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Detection of no-model input/output combination in transfer matrix in closed-loop MIMO systems ⋆

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Abstract: A method to detect input/output (IO) combinations with no-model or poor model in the transfer matrix of a closed-loop MIMO system is proposed. Traditional approaches to IO selection are not adequate when used to detect no-model IO combination of a closed-loop identification process. The feedback effect, controller action and the characteristics of the excitation signal employed during the pre-identification stage cause this limitation. In this proposal the detection of no-model or poor model IO combinations is made based on regularity of low values of polynomial coefficients of parametric identification models. This information is gathered during the pre-identification stage. Improvement in model estimation is obtained once these "null" combinations are zeroed, before the identification process takes place. A study case involving identification of a 2×2 MIMO system is discussed.

Keywords: no-model IO combination; closed-loop system identification; MIMO systems; MPC

1. INTRODUCTION

The key to Model Predictive Control (MPC) success is a good process model (Zhu, 2006). Thus, accurate model identification is crucial in MPC applications. Issues such as IO selection, system order and time delay estimation are critical for the process modeling quality (Lennox et al., 2001). Similarly, lack of previous information of non-existent model for specific IO combinations affects the quality of the process modeling.

System identification packages focused on industrial process system applications, such as TaiJi, developed by Y. Zhu (Gao, 2008) and Profit Stepper (User's-Guide, 2007) acquire initial IO no-model information from the knowledge of the plant operation personnel. These approaches stems from the operator experience and technological plant information. If a change occurs, because of technological variation, plant or equipment malfunction, or any other reason, and it is not properly updated, the identification process could be affected. This kind of model-plant mismatch should be avoided.

IO no-model information allows setting zeros in the i-jth positions of the transfer matrix, where no model or a very poor one could be found. Improvements on estimation of MISO parameters involving no-model IO combinations of the transfer matrix are found when null IO combinations are zeroed. Additionally, general computational effort required to estimate model process properties is decreased.

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In the closed-loop identification of a linear MIMO process, no-model detection using correlation analysis is not well suited if used during the pre-identification or pre-test stage. One reason is because during this stage only small series of positive and negative pulses are employed as excitation signal. This kind of signal does not allow performing confident statistical procedures. Similarly, procedures based on open-loop steady-state gain matrix can fail when applied to closed-loop systems, mainly because of the feedback effect and the controller action.

In this paper a method to detect no-model IO combinations in a closed-loop MIMO transfer matrix is proposed. Detection is made from the analysis of parametric model coefficient values obtained during the pre-test stage. Repeatability of this behaviour is proven through a Monte Carlo simulation (MCS). The method is intended to be employed in closed-loop identification.

Although this method could also be implemented during identification experiments, it is an advantage to do it during the pre-identification stage. That is because information related to no-model IO combination, as well as those others acquired during the pre-test, such as process gains, time constants and time delays, allow fixing conditions and eventually improving the succeeding identification process.

The paper is organized as follows, Section 2: input selection methods and their limitations for no-model detection in MIMO closed-loop identification are reviewed; Section 3: numerical results of some methods applied to IO no-model detection are discussed, Shell Benchmark plant (Cott, 1995a) is employed for simulations; Section 4: the proposed method is presented and its results for the same plant are discussed. Finally, conclusions are drawn in Section 5.

2. IO MODEL SELECTION METHODS

Cao (1997) introduced the Single-Input Effectiveness (SIE) method to select inputs to be included in a control scheme. SIE considers $\boldsymbol{G}(s)$ an mxm matrix, which represents an open-loop MIMO linear system with frequency response matrix $\mathbf{G}(i\omega)$ and steady-state gain matrix $\boldsymbol{K}$. The output vector y can be derived as

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

where u is the input vector.

The method defines two indexes. The first is the Input Effectiveness (IE), η, which is the ratio of the norm of u_n and u.

$$\eta = \frac{\|u_n\|_2}{\|u\|_2} \tag{2}$$

where u_n is the projection of input vector u in $\boldsymbol{K}_n$ (null space of $\boldsymbol{K}$).

The second index is the Input Ineffectiveness (IIE), ζ. This is the ratio of the norm of u_c and the norm of u.

$$\zeta = \frac{\|u_c\|_2}{\|u\|_2} \tag{3}$$

where u_c is the u_n complement.

Single-IE (SIE), η_i, for the ith input vector (u_i) can be computed considering an ith unitary natural vector $\mathbf{e}_i$.

$$\eta_i = \|\boldsymbol{K}^+\boldsymbol{K}\mathbf{e}_i\|_2, \qquad 0 \leq \eta_i \leq 1 \tag{4}$$

where $\boldsymbol{K}^+$ is the pseudo or generalized inverse of $\boldsymbol{K}$.

Single-IIE, ζ_i, for the ith input vector (u_i) is obtained as:

$$\zeta_i = \sqrt{1-\eta_i^2}, \qquad 0 \leq \zeta_i \leq 1 \tag{5}$$

Consider that $\boldsymbol{K}$ can be represented by a set of linear MISO systems. For each one of these systems, values of η_i close to 0 means low effectiveness of the ith input over the output y, whereas values near 1 indicate significant effectiveness. This criterion is usually to be properly employed to include or exclude input on a control scheme for the system represented by $\boldsymbol{K}$.

On the other hand, values of η_i and consequently ζ_i, can also be derived using Singular Value Decomposition (SVD), (Cao, 1997), since $\boldsymbol{K}$ can be factorized as:

$$\boldsymbol{K} = \boldsymbol{U}\Sigma\boldsymbol{V}^H \tag{6}$$

where $\boldsymbol{V}^H$ is the conjugate transpose of $\boldsymbol{V}$.

Then, η_i can be computed as:

$$\eta_i = \|\boldsymbol{K}^+\boldsymbol{K}\mathbf{e}_i\|_2 = \sqrt{\mathbf{e}_i^T\boldsymbol{V}_1\boldsymbol{V}_1^H\mathbf{e}_i} \tag{7}$$

where $\boldsymbol{V}_1$ are the first k columns of $\boldsymbol{V}$, being k the rank of $\boldsymbol{K}$.

Thus, using SVD could yield the same estimate of effectiveness, η_i, for every ith input over an output y of $\boldsymbol{K}$.

Principal Component Analysis (PCA) is a multivariate analysis tool which can also use SVD to factorize a $\boldsymbol{K}$ matrix. This factorization allows identifying relevant inputs and representing them in a new axis system. A consequent reduction of data dimensionality is achieved through the covariance analysis of the different elements (vectors) of the system.

In (Perreault and Westwick, 2005) an algorithm based on PCA was developed for selecting optimal inputs to be used in the identification of a linear MISO plant. In this case, the algorithm employed QR factorization.

PCA was also the tool employed in (Zamprogna, 2005) to develop a methodology to select inputs to be used in a soft sensor for a batch distillation unit. Once again, variables of the process were analysed to obtain those with significant gains with respect to an output variable. Those with very low or close to zero steady-state gain are discarded, which implies that poor or no-model is going to be found for that IO combination.

Relative Gain Array (RGA) was first introduced by Bristol (1966) for steady-state as a measure of process interactions. Skogestad and Morari (1987) and Sokgestad and Postlethwaite (1996) established that RGA is mostly a measure of achievable control quality in a much wider sense, more than just a tool for pairing controlled and manipulated variables. Waller and Waller (1995) related RGA and SVD as measures to estimate the effect of inputs over outputs in a 2×2 MIMO system. Employment of this tool as both a measure of process interactions as well as a measure of effectiveness for pairing of controlled and manipulated variables was also shown in (Seborg et al., 2004). Extensions of the method for process dynamics conditions were also stated in that work. Relative Gain Array method, in general (even for non square systems) and for steady-state conditions can be defined as:

$$RGA = \wedge = \boldsymbol{K} \times (\boldsymbol{K}^+)^T \tag{8}$$

More conceptually $\wedge$ can be understood as:

$$RGA = \wedge = [\lambda_{ij}]_{m\times m} \tag{9}$$

where λ_{ij} are the ratios of k_{ij}, gain of the i-jth model of $\boldsymbol{K}$ with all the loops open and k_{ij}^*, gain of the i-jth with only ith loop open.

$$\lambda_{ij} = [\frac{g_{ij}}{g*_{ij}}] \tag{10}$$

The equivalence between λ_{ij} and η_j^2 was proved in (Cao, 1997).

The cross correlation function, r_{ij}, presented in (11) is an immediate tool to measure a significant association between an output, y_i, and an input signal, u_i.

$$r_{ij} = E[u_i(t)y_i(t+\tau)] \tag{11}$$

This tool was employed in (Aguirre, 2007) and (Jeronimo, 2004). In this last work a procedure to select relevant variables to be used as inputs in a MIMO control system was proposed. The procedure was implemented in open-loop configuration.

Limitations of cross-correlation methods when employed to detect input/output effect in closed-loop have been stated in (Box and McGregor, 1974). However, good results can be obtained if input signal is dithered. In (Webber and Gupta, 2008) a closed-loop cross-correlation method is employed for detecting model 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 correlation between the prediction error and input u. A dithering in the set-point (u) is required to use this signal as excitation.

The aforementioned approaches mostly consider a steady-state gain matrix $\boldsymbol{K}$, which contains every i-jth gain obtained with the system in open-loop configuration. In MPC configurations where a regulatory layer with PID is maintained (Van Lith, 2009), for example loops with potentially unmeasured disturbances such as distillation column top (Conneally et al., 1999), open or closed-loop means to open or close the MPC level, but regulatory loops remain closed (Xie, 2004). Therefore, in this MPC configuration, $\boldsymbol{K}$ as an open-loop steady-state gain matrix is not frequently available. Economics and safety issues can also make regulatory layer open loop an almost prohibitive alternative. All these facts limit the application of some of the previous methods as a tool to detect no-model IO combinations in a closed-loop MIMO system.

Besides, the detection of no-model IO combination in closed-loop MIMO systems employing the above mentioned approaches could also fail because of the controller action. A properly designed and tuned controller will lead the direct steady-state gains (main diagonal) close to unity and secondary diagonal steady-state gains close to zero (decoupling). Thus, secondary diagonal IO combinations will have their closed-loop steady-state gains approximately equal to zero and equal each other, in spite of having or no a model. Ill-conditioned plants are beyond the scope of this work, therefore RGA and SVD values will be analyzed only in the context of a well-conditioned plant.

Finally, the spectral approach provides effective criterion for detection of no-model IO combination. TaiJi (Gao, 2008) implements this approach during the identification stage. In this application, an upper error bound (superior error limit) on frequency response estimation is defined. During each identification loop this limit is compared with the error obtained for the estimated model. Models (and consequently their IO combinations) with error in frequency response estimation, higher than the superior error limit are discarded. This procedure is accomplished during the identification stage, when a wider range of frequencies of input signals can be used to excite the process. The method proposed in this paper is intended to be implemented during the pre-test stage, due to the impact of IO no-model information in succeeding identification stages.

3. APPLICATION OF IO SELECTION METHODS FOR IO NO-MODEL DETECTION

IO selection methods previously reviewed are employed in order to detect no-model or poor model IO combination during the pre-test stage.

3.1 Plant used in process simulations

The plant employed in the simulations was the distillation column described in (Cott, 1995a), (Cott, 1995b). A simplified diagram of this 2×2 plant is shown in Fig. 1.

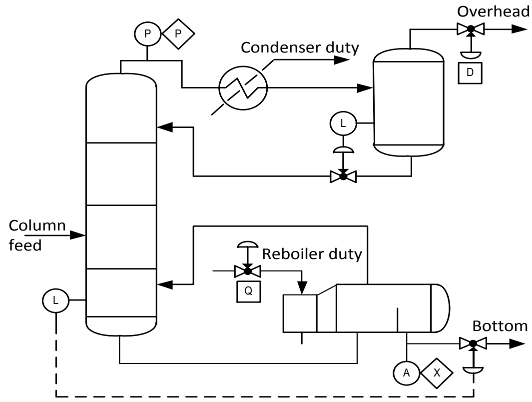

Fig. 1. Diagram of the distillation column (Cott, 1995a).

The plant discrete time transfer matrix is shown in (12).

$$\boldsymbol{G}(q) = \begin{bmatrix} \dfrac{-0.61 + 0.40q^{-1}}{1 - 1.53q^{-1} + 0.57q^{-2}} & \dfrac{-0.11 + 0.092q^{-1}}{1 - 1.53q^{-1} + 0.57q^{-2}} \\ 0 & 0.076\dfrac{5 \times 10^5}{q^{-7} - 1500} + 0.9235q^{-1} \end{bmatrix} \qquad (12)$$

The system inputs are overhead vapor flow MV-1 (D), and reboiler flow MV-2 (Q) and the outputs are top pressure CV-1 (P) and reboiler outlet composition CV-2 (X), Fig. 1.

3.2 Results of some of the previous approaches used to detect no-model IO combinations

For all the results shown next, $\boldsymbol{K}$ is the steady-state gain matrix determined in regulatory closed-loop.

Single-Input Effectiveness (SIE) method: vectors η_{I1}^2 and η_{I2}^2 contain values of indexes obtained when the IE method is applied separately, considering $\boldsymbol{K}$ (2×2) as two MISO systems. Vector η_{I1} represents combination CV-1; MV-1 and CV-1; MV-2.

$$\eta_{I1}^2 = [\,0.999718 \;\; 0.000281\,]$$

the second vector η_{I2} represents combination CV-2; MV-1 and CV-2; MV-2.

$$\eta_{I2}^2 = [\,0.000148 \;\; 0.999851\,]$$

Values of 0.000281 and 0.000148 shown above correspond to IO combinations CV-1; MV-2 and CV-2; MV-1. Both are in the same order of magnitude, although between CV-1; MV-2 there is a model, but IO combination CV-2; MV-1 has no model. Thus, there is no strong numerical evidence about whether or not a model exists for those IO combinations. The reason for this ambiguity is due to the action of the controller. The behaviour of the system with closed-loop regulatory control implies that numerical difference between η_{I1}^2 and η_{I2}^2 values will hardly exist, regardless of the existence or no of model between these IO combinations. Values of η^2_{I1} and η^2_{I2} do not allow identifying such a radical difference.

Relative Gain Array method: the values obtained were expected, once the relative gain array was calculated using (8) with the closed-loop steady-state gain matrix:

$$\wedge = \begin{bmatrix} 0.999905662 & 0.000094338 \\ 0.000094338 & 0.999905662 \end{bmatrix}$$

$\wedge$ calculated shows a good measure of decoupling guaranteed by the controller action. Values of $\lambda_{i,j}$ imply that the IO of the inverted diagonal are decoupled. Regulatory control closed-loop condition "hides" information about IO combinations with no-model.

Cross correlation functions were not implemented in this work, considering that during the plant excitation for pre-test stage, only small series of positive and negative impulses were used as excitation signal.

Results obtained by using the SVD method according to (6) and (7) were equivalent to SIE results using (4). For the sake of brevity these are not discussed.

PCA method was not implemented considering the small dimensionality of the simulated plant (2×2).

4. CLOSED-LOOP IO NO-MODEL DETECTION: PROPOSED METHOD

The proposed method is based on values and regularity of coefficients of the model structures employed during pre-test. Input excitation signals employed were two pulses (positive and negative). Pulse duration corresponded to two settling time (t_s). Similar signals, but separated each other one t_s, were applied to each input. Because of the spectral characteristic of this excitation signal, results obtained are related to low frequency system response.

The main idea of this proposal is to gather the IO no-model information from this stage, where a minimum impact on the process must be guaranteed (Seborg et al., 2004) and, on the other hand, to use this information not only to plan identification data acquisition but also to maximize improvements of this process with this information.

It was assumed that the 2×2 MIMO system represented by (12) can be modelled by two 2×1 MISO models. An *autoregressive with exogenous input* (ARX) model structure was employed to obtain a first approach to the process model information. The choice of this structure was based on its simplicity to obtain the system response.

The MISO ARX model structure has the form:

$$A(q)y(k) = \sum_{i=1}^{m} B_i(q)u_i(k) + e(k) \quad (13)$$

where $y(k)$ is the process output at time k. $u_i(k)$ are the m process inputs and $e(k)$ is white noise. Polynomials $A(q)$ and $B(q)$ are defined as:

$$A(q) = 1 + a_1q^{-1} + ... + a_{n_a}q^{-n_a} \quad (14)$$

$$B_i(q) = b_{i1}q^{-1} + b_{i2}q^{-2} + ... + b_{n_{bi}}q^{-n_{bi}} \quad (15)$$

n_a is the autoregressive order, n_b is the order with respect to exogenous input(s) and q^{-1} is the backward shift operator.

Simulations were performed employing normalized input and output vectors. White noise (filtered according to (Cott, 1995b) for $e_P(k)$ and $e_X(k)$) and unmeasured disturbances were added. Random seeds for stochastic signal generation were used for every realization. Signal to Noise Ratio (SNR), specified as the ratio of output and noise variances, was set to 27.

Average values for a first set of 20 realizations pre-identifying the model are shown in Table 1.

Table 1. $A(q)$ and $B_i(q)$ polynomial coefficient averages for 20 realizations for MISO models.

Model	a_1	b_1	b_2
CV-1;MV-1	0.7370	0.2381	0.0265
;MV-2		-0.0624	0.0594
CV-2;MV-1	0.9442	-4.514×10^{-4}	7.687×10^{-4}
;MV-2		0.0417	0.0148

The regularity found in the order of magnitude of polynomial B of the ARX model for CV-2; MV-1 (no-model IO combination) marked a difference when compared to the other b_i coefficients of the obtained model. Those very low values of b_i (10^{-4}) obtained for CV-2; MV-1 indicates that there is no energy transfer between this input and this output. Consequently, contribution of MV-1 to CV-2 will be affected by these very low value coefficients. This is consistent with the model shown in (12).

4.1 Repeatability of $B_i(q)$ coefficient values for no-model IO combination

In order to evaluate the method results for a large amount of repetitions a Monte Carlo simulation (MCS) was conducted. For this test, input and output vectors of the simulated plant generated along 100 realizations were collected. Signal to Noise Ratio (SNR) was also kept at 27 (ratio of variances, dimensionless).

Neglecting variations for $A(q)$ coefficients in the 100 realizations were found. Mean values and standard deviation of $A(q)$ are shown in Table 2 for both MISO models.

Table 2. Mean value and standard deviation of $A(q)$ for 100 realizations for MISO models.

Model	mean value (a_1)	stdev (a_1)
CV-1;MV-1	-0.7367	1.344×10^{-4}
;MV-2		
CV-2;MV-1	-0.9442	6.260×10^{-5}
;MV-2		

Values of parameters $B_i(q)$ followed the same behavior detected for a small amount of realizations.

Figure 2 shows histograms of B_i coefficients for both MISO models, with respect to output CV-1 (left) and to output CV-2 (right). An evident difference is again observed in b_1 and b_2 for the IO combination CV-2; MV-1 (no-model). While the rest of combinations kept its mean values between -0.06150 and 0.2380, b_i coefficients for no-model IO combination fall to a range of 10^{-4}, see Table 3. These values dispersion was computed using its

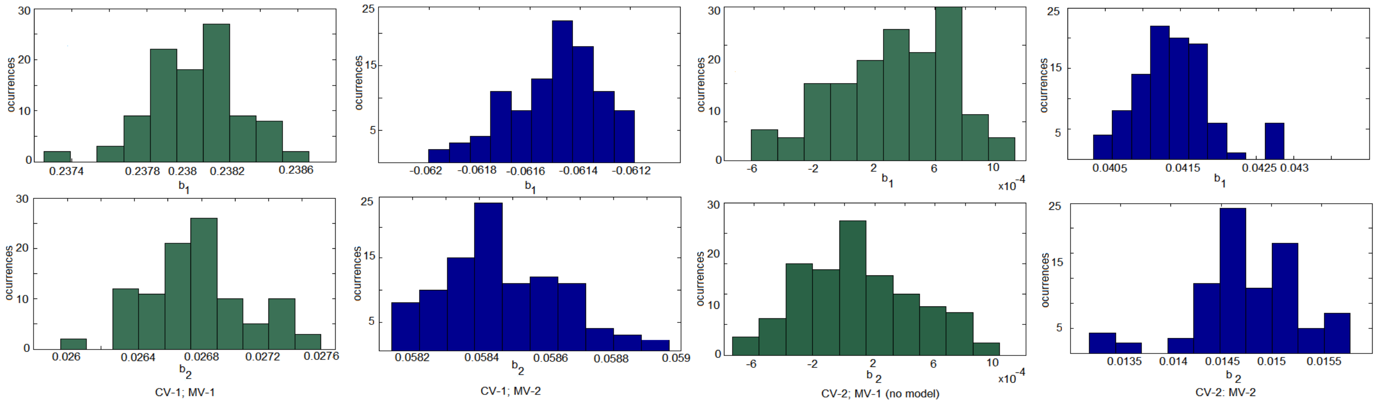

Fig. 2. Values of b_1 and b_2 of $B_i(q)$ along 100 realizations, for MISO models with respect to output CV-1 (left) and with respect to output CV-2 (right), considering n_a=1, n_b=[2 2] n_k=[1 1] and n_a=1, n_b=[2 2] n_k=[1 8], respectively.

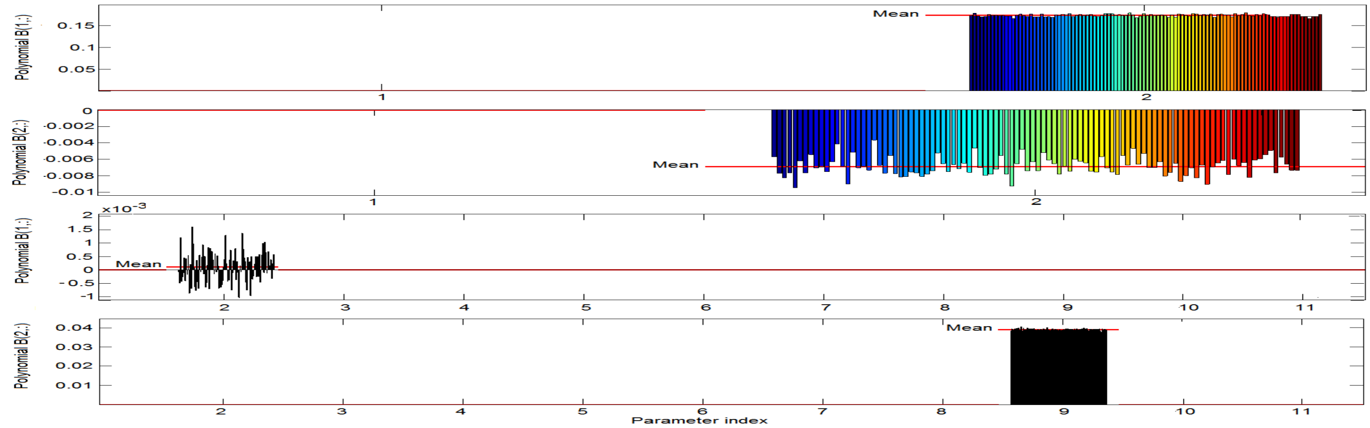

Fig. 3. Distribution of b_1 for $B_i(q)$ along 100 realizations for MISO models with respect to output CV-1 (up) and with respect to output CV-2 (down), considering n_a=1, n_b=[1 1] n_k=[1 1], and n_a=1, n_b=[1 1] n_k=[1 8], respectively.

standard deviation (stdev in Table 3) but no significant differences were noticed between the sets of b_i coefficients. Mean values of $B_i(q)$ for CV-2; MV-1 did not change when the number of realizations was increased to 100. Standard deviation also maintained its low values.

Two additional runs of 100 realizations of pre-identification were conducted to check the influence of small changes in the order of the ARX model structure employed. The order of polynomial B_i was set to 1 and 3. The order of A_i was maintained fixed. The first run ($n_b = 1$) was conducted with SNR reduced to 10, a more severe noise condition.

Figure 3 shows the results obtained for n_b=[1 1]. Coloured bars show the values of B_i coefficient for models CV-1; MV-1 and CV-1; MV-2. Black bars show the values of B_i coefficient for the CV-2; MV-1 and CV-2; MV-2. Each bar represents one realization. The mean value for b_1 coefficient for the no model combination CV-2; MV-1 was 1.131×10^{-4} and its standard deviation was 1.589×10^{-4}.

The differences and the size order results of B_i polynomial coefficients for this no model IO combination were also repeatable after changes of the system order and SNR values. It can be concluded that this difference of order of magnitude in coefficients of the $B_i(q)$ of the ARX model obtained during the pre-test, can be taken as an indicator of no-model IO combination for the tested conditions.

For identification in industrial context where repeatability tests can not be implement through an MCS, this analysis can be performed using routine operating data available on DCS. Recent theoretical and practical considerations have been proposed in (Shardt and Huang, 2011) for using these data for closed-loop identification.

Consequently, the method tests should be extended to other different conditions, such as the use of operational data, several model plants and model dimension, higher uncertainties and eventually different model structures, before generalizing this result.

4.2 Influence of zeroing no-model IO combination on system identification quality and computational effort

FIT index was the criterion chosen to measure the identification process quality, before and after the IO null model was zeroed. Values obtained not only for identification using ARX model structure, but also using ARMAX and BJ, are shown in Table 4. These values correspond only to the MISO model related to CV-2.

Table 4. FIT for models involving CV2, before and after zeroing no-model IO combination.

Model	FIT [%] before zeroing	FIT [%] after zeroing
ARX	77.31	81.93
ARMAX	81.95	83.56
BJ	79.45	81.15

Values of FIT improved up to 4.63%, once zero was assigned to the no model position in the transfer matrix.

Table 3. $B_i(q)$ coefficient averages for 100 realizations for MISO models.

Model	b_1	stdev b_1	b_2	stdev b_2
CV-1;MV-1	0.238	2.536×10^{-4}	0.026	3.082×10^{-4}
;MV-2	-0.061	1.789×10^{-4}	0.058	1.786×10^{-4}
CV-2;MV-1	3.236×10^{-4}	3.908×10^{-4}	8.527×10^{-4}	5.286×10^{-4}
;MV-2	0.041	3.878×10^{-4}	0.0147	5.465×10^{-4}

Considering the original FIT values, an improvement of 4.63% can be taken as valuable. Computational effort in a succeeding identification process was also quantified. The most remarkable time saving was obtained in the order selection procedure. The method employed was to look for the system order with the higher FIT. The spent time was reduced by up to 22%.

Additionally, MPC can also be favoured in terms of computational effort, once no-model IO combinations are unconsidered, even though benefits will vary for each particular system configuration. These improvements will be much more noticeable for large systems where more than one existing no-model IO combinations are detected.

5. CONCLUSION

IO selection methods employed were not able to identify no-model IO combinations in a transfer matrix of a closed-loop MIMO process. Controller action generally leads to a decoupled condition which hides information about model existence for IO combinations. In MPC applications with PID layer, this regulatory loop usually remains closed, so methods which employ $\boldsymbol{K}$ defined as an open-loop (regulatory loop) steady-state gain matrix are not suitable. Regularity of $B_i(q)$ coefficients found in parametric model structures, ARX in this case, resulted in a clear indication of no-model IO combination. Repeatability of this result was verified through a Monte Carlo simulation. The previous knowledge of no-model IO combination resulted in a decrease of computational effort for the succeeding identification steps. The application of this knowledge also improved the identification performance index employed.

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