An adaptive control strategy for a class of recycled depollution bioprocesses

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This paper presents the design of a nonlinear multivariable adaptive control strategy for a class of wastewater depollution bioprocesses that are carried out in recycle bioreactors. The adaptive control structure is achieved by combining a linearizing control law with a new state observer and a parameter estimator, which play the role of the software sensors for on-line estimation of biological states and parameter variables of interest of the bioprocess. Simulation results are included to illustrate the performance of both estimation and control algorithms.

Key words: *Nonlinear systems, Adaptive control, On-line estimation, Wastewater bioprocess.*

Introduction

The control of bioprocesses is an important problem attracting wide attention. The main motivation is to improve the operational stability and the production efficiency of such living processes. Two known factors make bioprocesses control particularly difficult. First, these processes exhibit large nonlinearities, strongly coupled variables and often poorly understood dynamics. Second, the on-line measurements of biological process variables (biomass and/or product concentrations), which are essential for control design, is hampered by the lack of cheap and reliable on-line sensors. The nonlinearity of the bioprocesses and the uncertainty of kinetics impose the adaptive control strategy as a suitable approach (Dochain, Vanrolleghem, 2001; Nejjari et al., 1999; Petre, 2002). So, the difficulties encountered in the measurement of the state variables of the bioprocesses impose the use of the so-called "software sensors" (Dochain, Vanrolleghem, 2001). Note that these software sensors are used not only for the estimation of unmeasurable concentrations but also for the estimation of the kinetic parameters (Dochain, Vanrolleghem, 2001; Petre, Selişteanu, 2005).

This paper presents the design of a multi-variable adaptive nonlinear control strategy capable of dealing with the model uncertainties in an adaptive way for a class of depollution bioprocesses for removal of two pollutants that are carried out in recycle bioreactors. Although for this depollution bioprocess were reported some nonlinear and adaptive control algorithms (Nejjari et al., 1999; Petre, 2002; Petre et al., 2008), in this paper, a new multivariable adaptive control algorithms is proposed and analyzed. More exactly, the problem of adaptive controlling of two reactant concentrations with two control inputs is illustrated in the case of the mentioned process. Assuming that the process relative degree is known, the adaptive algorithm is based on the nonlinear structure of the process model and is achieved by combining a linearizing control law (Isidori, 1995) with a new state observer and a parameter estimator which play the role of the software sensors for the on-line estimation of biological states and parameter variables of interest of the bioprocess. The resulted control method is applied in a depollution control problem in the case of a wastewater treatment process with active sludge, for which kinetic dynamics are strongly nonlinear and not exactly known.

Dynamical model of bioprocess

The activated sludge process is an aerobic process of biological wastewater treatment (Nejjari et al., 1999). The aim of the wastewater treatment is to reduce the quantities of organic matter, nitrogen, phosphorus and solid matters in suspension. Usually, a wastewater treatment with active sludge is operated in at least two interconnected tanks: an aerator in which the biological degradation of the pollutants takes place and a sedimentation tank (settler) in which the liquid is clarified, that is the biomass is separated from the treated wastewater. A sche-matic view of this bioprocess with two influent pollutants is shown in fig. 1. This wastewater treatment is a very complex process, strong nonlinear and characterized by uncertainties regarding its parameters. In this paper, a simplified model of a wastewater treatment process for the removal of two pollutants (S_1 and S_2) from the treated water will be used. The dynamics of the plant (aerator + settler) is described by the following mass balance equations (Nejjari et al., 1999):

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(Review and revised version 23. 2. 2010)

$$\dot{X}(t) = \mu(t)X - D(1+r)X + rDX_r \qquad (1)$$

$$\dot{S}_1(t) = -(\mu(t)/Y_1)X - D(1+r)S_1 + DS_{in1} \qquad (2)$$

$$\dot{S}_2(t) = -(\mu(t)/Y_2)X - D(1+r)S_2 + DS_{in2} \qquad (3)$$

$$\dot{C}(t) = -k_C(\mu(t)/Y_1 + \mu(t)/Y_2)X - D(1+r)C + \alpha W(C_{\max} - C) + DC_{in} \qquad (4)$$

$$\dot{X}_r(t) = D(1+r)X - D(\beta + r)X_r \qquad (5)$$

where X, S_1, S_2, C and X_r are the concentrations of the biomass (active sludge) in the aerated tank, of the substrate (pollutant) 1, of the substrate (pollutant) 2, of the dissolved oxygen and of recycled biomass respectively, $C_{\max}$ is the maximum concentration of dissolved oxygen,

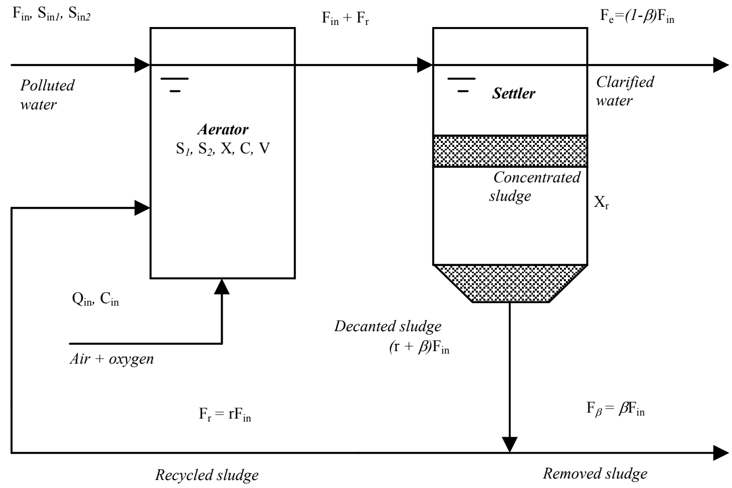

Fig. 1. Schematic view of an activated sludge process.

D = F_{in}/V – the dilution rate (F_{in} the influent flow rate and V the constant aerator volume), μ – the specific growth rate, Y_1 and Y_2 are the consumption coefficients of substrates S_1 and S_2 respectively, r – the rate of recycled sludge, β – the rate of removed sludge, k_C – a model constant, W – the aeration rate, S_{in1} and S_{in2} are the concentrations of influent substrates S_1 and S_2 respectively, and C_{in} is the concentration of dissolved oxygen in the inflow.

Control strategies

The main control objective in the case of the activated sludge process is to maintain the wastewater degradation at a desired low level, despite the load and concentration variations of the pollutants. Furthermore, an adequate control of dissolved oxygen concentration in aerator is very important. Then, the *controlled variables* are concentrations of pollutant $P = P_1 + P_2$ and dissolved oxygen C inside the aerator, that is $y = [P\ C]^T$. Regarding the *input control variables*, the most realistic case is that when the rate of recycled sludge r and the air flow rate W are the control inputs: $u = [r\ W]^T$.

From (1)-(5) it can be seen that relative degrees of both controlled variables P and C, respectively, are equal to 1; therefore a square model [Petre *et al*. 2008] with two inputs and two outputs is obtained:

$$\dot{P}(t) = -(1/Y_1 + 1/Y_2)\mu(t)X - D(1+r)P + D(S_{in1} + S_{in2}) \qquad (6)$$

$$\dot{C}(t) = -k_c(1/Y_1 + 1/Y_2)\mu(t)X - D(1+r)C + \alpha W(C_{\max} - C) + DC_{in} \qquad (7)$$

For this class of wastewater treatment processes, the *control objective* is to make outputs y to track some specified piecewise constant references $y^* = [P^*\ C^*]^T$.

For this process we consider that the specific growth rate μ(t) is described by a Monod-type model, i.e. (Nejjari et al., 1999):

$$\mu(t) = \mu_{\max}\frac{S_1}{K_{S1} + S_1}\cdot\frac{S_2}{K_{S2} + S_2}\cdot\frac{C}{K_C + C} \qquad (8)$$

with $\mu_{\max}$ – the maximum specific growth rate of the microorganisms, K_{S1}, K_{S2} – the saturation constants for the substrate S_1 and S_2 respecti-vely, K_C – the saturation constant for oxygen.

Firstly, we consider the ideal case when the process is completely known, and all the state variables are available for on-line measure-ments. It can be shown, after long but rather straightforward calculations applied to linear approximations of the model (6), (7), (8) that, the process is minimum phase. Assuming that for the closed loop system we wish to have a first order linear stable dynamical behaviour as

$$(\dot{y}^* - \dot{y}) + \Lambda \cdot (y^* - y) = 0 \tag{9}$$

with $\Lambda = diag\{\lambda_1, \lambda_2\}$, $\lambda_1, \lambda_2 > 0$, then, under the above conditions, from (6), (7) and (9) we obtain the following *multivariable decoupling feedback linearizing control law*:

$$\begin{bmatrix} r \\ W \end{bmatrix} = B^{-1} \cdot \left(\begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \cdot \begin{bmatrix} P^* - P \\ C^* - C \end{bmatrix} - \begin{bmatrix} D(S_{in1} + S_{in2} - P) \\ D(C_{in} - C) \end{bmatrix} - \begin{bmatrix} -(1/Y_1 + 1/Y_2) \\ -k_C(1/Y_1 + 1/Y_2) \end{bmatrix} \mu X \right) \tag{10}$$

where the matrix $B = \begin{bmatrix} -DP & 0 \\ -DC & \alpha(C_{max} - C) \end{bmatrix}$ is nonsingular and so invertible as long as P and $C_{max} - C$ are different from zero (conditions satisfied in a normal process operation).

Since the prior knowledge concerning the process assumed previous is not realistic, in the following we will develop an *adaptive control algorithm* under the following realistic conditions: the specific growth rate μ is incompletely known and time-varying, the concentrations of biomasses X and X_r are not accessible, and the only measurements available on-line are: the output pollution level y, the dissolved oxygen concentration C and the influent substrate concentrations S_{in1} and S_{in2}. Under these conditions an *adaptive controller* is obtained by combining the linearizing control law (10) with a new state observer for the estimation of the unknown state X and a parameter estimator for the estimation of the unknown specific growth rate μ.

The unmeasured variables X and X_r can be estimated by using an asymptotic state observer (Dochain, Vanrolleghem, 2001). For that, let us define the auxiliary variables z_1, z_2 and z_3 as follows:

$$\begin{aligned} z_1 &= (1/Y_1 + 1/Y_2)X + P \\ z_2 &= K_C(1/Y_1 + 1/Y_2)X + C \\ z_3 &= X_r \end{aligned} \tag{11}$$

whose dynamics derived from model (1)-(5) are independent of the unknown kinetics:

$$\begin{aligned} \dot{\hat{z}}_1 &= -D(1+r)\hat{z}_1 + D\big((1/Y_1 + 1/Y_2)r\hat{z}_3 + S_{in1} + S_{in2}\big) \\ \dot{\hat{z}}_2 &= -D(1+r)\hat{z}_2 + D\big(K_C(1/Y_1 + 1/Y_2)r\hat{z}_3 + C_{in}\big) + \alpha W(C_{max} - C) \\ \dot{\hat{z}}_3 &= -D(\beta + r)\hat{z}_3 + D(1+r)(\hat{z}_1 - P)\big(Y_1 Y_2/(Y_1 + Y_2)\big) \end{aligned} \tag{12}$$

Then, from (11) and (12) the estimates of X and X_r are given by:

$$\hat{X} = (\hat{z}_2 - P)/(1/Y_1 + 1/Y_2)\,,\ \hat{X}_r = \hat{z}_3 \tag{13}$$

Now, the incompletely known specific growth rate μ in (8) can be rewritten as follows:

$$\mu(S_1, S_2, C) = S_1 S_2 C \cdot \theta \tag{14}$$

where θ is an unknown function depending of the process components, which will be on-line estimated by using an appropriately parameter estimator.

Using (12), (13) and (14), the *adaptive* version of the controller (10) is given by:

$$\begin{bmatrix} r \\ W \end{bmatrix} = B^{-1} \left(\begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \cdot \begin{bmatrix} Y^* - Y \\ C^* - C \end{bmatrix} - \begin{bmatrix} D(S_{in1} + S_{in2} - Y) \\ D(C_{in} - C) \end{bmatrix} + \begin{bmatrix} -S_1 S_2 C(\hat{z}_1 - S)\hat{\theta} \\ -S_1 S_2 C(\hat{z}_2 - C)\hat{\theta} \end{bmatrix} \right) \tag{15}$$

In (15) the variables $\hat{z}_1$ and $\hat{z}_2$ are calculated via equations (13) and $\hat{\theta}$ is updated by using an observer-based parameter estimator [Petre 2002] that here is particularized as follows:

$$\dot{\hat{P}} = -S_1 S_2 C(\hat{z}_1 - P)\hat{\theta} + D(S_{in1} + S_{in2} - (1+r)P) \quad + \omega_1(P - \hat{P}) \tag{16}$$

$$\dot{\hat{C}} = -S_1 S_2 C(\hat{z}_2 - C)\hat{\theta} + D(C_{in} - (1+r)C) \ + \alpha W(C_{max} - C) + \omega_2(C - \hat{C}) \tag{17}$$

$$\dot{\hat{\theta}} = -\gamma_1 S_1 S_2 C(\hat{z}_1 - P)(P - \hat{P}) \ - \gamma_2 S_1 S_2 C(\hat{z}_2 - C)(C - \hat{C}) \tag{18}$$

where ω_1, ω_2, γ_1 and γ_2 are positive design parameters used to control the stability and convergence of the estimator (see [Sastry and Bodson 1989, Petre 2002], for stability and convergence properties).

Simulation results. Conclusions

The performance of the designed multi-variable adaptive controller (15) by comparison to the exactly linearizing controller (10) (which can be used as benchmark), has been tested by performing extensive simulation experiments.

The values of bioprocess parameters used in simulations are given in [Petre *et al*. 2008].

The system's behaviour was analyzed assuming that the pollutant concentrations S_{in1} and S_{in2} act as perturbations of the form $S_{in1}(t) = 800(1+0.2\sin(\pi t/ 20))$, $S_{in2}(t) = 700(1+0.2\cos(\pi t/ 15))$, and the kinetic coefficient μ_{max} is time-varying as $\mu_{max}(t) = \mu^0_{max}(1+0.1\sin(\pi t/10))$. Also, the influent flow rate F_{in} is time-varying. The gains and the tuning parameters of the control laws (10) and (15) are $\lambda_1 = 0.4$, $\lambda_2 = 1.5$, $\omega_1 = \omega_2 = -50$, $\gamma_1 = \gamma_2 = 2.0\text{e-}6$.

The behaviour of closed-loop system using adaptive controller, by comparison to the exactly linearizing law is presented in Fig. 2.

The first two graphics correspond to the controlled variables *P* and *C* respectively and the last two graphics correspond to the two control inputs. It can be seen that the response of the overall system with adaptive controller, even if this used much less a priori information, is comparable to those obtained using the linearizing controller.

Note also the regulation properties and the ability of the adaptive controller to maintain the pollutant *P* at a very *low level* despite the high load variations (for S_{in1}, S_{in2} and F_{in}), and time variation of process parameters.

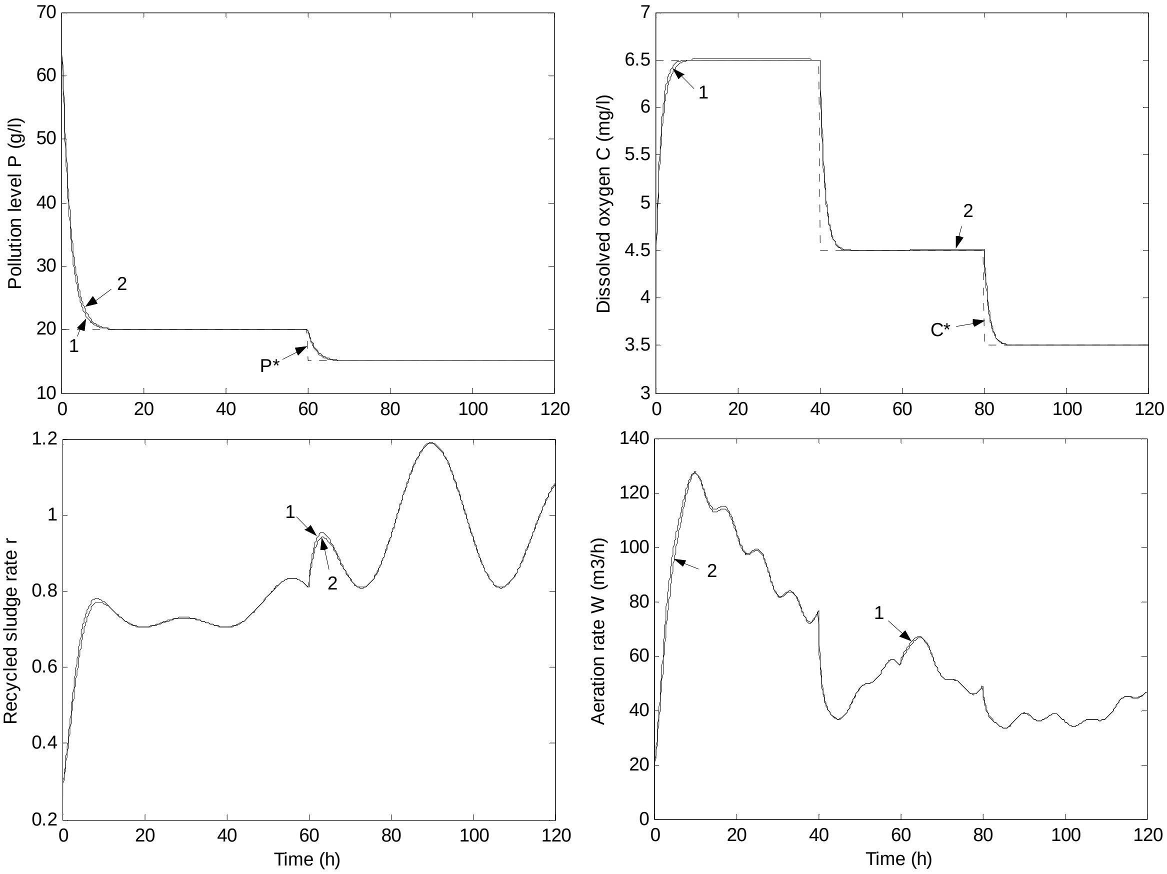

Fig. 2. Simulation results of adaptive control – 2, by comparison to exactly linearizing control – 1.

Acknowledgement
This work was created in the frame of the research project CNCSIS Id548/2009, Romania.

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