Multivariable adaptive control of bioprocess

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Abstract : **This paper presents a multivariable adaptive control of a continuous-flow fermentation process for the alcohol production. The linear quadratic control strategy is used for the regulation of substrate and ethanol concentrations in the bioreactor. The control inputs are the dilution rate and the influent substrate concentration. A robust identification algorithm is used for the on-line estimation of a linear MIMO model's parameters. Experimental results of a pilot-plant fermenter application are reported and show the control performances.**

Key Words : **Multivariable adaptive control, Linear Quadratic Gaussian controller, Alcoholic fermentation.**

1. INTRODUCTION

During the last years, there has been an intensive research in the application of the adaptive control approach to bioprocess controls [Bastin and Dochain 90]. This approach has to cope with the physical time-varying parameters uncertainties. Most of those studies deal with the control problem of a single input/single output system to represent the bioprocess.

The biotechnological processes to be controlled are inherently multivariable in nature. Indeed when searching an optimal steady state for an alcoholic fermentation process, a double setpoint is generally defined for both substrate and product concentrations. Those setpoints can correspond to the stationnary state in which the process productivity is maximal. The control scheme allows to speed up the transitory state to a steady state and ensure the follow-up of reference trajectories.

Among the adaptive control algorithms, Linear Quadratic Gaussian (LQG) control appear as being the most attractive. This adaptive control algorithm, is based on the minimization of a quadratic cost function. This control scheme is associated with a robust estimator in charge of unknown parameters estimation. The theoretical and experimental results have been reported in the literature for this approch [Samson 82, Roux *et al.* 92]. Based on linear multivariable model, a LQG controller has been studied and analysed [M'Saad and Sanchez 92].

In this paper, the multivariable LQG is applied to the control of both substrate and ethanol concentrations inside an alcoholic fermentation process. Since the carbon dioxide production rate is strongly related to ethanol production rate [Mota *et al.* 87] and responses quickly to the change of dilution rate [Sato and Yoshizawa 88], ethanol production rate can be derived from the on-line carbon dioxide production rate. In this study, we then consider the substrate concentration and the carbon dioxide production rate as the output variables, and the dilution rate and the influent substrate concentration as the input variables of an identified model; the last one is applied to the on-line control of a continuous alcoholic fermentation process. This control scheme would allow the tracking of prespecified reference trajectories for both substrate concentration rate and carbon dioxide production rate.

The paper is organized as follows: in section 2 the experimental pilot-plant fermenter is described. The control algorithm is given in section 3 and the parameter estimator is presented in section 4. In section 5, the adaptive LQG control is applied to the biorector and some results are discussed. A general conclusion ends the paper.

2. DESCRIPTION OF THE FERMENTATION PROCESS

The experimental alcoholic fermentation plant we are concerned with is a typical continuous fermentation process. The growth medium, composed of several mineral salts and vitamins, and containing a carbon-rich substrate (glucose), continuously flows through a bioreactor, whose biological activity is sustained in order to accomplish the conversion of substrate into alcohol product. The strain used is *Saccharomyces cerevisiae UG5*. The glucose source is cerelose. Stirrer speed, temperature and pH are monitored and maintained under local analogue control in 2 l SGI 2M fermenter. A level sensor is used to maintain the fermenter at constant volume.

The influent glucose concentration and the dilution rate are used as control inputs in order to regulate the substrate and the ethanol concentrations in the reactor. The values of the typical operating variables and parameters for the experimental plant are summarized in table 1.

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Table 1 : Operating variables and parameters

Parameters	Values
Active volume (l)	1.5
Temperature (°C)	30
Stirrer speed (rpm)	200
pH	3.8
Dilution rate (1/h)	0.02 - 0.26
Influent substrate concentration (g/l)	10 - 300

The on-line glucose analysis is carried out by an YSI 27A enzymatic analyser fully automated by LAAS-CNRS [Queinnec *et al.* 92]. The output gas flow of the reactor is almost completly formed of carbon dioxide, oxygen and nitrogen. The carbon dioxide production rate is measured on-line through the Guy-Lussac stoechiometric equation which gives the carbon dioxide production rate. The operation principle is to measure the time that the gas takes to push a given volume of water.

All procedures for sampling, injection and control of the analyser are managed by a Programmable Logic Computer (PLC). The pilot is linked to a PC compatible microcomputer. Process monitoring and control are achieved using dedicated software written in Turbo Pascal composed of a group of tasks including data acquisition and storage, graphic display, printing, PLC management, parameter estimation and evaluation of the control signal if necessary. Interfacing between the microcomputer and the process is carried out by a RTI 815 board from Analog Devices' family.

3. LINEAR QUADRATIC CONTROL

Our strategy consists of two inputs and two outputs control system. The output variables are the substrate concentration *S(t)* and the carbon dioxide production rate *CER(t)* and the input variables are the dilution rate *D(t)* and the influent substrate concentration $s_a(t)$. The dynamic of the alcoholic fermentation process can be described around their steady state values by the following incremental model representation

$$\Delta(q^{-1})A(q^{-1})y(t) = B(q^{-1})\Delta(q^{-1})u(t-1) + C(q^{-1})\xi(t) \qquad (1)$$

where $A(q^{-1})$, $B(q^{-1})$, $C(q^{-1})$ and $\Delta(q^{-1})$ are mxm polynomial matrices

$$A(q^{-1}) = I + A_1 q^{-1} + \ldots + A_{na} q^{-na}$$
$$B(q^{-1}) = B_0 + B_1 q^{-1} + \ldots + B_{nb} q^{-nb}$$
$$C(q^{-1}) = I + C_1 q^{-1} + \ldots + C_{nc} q^{-nc}$$
$$\Delta(q^{-1}) = (1 - q^{-1})I$$

y(t) : output vector
u(t) : input vector
q^{-1} : backward shift operator
I : mxm identity matrix

The matrix integrator $\Delta^{-1}(q^{-1})$ is introduced to eliminate the steady-state error. t denotes the discrete time index (number of sampling period). $\xi(t)$ is a vector of m uncorrelated sequences of random variables with zero mean value and finite variances. The matrix $A(q^{-1})$ and $B(q^{-1})$ are relatively left coprime. The controllability and observability of the system are assumed.

By using a simple algebraic manipulation, the process model representation, equation 1, can be written as follows

$$\overline{A}(q^{-1})y^c(t) = B(q^{-1})\Delta u(t-1) - A(q^{-1})\Delta y_r(t) + C(q^{-1})\xi(t) \qquad (2)$$

where

$$y^c(t) = y(t) - y_r(t) \qquad (3)$$
$$\overline{A}(q^{-1}) = \Delta(q^{-1})A(q^{-1}) = I + \overline{A}_1 q^{-1} + \ldots + \overline{A}_{na+1} q^{-na-1} \qquad (4)$$

$\{y_r(t)\}$ represents the desired reference sequence vector which is chosen so that $\Delta y_r(t) \approx 0$. Generally, this assumption is not very restrictive .

The dynamic behaviour can also be represented by the motion of a point in an *n*-dimensional space. Several internal representations of linear discrete systems in terms of state-space exist.

From equation 1, a state space model is obtained

$$X(t+1) = A_0 X(t) + B_0 u(t) + G_0 \xi(t) \qquad (5)$$
$$y^c(t) = C_0 X(t) + \xi(t)$$

with

$$A_0 = \begin{bmatrix} -\overline{A}_1 & I & & \\ \cdot & & \cdot & \\ \cdot & & & \cdot \\ \cdot & & & I \\ -\overline{A}_n & \cdot & \cdot & 0 \end{bmatrix}, \quad B_0 = \begin{bmatrix} B_0 \\ \cdot \\ \cdot \\ \cdot \\ B_{n-1} \end{bmatrix},$$

$$G_0 = \begin{bmatrix} C_1 \\ \cdot \\ \cdot \\ \cdot \\ C_n \end{bmatrix}, \quad C_0^T = \begin{bmatrix} I \\ \cdot \\ \cdot \\ \cdot \\ 0 \end{bmatrix}$$

where $n = \max(n_a + 1, n_b + 1, n_c)$.

In general, some states of system are not accessible then the following state observer [Samson 82] is used

$$\hat{X}(t) = H\Psi(t-1) \qquad (6)$$
$$\varepsilon(t) = y^c(t) - C_0 \hat{X}(t)$$

where

$$H=\begin{bmatrix} -\bar{A}_1 & . & . & . & -\bar{A}_n & B_0 & . & . & . & B_{n-1} & P_1 & . & . & . & P_n \\ . & & & . & & . & & & . & & . & & & . & \\ . & & . & & & . & & . & & & . & & . & & \\ . & . & & & & . & . & & & & . & . & & & \\ -\bar{A}_n & & & & & B_{n-1} & & & & & P_n & & & & \end{bmatrix}$$

$$\Psi^T(t-1)=\left[y^{cT}(t-1) \quad \ldots \quad y^{cT}(t-n) \quad \Delta u^T(t-1) \quad \ldots \quad \Delta u^T(t-n) \quad \varepsilon^T(t-1) \quad \ldots \quad \varepsilon^T(t-n)\right]$$

and $\varepsilon(t)$ denotes the observer error and the polynomial matrix $P(q^{-1})$ corresponds to the observer dynamics.

The control objective is based on the minimisation of the following cost function

$$J=\lim_{T\to\infty}\frac{1}{T}E\left\{\sum_{j=1}^{T}y^{cT}(t+j)y^{c}(t+j)+\Delta u^T(t+j-1)\Omega\Delta u(t+j-1)\right\} \tag{7}$$

where Ω is an mxm weighting positive matrix. The control law which realizes the above control objective is given by

$$\Delta u(t)=-K(t)\hat{X}(t)+G(t) \tag{8}$$

with

$$K(t)=\left[\Omega+B_0^T R(t)B_0\right]^{-1}B_0^T R(t)A_0 \tag{9}$$

$$G(t)=\left[\Omega+B_0^T R(t)B_0\right]^{-1}B_0^T R(t)G_0\left(y^c(t)-C_0\hat{X}(t)\right) \tag{10}$$

The matrix $R(t)$ is the solution of the following algebraic Riccati equation

$$R(t+1)=A_0^T\left[R(t)-R(t)B_0\left[\Omega+B_0^T R(t)B_0\right]^{-1}B_0^T R(t)\right]A_0+C_0^T C_0 \tag{11}$$

where $R(0)>0$.

When $t\to\infty$, $R(t)\to R^*$, where R^* corresponds to the unique positive definite matrix solution of the algebraic Riccati equation.

$$R^*=A_0^T\left[R^*-R^*B_0\left[\Omega+B_0^T R^*B_0\right]^{-1}B_0^T R^*\right]A_0+C_0^T C_0 \tag{12}$$

The Riaccati equation is iterated only once, starting each time from the resultant of the iteration performed at the previous sample instant. This significantly reduced the computational burden.

The implemented control input $u(t)$ at time t is

$$u(t)=u(t-1)+\Delta u(t) \tag{13}$$

4. THE PARAMETER ESTIMATOR

The adaptive controller is obtained by simply invoking the certainty equivalence principle, which consists of replacing the process model parameters $\theta=\left[A_1,\ldots,A_{na},B_0,\ldots,B_{nb},C_1,\ldots,C_{nc}\right]^T$ by their estimates when deriving the control law. To estimate the model parameters, equation (1), the following RLS parameter adaptation algorithm has been used

$$\theta(t+1)=\theta(t)+\varepsilon(t+1)F(t)\phi(t) \tag{14}$$

$$\varepsilon(t+1)=y(t+1)-\theta(t)\phi(t)$$

$$F(t+1)=\frac{1}{\lambda_1(t)}\left[F(t)-\frac{F(t)\phi(t)\,\phi(t)^T F(t)}{\frac{\lambda_1(t)}{\lambda_2(t)}+\phi(t)^T F(t)\phi(t)}\right],$$

$0<\lambda_1(t)\le 1,\qquad 0\le\lambda_2(t)<2,\qquad F(0)>0$

$F(t)$ is the adaptation gain matrix and $\phi(t)$ is the obseravtion vector containing the delayed outputs, inputs and the sequences of random variables.The parameters $\lambda_1(t)$ and $\lambda_2(t)$ are forgetting factors, which are chosen to provide a better adaptation.
The numerical robustness of the estimation algorithm and consequently that of the adaptive control algorithm can be increased by using [M'Saad *et al.* 86] : Data filtering and conditioning, normalisation of data, factorization UD of the adaptation gain matrix, lower bound of the adaptation gain and parameter estimation freezing.

5. APPLICATION

The LQG multivariable controller described above has been implemented on the pilot-plant fermentor. Real-time experiment is conducted to emphasize the performance of the proposed adaptive controller. Several experiments have been performed to determine a suitable tuning parameters values. We have kept a set of design parameters that seems to be satisfactory. The results presented in this study are carried out according to the following experimental planning.
Recall that the objective is to regulate both the substrate concentration and the carbon dioxide production rate at the desired profils by acting on the dilution rate $D(t)$ and on the influent substrate concentration $S_a(t)$.

Both inputs $D(t)$ and $s_a(t)$ are applied through auxiliary controls. $D(t)$ corresponds to the total of two specific flow rates $D_1(t)$ and $D_2(t)$. $D_1(t)$ represents the specific flow rate of a solution without glucose. $D_2(t)$ corresponds to the specific substrate feeding rate from a solution with $s_m(t)$ glucose concentration. The relationships among $D(t)$, $s_a(t)$, $D_1(t)$ and $D_2(t)$ are given by the following equations

$$D(t) = D_1(t) + D_2(t) \tag{15}$$
$$s_a(t) = \frac{D_2(t)}{D_1(t) + D_2(t)} s_m(t)$$

The sampling period is set to 10 minutes. The plant model structure is $m = 2$, $na = 2$, $nb = 1$ and $nc = 0$. The reference sequence is generated by the equation $(1 - 1.6q^{-1} + 0.64q^{-2})y_r(t) = 0.04\,u_r(t-1)$. The control design parameters are $P(q^{-1}) = I$, $\Omega = \begin{pmatrix} 0.01 & 0 \\ 0 & 0.005 \end{pmatrix}$ and $R(0) = 100I$.

The parameter estimator initial values are $F(0) = 1000I$, $\theta(0) = 0$, $\lambda_1(t) = 0.95$ and $\lambda_2(t) = 1$. The gain matrix trace is constrained to be not less than 0.1. A preliminary open-loop identification is used to get a reasonable initial values for both the parameter estimates and the adaptation gain. For this, two decorrelated PRBS inputs are applied, during 2 hours, to the process.

Data from a real-life experiment are shown on figures 1-6. Figures 1 and 2 show the time evolution of the substrate concentration $S(t)$ and the carbon dioxide production rate $CER(t)$ respectively.

The set-point of $S(t)$ was changed from 5 g/l to 7g/l at t=6h30, and then to 5 g/l at t=17h30. The set-point of $CER(t)$ was changed from 4 g/l to 3 g/l at t=13h30, and then to 4 g/l at t=23h30.

The corresponding off-line measurements of ethanol concentration are given in figure 3. At the steady-state, the ethanol concenteration reached 54 g/l and 39 g/l.

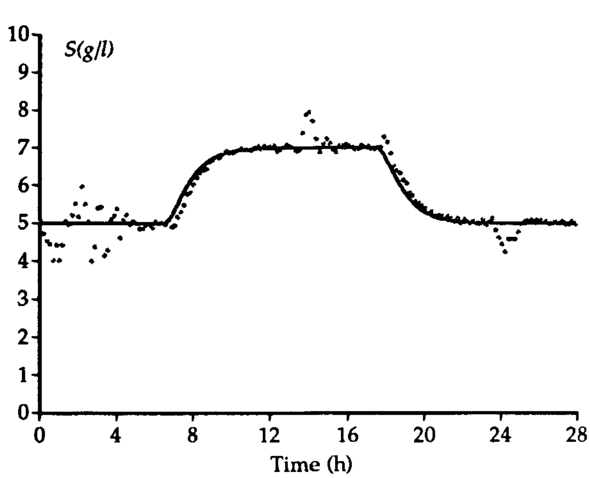

Fig.1: Substrate concentration evolution.

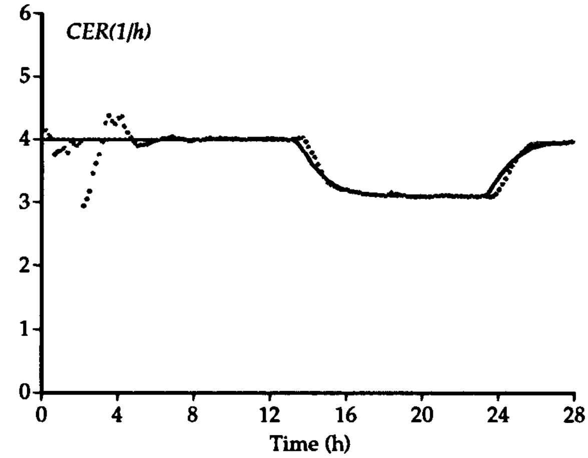

Fig.2: Carbon dioxide production rate evolution.

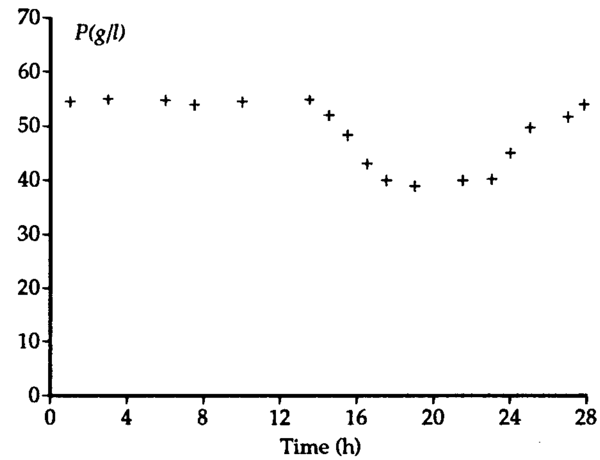

Fig.3: Off-line ethanol concentration evolution.

Figure 4 shows the time evolution of the two auxiliary control variables $D_1(t)$ and $D_2(t)$. The time evolution of the input variables, that are the dilution rate $D(t)$ and the influent substrate concentration $s_a(t)$, are shown on figures 5 and 6 respectively.

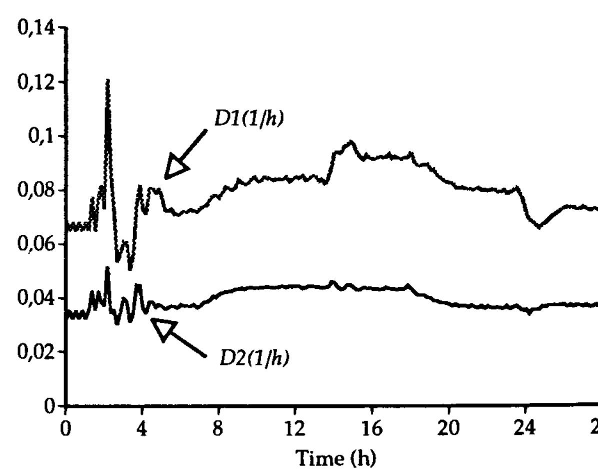

Fig.4: Specific flow rate without/with glucose.

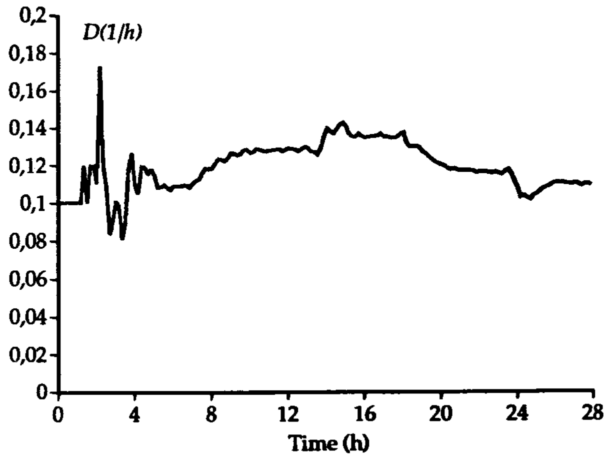

Fig.5: Dilution rate evolution.

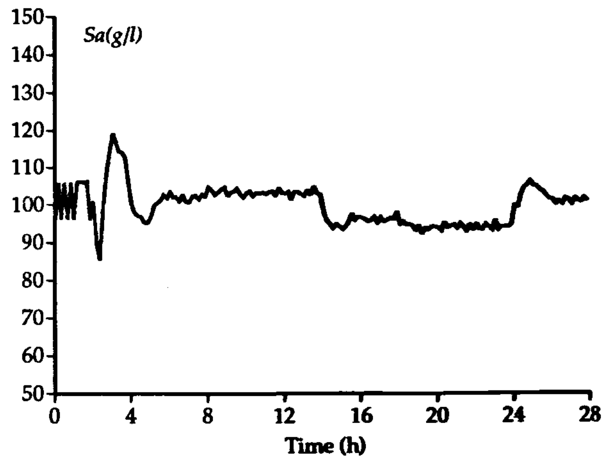

Fig.6: Influent substrate concentration evolution.

After a transient for the adaptation during the initial stage, the outputs $S(t)$ and $CER(t)$ follow the desired reference model. We note that the steady-state regulation errors, figures 1 and 2, are kept within acceptable limits.

These experimental results confirm the multivariable nature of the fermentation process. Indeed, it is clearly shown that a variation of one of the inputs induces significant variations of both outputs. In the present study, the selection of optimal set-points is not discussed.

External disturbances, set-point changes, are efficiently rejected by the multivariable controller. The control variables $D(t)$ and $s_a(t)$ remain smooth.
In spite of the variation of the desired outputs, the control of the fermentor is perfectly performed by the LQG control algorithm presented above.

6. CONCLUSION

In this paper, an adaptive multivariable LQG control startegy for an alcohlic fermentation process and application results have been presented. Experimental results on a pilot-plant fermentor have been presented to illustrate the behaviour of the control bioprocess.
The good behaviour of the adaptive control scheme on a linear multivariable model of a fermentation process shows the feasibility of such a control strategy.
It is worth noticing that the proposed adaptive LQG controller could be used directly to control the ethanol concentration when on-line measurements are available.

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