15th Triennial World Congress, Barcelona, Spain

IDENTIFICATION AND CONTROL OF AN INDUSTRIAL POLYMERISATION PROCESS

Geoffrey Mourue [*] **Pierre Descamps** [**] **Denis Dochain** [*]
Vincent Wertz [*]

[*] *Cesame, Université Catholique de Louvain*
avenue G. Lemaître 4-6, B-1348 Louvain-La-Neuve, Belgium
fax : 32-10-472180, e-mail : dochain@csam.ucl.ac.be
[**] *DowCorning, Seneffe, Belgium*

Abstract: This paper deals with the application of identification and control to an industrial polymerisation process. The final control objective in the present process is to obtain a polymer of a viscosity as homogeneous as possible. The process is characterized by two key inputs : the catalyst feed rate and the air flow rate in the reactor. The first input is the control input, and the second plays indeed the role of a disturbance. The model identification (e.g. (Ljung, 1987) also put in evidence a drift in the gain of the transfer function between the polymer viscosity and the catalyst feed rate. The drift is due to the coating of the reactor with high viscosity polymer. The identified model is used to design a predictive controller with feedforward action of the air flow rate. The present study covers all aspects from the model structure and parameter identification to the control design and control performance evaluation.

Keywords: Process control, identification, predictive control, adaptive control

1. DESCRIPTION OF THE PROCESS

The process under study is a continuous industrial polymerisation reactor, in which polymerisation is gradually taking place along the reactor. Reactants and air flow are injected in the reactor at high temperature. The air slips through the reactant. The residence time of the air in the reactor is significantly smaller than the residence time of the reactants. The determination of the residence time of the reactants is not straightforward because of the air flow speed decreases along the reactor due to the progressive increase of the viscosity. However the residence time can be estimated via signal analysis at process shut down.

The kinematic effect of the air is to push the increasingly viscous mixture through the reactor. A second effect of the air, which is almost equivalently important, is the elimination from the reaction medium of the byproduct released by the polymerisation reaction. Other factors have some influence on the dynamics of the process, more precisely on the viscosity of the produced polymer :

- the catalyst flow is a factor that determines the polymer viscosity : a flow increase activates the polymerisation, which in turn increases the viscosity of the polymer;
- as already explained, the air in the reactor activates the polymerisation : an air flow rate increase induces a better drying of the polymer, this increases the degree of polymerisation of the formed macromolecules, and the reaction mixture becomes more viscous and remains longer in the reactor;
- a neutralizing agent is injected at the end of the reactor to stop the polymerisation reaction in order to prevent the continuation of the reaction in the pipes;

- the temperature plays an important role : since the reaction is exothermic, an increase of the reactant or air temperature increases the kinetics of the reaction via the increase of the polymer temperature.

The available data for process identification are the polymer viscosity, the catalyst inlet flow rate and the air flow rate. From the above considerations, it is clear that the viscosity is the process output that will be the controlled output in the control loop. The other two variables are the process inputs. The catalyst flow rate will be the control and the air flow rate is a disturbance input.

Since the air compressor is not continuous but of charge-discharge type, it plays the role of an oscillator.

2. IDENTIFICATION OF THE PROCESS DYNAMICS

2.1 *Data sets, identification assumptions and data pretreatment*

Two experiments have been performed on the industrial reactor. In both experiments, the regulation loop was opened for some time during which a pulse on the catalyst flow has been applied. The data of the first experiment are presented in Figure 1. Note the effect of the pulse on the data of air flow rate during the pulse, which emphasizes the close connection between both flow rates inside the reactor.

Several assumptions about the operation of the reactor can be formulated. These result from the experience gained in the control and operation of the process. These basic assumptions has guided the search for a model of the process, in the sense that any model that would violate one of these or give a result too far away from these would be rejected. These basic assumptions are :

- The static gains between the catalyst flow and the viscosity, and between the air flow and the viscosity are both positive. Indeed an increase of catalyst flow will result in an increase of polymerisation rate and therefore of polymer viscosity. Similarly, an increase of air flow rate will generate a better drying of the polymer, speed up the polymerisatiom and therefore also increase the polymer viscosity.
- The static gain between the catalyst flow and the polymer viscosity obtained from model identification must be in agreement with data coming the kinetic studies about the polymerisation reaction.
- The residence time obtained from model identification must be in agreement with mass balance calculations.

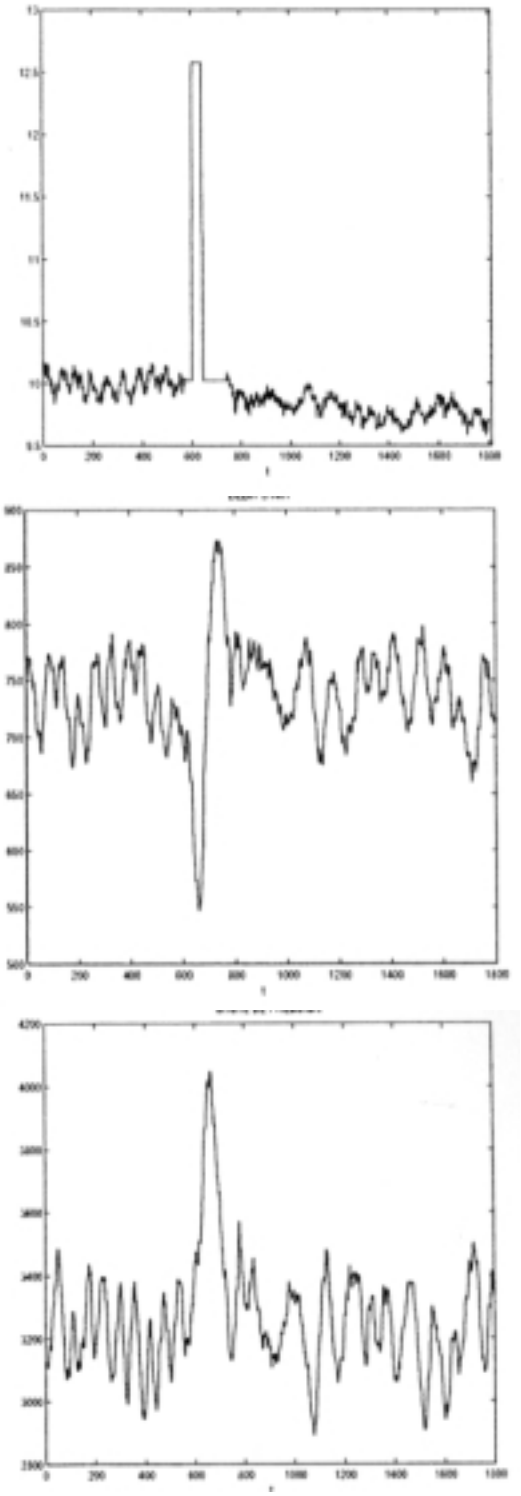

Fig. 1. Experimental dataset (pulse A). Top : air flow rate, middle : catalyst flow rate, bottom : viscosity

- The time delay for transfer function between the air flow rate and the viscosity must be smaller than the time delay between the catalyst flow rate and the viscosity.
- The response time of the polymer viscosity to a set point change must be lower than 4 minutes.

The data acquisition sampling period is equal to one second : $T_e = 1$ s. The spectrum of the 3 signals from both datasets shows that a large part of the spectrum power is concentrated between 0 Hz and 0.05 Hz. For values larger than 0.05 Hz, the useful information about the signal is basically embedded in the noise. We can thus reduce the sampling frequency to 0.1 Hz (i.e. the double of 0.5 Hz). The sampling period is now : $T_e = 10$ s. In order to avoid the folding up of the spectrum, the decimation of the sampling rate by a factor 10 is preceded by a low-pass filtering of the data until the transition frequency of 0.05 Hz.

A first secondary lobe at the frequency of 0.05 Hz is visible on the spectra of the air flow rate and of the viscosity. This secondary peak comes from the air compressor, which is of the load-charge type. The alternation of the periods of load and discharge creates an oscillation of low amplitude on the air flow rate at a frequency of 0.05 Hz. This external excitation at 0.05 Hz has nothing to do with the dynamics of the process and must be removed before the identification by using an appropriate filter.

Finally, before performing the identification, the signals are scaled, i.e. their average value is subtracted from the full data sample. The identification will result in finding a linear model that is valid around the operation point of the process.

2.2 *Identification of the time delays*

The method of correlations is used to estimate the time delays between the two inputs (catalyst flow rate, air flow rate) and the output (viscosity).

2.2.1. *Time delay between the catalyst flow rate and the viscosity* We have analysed the impulse response of the viscosity with respect to the pulse of catalyst flow rate in open loop. The correlation between both signals (Figure 2) exhibits a maximum at time t = 3 for both data files. The time delay is therefore most probably close to 30 s. Validation of the estimation of the time delay has performed via the simulation of ARX models with polynomials A and B of order 2 with time delays of 20, 30 and 40 s, respectively. The simulation with a time delay of 20 and 30 s are correct while those with a time delay of 40 s are worse.

2.2.2. *Time delay between the air flow rate and the viscosity* Four correlation functions have been calculated : on both data files for the complete datasets and for the restriction to the open loop experiment. From these datasets, the time delay between the air flow rate and the viscosity has been estimated at 30 seconds.

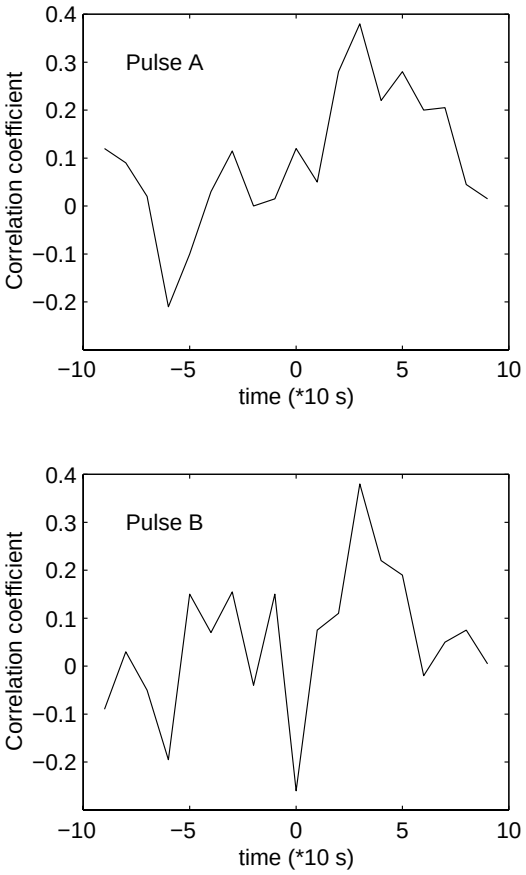

Fig. 2. Correlation coefficients between the catalyst flow rate and the product viscosity for both experiments

2.3 *SIS0 Models : identification of ARX models*

Since the objective is to have a model as simple s possible, identification has first started with SISO (Single Input Single Output) models. One of the goal is to determine if the catalyst is the only factor acting on the polymer viscosity or if it is necessary to introduce a disturbance in the model to fully explain the variations of the viscosity. The results of both models are compared. The datasets are separated in two data sets : one for identification, one for validation. Identification has been first performed separately on each dataset, pulse A experiment and pulse B experiment. For the pulse A experiment, the data used for identification are the data after the pulse; for the pulse B experiment, the data before the pulse have been considered for identification.

Identification is first performed with ARX (AutoRegressive with eXogenous input) models. ARX models are of the following form :

$$A(q)y(t) = B(q)u(t) + e(t) \qquad (1)$$

where $A(q)$ and $B(q)$ are polynomials in q of order n_A and n_B, respectively.

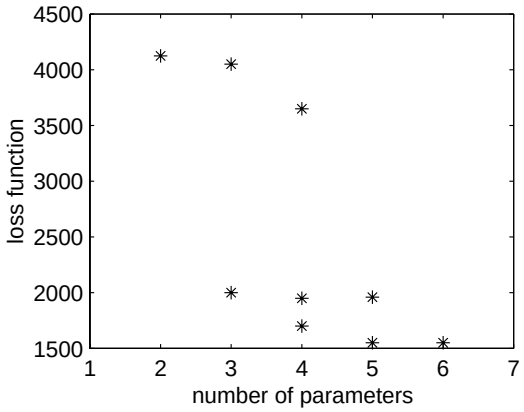

Fig. 3. Mean Quadratic Prediction Error for pulse A experiment identification

The identification results for models for which the sum of the parameters $n_A + n_B$ lies between 2 and 6 are summarized in Figure 3 (for pulse A data; the results are similar for pulse B data) that gives the mean square prediction error (MSPE) for each model. The best model has the following polynomials :

- Pulse A

$$A(q) = 1 - 1.73\,(\pm 0.3)\,q^{-1} + 1.28\,(\pm 0.15)\,q^{-2} - 0.36\,(\pm 0.09)\,q^{-3}$$
$$B(q) = 60.44\,(\pm 65.4)\,q^{-3}$$

- Pulse B

$$A(q) = 1 - 1.67\,(\pm 0.07)\,q^{-1} + 1.37\,(\pm 0.11)\,q^{-2} - 0.55\,(\pm 0.07)\,q^{-3}$$
$$B(q) = 147.1\,(\pm 61)\,q^{-3}$$

Both SISO models suffer from the same drawback : the uncertainty on the static gain is much too large; moreover. That's why more data have considered for the identification, i.e. all the data from the pulse A experiment plus the last data of the pulse B experiment starting from the pulse. The best resulting model has the following polynomial:

$$A(q) = 1 - 1.66\,(\pm 0.07)\,q^{-1} + 1.29\,(\pm 0.05)\,q^{-2} - 0.46\,(\pm 0.06)\,q^{-3}$$
$$B(q) = 57.12\,(\pm 11.3)\,q^{-3}$$

If the uncertainty on the static gain is now lower, the model is still not able to reproduce correctly the oscillations on the viscosity signal (see Figure 4). This motivated us to look for alternative solutions, i.e. the identification of OE models, and the identification of MISO models (with the air flow rate as a second (disturbance) input).

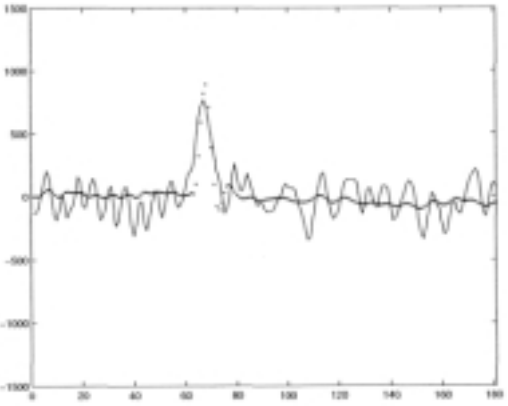

Fig. 4. Validation of the ARX model (- : data, ... : simulation)

2.4 *SISO models : identification of OE models*

An OE model can be written under the following form :

$$y(t) = \frac{B(q)}{F(q)}u(t) + e(t) \qquad (2)$$

The best OE model obtained by identification from the datasets is characterized by the following polynomials :

$$F(q) = 1 - 1.194q^{-1} - 0.51q^{-2}$$
$$B(q) = 196.4q^{-3} - 226.6q^{-4} + 142.1q^{-5}$$

However it appeared that the OE model was not able either to correctly handle the oscillations observed in the polymer viscosity data.

2.5 *MIS0 Models*

The identification of MISO models appears to be necessary to handle these oscillations. The ARX model is now written as follows :

$$A(q)y(t) = B_{cata}(q)u_{cata}(t) + B_{air}(q)u_{air}(t) + e(t) \qquad (3)$$

We have followed for the identification the same procedure than hereabove. The best MISO model has the following polynomials :

$$A(q) = 1 - 0.81\,(\pm 0.04)\,q^{-1} \qquad (4)$$
$$B_{cata}(q) = 105\,(\pm 15)\,q^{-3} \qquad (5)$$
$$B_{air}(q) = 0.51\,(\pm 0.15)\,q^{-3} \qquad (6)$$

The performance of the identified model have largely improved, although they are still far from being perfect, as it can be seen from Figure 5 which compares the data with the simulated model for the pulse B experiment. We have also

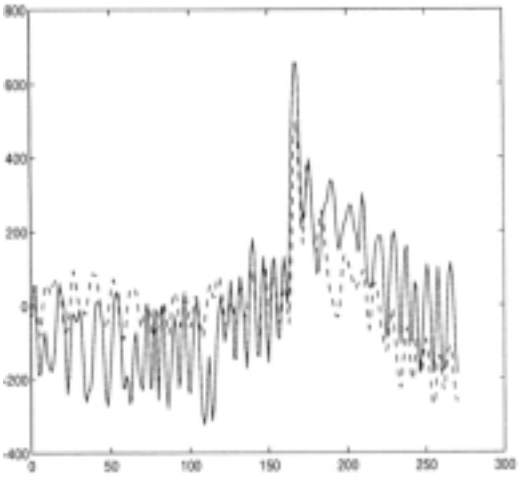

Fig. 5. Validation of the MISO model (straight line : data, dotted line : validation)

been able to evaluate the respective importance of both inputs from the identified model : the polymer viscosity dynamics is influenced at 66% by the catalyst flow rate and at 33% by the air flow rate. This justifies to design a controller that includes feedforward action for compensating the influence of the air flow rate on the polymer viscosity dynamics.

3. CONTROL OF THE POLYMERISATION PROCESS

The final objective of this work was to design a controller. The identified model serves as a basis for the controller design. As we have already mentioned, the polymer viscosity, the catalyst flow rate and the air flow rate are the controlled output, the control input and the disturbance input. From the above study, it appears obvious that the controller

- should include a feedforward action to compensate the influence of the disturbance input;
- should be adaptive in order to handle phenomena like the drift observed in the polymer viscosity in the last part of the pulse B experiment, as well as possibly the process nonlinearities that have not been included in the linear identified model.

3.1 *Design of the feedforward controller*

The design of the controller with feedforward action has considered the IMC structure, as shown in Figure 6, which has been compared to a PI regulator. In the comparison, two different parameter of the PI have been considered : the Ziegler-Nichols settings, and a calibration aimed at minimizing the closed-loop settling time. The proportional gain and the integration constant are equal to :

$$\text{Ziegler} - \text{Nichols} : K_p = 2.7\,10^{-3}, \tau_i = 73.5$$
$$\text{Min. Settling Time} : \quad K_p = 2\,10^{-3}, \tau_i = 60$$

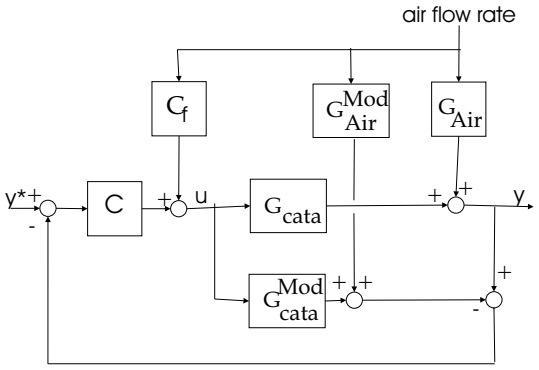

Fig. 6. IMC structure with feedforward action

The performance of both controllers (IMC, PI) have been compared in different conditions :

(1) tracking (step change of the set point);
(2) regulation (disturbance rejection)

for the nominal model but also in presence of model uncertainties (to test the robustness of the controller in presence of process dynamics that differs from the nominal one given by the linear identified model). In that case, two different models have been considered for the dynamics between the catalyst flow rate and the product viscosity, i.e. :

$$G_1(q) = \frac{120q^{-3}}{1 - 0.85q^{-1}} \tag{7}$$

$$G_2(q) = \frac{90}{1 - 0.77q^{-1}} \tag{8}$$

This corresponds to a deviation of 15 % for the gain and of 5 % for the time constant. The static gains and the settling times in open loop for the nominal model, G_1 and G_2 are equal to 545, 750, 375, and 170 s, 200 s and 140 s, respectively. Table 1 synthetises the results obtained with the three controllers (IMC, PI (Ziegler-Nichols (ZN)), PI (Minimum Settling Time (MST))) and the three models in tracking conditions. It compiles the values of the settling time in closed loop, the values of the IAE (Integral of the Absolute value of the Error) and ITAE (Integral of the Time-weighted Absolute Error) criteria (e.g. (Seborg *et al.*, 1989)), and the values of overshoot in all cases.

Figures 7 and 8 show the performances of the IMC with and without feedforward action (Figure 7) and of both PI regulators with feedforward action (Figure 8), when a ramp of air flow rate is applied to the process (straight line at the bottom in both figures).

Model	Control.	CLST (s)	IAE	ITAE	OS (%)
$G_{nom}(q)$	IMC	30	150	300	0
	PI (ZN)	190	264	1381	5
	PI (MST)	90	274	1179	0
$G_1(q)$	IMC	80	191	585	20
	PI (ZN)	170	326	1719	24
	PI (MST)	130	269	1133	14
$G_2(q)$	IMC	150	216	939	0
	PI (ZN)	180	400	3050	0
	PI (MST)	180	398	3059	0

Table 1. Controllers' performance in tracking conditions (CLST = Closed loop settling time; OS = overshoot)

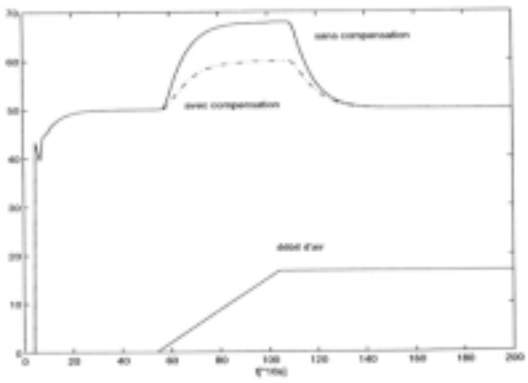

Fig. 7. IMC with (straight line) and without (dotted line) feedforward action

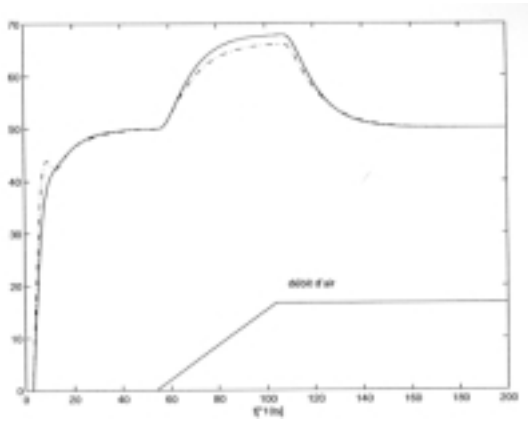

Fig. 8. ZN (dotted line) and MST (straight line) PI regulators with feedforward action

Note that in all cases, the IMC performs better and that the introduction of the feedforward action is largely justified by the improvement of the closed loop performance.

3.2 *Design of the adaptive controller*

The final important improvement that has been tested in the incorporation of a parameter adaptation in the controller structure in order to handle the drift observed in the product viscosity signals after the open loop response to air flow rate steps.

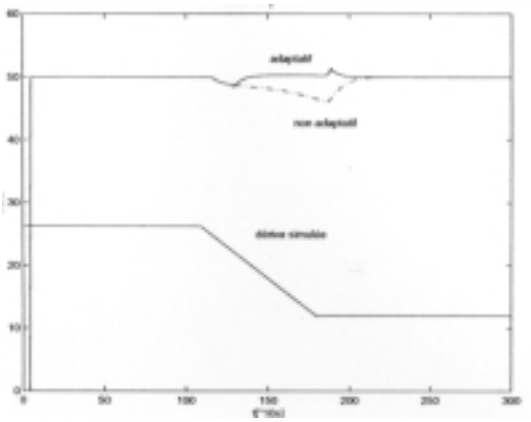

Fig. 9. adaptive (straight line) vs non-adaptive (dotted line) controllers (straight line at the bottom : simulated drift)

For the purpose of the control design and performance evaluation, the drift has been modelled by considering a linearly time dependent gain in the transfer function between the air flow rate and the product viscosity. The adaptive controller is indeed the IMC previously designed where the gain between air flow rate and product viscosity is estimated on-line by a recursive least squares estimation algorithm. Figure 9 compares the performance of the adaptive and non-adaptive versions of the IMC controller. Note the improvement gained with the adaptive controller.

4. CONCLUSIONS

In this paper, we have presented the application of model identification and control to an industrial polymerisation reactor. The identification study has resulted in the selection of a MISO model between the outputs (product viscosity) and the two inputs (catalyst flow rate, air flow rate). The identified model has served as a basis for the design and evaluation of the performance of an adaptive IMC controller whose performance proved to be superior to those of PI and non-adaptive IMC controllers.

Acknowledgements : This paper presents research results of the Belgian Programme on Interuniversity Poles of Attraction initiated by the Belgian State, Prime Minister's Office, Science, Technology and Culture. The scientific responsibility rests with its authors.

5. REFERENCES

Ljung, L. (1987). *System Identification - Theory for the User*. Prentice-Hall. Englewood Cliffs, NJ.

Seborg, D.E., T.F. Edgar and D.A. Mellichamp (1989). *"Process Dynamics and Control"*. John Wiley. New York.