Iterative Learning Control of Depollution Bioprocesses

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***Abstract*— The paper addresses the design and analysis of Iterative Learning Control (ILC) method for a wastewater biodegradation process. The bioprocess is considered to take place inside a continuous stirred tank bioreactor. The use of this kind of control methods is motivated by its advantages in the case of complex nonlinear systems like biotechnological processes. There were used two ILC algorithms – one considered a classical approach in the field (PD – type learning algorithm), and the second one which try to exploit some characteristics of the input signal (exponential learning algorithm). These control methods are implemented for the depollution control problem in the case of an anaerobic digestion process. This bioprocess is characterized by strongly nonlinear and not exactly known reaction rates. Furthermore, not all the state variables are measurable. The performance and effectiveness of the presented control algorithms are proven by simulation results.**

Keywords*— *wastewater biodegradation process, iterative learning control, nonlinear systems

I. Introduction

In the last period, biotechnology is one of the most important research areas for many industrial domains: agriculture, pharmaceutical, food industry, energy, environment etc. Essentially, a bioprocess is a chain of chemical reactions that take place inside a bioreactor with mention that in these reactions are involved living microorganisms (bacteria). Modelling and control of these processes are the main aspects that must be solved in order to increase the productivity. The importance of the domain is reflected by the large number of workshops, conferences, research projects and journals or special issues dedicated to these topics.

Mathematical modelling of these processes is obstructed by the strong nonlinear characteristics, coupled variables and poorly understood dynamics. Many efforts have been made in order to capture as many as possible of the bioprocesses characteristics in order to develop reliable control algorithms. The most difficult features in the model are the reaction rates where the non-linear character of the process resides and where some of the model parameters are not identifiable. There exists a series of results on bioprocesses modelling, the most cited being the well-known dynamical model presented by Bastin and Dochain in [1]. The parametric models are the most used and were tested all spectrum of such models (the set of nonlinear differential/difference equations, polynomial models, neural networks, fuzzy models, etc.). All the methods used in nonlinear system identification were applied, starting with prediction error methods up to heuristic algorithms. Starting from these models, two main approaches for control bioprocess must be highlighted: optimal and adaptive control algorithms. The first class of algorithms (optimal control algorithms) provides a theoretical realizable optimum under the assumption of a perfectly known model. This is the main drawback of these methods in real-life applications. On the other hand, the adaptive controllers do not guarantee optimality of the control results. But the most intriguing aspect in the control problem is the fact that the model is changing from one experiment to another according to a series of parameters that changes in time. So, the control algorithms that realize a balance between model accuracy and control needs are the most successful in the biotechnological field.

This paper approaches the use of Iterative Learning Control (ILC) method in order to control a complex biotechnological process: the biodegradation process of wastewater organic matter in a wastewater treatment plant. The process is an anaerobic digestion one and the control goal is to keep the pollution at a specified low level despite any influent pollutant variation and time varying of some typical process parameters. Treatment of industrial wastewaters by using microbial degradation is one of the most important waste management processes [2].

The starting point of ILC methods is considered the paper of Arimoto *et al.* [3], and this method is largely used especially in repetitive processes like robot manipulators. Although initially this method was used off-line, the control law being improved from one iteration to another, on-line variants have been developed that adjust the command from one sampling period to another. The ILC was used also in fed-batch bioprocesses and several results have been reported in the literature [4], [5]. The main advantage over other control methods is represented by the fact that ILC design is

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model independent, which is a key factor in a complex system like a bioprocess. ILC uses information from previous steps in order to improve the tracking performance. There are numerous variants of the ILC method, but in our study, we used only two of them: the PD – type learning algorithm (denoted in the following PD-ILC) and the general high-order ILC algorithm (denoted G-ILC). The two control algorithms are tested by numerical simulation considering a simplified reaction scheme of the depollution bioprocess.

The paper is organized in the following manner. Section II is devoted to description and modelling of a complex anaerobic digestion bioprocess. The Iterative Learning Control strategies for nonlinear bioprocesses are presented in Section III. The results of the simulations conducted in Section IV illustrate the performance of the proposed control algorithms. Finally, Section V is dedicated for some future research direction in this topic and conclusions.

II. Mathematical Model of Wastewater Biodegradation Process

A. Process Description

Wastewater treatment processes are among the most important biotechnological processes. There are numerous research books, journals and conference papers dedicated to modelling and control of this kind of bioprocesses. The importance of studying these processes is evident not only from the point of view of scientific research, but also of environmental issues that need to be solved with stringency. One of the most commonly used wastewater treatment techniques is anaerobic decomposition with production of methane gas. The wastewater biodegradation process is an anaerobic digestion bioprocess where bacteria decompose organic matter to methane gas, carbon dioxide and water. This process consists of four metabolic phases: two to produce acids and two for methanisation. A schematic view of this bioprocess is presented in Fig. 1. As one can see, the biodegradation process is a very complex one and a simplified reaction scheme is composed of four reactions and ten components [6]. In the first stage, the glucose from the wastewater is decomposed in hydrogen, fat volatile acids (propionic acid and acetates) and inorganic carbon under action of the acidogenic bacteria. In the second stage, the propionic acid CH_3CH_2COH is decomposed by ionized hydrogen in acetates, carbon dioxide CO_2 and H_2.

B. Nonlinear Mathematical Model

In order to analyse the control methods based on ILC, a simplified reaction scheme (with only two reactions) was considered:

$$x_2 \overset{r_1 \leftarrow}{\rightarrow} x_1 + x_4 \tag{1}$$

$$x_4 \overset{r_2 \leftarrow}{\rightarrow} x_3 + x_5 \tag{2}$$

where the following notations were used:

x_1 – acidogenic bacteria;

x_2 – glucose pollutant concentration;

x_3 – Obligate Hydrogen Producing Acetogens (OHPA);

x_4 – acetate;

x_5 – methane gas;

r_1 – rate of the acidogenic reaction;

r_2 – rate of the methanisation reaction.

If the anaerobic digestion process takes place inside a Continuous Stirred Tank Reactor, the dynamical model represented by state equations is the following:

$$\dot{x}_1 = r_1 - Dx_1 \tag{3}$$

$$\dot{x}_2 = -k_1 r_1 - Dx_2 + DS_{in} \tag{4}$$

$$\dot{x}_3 = r_2 - Dx_3 \tag{5}$$

$$\dot{x}_4 = k_2 r_1 - k_3 r_2 - Dx_4 \tag{6}$$

$$\dot{x}_5 = k_4 r_2 - Dx_5 - q_1 \tag{7}$$

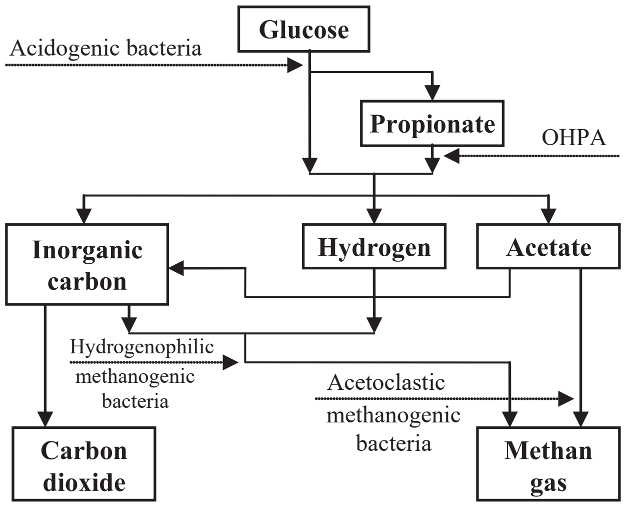

Fig. 1. Anaerobic digestion process scheme.

with k_i $(i = 1, 2, 3, 4)$ the yield coefficients, D the dilution rate, S_{in} the influent substrate concentration and q_1 the gaseous outflow rate of CH_4.

Putting these equations in matrix form, one gets the well-known equation:

$$\dot{\overline{x}} = K \cdot \overline{r} - D\overline{x} + \overline{f} - \overline{q} \tag{8}$$

where:

$\overline{x} = [x_1\ x_2\ x_3\ x_4\ x_5]^T$ - the state vector;

$\overline{r} = [r_1\ r_2]^T$ - the vector of reaction rates;

$$K = \begin{bmatrix} 1 & 0 \\ -k_1 & 0 \\ 0 & 1 \\ k_2 & -k_3 \\ 0 & k_4 \end{bmatrix}$$ - the yield coefficient's matrix;

$\overline{f} = [0 \;\; DS_{in} \;\; 0 \;\; 0 \;\; 0]^T$ - the vector of inflow rates;

$\overline{q} = [0 \;\; 0 \;\; 0 \;\; 0 \;\; q_1]^T$ - the vector of gaseous outflow rates.

In our study one considered that the reaction rate r_1 is a Monod type model described by the equation:

$$r_1 = \alpha x_1 x_2 \, , \; \alpha = \alpha^* / (K_M + x_2) \tag{9}$$

and reaction rate r_2 is a Haldane type model described by the equation:

$$r_2 = \beta x_3 x_4 \, , \; \beta = \beta^* / (K_H + x_4 + x_4^2 / K_I) \tag{10}$$

As one can see, even the simplified model is a complex one, with a strong nonlinear character. Obtaining an accurate model from noisy measurements is a difficult task and many parameters of the model can change in time due to the change of working conditions (like modifications of temperature, concentrations of some reactants etc.).

In the following, we consider as controlled variable the output pollution level y defined as:

$$y = c_1 x_2 + c_2 x_4 \tag{11}$$

where c_1 and c_2 are known conversion constants, and as input control we select the dilution rate, $u = D$. The control goal is to maintain the pollution to a low level by controlling the dilution rate.

III. Iterative Learning Control Strategies

Specialty literature presents many control strategies based on ILC. In this paper we will use two ILC methods to control the pollution level in wastewater treatment bioreactor: a classic PD – type learning algorithm and an exponential type learning algorithm.

A. PD – type Iterative Learning Algorithm (PD-ILC)

One of the most simple but effective approach to control complex nonlinear systems is represented by an ILC algorithm with iterative learning adjustment of command of PD – type. The adaptation formula is a combination of a P – type learning algorithm:

$$u(k \cdot T_s + T_s) = u(k \cdot T_s) + k_p e(k \cdot T_s) \tag{12}$$

and a D – type learning algorithm:

$$u(k \cdot T_s + T_s) = u(k \cdot T_s) + k_d \frac{e(t)}{dt} \tag{13}$$

In these relations, $e(t)$ is the tracking error, $k_p, k_d > 0$ are the gains associated to P and respectively D laws, T_s represents the sampling time and by notation $u(k \cdot T_s)$ one understands the value of the signal $u(t)$ at the k^{th} sampling moment $t = k \cdot T_s$. In the following derivations, for simplicity, one replace $u(k \cdot T_s)$ by subscript notation u_k, eliminating the sampling time. So, combining (12) and (13) one get the PD – type learning algorithm:

$$u_{k+1} = \mathrm{u}_k + k_p e_k + k_d \frac{de(t)}{dt} \tag{14}$$

Since relations (12) and (13) are a combination discrete - continuous, the derivative of the error is approximated using the backward difference operator:

$$\frac{de(t)}{dt} \cong \frac{e_k - e_{k-1}}{T_s} \tag{15}$$

On get the recursive form of the algorithm:

$$u_{k+1} = \mathrm{u}_k + k_p e_k + k_d \frac{e_k - e_{k-1}}{T_s} \tag{16}$$

B. General – type Iterative Learning Algorithm (G-ILC)

In this approach, the command applied at the input of the system is calculated using the following function:

$$u_{k+1} = \Gamma(q)\left(u_{k-1} + \Psi(q) \cdot e_{k-1}\right) \tag{17}$$

This function is described by two linear filters: $\Gamma(q)$ and $\Psi(q)$, where q is the forward time-shift operator $q \cdot u_k = u_{k+1}$ and $q^{-1} \cdot u_k = u_{k-1}$. There are three main approaches for G-ILC design: heuristic, model-based and optimization-based design.

In the heuristic case (which is suited for systems with unknown model), $\Gamma(q)$ is selected as a low pass filter and $\Psi(q)$ has the form $\Psi(q) = \sigma \cdot q^{-\lambda}$ with $0 < \sigma \le 1$ and λ equal with system order. The last two design procedures are based on a linearized model of the nonlinear system. If the one denote by M_L the linearized model of the process, then $\Psi(q) = M_L^{-1}$ (so $\Psi(q)$ is a model of the inverted system dynamics). If M_L is an exact model of the controlled system and the inversion of the model is errors free, then the convergence of the algorithm is provided.

In the case of nonminimum phase systems the resulting filter is unstable so, a stabilizing filter should be added [7]. For the minimum phase system, the performance of the system depends on the accuracy of the model. If the differences between real system and model are significant, the transient behaviour deteriorates. Usually the most important uncertainties appear at high frequencies so, again, $\Gamma(q)$ is chosen as a low pass filter.

The optimization-based design uses the impulse response matrix model and minimizes a quadratic cost function [7]. In our study one used the heuristic approach, considering that the process model is unknown.

The ILC general scheme is presented in Fig. 2, where one have:

u_k – command signal

v_k – reference

y_k – output of the system (controlled variable)

e_k – system error.

IV. Simulation Results and Discussions

The performance of the designed ILC controllers has been tested through numerical simulation experiments using the process model (3)-(7).

The model was discretized using a fourth order Runge-Kutta routine to approximate the solutions of the system of ordinary differential equations. In all simulations a sampling time T_s of 6 minutes was considered.

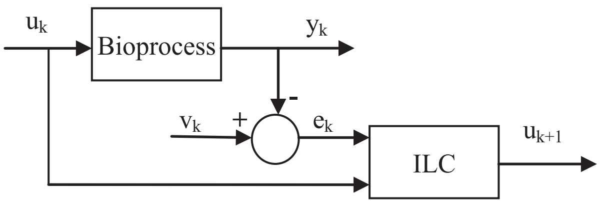

Fig. 2. The ILC control scheme.

The value of yield coefficients of the reduced model used: k_1 = 5.4, k_2 = 1.4, k_3 = 14.7, k_4 = 11, and the values of the conversion coefficients c_1 and c_2 in (11) are: c_1 = 1.2, c_2 = 0.75. The reaction rate r_1 is a Monod type of form:

$$r_1 = \alpha x_1 x_2 \ \text{ with } \ \alpha = \alpha^* / (K_M + x_2),$$

where $\alpha^* = 0.25\ h^{-1}$, $K_M = 0.75\ g/l$.

The reaction rate r_2 was considered a Haldane type:

$$r_2 = \beta x_3 x_4 \quad \beta = \beta^* / (K_H + x_4 + x_4^2 / K_I)$$

where $\beta^* = 0.75\ h^{-1}$, $K_H = 4\ g/l$, $K_I = 21\ g/l$.

Simulation results for 30 hours in PD-ILC case are presented in Figs. 3–5. The design parameters used were $k_p = 0.3$ and $k_d = 0.015$. Fig. 3 depicts the reference tracking behaviour of the control system for a step variance of the reference (at moment t = 15h) from 10[g/l] to 5[g/l] and Fig. 4 presents time evolution of the corresponding command signal (dilution rate D). Figure 6 presents the disturbance rejection capabilities of the PD-ILC controller for a step modification of the perturbation S_{in} from 30[g/l] to 60[g/l], as in Fig. 5.

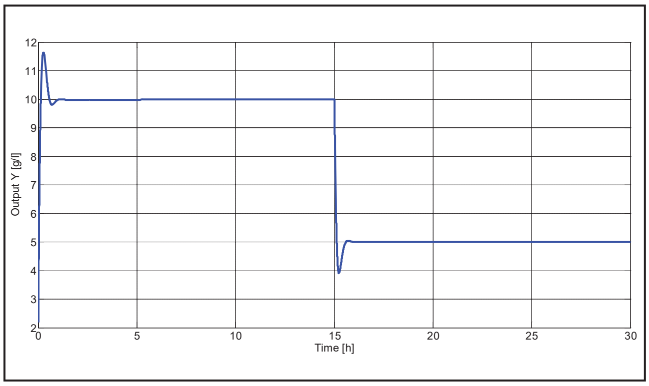

Fig. 3. Time evolution of output y (PD-ILC controller) – reference tracking.

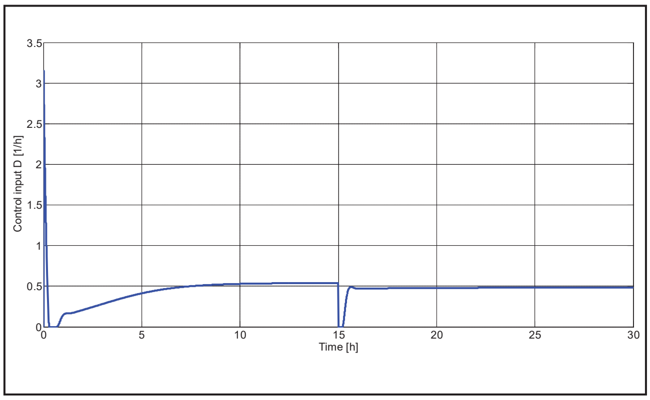

Fig. 4. Time evolution of command D - (PD-ILC controller).

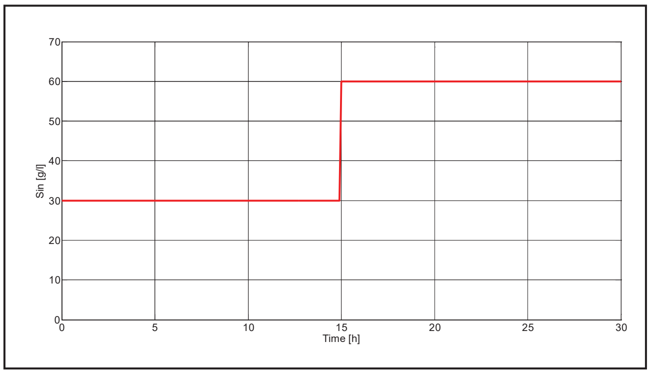

Fig. 5. Time variation of perturbation Sin.

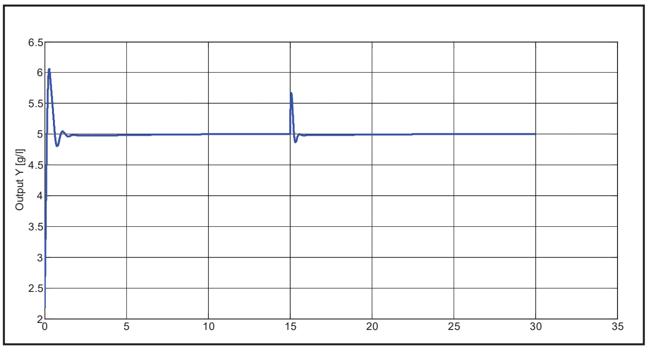

Fig. 6. Time evolution of output y (PD-ILC controller) – perturbation rejection.

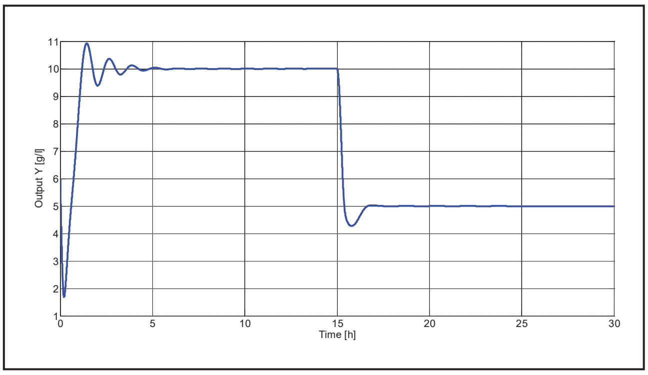

Fig. 7. Time evolution of output y (G-ILC controller) – reference tracking.

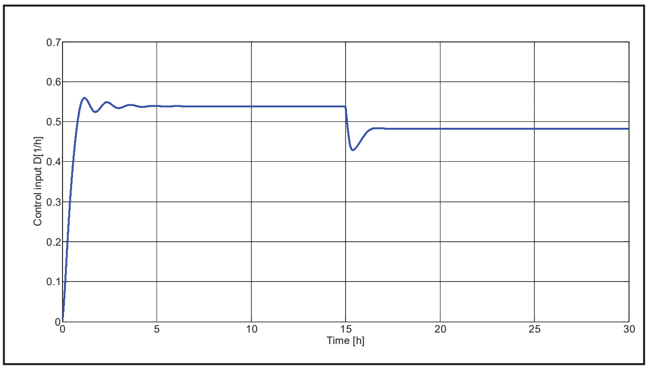

Fig. 8. Time evolution of command D - (G-ILC controller).

For the G-ILC case, $\Gamma(q)$ was chosen as a second order low pass filter, and for the term $\Psi(q) = \sigma \cdot q^{-\lambda}$, $\sigma = 0.8$ and $\lambda = 5$. Figs. 6–7 present the reference tracking in the G-ILC case. One can notice a smaller overshoot but a longer settling time, the control input being smoother in this case (see Fig.7).

V. Conclusions

In this paper the Iterative Learning Control method (the on-line variant) was used in order to control a complex biotechnological process: the biodegradation of wastewater organic matter with production of methane gas. Even a detailed description of the bioprocess was presented, the ILC method has the very important characteristic that the controller design is model independent. This special aspect makes the ILC method a powerful tool in controlling such nonlinear complex systems. Two popular (between practitioners) variants of the ILC were presented: a PD – type learning algorithm and a general high-order variant. These two approaches were tested by numerical simulation considering as benchmark a simplified reaction scheme of the wastewater depollution process. From simulations one follows that these two variants have similar results, with a smaller overshoot in G-ILC case and smaller settling time in PD-ILC case. This study demonstrates the feasibility of ILC method in control complex nonlinear systems even if the process is not very well known or some parameters vary over time. In the future research the stability aspects will be analysed and more variants on different classes of biotechnological systems will be tested. The proposed control strategy will be tested also on real plants.

Acknowledgment

This work was supported by ANCS, project TISIPRO no. 61/05.09.2016, 2016-2021, ID / Cod My SMIS: P_40_416 / 105736.

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