

Comparison PID and MPC Control, Applied to a Binary Distillation Column

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Abstract— Using binary distillation column in the industry is currently imperative, the reason why the control parameters that are highly nonlinear necessary to apply classic strategies as advanced control and raised here. These techniques are the PID controller and the MPC; the data that are to perform the calculations are of IFAC event whose mixture is alcohol with water. Finally with the help of software MATLAB® / Simulink simulations for comparing which of the two drivers is the best delivery results when controlling the composition on the bottom, top and pressure in binary distillation column performed.

Index Terms— Chemical Industry, Distillation Columns, MPC (Predictive Control Method), PID Control.

I. INTRODUCTION

Distillation is by far the most important separation technique in the process industry worldwide. The United States includes 40,000 consuming distillation columns 3% of all energy consumed in the country. For these reasons, improving process control and can have a major significant impact on reducing energy consumption and, besides quality and protection of environmental resources of the product.

Monitoring and modelling of distillation columns is a complex task because the case has several characteristics that make it difficult to control by conventional methods; It is a non-linear and subject to operating restrictions process, all these features limit the effectiveness of linear controllers (Werdan, 2016).

This The need for professionals who can work in the oil industry, is growing in Ecuador so it is important that students of the National University of Loja will relate more to this process in their academic training so one of the objectives of this paper is intended to raise awareness of this process. An application to understand this process and how it controls is a simple classical binary distillation tower where unlike those used in the oil industry is responsible for separating a liquid mixture of two substances with different degrees of volatility document is a template. Some programs allow us to design and control of some of the parameters of a binary distillation column, and then discuss some of them: In Figure 1 the response of a distillation column, where the input or manipulated variable (MVs), is on the y-axis, during the output or controlled variable so that the process reaches a certain form (CVs) indicated, it is on the x-axis.

It is a MIMO process with three inputs (heat reflux, food) and four outputs (above composition, pressure, temperature and

composition at the bottom) (Seborg, Edgar, & Duncan, 2004).

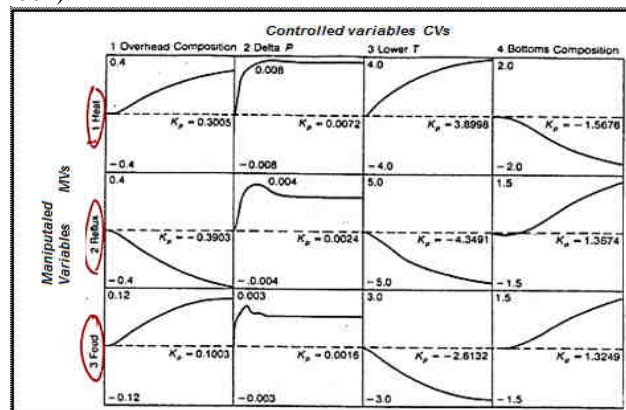


Fig. 1 Here the response to a step, to a distillation column with three inputs and four outputs, each model represents the reaction for 120 minutes; Source was shown. (Hokanson, 1992).

Boroto demonstrates the control of a binary distillation column of a plant for ethanol production, taking as experimental data taken from the literature and verified with those observed in a column of the Cuban plant "Melanie Hernández", in the province of Sancti Spiritus. The developed systems digitally simulated by MATLAB® and performance (Boroto, 2015) verified.

Distillation is a common technique for separation of liquid streams with two or more components and is one of the most important unit operations in the chemical industry (Luyben W, 1996). The design and control of a distillation column are of great importance, as it allows product streams with the purity required, either for sale or use in other chemical processes (Bequette, 1998).

In most industries the distillation columns have schemes linear control and correspond to cascade type (Rovaglio, 1999) controls, which must raise by the nonlinear dynamics presented by this kind of system (Alzate Ibañez, 2010).

Due to the compound nature of distillation columns found in plants, which follow the results on the design and analysis of control techniques including smart and its application in the development of predictors that allow the application shown Predictive Model Based Control ("Model Predictive, Predictive Control", MPC). For the solution of the distillation column which arises in this work MATLAB® / Simulink is used to simulate the behaviour of the process and for this data to be displayed below will use

1.1 PID Control.

It is the most used in industry and is called a three term controller or PID controller.

It is mainly present when the system's behaviour does not comply with the desired specifications (Richard C. Dorf,

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2008).

Differential equations can describe their digital controllers continuous-time systems whose signals are continuous in time. Discrete systems which involve data or signals sampled digital signals and can also be described by difference equations after appropriate discretization of the continuous time signals.

Digital controllers only operate on numbers; decision-making is one of its essential functions. These are often used to solve problems related to the optimal global operation of industrial plants (Kuo, 2012).

It can note that most of the manufactured analogue pneumatic and electronic controllers are the series type, while in today's digital electronic controllers. It is usually possible to select the type of equation of PID desired, although not all manufacturers provide full information on how the internally built their drivers (Ruiz, Costa Rica, 2002).

1.2 MPC Control.

A control technique that, in particular, benefits from these latest developments is model-predictive control (MPC) (Camacho & Bordons, 2004), (Rawlings & Mayne, 2009). MPC is an optimization-based control technique that uses: 1) A mathematical model of a system to predictive the system's behavior over a given horizon, 2) an objective function that represents what systems behavior is desirable, 3) a mathematical formalization of operational constraints that have to be satisfied, 4) measurements of the state of the system at each time step, and 5) any information regarding upcoming disturbances that may be available.

MPC has been popular in practical applications since its very early days. It's ability to handle complex phenomena, such as actuator constraints and multiple control objectives, in an explicit manner, while being able to take into account possible forecasts regarding disturbances and time delays in system dynamics in particular important in refining (Richalet & Rault, 1978), solar plants (Camacho & Berenguel, Robust adaptive model predictive control of a solar plant with bounded uncertainties, 1997), or aerospace (Hegnraes & Gravdahl, 2005), to name a few of the many fields in which it is applied (Qin & Badgwell, 2003). Despite the strengths of centralized MPC, there are several issues that can prohibit the successful implementation of MPC in a centralized control setting:

- a. If the system is too complex, solving the MPC optimization problem will take too much time, for the control of traffic on highways (Frejo & Camacho, 2012)
- b. The structure of the system could be flexible, and it could therefore be impossible to have a constant model structure also hinders the implementation of classical centralized or hierarchical control schemes. This hindrance would be the case, for example, in plug and play systems (Riverso, Farina, & Ferrar-Trecate, 2013), such as smart grids or building automation systems, in which subsystems can be connected and/or disconnected at any time.
- c. The control systems infrastructure may be implemented in a way in which technical constraints regarding the transmission of information arise. An example is the implementation of a control scheme using a wireless sensor and actuator network (Xia, Tian, Li, & Sung, 2007).

- d. Beside the technical limitations, there may be constraints on the information flows. For example, considerer systems that spread over large geographical areas or owned by several entities, with each responsible for the proper functioning of a part of the systems such as water systems (Negenborn, Van Overloop, Keviczky, & De Scutter, 2009), which may be partitioned in regions controlled by different water boards for political reasons. A similar problem arises in supply chains (Maestre, de la Peña, & Camacho, 2009) and logistics networks (Nabais, Negenborn, C, & Botto, 2013), where the entities involved may not be willing to share information.

II. MATERIALS AND METHODS

For nonlinear systems there are a large variety of structures and techniques such as, neural networks, support vector machines least squares (LVS-SVMs), fuzzy logic (B. Huick, 2011). This article applies a predictive control

2.1 Description of the process

The problem describes a fairly realistic problem of a binary distillation column, and has the feature that pressure variation is included in the model's description: the system is multivariable, with 3 inputs and 3 outputs, and includes one disturbance input, this is presented in (Fig. 2).

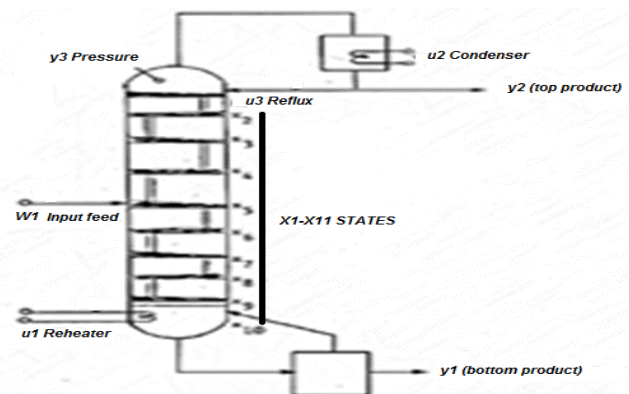


Fig. 2 Binary distillation column with pressure variation

The equation 1, 2, 3 of binary distillation column with n plates for a general binary system of components is given in the above reference. This following linearized model is obtained from the above reference, for a column containing 8 plates:

$$\dot{X} = Ax + Bu + Ew \quad (1)$$

$$y = Cx \quad (2)$$

$$ym = x \quad (3)$$

Where u , is the input $u=u1, u2, u3$

$u1$ = Reboiler steam temperature, $u2$ =Condenser coolant temperature, $u3$ =Controlled reflux

Y is the output $y=y1, y2, y3$

$y1$ =Composition of more volatile component in the bottom product

$y2$ =Composition of more volatile component in top product

$y3$ =Pressure

$X1$ =Composition of more volatile component in condenser

X10=Composition of more volatile component in reboiler
 X11=Pressure
 X2=Composition of more volatile component in the plate #1

 X9=Composition of more volatile component in the plate #8
 W1=Change of input feed concentration
 It is desired to design a controller to regulate 3 outputs y1, y2, y3 against the unmeasurable disturbance W1 and other unmeasurable disturbances, with as fact a settling time as possible, subject to the constraint.
 $|u_1| \leq 2.5, |u_2| \leq 2.5, |u_3| \leq 0.30 \quad t \geq 0$

For W1=1 in this problem, the choice of what measurable outputs to use in the controller, is considered to be part of the problem statement; in general, a controller which uses the fewest number of output measurements is desirable [9].

2.2 Process variables

The process under study is a distillation tower whose variables are: Temperature, Pressure, Level and Flow, variables involved in the analysis are input (u1, u2, u3) which are replaced by the following abbreviations (Tf, Tr, Re) and output (y1, y2, y3). Which are replaced by the following abbreviations for greater understanding (Cf, Ct, Pt), which can be seen in TableI.

TABLE I. PROCESS VARIABLES

.MODELO DE LA PLANTA	
Input variables	Output variables
Reboiler steam temperature (Tf) [°C]	Composition of more volatile component in the bottom product (Cf) [g/ml x100 =%, or mole

		fraction is dimensionless]
Condenser temperature (Tr) [°C]	coolant	Composition of more volatile component in top product (Cto) [g/ml x100 =%, or mole fraction is dimensionless]
Controlled [g/min]	reflux (Re)	Pressure in the top (Pt) [which is the same or Pascal Pa]
Disturbances		
Change of input feed concentration (W1) [g/min]		

2.3 Development of PID control strategy.

Below in Figure 2 and 3 shown, the process response to a signal echelon open loop and the reaction of this same process when the exemplary system PID control is applied respectively.

The first row of both Figure two three indicates that the first entry, which is the temperature in the reboiler is interacting with the three outputs, the same criterion applies to the following two entries such as the temperature in the condenser and Ebb

2.4 Development of MPC control strategy.

In Figure 4 is shown as the three outputs controlled by the desired parameters such as Composition in the background, Tope and pressure values Fra.Mo 0.15, 0.85 and 1 atm Fra.Mo. As shown in this figure predictive control allows you to control the three outputs which do not happen with the PID controller

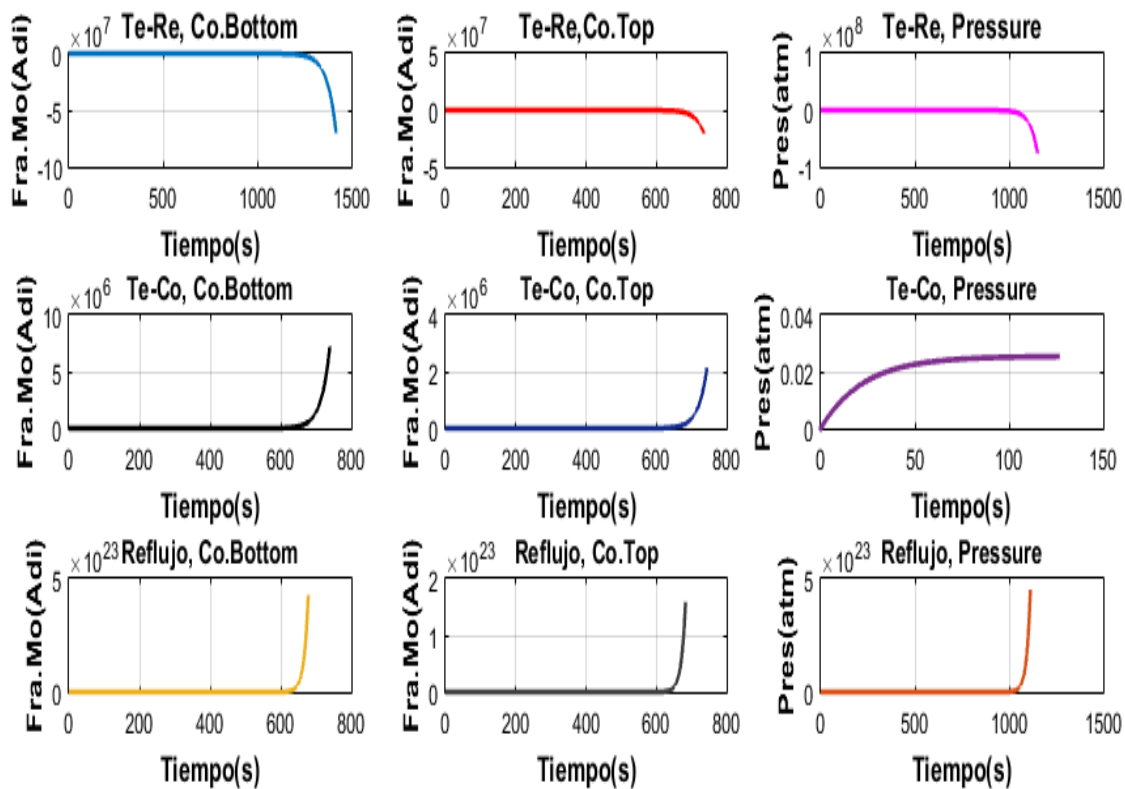


Fig. 2 Response process open loop, when excited with a step input

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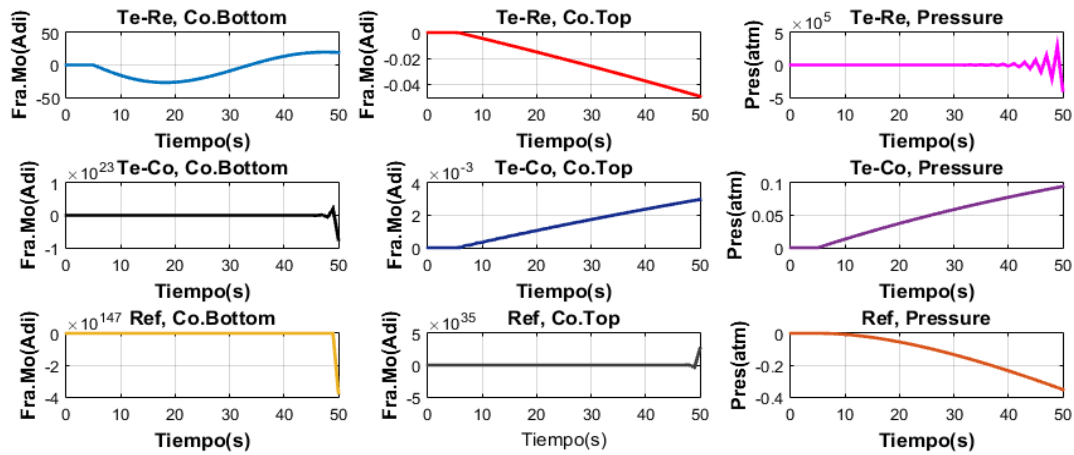


Fig. 3 Process response, when it controlled with a PID.

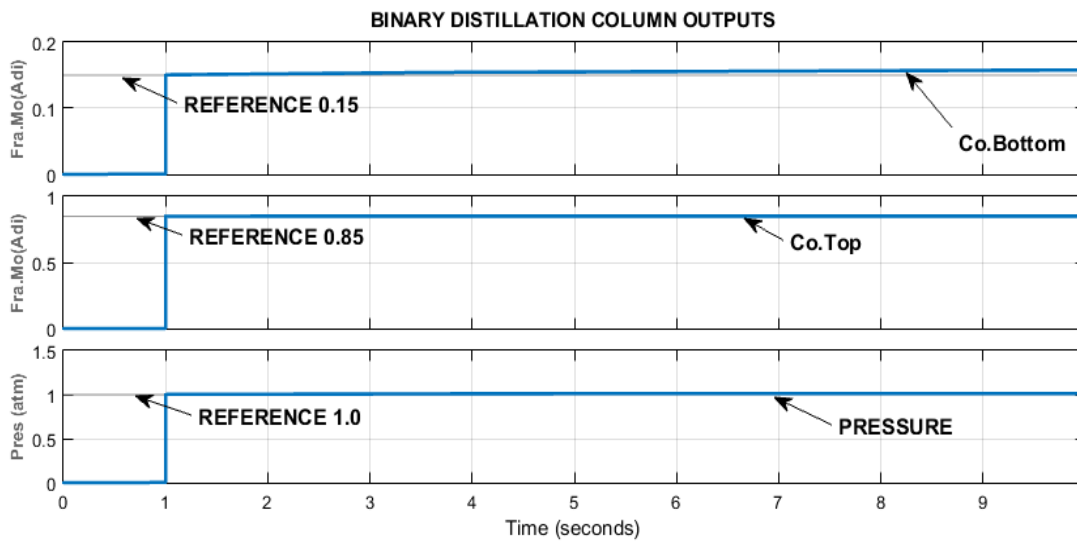


Fig. 4 Process response, when it controlled with a MPC.

A. Results Table

The following Table 5 shows the results obtained with the different control strategies applied in this work.

Table 5: Result of applying different drivers for the control loop, where n / m is not measurable.

	CONTROLL	CONTROLLER 2(MPC)		
	ERI(PID)	Co.BOTTOM	Co.TOP	PRESSURE
<i>MÁXIMUN OVERSHOOT</i>	n/m	0%	0%	0%
<i>STABILIZATION TIME</i>	n/m	1 s	1 s	1 s
<i>RISE TIME</i>	n/m	1 s	1 s	1 s
<i>STATE STABLE</i>	n/m	1 s	1 s	1 s

III. DISCUSSION

Unlike other jobs where other parameters such as flow or the position of the solenoid valves controlled, here the variables to controlled are the composition in the Fund, Tope and pressure in the binary column distillation. Also must emphasize the method predictive applied to this system of three input variables and three output, yielding very favorable results.

IV. CONCLUSION

- a. Based PID control does not allow monitoring of the parameters to monitored, as the system becomes unstable when the Autotune.
- b. MPC-based control has excellent results, in addition to allowing the three output control variables
- c. To simulate the PID controller, use MATLAB[®]/ Simulink
- d. The mole fractions value is dimensionless and petite to this article, so I will split tube ten the value of the location of the poles was 0.9

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