TRACKING SUBSTRATE TRAJECTORIES IN CONTINUOUS AEROBIC WASTEWATER REACTORS VIA NONLINEAR PI CONTROLLERS

Aguilar-Lopez, R[1], Neria-Gonzalez, Ma I[2] & Soto-Corte, G.

[1]Departamento de Energia, Universidad Autonoma Metropolitana-Azcapotzalco, Av. San Pablo No. 180, Reynosa-Tamaulipas, 02200;,Azcapotzalco, México DF, México
E-mail: raguilar@correo.azc.uam.mx
Fax: + (52) 5394 7378
[2] Departamento de Microbiologia Escuela Nacional de Ciencias Biologicas-IPN

Received: September 1st, 2005. Accepted: January 26th, 2006

ABSTRACT

This work addresses the problem of robust tracking of the substrate concentration in a continuous bioreactor in an industrial wastewater treatment plant of an oil refinery. The entire nonlinear operating region of the process was approached by several linear models. The suggested global controller is designed considering an average between the linear single controllers designed for each operating region. The averaging methodology is conducted via interpolation, considering Gaussian distributions as the interpolating functions. The robust properties of the global controller are shown by employing a Lyapunov function. The corresponding performance of the proposed methodology is illustrated via numerical simulations.

RESUMEN

En este trabajo se presenta el problema de seguimiento robusto de la trayectoria de referencia de la concentración de sustrato en un bioreactor de una planta industrial de tratamiento de agua residual de una industrial de refinación de petróleo. Mediante varios modelos lineales, se aproxima la región completa de operación de la planta. Se sugiere un controlador global considerando para su diseño un promedio entre los controladores lineales previamente diseñados para cada región de operación modelada por su correspondiente aproximación lineal. La metodología para promediar los controladores individuales es realizada tomando como funciones interpolantes las distribuciones gausianas. La robustez de la metodología propuesta es mostrada mediante un análisis de estabilidad de Lyapunov. El desempeño del esquema de control propuesto se muestra por medio de simulaciones numéricas

KEYWORDS: Reactor Modelling, Simulation, Averaged Controller, Robust Performance, Tracking.

1. INTRODUCTION

Biochemical processes have been playing more important roles during the last years and are currently one of the most important areas in transformation industries. Continuous bioreactors are frequently used in process industries for production or degradation of a wide range of biological compounds, for example, during aerobic digestion in wastewater treatment. However, these processes can exhibit complex dynamic behaviour, such as steady-state multiplicity, limit cycles, and instabilities, in addition to time-variant parameters, which difficult monitoring and control duties [1].

Also, industrial processes are required to exhibit high flexibility under changing market conditions, constrained security rules and environmental regulations. In these situations, conventional procedures for the stabilisation of process operations cannot provide enough capability to reach the required performance.

In order to solve this problem, control engineers have to design ad hoc control schemes to enable them to deal with demanding operating conditions. A number of papers have been published in the open literature [2-7] dealing with new controller designs under the framework of gain-scheduling, and predictive, optimal and nonlinear control theories. However, because of their mathematical complexity, most of them cannot be applied to industrial plants. For this reason, part of the control theory research has to be focused on practical application in industrial processes.

Due to their easy implementation and manipulation by plant operators, linear controllers are widely employed in industrial processes, despite the fact that linear approaches are not robust when the operating conditions change suddenly and/or strong disturbances are present. For example, Chang et al. [8], Khalil [9] and Aguilar et al. [10] have proposed novel approaches to design nonlinear PI and PID type controllers using more sophisticate techniques that allow new friendly tuning rules for the controller's gains and assuring semi-global robust performance. An important issue arises when the dynamic behaviour of the process varies due to changing operating conditions, which cause unsatisfactory closed-loop performance. In order to tackle this problem, a multimodel control design approach has been applied under the frame of predictive and optimal control theory [11-14].

A typical example of processes that exhibit non-linear behaviour and time-varying parameters is biochemical reactors. Their operation is known as difficult to reproduce and control. Therefore, this paper addresses the tracking problem for substrate control in a class of continuous bioreactors. A relatively simple continuous bioreactor serves as a benchmark problem for advanced non-linear analysis and control techniques. To consider system nonlinearities, stability, and performance objectives over large operating regions, a multi-region linear model representation of the system is developed. The suggested control consists of the average of the linear controllers designed for each single operating region.

2. BIOREACTOR MODEL DESCRIPTION

A continuous stirred tank bioreactor employed for wastewater treatment is considered as an example of application. Wastewater contains a complex mixture of solids and dissolved components. In treatment plants, these contaminants have to be reduced or chemically transformed into less pollutant compounds. The overall system design used to accomplish this objective varies depending upon the type and amount of wastewater to be treated, economic and environmental considerations, and process performance.

Description of the dynamic behaviour of this class of systems might be fairly complex and involve a large set of differential equations. However, for control and identification purposes, a reduced order model that adequately describes the dynamic behaviour of the key state variables, biomass and substrate concentrations, is sufficient.

The mathematical model described below is related to a bioreactor employed for wastewater treatment in a petroleum refinery. It contains the corresponding mass balances for biomass, substrate and oxygen concentrations, which are represented by a set of nonlinear ODE's. The following section explains the determination of the bioreaction rate parameters.

Biomass (X_1) mass balance equation:

$$\dot{X}_1 = -DX_1 + \mu(X_2)X_1 \tag{1}$$

Substrate (X2) mass balance equation:

$$\dot{X}_2 = D(X_{2f} - X_2) - \Omega(X_1, X_2) \tag{2}$$

Oxygen (X3) mass balance equation:

$$\dot{X}_3 = F_0\left(X_{3f} - X_3\right) + \frac{0.2031}{X_1}\left(D\left(X_{2f} - X_2\right) - \Omega(X_1, X_2)\right) \tag{3}$$

Measured output:

$$Y = X_2 \tag{4}$$

Here, $\Omega\left(X_1, X_2\right) = \mu\left(X_2\right)^{X_1 / Y_d}$ represents the kinetic term and Y is the measured system output. For other variable definitions see Nomenclature section.

Yield coefficient and specific growth rate are given as follows:

$$Y_d = 0.3723 \tag{5}$$

$$\mu(X_2) = \frac{\mu_{\max} X_2}{K_s + X_2} = \frac{1.064 X_2}{43.9 + X_2} \tag{6}$$

2.1 Experimental determination of the biokinetic coefficients

The complete studies are described in reference [15]; some important data are described in this subsection: 5 bench-scale continuous bioreactors without solids recycle were used and operated simultaneously in parallel. These units are made of Plexiglas with a volume capacity of 11 litres. Air was supplied using air stone diffusers in the reactor bottom to keep the dissolved oxygen (DO) concentration at values higher than 2.0 mg/L. The bubbles produced during aeration kept the contents of the bioreactor well mixed and homogeneous. Wastewater from aeration lagoons of a Mexican refinery was used for the experiments. The refinery wastewater was fed continuously from a reservoir (with constant head) to the chambers by means of four peristaltic pumps adjusted at different flow to obtain different residence times (0.5, 1, 2, 3 and 4 days). The bioreactors had an overflow weir for the effluent. Start-up was performed with refinery wastewater and inoculated with biological sludge obtained from the refinery's aerated lagoon. Steady state operation was reached after 4 weeks. Samples were extracted daily from the wastewater reservoir and in the exit of each chamber. Biochemical oxygen demand (BOD), chemical oxygen demand (COD) and volatile suspended solids (VSS) were determined for each sample. Oxygen uptake rate was measured by extracting aerated mixed liquor from the bioreactor into a Winkler bottle with a magnetic bar. A DO probe electrode monitored variation in DO concentration. As usual, the follow equations were used to determine biokinetic coefficients:

$$r_s = \frac{\mu_{\max}}{Y_d} \frac{X_1 X_2}{K_s + X_2} = \frac{X_{2o} - X_2}{\theta} \tag{6a}$$

Linearizing equation (6a) and taking the inverse, equation (6b) is obtained.

$$\frac{X_1 \theta}{X_{2o} - X_2} = \frac{Y_d K_s}{\mu_{\max}} \frac{1}{X_2} + \frac{Y_d}{\mu_{\max}} \tag{6b}$$

K_s was obtained by plotting $\frac{X\theta}{S_o - S}$ versus $\frac{1}{S}$.

The Y_d value was obtained, independently, by measuring the slope of equation (6c).

$$\frac{1}{\theta} = Y_d \frac{r_s}{X_1} - k_d \tag{6c}$$

Using this value, $\mu_{\max}$ was calculated from equation (6a).

3 CONTROLLER DESIGN

3.1. Linear Multi-Model identification

In order to find feasible operating regions, an input/output mapping is constructed by modelling the process as described in the above section. From this input/output mapping, corresponding linear models for each region were identified empirically via a classical identification procedure, which consists of a step perturbation in the control input (related to dilution rate) and the corresponding system output (substrate concentration) response. It was found that three regions contain the whole range between null dilution rate and washout zone. This procedure is an off-line process for which prior knowledge of the system is very important; therefore, there are no rigorous theoretical methodologies to calculate the exact number of approximating linear models that adequately represents the original plant [7]. Models for the three feasible operation regions are shown in Table I.

Table I. Linear multi-models for the proposed three regions

Model I	Model II	Model III
$G_1(s) = \frac{80}{7.5\,s + 1}$	$G_2(s) = \frac{621.42}{4\,s + 1}$	$G_3(s) = \frac{2729.4}{27\,s + 1}$

As we can see, the three regions considered are modelled by first order systems. Nevertheless, steady-state gains change in one order of magnitude when moving away from each of the operating regions considered. Therefore, any controller designed for a specific region is expected to exhibit poor closed-loop performance when operating in another region.

3.2 Controller design

The control target is the substrate concentration in the bioreactor; the manipulated variable is the input volumetric flow, which is related to the dilution rate. Due to the popularity of the conventional Proportional-Integral (PI) controller, the implementation of a PI controller for each of the operating regions suggested above was performed. Each PI control was tuned following Internal Model Control (IMC) guidelines, which provide some robustness properties for linear systems [16]. Controllers for each region are shown in Table II.

Table II. PI controllers for each operating region

Controller I	Controller II	Controller III
$D_1 = 0.2 - 0.0125\left(1 - \frac{1}{7.5s}\right)$	$D_2 = 0.7 - 1.6E\text{-}3\left(1 - \frac{1}{4s}\right)$	$D_3 = 0.85 - 3.6E\text{-}4\left(1 - \frac{1}{27s}\right)$

The main feature of the proposed design of control law consists of providing a smooth transition between the three operating regions of the bioreactor. A normal average of the individual controllers given for each of the operating regions mentioned above is proposed. The following controller is obtained (Equation 7).

$$D = \frac{\sum_{i=1}^{3} w_i(x_2) D_i}{\sum_{i=1}^{3} w_i(x_2)} \tag{7}$$

Here, $\mathrm{w_i(x_2)} = \exp\left(\frac{-(\mathrm{x_2} - \mathrm{x_{2,av}})^2}{\sigma^2} \right)$.

$w_i(X_2)$,'s functions are normal Gaussian distributions based on the statistical properties of each operating region. They are used as weighting factors for the control of each individual operating region. After some algebraic manipulations, the control input for the bioreactor can be represented as:

$$D = D_o + \mathrm{K}_P(x)\left(x - \sum_{i=1}^{3} x_{sp,i} \right) + \mathrm{K}_I(x) \int_0^t \left(x - \sum_{i=1}^{3} x_{sp,i} \right) d\tau \tag{8}$$

Here, the following definitions were introduced:

$$D_o = \sum_{i=1}^{3} w_i(x) D_{oi} \tag{8.1}$$

$$\mathrm{K}_P(x) = \frac{\sum_{i=1}^{3} w_i(x) k_{P,i}}{\sum_{1}^{3} w_i(x)} \tag{8.2}$$

$$\mathrm{K}_I(x) = \frac{\sum_{i=1}^{3} w_i(x) k_{I,i}}{\sum_{1}^{3} w_i(x)} \tag{8.3}$$

In the resulting controller, $\mathrm{K}_P(x)$ is the proportional-type gain, $\mathrm{K}_I(x)$ is the integral-type gain and D_o is a 'dc-type' bias. Now, for any given compact set $\aleph x \subset \Re^n$, all closed-loop signals with initial conditions $(X_1(0), X_2(0), X_3(0))^T \text{ in } \aleph x$ should remain bounded (semi-global boundness) and the output tracking error will be sufficiently small.

This particular controller realization is equivalent to a nonlinear PI control law, where the controller gains are a function of the states of the process. It is important to note that this representation should be friendly enough for plant operators, because the tuning of the proposed controller depends only on basic statistical properties of the operating regions (e.g. standard deviation and average) and the tuning rules considered (IMC, in this case).

3.3 Stability considerations

Consider the following canonical representation of the mathematical bioreactor model:

$$\begin{aligned} \dot{x} &= f(x) + g(x)u \\ y &= Cx \end{aligned} \tag{9}$$

Here, $x \in \Re^2, f: \Re^2 \to \Re^2, g: \Re^2 \to \Re^2, u \in \Re, C = \begin{bmatrix} 0 & 1 \end{bmatrix}$.

The closed-loop state equations can be represented as follows (Equation 10).

$$\begin{aligned} \dot{x} &= f(x) + g(x)\left(\mathrm{K}_P(x)e + e_1\right) \\ \dot{e}_1 &= \mathrm{K}_I(x)e \\ y &= Cx \end{aligned} \tag{10}$$

As can be observed, the above system represents a dynamic state feedback controller for the open loop system (9), which provides robust tracking of arbitrary constant set point. It is possible to define the tracking error as $e = y - \sum_{i=1}^{3} y_{sp,i} = x - \sum_{i=1}^{3} x_{sp,i}$, and to consider the following Lyapunov function:

$$V = e^T P e + e_1^T Q e_1 \geq 0 \tag{11}$$

Here, $P = P^T > 0 \; and \; Q = Q^T > 0$. Taking the derivative of the Lyapunov function, the following expression is obtained (Equation 12).

$$\dot{V} = 2e^T P\left(f(x) + g(x)\left(\mathrm{K}_P(x)e + e_1\right)\right) + 2e_1^T Q\left(\mathrm{K}_I(x)e\right) \tag{12}$$

In order to ensure stability, the last derivative should be negative semi-definite. Several combinations of the different terms of the above equation could be considered, though in accordance to practical situations, the control engineer can only manipulate the controller gains, therefore, the following conditions have to be taken:

$$\begin{aligned} f(x) + g(x)\left(\mathrm{K}_P(x)e + e_1\right) &\leq 0 \\ \mathrm{K}_I(x)e &\leq 0 \end{aligned} \tag{13}$$

Consequently:

$$\begin{aligned} \mathrm{K}_p(x) &\leq -e^{-1}\left(g(x)^{-1} f(x) - e_1\right) \\ \mathrm{K}_I(x) &\leq 0 \end{aligned} \tag{14}$$

From equations (8.2) and (8.3) we can note that the particular control gains obey the restriction given by (14); hence, process stability is assured.

4. NUMERICAL RESULTS

Standard identification procedures were followed in order to obtain empirical models of the entire operating region considering limits between the washout condition and the null input flow for the dilution rate. As can be observed in Figure 1, three empirical regions were identified to construct the corresponding linear models.

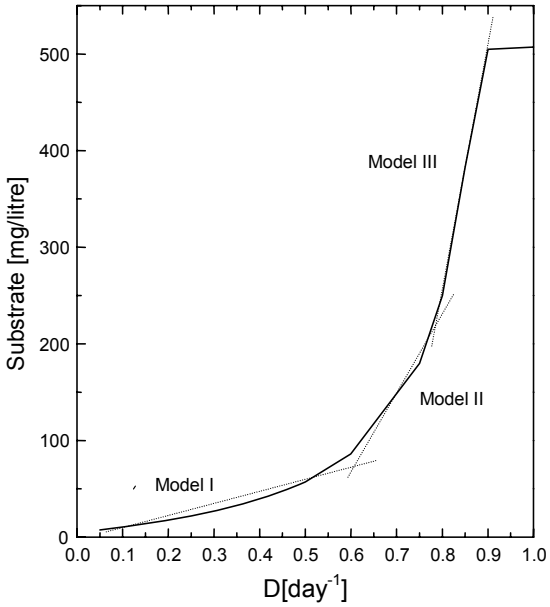

Figure 1. Input/Output map for the bioreactor.

Figure 2 shows the closed-loop performance of the substrate concentration in the bioreactor, considering changes in the set point, at 175 days the reference point change from 300 mg/L to 150 mg/L, at 275 days the reference is moved again from 150 mg/L to 40 mg/L. Note that the proposed controller shows the best performance, because it does not present overshoots and the settling times are small enough. Individual controllers D1, D2 and D3 present poor performance when the set point changes arise. Controller's effort is shown in Figure 3, as expected the controller proposed shows the best performance.

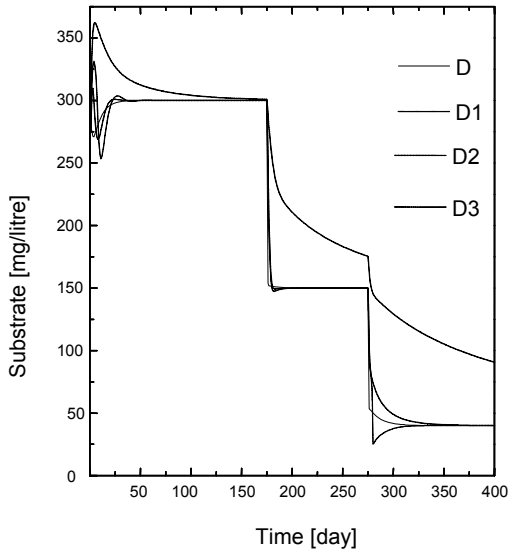

Figure 2. Closed-loop performance with the controller proposed and the control law for each linear model.

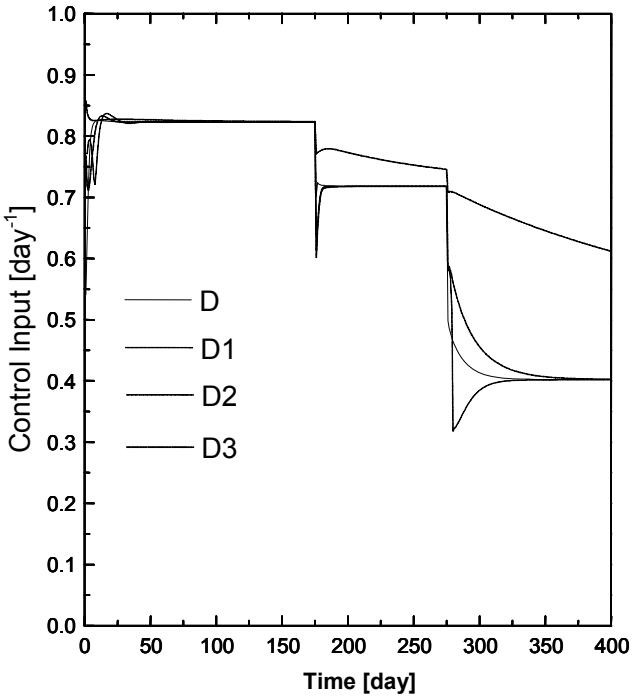

Figure 3. Closed-loop performance of the control input (dilution rate).

5. CONCLUSIONS

In this paper, the robust tracking problem for the substrate concentration in a class of continuous bioreactors is tackled with a nonlinear PI controller. Several operating regions were selected in order to cover a large range of operating conditions of the bioreactor. In these regions, empirical linear models were identified and individual controllers were designed. The proposed controller, which is valid for the entire operating region, is designed considering an average between the controllers for each individual operating region. The averaging methodology is carried out via interpolating functions such as Gaussian distributions, and the robust properties of the resulting controller are probed employing a robust control Lyapunov function. Numerical simulations were carried out in order to show the good performance of the control scheme proposed.

6. NOMENCLATURE

6.1 Latin variables

D.-	Dilution rate	$[day^{-1}]$
D_o.-	dc-type biass	
$G_j(s)$.-	j-th transfer function	
k_d	Endogenous decay coefficient	$[day^{-1}]$
K_I.-	Controller's integral gain	
K_P.-	Controller's proportional gain	

K_s	Half-velocity constant	$[mg \bullet L^{-1}]$
r_s	Rate of substrate utilization	$[mg \bullet day^{-1} L^{-1}]$
s.-	Complex variable in the Laplace domain	
w.-	Normally distributed weight factors	
X_1.-	Biomass fraction	$[mg \bullet L^{-1}]$
X_{2o}.-	Initial substrate concentration	$[mg \bullet L^{-1}]$
X_2.-	Substrate concentration	$[mg \bullet L^{-1}]$
X_3.-	Oxygen concentration	$[mg \bullet L^{-1}]$
Y.-	System output	
Y_d.-	Substrate yield coefficient	

6.2 Greek variables

μ.-	Specific grow rate	[day-1]
μ_{max}.-	Maximum Specific grow rate	[day-1]
Ω.-	Kinetic substrate consumption term	
θ	Residence time	[day]

7. REFERENCES

[1] Bastin, G., Dochain, D., On-line estimation and adaptive control of bioreactors, Elsevier, Amsterdam, NL., 1990.

[2] Bequette, B. W., Nonlinear control of chemical process, Ind. Eng. Chem. Res., Vol. 30, pp. 1391-1413., 1991.

[3] Rugh, W., Analytical framework for gain scheduling, IEEE control system magazine, Vol. 11, pp. 79-84, 1991.

[4] Szederkényi, G., Kristensen, N. R., Hangos, K. and Jørgensen, S., Nonlinear analysis and control of a continuous fermentation process, Comp. & Chem. Eng., Vol. 26, pp. 659-670, 2002.

[5] Braake, H. A., van Can, E. J. and Scherpen, J. M., Control of nonlinear chemical process using neural models and feedback linearization, Comp. & Chem. Eng., Vol. 22, pp. 1113-1127, 1998.

[6] Aguilar, R., González, J., Barrón, M., Martínez-Guerra, R., Maya-Yescas, R., Robust PI^2 controller for continuous bioreactors, Process Biochemistry, Vol. 36, No.10, pp. 1007-1014, 2001.

[7] Galán, O., Romagnoli, J., Palazoglu, A., Robust H∞ control of nonlinear plants based on multi-linear models: application to bench-scale pH neutralization reactor, Chem. Eng. Sci., Vol. 55, pp. 4435-4450, 2000.

[8] Chang, G. W., Espinosa, G., Mendez, E., Ortega, R., Tuning rules for PI gains of field oriented controllers in industion motors, IEEE Trans. Ind. Electron, Vol. 64, pp. 679-692, 1996.

[9] Khalil, H. K., Universal integral controllers for minimum phase nonlinear systems, IEEE Trans. Aut. Ctrl., Vol. 45, pp. 490-494, 2000.

[10] Aguilar, R., Martínez, R., Poznyak, A., Maya, R., Temperature control for Catalityc cracking reactors via robust PID controller, J. of Proc. Ctrl., Vol. 12, No. 6, pp. 695-705, 2002.

[11] Banerjee, A. and Arkun, Y. (1998). Model predictive control of plant transitions using a new identification technique for interpolating nonlinear models. J. of Proc. Ctrl., Vol. 8, pp. 441-457.

[12] Shoeming, E. Snaider, M., Ly, U., Mixed H2/H∞: control of multimodel plant, J. Guiadance, Ctrl and Dyn., Vol. 18, pp. 525-531, 1995.

[13] Foss, B. A., Johasen, T., Sorensen, A. V.,). Nonlinear predictive control using local models – applied to batch fermentation process, Ctrl. Eng. Prac., Vol. 3, pp. 389-398, 1995.

[14] Narendra, K. S., Balakhisnan, J., Ciliz, M., Adaptation and learning using multiple models, switching and tuning, IEEE control systems magazine, Vol. 15, pp. 37-51, 1995.

[15] Martínez, R., Baltasar, R., Experimental biokinetic parameters estimation of a wastewater petroleum refinery, B. Sc. Thesis, Universidad Autónoma Metropolitana, (in Spanish), 1999.

[16] Morari, M., Zaforiou, E., Robust Process Control, Prentice Hall, 1991.