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Detection of No-Model Input/Output Combinations in a Fluid Catalytic Cracking Unit

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Abstract: A method is proposed to detect if there is no coupling between an input and an output in systems operating in open-loop. The proposed technique is applicable to multiple input multiple output (MIMO) systems, i.e., the intent is to detect zeros in a transfer matrix. Traditional approaches to input/output (IO) selection are usually performed after the plant model is identified. The proposed approach is applied during the pre-identification stage and it is based on cross-correlation and fuzzy logic analysis. A study case involving identification of a 20×10 real system is discussed, as well as the advantages of detecting no-model IO pairs in the identification process.

Keywords: Zeros in the transfer matrix, Systems identification, Multivariable identification, Cross-correlation analysis, Fuzzy logic, Fluid Catalytic Cracking Unit.

1. INTRODUCTION

Advanced controllers use models to describe the relationships among the system variables. The objective of this controller is to determine the control signals (inputs) that will make a process to satisfy physical constraints and at the same time minimize (or maximize) its performance index. The performance of such control structures relies, mainly, on the accuracy of these models. Thus, the choice of the plant model is an important part of the strategy of the Control System Design. It involves six stages: definition of control objectives, derivation of a nominal model G_0, control structure design, controller design, control system evaluation and tuning, and finally, control implementation (Van der Wal and de Jager, 2001).

The objective of the estimation of the models is to obtain mathematical expressions that are able to predict the response of the physical system to all inputs. In practice, even around an operating point, it is impossible to propose a linear model that exactly matches the real system. So, any model has errors. Process models are usually based on a statistical model whose building consists of the iteration of the next steps: Identification, Fitting and Diagnostic Checking (Box and MacGregor, 1974).

To reduce the number of iterations, a pre-identification stage is usually applied, in which the process is excited by pulses or steps. Notice that it is a signal with excitation persistence of order one, so that the models obtained are not adequate for control purposes. Its objective is to provide preliminary features of the system, like steady-state gain, settling time, time delay and IO combination analysis.

Generally, issues related to IO selection are part of the Control Structure Design stage, after the plant model has been estimated. IO selection is described as the procedure of selecting suitable variables u to be manipulated by the controller (plant inputs) and suitable variables y to be supplied to the controller (plant outputs). This approach can lead to model-plant mismatch and poor controller performance, since models can be identified in IO pairs where a relation does not exist (IO pairs with no-model). An extensive survey of methods for IO selection can be found in Van der Wal and de Jager (2001).

In this paper, a method to detect no-model IO combinations for open-loop MIMO systems is proposed. The main contributions of this work are the integration of cross-correlation analysis, filtering of the IO signals and an inference based on fuzzy logic and its application during the pre-identification step. Although this method could also be applied during the identification step, it provides important advantages if performed previously. No-model IO combination knowledge can reduce experiment time in an identification, decrease model parameter variance, improve the accuracy of the remaining models in the transfer matrix and provide a matrix that informs about

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the existence or not of relations (models) between the IO pairs. These issues are addressed along this paper.

2. IO MODEL SELECTION METHODS

There are many papers that address the issue of the no-model IO combination. The most common methods used for this purpose are based on the controllability of the model. Methods based on controllability of inputs and outputs seek to determine which candidate sets of inputs and outputs will be eliminated or kept, based on a quantitative measure of this controllability. Some of these methods are based on the singular value decomposition. The methods based on the minimum singular value select candidate sets of inputs and outputs that maximize the smallest singular value in defined frequencies. Some methods that use or support this approach were proposed in Tzouanas et al. (1990), Havre et al. (1996) and Skogestad and Postlethwaite (1996). Some derivations of these methods are presented next.

2.1 Single-Input Effectiveness

The Single-Input Effectiveness (SIE) method (Cao and Rossiter, 1997) select inputs to be included in a control scheme. It considers $\mathbf{G}(s)$ as a $m \times n$ matrix, representing an open-loop MIMO linear system with frequency response matrix $\mathbf{G}(j\omega)$ and steady-state gain matrix $\mathbf{K}$. The output vector $\mathbf{y}$ is derived as

$$\mathbf{y} = \mathbf{K}\mathbf{u} \tag{1}$$

where

$$\mathbf{u} = \mathbf{u}_n + \mathbf{u}_c \tag{2}$$

is an input vector of dimension $n \times 1$. Note that $\mathbf{u}_n \in \mathbf{K}_0$ and $\mathbf{u}_c \in \mathbf{K}_0^{\perp}$ where $\mathbf{K}_0$ is the null space of $\mathbf{K}$ and $\mathbf{K}_0^{\perp}$ is the orthogonal complement of $\mathbf{K}_0$. Using (2), the output vector can be calculated as:

$$\mathbf{y} = \mathbf{K}\mathbf{u} = \mathbf{K}\mathbf{u}_n + \mathbf{K}\mathbf{u}_c = \mathbf{K}\mathbf{u}_c \tag{3}$$

It shows that only the orthogonal projection $\mathbf{u}_c$ of $\mathbf{u}$ affects the output. The following indices are proposed in Cao and Rossiter (1997). A ratio of the norms of $\mathbf{u}_c$ and $\mathbf{u}$ is defined to describe the effectiveness of an input vector (IE):

$$\eta = \frac{\|\mathbf{u}_c\|_2}{\|\mathbf{u}\|_2} \tag{4}$$

The input ineffectiveness (IIE) of $\mathbf{u}$, ζ, is defined as the ratio of the norms of $\mathbf{u}_n$ and $\mathbf{u}$:

$$\zeta = \frac{\|\mathbf{u}_n\|_2}{\|\mathbf{u}\|_2} \tag{5}$$

Single-IE (SIE), η_j, for the j-th input vector $\mathbf{u}_j$ can be computed considering a vector $\mathbf{e}_j$ defined as the j-th column of the $n \times n$ identity matrix.

$$\eta_j = \|\mathbf{K}^{+}\mathbf{K}\mathbf{e}_j\|_2, \qquad 0 \le \eta_j \le 1 \tag{6}$$

where $\mathbf{K}^{+}$ is the pseudo or generalized inverse of $\mathbf{K}$. Single-IIE, ζ_j, for the j-th input vector $\mathbf{u}_j$ is obtained as:

$$\zeta_j = \sqrt{1 - \eta_j^2}, \qquad 0 \le \zeta_j \le 1 \tag{7}$$

The process transfer matrix $\mathbf{G}(s)$ can also be represented by a set of linear MISO systems. From them, values of η_j near 0 mean low effectiveness of the j-th input over the output $\mathbf{y}$. In the same way, values near 1 indicate significant effectiveness of the j-th input over the output $\mathbf{y}$. This criterion is employed to include or exclude inputs in a control scheme for the system represented by $\mathbf{G}(s)$. Furthermore, values of η_j and consequently ζ_j, can also be derived using Singular Value Decomposition (SVD), since $\mathbf{K}$ can be factorized as:

$$\mathbf{K} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^{H} \tag{8}$$

where $\mathbf{U}$ is a $m \times m$ real or complex unitary matrix, $\mathbf{\Sigma}$ is a $m \times n$ rectangular diagonal matrix with nonnegative real numbers in the diagonal and $\mathbf{V}^{H}$ is the conjugate transpose of $\mathbf{V}$, which is a $n \times n$ real or complex unitary matrix. Then, η_j can be obtained as:

$$\eta_j = \|\mathbf{K}^{+}\mathbf{K}\mathbf{e}_j\|_2 = \sqrt{\mathbf{e}_j^T\mathbf{V}_1\mathbf{V}_1^H\mathbf{e}_j} \tag{9}$$

where $\mathbf{V}_1$ is the first k columns of $\mathbf{V}$, being k the rank of $\mathbf{K}$. Thus, using SVD could yield the same estimate of effectiveness, η_j, for every j-th input over an output $\mathbf{y}$ of $\mathbf{K}$. In a similar manner, in Perreault et al. (2005) was proposed the Principal Component Analysis (PCA) that uses the SVD to factorize the $\mathbf{K}$ matrix. It allows to identify relevant inputs and represents them in a new axis system. Based on this algorithm, a tool for selecting optimal inputs to be used in an identification process of a linear MISO plant was developed.

2.2 Relative Gain Array

Similar to PCA, the Relative Gain Array (RGA) was first introduced by Bristol (1966) for steady-state as a measure of process interactions. Skogestad and Morari (1987) established that RGA is mostly a measure of achievable control quality in a much wider sense, more than just a tool for choosing pairs.

RGA is a normalized gain matrix that describes the impact of each control variable in each output. The normalization of these gains is based on the potential impact of each pair of input and output. The RGA method can be defined as:

$$RGA = \wedge = \mathbf{K} \times (\mathbf{K}^{+})^{\mathbf{T}} \tag{10}$$

More conceptually, $\wedge$ can be understood as:

$$RGA = \wedge = [\lambda_{ij}]_{mxm} \tag{11}$$

where λ_{ij} is the ratio of k_{ij}, gain of the $i-j$-th element of $\mathbf{K}$ with all the loops open and k_{ij}^{*}, gain of the $i-j$-th element of $\mathbf{K}$ with only the j-th loop open, see (12).

$$\lambda_{ij} = \frac{k_{ij}}{k_{ij}^{*}} \tag{12}$$

In Skogestad and Morari (1987), $\wedge$ is employed for steady-state and the equivalence between λ_{ij} and η_j^2 was proved in Cao and Rossiter (1997).

There are two ways to calculate the RGA, the first is an experimental form and the second is by the stationary gain matrix of the process.

The work by Chang and Yu (1990) showed that it is possible to use the sum of the rows of the matrix elements for selection of the outputs to be used. In Cao (1996) the authors extended this analysis to use the sum of the columns of the matrix for selection of entries to be used. In both cases, if the sum is much smaller than the index under examination (input or output), it should be disregarded.

2.3 Cross-correlation

Another important approach to solve this problem is to apply the Cross-correlation function. This technique detects and measures significant associations between an output, y_i, and an input signal, u_j.

Some limitations of cross-correlation methods to detect input/output effects in closed-loop were stated in (Box and MacGregor, 1974). However, good results can be obtained if the input signal is dithered. In Webber and Gupta (2008), a closed-loop cross-correlation method is employed for detecting model-plant mismatch in MIMO model-based controllers. In this proposal, IO subset pairings of a linear MIMO system which demand re-identification are detected. The method is based on the comparison of the correlation between the prediction error and input $\mathbf{u}$. A dithering in the set point $\mathbf{u}$ is required to use this signal as excitation. In this sense, the cross-correlation function had already been employed in Aguirre (2007) and Ljung (1999) to detect and measure significant associations between an output and an input signal, but never as a tool to detect IO combinations in the pre-identification stage.

3. THE PROPOSED METHOD OF DETECTION OF ZEROS IN THE TRANSFER MATRIX

Different of the presented methods, the one proposed here is focused on obtaining a preliminary information about the IO combination in the pre-identification stage. It is based on the cross-correlation analysis for MIMO $m \times n$ systems. The algorithm is based on three steps and its name is Fuzzy Inference based on Filtered Cross-correlation (FIFC).

3.1 Step 1

Consider a MIMO system described by:

$$\mathbf{y}(t) = \mathbf{G}(q)\mathbf{u}(t) + \upsilon(t) \tag{13}$$

where $\mathbf{G}(q)$ is a $m \times n$ transfer matrix representing the process model, $\mathbf{u}$ is a $n \times 1$ input vector and $\mathbf{y}$ and υ are $m \times 1$ output and disturbance vectors, respectively.

In this work the MIMO model is divided into m MISO models as follows:

$$y_i(t) = \mathbf{G}_i(q)\mathbf{u}(t) + \upsilon_i(t) \tag{14}$$

where $\mathbf{G}_i$ is the i-th row of $\mathbf{G}$ for $i = 1 \ldots m$. The first step of the method consists in determining directly the linear correlation between the input and output signals used in the pre-identification stage. Herein the cross-correlation used is the Pearson product-moment correlation coefficient, or simply Pearson's correlation defined by:

$$\rho^{(1)}_{yu}(i,j) = \texttt{corr}(y_i, u_j) = \frac{R^N_{y_i u_j}(\tau)}{\sigma_{y_i}\sigma_{u_j}} \tag{15}$$

where σ_{y_i} and σ_{u_j} are the standard deviations of the signals y_i and u_j, respectively and $R^N_{y_i u_j}$ is the covariance of the signals y_i and u_j, each one composed of N points. This correlation is exact when signals y_i and u_j are orthogonal.

3.2 Step 2

As the signals are usually subject to disturbances and measurement noise, another computation is required. This step consists in a preliminary estimation of the model. For this, consider that a SISO system:

$$y_i(t) = G_{ij}(q)u_j(t) + \upsilon_i(t) \tag{16}$$

could be described by:

$$y_i(t) = \sum_{k=1}^{\infty} g_{ij}(k)u_j(t-k) + \upsilon_i(t) \tag{17}$$

where $g_{ij}(k)$ are the impulse response parameters of G_{ij}. If the input is subject to a quasi-stationary sequence with:

$$\bar{E}u_j(t)u_j(t-\tau) = R_{u_j}(\tau) \tag{18}$$

and

$$\bar{E}u_j(t)\upsilon_i(t-\tau) \equiv 0 \tag{19}$$

where (19) is valid only for open-loop systems, then in accordance with the Theorem 2.2 of Ljung (1999),

$$\bar{E}y_i(t)u_j(t-\tau) = R_{y_i u_j}(\tau) = \sum_{k=1}^{\infty} g_{ij}(k)R_{u_j}(k-\tau). \tag{20}$$

It can be demonstrated that if the input is not white noise, it is possible to estimate the covariance and cross-covariance as:

$$\hat{R}^N_{u_j}(\tau) = \frac{1}{N}\sum_{t=\tau}^{N} u_j(t)u_j(t-\tau) \tag{21}$$

and solve

$$\hat{R}^N_{y_i u_j}(\tau) = \sum_{k=1}^{M} \hat{g}_{ij}(k)\hat{R}^N_{u_j}(k-\tau) \tag{22}$$

for $\hat{g_{ij}}(k)$. Thus, a good estimate of $g_{ij}(k)$ when the input is not white noise is to truncate (17) at p and treat it as a p-order Finite Impulse Response (FIR) model (Ljung, 1999).

In open-loop, the bias errors in the deterministic part of the model can generally be minimized by using high order FIR models, where its order is set equal to the settling time of the process, which can be estimated in the pre-identification stage. Then, with the input signals filtered by the high order FIR, it is calculated again the linear correlation, but now between the input signal and the estimated output.

$$\rho^{(2)}(i,j) = \texttt{corr}(\hat{y}_i, u_j) = \frac{\hat{R}^N_{\hat{y}_i u_j}(\tau)}{\sigma_{\hat{y}_i}\sigma_{u_j}} \tag{23}$$

The objetive of this procedure is to obtain a filtered estimate of the linear correlation matrix.

To evaluate the performance of the MISO model obtained by the FIR structure, the index FIT was employed. This index is based on the difference between the real and the estimated outputs and may be expressed by the equation:

$$\text{FIT}_i = 1 - \frac{\sqrt{\sum_{t=0}^{N}\left(\hat{y}_i(t) - y_i(t)\right)^2}}{\sqrt{\sum_{t=0}^{N}\left(y_i(t) - \bar{y}_i(t)\right)^2}} \tag{24}$$

where $\bar{y}_i(t)$ is the mean of $y_i(t)$.

3.3 Step 3

The third step consists in analyzing the outcomes obtained by the correlations of the steps 1 and 2. It was used a fuzzy

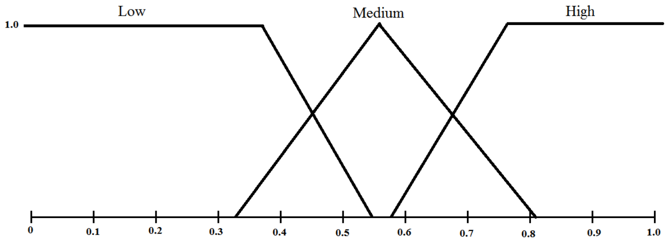

Fig. 1. Universe of discourse for input correlation in step 1 ($\rho^{(1)}(i,j)$).

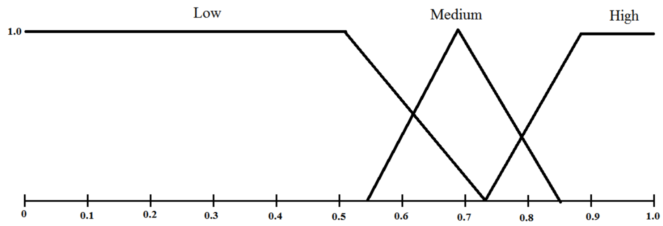

Fig. 2. Universe of discourse for input correlation in step 2 ($\rho^{(2)}(i,j)$).

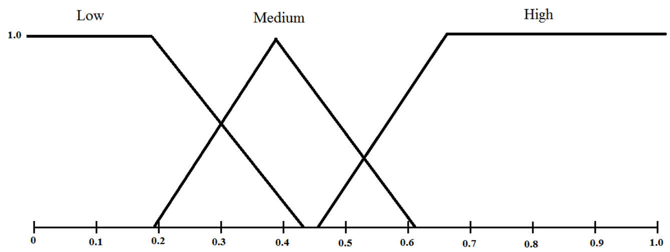

Fig. 3. Universe of discourse for the FIT index of the FIR model.

inference machine as an expert system for taking decisions. It was designed by following the standard procedure of fuzzy controller design, which consists of fuzzification, control rule base establishment and defuzzification.

The fuzzification is a mapping from the crisp domain into the fuzzy domain. In others words, it means to assign linguistic values, defined by a small number of membership functions to each input variable. Three membership functions were used for each universe of discourse (two trapezoidal and one triangular) named Low, Medium and High. In addition to correlations $\rho^{(1)}(i,j)$ and $\rho^{(2)}(i,j)$, a index FIT was used as a third input to the fuzzy inference machine. Observe that the membership function Low of the universe of discourse relative to $\rho^{(2)}(i,j)$ is shifted to right due to the fact that when the signal is filtered, its form is usually similar to the input signal, then the cross-correlation between they tend to be higher. The index FIT is used to make a weighting of the correlation value $\rho^{(2)}(i,j)$, thus correlation $\rho^{(2)}(i,j)$ is taken into consideration only if the adherence of the model to the plant, evaluated by the FIT index, is good.

Figures 1, 2 and 3 show the membership functions used by each linguistic input variable. All the input variables are normalized in the range $[0,1]$. The setting of each membership function was made in empirical form.

A classical interpretation of Mandani for the rule bases was used. For the logic operations `and` and `or` were used the `min` and `max` functions. Then through a set of If-Then

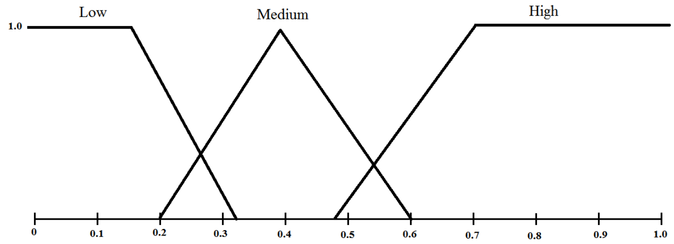

Fig. 4. Universe of discourse for the output χ.

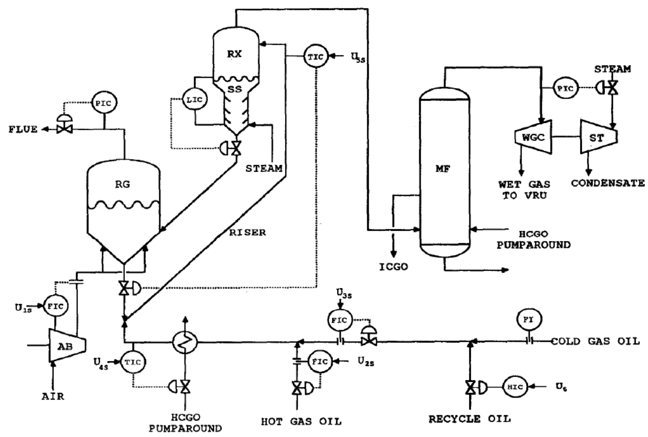

Fig. 5. FCC Unit flow diagram Grosdidier et al. (1993).

rules it was possible to implement the fuzzy algorithm. A total of 27 rules were used by the inference machine.

The centroid or center of gravity method was used for defuzzification. It determines the center of the area of the combined membership functions. The output linguistic variable has also three membership functions: Low, Medium and High, like the input linguistic variables (Figure 4).

4. RESULTS

In this section the proposed method and the ones presented in Section 2 are tested. The experiment consists of detecting no-model IO pairs in a Fluid Catalytic Cracking Unit of the Brazilian company Petrobras. The no-model IO pair detection is based on the signals used in the pre-identification stage.

The complete unit has 39 controlled variables and 20 manipulated variables, but the study was performed only in a subsystem of the plant composed by 20 controlled variables ($y_i, i = 1\ldots20$) and 10 manipulated variables ($u_j, j = 1\ldots10$). Each test had an average duration of approximately 2 hours. Their implementation was performed in about two weeks.

The tests should start when the plant was stable and the excitation in the manipulated variables tested must be of sufficient magnitude to cause measurable changes in the controlled variables relating to such variations. The signals employed to excite the plant were steps or pulses with a sample time of 1 minute. In all the cases only one manipulated variable at a time was excited. The process was subject to unmeasured disturbances and noise. When the no-model IO pair detection method is used, the result of the matrix χ is shown in Equation (25).

Next it is proposed to create a margin of decision to specify when there is a model. It is assumed that when the decision index is higher than 0.5, there is a great possibility of existing models, so it is used 1 in this position of the matrix. On the other hand, if the range of decision is between 0.2 and 0.49, there are doubts about the existence of models. In this case it is used 0.5 in this position of the matrix. Finally, if the decision index is lower than 0.2, it is almost certain that there is no model in this IO pair, so a 0 is used in this position. Using these assumptions, it is created a new matrix show in (26).

$$\chi = \begin{bmatrix} 0.23 & 0.12 & 0.74 & 0.12 & 0.12 & 0.78 & 0.12 & 0.40 & 0.12 & 0.13 \\ 0.12 & 0.14 & 0.13 & 0.12 & 0.12 & 0.12 & 0.23 & 0.12 & 0.12 & 0.14 \\ 0.14 & 0.12 & 0.14 & 0.12 & 0.12 & 0.12 & 0.13 & 0.34 & 0.12 & 0.13 \\ 0.13 & 0.13 & 0.13 & 0.12 & 0.13 & 0.12 & 0.12 & 0.14 & 0.12 & 0.13 \\ 0.13 & 0.12 & 0.12 & 0.12 & 0.13 & 0.12 & 0.12 & 0.12 & 0.13 & 0.13 \\ 0.28 & 0.12 & 0.66 & 0.12 & 0.19 & 0.79 & 0.53 & 0.13 & 0.12 & 0.14 \\ 0.20 & 0.27 & 0.33 & 0.12 & 0.12 & 0.12 & 0.65 & 0.15 & 0.14 & 0.30 \\ 0.12 & 0.14 & 0.13 & 0.12 & 0.14 & 0.12 & 0.40 & 0.33 & 0.28 & 0.57 \\ 0.12 & 0.12 & 0.32 & 0.13 & 0.70 & 0.13 & 0.62 & 0.36 & 0.18 & 0.22 \\ 0.12 & 0.12 & 0.32 & 0.13 & 0.69 & 0.13 & 0.67 & 0.40 & 0.25 & 0.14 \\ 0.14 & 0.13 & 0.13 & 0.12 & 0.28 & 0.25 & 0.12 & 0.12 & 0.12 & 0.75 \\ 0.34 & 0.12 & 0.13 & 0.12 & 0.12 & 0.12 & 0.12 & 0.40 & 0.40 & 0.58 \\ 0.34 & 0.12 & 0.13 & 0.12 & 0.12 & 0.12 & 0.12 & 0.40 & 0.40 & 0.57 \\ 0.30 & 0.24 & 0.37 & 0.12 & 0.12 & 0.24 & 0.52 & 0.20 & 0.13 & 0.13 \\ 0.17 & 0.14 & 0.21 & 0.13 & 0.80 & 0.13 & 0.40 & 0.40 & 0.40 & 0.40 \\ 0.41 & 0.12 & 0.12 & 0.14 & 0.78 & 0.14 & 0.48 & 0.12 & 0.35 & 0.20 \\ 0.13 & 0.13 & 0.13 & 0.12 & 0.13 & 0.12 & 0.12 & 0.40 & 0.77 & 0.70 \\ 0.13 & 0.17 & 0.44 & 0.12 & 0.12 & 0.12 & 0.62 & 0.14 & 0.16 & 0.13 \\ 0.24 & 0.12 & 0.14 & 0.12 & 0.30 & 0.40 & 0.13 & 0.33 & 0.14 & 0.32 \\ 0.12 & 0.13 & 0.13 & 0.12 & 0.14 & 0.12 & 0.14 & 0.12 & 0.23 & 0.13 \end{bmatrix} \quad (25)$$

$$\Phi_{FIFC} = \begin{bmatrix} 0.5 & 0 & 1 & 0 & 0 & 1 & 0 & 0.5 & 0 & 0 \\ 0 & 0 & 0 & X & 0 & 0 & X & 0 & 0 & 0 \\ X & X & X & X & 0 & 0 & 0 & 0.5 & 0 & 0 \\ 0 & 0 & X & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & X & X & X & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0.5 & 0.5 & 0 & 0 & 0 & 1 & X & 0 & 0.5 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0.5 & 0.5 & 1 \\ 0 & 0 & 0.5 & 0 & 1 & 0 & X & 0.5 & 0 & 0.5 \\ 0 & 0 & 0.5 & 0 & 1 & 0 & X & 0.5 & 0.5 & 0 \\ 0 & 0 & 0 & 0 & 0.5 & 0.5 & 0 & 0 & 0 & 1 \\ 0.5 & 0 & 0 & 0 & X & 0 & 0 & 0.5 & 0.5 & X \\ 0.5 & 0 & 0 & 0 & X & 0 & 0 & 0.5 & 0.5 & X \\ 0.5 & 0.5 & 0.5 & 0 & 0 & 0.5 & 1 & 0 & 0 & 0 \\ X & 0 & 0.5 & 0 & 1 & 0 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0 & 0 & 0 & 1 & 0 & 0.5 & 0 & 0.5 & X \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & X & X \\ 1 & 0 & 0 & 0 & 0.5 & 0.5 & 0 & 0.5 & 0 & 0.5 \\ 0 & X & 0 & 0 & 0 & X & 0 & 0 & X & 0 \end{bmatrix} \quad (26)$$

The result obtained in (26) was compared with the expected matrix given by Petrobras, thus the X in the matrix represents an error in the estimation in that position. The error rate represents 12% of the estimative, whilst the rates of hit and doubt are 67% and 21%, respectively. A more detailed analysis shows that in the majority of doubt cases either the amplitude of the excitation signal is insufficient or the disturbance signal hide the system response. Figure 6 presents the performance of the IO pair (y_1, u_1). This is a typical case where the user expects the existence of a model between the input and output signals, but in accordance with the system response there is not clear evidence of that relationship.

Although the filtered signal can present a high cross-correlation with the input signal, as the index FIT associated with this model is low, this input is penalized by the inference fuzzy machine. On the other hand, a less common case appears in the IO pair (y_{12}, u_1) which is shown in Figure 7. Here, there is a clear indication of a model that relates the input and output signals; however, it is not expected by the user. This phenomenon should indicate an error in the test, an unknown relationship in the plant or even a system malfunction. In this sense, the power of the FIFC method over the others is to offer the possibility of doubt when there is no absolute certainty of the model existence.

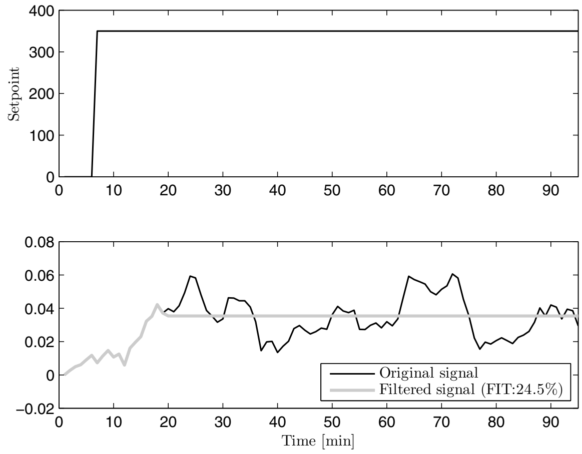

Fig. 6. Analysis of the IO pair (y_1, u_1).

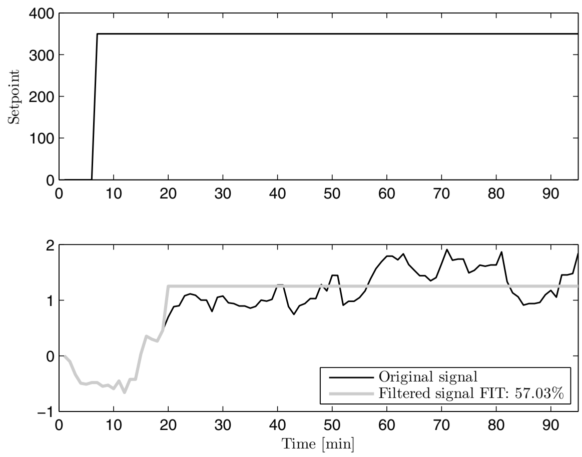

Fig. 7. Analysis of the IO pair (y_{12}, u_1).

Table 1 presents the hit rate of the methods discussed here and the FIFC proposed. Observe that even without taking into consideration the doubt cases, the FIFC method is better than the others. The poor performance of the other methods could be explained because they are based on an identified model and the input signals used in this stage are not good for identification purposes, then the models obtained are poor. The objetive of the no-model IO pair detection is to help in the design of the identification stage. Thus, matrix Φ_{FIFC} can be a good starting point for the planning and configuration of the excitation signals.

Table 1. No-model IO pair detection of each method.

	Φ_{FIFC}	Φ_{SIE}	Φ_{RGA}
Hit	67%	40.5%	45%

Usually it is necessary to divide the plant into sub-plants for identification purposes, due to the fact that it is not recommended to excite a great number of manipulated variables at the same time. To generate this division matrix, Φ_{FIFC} is useful again. After discussing with the plant personnel, all the doubt cases were resolved and the hit rate reached 88%. Once the matrix Φ_{FIFC} is validated, the next stage consists of grouping the IO pairs for identification purposes. Constraints in the design of the identification stage for this plant require the excitation of at most five variables at a time. Thus, using the algorithm proposed in Massaro (2014), the matrix was divided into small groups as is shown in (27).

$$
\begin{array}{ccccccccccc}
0 & 3 & 1 & 6 & 2 & 4 & 7 & 5 & 10 & 8 & 9 \\
1 & 1^{(1)} & 1^{(1)} & 1^{(1)} & 0^{(1)} & 0^{(1)} & 0 & 0 & 0 & 0 & 0 \\
3 & 1^{(1)} & 1^{(1)} & 0^{(1)} & 1^{(1)} & 1^{(1)} & 0 & 0 & 0 & 0 & 0 \\
6 & 1^{(1)} & 1^{(1)} & 0^{(1)} & 0^{(1)} & 0^{(1)} & 1^{(2)} & 0^{(2)} & 0^{(2)} & 0^{(2)} & 0 \\
14 & 1^{(1)} & 1^{(1)} & 0^{(1)} & 0^{(1)} & 0^{(1)} & 1^{(2)} & 0^{(2)} & 0^{(2)} & 0^{(2)} & 0 \\
15 & 1^{(1)} & 1^{(1)} & 0^{(1)} & 0^{(1)} & 0^{(1)} & 0^{(2)} & 1^{(2)} & 1^{(2)} & 0^{(2)} & 0 \\
5 & 1^{(1)} & 0^{(1)} & 1^{(1)} & 1^{(1)} & 1^{(1)} & 0^{(2)} & 0^{(2)} & 0^{(2)} & 0^{(2)} & 0 \\
7 & 1^{(3)} & 0^{(3)} & 0^{(3)} & 0 & 0 & 1^{(2)} & 0^{(2)} & 0^{(2)} & 1^{(2)} & 0 \\
9 & 1^{(3)} & 0^{(3)} & 0^{(3)} & 0 & 0 & 0^{(2)} & 1^{(2)} & 0^{(2)} & 0^{(2)} & 0 \\
10 & 1^{(3)} & 0^{(3)} & 0^{(3)} & 0 & 0 & 0^{(2)} & 1^{(2)} & 0^{(2)} & 0^{(2)} & 0 \\
4 & 1^{(3)} & 0^{(3)} & 0^{(3)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
19 & 0^{(3)} & 1^{(3)} & 1^{(3)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
16 & 0^{(3)} & 1^{(3)} & 0^{(3)} & 0^{(4)} & 0^{(4)} & 0^{(4)} & 1^{(4)} & 1^{(4)} & 0 & 0 \\
20 & 0^{(3)} & 0^{(3)} & 1^{(3)} & 0^{(4)} & 0^{(4)} & 0^{(4)} & 0^{(4)} & 0^{(4)} & 0 & 0 \\
2 & 0 & 0 & 0 & 1^{(4)} & 1^{(4)} & 0^{(4)} & 0^{(4)} & 0^{(4)} & 0 & 0 \\
18 & 0 & 0 & 0 & 0^{(4)} & 0^{(4)} & 1^{(4)} & 0^{(4)} & 1^{(4)} & 0 & 0 \\
13 & 0 & 0 & 0 & 0^{(4)} & 0^{(4)} & 0^{(4)} & 1^{(4)} & 0^{(4)} & 0 & 0 \\
12 & 0 & 0 & 0 & 0 & 0 & 0 & 1^{(5)} & 0^{(5)} & 0^{(5)} & 0^{(5)} \\
17 & 0 & 0 & 0 & 0 & 0 & 0 & 0^{(5)} & 1^{(5)} & 1^{(5)} & 1^{(5)} \\
8 & 0 & 0 & 0 & 0 & 0 & 0 & 0^{(5)} & 1^{(5)} & 1^{(5)} & 1^{(5)} \\
11 & 0 & 0 & 0 & 0 & 0 & 0 & 0^{(5)} & 1^{(5)} & 0^{(5)} & 0^{(5)}
\end{array}
\tag{27}
$$

The first row and column represent the original positions of the IO pair in matrix Φ_{FIFC}, respectively. Index $^{(k)}$ was used to group the IO pairs. Notice that five groups were obtained.

5. CONCLUSIONS

A new method for detection of no-model IO pairs in the transfer matrix is discussed. The method is based on the fuzzy analysis of a linear correlation between the output and the inputs in MISO models and its use is suggested in the pre-identification stage. It resembles the instrumental-variables (IV) method, but unlike it, our method filters only the signal noise using simple models as filters, whereas IV methods filter the residual noise through different predictors. The residual noise is composed of signal noise, modeling errors and multiplicative noise, which is more complex to analyze and filter than just signal noise.

To test the algorithm, a FCC process plant with some no-model IO combinations was used. In this sense, a real dataset provided by Petrobras was used. The experiment shows that the FIFC method is useful, not only to detect no-model IO pairs, but also to indicate errors in the test, unknown relationships in the plant or even a system malfunction. From the real dataset the method was validated, with an error of only 12% in the IO pair detection. Finally, information obtained from matrix Φ_{FIFC} was used to divide the IO pairs in groups for identification purposes.

REFERENCES

Aguirre, L.A. (2007). *Introduction to system identification: linear and non-linear techniques applied to real systems.* Editora UFMG, Minas Gerais, Brazil. /In Portuguese/.

Box, G. and MacGregor, J. (1974). The analysis of closed-loop dynamic-stochastic systems. *Technometrics*, 16(3), 391–398.

Bristol, E. (1966). On a new measure of interaction for multivariable process control. *IEEE Transactions on Automatic Control*, 11(1), 133–134.

Cao, Y. (1996). An extension of singular value analysis for assessing manipulated variable constraints. *Journal of Process Control*, 6(1), 37–48.

Cao, Y. and Rossiter, D. (1997). An input pre-screening technique for control structure selection. *Computers & Chemical Engineering*, 21(6), 563–569.

Chang, J. and Yu, C. (1990). The relative gain for non square multivariable systems. *Chemical Engineering Science*, 45(5), 1309–1323.

Grosdidier, P., Mason, A., Aitolahti, A., Heinonen, P., and Vanhamaki, V. (1993). FCC unit reactor-regenerator control. *Computers Chemistry Engineering*, 17(2), 165–179.

Havre, K., Morud, J., and Skogestad, S. (1996). Selection of feedback variables for implementing optimization control schemes. In *UKACC, International Conference on Control*, volume 1, 491–496.

Ljung, L. (1999). *System Identification: Theory for the user.* Prentice Hall, 2nd edition.

Massaro, L. (2014). *Determination of zeros in the transfer matrix of MIMO systems based on correlation analysis.* Master's thesis, University of São Paulo. /In Portuguese/.

Perreault, E., Westwick, D., Pohlmeyer, E., Solla, S., and Miller, L. (2005). Optimal input selection for MISO systems identification: Applications to BMIs. In *2nd International IEEE EMBS Conference on Neural Engineering*, 167–170.

Skogestad, S. and Postlethwaite, I. (1996). *Multivariable feedback control: Analysis and design.* UK John Wiley and Sons.

Skogestad, S. and Morari, M. (1987). Implications of large RGA-elements on control performance. *Industrial & Engineering Chemistry Research*, 26(11), 2323–2330.

Tzouanas, V.K., Luyben, W.L., Georgakis, C., and Ungar, L.H. (1990). Expert multivariable control 1. struture and design methodology. *Industrial and Engineering Chemistry Research*, 29(3), 382–389.

Van der Wal, M. and de Jager, B. (2001). A review of methods for input/output selection. *Automatica*, 37(4), 487–510.

Webber, J. and Gupta, Y. (2008). A closed-loop crosscorrelation method for detecting MPM in MIMO model-based controllers. *ISA Transactions*, 47(4), 395–400.