PROPYLENE/PROPANE DISTILLATION COLUMN MODEL BASED CONTROL – A NEW APPROACH

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Abstract: *Firsts model based control algorithms have used only linear process models, but as this control methods were implemented and tested in some cases appeared robustness problems due to process nonlinearities. Therefore, in order to eliminate this inconvenience, new control methods based on the nonlinear model of the process were used but, the main disadvantage in this case is the complexity of the obtained algorithm over the linear one. The main objective of this paper is to bring some relevant contributions on model based control of a distillation process. Because the process is a nonlinear one, with gains and dynamics that changes substantially with the operating point, the main feature of the proposed model based control structures will be the ability to take account of these nonlinearities. As a compromise between the linear and nonlinear model based control approach, the model in which the proposed control algorithms rely will be a nonlinear one, but represented as a reunion of linear models, one for each operating point.*

Keywords: *Model Predictive Control, Internal Model Control, Distillation process, Process identification.*

1. INTRODUCTION

A way to achieve the plant profitability is by applying an advanced control method.

Advance control methods such as model based process control techniques can be classified into two main categories:

- Model Predictive Control (MPC) method with its Dynamic Matrix Control (DMC) variant;
- Internal Model Control (IMC) method.

As a result of a literature study regarding these control strategies the conclusion was that Model Predictive Control (MPC) technology made a significant impact on industrial control engineering. The Internal Model Control (IMC) strategy, although didn't have the same impact was sometimes used for its simplicity.

This paper presents the results obtained with the two control strategies for controlling a propylene/propane distillation column.

Using the HYSYS® simulation environment the process was simulated in order to obtain a simplified model which can be used in the proposed control structures. The simulation data were processed using the Markov parameters identification procedure and the simplified model was obtained as a second order transfer function with dead time. The use of Markov parameters procedure, in order to find the simplified process model, is a contribution of this work. The transfer function parameters (the two time constants and the gain) differ from one operating point to another, due to process nonlinearities. This variation was modeled, so that the new model parameters can be obtained using a simpler dependence equation, between some values already determined, regardless of the process operating point.

The main contribution on model based control of the distillation process is that the two controllers (the predictive and internal model one) will use a nonlinear process model obtained as a reunion of linear models, one for each operating point.

2. DISTILLATION PROCESS MODEL IDENTIFICATION

The distillation column (figure 1) has the L-B, Shinskey approach [7] controlled structure (the reflux flow is used for controlling the propylene composition and the bottom product flow is used for controlling the propane composition).

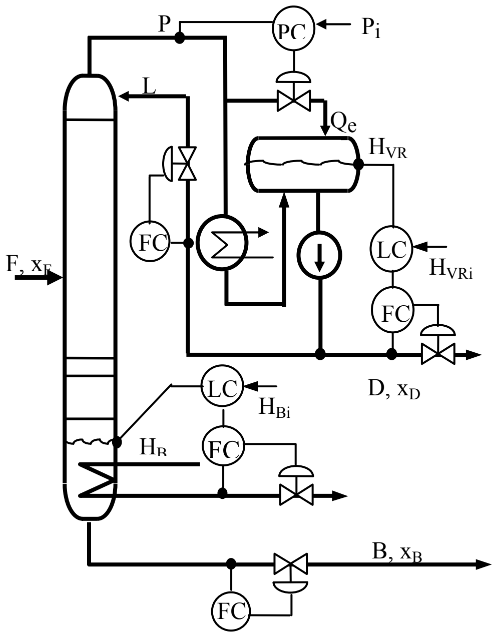

Fig. 1. Propylene(C3')/propane(C3) distillation column:

PC – pressure controller, FC – flow controller, LC – level controller, AT – composition transducer, L – reflux flow, L_i – reflux flow setpoint, P - pressure, P_i – pressure setpoint, B – bottom product flow, B_i – bottom product flow setpoint, H_{VR} – reflux tank level, H_{Vri} – reflux tank level setpoint, H_B – bottom column level, H_{Bi} – bottom column level setpoint, F – feed flow, x_F – feed composition, x_B – bottom composition, x_{Bi} - bottom composition setpoint, x_D – top composition, x_{Di} – top composition setpoint.

The process is a multivariable one (figure 2), with two outputs (the propylene (top) and propane (bottom) composition) and four main inputs, two controlled variable (the reflux and bottom product flows) and two disturbances (the feed flow and feed composition).

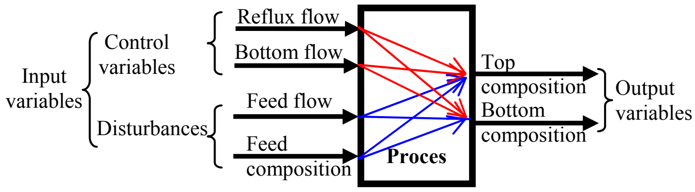

Fig. 2. Distillation process input and output variables.

Using the data of an industrial column the process was simulated using the HYSYS® simulation environment. The simulator was validated for the static regime using the industrial data and for the dynamic regime using data from literature.

Analyzing the input/output data for different operating points and different channels, it was observed that the process behavior is nonlinear for controlled variables – outputs and disturbances – outputs channels. The nonlinear behavior is characterized by different gains and transient times.

As a contribution, using the Markov parameters identification procedure (figure 3), models of the process were determined for every process channel. The simulation data are the process response (top and bottom composition variation) to input (control variables and disturbances) step changes.

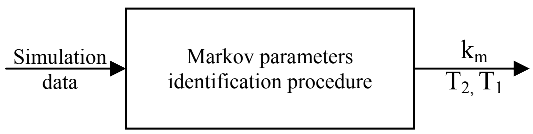

Fig. 3. Markov identification procedure.

The process models are described by second order transfer functions with dead time (1), having different gains and time constants for each operating point and process channel.

$$G(s) = \frac{k_m e^{-\tau s}}{T_2 s^2 + T_1 s + 1} \quad (1)$$

k_m is the process gain, τ is the dead time and $\sqrt{T_2}$ şi T_1 are time constants.

Another contribution is that the model parameters – operating point variation for all process channels was modeled, so that for each operating point in which the process is, the model parameters can be easily determined using a simple linear equation.

3. MODEL PREDICTIVE CONTROL ALGORITHM

Model Predictive Control is a model based control strategy that uses the process model to calculate the control efforts, in order to minimize an objective function without violating input or output constraints.

Theoretical and practical issues associated with Model Predictive Control technology are summarized in several important articles. Some excellent papers are offered by Kwon (1994), Morari and Lee (1997), Camacho and Bordons (1999), Rawlings (2000), Qin and Badgwell (2003).

The methodology of a predictive controller consists in predicting, at each time *t*, the future outputs for a determined horizon *p*, called the prediction horizon. This prediction of the outputs is based on the model of the process and depends on the known values of past inputs and outputs up to instant *t*. The set of future control signals is calculated by optimizing a given criterion (called objective function or performance index) in order to keep the process as close as possible to the reference trajectory, which can be the set point or an approximation of it. The control effort is included in the objective function in most cases. Weights are used to adjust the influence of each term in the equation. The solution to the problem is the future control sequence that minimizes the objective function equation. A typical objective function equation of a single-output single-input process is [5]

$$J = \min_{\Delta C(k)} [\sum_{l=1}^{p} \left\| \Gamma_l^y \cdot [y(k+l \mid k) - r(k+l)] \right\|^2 + \\ + \sum_{l=1}^{m} \left\| \Gamma_l^c \cdot [\Delta c(k+l-1)] \right\|^2], \quad (2)$$

where, *p* is the prediction horizon and *m* is the controlled variable horizon.

It is a quadratic function of future inputs, $\Delta c(k+l-1)$ and the error between future values of reference $r(k+l)$ and predicted outputs, $y(k+l \mid k)$. Weights Γ_l^y and Γ_l^c are used to adjust the influence of the error and inputs respectively.

Once the control sequence has been obtained only the first control move is implemented. Subsequently the horizon is shifted and the values of all sequences are updated and the optimization problem is solved once again.

Figure 4 illustrates the structure of such a system.

The controller tuning parameters are:
- the sampling time;
- the controlled variable horizon;
- the prediction horizon;
- the weight matrices that are used in optimization procedure.

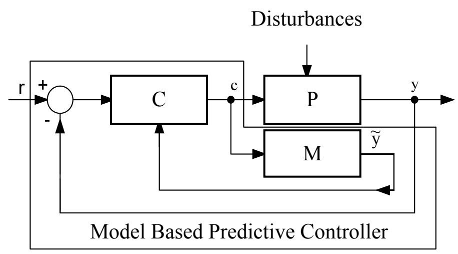

Fig. 4. Model Predictive Control system structure: r – setpoint, c – controlled variable, y – process output, ỹ - predicted process output, C – controller, M – process model, P - process.

4. INTERNAL MODEL CONTROL ALGORITHM

An Internal Model Control system has in the control structure a controlled process model (figure 5), in order to compare the process output y with the process model output y_m. [3]

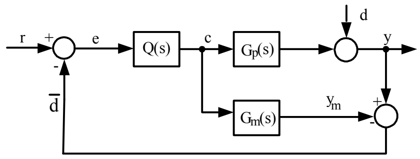

Fig. 5. Internal Model Control structure.

As the static error to be zero for a step in setpoint or a step in disturbance it is required that the control system to be stable and the controller static gain to be equal to the inverse of the model static gain:

$$Q(0) = \frac{1}{G_{\mathrm{m}}(0)} \ . \tag{3}$$

The simplest form for internal model strategy is the one in which the transfer function $Q(s)$ is chosen as a zero order transfer function, equal to the inverse of the model gain:

$$Q(\mathrm{s}) = \frac{1}{G_{\mathrm{m}}(0)} \ . \tag{4}$$

The controller transfer function, which contains the primary controller Q and the model $\mathrm{G_m}$, is:

$$G_{\mathrm{C}}(s) = \frac{Q(s)}{1 - Q(s) \cdot G_{\mathrm{m}}(s)} = \frac{1}{G_{\mathrm{m}}(0) - G_{\mathrm{m}}(s)} \ . \tag{5}$$

To have a tunable controller, in its structure was introduced the static gain K, (figure 6) with a standard value equal to 1. As natural, as we increase the value of K, we obtain an increase in the controlled variable power. The controller has the transfer function:

$$G_{\mathrm{C}}(s) = \frac{K}{G_{\mathrm{m}}(0) - G_{\mathrm{m}}(s)} . \tag{6}$$

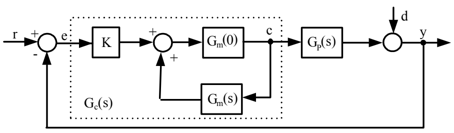

Fig. 6. Internal Model Control structure with tunable controller.

5. NONLINEAR ADAPTABLE MODEL BASED CONTROL OF THE DISTIILATION COLUMN

Because the distillation process is a nonlinear one it is wise to use a model based control structure, which can take account of the process nonlinearities by changing the process model according to the operating point. This proposed control structure will be named Nonlinear Adaptable Model Based structure; nonlinear, because the process model is a nonlinear one, but represented as a reunion of linear models and adaptable, because the model parameters are adapted automatically to the operating point.

The distillation column is simulated using ASPEN HYSYS simulation environment, and the control structure is implemented in MATLAB.

At each simulation initialization step, using a communication system between HYSYS and MATLAB, the bottom and top composition, the feed flow and composition are sent from the process to the control structure, in MATLAB. Here, using these data the model parameters (time constants and gain) are determined and loaded in controller. Using these model parameters the two controlled variables (reflux flow and bottom product flow) are computed and sent at each sampling instant to the process, in HYSYS. (figure 7)

When a change in composition setpoint is done, or when the disturbances changes the model identification procedure is renewed and the new model parameters loaded. (figure 8)

The controller is a predictive and internal model one.

The results obtained using the two proposed model based algorithms are compared with the ones obtained with the conventional structures.

The dynamic system behavior analysis consisted of changing the compositions setpoint, the disturbances and the controllers' tuning parameters, in the case when the process model is a nonlinear adaptable to the operating point or a linear one (non-adaptable) determined for a medium operating point, 0.97 molar fraction.

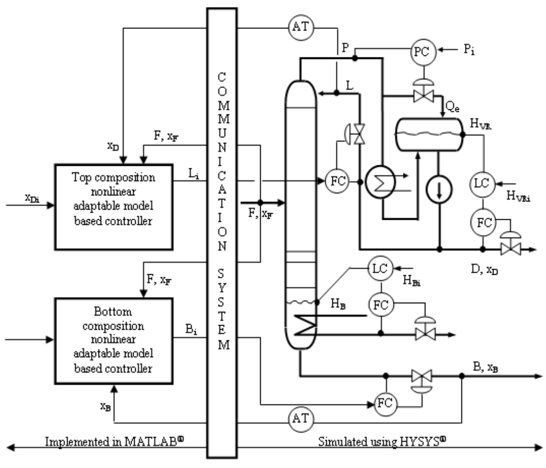

Fig. 7. Proposed model based control system structure.

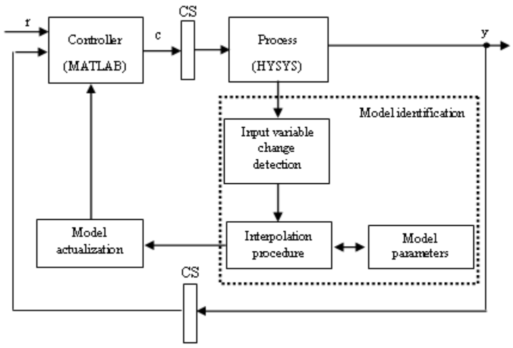

Fig. 8. Implemented system structure: CS – communication system, r – setpoint, c-controlled variable, y – output variable.

The top composition model predictive controller has the following default simulation parameters:

- prediction horizon – is a function of time constant T_1;
- controlled variable time horizon – 30 sampling instants;
- controlled variable weight – 0.2 (minimum value: 0, maximum value: 1);
- sample time – 30 seconds.

The bottom composition model predictive controller has the following default simulation parameters:

- prediction horizon – is a function of time constant T_1;
- controlled variable time horizon – 50 sampling instants;
- controlled variable weight – 0.6 (minimum value: 0, maximum value: 1);
- sample time – 1 minute.

For each top composition trend the first figure presents the setpoint and controlled variable (top composition) variation, and the second one the control variable (reflux flow) variation over time, in minutes.

Similarly, for each bottom composition trend the first figure presents the setpoint and controlled variable (bottom composition) variation, and the second one the control variable (bottom product flow) variation over time, in minutes.

In order to represent the trends MATLAB environment was used because the controllers were implemented in this environment.

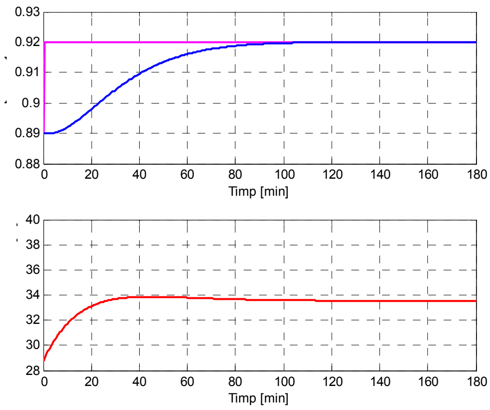

Fig. 9. Top composition and reflux flow trends when the controller setpoint increases from 0.89 mol. fr. to 0.92, using the NAMPC (Nonlinear Adaptable Model Predictive Control).

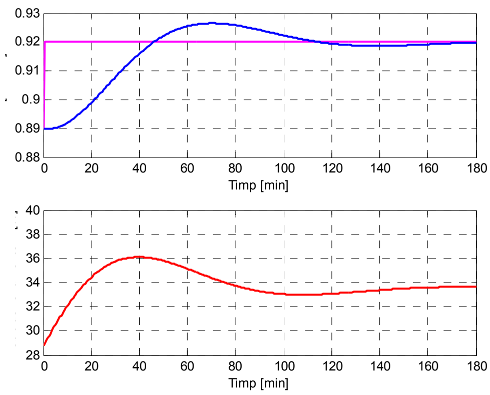

Fig. 10. Top composition and reflux flow trends when the controller setpoint increases from 0.89 mol. fr. to 0.92, using the nAMPC (non-Adaptable Model Predictive Control).

From the simulations represented in figures 9 and 10, we can easily observe that if we use the non-adaptable control structure the controlled system transient time is bigger than the one obtained with the adaptable structure and, also, in the process output appear oscillations.

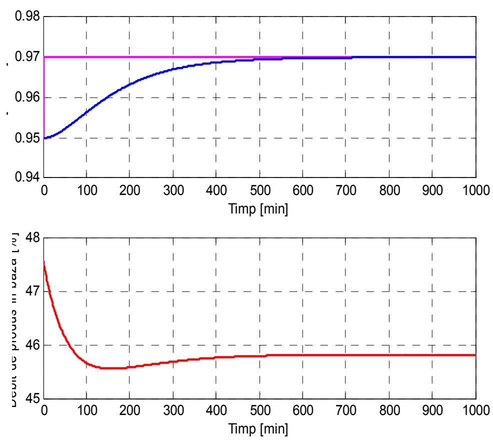

Fig. 11. Bottom composition and bottom product flow trends when the controller setpoint increases from 0.95 mol. fr. to 0.97, using the NAMPC.

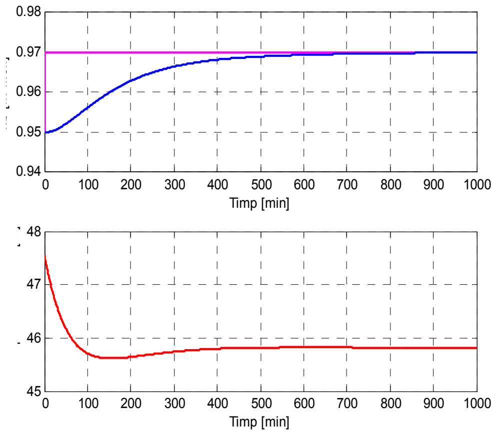

Fig. 12. Bottom composition and bottom product flow trends when the controller setpoint increases from 0.95 mol. fr. to 0.97, using the nAMPC.

Similarly, for the bottom composition control we obtain a better transient response when we use the proposed adaptable control structure (fig. 11) and not the classical, non-adaptable one (fig. 12).

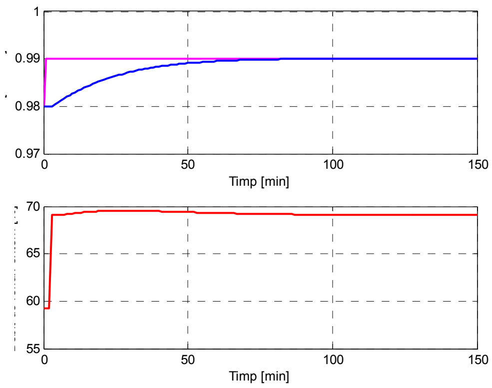

Fig. 13. Top composition and reflux flow trends when the controller setpoint increases from 0.98 mol. fr. to 0.99, using the NAIMC (Nonlinear Adaptable Internal Model Control), K=1 (the tuning parameter).

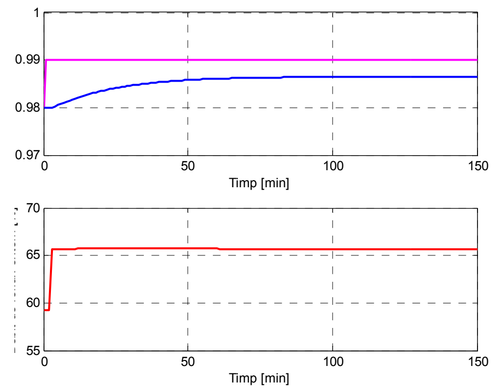

Fig. 14. Top composition and reflux flow trends when the controller setpoint increases from 0.98 mol. fr. to 0.99, using the nAIMC (non-Adaptable Internal Model Control), K=1 (the tuning parameter).

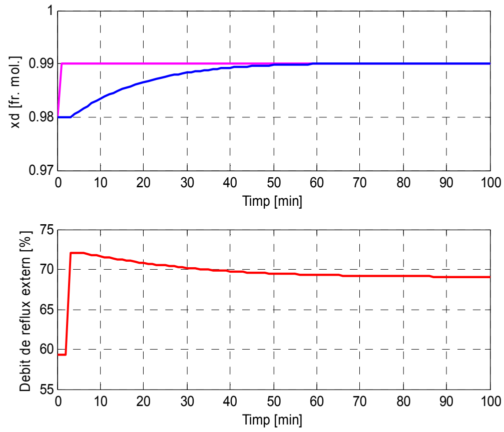

Fig. 15. Top composition and reflux flow trends when the controller setpoint increases from 0.98 mol. fr. to 0.99, using the NAIMC, K=1.3 (the tuning parameter).

As we can see, comparing figure 13 and 14, when we use the non-Adaptable structure the system has static error.

When we use the adaptable structure and increase the controller gain we observe that the transient time decreases, leading to a better response.

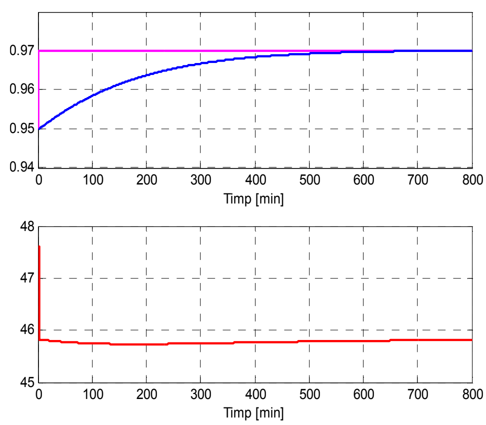

Fig. 16. Bottom composition and bottom product flow trends when the controller setpoint increases from 0.95 mol. fr. to 0.97, using the NAIMC, K=1.

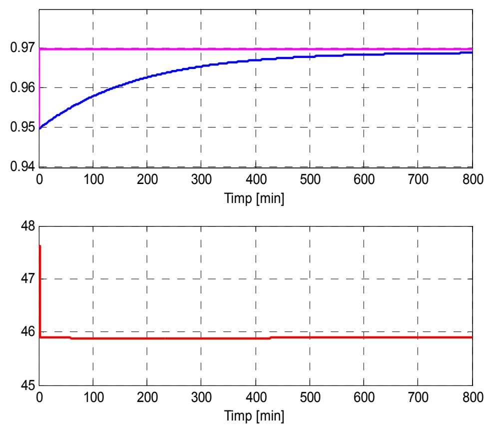

Fig. 17. Bottom composition and bottom product flow trends when the controller setpoint increases from 0.95 mol. fr. to 0.97, using the nAIMC, K=1.

Similarly, for the bottom composition control, when the non-adaptable structure is used the system has static error.

5. CONCLUDING REMARKS

Two Nonlinear Adaptable Model Based Control strategies were proposed for controlling the top and bottom product compositions for a propylene/propane distillation column. The main idea and contribution of this paper was to use a nonlinear model of the process represented as a reunion of linear models. The linear models were obtained from simulation data using Markov identification procedure and are second order transfer functions with dead time which differ from one operating point to another by gain and two time constants. These model parameters are automatically determined function of the operating point using a simple linear equation, practically they are adapted to the operation point. This is also a contribution of this work.

Simulation results demonstrated the advantages of the proposed control structures over them conventional counterpart.

The propylene/propane distillation process is a multivariable one, with two outputs (the propylene and propane composition) and four main inputs, two controlled variable (the reflux and bottom product flows) and two disturbances (the feed flow and feed composition).

The dynamic system behavior analysis consisted of changing the compositions setpoint and the tuning controllers' parameters.

The model predictive controller tuning parameters are: the sampling time, controlled variable horizon and controlled variable weight. The internal model controller has only one tuning parameter, the gain K.

The proposed adaptable control structure, in comparison with the non-adaptable one, leads to a better transient response.

For the Nonlinear Adaptable Internal Model Controller an increase in the gain value leads to a decrease in the transient time.

When the non-adaptable structure is used the control system has static error.

The two proposed control structures offer almost the same dynamic performances, better than the ones obtained with the conventional algorithms. The internal model structure distinguishes by its simplicity, in implementation and tuning.

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