VIBRATION SATELLITE QUALIFICATION TESTING BY EMPLOYING WANG & MENDEL LEARNING ALGORITHM AND TAKAGI-SUGENO FUZZY MODELING

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Abstract. *The Wang & Mendel algorithm for modeling for dynamic behavior in vibration testing during satellite qualification is proposed in this paper. Vibration testing is carried out for emulating launchings to avoid breaks and other damages of space systems. Further, such a testing also allows feasible adjustments in the structure model by dynamic behavior analysis. Forecasting dynamic behavior is accomplished by obtaining a model that best represents the actual system in a process named system identification. Takagi-Sugeno fuzzy system approach is employed to represent space devices underlying space qualification tests. Fuzzy systems are universal approximators, that is, they are able to represent any system. They are able to deal with both qualitative information (expertise, heuristic knowledge) and quantitative (data) information. Nevertheless, when dealing with data this approach requires other techniques working in synergy for adjustment of their parameters. This paper addresses the use Wang & Mendel learning algorithm for tuning Takagi-Sugeno modeling by using experimental data from vibration space qualifying tests. The resulting fuzzy model is used to describe the dynamical behavior through data measured during the qualification of space systems in Integration and Testing Laboratory (LIT) at the National Institute of Space Research (INPE). The objective in this paper is, then, to study the feasibility of employing such a nonlinear identification technique for estimating the future behavior of vibration systems. For rule base extraction by using the Wang & Mendel algorithm the model is set to deal with different membership functions in order to define the optimized one. The proposed method employs Gaussian membership functions in the input universe of discourse while the output is selected to be a singleton membership function. The conjunction operator chosen is to be the minimum. The problem is composed of two parts. In the first one, the model uses part of signals of low amplitude for tuning the fuzzy system and then it is validated with the remaining set of data. Afterwards, 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. The criterion for validation of the models adopted was Pearson multiple correlation coefficients. 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. These results were improved when used the variation of the signal of low amplitude as input.*

Keywords: *Satellite Qualification; Vibration Testing; Fuzzy Modeling; Wang & Mendel (WM) Algorithm.*

1. INTRODUCTION

Computational Intelligence has been considered as the successor of Artificial Intelligence and the way of the future computing (Venayagamoorthy, 2009). It is mainly composed by Fuzzy Systems (FIS – Fuzzy Inference System), Artificial Neural Networks (NN) and Evolutionary Computing (EC), Immune Systems (IS), Swarm Intelligence (SI) along with hybrid systems concerning the field of searching, optimization and machine learning (Venayagamoorthy, 2009; van Eck et al., 2006; Konar, 2005). This approach presented a boost during the 90's, driven by an increasing interest of engineers, economists, and many other professionals to apply these promising tools in their specific fields, aiming for problem solving automation and fast evaluation of possible solutions. Computational Intelligence is largely employed in control system design, modeling and identification, and decision support system.

Despite the success of deterministic mathematical applied to dynamic modeling, Computational Intelligence (CI) has been presented as an important alternative that has also taking part in dynamic modeling and identification. Among the techniques that compose Computational Intelligence, one of the most prominent is Fuzzy System.

Fuzzy system intertwined with the bioinspired meta-heuristic by using swarm intelligence simulating social behavior and interactions of individuals (particles) – known as Particle Swarm Optimization (PSO) – for space system modeling were applied in (Marinke et al., 2005; Araujo et al., 2006; Araujo and Coelho, 2007; Araujo and dos S. Coelho, 2008). A PSO-modified technique which introduces a simulation of the action of atmosphere turbulence named Particle Swarm Optimization with Turbulence (PSOT) (da Luz, 2007; Becceneri et al., 2006) used together with fuzzy system was employed in the space sector in (Araujo et al., 2009). In turn, fuzzy system working in synergy with artificial neural network for modeling vibration dynamic behavior was applied in (Araujo and Marinke, 2008).

Embracing fuzzy set theory and fuzzy logic, fuzzy systems are universal approximators able to deal with both qualitative information (expertise, heuristic knowledge) and quantitative (data) information (Guillaume, 2001; Sugeno and Yasukawa, 1993). From the perspective of data-driven analysis and design Takagi-Sugeno fuzzy systems became an option to cope with complex, nonlinear dynamical modeling problem.

Takagi-Sugeno (T-S) fuzzy model (Takagi and Sugeno, 1985) is an alternative for fuzzy system representation when dealing with data. It is able to approximate highly nonlinear functions and exhibits simple structure by using a small number of implication rules (Takagi and Sugeno, 1985; Sugeno and Kang, 1988). T-S model divides the input space in the same manner that Mamdani fuzzy system (Mamdani and Assilan, 1975) but aims to approximate structure of the local models to a linear model in the consequent of the rule. Another advantage of employing this approach is that it reduces the problem complexity by restricting the number of rules that will be processed in each subsystem, and then interpolating them to obtain the global model.

The T-S fuzzy model is characterized as a set of IF-THEN rules where the consequent part are linear sub-models describing the dynamical behavior of distinct operational conditions meanwhile the antecedent part is in charge of interpolating these sub-systems. This model can be represented as follows:

$$R_j : \text{IF } x_1 \text{ is } A_{1j} \text{ AND} \ldots \text{AND } x_m \text{ is } A_{mj} \text{ THEN } y_j = f(\cdot) \tag{1}$$

The "THEN functions" constitutes the consequent part of the j-th rule of the fuzzy system that is characterized, but not limited to, as a linear polynomial, $y_j = b_0^j + b_1^j u_1^j + \ldots + b_{q_j}^j u_{q_j}^j$. The j-th rule output, $y_j = f(\mathbf{u}, \mathbf{b}^j)$, is function of the consequent input vector, $\mathbf{u} = [u_1^j, \ldots, u_{q_j}^j]^T$, comprising q_j terms and the polynomial coefficient vector, $\mathbf{b} = [b_1^j, \ldots, b_{q_j}^j]^T$, that compose the consequent parameter set.

The global model is, then, obtained by the interpolation between these various local models:

$$y = \sum_{j=1}^{N} h_j(\mathbf{x}) y_j(\mathbf{u}^j) \ , \tag{2}$$

where N denotes the maximal number of rules and $h_j(z)$ is the normalized firing strength of $R^(j)$, defined as:

$$h_j(\mathbf{x}) = \frac{\mu_j(\mathbf{x})}{\sum_{j=1}^{M} \mu_j(\mathbf{x})} \ , \tag{3}$$

with:

$$\mu_j(\mathbf{x}) = \mu_{A_1^j}(x_1)\mu_{A_2^j}(x_2) \ldots \mu_{A_m^j}(x_m) \ , \tag{4}$$

for linguistic labels, A_i^j, associated to a membership function.

When linguistic labels A_i^j are determined by Gaussian membership functions,

$$\mu_{A_{1j}}(z_i) = \exp\left[-\frac{1}{2}\frac{(z_i - m_{ij})^2}{\sigma_{ij}^2}\right] \tag{5}$$

where m_{ij} and s_{ij} are the centers (mean value) and the spreads (standard deviations) of the Gaussian function – respectively defining the core and the support of membership functions – then equation (1) may be rewritten as:

$$R_j : \text{IF } x_1 \text{ is } \exp\left[-\tfrac{1}{2}\tfrac{(z_i - m_{1j})^2}{\sigma_{1j}^2}\right] \text{ AND} \ldots \text{AND } x_m \text{ is } \exp\left[-\tfrac{1}{2}\tfrac{(z_i - m_{mj})^2}{\sigma_{mj}^2}\right] \text{ THEN } y_j = b_0^j + \ldots + b_{q_j}^j u_{q_j}^j \ . \tag{6}$$

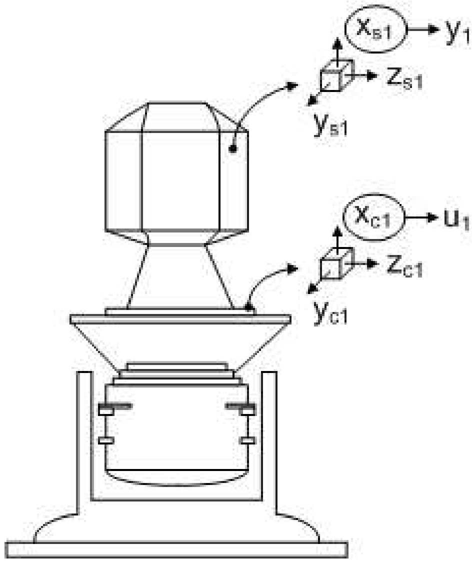


Figure 1. Space Vibration Test System.

The question that comes up is how are the best feasible adjustment of the m_{ij}, s_{ij}, and b_i parameters for all i, j for tuning the fuzzy system in (6). When heuristic systems are developed knowledge extracted from specialists are directly employed to tune the fuzzy system. However, when dealing with data, an additional technique is necessary to optimize those parameters. These techniques encompasses, for instance, but not limited to, Gath-Geva clustering (GG) algorithm, Wang & Mendel learning (WM) algorithm, subtractive learning (S) algorithm, Hard C-means (HCM) algorithm, Fuzzy C-Means (FCM) algorithm, Gustafson-Kessel (GK) algorithm, adaptive neural-fuzzy inference system (ANFIS), only to mention few.

This paper addresses the Wang & Mendel learning algorithm (Wang and Mendel, 1992) for modeling the dynamical behavior in vibration testing during satellite qualification since fuzzy systems, in general, and Takagi-Sugeno fuzzy systems, in particular, is not characterized by possessing any learning process. This approach is effective for rule base extraction when processing numerical data and presents simple computational characteristic, as describe next.

1.1 Space Vibration Test Modeling

The resulting fuzzy model is used to describe the dynamical behavior through data measured during the qualification of space systems in Integration and Testing Laboratory (LIT) at the National Institute of Space Research (INPE). This paper focuses on vibration testing.

Vibration testing is employed for emulating vibrations present during the launching. Such a testing is 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. 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. Due to that estimating future dynamical behavior when using high amplitude testing signals is important to safe satellites or other space devices. Moreover, 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 simplified structure of the electro-dynamic vibration system is depicted in Fig. 1 where x_{lm}, y_{lm}, and z_{lm} are displacements in the axis, x, y, and z, respectively. The index l, when is related to c corresponds to the sensor on the control system while the sensor on the specimen underlying the testing is represented by the index s. The index m is related to the number of the sensor used in the test. In this paper, only the displacement in x direction is took into account. While, the sensor x_{c1} compose the input variable, $u_1(k)$ of the universe of discourse, U_1, corresponding to the displacement of the electro-dynamic vibration system, the sensor x_{s1} is related to the output variable, $y(k)$ of the universe of discourse, Y, corresponding to the displacement of the space systems under test.

It is also worth mentioning that a second input is taken into account by using the previous input of the system, that is, $u_1(k-1)$. This is important because when dealing with fuzzy model identification, the input universe of discourses composing the input space X are chosen to be finite number of past inputs and past outputs of the system representing the system dynamics (Barada and Singh, 1998). The T-S model is, then, represented by the regression type of rules that maps the current state and input variable into the output variable and Eq. (6) is related to

$$y_p(k+1) = \sum_{i=0}^{n-1} a_i y_p(k-i) + \sum_{j=0}^{m-1} b_i u_p(k-j), \tag{7}$$

where a_i and b_j are constant unknown parameters when dealing, for instance, with discrete, linear, time-invariant, single-input-single-output systems. In doing so, the Eq. 6 can be rewritten, in the simplified membership function representation, as in the following form:

$$\begin{aligned} \mathrm{R}^{(j)}:\ & \text{IF } y(k) \text{ is } A_1^j \text{ AND } \ldots \text{ AND } y(k-n+1)\ A_n^j \text{ AND } u(k) \text{ is } B_1^j \text{ AND } \ldots \text{ AND } u(k-m+1)\ B_m^j \\ & \text{THEN } \widehat{y}_j(k+1) = \textstyle\sum_{i=0}^{n-1} a_p^j y(k-i) + \sum_{p=0}^{n-1} b_p^j u(k-p) + c^j \end{aligned} \tag{8}$$

The objective of the optimization process consists of determining (tuning) these unknown parameters, a_i, b_i, c_i, A_i, i.e., ($m_{A_{ij}}$, $s_{A_{ij}}$, for all i, j), and B_i, i.e., ($m_{B_{ij}}$, $s_{B_{ij}}$, for all i, j), when using measured input-output. These parameters compose the matrix θ and the performance of the WM-TS Fuzzy model output estimation, $\hat{y}(k)$, is used for computing the minimum square error when compared with the current output, $y(k)$, as given by:

$$\min_\theta = \sum_{k=1}^{N} ||\hat{y}(k) - y(k)|| \,. \tag{9}$$

The estimate output (or fuzzy function approximation) $\widehat{y}(k+1)$ in (9) is used for computing the square error when compared with the actual output, $y(k+1)$. This activity corresponds to the parameter-learning task and, consequently, the parameter estimation process. The identification of T-S system is realized in this paper based on Wang & Mendel learning algorithm for optimization of those parameters.

1.2 Wang & Mendel Learning Algorithm

The Wang & Mendel learning method is in charge of finding out the parameters for designing the fuzzy system. It comprises five steps and is characterized for being a simple and straightforward method not requiring time-consuming training.

Suppose there is a set of input-output mapping in the form:

$$\left(x_1^{(1)},\ldots,x_j^{(1)}\ldots x_n^{(1)},y^{(1)},\right),\left(x_1^{(2)},\ldots,x_j^{(2)}\ldots x_n^{(2)},y^{(2)},\right),\ldots\left(x_1^{(m)},\ldots,x_j^{(m)}\ldots x_n^{(m)},y^{(m)},\right)\,. \tag{10}$$

where the input is given by x_j, such that n represented the inputs, and the output is y, such that m represented the number of epochs. The input-output mapping, $f : x_1^{(m)},\ldots,x_j^{(m)}\ldots x_n^{(m)} \rightarrow y^{(m)}$, is determined by fuzzy IF-THEN rules.

The main steps of the global version of Wang & Mendel are:

- *Step 1*:

  Divide the Input and Output Spaces into Fuzzy Regions :

  – *The interval in which the input and output variables lie in their respective universe of discourse is represented by* $[x_1^-, x_1^+], \ldots [x_j^-, x_j^+], \ldots, [x_n^-, x_n^+], [y^-, y^+]$.
  – *Divide each domain into 2N+1 regions and assign each one a multidimensional fuzzy membership function.*
  – *Ruspini partition is setup.*
  – *Obs. 1: Any shape of the membership function may be chosen.*
  – *Obs. 2: Different N's may be chosen for each universe of discourse, or not.*

- *Step 2*:

  Generate Fuzzy Rules from Given Input Data :

  – *Determine the degrees of given* $x_1^{(i)}, x_2^{(i)}, \ldots, x_j^{(i)}, \ldots, x_n^{(i)}, y^{(i)}$, *taking into account their respective membership functions.*
  – *Assign a given* $x_1^{(i)}, x_2^{(i)}, \ldots, x_j^{(i)}, \ldots, x_n^{(i)}, y^{(i)}$, *to the region with maximum degree.*
  – *Obtain one rule from one set of input of the input-output epoch.*
  – *Obs. 1: The fuzzy IF-THEN rules uses logical connective among the input statements and any of the T-norm may be set.*

- *Step 3*:

Assign a Degree, $D(Rule)$**, to Each Rule** according to:

$$D(Rule_i) = m_{Ai}(x_1)m_{Bi}(x_2)\dots m_{Ni}(x_n)m_Z^(y)\ . \quad (11)$$

The assigned degree, $m^{(i)}$, for the i-th epoch is used to redefine the degree of the i-th rule as:

$$D(Rule_i) = m_{Ai}(x_1)m_{Bi}(x_2)\dots m_{Ni}(x_n)m_{Zi}(y)m^{(i)}\ . \quad (12)$$

such that the degree of a rule is defined as the product of the degrees of its components and the degree of the epoch which generates this rule.

- *Step 4*:

Create a Combined FAM Bank (multidimensional Fuzzy Matrix) : The cells of the multidimensional fuzzy matrix are filled with fuzzy rules by following a specific strategy.

  – FAM Bank is assigned rules from either those generated from numerical data or linguistic rules;
  – If there is more than one rule in one box of the FAM bank, use the rule that has maximum degree.

- *Step 5*:

Determine a Mapping based on the Combined FAM Bank (defuzzification strategy) :

  – Combine the antecedents of the i-th fuzzy rule according to:

$$m^i_{o^i_j} = m_{I^i_1}(x_1)m_{I^i_2}(x_2)\dots m_{I^i_j}(x_j)\dots m_{I^i_n}(x_n)\ , \quad (13)$$

  where o^i denotes the output region of the i-th rule, and I^i_j denotes the input region.

  – Determine the output by using the centroid defuzzification formula:

$$y = \frac{\sum_{i=1}^{K} m^i_{o^i_j}\overline{y}^i_j}{\sum_{i=1}^{K} m^i_{o^i_j}}\ . \quad (14)$$

  where $\overline{y}$ denotes the center value of region o^i, the smallest absolute value among all the points at which the membership function for this region has membership value equal to one, and K is the number of fuzzy rules in the combined FAM Bank.

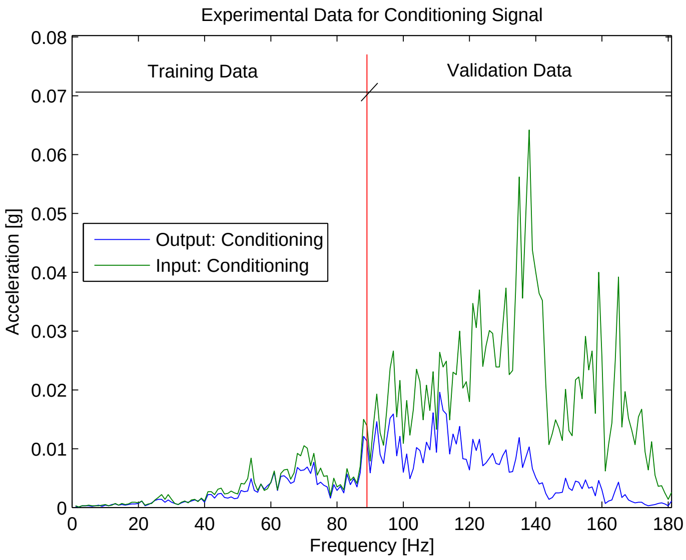
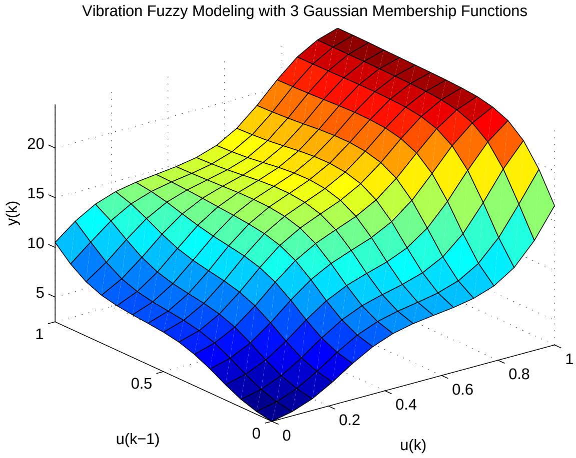
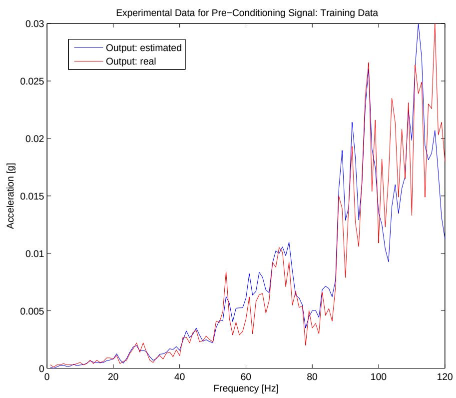


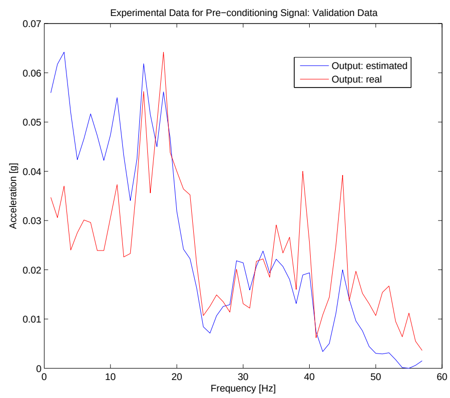
Figure 2. Experimental data for conditioning signals.



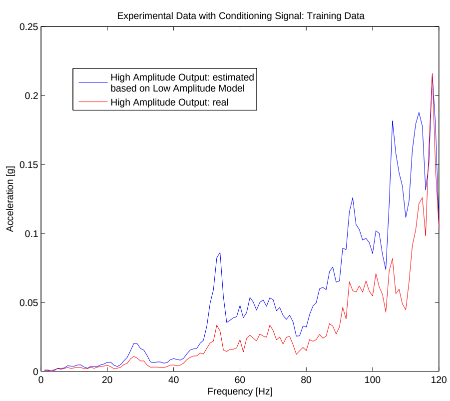
(a) Estimate Fuzzy Model with 3 Gaussian Membership Functions.



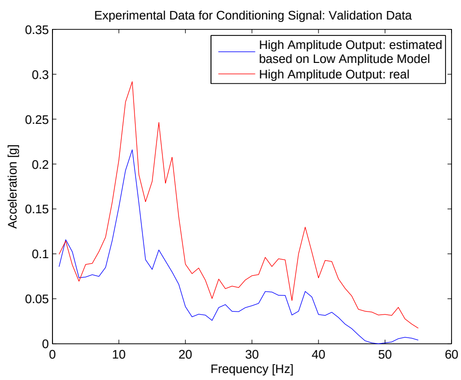
(b) Training Dynamical Response for Conditioning Signal: Experimental Data and Estimate Output, Reduced Amplitude.



(c) Validate Dynamical Response for Conditioning Signal: Experimental Data and Estimate Output, Reduced Amplitude.



(d) Training Dynamical Response for Conditioning Signal: Experimental Data and Estimate Output, High Amplitude.



(e) Validate Dynamical Response for Conditioning Signal: Experimental Data and Estimate Output, High Amplitude.

Figure 3. Estimate Fuzzy Model with 4 Gaussian Membership Functions.

1.3 Results

To best obtain the optimized fuzzy input-output mapping during learning from data, the Wang & Mendel algorithm is set to deal with different number of membership functions. The proposed method employs Gaussian membership functions in the input universe of discourse while the output is selected to be a singleton membership function as before mentioned in (6).

Actual data with high and low amplitude signals were used for eliciting the fuzzy model. The model uses part of signals of low amplitude (Training Data) for tuning the fuzzy system and then it is validated with the remaining set of data (Validate Data) as depicted in Fig. 2. Afterwards, the computed WM-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, allowing eventual adjustments.

The input-output mapping for the estimate fuzzy model when employing three membership functions is shown in Fig. 3(a). The training dynamical response for conditioning signal with experimental data and estimate output with reduced amplitude is illustrate in Fig. 3(b). Notice that the estimate output is quite similar to the experimental data. This is justified due to the fact that this experimental output data, together with the experimental input data, were employed in the training task. The validate dynamical response for conditioning signal with experimental data and estimate output with reduced amplitude is illustrated in Fig. 3(c). Although not presenting an equivalent result than latter one, the estimate output follows most of the main dynamical behavior in this not trained part of the reduced amplitude signal data.

In what follows, fuzzy model was employed in the attemptive to estimate a second output but now with a new high amplitude input signal. Here the same interval of training and validation is followed for making the comparative analysis easier. The training dynamical response for conditioning signal with experimental data and estimate output with high amplitude is illustrate in Fig. 3(d). Concerning the validate interval, the dynamical response for conditioning signal with experimental data and estimate output with high amplitude is illustrate in Fig. 3(e). Although the estimate dynamic output does not reach the same amplitude in both intervals, they capture mostly the dynamic of the experimental data. It is worth mentioning that, here, only the fuzzy inference system for modeling the space vibration testing with three membership functions was employed. Results are promising and new research in the number of membership functions and rules must be investigated. Another result that should be pointed out is that the fuzzy model was obtained with the Wang & Mendel learning algorithm that has shown its effectiveness in this task even being recognized as a simple and straightforward method.

Additionally, these results were obtained with the lower amplitude of the reduced amplitude signal data, demonstrating its robustness and capacity of generalization.

2. CONCLUSION AND FUTURE WORK

To obtain a feasible input-output mapping by learning from data this paper employed the Wang & Mendel learning algorithm for tuning a Takagi-Sugeno fuzzy model. Results has shown that combining Wang & Mendel learning algorithm and fuzzy systems it is possible to obtain hybrid models with the capacities of learning, adaptation, optimization when applied to space qualification activity. In this paper, the Takagi-Sugeno fuzzy model was employed to describe the dynamic vibration system used to emulate environmental conditions during space launching moment. 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. Afterwards, the estimate fuzzy model is employed to estimate a distinct dynamical behavior when a new input signal of high amplitude is applied to the space system. In these conditions results show to capture the main dynamic characteristics of the experimental data. In this sense, the WM-TS fuzzy modeling becomes an alternative for forecasting dynamic satellite behaviors under distinct exogenous input. It is also shown that the models have good capacity of generalization. These results were improved when used the variation of the signal of low to high amplitude as input.

In order to check if a better performance for the estimate model can be reached, research is going to be verity if the number of membership functions and rules interfere in the results. Also, comparative analysis along with other methods, especially from computational intelligence, will be carried out.

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