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MULTIVARIABLE SUBSPACE IDENTIFICATION AND PREDICTIVE CONTROL OF A HEAT-INTEGRATED SUPERFRACTIONATOR RIGOROUS MODEL

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Abstract: The control of a heat-integrated superfractionator is addressed in this paper. A multivariable subspace identification method is proposed to overcome the difficulties associated to the large time constants of the process and identify a linear process model, upon which a constrained predictive controller is developed. The effectiveness of the proposed identification and control algorithm is shown by means of closed-loop rigorous dynamic simulation results. *Copyright 2006 IFAC* ©

Keywords: Multivariable subspace identification, heat-integrated distillation, predictive control, test design, rigorous simulators.

1. INTRODUCTION

In the process industries, Advanced Process Control (APC) plays a fundamental role for the achievement of economical benefits with respect of safety and quality constraints. APC systems perform multivariable model-based control and require, therefore, a model of the process to be controlled. For simple (small) processes this model can be derived from fundamental equations, but in most cases a (linear) model is identified from data, either collected during specific tests or historical one. Model Predictive Control (MPC) algorithms are the kinds of APC systems most widely used in the process industries, especially in refinery and petrochemical plants (Qin and Badgwell, 2003).

Traditionally, model identification for MPC design is conducted in an "open-loop" fashion, i.e. starting from some steady state, each manipulated variable is varied, usually once at a time according to some pattern (often sequences of steps, from which the usual name of "step tests"), and data of all output variables are collected. Then, using identification techniques, a multiple-input single-output (MISO) model is obtained for each output variable. This step test MISO identification approach has several drawbacks:

(1) The time required to complete step tests in all variables can be very long, since one typically waits until all controlled variables reach a steady state (so that the model gains can be obtained) before introducing a new step. For some processes, like superfractionators, waiting for a new steady state can be "impractical" (times-to-steady-state are of the order of several days), and some modifications may be necessary (Pannocchia and Brambilla, 2005).
(2) The quality of the obtained model can be poor because open-loop uncorrelated input signals may not excite the process dynamics in all relevant "directions" (Koung and MacGregor, 1994; Zhu, 2001). Moreover MISO identification of ill-conditioned processes can result in erroneous models (Dayal and MacGregor, 1997).
(3) Open-loop unstable or integrating processes cannot be handled with open-loop tests.

Mainly for these reasons, open-loop identification methods based on different multivariable input sig-

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nals and/or closed-loop identification methods have become more popular during the last decade [see e.g. Hjalmarsson *et al.* (1996), Forssell and Ljung (1999), Zhu (2001), Zhu and Butoyi (2002) and references therein]. With regards of methods for computing the model parameters it is remarkable to notice that most of current research is focused on subspace methods (Verhaegen and Dewilde, 1992*a*; Verhaegen and Dewilde, 1992*b*; Van Overschee and De Moor, 1994; Favoreel *et al.*, 2000; Wang and Qin, 2002; Huang *et al.*, 2005). The strength of these methods is due to their numerical robustness, applicability to both open-loop and closed-loop data (with some extra care), and the fact that they directly generate state-space models which are becoming the standard models in industrial MPC algorithms (Qin and Badgwell, 2003).

In the present paper, a rigorously simulated heat-integrated distillation process is studied to evaluate the effectiveness of subspace identification techniques for the design of constrained multivariable predictive control algorithms. As well-known, distillation (the separation method most widely used in the process industries) is particularly energy consuming. It is estimated that 3% of energy consumption of the world is due to distillation processes (Engelian *et al.*, 2003), and therefore a natural interest in heat-integrated processes is justified. However, heat integration introduces a number of issues, especially from a control point of view [see e.g. (Ding and Luyben, 1990; Hansen *et al.*, 1998; Engelian *et al.*, 2003; Engelian and Skogestad, 2004) and references therein], mainly due to relevant interactions among process variables. Therefore, these characteristics along with the presence of dynamics with large time constants make multivariable model identification and control particularly suited for these processes. The process model used by the controller is obtained by means of a subspace multivariable identification, and closed-loop results are presented to show to achievable benefits.

2. MULTIVARIABLE SUBSPACE IDENTIFICATION

2.1 Overview of subspace identification methods

Discrete linear time-invariant systems are considered in this paper, in the following form:

$$\begin{aligned} x_{k+1} &= A_p x_k + B_p u_k + w_k \\ y_k &= C_p x_k + v_k \end{aligned} \tag{1}$$

in which $x \in \mathbb{R}^{n_p}$ is the state vector, $u \in \mathbb{R}^m$ is the input vector, $y \in \mathbb{R}^p$ is the output (measured) vector, the (true) system matrices (A_p, B_p, C_p) have appropriate dimensions, $w \in \mathbb{R}^{n_p}$ and $v \in \mathbb{R}^p$ are (unmeasured) noise vectors. The basic identification problem is to find estimates of the system matrices (A, B, C) and order n, and possibly of the statistical properties, i.e. the covariance, of w and v. Notice that the feed-through from u to y is omitted in (1) because this is the typical case of most processes. If necessary, one can add the appropriate term and estimate the corresponding matrix (typically denoted with D).

Subspace identification methods achieve these goals by starting from the Kalman predictor:

$$\begin{aligned} \hat{x}_{k+1} &= A\hat{x}_k + Bu_k + Ke_k \\ y_k &= C\hat{x}_k + e_k \end{aligned} \tag{2}$$

in which $\hat{x} \in \mathbb{R}^n$ is the predicted state, $e \in \mathbb{R}^p$ is noise, (A, B, C) are the model matrices and $K \in \mathbb{R}^{n \times p}$ is the Kalman predictor gain matrix (to be determined). Given an arbitrary time-point k, the vector of future outputs can be constructed as:

$$y_k^f = \begin{bmatrix} y_k \\ y_{k+1} \\ \vdots \\ y_{k+r-1} \end{bmatrix} \tag{3}$$

in which r is a positive integer. A similar straightforward definition can be made for the vectors of future inputs and noise, denoted with u_k^f and e_k^f, respectively. From (2), one can write

$$y_k^f = \Gamma_r \hat{x}_k + H_r^u u_k^f + H_r^e e_k^f \tag{4}$$

in which Γ_r is the extended observability matrix, H_r^u and H_r^e are lower block-triangular Toeplitz matrices associated to inputs and noise:

$$\begin{aligned} \Gamma_r &= \begin{bmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{r-1} \end{bmatrix} \\ H_r^u &= \begin{bmatrix} 0 & 0 & \cdots & \cdots & 0 \\ CB & \ddots & \ddots & & \vdots \\ CAB & \ddots & \ddots & & \\ \vdots & & \ddots & \ddots & \\ CA^{r-2}B & \cdots & CAB & CB & 0 \end{bmatrix} \\ H_r^e &= \begin{bmatrix} I & 0 & \cdots & \cdots & 0 \\ CK & \ddots & \ddots & & \vdots \\ CAK & \ddots & \ddots & & \\ \vdots & & \ddots & \ddots & \\ CA^{r-2}K & \cdots & CAK & CK & I \end{bmatrix} \end{aligned} \tag{5}$$

Then, one can rewrite the basic relation (4) for N time-points as:

$$Y^f = \Gamma_r \hat{X} + H_r^u U^f + H_r^e E^f \tag{6}$$

in which

$$\begin{aligned} Y^f &= \begin{bmatrix} y_1^f & y_2^f & \cdots & y_N^f \end{bmatrix} \\ U^f &= \begin{bmatrix} u_1^f & u_2^f & \cdots & u_N^f \end{bmatrix} \\ E^f &= \begin{bmatrix} e_1^f & e_2^f & \cdots & e_N^f \end{bmatrix} \\ \hat{X} &= \begin{bmatrix} \hat{x}_1 & \hat{x}_2 & \cdots & \hat{x}_N \end{bmatrix} \end{aligned} \tag{7}$$

Starting from (6), subspace methods obtain an estimate of Γ_r and H_r^u (from which the model matrices can be calculated) by removing the noise and/or the future input terms with appropriate matrix multiplications, i.e. by projection onto some subspaces. Each method differs from the others in the matrices used

to perform these projections and in the way the final model matrices are obtained from Γ_r and H_r^u. In the next sections the orthogonal projection approach (Huang *et al.*, 2005; Wang and Qin, 2002) is reviewed, and a modification used in this work is proposed.

2.2 Orthogonal projection method (modified)

The key idea is to use instrumental variables to remove the noise from (6), i.e. to multiply (6) by a matrix W^T such that $\lim_{N\to\infty} \frac{1}{N} E_f W^T$. Thus, one can write

$$\begin{bmatrix} I & -H_r^u \end{bmatrix} Z_f W^T = \Gamma_r \hat{X} W^T \tag{8}$$

in which

$$Z_f = \begin{bmatrix} Y_f \\ U_f \end{bmatrix} \tag{9}$$

Then, multiplying (8) on the left by a matrix $\Gamma_r^\perp$ such that $\Gamma_r^\perp \Gamma_r = 0$, permits one to obtain:

$$\Gamma_r^\perp \begin{bmatrix} I & -H_r^u \end{bmatrix} Z_f W^T = \Gamma_r^\perp \begin{bmatrix} I & -H_r^u \end{bmatrix} Z = 0 \tag{10}$$

in which $Z = Z_f W^T$.

Wang and Qin (2002) chose $W = Z_p$, which is the matrix of past outputs and inputs, whose definition is straightforward. This serves as a good instrument because E_f (future noise) is independent of Z_p (past outputs and inputs). Huang *et al.* (2005) instead propose using $W = Z_p^T (Z_p Z_p)^{-1} Z_p$, which performs an orthogonal projection onto the row space of Z_p. This latter method is used in this work. Performing an SVD of Z leads to

$$Z = \begin{bmatrix} U_1 & U_2 \end{bmatrix} \begin{bmatrix} \Sigma_1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix} \tag{11}$$

in which the dimension of Σ_1, i.e. the rank of Z, should be equal to $mr + n$ (Wang and Qin, 2002, Lemma 1). In practice, the rank and consequently the order n are determined from the singular values, using e.g. an Akaike Information Criterion as in (Wang and Qin, 2002) or using a heuristic PCA approach (Micchi, 2005). From (11), one obtains that (10) is satisfied if

$$\Gamma_r^\perp \begin{bmatrix} I & -H_r^u \end{bmatrix} = M U_2^T \tag{12}$$

in which M is an arbitrary non-singular matrix of dimension $pr - n$ (usually chosen equal to the identity matrix). Finally, by partitioning

$$M U_2^T = \begin{bmatrix} P_1^T & P_2^T \end{bmatrix} \tag{13}$$

in which $P_1 \in \mathbb{R}^{pr \times (pr-n)}$, it follows from (12) that

$$P_1^T \Gamma_r = 0 \tag{14}$$

$$-P_1^T H_r^u = P_2^T \tag{15}$$

which can be easily solved to compute Γ_r and H_r^u, from which it is possible to obtain the system matrices as described next.

Given the computed estimate of the extended observability matrix $\hat{\Gamma}_r$, it is straightforward to compute A and C from the following relations:

$$C = \hat{\Gamma}_r(1:p,:) \tag{16}$$

$$\hat{\Gamma}_r(p+1:pr,:) = \hat{\Gamma}_r(1:p,:) A \tag{17}$$

in which a MATLAB notation is used and the last equation is solved for A in a least-square sense. Wang and Qin (2002) and Huang *et al.* (2005) propose using the first block column of H_r^u to compute B (and D if appropriate) with a least-square equation. This method was investigated in (Micchi, 2005) who found that poor estimation of B (and D) is obtained in a number of cases. Therefore a different approach is used in this work. Given A and C, let $\hat{y}_{k|B}$ denote the estimate of y_k given past inputs and a generic matrix B, i.e.

$$\hat{y}_{k|B} = C \sum_{j=0}^{k-1} A^j B u_j \tag{18}$$

By differentiating $\hat{y}_{k|B}$ with respect to the elements of B, (18) can be rewritten as follows:

$$\hat{y}_{k|B} = \varphi_k \operatorname{Vec} B \tag{19}$$

where $\varphi_k \in \mathbb{R}^{p \times nm}$ is the corresponding Jacobian matrix and Vec is the operator that builds a vector from a matrix by stacking its columns on top of each other. Then, given N measured output vectors $y_1, \ldots, y_N$, the following least-square regression problem can be posed:

$$\underset{\operatorname{Vec} B}{\operatorname{argmin}} \sum_{k=1}^{N} \|y_k - \hat{y}_{k|B}\|_2^2 \tag{20}$$

whose solution is

$$\operatorname{Vec} B = (\Phi^T \Phi)^{-1} \Phi^T Y_N \tag{21}$$

in which

$$\Phi = \begin{bmatrix} \varphi_1 \\ \varphi_2 \\ \vdots \\ \varphi_N \end{bmatrix}, \qquad Y_N = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} \tag{22}$$

Notice that in these formulae a zero initial condition is assumed; but the initial state x_0 can be estimated with straightforward extensions. Also notice that existence of $(\Phi^T \Phi)^{-1}$ depends on the input signal being sufficiently exciting.

3. PREDICTIVE CONTROL

The model predictive control algorithm used in this work is based on three modules: a state and disturbance estimator, a steady-state target optimizer and a dynamic input sequence optimizer, which are executed at each sampling time, as described next.

3.1 State and disturbance estimation

Given the (identified) state-space matrices (A, B, C), the system model is augmented with fictitious disturbances to guarantee offset-free control (Pannocchia and Rawlings, 2003), as follows:

$$\begin{aligned} \begin{bmatrix} x_{k+1} \\ d_{k+1} \end{bmatrix} &= \begin{bmatrix} A & B_d \\ 0 & I \end{bmatrix} \begin{bmatrix} x_k \\ d_k \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u_k \\ y_k &= \begin{bmatrix} C & D_d \end{bmatrix} \begin{bmatrix} x_k \\ d_k \end{bmatrix} \end{aligned} \tag{23}$$

in which $d \in \mathbb{R}^p$ is the integrating disturbance, (B_d, D_d) are matrices of suitable dimensions, chosen to satisfy an appropriate detectability condition (Pannocchia and Rawlings, 2003). The augmented state is estimated, at each sampling time, from the measured output vector y_k by using a steady-state Kalman filter:

$$\begin{aligned} \hat{x}_{k|k} &= \hat{x}_{k|k-1} + L_x e_k \\ \hat{d}_{k|k} &= \hat{d}_{k|k-1} + L_d e_k \end{aligned} \tag{24}$$

in which $e_k = y_k - (C\hat{x}_{k|k-1} + D_d\hat{d}_{k|k-1})$, while $\hat{x}_{k|k-1}$ and $\hat{d}_{k|k-1}$ are the state and disturbance vectors predicted at the previous sampling time, as discussed at the end of Section 3.3.

3.2 Steady-state target calculation

Using the disturbance estimate $\hat{d}_{k|k}$, a steady-state optimization problem is solved to find the current targets for states and inputs such that offset in (some) controlled variables is (possibly) removed and the constraints satisfied. To this aim, it is assumed that a subset of the measured output vector, $z = H_z y$ has a known setpoint vector $\bar{z}$, and the following quadratic program (QP) is considered:

$$(\bar{x}_k, \bar{u}_k) = \underset{x_s, u_s}{\operatorname{argmin}}\ u_s^T \bar{R} u_s \tag{25a}$$

subject to:

$$x_s = Ax_s + Bu_s + B_d\hat{d}_{k|k} \tag{25b}$$

$$\bar{z} = H_z(Cx_s + D_d\hat{d}_{k|k}) \tag{25c}$$

$$u_{\min} \le u_s \le u_{\max} \tag{25d}$$

$$y_{\min} \le Cx_s + D_d\hat{d}_{k|k} \le y_{\max} \tag{25e}$$

in which $\bar{R}$ is a symmetric positive definite matrix, $u_{\min}$ ($u_{\max}$) and $y_{\min}$ ($y_{\max}$) are vectors which contain the minimum (maximum) limits for inputs and outputs, respectively. If, for a given disturbance estimate $\hat{d}_{k|k}$, the problem (25) turns out to be infeasible, a second QP is posed by softening setpoint constraints (25c) and output constraints (25e), i.e. by solving

$$\min_{x_s, u_s, \eta_s, \epsilon_s}\ u_s^T \bar{R} u_s + \eta_s^T \bar{Q} \eta_s + \epsilon_s^T \bar{P} \epsilon_s \tag{26a}$$

subject to:

$$x_s = Ax_s + Bu_s + B_d\hat{d}_{k|k} \tag{26b}$$

$$\bar{z} = H_z(Cx_s + D_d\hat{d}_{k|k}) + \eta_s \tag{26c}$$

$$u_{\min} \le u_s \le u_{\max} \tag{26d}$$

$$y_{\min} - \epsilon_s \le Cx_s + D_d\hat{d}_{k|k} \le y_{\max} + \epsilon_s \tag{26e}$$

in which $\bar{Q}$ and $\bar{P}$ are positive definite matrices.

3.3 Optimal input sequence calculation

Having computed the state and input targets, and defined the corresponding output target vector as $\bar{y}_k = C\bar{x}_k + D_d\hat{d}_{k|k}$, an optimal input sequence vector $\mathbf{v}_k = \begin{bmatrix} v_{0,k}^T & v_{1,k}^T & \cdots & v_{N-1,k}^T \end{bmatrix}^T$, is computed (along with a corresponding vector of slacks for output constraints, ϵ_k) from the following optimization problem:

$$(\mathbf{v}_k, \epsilon_k) = \underset{\mathbf{v}, \epsilon}{\operatorname{argmin}}\ (\bar{x}_k - w_N)^T P (\bar{x}_k - w_N) + \sum_{j=0}^{N-1} \left\{ \Delta v_j^T S \Delta v_j + r_j^T Q r_j + \epsilon_j^T Q^\epsilon \epsilon_j \right\} \tag{27a}$$

subject to:

$$w_0 = \hat{x}_{k|k}, \quad v_{-1} = u_{k-1} \tag{27b}$$

$$w_{j+1} = Aw_j + Bv_j + B_d\hat{d}_{k|k} \tag{27c}$$

$$r_j = \bar{y}_k - (Cw_j + D_d\hat{d}_{k|k}) \tag{27d}$$

$$u_{\min} \le v_j \le u_{\max} \tag{27e}$$

$$y_{\min} - \epsilon_j \le Cw_j + D_d\hat{d}_{k|k} \le y_{\max} + \epsilon_j \tag{27f}$$

in which N is a positive integer (referred to as horizon), $\Delta v_j = v_j - v_{j-1}$, the matrices S, Q, Q^ϵ are symmetric positive definite and the symmetric positive semidefinite matrix P is computed from an appropriate Riccati equation associated to (27). Given the optimal input vector $\mathbf{v}_k$, only the first component is injected into the plant, i.e.

$$u_k = v_{0,k} \tag{28}$$

and the predicted state and disturbance vectors for the next sampling time are accordingly defined:

$$\begin{aligned} \hat{x}_{k+1|k} &= A\hat{x}_{k|k} + Bu_k + B_d\hat{d}_{k|k} \\ \hat{d}_{k+1|k} &= \hat{d}_{k|k} \end{aligned} \tag{29}$$

4. CASE STUDY

4.1 Process description

The separation of propane and propylene is considered as a case study. Due to the very low relative volatility, this separation is conducted in superfractionators, i.e. columns with large number of trays and high reflux ratios, and is therefore particularly suited for heat-integration via thermo-compression because of the small difference in boiling temperature between top and bottom products.

The process layout is depicted in Figure 1 along with the regulatory PID control loops. Due too the high reflux ratios, reflux rate is used to control the condenser drum, which is common practice in superfractionator columns. The column has 210 stages, it operates at a top pressure of 9.5 bar (bottom pressure is 10.6 bar) and the vapor phase feed enters the column at stage 166. The top stage vapor is compressed at a pressure of 19 bar and then it is partially condensed in a heat exchanger (condenser/reboiler), whose cold fluid is the liquid draw from the bottom of the column, which is consequently vaporized to generate the boil-up flow returned to the last stage of the column. The condenser/reboiler operates with an average ΔT of $25 \div 30^{\circ}$C, and the vapor/liquid stream leaving this exchanger is totally condensed and sub-cooled in a trim cooler. Details of the main operating variables are reported in Table 1. Further details regarding this study can be found in (Bulleri, 2005).

Table 1. Main operating variables

Feed rate (tonne/hr)	Feed propylene fraction	Internal reflux ratio	Distillate rate (tonne/hr)	Distillate propylene fraction	Bottom propane fraction
20.0	0.70	12.1	13.3	0.9955	0.9162

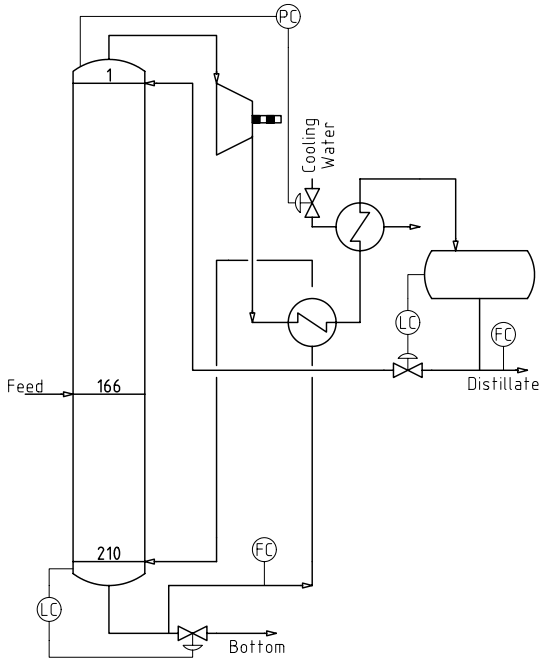

Fig. 1. Heat-integrated distillation process layout

The process is simulated using the rigorous dynamic simulator HYSYS™ (version 3.2), while the predictive controller is implemented in MATLAB (version 7.0.1). Dynamic communication between the two environments is achieved using appropriate exchange spreadsheet modules. The predictive controller, at each sampling time, reads the values of all controlled variables from the process simulator, performs its internal calculations and returns the value of the manipulated variables (i.e. the setpoints of regulatory PID controllers) to the process simulator.

4.2 Identification and control results

Three manipulated variables and seven controlled variables are considered for design of the predictive controller. The manipulated variables are the setpoints of distillate and boil-up flow-rate controllers and of the column pressure controller. The controlled variables are the opening percents of all control valves and the distillate propylene fraction and bottom product propane fraction. For these latter variables desired setpoints are defined, while all control valves are only required to meet inequality constraints, as shown in Table 2.

Data for identification are obtained by perturbing the reference value of the manipulated variables with Generalized Binary Noise [GBN, see e.g. (Zhu, 2001)] signals. Notice that these input signals affect all manipulated variables simultaneously and independently of the controlled variables, i.e. a multivariable open-loop test design is performed.[2] Compared to traditional step tests, these signals usually have shorter duration; moreover, they excite the process dynamics much more thoroughly, thus allowing a more effective model identification. For the present application, a traditional step approach would have required an overall plant testing time at least 20÷30 times larger than that required using multivariable GBN signals. Using these data, the orthogonal projection method is applied and a (stable) state-space linear model of order $n = 12$ is obtained and used to implement the predictive controller described in Section 3.

Table 2. Upper and lower limits (and reference setpoints) for MVs and CVs.

Variable	Lower	Setpoint	Upper
Dist. rate (tonne/hr)	12.6	–	14.0
Boilup rate (tonne/hr)	150	–	173
Pressure (bar)	9.4	–	9.6
Boilup OP (%)	10	–	90
Reflux OP (%)	10	–	90
Bottom OP (%)	10	–	90
Distillate OP (%)	10	–	90
Cool. Water OP (%)	10	–	90
Dist. propyl. frac.	0.97	0.9955	0.9984
Bottom propane frac.	0.85	0.9162	0.982

For comparison with the proposed MPC regulator, two decentralized (PI controllers cascaded on corresponding flow-rate controllers) quality control schemes are considered: DV (distillate rate controls the distillate composition, boil-up rate controls the bottom composition) and VD (vice-versa). As an example, closed-loop simulation results of a setpoint change in the compositions of the products are reported. Due too space limitations, closed-loop results for disturbance changes, as well as specific robustness analysis results are not presented. It should, however, be mentioned that since the plant is simulated with a rigorous nonlinear model, an intrinsic mismatch exists between the plant and the linear model used in the MPC regulator. The controllers are required to reduce the purity of both products: the distillate propylene fraction changes from 0.9955 to 0.993 while the bottom product propane fraction changes from 0.9162 to 0.913. In Figure 2 the behavior of the products' compositions is reported for each controller, while in Figure 3 the behavior of distillate and boil-up rate is reported for each controller. From these figures, the benefits of using a multivariable constrained control algorithm are evident, since the products' compositions reach their setpoint much more quickly (notice the large time scale) due a more coordinate action of the manipulated

[2] Closed-loop tests, other signals (PRBS, steps, ...) and several subspace and prediction error methods were studied and compared in (Micchi, 2005).

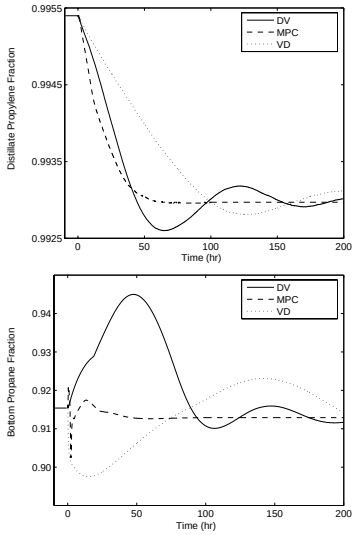

Fig. 2. Products' composition for three controllers.

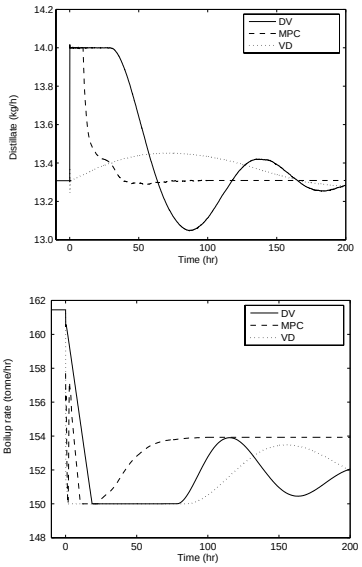

Fig. 3. Distillate and boilup rate for three controllers.

variables and an appropriate saturation of the constraints when necessary. These results also indicates that multivariable subspace identification methods are effective for superfractionators, which present large time constants and for which traditional step tests are, therefore, impractical.

5. CONCLUSIONS

In this paper the effectiveness of subspace multivariable identification techniques was studied for a heat-integrated distillation process simulated with a rigorous dynamic simulator model. This process is characterized by large time constants and hence traditional step tests are undesirable and impractical. Generalized Binary Noise signals were successfully used to obtain informative input/output data. A (modified) orthogonal projection algorithm was implemented to identify a state-space model used to build a constrained multivariable predictive controller, whose effectiveness was tested in closed-loop simulations.

A final remark concerns the potential benefits and flexibility of using rigorous simulators, which can prove useful for shortening the model identification and controller design/commissioning phases in APC projects, especially for processes with large number of variables (Pannocchia *et al.*, 2005) and/or slow processes like the one considered in this paper.

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