

INTELLIGENT CONTROL STRATEGY FOR AN ANAEROBIC FLUIDIZED BED REACTOR

S. Carlos-Hernandez^a, J.F. Beteau^b and E.N. Sanchez^c

^a*CINVESTAV del IPN, Km 13, Carr. Saltillo-Mty 25900 Ramos Arizpe, Mexico
email: salvador.carlos@cinvestav.edu.mx*

^b*Laboratoire d'Automatique de Grenoble, Rue de la Houille blanche 38034 St Martin d'Herès, France*

^c*CINVESTAV del IPN, Apdo Postal 31-438, Plaza La Luna, 45090 Guadalajara, Mexico*

Abstract: This paper deals with the control of the anaerobic digestion process in a fluidized bed reactor. The main idea is to develop a supervision mechanism which selects the most appropriate control action in function of the process state and the operating conditions. The supervisor is built on the basis of the Takagi-Sugeno algorithm and the control actions are implemented as fuzzy L/A PI controllers. The empirical knowledge is considered to build the fuzzy rules of the control strategy. *Copyright © IFAC 2007.*

Keywords: bioprocess control, anaerobic digestion control, supervisor control, intelligent control strategy, fuzzy control, PI controllers, wastewater treatment.

1. INTRODUCTION

Anaerobic digestion is a biological process used to transform progressively organic loads into biogas. Several studies (Buswell and Sollo, 1948; Bryant, 1979; Klass, 1984; Pind et al., 2003) have demonstrated that the produced gas is composed principally by methane and carbon dioxide; other gases are produced in minimal proportion. That is meaning, the most of the produced biogas can be used as an energy source. Then, the anaerobic digestion offers environmental and energetic benefits. However, this is a complex process composed by several phenomena and stages which have different dynamics which must be in equilibrium to avoid blockages. Furthermore, the process is sensitive to variations in the operating conditions such as the input flow rate, the pollutant concentration, pH, temperature, etc.

The anaerobic digestion is available to operate even if there are small variations in the operating conditions, but if those variations are larger, it is necessary to apply a control action to keep the process working. The conventional way to control this process is using only one control action, usually

dilution rate, addition of a base or input substrate, in order to reach one objective, usually avoid instability, enhance methane production or reject disturbances. Several methods and techniques have been tested to control anaerobic digestion as shown in (Yamuna Rai and Kamachandra Rao, 1999; Van Lier et al., 2001). The linear controllers are easy to design and implement, but they are limited to local operating points and frequently they are not the most adequate for the bioprocesses. Otherwise, the non-linear control allows considering the non-linear dynamics of the processes improving performances, the main disadvantage of these techniques is the complexity of the control laws and sometimes, the real implementation (Hilgert, et al., 2000; Seok, 2003). In recent years, intelligent control has been studied to be applied on bioprocesses because it is easy to design, it allows considering the empirical knowledge and the implementation is relatively simple (Muller et al., 1997; Honda and Kobayashi, 2004). The proposed strategy here is an integrated one which considers different control actions (dilution rate, addition of a base, open loop) to reach several objectives (avoid instability, disturbance rejection, methane production). The main idea is to detect disturbances supervising some key variables

such as biomass, methane production and daily organic daily load (ODL). These variables are indicators of the biological activity into the reactor and they allow determining the process state. With this supervision, the control system will determine if a control action is necessary or not. If yes, then the supervisor will select the most adequate control action according to the operating conditions. If not, the anaerobic digestion process will operate without a control action. It is important to remark that some variables cannot be measured from a perspective of automatic control, in example; the existing biomass sensors are designed from a biologic perspective and are not adapted to design controllers. To solve this situation, virtual sensor known as state observers are required. In previous works, a similar strategy was tested in a completely stirred tank reactor (CSTR) (Sanchez et al., 2001a; 2001b). Also, state observers were proposed for both CSTR and Fluidized Bed Reactor (FBR) (Carlos-Hernandez et al., 2005). Here, In this paper, a FBR is considered: the hydrodynamic behaviour is more complex and then some modifications are required. Furthermore the supervisor system is improved: only two fuzzy variables and six inference rules are considered.

2. THE ANAEROBIC DIGESTION IN FBR

Anaerobic digestion is a bioprocess widely used to treat effluents with high organic load. The bioprocess is composed by four successive stages: hydrolysis, acidogenesis, acetogenesis and methanogenesis. The input complex molecules (substrate) are degraded by means of anaerobic bacteria (biomass) producing biogas: methane (CH₄) and carbon dioxide (CO₂). The stages can be classified as very fast (acidogenesis, acetogenesis), fast (hydrolysis) and slow (methanogenesis). The last one is considered as the limiting stage because it has the slowest dynamic, it is the most sensitive to variations on the operating conditions (Mousa and Forster, 1999, Otton et al., 2000), but in this stage the methane is synthesized. Then, this is the most interesting stage from a control and energy perspectives. By this reason, only the methanogenesis will be considered in this paper.

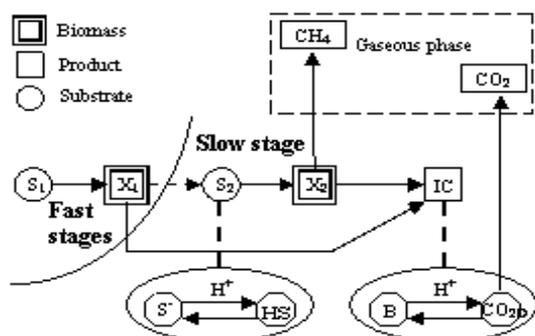


Fig. 1. Functional scheme of anaerobic digestion

Dynamic of the very fast stages is assumed to be neglected. Hydrolysis dynamic cannot be neglected

because it is faster than methanogenesis but not as acidogenesis and acetogenesis. Then it is possible to consider the two phases of figure (1): slow stage (methanogenesis) and fast stages (the other phases).

2.1 Physico-chemical phenomena

These phenomena correspond to equilibria and matter conservation. Usually they are represented by algebraic equations. From the acid-base equilibrium between acetate (S⁻) and non-ionized acetic acid (HS) two equations are deduced; first one, for the substrate conservation, and second one, for acid-base equilibrium with an equilibrium constant K_a. An algebraic equation is stated considering inorganic carbon production (IC) from bicarbonate (B) and carbon dioxide CO_{2d} and another equation for equilibrium between them by means of the constant K_b. The fifth equation represents the electroneutrality in the reactor, where Z is stands for the cations. The set of algebraic equations is:

$$\begin{aligned} H^+ S^- - K_a HS &= 0 \\ HS + S^- - S &= 0 \\ H^+ B - K_b CO_{2d} &= 0 \\ B + CO_{2d} - IC &= 0 \\ B + S^- - Z &= 0 \end{aligned} \quad (1-5)$$

2.2 Biological phenomena

The biological activity (biomass evolution, substrate consumption and inorganic carbon produced) is represented by ordinary differential equations. The substrate produced in the fast stages is the input substrate for the methanogenesis. This substrate is considered as *acetic acid* equivalent and it is named S₂. The bacteria population (biomass) is known as X₂ which grows at a rate μ consuming the substrate. Y₁ is the consumption yield coefficient. The inorganic carbon evolution is a result of the biological phase and the law of partial pressure for the dissolved carbon dioxide must be considered. In addition, the cations are biologically inert, that is meaning, its evolution depends only on the input substrate. Then, the dynamic part of the model is:

$$\begin{aligned} \frac{dX_2}{dt} &= \mu X_2 \\ \frac{dS_2}{dt} &= -Y_1 \mu X_2 \\ \frac{dIC}{dt} &= \lambda Y_1 Y_2 \mu X_2 \\ \frac{dZ}{dt} &= 0 \end{aligned} \quad (6-9)$$

$$\text{where } \mu = \frac{\mu_{\max} HS}{k_s + HS + HS^2/k_i}, \text{ and } \lambda = \frac{PCO_{2d}}{P_i - PCO_{2d}}$$

P_i is stands for total the pressure and PCO_{2d} for the partial pressure of the dissolved carbon dioxide.

Finally, methane and carbon dioxide flow rates are stated as process outputs. Both variables are typically measured in this kind of process.

$$\begin{aligned} Q_{CH_4} &= Y_1 Y_2 \mu X_2 \\ Q_{CO_2} &= \lambda Y_3 Y_2 \mu X_2 \end{aligned} \quad (10-11)$$

2.3 Hydrodynamic phenomena

Hydrodynamic behaviour of a FBR (figure (2)) is complex due to spatial distribution, and the substrate feedback.

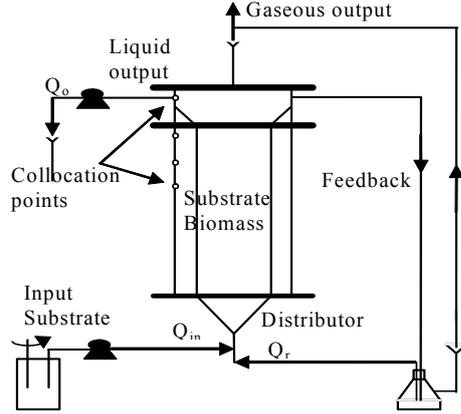


Fig. 2. Structure of a fluidized bed reactor.

Fluidization is an operation to keep homogeneous agitation of solid particles in a liquid or gaseous environment. In this case, hydrodynamic of soluble components was deduced from experiments resulting a piston with axial dispersion behaviour as explained in (Otton *et al.*, 2000).

$$\frac{\partial x(t, z)}{\partial t} = -U_i \frac{\partial x(t, z)}{\partial z} + D_a \frac{\partial^2 x(t, z)}{\partial z^2} \quad (12)$$

where U_i is the interstitial speed and D_a is the axial dispersion coefficient. Both were determined experimentally as reported in (Otton *et al.*, 2000).

This is a distributed parameters system. To approach the system to a finite dimension model there exist several methods, for example: pondering remaining and orthogonal collocation; first one is an exact solution but the generated model is complex and hard to use in a control perspective; second one is not an exact solution but the model is easier to use in a control perspective and the physical sense is respected (Dochain *et al.*, 1992). Thus, second method was chosen. A spatial discretization in four points (four different heights in the reactor) was considered. Now, the model depends on time only.

2.4 The complete process

The axial dispersion affects soluble components such as substrate, inorganic carbon and cations. Since

biomass is attached to a solid material (Biolite™), it follows a completely stirred behaviour. The bacteria attached to the solid support are considered as active biomass and they are represented by the growth rate (μ). The other bacteria are considered as inactive biomass and they are represented by the death rate (k_d). In general, k_d is assumed to follow a first order kinetics; so, it can be deduced from substrate consumption measures. In the complete model, the algebraic part is composed by twenty equations since (1-5) are valid in every collocation point. The differential equations are modified as follows:

$$\begin{aligned} \frac{dX_2}{dt} &= (\mu - k_d) X_2 \\ \frac{dS_{2i}}{dt} &= \mu Y_1 X_2 + [l_{ij}] S_{2i}^r + l_{0i} ((1-r) S_{2in} + r S_{24}^r) \\ \frac{dIC_i}{dt} &= \lambda_{yf} Y_1 Y_2 \mu X_2 [l_{ij}] IC_i^r + l_{0i} ((1-r) IC_{in} + r IC_4^r) \\ \frac{dZ_i}{dt} &= [l_{ij}] Z_i^r + l_{0i} ((1-r) Z_{in} + r Z_4^r) \end{aligned} \quad (13-16)$$

where $\mu = \frac{\mu_{max} HS}{k_s + HS + HS^2/k_i}$, and $\lambda_{yf} = \frac{K_h - 2CO_{2d}}{K_h - CO_{2d}}$, $r = Q_f / (Q_f + Q_{in})$ is the feedback rate, Q_f is the feedback flow rate, Q_{in} is the input flow rate, l is the collocation matrix, $i=1, \dots, 4$ is the index of collocation points and the upper index tr indicates a function depending on the time and the feedback flow.

The total methane and carbon dioxide flow rates are the sum of the flow rates in each collocation point.

$$\begin{aligned} Q_{CH_4T} &= Q_{CH_4_1} + Q_{CH_4_2} + Q_{CH_4_3} + Q_{CH_4_4} \quad (17-18) \\ C_{CO_2T} &= Q_{CO_2_1} + Q_{CO_2_2} + Q_{CO_2_3} + Q_{CO_2_4} \end{aligned}$$

All the parameters were identified considering a fluidized bed prototype with a nominal volume of 11 lt. The complete process was analyzed globally and locally in (Beteau *et al.*, 2005 and Carlos-Hernandez *et al.*, 2004). The results of those analyses are that the model has two equilibria points. The first one is the operating point, where the conditions are adequate for the process operation. Second one is the washout point, which is characterized by the absence of active biomass into the reactor. Then, washout is to be avoided. Also, the process is locally observable and controllable around several operating points.

3. CONTROL STRATEGY

3.1 Control actions

The main control objectives of anaerobic digestion are to keep stable the process, and to respect a compromise between the CH_4 and the output pollution indicated by de chemical oxygen demand (COD). An interesting objective is to combine

different control actions to reach both objectives. In next lines, three control actions are described.

Open loop. Anaerobic digestion process is able to work correctly even in presence of small disturbances. This implies economical advantages since control actions are not applied.

Base addition. This action is used to keep acidity level in optimal conditions and allows a high CH₄ production but large disturbances cannot be rejected. Usually bicarbonate (B) is used, and the objective is to regulate the bicarbonate into the reactor.

Flow rate. It allows to control biological variables: biomass and substrate; furthermore it is possible to reject very large disturbances. This action implies the control of pumps to determine the input flow rate, and then it is necessary to stock eventual exceeding substrate. The objective is also to regulate B into the reactor, this is equivalent to regulate the substrate: as cations are biologically inert and knowing that $Z=B+S_2$, the evolution of B is inverse to S₂.

3.2 Control laws design

In this case, the control objective is the bicarbonate regulation, and in order to simplify the design and the implementation, only one measure (B on the fourth collocation point) and one actuator (for the control variable on the reactor input) are considered. The control actions are implemented as PI controllers combining the advantages of the L/A and fuzzy techniques. The first one considers the positivity constraints imposed by the concentrations and input flow rates; in addition, the tuning of PI L/A considers the actuators saturation (Beteau *et al.*, 1991). The fuzzy method used is the minimal PI; in this case the proportional and integral gains adapt its values according to the operating conditions (Ying *et al.*, 1990; Chen and Ying, 1993). The discrete PI L/A expressions for the selected control actions: bicarbonate addition and input flow rate are:

$$b_{inc_k} = (b_{inc_{k-1}} - b_{inc_k}) \left(\frac{B_{k-1}}{B_k} \right)^{K_i} \left(\frac{B_k^*}{B_k} \right)^{K_p} + b_{inc_min} \quad (19)$$

$$Q_{ink} = Q_{k-1} \left(\frac{B_{k-1}}{B_k} \right)^{K_i} \left(\frac{B_k^*}{B_k} \right)^{K_p} \quad (20)$$

where b_{inc} is the added base (in this case, bicarbonate), B is the measured bicarbonate in the fourth collocation point, B* is the reference, b_{inc_min} is the minimal value for the bicarbonate, Q_{in} is the input flow rate and k is a determined instant. K_i and K_p are the integral and proportional gains respectively. They are computed from the error and the rate change of the error as shown in next lines.

From figures (3) and (4), four fuzzy rules are stated (e : error, r : rate):

If e is positive and r is positive then o is negative
 If e is positive and r is negative then o is zero
 If e is negative and r is positive then o is zero
 If e is negative and r is negative then o is positive

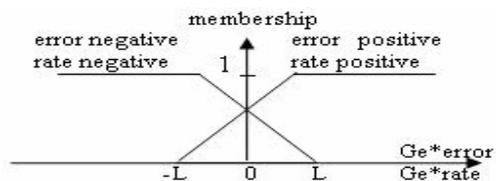


Fig. 3. Inputs fuzzyfication for the fuzzy PI.

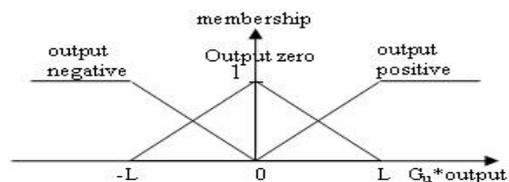


Fig. 4. Output fuzzyfication for the fuzzy PI.

And the defuzzyfication to compute the proportional and integral gains is determined by two conditions:

If $Gr|r_k| \leq Ge|e_k| \leq L$

$$K_i = \frac{0.5 * L * Gu * Ge}{2L - Ge|e_k|} \quad (21)$$

$$K_p = \frac{0.5 * L * Gu * Gr}{2L - Ge|e_k|}$$

And, if $Ge|e_k| \leq Gr|r_k| \leq L$

$$K_i = \frac{0.5 * L * Gu * Ge}{2L - Gr|r_k|} \quad (22)$$

$$K_p = \frac{0.5 * L * Gu * Gr}{2L - Gr|r_k|}$$

3.3 Supervisor system design

The supervisor has three tasks: i) detect disturbances, ii) determine if a control action is necessary or not, and iii) select the most adequate control action allowing smooth switching between them. The tasks i) and ii) are achieved monitoring the variables which are indicators of disturbances and of the biological activity into the reactor. Two variables are proposed: methane production and ODL/X₂. First one changes when a disturbance arrives to the process, empirical knowledge allows determining the variation of methane production in function of the amplitude of the disturbance. Second one represents the maximal quantity of organic load that a biomass unit can treat in a working day; there exists a limit for this variable. Above the limit, a control action is required in order to avoid washout; below this limit, the process can work in open loop. Third task is achieved implementing a selection mechanism based on the Takagi-Sugeno algorithm as follows. First, the indicators are fuzzyfied as shown in figure (5).

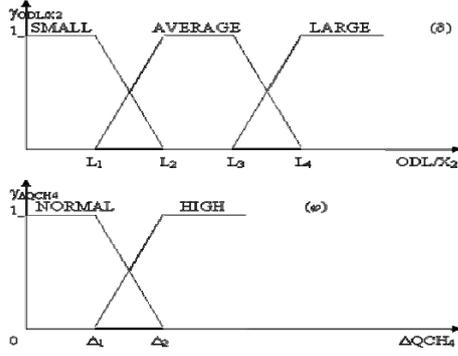


Fig. 5. Fuzzyfication for the supervisor.

From empirical knowledge, each fuzzy set is associated with a control action. This information is used to build the fuzzy rules which have next form:

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} , Q_{in} or open loop.

Defuzzification is made as follows (average center):

$$u = \frac{\sum_{j=1}^R \gamma_j u_j}{\gamma_j} \quad (23)$$

where $\gamma_j = \gamma_{COJ/X_2} * \gamma_{\Delta QCH_4}$ 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 .

4. RESULTS

A set of realistic simulations are considered to validate the proposed methodology. In all cases, the amplitude of disturbances (A_2) is given as a normalized percentage of the initial value: $A_2=1$ represents the 100 percent of the initial value.

First, a step $A_2=1$ on the substrate input is considered (Figure (6)). As we can see, the control actions are not applied because the disturbance is a little one and the process itself can reject it. Then, the process behaviour is as in open loop. The supervisor works according to requirements of this kind of disturbances. After that, a step of bigger amplitude ($A_2=4$) is applied on the substrate input. According to the empirical knowledge, the process needs a control action to reject the disturbance. In this case, the supervisor determines the application of control actions as shown in figure (7). The control actions allow the bicarbonate regulation and the disturbance rejection. Furthermore, the input substrate increases due to the disturbance, and then the methane production increases also with the application of the control actions. On figure (8), a disturbance $A_2=7$ is considered. In this case, the bicarbonate regulation is more difficult in the first three collocations points: B

goes beyond the reference and it arrives to a new equilibrium point. In the fourth collocation point the bicarbonate has a negligible static error. This is a normal situation because only the fourth collocation point was considered as the measure for tuning the controller; then in presence of big disturbances the regulation of bicarbonate on the three lower collocation points is not guaranteed. Furthermore, Q_{in} action is adequate to reject big disturbances but likely it is not well adapted for B regulation. However, the disturbance is rejected, the process keeps on the operating region and the methane production is increased.

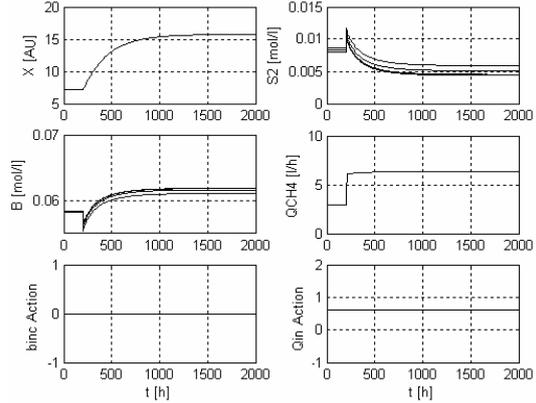


Fig. 6. Response considering small disturbance $A_2=1$.

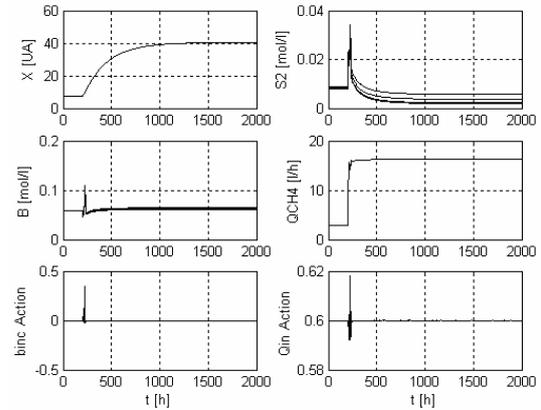


Fig. 7. Response considering medium disturbance $A_2=4$.

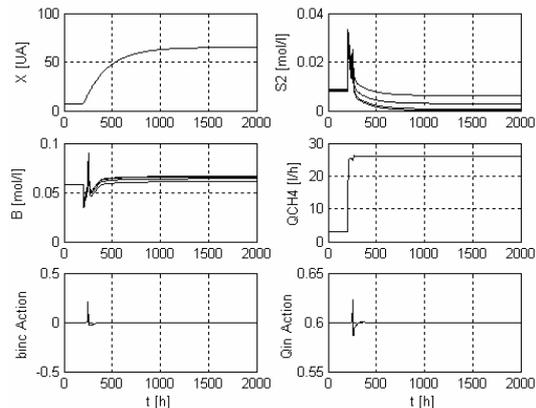


Fig. 8. Response considering large disturbance $A_2=7$.

5. CONCLUSIONS AND PERSPECTIVES

In this paper the control of anaerobic digestion in a fluidized bed reactor was presented. The process model was discretized on space by the orthogonal collocation method. An intelligent control strategy was proposed for the described bioprocess. This strategy is composed by fuzzy PI L/A controllers and a Takagi-Sugeno supervisor which detects the process operating conditions and determines the application of a control action. The strategy is easy to design and the results obtained from realistic simulations are forth encouraging because it allows improving enhancements: large disturbances rejection, keeping system on operation region and high methane production. Two control actions are considered to regulate B: adding a base (b_{inc}) and the input flow rate (Q_{in}). The bicarbonate is well regulated on the fourth collocation point because this is the output point used to tune the controllers. In the lower collocation points, the bicarbonate is not well regulated in presence of large disturbances. To improve this situation a deeper study of Q_{in} action must be developed, and also, it is possible to consider a different control action. The real time implementation is also an immediate future work.

REFERENCES

- Beteau, J.F., E. Ferret, M. Lakrori and A. Cheruy (1991). Bioprocess control: An original approach taking into account some bioprocess constraints. *American Control Conference*. Boston, USA.
- Beteau, J.F., V. Otton, J.Y. Hihn, F. Delpech and A. Cheruy (2005). Modelling of anaerobic digestion in a fluidised bed with a view to control. *Biochemical Engineering Journal*, **Vol. 24**, pp. 255-267.
- Buswell, A.M., and F.W. Sollo (1948). The mechanism of methane fermentation. *Journal of American Chemistry Society*. **Vol. 70**, pp. 1778-1780.
- Bryant, M.P. (1979). Microbial methane production. Theoretical aspects. *Journal of Animal Science*. **Vol. 48**, pp. 193-201.
- Carlos-Hernandez S., G. Mallet and J.F. Beteau (2004). Modelling and analysis of the anaerobic digestion process. Proceedings of IFAC Symposium on Structures Systems and Control, Oaxaca, Mexico.
- Carlos-Hernandez S. (2005). Integrated intelligent control strategy for wastewater treatment plants by anaerobic digestion. In French, Ph.D. Thesis. Institut National Polytechnique de Grenoble, France.
- Chen G. and H. Ying (1993). On the stability of fuzzy pi control systems. *Proceedings of the 3rd Int'l Conf. on Industrial Fuzzy Control and Intelligent Systems*, pp. 128-133.
- Dochain D, PA Vanrolleghem and N. Tali-Maamar (1992). Modeling and adaptive control of non linear distributed parameters bioreactors via orthogonal collocation, *Automatica*, **Vol. 28 No. 5**, pp. 873-883.
- Hilgert, N., J. Harmand, J.P. Steyer and J.P. Vila. (2000) Nonparametric identification and adaptive control of an anaerobic fluidized bed digester. *Control Engineering Process*, **Vol 8, No. 4**, pp. 367-376.
- Honda, H. and T. Kobayashi (2004). Industrial applications of fuzzy control on bioprocesses. *Advances on Biochemical Engineering and Biotechnology*, **Vol. 87**, pp. 151-171.
- Klass, D.L. (1984). Methane from anaerobic fermentation. *Science*, **Vol. 223, No. 4640**, pp. 1021-1028.
- Mousa, L. and C. F. Forster (1999). The Use of Glucose as a Growth Factor to Counteract Inhibition in Anaerobic Digestion. *Process Safety and Environmental Protection*, **Vol. 77, No. B4**, pp. 193-198.
- Muller A., S. Marsilli-Libelli, A. Aivasidis, T. Lloyd, S. Kroner, and C. Wandrey. (1997) Fuzzy control of disturbances in a wastewater treatment process. *Water Research*, **Vol. 31, No. 12**, pp. 3157-3167.
- Otton, V., JY. Hihn, JF Beteau, F. Delpech and A. Cherury (2000). Axial dispersion of liquid in fluidized bed with external recycling. *Bioch. Engineering Journal*, **Vol. 4**, 129-136.
- Pind, P.F, I. Angelidaki and B. K. Ahring (2003). Dynamics of the anaerobic process: Effects of volatile fatty acids. *Biotechnology and Bioengineering*, **Vol. 82, No. 7**, pp. 791-801.
- Sanchez, E.N., J.F. Beteau and S. Carlos-Hernandez (2001a). Fuzzy supervisory control for a wastewater anaerobic treatment plant. *IEEE International Symposium on Intelligent Control*, Proceedings pp. 343-347.
- Sanchez, E.N., J.F. Beteau, and S. Carlos-Hernandez (2001b). Hierarchical fuzzy control for a wastewater anaerobic treatment plant. *IEEE International Conference on Systems, Man and Cybernetics*, **Vol 5**, pp. 3285-3290.
- Seok, J. (2003) Hybrid adaptive optimal control of anaerobic fluidized bed bioreactor for the de-icing waste treatment. *Journal of Biotechnology*, **Vol. 102**, pp. 165-175.
- Van Lier, J.B, A. Tilche, B.K. Ahring, H. Macarie, R. Moletta, M. Dohanyos, L.W. Hulshoff Pol, P. Lens and W. Verstraete (2001). New perspectives in anaerobic digestion. *Water Science and Technology*. **Vol. 43, No. 1**, pp. 1-18.
- Yamuna Rai, K. and V.S. Ranachandra Rao (1999). Control of Fermenters – a review. *Bioprocess Engineering*. **Vol. 21**, pp. 77-88.
- Ying, H, W. Siler, and J.J. Buckley (1990). Fuzzy control theory: a non linear case. *Automatica*, **Vol. 26, No. 3**, pp. 513-520.