A PROPOSAL OF FUZZY MULTIVARIABLE IDENTIFICATION FOR LIQUID INCINERATION NONLINEAR PROCESS COMBUSTION CONTROL

Felipe de Mello Almeida
*Control and Intelligent Systems Laboratory, State University of Campinas, São Paulo-SP, Brazil
felipe@dmcsi.fee.unicamp.br

Gilmar Barreto*
barreto@dmcsi.fee.unicamp.br

Abstract. The multivariable nonlinear process control is a important and challenger problem. To develop adaptive and efficient controllers, it is need to implement the process identification, so that an accuracy mode can be obtained. The BASF industry has an complex liquid incineration process, where the residues are decimated by oxidation in high temperature. This process is controlled for an operator of control room by supervisory system, where the stages of incineration are automatized; however the Distributed Control System (DCS) does not control the combustion process due to complexity of the multivariable system. Liquid incineration process needs intelligent controllers. The identification of this incineration complex system is the first step to develop the controller. Fuzzy systems has been effectively used to identify nonlinear dynamic systems, but generally single input and single output are considered. This paper presents a fuzzy model that is effectively used to represent multivariable dynamic systems. The identification was realized by Takagi-Sugeno (TS) fuzzy model, where the modified Gath-Geva clustering algorithm was used to determine the antecedent part of fuzzy sets.

Keywords: *System identification, Liquid effluent incinerator, Fuzzy systems, Combustion intelligent controller, Takagi-Sugeno fuzzy model.*

1. Introduction

The main objective in problems of adaptive control, is to develop a controller that can self-tuning according to the controlled plant characteristics, so that takes care of predefined project specifications. These efforts had been initiated in 1960 and in 1980 the researches had grown in satisfactory way in terms of two great directions: self-tuning control and model based control. This growth has opened the doors for a wide band of applications. However, the research in the area of complex adaptive control algorithms still continues, where employs computational strategies directed to the intelligent behavior, are widely used as tools. A great contribution has been given in the intelligent adaptive control area with self-tuning control approach considering the impact of neural networks, genetic algorithms and fuzzy systems. In this paper a unit of liquid residues incineration, that is part of the complex unit of energies in the BASF industry, located in Resende-RJ. The choice of this process was motivated by the potential of improvement on combustion system control on the incineration process. This process is controlled for an control room operator by supervisory system, where the stages of incineration are automatized, however the Distributed Control System (DCS) (Honeywell, 1998) does not control the combustion process because of instability physicist-chemistries characteristics of its residues and the complexity of the dynamic process which presents a multivariable system with nonlinear inputs and outputs. There is necessity to develop an intelligent controller for this combustion process following reasons (Almeida and Barreto): Avoiding emission of gas from combustion, out of standards by ambient agency; To improve the efficiency on reside burning, so that reduce the fuel consumption in the incinerator, getting reduction of the refractory consuming and minimizing costs; To eliminate the necessity of the process operator, to realize the burning control by supervisory system, getting more time to realize other pertinent activities in occupation.

The idea simultaneous of identification and fuzzy control was suggested (Driankov and Hellendoorn,1996), with reference in a based heuristical fuzzy controller in the process model. The adaptive controller contains an explicit process model, that uses the fuzzy identification of the system. The similar structure is shown in the Figure (1):

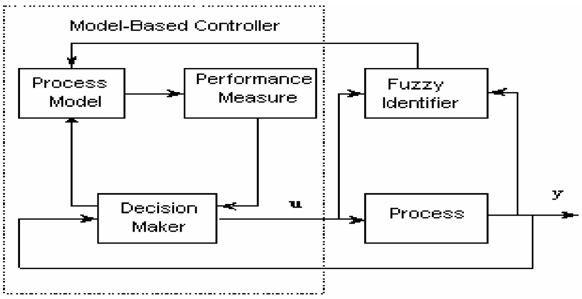

Figure 1 - Adaptive controller based on the fuzzy model

The algorithm of the controller can be viewed by the following steps:

- **First Step:** To obtain the process model using a fuzzy identification of the multvariable process;

- **Second Step:** To determine a controller that can self-tuning according to the characteristics of the controlled plant using a algorithm based process model. In this paper, we will approach first step to construct the adaptive controller algorithm, that consists of getting an process model using multivariable fuzzy identification. The step second is an activity that is not part of this work and being suggested for future proposals.

The fuzzy models identification is an effective tool for the approach of nonlinear dynamic systems on the basis of measured data. Among the different fuzzy modeling techniques, the Takagi-Sugeno model (Takagi and Sugeno, 1985) has attracted most attention. This model consists of rules if-then with fuzzy antecedents and mathematical functions in the consequence part. The fuzzy sets partition the input space into a number of fuzzy regions, while the consequence functions describe the system's behavior in these regions. The construction of a model TS is usually done in two steps. In the first step, the fuzzy sets (membership functions) in the rule antecedents are determined. This can be done manually, using knowledge of the process, or by data-driven techniques. In the second step, the parameters of the consequent functions are estimated. As these functions are usually chosen to be linear in their parameters, standard linear least-squares methods can be applied. The bottleneck of the construction procedure is the identification of the antecedent membership functions, which is a nonlinear optimization problem. Fuzzy clustering in the Cartesian product-space of the inputs and outputs is another tool that has been quite extensively used to obtain the antecedent membership. Attractive features of this approach are the simultaneous identification of the antecedent membership functions along with the consequent local linear models and the implicit regularization. In this paper, a multivariable incineration process is represented by a MIMO (Multiple Input Multiple Output) fuzzy models, that consists of local linear MIMO ARX (Auto Regressive with exogenous inputs) models and a algorithm clustering is boarded that is able to generate such MIMO fuzzy models. The fuzzy clustering can be divided in supervised and unsupervised (Silva, 2003). The supervised algorithms need to know the cluster number a priori and the localization of the cluster centroids is not known, where an initial assumption has of being made, also it has difficulties to find clustering with spherical forms. The unsupervised algorithms do not need to know the number of clusters a priori; therefore they have the intention to find them. Gath-Geva unsupervised algorithm (Gath and Geva, 1989), can determine the variations of the forms, the densities and the number of points in each clustering. The Gath-Geva algorithm (GG) is derived from a combination of the fuzzy K-Means algorithm and the fuzzy maximum likelihood estimation (FMLE). To preserve the partitioning of the antecedent space, linearly transformed input variables can be used in the model. This may, however, complicate the interpretation of the rules. To form an easily interpretable model that does not use the transformed input variables, the Gath-Geva algorithm is modified (Abonyi, Babuska and Szeifert, 2002), based on the expectation-maximization (EM) identification of Gaussian mixture models. The Gath-Geva modified algorithm can easily be represented by an interpretable TS fuzzy model. This approach is extend in this paper to MIMO process and has been applied to the identification of the effluent liquids incineration process, viewed before. The results are compared with others algorithms in the literature.

2. Description of the Incineration Process

To accomplishing incineration system identification, we study the process characteristics that follow below (Cunha, 2003).

2.1 Liquid effluent incinerator

The effluent liquids incinerator was developed to receive residues from industrial plants. The incinerator is a unit developed and manufactured by the T-Thermal, type Sub-X Down Fired, to incinerate liquid residues through oxidation in high temperature, shows the figure (2), the unit representation:

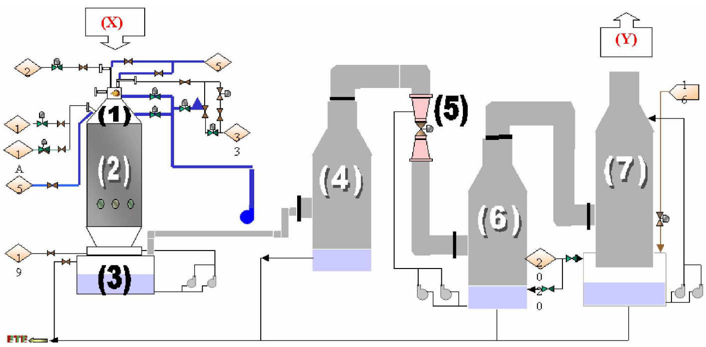

Figure 2 - Diagram of the Incineration Process

The unit is basically composed of a combustion chamber (1), oxidation chamber (2), cooling tank (3), initial separation tower (4), particle breaker (5), final separation tower (6) and a gas washer (7). The oxidation chamber is a vertical cylindrical furnace covered by refractory bricks, located on the cooling tank. Combustible oil burners and the organic effluent burners are mounted in a double arrangement in the top of the combustion chamber. The watery effluent injectors are located directly below of the combustion chamber. The cooling tank is a tank manufactured in polyester covered glass fiber located below of the oxidation chamber and includes a funnel manufactured in Hastelloy C. In this tank leaves two ducts connecting the initial separator, one for gas exit and another one for water return. In the top of this separator we have another duct that leads the gases for the particle breaker and final separator. In this final separator has a duct binded to the gas washer that is a tower with plastic wadding. Above of the gas washer is located chimney that leads the gas to the atmosphere. All the equipment after the cooling tank are manufactured in polyester covered glass fiber, with exception of the particle breaker, manufactured in stainless steel 316L. The oil type 2A and organic effluent generated for the industrial units are used as heat source for the incinerator. The combustion air is supplied by a blower. The capacity of the combustion chamber is of 6 million Kcal/h. The air/combustive relation is adjusted in accordance with stoichiometric calculations. In these conditions, desires to obtain an efficient effluent toxics destruction of at least 99,99%. The combustion products are unloaded in the cooling tank passing for the Hastelloy C funnel. The gases leave of the cooling tank for the duct of exit of gases, passing to the initial separator, whose function is to minimize water transport, in the liquid state, presents in the gas. In the initial separator the gas follows to particle breaker (solid particles of one micron diameter). The recycled water through this washer is collected in the final separator; there are a constant draining of this water to prevent the extreme concentration of dissolved impurities. The gas leaves the final separator and follows to the gas washer. The gas washer is a tower with plastic filling where the gas flows to top, being washed and neutralized for a water solution with sodium hydroxide that is launched under sprayed form in the top of the tower, the gases leave for the chimney, located above of the washer of gases. As argued previously in item 1, the identification of the process will make possible to development of the combustion control of the effluent burning, through an intelligent controller, Figure (3).

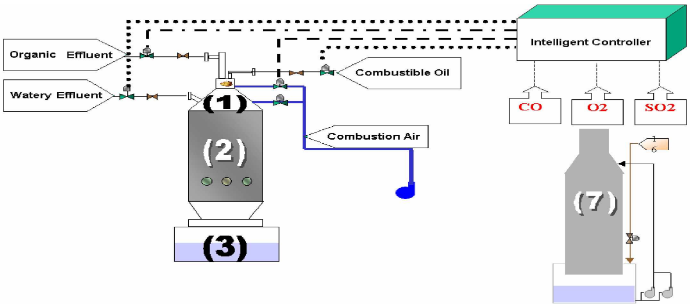

Figure 3 - Adaptive controller interacting with its variables

3. Takagi-Sugeno Fuzzy Model

Multiple-input, multiple-output (MIMO) dynamic process can be represent by the following nonlinear vector function:

$$\mathbf{y}(k+1)=f\,(\boldsymbol{y}(k),..,\boldsymbol{y}(k-n_a+1),\boldsymbol{u}(k-n_d),..,\boldsymbol{u}(k-n_b-n_d+1)) \tag{1}$$

where f represents the nonlinear model, $\boldsymbol{y}=[y_1,\ldots,y_{ny}]^T$ is an n_y dimensional output vector, $u=[u_1,\ldots,u_{nu}]^T$ is an n_u dimensional input vector, n_a and n_b are maximum lags considered for the outputs and inputs, respectively, and n_d is the minimum discrete dead time. While it may not be possible to find a model that is universally applicable to describe the unknown f system, it would certainly be worthwhile to build local linear models for specific operating points of the process. The modeling framework that is based on combining a number of local models, where each local model has a predefined operating region in which the model is valid is called operating regime based model. This model is formulated as:

$$\boldsymbol{y}(k+1)=\sum_{i=1}^{c} a_i\,(\boldsymbol{x}(k))\,\left(\sum_{j=1}^{na}\alpha_j^i(\,y(k-j+1)+\sum_{j=1}^{nb}\beta_j^i\,u(k-j-nd+1)+c^i\,\right) \tag{2}$$

where the a function describes the operating regime of the $i=1,\ldots,c$-th local linear ARX model, where $\chi=[\chi_1,\ldots,\chi_n]^T$ is a vector, which is usually a subset of the previous process inputs and outputs:

$$\chi(k)=\{\,\boldsymbol{y_1}(k),\ldots,\boldsymbol{y_1}(k-n_a+1),\ldots,\boldsymbol{y_{ny}}(k-n_a+1),\boldsymbol{u_1}(k-n_d),\ldots,\boldsymbol{u_{nu}}(k-n_b-n_d+1)\} \tag{3}$$

The local models are defined by the $\Xi = \{\alpha_j^i, \beta_j^i, \gamma^i\}$ parameter set. The complete model, can conveniently be represented by Takagi-Sugeno fuzzy model [6]. This Tagaki-Sugeno fuzzy model is formulated by rules as :

$$\boldsymbol{R_i}: \text{ Se } \chi_1 \text{ é } \boldsymbol{A_{i,1}} \text{ e ...e } \chi_n \text{ é } \boldsymbol{A_{i,n}} \text{ então } \boldsymbol{y}^{\mathbf{i}}(k+1) = \sum_{j=1}^{n_a} \alpha_j^i \boldsymbol{y}(k-j+1) + \sum_{j=1}^{n_b} \beta_j^i \boldsymbol{u}(k-j-n_d+1) + \gamma^i, [\zeta_i] \tag{4}$$

where $\boldsymbol{A}_{i,j}(\chi)$ is the ith antecedent fuzzy set for the jth input and $\zeta_i = [0,1]$ is the weight of the rule that represents the desired impact of the rule. The value of ζ_i is often chosen by the designer of the fuzzy system based on his or her belief in the goodness and accuracy of the i-th rule. When such knowledge is not available $\zeta_i = 1\ \forall_i$.
The one-step-ahead prediction of the MIMO fuzzy model, $\mathbf{y}(k+1)$, is inferred by computing the weighted average of the output of the consequent multivariable models,

$$\boldsymbol{y}(k+1) = \sum_{i=1}^{c} a_i(\boldsymbol{x}(k))\ \boldsymbol{y}^{\mathbf{i}}(k+1) \tag{5}$$

where c is the number of rules and a_i is the weight of the ith rule,

$$a_i(x(k)) = \frac{\zeta_i \prod_{j=1}^{n} A_{j,i}(x_j)}{\sum_i^c \zeta_i \prod_{j=1}^{n} A_{j,i}(x_j)} \tag{6}$$

to represent the $A_{j,i}(x_j)$ fuzzy set, in this paper Gaussian membership function is used.

4. Consequent Parameters Identification

The local models can be interpreted as a local dynamic behavior of the complete fuzzy model. The identification of the parameters of the consequence of the rule, force the linear model to adjust the system separately and local, resulting in the consequences of the rules that are linearizations of the nonlinear system (Abonyi and Szeifert, 2001). Then the local fuzzy models, gotten for the local identification produce a representation of the state space. The fuzzy model can be interpreted with a system LPV (Linear Parameter Varying) described in (2), where the parameters of the rule consequence are estimated separately by dividing the identification task into c weighted least-squares problems. The fuzzy model can be formulated in the following compact form:

$$\boldsymbol{y}(k+1) = \sum_{i=1}^{c} a_i(\boldsymbol{x}(k))\, [\vartheta(k)\ I_{1xny}]\ \Xi_i^T + \xi(k) \tag{7}$$

where $\vartheta(k)$ is the regressor vector,

$$\vartheta(k) = [\boldsymbol{y}(k),.,\boldsymbol{y}(k-n_a+1), \boldsymbol{u}(k-n_d),.,\boldsymbol{u}(k-n_u-n_d+1)^T] \tag{8}$$

Ξ is the parameter matrix of the i-th local model (rule), $\Xi_i = [\alpha_1^i,...,\alpha_{ny}^i, \beta_1^i,..., \beta_{nu}^i, \gamma^i]$ and $\xi(k)$ is a zero mean white noise sequence. The output of this model is linear in the elements of the α_j^i, β_i^i consequent matrices and the c^i offset vector. Therefore, these parameters can be estimated from input-output process data by linear least-squares techniques. The N identification data pairs and the truth values of the fuzzy rules are arranged in the following matrices.

$$\vartheta = [\vartheta^T(1) \mid \vartheta^T(2) \mid ... \mid \vartheta^T(N)]^T \tag{9}$$

$$\mathbf{Y} = [\boldsymbol{y}(2) \mid \boldsymbol{y}(3) \mid ... \mid \boldsymbol{y}(N+1)]^T \tag{10}$$

$$a_i = \begin{bmatrix} a_i(1) & 0 & ... & 0 \\ 0 & a_i(2) & ... & 0 \\ . & . & ... & . \\ 0 & 0 & ... & a_i(N) \end{bmatrix} \tag{11}$$

By using this notation, the weighted least squares solution of Ξ_i is :

$$\Xi_i = [\vartheta^T a_i \vartheta]^{-1} \vartheta^T a_i Y \tag{12}$$

As this method forces the local models to fit the data locally, it does not give an optimal fuzzy model in terms of a minimal global prediction error, but it ensures that the fuzzy model is interpretable as a Linear Parameter Varying (LPV) system.

5. Clustering for the Antecedent Identification

The previous section has showed how consequent part of the TS model can be identified by weighed least squares method when the antecedent membership functions (rule-weights) are given. The bottleneck of the identification of TS models is the data-driven identification of the antecedent part of the TS model that requires nonlinear optimization. Hence, for this purpose often heuristic approaches, like fuzzy clustering methods are applied. The objective of clustering is to partition the identification data Z in c clusters, where the available identification, Z=[ϑ , Y] formed from a regression data matrix ϑ and a regression vector Y, that they can be grouped of the following form Zk=[ϑ (k), Y(k+1)^T], where the k subscript denotes the *k*th row of the Z matrix. The clustering obtains the fuzzy partition of the Z data. The fuzzy partition is represented by the U = [$\mu_{i,k}$]$_{cxn}$ matrix, where $\mu_{i,k}$ element the degree of membership, how the $\mathbf{z}_k$ observation is in the cluster i= 1, …, c. Different cluster shapes can be obtained with different kinds of clustering algorithm based on different prototype, point or linear varieties (FCV) or with different distance measure. Mostly, the Gustafson-Kessel clustering algorithm is applied to identify TS models (Gustafson and Kessel,1979). A drawback of the this algorithm is that only clusters with equal volumes can be found and the resulted clusters cannot be directly used to form membership functions. The Gath and Geva clustering (GG) algorithm does not suffer from these problems. Gath and Geva interpret the data as normally distributed random variables and assume that the normal (Gaussian) distribution with expected value v_i and covariance matrix F_i is chosen for generating the datum with a priori probability $p(n_i)$ (Gath and Geva,1989). In (it has been shown how antecedent fuzzy sets and the corresponding consequent parameters of the antecedent space, linearly transformed input variables can be used in the model. This may, however, complicate the interpretation of the rules. To form an easily interpretable model that does not use the transformed input variables, o Gath-Geva clustering algorithm is modified, based on the Expectation Maximization (EM) identification of Gaussian mixture models (Abonyi, Babuska and Szeifert,2002). In this paper this technique is extended for the identification of MIMO fuzzy models that will be applied in the specific case of the incinerator, where each cluster contains an input distribution, a local model and an output distribution.

$$p(\vartheta, y) = \sum_{i=1}^{c} p(\vartheta, y, n_i) \ = p(y \mid \vartheta, n_i)\, p(\chi \mid n_i)\, p(n_i) \tag{13}$$

the input distribution is parameterized as an unconditional Gaussian (Abonyi, Babuska and Szeifert,2002) and defines the domain of influence of a cluster similarly to multivariate membership functions (6).

$$p(\chi \mid n_i) = \frac{\exp(-\frac{1}{2}(\chi - v_i)^T (F_i^x)^{-1}(\chi - v_i))}{(2\pi)^{\frac{n}{2}}\sqrt{|F_i^x|}} \tag{14}$$

while the output distribution is taken to be :

$$p(y \mid \chi, n_i) = \frac{\exp(-(y - \vartheta^* \Xi_i^T)^T (F_i^y)^{-1}(y - \vartheta^* \Xi_i^T))}{(2\pi)^{\frac{no}{2}}\sqrt{|F_i^y|}} \tag{15}$$

where the F^x and F^y covariance matrix are calculated as :

$$F_i^x = \frac{\sum_{k=1}^{N} (\chi_k - v_i)(\chi_k - v_i)^T\, p(n_i \mid \vartheta_k)}{\sum_{k=1}^{N} p(n_i \mid \vartheta_k)} \tag{16}$$

$$F_i^y = \frac{\sum_{k=1}^{N} (y_k - \vartheta_k^* \Xi_i^T)(y_k - \vartheta_k^* \Xi_i^T)^T\, p(n_i \mid z_k)}{\sum_{k=1}^{N} p(n_i \mid z_k)} \tag{17}$$

where ϑ^* = [ϑ , $I_{1x\,no}$] e ϑ^* = [ϑ , $I_{1x\,no}$].

The identification of the model means the determination of the parameters of the clusters. Bellow, the EM identification of the model is presented that is re-formulated in the form of Gath-Geva fuzzy clustering.

4.2 Clustering Algorithm

The clustering is based on the minimization of the sum of weighted squared distances between the data points, $\mathbf{z}_k$ and cluster prototypes, n_i.

$$J(Z,U,n)=\sum_{i=1}^{c}\sum_{k=1}^{N}(\mu_{i,k})D_{i,k}^{2}(z_k,n_i) \tag{18}$$

To get a fuzzy space, the membership values have to satisfy the following conditions:

$$U\in\Re^{cxN}\mid \mu_{i,k}\in[0,1],\forall_{i,k};\sum_{i=1}^{c}\mu_{i,k}=1,\forall_k;0<\sum_{k=1}^{N}\mu_{i,k}<N,\forall_i \tag{19}$$

The minimization of the (18) represents a non-linear optimization problem that is subject to constrain defined by (19) and can be solved by using a variety of available methods. The most popular method however is the alternating optimization (AO), which is formulated in (Abonyi, Babuska and Szeifert, 2002).

6. Identification of the Liquid Incineration

The identification of the liquid effluent incineration process will be made by the Takagi-Sugeno fuzzy model using the modified Gath-Geva clustering algorithm. This identification gets a model in real time of the process, being tuned its implementation, for example in a adaptive controller as viewed in section 3.

6.1 System Characteristics:

To get one better structure of TS fuzzy model of process, we verify some pertinent characteristics to the incineration system (Cunha, 2003), such as:

- System MIMO: Multiple input and multiple output (4 inputs and 3 outputs):

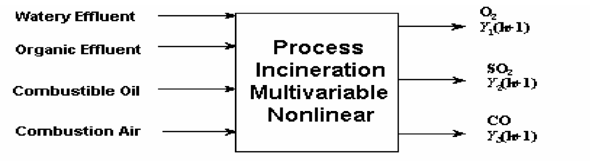

Figure 4 - System Incineration

- Correlation in the input variables: The four input variables are all correlated, the burning reason according to stoichiometric parameters is of 4kg of watery effluent for 1 kg of fuel (combustible oil + organic effluent) and 11,32 m^3/h of combustion air. All the inputs variables influence in the outputs variables.

- Correlation in the output variables: There are certain particularitities, such as:

▪ The output variable one, O_2 concentration, haven't correlation with the others two output variables, its value is given directly for the gas analyzer;

▪ The output variable two, SO_2 concentration is get by the calculation in Feema-RJ (State Foundation of Environment Engineering) resolution for SO_2 analysis SO_2 for dry base in 11% O_2:

$$SO_2 \text{ corrected concentration} = \frac{SO_2 \text{ analyzed}.(O_2 \text{ atmosphere - 11 \%})}{(O_2 \text{ atmosphere - } O_2 \text{ analyzed})} \tag{20}$$

where we can observe that output two is correlated with output one, therefore the calculation of the SO_2 concentration depends to the O_2 value;

▪ The output variable three, CO concentration is get by the calculation in Feema-RJ (State Foundation of Environment Engineering) resolution for analysis CO for dry base in 11% O_2:

$$CO \text{ corrected concentration} = \frac{CO \text{ analyzed}.(O_2 \text{ atmosphere - 11 \%})}{(O_2 \text{ atmosphere - } O_2 \text{ analyzed})} \tag{21}$$

where we can observe that output three is correlated with output one, therefore the calculation of the CO concentration depends to the O_2 value;

- **Gray-Box Model:** We have the knowledge of some characteristics of the process, where the parameters must be determined from the observed data.

6.2 Structure of TS Fuzzy Model:

Due to the characteristics in item 8.1, we can structuralize the Takagi-Sugeno fuzzy model in the form of MIMO structure as 3 connected MISO, where we verify the correlation among the data of the system. We search of this form to optimize the identification process. The multivariable fuzzy model follows described below for the figure (5):

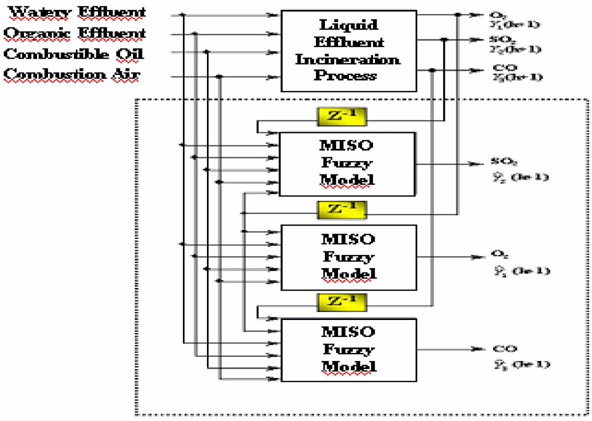

Figure 5 - MIMO Fuzzy Model

Knowing the structure of the system with 3 MISO (Multiple Input Simple Output) systems, that generate a MIMO system when connected. The fuzzy sets (the regions of operation of the local model) are defined in the domain of the outputs of the incinerator. For each system rule the following configuration is:

For Output 1 (O_2) : $\boldsymbol{R_i}$ **:** If $\mathbf{y_1}(k)$ *é* $\boldsymbol{A_i}$ then $\boldsymbol{y}_1^i(k+1) = \alpha_1^i \boldsymbol{y_1}(k) + \beta_1^i \boldsymbol{u}(k) + \gamma^i$ (22)

For Output 2 (SO_2) : $\boldsymbol{R_i}$ **:** If $\mathbf{y_2}(k)$ *é* $\boldsymbol{A_i}$ then $\boldsymbol{y}_2^i(k+1) = \alpha_2^i \boldsymbol{y_2}(k) + \beta_2^i \boldsymbol{u}(k) + \gamma^i$ (23)

For Output 3 (CO) : $\boldsymbol{R_i}$ **:** If $\mathbf{y_3}(k)$ *é* $\boldsymbol{A_i}$ then $\boldsymbol{y}_3^i(k+1) = \alpha_3^i \boldsymbol{y_3}(k) + \beta_3^i \boldsymbol{u}(k) + \gamma^i$ (24)

In this example, the number of rules was determined manually. However the identification of the numbers of the rules is an important challenge. The algorithm considered by Gath and Geva (Gath and Geva, 2003) the application of cluster validity measures like fuzzy hypervolume and density, can be applied for this purpose.

7. Experimentation and Results

The system identification using TS MIMO fuzzy model, with the modified GG algorithm, was realized. For the modeling stage of the parameters, 6000 samples (6000 minutes of incineration process operation) are collected for experiment, to get the model of the process. For the validation stage of the model, others 6000 samples were used. Two criteria had been used for the validation of the fuzzy models:

-VAF : (*Variance Accounted For*)

$$\textbf{VAF}\ (\%) = 100 \times \left[1 - \frac{\operatorname{var}(Y - \hat{Y})}{\operatorname{var}(Y)}\right] \tag{25}$$

where Y is the nominal output of the incineration process, $\hat{Y}$ is the estimate output of the model and *var* is the variance of the signal. How much is lesser the difference between the real output and the estimate output, the VAF value approaches to 100%.

-MSE(*Mean Square Error*)

$$\textbf{MSE} = \frac{1}{N}\sum_{K=1}^{N}(Y_k - \hat{Y}_k)^2 \tag{26}$$

where Y_k is the nominal output of the incineration process, $\hat{Y}_k$ is the estimate output of the model and N is the number of points. How much lesser the difference between the real output and the estimate output, the MSE value approaches to zero. A comparative analysis is established between modified Gath-Geva algorithm (Modif. GG) and the Gustafson-Kessel (GK) algorithm. The table (2), presents the efficiency of the fuzzy clustering algorithms that had been used in the liquid incineration system identification process for each output variable:

	VAF(%)	MSE		VAF(%)	MSE		VAF(%)	MSE
Output 1 (O_2)			**Output 2 (SO_2)**			**Output 3 (CO)**		
GK	97.51	0.33	GK	96.48	0.45	GK	95.51	0.52
Modif. GG	98.9	0.28	Modif. GG	98.64	0.31	Modif. GG	98.83	0.39

Table 1- Efficiency of the clustering algorithms

In table (2), we can observe that modified Gath-Geva algorithm had a better performance that the Gustafson-Kessel algorithm. A comparative between the real outputs and the estimate output for the TS fuzzy model by modified Gath-Geva algorithm, is showed in figures 6, 7 and 8:

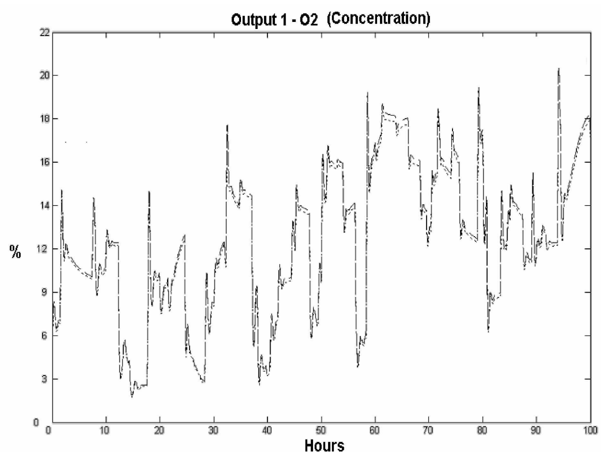

Figure 6 – Measured(-) and predicted(--)process outputs

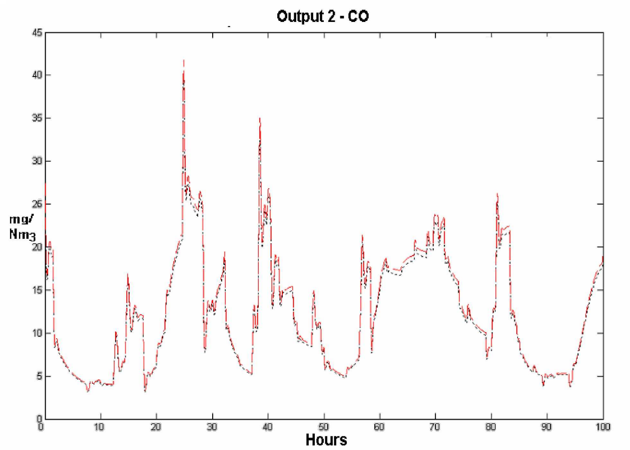

Figure 7 – Measured(-) and predicted(--)process outputs

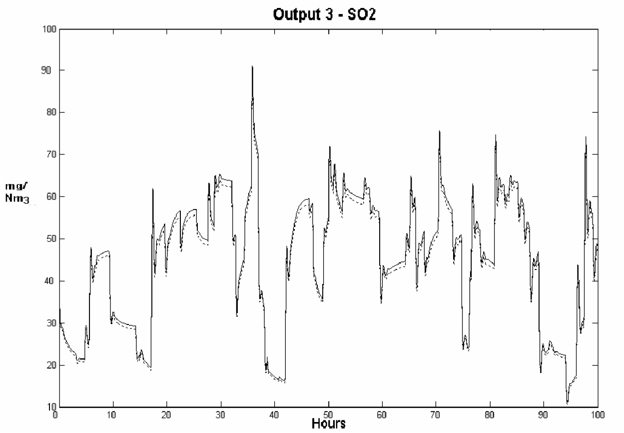

Figure 8 – Measured(-) and predicted(--)process outputs

8. Conclusions

In this paper the identification of nonlinear multiple input multiple output is discussed. A fuzzy model structure has been proposed, where the liquids effluents incineration process in the BASF industry, is represented by a MIMO fuzzy model that consists of local linear MIMO ARX models. The antecedent part of TS model was identified by modified Gath-Geva algorithm. For future works, the development of a adaptive controller for the combustion system using obtained model of the incineration process makes necessary.

9. References

Abonyi, J. and Babuska, R.,2002, "Modified Gath-Geva fuzzy clustering for identification of Takagi-Sugeno fuzzy models". IEEE Transactions on Systems, Man and Cybernetics, Part B: 32:612-621.

Abonyi, J. and Szeifert, F.,2001, "Identification of MIMO Process by Fuzzy Clustering". IEEE International Conference on Intelligent Systems, Finland.

Almeida, F.M. and BARRETO, G.,2004, "Liquid Effluent Incineration : Contribution for its Modeling and Identification". IEEE Sixth International Conference on Industrial Applications – VI INDUSCON, October 12-15 Outubro, Joinville-Brazil.

Cunha, J.R.,2003, "Operation Handbook of the Effluents Incinerator". Rev.06, UTL-001, BASF.

Gath, G. and Geva, A.B.,1989, "Unsupervised optimal fuzzy clustering". IEEE Transactions on Pattern analysis and Machine Intelligence,7:773-781.

Gustafson, D.E. and Kessel, W.C.,1979, "Fuzzy clustering with fuzzy covariance matrix". In Proceedings of the IEEE CDC, San Diego, pages: 761-766.

Hellendoorn, H. , Driankov, D. and Reifrrank, M.,1996, "An Introduction to Fuzzy Control". Springer.

Honeywell.,1998, "Technician Handbook of the Distributed Control System". MT-04, BASF.

Takagi, T. and Sugeno, M.,1985 "Fuzzy identification of systems and its application to modeling and control". IEEE Transactions on Systems, Man and Cybernetics, 15(1):116-132.