An Adaptive Control Scheme for a Lactic Acid Production Process with Unknown Inputs

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***Abstract*—A novel multivariable adaptive control scheme for a lactic fermentation biotechnological process with unknown inputs taking place inside two sequenced Continuous Stirred Tank Reactors (CSTRs) is developed. The design of the control scheme is achieved under the hypothesis that the influent substrate concentrations and the reaction kinetics are unknown and time-varying, but also a part of the state variables are unmeasurable. The adaptive controller includes a linearizing controller connected with two state observers used for the real-time estimation of the unknown input substrate concentrations and with a parameter estimator which is used for kinetics estimation. The estimation of unknown influent substrate concentrations is realized by using the measurements of the internal substrate and lactic acid concentrations. The proposed parameter estimator employs the information which is provided on-line by two sliding-mode state observers. The performance of the designed control scheme is evaluated via simulation experiments conducted for a lactic acid production process (LAPP) carried out inside two sequenced CSTRs. The dynamics of the considered bioprocess is described by a nonlinear, incompletely known and time varying model.**

Keywords—Adaptive control, Nonlinear systems, On-line estimation, Lactic fermentation bioprocesses

I. INTRODUCTION

Fermentation bioprocesses are one of the most important processes in biotechnology. Usually, these bioprocesses take place in stirred tank reactors with homogeneous culture and their evolution is expressed by a system of ordinary differential equations, which characterizes the energy and mass balances. In the industrial practice, a vital engineering challenge of controlling of fermentation processes consists in the improvement of stability as well as the enhancement of operational process efficiency. One of the difficulties that arise in the advanced control design for these living processes consist in the fact that for a lot of cases, their models contain yield coefficients and kinetic parameters characterized by time variation and high uncertainty, because of their inherently large natural variations [1-3]. Furthermore, a demanding issue is to find cheap and adequate sensors used for the measurement of essential biological variables [1,2]. To surmount these impediments, various control strategies were designed, analysed and tested. Among these we can highlight: input output linearization techniques [1,4], adaptive and optimal control structures [1,3,5-7], neural based control [8,9], sliding mode control [10], robust-adaptive control [11,12], and so on. Nearly all these methods need the design of the so-called “software sensors”, i.e. state observers (such as asymptotic observers and interval observers) and parameter estimators, which are necessary for real-time estimation of component’s concentrations, and moreover for the reconstruction of uncertain kinetic parameters or reaction rates [1,2,11-15]. To deliver accurate estimation of the unknown states, the asymptotic observers require the knowledge of process inputs (e.g. substrate input concentrations). But in the industry there are several processes for which the complete knowledge of the inputs is unavailable; therefore, the mentioned classical observers cannot be applied. For these situations, the interval observers or interval sliding mode observers constitute a viable solution. These observers do not deliver an estimated value but a certain range of variation of the estimated variable [11,12,14,15].

In this work we propose a novel multivariable indirect adaptive control method for a LAPP taking place inside two CSTRs sequentially connected. This process must be controlled in order to obtain a maximal quantity of lactic acid as well to avoid the instability which can exists due to unavoidable disturbances produced by loading rate variations [3,6]. In the recent literature, some adaptive schemes were proposed for this bioprocess [3,5,6], designed under the condition of influent flow rates full knowledge. Also, robust-adaptive strategies were designed in [12] by using interval observers which consider the known bounds of the unknown input concentrations [14]. In this work, an innovative adaptive control strategy is developed and analysed. The proposed adaptive control algorithm is designed under the realistic hypotheses that the influent substrate concentrations are completely unknown and time-varying, some process state variables cannot be measured, and the reaction kinetics are time-varying and completely unknown. The suggested adaptive structure includes a linearizing controller for which all the unknown variables are substituted by their on-line estimations computed by using suitably state observers and a parameter estimator necessary for real-time calculation of the completely unknown process kinetic rates. Unlike the approach developed in [12], we propose two sliding mode state observers (SMO) in order to estimate the two unknown input substrate concentrations, based on the measurements of the internal substrate and lactic acid concentrations. Two reaction rates in two sequenced reactors are assumed to be unknown and are reconstructed through a parameter estimator, in fact an OBE (observer-based estimator), which uses also the real-time information given by the two SMOs.

The paper structure is as follows. After presentation of lactic fermentation process model in Section II, Section III is dedicated to the estimation and control strategies. In Section IV, the behaviour and the performance of proposed algorithms are fully analysed via realistic numerical simulations. Finally, Section V completes the paper.

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II. BIOPROCESS MODELLING ISSUES

Traditionally, the food industry was and remains the domain where the lactic acid (LA) has a variety of utilizations. Also, LA is widely used in the textile industry as well as in pharmaceutical and cosmetic bioindustry [3,10]. In the last decades, the lactic acid is used for production of novel biodegradable polylactic products. Therefore, in the last ten years there was a high interest in the modelling and controlling of lactic acid production by using cheaper substrates, e.g. wheat flour [7, 16-18]. It was shown that the growth and productivity of LAPP is affected by the limiting restrictions of the nutrient and the inhibitory effect produced by LA accumulation in the reactor [3,19,20]. Another specificity is that the fertility of culture medium can influence the growth dynamics [3,19]. A dynamical model which takes into account both the inhibitory and the nutritional effects in the case of a lactic acid production obtained by growing *Lb. casei* bacteria inside a batch bioreactor is presented in [3]. In this paper, we use a model, which corresponds to a continuous process that takes place inside two CSTRs sequentially connected [3] (Figure 1). Assuming that each bioreactor has same constant volume V, for these two-connected CSTRs, the mathematical model, obtained by mass balance, consists in a set of nonlinear differential equations [3]. Note that this model is the same used in [3,12], but for an easy understanding, a short description is recalled in this paper:

First stage:

$$\dot{B}_1 = (\mu_1 - k_d)B_1 - D_1 B_1 \quad (1)$$

$$\dot{P}_1 = \nu_{p1} B_1 - D_1 P_1 \quad (2)$$

$$\dot{S}_1 = -q_{s1} B_1 + D_{11} S_{in1} - D_1 S_1 \quad (3)$$

$$\dot{\alpha}_1 = D_{12}\alpha_{in1} - D_1\alpha_1, \text{ with } D_1 = D_{11} + D_{12} \quad (4)$$

Second stage:

$$\dot{B}_2 = (\mu_2 - k_d)B_2 + D_1 B_1 - (D_1 + D_2)B_2 \quad (5)$$

$$\dot{P}_2 = \nu_{p2} B_2 + D_1 P_1 - (D_1 + D_2)P_2 \quad (6)$$

$$\dot{S}_2 = -q_{s2} B_2 + D_1 S_1 + D_2 S_{in2} - (D_1 + D_2)S_2 \quad (7)$$

$$\dot{\alpha}_2 = D_1\alpha_1 - (D_1 + D_2)\alpha_2 \quad (8)$$

where B_k, S_k, P_k and α_k with k = 1, 2 are as follows: the concentrations of bacteria (biomass), substrate (glucose), LA, and the enrichment factor in the two connected reactors. μ_k, ν_{pk} and q_{sk} (k = 1, 2) represent, respectively, specific growth rates of bacteria, lactic acid production, and substrate consumption in each reactor. k_d is the bacteria death rate.

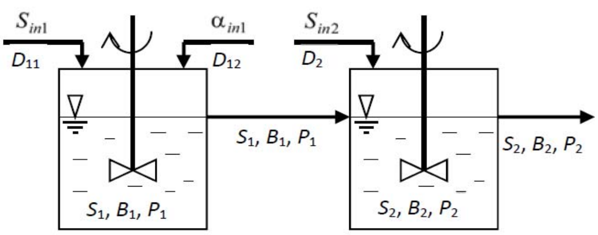

Fig. 1. Two connected reactors for lactic acid production.

D_{11} is the dilution rate of S_1 continuously fed in the first bioreactor with the concentration S_{in1}. D_{12} is the dilution rate of α_1 added in the first bioreactor with the influent concentration α_{in1}. D_2 is the dilution rate of substrate S_2 added in the second bioreactor with the concentration S_{in2}. In the second bioreactor no enrichment factor is feeding.

In the model (1)-(8) the specific rates in each reactor are described by [3]:

$$\mu_k = \bar{\mu}_{\max k}\left(\frac{\bar{K}_{P_k}^{gc}}{\bar{K}_{P_k}^{gc} + P_k}\right)\left(\frac{S_k}{\bar{K}_S^{gc} + S_k}\right)\left(1 - \frac{P_k}{P_C^{gc}}\right),$$

$$\nu_{pk} = \eta\mu_k + \beta\left(\frac{S_k}{\bar{K}_{S_k}^{rc} + S_k}\right), q_{sk} = \frac{\nu_{pk}}{Y_{PS}}, \ k = 1, 2 \quad (9)$$

where $\bar{\mu}_{\max k}$ denotes the maximum value of μ_k, P_C^{gc} is the critical value of lactic acid concentration, $\bar{K}_{P_k}^{gc}$ is the lactic acid inhibition constant, $\bar{K}_S^{gc}$ and $\bar{K}_{S_k}^{rc}$ are the affinity constants of the growing bacteria, and respectively of the resting bacteria for substrate, and Y_{PS} represents the constant conversion coefficient of substrate to lactic acid. It should be noted that the superscripts *gc* and *rc* highlight the parameters related to bacteria in the stages of growing and respectively in the resting stage. Finally, in (9), β and η are two positive constants.

In (9), some process parameters can be readapted function of the enrichment factor α_k as [3]:

$$\bar{\mu}_{\max k} = \frac{\mu_{\max}(\alpha_k - \alpha_0)}{K_{\alpha\mu} + (\alpha_k - \alpha_0)}, \ \bar{K}_{P_k}^{gc} = \frac{K_{P\max}^{gc}(\alpha_k - \alpha_0)}{K_{\alpha P} + (\alpha_k - \alpha_0)},$$

$$\bar{K}_{S_k}^{rc} = \frac{K_{S\max}^{rc}(\alpha_k - \alpha_0)}{K_{\alpha S} + (\alpha_k - \alpha_0)}. \quad (10)$$

where $K_{\alpha\mu}$, $K_{\alpha P}$ and $K_{\alpha S}$ are saturation constants and α_0 is the minimal nutritional factor. $\mu_{\max}$, $K_{P\max}^{gc}$ and $K_{S\max}^{rc}$ are the limit values of each specified parameter. Relations (10) express the nutritional restrictions, which are based on a batch growth model suggested in [19].

III. CONTROL STRATEGIES

Like in [12], the *control objective* of the proposed control structure consists to regulate the reactor's load for the substrate conversion to lactic acid via fermentation. Under the assumptions that the model (1)-(8) is incompletely known and time varying and the two influent substrate concentrations are unknown and time-varying, the process control purpose is to keep the bioprocess at certain operating points corresponding to a large LA production rate that is to a minimal concentration of the unconsumed substrate. It has been shown that these requests are achieved if the bioprocess operating points are regulated around certain values of the concentrations of S_1 and S_2 inside the two reactors, denoted by S_1^* and S_2^* (see steady state study in [3]). The best values of these set points are $S_1^* = 3$ g/l and $S_2^* = 5$ g/l. This selection ensures the achievement of the two above stated aims. Then, as control inputs we chose the dilution rates D_1 and D_2. In conclusion, we will have a multivariable control scheme characterized by two outputs S_1 and S_2, and by two inputs D_1 and D_2, i.e., $y = [S_1\ S_2]^T$, $u = [D_1\ D_2]^T$.

A. Exact linearizing feedback control

Let's take into consideration the ideal case when completely knowledge concerning the bioprocess (state variables, kinetics and yield coefficients) is available. Also, assume that for the closed loop behaviour of the system composed by the two connected reactors it is desirable to have a first order linear stable comportment given by:

$$(\dot{y}^* - \dot{y}) + \Lambda \cdot (y^* - y) = 0\,, \tag{11}$$

where $y^* = [S_1^*\ S_2^*]^T$ is piecewise constant desired values of S_1 and S_2, and $\Lambda = diag\{\lambda_k\}, \lambda_k > 0,\ k = 1, 2$.

From the equations (1)-(8) one can deduce that the dynamic of controlled variables can be expressed as:

$$\begin{bmatrix} \dot{S}_1 \\ \dot{S}_2 \end{bmatrix} = \begin{bmatrix} -D_{12}S_{in1} \\ 0 \end{bmatrix} - \begin{bmatrix} B_1 & 0 \\ 0 & B_2 \end{bmatrix} \cdot \begin{bmatrix} q_{s1} \\ q_{s2} \end{bmatrix} + \begin{bmatrix} S_{in1} - S_1 & 0 \\ S_1 - S_2 & S_{in2} - S_2 \end{bmatrix} \cdot \begin{bmatrix} D_1 \\ D_2 \end{bmatrix}, \tag{12}$$

Then, the input-output model (12) has the relative degree [21] equal to one. Thus, from (11) and (12), by using the linearization technique, the next *exact multivariable control law* is obtained:

$$\begin{bmatrix} D_1 \\ D_2 \end{bmatrix} = \begin{bmatrix} S_{in1} - S_1 & 0 \\ S_1 - S_2 & S_{in2} - S_2 \end{bmatrix}^{-1} \left(\begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \cdot \begin{bmatrix} S_1^* - S_1 \\ S_2^* - S_2 \end{bmatrix} - \begin{bmatrix} -D_{12}S_{in1} \\ 0 \end{bmatrix} + \begin{bmatrix} B_1 & 0 \\ 0 & B_2 \end{bmatrix} \cdot \begin{bmatrix} q_{s1} \\ q_{s2} \end{bmatrix} + \begin{bmatrix} \dot{S}_1^* \\ \dot{S}_2^* \end{bmatrix} \right). \tag{13}$$

In a normal operation of the reactors we have $S_1 < S_{in1}$ and $S_2 < S_{in2}$, which is a sufficient condition for the non-singularity of decoupling matrix $G = \begin{bmatrix} S_{in1} - S_1 & 0 \\ S_1 - S_2 & S_{in2} - S_2 \end{bmatrix}$. So, it is invertible.

The control law (13) directs to a linear model of the tracking error $e_y = y^* - y$ described by $\dot{e}_y = -\Lambda e_y$. The equilibrium $e_y = 0$ is an exponential stable point of this model as long as $\lambda_1, \lambda_2 > 0$. This control law represents the foundation for the designing of the adaptive controller, but also a benchmark in order to analyse the performance and the comportment of the closed loop system in this ideal case in comparison with the proposed adaptive system.

B. A new multivariable adaptive controller

Since a prior knowledge related to process considered in subsection *A* is not realistic, we will derive a new adaptive control algorithm under the next more realistic conditions:

- the concentrations S_{in1} and S_{in2} of the two influent substrates are time-varying and unknown;
- the unknown specific growth rates μ_k, ν_{pk} and q_{sk} (k = 1, 2) are time-varying;
- the unmeasurable variables are B_1 and B_2;
- the real-time measurements are: S_1, P_1, and S_2, P_2.
- the other process variables (D_{12}, α_{in1}, etc.) and coefficients are known.

Under these assumptions a new *adaptive controller* is achieved as follows.

Because the controller (13) depends on the states B_1, B_2, S_1, S_2 from which only S_1 and S_2 can be real-time measured, as well as of the unknown concentrations S_{in1} and S_{in2}, the conclusion is that all unavailable states must be calculated or estimated.

To estimate S_{in1} and S_{in2} we propose two simplified variants of the generalized sliding-mode observer designed in [22,23] and used in [24] under the assumption that for the two cascaded bioreactors the variables S_1, P_1 and S_2, P_2 are measurable on-line.

Estimation of S_{in1}. We denote by $Z_{S1} = P_1 + Y_{PS}S_1$ a linear combination of real-time measurements of S_1 and P_1 in the first reactor. Then from model (1)-(8) the dynamic of Z_{S1} is provided by the linear differential equation:

$$\dot{Z}_{S1} = -DZ_{S1} + Y_{PS}(D_1 - D_{12})S_{in1}\,, \tag{14}$$

Then, an observer able to calculate the on-line estimation $\hat{S}_{in1}$ of the unknown S_{in1} is given by:

$$\begin{aligned} \dot{\hat{Z}}_{S1} &= -D_1 Z_{S1} + Y_{PS}(D_1 - D_{12})\hat{S}_{in1} - L_{S1}\alpha_{11}\phi_{11}(e_{S1})\,, \\ \dot{\hat{S}}_{in1} &= -L_{S1}^2\alpha_{21}Y_{PS}(D_1 - D_{12})\phi_{21}(e_{S1})\,, \quad L_{S1}, \alpha_{11}, \alpha_{21} > 0, \end{aligned} \tag{15}$$

where $e_{S1} = \hat{Z}_{S1} - Z_{S1}$, and [24]:

$$\begin{aligned} \phi_{11}(e_{S1}) &= \beta_{11}\,|\,e_{S1}\,|^{1/2}\ \mathrm{sign}(e_{S1}) + \beta_{21}e_{S1} \\ \phi_{21}(e_{S1}) &= \frac{\beta_{11}^2}{2}\mathrm{sign}(e_{S1}) + \frac{3}{2}\beta_{11}\beta_{21}\,|\,e_{S1}\,|^{1/2}\ \mathrm{sign}(e_{S1}) + \beta_{21}^2 e_{S1} \end{aligned} \tag{16}$$

with $\beta_{11}, \beta_{21} > 0$. It can be noticed that we have five tuning parameters: $L_{S1}, \alpha_{11}, \alpha_{21}, \beta_{11}, \beta_{21}$.

Estimation of S_{in2}. We denote by $Z_{S2} = P_2 + Y_{PS}S_2$ a linear combination of the real-time measurements of S_2 and P_2 in the second reactor. From model (1)-(8) the dynamic of Z_{S2} is provided by the next linear differential equation:

$$\dot{Z}_{S2} = D_1 Z_{S1} - (D_1 + D_2)Z_{S2} + Y_{PS}D_2 S_{in2}\,, \tag{17}$$

Like in the case of S_{in1}, an observer able to provide the real-time estimation $\hat{S}_{in2}$ is given by:

$$\begin{aligned} \dot{\hat{Z}}_{S2} &= D_1 Z_{S1} - (D_1 + D_2)Z_{S2} + Y_{PS}D_2\hat{S}_{in2} - L_{S2}\alpha_{12}\phi_{12}(e_{S2})\,, \\ \dot{\hat{S}}_{in2} &= -L_{S2}^2\alpha_{22}Y_{PS}D_2\,\phi_{22}(e_{S2})\,, \quad L_{S2}, \alpha_{12}, \alpha_{22} > 0, \end{aligned} \tag{18}$$

where $e_{S2} = \hat{Z}_{S2} - Z_{S2}$, and

$$\begin{aligned} \phi_{12}(e_{S2}) &= \beta_{12}\,|\,e_{S2}\,|^{1/2}\ \mathrm{sign}(e_{S2}) + \beta_{22}e_{S2} \\ \phi_{22}(e_{S2}) &= \frac{\beta_{12}^2}{2}\mathrm{sign}(e_{S2}) + \frac{3}{2}\beta_{12}\beta_{22}\,|\,e_{S2}\,|^{1/2}\ \mathrm{sign}(e_{S2}) + \beta_{21}^2 e_{S2} \end{aligned} \tag{19}$$

with $\beta_{12}, \beta_{22} > 0$. This observer has also five tuning parameters: $L_{S2}, \alpha_{12}, \alpha_{22}, \beta_{12}, \beta_{22}$.

Since the specific growth rates q_{si} (i = 1, 2) are unknown and B_1 and B_2 are not measurable, then the reaction rates $r_1 = q_{s1}B_1$ and $r_2 = q_{s2}B_2$ in (3) and (7) respectively, as well as in (12), can by expressed as $q_{s1}B_1 = \rho_1$, $q_{s2}B_2 = \rho_2$, where ρ_1 and ρ_2 are unknown time-varying parameters that can be summarized in the unknown vector $\rho = [\rho_1 \; \rho_2]^T$. Then the control law (14) becomes:

$$\begin{bmatrix} D_1 \\ D_2 \end{bmatrix} = \begin{bmatrix} \hat{S}_{in1} - S_1 & 0 \\ S_1 - S_2 & \hat{S}_{in2} - S_2 \end{bmatrix}^{-1} \left(\begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \cdot \begin{bmatrix} S_1^* - S_1 \\ S_2^* - S_2 \end{bmatrix} + \begin{bmatrix} D_{12}\hat{S}_{in1} \\ 0 \end{bmatrix} + \begin{bmatrix} \rho_1 \\ \rho_2 \end{bmatrix} + \begin{bmatrix} \dot{S}_1^* \\ \dot{S}_2^* \end{bmatrix} \right), \qquad (20)$$

where $\hat{S}_{in1}$ and $\hat{S}_{in2}$ are on-line estimations of unknowns S_{in1} and S_{in2} given by the estimators (15) and (18) respectively. In (20) instead of the unknown parameters ρ_1 and ρ_2 will be used their estimated values $\hat{\rho}_1$ and $\hat{\rho}_2$ provided on-line by a suitable parameter estimator, in fact an OBE [1,2,11,12], implemented using only the variables S_1 and S_2 whose dynamics are rewritten as follows:

$$\begin{bmatrix} \dot{S}_1 \\ \dot{S}_2 \end{bmatrix} = -\begin{bmatrix} \rho_1 \\ \rho_2 \end{bmatrix} + \begin{bmatrix} -D_{12}S_{in1} \\ 0 \end{bmatrix} + \begin{bmatrix} S_{in1} - S_1 & 0 \\ S_1 - S_2 & S_{in2} - S_2 \end{bmatrix} \cdot \begin{bmatrix} D_1 \\ D_2 \end{bmatrix} \qquad (21)$$

Then the estimator for the real-time computation of $\hat{\rho} = [\hat{\rho}_1 \; \hat{\rho}_2]^T$ is particularized as in the following relations:

$$\begin{aligned} \dot{\hat{S}}_1 &= -\hat{\rho}_1 - D_{12}\hat{S}_{in1} + (\hat{S}_{in1} - S_1) D_1 + \omega_1 (S_1 - \hat{S}_1), \\ \dot{\hat{S}}_2 &= -\hat{\rho}_2 + (S_1 - S_2) D_1 \hat{S}_{in1} + (\hat{S}_{in2} - S_2) D2_1 + \omega_2 (S_2 - \hat{S}_2), \end{aligned} \qquad (22)$$

$$\begin{aligned} \dot{\hat{\rho}}_1 &= \gamma_1 (S_1 - \hat{S}_1), \\ \dot{\hat{\rho}}_2 &= \gamma_2 (S_2 - \hat{S}_2), \end{aligned} \qquad (23)$$

where $\gamma_k > 0$, $k = 1, 2$ (the gains of updating laws (22)), and $\omega_k < 0$, $k = 1, 2$, are tuning parameters, whose values are chosen so that to assure the stability as well as the tracking properties of the parameter estimator (details can be found in [1,2,11]), and $\hat{S}_{in1}$ and $\hat{S}_{in2}$ are on-line estimations of unknown concentrations S_{in1} and S_{in2}.

Then, *the new multivariable adaptive controller* is achieved as a combination of observers (15)-(16) and (17)-(18) with the parameter estimator (22)-(23) and with the control law (20) rewritten as follows:

$$\begin{bmatrix} D_1 \\ D_2 \end{bmatrix} = \begin{bmatrix} \hat{S}_{in1} - S_1 & 0 \\ S_1 - S_2 & \hat{S}_{in2} - S_2 \end{bmatrix}^{-1} \left(\begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \cdot \begin{bmatrix} S_1^* - S_1 \\ S_2^* - S_2 \end{bmatrix} + \begin{bmatrix} D_{12}\hat{S}_{in1} \\ 0 \end{bmatrix} + \begin{bmatrix} \hat{\rho}_1 \\ \hat{\rho}_2 \end{bmatrix} + \begin{bmatrix} \dot{S}_1^* \\ \dot{S}_2^* \end{bmatrix} \right). \qquad (24)$$

The adaptive control system is depicted in Figure 2.

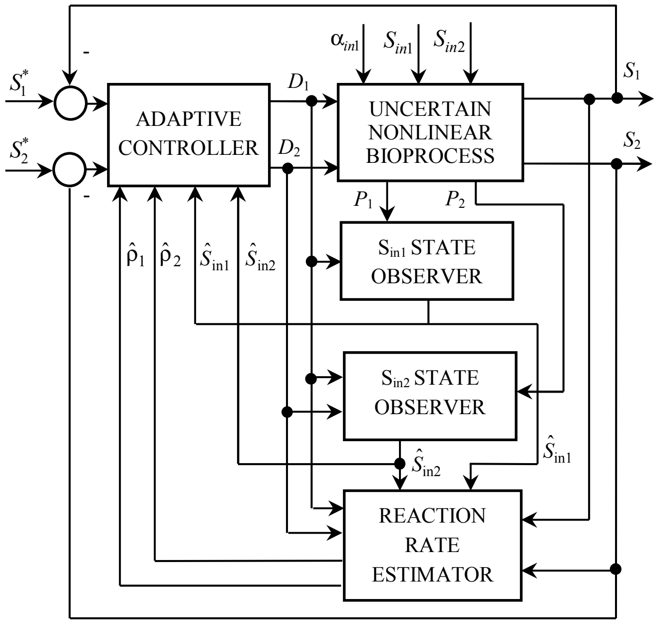

Fig. 2. The block representation of the new adaptive controlled system

IV. Simulation Results and Comments

The performance and the behaviour of the proposed adaptive controller are examined using realistic simulation conditions. For a correct evaluation, the numerical simulations were conducted by using the mathematical model equations (1)-(10) under identical circumstances. The simulations were performed using the next values for the yield and kinetic coefficients [3,9,12]:

$\mu^0_{\max}$ = 0.45 h^{-1}, $\overline{K}_S^{gc}$ = 0.5 g/l, $K_{S\max}^{rc}$ = 12 g/l, $K_{P\max}^{gc}$ = 15 g/l, δ = 3.5, η = 3.5, β = 0.9 h^{-1}, α_0 = 0.02 g/l, $K_{\alpha\mu}$ = 0.2 g/l, $K_{\alpha P}$ = 1.1 g/l, $K_{\alpha S}$ = 4 g/l, P_C^{gc} = 95 g/l, Y_{PS} = 0.98 g/g, k_d = 0.02 h^{-1}, D_{12} = 0.025 h^{-1}, α^0_{in1} = 6 g/l.

The performance of the adaptive controller (24), by comparison with the exact linearizing control law (13) (this controller produces the best response and is used as benchmark), has been extensively tested in the following conditions:

- the input concentrations S_{in1} and S_{in2} are time-varying, as in Figures 3 and 4, and are assumed completely unknown;
- the specific rates μ_k, ν_{pk} and q_{sk} ($k = 1, 2$) are unknown and time-varying;
- the concentration of the influent enrichment factor α_{in1} is time varying as:

$$\alpha_{in1}(t) = \alpha^0_{in1} \cdot (1 + 0.25 \cdot \sin(\pi t / 20)). \qquad (26)$$

- the kinetic coefficient $\mu^0_{\max}$ is also supposed a time varying parameter as: $\mu^0(t) = \mu^0_{\max}(1 + 0.1 \cdot \sin(\pi t / 40))$;
- the state variables B_1 and B_2 are not measurable;
- the measurements accessible on-line are: S_1, P_1 and S_2, P_2.
- the other variables, coefficients and parameters (D_{12}, α_{in1}, Y_{PS}, etc.) are known.

Remark 1. The variation form and the expressions of S_{in1} and S_{in2} are given only for the comprehensiveness and reproducibility of simulation results. □

The comportment of the closed-loop system under the above assumptions is given in Figures 5-10. The graphics in Figure 5 depict the evolution of the controlled variables S_1 (down) and S_2 (up), and Figure 6 shows the profiles of the control inputs D_1 (up) and D_2 (down). To check the regulation properties, the simulations were planned such that the set points have several changes in the vicinity of the operational values $S_1^* = 3$ g/l, $S_2^* = 5$ g/l. Taking in account the practical reality, we supposed that the measurements of S_1 and S_2 are vitiated with additive zero mean white noise (5% from its nominal values). From Figures 5 and 6 one can observe that the controlled variables S_1 and S_2 track their references, while the control variables D_1 and D_2 are maintained in their physical limits. The profiles of the estimates of the unknowns S_{in1} and S_{in2} delivered by the observers (15)-(16) and (18)-(19) are presented in Figures 7 and 8, from which is visible that the observer performs suitably even if the measurements are affected by noise.

The estimations of the unknown reaction rates ρ_1 and ρ_2 are plotted in Figures 9 and 10, from which it can be seen that the OBE works very well.

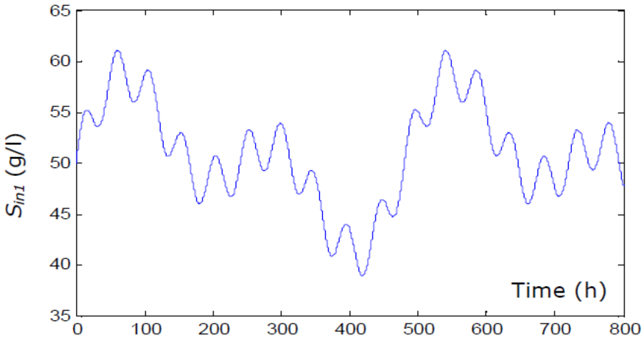

Fig. 3. The time profile of S_{in1}.

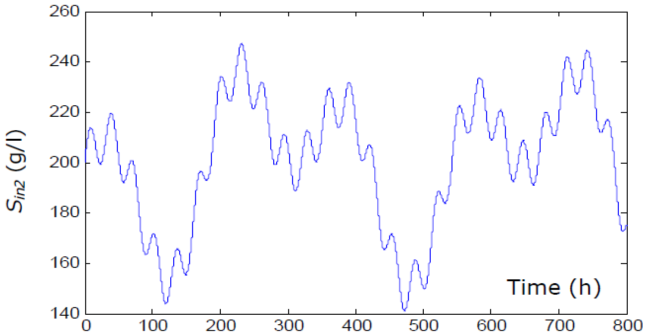

Fig. 4. The time profile of S_{in2} ,

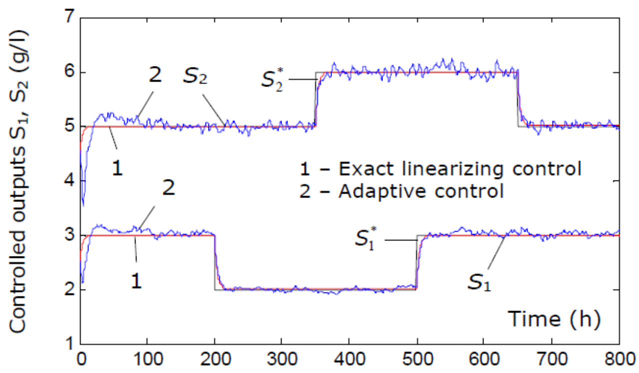

Fig. 5. The time evolution of outputs S_1 and S_2.

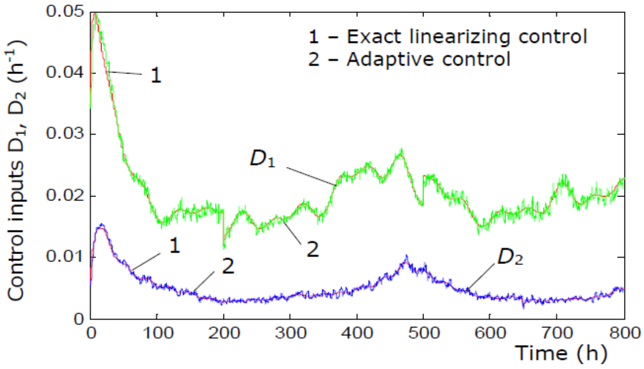

Fig. 6. Profile of control inputs outputs D_1 and D_2 .

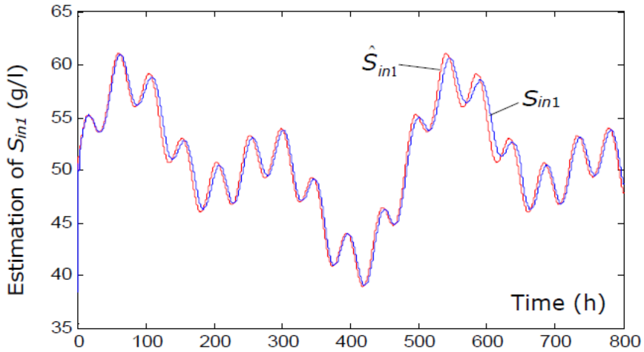

Fig. 7. Estimation of unknown variable S_{in1}.

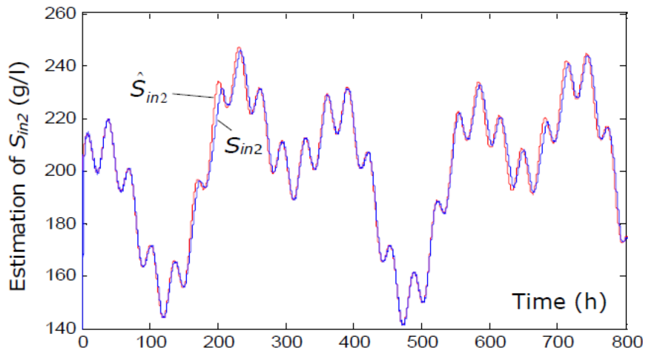

Fig. 8. Estimation of unknown variable S_{in2}.

For control laws (25) and (13), the used gain values are $\lambda_1 = \lambda_2 =$ 0.25, and the tuning parameters of the observers (15)-(16) and (18)-(19) have been set to the next values:

$$L_{S1} = 2.5,\ \alpha_{11} = 0.5,\ \alpha_{21} = 50,\ \beta_{11} = 0,\ \beta_{21} = 2.5,$$
$$L_{S2} = 2.95,\ \alpha_{12} = 0.25,\ \alpha_{22} = 275,\ \beta_{12} = 0.5, \beta_{22} = 3.25,$$

and of OBE (23)-(24) to:

$$\omega_1 = -0.75,\ \omega_2 = -0.5,\ \gamma_1 = 0.5,\ \gamma_2 = 0.4.$$

The obtained profiles presented in Figures 5-10 illustrate that the comportment of the whole adaptive system is proper, being very close to the comportment of closed loop system in the benchmark case (known bioprocess model) when is used the exact linearizing controller (13).

The adaptive controller can keep the outputs S_1 and S_2 very close to their desired value, despite many realistic disturbances and uncertainties: high variation and uncertainty related to S_{in1} and S_{in2}, the time variation of α_{in1}, time variation and uncertainty of the process growth rates.

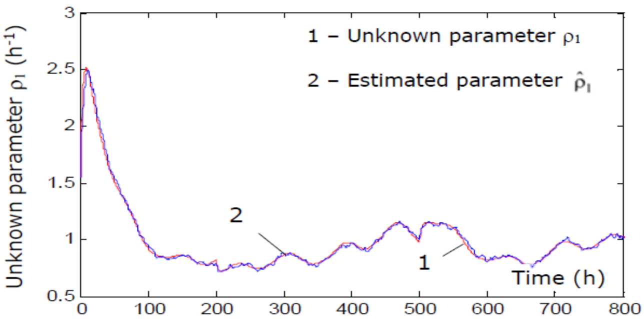

Fig. 9. Unknown parameter ρ_1 and its estimated value $\hat{\rho}_1$.

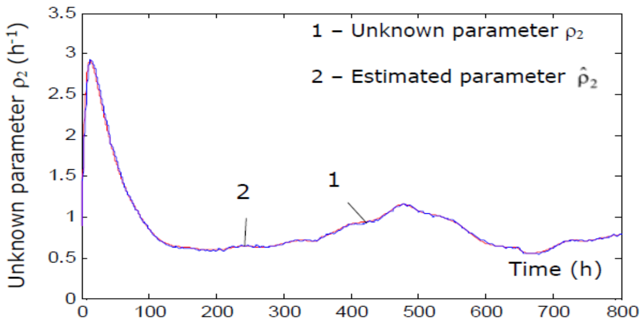

Fig. 10. Unknown parameter ρ_2 and its estimated value $\hat{\rho}_2$.

V. Conclusion

In this work a novel multivariable adaptive control scheme for a continuous lactic fermentation process was developed and analysed. The adaptive control algorithm is designed under the assumption that the influent substrate concentrations as well as the reaction kinetics are unknown and time-varying, and some states are unmeasurable.

The adaptive control scheme was obtained as a combination of an exact linearizing controller with two sliding mode state observers used for real-time computation of the two unknown influent substrate concentrations and with a parameter estimator used for the reconstruction of unknown process kinetic rates. To estimate the unknown input substrate concentrations, the two observers needed the measurements of the internal substrate and lactic acid concentrations. It must be noted that the parameter estimator used for the real-time reconstruction of the unknown kinetics uses also the real-time information delivered by the two sliding mode state observers.

The numerical simulations conducted under some rough but realistic circumstances, such as uncertainties and noisy measurements, show a suitable behaviour and quite good performance of the controlled bioprocess. It is expected that this kind of control scheme to behave well in real operating conditions of these lactic fermentation bioprocesses.

This type of adaptive control strategy is appropriate also for wastewater treatment bioprocesses, where the evolution of influent concentration substrates is unpredictable.

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References

[1] G. Bastin and D. Dochain, On-line Estimation and Adaptive Control of Bioreactors. Amsterdam: Elsevier, 1990.

[2] D. Dochain (Ed.), Bioprocess Control, ISTE Ltd., 2008.

[3] C. Ben Youssef, V. Guillou, and A. Olmos-Dichara, "Modelling and adaptive control strategy in a lactic fermentation process," *Control Engineering Practice*, vol. 8, pp. 1297-1307, 2000.

[4] G.S. Cardoso and L. Schnitman, "Analysis of exact linearization and aproximate feedback linearization techniques," *Math. Probl. Eng.*, vol. 2011, Article ID 205939, 17 pages, 2011, Hindawi Pub. Corp.

[5] E. Petre, D. Selişteanu, and D. Sendrescu, "An indirect adaptive control strategy for a lactic fermentation bioprocess," in *Proc. IEEE Int. Conf. on Autom., Quality and Testing, Robotics (AQTR 2010)*, pp. 175-180, Cluj-Napoca, Romania, May 2010.

[6] E. Petre and D. Selişteanu, "Adaptive control of a fermentation bioprocess for lactic acid production," *Math. Probl. Eng.*, Article ID 936034, 20 pages, 2012, Hindawi Pub. Corp.

[7] B.H. Lunelli et al., "Real-time optimization for lactic acid production from sucrose fermentation by Lactobacillus plantarum," in: Pistikopoulos E.N., Georgiadis M.C., Kokossis A.C. (eds) *Computer Aided Chemical Engineering*, vol. 29, 2011, pp. 1396-1400.

[8] D. Selişteanu, E. Petre, and V. Răsvan, "Sliding mode and adaptive sliding mode control of a class of nonlinear bioprocesses," *Int. J. Adaptive Control & Signal Proc.*, vol. 21, no. 8-9, 2007, pp. 795-822.

[9] E. Petre, D. Selişteanu, and D. Şendrescu, "Neural networks based adaptive control of a fermentation bioprocess for lactic acid production," in: Watada J., Phillips-Wren G., Jain L.C., Howlett R.J. (eds) *Intelligent Decision Technologies. Smart Innovation, Systems and Technologies*, vol 10, 2011, pp. 201-212. Springer, Berlin.

[10] R. Rashid, S.M. Mohamed Esivan, S.R. Radzali, and A. Idris, 2010. "Software sensor for measuring lactic acid concentration: Effect of input number and node number," *Journal of Applied Sciences*, vol. 10, 2010, pp. 2578-2583.

[11] E. Petre and D. Selişteanu, "A multivariable robust-adaptive control strategy for a recycled wastewater treatment bioprocess," *Chemical Engineering Science*, Elsevier, vol. 90, 2013, pp. 40-50.

[12] E. Petre, D. Selişteanu, and M., Roman, "Nonlinear Robust Adaptive Control Strategies for a Lactic Fermentation Process," *Journal of Chemical Technology and Biotechnology* , Vol. 93, pp. 518–526, DOI: 10.1002/jctb.5383, 2017.

[13] D. Selisteanu, S. Tebbani, M. Roman, E. Petre, and V. Georgeanu, "Microbial production of enzymes: Nonlinear state and kinetic reaction rates estimation," *Biochem. Eng. J.*, vol. 91, pp. 23-36, 2014.

[14] A. Rapaport and D. Dochain, "Interval observers for biochemical processes with uncertain kinetics and inputs," *Mathematical Biosciences*, vol. 193, no. 2, 2005, pp. 235–253.

[15] H. Oubabasa, S. Djennounea, M. Bettayebb, "Interval sliding mode observer design for linear and nonlinear systems," *Journal of Process Control,* vol. 61, pp. 12–22, 2018.

[16] K. Gonzalez et al., "Modeling the continuous lactic acid production process from wheat flour," *Appl. Microbiol Biotechnol.*, vol. 100, no. 1, pp. 147-59, 2016.

[17] K. Gonzalez et al., "Adaptive control of lactic acid production process from wheat flour," *9th IFAC Symposium on Advanced Control of Chemical Processes (ADCHEM 2015)*, Jun 2015, Whistler, Canada, *IFAC – PapersOnLine*, vol. 48, no. 8, pp.1087-1092, 2015.

[18] K. Gonzalez et al., "Regulation of lactic acid concentration in its bioproduction from wheat flour," *Control Engineering Practice*, vol. 54, pp. 202 – 213, 2016.

[19] B. Bibal, Dynamique de croissance de streptococcus cremoris et comportament en reactor a haute densite cellulaire, Ph.D. thesis, Institut National des Sciences Appliquees, Toulouse, France, 1989.

[20] Yu.L. Gordeeva, E.G. Rudakovskaya, E.L. Gordeeva, and A.G. Borodkin, "Mathematical modeling of biotechnological process of lactic acid production by batch fermentation: A review," *Theoretical Foundations of Chem. Eng.*, vol. 51, no. 3, pp. 282–298, 2017.

[21] A. Isidori, Nonlinear Control Systems. 3rd ed., Berlin: Springer, 1995.

[22] J.A. Moreno, "Lyapunov approach for analysis and design of second order sliding mode algorithms," in: *Sliding Modes after the first decade of the 21st Century* (L. Fridman, J. Moreno & R. Iriarte, eds). Springer. LNCIS, vol. 412, pp. 113–150, 2011.

[23] J.A. Moreno, "On discontinuous observers for second order systems: Properties, analysis and design," in: *Advances in Sliding Mode Control–Concepts, Theory and Implementation* (B. Bandyopadhyay, S. Janardhanan & Sarah K. Spurgeon, eds). Springer-Verlag, LNCIS, Vol. 440, pp. 243–265, 2013.

[24] M. Sbarciog, J. A. Moreno, and A. Vande Wouwer, "Application of super-twisting observers to the estimation of state and unknown inputs in an anaerobic digestion system," *Water Science & Technology*, vol. 69, no.2, pp. 414-421, 2014.