SPACE ENVIRONMENTAL EMULATION IN A NONLINEAR THERMAL-VACUUM CHAMBER BY USING GATH-GEVA LEARNING ALGORITHMS AND FUZZY SYSTEMS

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Abstract. *Forecasting space environmental emulation and satellite qualification in a nonlinear thermal-vacuum chamber by using Gath-Geva learning algorithms and fuzzy systems is proposed in this paper. Advantages of identifying a model for environmental simulation unit are, for instance, the ability to detect loss of vacuum, presence of unknown heat sources or sinks, training of thermal-vacuum operators, development of a supervisor decision-support system for helping to control the whole operation, checking the instantaneous operation or even operator's behavior or performance, and, ultimately design an automatic control for the whole system. Eliciting mathematical models from data to forecast nonlinear behavior is usually not a simple task mainly when dealing with thermal-vacuum systems. The use of fuzzy logic is a complement for consolidate or discard relationships when data are imperfect and it is an effective tool to explore the meanings of variables when database are available. The objective is the identification of system based on the Gath-Geva learning algorithms employed to optimize the solution for finding out a nonlinear-parameter representation associate to Takagi-Sugeno fuzzy modeling. A fuzzy system is a nonlinear mapping represented by a set of IF-THEN rules and an associated fuzzy inference mechanism in which each element inside a fuzzy region assumes a degree of fulfillment which are associate with uncertain, imprecision and vague information. The efficiency of these algorithms for generating the set of rules and the membership functions are, then, verified.*

Keywords: *Nonlinear modeling, Thermal-vacuum System, Gath-Geva learning, Fuzzy Modeling*

1. INTRODUCTION

Modeling systems has always attracted attention of mathematicians, engineers, and scientists, in general, who has the world like its own analysis object. Unfortunately, creating a mathematic model is a hard task. The real world could never been represented in its totality by any of the knowing tools available. Whenever there is interest in representing any system there is also a difference from the real world model to the estimate model called error. Nevertheless, parts of the real world can be modeled in the most approximate form from its reality when is given a database for describing, the closest as possible, how the system behaves (Fig. 1). This dynamical behavior results in an output that can appropriately represent the reality if the difference between the real system output with the observed output is minimum. Hence, the attemptive of modeling a real system via the use of real data to produce a feasible description of it as long as this error is small is called identification.

Based on fuzzy set theory and fuzzy logic, fuzzy system approach also assumes an important role when attempting

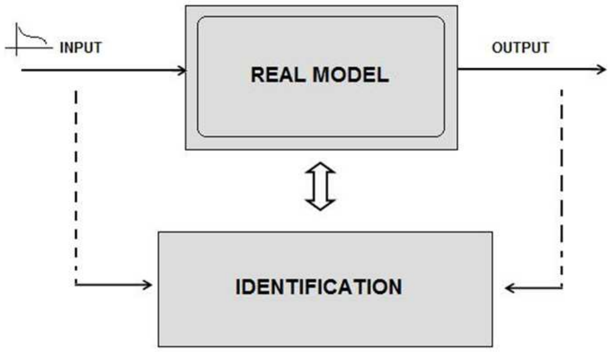


Figure 1. Simplified model for system identification

to represent dynamical systems. Takagi and Sugeno (1985) (T-S) fuzzy model, in particular, is especially adequate for dynamical identification when dealing with data. It is able to approximate highly nonlinear functions and exhibits simple structure (Takagi and Sugeno, 1985; Sugeno and Kang, 1988). The difficult task of modeling and simulating complex real-world systems for control systems development is well documented. Even if a relatively accurate model of a dynamic system can be developed, it is often complex to use in controller development especially for many conventional control design procedures that require restrictive assumptions for the plant (Passino and Yurkovich, 1998). A fuzzy system is a *nonlinear mapping* from input space vectors, X_n, to a scalar output space, Y, in the form, $f : X_n \to Y$, such that X_n and Y are universe of discourses that define the input-output space, $X_n \times Y$, and an associated fuzzy inference mechanism. For instance, when using fuzzy sets to part the input universe of discourse, $A = \{x \in X_1\}$, into an output universe of discourse, $B = \{y \in Y\}$, it is represented as $f : A \to B$. These items of input space will be compared to the linguistic terms (i.e. labels) using IF-THEN rules. A block diagram for fuzzy system approach for representing, manipulating, and implementing a fuzzy systems, in general, and a fuzzy control system, in particular, is shown in Fig. 2.

Takagi-Sugeno modeling divides the input space by using membership functions but aims to approximate structure of the local models to a linear model in the consequent of the rule. This characteristic reduces the number of rules that will be processed in each subsystem that, in turn, are interpolated to form the global model. The structure identification is related to find out both the premise and the consequent of the production rules, respectively. It has received a great deal of attention and has been employed in many applications in nonlinear system identification is fuzzy modeling. In particular, when applied to model a thermal-vacuum chamber used to qualify satellites and space devices, examples are (Araujo and dos S. Coelho, 2008; Araujo et al., 2006; Marinke et al., 2005). Nevertheless, they are based on Particle Swarm Optimization for fuzzy model structure and parameter identification. In this paper, instead, the Gath-Geva learning algorithm (Gath and Geva, 1989) is used. This approach can easily be implemented in synergy with T-S fuzzy model. Similar to other fuzzy clustering algorithms, this method is employed in the search for clusters, but differentiates by extracting a significant reduced number of optimized rules. It shows as result a more flexible, transparent and mobile response.

Finding out a model for representing dynamical behavior is of particular important when dealing with nonlinear, time delay thermal-vacuum chambers used for satellite qualification. Thermal-vacuum chambers are used to reproduce as close

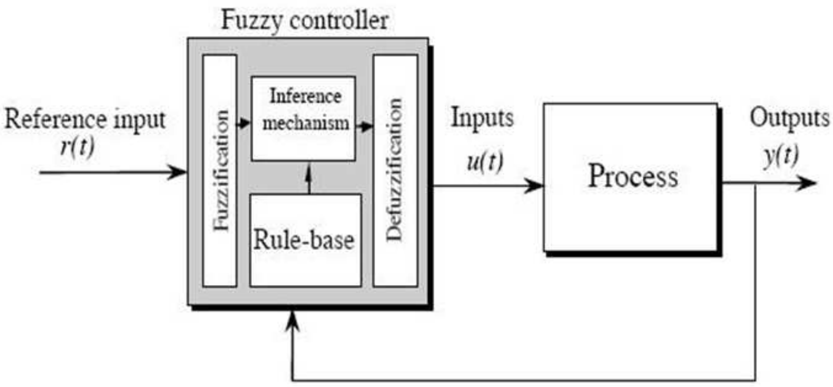


Figure 2. Fuzzy Control System Block Diagram.

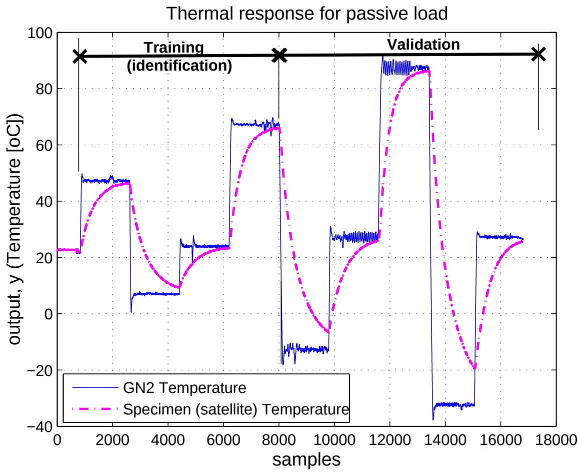


Figure 3. Experimental data from the thermal-vacuum system used at Brazilian National Institute for Space Research (INPE)

as possible environmental conditions of expected post-launch environments which satellites will experience during their inflight live (Garner, 1996; Gilmore, 1994). The nonlinear modeling by using Gath-Geva learning algorithm and Takagi-Sugeno fuzzy system is accomplished with experimental data (Fig. 3) obtained from the thermal-vacuum system used at National Institute for Space Research (INPE – Instituto Nacional de Pesquisas Espaciais). The thermal-vacuum system is not only nonlinear (High Vacuum Systems Inc., 1987) but presents time-delay, is time-varying, and works in diverse operational conditions defined by various set points used during the test (Marinke et al., 2005; Araujo et al., 2000, 2001). Continuous and dashed lines represent input and output data, respectively.

2. IDENTIFICATION OF T-S FUZZY MODELING THROUGH GATH-GEVA LEARNING ALGORITHM

2.1 Takagi-Sugeno Fuzzy Modeling

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:

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

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, $y_j = b_0^j + b_1^j u_1^j + \dots + b_{q_j}^j u_{q_j}^j$. The j-th rule output, $y_j = f(\mathbf{u}, \mathbf{b}^j)$, is function of the consequent input vector, $\mathbf{u} = [u_1^j, \dots, u_{q_j}^j]^T$, comprising q_j terms and the polynomial coefficient vector, $\mathbf{b} = [b_1^j, \dots, b_{q_j}^j]^T$, that compose the consequent parameter set.

The global model is, then, obtained by the interpolation between these various local models. So the TS model consists of linguistic rules represented by the following general form:

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

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:

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

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

The Takagi-Sugeno fuzzy model is also understood as an interpolation fuzzy system or model-based approach and provides as advantages efficient and computationally attractive solutions to a wide range of modeling problems. This technique introduces a powerful multiple model structure that is capable to approximate nonlinear dynamics, multiple operation modes and significant parameter and structure variations (Angelov and Filev, 2004). Takagi-Sugeno fuzzy inference systems are especially used for modeling nonlinear and complex systems.

2.2 Gath-Geva Clustering for Identification of Takagi-Sugeno modeling

Clusters of different shapes can be obtained when adjusting the T-S model by using appropriate cluster prototypes or by using different distance measures (Gath and Geva, 1989). Fuzzy clustering in the Cartesian product-space of the inputs and outputs is a tool that has been quite extensively used to obtain the antecedent membership functions. The Gath-Geva (GG) learning algorithm is based on clustering approach. There are diverse clustering algorithms for learning.

For initialization of the clustering, a set of cluster centers needs to be estimated. The number of clusters has an upper bound found through the subtractive clustering, which is initially used. The initial memberships are calculated according to the fuzzy c-means clustering through a Euclidian distance (Gath and Geva, 1989).

$$J(Z,U,V) = \sum_{i=1}^{c}\sum_{k=1}^{N} \mu_{i,k}^{m} D_{i,k}^{2} \ , \tag{5}$$

where $V = [v_1, \dots, v_c]$ contains the cluster centers and $m \in [1, \infty)$ is a weighting exponent that determines the fuzziness of the resulting clusters, being, in usually set to $m = 2$. In turn, the fuzzy partition matrix has to satisfy the following conditions:

$$\begin{aligned} &(i) \quad U \in \Re^{c\times N}, \ \mu_{i,k} \in [0,1], \ \forall\, i,k \ ; \\ &(ii) \ \textstyle\sum_{i=1}^{c} \mu_{i,k} = 1 \ , \ \forall\, k \ ; \\ &(iii) \ 0 < \textstyle\sum_{k=1}^{N} \mu_{i,k} < N \ , \ \forall\, i \ . \end{aligned} \tag{6}$$

The main steps of the global version of Gath-Geva are:

- *Initialization*: Given a set of data Z specify c:

  Choose the weighting exponent, $m > 1$, and the termination tolerance $\epsilon > 0$;

  Initialize the partition matrix satisfying (6);

  Repeat for $i = 1, 2, \dots$;

- *Step 1*:

  Compute the cluster centers according to:

$$v_i^{(l)} = \frac{\sum_{k=1}^{N} \mu_{i,k}^{(l-1)} z_k}{\sum_{k=1}^{N} \mu_{i,k}^{(l-1)}} \ , \ 1 \le i \le c \ . \tag{7}$$

- *Step 2*:

  Compute the distance measure , $D_{i,k}^2$, based on the fuzzy covariance matrices of the cluster, according to:

$$F_i^{(l)} = \frac{\sum_{k=1}^{N} \mu_{i,k}^{(l-1)} \left(z_k - v_i^{(l)}\right)\left(z_k - v_i^{(l)}\right)^T}{\sum_{k=1}^{N} \mu_{i,k}^{(l-1)}} \ , \ 1 \le i \le c \ . \tag{8}$$

  The distance function is chosen as:

$$D_{i,k}^2(z_k, v_i) = \frac{(2\pi)(\frac{n+1}{2})}{\alpha_i} exp\left(\frac{1}{2}\left(z_k - v_i^{(l)}\right)^T F_i^{-1}\left(z_k - v_i^{(l)}\right)\right) \ . \tag{9}$$

  with the *a priori* probability α_i, determined as:

$$\alpha_i = \frac{1}{N}\sum_{k=1}^{N} \mu_{i,k}^{(l-1)}. \tag{10}$$

- *Step 3*:

  Update the partition matrix according to:

$$\mu_{i,k}^{(l)} = \frac{1}{\sum_{j=1}^{c}} \left(D_{i,k}(z_k, v_i)/D_{j,k}(z_k, v_j)^{2/(m-1)}\right) \ , \ 1 \le i \le c \ , \ 1 \le k \le N \ . \tag{11}$$

- *Stop Criteria*:

  Perform until

$$\left\| U^{(l)} - U^{(l-1)} \right\| < \epsilon \ . \tag{12}$$

One of the main advantages of the GG clustering algorithm is its characteristic of adaption on covariant shapes and various densities, especially when compared to other usual methods. The use of GG clustering algorithm has immediate appealing because the parameters of the univariate membership functions can directly be derived from the parameters of the clusters. Through a linear transformation of the input variables, the antecedent partition can be accurately captured and no decomposition error occurs.

The Gath-Geva clustering algorithm generalize the maximum chance estimation for the fuzzy clustering and it is based on the minimization of the sum of weighted squared distances between the input data point and the clusters centers. They assume that the normal distribution with the expected value for the cluster center, the covariance matrix, and the priory probability are used to generate the cluster parameters.

3. NONLINEAR THERMAL-VACCUM SYSTEM IDENTIFICATION

The identification of the model through the estimated T-S fuzzy model based on Gath-Geva clustering learning algorithm is obtained upon a nonlinear thermal-vacuum chamber used for satellite qualification. Thermal-vacuum chambers are used to reproduce as close as possible environmental conditions in their operational life. This paper looks to identify the TS model using Gath-Geva fixed clustering search algorithm that find the centers of the set points and gather them together in a way to find how the system behaves extracting the base of rules and so the number of Gaussian membership functions.

Based on the exposed dataset shown in Fig. 3 in this paper not only the GG algorithm is investigated but the use of sequential and randomized training data set. The original, sequential data is permuted to compose the second set of data, composing the same data but in a different order. The advantage of such a modification is that a persistent training dataset is employed as illustrate in Fig. 4 for input dataset and Fig. 5 for output dataset.

The first part of the experiment consists in training. To the training part be effective must be set the input and output

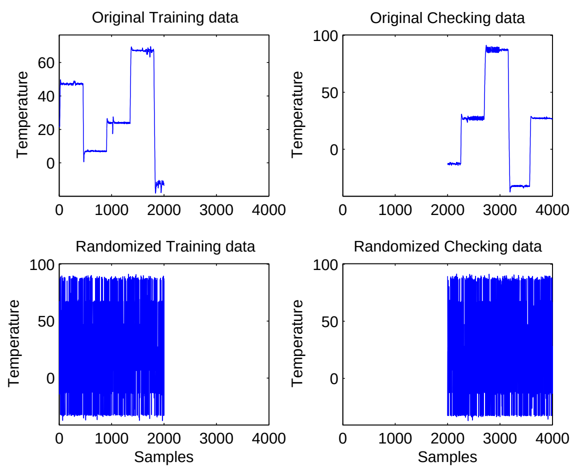


Figure 4. Input training and validation experimental data in sequential and randomized distribution.

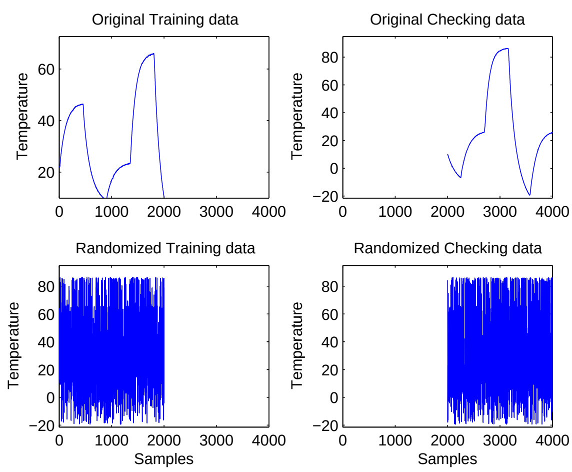
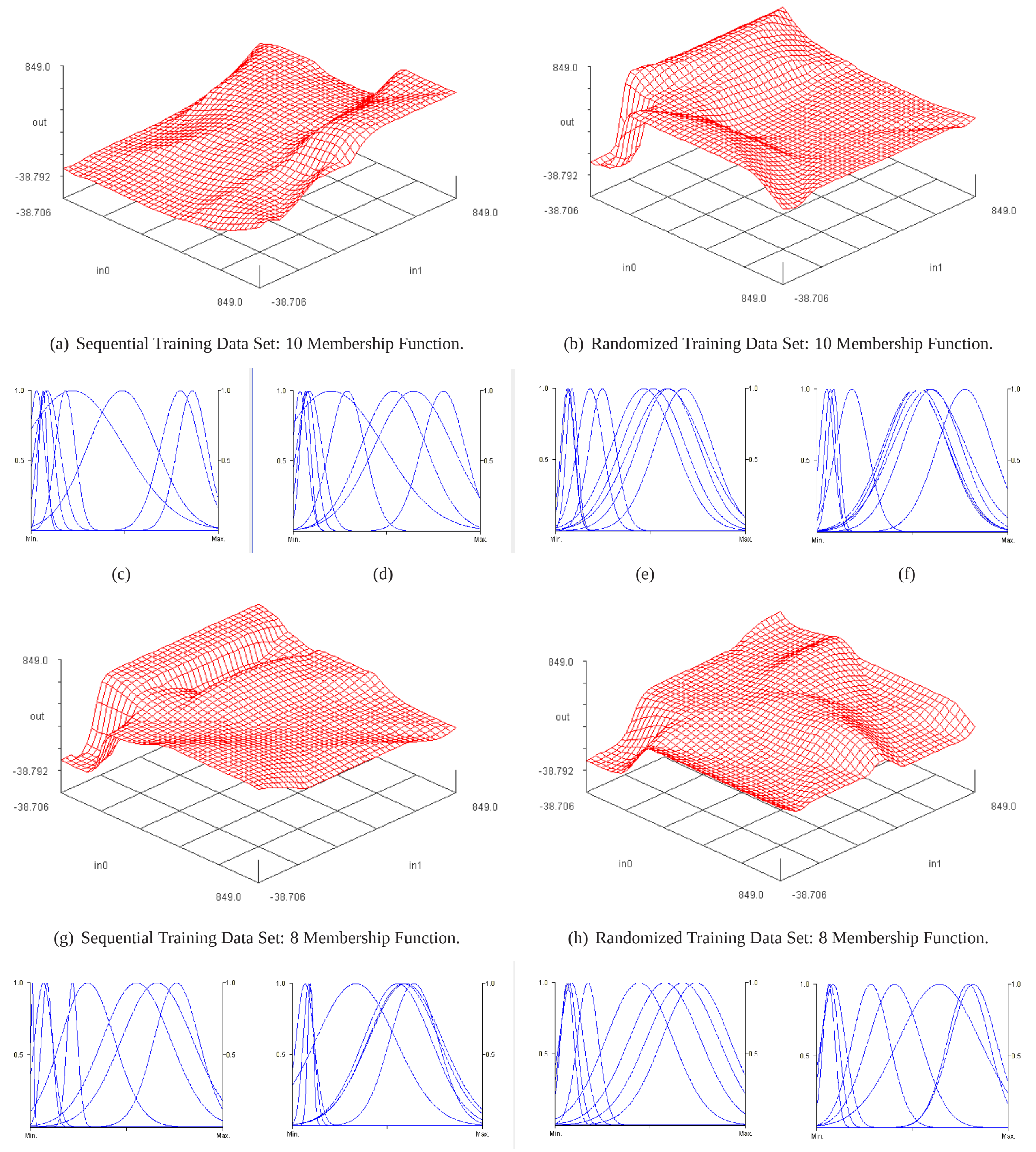


Figure 5. Output training and validation experimental data in sequential and randomized distribution.



(a) Sequential Training Data Set: 10 Membership Function.

(b) Randomized Training Data Set: 10 Membership Function.

(c) (d) (e) (f)

(g) Sequential Training Data Set: 8 Membership Function.

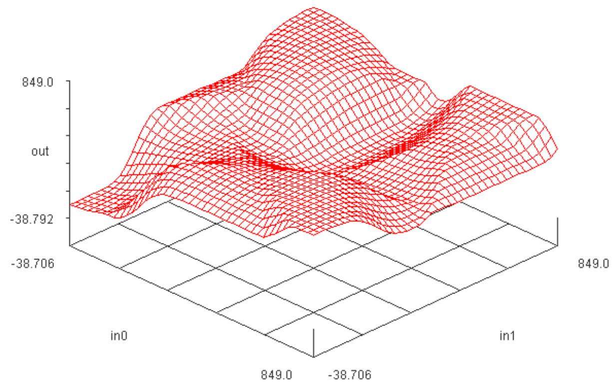
(h) Randomized Training Data Set: 8 Membership Function.

(i) (j) (k) (l)

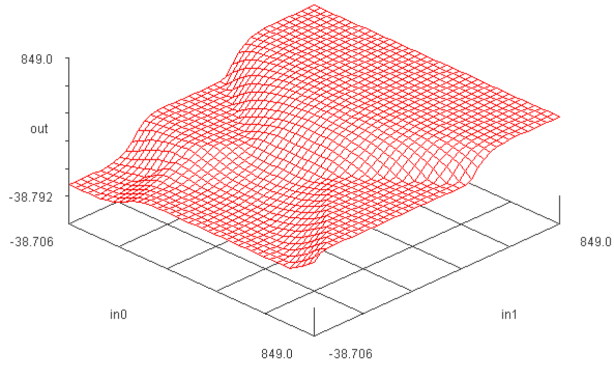
Figure 6. Takagi-Sugeno Fuzzy System based on Gath-Geva Clustering Learning Algorithm.

system data with no order so the clustering algorithm must be capable to detect and learn the dynamical behavior of the dataset. Representing 50% of dataset GG learning algorithm extracted 10 rules and 10 membership functions for original sequential training data set and for randomized training data set producing nonlinear fuzzy mapping as shown, respectively, in Fig. 6(a) and 6(b). Their associate membership are depicted in Fig. 6(c) and 6(d) for the first dataset and in Fig. 6(e) and 6(f) for the second dataset. During the training part, the algorithm is capable to extract the system behavior. To see if all training was correct, the last non used samples were used to validate the model system. It was only given the set of inputs from the system, and so, the algorithm must be capable to provide the estimated output.

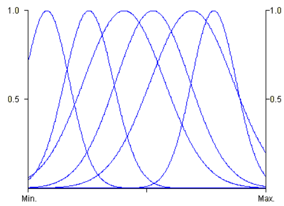
The rule base extraction and the membership that comprise the knowledge base by using the Gath-Geva algorithm is based on fixed clustering (Fig. 8). The parameters that compose the input universe of discourses are the vectors

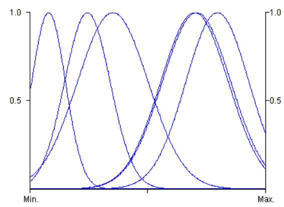


(a) Sequential Training Data Set: 6 Membership Function.



(b) Randomized Training Data Set: 6 Membership Function.


(c)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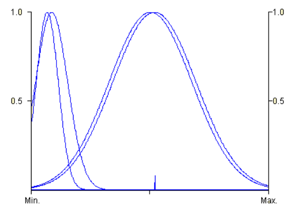
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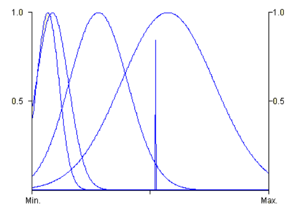
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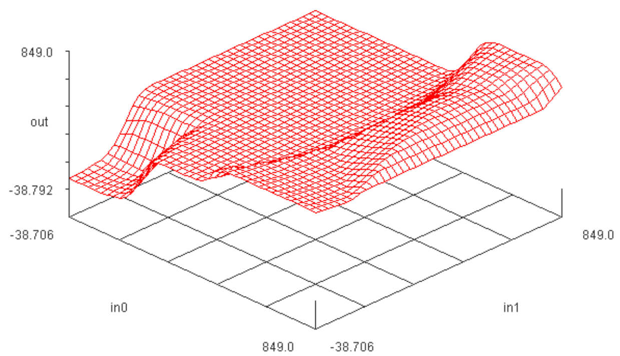
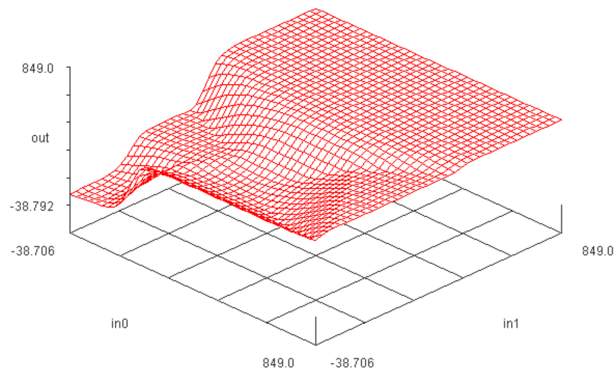
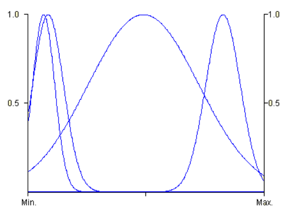
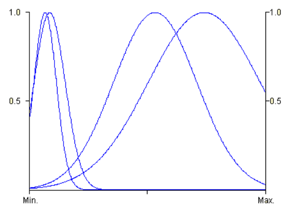


(g) Sequential Training Data Set: 4 Membership Function.



(h) Randomized Training Data Set: 4 Membership Function.


(i)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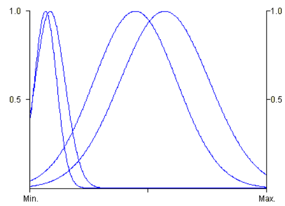
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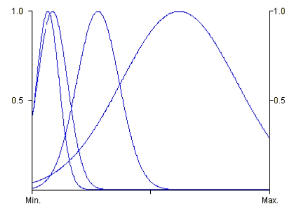
(l)

Figure 7. Takagi-Sugeno Fuzzy System based on Gath-Geva Clustering Learning Algorithm.

$[u(k); u(k-1)]$ while the output universe of discourse is given by the vector is $y(k)$. The GG algorithm is configured to 10, 8, 6, and 4 clusters that, actually, correspond to the same amount of membership functions. This method is setup to Gaussian membership functions in the input universe of discourse; and the conjunction operator corresponding to the conjunctive logic connective is the minimum. GG learning algorithm allows to extract the number of rules and to determine the premise and consequent elements, as before mentioned, this method is applied here to obtain the values that determine the position and the shape of the membership functions and, thus, to determine the premise space partition. The membership functions are setting up from 2 to 10 in the production rules. Note that the similarity in the distribution of membership function in the universe of discourses are due to the GG algorithm extract fixed number of clusters disposed as shown in Fig. 8.

Rule Base through GG Algorithm.

				u(k)		
		MF_0	**...**	**MF_i**	**...**	**MF_n**
	MF_0	$f_0(.)$				
	...		...			
u(k-1)	**MF_i**			$f_i(.)$		
	...				...	
	MF_n					$f_n(.)$

Figure 8. Fuzzy System Structure through GG Clustering Learning Algorithm.

The GG learning algorithm extracted 8 rules and 8 membership functions for original sequential training data set and for randomized training data set producing nonlinear fuzzy mapping as shown, respectively, in Fig. 6(g) and 6(h). Their associate membership are depicted in Fig. 6(i) and 6(j) for the first dataset and in Fig. 6(k) and 6(l) for the second dataset.

The T-S fuzzy modeling with extracted 6 rules and 6 membership functions for original sequential training data set and for randomized training data set producing nonlinear fuzzy mapping as shown, respectively, in Fig. 7(a) and 7(b). Their associate membership are depicted in Fig. 7(c) and 7(d) for the first dataset and in Fig. 7(e) and 7(f) for the second dataset. The GG learning algorithm extracted 4 rules and 4 membership functions for original sequential training data set and for randomized training data set producing nonlinear fuzzy mapping as shown, respectively, in Fig. 7(g) and 7(h). Their associate membership are depicted in Fig. 7(i) and 7(j) for the first dataset and in Fig. 7(k) and 7(l) for the second dataset.

4. CONCLUSION AND FUTURE RESEARCH

Gath-Geva learning algorithm has shown its effectiveness in fuzzy modeling of nonlinear dynamic systems as results demonstrate. The use of Takagi-Sugeno fuzzy Model is an alternative for representing the imperfect database available for the test while the Gath-Geva learning algorithm is in charge of tuning its parameters in an effective way.

These techniques were employed to model a nonlinear thermal-vacuum chamber used in satellite and space devices qualification. Gath-Geva learning algorithm is flexible in distribution of membership functions even being characterized by employing a reduced number of rules and membership functions meanwhile fuzzy system representation is able to deal with inherent imprecise and uncertain information in data. Moreover, since fuzzy system is a universal approximator, it was able to predict future dynamical behavior with distinct high intensity input signals from those used during the training by presenting a model based on experimental data of low intensity.

Due to the results obtained in this paper, future research will assess and explore the limits of the proposed Gath-Geva learning algorithms employed to optimize the nonlinear-parameter associate to Takagi-Sugeno fuzzy modeling. Further, it will be included a comparative analysis with other local search methods, such as simulated annealing, and randomized search methods, such as Particle Swarm Optimization and Genetic Algorithm.

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