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Identification of the Dynamic Model of a Distillation Column

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Abstract— *This paper presents the results of the identification of the dynamic equations of a binary distillation column. Due to the many characteristics that involve multi-variable systems, we use a linear identifier to estimate the top and bottom concentrations of a generic column, considering as input the injected steam flow in the heat exchanger of the reboiler and the recycle rate. The use of linear models is justified, considering that, in practice, it works in very narrow bands around the setpoints. Within these ranges, the linear models are quite accurate. The set of input and output data, necessary to proceed with the identification of the system, was obtained based on a theoretical model of a generic binary distillation column. In practice, these data should be obtained directly from a industrial process. The details of the simulation, as well as the results of the identification process, are presented.*

Keywords— ***Distillation column, System identification, Predictive control.***

I. INTRODUCTION

Due to the great complexity in the equations that determine the behavior of the chemical industry processes, the use of physical laws in the modeling of these systems becomes impracticable in many cases. To solve this problem, a considerable computational effort is used to identify these systems based on input and output data of the processes. In this way, the systems identification techniques are necessary for the construction of these models(Aguirre, 2007).

The dynamic model identification can be performed in real time, or in batch mode. Large response times and parameters that vary slowly, usually appear in most industrial chemical processes. For this reason, offline identification becomes necessary even when the goal is the synthesis of adaptive or predictive controllers. The offline identification gives the designer the possibility to know and understand the dynamics of a given system, replicating its real behavior, through a set of experimental data.

In this work, the set of input and output data sets required to identify the system was obtained based on a theoretical model of a generic binary distillation column found in (Skogestad and Postlethwaite, 2007). In practice, these data should be obtained directly from the industrial process. The ident toolbox of the Matlab system was used to identify the predictive model. The details of the simulation, as well as the results of the identification process, are presented in section 4 of this paper. Initially, a summary of the operating principles of binary distillation columns is presented.

II. DISTILLATION COLUMNS

Distillation is a unitary operation widely used in chemical industries to separate components. The separation of the phases from a liquid-liquid mixture is carried out by differences in the volatile compositions between the chemical components of the mixture. The component with the lowest boiling point, i.e., more volatile, is called distillate, the other component having a higher boiling point or less volatile is called a residue, or bottom product. When heat is supplied to the mixture, the more volatile substance will vaporize first. In order to carry out this process, a large amount of energy is required, which can involve about 30 to 40% of total energy resources in processes common to the chemical industry(Yang and Lee, 1997). Distillation columns require control systems capable of keeping the process stable and efficient. Thus, the identification techniques presented in this paper are intended to assist the design of such controllers.

Although current distillation plants present great efficiency in the separation process, regarding energy efficiency, they have very low results. Precise and robust control of distillation columns would help increase the profitability of the plant by saving energy and improving the recovery of the final product.

2.1 Distillation Process

The binary distillation is a process used to separate only two products with different compositions. It consists in separating a mixture composed of two pure liquids, with different boiling points (different volatilities). By the time the blend is heated, the more volatile components are removed at the top of the column, and the less volatile components are removed by the lower part of the column, as shown in Figure 1. For example, a mixture of ethanol and water may be separated by distillation because ethanol is more volatile than water.

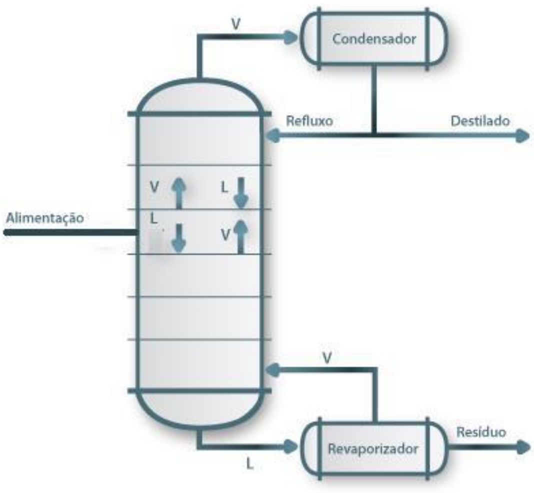

Fig.1: Schematic of a distillation column

The binary distillation column, shown in Figure 1, presents some advantages, such as simple operation, low initial investment when compared to other separation processes and is often considered a process with low operational risk. A disadvantage in the distillation process is the low energy efficiency and the need for thermal stability by the components at their boiling points.

2.2 Components of a distillation column

There are several components in a distillation column that are intended to make the transfer of thermal energy, such as:

• Vertical vessel where the liquid component is separated;

• Internal components of the column, such as trays used to increase component separation;

• Reamer to provide the vaporization required for the distillation process;

• Condenser to cool and condense the steam leaving the top of the column;

• Recycle drum, used to store the condensed steam from the top of the column, so that some part of the product can be returned to the distillation process to improving the concentration of the final product.

The diagram of a typical ethanol distillation system, consisting of three columns, in series, is shown in Figure 2.

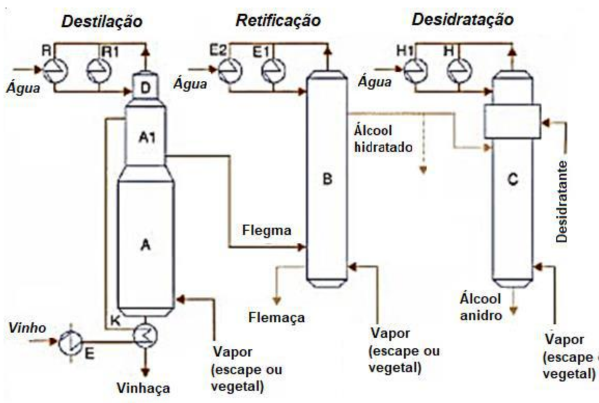

Fig.2: Diagram of a typical distillation column.

2.3 Working principle

From the control point of view, the binary distillation column (Fig. 3)is a multivariate system with the following control variables (SKOGESTAD, 1990):

• Reflux flow;

• Steam flow;

• Distillate flow rate;

• Flow of the bottom product;

• Condenser flow rate responsible for the removal of heat.

The five process variables are:

• Pressure at the base, intermediate or top;

• Bottom level;

• Reflux tank level;

• Composition of the bottom product;

• Composition of the distillate product.

There are several possibilities that can be used as control strategies for distillation columns.The distillation columns are, in practice, controlled hierarchically, first the level and pressure controllers are designed. Controlstrategies with multiple inputs and multiple outputs can be applied in such a way to regulate pressure and levels in the bottom and in the top tanks. This maintains the stock of material that ensures safe operation of the column and prevents the occurrence of drainage and flooding (Luyben, 1992). Another detail is that the dynamics of the composition and level control loops are decoupled, and the quality controls of the bottom and top products are simplified by reducing the column model to a system with only 2 inputs and two outputs (Skogestad et al., 1990; Luyben, 1992).This simplified model is used in the identification process presented below.

III. IDENTIFICATION OF THE LINEAR PREDICTIVE MODEL OF A DISTILLATION COLUMN

For the development of this work, the data obtained from thesimulation of a binary column presented in (Skogestad and Postlethwaite, 2007) were used. This model consists of a first order transfer function (1), having as input the recycle rate (L) and the vapor flow (V) of the referent. The outputs are the concentrations of the top product (yD) and the bottom product (yB), (Figure 3).

$$\boldsymbol{G(s)} = \frac{\mathbf{1}}{\mathbf{75s+1}}\begin{pmatrix} \mathbf{87.8} & \mathbf{-86.4} \\ \mathbf{108.2} & \mathbf{-109.6} \end{pmatrix} \quad (\mathbf{1})$$

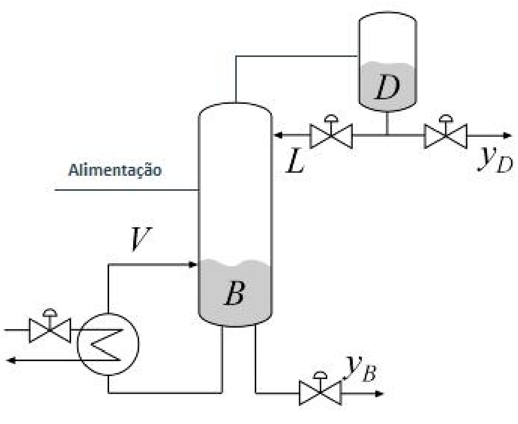

Fig.3: Distillation column.

In this work, the transfer function presented in (1) was used only to generate data, through simulations that allowed the identification of the predictive model. In anactual distillation column, the data should be obtained directly from the process.

This process exhibits strong coupling and large variations in steady-state gains for some combinations of L and V (Skogestad and Postlethwaite, 2007).

IV. DEVELOPMENT AND RESULTS OF THE IDENTIFICATION OF A DISTILLATION COLUMN

The dynamic equation of the distillation column can be generated with predictive characteristics, that is, based on the current input data obtained directly from the process, we infer the values that will occur at the exit, in the next sampling instants. This is the main tool for the implementation of predictive controllers. Thus, the results obtained in this work should be used in further works of predictive control for distillation columns.

To identify the dynamic model of the distillation column, data corresponding to the following quantities were generated:

Input: - steam flow at the inlet of the boiler (range 0 to 1200 kg / h); - opening of the recycle valve (range from 0 to 100%).

Output: - top product concentration (range 0 to 100%); - concentration of the background product (range 0 to 100%).

In order to obtain the necessary data for the identification process, the transfer function presented in (1) was simulated using the Simulink tool of the Matlab system, using random values for the steam flow (V) and for the recycle rate (L).

Two sets of data were generated with a sampling interval of 1 second, the first set corresponding to the training data and the second one to the validation data.

Among the various options available, the order status model 8 presented in (2) showed the best results:

$$\begin{cases} \dot{\boldsymbol{x}} = \boldsymbol{Ax} + \boldsymbol{Bf} \\ \boldsymbol{y} = \boldsymbol{Cx} \end{cases} \quad (\mathbf{2})$$

In equation (2) we have:

$\dot{\boldsymbol{x}}$: derived from x with respect to time (dx / dt)

$\boldsymbol{x}$: state vector, $\boldsymbol{x} \in \mathbb{R}^{\mathbf{8}}$

A: order status matrix 8x8

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B: 8x2 order entry matrix

f: input vector ($\boldsymbol{f} \in \mathbb{R}^2$),corresponding to the steam flow of theand the percentage of recycle.

y: output vector ($\boldsymbol{y} \in \mathbb{R}^2$), corresponding to the concentrations oftop and bottom.

C: output matrix of order 2x8.

In the identification process, matrices A, B and C were estimated and are presented in equations 3, 4 and 5, respectively.

$$\boldsymbol{A} = \begin{bmatrix} \mathbf{3.751} & \mathbf{155.6} & \mathbf{6.221} & \mathbf{11.44} & \mathbf{12.98} & \mathbf{-84.74} & \mathbf{-14.71} & \mathbf{-41.65} \\ \mathbf{100.3} & \mathbf{4161} & \mathbf{164.3} & \mathbf{306.4} & \mathbf{345.9} & \mathbf{-2264} & \mathbf{-391.9} & \mathbf{-1113} \\ \mathbf{140.6} & \mathbf{5827} & \mathbf{226.6} & \mathbf{430.4} & \mathbf{482.5} & \mathbf{-3167} & \mathbf{-545.9} & \mathbf{-1557} \\ \mathbf{-322} & \mathbf{-13350} & \mathbf{-527.8} & \mathbf{-983} & \mathbf{-1110} & \mathbf{7265} & \mathbf{1259} & \mathbf{3571} \\ \mathbf{-81.54} & \mathbf{-3376} & \mathbf{-126.9} & \mathbf{-252.3} & \mathbf{-277.4} & \mathbf{1828} & \mathbf{311} & \mathbf{898.7} \\ \mathbf{101.1} & \mathbf{4196} & \mathbf{167.8} & \mathbf{307.7} & \mathbf{349.8} & \mathbf{-2286} & \mathbf{-397.5} & \mathbf{-1124} \\ \mathbf{101.3} & \mathbf{4207} & \mathbf{171.6} & \mathbf{306.7} & \mathbf{352.7} & \mathbf{-2297} & \mathbf{-402.4} & \mathbf{-1129} \\ \mathbf{41.54} & \mathbf{1719} & \mathbf{62.68} & \mathbf{129.3} & \mathbf{140.3} & \mathbf{-928.4} & \mathbf{-156.3} & \mathbf{-456.8} \end{bmatrix} \mathbf{(3)}$$

$$\boldsymbol{B} = \begin{bmatrix} \mathbf{1.046} & \mathbf{-1.048} \\ \mathbf{28} & \mathbf{-28.04} \\ \mathbf{39.25} & \mathbf{-39.29} \\ \mathbf{-89.82} & \mathbf{89.96} \\ \mathbf{-22.76} & \mathbf{22.78} \\ \mathbf{28.22} & \mathbf{-28.26} \\ \mathbf{28.25} & \mathbf{-28.3} \\ \mathbf{11.61} & \mathbf{-11.61} \end{bmatrix} \mathbf{(4)}$$

$$\boldsymbol{C} = \begin{bmatrix} \mathbf{380} & \mathbf{-7.26} & \mathbf{0.8163} & \mathbf{-13.1} & \mathbf{-6.333} & \mathbf{1.156} & \mathbf{-1.055} & \mathbf{-2.748} \\ \mathbf{480.2} & \mathbf{-9.737} & \mathbf{3.471} & \mathbf{-14.39} & \mathbf{-12.21} & \mathbf{3.906} & \mathbf{-1.593} & \mathbf{-10.11} \end{bmatrix} \mathbf{(5)}$$

To prove the effectiveness of the model obtained, the validation data were applied in the simulation and in the prediction tests. They are shown in the following section.

4.1. Simulation Testing

In this test, the values of the state variables obtained by simulation at the current instant are used to calculate the outputs at the later time. Figure 9 shows the actual and the simulated values in the same plot. It is possible to prove the effectiveness of the model, both visually, since it is difficult to visualize the two functions, as numerically, since a hit rate of 93.64% was obtained, as shown in Figure 10.

This type of model is, in general, used for simulation and analysis of the process, with a view to the design of controllers.

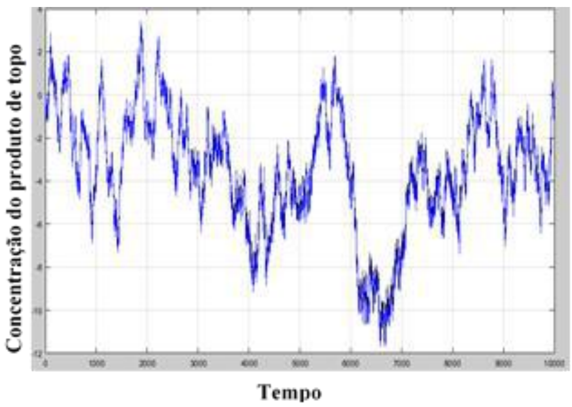

Fig.9: Comparison of the simulation result with the data used for model validation.

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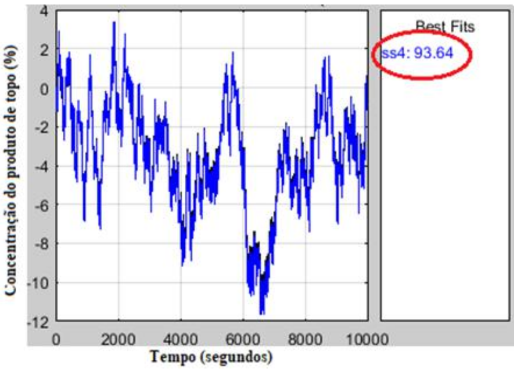

Fig.10: Hit rate in the simulation with the data used for model validation.

PREDICTION TEST

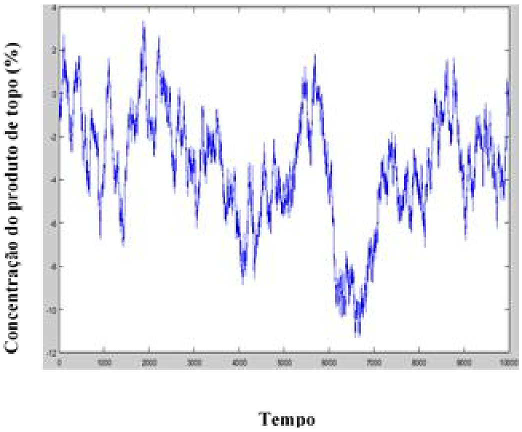

Fig.11: Comparison of the forecast result with the data used for model validation.

In this test, the measured quantities are used at the current instant, in the process itself, to infer the values that will occur at the exit in the next instants (Figure 11). In this way, there is no accumulation of error, obtaining a higher rate of correctness. In the case of this work, we obtained 99.45%, as can be observed in Figure 12.

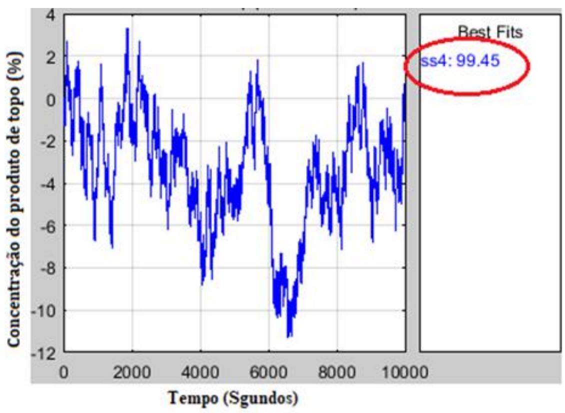

Fig.12: Forecast accuracy rate with the data used for model validation.

This type of model is used in strategies of predictive and adaptive control.

V. CONCLUSION

The results obtained in this work indicate the feasibility of the use of linear models for the identification of the dynamic equation of distillation columns. Mainly, in the case of the prediction model, a very satisfactory result was obtained with a hit rate of 99.45%. Although the data used in this work for the estimation of the dynamic equations were obtained by simulation, it is expected that the use of actual plant data will also produce satisfactory results, which would enable its application in predictive or adaptive control strategies.

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