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Advanced Control of an Industrial Process

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Abstract

The biggest challenge of any industrial process is the reduction of variable costs while maintaining product quality. Advanced control is the most effective technology available to achieve this objective. The common characteristic for this methodology is the use of process models. Some of the advanced control methods are: adaptive control, model based predictive control, internal model control, fuzzy control, robust control, neural network based control and optimal control. Model Based Predictive Control (MBPC), is one of advanced control methods used successfully in industrial control applications. In this paper will be outlined the performances that can be obtained using a model based predictive algorithm for controlling an industrial process.

Key words: *advanced control, model based predictive control, distillation process.*

Introduction

It is well known the fact that between the process increasing profitability methods, a special place is reserved for advanced control methods.

Model Based Predictive Control, as an advanced control method, is a model based control strategy that uses the process model to calculate the control efforts. These values are computed in order to minimize an objective function without violating input or output constraints.

MBPC method was the issue of many important studies [3, 6, 10].

The firsts MBPC algorithms, such as, Model Predictive Heuristic Control [11], Dynamic Matrix Control [4], Extended Prediction Self-Adaptive Control [5], Generalized Predictive Control [9] have used only linear process models.

In order to obtain higher performances, the use of nonlinear process models became a necessity.[1] But these methods offer valid solutions only for particular cases and beside this, the obtained algorithm is extremely complex than linear MBPC one.

Model based predictive control algorithm

The main idea of predictive algorithms is the use of an explicit model of the process for predicting the way that the process output will evolve in the future, over a specified time horizon [6]. These predictions are used for finding a control variable values sequence that minimizes an objective function, without violating some input or output constraints. At each sampling instant, the updated plant information is used to solve an open-loop optimal control problem, but only the first element of the optimal control vector is actually applied to the real process. All other elements of the optimal control vector can be either not calculated or forgotten because at the next sampling instant all calculus-sequences are performed again based on the new output measurement. This algorithm can be decomposed in two containing parts: a predictor and an optimizer.

The control variable values are computed so that the future process behavior to be optimized over a time horizon named the prediction horizon (1).

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

In equation (1), y is the output value, r - the setpoint value, k – the current step, p – the prediction horizon value, m – the control horizon value, c – the control value and Γ_l^c is the control weight.

The objective function optimization is done by minimizing the sum of differences between the predicted process output values y(k+l) and the setpoint values r(k+l), starting from the current step k, for p steps in the future, without strong variations of the error, so that the output value to be as close as possible to the setpoint trajectory, thus being avoided strong deviations.

The control variable variations which make the output process value to follow the setpoint trajectory must not be too aggressive. This disadvantage can be eliminated by using a control variable weight Γ_l^c. As these weight values are bigger, the control variable variations will be smallest, and the output will not follow the setpoint trajectory close enough. Though, finding the optimal value for this weight will have as result the setpoint trajectory following with low energy consumption.

Figure 1 illustrates the structure of a MBP control system.

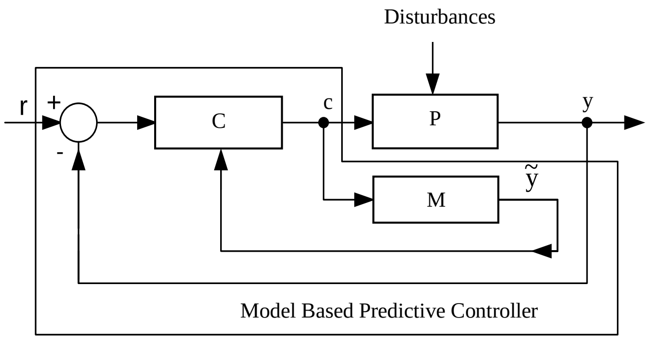

Fig. 1. MBPC system structure:
r – setpoint, c – control variable, y – process output, $\tilde{y}$ - predicted process output,C – controller, M – process model, P - process.

The most important feature of model based predictive control algorithms is the fact that at each sampling instant a new optimisation problem is solved, which leads to a new controller, obtained by tuning the previous one.

The tuning parameters are:

- the sampling time;

- the control variable horizon;

- the prediction horizon;

- the weight matrices that are used in the optimization procedure.

Model based predictive control of an industrial process

In order to implement the control strategy that was described in previous section of this paper, a binary propylene/propane distillation column from a catalytic cracking unit was used. (figure 2) The distillation column has the L-B control structure (the reflux flow is used for controlling the propylene composition and the bottom product flow is used for controlling the propane composition). [12] The process is a multivariable one, with two outputs (the propylene and propane composition) and four main inputs, two control variables (the reflux and bottom product flows) and two disturbances (the feed flow and feed composition).

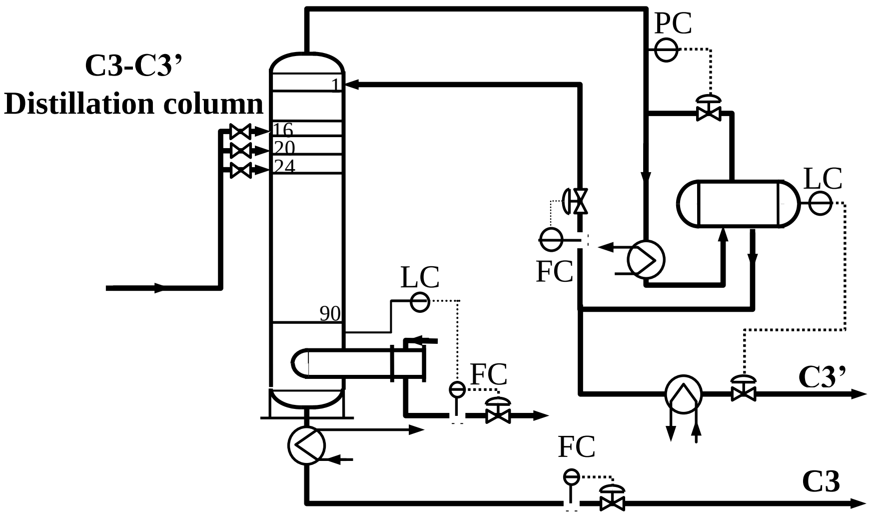

Fig. 2. Propylene/propane distillation column:
PC – pressure controller, FC –flow controller, LC – level controller.

Using available input-output data models of the process were identified the for every process channel. These models are described by second order transfer functions with dead time [2]:

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

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

For example,

- for the propylene composition – reflux flow channel and the operation point x_D=0.90 fr. mol., the model is:

$$G_v = \frac{0.0058 \cdot e^{-3 \cdot s}}{34 \cdot s^2 + 26 s + 1}, \tag{3}$$

- for the propylene composition – reflux flow channel and the operation point x_D=0.92 fr. mol., the model is:

$$G_v = \frac{0.0042 \cdot e^{-3 \cdot s}}{32 \cdot s^2 + 25s + 1}, \tag{4}$$

- for the propylene composition – reflux flow channel and the operation point x_D=0.95 fr. mol., the model is:

$$G_v = \frac{0.003 \cdot e^{-3 \cdot s}}{29 \cdot s^2 + 23s + 1}, \tag{5}$$

where the time constant measurement unit is minutes.

Simulation results

The dynamic system behavior analysis consisted of modifying the compositions setpoint, the disturbances and the tuning controllers' parameters. (figures 3 to 8).

The proposed model predictive controller was implemented using MATLAB® simulation environment, and the process was simulated using the HYSYS® simulator.

For top composition MBP controller has the following default simulation parameters:

- prediction horizon – is variable, and it is calculated using the process model time constant T_1, from (2), being $\frac{4 \cdot T_1}{T}$ [7];

- control variable time horizon – 30 sampling time;

- output weight – 1 (minimum value: 0, maximum value: 1);

- control variable weight – 0.2 (minimum value: 0, maximum value: 1).

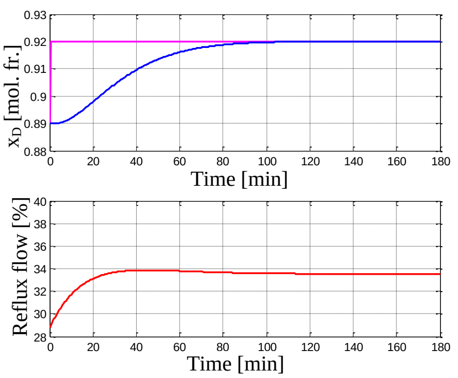

Fig. 3. Top composition trend when the controller setpoint increases from 0.89 mol. fr. to 0.92 mol. fr..

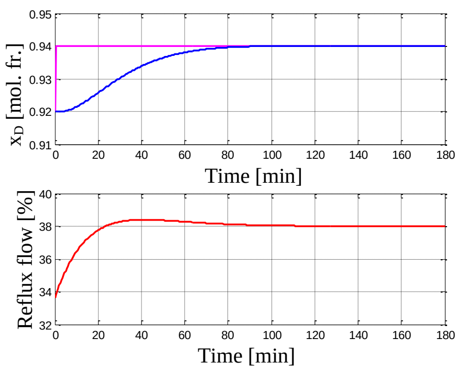

Fig. 4. Top composition trend when the controller setpoint increases from 0.92 mol. fr. to 0.94 mol. fr..

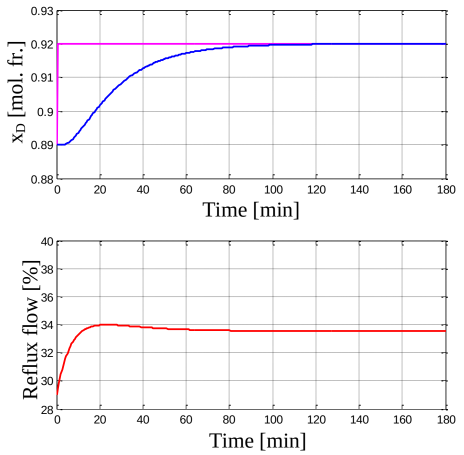

Fig. 5. Top composition trend when the controller setpoint increases from 0.89 mol. fr. to 0.92, control variable time horizon is 25.

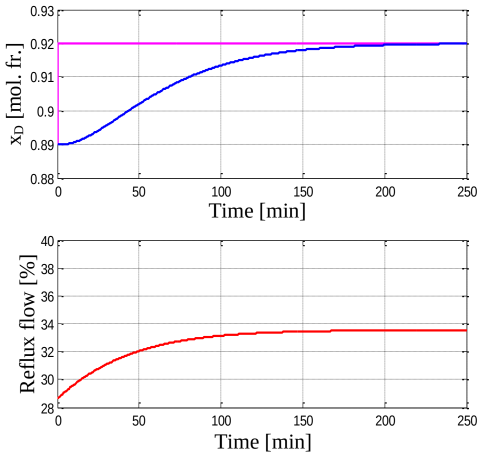

Fig. 6. Top composition trend when the controller setpoint increases from 0.89 mol. fr. to 0.92, control variable weight is 0.7.

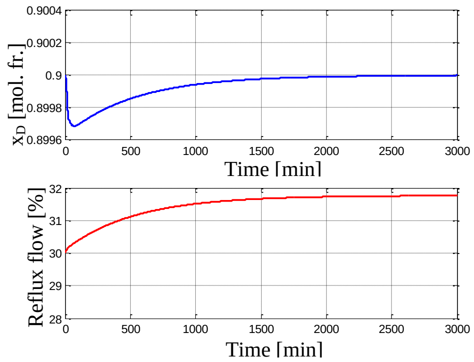

Fig.7. Top composition trend when the feed flow increases from 241.5 kmol/h to 246.5 kmol/h.

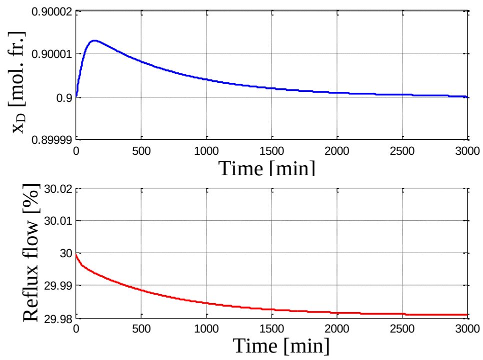

Fig.8. Top composition trend when the feed composition increases from 0.57 mol. fr. to 0.6 mol. fr..

Conclusions

In this paper were presented the performances that can be obtained using an advanced control method for controlling the top and bottom product composition of a binary propylene/propane distillation column from a catalytic cracking unit.

The MBPC tuning parameters are: the sampling time, the prediction horizon, control variable horizon, output and control variable weight.

As can be seen from the above trends, the behavior of the process and the control system was studied for different values of the tuning parameters, observing that a decreasing of the control variable horizon or a decreasing of the control variable weight, from the default values, can lead to an increasing of the transient time.

Also we can observe that the process output value reaches the setpoint value with the best dynamic performances for the default values of the tuning parameters.

The control system has a robust behavior when a disturbance appears in the process.

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Reglarea avansată a unui proces industrial

Rezumat

O mare provocare a proceselor industriale este reducerea costurilor simultan cu menţinerea calităţii produselor. Reglarea avansată este cea mai fiabilă tehnologie disponibilă pentru îndeplinirea acestui deziderat. Trăsătura de bază a acestor metode este folosirea modelului procesului. Câteva dintre metodele avansate de reglare sunt: reglarea adaptivă, reglarea predictivă, reglarea cu model intern, reglarea fuzzy, reglarea robustă, reglarea cu reţele neuronale şi reglarea optimală. Reglarea predictivă bazată pe model este una dintre metodele avansate de reglare folosită cu succes în aplicaţiile de reglare a proceselor industriale. În această lucrare vor fi puse în evidenţă performanţele ce pot fi obţinute folosind acest algoritm pentru reglarea unui proces industrial.