Adaptive Control for a De-pollution Bioprocess

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***Abstract*— This paper deals with the design of an interval observer for estimation of some state variables in an uncertain biotechnological process. The observer is applied to estimate the biomass concentration in an anaerobic bioprocess with a simplified mathematical model. In this approach only the bounds of the biomass concentration and the synthesis product concentration can be estimated by using appropriately designed interval observer. Based on this observer a robust-adaptive control strategy of a substrate inside the reactor is proposed. The performance of the proposed adaptive control strategy is illustrated by numerical simulations applied in the case of an anaerobic bioprocess for which kinetic dynamics are highly nonlinear, time-varying and incompletely known.**

Keywords- interval observer; adaptive control; wastewater treatment bioprocess; biomass estimation.

I. INTRODUCTION

In the case of biotechnological processes, a frequent and important challenge is finding adequate and reliable sensors to measure all important state variables of the plant. Nowadays, there are a number of on-line sensors able to provide state information, but they are very expensive and their maintenance is usually time consuming [1].

Furthermore, the biological systems contain living organisms that are not perfectly described by the physical laws, are strongly nonlinear, and they have poorly understood dynamics. This is one strong motivation for using robust methods for the control of this type of systems and for the estimation of the variables that are not measured [2]. By using control methods for the processes in the living organisms, the engineering motivation is to achieve better operational stability and production efficiency [3].

As biotechnological processes have gained an increasing importance in everyday life, a series of observers for nonlinear biological processes have been proposed, that can be chosen in accordance with the information available on the model that is being used [4].

In the last decade, the optimization of this kind of processes and mainly of wastewater treatment receives increased attention. The scientists are interested of designing new control strategies that guarantee a better process working and efficiency. However, these controllers often require high quality measurements or efficient state estimation procedures [10].

If a high gain observer is used for obtaining a good estimation of the internal state, the availability of a good model is necessary [3].

If in the parameters model is a large number of uncertainties, the best option is to use an interval observer, because this method provides an estimate of the quality [1].

Starting from the determination of the control law, we continued by considering all the states in the system known, in order to see how this is acting in open loop, and then in close loop.

Then, we considered that the process model was not completely known, and we proceeded to make estimations for unknown parameters.

The traditional control design involves complicated mathematical analysis and has difficulties in controlling highly nonlinear and time varying plants as well. A powerful tool for nonlinear controller design is the feedback linearization [5], but its use requires the complete knowledge of the process. In practice, there are many processes described by highly nonlinear dynamics; thus an accurate model for these processes is difficult to develop. Therefore, in recent years, great progress in development of adaptive and robust adaptive controllers has been noticed, due to their ability to compensate for both parametric uncertainties and process parameter variations. An important assumption in previous works on nonlinear adaptive control was the linear dependence on the unknown parameters [5].

Adaptive controllers have a strong advantage to the classical PID controller by the fact that can eliminate errors faster and with significantly reduce fluctuations. This advantage allows the process to have a higher profitability [9]. An important disadvantage of adaptive controllers is the requirement of a technical expertise for understanding how they can be fixed if they fail [9].

This paper is divided in five sections: in Section II, the mathematical model of a de-pollution process is described; Section III presents an adaptive control strategy, Section IV is dedicated to the formulation of an interval observer, and Section V concludes the paper.

II. MATHEMATICAL MODEL

Pollution can be defined by the modification of the physical, chemical and biological components which is damaging for the human beings and for the environment.

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Pollution is obtained by adding pollutants in the environment [6].

In the last few years, the importance of biotechnology and of automatic control for de-pollution processes is permanently growing [6].

In this paper, we consider a process described by the following reaction [6]:

$$S \xrightarrow{r \leftarrow} X + P \quad (1)$$

In equation (1), the following symbols appear:

X – Biomass concentration [g/l]
S – Substrate concentration [g/l]
P – Synthesis product concentration [g/l]
r – reaction rate that is defined by the equation:

$$r = \mu(S,P)X$$

This model is a very simple one, because only one main bacterial population is considered.

This is a prototype of the de-pollution bioprocesses whose dynamic model is described by the equations [6].

$$\frac{dX}{dt} = \mu(S,P)X - DX_1 \quad (2)$$

$$\frac{dS}{dt} = -k_1\mu(S,P)X - D(S - S_{in}) \quad (3)$$

$$\frac{dP}{dt} = k_2\mu(S,P)X - DP \quad (4)$$

Beside the symbols from equation (1), in the system (2)-(4), there are also present the variables:

D – Dilution rate [h^{-1}]
μ – Specific growth rate [h^{-1}]
k_1, k_2 – maintain constant [dimensionless]
S_{in} – feed substrate concentration [g/l]

Specific growth rate is assumed to be of the following form [4]:

$$\mu(S,P) = \mu^* \frac{S}{K_M + S + S^2/K_I} \frac{P}{K_P + P}\left(1 - \frac{P}{P_L}\right) \quad (5)$$

The maximum specific growth rate is noted with μ^*; K_M is a notation for half the saturation constant associated with S, and with K_I the inhibition constant is noted [1].

The kinetic parameters necessary to calculate the specific grow rate have the following values [6]:

$$\mu^* = 0.53\,h^{-1}; \quad K_M = 0.26\,g/l \quad K_I = 297\,g/l;$$
$$K_P = 7.77\,g/l \qquad P_L = 85.81\,g/l$$

The yield coefficients for the proposed model are [6]: $k_1 = 1.5$ and $k_2 = 1$.

The initial condition that are use for this paper are [6]: $X(0) = 0.37$, $S(0) = 90$, $P(0) = 6.1$, $S_{in}(0) = 100$.

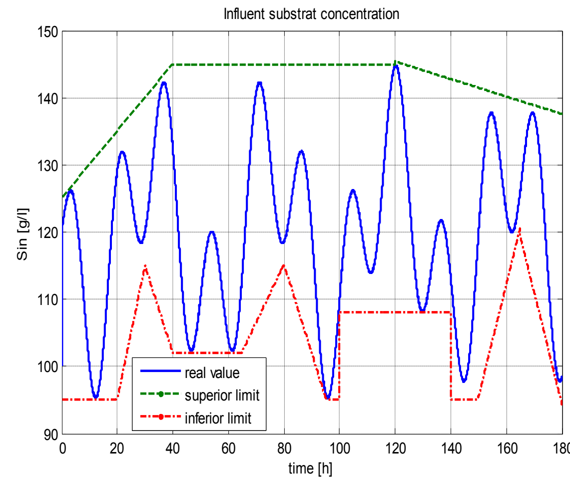

Figure 1. The evolution of feed substrate concentration S_{1in}.

In figure 1, a possible form for the real feed substrate is presented. Because we don't know anything about the real shape of feed substrate evolution, we can choose any form that is placed in a bounded domain ranges between the two limits: an inferior limit denoted by S_{in}^- and a superior limit denoted by S_{in}^+. Because of only this limits of the feed substrate concentration must to be known, the shape of real feed substrate can be completely random.

The real feed substrate concentration in Fig. 1 is also corrupted with an additive white noise with zero average (5% from their nominal values).

III. CONTROL STRATEGIES

A. Control Objective

The control objective consists in the adjustment of the system in order reduce the level of pollution in the wastewater. To be exact, considering that the process model (2)-(4) is incompletely known, its parameters are time varying and not all the states are available for the measurements, the control goal is to maintain the process at some operating points, which correspond to a minimal pollution rate [7].

We have chosen that the operating point is best to be kept around the point $S^* = 35$ g/l.

B. Exactly Linearizing Feedback Controller

First, we want to evaluate the ideal case where all the knowledge concerning the process (kinetics, yield coefficients and state variables) is available [14].

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Let us consider a closed loop system whose dynamics are in accordance with a stable first order linear system, which is described by the equation below [15]:

$$\frac{d}{dt}\left(S^* - S\right) + \lambda_1\left(S^* - S\right) = 0 \tag{6}$$

Assuming $\lambda_1 = 0.5$, $\frac{dS^*}{dt} = 0$, we will have:

$$\frac{dS}{dt} = \lambda_1\left(S^* - S\right) \tag{7}$$

Replacing $\frac{dS}{dt}$ in (3) with (7), we will obtain:

$$\lambda_1\left(S^* - S\right) = -k_1\mu(S,P)X - D\left(S - S_{in}\right) \tag{8}$$

The control law, which is deduced from the above equation, is given by:

$$D = \frac{1}{S_{in} - S}\left(\lambda_1\left(S^* - S\right) + k_1\mu(S,P)X\right) \tag{9}$$

Because in real experiments some states are not available for on-line measurements, in Section IV, we will estimate the biomass concentration using an interval observer. This means that the biomass concentration is only defined by its superior and inferior bounds. Since the control law (9) depends on X this becomes an adaptive control law described by the following equation:

$$D = \frac{1}{S_{in} - S}\left(\lambda_1\left(S^* - S\right) + k_1\mu(S,P)\hat{X}\right) \tag{10}$$

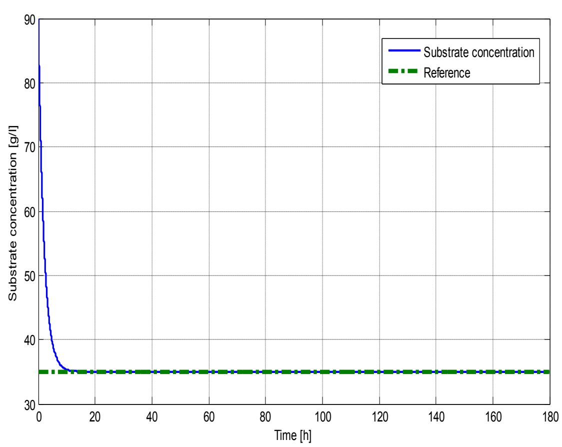

Figure 2. Substrate concentration when the reference is 35 (g/l).

In the equation (10), $\hat{X}$ stand for the arithmetical mean between the two estimated bounds of the biomass concentration.

Figure 2 presents the profile of controlled variable S when the reference is set to 35 g/l.

IV. Interval Observers

Over the last ten years, a series of techniques were developed from which we mention: state estimation by means of convex sets, interval observers and bounded error estimators using interval analysis [2].

Interval observers provide state limits that will be estimated: the upper bound of the state vector provided by the upper observer, and a lower bound determined by the lower observer [3].

Interval observers were introduced in a general context by using the concept of framer, which is definite as a unique pair of estimates able to provide uncertain state limits, without taking into consideration any stability constraint [5].

Interval observers are based on positive differential systems and offer a way to deal with uncertainty in the system, when known bounds of the uncertain terms are available [5].

Note that in this process the feed substrate concentration S_{in} can be considered a disturbance whose exact values are not compulsory to be known, but, in the same time the values of S_{in} can vary between two known limits (an upper limit denoted with "+" and a lower limit denoted with "–"). Knowing these two limits we attempt to estimate all the other immeasurable state variables in model (3) by using all available information.

Therefore in the following we consider that the condition $S_{1in}^- \le S_{1in} \le S_{1in}^+$ is fulfilled.

To estimate the values of the biomass concentration X_1 and the synthesis product concentration P, first we introduce the following two additional variables [8]:

$$z_1 = k_1 X + S \tag{11}$$

$$z_2 = S + \frac{k_1}{k_2}P \tag{12}$$

The dynamics of z_i, $i = 1, 2$ deduced from the process model are expressed by the following linear stable equations [8]:

$$\begin{aligned} \frac{d\hat{z}_1^+}{dt} &= -D\left(\hat{z}_1^+ - S_{in}^+(t)\right) \\ \frac{d\hat{z}_1^-}{dt} &= -D\left(\hat{z}_1^- - S_{in}^-(t)\right) \end{aligned} \tag{13}$$

$$\frac{d\hat{z}_2^+}{dt} = -D\left(\hat{z}_2^+ - S_{in}^+(t)\right)$$
$$\frac{d\hat{z}_2^-}{dt} = -D\left(\hat{z}_2^- - S_{in}^-(t)\right) \tag{14}$$

that are independent of the process kinetics that could be completely unknown.

Because S_{in} is known only by its upper and lower limit, we can observe that in equations (13), (14), the additional values z_1, and z_2, can only be determined by their upper and lower limit values. For this reason, the real values of X_1 and P are located in an interval that is bound by these parameters' limits.

The on-line estimations of X_1 and P are given by the following equations:

$$\hat{X}^+ = \frac{1}{k_1}\left(\hat{z}_1^+ - S\right)$$
$$\hat{X}^- = \frac{1}{k_1}\left(\hat{z}_1^- - S\right) \tag{15}$$

$$\hat{P}^+ = \frac{1}{k_1}\left(\hat{z}_2^+ - S\right)$$
$$\hat{P}^- = \frac{1}{k_1}\left(\hat{z}_2^+ - S\right) \tag{16}$$

In equations (15) – (16) $\hat{X}_1$ and $\hat{P}$ represent the estimations of the biomass concentration X_1 and of the synthesis product concentration P, and the symbols "+" and "–" denoted respectively the upper and lower limits.

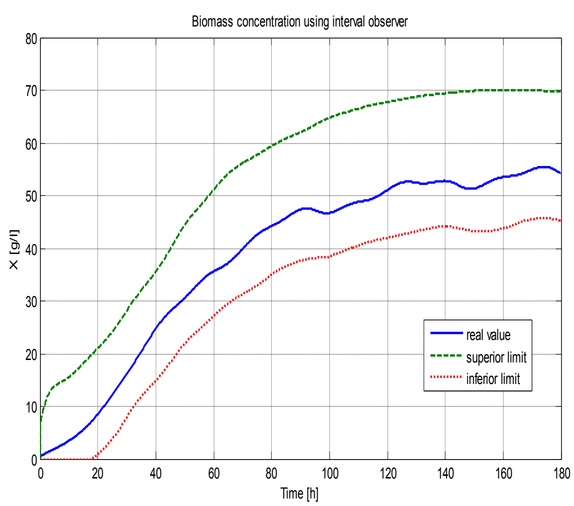

Figure 3. Profile of estimates of unknown biomass concentration versus its real value.

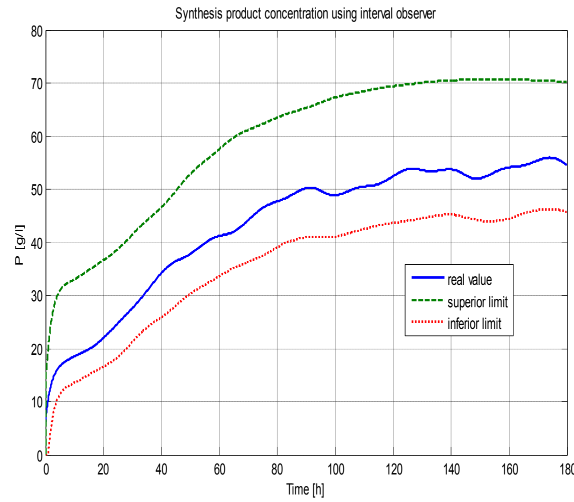

Figure 4. Profile of estimates of synthesis product concentration versus its real value.

The simulations have been carried out using the model comprised of the equations (2) – (4), considering that the process lasts for 180 hours and that the input concentrations are in a guaranteed interval.

The performance of designed interval observers (15)-(16) has been tested by performing extensive simulation experiments. The simulations were carried out by using the process model (2) – (4) under identical and realistic conditions.

In figure 3 and figure 4, the graphics marked with continuous line correspond to values of real concentration of S_{in}, as it should be known while the graphics marked with dotted and interrupt lines correspond respectively to known upper and lower limits of S_{in}.

Using different shapes of feed substrate concentration that are included between two known limits, it can be seen that the behaviour of the proposed interval observers are good, the values of the estimated biomass X_1 and of the synthesis product P remaining between the limits determined from equations (15) and (16).

V. CONCLUSION

In this paper, an interval observer for estimation of some uncertain state variables in an uncertain biotechnological process was designed. Using an interval observer only an upper and a lower bound of the biomass concentration and the synthesis product concentration can be estimated by using an appropriately interval observer. The designed observer was used in an adaptive control problem of a substrate inside a bioreactor.

The effectiveness and performance of the designed interval observers as well as of the adaptive control strategy were illustrated by numerical simulations applied in the case of an anaerobic bioprocess.

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