Fuzzy Control Strategy for an Anaerobic Wastewater Treatment Process

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In this paper, a fuzzy control strategy (FCS) for an anaerobic wastewater treatment process is proposed in order to reject large disturbances on input substrate allowing a high methane production. This strategy is composed of: i) a state observer, which is based on a principal components analysis (PCA) and Takagi-Sugeno (TS) algorithm; it is designed to estimate variables hard to measure: biomass and substrate, ii) proportional-integral (PI) controllers based on a combination of the L/A (logarithm/antilogarithm) and fuzzy approaches; these controllers have variable gains and are designed to regulate bicarbonate in the reactor by two control actions: a base supplying (b_{inc}) and dilution rate (D) changes, iii) a TS supervisor which detects the process state, selects and applies the most adequate control action, allowing a smooth switching between open loop and closed loop. Applicability of the proposed structure in a completely stirred tank reactor (CSTR) is illustrated via simulations. The obtained results show that the process works in open loop in presence of small disturbances. For large disturbances, the supervisor allows the control actions to be applied avoiding washout; after that, the process returns to open loop operation. In general, the FCS improves the performances of the anaerobic process and is feasible for application in real processes, since the control scheme shows a good compromise between efficiency and complexity.

Key words:
Fuzzy control, state estimation, anaerobic digestion, wastewater treatment

Introduction

Among the main challenges imposed by anaerobic digestion, there are its sensitivity to changes on operation conditions, process parameters uncertainty, and high non-linear dynamics. Several techniques have been already implemented in order to overcome these problems. Linear approaches[1,2] are efficient around local operating points; however, they are unreliable for major variations in operating conditions. Linearizing feedback control[3,4] considers process non-linearities and improves process performances but a good knowledge of the model structure is required. Robust control[5,6] deals with controllers allowing adequate performance independently of changes in the process dynamics; an inconvenience of this approach can be the necessity to predefine operation intervals with uncertain bounds. Adaptive control approaches[7–9] allow the controller adaptation to reduce the effect due to parameter variations and to uncertainties, but a good knowledge of process structure is required, which cannot be guaranteed. Additionally, linearizing, robust and adaptive approaches often present complex structures difficult to implement. Intelligent control (neural nets, fuzzy logic and hybrid schemes) is emerging as an adequate alternative to control anaerobic wastewater treatment, with important results reported in different publications;[10–13] however, frequently, many parameters must be tuned empirically, which can be a hard task. Other interesting approaches are PID based schemes, which allow the process to reach good performances in substrate and alkalinity regulation; since its operation range is conditioned by process non-linearities, PID improvement or combination with other control approaches is an active research topic.[14,15] The L/A approach[16–17] allows the controller to take into account process positivity constraints by means of logarithmic and antilogarithmic transformations. Other alternatives for anaerobic wastewater treatment, as integrated control strategies,[18,19] improve process performances by increasing methane production and avoiding washout; however, an oscillatory behavior is produced due to switching between control laws.

Considering all the above, the first contribution of this paper is the combination of PI L/A and fuzzy

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PI minimal[20,21] approaches; this new fuzzy PI L/A is able to modify on-line its gains as a function of the operating conditions in order to enlarge the controller operating range. The second contribution is a novel application: the synthesis of a fuzzy control structure for anaerobic wastewater treatment plants, which combines different control actions to avoid washout in the presence of large disturbances on substrate input and allowing in consequence a high methane production. A completely stirred tank reactor (CSTR) was considered in order to validate the proposed strategy.

Anaerobic digestion preliminaries

Process description

Anaerobic digestion degrades complex molecules by anaerobic bacteria through four successive stages (hydrolysis, acidogenesis, acetogenesis and methanogenesis). The one considered in this paper is a synthetic substrate similar to paper mill effluents, composed of corn starch, maltose, glucose, lactic acid, acetic acid, propionic acid, ammonium chloride, potassium hydrogen-phosphate, iron III chloride, cobalt chloride, nickel nitrate, calcium chloride and magnesium sulfate; the exact composition can be found in the corresponding reference.[22] The substrate organic components are classified as equivalent glucose $[S_1]$ and equivalent acetate $[S_2]$. The first one is assumed to model complex molecules, and the second represents molecules which are transformed directly in acetic acid. Biomass is also classified in two types noted $[X_1]$ and $[X_2]$; $[X_1]$ represents the bacteria populations, which transform equivalent glucose substrates, and $[X_2]$ stands for bacteria degrading equivalent acetate substrates. This classification allows the process to be represented by only two stages: the methanogenesis, which is the limiting one, and a preliminary stage. Thus, a mathematical model of the process is deduced as follows. On one side, the physico-chemical phenomena are modelled by a set of five algebraic equations, which represent the chemical acid-base equilibrium and the conservation of mass. On the other side, the biological phenomena and electroneutrality are modelled by a set of six ordinary differential equations, which represent the dynamic part of the process. Finally, the gaseous phase (CH_4 and CO_2) is considered as the model output. The model is formulated as:

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

with:

$$
\begin{aligned}
x_a &= [[\mathrm{HAc}]\,[\mathrm{Ac}^-]\,[\mathrm{CO}_2]_d\;[\mathrm{HCO}_3^-]\,[\mathrm{H}^+]] \\
x_d &= [[X_1]\,[S_1]\,[X_2]\,[S_2]\,[\mathrm{IC}]\,[\mathrm{B}^{Z+}]] \\
u &= [[S_1]_{in}\;[S_2]_{in}\;[\mathrm{IC}]_{in}\;[\mathrm{B}^{Z+}]_{in}\;D] \\
y &= [F_{CH_4}\;F_{CO_2}]
\end{aligned}
\tag{2}
$$

where the different symbols are defined as follows: [HAc] non-ionized acetic acid (mol dm^{-3}), $[Ac^-]$ ionized acetic acid (mol dm^{-3}), $[CO_2]_d$ dissolved carbon dioxide (mol dm^{-3}), $[H^+]$ ionized hydrogen, $[HCO_3^-]$ bicarbonate (mol dm^{-3}), [IC] inorganic carbon (mol dm^{-3}), B^{Z+} the total of cations (mol dm^{-3}), $[S_1]_{in}$ the fast degradable substrate input (mol dm^{-3}), $[S_2]_{in}$ the slow degradable substrate input (mol dm^{-3}), $[IC]_{in}$ the inorganic carbon input (mol dm^{-3}), $[B^{Z+}]_{in}$ the input cations (mol dm^{-3}), D the dilution rate (h^{-1}), F_{CH_4} methane flow rate (mol h^{-1}) and F_{CO_2} carbon dioxide flow rate (mol h^{-1}).

The effect of pH is included in the model by using Haldane growth rates as a function of [HAc] which is directly influenced by this parameter. Besides, Haldane equation allows saturation and inhibition to be considered by means of constants K_s (mol dm^{-3}) and K_i (mol dm^{-3}), respectively. The specific growth rate for $[X_2]$ is calculated as:

$$
\mu_2 = \frac{\mu_{2\,\max}[\mathrm{HAc}]}{K_{s2} + [\mathrm{HAc}] + \dfrac{[\mathrm{HAc}]^2}{K_{i2}}}
\tag{3}
$$

The parameters for this model were experimentally identified[23] and updated,[24] considering a CSTR with a nominal volume $V = 5$ dm^3. Besides, for a real prototype the hydraulic residence time distribution (HRTD) has important effects over the substrate degradation as shown by different authors.[25,26] In the present publication, a hydraulic residence time equal to 12.5 h is considered since the input flow rate is $Q = 0.4$ dm^3 h^{-1}; the respective HRTD corresponds to an ideal CSTR.

Indeed, there exist more complete models for anaerobic digestion such as the ADM1,[27] which considers 26 state variables and 8 algebraic variables, and models many phenomena; however, a global analysis of the ADM1 becomes a very complex task. Even if not all the phenomena involved in the process are included in the model (1–2), it is adequate for global analysis of the methanogenesis stage (the most important stage concerning process stability) by the phase portrait method, which requires two variables. The reduction of this model (1–2) is easier than a reduction of the ADM1. Additionally, the model is used to evaluate the proposed control strategy. In future works, the control strategy will be verified on other models such as the ADM1 as well as in real time.

Model analysis

In Carlos-Hernandez *et al.* 2004,[28] the authors present an analysis of matrix eigenvalues considering several operating points (local analysis). Even if that analysis allows the determination of process stability for all the considered points, it is hard to obtain further information about the influence of operating conditions on stability. For this reason, a global analysis is done using phase portraits.[29] This method consists of drawing the trajectories for different initial conditions in the phase plane. Then, qualitative analysis can be done in order to obtain information concerning process stability. The phase portrait can be applied for a two variables system. For this reason, model (1–2) is reduced by singular perturbations in order to separate the fast from the slow dynamics. Since the slow stage is the most important for the analysis presented in this paper, only methanogenesis dynamics are considered ($[S_2]$ and $[X_2]$). The fast dynamics are neglected, but the phenomena associated with them are still present; then, terms concerning the fast dynamics are included in the slow dynamics expression.

Fig. 1 displays a phase portrait obtained from this reduced model via simulations; different 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 microorganisms reach a maximal growth; consequently, the substrate is transformed and reaches a minimal value. This point is known as the functioning point. 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 that 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 separating the attraction regions is known as the stability limit. Additionally, when trajectories are reaching the equilibrium point, a change of direction appears, indicating a disturbance inception.

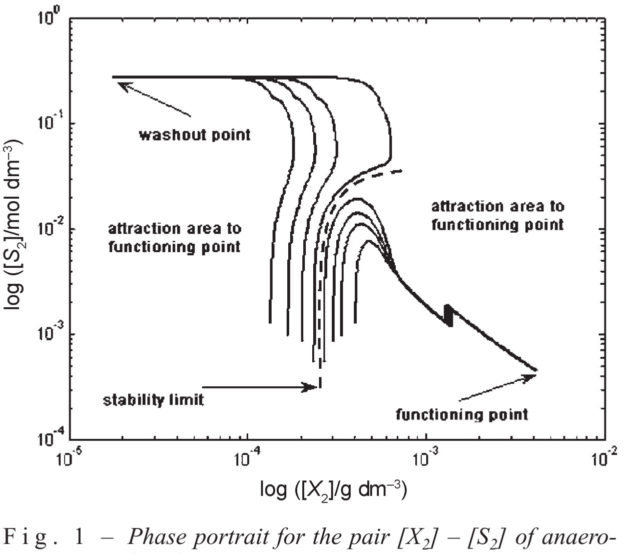


Fig. 1 – *Phase portrait for the pair $[X_2]$ – $[S_2]$ of anaerobic digestion*

Simulations show that the anaerobic process is able to reject small disturbances on the input substrates; however, for large disturbances the microorganisms are unable to treat the substrate, which increases causing washout. Then, for large disturbances, control strategies must be implemented in order to avoid stability limit crossings.

Synthesis of a fuzzy control strategy

The structure of the proposed strategy is shown in Fig. 2.

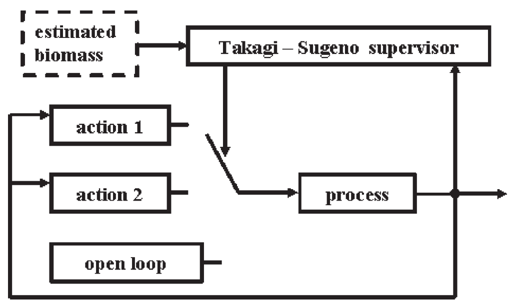


Fig. 2 – *Fuzzy integrated control strategy for the anaerobic digestion*

The main idea of this control scheme is to combine different control actions in order to minimize their drawbacks and to profit from their advantages: dilution rate (D) changes reject larger disturbances and supplying a base (b_{inc}) allows the process to produce a large amount of methane. Besides, the FCS permits detection of trajectories leading to washout; consequently, the most adequate control action is applied in order to avoid this phenomenon.

State observer description

Biomass soft sensors have different advantages in comparison with hard sensors. The former are less expensive and easy to implement and use; besides, the existing solid sensors are built from a biological approach, and are inadequate for automatic control. For example, they are based on turbidity or capacitance properties, and then it is difficult to determine different microorganism populations.

In a previous paper[24] a TS observer for anaerobic digestion in a CSTR was developed. This structure is based on several linear observers, which are interpolated by a fuzzy algorithm in order to obtain the non-linear dynamics. The inference rules are composed of linguistic variables as premises and dynamic systems (instead of linguistic variables) as consequents. For premises, a PCA is used as a guide to select the fuzzy input variables and the number of fuzzy sets for each variable: pH and D, 5 and 4 fuzzy sets, respectively, as illustrated in Fig. 3. Each combination of fuzzy sets corresponds to a process equilibrium point; for each one of these points, a local observer is synthesized. These local observers are validated around the respective equilibrium point, and are used as output variables in the consequents, meaning that the tuning of input fuzzy variables implies initialization of the output ones. The fuzzy system output is determined from the average center method, and since no fuzzy sets are used in the consequents, an additional procedure to tune output variables is not required.

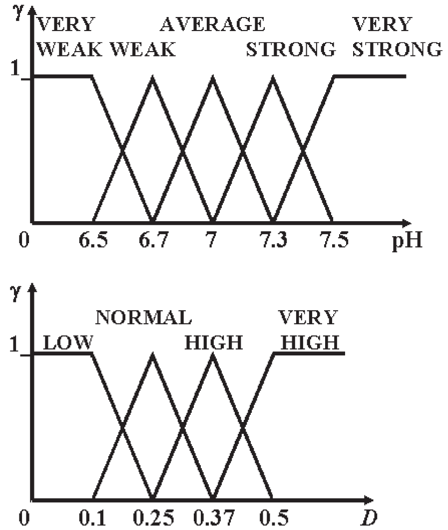


Fig. 3 – *Fuzzyfication of input variables for the state observer*

Twenty inference rules are deduced, with the following structure:

IF pH is $pH(\iota)$ AND D is $D(\upsilon)$

THEN the observed state is

$$\frac{d\hat{x}}{dt} = A_i\hat{x} + B_i u + K_i(y - \hat{y}) \qquad (r1)$$

$$y = C_i\hat{x}$$

where ι stands for VERY WEAK, WEAK, AVERAGE, STRONG or VERY STRONG for pH fuzzy sets; and υ stands for LOW, NORMAL, HIGH or VERY HIGH for D fuzzy sets, i = 1,…, 20, $A\in\mathbf{R}^{3x3}$ is the state matrix, $B\in\mathbf{R}^{3x3}$ is the input matrix, $C\in\mathbf{R}^{2x3}$ is the output matrix and $K\in\mathbf{R}^{3x2}$ is the observer vector gains. Note that the observer model considers only three state variables ([X_2], [S_2], [IC]) related to methanogenesis; then, the fuzzy observer has 3 inputs ([S_2]$_{in}$, [IC]$_{in}$ and D) and 3 outputs ([X_2], [S_2] and [IC]).

From this fuzzy rules structure, it is easy to see that the active observers at each instant are determined by pH and D. It is important to note that a maximum of 4 local observers are active simultaneously.[24] To recover the non-linear dynamics, the estimated states supplied by the local observers are interpolated using the defuzzyfication algorithm described by:

$$\frac{d\hat{x}}{dt} = \frac{\sum_{i=1}^{R}\gamma_i\{A_i\hat{x} + B_i u + K_i(y - \hat{y})\}}{\sum_{i=1}^{R}\gamma_i} \qquad (4)$$

$$\hat{y} = \frac{\sum_{i=1}^{R}\gamma_i\{C_i\hat{x}\}}{\sum_{i=1}^{R}\gamma_i}$$

γ is known as the membership function and is calculated as:

$$\gamma_i = \prod \gamma[v_j^k] \qquad (5)$$

where $\gamma[v_j^k]$ is the membership degree of variable v_j on the fuzzy set V_k and $\sum_{i=1}^{r}\gamma_i = 1$.

The experiments for the model and observer validation were performed during 10 days (batch experiment) and 30 days (continuous experiments), as shown in a previous work.[24]

Control law synthesis

A PI controller based on fuzzy logic and L/A approaches is proposed for bicarbonate regulation. The **L/A approach** is based on logarithmic and antilogarithmic (exponential) transformations, which allow the controllers to take into account positivity constraints for the process variables.[16,17] In fact, the inputs and states (flows and concentrations) must always be positive since negative values are unreal. The L/A approach is applied in order to fulfill positive constraints as follows: a logarithmic transformation is done to lead the signals from the real constraint domain to a fictive unconstraint one, where the information is processed. Then, an exponential transformation is done to return from the fictive to the real domain. A PI L/A controller for bioprocess[27] is based on a discrete PI represented by eq. (6), where u_k is the controller output, y the process output, y^* the setpoint, K_p and K_i the proportional and integral gains respectively, T_s is the sampling time and k is an integer representing samples.

$$u_k = u_{k-1} + K_p(y_{k-1} - y_k) + T_s K_i(y_k^* - y_k) \quad (6)$$

Eq. (7) is the L/A equivalent of (6); it is necessary to replace mathematical operations as follows: addition by multiplication, subtraction by division and multiplication by exponential:

$$U_k = U_{k-1}\left(\frac{Y_{k-1}}{Y_k}\right)^{K_1}\left(\frac{Y_k^*}{Y_k}\right)^{T_s K_2} \quad (7)$$

The structure of the fuzzy PI L/A proposed in this paper is similar to (7), replacing K_1 and K_2 by K_{1f} and K_{2f} (8–9), which are time-variant and on-line computed as a function of the error and its respective change rate. Eqs. (8) and (9) are based on the **minimal fuzzy PI** approach.[20,21] The input fuzzy variables selection is based on the output error signal from a specific process (in this case error on bicarbonate regulation). Two input variables are selected: error (e_k) and change of error rate, named rate for short (r_k). One output fuzzy variable is selected, and is related to the control action required to minimize the respective error. Fuzzyfication of variables is shown in Fig. 4, where G_e, G_r and G_u are scalers for error, rate and output, which are specially important when signals are small. Then, four fuzzy rules are deduced ($r2$ – $r5$).

If error = error positive AND rate =
= rate positive then output = output negative ($r2$)

If error = error positive AND rate =
= rate negative then output = output zero ($r3$)

If error = error negative AND rate =
= rate positive then output = output zero ($r4$)

If error = error negative AND rate =
= rate negative then output = output positive ($r5$)

Defuzzyfication is done by using the average center method. The tuning methodology is detailed in two papers dealing with minimal fuzzy PI.[20,21] From the defuzzyfication stage, (8) and (9) are obtained.

$$K_{1f} = \frac{0.5LG_uG_r}{2L - G_e|e_k|} \qquad K_{2f} = \frac{0.5LG_uG_e}{2L - G_e|e_k|} \qquad \text{If } G_r|r_k| \le G_e|e_k| \le L \quad (8)$$

$$K_{1f} = \frac{0.5LG_uG_r}{2L - G_r|r_k|} \qquad K_{2f} = \frac{0.5LG_uG_e}{2L - G_r|r_k|} \qquad \text{If } G_e|e_k| \le G_r|r_k| \le L \quad (9)$$

L is selected according to the process dynamic; it represents the permissible amplitude of the error. G_u, G_e and G_r are tuned as follows. First, the values of the static gains of the fuzzy PI L/A (when $e_k = r_k = 0$) are computed from (8) and (9) as:

$$K_{1s} = 0.25\,G_uG_r \qquad K_{2s} = 0.25\,G_uG_e \quad (10)$$

After that, it is assumed that the fuzzy static gains are equal to the PI L/A gains (before fuzzyfication):

$$K_1 = 0.25\,G_uG_r \qquad K_2 = 0.25\,G_uG_e \quad (11)$$

Combining (10) and (11), then:

$$G_u = \frac{4K_1}{G_r} = \frac{4K_2}{G_e} \quad (12)$$

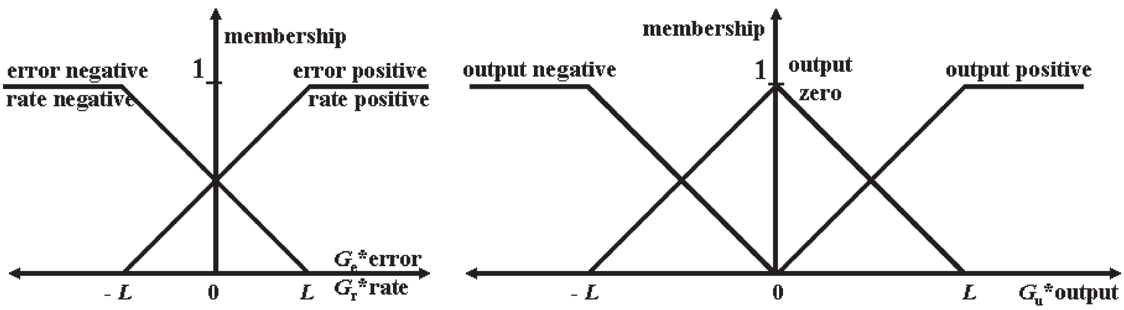


Fig. 4 – *Fuzzyfication of input and output variables for the minimal fuzzy PI*

Fixing $G_u = 4$ in (12), it is easy to see that $G_r = K_1$ and $G_e = K_2$.

Following the methodologies described above, it is possible to obtain discrete fuzzy PI L/A controllers for anaerobic digestion considering dilution rate changes (D_k) and bicarbonate supply (b_{inc_k}) as:

$$D_k = (D_{k-1})\left(\frac{[HCO_3^-]_{k-1}}{[HCO_3^-]_k}\right)^{K_{1f}}\left(\frac{[HCO_3^-]_k^*}{[HCO_3^-]_k}\right)^{T_s K_{2f}} \quad (13)$$

$$b_{inc\_k} = (b_{inck-1} - b_{inc\_min}) \cdot \cdot \left(\frac{[HCO_3^-]_{k-1}}{[HCO_3^-]_k}\right)^{K_{1f}}\left(\frac{[HCO_3^-]_k^*}{[HCO_3^-]_k}\right)^{T_s K_{2f}} + b_{inc\_min} \quad (14)$$

The integral and proportional gains are computed with eqs. (8–9). Then, the fuzzy PI L/A approach allows the controller to take into account positivity constraint of variables, and also allows the gains to change as a function of operation conditions.

Fuzzy supervisor control development

The supervisor has two main tasks: i) detect the process state, and ii) select the most adequate control action allowing smooth switching (if required) between them. The implicit idea is to detect the attraction region where the process is working; if any operating conditions cause the process to move away from the operating domain, the supervisor must determine and apply the control action which allows the bacteria to grow in order to avoid washout. Besides, if a variation on the operation conditions can be managed by the process itself, the supervisor must allow the system to operate in open loop. These objectives are achieved monitoring the variables that are indicators of the biological activity inside the reactor as a consequence of variations on the operating conditions. Two variables are proposed for the fuzzy inference rules: increase of methane production (ΔF_{CH_4}) and organic daily load per biomass unit ($ODL/[X_2]$). The number of fuzzy sets for each variable is determined as follows: a series of simulations are performed in order to classify the input variables behavior as a function of the operation conditions. This analysis allows ΔF_{CH_4} to be expressed as a function of the disturbance amplitude: a low variation is caused by a small disturbance that can be rejected by the process without a control action; meanwhile, a high variation is caused by a larger disturbance that requires a control action to be rejected. Then, two fuzzy sets are chosen as shown in Fig. 5; the first one indicates that a control action is required, and the second one points out that the process is able to operate in open loop. Besides, $ODL/[X_2]$ represents the maximal quantity of organic load that a biomass unit can treat during a working day. There exists a limit for this variable; above it, a control action is required to avoid washout, and below this limit, the process 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. Concerning the output fuzzy variables, three operation regions for the process are identified: open loop, closed loop with b_{inc} action, and closed loop with D action. Since no fuzzy sets are used in the consequents, an additional procedure to tune output variables is not required.

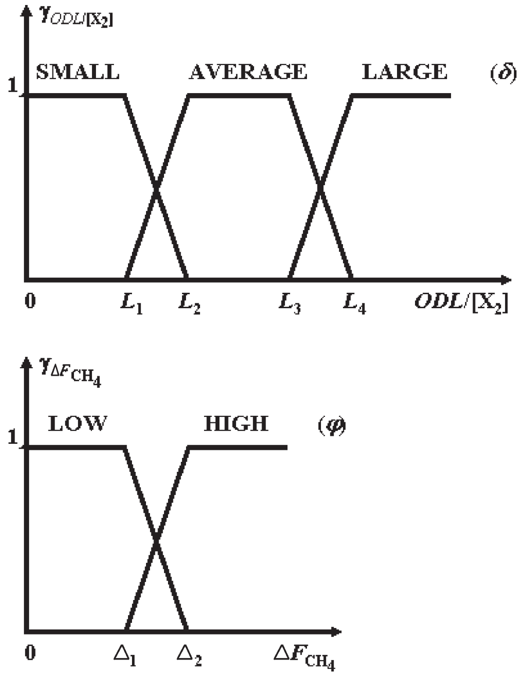


Fig. 5 – *Fuzzyfication of input variables for the supervisor*

The Takagi-Sugeno algorithm[30,31] is used to define the supervisor. From empirical knowledge, each fuzzy set is associated with a control action; then six fuzzy inference rules are deduced (r6-r11):

If $ODL/[X_2]$ is SMALL and ΔF_{CH_4} is LOW then u = *open loop* (r6)

If $ODL/[X_2]$ is SMALL and ΔF_{CH_4} is HIGH then u = *open loop* (r7)

If $ODL/[X_2]$ is AVERAGE and ΔF_{CH_4} is LOW then $u = b_{inc}$ (r8)

If $ODL/[X_2]$ is AVERAGE and ΔF_{CH_4} is HIGH then $u = b_{inc}$ (r9)

If $ODL/[X_2]$ is LARGE and ΔF_{CH_4} is LOW then $u = D$ (r10)

If $ODL/[X_2]$ is LARGE and ΔF_{CH_4} is HIGH then $u = D$ (r11)

Defuzzyfication is done using the average center method (15):

$$u = \frac{\sum_{j=1}^{R} \gamma_j u_j}{\sum_{j=1}^{R} \gamma_j} \tag{15}$$

where $\gamma_j = \gamma^{k}_{ODL/[X_2]} \cdot \gamma^{l}_{\Delta F_{CH_4}}$ and $\sum_{j=1}^{R} \gamma_j = 1$; with R the number of rules, k and l the k^{st} and the l^{st} fuzzy sets of $ODL/[X_2]$ and ΔF_{CH_4}, respectively; the symbol * indicates multiplication.

Simulations results and discussion

The proposed strategy is compared with classical PI controllers considering the same tuning methodology and the same operation conditions. Classical PI controllers are implemented independently without the supervisor control. A set of simulations close to experimental conditions are performed considering disturbances on $[S_2]_{in}$. This kind of disturbance is selected since input substrate increases are the most difficult to reject in real systems. The amplitude of disturbances (A_2) is given as a normalized percentage ($A_2 = 1$ is 100 % of the initial value). All simulations are performed for 900 h (37 days).

A disturbance $A_2 = 1.5$ is incepted at time $t = 50$ h; the process behavior is shown in Fig. 6. It can be seen that the PI for b_{inc} action allows the bicarbonate to be regulated in short time; additionally, biomass $[X_2]$ increases and leads to a new equilibrium point. The PI for D action does not have a relevant influence on bicarbonate regulation and biomass growth. Concerning the FCS, ΔF_{CH_4} belongs to LOW and $ODL/[X_2]$ belongs to SMALL; both fuzzy sets are associated to OPEN LOOP operation; then a control action is not required since the process itself is able to reject the disturbance. For this reason, the supervisor allows the process to operate in open loop (b_{inc} and D constants at equilibrium values); consequently, $[HCO_3^-]$ reaches the set point by itself and $[X_2]$ grows also by itself until it reaches a new equilibrium value.

A disturbance $A_2 = 2.2$ is incepted at time $t = 50$ h; the process behavior is shown in Fig. 7. The PI for b_{inc} action is unable to reject the disturbance; $[HCO_3^-]$ is not regulated and $[X_2]$ reaches washout. The PI for D action allows the process to reject the disturbance; $[HCO_3^-]$ is regulated and $[X_2]$ increases and reaches a new equilibrium point. On the other side, the FCS works as follows: when the disturbance is incepted, ΔF_{CH_4} belongs to HIGH (associated to closed loop) meanwhile $ODL/[X_2]$ belongs to LARGE (associated to D action). Then,

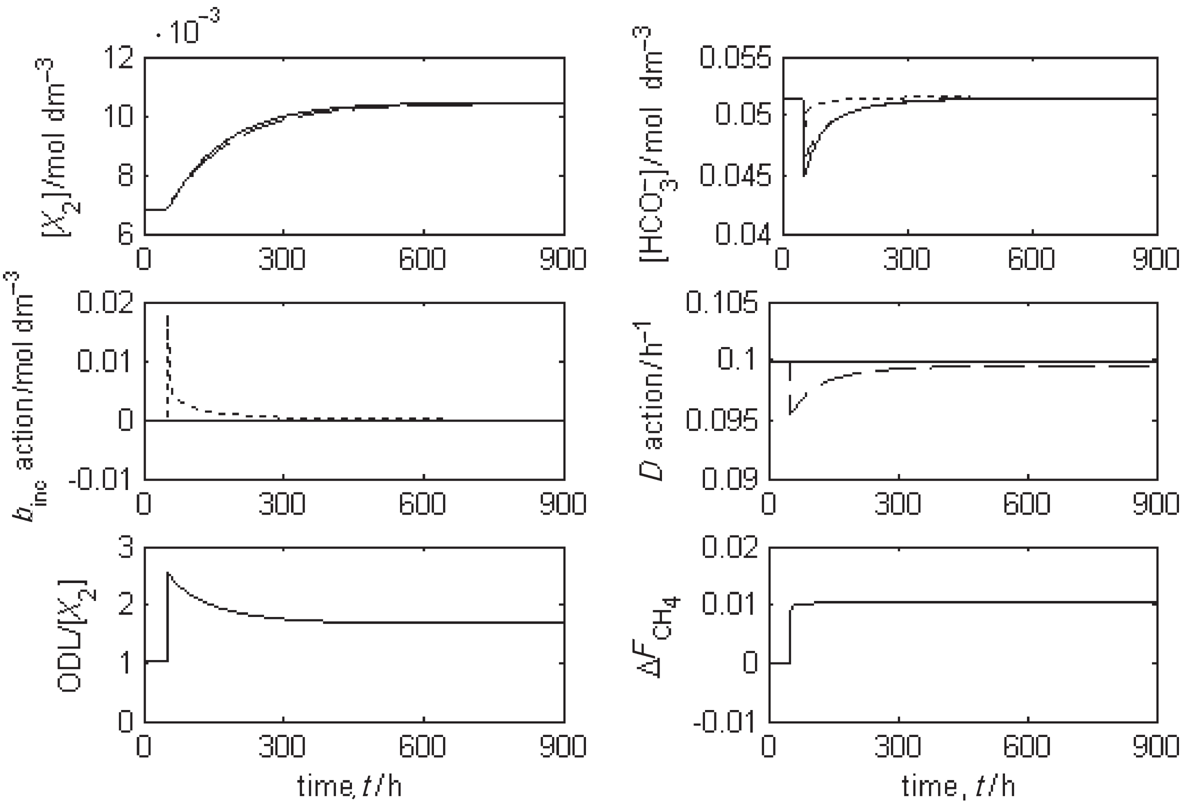
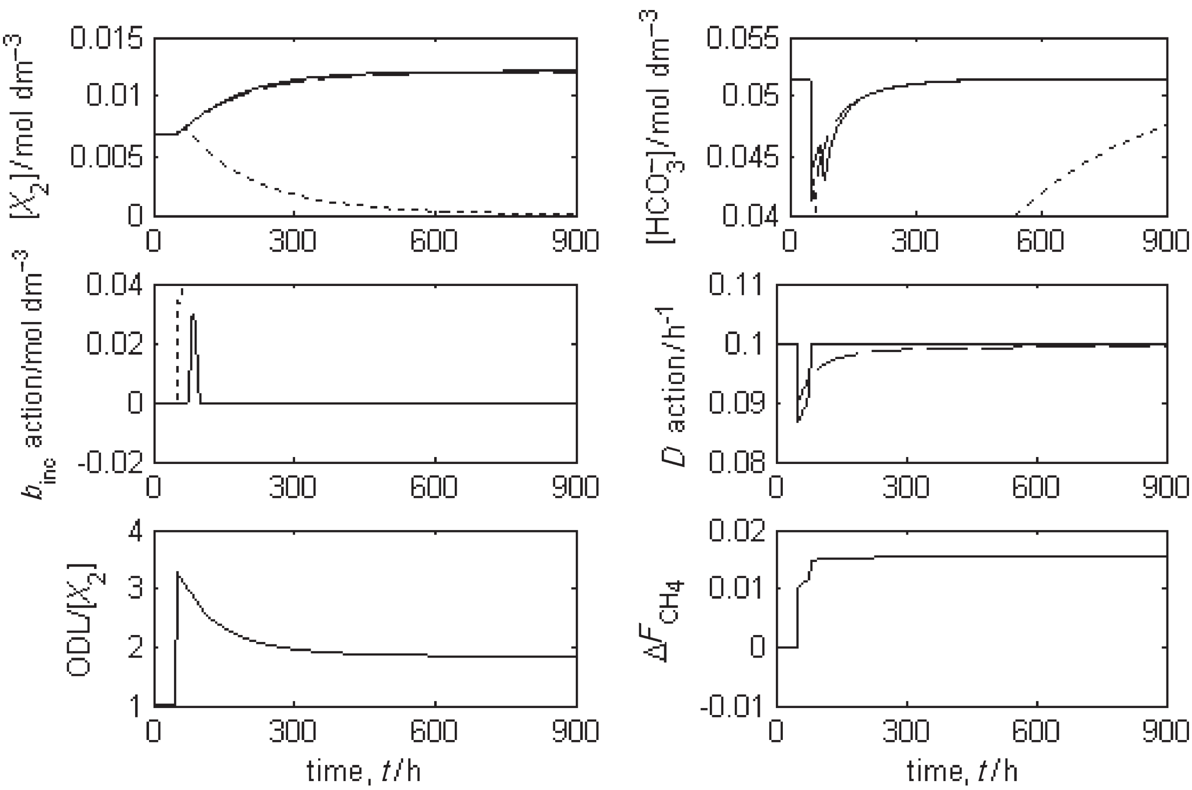


Fig. 6 – *Comparison of the FCS with PI controllers considering a small disturbance on $[S_2]_{in}$. PI for b_{inc} action: doted line, PI for D action: dashed line, FCS: continuous line*



F i g . 7 – *Comparison of the FCS with PI controllers considering A_2 = 2.2. PI for b_{inc} action: doted line, PI for D action: dashed line, FCS: continuous line*

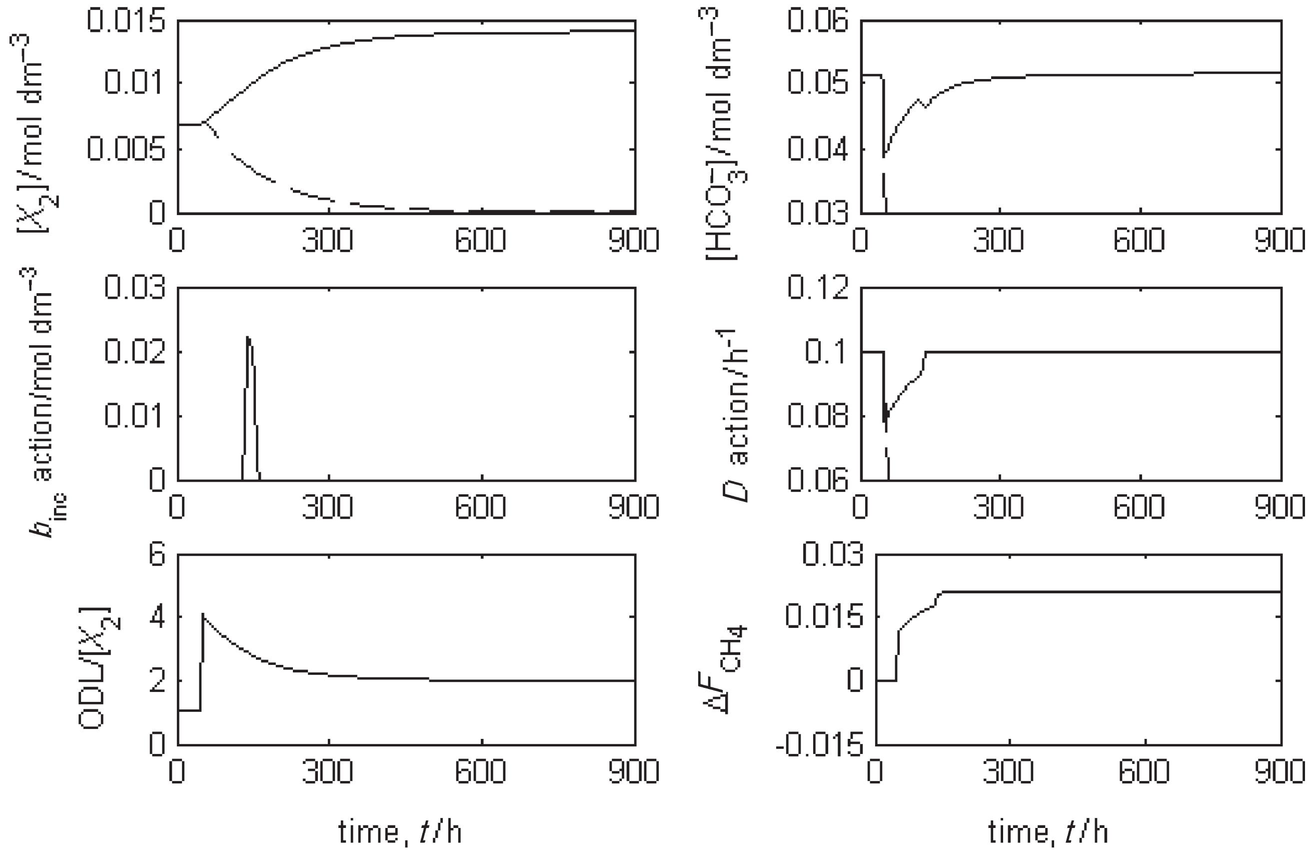
the supervisor allows the D action to be applied; consequently, [HCO_3^-] starts to be regulated and [X_2] tends to a new equilibrium value. As the action is applied, ΔF_{CH_4} continues to belong to HIGH, meanwhile ODL/[X_2] decreases and belongs to AVERAGE (associated to b_{inc} action). Then, action D is progressively stopped and b_{inc} starts to be applied. Consequently, [X_2] and [HCO_3^-] decrease when D is stopped; when b_{inc} is applied [X_2] and [HCO_3^-] increase again leading to a new equilibrium point. Finally, ΔF_{CH_4} leaves HIGH and belongs to LOW (associated to open loop); meanwhile ODL/[X_2] decreases and belongs to SMALL (associated to open loop). This situation implies the disturbance has been rejected. Then, the supervisor stops b_{inc} action and the process operates in open loop again. If other disturbance is incepted, the process will operate similar to the previous description.

As a subsequent test, the disturbance amplitude is increased to $A_2 = 3$ and incepted at time $t = 50$ h; the process behavior is shown in Fig. 8. The PI for D action is unable to reject the disturbance; [HCO_3^-] is not regulated and [X_2] reaches washout. Concerning the FCS, the process behaviour is similar to the description for $A_2 = 2.2$. In this case, D action is applied longer in comparison with previous simulations. This is a normal situation since the disturbance is larger.

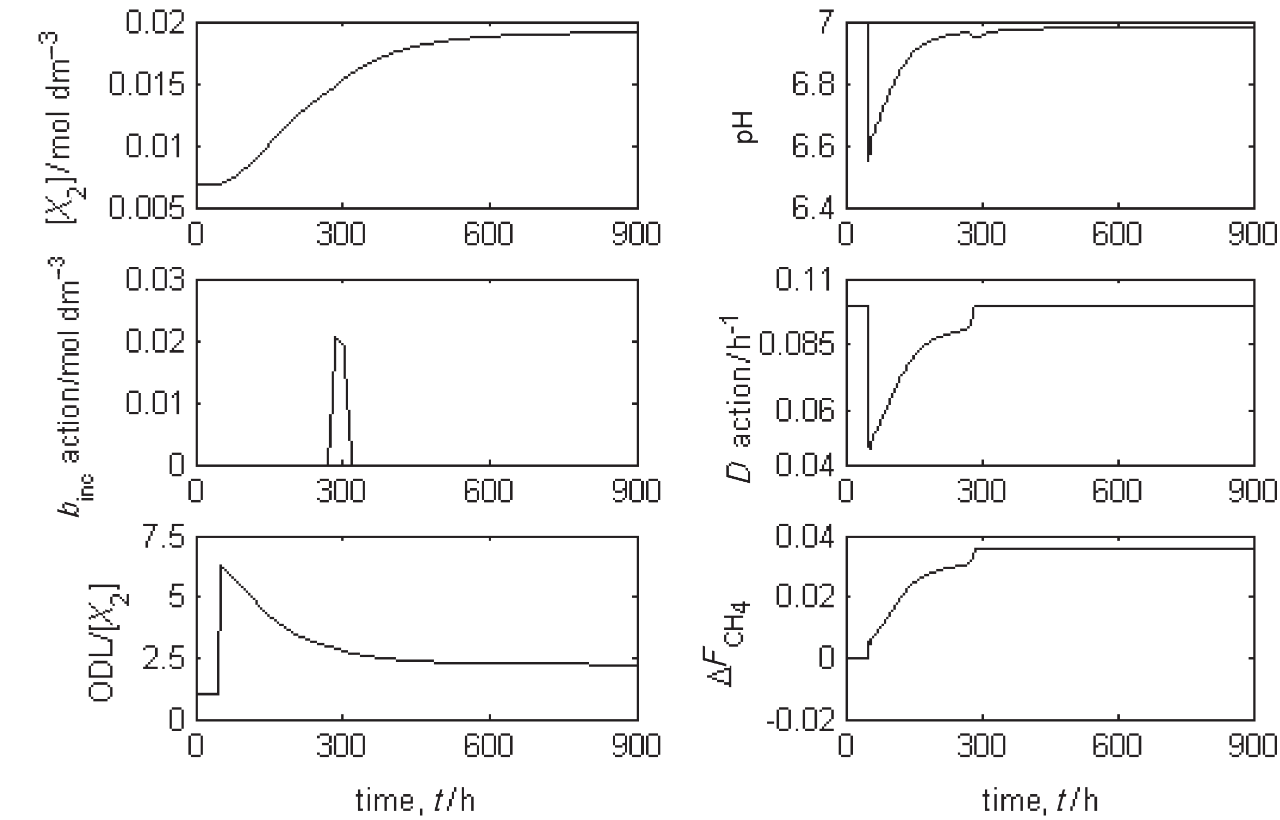
With the proposed control strategy the process is able to operate adequately for disturbances until $A_2 = 5$. For $5 < A_2 < 6.5$ the washout is not reached; however, the control actions require a lot of time to reject the disturbance and then the bicarbonate regulation becomes slow. For $A_2 > 6.5$ the washout phenomena cannot be avoided.

Another kind of simulation considering the pH effect is performed. A disturbance corresponding to 10 % on pH is incepted at time $t = 50$ h. The independent classical PI controllers are not considered for this test. The results are shown in Fig. 9. The process behaviour is similar as for the previous descriptions. The supervisor determines the disturbance amplitude and allows the corresponding control actions to be applied; pH returns to the equilibrium value and [X_2] increases reaching a new equilibrium point.

From the previous simulations, it is possible to conclude that the proposed control strategy enhances the process performance. The supervisor detects a disturbance on the input substrate and determines 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 bicarbonate used by control actions is saved. When control actions are required, the supervisor carries out a smooth switching, avoiding oscillations.



F i g . 8 – *Comparison of the FCS with PI controllers considering a large disturbance on $[S_2]_{in}$. PI for D action: dashed line, FCS: continuous line*



F i g . 9 – *FCS performance considering the pH effect*

Conclusions

It is possible to conclude that fuzzy control is an interesting alternative for improving anaerobic process performance. The main advantages of the proposed control scheme are as follows:

i) it allows different control actions to be combined in order to minimize individual drawbacks and profit from their advantages, which allows larger disturbances rejection and methane production increases; ii) it allows detection of the trajectories leading to washout; by the selection of the most adequate control action (D, b_{inc} or even open loop), iii) feasible measures such as biogas and bicarbonate are required; for restrictive variables such as biomass a state observer is proposed, and iv) the proposed control strategy shows a good compromise between efficiency and complexity for real-time implementation.

The obtained simulation results evince an improved performance of the anaerobic process in the presence of large disturbances on the input substrate. Small disturbances are rejected by the process itself (open loop operation); for large disturbances, a combination of b_{inc} and D actions is done in order to reject disturbances. After this rejection, the process returns to open loop mode operation.

Different subjects are identified for further developments as: a) a methodology to tune the supervisor parameters in order to formalize the empirical knowledge, and b) the experimental validation of the proposed strategy; which would allow the user to analyze the influence of the FCS over the hydraulic residence time distribution.

List of symbols

A_2 – amplitude of disturbance
(A_i, B_i, C_i) – state space representation for the ith equilibrium point
B^{Z+} – Total of cations, mol dm^{-3}
b_{inc} – supplying base action, mol dm^{-3}
D – dilution rate, h^{-1}
e – error
F – molar flow rate, mol h^{-1}
f – set of non-linear functions
G_e, G_r, G_u – scalers for error, rate and output
g – set of linear algebraic equations
h – set of non-linear functions depending on dynamic variables
K_{s2} – saturation constant, mol dm^{-3}
K_{i2} – inhibition constant, mol dm^{-3}
K_p, K_i – proportional and integral gains
K_1, K_2 – PI L/A gains
K_{1f}, K_{2f} – fuzzy PI L/A gains
L – permissible amplitude of error
Q – volume flow rate, dm^3 h^{-1}
R – number of rules
r – change of error rate
T_s – sample time, h
t – time, h
U – dynamic of inputs in the L/A domain
u – dynamic of inputs in the real domain
V – volume, dm^3
z – charge number of a cation B
x_a – physico-chemical part of process
x_b – biological dynamic part of the process
[S] – substrate concentration, mol dm^{-3}
[X] – biomass concentration, mol dm^{-3}
Y – dynamic of outputs in the L/A domain
y – dynamic of outputs in the real domain
μ – specific growth rate, h^{-1}
ι – pH fuzzy sets
υ – D fuzzy sets
γ – membership function

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