# NEUROFUZZY MODEL OF AN INDUSTRIAL PROCESS, REDUCING COMPLEXITY BY USING PRINCIPAL COMPONENT ANALYSIS

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## Abstract

A Neurofuzzy model of a mixing chamber pressure has been proposed. The process is a part of a copper smelter plant. The principal component analysis (PCA) method has been used to reduce the inputs space for a recurrent fuzzy model. The coupling among variables and their mutual influence between themselves, are taken into account by the projection into the PCA axis. The model have been validated with real data from the factory. The validation result shows that the model is suitable for simulation.

**Keywords:** Neurofuzzy modeling, Industrial process, Principal Component Analysis.

Figure 1: General view of the copper smelter [1]

## 1 Introduction

The process studied in this work is a part of Atlantic Copper Smelter facilities in Huelva (Spain), whose anual production is around three hundred thousand tons of copper [1]. This plant includes a Flash Furnace and four Pierce-Smith converters, two of them blowing simultaneously. The three currents of gases generated in these processes are mixed in the mixing chamber and sent to three acid plants operating in parallel (see figure 2). It is very important to maintain the gas pressure in the mixing chamber at a desired value, always bellow ambient pressure in order to avoid gas losses to the atmosphere. That pressure depends on other variables of the production line and it is very difficult to get an accurate prediction of it. On the one hand, the causes of the pressure oscillations are hard to detect. Moreover, due that there are different control system in the copper smelter and the acid plant, no clocks synchronization is possible, so there are considerable uncertainties when trying to measure cause-effect delays. A suitable model for prediction one step ahead, has been developed in [1]. Other models have been made in [5] and [6]. All of them are prediction models, because the actual pressure value at time k $P_{MC}(k)$ is used to predict $P_{MC}(k+1)$. Taking into account that the converters operate on a batch mode, while those of the flash furnace and acid plants are continuous, extremely high disturbances both in flow and $SO_2$ concentration occur at the acid plants inlet due to the converters' operating schedule. The existing control strategy, based on independent single loop PID controllers, is not able to cope with those disturbances [1]. Advanced control schemes should be applied, but it would be interesting to have a model suitable for simulation. In this case, it is difficult to derive a precise mathematical model, based on first principles. Besides, the computation of the solution of models obtained through this methodology may require a large computational effort making them useless for real time tasks like control or optimization. Neurofuzzy modeling, which permits an easy way to derive successful models, is a good alternative which can be employed to overcome such limitations [2],[3],[7] and [9]. Fuzzy Neural Networks (FNN) combine the capability of uncertainty handling in information with learning skill. Recurrent Fuzzy Neural Network (RFNN) have proven to be an excellent choice in order to

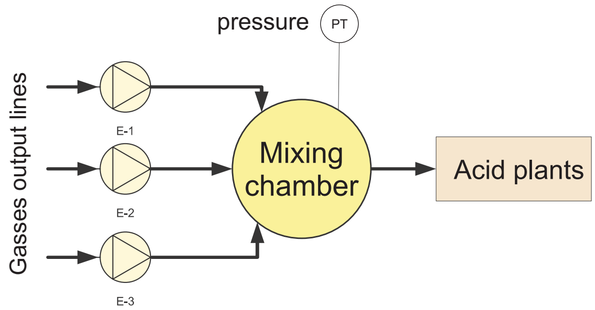


Figure 2: gas mixing. Acid plants

get the dynamics of nonlinear and complex systems. They are systems which have the same advantages than recurrent neural networks [10]. RFNN are also known as *Fuzzy Dynamical Systems* (see figure 3) and extend the application domain of FNN to temporal problems. Feedback allows to capture dynamics and change. Principal Component Anal-

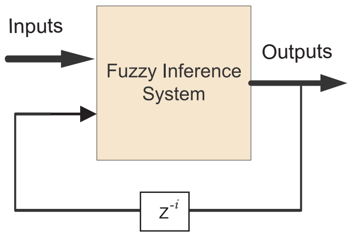


Figure 3: Dynamical Neurofuzzy System

ysis is a well know technique in the field of multivariate methods [8]. The use of PCA reduces the space of input variables and obtain new uncorrelated variables in order to simplify the Fuzzy system. This paper is organized as follows. In section 2, a formulation for dynamic neurofuzzy model is shown. An introduction to Principal Components Analysis is given in section 3. In section 4, the neurofuzzy model for the mixing chamber pressure is presented, giving the validation results. Conclusions are given in section 5.

## 2 Dynamic Neurofuzzy Model formulation

In the neurofuzzy model proposed by Takagi-Sugeno (TS)[12], the structure of antecedent describes fuzzy regions in the inputs space, and the one of consequent presents non-fuzzy functions of the model inputs. We can use recurrent functions with NARMAX structure (*Nonlinear Auto Regressive Moving Average with eXogenous input*), of the kind:

$$\hat{y}(k+1) = f(y(k),...,y(k-m),u(k),...,u(k-n)) \quad (1)$$

Where $u, y$ are respectively the inputs and outputs of the system, the Neurofuzzy system may be described, for each rule, in the following way:

$R_j$ :
IF $x_1$ is $F_{1j}, \ldots,$ and $x_n$ is $F_{nj}$,
THEN:

$$y_j = g_{j1}x_1 + g_{j2}x_2 + \ldots + g_{jn}x_n + c_j \quad (2)$$

Where $g_{ji}$ and $c_j$ are constant terms, $X = \begin{bmatrix} x_1 & x_2 & \ldots & x_n \end{bmatrix}^T$ is the input vector of the neuro-fuzzy system, $F_{ij}$ is the fuzzy set respective to $x_i$ on the rule $j$, $y_j$ is the output of the model respective to the operating region associated to the rule. $x_i$ can represent a real input to the system or any other variable, for instance the previous values of inputs or outputs. Thus, we could formulate the consequent (2) like

$$y_j(k) = a_j(z^{-1})y(k-1) + b_j(z^{-1})u(k-d) + c_j \quad (3)$$

Where $a_j(z^{-1}) = a_{1j} + a_{2j}z^{-1} + \ldots + a_{n_y j}z^{-(n_y-1)}$ and $b_j(z^{-1}) = b_{0j} + b_{1j}z^{-1} + b_{2j}z^{-2} + \ldots + b_{n_u j}z^{-n_u}$

$d$ is the dead time. If $\mu_{ij}(k)$ is the membership degree of $x_j(k)$ in the fuzzy set $F_{ij}$ and the number of implications or rules is $L$, the RFNN complete model is described by

$$y(k) = \sum_{j=1}^{L} w_j(k)\left[a_j(z^{-1})y(k-1) + b_j(z^{-1})u(k-d)\right] + \xi(k) \quad (4)$$

Where

$$w_j(k) = \frac{\bar{\mu}_j(k)}{\sum_{j=1}^{L}\bar{\mu}_j(k)}, \qquad \bar{\mu}_j(k) = \prod_{i=1}^{n}\mu_{ij}(k)$$

and

$$\xi(k) = \sum_{j=1}^{L} w_j(k)c_j$$

Rewriting equation (4) as

$$\bar{a}(z^{-1})y(k) = \bar{b}(z^{-1})u(k-d) + \xi(k) \quad (5)$$

Where

$$\bar{a}(z^{-1}) = 1 - \bar{a}_1 z^{-1} - \bar{a}_2 z^{-2} - \ldots - \bar{a}_{n_y} z^{-n_y} \quad (6)$$

$$\bar{b}(z^{-1}) = 1 - \bar{b}_1 z^{-1} - \bar{b}_2 z^{-2} - \ldots - \bar{b}_{n_u} z^{-n_u} \quad (7)$$

$$\bar{a}_i = \sum_{j=1}^{L} w_j(k)a_{ij}z^{-i} \quad (8)$$

$$\bar{b}_i = \sum_{j=1}^{L} w_j(k)b_{ij}z^{-i} \quad (9)$$

In [4] a dynamic Neurofuzzy Model is used for simulation. We propose an improvement of that model, using a major number of inputs, including squares of variables, to provide also a non linear dependence for each rule. A PCA has been used both in a model used in [4] as the one proposed here. In the first, the analysis is directed just to get uncorrelated variables, in the second also much more simplification is achieved in the FIS.

## 3 Principal Components Analysis

Due to coupling between variables and the difficulty to make experimental tests, the use of PCA provides two characteristics: to achieve new uncorrelated variables and condensation of all the information in a smaller space, providing a simpler *Adaptive Neural Fuzzy Model* (ANFIS). It will permit the addition of others input variables, without complexity increasing. The aim of PCA is to reduce system dimension, minimizing missing information. The idea behind PCA is to form a minimum number of new variables to describe the variation of the original data by using linear combinations of the original variables.

Let $\alpha$ be a vector of $p$ variables, $\alpha = \begin{bmatrix} \alpha_1 & \alpha_2 & \ldots & \alpha_p \end{bmatrix}$

And $A \in \mathbb{R}^{n\times p}$ a data matrix generated by the $p$ variables, where $n$ is the number of data. The aim of PCA is to find a base $\delta = \begin{bmatrix} \delta_1 & \delta_2 & \ldots & \delta_k \end{bmatrix}$ where $k < p$, which defines a new subspace retaining the maximum information of the original data.

$$\begin{gathered}\delta_1 = w_{11}\alpha_1 + w_{12}\alpha_2 \ldots + w_{1p}\alpha_p \\ \delta_2 = w_{21}\alpha_1 + w_{22}\alpha_2 \ldots + w_{2p}\alpha_p \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ \delta_k = w_{k1}\alpha_1 + w_{k2}\alpha_2 \ldots + w_{kp}\alpha_p\end{gathered}$$

Then the data matrix will be $D \in \mathbb{R}^{n\times k}$.
It is demonstrated that

$$\mu_D = E(D) = E(W^T A) = W^T E(A) \tag{10}$$

And the covariance matrix of $D$ is equal to

$$\Sigma_D = E\{(D-\mu_D)(D-\mu_D)^T\} = W^T \Sigma_A W \tag{11}$$

The goal is to get the maximum data variance in the new axes, that is maximum $\Sigma_D$, imposing the orthonormality constraint on it:

$$W^T W = I \tag{12}$$

We have to maximize:

$$W^T \Sigma_A W - \lambda(W^T W - I) \tag{13}$$

deriving and making it equal to zero, we have

$$(\Sigma_A - \lambda I)W = 0 \tag{14}$$

The problem is just one of calculation of eigenvectors of $\Sigma_A$. The associated components to greater eigenvalues of $\Sigma_A$ are the most meaningful to build the data space. They are named *Principal Components* of the system. In order to choose how many principal components to use, a criterium based on the weight of each eigenvalue with respect to the other, can be used:

$$\frac{\sum_{i=1}^{l} \lambda_i}{\sum_{i=1}^{n} \lambda_i} \geq n \tag{15}$$

being $n$ a measurement of desired information.

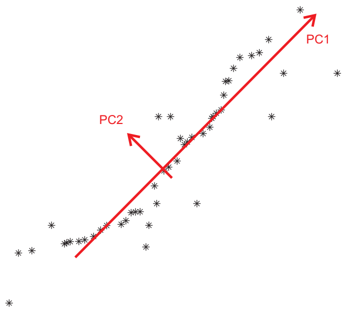


Figure 4: Principal Components

Table 1: List of variables

| *Description* | *Units* | *Type* |
|---|---|---|
| Pressure in mixing chamber | mbar | Output |
| Flow to plant 1 | KN$m^3$/h | Manipulated |
| Flow to plant 2 | KN$m^3$/h | Manipulated |
| Flow to plant 3 | KN$m^3$/h | Manipulated |
| Dilution flow to plant 1 | N$m^3$/h | Manipulated |
| Dilution flow to plant 2 | N$m^3$/h | Manipulated |
| Dilution flow to plant 3 | N$m^3$/h | Manipulated |
| Reference for flash furnace feeding | Tons/h | Disturbance |
| Flow control valve for flash furnace | % | Disturbance |
| Fan speed in flash furnace | rmp | Disturbance |
| Reference for fan speed line 1 | rpm | Disturbance |
| Reference for fan speed line 2 | rpm | Disturbance |

## 4 Neurofuzzy Model of Mixing Chamber

After a preliminary study based on some experiments with steps on the variables[1], the evolution of the pressure in the mixing chamber ($P_{MC}$), is influenced by others that are divided into two groups: control signals and disturbances. In table 1 a brief description of the considered variables is given, whereas in figure 5 a scheme with the situation of each of them is presented.

In [4], the inputs are the current samples of the variables of Table 1 and the previous samples of them, forming a

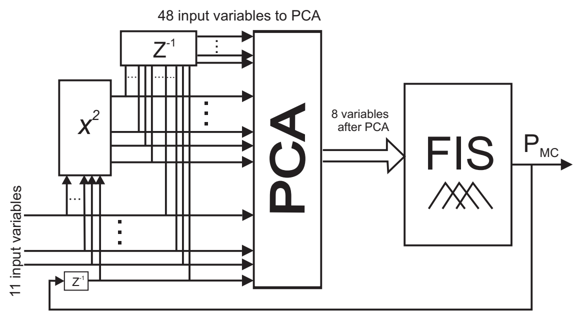


Figure 6: Neurofuzzy scheme proposed

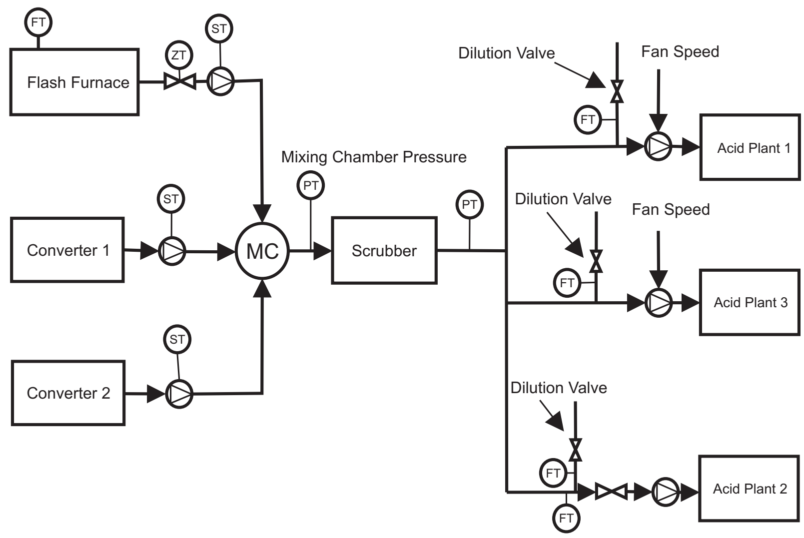


Figure 5: Process, manipulated variables and disturbances

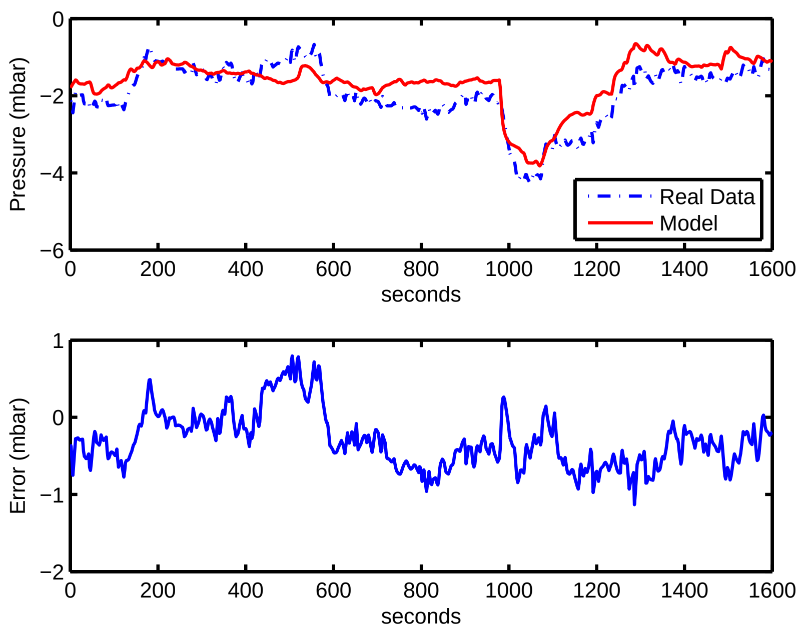


Figure 7: Validation of the model used in [4]

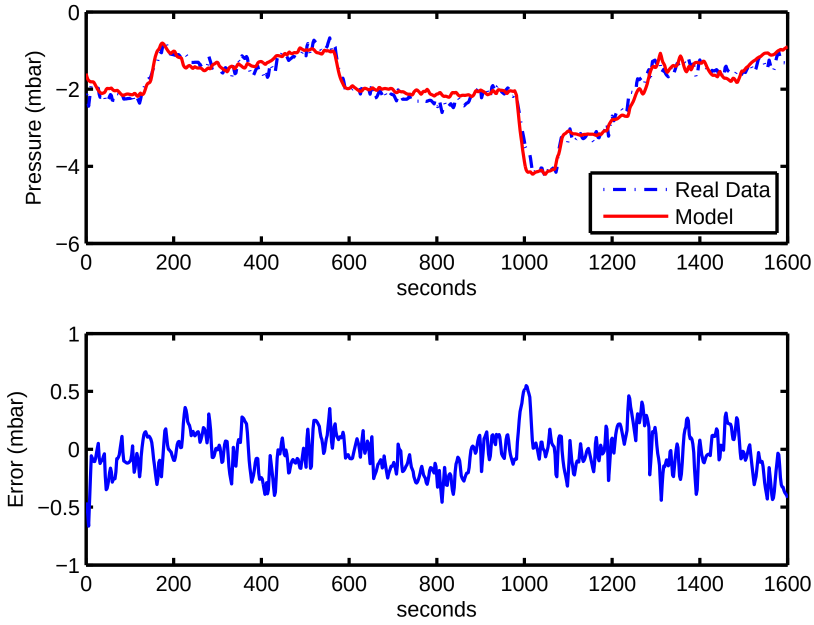


Figure 8: Validation of the proposed model

number of 24 inputs. After a PCA using all the nonzero eigenvalues, 21 components are obtained. As mentioned at the end of the introduction, the addition of entries does not complicate the model when using PCA. For this work, we have taken into account the input variables listed in Table 1 and their squares, to give to the model, quadratic elements of the input variables of the system. Figure 6 presents the scheme followed to obtain the neurofuzzy model. The inputs are the variables presented in table 1, including Pressure in mixing chamber, their squares and the previous samples of all of them. To carry out the PCA, data have been used for nearly three hours of operation, sampled every 2 seconds. With a loss of information from 1%, the new principal components are 7. Using these new uncorrelated variables as inputs to the fuzzy system, and the next sampling pressure as output, an ANFIS is designed, using Subtractive clustering technique [3]. The performance of the models can be seen in figures 7 and 8, where it is validated using a real data set from the process. It is important to note that $P_{MC}(t-1)$ is generated by the models output in the previous sampling. Looking at the figures we see that the error does not grow indefinitely, this fact makes the models, appropriate to simulate the process. In figure 7, the mean error is $0.4099°C$, while the new model proposed in this work, the mean error is $0.1469°C$, obtaining an improvement.

## 5 Conclusions

A Neurofuzzy model, suitable for simulation, of a mixing chamber pressure has been designed. The PCA method has been used to reduce the inputs space for a recurrent fuzzy model. Using this technique, a previous increment of input has been added, including quadratic elements and previous samplings. The coupling among variables and their mutual influence between themselves is taken into account by the projection into the PCA axis. The model have been validated with real data from the factory. The validation result shows that the model is suitable for simulation. In comparison with other simulation models of the same plant, an improvement has been got.

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