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A new method for structure identification of fuzzy models and its application to a combined cycle power plant

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This paper presents a new method for structure identification based on sensitivity analysis to determine the significant input variables of a fuzzy model. The sensitivity method is favorably compared against an heuristic method in two different examples. The proposed method is also used to develop fuzzy models for a combined cycle power plant from real time data.

Keywords: fuzzy models, structure identification, combined cycle power plant

1. INTRODUCTION

Most industrial processes have a non linear behavior, so that it becomes necessary to build non linear models for designing automatic control algorithms, fault detection and other applications.

There are many methods for non linear model identification, but most of them assume that the structure of the system is given *a priori* [1]. This paper analyses the structure identification problem, defined by the selection of significant input variables among all possible ones.

Haber [1] resumes methodologies for structure identification of general non linear dynamic models. First, the trivial way of searching the best structure is to adjust models for all possible structures. A more economic way is to apply stepwise regression [1]. The stepwise regression starts by selecting the component which is most closely correlated with the output variable determining the first model. The residue of this model is correlated with the remainder candidate variables. In each next step, the variable to be included is the particular term that gives the largest correlation with the previous step residue.

In the neural network modeling area, there exist also some structure identification works done. Cibas [2] proposes to use the sum of the influences of all weights going out of an input neuron, as an importance measure of the corresponding input variable. On the other hand, Savit [3] and Pi [4] develop a statistical approach to input variable selection based on calculating the conditional probabilities of the output variables. Muñoz [5] proposes to select the significant input variables based on the analysis of the derivatives of the model output regarding its inputs.

Also, for fuzzy modeling, Sugeno & Yasukawa [6] propose an heuristic method based on selecting some input variables increasing the number of inputs one by one, according to a criterion. On the other hand, Bastian [7] selects the optimal input variables according to the influence of each of them, that is calculated replacing an input variable with a random noise signal. Wang [8] uses a fuzzy discretization technique to determine which inputs variables will be included in the fuzzy model.

This paper presents a new method for structure identification of fuzzy models based on a sensitivity analysis, where the influence of each input variable is calculated to determine the optimal structure. As proposed by Muñoz [5], these influences or sensitivities are defined by the derivatives of the output model with regard to each input variable.

Fuzzy models have been successfully used in many industrial processes. As an application of the proposed structure identification method for fuzzy models, combined cycle power plants are analysed. These plants are of great interest due to their high efficiencies and their low investment costs. As a first step to improve the efficiency of these power plants, fuzzy models of the process will be developed in order to design advanced control algorithms.

The content of this paper is as follows. First, the fuzzy modeling is presented and then, the new method for structure identification of fuzzy models is described. Next, two different examples are shown and compared. After that, fuzzy models of a thermal power plant boiler are developed from real time data. Finally, conclusions are presented.

2. FUZZY MODELING

2.1 Fuzzy models

This paper considers mainly the use of the Non-Linear Autoregressive with eXogenous variable (NARX) models [9]. The structure of these models is given by the following equation:

$$y(k) = f(\mathbf{x}(k)) \tag{1}$$

$$\mathbf{x}(k) = \begin{bmatrix} y(k-1) \\ \vdots \\ y(k-na) \\ u(k-nk-1 \\ \vdots \\ u(k-nk-nb) \end{bmatrix} = \begin{bmatrix} x_1 \\ \vdots \\ x_{na} \\ x_{na+1} \\ \vdots \\ x_{na+nb} \end{bmatrix} \tag{2}$$

where $y(k)$ is the output variable, f is the non linear function to be estimated, $\mathbf{x}(k)$ is a vector of the model input variables and $u(k)$ corresponds to the process input variable. The f non-linear function for Takagi & Sugeno fuzzy models, given by [10], is:

$$\begin{aligned} &\text{if } y(k-1) \text{ is } A_1^r \text{ and } \cdots \text{ and } y(k-na) \text{ is } A_{na}^r \text{ and} \\ &u(k-nk-1) \text{ is } A_{na+1}^r \text{ and } \cdots \text{ and} \\ &u(k-nb-nk) \text{ is } A_{na+nb}^r \text{ then } y_r(k) = g_0^r + g_1^r y(k-1) + \ldots + \\ &g_{na}^r\, y(k-na) + g_{na+1}^r\, u(k-nk-1) + \ldots + \\ &g_{na+nb}^r\, u(k-nm-nk) \end{aligned} \tag{3}$$

where A_i^r are fuzzy sets, g_i^r are consequence parameters and y_r is the output of rule r. In this case, the input variables of the premises of each rule are combined by 'and' operators and the output variables, given by linear models, consider different operating regions. The output of the fuzzy model is obtained by weighting the output of each rule, y_r, by their activation degree, w_r, that is:

$$y(k) = \frac{\sum_{r=1}^{N_r} w_r\, y_r(k)}{\sum_{r=1}^{N_r} w_r} \tag{4}$$

where N_r is the number of rules and the activation degree w_r is:

$$w_r = \mu_1^r \cdots \mu_i^r \cdots \mu_{na+nb}^r \tag{5}$$

with μ_i^r as the membership degree of fuzzy set A_i^r. The following differentiable membership function is used:

$$\mu_i^r = \exp(-0.5(a_i^r(x_i - b_i^r))^2) \tag{6}$$

where a_i^r and b_i^r membership function parameters and x_i is an input variable defined in equation (2).

2.2 Identification procedure

The main steps of an identification procedure based on fuzzy logic are presented in Figure 1 [10]. First, it is necessary to select data from the process. After that, the significant input variables of the fuzzy model are selected. Then, the premise and consequence parameters of the fuzzy model are calculated. Finally, the fuzzy model is validated. Next, the main steps of this procedure are described in detail.

Data selection

For any non linear model identification method, the data must include enough information to cover the different operating regions of the process.

Necessary data sets for the modeling are:

- *The training set.* From these data, the fuzzy model structure and its parameters are obtained.
- *The validation set.* New data for evaluating the behavior of the determined model.

Premise and consequence parameters estimation

The method proposed by Sugeno & Yasukawa [6] minimizes the number of rules making a partition of the output

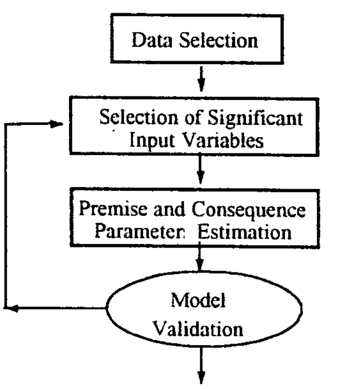

Figure 1 Flow diagram

variables universe that is projected to the input universe finding the optimal fuzzy sets and rules. This partition is based on a fuzzy clustering method.

A clustering procedure is a way of classifying data in different groups or clusters, so that, the elements in a single cluster are clearly similar under certain criterion. In fuzzy clustering, an element can belong to more than one cluster getting a membership degree to each one. The criterion used for fuzzy clustering is to minimize the distance from any datum to the center of each fuzzy cluster. The method finds the optimal number of clusters and the membership degree of data to each cluster.

After that, given a fuzzy cluster B in the output variable universe, a fuzzy cluster A can be induced in the input space (see Figure 2). The projection of this cluster in the axes of each input variable gives the fuzzy sets and the premise parameters for the inputs.

Next, the consequence parameters are calculated using the Takagi & Sugeno method based on least squares [10]. This method consist in minimizing the error between the process output and the fuzzy model output.

Selection of significant input variables

An heuristic method for selection of significant input variables, proposed by Sugeno [6], is described.

For the NARX model defined in equation (1), (na + nb) input variables are input candidates, thus the total possible models considering all the input variables are $2^{na+nb} - 1$.

Similarly to stepwise regression, the heuristic method consists in selecting some input variables from among all the input variable candidates, increasing the number of inputs one by one, according to a regularity criterion [6]. In this case, the following criterion is used:

$$RC = \frac{\left[\sum_{i=1}^{k_A} (y^A(i) - y^{AB}(i)) + \sum_{i=1}^{k_B} (y^B(i) - y^{BA}(i))\right]}{2} \qquad (7)$$

where k_A and k_B are data number from two data groups of training set A and B, $y^A(i)$ and $y^B(i)$ are the output data from groups A and B, $y^{AB}(i)$ is the model output for group A estimated with the model identified using the group B data, and $y^{BA}(i)$ is the model output for group B

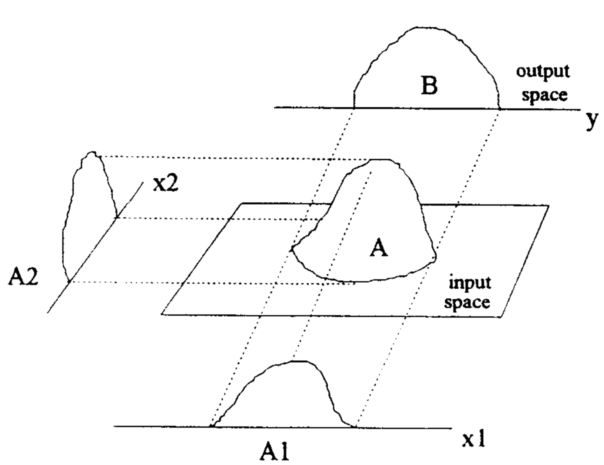

Figure 2 Projection of a fuzzy cluster

estimated with the model identified using the group A data. As we can see, two models are estimated at each stage.

First, we start with (na + nb) fuzzy models with one input variable each. The regularity criterion (RC) is calculated for each model and the model with minimum RC is selected. Next we fix the one input variable selected above, adding other input variable to the fuzzy model from among the remaining possible input variables. The process continues until the value of RC increases.

Model validation

The fuzzy model is evaluated using a validation set. Then, if the adjusted model evaluation using an error index is small, the model identification procedure ends. Otherwise it is necessary to review the significant input variable selection to find if any important process variable is not included.

In this work, the following error index is used:

$$e^2 = \frac{\sum_{i=1}^{M} (y(i) - \hat{y}(i))^2}{M} \qquad (8)$$

where y(i) is the process output, $\hat{y}(i)$ is the estimated output using the determined fuzzy model and M is the number of data for validation set.

3. A NEW METHOD FOR STRUCTURE IDENTIFICATION OF FUZZY MODELS

This new method uses similar steps of the identification procedure described in section 2.2, but the selection of significant input variables is based on sensitivity analysis.

The sensitivity method consists in fitting an initial model using the maximum possible input variables. The maximum order of the initial fuzzy model is defined by the process knowledge. Then, the influences or sensitivities for each input variable are calculated [11, 12].

Each input and output variable is normalized in order to eliminate the effect of size and units.

In general, the input variable sensitivity ξ_i of a NARX model (see equation (1)) is defined by [11, 12]:

$$\xi_i(\mathbf{x}) = \frac{\partial f(\mathbf{x})}{\partial x_i} \qquad (9)$$

where f is a non linear function, **x** is a vector of input variables (see equation (2)) and x_i is an input variable.

The sensitivity of each input variable represents the relevance of this input with respect to the model output. For example, Figure 3 shows that the input variable x_2 is irrelevant to the model output, i.e.

$$\frac{\partial f(x_1, x_2)}{\partial x_2} = 0$$

For fuzzy modeling, the input variable sensitivity (see equations (4)–(6)) is given by:

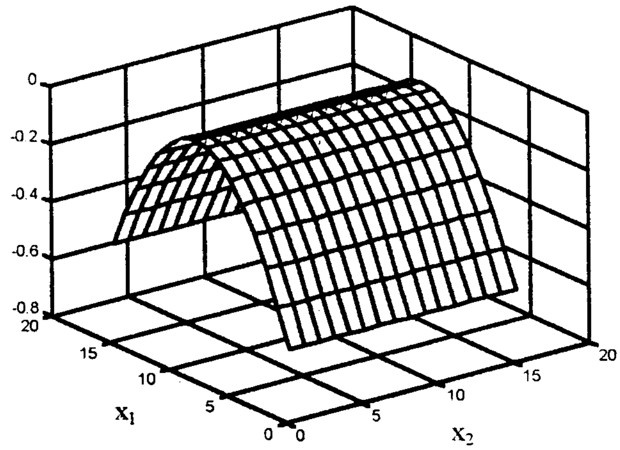

Figure 3 Non linear function $y = f(x_1, x_2)$

$$\xi_i(x) = \frac{\sum_{r=1}^{N_r}\left(\frac{\partial w_r}{\partial x_i} y_r + \frac{\partial y_r}{\partial x_i} w_r\right)\sum_{r=1}^{N_r} w_r - \sum_{r=1}^{N_r}\left(\frac{\partial w_r}{\partial x_i}\right)\sum_{r=1}^{N_r}(w_r y_r)}{\left(\sum_{r=1}^{N_r} w_r\right)^2} \quad (10)$$

where

$$\frac{\partial w_r}{\partial x_i} = \frac{\partial \mu^r_i}{\partial x_i} \times \mu^r_1 \times \cdots \times \mu^r_{i-1} \times \mu^r_{i+1} \times \cdots \times \mu^r_{na+nb}$$

$$\frac{\partial \mu^r_i}{\partial x_i} = \mu^r_i \times c^r_i$$

$$c^r_i = -(a^r_i \times (x_i - b^r_i)) \times a^r_i$$

$$\frac{\partial y_r}{\partial x_i} = g^r_i$$

Then, the sensitivity ξ_i with regard to input variable x_i of a fuzzy model is:

$$\xi_i(x) = \frac{\sum_{r=1}^{N_r}(w_r c^r_i y_r + g^r_i w_r)\sum_{r=1}^{N_r} w_r - \sum_{r=1}^{N_r}(w_r c^r_i)\sum_{r=1}^{N_r}(w_r y_r)}{\left(\sum_{r=1}^{N_r} w_r\right)^2} \quad (11)$$

The sensitivities $\xi_i(\mathbf{x})$ depend on input variables $\mathbf{x}$, and they are evaluated using the training set. To compare the sensitivities of each input variable, the following index is defined:

Table 1 Values of RC criterion and error indices, heuristic method

Model	Input variables	RC	e^2
1	x_1	**0.5701**	**0.4791**
2	x_2	0.7090	0.4949
3	x_3	1.2117	1.0018
4	x_4	1.4706	1.0624
5	x_1–x_2	**0.2545**	**0.0502**
6	x_1–x_3	0.7838	0.4373
7	x_1–x_4	1.0683	0.4819

$$I_i = \mu_i^2 + \sigma_i^2 \quad (12)$$

where μ_i is the mean and σ_i is the standard deviation of the sensitivities. Then, the input variables with smallest indices I_i can be eliminated.

Next, the fuzzy model is obtained using just input variables with largest associated sensitivities.

4. EXAMPLES

4.1 Non linear static system

The following non-linear static system is defined by [6]:

$$y = (1 + x_1^{-2} + x_2^{-1.5})^2 \quad (13)$$

with $x_1 \geq 1$ and $x_2 \leq 5$. From this system equation, 50 input-output data are obtained. Also, we include data for x_3 and x_4 as dummy inputs to check the identification method.

Fifty training data and fifty validation data are considered. Premise and consequence parameters are determined using the methods described in section 2.2.

The structure identification based on an heuristic method (see section 2.2) and a new sensitivity method (see section 3) are used and compared for selection of significant input variables.

Heuristic method

In this case, there are four input variable candidates (x_1, x_2, x_3 and x_4) and thus, 15 ($2^4 - 1$) fuzzy models are possible to build. The data group A consists of the first 25 data of the training set, and group B has the last 25 data of the same set.

First, we build four fuzzy models with one input variable each. For each model the RC criterion is calculated as showing Table 1. We select the model with minimum RC (model 1). After that, we fix the one input variable selected above, adding another inputs from among the remaining three candidates. Then, the model 5 with x_1 and x_2 is selected, according to RC value. We do not continue adding input variables because the last two values of RC are bigger than the minimal RC at the previous step. Finally, we evaluated seven of 15 possible models.

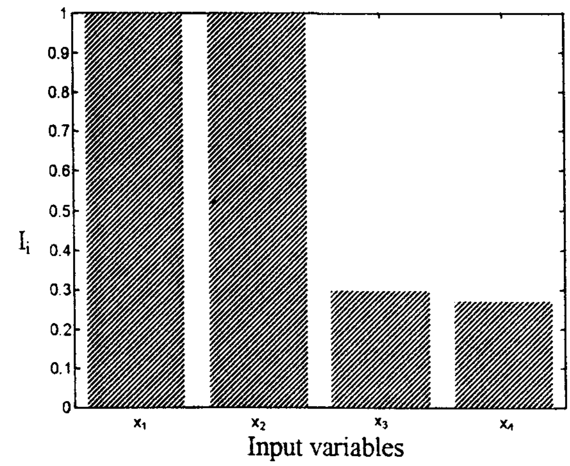

Figure 4 Sensitivity indices

Also, in Table 1, we can observe the error indices, defined in equation (8), for the seven fuzzy models using validation set.

Sensitivity method

The initial fuzzy model structure considered four input variables (x_1, x_2, x_3 and x_4).

Figure 4 presents the sensitivity indices of the proposed initial model using four input variables. Variables x_3 and x_4 show the smallest indices of the sensitivities, so that these variables will not be included in the fuzzy model. In this way the selected structure uses the true input variables x_1 and x_2.

Table 2 shows the error indices of the initial model proposed (model 1) and the obtained model with the true input variables (model 2), using the validation set.

Comparative analysis

With heuristic method, it is necessary to build more models (7 models) than with sensitivity method (2 models), obtaining the best model in less timing.

Figure 5 presents the fuzzy model behavior for the fifty data (validation set) using x_1 and x_2 as input variables.

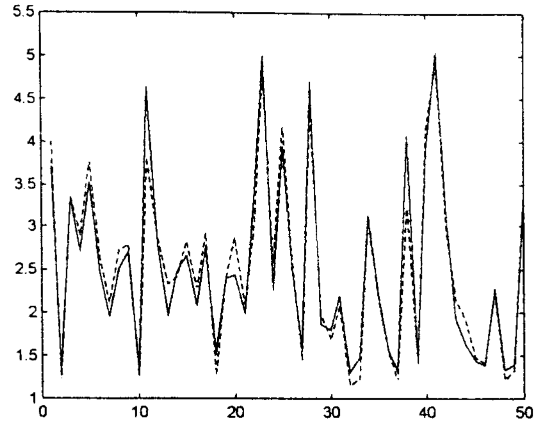

Figure 5 Output of fuzzy model (dotted line) and real output (solid line) for non-linear static system

4.2 Dynamic non linear system

This example of dynamic system identification was presented by Chen [13]. The example is given by the following equation:

$$y(k) = (0.8 - 0.5 \exp(-y^2(k-1)))\, y(k-1) \\ -(0.3 + 0.9 \exp(-y^2(k-1)))\, y(k-2) + u(k-1) \\ + 0.2u(k-2) + 0.1\, u(k-1)\, u(k-2) + \varepsilon(k) \quad (14)$$

where y(k) is the output variable, u(k) is the input variable given by uniform distribution ($\mu = 0$, $\sigma = 1$) and $\varepsilon(k)$ is white noise ($\mu = 0$, $\sigma = 0.2$).

250 training data and 250 validation data are considered. Also, the premise and consequence parameters are determined using the method described in section 2.2.

For selection of significant input variables, the heuristic method (see section 2.2) and the sensitivity method proposed (see section 3) are used and compared.

Heuristic method

Due to the process being dynamical, we consider the regressive components of y(k) and u(k) as input variables. In this work, we use just eight input variable candidates (y(k – 1), ..., y(k – 4), u(k – 1), ..., u(k – 4)). Thus, 255 (2^8 – 1) fuzzy models are possible to build.

First, we build eight fuzzy models with one input variable each. For each model the RC criterion is calculated as showing Table 3. We select the model with minimum RC (model 1). Next, we fix the one input variable selected above (y(k – 1)), adding another input from among the remaining seven candidates. Again, for each model the RC criterion is calculated and we select the model with minimum RC (model 9). We continue the above process adding input variables with values of RC smaller than the minimal RC at the previous step. Finally, we evaluate twenty of the 255 possible models and find the true input variables (model 20): y(k – 1), y(k – 2), u(k – 1) and u(k – 2).

Table 3 Values of RC criterion and error indices, heuristic method

Model	Input variables	RC	e^2
1	y(k – 1)	**0.4980**	**2.4178**
2	y(k – 2)	0.8617	4.1282
3	y(k – 3)	0.8782	3.8439
4	y(k – 4)	0.9015	3.6382
5	u(k – 1)	0.6834	3.0644
6	u(k – 2)	0.5287	2.5359
7	u(k – 3)	0.8302	3.7379
8	u(k – 4)	0.9764	3.8832
9	y(k – 1) – y(k – 2)	**0.2535**	**1.4959**
10	y(k – 1) – y(k – 3)	0.4221	5.9535
11	y(k – 1) – y(k – 4)	0.5020	3.7137
12	y(k – 1) – u(k – 1)	0.3000	2.0404
13	y(k – 1) – u(k – 2)	0.3958	9.7553
14	y(k – 1) – u(k – 3)	0.5107	7.5120
15	y(k – 1) – u(k – 4)	0.4867	2.4165
16	y(k – 1) – y(k – 2) – y(k – 3)	0.2958	1.4165
17	y(k – 1) – y(k – 2) – u(k – 1)	**0.0273**	**0.5244**
18	y(k – 1) – y(k – 2) – u(k – 2)	0.3025	1.4551
19	y(k – 1) – y(k – 2) – u(k – 4)	0.3029	1.4685
20	y(k – 1) – y(k – 2)–u(k – 1) – u(k – 2)	**0.0172**	**0.4696**

Table 2 Values of error indices, sensitivity method

Model	Input variables	e^2
1	$x_1 - x_2 - x_3 - x_4$	0.1106
2	$x_1 - x_2$	**0.0502**

Sensitivity method

The initial fuzzy model structure considers eight input variables (y(k – 1), ..., y(k – 4), u(k – 1), ..., u(k – 4)).

Figure 6 presents the sensitivity indices of the proposed initial model using eight input variables. In the graphic, the variables (y(k – 3), y(k – 4), u(k – 3), u(k – 4)) show the smallest indices of the sensitivities, and thus these variables will not be included in the fuzzy model. In this way, the obtained structure uses the true input variables: y(k – 1), y(k – 2), u(k – 1) and u(k – 2).

Table 4 shows the error indices of the initial model proposed (model 1) and the obtained model with the true input

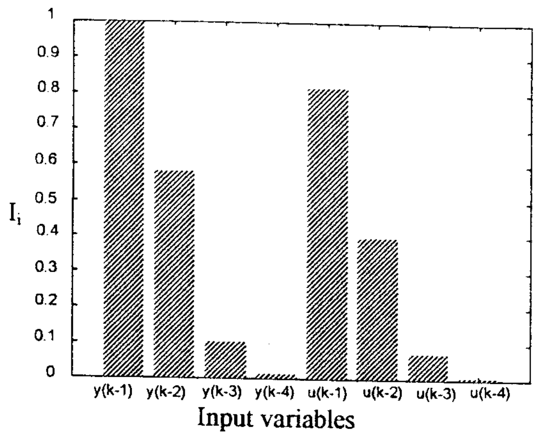

Figure 6 Sensitivity indices

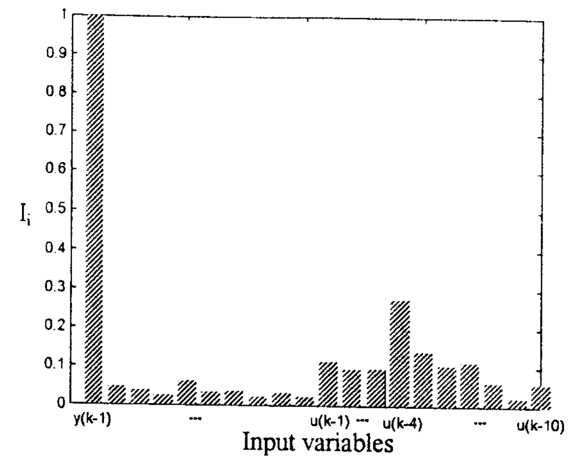

Figure 8 Sensitivity indices

Table 4 Values of error indices, sensitivity method

Model	Input variables	e^2
1	y(k − 1) − y(k − 2) − y(k − 3) − y(k − 4)	0.5802
2	u(k − 1) − u(k − 2) − u(k − 3) − u(k − 4)	**0.4696**

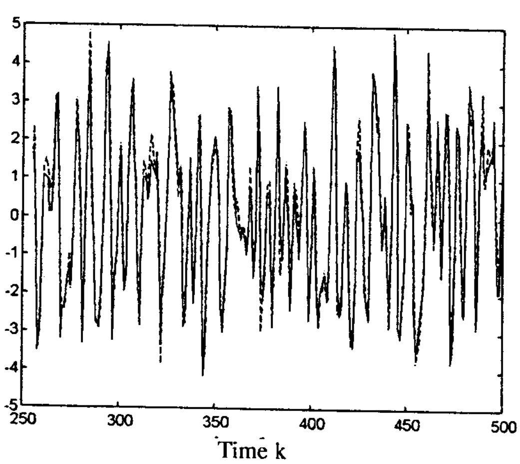

Figure 7 Output of fuzzy model (dotted line) and real output (solid line) for dynamic non-linear system

variables (model 2), using the validation set.

Comparative analysis

In this case, 20 models are built using heuristic method and 2 models using sensitivity method. Thus, the fuzzy model is obtained in less time, using the sensitivity method proposed.

Figure 7 presents the fuzzy model behavior for the validation set.

5. APPLICATION TO A COMBINED CYCLE POWER PLANT

5.1 Thermal power plant 'New Renca'

The thermal power plant 'New Renca' is located in Santiago of Chile. With a power of 370 MW, it is the first Chilean combined cycle power plant that generates electricity from natural gas with high efficiency. The gas turbine of this plant has a power of 200 MW, and the steam turbine 170 MW.

'New Renca' has a maximum efficiency of 54.4%, the highest commercially available nowadays. It started to operate during October 1997.

The steam and gas turbine are supervised using Mark V automation system. Boiler and the other plant equipment are supervised using a Foxboro Distributed Control System.

5.2 Identification using real time data

As an example of the thermal power plant real time modeling, the high pressure drum level (L(k)) is considered as

Table 5 Values of error indices, sensitivity method

Model	Input variables	e^2
1	y(k − 1) − ··· − y(k − 10) u(k − 1) − ··· − u(k − 10)	0.4229
2	y(k − 1) − u(k − 4)	**0.4005**

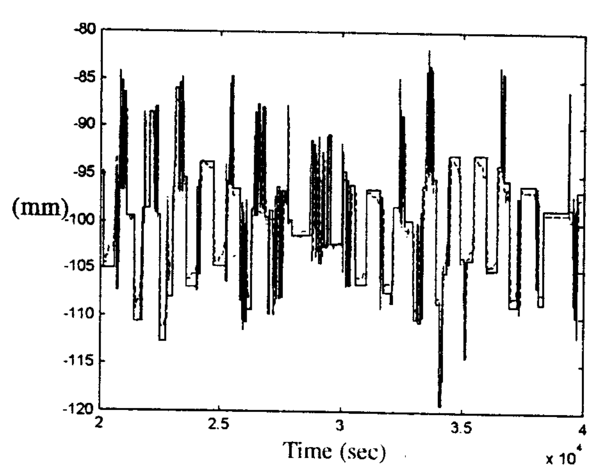

Figure 9 Output of fuzzy model (dotted line) and real output (solid line) for high pressure drum level

output variable and the control valve of feedwater flow (x(k)) as manipulated variable.

1000 training data and 1000 validation data are used, using 20 second sampling period. The premise and consequence parameters are determined using the method described in section 2.2.

The selection of significant input variables using sensitivity method considers twenty inputs variables (L(k – 1), ..., L(k – 10), x(k – 1), ..., x(k – 10)). Due to the time constants associated to the process, just the regressive components until ten previous time instants are included.

Figure 8 presents the sensitivity indices of the proposed initial model using twenty input variables. The variables with the least indices values of the sensitivities will not be included in the fuzzy model. By this way, the optimal structure is obtained with the following input variables: y(k – 1) and u(k – 4).

Table 5 shows the error indices of the initial model proposed (model 1) and the obtained model with the true input variables (model 2), using the validation set.

Figure 9 presents the optimal fuzzy model behavior for the validation set.

6. CONCLUSIONS

In this work, a new structure identification for fuzzy modeling based on a sensitivity analysis is presented.

The proposed method is favorably compared to an heuristic method. Also, the method was applied to a combined cycle power plant using real time data.

The sensibility method permits to study the complete universe of possible models, within a maximum complexity defined by the initial model order.

Also, the proposed method allows to obtain the best structure by adjusting just two fuzzy models in contrast to an heuristic method, for which many fuzzy models are necessary to build.

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REFERENCES

1 **Haber, R. and Unbehauen, H.** (1990). Structure identification of nonlinear dynamic systems – a survey on input/output approaches. *Automatica*, Vol. 26, N° 4, pp. 651–678.

2 **Cibas, T., Fogelman, F., Gallinari, P. and Raudys, S.** (1994). Variable selection with optimal cell demage. *Proc. of the International Conference on Artificial Neural Networks, ICANN'94*, Sorento, Italy, pp. 727–730.

3 **Savit, R. and Green, M.** (1991). Time series and depend variables, *Physica*, Vol. D50, pp. 95–116.

4 **Pi, H. and Peterson, C.** (1994). Finding the embedding dimension and variable dependencies in time series. *Neural Computation*, Vol. 6, pp. 509–520.

5 **Muñoz, A. and Czernichow, T.** (1998). Variable selection using feedforward and recurrent neural networks. *International Journal of Engineering Intelligent Systems*, Vol. 6, N° 2, pp. 91–102.

6 **Sugeno, M. and Yasukawa, T.** (1993). A fuzzy-logic-based approach to qualitative modeling. IEEE Transactions on Fuzzy Systems, Vol. 1, N° 1, February, pp. 7–31.

7 **Bastian, A.** (1995). Towards a fuzzy system identification theory. *Proc. of the VI IFSA World Congress*, July 22–28, Sao Paulo, Brazil, pp. 69–72.

8 **Wang, L. and Langari, R.** (1995). Building Sugeno-type models using fuzzy discretization and orthogonal parameter estimation techniques. *IEEE Transactions on Fuzzy Systems*, Vol. 3, N° 4, pp. 454–458.

9 **Chen, S. and Billings, S.** (1989). Representation of non-linear systems: The NARMAX model. *International Journal Control*, Vol. 49, N° 3, pp. 1013–1032.

10 **Takagi, T. and Sugeno, M.** (1985). Fuzzy identification of systems and its applications to modeling and control. *IEEE Transactions Systems, Man and Cybernetics.*, Vol. SMC-15, pp. 116–132.

11 **Czernichow, T.** (1996). Apport des réseaux à la prévision de séries temporelles, application à la prevision de consommation d'électricité. *Thèse de Dortorat*, Université Paris 6.

12 **Muñoz, A.** (1996). Aplicación de técnicas de redes neuronales artificiales al diagnóstico de procesos industriales. *Tesis de Doctorado*, Universidad Pontificia Comillas, Madrid.

13 **Chen, S., Billings, S. and Grant, P.** (1990). Nonlinear system identification using neural networks. *International Journal of Control*, Vol. 51, N° 6, pp. 1191–1214.