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Neurofuzzy Control Strategy for an Abattoir Wastewater Treatment Process

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Abstract: In this paper a neurofuzzy control strategy, composed by a neural observer and a fuzzy supervisor, for an anaerobic wastewater treatment process is proposed. The neural observer is based on a recurrent high order neural network (RHONN) which is trained by an extended Kalman filter. The main objective of the observer is to estimate methanogenic biomass, which is employed by a fuzzy supervisor. The tasks of this supervisor are: to detect the biological activity inside the bioreactor, to select and to apply an adequate control action depending on the operating conditions in order to avoid washout. The applicability of the proposed scheme is illustrated via simulations considering the model of a prototype bioreactor which is used to treat effluents collected from an abattoir.

Keywords: bioprocess, anaerobic digestion, neural observer, wastewater treatment, fuzzy control.

1. INTRODUCTION

Abattoirs produce large quantities of wastes and effluents containing a lot of organic pollutants. In many cases, a lot of them are directly rejected to ecosystems without an adequate treatment process (Mittal, 2006; Arvanitoyannis and Ladas, 2008); causing environmental damages and even affecting people life quality. Besides, abattoirs operation requires services as electricity and big quantities of water. Then, the adequate operation of abattoirs is a priority in order to avoid, or at least to minimize, environmental troubles. Efficient processes to treat effluents from abattoirs are an important stage of this production chain which requires special attention.

Anaerobic digestion is one of the more adequate processes to treat wastewater with high organic load. The complex organic molecules are progressively transformed by different bacteria populations in successive stages. The final products of anaerobic digestion are the treated water and a biogas mainly composed of methane and carbon dioxide. Then, these products have additional value since they can be used to offset treatment costs (Ross, 1991); i.e: reusing and/or recycling treated water and employing biogas for energy generation. However, this bioprocess imposes challenges, such as sensitivity to changes on operating conditions (overloads, disturbances), parameters uncertainty (biological growth rates) and high non-linear dynamics. Besides, there exist variables hard to measure due to technical and/or economical constraints, e.g. biomass sensors are expensive, and are based on turbidity or capacitance properties; then, it is difficult to determine specific micro-organism populations and to integrate the provided measures to control strategies. On the other hand, substrate (directly related to COD or BOD) is determined off-line by chemical analysis requiring at least three hours (case of COD) or even days (case of BOD). Then, estimation and control strategies are required in order to guarantee adequate performances.

Anaerobic digestion has been an active research subject from the automatic control viewpoint since many years ago. Different control approaches have been studied as an alternative to improve this kind of process; i.e: linear approaches (Heinzle et al., 1993; Batstone and Steyer, 2007), linearizing feedback control (Bernard et al., 2001; Simeonov and Queinnec, 2006), robust control (Mendez-Acosta et al., 2008; Garcia-Sandoval et al., 2008), adaptive control (Dochain, 1991; Mailleret et al., 2004; Petre et al., 2008;). For most of these approaches, a good knowledge of process structure is required, which cannot be guaranteed. Recently, artificial neural networks and fuzzy control have been proposed as an interesting alternative to deal with anaerobic process problematic (Muller et al., 1997; Murnleiter et al., 2002; Baruch et al., 2008); also, improvement of PID based schemes is being considered as an option to regulate substrate and alkalinity (Alvarez-Ramirez et al., 2002; Yordanova, 2004; Lakrori, 1989; Dantigny et al., 1989). Integrated strategies, which combine control approaches, allow different opposite objectives (such as high methane production and rejecting large hydraulic disturbances) to be reached at same time (Lemos et al., 1999; Soehartanto et al., 1999); however, problems concerning switching between control actions should be solved.

In this paper, a neurofuzzy control strategy, composed of a neural observer and a fuzzy supervisor, is proposed. The neural observer is based on a recurrent high order neural network (RHONN) which is trained using an extended Kalman filter. The main objective is to estimate methanogenic biomass (and substrate related to COD), which is employed by a fuzzy supervisor. The supervisor uses two variables in order to detect the biological activity inside the bioreactor; with this information, it is possible to determine if the process is going to washout or to the operation point. Depending on the process state, an adequate control action (adding a base or modifying dilution rate) is applied. The proposed scheme is validated via simulations on a model obtained from a prototype bioreactor, which is used to treat real effluents from an abattoir.

2. COMPONENTS AND METHODS

2.1. Abattoir effluents characterization

The samples for this work are collected from an abattoir located at Saltillo, Coahuila, Mexico. A characterization, after separation of solid materials is done and the results are shown in Table 1. An important difference with other effluents is that abattoir wastewater contains higher organic load, higher quantities of fats, coliforms and other components; that means it is a more complex substrate. The inoculum (bacteria populations used in the experiments) is obtained from a brewery wastewater treatment plant. Then a preliminary stage is required for the bacteria adaptation to the abattoir substrate.

Table 1. Abattoir effluents composition

Item	Value
Soluble solids	33.5 %
pH	8.0-8.5
Total solids	5166 mg L^{-1}
Total volatile solids	3387 mg L^{-1}
Fats (Soxleth)	1057 mg L^{-1}
Alkalinity (as $CaCO_3$)	1791 mg L^{-1}
COD	5945 mg L^{-1}

2.2. Experimental set-up

First, it is important to mention that bacteria are fixed on a solid support, a Mexican natural zeolite is considered to this end; results obtained in previous works show the potential of this material to be used as support for anaerobic bacteria (Diaz-Jimenez et al., 2008).

Experiments are performed as follows. 4.5 L of wastewater and 500 mL of zeolite colonized by anaerobic bacteria are filled in a 7 L glass reactor, with an initial COD equal to 5800 mg L^{-1} and an initial pH of 7.2. Performances of the wastewater treatment process are evaluated by developing batch tests, with 15 days duration for each one. An example of the obtained results is shown in Fig. 1.

Different tests are performed with similar operating conditions; the obtained results are used for parametric identification of a methanogenesis stage mathematical model. COD, biogas and pH are measured to calculate the model parameters. The model considered in this work is composed of algebraic equations to represent acid-base equilibria and conservation of materials, and differential equations to model the process dynamics. Biogas (methane and carbon dioxide) is considered as the process output.

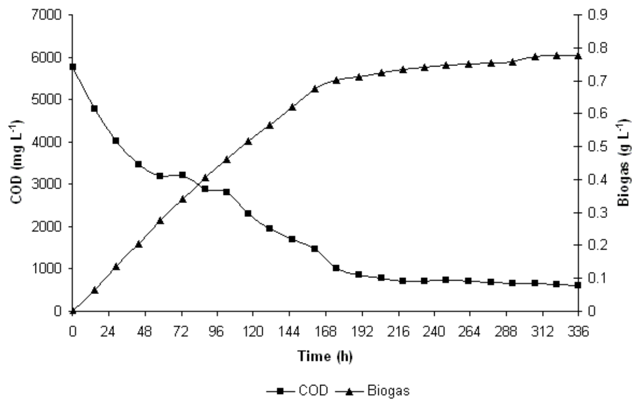

Fig. 1. Biogas production and COD transformation.

The structure of the model is shown in equation (1).

$$
\begin{aligned}
& g(x_a, x_d) = 0 \\
& \dot{x}_d = f(x_a, x_d, u) \\
& y = h(x_d)
\end{aligned}
\tag{1}
$$

with:

$$
\begin{aligned}
x_a &= [HS \quad S^- \quad CO_{2d} \quad B \quad H^+] \\
x_d &= [X_1 \quad S_1 \quad X_2 \quad S_2 \quad IC \quad Z] \\
u &= [S_{1in} \quad S_{2in} \quad IC_{in} \quad Z_{in} \quad D] \\
y &= [QCH_4 \quad QCO_2]
\end{aligned}
$$

where x_a and x_d are algebraic and dynamic variables, respectively; u represents the input vector, y the process outputs; g is a set of linear algebraic equations, f a set of non-linear differential equations and h output functions depending on dynamic variables. The different symbols are defined as follows: HS non ionized acetic acid, S^- ionized acetic acid, CO_{2d} dissolved carbon dioxide, B bicarbonate, H^+ ionized hydrogen, S_1 complex molecules equivalent to glucose, S_2 molecules directly transformed in acetic acid, X_1 represents the bacteria population which transforms S_1, X_2 represents the bacteria population which degrades S_2, IC inorganic carbon, Z the total cations, S_{1in} the fast degradable substrate input, S_{2in} the slow degradable substrate input, IC_{in} the inorganic carbon input, Z_{in} the input cations, D the dilution rate, QCH_4 methane flow rate and QCO_2 carbon dioxide flow rate.

The effect of pH is included on the model by using Haldane growth rates as a function of HS which is directly influenced by this parameter. Besides, Haldane equation allows saturation and inhibition to be considered by means of constants K_s and K_i, respectively. The growth rate for X_2 is calculated as:

$$\mu_2 = \frac{\mu_{2\max} HS}{K_{s2} + HS + HS^2 / K_{i2}} \tag{2}$$

3. PROCESS ATTRACTION REGIONS

Singular perturbations method is used to reduce the process model; after that, a phase portrait analysis is done to determine the attraction regions of the considered process. This is shown in Fig. 2.

Several initial conditions are used to simulate the process, and the respective trajectories are drawn on the phase plane. A typical step on the input substrate is also considered for the simulations. Two operating regions are easily distinguished. On the right region, trajectories have an origin with high substrate concentration, and as the substrate is degraded, they converge to a point where the micro-organisms reach a maximal growth; consequently, the substrate is transformed and reaches a minimal value. This point is known as the functioning one. Indeed, the attraction area to the functioning point is the desired region for process operation. On the other hand, trajectories on the left region converge to a point where the micro-organisms disappear from the reactor, which implies the substrate attains a maximal value because treatment is not possible. This point is known as washout, and to operate the process on its attraction area is undesirable and must be avoided. The line which separates the attraction regions is known as the stability limit.

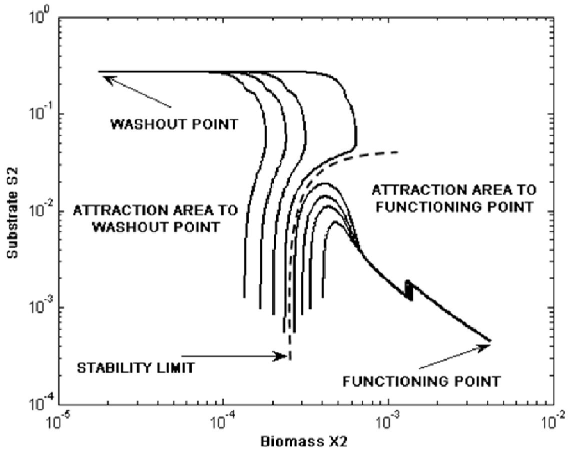

Figure 2. Phase portrait of anaerobic digestion

Simulations show that the anaerobic process is able to reject small disturbances on the input substrates; however, for large disturbances the micro-organisms are not able to treat the substrate, which increases causing washout. Then, for large disturbances, control strategies must be implemented in order to avoid stability limit crossings. Additionally, a supervisor mechanism is required in order to determine when a control action is required.

4. NEUROFUZZY CONTROL STRATEGY

The proposed control scheme is represented in Fig. 3. It is an integrated control strategy. The main idea is to detect the process state by means of a supervisor, which uses the information from the process and from a state observer to select the most adequate control action in order to avoid washout.

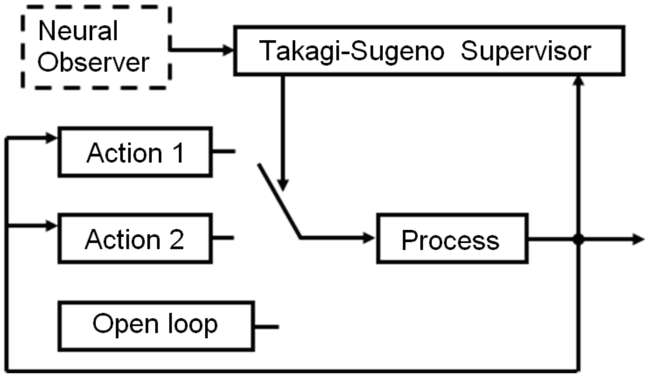

Figure 3. Neurofuzzy control strategy

4.1. Neural Observer Description

Methane production, biomass growth and substrate degradation are good indicators of the biological activity inside the reactor. These variables can be used for monitoring the process and to design control strategies. The existing biomass sensors are quite expensive, and are designed from the biological viewpoint; hence, they are not reliable for control purposes. Furthermore, substrate measure is done off-line by chemical analysis, which requires at least two hours. Then, an observer based on a RHONN trained with an extended Kalman filter (Rovithakis and Chistodoulou, 2000; Sanchez et al., 2008) is proposed for estimation of methanogenic biomass (X_2) and substrate related to COD (S_2). The observer structure is shown in Fig. 4 and represented by equations (3)-(5).

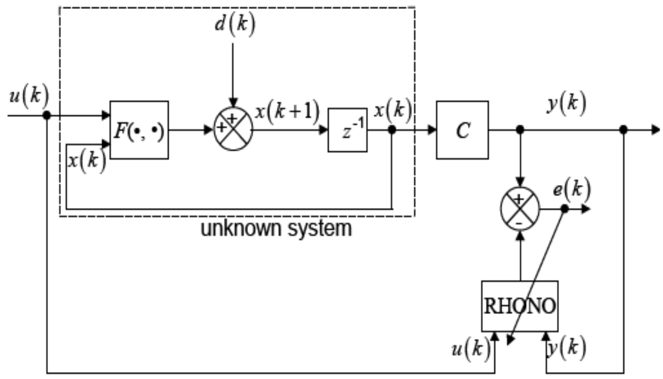

Figure 4. Neural observer scheme.

where k is a real number representing a time sample, $x \in \mathbf{R}^n$ is the state vector, $u \in \mathbf{R}^m$ the input vector, $y \in \mathbf{R}^p$ the output vector, $d \in \mathbf{R}^n$ a disturbance vector, e the output error and $F(\cdot,\cdot)$ a smooth vector field.

$$
\begin{aligned}
\hat{X}_2(k+1) &= w_{11}S\left(\hat{X}_2(k)\right) + w_{12}S^2\left(\hat{X}_2(k)\right) + w_{13}S\left(I\hat{C}(k)\right) \\
&\quad + w_{14}S^2\left(\hat{X}_2(k)\right)D_{in}(k) + L_1 e(k) \\
\hat{S}_2(k+1) &= w_{21}S\left(\hat{S}_2(k)\right) + w_{22}S^2\left(\hat{S}_2(k)\right) + w_{23}S\left(I\hat{C}(k)\right) \\
&\quad + w_{24}S^2\left(\hat{S}_2(k)\right)D_{in}(k) + w_{25}S^2\left(\hat{S}_2(k)\right)S_{2in}(k) + L_2 e(k) \\
I\hat{C}(k+1) &= w_{31}S\left(I\hat{C}(k)\right) + w_{32}S^2\left(I\hat{C}(k)\right) + w_{33}S\left(\hat{X}_2(k)\right) \\
&\quad + w_{34}S^2\left(I\hat{C}(k)\right)D_{in}(k) + w_{35}S^2\left(I\hat{C}(k)\right)IC_{in}(k) + L_3 e(k)
\end{aligned} \tag{3}
$$

with the output given as:

$$\hat{Y}_{CH4} = R_1 R_2 \hat{\mu}_2 \hat{X}_2 \tag{4}$$

$$\hat{Y}_{CO2} = \lambda R_2 R_3 \hat{\mu}_2 \hat{X}_2 \tag{5}$$

where R1, R2, R3 are yield coefficients, λ is a coefficient considering the partial pressure for CO_2.

It is assumed that pH, methane and carbon dioxide are measured, as well as the inputs. Besides, the EKF training is performed on-line. The hyperbolic tangent is used as the activation function:

$$S(x) = \alpha \tanh(\beta x) \tag{6}$$

with $\alpha = \beta = 1$. This function is used because the antisymmetric functions allow the neural network to learn the respective dynamics in a faster way in comparison with other activation functions (Sanchez and Alanis, 2006). In addition, the hyperbolic tangent derivative is easy to obtain.

The neural observer requires on-line measurement of input variables. Among these variables, input substrate is the more restrictive since it is obtained off-line from chemical analysis. Nevertheless, a previous validation stage show that the observer is few sensitive to variations on the input substrate; then, at present time, the delays induced by chemical analysis are not a main problem for the observer. However, some alternatives are currently studied in order to solve this situation (considering unknown inputs, interval inputs, etc.) for further applications at pilot plant scale.

4.2. Fuzzy supervisor

From the phase portrait analysis and empirical experience, it is known that anaerobic digestion is able to work adequately even in presence of small input disturbances. However, in presence of large disturbances, a control law is required in order to maintain the process stability and consequently substrate degradation and methane production.

The organic daily load per biomass unit (ODL/X_2) defined as in (7) is important regarding process operation limits due to its relation with disturbances amplitude on input substrate.

$$ODL/X_2 = \frac{DA_2 S_{2in}}{\hat{X}_2} \tag{7}$$

where D is the dilution rate, A_2 the disturbance amplitude (dimensionless) on the input substrate, S_{2in} the input substrate before the disturbance inception and $\hat{X}_2$ is the observed biomass.

In presence of a disturbance on S_{2in}, ODL/X_2 can abruptly increase up to a value, which exceeds the conditions of stability limits (critical value); therefore the process tends to washout. If ODL/X_2 is above its critical value then a control law must be applied in order to allow biomass growth, and hence, diminishing ODL/X_2 and leading the process to the functioning region. In contrast, if ODL/X_2 is under its critical value then the system can work in open loop. Then, the input disturbances can be classified by this variable into small, average and large. For this reason, three fuzzy sets are determined as shown in Fig. 5. On the other hand, disturbances on input substrate affect methane production: a small variation on the methane production could be caused by small disturbances which can be rejected by the process without a control action; meanwhile, a high variation is caused by a larger disturbance which requires a control action. Then, two fuzzy sets are chosen as shown in Fig. 5.

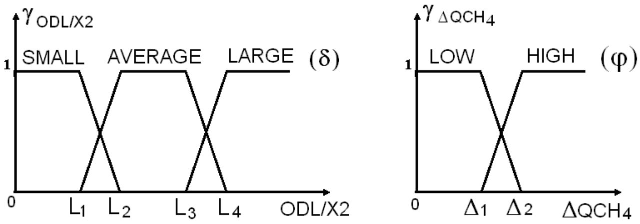

Fig. 5. Fuzzy sets for the supervisor.

For small disturbances, the process is able to operate in open loop. For closed loop, two PI L/A control actions (Lakrori, 1989; Dantigny et al., 1989) could be applied in order to regulate bicarbonate inside the reactor: a) adding a base (8), which allows the process to have high methane production, but rejecting only small disturbances (bigger than for open loop), and b) dilution rate (9), which cause low methane production but allow large disturbances to be rejected.

$$b_{inc\_k} = (b_{inck-1} - b_{inc})\left(\frac{B_{k-1}}{B_k}\right)^{K_{1b}}\left(\frac{B_k^*}{B_k}\right)^{K_{2b}} + b_{inc\_\min} \tag{8}$$

$$D_k = D_{k-1}\left(\frac{B_{k-1}}{B_k}\right)^{K_{1D}}\left(\frac{B_k^*}{B_k}\right)^{K_{2D}} \tag{9}$$

where k is an integer which represent a sample time, b_{inc} is the added base, B is the measured bicarbonate, B^* is the reference, b_{inc_min} is the minimal value for the bicarbonate, D is the dilution rate, K_{1b} (K_{1D}) and K_{2b} (K_{2D}) are the proportional and integral gains respectively for each control action.

From this information, six fuzzy rules having the next form are deduced:

If ODL/X_2 is (δ) and ΔQCH_4 is (φ) then u_i

where (δ) can be LITTLE, AVERAGE or BIG; (φ) can be NORMAL or HIGH, and u_i can be b_{inc}, D or open loop.

Defuzzification is done as follows:

$$u = \frac{\sum_{j=1}^{R} \gamma_j u_j}{\gamma_j} \qquad (10)$$

where $\gamma_j = \gamma_{ODL/X2} * \gamma_{\Delta QCH4}$ and $\sum_{j=1}^{R} \gamma_j = 1$; R is the number of rules, l and k are stand for the l^{st} and the k^{st} fuzzy sets of COJ/X_2 and ΔQCH_4, respectively.

5. RESULTS AND DISCUSION

A set of simulations close to real conditions and considering a model experimentally validated are done in order to evaluate the performances of the control strategy. A disturbance A_2=1.4 inception occurs at time t=50 h; the process behavior is shown in Figure 6. ΔQCH_4 belongs to LOW and *ODL/X2* belongs to SMALL; both fuzzy sets are associated to OPEN LOOP; then a control action is not required. For this reason, the supervisor allows the process to operate in open loop (b_{inc} and D constants at equilibrium values). A brief oscillatory period is remarked on X_2 when the disturbance inception occurs, this behaviour is induced by the neural observer; a deeper study is in progress concerning the integration of the neural observer in the control strategy.

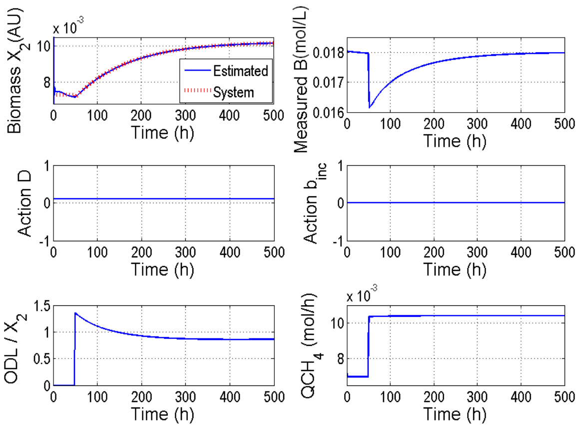

Figure 6. Performance with small disturbance on S_{2in}

A disturbance A_2=2.2 is considered at time t=50 h; the obtained results are shown in Figure 7. The control strategy induces the next behavior: ΔQCH_4 belongs to HIGH (associated to closed loop) meanwhile *ODL*/X_2 belongs to LARGE (associated to *D* action). Then, the supervisor allows the *D* action to be applied; consequently, *B* starts to be regulated and X_2 tends to a new equilibrium value. As the action is applied, ΔQCH_4 continues to belong to HIGH, meanwhile *ODL*/X_2 decreases and belongs to AVERAGE (associated to b_{inc} action). Then, action D is progressively stopped and b_{inc} starts to be applied. Consequently, X_2 and B decrease when D is stopped; when b_{inc} is applied X_2 and B increase again leading to a new equilibrium point. Finally, ΔQCH_4 leaves HIGH and belongs to LOW (associated to open loop); meanwhile *ODL*/X_2 decreases and belongs to SMALL (associated to open loop). That means, the disturbance has been rejected. Then, the supervisor stops b_{inc} action and the process operates in open loop again. On the other side, large disturbances affect the estimation of X_2; nevertheless, the control strategy is able to keep the process in the operating point attraction region.

A disturbance corresponding to 10% on *pH* is considered at time t=50 h. this disturbance represents a change on the acidity level on the input substrate due to other operating condition in the abattoir (kind of sacrificed animals, etc.) This change on pH implies a modification on the bicarbonate reference. The process behavior is shown in Figure 8. The supervisor evaluates the process state determining that ΔQCH_4 and *ODL/X2* belong LOW and SMALL respectively; then, control actions are not required. On the other side, pH comes to a new equilibrium point as well as bicarbonate.

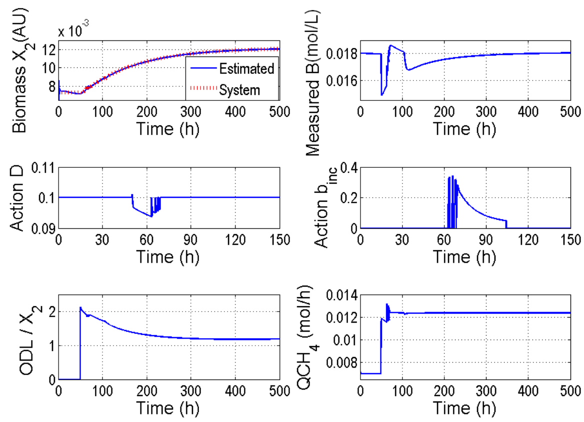

Fig. 7. Performance with small disturbance on S_{2in}

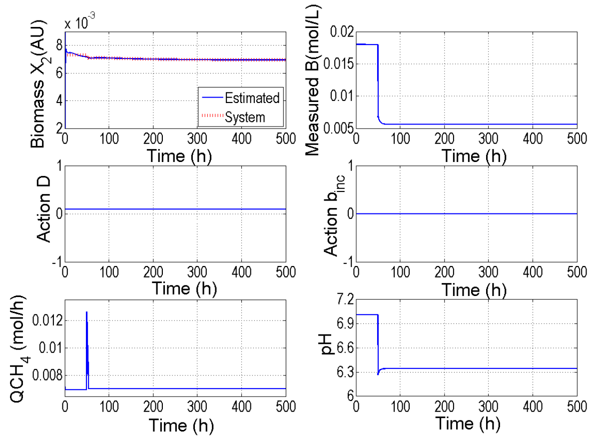

Fig. 8. Performance with disturbance on pH

6. CONCLUSIONS AND PERSPECTIVES

From simulations, it is possible to conclude that the proposed control strategy enhances the process performance. The supervisor detects the biological activity inside the reactor and applies the required control action in order to keep the system on the operating area. For small disturbances the supervisor determines that a control action is not necessary and the system operates in open loop. This is an economic advantage since energy and the basic solution used by control actions is saved. The control strategy allows the process to reject large disturbances, this implies the treatment of high quantities of substrate and to obtain a high biogas production.

Some works are in progress in order to improve the integration of the observer in the control strategy. The idea is to avoid the oscillations on biomass in face of large disturbances. Other current work concerns the study of a neural observer with interval inputs in order to overcome the difficulty to measure the input substrate. In addition, different opportunities exist for further developments as: a methodology to tune the supervisor parameters, in order to formalize the empirical knowledge, and the experimental validation of the proposed strategy.

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