equal to 10.3% when prior knowledge of the activity has a one minute duration, and reducing the value to 5.8% when the prior time for analysis is 8 minutes.

The predictor based on the static neighbor graph (SNG) [20] is designed to predict future locations of PUs according to prior information collected from the mobility topology of said licensed users. Initially, a graph is built in order to represent the mobility history of PUs. To that end, when a secondary user observes the movement of a PU from location $i$ to $j$, a directed line segment $(i,j)$ is added to the graph, and the weight of the line segment is established as $\omega_{ij} = 1$ (if line segment $(i,j)$ is not in the graph), or 1 is added to the weight of the line segment $\omega_{ij} = \omega_{ij} + 1$ (if line segment $(i,j)$ is in the graph). After the graph is obtained, a normalization procedure is performed on the line segments so that $\forall i, \sum_j \omega_{ij} = 1$. 


After that, the mobility of the PUs is predicted in the following manner: if a PU's location is \( i \), and the cognitive user finds the location \( i \) in the graph, a list \( (j, \omega_{ij}) \) is returned for all line segments \( (i,j) \) and, after that, the PU's future location is predicted as \( j = \arg \max \omega_{ij} \) [21]. An interesting feature of SNG-based PU prediction is that valuable additional information on network structure can be obtained.

The statistical approach based on binary time series that is described in [22] provides the deterministic and non deterministic behavior of channel use in order to predict future PU occupation. The authors reduce the complexity of the analysis and the amount of memory storage needed by assuming a sequence of binary states, thus also simplifying spectrum occupation ("1" for empty, "0" for in use). In the tests that were conducted, the short range prediction factor is highly satisfactory for the first two tests; however, in the third sample, the success of the prediction is strongly degraded because the model does not update itself and, in addition, the behavior of the data is not deterministic. In theory, this problem could be resolved by increasing the order at the expense of an exponential increase of the parameters for generating the prediction. From a deterministic perspective, the estimation is quite solid for the first four time slots according to tests conducted for three different bands in a GSM network during a capture with duration of 17 ms. The state of the art described in [7] can be synthesized by saying that since there is no guarantee that a band is available during the period required by a SU for transmission, it's important to take into account how frequently PUs appear. Using CR's learning ability, a PU's history of spectrum use activity can be used to predict the spectrum's future profile, a process that is achieved through characterization. SUs can decide on the best spectrum bands available for transporting their data considering the future behavior of PUs. This last approach captures what is intended in this paper, which is to characterize PUs using an ANFIS (Adaptive Neuro-Fuzzy Inference System) methodology that includes the integration of the ANFIS-GRID methods (model that includes the concept of Grid Partition) And ANFIS-FCM (supported in Fuzzy c-Means clustering).

### 3 PUs Prediction with ANFIS

The developed ANFIS architecture, includes the functions of high and low membership interconnected as shown in Fig. 2, resulting in nine rules with T-standard product \( (\pi_n) \) and Takagi Sugeno type inference. It consists of three inputs and one output; five layers, where the modeling is based on [23], [24], and is represented by Eq (1-10).
Layer 1. Each node i is adaptive and represented mathematically by the functions of Eq. (1-3).

\[ O_{1,i} = \vartheta D_i(X_i); \forall i = 1, 2, 3 \]  
\[ O_{1,i} = \vartheta E_i(X_2); \forall i = 1, 2, 3 \]  
\[ O_{1,i} = \vartheta H_i(X_3); \forall i = 1, 2, 3 \]  

where, \( O_{1,i} \) is the output of node i (which specifies the degree to which the given \( X_i \) satisfies \( D_i \) quantizer, \( E_i \) and \( H_i \)); \( X_i \) corresponds to the system input; \( D_i, E_i, H_i \) are the linguistic labels associated with the membership function \( \vartheta \) given by Eq. (4).

\[ \vartheta(X; a, b) = e^{-\frac{(X-a)^2}{2b^2}} \]  

where \( a \) represents the center of the Gaussian function; \( b \), determines the width.

Layer 2. At this level the triggering force of each rule is calculated. The triggering force refers to the application of the T-standard (computing operation whose objective is to calculate the linguistic statement "and" for rules of the type “If \( X_1 \) is \( D_1 \) and \( X_2 \) is \( D_2 \) and \( X_3 \) is \( D_3 \) \( \Rightarrow \) \( Y \) is \( C_1 \) ” where \( X \) and \( Y \) refer to the variables of the antecedent and \( F \) to the consequent). Mathematically the output is given by Eq. (5).
\[ O_{2,1} = W_i = \delta D_i(X_1) \ast \delta E_i(X_2) \ast \delta F_i(X_3) \quad (5) \]

\forall i = 1, 2, 3

**Layer 3.** In this layer the average of the outputs of the previous level is obtained and generate normalized weights (N in Fig. 2), in order to establish the relationship between the strength of a particular rule, and the sum of the forces of all other rules in order to know to what extent a rule "is met" over the others (Eq. (6)).

\[ O_{3,i} = \overline{W}_i = \frac{W_i}{\sum_{1}^{20} W_i} = \frac{W_i}{W_1 + W_2 + W_3 + \cdots + W_{20}} \quad (6) \]

where, \( \overline{W}_i \) represents the normalized triggering forces of the rules, and \( W_i \) the output of the previous layer.

**Layer 4.** Here the parameters of the consequent are defined, where the function of each node corresponds to a combination of the layer 3 output and a Takagi Sugeno type simple linear equation (see Eq. 7).

\[ O_{4,i} = \overline{W}_i \ast f_i = O_{3,i} = \overline{W}_i(S_iX_1 + T_iX_2 + U_iX_3 + Z_i) \quad (7) \]

where \( S_i, T_i, U_i, Z_i \) are the set of parameters of the consequent of the rules "If \(-\) Then" and where these rules are of the type (Eq. (8)):

\[ If \ X_1 = D_i \text{ and } X_2 = E_i Then \ f_i = S_iX_1 + T_iX_2 + Z_i \quad (8) \]

**Layer 5.** Corresponds to the output or response, and is given as the sum of all incoming signals (layer 4 output). Mathematically it can be represented as Eq. (9).

\[ O_{5,i} = Y = \sum_{i}^{20} \overline{W}_i \ast f_i = \frac{\sum_{1}^{20} W_i f_i}{\sum_{1}^{3} \overline{W}_i} \quad (9) \]

If it is established that the values of the premise parameters are fixed [25], the ANFIS response can be written as a linear combination of the consequent parameters (Eq. (10)).

\[ O_{5,i} = \sum_{1}^{20} \frac{W_1}{W_1 + W_2 + W_3} f_1 + \frac{W_2}{W_1 + W_2 + W_3} f_2 + \frac{W_3}{W_1 + W_2 + W_3} f_3 \\
+ \frac{W_4}{W_4 + W_5 + W_6} f_4 + \frac{W_5}{W_4 + W_5 + W_6} f_5 + \frac{W_6}{W_4 + W_5 + W_6} f_6 \\
+ \frac{W_7}{W_7 + W_8 + W_9} f_7 + \cdots \\
+ \frac{W_{20}}{W_1 + W_2 + W_3} f_{20} \quad (10) \]
4 Methodology and Description of the Implemented ANFIS Algorithm

4.1 Capture and Processing of Spectrum Information

For data capture, the first step was to determine what wireless network application would be used to evaluate the ANFIS technique [26]. Cellular (GSM) communications were chosen as the main objective. The second step was to select the spectrum detection technique to be used. Energy detection was selected because it's easily implemented and has low requirements [27]. The manner in which data capture was performed is shown in Fig. 3; Table 1 [27] shows the spectrum measurement technical specifications. Table 2 [27] shows the characteristics of the cluster used as a computing resource for the development of the algorithm and the execution of the training and prediction tests.

![Interconnection of equipment for capturing spectrum occupation data](image)

Figure 3. Interconnection of equipment for capturing spectrum occupation data [27].

<table>
<thead>
<tr>
<th>Equipment</th>
<th>Specifications</th>
<th>Model reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectrum analyzer</td>
<td>9 KHz - 7.1 GHz</td>
<td>MS2721B Anritsu</td>
</tr>
<tr>
<td>Discone antenna</td>
<td>25 MHz - 6 GHz</td>
<td>Super-M Ultra Base</td>
</tr>
<tr>
<td>Low noise amplifier</td>
<td>20 MHz - 8 GHz</td>
<td>ZX60 - 8008 -S+</td>
</tr>
<tr>
<td>Broadband cable</td>
<td>DC – 18 GHz</td>
<td>CBL-6FT SMNM+</td>
</tr>
</tbody>
</table>
Table 2. Cluster Specifications

<table>
<thead>
<tr>
<th>Feature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equipment and brand</td>
<td>KVM Virtual Machine - BIOS Openstack Foundation 2015.1</td>
</tr>
<tr>
<td>Brand</td>
<td>DELL R900 server</td>
</tr>
<tr>
<td>Number of processors</td>
<td>Intel(R) Xeon(R) CPU E7450 @ 2.40GHz, 24 Cores</td>
</tr>
<tr>
<td>RAM</td>
<td>64GB DDR2</td>
</tr>
<tr>
<td>Storage system</td>
<td>1000GB ext4</td>
</tr>
<tr>
<td>Operating system</td>
<td>Ubuntu server 14.04.04 with an XFCE4 desktop environment</td>
</tr>
</tbody>
</table>

The database of power intensities of the radioelectric spectrum for GSM used for the evaluation of the ANFIS algorithm as a method for the characterization (modeling and prediction) of PUs, were provided by [28]; and in order to make a better use of the information, we proceeded to obtain the average of the power levels that existed in each band (Fig. 4), for the construction or generation of the final analog signal that would represent the behavior of the PU in each spectral band in GSM.

![Figure 4. Obtaining the final power level representing the presence or absence of a PU.](image)

After obtaining the sample or signal to be characterized, the algorithm normalizes the data to minimize its variation by placing them in the 0 and 1 interval (a graphic example of this is shown in Fig. 5).
Finally, before conducting ANFIS network training, a moving average filter is implemented to smooth out high frequency fluctuations or eliminate trends that can be considered as noise (see Fig. 6).

Said filter represented in Eq. (11) processes the current data from the consideration of the 4 previous samples.

\[ y_T = \frac{1}{4} y_t + \frac{1}{4} y_{t-1} + \frac{1}{4} y_{t-2} + \frac{1}{4} y_{t-3} + \frac{1}{4} y_{t-4} \]
4.2 Description of the operation of the algorithm

The performance of the proposed algorithm was tested for PU behavior with real data sequences (GSM traces), based on the premise that 50% of the data is used in the ANFIS network training stage, and the other 50% for validation (estimating the prediction).

The membership functions of layer 1, for the training of the ANFIS model in Matlab software [29], are as shown in Fig. 7, where the inputs are universes \( y(k-1), y(k) \) (M (1)), and (3), where each of them has two sigmoidal sets (mf1, mf2), plus an output universe \( U(k) \) with the linear sets mf1, mf2, mf3, mf4, mf5 and mf6.

![Figure 7. Anfis system based on the Sugeno model.](image)

The FIS structure (Fuzzy Inference System) responsible for specifying the system parameters for the learning of the ANFIS within the simulations performed arose from the integration of the ANFIS-GRID methods [30], and ANFIS-FCM [31] as shown in the block diagram of the prediction algorithm shown in Fig. 8.

The proposed system starts by obtaining channel data, then generates a single column of data which represents the average power levels for each spectral band; then it finds the maximum and minimum values of said column and proceeds to perform the normalization of the signal and apply the filtering described in Eq. (11), to then join the input and output data (see Fig. 7) in a two-column array, where the inputs \( Y \) are divided into 3 subgroups and the outputs \( U \) into 6 subgroups according to Eq. (11 and 12).

\[
Y = \{y(k-1), y(k-2), y(k-3)\} \\
U = \{u(k-1), u(k-2), u(k-3), \ldots, u(k-6)\}
\] (11) (12)

Then a sequential search is generated in order to create three groups of data (thus avoiding saturating the ANFIS with too much information), according to the form given in Eq. (13 to 15):

\[
Group 1 = y(k-1), y(k-2), y(k-3)
\] (13)
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\[ \text{Group 2} = y(k-1), y(k-2), y(k-3) \] (14)

\[ \text{Group 3} = u(k-2), ..., u(k-6) \] (15)

In addition, the algorithm generates an exhaustive search in order to determine possible learning patterns that may be present in the training and learning stage of the model.
From the data received in the previous step, the model is trained and tested by adjusting the number of membership functions in ANFIS-GRID and the number of clusters in ANFIS-FCM until the smallest possible error is found between the desired output and the output delivered by the algorithm. It should be noted that the ANFIS-GRID fuzzy inference system is the combination of grid partition and ANFIS.

Grid partition divides the data space into rectangular sub-spaces using axis-parallel partition based on pre-defined number of membership functions and their types in each dimension [32]. Premise fuzzy sets and parameters are calculated using the least square estimate method based on the partition and MF (Membership Functions) types.

When constructing the fuzzy rules, consequent parameters in the linear output MF are set as zeros. Hence, it is required to identify and refine parameters using ANFIS [32]. The combination of grid partition and ANFIS has been reported in [33], [34]. The wider application of grid partition in FL and FIS is blocked by the curse of dimensions, which means that the number of fuzzy rules increases exponentially when the number of input variables increases [35].

On the other hand, ANFIS-FCM bases its operation on Fuzzy c-Means (FCM), which is an information clustering technique where each of the data belongs to a cluster at a certain level specified by a degree of membership [36]. Dunn introduced this algorithm in 1973 [37]. FCM algorithm is the fuzzy mode of K-means algorithm and it does not consider sharp boundaries between the clusters [38], [39]. Thus, the significant advantage of FCM is the allowance of partial belongings of any object to different groups of the universal set instead of belonging to a single group totally [40]. FCM is based on minimization of the objective function of Eq (16) [41].

\[
J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^m \left\| x_i - C_j \right\|^2; \quad 1 \leq m \leq \infty \tag{16}
\]

Where \( m \) is any real number greater than 1, \( \mu_{ij} \) is the degree of membership of \( x_i \) in the cluster \( j \), \( x_i \) is the \( i \)-th of \( d \)-dimensional measured data, \( C_j \) is the \( d \)-dimension center of the cluster, and \( \left\| x_i - C_j \right\| \) is any norm expressing the similarity between any measured data and the center. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership \( \mu_{ij} \) and the cluster centers \( C_j \) by Eq (17,18). This iteration will stop when \( \varepsilon \) is termination criterion between 0 and 1, whereas \( k \) are iteration steps. This procedure converges to a local minimum or a saddle point of \( J_m \) [41].

\[
\mu_{ij} = \frac{1}{\sum_{k=1}^{C} \left( \frac{\left\| x_i - C_j \right\|}{\left\| x_i - C_k \right\|} \right)^{2/(m-1)}} \tag{17}
\]
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\[ C_j = \sum_{i=1}^{N} \frac{\mu_{ij}^m \cdot x_j}{\sum_{i=1}^{N} \mu_{ij}^m} \]  \hspace{1cm} (18)

5 Analysis of Results

The validation of the proposed Anfis system was done using the Matlab software using a data pattern of 1000 samples, of which 50% were used in the training phase and the other 50% in the validation phase (Prediction estimate) for a spectral channel in the GSM uplink band. In the ANFIS learning phase, the antecedent and consequent parameters are trained using the backpropagation algorithm, obtaining the difference between the summation of the points from the input data and the sum of the points from the data given by the ANFIS and propagating the error from the outputs to the inputs to adjust the variables and decrease the value of the error.

Fig. 9 shows the comparison of the sequence used for the training and the one calculated by the model; It is observed that the training stage is quite successful since it is able to follow the chaotic behavior of the PU in the channel even for small variations in the signal.

To determine how adequate the training success process is (by using the backpropagation algorithm), the root mean square error (RMSE) of Eq. (18) is used; This metric determines the extent to which the model does not adjust to the actual signal behavior [42], [43] and will represent a better behavior when its value is closer to zero.

\[ RMSE = \sqrt{\frac{\sum_{i=1}^{n} (d_i - O_i)^2}{n}} \]  \hspace{1cm} (19)

where, \( d_i \): refers to the actual given training pattern; \( O_i \): corresponds to the response given by the Anfis model; and \( n \) to the number of data.

The most optimal value found for the RMSE variable (corresponding to Fig. 9) was 0.0042639 using a “gbellmf” type activation function, with an error ranging from -0.01 to +0.15, parameters indicating a difference and minimum variation between the desired training data and those obtained by the ANFIS algorithm, which allows to infer that the system is a good estimator to describe and forecast PU signals in GSM bands. The validation step (estimation of future PU behavior) is shown in the upper part of Fig. 10, where the verification sequence for 500 samples is compared to that calculated in the ANFIS prediction, obtaining a RMSE value of 0.004451 and an error variation of -0.01 to +0.012 for a “gbellmf” type activation function.
Figure 9. PU behavior training on a GSM channel (modeling) with ANFIS.

Figure 10. Validation of the ANFIS model estimating a future prediction of PU behavior for 500 data.
When analyzing the dispersion for the first 20 training data, it is found to be approximately 0.001 and for the last 20 validation data it is 0.0033, a value that although a little higher allows to conclude that the estimated prediction is very close to the test data, a condition which can be corroborated by the proximity shown between the points of the scatter plots (bottom of Fig. 10).

6 Discussion

In this section, the objective is to study the performance of the proposed system by validating it with the LSTM technique [44] for RMSE, prediction accuracy, correlation coefficient and computational time metrics. The response of the LSTM algorithm for the same PU input behavior during training and validation is summarized in Fig. 11, 12 and Table 3.
Table 3. Results found with LSTM.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Training Phase (Modeling)</th>
<th>Validation Phase (Prediction)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>0.0058962</td>
<td>0.0056982</td>
</tr>
<tr>
<td>Error Variation</td>
<td>-0.019 and +0.018</td>
<td>-0.0185 and +0.015</td>
</tr>
<tr>
<td>Data Dispersion</td>
<td>0.010</td>
<td>0.018</td>
</tr>
</tbody>
</table>

The analysis of the outputs delivered by ANFIS and LSTM starts from the results stored in the training and test databases and are summarized in Table 4. It can be seen in the first place that the training values have a better response than the test results, with the exception of the metric that identifies the time required for the execution of the models, which is considerably smaller in the test stage, because the degree of parameter adjustment to decrease the error between the desired output and the one delivered by the algorithms is applied in the learning phase.

Although it is true that the time required for training and testing of ANFIS represents 52.086% more than in LSTM, the accuracy in the future prediction of the channel occupation status is much more accurate in ANFIS with 93.94%, which would imply a lower probability of collisions between the PU and the potential candidate node to use the available licensed spectrum. It should also be noted that the behavior of the variable "prediction accuracy" presents a slightly better performance in the training compared to the values found in the test phase, but it should be noted that neither the ANFIS nor the LSTM are able to reduce the error in the learning phase to zero.

Taking the "RMSE" and "correlation coefficient" metrics as reference, it is concluded that they have a similar but slightly better trend in ANFIS, indicating that it is the best option in terms of obtaining better forecasts.

In synthesis, when comparing the results globally, it can be established that the ANFIS method is more adequate than LSTM if the existence of possible collisions between PUs and SUs is not tolerable within the cognitive radio system when they coexist simultaneously within the wireless network; However the main advantage of LSTM is that the robustness of the hardware needed for implementation would be much lower than that required by ANFIS [45].

Table 4. Statistical Results of ANFIS and LSTM systems.

<table>
<thead>
<tr>
<th>Performance indicators</th>
<th>Training data</th>
<th>Testing data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ANFIS</td>
<td>LSTM</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.0042639</td>
<td>0.004451</td>
</tr>
<tr>
<td>Prediction accuracy (%)</td>
<td>93.67</td>
<td>72.88</td>
</tr>
<tr>
<td>Correlation coefficient</td>
<td>0.94</td>
<td>0.71</td>
</tr>
<tr>
<td>Computational time (s)</td>
<td>32.97</td>
<td>17.54</td>
</tr>
</tbody>
</table>
7 Conclusions

This article proposes the use of a hybrid neuro-fuzzy algorithm that integrates the ANFIS-GRID and ANFIS-FCM methods for the characterization of licensed users in GSM cellular bands. The inclusion in the ANFIS of membership functions based on Grid partition and c-means clustering improves the modeling (in the training stage) and forecast (in the test phase) capacity of channel use. The results of the simulation confirm that the proposed system has a greater success percentage in the prediction of the chaotic behavior of PUs in cognitive radio than other paradigms such as the one based on deep learning called LSTM; Notwithstanding the integration of ANFIS-GRID and ANFIS-FCM has an added computational cost in learning time and execution of the application.

Ensuring a prediction accuracy percentage above 90%, certifies that the changing nature of the channel status (busy/idle) can be predicted with a high level of accuracy, allowing the digital representation of the presence (with a binary 1) or absence (with a binary 0) of the PU; A representation that could be used in the spectral decision step for selecting the best available spectral bands to be opportunistically occupied by the secondary users in transporting information flows in the GSM cellular wireless network.

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Estimation of future occupation of spectral channels

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Estimation of future occupation of spectral channels


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