Internal Excitation Approaches for Closed-loop Identification of Processes Controlled by MPC

Oscar A. Z. Sotomayor[1], Darci Odloak[2]

[1]*Department of Electrical Engineering*
Center for Exact Sciences and Technology, Federal University of Sergipe (UFS), BRAZIL
E-mail: oscars@ufs.br
[2]*Department of Chemical Engineering*
Polytechnic School of the University of São Paulo (EPUSP), BRAZIL
E-mail: odloak@usp.br

Abstract: This work is concerned with the model re-identification of processes controlled by MPC systems. The MPC system considered here has a two-layer structure, where in the upper layer a steady-state optimization algorithm determines a set of optimal targets for the process inputs and passes this set to the MPC controller that determines the best way to drive the process to such targets. This is the case of several commercial MPC packages applied in industry. In this paper, it is proposed two internal excitation approaches aiming to obtain closed-loop data sufficiently rich for process identifiability. Here, the term internal is used to indicate that the excitation test signal is applied within the MPC control structure. In the first excitation approach, the test signal is introduced as a weighting factor in the objective function of the target calculation layer. In the second approach, the test signal is injected as a dither signal in the objective function of the dynamic controller layer. These two approaches are compared to the usual method where the excitation signal is added to the controller output. The application of the methodologies is illustrated through numerical simulations carried out on a depropanizer column of the oil industry. The results show the effectiveness of the proposed approaches and their good potential to be applied in practice.

1. INTRODUCTION

Model identification has become a bottleneck of MPC technology. It is the most expensive, difficult and time-consuming step of the MPC project. Although industrial processes present nonlinear dynamic characteristics, typically, empirical linear and time-invariant (LTI) models based on process input-output data obtained in open-loop operation are used in MPC implementation (Qin & Badgwell, 2003). While this approach is only acceptable at operating conditions around the operating point where the model was obtained, the control system with this model works satisfactorily in most applications.

However, after some operation time (2-3 years), MPC is seldom performing as when it was commissioned. The main cause of this problem is related to the model deterioration resulting from changes in the dynamics of the plant or persistent unmeasured disturbances that force the plant to a different operating point (Conner & Seborg, 2005). Changes in the dynamics of the plant may result from fatigue conditions, fouling, debottlenecking, etc, or changes in the operating conditions or product specifications. 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 of 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 (Gugaliya et al., 2005). 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 (Van den Hof, 1998; Forssell & Ljung, 1999; Hjalmarsson, 2005). Important aspects on model identification have been studied and several identification strategies have been proposed, which can be categorized as variants of the following three approaches (Forssell & Ljung, 1999): 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. For this sort of control strategy, the direct method is the recommended choice for closed-loop identification. See for example Rivera & Flores (1999).

In closed-loop identification, the use of routine operating data would be an ideal goal. But, the inherent reduction in the excitation resulting from the presence of the controller may result in a poor signal-to-noise ratio. In this case, and in order to achieve the necessary and sufficient conditions for process identifiability, an external persistently exciting (PE) test signal is required. External excitation is a dither signal that may be introduced on the controlled variable set-point and/or on the manipulated variable (added to the controller output).

However, adding such a signal is often undesirable or too expensive, and 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.

The main goal of this paper is to compare internal excitation approaches that exploit the two-layer structure of MPC packages. Motivation for this work is due primarily to commercial needs and as an attempt to overcome the significant gap between practical applications and theory in closed-loop identification with MPC. In the proposed methodologies an external PE test signal is applied within the MPC control structure: (a) the test signal is introduced in the objective function of the target calculation layer, and (b) the test signal is injected in the objective function of the dynamic MPC control layer. These approaches does not modify the optimization code and they allows the adequate excitation of the process coupled with the continuous operation of the system as the process constraints and product specification can be satisfied during the test. Results from the proposed excitation methodologies are also compared with the one provided by a conventional external excitation procedure in the closed-loop identification of an industrial depropanizer column.

2. THE TWO-LAYER MPC STRUCTURE

In modern processing plants, MPC control systems are usually implemented in a two-layer scheme (Ying & Joseph, 1999; Qin & Badgwell, 2003; Nikandrov & Swartz, 2009). The two-layer MPC considered here is shown in Figure 1. The upper layer usually corresponds to a simplified steady-state target optimization and the lower layer stands for a constrained dynamic optimization in which the outputs are controlled in specified zones or ranges instead of fixed references. It is at the dynamic layer where the main control objectives (setpoint tracking, disturbance rejection) are pursued. All commercial MPC packages offer the option of zone control. In the target calculation layer, one searches for the optimum steady-state values to the system (input targets), by usually solving a linear or quadratic objective function subject to bound constraints in the inputs and outputs. The outputs at the optimal steady-state are computed through a static model, consistent with the dynamic MPC model, and the available steady-state output prediction computed at the previous time step in the MPC algorithm. The optimal input targets are sent to the dynamic layer, where the control cost is extended with a term that penalizes the distance between the present value of the input and the optimal target. Both layers are executed with the same sampling period.

In this paper, the target calculation layer solves a LP (linear programming) problem where the objective may be to maximize production by forcing one or more inputs to their bounds, while keeping the outputs inside the bounds:

$$\min_{\Delta u_s,\delta_y} W_1^T \Delta u_s + \left| W_2^T \delta_y \right| \tag{1}$$

subject to:

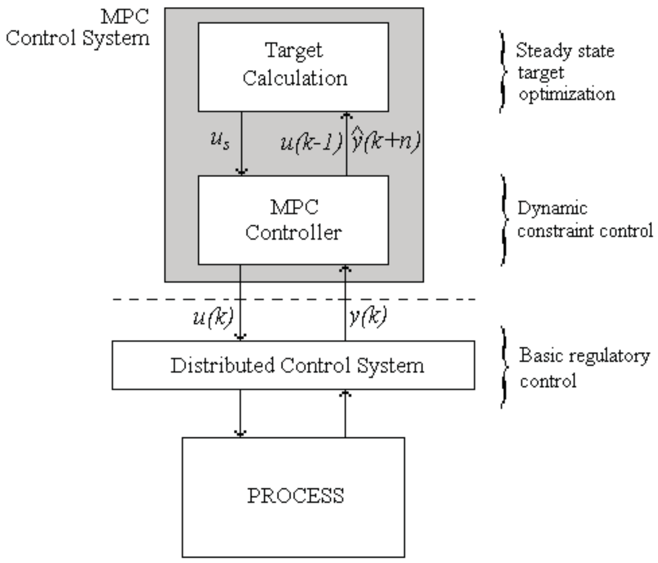


Fig. 1. Two-layer MPC structure

$$\begin{aligned} &\Delta u_s = u_s - u(k-1) \\ &y_s = G_0 \Delta u_s + \hat{y}(k+n) \\ &u_{\min} \le u_s \le u_{\max} \\ &y_{\min} \le y_s + \delta_y \le y_{\max} \end{aligned} \tag{2}$$

where $u(k-1)$ is the last implemented control action, k is the present time, u_s is the vector of steady-state targets for the manipulated inputs, y_s is the vector of predicted output at steady-state, $\hat{y}(k+n)$ is the prediction of the controlled output at time instant $k+n$ (n is the model horizon or settling time of the process in open-loop) computed at time k, δ_y is the vector of slack variables for the controlled outputs, G_0 is the steady state gain matrix model, W_1 and W_2 are weight vector of appropriate dimensions, $u_{\min}$ and $u_{\max}$ are the bounds of the manipulated inputs, $y_{\min}$ and $y_{\max}$ are the bounds of the controlled outputs.

As a result of the solution to the problem formulated in (1) and (2), it is obtained the input target u_s that is passed to the dynamic layer, which typically solves the following QP (quadratic programming) problem:

$$\begin{aligned} &\min_{\Delta u} \sum_{i=1}^{p} \left\| Q\left(\hat{y}(k+i) - y_{sp}\right) \right\|_2^2 + \sum_{j=1}^{m} \left\| R \Delta u(k+j-1) \right\|_2^2 + \\ &\sum_{j=1}^{m} \left\| R_u \left(u(k+j-1) - u_s\right) \right\|_2^2 \end{aligned} \tag{3}$$

subject to:

$$\begin{aligned} &-\Delta u_{\max} \le \Delta u(k+j-1) \le \Delta u_{\max}\,, \quad j = 1,\cdots,m \\ &u_{\min} \le u(k+j-1) \le u_{\max}\,, \qquad j = 1,\cdots,m \end{aligned} \tag{4}$$

with $u(k+j-1) = u(k-1) + \sum_{i=1}^{j} \Delta u(k+i-1)$

where $\hat{y}(k+i)$ is the output prediction at time $k+i$, y_{sp} is the setpoint to the system output, $\Delta u = \left[\Delta u(k)^T \quad \Delta u(k+1)^T \quad \cdots \quad \Delta u(k+m-1)^T \right]^T$ is the vector of control moves, $\Delta u_{\max}$ is the upper limit to the control moves, m is the control horizon, p is the prediction horizon, and Q, R and R_u are diagonal weighting matrices of appropriate dimensions. Note that only the first element of the computed input sequence Δu is implemented in the plant, i.e. $u(k) = \Delta u(k) + u(k-1)$.

In this controller, the zone control strategy is implemented as follows: if the prediction of a given output is inside its reference zone or range, the error in this output is considered to be equal to zero and the output is not included in the controller optimization problem. When the output prediction lies outside the corresponding reference range, depending on whether the prediction is above or below the max or min values of this range, one of these bounds is adopted as the output reference. In general, the zone control strategy is used as an attempt to release some degrees of freedom to allow the inputs to approach their optimal targets (constraints pushing) and to smooth out the system response. For more details see Sotomayor et al. (2009).

The two-layer MPC algorithm as described above is similar to the structure of several MPC packages widely applied to control the refining and petrochemical processes. For instance, this MPC algorithm, with slight modifications, is supported by the advanced control package SICON@, which is the standard process control software in the oil refineries of PETROBRAS in Brazil.

3. INTERNAL EXCITATION APPROACHES

To solve the problem of lack of excitation during normal operation of MPC systems, some authors have proposed a new class of excitation methods for MPC that can be considered as internal excitation methods. Genceli & Nikolaou (1996) use the MPCI framework (model predictive control and identification) where the PE characteristic of the inputs is imposed as a constraint in the optimization problem related to the MPC. The drawback of this method is that the additional constraint is non-convex, resulting in a non-convex optimization problem. Since solving non-convex problems is significantly more involved than solving convex problems, the additional non-convex constraints are undesirable and the method cannot be directly applied to existing commercial MPC packages, without extensive modifications of the controller code, which limits its practical application.

On the other hand, a reasonable consideration of the layered MPC is that when the model is biased, the target calculation layer will change the input target to the dynamic layer quite often, and so, the input target could be viewed as a possible test signal. However, to assume that these natural moves on the input targets will be PE is a questionable matter. Here, taking advantage of the layered structure of MPC, and in order to guarantee the necessary excitation of the input targets, an external PE test signal, namely a binary signal of magnitude ± 1, is applied within the MPC control structure according to the following approaches:

Method 1. Introducing the test signal into the LP layer

Given that the weight vector W_1 in the objective function of the target calculation layer is usually available to be set on-line by the user of the MPC package, the external test signal can be introduced in the MPC system as a variable that multiplies W_1. Thus, Equation (1) is re-written as follows:

$$\min_{\Delta u_s, \delta_y} \left(W_{exc} \otimes W_1 \right)^T \Delta u_s + \left| W_2^T \delta_y \right| \tag{5}$$

subject to (2)

where W_{exc} is a vector whose elements are the components of the binary test signal and operator $\otimes$ denotes the Schur (or element-by-element) product. Then, if the product $W_{exc,i} W_{1,i}$ is positive (negative), the solution to the LP problem will tend to reduce (increase) input u_i until it reaches its lower (upper) bound or the output predictions lies outside the control zones. Note that if W_{exc} is set equal to a vector of ones, then the excitation procedure will end and the original objective function (1) is recovered. This method is described with details in Sotomayor et al. (2009).

Method 2. Introducing the test signal into the dynamic layer

In this case, the external test signal, conveniently scaled, is injected as a dither signal in the input target u_s that enters the MPC layer. This is similar to writing the objective function (3) as follows:

$$\begin{aligned} \min_{\Delta u} \sum_{i=1}^{p} \left\| Q \left(\hat{y}(k+i) - y_{sp} \right) \right\|_2^2 + \sum_{j=1}^{m} \left\| R \Delta u(k+j-1) \right\|_2^2 + \\ \sum_{j=1}^{m} \left\| R_u \left(u(k+j-1) - (u_s + u_{s,dith} \right) \right\|_2^2 \end{aligned} \tag{6}$$

with $u_{s,dith} = \lambda W_{exc}$, subject to (4), where W_{exc} is the excitation vector as defined in Section 3.1 and λ is a scaling factor. Then, the achievement of excitation of the system will largely depend on the value of tuning parameter R_u, which will define if the MPC layer will implement the input target faster than the main process dynamics. Observe that if λ is set equal to zero, the excitation procedure is ended and the original cost function (3) is obtained.

Particularly, Method 1 can be easily implemented in existing MPC packages with a structure similar to the one detailed in Section 2, as the excitation signal is introduced through a tuning parameter of the controller. In both methods the MPC problem is still solved through a QP, and the problem is reduced to design the binary sequence for W_{exc} such that the on-line solution of the problems (5)-(2) and (6)-(4) produces persistent excited inputs, which is the primary requirement for the process identifiability (Ljung, 1999).

As it will be shown in the application section, with the approaches proposed here, the inputs can be adequately excited and if the outputs are controlled within zones, the feedback effect on the test data may be minimized. Also, the approaches attend the process safety requirements and the product specifications can be satisfied adequately.

In the next section it is illustrated the application of the proposed excitation procedures to the closed-loop identification of a depropanizer column. The identification procedure follows same steps as the usual identification methodology applied to industrial processes (Ljung, 1999): design of the test signal and generation of dataset, model structure selection, computation of the model parameters and model validation.

4. APPLICATION: DEPROPANIZER COLUMN

Figure 2 presents the process considered in this work. It is an industrial depropanizer column of the FCC unit at the PETROBRAS Refinery of Cubatão (RPBC), Brazil.

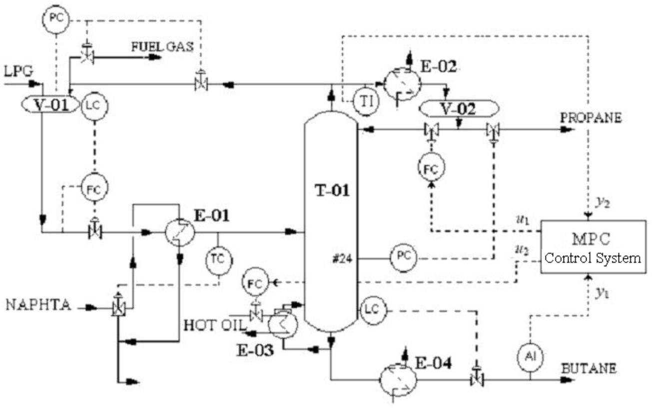


Fig. 2. Schematic diagram of the depropanizer column

In the depropanizer column, the C3 stream (propane and propene) is separated from a C4 stream (butane and butene). The operation of this process is controlled by a commercial MPC system as detailed in Section 2. Basically, it is a 2x2 control system, where the output variables y_1 and y_2 are the molar concentration (%) of C3 in the bottom stream and the temperature (°C) at the first stage of the top section of the column, respectively. The input variables u_1 and u_2 are the reflux flowrate to the top of the column (m^3/d) and the flowrate of hot oil to the reboiler (m^3/d), respectively. Transfer function models of order 2 corresponding to points FD and 1 from Porfirio et al. (2003) are used to simulate the "true" process and to represent the nominal process model (as it is used by the MPC system), respectively. MPC tuning parameters are here omitted but they can be found in Sotomayor et al. (2009).

PE test signal and generation of the dataset

Based on the guidelines provided by Zhu (2001) and a priori knowledge of the process (already existing model in the MPC), two independent GBN (generalized binary noise) (Tulleken, 1990) signals of magnitude ± 1 are designed. These test signals are applied directly to the LP layer of the MPC system if Method 1 is used or they are firstly scaled using $\lambda_1 = 0.065 u_{s,1}$ and $\lambda_2 = 0.07 u_{s,2}$, respectively, and applied to the MPC dynamic layer if excitation Method 2 is employed. In addition to the these excitation approaches, the system is also perturbed using a conventional external excitation as in MacArthur &. Zhan (2007). For this purpose, the MPC controller first calculates the normal movement for each controller output. New projected outputs are computed by superimposing a dither signal on the moves proposed by the controller. The projected outputs are then compared to the controller's high and low limits (constraints). Projected moves are then modified to ensure that all constraints are honored. In the present case, the dither signals are the GBN test signals scaled to ± 0.0034 and ± 0.0043, respectively. In all the cases, the duration of the excitation test is 4500 min. The data were collected with a sampling time of 1 min, resulting 4500 samples of input-output data.

For better identification results, the dataset is normalized, de-trended and filtered. Next, the dataset is divided into two subsets, where the first one containing 3000 data points is used to identify the model while the second one containing the remaining points is used to cross-validate the model. The PE characteristic of the inputs for the three cases is tested for order $\eta = 4$, which means that 2nd-order transfer functions can be satisfactory identified (Söderström & Stoica, 1989).

Model structure selection

In the present paper, it is considered that the model structure is defined by a continuous-time multi-input and single-output (MISO) output-error (OE) transfer function model, with the stochastic model parameterized as unitary:

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

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

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

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, $\hat{\theta}_{j,i}$ is the estimated 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 $\rho_{j,i} = \left[\hat{b}_{j,i,m_{j,i}} \cdots \hat{b}_{j,i,0} \; \hat{a}_{j,i,(n_{j,i}-1)} \cdots \hat{a}_{j,i,0} \; \hat{\theta}_{j,i} \right]^T \in \mathbb{R}^{q_{j,i}}$, with $q_{j,i} = n_{j,i} + m_{j,i} + 2$, where $n_{j,i}$ and $m_{j,i}$ denotes the denominator and numerator orders of $\hat{G}_{j,i}(s,\rho_{j,i})$, respectively.

Computation of the model parameters

The goal is to build a model as defined in eq. (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. Thus, the task of the identification procedure is to compute the vector of model parameters:

$$\rho_j = \left[\rho_{j,1}^T \cdots \rho_{j,nu}^T\right]^T \in \mathbb{R}^{q_j \times 1}, \quad q_j = \sum_{i=1}^{n_u} q_{j,i} \tag{8}$$

Here it is used the CONTSID toolbox (Garnier et al., 2008) to find the vector ρ_j for each closed-loop sampled dataset from the depropanizer column, assuming $n_u = n_y = 2$, $n_{j,i} = 2$ and $m_{j,i} = 1$. The identification is carried out off-line considering the values of the parameters of the existing (old) process model as the initial solution to the identification problem.

Three new models are obtained and they are evaluated based on the following performance criteria:

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

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

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.

Model validation

Figure 3 shows the step response comparison between the old model and the new models obtained with the three excitation methods considered here. Observing the responses of the old model used in the controller and the new models obtained with the re-identification procedure, one may conclude that the re-identification of the process model is quite justified not only because of the difference between the gains of the old and new models, but also because of the different dynamics. Also, observing the responses of the re-identified models, one can confirm that the model obtained with excitation method 3 is, in general, inferior to the models obtained with the two other excitation methods, showing a significant bias on the gain of $\hat{G}_{2,1}$. Moreover, from a practical point of view, one may conclude that the internal excitation methods 1 and 2 can be considered equivalent in terms of the model that is obtained, particularly if the step response of the process is to be used as in several MPCs. This result is in concordance with the performance indicators obtained from the cross-validation procedure of the three new models (not presented here).

5. CONCLUSIONS

Three closed-loop excitation methods for systems being controlled by MPCs with a two layer structure were studied here. These excitation methods allow the closed-loop model re-identification that should be used for periodic MPC monitoring and maintenance and for the design of an explicit adaptive MPC. The first two methods are based on the introduction of a persistently exciting signal within the MPC structure. The third method corresponds to the traditional approach of adding the excitation signal to the controller output. The three methods showed equivalence in terms of producing a data set that is adequate for model identification. The main difference between the excitation methods lies in the implementation of the approach in practice. Method 1 introduces the excitation signal in the coefficients of the objective function of the target calculation layer which are usually available as tuning parameters of the controller. So, there is no need of any modification in the controller code and the method does not require any particular attention of the operator while the process excitation is performed. Thus, this method seems to be the most adequate in practical terms. Method 2 adds the excitation signal to the input target of the dynamic layer of the controller. Besides, some new tuning parameters this method requires a slight modification in the controller code and, consequently, can only be implemented if the source code is available. The third or conventional method, that adds the excitation signal to the output of the controller, requires more care in the design stage and more attention of the operator because the control action really injected in the process will not satisfy the process constraints.

REFERENCES

Conner, J.S., D.E. Seborg (2005). Assessing the need for process re-identification. *Industrial & Engineering Chemistry Research*, **44**(8): 2767-2775.

Forssell, U., L. Ljung (1999). Closed-loop identification revisited. *Automatica*, **35**(7): 1215-1241.

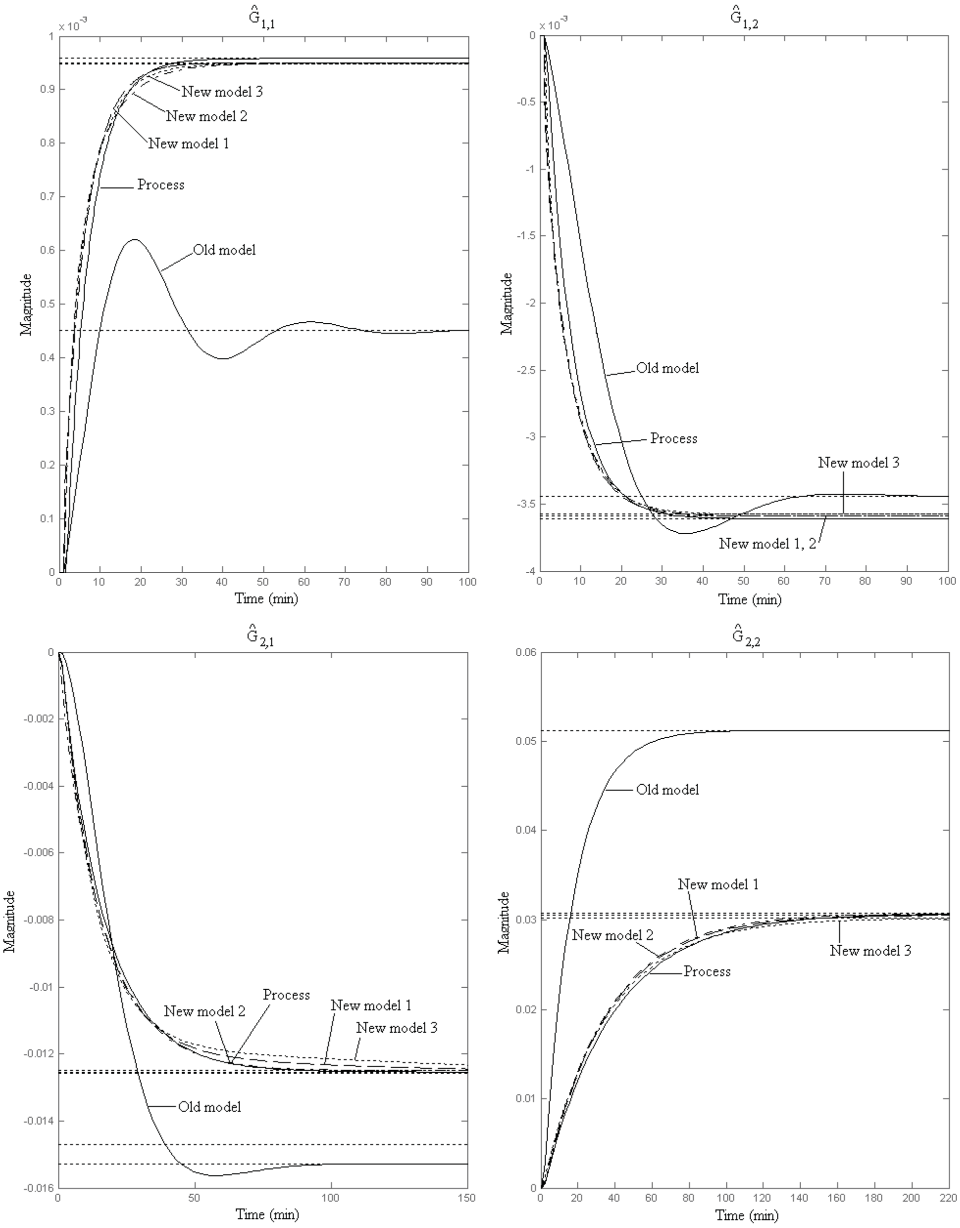
Garnier, H., M. Gilson, T. Bastogne, M. Mensler (2008). The CONTSID toolbox: A software support for continuous-time data-based modelling. In. H. Garnier & L. Wang (Eds.), *Identification of continuous-time models from sampled data*. Berlin: Springer.

Genceli, H., M. Nikolaou (1996). New approach to constrained predictive control with simultaneous model identification. *AIChE Journal*, **42**(10): 2857-2868.

Gugaliya, J.K., S.C. Patwardhan, R.D. Gudi, H. Raghavan, R. Yelchuru (2005). Model maintenance for industrial process control. In: *2005 AIChE Annual Meeting*, Cincinnati – OH.

Hjalmarsson, H. (2005). From experiment design to closed loop control. *Automatica*, **41**(3): 393-438.

Ljung, L. (1999). *System identification – Theory for the user* (2nd Ed.), Upper Saddle River, NJ: Prentice-Hall.



(a)

Fig. 3. Step response for the depropanizer column

MacArthur, J., C. Zhan (2007). A practical global multi-stage method for fully automated closed-loop identification of industrial processes. *Journal of Process Control*, **17**(10): 770-786.

Nikandrov, A., C.L.E. Swartz (2009). Sensitivity analysis of LP-MPC cascade control systems. *Journal of Process Contro,* **19**(1): 16-24.

Porfirio, C.R., E.A. Neto, D. Odloak (2003). Multi-model predictive control of an industrial C3/C4 splitter. *Control Engineering Practice*, **11**(7): 765-779.

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

Rivera, D.E., M.E. Flores (1999). “Plant-friendly” closed-loop identification using model predictive control. In: *1999 AIChE Annual Meeting*, Dallas – TX.

Söderström, T., P. Stoica (1989). *System identification*. Hemel Hempstead, UK: Prentice-Hall.

Sotomayor, O.A.Z, D. Odloak, L.F.L. Moro (2009). Closed-loop model re-identification of processes under MPC with zone control. *Control Engineering Practice*, **17**(5): 551-563.

Tulleken, H.J.A.F. (1990). Generalized binary noise test-signal concept for improved identification-experiment design. *Automatica*, **26**(1): 37-49.

Van den Hof, P.M.J. (1998). Closed loop issues in system identification. *Annual Reviews in Control*, **22**(1): 173-186.

Ying, C.-M., B. Joseph (1999). Performance and stability analysis of LP-MPC and QP-MPC cascade control systems. *AIChE Journal*, **45**(7): 1521-1534.

Zhu, Y. (2001). *Multivariable system identification for process control*. Oxford, UK: Elsevier Science Ltda.