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REALIGNED MODEL PREDICTIVE CONTROL OF A PROPYLENE DISTILLATION COLUMN

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Abstract - In the process industry, advanced controllers usually aim at an economic objective, which usually requires closed-loop stability and constraints satisfaction. In this paper, the application of a MPC in the optimization structure of an industrial Propylene/Propane (PP) splitter is tested with a controller based on a state space model, which is suitable for heavily disturbed environments. The simulation platform is based on the integration of the commercial dynamic simulator Dynsim® and the rigorous steady-state optimizer ROMeo® with the real-time facilities of Matlab. The predictive controller is the Infinite Horizon Model Predictive Control (IHMPC), based on a state-space model that that does not require the use of a state observer because the non-minimum state is built with the past inputs and outputs. The controller considers the existence of zone control of the outputs and optimizing targets for the inputs. We verify that the controller is efficient to control the propylene distillation system in a disturbed scenario when compared with a conventional controller based on a state observer. The simulation results show a good performance in terms of stability of the controller and rejection of large disturbances in the composition of the feed of the propylene distillation column.
Keywords: Model Predictive Control; Process Optimization; Dynamic simulation; Propylene distillation.

INTRODUCTION

Since the early applications of Model Predictive Control (MPC) in industry, more than three decades ago, this control method has shown a continuous development. It has been largely implemented in areas such as oil refining, chemical, food processing, automotive and aerospace industries (Qin and Badgwell, 2003) and, nowadays, continues to gain the interest in other fields such as in medical research (Lee and Bequette, 2009).

As is usual in the process industry, there is a hierarchical control structure (Engell, 2007) in which, based on a complex non-linear stationary model of the plant and on an economic criteria, a Real Time Optimization (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 calculated so that the system is driven to the RTO targets through the minimization of a control cost function. 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 prediction horizon (Rawlings and Muske, 1993). However, to produce an offset-free tracking operation, the model can be written in the incremental form in the inputs, which 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 (Rodrigues and Odloak, 2003; Gonzáles and Odloak, 2009).

Several successful MPC implementations are cited in the literature. Pinheiro *et al*. (2012) studied the

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implementation of APC in a Fluid Catalytic Cracking (FCC) Unit through rigorous modeling and simulation of the process. Hinojosa and Odloak (2013, 2014) studied the implementation of state-observer-based MPC's in the Propylene/Propane splitter. Carrapiço *et al*. (2009) implemented an IHMPC in an industrial deisobutanizer column, using a space-state model that reproduces the step response of the transfer function model and takes into account time delays and integrating modes. This sort of state-observer-based advanced controller has been successfully implemented in industrial applications.

Nowadays, several researchers propose to integrate an economical term into the controller cost function, so that the controller drives the process system to an economical optimum. The classical approach corresponds to the multi-layer structure in which Real Time Optimization (RTO) and MPC are executed in different layers of the control structure. There are several approaches to integrate RTO into the MPC structure, the so called Economic MPC or one-layer approach. First, the inclusion of an economic function term (feco) and the nonlinear steady-state model in the advanced controller was proposed, producing what was called the optimizing controller (Zanin *et al*., 2002). The main disadvantage of this strategy is that the optimization problem that defines the controller is a non-linear one, which becomes difficult to solve within the controller sampling time. It may require a high computational effort and does not guarantee the convergence to a global optimum.

To circumvent that problem, different approaches were proposed for the Economic MPC controller where the gradient, reduced gradient or Lyapunov-based techniques were used to provide a controller that ensures stability, constraint satisfaction and a low computational cost solution (Adetola and Guay, 2010; Alamo *et al*., 2014; Amrit *et al*., 2011; De Souza *et al*., 2010; Ellis *et al*., 2013).

Alongside with performance, the closed-loop stability of the system is another concern when one designs a model predictive controller. Stability is often proved assuming that the state is measured or exploiting the separation principle. In the usual case, the system state is not measured and the separation principle is only applicable when the control law calculated by the controller is linear (Zheng and Morari, 1995; Maciejowski, 2002). So, the approach cannot be applied when the control optimization problem is constrained. A method to overcome this issue consists in avoiding the use of a state observer by considering a non-minimal realigned model where the state is composed of the past measured outputs and inputs of the system (Maciejowski, 2002).

One can expect that a controller based on such a realignment model would be more robust and efficient in terms of stability and non-measured disturbance rejection than a controller in which a state observer is required. Nevertheless, to our knowledge, no such study can be found in the MPC literature.

Recent papers dealing with model predictive control based on such realigned models include Wang and Young (2006), González *et al*. (2009), Perez *et al*. (2014) and Zhang *et al*. (2011). In this work, the model representation proposed in González *et al*. (2009) is also adopted.

As plant designs are becoming more complex, integrated and interactive, they tend to represent a challenge of increasing complexity for dynamic control (Svrcek *et al*., 2000). Nevertheless, the use of a first principles-based dynamic simulation can help in the understanding of process dynamics and the design of 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 reduce plant step-tests and to minimize the implementation time. Besides, rigorous steady-state and dynamic models are useful to analyze new control strategies, to develop inferences, to train the operating personal and to tune new APC strategies (Alsop and Ferrer, 2006).

The main scope of this work is the implementation of an advanced control strategy, based on the Infinite Horizon Model Predictive Control (IHMPC) in the highly non-linear industrial Propylene/Propane (PP) splitter. The approach considers a model representation that does not require a state observer/estimator. The closed-loop performance of this controller is tested through the dynamic simulation of the process for typical disturbed operating scenarios and compared with the performance of a conventional state-estimator-based controller. The control scheme considered here assumes that a RTO layer is present in the control structure and provides targets for the manipulated inputs of the distillation system and that the outputs are controlled inside zones instead of at fixed set points.

THE CONTROL PROBLEM OF THE PROPYLENE/PROPANE SPLITTER

The industrial Propylene/Propane splitter studied here is schematically represented in Dynsim in Figure 1. This system is designed to produce high-purity propylene (99.5%), which is separated from the propane stream that contains other hydrocarbons with four atoms of carbon. A typical description of the feed composition usually involves about ten components and the propylene stream is produced as the top stream of the splitter, while 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 the operating costs, it includes an energy recovery system (heat pump) where the top vapor is recompressed and condensed in the reboilers at the bottom of the column. The heat transfer area of the reboilers depends on the liquid level inside the bottom drum and can be modified through the manipulation of the liquid level.

The required high purity of the propylene product implies that a high reflux ratio is necessary, which means that a large amount of energy is transferred through the variable heat transfer area of the bottom reboilers. The high consumption of energy is one of the typical ingredients that justify the implementation of advanced control and optimization strategies in refining processes. The main purpose of this study is to verify if a multivariable advanced controller based on a state-space representation that does not require a state observer/estimator can give a good performance in terms of producing an economic benefit while maintaining the product qualities. In the controller considered here, the manipulated inputs are the feed flow rate, the reflux flow rate and the heat pump flow rate.

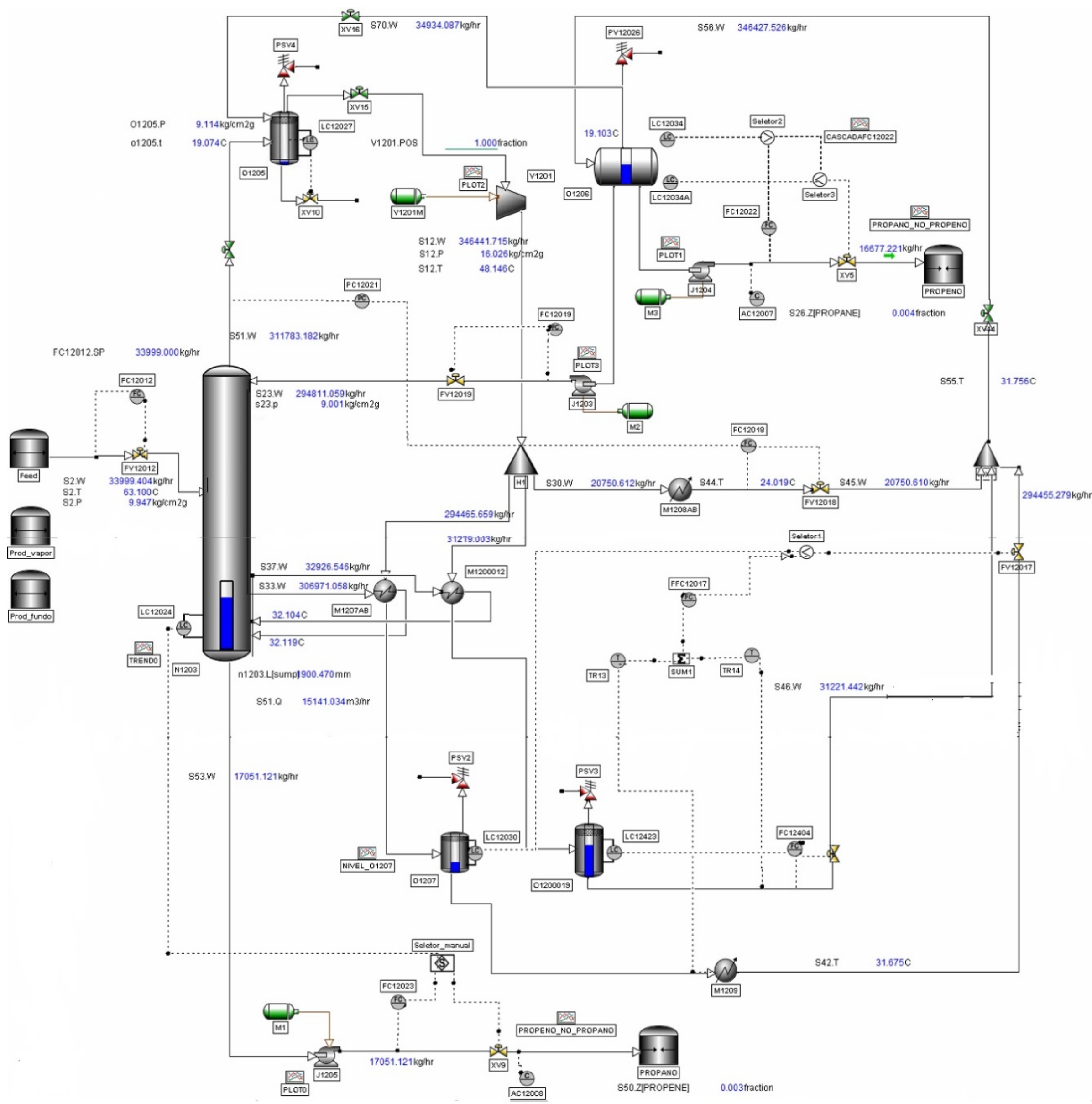

Figure 1: Schematic representation of the Propylene/Propane splitter.

The controlled outputs are the molar concentration of propane in the propylene stream, the propylene molar concentration in the propane stream and the level of liquid in the bottom separator, which affects the heat transfer area in the bottom reboilers. The controller is expected to provide a good performance in terms of driving the system inputs to the optimum targets produced by the RTO layer, while keeping the system outputs inside the control zones that are defined by the operators. Stability is an additional issue that will be observed.

FORMULATION OF THE REALIGNED MODEL

Consider the system with *nu* inputs and *ny* outputs, which can be represented by the following difference equation model (Maciejowski, 2002; Perez, 2006):

$$y(k) = -\sum_{i=1}^{na} A_i y(k-i) + \sum_{i=1}^{nb} B_i u(k-i) \qquad (1)$$

where *na* and *nb* are the number of poles and zeros of the system respectively. Then, the model represented in Eq. (1) corresponds to the following state space model in the output realigned form (González *et al*., 2009):

$$\begin{aligned} x(k+1) &= Ax(k) + B\Delta u(k) \\ y(k) &= Cx(k) \end{aligned} \qquad (2)$$

where,

$$A = \begin{bmatrix} A_y & A_{\Delta u} \\ 0 & \underline{I} \end{bmatrix},\ B = \begin{bmatrix} B_{\Delta u} \\ \overline{I} \end{bmatrix},\ C = \begin{bmatrix} C_y & C_{\Delta u} \end{bmatrix},$$

$$A_y = \begin{bmatrix} I_{ny} - A_1 & A_1 - A_2 & \cdots & A_{na-1} - A_{na} & A_{na} \\ I_{ny} & 0 & \cdots & 0 & 0 \\ 0 & I_{ny} & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I_{ny} & 0 \end{bmatrix} \in \Re^{ny(na+1)\times ny(na+1)},$$

$$A_{\Delta u} = \begin{bmatrix} B_2 & \cdots & B_{nb-1} & B_{nb} \\ 0 & \cdots & 0 & 0 \\ 0 & \cdots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & 0 & 0 \end{bmatrix} \in \Re^{ny(na+1)\times nu(nb-1)},$$

$$\underline{I} = \begin{bmatrix} 0 & \cdots & 0 & 0 \\ I_{nu} & \cdots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & I_{nu} & 0 \end{bmatrix} \in \Re^{nu(nb-1)\times nu(nb-1)},\ B_{\Delta u} = \begin{bmatrix} B_1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \in \Re^{ny(na+1)\times nu}$$

$$\overline{I} = \begin{bmatrix} I_{nu} \\ 0 \\ \vdots \\ 0 \end{bmatrix} \in \Re^{nu(nb-1)\times nu},\ C_y = \begin{bmatrix} I_{ny} & 0 & \cdots & 0 \end{bmatrix} \in \Re^{ny\times ny(na+1)},$$

$$C_{\Delta u} = \begin{bmatrix} 0 & 0 & \cdots & 0 \end{bmatrix} \in \Re^{nu(nb-1)}$$

The state of the model defined in (2) then splits as follows:

$$x(k) = \begin{bmatrix} x_y(k) \\ x_{\Delta u}(k) \end{bmatrix} \in \Re^{nx}, \quad nx = (na+1)ny + (nb-1)nu$$

where,

$$x_y = \begin{bmatrix} y(k)^T & y(k-1)^T & \cdots & y(k-na+1)^T & y(k-na)^T \end{bmatrix}^T \quad (3)$$

$$x_{\Delta u}(k) = \begin{bmatrix} \Delta u(k-1)^T & \Delta u(k-2)^T & \cdots & \Delta u(k-nb+1)^T \end{bmatrix}^T \quad (4)$$

The partition of the state defined in (3) and (4) is convenient in order to separate the state components related to the system output at past sampling steps from those related to the input. Also, since the model is written in terms of the input increment, model (2) contains the modes of model (1) plus *ny* integrating modes.

IHMPC WITH ZONE CONTROL AND OPTIMIZING TARGETS

The controller with infinite prediction horizon (IHMPC) presented in González *et al*. (2009) was extended here to include economic targets for the inputs and zone control for the outputs. This controller was considered in the simulation of the control of a Propylene/Propane splitter in order to evaluate the effect of considering a realigned model based controller instead of a controller that requires the use of a state observer as in the conventional IHMPC, which usually results in a slower closed-loop system. Next, how this controller was built is briefly described. The cost function of the controller is the following one:

$$\begin{aligned} V_k = & \sum_{j=0}^{\infty} \left(y(k+j\,|\,k) - y_{sp,k} - \delta_{y,k} \right)^T Q_y \left(y(k+j\,|\,k) - y_{sp,k} - \delta_{y,k} \right) \\ & + \sum_{j=0}^{\infty} \left(u(k+j\,|\,k) - u_{des,k} - \delta_{u,k} \right)^T Q_u \left(u(k+j\,|\,k) - u_{des,k} - \delta_{u,k} \right) \\ & + \sum_{j=0}^{m-1} \Delta u(k+j\,|\,k)^T R \Delta u(k+j\,|\,k) \\ & + \delta_{y,k}{}^T S_y \delta_{y,k} + \delta_{u,k}{}^T S_u \delta_{u,k} \end{aligned} \quad (5)$$

where $\Delta u(k+j\,|\,k)$ is the control move computed at time k to be applied at time $k+j$ and 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 respectively the output set point and input optimizing target. Finally, $\delta_{y,k}$ and $\delta_{u,k}$ are slack variables that extend the attraction domain of the controller to the whole definition set of the states.

If the system defined in (1) is open loop stable, then one can define $A_\infty = \lim_{j \to \infty} A^j$ and the infinite horizon cost function defined in (5) can be reduced to the following finite horizon cost:

$$\begin{aligned} V_k = & \sum_{j=0}^{m} \left(y(k+j\,|\,k) - y_{sp,k} - \delta_{y,k} \right)^T Q_y \left(y(k+j\,|\,k) - y_{sp,k} - \delta_{y,k} \right) \\ & + x(k+m\,|\,k)^T \bar{Q}_y x(k+m\,|\,k) \\ & + \sum_{j=0}^{m-1} \left(u(k+j\,|\,k) - u_{des,k} - \delta_{u,k} \right)^T Q_u \left(u(k+j\,|\,k) - u_{des,k} - \delta_{u,k} \right) \\ & + \sum_{j=0}^{m-1} \Delta u(k+j\,|\,k)^T R \Delta u(k+j\,|\,k) \\ & + \delta_{y,k}{}^T S_y \delta_{y,k} + \delta_{u,k}{}^T S_u \delta_{u,k} \end{aligned} \quad (5a)$$

where $\bar{Q}_y$ is obtained from the solution to the following equation

$$\begin{aligned} & \bar{Q}_y - \left(A - A_\infty \right)^T \bar{Q}_y \left(A - A_\infty \right) \\ & = \left(A - A_\infty \right)^T C^T Q_y C \left(A - A_\infty \right) \end{aligned}$$

and the following equations are assumed to be satisfied:

$$C A_\infty x(k+m\,|\,k) - y_{sp,k} - \delta_{y,k} = 0 \quad (5b)$$

$$u(k+m-1\,|\,k) - u_{des,k} - \delta_{u,k} = 0 \quad (5c)$$

In the proposed approach, the output set-point $y_{sp,k}$ becomes a decision variable of the control problem as the output has no optimizing target and, consequently, the output needs only to be kept within its operating zone. The cost defined in (5) explicitly incorporates an input deviation penalty that tries to accommodate the system into an optimal economic stationary point. It is easy to show that the cost defined in Eq. (5) will be equivalent to the cost (5a) if the terminal constraints (5b) and (5c), which are related with the infinite sums, are included in the control problem. As it is not always possible to satisfy these constraints after a finite number of time steps, one needs to include the slack variables $\delta_{y,k}$ and $\delta_{u,k}$ 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 effect of the last control action starts to be detected by the output with the largest time delay.

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

$$\begin{aligned} &\Delta u_{\min} \le \Delta u(k+j\,|\,k) \le \Delta u_{\max}, \quad j=0,1,\dots,m-1 \\ &u_{\min} \le u(k+j\,|\,k) \le u_{\max}, \qquad j=0,1,\dots,m-1 \end{aligned} \tag{6}$$

Since 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, one should not impose the exact value of the inputs at the end of the control horizon. Then, the relaxed constraint is used as shown in Eq. (5c).

The slack variable $\delta_{u,k}$, by definition, is unrestricted and guarantees feasibility of Equation (5c) under any condition. As is typically done, the use of this slack variable is heavily penalized in the objective function to prevent the controller from choosing $\delta_{u,k} \neq 0$ instead of a possible control move.

As explained before, in the MPC considered here, there are no fixed set-points for the outputs as in the conventional MPC formulations. Instead, there is a control zone to where the controller must drive the output variables. As a result, the value of $y_{sp,k}$ is not a fixed parameter proposed by the real time optimization layer and it becomes a constrained decision variable of the control optimization problem. The constraint that must be imposed to these set-points corresponds to the definition of the control zone:

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

Finally, the problem that defines the controller corresponds to the minimization of the cost function (5a) subject to a terminal constraint that forces the infinite sum of the squared output error to be bounded and subject to constraints (5b), (5c), (6) and (7).

PROCESS SIMULATION AND OPTIMIZATION

In order to calculate the optimum operating point of the Propylene/Propane splitter, the steady-state simulation of the process is performed using the software ROMeo, which is a rigorous equation-based steady-state optimizer. The dynamic simulation is developed in Dynsim, which is a first-principles dynamic simulation software. ROMeo and Dynsim are trademarks of Invensys.

Steady-State Simulation and Optimization

Initially, one simulates the steady-state process with ROMeo's simulation mode based on information of the real process and equipmental data. After that, the optimization mode is triggered considering the selected controlled and manipulated variables and their respective constraints. The input optimizing targets $u_{des,k}$ are then determined by ROMeo, which considers the rigorous steady-state model of the process in the calculation of the optimum operation point of the plant, based on the economic function that is defined as:

$$\begin{aligned} f_{eco} = &\sum_{i=1}^{products} PPS_i * PFR_i - \sum_{i=1}^{feeds} PFS_i * FFR_i \\ &- \sum_{i=1}^{utilities} PU_i * UC_i \end{aligned} \tag{8}$$

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], and *UC*: Electricity consumption [kW-h/h].

The economic function defined in Eq. (8) is maximized, producing the optimum input targets subject to the following constraints:

– The rigorous steady-state model that relates the system inputs and measured disturbances to the outputs.
– Lower and upper bounds to the input targets.
– Lower and upper bounds to the controlled outputs.

The hierarchical structure that integrates the RTO and MPC layers via the optimizing targets to the MPC layer and, subsequently, the set-point to the regulatory loops of the Distributed Control System (DCS) is shown in Figure 2.

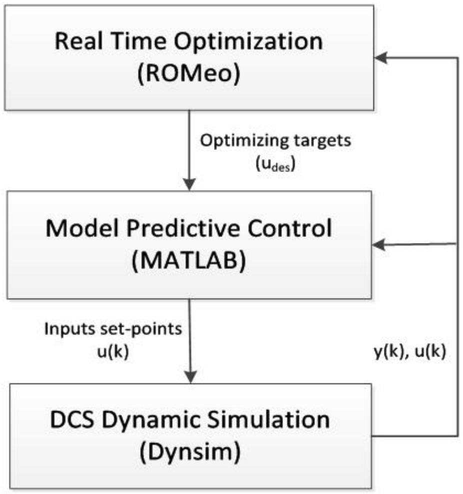

Figure 2: Hierarchical control structure of the Propylene system.

Dynamic Simulation

The dynamic simulation of the propylene distillation column is developed in the simulation package Dynsim. The idea is to use the rigorous dynamic simulation as a virtual plant in order to reduce 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. All the real plant 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 helps to identify the system model corresponding to the most common operating point. This identification experiment in the real plant would be difficult and expensive because of the large settling time of the distillation column (about 20 to 30h).

REAL-TIME DATA TRANSFER

In the simulation framework considered here, the MPC controller is supposed to run in Matlab and the steady-state optimization in ROMeo. The dynamic simulation that represents the true plant is performed in Dynsim and, consequently, it is necessary to include a communication interface using OPC technology to allow the real-time data transfer between Dynsim, MATLAB and ROMeo. The OPC facility was developed 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 several 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 can be configured according to the controller sample time and the real-time dynamic simulation pace. A representative scheme of this communication structure is shown in Figure. 3. Moreover, in order to implement the control action in the dynamic simulation at each time interval that corresponds to the sampling time of the advanced controller, the code was adapted to use the "timer" function of Matlab.

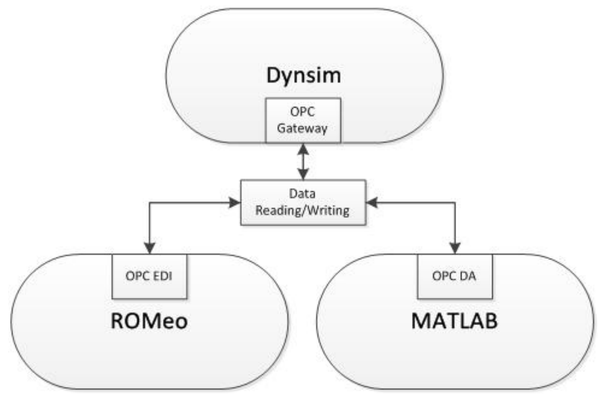

Figure 3: Matlab, Dynsim and ROMeo OPC interface.

SIMULATION 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. The controlled variables are the following: y_1 is the liquid level in the main reboiler (LC-5), y_2 is the propane molar percentage in the propylene product (AC-1) and y_3 is the propylene molar percentage in the propane product (AC-2). The manipulated variables correspond to: u_1 the heat pump flow rate (FC-3), u_2 the feed flow rate (FC-1) and u_3 the reflux flow rate (FC-2) as represented in Figure 1.

The transfer functions relating the inputs and the outputs of the system are shown in Table 1.

It is important to explain the stable transfer functions of the first controlled variable. Most of the liquid levels can be described by an integrating behavior, but it is not the case for this system. This particular behavior was also verified by step tests for model identification in the real PP splitter.

Table 1: Transfer functions of the Propylene system.

	u_1	u_2	u_3
y_1	$\frac{-1.035467}{29s+1}$	$\frac{1.3033140\times10^{-1}}{118.72s+1}$	$\frac{1.45008\times10^{-1}}{118.6s+1}$
y_2	$\frac{-5.589\times10^{-5}s+2.73\times10^{-6}}{s^2+2.156\times10^{-2}+7.439\times10^{-5}}$	$\frac{1.496\times10^{-6}}{s^2+1.688\times10^{-2}+9.857\times10^{-5}}$	$\frac{-3.141\times10^{-6}\exp(-111s)}{0.6s^2+1.355\times10^{-2}s+7.557\times10^{-5}}$
y_3	$\frac{3.027\times10^{-4}s-3.267\times10^{-5}}{0.2s^2+1.034\times10^{-2}+7.56\times10^{-5}}$	$\frac{1.35\times10^{-4}}{1.4s^2+4.418\times10^{-2}+4.425\times10^{-4}}$	$\frac{1.942\times10^{-5}}{s^2+1.49\times10^{-2}+5.535\times10^{-5}}$

The output zones and input constraints provided by the process operators, as well as the maximum input increments, are shown in Tables 2 and 3.

The tuning parameters of the controller considered here are shown in Table 4.

Table 2: 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 3: Input constraints of the PP splitter.

Input	Δu_{max}	u_{min}	u_{max}
u_1 (ton/h)	1.5	220	350
u_2 (ton/h)	0.2	10	45
u_3 (ton/h)	1.3	200	320

Table 4: Tuning parameters of the IHMPC-RM.

Tuning parameter	IHMPC-RM
T (min.)	10
m	3
R	$diag([0.5 \quad 3 \quad 0.5])$
Q_y	$diag([6 \quad 25 \quad 2])$
Q_u	$diag([0.01 \quad 10 \quad 0.1])$
S_y	$diag([10^{10} \quad 10^{10} \quad 10^{10}])$
S_u	$diag([10^4 \quad 10^8 \quad 10^5])$

The sampling time T=10 min was selected because of the slow behavior of the system due to its large settling time. In order to automate the reading and writing of data, from and to the dynamic simulation, the timer function of Matlab is used intensively. First, the data from Dynsim is read with a period of 30 sec and sent to Matlab, where the average of the last 20 readings is computed. Next, based on this average, the MPC algorithm is run with a sampling time of 10 minutes and the new values of the control inputs are computed. These inputs are the set-points to the PID controllers that are part of the dynamic simulation and they are sent to Dynsim through the OPC interface mentioned in a previous section. In addition, the RTO function is executed to produce a new optimum operating point, the transfer of data from ROMeo to Dynsim is done through the export function of OPC EDI, in the same way as the reading of data is done using the import and download functions.

Two simulation cases are presented for the test of the proposed controller and compared with a state-estimator-based controller that is formulated using an IHMPC with the OPOM system representation (Hinojosa and Odloak, 2013).

As any MPC controller based on a state-space model where the state is not measured, the controller needs the inclusion of a state estimator whose basic expression can be summarized as follows:

$$\hat{x}(k+1|k) = A\hat{x}(k|k) + B\Delta u(k) + K_F\left(y(k) - C\hat{x}(k|k)\right)$$

where $\hat{x}(k+1|k)$ is the estimated state at sampling time (k+1) computed with information up to sampling time k, $\hat{x}(k|k)$ is the estimated state at sampling time (k) computed with information up to sampling time k, and $y(k)$ is the real output of the system at sampling time (k)

In this case, the error estimation measurement is the comparison between the real output and the simulated output of the system $\left(y(k) - C\hat{x}(k|k)\right)$. This error is used as a feedback correction.

Here, the state estimator is the Kalman filter (K_F) that is based on the following equations:

$$P = APA^T + W - \left(APC^T\right)\left(CPC^T + V\right)^{-1}\left(CPA^T\right)$$

$$K_F = \left(APC^T\right)\left(CPC^T + V\right)^{-1}$$

where P is the error estimation covariance matrix and the filter can be tuned through the parameters V and W, which are the noise covariances. For a fair comparison both controllers use the same tuning parameters as shown in Table 4. The state observer parameters are:

$$V = 0.5 \times I_{ny} \in \Re^{ny \times ny}$$

$$W = 0.5 \times I_{nx} \in \Re^{nx \times nx}$$

In the first experiment, the IHMPC-RM performs in a scenario where the operating objective is to maximize the economic benefit and the feed flow rate is allowed to be increased. In the second experiment the same controller aims to reject unmeasured disturbance in the feed composition. In the first simulation experiment, the closed loop simulation began at the normal operating point of the plant, which in terms of the manipulated inputs and controlled outputs, corresponds to u_0 = [302 30 268] and y_0=[42 0.27 1], respectively. Observe that, at the initial steady state, output y_2 is slightly above its maximum bound. At this initial steady state, the economic function corresponds to the value f_{eco}= 14 300$/h. Then with the assumed market scenario, ROMeo computes a new optimum operating point and defines the optimum targets to the MPC layer. The optimum input targets are u_{des} = [329.6 34 294.8], which correspond to an increment of the feed flow rate while the optimizer tends to minimize the heat pump flow rate and the reflux flow rate. It can be shown that the new set of input targets corresponds to a steady state where outputs y_2 and y_3 lie at the upper boundary of their control zones y_{des} = [23.8 0.45 2]. At this new steady state, the value of the economic function is increased to f_{eco}= 16 000 $/h as shown in Figure 6.

Figures 4 and 5 show that the controller manages to drive outputs y_2 and y_3 to their output zones while the three inputs are led to the targets that maximize the economic function at steady state. From Figure 6, one can observe that, at the early stages of this simulation, the economic function reaches values below the initial value. This behavior indicates a conflict between the control objective, which is to bring y_2 to its control zone, and the economic objective. Also, it is clear that the controller is prioritizing the control objective that is the correct action to be taken if such conflict occurs. Then, this simulation shows that, considering the speed of response of the closed loop system, the controller based on the realigned model (blue dashed line) can be more efficient for the control of the propylene system than the IHMPC-OPOM (red dashed line).

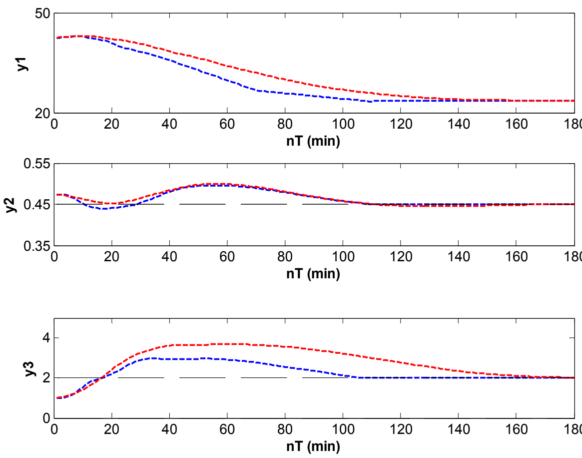

Figure 4: Outputs of the PP system. IHMPC-RM (blue dashed line), IHMPC-OPOM (red dashed line) and output zone bounds (black dashed lines).

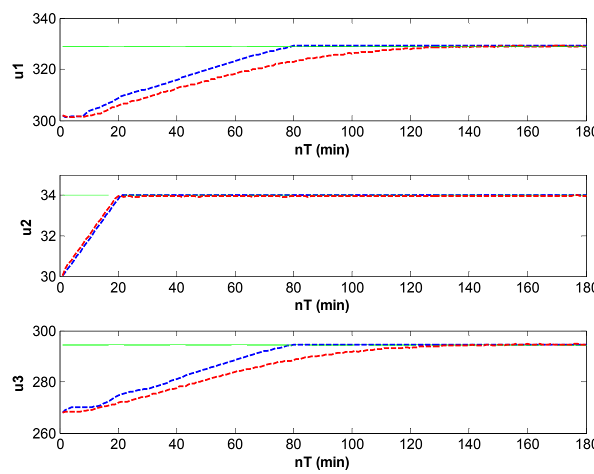

Figure 5: Inputs of the PP system. IHMPC-RM (blue dashed line), IHMPC-OPOM (red dashed line) and input targets (green dashed line).

The second simulation experiment starts when the system reaches the new optimum steady-state at the end of the first simulation experiment, and a feed composition disturbance, unknown to the controller, is introduced into the system. This means that at sampling time $nT = 180$, the feed composition takes the new values shown in the second column of Table 5.

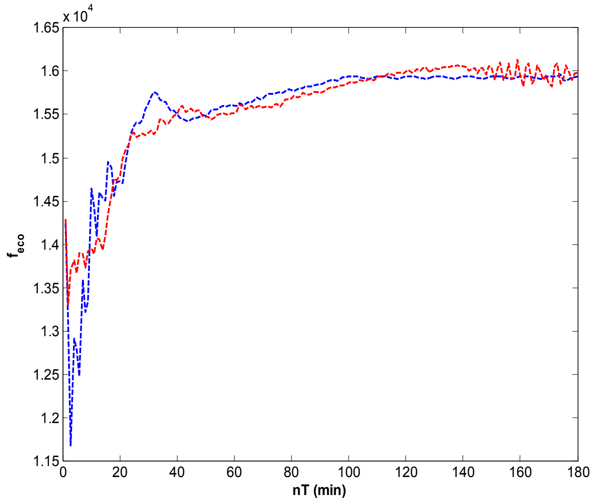

Figure 6: Economic function with IHMPC-RM (blue dashed line) and IHMPC-OPOM (red dashed line).

Table 5: Feed molar composition of the Propylene/ Propane splitter.

Component	First Simulation % molar fraction	Second simulation % molar fraction
Ethane	0.0102	0.0118
Propylene	64.41	50.37
Propane	34.77	48.69
i-Butene	0.337	0.3895
1-Butene	0.061	0.0705
Cis-2-Butene	0.0334	0.0386
Trans-2-Butene	0.0334	0.0386
1,3-Butadiene	0.012	0.0134
i-Butane	0.298	0.3442
n-Butane	0.0334	0.0386

Again, the objective of the controller is to drive the inputs to their new targets that correspond to the new feed composition and to maintain the outputs inside their respective control zones. Assuming that the feed disturbance is known to ROMeo, a new optimum steady-state is computed in the RTO layer and corresponds to the following targets u_{des} = [325.7 34 295.4] and y_{des} = [26.1 0.45 0.35].

Now, analyzing the IHMPC-RM responses presented in Figures 7 and 8 it is easy to realize that, in this simulation case, the IHMPC-RM has a much better performance than in the previous case, also when compared with the IHMPC-OPOM performance. The controlled variables respond faster and can be kept inside their control zones more efficiently. Basically, in this case there is no conflict between the control and the economic objectives. For instance, the controlled output y_2, which starts the simulation at a point already on the upper bound of its control zone, tends to be kept inside its control zone along the whole simulation time. Figure 8 shows the calculated inputs for the controller and the optimizing input targets (green line) calculated by ROMeo and corresponding to the new feed composition shown in Table 5. Because of the new feed composition, the flow rate of the propylene product needs to be decreased while the propane product flow rate is increased. The consequence is that the economic function tends to decrease, although the optimizer tries to increase the propylene production, which represents the most valued product. The new steady state corresponds to f_{eco}=13 550 $/h as shown in Figure 9.

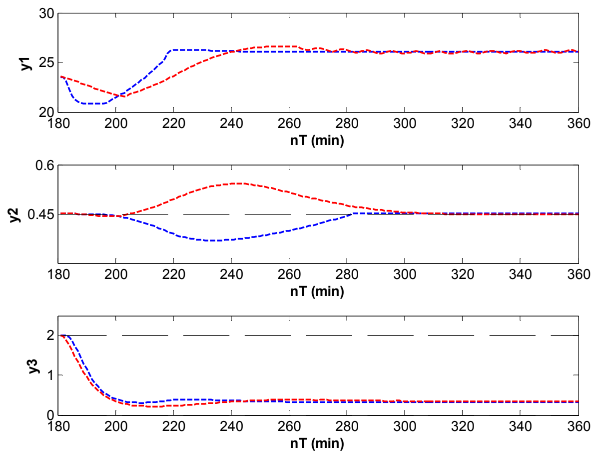

Figure 7: Outputs with IHMPC-RM (blue solid line), IHMPC-OPOM (red dashed line) and output zone bounds (black dashed lines).

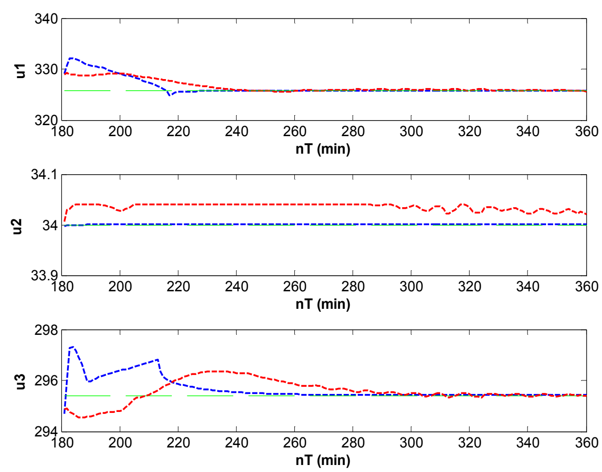

Figure 8: Inputs with IHMPC-RM (blue dashed line), IHMPC-OPOM (red dashed line) and input targets (green solid line).

Once more, the simulation of the new scenario shows that, with the proposed tuning parameters, the IHMPC based on the realigned model can have a good performance in terms of speed of disturbance rejection and stability.

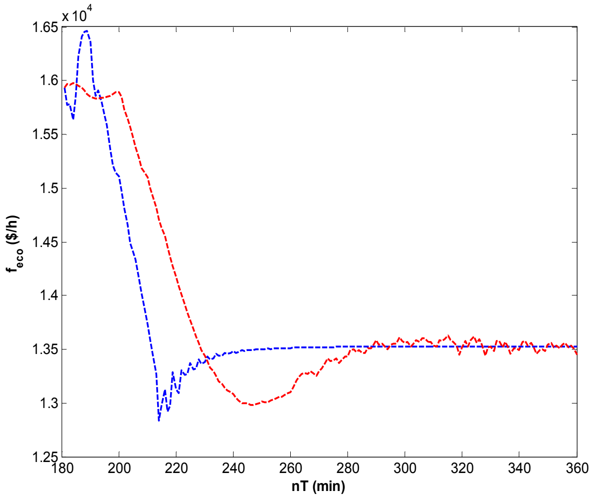

Figure 9: Economic function of the PP process with IHMPC-RM (blue dashed line) and IHMPC-OPOM (red dashed line).

Table 6 summarizes some performance indicators in terms of the time period that the system remains outside the product quality specification for the propylene and propane products using both controllers. It is easy to see that the IHMPC-RM had a better performance in terms of stability and robustness as it requires a smaller stabilization time and maintains the products inside the quality specifications for more time when compared with the IHMPC-OPOM performance.

Table 6: Feed molar composition of the Propylene/ Propane splitter.

	First simulation experiment			Second simulation experiment		
	θ_{y_2}	θ_{y_3}	t_{st}	θ_{y_2}	θ_{y_3}	t_{st}
IHMPC RM	0.44	0.47	1100	0	0	1000
IHMPC OPOM	0.5	0.78	1600	0.56	0	1200

θ_{y_2} is the fraction of simulation time that the controlled variable y_2 remained outside its control zone.
θ_{y_3} is the fraction of simulation time that the controlled variable y_3 remained outside its control zone.
t_{st} is the time in minutes that the controller required to stabilize the process system.

CONCLUSIONS

In this work, a study is presented of the implementation of the IHMPC based on a realigned state-space model formulation. The realigned model that does not require a state observer/estimator, as required by the majority of the state space model-based advanced controllers, is used in this controller. The study is performed through simulation of an existing Propylene/Propane separation unit of an oil refinery using the commercial dynamic simulation software (Dynsim) associated with a real time optimizer (ROMeo) and the real-time facilities of Matlab. In the proposed approach, the controller implements the zone control of the outputs and includes optimizing targets for the inputs. In the first simulation experiment, the effect on an increment in the feed flow rate was simulated. The RTO layer defined optimizing targets for the inputs, which were driven to that optimal operating point and the controlled variables were stabilized inside their control zones. The IHMPC-RM showed a better performance than the conventional IHMPC in the control of the controlled variable y_3, minimizing the loss of propylene in the propane stream. In the second experiment, a non-measured disturbance, unknown to the controllers, was introduced into the system. The IHMPC-RM rejected the disturbance and stabilized the system faster than the conventional IHMPC, which is a state-observer-based MPC.

Based on the simulation examples that were presented, we reach to the conclusion that, from the economic and stability viewpoint, the IHMPC-RM shows promising perspectives, particularly for the case of rejection of non-measured disturbances in the feed stream composition, which is the most common disturbance in the daily operation of the Propylene/ Propane separation system.

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