APPLICATION OF MULTIVARIABLE PREDICTIVE CONTROL IN A DEBUTANIZER DISTILLATION COLUMN

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Abstract: This article presents an application of Model Predictive Control (MPC) in chemical industry. An implementation of multivariable generalized predictive control in a simulated process (in Hysys software) was developed as part of a complete research about MPC application in petrochemical industry. The process consists of a debutanizer distillation column. This column was identified (using a second order linear model) with multivariable recursive least squares algorithm to estimate its parameters.

Keywords: Predictive Control, Distillation Column, Identification, Multivariable control, Debutanizer.

1. INTRODUCTION

The control system used in petrochemical industry (Petrobras, Guamaré-RN) is only regulatory control (classic PID). Furthermore, PIDs used are considered of an isolated form (without consider couplings between control loops). This consideration is not recommended because the system performance will be poor. The most part of industrial processes have an amount of variables that may be controlled and others may be manipulated. The reasonable choice of theses variables is an important step to control system performance.
When one manipulated variable has effect over two or more controlled variable, we can say that process is coupled. Some approaches apply decoupling compensators to attenuate the coupling between control loops. In projects of decoupling compensators, the number of inputs must be equal the number of outputs. Furthermore, in processes with complex dynamic, these compensators are not achievable, Camacho & Bordons (1999).
Multivariable predictive control is the most suitable control technique applied to control chemical processes, because it considers time delay, coupling (in multivariable Auto Regressive, Integral, Moving Average, with exogenous input model), and may be applied in unstables processes and with non minimal phase processes. Other advantage is the treatment of constrains (that is very easy to include in this algorithm).
Multivariable predictive control derives of Generalized Predictive Control, proposed by Clarke (1987). Other results applying GPC are showed in Richalet et al., (1993). A recent application of constrained Generalized Predictive Control in petrochemical industry is showed in Volk et al. (2004). Other important application is showed in Almeida et al. (2000).
Debutanizer distillation column is usually used to remove the light components from the gasoline stream to produce Liquefied Petroleum Gas (LPG). It produces either stabilized gasoline that can be included in pool gasoline. In this article is used a distillation column simulated in Hysys software. Both identification and control algorithm, developed in MATLAB®, communicate with Hysys software through Dynamic Data Exchange (DDE) protocol.

2. FORMULATION OF MULTIVARIABLE GENERALIZED PREDICTIVE CONTROL

Generalized predictive control is based in linear models that describe the process behaviour. The choice of linear model depends of process. Some processes have dynamics that cannot be represented by a single linear model. In these cases, other models, like bilinear models, showed in Goodhart et al. (1994) or compensated models showed in Fontes et al. (2002) and Fontes et al. (2004), may be used.
In this article, a multivariable linear model has been represented the process with a reasonable precision. The model considered is ARIMAX (Auto Regressive, Integral, Moving Average, with exogenous Input) model.

2.1 Multivariable Model

Multivariable ARIMAX model with m-inputs and n-outputs may be written as:

$$A(q^{-1})y(k) = B(q^{-1})u(k-1) + C(q^{-1})\frac{e(k)}{\Delta} \quad (1)$$

where $A(q^{-1})$, $B(q^{-1})$ and $C(q^{-1})$ are monic-polynomial matrices of dimensions $n \times n$, $n \times m$ and $n \times n$, respectively. These matrices are given by:

$$A(q^{-1}) = I_{n\times n} + A_1 q^{-1} + A_2 q^{-2} + \ldots + A_{na} q^{-na} \quad (2)$$

$$B(q^{-1}) = B_0 + B_1 q^{-1} + B_2 q^{-2} + \ldots + B_{nb} q^{-nb} \quad (3)$$

$$C(q^{-1}) = I_{n\times n} + C_1 q^{-1} + C_2 q^{-2} + \ldots + C_{nc} q^{-nc} \quad (4)$$

The operator Δ is defined as $\Delta = 1 - q^{-1}$, $y(k)$ is the output vector of dimension $n \times 1$, $u(k)$ is the input vector of dimension $m \times 1$ and $e(k)$ is the vector of white noise with zero mean. When process has transport delay, the model must include this delay through an interaction matrix.

2.2 Objective Function

GPC algorithm calculates a sequence of control effort. This sequence is obtained by the minimization of an objective function given by:

$$J = \sum_{i=N_1}^{N_2} \left\| \hat{y}(k+i) - r(k+i) \right\|_R^2 + \sum_{i=1}^{N_3} \left\| \Delta u(k+i-1) \right\|_Q^2 \quad (5)$$

where N_1 is the minimum prediction horizon, N_2 is the prediction horizon, N_3 is the control horizon, $\hat{y}(k+i)$ is the optimum i-step ahead predicted output, $r(k+i)$ is the future reference trajectory, R and Q are weighting matrixes of error signal and control effort, respectively. R and Q must be positive definite. The norm showed in equation (5) is given by:

$$\left\| v \right\|_X^2 = v^T X v \quad (6)$$

2.3 The Predictor

The case used in this article is when $C(q^{-1}) = I_{n\times n}$. The reason for this is that the colouring polynomials are very difficult to estimate with sufficient accuracy in practice according to Camacho & Bourdons (1999). The optimum output prediction, i-step ahead, may be written by the following expression:

$$\begin{aligned} \hat{y}(k+i) &= F_j(q^{-1})y(k) + \\ &E_j(q^{-1})B(q^{-1})\Delta u(k+i-1) \end{aligned} \quad (7)$$

where $F_j(q^{-1})$ and $E_j(q^{-1})$ are polynomial matrices and may be calculated by Diophantine equation:

$$I_{n\times n} = E_i(q^{-1})\tilde{A}(q^{-1}) + q^{-i}F_i(q^{-1}) \quad (8)$$

where

$$\tilde{A}(q^{-1}) = \Delta A(q^{-1}) \quad (9)$$

The model considered is linear and causal. For this reason, we can separate output prediction in two parts: free response and forced response. Free response in step k considers zero the future variation in inputs. Forced response considers only future variation of inputs. The predictor may be rewriting making:

$$E_i(q^{-1})B(q^{-1}) = G_i(q^{-1}) + q^{-i}G_{ip}(q^{-1}) \quad (10)$$

where the degree of $G_i(q^{-1})$ is less than i. The end expression of predictor is given by:

$$\begin{aligned} \hat{y}(k+i) &= G_j(q^{-1})\Delta u(k+i-1) + \\ &G_{jp}(q^{-1})\Delta u(k-1) + F_j(q^{-1})y(k) \end{aligned} \quad (11)$$

The first term of (10) is the forced response and the two last is the free response.

2.4 The Control Law

Equation (10) may be written of matrix form:

$$y = Gu + f \quad (12)$$

where f represents the free response and G represents the forced response matrix. The minimization of cost function showed in equation (5) is obtained in analytical form:

$$\frac{\partial J}{\partial u} = 0 \quad (13)$$

If there are no constraints, the optimum control law can be expressed as:

$$u = (G^T R G + Q)^{-1} G^T R (w - f) \quad (14)$$

Because of the receding control horizon, only $\Delta u(k)$ is needed at instant k. Thus, only the first m rows of equation (12) are computed.

3. IDENTIFICATION OF PROCESS MODEL AND THE CONTROL STRATEGY

The distillation column developed is Hysys is showed in figure 1.

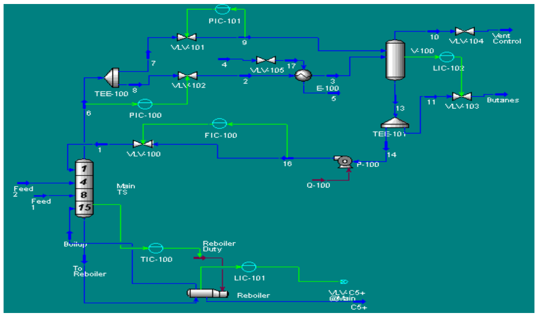

Fig.1. Debutanizer distillation column developed in Hysys software.

The process variables chosen are concentration of i-pentene in butanes stream and concentration of i-butene in C5 stream. The manipulated variables chosen are reflux flow rate (manipulating the setpoint of FIC-100 in m^3/h) and thermal load (manipulating the setpoint of TIC-100 in ^oC). Steps were applied in both manipulated variable to identify the dominant dynamic. Figure 2 shows the behaviour of i-pentane concentration, applying a step in reflux flow rate (FIC-100 setpoint).

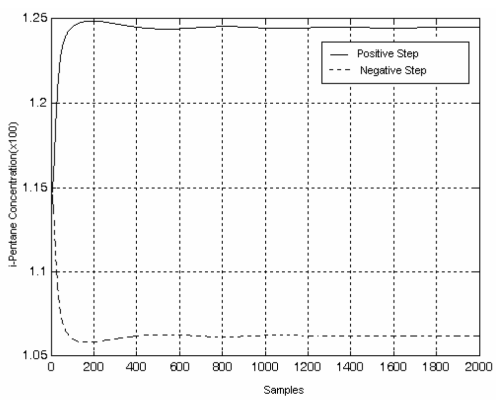

Fig.2. Concentration of i-pentane (x100) applying a ±5% step in reflux flow rate.

Figure 3 shows the behaviour of i-butene concentration, applying a step in reflux flow rate (FIC-100 setpoint).

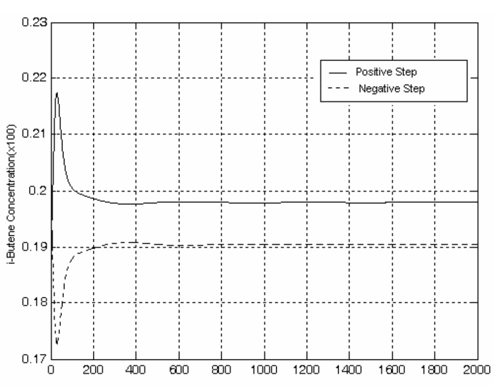

Fig.3. Concentration of i-butene (x100) applying a ±5% step in reflux flow rate.

The percent change in TIC-100 setpoint was ±3% to not cause saturation in controllers. The process behaviours like a second order system. The time response is around 300 minutes in both loops. The best sample rate considered in estimation is 4 minutes.

Figure 4 shows the behaviour of i-pentene concentration, applying a step in reboiler temperature (TIC-100 setpoint).

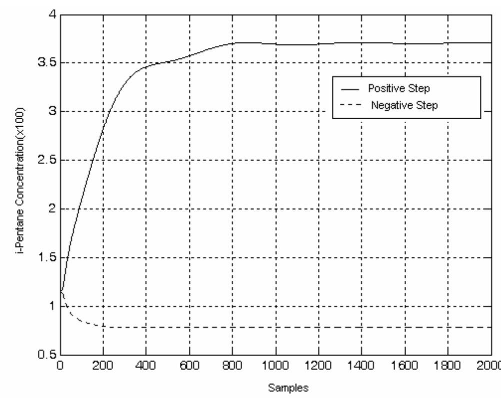

Fig.4. Concentration of i-pentene (x100) applying a ±3% step in reboiler temperature.

Figure 5 shows the behaviour of i-butene concentration, applying a step in reboiler temperature (TIC-100 setpoint).

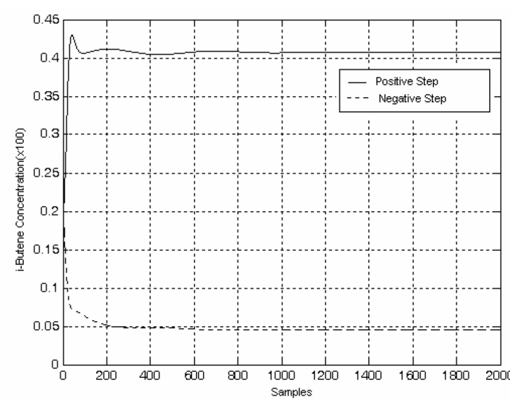

Fig.5. Concentration of i-butene (x100) applying a ±3% step in reboiler temperature.

Recursive Least Squares returned the following parameters (showed in the model):

$$\begin{aligned} y_1(k) &= 1.7860 y_1(k-1) - 0.8006 y_1(k-2) \\ &- 1.0753.10^{-5} u_1(k-1) + 1.1011.10^{-5} u_2(k-1) \\ &+ 3.5585.10^{-6} u_1(k-2) + 6.3250.10^{-7} u_2(k-2) \end{aligned} \tag{15}$$

$$\begin{aligned} y_2(k) &= 1.6974 y_2(k-1) - 0.7572 y_2(k-2) \\ &+ 2.0416.10^{-5} u_1(k-1) - 3.7760.10^{-5} u_2(k-1) \\ &- 1.7824.10^{-5} u_1(k-2) + 5.1200.10^{-6} u_2(k-2) \end{aligned} \tag{16}$$

4. RESULTS

The model identified and showed in equations (13) and (14) is an incremental model. The implemented algorithm reads from Hysys the deviation of process variables (in relation of operation point) and calculates the free response. The free response is used to calculate the increment of manipulated variable. A previous implementation (only simulation) was developed to try obtaining an adequate tuning. A good set of tuning parameters is:

$$R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \qquad (17)$$

$$Q = \begin{bmatrix} 12.10^3 & 0 \\ 0 & 12.10^3 \end{bmatrix} \qquad (18)$$

$$N_{2,1} = N_{2,2} = Nu = 30 \qquad (19)$$

A reference (deviation) of 12% in relation of i-pentene concentration was applied as reference in algorithm. In C5 stream, i-butene concentration was not disturbed. The process behaviour (read from Hysys) is showed in figure 6. Concentration reference of i-butene was not changed.

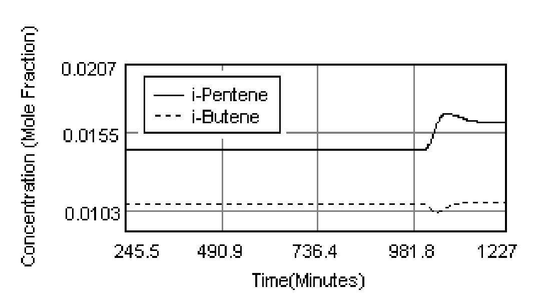

Fig.6. Concentration of i-pentene and i-butene controlled by MIMO GPC.

Figure 7 shows the control effort (FIC-100 Setpoint).

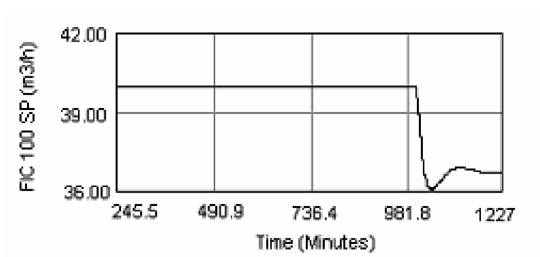

Fig.7. FIC-100 setpoint (m^3/h) calculated by MIMO GPC

Figure 8 shows the control effort (TIC-100 Setpoint).

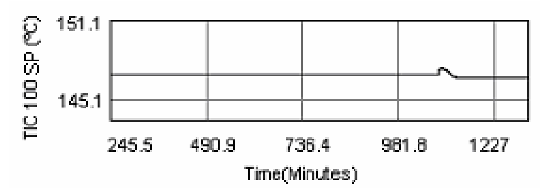

Fig.8. TIC-100 setpoint (^oC) calculated by MIMO GPC

Other result, changing both references (disturbing 12% in i-pentene and 15% in i-butene), is showed in figure 9.

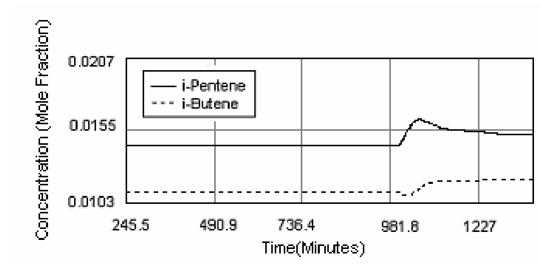

Fig.9. Concentration of i-pentene and i-butene controlled by MIMO GPC.

Figure 10 shows the control effort (FIC 100 Setpoint).

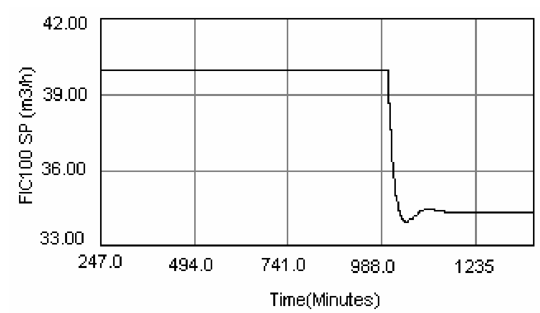

Fig.10. FIC-100 setpoint (m^3/h) calculated by MIMO GPC

Figure 11 shows the control effort (TIC 100 Setpoint).

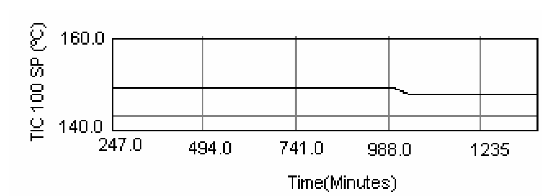

Fig.11. TIC-100 setpoint (^oC) calculated by MIMO GPC

Results show that using Multivariable GPC, time response was decreased around 57%. Without GPC controller the process has response time of 300 minutes and, with GPC, response time is around 130 minutes. It is clear the increase in performance of column. Due to the good choice of parameters tuning, control effort does violate constraints.

5. CONCLUSIONS

This paper shows the application of multivariable predictive control in petrochemical industry. This research indents to confirm that predictive control is an excellent technique and that must be better explored by industry. It intends to research alternative techniques of non linear predictive control. Academy has showed goods results that justify the use of these control algorithms. The next step of research is to identify the model (simulated in Hysys) of a debutanizer distillation column localized in Unit of Natural Gas Production (UPGN2) and apply non linear predictive control techniques. This unit belongs to Petrobras Company in Guamaré-RN.

6. REFERENCES

Almeida, E., Rodrigues, M.A., Odloak, D. (2000). Robust Predictive Control of a Gasoline Debutanizer Column. Brazilian Journal of Chemical Engineering, vol. 17, São Paulo.

Camacho, E. F., Bordons, C. (1999). *Model Predictive Control*, chapter 6, page 131, Springer editor, 1st edition.

Clarke, D. W., Mohtadi, C., Tuffs, P.S. (1987). Generalized Predictive Control. Part I. The Basic Algorithm. *Automatica*, 23(2):137-148, 1987.

Fontes, A. B., Maitelli, A.L., Salazar, A. O. (2002). A New Bilinear Generalized Predictive Control Approach: Algorithm and Results. 15th Triennial IFAC World Congress, Barcelone, Spain.

Fontes, A. B., Maitelli, A.L., Cavalcanti, A. L. O. (2004). Bilinear Compensated Generalized Predictive Control: An Adaptive Approach. 5th Asian Control Conference, Melbourne, Australia.

Goodhart, S. G., Burnham, K. J., James, D.J.G. (1994). Bilinear Self-tuning Control of a high temperature Heat Treatment Plant. IEEE Control Theory Appl.: Vol. 141, n.º 1, January.

Richalet, J. Industrial Applications of Model Based Predictive Control. *Automatica*, 29(5):1951-1274, 1993.

Volk, U., Kniese, D.W., Hahn, R., Haber, R., Schmitz, U. (2004). Optimized multivariable predictive control of an industrial distillation column considering hard and soft constraints. *Control Engineering Practice*, 13(2005):913-927.