

## MULTIVARIABLE CLOSED-LOOP IDENTIFICATION WITH CONSTRAINED MPC CONTROL – A CASE STUDY IN AN INDUSTRIAL DEPROPANIZER COLUMN

## IDENTIFICACIÓN EN LAZO CERRADO DE PROCESOS MULTIVARIABLES CON CONTROL PREDICTIVO CON RESTRICCIONES – CASO DE ESTUDIO DE UNA COLUMNA DEPROPANIZADORA INDUSTRIAL

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### ABSTRACT

*This paper deals with the model re-identification in closed-loop systems with already existing MPC controllers. It is assumed that the controller has a two-layer structure, where in the upper layer a simplified economic optimization determines a set of optimal steady state values for the process inputs (targets) and passes this set to the MPC for implementation. This is the case of several commercial MPC packages applied in industry. This work focuses on the case where the existing process model shows signs of deterioration and there is significant benefit in obtaining a new model aiming a MPC re-commissioning procedure. It is proposed a new methodology to excite the system in closed-loop by introducing persistently exciting signals in the objective function of the economic layer. The approach allows the continuous operation of the system as the process constraints and product specification can be satisfied during the test. The application of the method is illustrated by simulation of a depropanizer column of the oil industry. The method is simple to be implemented in existing commercial MPC packages and the results show that the method has a good potential to be applied in practice.*

*Key words.*- Closed-loop identification, Model predictive control, Process model maintenance, Control performance assessment, Depropanizer column.

### RESUMEN

*El objetivo de este trabajo es la re-identificación del modelo de proceso que se utiliza en controladores predictivos (MPC) ya existentes usando datos de operación en lazo cerrado. Se asume que el controlador tiene una estructura en dos capas, donde en la capa superior un simple algoritmo optimización económica determina un conjunto de valores óptimos en estado estacionario ("targets"), los cuales son pasados al MPC para su implementación. Este es el caso de varios paquetes comerciales MPC aplicados en la industria. El presente trabajo enfoca el caso donde el modelo del proceso presenta signos de deterioro, por lo que obtener un nuevo modelo representa beneficios significativos en el procedimiento de re-comisionamiento del MPC. Se propone una nueva metodología para excitar el sistema en lazo cerrado,*

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*introduciendo señales de excitación persistente en la función objetivo de la capa superior del MPC. Esta estrategia permite la operación continua del sistema, respetando las restricciones del proceso y cumpliendo las especificaciones del producto. La aplicación del método se ilustra a través de simulaciones numéricas de una columna depropanizadora típico de la industria petrolera. El método es simple de ser implementado en controladores MPC existentes y los resultados muestran su gran potencial para aplicaciones prácticas*

*Palabras clave.- Identificación en lazo cerrado, Control predictivo, Mantenimiento del modelo del proceso, Evaluación del desempeño del control, Columna depropanizadora.*

## INTRODUCTION

Model predictive control (MPC) strategies have become the dominant approach in advanced process control applications [1]. The performance of these control systems depends heavily on the embedded process model [2], which is used to predict the future behavior of the process output along a prediction horizon that is long enough to encompass all the process dynamics that need to be taken into account in the computation of the control law. Thus, it becomes clear that a poor process model may result in poor output predictions, and a decrease in the control performance [3].

Although industrial processes present nonlinear dynamic characteristics, the current generation of commercially available MPC is based on linear and time-invariant (LTI) models identified, usually, from open-loop step test. While this approach is valid in small regions around the point where the model was obtained, the control system works satisfactorily in most applications. However, after some operation time (2 to 3 year approx.) MPC controllers seldom keep performing as they were initially designed. The main cause of the performance degradation of MPC is related to the model deterioration resulting from changes in the dynamic behavior of the plant or persistent unmeasured disturbances that force the plant to a different operating point [4]. Changes in the dynamics of the plant may result from fatigue conditions, fouling, debottlenecking, etc, or changes in the operating conditions or product specifications. Usual disturbances include the environment temperature, variations on the feedstock impurities or operating problems in an upstream process. Minor disturbances include process and instrumentation noises. In general, the above listed problems intensify with time and tend to accentuate the plant/model mismatch, leading to poor output prediction and, therefore, degradation

in the control system performance. In order to keep the performance of the MPC at an acceptable level, it is essential to carry out the MPC re-commissioning in a periodic basis, which means to re-identify the process model and, if necessary, to retune the MPC considering the new model [5]. However, due to production goals and safety aspects, model re-identification means, in most cases, to develop a new model based on plant data obtained in closed-loop conditions.

Closed-loop identification is a research subject with growing interest in the last decade [6, 7 y 8]. Important aspects on model identification have been studied and several identification strategies have been proposed. Production goals and safety aspects are the usual incentives to research in closed-loop identification in order to build a model that is relevant to process control. All closed-loop identification can be categorized as variants of the following three approaches: direct, indirect and joint input-output methods. Both indirect and joint input-output methods require prior knowledge of the controller or assume that it has a certain LTI structure. Obviously, these methods are not suitable for MPC applications, because MPC presents nonlinear and time-variant features, especially when operating under constraints [9]. For this sort of control strategy, the direct method (or open-loop method) is the recommended choice for closed-loop identification [10, 11 y 12].

In closed-loop identification, the use of routine operating data would be an ideal target. But, the inherent reduction in the excitation resulting from the presence of the controller may result in a poor signal-to-noise ratio. Theoretical studies show that in order to achieve necessary and sufficient conditions for process identifiability, a persistently exciting (PE) external signal is required [13]. In MPC systems, external excitation is a dither signal that may be introduced in the set-point [14], the controller output [15] or the feedback path. The



main disadvantage of this approach is that there is no guarantee that the process constraints and product specifications will be attended during the execution of the excitation procedure. On the other hand, an insufficient excitation may compromise the identification requirements. To overcome these problems, some authors have proposed the so-called internal excitation methods. Genceli and Nikolaou [16] propose the MPC (model predictive control and identification) where the PE characteristic of the inputs is imposed as a constraint in the control optimization problem. The resulting problem is a non-convex one, being necessary some modifications on the code of the control program. This is certainly not available for most of the practitioners. Sagias and Nikolaou [17] propose the extension of the cost function of the conventional MPC to address both control and identification objectives. The approach considers injection of a dither signal into the new cost function trying to force a predefined sequence of moves on the manipulated inputs. With this strategy the control problem remains convex and no new optimization code is needed.

The main goal of this paper is to establish a new closed-loop identification methodology of processes under MPC control. Motivation for this work is due primarily by commercial needs and as an attempt to overcome the significant gap between practical applications and theory in closed-loop identification with MPC. The proposed methodology takes into account that the identification procedure must be performed in an industrial environment where production cannot be interrupted and the process operation must be kept inside an operating window defined by product specification and equipment constraints. To finish the paper, an approach is proposed for MPC performance assessment, which uses results from the closed-loop identification methodology.

## THE PROPOSED METHODOLOGY

Most of the commercial MPC packages are implemented in a two-layer structure as part of a hierarchical control structure [18, 19 y 20]. The two-layer MPC considered here is shown in Figure 1, with both layers executed with the same sampling period. The upper layer usually corresponds to a simplified steady state economic optimization, in which the economic objective is represented as a linear combination of the process

inputs, and the lower layer stands for a QDMC (quadratic dynamic matrix control) algorithm in which the outputs are controlled in specified zones or ranges instead of fixed references. In the economic optimization we search for the optimum steady state values of the system inputs (input targets). This is done by optimizing a linear or quadratic economic objective subject to bound constraints in the system inputs and outputs. The outputs at the optimal steady state are computed through a steady state linear model and using the available output prediction in the MPC algorithm. The optimal input targets are sent to the MPC algorithm, where the control cost is extended to include a term that weights the distance between the present value of the input and the optimal target.

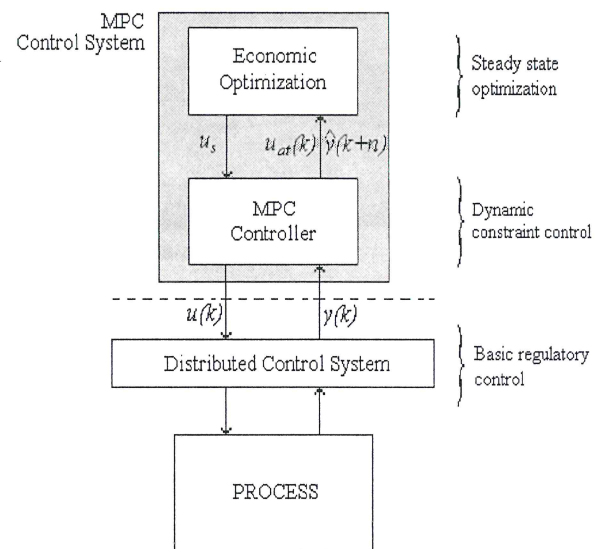


Fig. 1 Typical MPC layered structure.

A reasonable consideration is that when the process model is poor, the economic optimization layer will change the input target to the MPC layer quite often, and so, the input targets could be viewed as a possible test signal in the closed-loop identification procedure. However, to assume that these natural moves on the input targets will be sufficiently exciting is a questionable matter.

Taking advantage of the MPC layered structure (Figure 1), and in order to guarantee the necessary excitation of the process, which we are trying to re-identify, we propose a method where the PE test signal is introduced as a multiplier factor of the economic coefficients in the objective function of

the economic optimization layer. For this purpose, the economic optimization problem is re-written as follows:

$$\min_{\Delta u_s, \delta_y} -(W_1 \otimes W_{exc}) \Delta u_s + \|W_2 \Delta u_s\|_2^2 + \|W_3 \delta_y\|_2^2 \quad (1)$$

subject to constraints:

$$\begin{aligned} \Delta u_s &= u_s - u_{at} \\ y_s &= G_0 \Delta u_s + \hat{y}(k+n/k) \\ u_{\min} &\leq u_s \leq u_{\max} \\ y'_{\min} &\leq y_s + \delta_y \leq y'_{\max} \end{aligned} \quad (2)$$

where:

$u_{at}$  is the vector of manipulated inputs at present time  $k$ ,  $u_s$  is the vector of targets of the manipulated inputs,  $y_s$  is the vector of predicted outputs at steady state,  $\hat{y}(k+n/k)$  is the prediction of the controlled output at instant  $k+n$  ( $n$  is the model horizon or settling time of the dynamic process model) computed at time  $k$ ,  $\delta_y$  is the vector of slack variables for the controlled outputs,  $G_0$  is the steady state gain matrix of the process,  $W_1$  is the vector of economic coefficients of the manipulated inputs,  $W_2$  is the matrix of weights of the manipulated input moves,  $W_3$  is the matrix of weights of the output slack variable,  $W_{exc}$  is the time-variant weighting vector of the economic coefficients (persistently exciting test signals),  $u_{\min}$  and  $u_{\max}$  are the bounds of the manipulated inputs (the same as used in the control layer),  $y'_{\min}$  and  $y'_{\max}$  are the bounds of the controlled outputs (which zones can be smaller than or equal to the ones defined by  $y_{\min}$  and  $y_{\max}$  as used in the MPC layer).

In Equation 1, operator  $\otimes$  denotes the Hadamard (or Schur) product. On the above equations, the slack variable is included to guarantee existence of a solution to the optimization problem defined in Equations 1 and 2. If  $W_{exc}$  is set equal to a time-invariant vector of ones, the excitation procedure is ended and we have the original economic optimization problem.

As a result of the solution to the problem formulated in Equations 1 and 2, we obtain the input target  $u_s$  that is passed to the MPC layer, which solves the following quadratic program (QP) problem:

$$\min_{\Delta u} \sum_{i=1}^p \left\| Q(\hat{y}(k+i/k) - y_{sp}) \right\|_2^2 + \sum_{j=1}^m \left\| R \Delta u(k+j-1/k) \right\|_2^2 + \sum_{j=1}^m \left\| R_u \left( u_{at} + \sum_{i=1}^j \Delta u(k+i-1/k) - u_s \right) \right\|_2^2 \quad (3)$$

subject to constraints:

$$\begin{aligned} -\Delta u_{\max} &\leq \Delta u(k+j-1/k) \leq \Delta u_{\max}, \quad j=1, \dots, m \\ u_{\min} &\leq u_{at} + \sum_{i=1}^j \Delta u(k+i-1/k) \leq u_{\max}, \quad j=1, \dots, m \end{aligned} \quad (4)$$

where:

$\hat{y}$  is the output predictions,  $y_{sp}$  is the set-point of the system output,  $\Delta u$  is the vector of control moves,  $m$  is the control horizon,  $p$  is the prediction horizon,  $Q$  is the diagonal weight matrix of the controlled outputs,  $R$  is the diagonal weight of matrix of the manipulated inputs,  $R_u$  is the diagonal matrix that weights the distance between the computed input and the optimum target. In the controller defined by Equations 3 and 4, the zone control strategy is implemented as follows. Depending on the value of each output prediction  $\hat{y}_j$  at instant  $k+i$ , we may have the following cases:

$$(a) \quad y_{j,\min} \leq \hat{y}_j(k+i/k) \leq y_{j,\max}$$

In this case, the error on this output at time instant  $k+i$  can be ignored by the controller. This means that weight  $Q$  should be made equal to zero and the set-point can assume any value.

$$(b) \quad \hat{y}_j(k+i) > y_{j,\max}$$

In this case, the controller should bring the output back to the upper boundary of the control zone. Then, we should select the output set point such that  $y_{j,sp} = y_{j,\max}$ , and weight  $Q$  should be made equal to the value obtained in the controller tuning procedure.



(c) Analogously, if  $\hat{y}_j(k+i) < y_{j,\min}$

Then, this output should be brought back to the lower boundary of the control zone. In this case we make  $y_{j,sp} = y_{j,\min}$  and weight  $Q$  is selected as in the previous case.

The proposed method to excite the system in closed-loop can be considered as an internal excitation method, and it can be easily implemented in existing MPC packages<sup>1</sup>. Each test signal is designed with a different shape, such that the cross-correlation between the inputs is minimized. We will show, in the example section, that, with this approach, the inputs can be adequately excited, the feedback effect on the test data is minimized and the requirements about the test signal for the system to be identifiable are reached. Also the approach attends the process safety requirements and the specifications of the products are attended satisfactorily.

The other steps of the proposed methodology follow same steps of the identification methodology that is usually applied to industrial processes [21]: design of the test signal, selection of the model structure, computation of the model parameters and model validation. The development of each of these steps is illustrated in the case study of closed-loop identification that is presented to follows.

### CASE STUDY: DEPROPANIZER COLUMN

This work considers the process studied by Porfirio et al. [22]. It is a depropanizer column of the fluid catalytic cracking (FCC) unit at the PETROBRAS's Presidente Bernardes Refinery of Cubatão (RPBC), Brazil. In this process, the C3 stream (propane and propene) is separated from a C4 stream (butane, butene and other hydrocarbons with four atoms of carbon). A schematic diagram of the depropanizer column with some of the regulatory control loop (PID type) and MPC control system is shown in Figure 2.

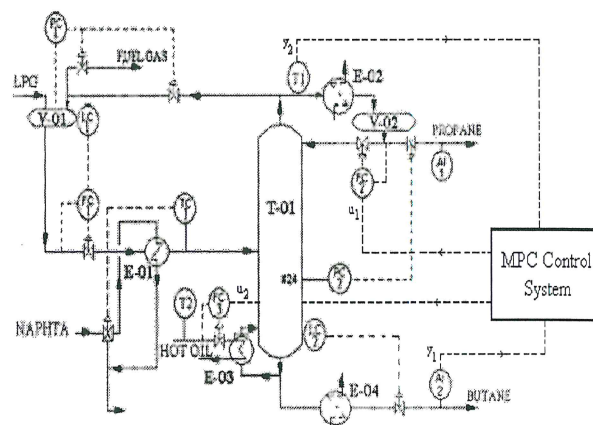


Fig. 2 Diagram of the depropanizer column.

In Figure 2, T-01 is the depropanizer column, E stands for heat exchanger and V designates a process vessel. The feed stream is liquefied petroleum gas (LPG) that comes from the top of a debutanizer column that separates the LPG from gasoline. The C3 stream is produced as the top stream of the depropanizer column and the C4 stream is produced as the bottom stream of the column. AI1 and AI2 are analyzers that measure the contents of C4 in the propane stream and the contents of C3 in the butane stream, respectively.

This process should be controlled such that the recovery of C4 is maximized, because this stream is sent to the alkylation unit where the C4 is converted into high-octane gasoline. For this purpose, the depropanizer is being controlled by a commercial MPC package similar to the one described in section 2. It is a 2x2 multivariable control system, where the output variables  $y_1$  and  $y_2$  are the molar composition of C3 in the bottom stream (%) and the temperature at the first stage of the top section of the distillation column (°C), respectively. The input variables  $u_1$  and  $u_2$  are the reflux flowrate to the top of the column (m<sup>3</sup>/d) and the flowrate of hot oil to the reboiler (m<sup>3</sup>/d), respectively.

To represent the “real” process and to represent the nominal process model (already existing model in MPC) in the simulations that will be performed here, the following transfer function matrices taken from [22] are considered:

<sup>1</sup> For instance, the two-layers MPC algorithm as described in Section 2, with slight modifications and without excitation procedure, is supported by the PETROBRAS advanced control package SICON, which is the standard process control software in the oil refineries of PETROBRAS.

Real process:

$$G_p(s) = \begin{bmatrix} \frac{(-2.218 \times 10^{-4})s + (5.656 \times 10^{-4})}{s^2 + 3.4948s + 0.5902} & \frac{(0.7413 \times 10^{-4})s - (1.452 \times 10^{-3})}{s^2 + 2.6987s + 0.4023} \\ \frac{(-1.135 \times 10^{-3})s - (1.235 \times 10^{-3})}{s^2 + 1.6380s + 0.09852} & \frac{(-0.3 \times 10^{-3})s + (0.2 \times 10^{-2})}{s^2 + 2.4298s + 0.0651} \end{bmatrix} \quad (5)$$

Old process model:

$$G_m(s) = \begin{bmatrix} \frac{(0.4227 \times 10^{-4})s + (0.1094 \times 10^{-4})}{s^2 + 0.1090s + 0.0243} & \frac{(-1.2055 \times 10^{-4})s - (0.03824 \times 10^{-3})}{s^2 + 0.1342s + 0.0111} \\ \frac{(-0.0873 \times 10^{-3})s - (0.1116 \times 10^{-3})}{s^2 + 0.1317s + 0.0073} & \frac{(1.3 \times 10^{-3})s + (0.7 \times 10^{-2})}{s^2 + 2.2605s + 0.1366} \end{bmatrix} \quad (6)$$

The main parameters of the controller are:

$$\begin{aligned} W_1 &= (500, -500), & W_2 &= \text{diag}(200, 200), \\ W_3 &= \text{diag}(10^3, 10^3), & Q &= \text{diag}(1.3, 1.2), \\ R &= \text{diag}(1.5, 1.5), & R_u &= \text{diag}(10, 10), \\ u_{\min} &= (2800, 1500), & u_{\max} &= (3250, 2000), \\ \Delta u_{\max} &= (10, 10), & y_{\min} &= (0.7, 48), \\ y_{\max} &= (1.0, 50), & y'_{\min} &= (0.8, 48.25), \\ y'_{\max} &= (0.95, 49.75), & n &= 120, \quad p = 60, \quad m = 2. \end{aligned}$$

The sampling time is  $\Delta t = 1$  min. As it can be noted from the input and output bounds, the operating window of the depropanizer column is quite narrow, which is a characteristic of high-purity distillation systems.

### PE signal design and generation of the dataset

The design of the test signal plays a major role in the excitation and identification procedures of the process system. In the closed loop identification strategy proposed here, the purpose is to design a PE test signal that produces a persistent excitation of the process input.

One of the PE signals most used in industrial practice is the pseudo-random binary sequence (PRBS) [23]. The energy content of this signal is distributed uniformly over the entire frequency range. However, in many situations, as the present one, we are interested in a particular frequency (or frequency range) other than the broad spectrum. The generalized binary noise (GBN) proposed by Tulleken [24] has a similar approach as the PRBS except an additional parameter related to the

switching probability. This allows manipulation of the power spectrum of the test signal, such that most energy can be concentrated in the low-frequency range. Another advantage of GBN is that the signal length is flexible and it has a minimum crest factor. Due to these facilities, GBN is considered as the most suitable signal for control-relevant identification of industrial processes [25].

Based on guidelines provided by Zhu [25] and a priori knowledge of the process ( $G_m$ ), two independent GBN signals of magnitude  $\pm 1$  are designed and they are applied in the economic optimization layer of the MPC. The duration of the excitation test is 4500 min, resulting 4500 samples of input-output data, which are shown in Figure 3.

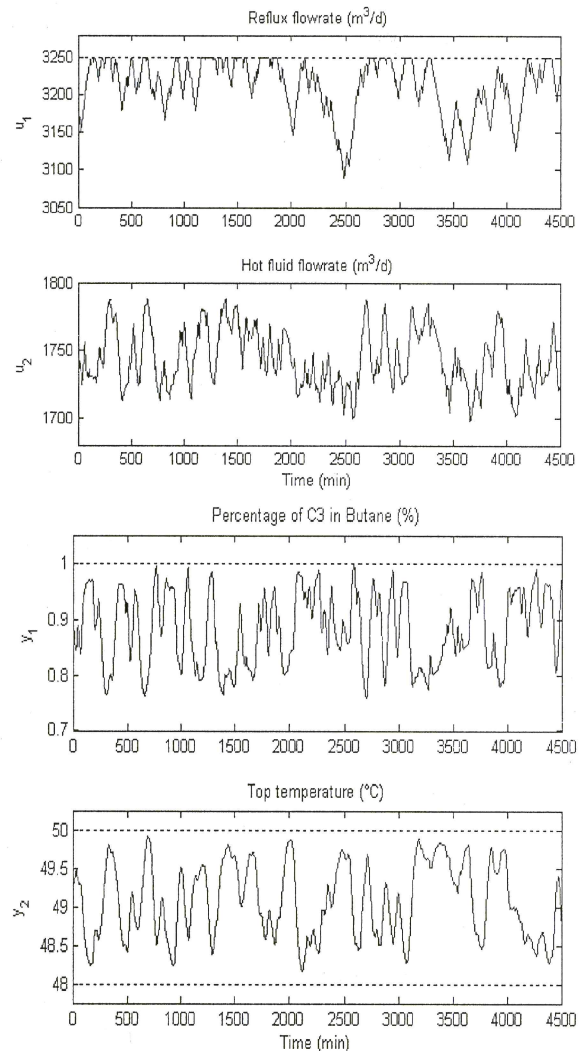


Fig. 3 Input-output dataset of the depropanizer column.



As can be seen in Figure 3, the excitation signal that was introduced in the MPC system did not compromise the operating objectives of the process, as both the inputs and outputs were inside the respective boundaries. The strategy of the zone control minimizes the feedback effect on the identification data, because during most of the time of the test, the control action aiming at controlling the outputs was not activated. With this strategy the closed-loop identification procedure approaches the direct or open-loop identification method procedure, which ignores the presence of the controller.

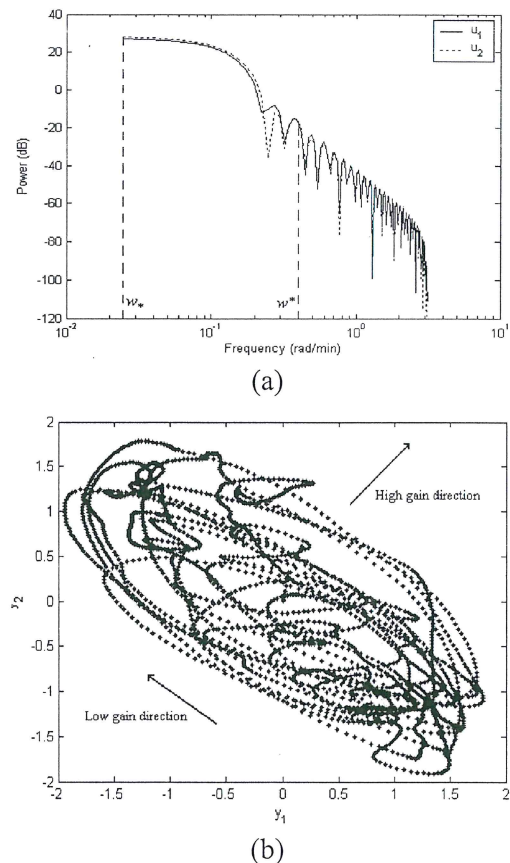
As usual, in any model identification procedure, the simulation data represented in Figure 3 should be normalized in order to make the inputs and outputs of the system equally important. This is done by subtracting from each input and output its computed mean and dividing the result by the standard deviation of that variable. Linear trends were also removed. Finally, the dataset is filtered with a low pass filter aiming to concentrate the identification results in the frequency range of interest.

A portion of this dataset (first 3000 samples) is used for identification purposes and another part (remaining 1500 samples) to subsequently validate the estimated models. Based on the covariance test [26], it can be proved that the inputs are PE of order 4, which guarantees the identification of new transfer functions of 2<sup>nd</sup>-order for the depropanizer column.

To verify the quality of the identification dataset, Figure 4(a) presents the power spectrum of the inputs. The selected part of the spectrum ( $w_*$ ,  $w^*$ ) indicates the desired frequency range where the model will be identified. In fact, a good model in the low and mid frequency ranges is essential for MPC control purposes [27].

Namely, low frequency (gain) model information is critical for steady state optimization. Here, dips at frequencies outside of the indicated bandwidth and other high-frequency contributions were not included in the identification procedure.

Figure 4(b) shows also that low and high output gain directions are well excited, allowing a good estimate in both directions.



**Fig. 4** (a) Power spectrum of the inputs, (b) Excitation of output gain directions.

### Model structure selection

All identified models have certain bias (or deterministic error) and variance (or stochastic error). The best model is obtained by minimizing the total error. But, there is a tradeoff between both parts of the error. By using nonparametric FIR (finite impulse response) models, bias error can be minimized (because of the reduced model structure and order limitations), but it can result in higher variance due to the larger number of parameters. On the other hand, by using low-order parametric models, variance error is reduced but bias error is inevitably larger [28].

In many industrial MPC controllers, the stochastic model is fixed a priori and the ‘best approximate process model’ within some chosen model structure needs to be estimated. In the present paper, it is considered that the process can be represented by continuous-time MISO (multiple-input, single-output) OE (output-error) transfer

function models, with the stochastic model parameterized as unitary, of the following form:

$$\hat{y}_j(t, \rho_j) = \sum_{i=1}^{n_u} \hat{G}_{j,i}(s, \rho_{j,i}) u_i(t - \theta_{j,i}) + \varepsilon_j(t); \quad j=1, \dots, n_y \quad (7)$$

where  $\hat{G}_{j,i}(s, \rho_{j,i})$  is the  $(j, i)_{th}$  transfer function defined as:

$$\hat{G}_{j,i}(s, \rho_{j,i}) = \frac{\hat{B}_{j,i}(s)}{\hat{A}_{j,i}(s)} = \frac{\sum_{k=0}^{m_{j,i}} \hat{b}_{j,i,k} s^k}{\sum_{k=0}^{n_{j,i}} \hat{a}_{j,i,k} s^k} \quad (8)$$

with  $\hat{a}_{j,i, n_{j,i}} = 1$ ,  $n_{j,i} \geq m_{j,i}$ , where  $u(t)$  is the input vector,  $\hat{y}(t, \rho)$  is the model output,  $\theta_{j,i}$  is the time-delay between the  $i_{th}$  input and the  $j_{th}$  output,  $\varepsilon(t)$  is the residual or total model error (bias plus variance),  $n_u$  and  $n_y$  are the number of inputs and outputs, respectively, and  $\rho_{j,i} = [\hat{b}_{j,i, m_{j,i}} \dots \hat{b}_{j,i, 0} \hat{a}_{j,i, (n_{j,i}-1)} \dots \hat{a}_{j,i, 0}]^T \in \mathbb{R}^{p_{j,i}}$ , with  $p_{j,i} = n_{j,i} + m_{j,i} + 1$ , where  $n_{j,i}$  and  $m_{j,i}$  denotes the denominator and numerator orders of  $\hat{G}_{j,i}(s, \rho_{j,i})$ , respectively. Therefore, the parameter vector is

$$\rho_j = [\rho_{j,1}^T \dots \rho_{j,n_u}^T]^T \in \mathbb{R}^{p_j \times 1}; \quad p_j = \sum_{i=1}^{n_u} p_{j,i} \quad (9)$$

### Identification procedure

The goal is to build a model as defined in Equation 7 based on closed-loop sampled data, focusing on the parameters of each transfer function  $\hat{G}_{j,i}(s, \rho_{j,i})$  rather than on the model error appearing in Equation 7. The pure time-delay  $\theta_{j,i}$  is supposed to be known a priori and to be a multiple of the sampling time  $\Delta t$ . Several procedures have been proposed, which are developed as extensions of the existing procedures that deal with SISO systems and that allow the identification of transfer functions with a common denominator. This approach may not be realistic in

several practical applications. In this work, it is used the CONTSID toolbox [29] that presents new methods in the time-domain to deal with processes described by continuous-time MISO systems with several transfer functions with different denominators. The OE method from the CONTSID toolbox is used to find the parameter vector  $\rho_j$  (Equation 9) for the depropanizer column, with  $n_u = n_y = 2$ ,  $n_{j,i} = 2$  and  $m_{j,i} = 1$ . The identification is carried out off-line using the identification dataset and considering the values of the parameters of the old process model (Equation 6) as the initial estimation for the identification algorithm. The re-identified model is:

New process model:

$$G_{new}(s) = \begin{bmatrix} \frac{(2.596 \times 10^{-4})s + (1.145 \times 10^{-4})}{s^2 + 0.8527s + 0.1201} & \frac{(-12.76 \times 10^{-4})s - (0.552 \times 10^{-3})}{s^2 + 1.157s + 0.1533} \\ \frac{(-2.619 \times 10^{-3})s - (0.677 \times 10^{-3})}{s^2 + 0.9872s + 0.05466} & \frac{(-144.3 \times 10^{-3})s + (24.06 \times 10^{-2})}{s^2 + 2.595s + 7.934} \end{bmatrix} \quad (10)$$

The old and new process models are evaluated based on the following performance criteria:

$$FIT = 100 \times \left( 1 - \frac{\text{norm}(y_j - \hat{y}_j)}{\text{norm}(y_j - \text{mean}(y_j))} \right) \quad (11)$$

$$R_T^2 = 1 - \frac{\text{var}(y_j - \hat{y}_j)}{\text{var}(y_j)}$$

where  $y$  is the true system output and  $\hat{y}$  the model output. Coefficient  $FIT$  indicates the percentage of the output variation that can be associated to the model, while coefficient  $R_T^2$  measures how well the model output explains the behavior of the system output, and this parameter will be close to 1 in low noise conditions. Simulation results of the old and new models are presented in Figure 5. Performance indicators and visual inspection show that the new model matches much better the system outputs than the available model in the MPC package. Loss function and Akaike's final prediction error (FPE) associated to each new model are also shown,



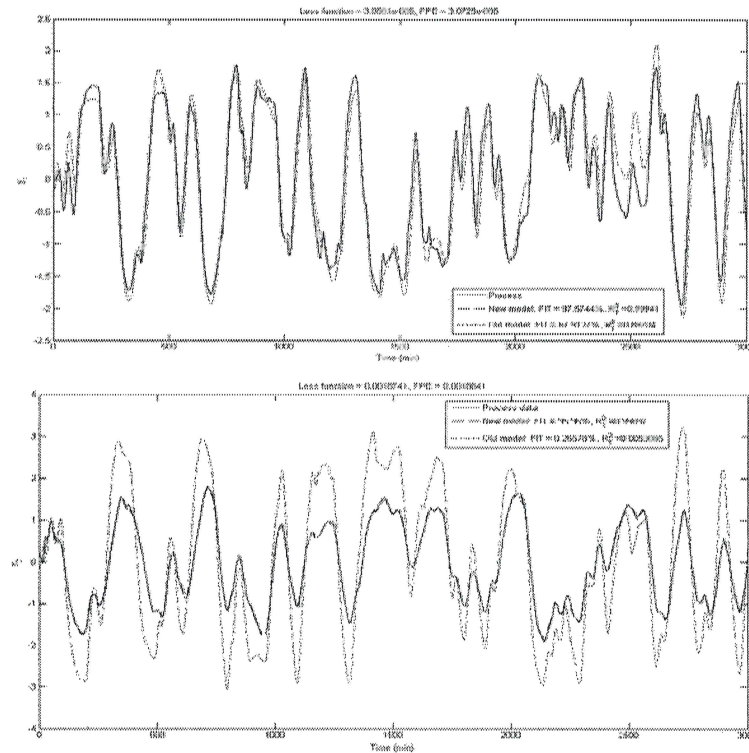


Fig. 5 Simulation results for the depropanizer column.

### Model validation

Here, the goal is to confirm whether the obtained model is an accurate representation of the process and to provide a basis for possible re-identification. The models can be validated in a variety of ways. Residual correlation test, Bode frequency response, pole-zero plots and cross-validation are often used. For the case of the depropanizer column, we will discuss some aspects as model error modeling, step response, interaction analysis and cross-validation.

**Model error modeling.**– It consists in building models that describe the dynamics relating the inputs to the residual, in order to verify, in the frequency domain, if any essential unmodeled dynamics are left. This idea has attracted much interest in the past decade, motivated by the linear robust control theory, and because it provides more freedom in investigating the residuals than the classical residual correlation test [30]. From Equation 7, we can interpret the residual as:

$$\varepsilon_j(t, \rho_j^e) = y_j(t) - \hat{y}_j(t, \rho_j) = \sum_{i=1}^{n_{ij}} \hat{G}_{j,i}^e(s, \rho_{j,i}^e) u_i(t - \theta_{i,j}) \quad (12)$$

where  $\hat{G}_{j,i}^e(s, \rho_{j,i}^e)$  is the model of the error corresponding to model  $\hat{G}_{j,i}(s, \rho_{j,i})$ , with denominator and numerator orders denoted by  $n_{j,i}^e$  and  $m_{j,i}^e$  ( $n_{j,i}^e \geq m_{j,i}^e \gg n_{j,i}$ ) respectively, and parameter vector  $\rho_j^e$  defined in a similar way as in Equation 9. In this study, the equation-error (EE) method from the CONTSID toolbox is used to compute the parameter vector  $\rho_j^e$ , with  $n_{j,i}^e = m_{j,i}^e = 10$ . This is performed using the residual as the output and the system inputs taken from the identification dataset as the inputs. Figure 6 shows the Bode plot of the models of the error and their confidence regions (3 standard deviation of the normal distribution).

As it can be observed, the new models  $\hat{G}_{j,i}(s, \rho_{j,i})$  are satisfactory within 99.6% probability at the frequency range of interest. The new model is compared with the old model, which contains large uncertainties.

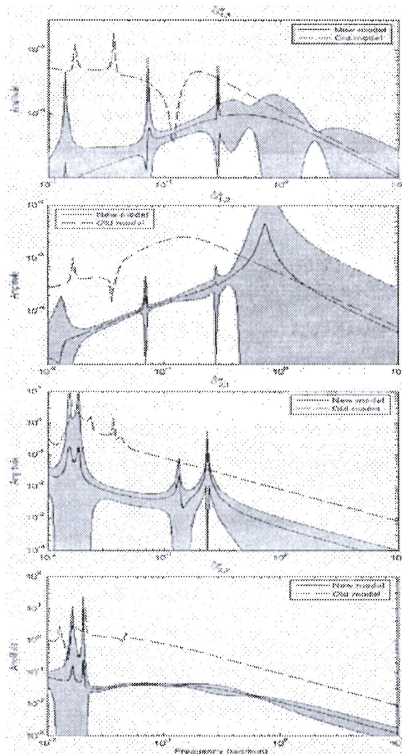


Fig. 6 Depropanizer model error models.

**Step response.**- In the plant-friendly identification procedure for MPC, step response is a logical approach for model validation. Figure 7 shows the step response comparison between the old model and the new model. As it can be noted, the new model captures the steady-state gains and the time constants of the process correctly. This means that using the new model the “dynamic matrix”, which contains the step response coefficients corresponding to the inputs to the depropanizer process, will be more successful than using the old model.

**Interaction analysis.**- Here it is studied the interaction behavior of the depropanizer models as a function of the frequency range in which we are interested. Here, we use the relative dynamic gain array (RDGA) number as an interaction measure, which is based on the Bristol’s RGA, defined as [31]:

$$RDGA_{number}(j\omega) = \|\|RDGA(j\omega) - I\|_{sum} \quad (13)$$

Where

$$RDGA(j\omega) = G(j\omega) \otimes (G(j\omega)^\dagger)^T \quad (14)$$

with  $(\dagger)$  denoting the Moore-Penrose pseudo-inverse. If the  $RDGA_{number}$  is close to zero, there is no interaction in the system (or it is negligible). As noticed in Figure 8, the new model has almost the same  $RDGA_{number}$  profile as the depropanizer true model, i.e. there is interaction in the whole frequency range of interest, which plays an important role in MPC control. The  $RDGA_{number}$  of the old model reveals less dynamic interaction than in the real plant. From medium to high frequencies, the interaction level corresponding to the old model decreases rapidly which may be inadequate for the purpose of multivariable control.

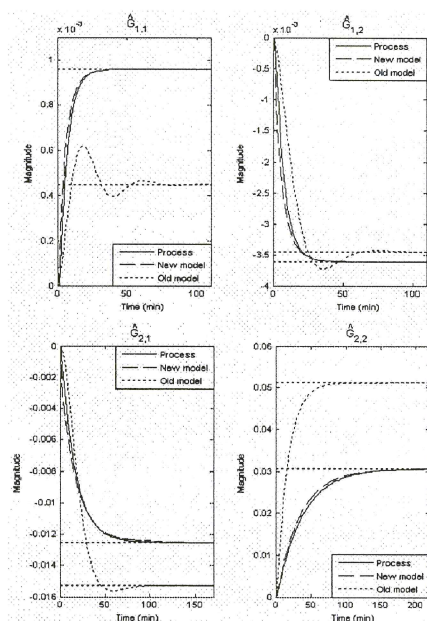


Fig. 7 Step response for the depropanizer column.

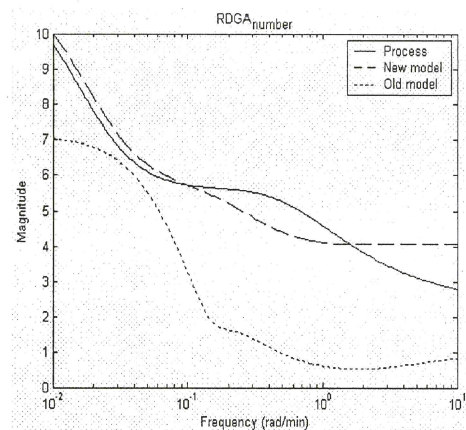


Fig. 8  $RDGA_{number}$  plot for the depropanizer column.



**Cross-validation.**- It is one of the most important and revealing tests for model validation. In this case, the validation dataset, which was not used in the identification procedure, is used to compare the model predictions. Cross-validation results from

the old and new models and its respective performance indicators are presented in Figure 9. These results show that the new model reproduces almost perfectly the dominant dynamics of the depropanizer system.

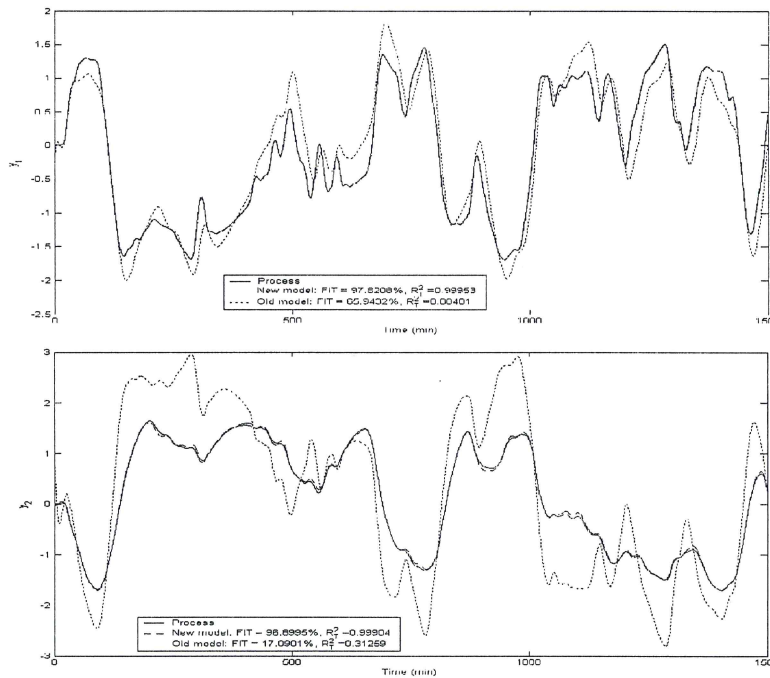


Fig. 9 Cross-validation results for the depropanizer column.

**ASSESSING THE MPC PERFORMANCE**

Several methods have been proposed for MPC performance assessment [32]. In this section, a methodology is proposed, which uses results from the cross-validation step. The method is based on Thornhill et al. [33] that propose a method for evaluation of the regulatory control performance. However, instead of evaluating the controller behavior, the methodology is used to evaluate the model by analyzing the time series of the observed error and to verify the existence of a predictable pattern beyond the control horizon for each of the outputs of the models. The comparison is performed in term of variances of the residues. The approach considers that if the MPC is to perform well, then its internal model should be able to predict the output of the process along a prediction horizon  $p$ , i.e. the model error should have no predictable components or it should not be distinguishable from a random walk stochastic process after time instant  $t + p$ . Thus, the proposed methodology demands a method to make

predictions of the error model  $p$ -steps ahead of the present time. Here, it is used an autoregressive time series model of the following form:

$$\hat{\varepsilon}_j(t+p) = a_0 + a_1\varepsilon_j(t) + a_2\varepsilon_j(t-1) + \dots + a_{n_a}\varepsilon_j(t-n_a+1) \tag{15}$$

where  $\varepsilon_j(t)$  is the model error described in Equation (12) and  $n_a$  is the order of the autoregressive model. Parameters  $a_i$  in Equation 15 can be fitted to a given dataset of  $n$  samples of the model error using a least squares fit procedure:

$$\begin{bmatrix} a_0 & a_1 & \dots & a_{n_a} \end{bmatrix}_j^T = X_j^\dagger Y_j \tag{16}$$

With

$$X_j = \begin{bmatrix} 1 & \varepsilon_j(1) & \varepsilon_j(2) & \dots & \varepsilon_j(n_a) \\ 1 & \varepsilon_j(2) & \varepsilon_j(3) & \dots & \varepsilon_j(n_a+1) \\ \vdots & \vdots & \vdots & \dots & \vdots \\ 1 & \varepsilon_j(n-p-n_a+1) & \varepsilon_j(n-p-n_a+2) & \dots & \varepsilon_j(n-p) \end{bmatrix}$$

$$Y_j = [\varepsilon_j(n_a + p) \quad \varepsilon_j(n_a + p + 1) \quad \cdots \quad \varepsilon_j(n)]^T$$

The difference between the actual and predicted model errors is the residue  $r_\varepsilon(t)$ , which mean and variance provide relevant information regarding the predictability of the model, or the model behavior.

In the present application, the model error, the residue and the prediction of the model error of the old and new models are shown in Figure 10, which are generated using the validation dataset and parameter values  $n_a = 30$  and  $n = 1500$  (although only the first 500 points are plotted in Figure 10). Parameter  $p$  is the same as used in the MPC controller.

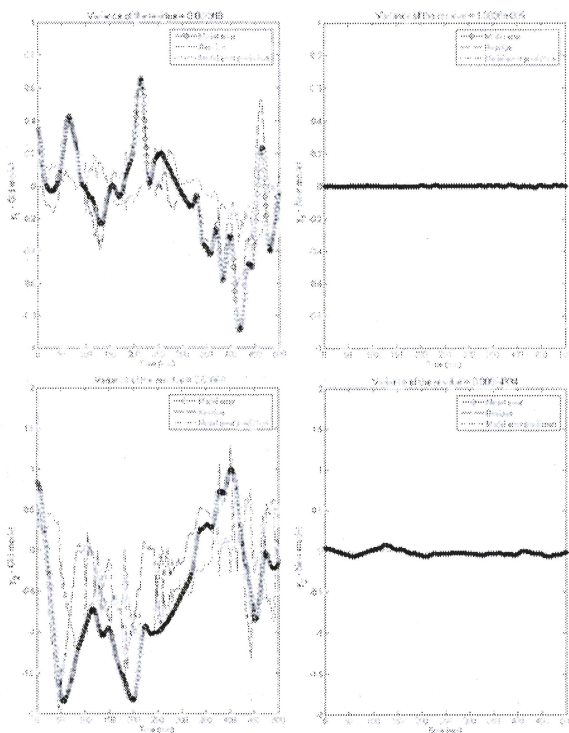


Fig. 10 Predictability of the depropanizer model errors.

From Figure 10, it can be observed that the new model presents much smaller variability of the residues and, therefore, a superior performance than the current model used in the controller. Particularly, the major variability of the residues of the old model corresponding to output  $y_2$  indicates that it is a very poor model, as it was demonstrated by the results of the previous section. The

methodology shown above can be used as a tool to decide the need or not of re-identifying the model of the process.

## CONCLUSIONS

In this work, it has been proposed a methodology to re-identify the process model in a closed loop strategy for multivariable industrial processes, which are controlled by MPC packages based on the two layer structure. The test signal is introduced in the economic coefficients of objective function of the economic layer of the controller. The test signal is then translated into optimal targets to the inputs of the system in the MPC algorithm, which uses the concept of zone control for the outputs.

The proposed methodology was tested by simulation in a linear model of an industrial depropanizer column<sup>2</sup>. The results show that the proposed method is very promising in terms of future practical application. The main feature of the method is that considerable time is saved in the identification procedure, and manpower is reduced in a large extent because the algorithm can operated unattended for several days or weeks, preserving product specifications and without jeopardizing plant safety. The method can serve as the basis for periodic MPC re-commissioning and for the design of an explicit adaptive MPC. Most details about the exposed closed-loop identification methodology can be seen in Sotomayor et al. [34 y 35].

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## REFERENCES

1. Qin, S. J., Badgwell, T. A., "A survey of industrial model predictive control technology". Control Engineering Practice, 11(7): pp. 733-764, 2003.

<sup>2</sup>Simulation results from a nonlinear model of an industrial FCC unit is presented in [34].



2. **Huang, B., Malhotra, A., Tamayo, E. C.**, “Model predictive control relevant identification and validation”. *Chemical Engineering Science*, 58(11): pp. 2389-2401, 2003.
3. **MacArthur, J. W., Zhan, C.**, “A practical global multi-stage method for fully automated closed-loop identification of industrial processes”. *Journal of Process Control*, 2007 (In press).
4. **Conner, J. S., Seborg, D. E.**, “Assessing the need for process re-identification”. *Industrial & Engineering Chemistry Research*, 44(8): pp. 2767-2775, 2005.
5. **Gugaliya, J. K., Patwardhan, S. C., Gudi, R. D., Raghavan, H., Yelchuru, R.**, “Model maintenance for industrial process control”. 2005 AIChE Annual Meeting, paper 520d, Cincinnati-OH, USA, 2005.
6. **Van den Hof, P. M. J.**, “Closed loop issues in system identification”. *Annual Reviews in Control*, 22(1): pp. 173-186, 1998.
7. **Forsell, U., Ljung, L.**, “Closed-loop identification revisited”. *Automática*, 35(7): pp. 1215-1241, 1999.
8. **Landau, I. D.**, “Identification in closed loop: a powerful design tool (better design models, simpler controllers)”. *Control Engineering Practice*, 9(1): pp. 51-65, 2001.
9. **Zafiriou, E.**, “Robust model predictive control of processes with hard constraints”. *Computers & Chemical Engineering*, 14(4-5): pp. 359-371, 1990.
10. **Rivera, D. E., Flores, M. E.**, “‘Plant-friendly’ closed-loop identification using model predictive control”. 1999 AIChE Annual Meeting, paper 227d, Dallas-TX, USA, 1999.
11. **Zhu, Y., Butoyi, F.**, “Case studies on closed-loop identification for MPC”. *Control Engineering Practice*, 10(4): pp. 403-417, 2002.
12. **Amjad, S., Al-Duwaish, H. N.**, “Closed loop identification with model predictive control: a case study”. 2003 SICE Annual Conference, Fukui, Japan, 2003.
13. **Gustavsson, I., Lung, L., Söderström, T.**, “Identification of processes in closed loop – identifiability and accuracy aspects”. *Automatica*, 13(1): pp. 59-75, 1977.
14. **De Klerk, E., Craig, I. K.**, “Multivariable closed-loop system identification of plants under model predictive control”. 13<sup>th</sup> IFAC Symposium on System Identification, Rotterdam, The Netherlands, 2003.
15. **Kline, S., Street, R., Patwardhan, R. S., Bae, A.**, “Closed loop identification for multivariable model predictive controller on a catalytic gasoline splitter”. 7<sup>th</sup> International Conference on Chemical Process Control, Lake Louise, Alberta, Canada, 2006.
16. **Genceli, H., Nikolaou, M.**, “New approach to constrained predictive control with simultaneous model identification”. *AIChE Journal*, 42(10): pp. 2857-2868, 1996.
17. **Sagias, D., Nikolaou, M.**, “Closed-loop identification of processes operating under model predictive control without external excitation”. 2001 AIChE Annual Meeting, paper 279i, Reno-NV, USA, 2001.
18. **Ying, C.-M., Joseph, B.**, “Performance and stability analysis of LP-MPC and QP-MPC cascade control systems”. *AIChE Journal*, 45(7): pp. 1521-1534, 1999.
19. **Rotava, O., Zanin, A. C.**, “Multivariable control and real-time optimization – an industrial practical view”. *Hydrocarbon Processing*, 84(6): pp. 61-71, 2005.
20. **Young, R. E.**, “Petroleum refining process control and real-time optimization”. *IEEE Control System Magazine*, 26(6): 73-83, 2006.
21. **Ljung, L.**, “System identification – theory for the user”, 2<sup>nd</sup> Ed., Prentice Hall, NJ, 1999.
22. **Porfírio, C. R., Neto, E. A., Odloak, D.**, “Multi-model predictive control of an industrial C3/C4 splitter”. *Control Engineering Practice*, 11(7): pp. 765-779, 2003.
23. **Godfrey, K. R.**, “Perturbation signals for system identification”. Prentice Hall, UK, 1993.
24. **Tulleken, H. J. A. F.**, “Generalized binary noise test-signal concept for improved identification-experiment design”. *Automatica*, 26(1): pp. 37-49, 1990.
25. **Zhu, Y.**, “Multivariable system identification for process control”. Elsevier Science Ltd., UK, 2001.
26. **Söderström, T., Stoica, P.**, “System identification”. Prentice-Hall, UK, 1989.
27. **Gopaluni, R. B., Patwardhan, R. S., Shah, S.L.**, “The nature of data pre-filters in MPC relevant identification – open and closed-loop issues”. *Automatica*, 39(9): pp. 1617-1626, 2003.

28. **Zhu, Y., Arrieta, E., Butoyi, F., Cortes, F.**, "Parametric versus nonparametric models in MPC process identification". *Hydrocarbon Processing*, 79(2): pp. 65-72, 2000.
29. **Garnier, H., Gilson, M., Bastogne, T., Mensler, M.**, "The CONTSID toolbox: a software support for continuous-time data-based modeling". In: *Identification of continuous-time models from sampled data*, Garnier, H. and Wang, L. (Eds.), Springer-Verlag, Berlin, 2008 (To appear).
30. **Ljung, L.**, "Model validation and model error modeling". Technical Report N°LiTH-ISY-R-2125, Linköping University, Sweden, 1999.
31. **Skogestad, S., Postlethwaite, I.**, "Multivariable feedback control – analysis and design". John Wiley & Sons Ltd., England, 1996.
32. **Sotomayor, O. A. Z., Odloak, D.**, "Performance assessment of model predictive control systems". 8<sup>th</sup> IFAC International Symposium on Advanced Control of Chemical Processes, CD Rom, Gramado-RS, Brazil, 2006.
33. **Thornhill, N. F., Öettinger, M., Fedenczuk, P.**, "Refinery-wide control loop performance assessment". *Journal of Process Control*, 9(2): pp. 109-124, 1999.
34. **Sotomayor, O. A. Z., Odloak, D., Moro, L. F. L.**, "Closed-loop identification of processes under model predictive control". *Chemical Engineering Research and Design*, 2007 (Submitted).
35. **Sotomayor, O. A. Z., Odloak, D., Moro, L. F. L., Tisza-Contreras, J. F.** "Re-commissioning model predictive control systems by closed-loop identification". 14<sup>th</sup> IEEE International Congress of Electronic, Electrical and Systems Engineering, Piura, Perú, 2007.

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