IDENTIFICATION AND CONTROL OF A DISTILLATION COLUMN

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Extended Abstract

The separation of propane and propylene is a major industrial operation carried out by a type of distillation column, called C3 splitter, which separates the two main hydrocarbons that form the mixture of input, both containing 3 carbon atoms, the heaviest of which is the propane (C3H8), which is extracted at the column bottom, while the lighter one, which is distilled and removed at the column head, is the propylene (C3H6). The splitter C3 is a column with a number of dishes rather higher than normal oil refining columns, since these two hydrocarbons, which have a low relative volatility, and quite close boiling points, require a relatively complicated and expensive separation procedure. The column that is considered in this paper, shown in Fig.1, is located in Milazzo, Italy, at the Rafffineria Mediterranea.

Fig.1 A view of the Milazzo petrochemical plant.(Splitter C3 is the last column to the right)

Identification of the dynamic behaviour of the distillation column is a fundamental issue for optimizing its performance as well as for monitoring and fault diagnosis. The application of system identification to distillation processes deals with the estimation of a set of unknown parameters of a

preset mathematical model on the basis of on-line input/output measurement. A number of methods have been proposed in the different years for his purpose (Andersen et Al, 1989; Skogestadt, 1997) and a number of commercially products have been implemented (Quin et Al, 2003).

In most of applications it is important that the mathematical models obtained by means of system identification methods can be directly used for control system design purposes. An identification method that is potentially capable to cope with these requirements is OKID (Observer Kalman Filter Identification), that has proven to be numerically very efficient and robust with respect to measurement noise and even in the presence of mild nonlinearities. A number of successful applications of this method in the area of structural mechanics, aerospace engineering have been developed during the recent years (Chen, C.-W.et Al.. ,1992; Phan, M. et Al.. ,1995) and marine vehicles (Tiano, A. et Al, 2007;Elkaim,G.H, 2009).

In the present application it is assumed that the distillation column is described by a linear time-invariant discrete time MIMO state space model of the form:

$$\begin{aligned}\mathbf{x}(k+1) &= \mathbf{A}\mathbf{x}(k)+\mathbf{B}\mathbf{u}(k)\\ \mathbf{y}(k) &= \mathbf{C}\mathbf{x}(k)\end{aligned} \tag{1}$$

with input vector $\mathbf{u}(k)\in\mathbf{R}^{\mathbf{m}}$, output vector $\mathbf{y}(k)\in\mathbf{R}^{\mathbf{p}}$, state vector $\mathbf{x}(k)\in\mathbf{R}^{\mathbf{n}}$, and system matrices $\mathbf{A}\in\mathbf{R}^{\mathbf{nxn}},\mathbf{B}\in\mathbf{R}^{\mathbf{nxm}},\mathbf{C}\in\mathbf{R}^{\mathbf{pxn}}$.

The identification problem consists of determining, on the basis of input/output discrete data $\{\mathbf{u}(k)\}_{k=0}^{N}\subset\mathbf{R}^{\mathbf{m}}$, $\{\mathbf{y}(k)\}_{k=0}^{N}\subset\mathbf{R}^{\mathbf{p}}$, the smallest state space realization that is compatible with a given accuracy. This means that the dimension n of state space vector as well as the coefficients of system matrices $\mathbf{A},\mathbf{B},\mathbf{C}$ have to be determined. According to the OKID algorithm (Phan, M., Horta, L.G., Juang, J-N. and Longman, R.W. ,1995), an observer is first applied to state equation (1), by using an observer gain matrix $\mathbf{G}\in\mathbf{R}^{\mathbf{nxp}}$ and, after setting

$$\overline{\mathbf{A}}=\mathbf{A}+\mathbf{GC},\quad \overline{\mathbf{B}}=\begin{bmatrix}\mathbf{B} & \mathbf{-G}\end{bmatrix}\in\mathbf{R}^{\mathbf{nx(m+p)}} \tag{2}$$

it is possible to rewrite equation (1) in the form:

$$\begin{aligned}\mathbf{x}(k+1) &= \overline{\mathbf{A}}\mathbf{x}(k)+\overline{\mathbf{B}}\mathbf{v}(k)\\ \mathbf{y}(k) &= \mathbf{C}\mathbf{x}(k)\end{aligned} \tag{3}$$

where $\mathbf{v}(k)=\begin{bmatrix}\mathbf{u}(k)\\ \mathbf{y}(k)\end{bmatrix}\in\mathbf{R}^{\mathbf{m+p}}$ is an “extended” input vector to the “system+observer” expressed by equation (3, where all the eigenvalues of the modified system matrix $\overline{\mathbf{A}}$, under an observability hypothesis, can be arbitrarily placed inside the unity circle. In this case, it can be recognized that the gain matrix $\mathbf{G}$ plays a role analogous to Kalman filter in state estimation.

From such equation, an r-step ahead predictor for both state and output vectors in response to arbitrary initial conditions and input values can be obtained. If the observer gain matrix $\mathbf{G}$ is such that all the eigenvalues of matrix $\overline{\mathbf{A}}=\mathbf{A}+\mathbf{GC}$ are inside the unity circle and if the predictor horizon length r is sufficiently large in such a way that $\bar{\mathbf{A}}^r \mathbf{x}(0) \cong \mathbf{0}$, then the following linear regression can be written:

$$\bar{\mathbf{Y}} = \theta \bar{\mathbf{F}} \tag{4}$$

$$\bar{\mathbf{Y}} = \begin{bmatrix} \mathbf{y}(r) & \mathbf{y}(r+1) & \ldots & \mathbf{y}(r+N-1) \end{bmatrix} \in \mathbf{R}^{\mathbf{pxN}}$$
$$\theta = \begin{bmatrix} \mathbf{C}\bar{\mathbf{B}} & \mathbf{C}\bar{\mathbf{A}}\bar{\mathbf{B}} & \ldots & \mathbf{C}\bar{\mathbf{A}}^{r-1}\bar{\mathbf{B}} \end{bmatrix} \in \mathbf{R}^{\mathbf{px(m+p)r}}$$

$$\bar{\mathbf{F}} = \begin{bmatrix} \nu(r-1) & \nu(r) & \ldots & \nu(r+N-2) \\ \nu(r-2) & \nu(r-1) & \ldots & \nu(r+N-1) \\ \ldots & \ldots & \ldots & \ldots \\ \nu(0) & \nu(1) & \ldots & \nu(N-1) \end{bmatrix} \in \mathbf{R}^{\mathbf{r(m+p)xN}} \tag{5}$$

$\bar{\mathbf{Y}}$ is a set of N predicted output vectors, $\bar{\mathbf{F}}$ is a matrix consisting of "extended" input vectors and θ is the vector of Markov parameters associated to system (3).

The vector of Markov parameters can be then determined by applying a standard Least Squares method :

$$\theta = (\bar{\mathbf{Y}}\,\bar{\mathbf{F}}^T)(\bar{\mathbf{F}}\,\bar{\mathbf{F}}^T)^{-1} \tag{6}$$

In this paper, since only "normal operating" closed-loop input-output data were available, a suitable modification of OKID has been used, which takes into account an existing feedback controller. (Park,M-S et Al, 2003).

In our case a model with two inputs and two outputs, respectively consisting of reflux flow rate, vapour boil-up rate, molar flux rates of products extracted at the head and at the bottom of the distillation column have been considered. The obtained identification results seem to be quite consistent with experimental data. In Figure 2 there are shown the time histories of input signals.

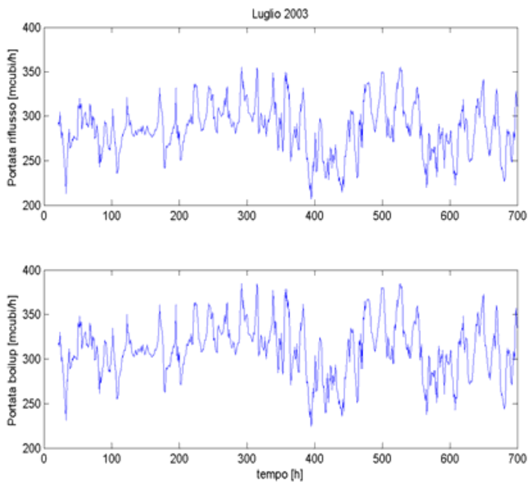
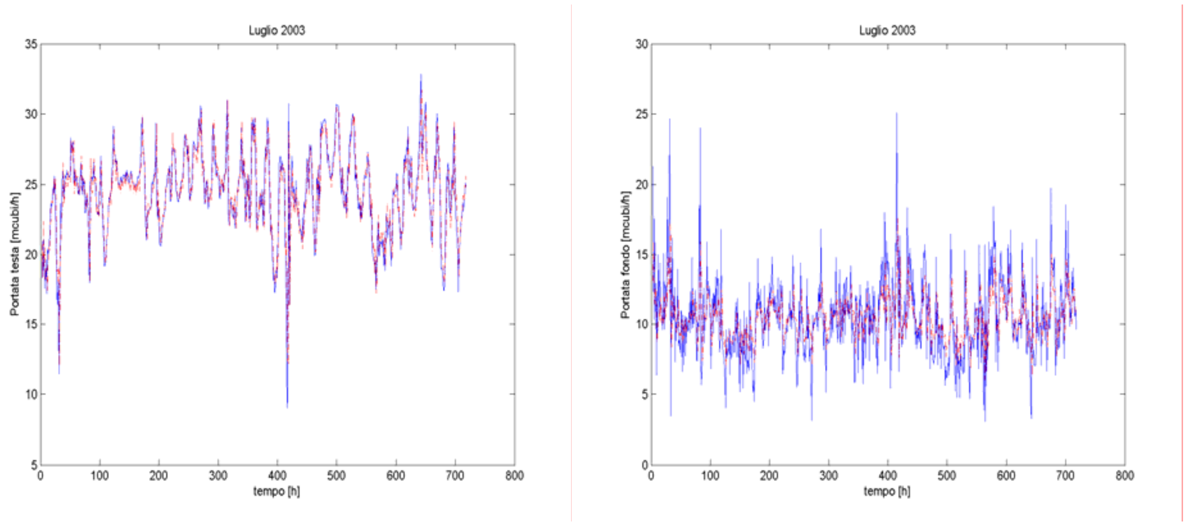


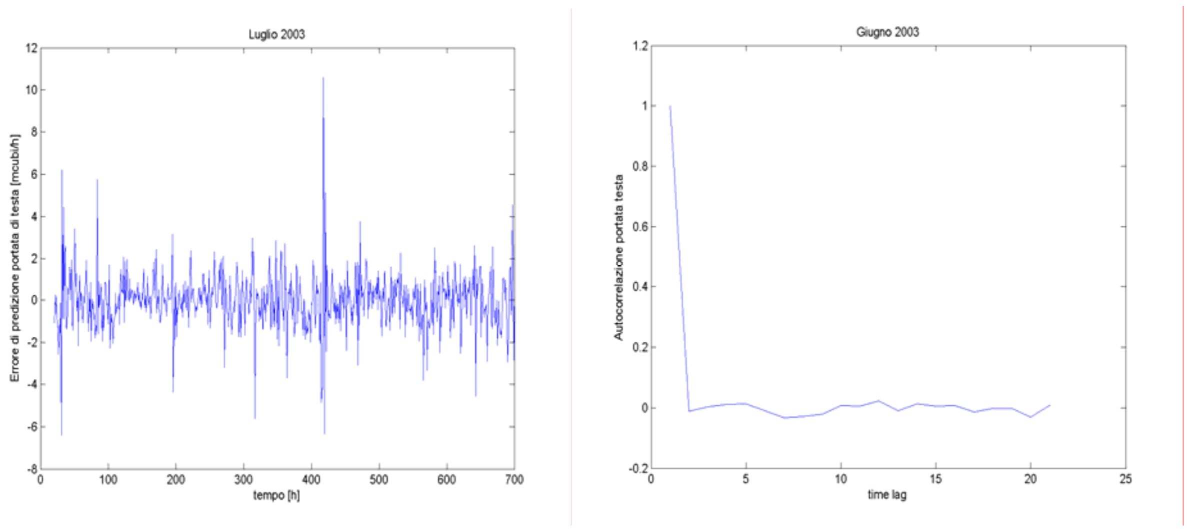
Figure 2: Time histories of input variables

In Figures 3 and 4 there are shown the outputs fitting and the prediction error time history and autocorrelation function, which validate the identification results.



a) b)

Figure 3: Fitting of head and bottom products flow rate



a) b)

Figure 4: Prediction error for head product flow rate and relative autocorrelation function.

On the basis of the identified models, the simulation of different control systems has been carried out, including pole assignment, LQG (Linear Quadratic Gaussian) and MPC (Model Predictive Control). An example of LQG control is shown in Figure 5. A more detailed comparison of the different control methods will be presented in the final version of the paper.

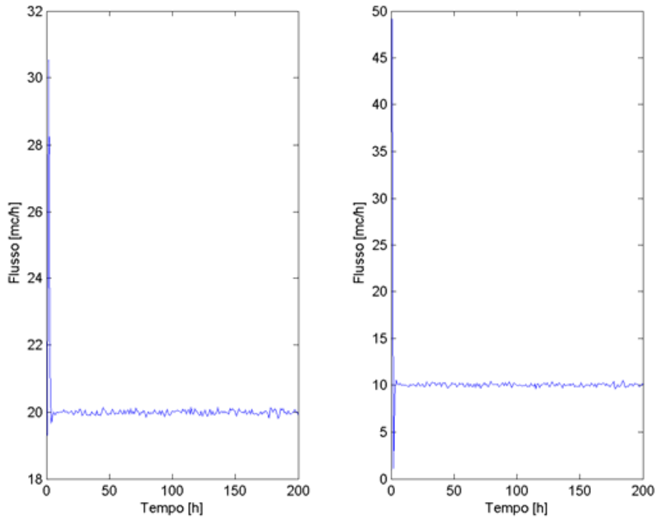


Figure 5. Simulation of LQG control of head and bottom product flow rates

As a concluding remark it can be stated that OKID closed-loop identification method, in combination with a standard linear control technique, can be a useful tool for control and monitoring of a distillation column.

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