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NEURO-FUZZY MODELING FOR FORECASTING FUTURE DYNAMICAL BEHAVIORS OF VIBRATION TESTING IN SATELLITES QUALIFICATION

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ABSTRACT

A neuro-fuzzy modeling for forecasting the future dynamical behavior in vibration testing during satellite qualification is proposed in this paper. Vibration testing is employed for emulating vibrations present during the lifetime launching. There are different levels of excitation during vibration testing in order to verify and assure that the satellite and their sub-systems will support the efforts when in orbit or during the launching. The analysis of the dynamical behavior can help not only to avoid breaks and other damages but also allows feasible adjustments in the structure model. The neuro-fuzzy model is used to describe the dynamical behavior through actual data measured during the qualification of space systems in the Integration and Testing Laboratory (LIT) at the National Institute of Space Research (INPE). The model uses part of a low amplitude signal for training the neuro-fuzzy system; the remaining set of data is used to validate the model. Afterward, the dynamical behavior is estimated when a new high amplitude input signal is applied. Results of the structural model used in the design of the satellite and of their sub-systems are confronted with the real behavior presented by the structure, allowing eventual adjustments. Results show the neuro-fuzzy modeling is a feasible solution for forecasting dynamic satellite behaviors under distinct exogenous input due to its capacity of generalization.

INTRODUCTION

The space qualification process encompasses different environmental tests for emulating most of the activities and operational conditions present at pre-launch, launch and post-launch operations.

A satellite is composed of several sub-systems that interact to each other to form a whole system. In order to reach a fully operational status, the total system and, in particular, the sub-systems must be tested and handled for emulating as closely as possible the space environmental conditions. Different from those environmental condition available on earth the satellite will be exposed to space conditions during its lunching and its working life [1], [2]. The interest here addresses the vibration testing.

The estimation of future dynamical behavior may be determined by using different tech-

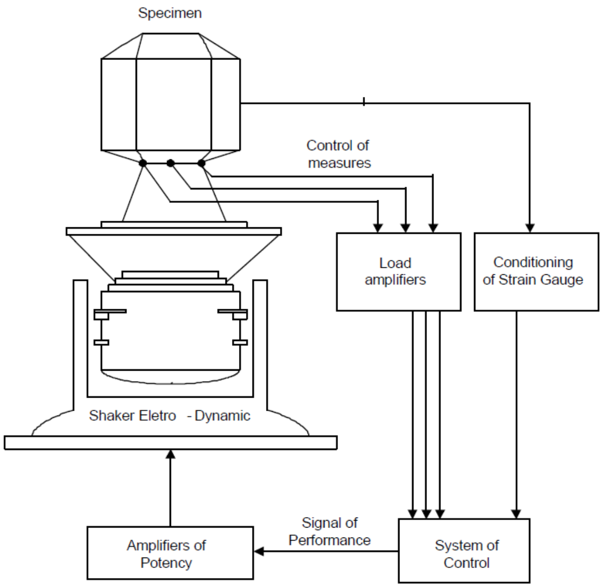


Fig. 1
OUTLINE FOR VIBRATION TESTING.

niques of system identification. Space systems, such as satellites, however, are inherently non-linear. While conventional identification techniques are adequate for models or systems that are linear in parameters, for systems that are usually non-linear, identification methods used in linear systems are not appropriated. Due to that suitable nonlinear approaches should be used.

Different approaches may be employed to deal with this sort of problem. The effectiveness of using computational/artificial intelligence techniques based on Particle Swarm Optimization and Fuzzy Logic modeling used to space system qualification are demonstrated in [3], [4], [5], [6]. The proposed approach is based on computational/artificial intelligence techniques inspired by biological neural model of human beings. These techniques, related to the field of Artificial Neural Networks (ANN), are mainly characterized by its ability to learn through experiences, to adapt to adverse conditions, and to be tolerant to noise [7], [8], [9].

The use of ANN in vibration systems and/or space sector is found in literature in diverse approaches. For instance, the neuro-fuzzy system design methodology employed for vibration control to adaptively adjust the fuzzy membership functions and dynamically optimize the linguistic-fuzzy rules was developed in [10]. A model multilayer perceptron neural network based on backpropagation through time algorithm is developed to minimize the general quadratic cost function in forward and backward pass stages. The problem of optimal large-angle single-axis maneuvers of a flexible spacecraft with simultaneous vibration suppression of elastic modes is discussed in [11]. The structure of a five-layer feedforward network is shown to determine systematically the correct fuzzy logic rules, tune optimally the parameters of the membership functions, and performing accurately the fuzzy inference. An adaptive structure with self-learning active vibration control system is developed in [12]. A fuzzy-neural network controller with adaptive membership functions is presented. The experimental setup of a two-bay truss structure with active members is constructed, and the FNN controller is applied to vibration suppression of the truss. The paper accomplished in [13] describes some of the techniques which are being proposed to control vibration aboard spacecraft in order to secure the high-quality microgravity environment. One of the presented techniques is a model of the element-finite type used by NASA for predict microgravity levels for Space Station Freedom.

The objective in this paper is to show the feasibility of employing a nonlinear identification technique denominated neuro-fuzzy modeling for forecasting the future behavior of vibration systems. The vibration testing is one of the tasks carried out to verify the structure of the satellite and their sub-systems in order to appropriately support the launcher lift-off and to guarantee useful life when in orbit (Fig. 1). Devices are exposed to the similar environmental conditions that will be demanded from launching to its working life.

The neuro-fuzzy model to describe the dynamical behavior is obtained through actual data measured during the qualification of space systems in Integration and Testing Laboratory (LIT) at the National Institute of Space Researches (INPE). The problem is composed of two parts. In the first one, the model uses part of signals of low amplitude for training the neuro-fuzzy system and then it is validated with the remaining set of data. Afterward, this proposed neuro-fuzzy model is employed to estimate a distinct dynamical behavior when a new input signal of high amplitude is applied to the space system. Results of the structural model used in the design of the satellite and of their sub-systems are confronted with the real behavior presented by the structure.

NEURO-FUZZY SYSTEM

The model used in this work is the well established hybrid system denominated Adaptive Neuro-Fuzzy Inference System (ANFIS) [14]. Used in a synergetic manner the fuzzy systems allows to deal with imprecise, uncertain and vague in information while the Artificial Neural Networks can learn with examples and produce output for inputs no present in the period of training due to its capacity of generalizing [15].

One of the main characteristics of fuzzy models is related to its capacity to mimic human reasoning allowing knowledge representation in the form fuzzy conditional rules and fuzzy sets theory. Fuzzy sets also is appropriate to deal with uncertainty, imprecise measures and incomplete information. Nevertheless, it does not allow learning by examples. In turn, artificial neural network are low-level computational algorithms presenting learning capacity. This approach is effective in the processing of numerical data and presents distributed computational characteristic allowing that each node in the network to adjust its connections to obtain the best possible input-output mapping after learning from data. When combining neural networks and fuzzy systems it is possible to obtain hybrid models with the capacities of learning, adaptation, optimization, being robust, dealing with large amounts of numerical data, knowledge representation through fuzzy rules [16], and the ability to deal with imperfect data, as well. The neuro-fuzzy model may assume the fuzzy Takagi-Sugeno (TS) model [17] and approach used in many problems of diverse areas. The T-S models may be represented by the following general form:

$$\begin{aligned} \mathrm{Rs}^{(j)} : \text{IF} < x_1 \text{ is } A_1^j > \text{AND} \ldots \\ \text{AND } < x_m \text{ is } A_m^j > \\ \text{THEN } y_j = f(\cdot) \ . \end{aligned} \tag{1}$$

The <IF statements> defines the premise part that is featured as linguistic terms in the proposition form, $< x_i$ is $A_i^j >$, while the <THEN functions> constitutes the consequent part of the j-th rule of the fuzzy system. The vector $\mathbf{x} = [\mathbf{x_1}, \ldots, \mathbf{x_i}]^\mathbf{T}$ represents the i-th input vector of the premise, $\forall \ i = 1, \ldots, m$, and so, the dimensionality of the premise space. The terms A_i^j are linguistic labels of fuzzy sets. The j-th rule output, $y_j = f(\mathbf{x^j}, \mathbf{w^j})$, is usually function of the consequent input vector, $\mathbf{x} = [\mathbf{x_1^j}, \ldots, \mathbf{x_{q_j}^j}]^\mathbf{T}$, $\mathbf{w} = [\mathbf{w_1^j}, \ldots, \mathbf{w_{y_j}^j}]^\mathbf{T}$, that compose the consequent parameter set. One of the advantage of the TS model does not contain defuzzification interface because it process and produces crisp data.

The firing strength of the j-th rule, $Rs^{(j)}$, represents its activation level and may, for instance, be chosen as the algebraic product:

$$w_j(\mathbf{z}) = \mathbf{w_{A_1^j}}(\mathbf{x_1})\mathbf{w_{A_2^j}}(\mathbf{x_2}) \ldots \mathbf{w_{A_m^j}}(\mathbf{x_m}) \ . \tag{2}$$

A neuro-fuzzy model equivalent to the Takagi-Sugeno system is depicted in Fig. 2.

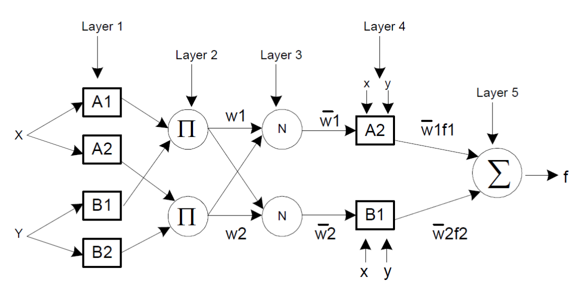


Fig. 2
ANFIS STRUCTURE.

This example has two inputs x, y, one output f and two rules. The ANFIS structure is composed by the following elements:

1) *Input Layer*:

Computes the degree of relevancy of the inputs x,y with relation of the subgroups fuzzy that form the partition of x and y, or either, the process of fuzzification.

2) *Membership Layer*:

Computes the degree of activation of each rule, with that degree the consequence of the rule is being taken care of. The function for this layer is a *T-norm* that uses the probabilistic form. In this, the outputs of the neurons given by eq. (3) are equivalent to (2):

$$w_1 = \mu_{A_1}(x_1) \cdot \mu_{A_2}(x_2) \cdot \mu_{A_3}(x_3) \tag{3}$$

3) *Rule and Norm Layer*:

Layer 3 is the degree of relevance of each rule, already normalized. Each point i calculates the reason for the firing strength of rule j for the sum of the firing strength of all the rules. The outputs of points this layer referring to Fig. 2 are:

$$\begin{aligned} \bar{w_1} &= w_1(w_1 + w_2 + w_3) \\ \bar{w_2} &= w_2(w_1 + w_2 + w_3). \end{aligned} \tag{4}$$

4) *Layer consequent*:

Layer 4 contains the function of activation of the neurons, consequence part of the rules (Ci). It is calculated by the product of the normalized firing strength ($S_i \forall i = 1, 2, 3$) and the value of the consequence of the rule. The output values of each point of this layer are given by:

$$\begin{aligned} H_1 &= \bar{w_1} \cdot C_1 \\ H_2 &= \bar{w_2} \cdot C_2. \end{aligned} \tag{5}$$

5) *Output layer*:

It computes the necessary output of the network as given by:

$$F = H_1 + H_2\ . \tag{6}$$

Learning on a neural network consists of adjusting values in the synaptic connections. It can be made by means of a system specialist or through an algorithm of learning [18]. The initial weights, the learning constant and momentum constant are among the most important factors determining the convergence of the backpropagation [15], [19].

The parameters of membership functions are estimate by means of the backpropagation algorithm. The algorithm backpropagation provides a supervised learning. This approach attempts to find out iteratively the low differentiates between the desired outputs and actual measured outputs obtained by the neural network, second a minimum error. The error signal is back-forwarded then of the output layer for each element of the previous intermediate layer that it contributes directly to the formation of the output. However, each element of the intermediate layer just receives a portion of the signal of error total, proportional just to the relative contribution of each element in the formation of the original output. This process repeats, layer after layer, until each element of the network receives an error signal that describes its relative contribution for the total error. Based on the error, the weights of the connections are updated for each element allowing the neural network to converge all the patterns of the training group [18].

In each iteration of the learning method the parameters of the premises are fixed. This output is calculated from the linear combination of the parameters of the consequent part.

The parameters of the consequences are identified by the method Least Mean Square-LMS, which it carries through the adjustment of the coefficients that will be used in the synaptic weights during the stage of backpropagation. The error signals backward propagated to adapt the parameters of the premises, by means of the descending gradient [18].

PROBLEM FORMULATION

The qualification of space systems in Brazil is accomplished by the Integration and Testing Laboratory (LIT) at the National Institute of Space Researches (INPE). Space systems are submitted to extensive ground testing to ensure their successful operation. The nature of environmental simulation is able to emulate flights or other environmental conditions. There are standards that settle environmental criteria, testing requirements, and test methods to ensure that system can reach post-launch requirements.

Vibrations caused by the operation of launch vehicle engines can be transmitted to the satellite mechanically and acoustically. During the lift-off space systems suffer vibration transmitted for the useful load demands that tests are accomplished in agreement with the characteristics of each specimen. Resulting shocks induce vibrations that correspond for 10 times the value of originating from acceleration the gravitational force of the Earth.

The vibration testing is one of the tasks carried out to verify the structure of the satellite and their sub-systems in order to support the lift-off of the rocket appropriately (Fig. 1). Devices are exposed to the similar environmental conditions that will be demanded from the lift-off to the useful life when in orbit. Results of the structural model used in the design of the satellite and of their sub-systems are confronted with the real behavior presented by the structure, allowing eventual adjustments.

Their consequences are, for instance, wire chafing, loosening of fasteners, intermittent electrical contacts, touching and shorting of electrical parts, seal deformation, component fatigue, optical misalignment, cracking and rupturing, loosening of particles of parts that may become lodged in circuits or mechanisms, and excessive electrical noise.

Vibration test standard are classified as development, qualification, acceptance, pre-launch validation, or other specific tests. Random vibration test is defined in which all frequencies are present at all times in various combinations of intensity. The spectra are defined in terms of acceleration spectral density and are defined over a relevant frequency range. The vibration levels are deliberately chosen to be greater than the expected levels in service (Fig. 3).

Conditioning testing is used to prove to the customer the ruggedness and structural adequacy of a design and demonstrate that adequate margins exist in the final product to assure that required specifications are met.

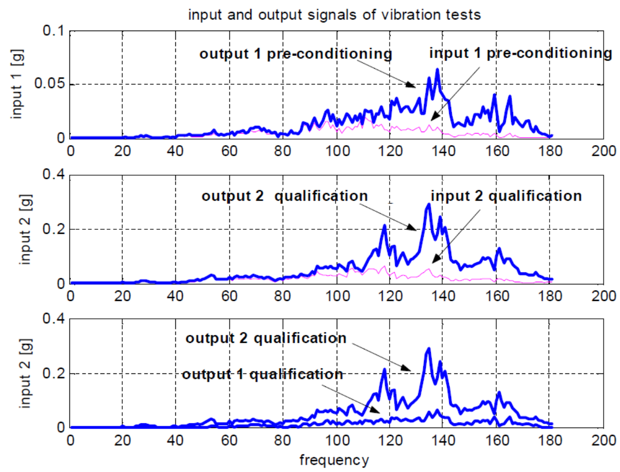


Fig. 3

A) PRE-CONDITIONING: INPUT x OUTPUT B) ACCEPTANCE: INPUT x OUTPUT C) PRE-CONDITIONING x ACCEPTANCE OUTPUT.

Acceptance testing is used to prove that production units are as high in quality as was the qualification model. Amplitudes applied in acceptance testing are somewhat greater than the average signal level expected in service, but lower than the level used in qualification test.

Good acceptance amplitude, with levels

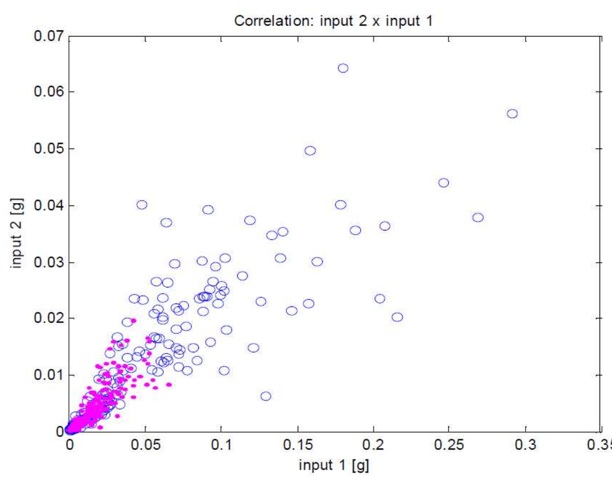


Fig. 4

OUTPUT (O) AND INPUT (.) CORRELATIONS.

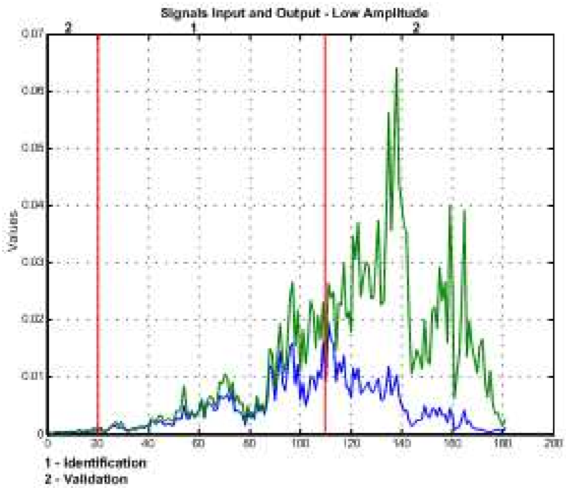


Fig. 5
DATA FOR IDENTIFICATION AND VALIDATION.

slightly over those expected in service would be sufficiently severe to detect and eliminate causes of infant mortality, but would not be severe as to encroach on the service life of a reliable design. Prior to the application of the randomly conditioning signal of higher amplitude, a preliminary lower level excitation may be necessary for equalization and preliminary analysis.

Close examination of a preliminary lower level can be very useful in finding out the important dynamical behaviors of the specimen. This analysis can assist, for instance, to determine critical frequencies in which mechanical resonance and other effects occur or in which malfunction, deterioration of performance are exhibited. Thus, the advantage of forecasting future dynamical behavior is useful to minimize and avoid damages when a high level of excitation signal is employed in conditioning testing. Besides, the upper displacement achieved by estimation techniques can help in determining notching levels used to limit and protect satellites.

Reliable methods will afford the opportunity of identifying crossover frequencies and approximate future displacement to be performed by the electro-dynamical vibrator used during the tests where the actual input level is greater than the level used in preliminary analyses.

The performance parameter measurements should establish a baseline that can be used to assure that there are no data trends established in successive tests which indicate a constant degradation of performance within specification limits that could result in unacceptable performance in flight. It is demanded therefore, that studies are accomplished in the intention of obtaining models capable to reduce the effects of this vibration and to guarantee that the space mission has their project requirements met.

EXPERIMENTAL RESULTS

The type and the amount of membership functions that compose the models are the parameters modified to check which better model represents the dynamics of the system. The learning method is also modified during the simulations. The method backprogation approach is used in its original form and in the hybrid form, such that, the filter least mean square is used as auxiliary mechanism. The learning method in the hybrid form (backpropagation with LMS) provides the best results.

The data used for system identification is shown in Fig. 5. The process of identification is accomplished by using two structures. In the first, the system presents one input associated to low amplitude signals. In the second, it is utilized as input the low amplitude signals and signal variation. Several combinations of data set were tested. For the current application, the data selected is the most appropriate. To validate the model it is used all the data set of low and high amplitude.

The root mean square error is used as measure of precision of the model. The closer of unit value, the better are the results supplied by the model. The stop criterion used is 300 epochs for the model with one input and 180 epochs for the model with two inputs. For the learning parameters: (i) initial step-size, (ii) tax of decrement (step-size decrease rate), and (iii) tax of increase (step-size increase rate) are selected, respectively, the values, 0.01, 0.09

TABLE 1

NEURO-FUZZY MODELS WITH ONE INPUT.

Amount of membership functions	Bell Amplitude Low	High	Gaussian Amplitude Low	High
2	0.0098	0.0476	0.0097	0.0563
3	0.0096	0.0561	0.0098	0.0628
4	0.0097	0.0502	0.0097	0.0586
5	0.0099	0.0427	0.0097	0.0536
6	0.0096	0.0651	0.0097	0.0575

*Learning method backpropagation with LMS filter.

TABLE 2

NEURO-FUZZY MODELS WITH TWO INPUTS.

Amount of membership functions	Bell Amplitude Low	High	Gaussian Amplitude Low	High
2	0.0113	0.0500	0.0113	0.0500
3	0.0115	0.0645	0.0115	0.0645
4	0.0409	0.0576	0.0409	0.0576
5	0.0789	0.2946	0.0789	0.2946
6	0.0117	0.0796	0.0117	0.0796

*Learning method backpropagation.

and 1.1. After analyzing the data shown in the Table 1 and Table 2, the model that supplied the best results satisfying the RMSE criterion is selected.

The eq. (7) and eq. (9), respectively, represent the models with one and two inputs. The learning method backpropagation with LMS filter provides the best results for the models with one input. However, for the models with two inputs the learning method backpropagation provides better results.

The model with one input is given by:

$$\begin{aligned}
&R_1 : \text{IF } x_1 \text{ is } NZ \text{ THEN } y_1 = \text{ is } NZ\\
&R_2 : \text{IF } x_1 \text{ is } P \text{ THEN } y_2 = \text{ is } P\\
&R_3 : \text{IF } x_1 \text{ is } PS \text{ THEN } y_3 = \text{ is } PS\\
&R_3 : \text{IF } x_1 \text{ is } PM \text{ THEN } y_3 = \text{ is } PM\\
&R_4 : \text{IF } x_1 \text{ is } PL \text{ AND } x_m \text{ is } PL
\end{aligned} \tag{7}$$

where x_1 is concerned the low amplitude signal. The linguistic terms for one input ANFIS model are: NZ (near zero), P (positive), PS (positive small), PM (positive medium), and PL (positive large). The Bell membership functions given by eq. (8) provide the best results for the .

$$\mu_{M_i}(x_i) = \frac{1}{1 + |\dfrac{x-c}{a}|^{2b}} \ . \tag{8}$$

The fuzzy sets of model are shown in Fig. 6(a). The accuracy of the model when validated with signals of low and high amplitude is, respectively, shown in Fig. 6(e) and Fig. 6(f). In turn, the RMSE is show in Fig. 6(b).

The eliciting neuro-fuzzy model containing two input is given by:

$$\begin{aligned}
&R_1 : \text{IF } x_1 \text{ is } PS \text{ AND} x_m \text{ is } PS\\
&\qquad\qquad \text{THEN } y_1 = \text{ is } PS\\
&R_2 : \text{IF } x_1 \text{ is } PS \text{ AND } x_m \text{ is } PL\\
&\qquad\qquad \text{THEN } y_2 = \text{ is } PL\\
&R_3 : \text{IF } x_1 \text{ is } PL \text{ AND } x_m \text{ is } PS\\
&\qquad\qquad \text{THEN } y_3 = \text{ is } PS\\
&R_4 : \text{IF } x_1 \text{ is } PL \text{ AND } x_m \text{ is } PL\\
&\qquad\qquad \text{THEN } y_1 = \text{ is } PL
\end{aligned} \tag{9}$$

where x_1 is low amplitude signal and x_2 is its variation (varLow). The Gaussian membership function (10) is used. The RMSE is show in the Fig. 6(d). The control surface of the neuro-fuzzy model is show in the Fig. 6(c).

$$\mu_{M_i}(x_i) = exp\left[-\frac{1}{2}\frac{(z_i - m_ij)^2}{\sigma_ij^2}\right] \tag{10}$$

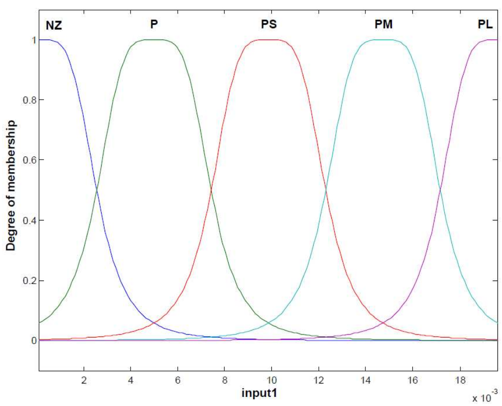
CONCLUSION

An alternative for forecasting the dynamic behavior of vibration systems in satellite qualification is proposed in this work.

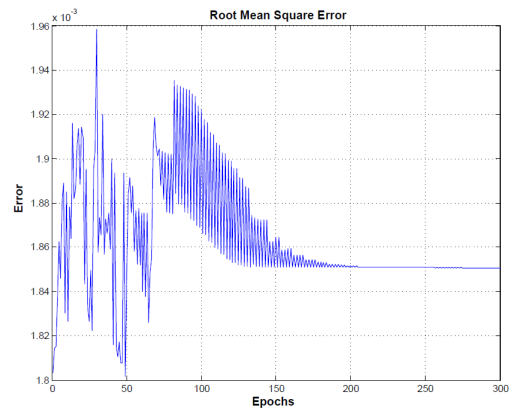
The neuro-fuzzy model is used for identification and modeling of non-linear system. Neuro-fuzzy is an hybrid model characterized as being robust, dealing with uncertain, imprecise measures and is able to learn with experience, i.e., data.

The analysis of the dynamic behavior can help to avoid breaks and other damages and to allow feasible adjustments in the structure model. Results show that the models have good capacity of generalization. These results were improved when used the variation of the signal of low amplitude as input. The criterion for validation of the models adopted is Root Mean Square Error. The RMSE values indicated in some cases accuracy of 99% and 95%.

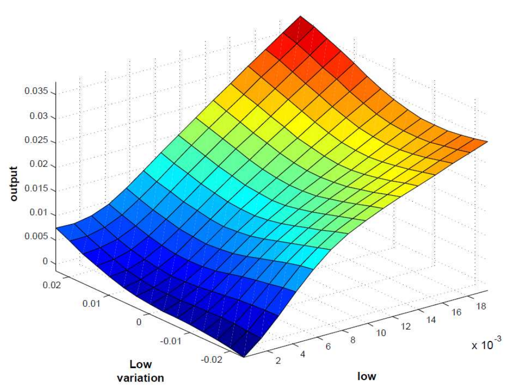
Future works can be carried through using others intelligent techniques, as Particle Swarm Optimization (PSO) in order to compare the



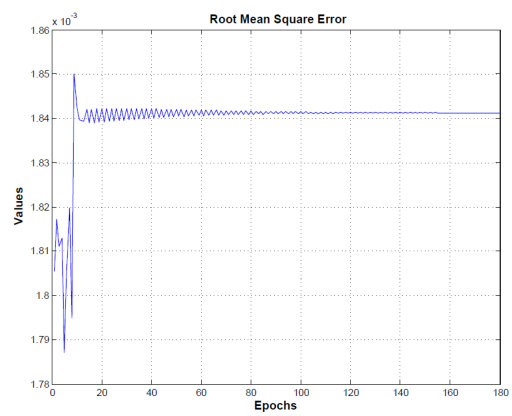
(a) Fuzzy sets of input of model with one input.



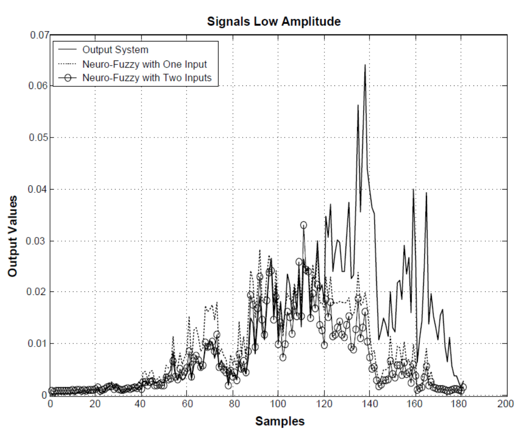
(b) RMSE for model with one input.



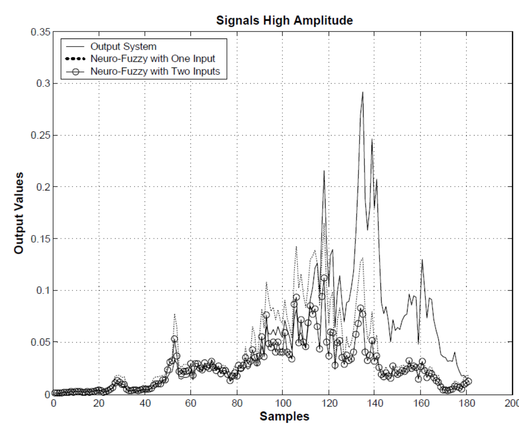
(c) Fuzzy surface for the two inputs model.



(d) RMSE for model with two inputs.



(e) System output and Neuro-Fuzzy models - results for signals of low amplitude



(f) System Output and Neuro-Fuzzy models - results for signals of high amplitude.

Fig. 6

NONLINEAR ANFIS MODELING WITH ONE INPUT (LOW AMPLITUDE) AND WITH TWO INPUTS (LOW AMPLITUDE AND ITS VARIATION).

answers produced for these techniques in the solution of the considered problem.

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