Preprints of the 10th IFAC International Symposium on Dynamics and Control of Process Systems
The International Federation of Automatic Control
December 18-20, 2013. Mumbai, India

Using Dynsim® to study the implementation of advanced control in a Propylene/Propane Splitter

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Abstract: In the process industry, advanced control is usually implemented so that they ensure stability and constraints satisfaction. Moreover, a competitive global market and environmental regulations results in the necessity for the economic optimization of the process operation. Real Time Optimization (RTO), which is based on an economic criterion, is usually performed in an upper level of the control structure and sends optimizing targets to the lower dynamic control layer where the advanced control drives the system to optimum targets. In this structure, the RTO employs a complex stationary non-linear model of the process for the optimization and the advanced control is usually implemented through a MPC based on a linear model. In this paper, the application of such optimization structure to an industrial Propylene/Propane (PP) splitter is tested in a simulation platform based on the integration of the commercial dynamic simulator Dynsim® and the rigorous steady-state optimizer ROMeo® with real-time facilities of Matlab. The advanced control is represented by an Infinite Horizon Model Predictive Controller (IHMPC), based on a space-state model in the incremental form that reproduces the step response model and considers the existence of zone control, optimizing targets for the inputs and can accommodate time delays. In this simulation platform the optimization and advanced control of a Propylene/Propane splitter of an oil refinery is studied. The simulation results show that proposed RTO/advanced control structure is stable and can be implemented in the real system.

Keywords: Model Predictive Control, Process Optimization, Dynamic simulation

1. INTRODUCTION

As is usual in the process industry, there is a hierarchical control structure [Engell, 2007] in which, based on an complex non-linear stationary model of the plant and on an economic criteria, a RTO layer computes optimizing targets, which are sent to a MPC layer. In the MPC layer, at each sample time, an optimal sequence of control inputs is computed so that the true system is driven to the RTO targets while the controller's cost function is minimized. This optimization problem includes constraints for the outputs and inputs. Two essential ingredients of this complex structure are stability and offset-free control. One of the usual forms to obtain guaranteed nominal stability in MPC is to adopt an infinite horizon prediction [Rawlings and Muske, 1993]. However, to produce an offset-free tracking operation, the model can be written in the incremental form in the inputs, this formulation adds integrating modes to the system output. The drawback of this formulation is that the integrating modes must be zeroed at the end of the control horizon to keep the infinite horizon cost bounded [Gonzales and Odloak, 2009].

Several successful MPC implementations are cited in the literature. In [Pinheiro et al., 2012], it was studied the implementation of APC in a Fluid Catalytic Cracking (FCC) Unit through rigorous modeling and simulation of the process. In [Carrapiço et al., 2009] an IHMPC was implemented in an industrial deisobutanizer column, using a space-state model that reproduces the step response of transfer function models and takes into account time delays and integrating modes.

Nonetheless, their model was not always observable and more recently, to circumvent this problem [Santoro and Odloak, 2012] developed a new space-state representation that still reproduces the step response model while preserving observability. This new space-state model is particularly suited to the implementation of the infinite horizon controller (IHMPC) with zone control and optimizing targets for stable, integrating and time-delayed systems with guaranteed nominal stability. Then, this sort of model will be adopted here.

As plant designs are becoming more complex, integrated and interactive, they represent a challenge of increasing complexity for dynamic control [Svrcek et al., 2000]. Nevertheless, the use of first principle-based dynamic simulation can help in the understanding of process dynamics and control strategies, especially in processes with many variables and/or long settling time. In this way, commercial advanced process controllers (APC) can be implemented using dynamic simulation in order to eliminate plant step-test and to show that rigorous steady-state and dynamic models are useful to analyze new

This work has been funded by CNPq-Brazil (under Grant 160465/2012-5).

control strategies, to develop inferences, to train and to tune new APC strategies [Alsop and Ferrer, 2006].

The main scope of this work is to study the implementation of an advanced control strategy, based on the Infinite Horizon Model Predictive Control (IHMPC), in an industrial Propylene/Propane (PP) splitter. Also, the closed-loop performance of this controller will be tested through the dynamic simulation of the process. The control scheme to be simulated assumes that a RTO layer is present in the real system and the RTO provides targets for the manipulated inputs.

2. CONTROL PROBLEM OF THE PROPYLENE/PROPANE SPLITTER

The industrial PP splitter studied here was designed to produce high-purity propylene (99.5%), which is separated from propane and contains other hydrocarbons with four atoms of carbon. A typical feed composition involves about ten components and the propylene stream is produced as the top stream of the splitter. The propane stream is obtained as the bottom product of the splitter.

The distillation system considered in this study is a heavy energy consumer, and to reduce costs, there is an energy recovery system (heat pump) where the top vapor is recompressed and condensed in the reboilers at the bottom of the column. The area exposed to heat transfer depends on the liquid level inside the bottom drum and can be varied through the manipulation of the liquid level.

The high purity required for the propylene product implies that a high reflux ratio will be required, which means that a large amount of energy will be manipulated through the variable heat transfer area of the bottom reboilers. These are typical ingredients that justify the implementation of advanced control and optimization strategies. Then, the purpose of this study is to verify if the use of a multivariable advanced controller will produce a significant increase in the economic benefit while maintaining the product qualities. Possible manipulated inputs of the advanced controller are: the feed flow rate, reflux flow rate and heat pump flow rate, and the controlled outputs are the molar content of propane in the propylene stream, propylene molar content in the propane stream and condensed liquid level in the bottom drum, which affects the exposed heat transfer area in the bottom reboilers. The controller to be implemented should have a good performance in terms of driving the system inputs to the optimum targets while keeping the system outputs inside zones that are defined by the operators. Stability is an additional issue to be considered.

3. STATE-SPACE FORMULATION

Here, we present briefly the model that is adopted in the advanced controller that is intended to be implemented in the PP splitter. For this purpose, consider a system with *nu* inputs and *ny* outputs, and assume that there is a transfer function relating inputs and outputs of the system. Then, we use a state space realization of the step response model also designated as Output Predictive Oriented Model (OPOM) originally presented in [Rodrigues and Odloak, 2003] and extended in [Santoro and Odloak, 2012] for the case of time delayed systems. For the time delay system, let us designate θ_{max} as the maximum time delay between an input and an output, and *na* as the maximum order of the transfer functions of the system.

Then, the state space model, which represents the PP splitter that has only stable poles, can be written as follows:

$$\begin{bmatrix} x^s(k+1) \\ x^d(k+1) \\ z_1(k+1) \\ z_2(k+1) \\ \vdots \\ z_{\theta_{\max}}(k+1) \end{bmatrix} = \begin{bmatrix} I_{ny} & 0 & B_1^s & B_2^s & \cdots & B_{\theta_{\max}-1}^s & B_{\theta_{\max}}^s \\ 0 & F & B_1^d & B_2^d & \cdots & B_{\theta_{\max}-1}^d & B_{\theta_{\max}}^d \\ 0 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & I_{nu} & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \cdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & I_{nu} & 0 \end{bmatrix} \begin{bmatrix} x^s(k) \\ x^d(k) \\ z_1(k) \\ z_2(k) \\ \vdots \\ z_{\theta_{\max}}(k) \end{bmatrix} + \begin{bmatrix} B_0^s \\ B_0^d \\ I_{nu} \\ 0 \\ \vdots \\ 0 \end{bmatrix} \Delta u(k) \quad (1)$$

$$\left[y(k) \right] = \left[I_{ny} \quad \Psi \quad 0 \quad 0 \quad \cdots \quad 0 \right] \begin{bmatrix} x^s(k) \\ x^d(k) \\ z_1(k) \\ z_2(k) \\ \vdots \\ z_{\theta_{\max}}(k) \end{bmatrix} \quad (2)$$

where,

$$x \in \mathbb{C}^{nx}, \quad nx = ny + nd + \theta_{\max} \cdot nu, \quad x^s \in \mathbb{R}^{ny}, \quad x^d \in \mathbb{C}^{ny \cdot nu \cdot na}$$
$$z_1, \ldots, z_{\theta_{\max}} \in \mathbb{R}^{nu}$$

The advantage of using the model structure defined in (1) is that the state components can be associated to the systems modes. The state component x^s corresponds to integrating modes related with the input incremental form and is equal to the predicted output steady-state, and component x^d corresponds to the dynamic modes that naturally tends to zero when the system approaches steady state. The state components $z_1, \ldots, z_{\theta_{\max}}$ are related with the time delay and correspond to last implemented input moves. For the case of non-repeated poles F is a diagonal matrix with components of the form $e^{\Delta t \cdot r_i}$ where r_i is a pole of the system and Δt is the sampling period.

Matrices B_l^s with $l = 1, \ldots, \theta_{\max}$ can be computed as follows:

If $l \neq \theta_{i,j}$, then $\left[B_l^s \right]_{i,j} = 0$

If $l = \theta_{i,j}$, then $\left[B_l^s \right]_{i,j} = d_{i,j}^0$

Construction of matrices B_l^d needs a little more attention. If there are no time delays (l = 0) then $B_0^d = D^d FN$, where matrices D^d and N are computed as follows:

$$N = \left.\begin{bmatrix} J \\ J \\ \vdots \\ J \end{bmatrix}\right\} ny, \quad N \in \mathbb{R}^{nd \times nu} \qquad J = \begin{bmatrix} na\left\{\begin{matrix} 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \cdots & 0 \end{matrix}\right. \\ na\left\{\begin{matrix} 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 1 & \cdots & 0 \end{matrix}\right. \\ \vdots \\ na\left\{\begin{matrix} 0 & 0 & \cdots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{matrix}\right. \end{bmatrix} \qquad J \in \mathbb{R}^{nu\, na \times nu}$$

$$D^d = \text{diag}\begin{pmatrix} d_{1,1,1}^d \cdots d_{1,1,na}^d \cdots d_{1,nu,1}^d \cdots d_{1,nu,na}^d \\ \cdots d_{ny,1,1}^d \cdots d_{ny,1,na}^d \cdots d_{ny,nu,1}^d \cdots d_{ny,nu,na}^d \end{pmatrix},$$

$$D^d \in \mathbb{C}^{nd \times nd}$$

$$D^d FN = \begin{bmatrix} d_{1,1,1}^d e^{r_{1,1,1}} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ d_{1,1,na}^d e^{r_{1,1,na}} & 0 & \cdots & 0 \\ 0 & d_{1,2,1}^d e^{r_{1,2,1}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & d_{1,2,na}^d e^{r_{1,2,na}} & \cdots & 0 \\ & & \vdots & \\ 0 & 0 & \cdots & d_{1,nu,1}^d e^{r_{1,nu,1}} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & d_{1,nu,na}^d e^{r_{1,nu,na}} \\ & & \vdots & \\ d_{ny,1,1}^d e^{r_{ny,1,1}} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & d_{ny,nu,na}^d e^{r_{ny,nu,na}} \end{bmatrix}, \quad D^d FN \in \mathbb{R}^{nd \times nu}$$

Alternatively, if $l \neq 0$, then each matrix B_l^d will have the same dimension as $D^d FN$ where those elements corresponding to transfer functions with dead time different from l are replaced with zeros.
Finally, matrix Ψ is defined as follows

$$\Psi = \begin{bmatrix} \Phi & & 0 \\ & \ddots & \\ 0 & & \Phi \end{bmatrix}, \qquad \Psi \in \mathbb{R}^{ny \times nd},$$

$$\Phi = \begin{bmatrix} 1 & \cdots & 1 \end{bmatrix}, \qquad \Phi \in \mathbb{R}^{nu\, na}$$

4. IHMPC WITH ZONE CONTROL AND OPTIMIZING TARGETS

Based on the work of [Gonzáles and Odloak, 2009], and considering that the propylene/propane splitter is an open loop stable system, we consider the following nominal cost function:

$$\begin{aligned} V_k = & \sum_{j=0}^{\infty} \left\| y(k+j\,|\,k) - y_{sp,k} - \delta_{y,k} \right\|_{Q_y}^2 + \sum_{j=0}^{m-1} \left\| \Delta u(k+j\,|\,k) \right\|_R^2 \\ & + \sum_{j=0}^{\infty} \left\| u(k+j\,|\,k) - u_{des,k} - \delta_{u,k} \right\|_{Q_u}^2 \\ & + \delta_{y,k}^T S_y \delta_{y,k} + \delta_{u,k}^T S_u \delta_{u,k} \end{aligned} \tag{3}$$

where $\Delta u\left(k+j\,|\,k\right)$ is the control move computed at time k to be applied at time $k+j$, m is the control or input horizon, Q_y, Q_u, R, S_y, S_u are positive weighting matrices of appropriate dimension, $y_{sp,k}$ and $u_{des,k}$ are the output set point and input optimizing target, respectively. The output set-point $y_{sp,k}$ becomes a decision variable of the control problem when the output has no optimizing target and consequently the output needs only to be kept within a zone. This cost explicitly incorporates an input deviation penalty that tries to accommodate the system into an optimal economic stationary point. The slack variable $\delta_{y,k}$ eliminates any infeasibility of the control problem. It can be shown that the cost defined in Eq. (3) will be bounded only if the following constraint is included in the control problem:

$$x^s\left(k+m+\theta_{\max}\,|\,k\right) - y_{sp,k} - \delta_{y,k} = 0 \tag{4}$$

Equation 4 means that, it is desired that the predicted values of the outputs at steady-state be equal to the set points. As it is not always possible to attain this target after a finite number of time steps, we include the slack variables, $\delta_{y,k}$, to guarantee the feasibility of the control problem. Nevertheless, the system has time delays and it is necessary to wait $m+\theta_{\max}$ time intervals until the last control action affects the output with the largest time delay.

As any model predictive controller, the IHMPC also allows the natural inclusion of operating constraints such as actuator bound limits. It is also usual to include constraints in the input control moves as follows:

$$\begin{aligned} & \Delta u_{\min} \le \Delta u\left(k+j\,|\,k\right) \le \Delta u_{\max} \quad j = 0,1,\ldots,m-1 \\ & u_{\min} \le u\left(k+j\,|\,k\right) \le u_{\max}, \qquad j \in \mathbb{N} \end{aligned} \tag{5}$$

The proposed controller considers the existence of input targets, u_{des}, and in order to assure that the term that penalizes the distance to this target is bounded even when the target is unreachable, we should not impose the exact value of the inputs at the end of the control horizon, instead of that a relaxed constraint will be used.

$$u\left(k+m-1\right) - u_{des,k} - \delta_{u,k} = 0 \tag{6}$$

The slack variable $\delta_{u,k}$, by definition, is unrestricted and guarantees feasibility of Eq. (6) under any condition. As it is done typically, the use of this slack variable in the objective function is heavily penalized to prevent that controller rather to use $\delta_{u,k} \neq 0$ instead of a possible control move.

As explained before, there are no fixed set points for the outputs as in the conventional MPC formulations and there will be a control zone in which the output variables must remain. As a result, the value of set points $y_{sp,k}$ is not a parameter proposed for the optimization layer and it becomes a decision variable of the optimization problem. The constraint that must be imposed to these set points is the definition of control zone:

$$y_{\min} \leq y_{sp,k} \leq y_{\max} \tag{7}$$

Finally, the objective function of the controller could be defined as:

$$\min_{\Delta u_k,\, \delta_{y,k},\, \delta_{u,k},\, y_{sp,k}} V_k$$

Subject to:

$$\begin{aligned}
&\Delta u_{\min} \leq \Delta u(k+j) \leq \Delta u_{\max} && j = 1,\ldots,m \\
&u_{\min} \leq u^b(k+j) \leq u_{\max} && j = 1,\ldots,m \\
&u(k+m-1) - u_{des} - \delta_{u,k} = 0 \\
&y_{\min} \leq y_{sp,k} \leq y_{\max} \\
&x^s(k+m+\theta_{\max}) - y_{sp,k} - \delta_{y,k} = 0
\end{aligned} \tag{8}$$

It is easy to show that the problem defined above can be characterized as quadratic programming because all constraints are linear and the objective function is quadratic. The advantage of solving a quadratic programming is the good robustness of the commercial solvers and the guarantee that the optimum solution is global optimum because of the convexity of the problem.

5. PROCESS SIMULATION AND OPTIMIZATION

The steady-state simulation of the process was performed using the software ROMeo, which is a rigorous equation-based steady-state optimizer. The dynamic simulation was developed in Dynsim, which is first-principle dynamic simulation software. ROMeo and Dynsim are trademarks of Invensys.

5.1 Steady-State Simulation and Optimization

Firstly, the steady-state process modeling was developed using ROMeo's simulation mode based on the real process and equipment data. After that, the optimization mode was triggered based on the selected controlled and manipulated variables and their respective constraints. The input optimizing targets were then determined by ROMeo, which considers the rigorous steady-state simulation model of the process to calculate the optimum operation point of the plant, based on the economic function that was defined as:

$$f_{eco} = \sum_{i=1}^{n^\circ\, products} PPS_i * PFR_i - \sum_{i=1}^{n^\circ\, feed} PFS_i * FFR_i - \sum_{i=1}^{n^\circ\, utilities} PU_i * UC_i \tag{9}$$

where,

PPS: Price of Product [\$/ton]
PFR: Product Flow Rate [ton/h]
PFS: Price of Feed [\$/ton]
FFR: Feed Flow Rate [ton/h]
PU: Price of electricity [\$/kW-h]
UC: Electricity consumption [kW-h/h]

5.2 Dynamic Simulation

The idea was to use the dynamic simulation as a virtual plant so that the costs related with the implementation of the advanced control, the controller tuning and the identification of the linear model to be included in the MPC will be significantly reduced in the real plant. All the real plant dynamic equipment data and regulatory PID control loops are included in the simulation in order to make the simulation as close as possible to the real plant. This dynamic simulation also helped to identify the system model corresponding to the most common operating point. This identification experiment would be difficult and expensive in the real system because of the large settling time of the distillation column. The idea is to compare the performance of the IHMPC based on the linear model obtained with the dynamic simulation and an existing model obtained through an identification experiment in the real plant.

6. REAL-TIME DATA TRANSFER

The advanced controller was developed in Matlab and steady-state optimization was done in ROMeo, while the dynamic simulation that represents the true plant was developed in Dynsim. Therefore, it was necessary to install a communication interface using OPC technology that allows the real-time data transfer between Dynsim, MATLAB and ROMeo. The OPC facility is designed to provide a common bridge for Windows based software applications and process control hardware. To obtain a successful communication, there must be at least one OPC server and one or various OPC clients. In this case, the OPC server is the OPC Gateway which lies in Dynsim and the OPC clients are the OPC DA which is part of the OPC toolbox of MATLAB, and the OPC EDI (External Data Interface) of ROMeo. Once the data transfer is established, reading and writing of data was configured accordingly to the controller sample time and real-time dynamic simulation speed.

7. RESULTS

The system considered in this study is the Propylene/Propane splitter of the propylene production unit of the Capuava Refinery (RECAP/PETROBRAS) located in São Paulo, Brazil. Figure 1 shows the schematic representation of the industrial system with the existing regulatory control strategies. In the simplified control strategy proposed here, the advanced controller (IHMPC) manipulates three variables: u_1 is the bottom heat pump flow rate (FC 3 in Fig.1), u_2 is the column feed flow rate (FC 1) and u_3 is the reflux flow rate (FC 2). The controlled variables are the following: y_1 is the liquid level in the main reboiler (LC 5), y_2 is the propane molar % in the propylene product (AC 1) and y_3 is the propylene molar % in the propane product (AC 2).

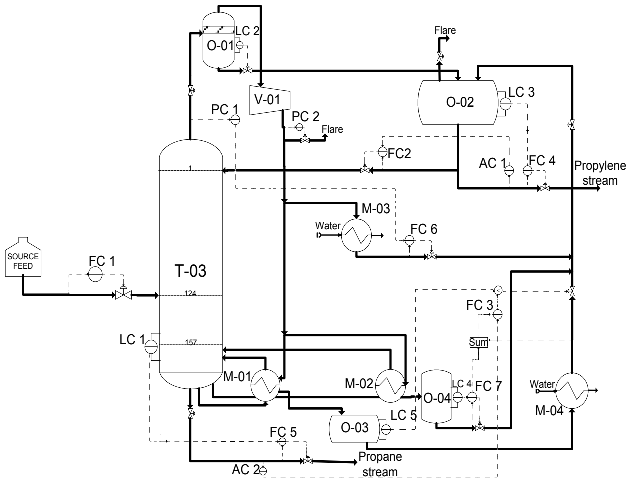

Fig.1. Schematic representation of the PP splitter

The transfer function model $G_1(s)$ corresponds to the model identified using step tests in the dynamic simulation at the normal operating condition, and model $G_2(s)$ corresponds to a similar identification experiment in the real distillation column at the design operation conditions. In these transfer functions the time constants are in minutes. It can be easily observed that there are some differences between the two models mainly related with the gains and time delays.

$$G_1(s)=\begin{bmatrix} \dfrac{-1.44}{31.5s+1} & \dfrac{0.1684\exp(-6s)}{159s+1} & \dfrac{0.1821\exp(-10s)}{119.8s+1} \\ \dfrac{(-7.657\times10^{-5}s+3.69\times10^{-6})\exp(-7s)}{s^2+0.017156s+6.439\times10^{-5}} & \dfrac{2.094\times10^{-6}\exp(-4s)}{s^2+0.01776s+9.857\times10^{-5}} & \dfrac{-3.501\times10^{-6}\exp(-98s)}{0.6s^2+0.013s+6.257\times10^{-5}} \\ \dfrac{0.0003423s-3.704\times10^{-5}}{0.2s^2+0.0142s+4.986\times10^{-5}} & \dfrac{0.0001589}{1.4s^2+0.0423s+4.194\times10^{-4}} & \dfrac{1.99\times10^{-5}\exp(-9s)}{s^2+0.0184s+5.66\times10^{-5}} \end{bmatrix}$$

$$G_2(s)=\begin{bmatrix} \dfrac{-1.035}{29s+1} & \dfrac{0.1303}{118.7s+1} & \dfrac{0.145}{118.6s+1} \\ \dfrac{-5.589\times10^{-5}s+2.73\times10^{-6}}{s^2+0.02156s+7.439\times10^{-5}} & \dfrac{1.496\times10^{-6}}{s^2+0.01688s+9.857\times10^{-5}} & \dfrac{-3.141\times10^{-6}\exp(-111s)}{0.6s^2+0.01355s+7.557\times10^{-5}} \\ \dfrac{0.0003027s-3.267\times10^{-5}}{0.2s^2+0.01034s+4.756\times10^{-5}} & \dfrac{0.000135}{1.4s^2+0.04418s+4.425\times10^{-4}} & \dfrac{1.942\times10^{-5}}{s^2+0.0149s+5.535\times10^{-5}} \end{bmatrix}$$

The output zones considered in the simulation case described here are given in Table 1, and input bounds as well as the maximum input moves, are shown in Table 2.

Table 1. Output zones of the PP splitter

Output	y_{min}	y_{max}
y_1 (% level)	4	80
y_2 (%molar)	0	0.45
y_3 (%molar)	0	2

Table 2. Input constraints of the PP splitter

Input	Δu_{max}	u_{min}	u_{max}
u_1 (ton/h)	0.15	220	350
u_2 (ton/h)	0.02	10	45
u_3 (ton/h)	0.13	200	320

The following tuning parameters were adopted for the MPC controller:

T = 1 min., m = 3, Q_y = diag (6 25 2), R = diag (0.5 3 0.5), Q_u = diag (0.1 10 1), S_y = 10^7*diag (1 10 1), S_u = 10^4*diag (0.1 100 1).

In order to automate the reading and writing of data, from and to the dynamic simulation, we used the timer function of Matlab and we follow the sequence: First, the data from Dynsim is read every 5sec and sent to Matlab where the average of last 12 data points is computed. Next, the MPC algorithm is run with a sampling time equal to 1 minute and new values of the control inputs are computed. These inputs are set-points to the dynamic simulation regulatory PID controllers that are sent to Dynsim through the OPC interface mentioned in section 6. In addition, the transfer of data from ROMeo to Dynsim is done by using the export function of OPC EDI, in the same way as the reading of data was done using the import and download functions.

Two simulation cases were considered. In the first experiment, IHMPC was implemented using model $G_1(s)$ (Controller 1) while in the second experiment the same controller was implemented with model $G_2(s)$ (Controller 2). In both cases, the closed loop simulation began at the normal operating point of the plant, which in terms of the manipulated inputs, corresponds to u_0 = [302 30 268] and to the outputs y_0 = [42 0.5 1]. The initial steady-state corresponds to f_{eco} = 14 800 \$/h. Then with the assumed market scenario, ROMeo computes a new optimum operating point and defines the optimum targets to the MPC. These input targets are u_{des} = [329.6 34 294.8] which corresponds to an increment of the feed flow rate while minimizing the heat pump flow rate and the reflux flow rate. For this point the value of the economic function is increased to f_{eco} = 16 400 \$/h.

The response of the closed loop system in the two cases can be seen in Figs. 2-4. In these figures, it is easy to realize that the two controllers are able to stabilize the plant and drive the system to optimum operating point, maintaining the controlled variables inside their respective zones while the manipulated variables are driven to their respective targets. This resulting is quite motivating in practical terms as it shows that the control strategy has robustness to significant change in the system model.

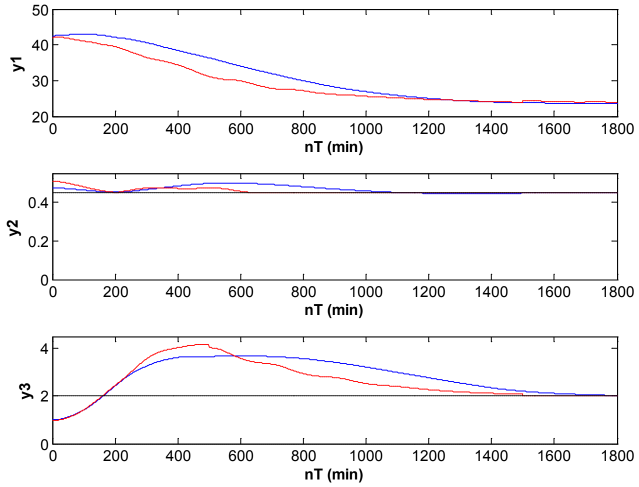

Fig. 2. Evolution of the outputs (- - - Controller 1) (—— Controller 2),

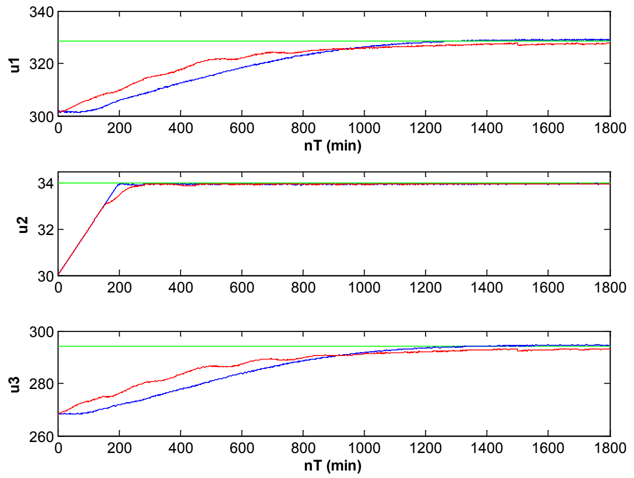

Fig. 3. Evolution of the inputs (- - - Controller 1) (—— Controller 2), (—— RTO targets)

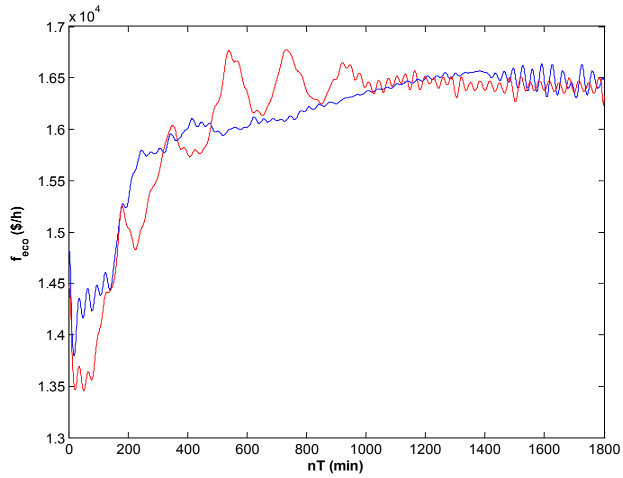

Fig. 4. Economic function (- - - Controller 1) (—— Controller 2)

Fig. 2 shows the true system controlled outputs for the Controller 1 (blue line) and Controller 2 (red line), and the output zones (dashed line) for the complete simulation time (1800 min). When comparing these controller performances, it is easy to realize that Controller 1 has a slightly better performance than Controller 2, because it uses the model identified using the same dynamic simulation as the true plant. We can see that with Controller 1, the controlled outputs y_2 and y_3, return faster to their control zones. In Fig. 3, the evolution of the manipulated variables is shown. The inputs are driven to their respective targets as it was expected, but Controller 1 is slightly faster than Controller 2. Fig. 4 shows the economic function of the process which can better stress the similarity in performance of these controllers.

8. CONCLUSIONS

In this work, we have presented a study on the implementation of the IHMPC on a Propylene production unit using commercial dynamic simulation software (Dynsim) associated with a real time optimizer (ROMeo). In the proposed approach, the controller implements zone control and optimizing targets for the inputs. Two linear models were considered to represent the Propylene splitter and the results show that the proposed strategy performs similarly in both cases and has some robustness to model uncertainty. This representative example shows that the proposed approach to design the advanced control implementations can be extended to other real applications.

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