Modelling, Monitoring and Control of Anaerobic Digestion Processes

Anaerobic disgestion is a biological waste and wastewater treatment process that produces methane as a by-product.

It is more and more largely used in wastewater treatment plants, often in combination with activated sludge.

One of the main drawback of the anaerobic digestion is its sensitivity to instability : without appropriate control action, the process can easily be led to a *wash-out* (i.e. a state where the bacteria have died and been removed from the reactor) under the action of varying influent waste concentration or influent flow rate, via the accumulation of volatile fatty acids.

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1 Introduction

This paper presents research results that have performed in the framework of an EEC project whose objective was to design and implement a monitoring and control system for anaerobic digesters. This work includes the development, identification and validation of a dynamical model, and the design and application of monitoring and control strategies.
The present paper is devoted to the activities of one research laboratory (CESAME) in the project.

The dynamical modelling of anaerobic digestion has been an active research area over the last three decades. Andrews [1] introduces the Haldane model to characterize growth inhibition, that can emphasize the process instability, i.e. the biomass wash-out via the accumulation of acids, and a model with a single bacterial population was proposed [8]. The representation of the process was then improved by considering three stages: solubilization of organics, acidogenesis and methanogenesis ([9]). Mosey [10] introduced a four population model with two acidogenesis reactions and two methanization reactions, that also emphasizes the role of hydrogen. Let us also mention the work of Rozzi [12] who emphasizes the role of alkalinity in anaerobic digestion via the introduction of electro-chemical equilibrium equations in the dynamical model. These modelling works have then been improved and detailed by other authors in order to get closer to the complexity of the process [3, 5, 6]. It results in detailed models of the process, that include various bacterial populations and substrates. As a result, the number of parameters in these models can become very large. The lack of phenomenological knowledge, the complexity of the process, its nonlinear nature and the lack of sensors explains why most of the existing models are generally only rough approximations. In this context, it is of great interest to derive models that would be as insensitive as possible to the lack of phenomenological knowledge. The model based on mass-balance considerations circumvents this difficulty by locating the biological lack of knowledge in dedicated terms, namely the reaction rates.
The use of such models for monitoring and control design has proved to be effective [2], because they minimize the number of assumptions in the model building exercise.

A mass balance based model has been derived to represent the dynamical behaviour of two anaerobic digesters (one pilot-scale, one industrial-scale) considered in the project. Its parameters have been calibrated for both reactors on the basis of experimental data and following a predefined design of experiments.

This mass balance model has served as a basis for the design of a software sensor that takes advantage of the partial information on the process dynamics and uses on-line gas. It computes the concentration of inorganic carbon, alkalinity and volatile fatty acids (VFA) in the digester. The predictions of this software sensor when implemented on both wastewater treatment reactors are very close to the actual off-line measurements. The proposed software sensor demonstrates the usefulness of advanced estimation techniques to monitor the time evolution of the process as well as for a better understanding of the internal working of the process.

Similarly the mass balance model has been used to design a model-based adaptive linearizing controller whose objective is to regulate the ratio of the partial alkalinity (PA) over the total alkalinity (TA) below some desired value (0.3) under which the process is assumed to remain in stable conditions and avoid VFA accumulation.
The adaptive linearizing controller has been calibrated via extensive numerical simulations with the mass balance model and implemented. The controller proved successful in maintaining the ratio of TA over PA below 0.3, even in presence of large variations of the organic load.

2 Model description

2.1 Reaction pathways

Let us consider here two bacterial populations: the acidogenic bacteria X_1 and the methanogenic bacteria X_2.
These populations intervene in the two following biological reactions:

Acidogenesis (with reaction rate r_1):

$$k_1 S_1 \xrightarrow{r_1} X_1 + k_2 S_2 + k_4 CO_2 \quad (1)$$

Methanogenesis (with reaction rate r_2):

$$k_3 S_2 \xrightarrow{r_2} X_2 + k_5 CO_2 + k_6 CH_4 \quad (2)$$

In the above reaction schemes, S_1 and S_2 represent the organic substrate (and its concentration), and the volatile fatty acids (VFA) (and its concentration), respectively. In the following we shall assume that S_2 is mainly composed of acetate and behaves like pure acetate.

Moreover we consider the chemical equilibrium between dissolved CO_2 and bicarbonate (B)

$$B + H^+ \rightleftharpoons CO_2 + H_2O \quad (3)$$

2.2 The alkalinity and the inorganic carbon balance

We assume that the operating pH range is between 6 and 8 ($6 \leq pH \leq 8$), and $T° \approx 38°C$. Let us consider the following variables to describe the dynamics of our process:

- The total organic carbon C_{TI} defined in the considered pH range as follows:

$$C_{TI} = CO_2 + B \quad (4)$$

- The total alkalinity Z is defined as the sum of acids in the medium. In the pH range considered, we have mainly

$$Z = B + S_2 \quad (5)$$

We assume that there is no other anions that influence significantly the alkalinity Z. In the pH range considered it is generally the case since $[OH^-]$, $[H_2CO_3]$, $[CO_3^{2-}]$ are negligible compared to B and S_2 (S_2 is mainly under its ionized form).

From the electric equilibrium of the charges in the medium, Z represents also the sum of the cations in the fermenter.
In the considered pH range, these cations are not significantly influenced by the biochemial reactions.

If we suppose that the measurements of pH are available, we can compute the ionized fraction $f_B(pH)$ of total inorganic carbon.
Indeed, it is straightforward from the definition of the dissociation constant pK_B of CO_2 that:

$$f_B(pH) = \frac{1}{1 + 10^{(pK_B - pH)}} \quad (6)$$

Thus, we directly deduce the bicarbonate concentration from the total inorganic carbon with the following relationship:

$$B = f_B(pH) C_{TI} \quad (7)$$

2.3 The dynamic model

From the considerations of reactions (1, 2, 3), we obtain the general model formulated for a CSTR in the following matrix form:

$$\frac{d\xi}{dt} = K r(\xi) - \mathcal{D}(\xi) + Q + F \quad (8)$$

with :

$$\xi^T = [X_1, X_2, Z, S_1, S_2, C_{TI}] \quad (9)$$

$$r(\xi)^T = [r_1(\xi), r_2(\xi)] \quad (10)$$

$$K^T = \begin{bmatrix} 1 & 0 & 0 & -k_1 & k_2 & k_4 \\ 0 & 1 & 0 & 0 & -k_3 & k_5 \end{bmatrix} \quad (11)$$

$$F^T = [0, 0, Z_{in}, S_{1in}, S_{2in}, C_{TIin}] \quad (12)$$

$$Q^T = [0, 0, 0, 0, 0, Q_{CO_2}] \quad (13)$$

$$\mathcal{D}(\xi)^T = [DX_1, DX_2, DZ, DS_1, DS_2, DC_{TI}] \quad (14)$$

The dilution rate D is the ratio of the influent flow rate over the volume of the fermenter. The terms S_{1in}, S_{2in}, C_{TIin}, are the influent concentrations of Z, S_1, S_2, C_{TI}, respectively. r_1 and r_2 are the reaction rates of reactions (1) and (2), respectively. k_i (i = 1 to 5) are yield coefficients.
The term Q_{CO_2} is the molar flow rate of CO_2 per volume of medium.

In fact, this model is an extension of the model proposed by [8] with two substrates and two bacterial populations.

For a fixed bed reactor, the biomass is attached on a support. It is therefore not affected by the dilution effect as in a CSTR. If the biomass do not leave the support, for a fixed bed reactor we must consider the following expression for the dilution effect on the state variables:

$$\mathcal{D}(\xi)^T = [0, 0, DZ, DS_1, DS_2, DC_{TI}] \quad (15)$$

Nevertheless some bacteria do not fix on their support or are detached by the liquid flow. In order to account for this phenomenon, we choosed thus to consider the following expression for $D(\xi)$:

$$\mathcal{D}(\xi)^T = [\alpha DX_1, \alpha DX_2, DZ, DS_1, DS_2, DC_{TI}] \quad (16)$$

where α is a parameter ($0 \leq \alpha \leq 1$) reflecting this effect. $\alpha = 0$ corresponds to an ideal fixed bed reactor with no biomass detachment, $\alpha = 1$ corresponds to an ideal CSTR.

Furthermore it is worth noting that for both pilot and industrial processes, we adopted a CSTR model. This choice is motivated as follows.
First of all, only measurements at the inlet and at the oulet of the reactors are available. Secondly, there is no clear experimental evidence of significant gradients inside the reactors. Finally the transport time delays appear to be negligible with respect to the other dynamical phenomenons.
The measurement of methane flow rate is available on-line. Because of the low solubility of the methane, this quantity is directly related to r_2 :

$$Q_{CH_4} = k_6 r_2(\xi)$$

where k_6 is a yield coefficient. The molar CO_2 flow rate Q_{CO_2} can also be computed using Henry's law:

$$Q_{CO_2} = k_L a(CO_2 - k_H P_{CO_2})$$

with k_La the liquid-gas transfer coefficient, K_H the Henry's constant, and P_{CO_2} the CO_2 partial pressure.

The CO_2 concentration can be computed by combining equations (4) and (5). Then we get the following relationship for

$$Q_{CO_2} = k_L a(C_{TI} + S_2 - Z - k_8 P_{CO_2}) \quad (17)$$

The modelling of biological kinetics is a difficult task for which a systematic methodology is still lacking. For sake of model simplicity and in line with other works on anaerobic digestion we shall consider the following models for the bacterial kinetics. We consider Monod type kinetics for the growth of acidogenic bacteria, i.e. :

$$\mu_1 = \mu_{1\max}\frac{S_1}{S_1 + K_{S1}} \quad (18)$$

where μ_{1max} is the maximum bacterial growth rate and K_{S1} the saturation constant associated with the substrate S_1. In order to emphasize possible VFA accumulation we have considered Haldane kinetics for the methanogenesis :

$$\mu_2 = \bar{\mu}_2\frac{S_2}{S_2 + K_{S2} + (\frac{S_2}{K_{I2}})^2} \quad (19)$$

where μ_2 is the maximum bacterial growth rate without inhibition, K_{S2} and K_{I2} the saturation and inhibition constants associated with the substrate S_2, respectively.

3 Model Identification

The model which has been developed in the first step of this paper includes 13 parameters μ_{1max}, K_{S1}, μ_2, K_{S2}, α, k_La, k_1, k_2, k_3, k_4, k_5, k_6, that have to be identified from experimental data. This identification step is very important to guarantee a large validity of the model.

Experiments have been designed covering a wide range of experimental conditions in order to develop and validate the model. This diversity is obtained via various organic loading rates (given by various dilution rates and various influent COD concentration).

To circumvent the structural and practical identifiability problems, we have chosen the following approach based on the following two points. First of all, we have decoupled the estimation into three groups of parameters : the kinetic parameters (μ_{1max}, K_{S1}, μ_2, K_{S2}, K_{I2}, α), the transfer coefficents (K_H, k_La), and the yield coefficients (k_i, i = 1 to 6). The motivation for this decoupling lies in the (already mentioned) difficult task of kinetics modelling, that generate usually large uncertainty in bioprocess dynamical models (see also [2]). Besides, estimation of the transfer coefficients is straightforward from gaseous and liquid measurements. The second important point of the identification procedure is the following : we focus on the steady state and we adjust the parameter to impose that the model predicts correctly the equilibria reached by the process. The identification procedure is described in details in ([4]).

During the modelling and identification process we make a particular effort to try to measure as many important process variables as possible (at least for steady state conditions). These are : S_1, S_2, Z, C, pH, q_C, q_M.

4 Software sensors

4.1 Mass conservation

From model (8), a linear combination of equations can lead to mass conservation equations independent of the kinetics r_1 and r_2. We consider thus the following auxiliary variables (see [2]) :

$$\begin{aligned} z_1 &= Z \\ z_2 &= S_2 - \frac{k_2}{k_4}C_{TI} \\ z_3 &= S_1 + \frac{k_1}{k_2}S_2 \end{aligned} \quad (20)$$

From model (8), we get readily:

$$\frac{dz_1}{dt} = D(z_{1in} - z_1) \quad (21)$$

$$\frac{dz_2}{dt} = D(z_{2in} - z_2) - \left(\frac{k_2k_5}{k_4k_6} + \frac{k_3}{k_6}\right)Q_{CH_4} + \frac{k_2}{k_4}Q_{CO_2} \quad (22)$$

$$\frac{dz_3}{dt} = D(z_{3in} - z_3) - \frac{k_1k_3}{k_6k_2}Q_{CH_4} \quad (23)$$

where :

$$\begin{aligned} z_{1in} &= Z_{in} \\ z_{2in} &= S_{2in} - \frac{k_2}{k_4}C_{TIin} \\ z_{3in} &= S_{1in} + \frac{k_1}{k_2}S_{2in} \end{aligned} \quad (24)$$

4.2 Mass balance based software sensors

The auxiliary variables z_1, z_2 and z_3 can now be asymptotically estimated with a convergence rate D as follows (see [2]):

$$\frac{d\hat{z}_1}{dt} = D(z_{1in} - \hat{z}_1)$$

$$\frac{d\hat{z}_2}{dt} = D(z_{2in} - \hat{z}_2) + \left(\frac{k_2k_5}{k_4k_6} - \frac{k_3}{k_6}\right)Q_{CH_4} + \frac{k_2}{k_4}Q_{CO_2} \quad (25)$$

$$\frac{d\hat{z}_3}{dt} = D(z_{3in} - \hat{z}_3) - \frac{k_1k_3}{k_6k_2}Q_{CH_4}$$

The variables $\hat{z}_1$, $\hat{z}_2$ and $\hat{z}_3$ denote the estimate of the auxiliary variables z_1, z_2 and z_3, respectively.

They can now be used to estimate online the inorganic carbon C_{IN} and substrates S_1 and S_2 from the gas measurements :

$$\begin{aligned} \hat{C}_{TI} &= \frac{\hat{z}_1 - \hat{z}_2}{\frac{k_2}{k_4} + f_B(pH)} \\ \hat{S}_2 &= \hat{z}_1 - f_B(pH)\hat{C}_{TI} \\ \hat{S}_1 &= \hat{z}_3 - \frac{k_1}{k_2}\hat{S}_2 \\ \hat{B} &= f_B(pH)\hat{C}_{TI} \end{aligned} \quad (26)$$

Since VFA corresponds to the intermediate alkalinity, the on-line measurement of the VFA is performed with the alkalinity measurements. Moreover the estimation of the on-line measurement of alkalinity Z can be used to check on-line that the software sensor is correctly working:

$$\hat{Z} = \hat{z}_1 \quad (27)$$

Note however that in the above equations, the knowledge of the influent substrate concentration S_{1in} is required in the computation of z_{3in}.

Parameters	pilot scale	industrial scale	Unit
k_1	12.1	13.7	gCOD/g X_1
k_2	181.2	168.2	mmol VFA/g X_1
k_3	1640	1640	mmol VFA/g X_2
k_4	169	230	mmol CO_2/g X_1
k_5	273	273	mmol CO_2/g X_2
k_6	1804	1804	mmol CH_4/g X_2
k_La	200	500	day^{-1}
K_{H_C}	22.3	22.3	mmol CO_2/atm

Table 1 : Values of the parameters of the mass balance model

4.3 Calibration and validation of the software sensor

The calibration of the asymptotic observer for C_{TI}, S_1, S_2 and B, and of the observer for the influent concentrations $S_{1,in}$ and $S_{2,in}$ has been the object of extensive simulations based the mass balance model identified with experimental data on both plants. The figures here below show the results obtained on both plants after their implementation. Figure 1 gives typical estimation results for the pilot digester at the INRA in Narbonne. Figure 2 gives the same results for the industrial plant at TAFISA in Pontevedra.

Note that the estimations of S_1, S_2 B and Z are quite reliable, even if they are based on gas measurements and even if the design of the observers is based on a very simplified model of the process.

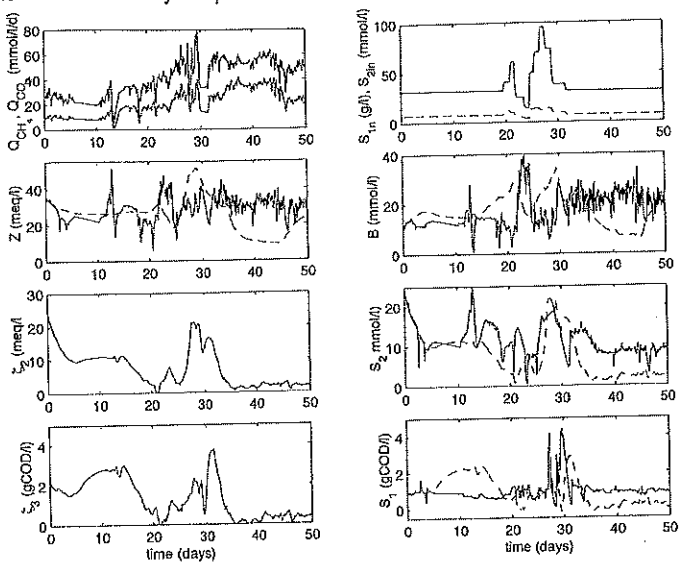

Fig. 1 Software sensor predictions for COD, VFA, total alkalinity Z and bicarbonate B in April-May 1999 on the pilot plant. The predictions (- -) are compared with the real-life data (-)

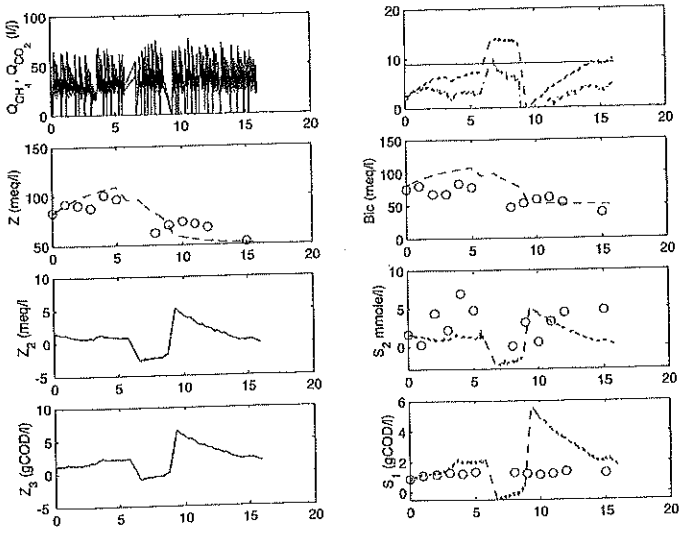

Fig. 2 Software sensor predictions for COD, VFA, total alkalinity Z and bicarbonate B and on the influent COD in the spring 1999 (15 days) on the industrial plant. The predictions (- -) and (-.) are compared with the real-life data (0)

5 Control of the alkalinity

5.1 Control objectives

As defined by all the partners in order to guarantee the stability of the process the alkalinity should be maintained in the following range:

$$\frac{IA}{TA} \leq 0.3 \text{ and } TA \geq 3g/l \tag{28}$$

The control actions will be the addition of alkalinity in the influent and the influent flow rate.

5.2 Design of the linearizing control law

In order to have a system whose variables correspond to the variables to be controlled, we consider the following change ofcoordinates (the notations are the same than in the previous reports):

$$w_1 = \frac{x_1}{Z}, w_2 = \frac{x_2}{Z}, w_3 = \frac{1}{Z}, w_4 = \frac{S_1}{Z}, w_5 = \frac{S_2}{Z}, w_6 = \frac{C_{TI}}{Z} \tag{29}$$

then we get the following system :

$$\begin{cases} \frac{dw_1}{dt} = (\mu_1 + D(1-\alpha) - \frac{Z_{in}}{Z})w_1 \\ \frac{dw_2}{dt} = (\mu_2 + D(1-\alpha) - \frac{Z_{in}}{Z})w_2 \\ \frac{dw_3}{dt} = D(\frac{Z_{in}}{Z} - 1)w_3 \\ \frac{dw_4}{dt} = D(\frac{S_{1in}}{Z} - w_4\frac{Z_{in}}{Z}) - k_1\mu_1 w_1 \\ \frac{dw_5}{dt} = D(\frac{S_{2in}}{Z} - w_5\frac{Z_{in}}{Z}) + k_2\mu_1 w_1 - \frac{k_3}{k_6}\frac{q_M}{Z} \\ \frac{dw_6}{dt} = D(\frac{C_{TI,in}}{Z} - w_6\frac{Z_{in}}{Z}) + k_4\mu_1 w_1 + \frac{q_C}{Z} - \frac{k_5}{k_6}\frac{q_M}{Z} \end{cases}$$

In this new coordinates, the control objectives are now:

$$w_5 \leq 0.3 \text{ and } w_3 \leq 0.3333 l/g \tag{30}$$

In fact this control problem can be decoupled in two control problems: as the dynamics of Z is very simple, it is trivial to achieve the desired alkalinity in the fermenter: indeed we just have to adjust Z_{in} to the objective value Z^*.

Then we have to control w_5 to the desired value w^*_5. Our closed-loop dynamics objective is to assign the dynamics of w_5 as follows:

$$\frac{dw_5}{dt} = \lambda(w_5^* - w_5), \ \lambda > 0 \tag{31}$$

where λ is a parameter that help to tune the convergence rate of the controller. By combining the dynamical equation in w_5 and the desired closed-loop dynamics (31), we obtain then the following control law:

$$D = \frac{\lambda Z(w_5^* - w_5) + k_3 q_M/k_6 - k_2\mu_1 X_1}{S_{2in} - w_5 Z_{in}} \tag{32}$$

Because the control law tends to force a linear closed loop dynamics (31) to the nonlinear process, the control law is called a linearizing control law (see [2], [11], [7]).

One way to eliminate X_1 (which is not measured on line) and μ_1 (which is basically unknown or at least largely uncrtain) is to consider a quasi steady-state (QSS) approximation for the mass balance equation of the organic substrate S_1.
This gives the following algebraic equation :

$$\mu_1 X_1 = \frac{1}{k_1}(DS_{1,in} - S_1) \tag{33}$$

Then the linearizing control law (32) becomes :

$$D = \frac{\lambda Z(w_5^* - w_5) + k_3 q_M / k_6}{S_{2in} - w_5 Z_{in} + \frac{k_2}{k_1}(S_{1,in} - S_1)} \tag{34}$$

Note that this control law can reach values higher than the dilution rate which was *a priori* applied. This control law has been tested in numerical simulations. It turns out to be efficient, and fast enough to be applied in practice.

But in fact this control law maintains the system at its the stability limit: generally the fraction of intermediate alkalinity over total alkalinity is much lower than 0.3 while no VFA accumulates. This means that a control action could maintain the ratio w_5 around a reasonable value $w^*_5 << 0.3 = w_5^{max}$, but in case of increase in the incoming organic loading rate, this regulation could be disconnected. Another controller could then avoid w_5 to be lower than w_5^{max}. For this it has to limit the dilution rate to a value lower than the maximal possible value which is in turn given by the control law obtained for $w^*_5 = w_5^{max}$.

5.3 Practical version of the linearizing control law

The practical implementation of the control law derived requires a number of modifications in order to guarantee its robust behaviour with respect to the uncertainty concerning the knowledge of the process dynamics (The mass balance model is already a simplification of the true dynamics, and we have further simplified the dynamical model equations to derive the control law) and the uncertainty concerning the measurements of the process variables.

The first important modification consists of introducing an adaptation mechanism. This is done in order to adapt the model dynamics considered for the control action (the dynamical equation in w_5) to its tru dynamics. This is performed by estimating on line one process parameter, $\theta = k_3/k_6$, as follows :

$$\frac{d\hat{\theta}}{dt} = \bar{C}_1(w_5^* - w_5),\ \bar{C}_1 > 0 \tag{35}$$

This estimation approach is known as a Lyapunov-based approach (see e.g. [2]). In practice, the choice of C_1 depends on the value of the methane gas flow rate Q_M as follows :

$$\bar{C}_1 = \frac{C_1}{q_M},\ C_1 > 0 \tag{36}$$

This allows to have closed-loop dynamics of the whole system (process + controller (34) (35) independent of the state of the process (see [11]).

Besides the advantage of estimating an physical parameter (the ratio of the yield coefficients k_3 and k_6), the above adaptation mechanism introduces an integral which is essential to guarantee zero steady-sate error of the closed-loop system. The control law (34) (35) is now called the adaptive linearizing controller.

The second important modification of the control law consists of replacing the value of S_1 by an estimate, typically that given by the asymptotic observer.

Thirdly, the control law can be modified to handle the fact that either the influent concentrations Z_{in}, $S_{1,in}$ and $S_{2,in}$ are badly known and even not accessible for on-line measurement (only off-line measurements are then available from time to time). Then these values are set to constant values based on the off-line measurements.

Another important feature of the practical implementation of the controller is the limitation of the control action when the value of w_5 is taking larger values than w^*_5, above a certain limit (chosen here equal to 0.01).

Typically, when w_5 is larger than $w_{5,limit} = 0.21$, then the control algorithm calculates a value for the control action on the basis of the control equation (34) in which the proportional action is removed and in which the value of w_5 at the denominator is replaced by $w_{5,limit}$:

$$D = \frac{\hat{\theta} q_M}{S_{2in} - w_{5,limit} Z_{in} + \frac{k_2}{k_1}(S_{1,in} - S_1)} \tag{37}$$

This allows to limit further the excursion of w_5 in the direction of the upper limit 0.3.

The implementation of the control law includes an anti-windup in order to avoid oscillations due to the integral action when the control input reaches its bounds (i.e. 0 or the maximum influent flow rate).

Finally the control algorithm software includes a number of test about the different variables in order to prevent undesired or absurd behaviour of the control system.

It is essential to note that the design of the controller induces in essence a lot of flexibility in its implementation, depending on the quality of information concerning e.g. the measurement of the influent load and flow rate.

5.4 Calibration and validation of the controller

Here again, the different versions of the adaptive linearizing controller have been extensively tested in numerical simulation. The objective is typically to tune properly the design parameters λ and C_1 in order to obtain the best closed-loop performances, by considering various typical and realistic process conditions via the use of the mass balance model of the process.

A first key conclusion of this extensive simulation study was that the controller was capable of controlling correctly the process and to maintain it in stable conditions, reinforcing us in our confidence to implement on the real processes.

A second conclusion is that the knowledge of the influent concentrations Z_{in}, $S_{1,in}$ and $S_{2,in}$ may have an important effect on the transient behaviour of the process and of the controller (although without any degradation of their steady state behaviour) : the transients are typically worse (slower convergence, larger overshoots) without imprecise or unknown values of Z_{in}, $S_{1,in}$ and $S_{2,in}$ when these are changing.

This emphasizes the key role played by the feedforward action

in the performance of the control law.

$$1/(S_{2in} - w_5 Z_{in} + \tfrac{k_2}{k_1}(S_{1,in} - S_1))$$

The adaptive linearizing controller has been successfully implemented on the pilot plant in Narbonne.

Figure 3 presents one set of control results. The figure compares open-loop (without control) results (in the column on the left) and closed-loop (with the adaptive linearizing controller) results (in the column on the right).

The five following variables are represented in each column from the top to the bottom : organic load (influent concentrations of organic matter $S_{1,in}$ (top) and volatile fatty acids $S_{2,in}$ (bottom))(gCOD/l), influent flow rate Q_{in} (l/h), ratio IA/PA, total alkalinity Z (meq/l), and volatile fatty acids S_2 (meq/l). During both experiments (open loop, and closed loop), the organic load have been changed several times (figures at the top), between 5 and 20 gCOD/l : this corresponds, in particular the increase to 20 gCOD/l, to variations that can possibly induce acid accumulation and process instability in open loop.

Note in particular that the ratio IA/PA is always below 0.3 with the adaptive linearizing controller (figure on the right, third level), while it grew to values larger than 0.5 in open loop (figure on the left, third level). This corresponds to an accumulation of VFA in open loop : these have reached a value larger than 2.5 meq/l (figure at the bottom, left hand side). The VFA remained always below 1.5 meq/l in closed loop with the adaptive linearizing controller (figure at the bottom, right hand side).

This illustrates the ability of the designed controller to maintain the process in stable conditions even in presence of the varying organic load.

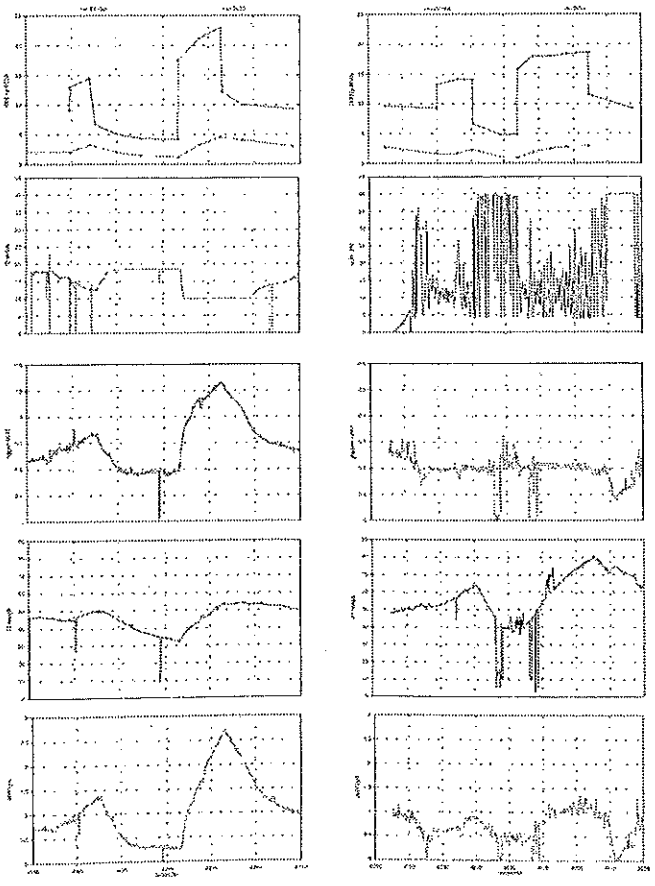

Fig. 3 Control of the ratio of the intermediate alkalinity over the total alkalinity on the pilot plant

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References

1. Andrews J.F. (1968). A mathematical model for the continuous culture of microorganisms utilizing inhibitory substrates, *Biotechnology and Bioengineering*, X, 707-723.
2. Bastin G. and D. Dochain (1990), *On-line Estimation and Adaptive Control of Bioreactors*, Elsevier, Amsterdam.
3. Batstone D., Keller J., Newell B. and Newland M. (1997). Model development and full scale validation for anaerobic treatment of protein and fat based wastewater. *Wat. Sci. Tech.*, 36, 423-431.
4. Bernard O., Hadj-Sadok Z., Dochain D., Genovesi A. and Steyer J-Ph. (2000). Dynamical model development and parameter identification for an anaerobic wastewater treatment process. *submitted for publication.*
5. Costello D.J., P.F. Greenfield and P.L. Lee (1991). Dynamic modelling of a single-stage high-rate anaerobic reactor - I. Model derivation, *Wat. Res.*, 25(7), 847-858.
6. Costello D.J., P.F. Greenfield and P.L. Lee (1991). Dynamic modelling of a single-stage high-rate anaerobic reactor - II. Model verification, *Wat. Res.*, 25(7), 859-871.
7. Dochain D. and M. Perrier (1993), Control design for nonlinear wastewater treatment processes, *Water Sci. Technol.*, 28 (11-12), 283-293.
8. Graef S.P.and Andrews J.F. (1974). Mathematical modeling and control of anaerobic digestion. *AIChE Symp. Series*, Water 1973, 101-131.
9. Hill D.T., and Bart C.L. (1977). A dynamic model for simulation of animal waste digestion. *J. Wat. Pollut. Control Fed*, 10, 2129-2143.
10. Mosey F. (1983). Mathematical modelling of the anaerobic digestion process : regulatory mechanisms for the formation of short-chain volatile acids from glucose", *Wat. Sci. Tech.*, 15, 209-232.
11. Perrier M. and D. Dochain (1993), Evaluation of control strategies for anaerobic digestion processes, *Int. J. Adaptive Cont. Signal Proc.*, 7 (4), 309-321.
12. Rozzi A. (1985). Anaerobic process control by bicarbonate monitoring, *Environmental Technology Letters*, 6, 594-601.

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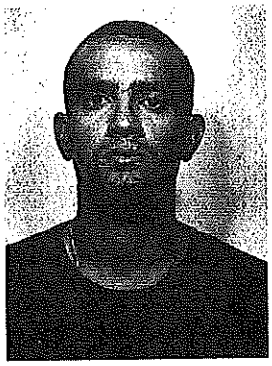

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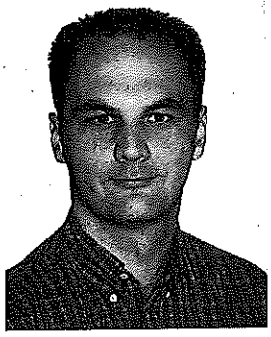
The research developed in my thesis deals with dynamic modelling and state estimation under uncertainty constraints related to the biological wastewater treatment field.
In 1998, I was in CESAME Laboratory of Louvain-La-Neuve University (Belgium), where I worked on the European project AMOCO related to monitoring and control of wastewater treatment processes of the wood industry.
In 2000, I joined the Department of Chemical Engineering of Ecole Polytechnique de Montrea, where I am currently involved in studying estimation theory for distributed parameter systems with application to pulp bleaching process.

Marco Pengov



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