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Neuro-Fuzzy Model for the Prediction of Spectral Occupancy

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Abstract

Modeling spectral occupancy in cognitive radio networks facilitate the prediction of the primary user's activity and contribute to an efficient use of the radio-electric spectrum. The purpose of this article is to develop a neuro-fuzzy model to predict the spectral occupancy in a Wi-Fi network (2.4 to 2.5 GHz). To achieve this, the ANFIS algorithm is implemented and its performance is evaluated for two types of membership functions, through the comparison of their results. The obtained results validate the performance of the neuro-diffuse model and its usefulness within cognitive wireless networks.

Keywords: ANFIS, cognitive radio, inferential fuzzy system, membership function, radio-electric spectrum, spectral handoff.

INTRODUCTION

As wireless technologies rapidly evolve, the spectral resource is becoming scarcer due to the prominent user demand. Therefore, it is crucial that the new communication systems use the frequency bands efficiently in terms of time, frequency and space [1]. However, the increase in wireless services requires more spectral resources which leads to scarcity within the available frequencies [2]. This makes it necessary to have intelligent, innovative and efficient models that satisfy all users that require one or several spectral opportunities [3].

Over the last years, the radio-electric spectrum has been much subdivided to give opportunity to different types of wireless services. As a collateral effect, the spectrum has become scarcer [4]. In contrast, several studies have identified that primary users (PU) of the licensed bands are not using it efficiently which would allow a secondary user (SU) to opportunely use the spectrum unused by the PU. This is known as spectral handoff [5].

There are currently several handoff strategies so that a SU profits from spectral opportunities. One of the most interest strategies is the proactive strategy since it minimizes the level of interference between the PU and the SU [6],[7]. In proactive handoff, it is necessary to predict the PU's spectral occupancy to determine the moment when the channel has to be changed. Hence, cognitive radio (CR) must have the capacity to learn and adapt to the radio environment [8],[9].

The recent development of computational models and their application in diverse areas of science has increased the implementation of problem-solving tools that also estimate unknown parameters. Cognitive radio has not been detached to this process and has required the development of methodologies within the criteria of sharing and flexibility of the spectrum. One of them is artificial intelligence in which the models based on fuzzy logic (FL) and artificial neural networks (ANN) that have the advantage of handling expert knowledge, the faculty of reasoning in the case of FL and the ability of ANN to learn and adapt. The combination of these advantages gives place to neuro-fuzzy models [10].

According to this, the present article intends to develop a neuro-fuzzy model that allows the prediction of the spectral occupancy in a cognitive radio network for the 2.4 – 2.5 GHz frequency band. Such model combines the advantages of FL and the learning ability of ANN. This work chose the ANFIS model proposed by Jang in 1993 due to the existence of tools focused on the implementation of these type of models such as MATLAB [11].

RELATED WORKS

According to Hong [2], with the purpose of creating a prediction model for the radio-electric spectrum's behavior with an efficient detection system and access for CR users, the ANN are adopted as an alternative. They develop a practical learning method applied to the spectrum activity and establish an effective prognostic concerning the states of the channels (inactive or occupied) in future time intervals. This prognostic is obtained initially through a supervised learning process so that the parameters created in the CR nodes define an *a priori* list with the resulting mobility data without interrupting the current transmission. The empirical results show that the method proposed in this document can conveniently match with the spectrum's future behavior through a RMSE (root mean square error). Additionally, due to the ANN's generalization capacity, the generated model can be harnessed in a service radio to predict the another service's spectrum behavior with acceptable accuracy [2].

In CR systems, the main requirement in the detection of the spectrum is the fast and precise detection of the PU's presence. Due to the previous statement, [10] proposes a spectrum detection method using an ANN considering that this computational tool possesses the adaptive learning and stable performance advantages whose main function is to train the sampling of the signals under a considerably low SNR (signal-to-noise ratio) and the detection of the PU's existence. According to the obtained results, the model has an adequate detection accuracy which offers stability in the transmission performance which simultaneously reduces the complexity of the factors and initial parameters of the physical detections of the radio-electric spectrum [10].

The authors in [12] propose a method for a FL-based control system where the spectral handoff is performed. The fuzzy control repeats a four-step cycle for its operation implementing them with four different processes. In first place, the different variables are measured. In second place, they are converted into fuzzy sets to express the measurement uncertainties (*fuzzyfication*). In third place, the control rules are evaluated depending on the fuzzy measurements (*de*fuzzification) and the results are sent to another set. In fourth place, the resulting set is converted into a clear value in the final step of the cycle. The FL is then used by the SU to define whether the spectral handoff needs to be carried out or a power modification is necessary to coexist with the PU. The decision is based on four descriptors: the intensity of the received signal, the distance between the PU and the SU, the PU's transmission power and the level of detected interference. The result is a 60% increase in the transmission's efficiency which is corroborated.

Engineers from the Electronics and Telecommunication Academy Sinhgad in India [13], assure that the spectral handoff is one of the main challenges in CR. To solve it, they propose a mobility-based spectral handoff that also considers QoS (quality of service) and priority. The system basically focuses in the SU's mobility (114 km/h) to define inter and intracellular handoffs to guarantee the quality of the SU's service. Additionally, a new resource usability handoff is used to prioritize some critical situations in the handoff. The proposed algorithm uses FL and ANN to make the handoff decision. During the handoff process, the SU can perform multiple handoffs in various channels to complete its transmission. The obtained results show that the use of fuzzy controller helps to approximate the parameter values according to the user request; additionally, the use of ANN improved the accuracy in the decision-making for diverse handoff situations. However, it had limitations due to the efficiency in a maximum of seven groups of cells within the transmission process [13].

According to the arguments of various foreign authors in [14], a neuro-fuzzy system is a popular framework to solve complex problems. If knowledge is expressed in linguistic rules, a fuzzy inference system can be built by specifying the fuzzy sets, operators and the base of knowledge. Furthermore, if the data is available or the system's behavior can be learnt through simulated (training) data, then the architecture and learning algorithm must be specified. The author develops a classification and explanation of this model under three categories: concurrent model, cooperative model and ANFIS-type integrated model [14].

METHODOLOGY

The main purpose of this Project is to detect the behavioral pattern of the PU's transmission within a frequency band when an SU is using the network. Therefore, it is intended to develop a neuro-fuzzy model based on rules and autonomous knowledge to take the correct decisions. This model possesses a reasoning engine of fuzzy inference and learning engine based on adaptive networks. The methodology is described in terms of spectral information, information processing, the neuro-fuzzy model and the validation of the proposed model.

Spectral information

The first step in the development of the project consisted on obtaining the real spectral occupancy data. To perform this task, a small measurement campaign was carried out in the Wi-Fi frequency band (2.4 – 2.5 GHz) for three weeks with approximately 20.000 information frames per hour that indicate the power transmitted in each channel. Due to the large amount of data, long processing delays were produced and the size of the spectral database had to be reduced to the segment of the most active day of the network (2 pm to 4 pm) which led to a more compact and reduce data structure (about 40.000 frames per day).

Information processing

A statistical method was used to satisfy the optimization and large data processing within the learning mode and inferential ability of the computational model.

In first place, a sampling and classification of the 461 channels is performed in the 2-hour selected range by selecting the *availability* parameter where it is determined whether a channel is available (1) or occupied (0) based on the *power* variable. Afterwards, a filter is implemented to organize the channels into three sets according to the level of repetitiveness in the availability levels: high for the channels belonging to a probability interval from 1 to 0.75, medium from 0.74 to 0.55 and low from 0.5 to 0.

From the classified channels, other characteristic parameters are generated (probability of availability for each minute and SNR) in order to consolidate a compact and characteristic heuristic base of the original data that can be processed by the hybrid predictive model.

Proposed neuro-fuzzy model

The proposed neuro-fuzzy model is based on the ANFIS (Adaptive Neuro-Fuzzy Inference System) which is a combination between FL and ANN. It uses the FL to build an inference mechanism on the uncertainty and neural networks that offer major computational advantages such as learning, adaptation, tolerance to failures, parallelism and generalization among others. This system classifies the data of an initial set with different parameters for the membership functions depending on the variables to process whilst describing the system's behavior so that ANFIS can adjust the system parameters with a given error criteria [8].

ANFIS uses two methods for data training whether it is individually or in a hybrid fashion:

- ✓ (Backward step)-(Descending gradient)
- ✓ (Forward step)- (Minimum square method)

The ANFIS algorithm is based on layers: Layer 1 performs the fuzzyfication process of the input variables and deploys the T-norm operators. Layer 2 computes the rules that come out from the first level. Layer 3 normalizes the rules. Layer 4 determines the subsequent parameter rules (in this type of architecture, backward propagation is used). Finally, layer 5 adjusts the parameters with mean-square estimation.

The input parameters are defined as the first target: *Availability probability* (AP) and *Signal-to-noise ratio* (SNR). Following Roger Jang's structure in his 1993 model, Fig. 1 represents the ANFIS structure adapted to this investigation.

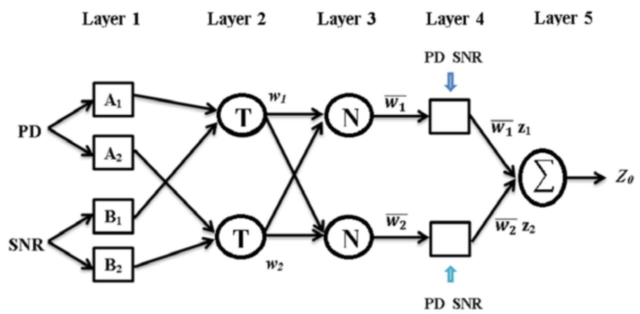

Figure 1: Proposed ANFIS model

Layer 1: The inputs in this layer correspond to SNR and AP. The node's output is the degree of membership for which the input variable satisfies the linguistic term associated to this node (see equation (1)).

$$O_i^1 = \mu_{A_i}(AP), \mu_{B_i}(SNR) \qquad (1)$$

Where AP and SNR are the inputs and $\mu_{A_i}(PD)$ and $\mu_{B_i}(SNR)$ is the output that represents the membership function of the input of linguistic variable *Ai*. In this case, the triangular membership function will be used.

Layer 2: Each node computes the level of activation related to its corresponding rule. Both nodes are represented with a T in Fig. 1 since they can represent any t-norm to model the AND operation. The nodes in this layer are known as rule nodes. See equation (2).

$$O_i^2 = w_2 = A_i(AP) * B_i(SNR) \qquad (2)$$

Layer 3: Each node in this layer is represented by an N in Fig. 1 to indicate the normalization of the activation degrees. The node's output is the normalized deactivation degree (with respect to the sum of the activation degrees) of the rule. See equation (3).

$$O_i^3 = \overline{w}_i = \frac{w_2}{w_1 + w_2}, i \qquad (3)$$

Layer 4: The output of the node corresponds to the product between the normalized activation degree and the individual output of each rule (see equation (4)).

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i AP + q_i SNR + r_i) \qquad (4)$$

Where p_i, q_i, r_i constitute the parameter set. The parameters of this layer are known as the consequent's parameters.

Layer 5: The only node of this layer calculates the system's total output (aggregation) as the sum of all individual inputs of this node (see equation (5)).

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (5)$$

The first layer represents the membership layer, the second layer is used to generate the triggering degree of the rule (T-norm), the third layer acts as a normalizer, the fourth rule computes the output and the final layer combines all the outputs in one only node.

As a last step, the ANFIS *backward step* is applied (see equation (6)).

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \qquad (6)$$

Where η is the learning rate that can be expressed as equation (7) indicates.

$$\eta = \frac{k}{\sqrt{\sum_{\alpha} \frac{\partial E}{\partial \alpha}^2}} \quad (7)$$

Fuzzy sets

In Fig. 2, the structure of the implemented fuzzy controller is shown with its respective inputs and outputs.

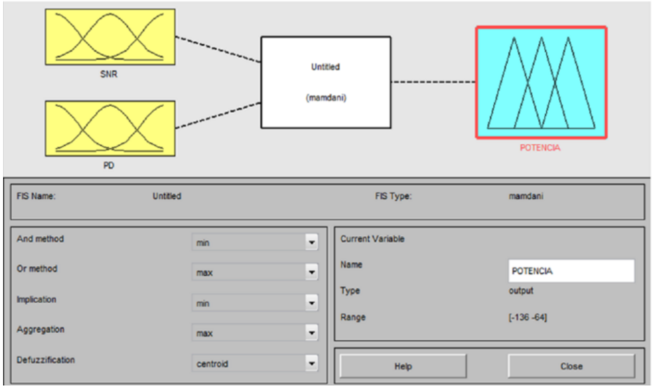

Figure 2: Fuzzy inferential controller (FIS)

The parameters of the membership functions (MF) are the SNR and AP inputs and the power output as described in Tables 1, 2 and 3 respectively.

Table 1. Parameters of the membership functions for the input *SNR*

Baja	-35 a 9.9 dBm	Trimf [-35 -10 15]	Trampf [-35 -35 -10 15]
Media	10 a 26 dBm	Trimf [7 15 31]	Trimf [7 15 31]
Alta	26 65 dBm	Trimf [15 40 65]	Trampf [15 40 65 65]

Table 2. Parameters of the membership functions for the input *AP*

Baja	0 a 30 %	Trimf [-50 0 50]	Trampf [-50 -50 0 50]
Media	30 a 72 %	Trimf [18 50 93]	Trimf [18 50 93]
Alta	72 a 100 %	Trimf [50 100 150]	Trampf [50 100 150 150]

Table 3. Parameters of the membership functions for the output *Power*

Baja	0 a 30 %	Trimf [-136 -115 -97.5]	Trampf [-136 -136 -115 -97.5]
Media	30 a 72 %	Trimf [-101 -97.5 -94]	Trimf [-101 -97.5 -94]
Alta	72 a 100 %	Trimf [-97.5 -85 -64]	Trampf [-97.5 -85 -64 -64]

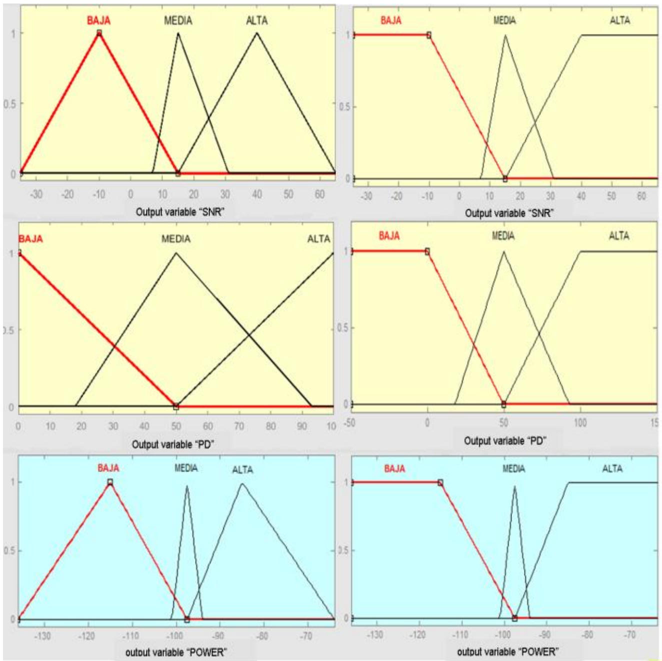

Figure 3: Graphical representation of the membership functions with inputs *SNR* and *AP* and output *power* with TRIMF (left) and TRAMPF (right)

Control rules

According to the synthesis of the implementation of the ANFIS model, Table 4 presents the linguistic control rules to complete the necessary FIS parameters.

Fig. 4 accurately represents the control rules and Fig. 5 shows the FIS model's vector output for the Takagi-Sugeno controller.

Table 4: Linguistic control rules

SNR	PD	POTENCIA
High	Low	High
High	Medium	High
High	High	High
Medium	Low	High
Medium	Medium	High
Medium	High	Medium
Low	Low	High
Low	Medium	Medium
Low	High	Low

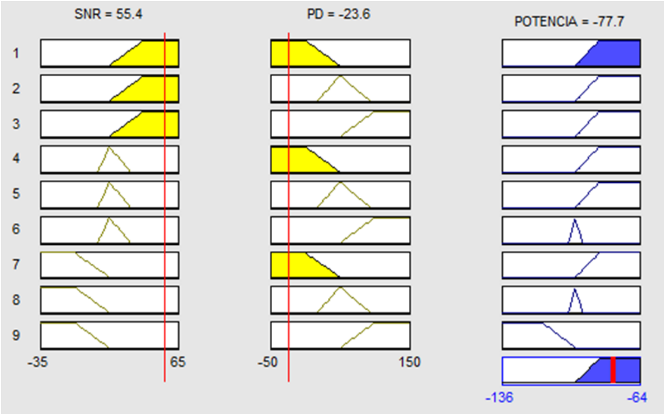

Figure 4: Control rules implemented in the membership functions

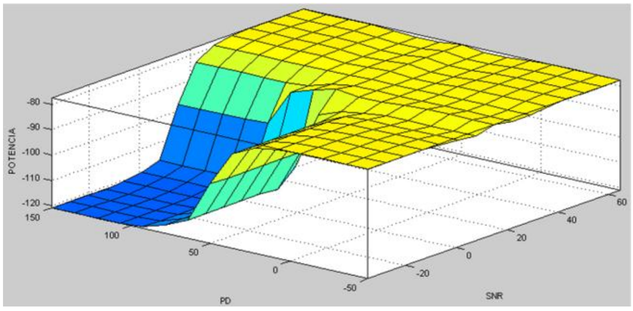

Figure 5: Graph of the FIS model vector output

Metrics and validation of the proposed model

To perform the cognition, self-organization and reconfiguration processes of the mentioned input parameters, the neuro-fuzzy model is developed with the help of the *ANFIS Editor* tool from MATLAB. It offers reasoning-based analysis with a fuzzy inference method and learning engine based on adaptive networks which finds different types of ANFIS which can be used depending on the targeted application.

This tool uses fuzzy sets for the mapping of the inputs while there is only one output and therefore a control based on linguistic rules using the Takagi-Sugeno method. The controllers' outputs can be checked for a posterior number of iterations through a hybrid backward propagation and MSE (mean square error) method that interacts with the FIS (Fuzzy Interference System). This leads to data training and learning which is applied to the inputs taking as a basis the changes in the characteristics of the assigned parameters.

According to the information processing, initial data are taken for training by the neural network which learns from the observed characteristics in each variable after leaving the control rules. Then, a posterior verification is performed to evidence the error resulting from the comparison of the two moments of output data (training and checking) which generates a chart of iterations VS the magnitude of the prediction error and finally it is validated for the FIS's output to identify the channel's future state.

In this case, two types of ANFIS were used depending on its membership functions: the ANFIS *trimf* (triangular membership function) and ANFIS *trapmf* (trapezoidal membership function). The development of this two branches offered different results both in the membership function of the output and in its graphical interpretation and linguistics.

RESULTS

Fig. 6 shows the comparison between the two types of MF (*trimf* and *trapmf*) for the system's two inputs (SNR and AP) before and after training. To generate the initial FIS, the genfis1 function was chosen since it generates a customization in the rules and type of the MF in order to build the neuro-fuzzy model.

Fig. 7 presents the training error in the model's learning process with the training-checking data and the FIS model structured with 9 rules and 9 membership functions in the output. Due to the density of the input/output data, only the first 100 parameter magnitudes were taken.

Due to the restriction of the ANFIS model, the outputs from MF cannot be linear; hence, the training error from both the training data and the checked data leads to a constant mean square error for each selected iteration number. 50 iterations were defined for this project. This process is performed so that there is no over-training in the learning process of adaptive networks.

The results showed mean square error (MSE) for the training data of 0.000460904 while the MSE for the checking data was 0.000657704.

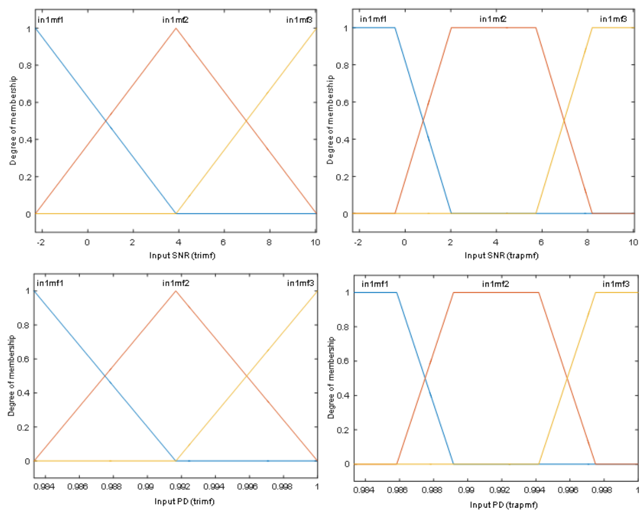

Figure 6: MF of the SNR input (upper part) and the AP input (lower part) for the Trimf function (on the left) y trapmf function (on the right)

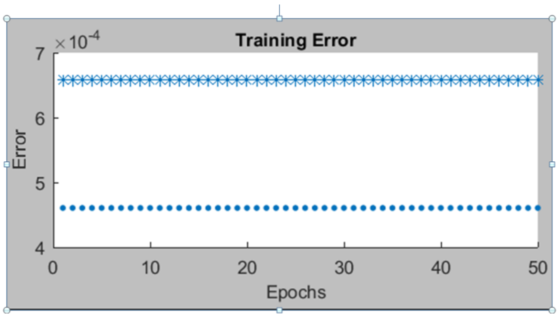

Figure 7: Training and checking data errors

Following up with the synthesis of the model, the next step involves the execution of the output results in both the training and checking data. In Fig. 8, the efficacy and accuracy of the developed prediction model can be seen as well as the coherence and similarity for the power data.

Additionally, Fig. 9 presents the average error obtained by the proposed ANFIS model for 500 data. Most of the errors do not exceed 5% showing an excellent performance from the model.

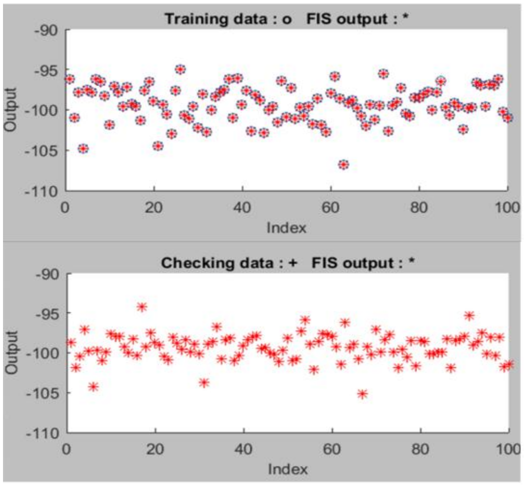

Figure 8: Output from the FIS with training and checking data

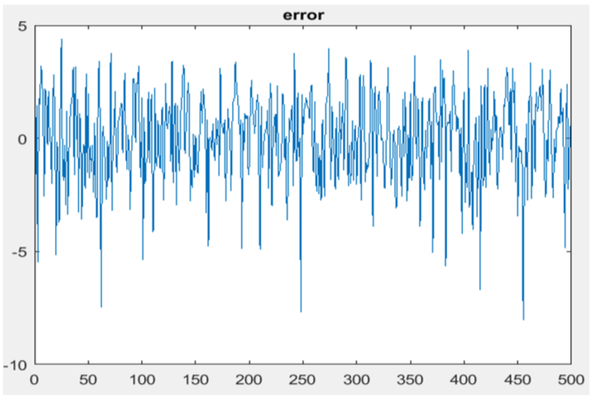

Figure 9: Error from the ANFIS model

CONCLUSIONS

The ANFIS system offers various alternatives for the modeling of characteristics in the radio environment within the radio-electric spectrum due to its high mathematical complexity and flexibility within adaptive networks.

The radio characteristics are also affected by the interference caused by certain hard-to-filter defects which makes difficult their posterior treatment since they directly affect the assigned parameters for each characteristic. The defects found cannot be avoided due to the previously specified structure. These defects include the noise and the interference caused by other communications.

The cognitive engine offers reasoning and learning capabilities within cognitive radio adopting a technique that efficiently uses the spectral resources.

The model developed can be easily implemented due to its simple structure based on the input parameters, availability probability and signal-to-noise ratio which allow the accurate estimation of the power level of the primary user's signal. This enables proactive spectral handoffs with an adequate performance in the reduction of the interference levels between users.

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