SLIDING MODE CONTROL OF AEROBIC BIOPROCESS USING RECURRENT NEURAL IDENTIFIER

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Abstract: The paper proposed a new adaptive control system containing a Recurrent Neural Network (RNN) identifier, a Sliding Mode (SM) controller, and an integral term. The SM control is derived defining the sliding surface with respect to the output tracking error. The state and parameter information to resolve the SM control is obtained from a RNN identifier, which permits the SM control to maintain the sliding regime when the plant parameters changed. The simulation results obtained with a continuous stirred tank reactor plant model confirmed the good quality of the control.

Keywords: sliding mode control, integral action, discrete-time systems, adaptive control, neural network models, backpropagation algorithms, identification, state estimation, biotechnology, aerobic continuous stirred tank reactor plant model.

1. INTRODUCTION

The Sliding Mode Control (SMC) raised a great fame in the last decade. The theory basis of such control in continuous time cases, is given in the fundamental book of Utkin, see (Utkin, 1992). The main definitions for the Discrete-Time Sliding Mode Control (DTSMC), are given by Utkin, see (Utkin, 1993; Utkin, 1998), and the designed control is bounded in an admissible domain. In (Korondi, *et al.*, 1995), the DTSMC has been applied for two-mass mechanical system where a full order observer is used to estimate the necessary state variables. To reduce the load plant perturbations, a PI-control action is added to the DTSMC. In (Fujisaki, *et al.*, 1994), it is proposed to use the discrete-time sliding mode to control multi-input, multi-output plants, where a stability analysis of the closed loop system is done. In more recent publications, see (Efe, *et al.*, 2001), a SMC is used for weight update of Radial Basis Function Neural Network adaptive controller of inverted pendulum system. This idea is first proposed by Sira-Ramirez, see (Sira-Ramirez and Colina-Morales, 1995), who updated the weights of an Adaline feedforward neural network by means of a SMC. In (Da, 2000) it is proposed a new type of SMC - Fuzzy-Neural Networks (FNN) SMC, which is developed for a class of large-scale systems with unknown bounds of high-order interconnections and disturbances. The author here proposed to eliminate the chattering caused by the discontinuous sign control function using a continuous output of the FNN to replace it. In some other publications like (Utkin, 1993), the chattering is eliminated substituting the sign function by saturation or dead-zone one, see (Fujisaki, *et al.*, 1994). In (Cao, *et al.*, 1994), a SMC of nonlinear systems is proposed using Neural Networks (NN). Here the NN of perceptron type is used to determine the sliding surface function and the control input. The chattering is eliminated using a sigmoid activation function instead of sign one. In (Liu and Handroos, 1999) the SMC is applied for a class of hydraulic position servo where good experimental results are obtained. The desired trajectory is defined by a two order reference model, the SMC is designed via Lyapunov function, and the saturation function is used instead of the sign function, so to reduce the degree of chattering. In (Ocheriah, 1997), a robust SMC is obtained for a class of uncertain dynamic delay systems. The SMC is designed by means of coordinate transformation and Lyapunov function, which guarantees uniform ultimate boundedness of all motions. In (Yoo and Ham, 1998), an adaptive fuzzy SMC of nonlinear systems is proposed. The unknown state and input nonlinearities are estimated by a fuzzy logic system and two Lyapunov function based design methods are given. In (Ha, 1996), a robust SMC with fuzzy tuning is proposed. The control action is adapted by means of fuzzy system so to compensate the influence of unmodelled dynamics and chattering. In (Misawa, 1997) a DTSMC for nonlinear systems with unmatched state and control uncertainties is proposed. The designed saturation function generates the necessary robust boundary layer which is used also to smooth the chattering. Finally, the paper of (Young, *et al.*, 1999) represents a practical engineer's guide to SMC for both continuous and discrete-time cases. The main problem of the SMC is that the sliding surface is defined with respect to the state error - see (Da, 2000; Yoo, et al., 1998), and not to the output error, so all state variables are to be known. Also the systems noise, uncertainties and chattering have to be overcame, see (Young, *et al.,* 1999).

The present paper proposes to define the sliding surface with respect to the output tracking error, and to use a nonlinear plant identification and state estimation Recurrent Neural Network (RNN), see (Baruch, *et al.*, 2002), which gives all the necessary state and parameter information to resolve the SMC. Furthermore, the adaptive abilities of the RNN permitted the SMC to maintain the sliding regime when the plant parameters changed. In order to overcome load plant perturbations, it is proposed to add an I-term to the control law.

The paper is organized as follows: part 2 give a short description of the RNN topology and learning; part 3 gives the block structure of the control and derive the sliding mode control algorithm; part 4 describes the aerobic stirred tank reactor nonlinear bioprocess plant model and gives graphical simulation results; part 5 represents the concluding remarks.

2. RECURRENT NEURAL NETWORK TOPOLOGY AND LEARNING

In (Baruch, *et al.,* 2001; Nava, *et al.*, 2004) a discrete-time model of Recurrent Trainable Neural Network (RTNN) and a dynamic Backpropagation (BP) weight updating rule, are given. The RTNN model is described by the following equations:

$$X(k+1) = AX(k)+BU(k) \tag{1}$$
$$Z(k)=\theta[X(k)] \tag{2}$$
$$Y(k) = \theta[CZ(k)] \tag{3}$$
$$A = \text{block-diag}\ (A_i);\ |A_i| < 0 \tag{4}$$

Where: X(k) is an N - state vector of the RNN; U(k) is a M - input vector; Y(k) is a L - output vector; Z(k) is an N – dimensional output vector of the hidden layer; $\theta(.)$ is a vector-valued activation function with appropriate dimension; A is an (NxN) weight state diagonal matrix; A_i are elements of A; B and C are weight input and output matrices with appropriate dimensions and block structure, corresponding to the block structure of A. As it can be seen, the given RTNN model is a completely parallel parametric one, so it is useful for identification and control purposes. The stability, controllability, and observability of this model are discussed and proved in (Baruch, *et al.* 2002; Nava, *et al.* 2004). Parameters of that model are the matrices A, B, C and the state vector X(k). The equation (4) is a stability preserving condition. The general BP-learning algorithm is given as:

$$W_{ij}(k+1)=W_{ij}(k)+\eta\Delta W_{ij}(k)+\alpha\Delta W_{ij}(k-1) \tag{5}$$

Where: W_{ij} (C, A, B) is the ij-th weight element of each weight matrix (given in parenthesis) of the RTNN model to be updated; ΔW_{ij} (ΔC_{ij} , ΔA_{ij}, ΔB_{ij}) is the ij-th weight correction of W_{ij} of each weight matrix (given in parenthesis); η, α are learning rate parameters. The weight updates ΔC_{ij} , ΔA_{ij}, ΔB_{ij} of the model weights C_{ij} , A_{ij}, B_{ij} , are given by:

$$\Delta C_{ij}(k) = [T_j(k) -Y_j(k)]\ \theta_j'(Y_j(k))\ Z_i(k) \tag{6}$$
$$\Delta J_{ij}(k) = R_1\ X_i(k-1) \tag{7}$$
$$R_1 = C_i(k)\ [T(k)-Y(k)]\ \theta_j'(Z_j(k)) \tag{8}$$
$$\Delta B_{ij}(k) = R_1\ U_i(k) \tag{9}$$

Where: T is a target vector and [T-Y] is an output error vector, both with dimension L; R_1 is an auxiliary variable; $\theta'(x)$ is the derivative of the activation function, which for the hyperbolic tangent is $\theta_j'(x) = 1-x^2$. The application of this RTNN model requires the target vector T normalization.

3. DESIGN OF AN ADAPTIVE SMC SYSTEM WITH NEURAL IDENTIFIER AND I-ACTION

Let us suppose that the studied nonlinear plant is Bounded – Input – Bounded - Output (BIBO) stable one, given by the equations:

$$X_p(k+1)=F[\ X_p(k),U(k),Of(k)\ ] \tag{10}$$
$$Y_p(k)=\varphi\ [\ X_p(k)\ ] \tag{11}$$

Where $X_p(k)$, $Y_p(k)$, U(k), Of(k) are plant state, output, input and offset vector variables with dimensions Np, L, M, where L=M is supposed; F and φ are smooth, odd, bounded nonlinear functions. The offset variable Of(k) is introduced in the input of the plant and represents all load changes and imperfections of the plant model. The block diagram of the control scheme is shown on Fig.1. It contains identification and state estimation RTNN, an indirect adaptive sliding mode controller and an I-term The stable nonlinear plant is identified by a RTNN with topology, given by equations (1) to (4) which is learned by the stable BP-learning algorithm, given by equations (5) to (9), where the identification error $E_i(k) = Y_p(k) – Y(k)$ tends to zero ($E_i \to 0$, $k \to \infty$).

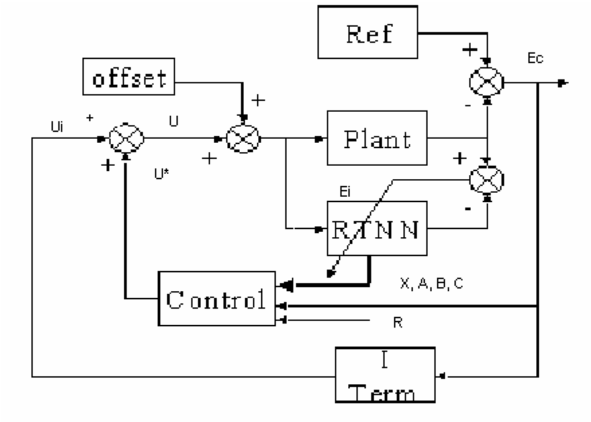

Fig.1. Block-diagram of the adaptive SMC system, with a neural identifier and an I - action.

This identification error could be considered acceptable if it reached a value below of 2% and it is considered as part of the offset. The linearization of the activation functions of the learned identification RTNN model, which approximates the plant (see equations. (1) to (3)), leads to the following linear local plant model:

$$X(k+1) = AX(k) + B[U(k) + Of(k)] \tag{12}$$
$$Y(k) = CX(k) \tag{13}$$

The systems control U(k) have two parts:

$$U(k) = U^*(k) + U_i(k) \tag{14}$$

Where: $U^*(k)$ is the dynamic compensation control part, based on SMC; $U_i(k)$ is the I-term control part, which is:

$$U_i(k+1) = U_i(k) + T_0 K_i E_c(k) \tag{15}$$

Where: T_0 is a period of discretization; K_i is a diagonal (LxL) I-term gain matrix.

Let us define the following sliding surface with respect to the output tracking error:

$$S(k+1)=E(k+1)+\sum_{i=1}^{P} \gamma_i E(k-i+1); \ |\gamma_i| < 1 \tag{16}$$

Where: S(.) is the sliding surface error function; E(.) is the systems output tracking error; γ_i are parameters of the desired error function; P is the order of the error function. The additional inequality in (16) is a stability condition, required for the sliding surface error function. The output tracking error is defined as:

$$E(k) = R(k) - Y(k) \tag{17}$$

Where R(k) is a L-dimensional reference vector and Y(k) is an output vector with the same dimension. The objective of the sliding mode control systems design is to find a control action which maintains the systems error on the sliding surface which assures that the output tracking error reaches zero in P steps, where P<N. So, the control objective is fulfilled if:

$$S(k+1) = 0 \tag{18}$$

The iteration of the error (17) gives:

$$E(k+1) = R(k+1) - Y(k+1) \tag{19}$$

Now, from (12) and (13), it is easy to obtain the input/output local plant model which is:

$$Y(k+1) = CX(k+1) = C[AX(k) + BU(k)] \tag{20}$$

From (16), (18), and (19), we could obtain:

$$R(k+1) - Y(k+1) + \sum_{i=1}^{P} \gamma_i E(k-i+1) = 0 \tag{21}$$

The substitution of (20) in (21) gives:

$$R(k+1)-CAX(k)-CBU(k)+\sum_{i=1}^{P} \gamma_i E(k-i+1)=0 \tag{22}$$

As the local approximation plant model (12), (13), is controllable, observable and stable, see (Baruch, *et al*., 2002; Nava, *et al*., 2004), the matrix A is diagonal, and L=M, than the matrix product (CB) is non-singular, and the plant states X(k) are smooth non-increasing functions. Now, from (22) it is possible to obtain the equivalent control capable to lead the system to the sliding surface which yields:

$$U_{eq}(k)=(CB)^{-1}[-CAX(k)+R(k+1)+\sum_{i=1}^{P} \gamma_i E(k-i+1)] \tag{23}$$

Following (Young, *et al.,* 1999), the SMC avoiding chattering is taken using a saturation function inside a bounded control level Uo, taking into account plant uncertainties. So the SMC part takes the form:

$$U^*(k) = \begin{cases} U_{eq}(k), & \text{if } \|U_{eq}(k)\| < Uo \\ -Uo\, U_{eq}(k)/\|U_{eq}(k)\|, & \text{if } \|U_{eq}(k)\| \geq Uo. \end{cases} \tag{24}$$

The proposed SMC copes with the characteristics of the wide class of plant model reduction neural control with reference model, defined in (Narendra and Parthasarathy, 1990), and it represents an indirect adaptive neural control, given in (Baruch, *et al*., 2001). As the aerobic bioprocess plant is a second order dynamical process, than we could accept P=1. In order to study the stability of the closed loop control system, let us accept Uo=1, and linearize the saturation function (24), supposing its gain to be equal to one. Then the SMC part yields:

$$U^*(k)=(CB)^{-1} [- CAX(k)+R(k+1)+ \gamma E_c(k)] \tag{25}$$

Where γ is a (LxL) diagonal control gain matrix. The identification and control errors $E_i(k)$, $E_c(k)$, are:

$$E_i(k) = Y_p(k) - Y(k); E_c(k) = R(k) - Y_p(k) \tag{26}$$

The RTNN identifier is proved to be convergent, see (Baruch, *et al*., 2002). So the RTNN output tends to the plant output ($Y(k) \to Y_p(k)$), and the control error is in fact the tracking error, $E_c(k)=E(k)=R(k)-Y(k)$.

The substitution of the control component U*(k), given by (25), in (14), and then – the obtained control signal U(k) - in the linear model (20), give us, after some mathematical manipulations, an expression for the error dynamics:

$$E_c(k+1) = -\gamma\, E_c(k) - (CB)U_i(k) - (CB)Of(k) \quad (27)$$

The equations (15) and (27) could be rewritten in operators form and the closed-loop systems error dynamics could be derived as:

$$U_i(z) = (z-1)^{-1} T_0\, K_i\, E_c(z) \quad (28)$$

$$(zI + \gamma)\, Ec = -(CB)\, Ui(z) - (CB)\, Of(z) \quad (29)$$

$$[(z-1)(zI + \gamma) + T_0\, (CB)\, K_i]\, Ec(z) = -(z-1)\, (CB)\, Of(z) \quad (30)$$

As it could be seen from the equation (30), the closed-loop systems stability could be assured by an appropriate choice of the diagonal gain matrices γ and $K_{i,}$, respectively. It could be seen also that the effect of the I-term on the control error resulted in the introduction of a difference on the offset which reduces substantially that error, especially for constant offset, and accelerates the RTNN learning.

4. MATHEMATICAL MODEL OF THE AEROBIC BIOPROCESS AND SIMULATION RESULTS

This model, taken form the paper of (see Georgieva, *et al.*, 2001 for more details), is given in the form:

$$\begin{bmatrix} \dot S \\ \dot x \\ \dot C \\ \dot E \end{bmatrix} = \begin{bmatrix} -c_{11} & 0 & -c_{13} \\ c_{21} & c_{22} & c_{23} \\ c_{31} & c_{32} & c_{33} \\ 0 & -c_{42} & c_{43} \end{bmatrix} \begin{bmatrix} \mu_1(S,O) \\ \mu_2(S,O,E) \\ \mu_3(S,O) \end{bmatrix} x - D\begin{pmatrix} S \\ X \\ C \\ E \end{pmatrix} - \begin{pmatrix} 0 \\ 0 \\ k_{CO_2} C \\ 0 \end{pmatrix} + \begin{pmatrix} DS^{in} \\ 0 \\ 0 \\ 0 \end{pmatrix} \quad (31)$$

$$\dot O(t) = \begin{bmatrix} -c_{O1} & -c_{O2} & 0 \end{bmatrix} \begin{bmatrix} \mu_1(S,O) \\ \mu_2(S,O,E) \\ \mu_3(S,O) \end{bmatrix} x - DO + k_{La}(O^* - O)$$

Where the state variables are:

$S(t)$	Substrate concentration (glucose) in the reactor;
$x(t)$	Biomass concentration (yeast) in the reactor;
$C(t)$	Concentration of the dissolved CO_2 in the reactor;
$E(t)$	Ethanol concentration in the reactor;
$O(t)$	Dissolved oxygen concentration in the reactor.

The other variables and constants are:

$D(t)$	Dilution rate considered as input;
$c_{ij} > 0$	Stoichiometric (or yield) coefficients corresponding to the production of one unit of biomass (i.e. yeast) in each reactor;
S^{in}	Glucose concentration in the feed;
O^*	Equilibrium concentration of the dissolved oxygen;.
k_{La}	Oxygen mass transfer constant;
$k_{CO_2} C(t)$	Gaseous CO_2 outflow rate proportional to $C(t)$.

The main objective is to keep the glucose concentration close to the reference values using the dilution rate $D(t)$ as manipulating function, where the input must be bounded. The process of yeast growth on glucose with ethanol production is described by three metabolic reactions. The first one is the reaction rate of the respiratory growth on glucose whose specific growth rate is:

$$\mu_1(S,O) = \begin{cases} c_{11}^{-1} \dfrac{q_{s,\max} S}{S+Ks} \cdot \dfrac{O}{O+Kc} & if\ \dfrac{q_{s,\max} S}{S+Ks} < \dfrac{q_{c,\max}}{a} \\ c_{11}^{-1} \dfrac{q_{c,\max} S}{a} \cdot \dfrac{O}{O+Kc} & if\ \dfrac{q_{s,\max} S}{S+Ks} > \dfrac{q_{c,\max}}{a} \end{cases} \quad (32)$$

Where:

$q_{s,\max}$	Maximal specific uptake rate of the glucose;
$q_{c,\max}$	Maximal specific uptake rate of the oxygen;
Ks	Saturation parameters for the glucose uptake;
Kc	Saturation parameters for the oxygen uptake;
$a = c_{O1} c_{11}^{-1}$	Stoichiometric coefficient of the oxygen.

The reaction rate of the respiratory growth on ethanol and the specific growth rate is:

$$\mu_2(S,O,E) = \frac{\mu_{e,\max} E}{Ke+E} \cdot \frac{Ki}{S+Ki} \cdot \frac{O}{O+\beta o} \quad (33)$$

Where:

$\mu_{e,\max}$	Maximal specific ethanol growth rate;
Ki	Inhibition parameter (free glucose inhibits ethanol uptake);
Ke	Saturation parameter for growth on ethanol;
βo	Saturation parameter for the free respiratory capacity available.

Finally, the reaction rate of the fermentative growth on glucose and the specific growth rate is:

$$\mu_3(S,O) = \begin{cases} c_{13}^{-1} \dfrac{q_{s,\max} S}{S+Ks} \cdot \dfrac{Kc}{O+Kc}, & if\ \dfrac{q_{s,\max} S}{S+Ks} < \dfrac{q_{c,\max}}{a} \\ c_{13}^{-1} \left[\dfrac{q_{s,\max} S}{S+Ks} - \dfrac{q_{c,\max}}{a} \cdot \dfrac{O}{O+Kc} \right], & if\ \dfrac{q_{s,\max} S}{S+Ks} > \dfrac{q_{c,\max}}{a} \end{cases} \quad (34)$$

Since the growth capacity of a population of micro organisms is strongly limited, the specific growth rate is bounded. The upper bounds are:

$$\mu_1(S,O) \le \bar{\mu}_1 := c_{11}^{-1} \frac{q_{c,\max}}{a} \quad (35)$$

$$\mu_2(S,E,O) \le \bar{\mu}_2 := \mu_{e,\max} \quad (36)$$

$$\mu_3(S,O) \le \bar{\mu}_3 := c_{13}^{-1} \frac{q_{c,\max}}{a} \quad (37)$$

The biochemical aerobic fermentation process model, given by equations (31) to (37), together with the parameters and the initial condition values of the variables, taken from the paper of (Georgieva, *et al.*, 2001), are used for simulation, adding a 10% (dmax=0.005 [g/l]) white measurement noise to the plant output and 10% (Of=0.02) offset to the plant input. The plant output $y_p(k)$ is normalized in the range (-1, 1) of the output of the neural identifier RTNN, $\hat{y}_p(k)$, so to form the identification error $e_i(k)$. The topology and learning parameters of the neural identifier RTNN are: (1, 5, 1), $\eta = 0.1$, $\alpha = 0.01$, and the control parameter is $\gamma = 0.9$. For sake of RTNN learning, the initial system identification is performed in closed-loop, computing the control $u(t)$ by the λ-tracking method, see (Georgieva, *et al.*, 2001), which is as follows:

$$\begin{aligned} & e(t) = y_p(t) - y_m(t) \\ & \mathbf{u(t)} = sat_{[0,u\max]}(\ k(t)e(t)) \\ & \dot{k}(t) = \delta \begin{cases} (|e(t)| - \lambda)^r & if \ |e(t)| > \lambda \\ 0 & if \ |e(t)| \le \lambda \end{cases} \end{aligned} \quad (38)$$

Where: $y_m(0) = 0.05$, $u_{max} = 0.0385$, λ= 0.0025, δ=45 and r=1. The period of discretization is chosen equal to $To = 0.01$, which means that it is equivalent to 1 hour of the time of the real process. After the initial RTNN learning completion, the control is changed by that, issued by a sum of SMC and the I-term control. The gain of the I-term is chosen as Ki=0.09. The graphical simulation results obtained applying a SMC with I-term, are given on Fig.2 a-d. For sake of comparison, in the Fig. 3 a-d, and Fig. 4 a-d, are given the same results applying a SMC without I-term, and a λ - tracking method of control.

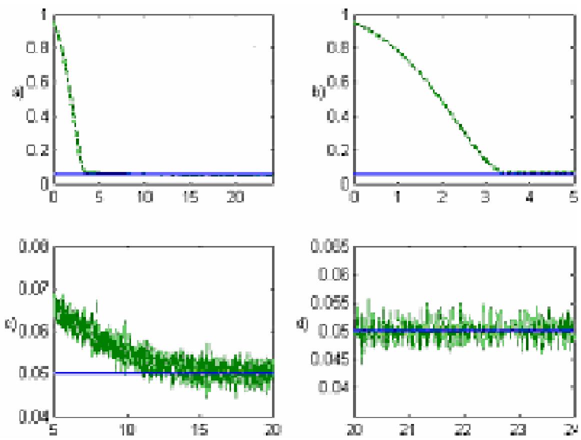

Fig.2. Graphical results of the SMC with I- term for different periods of time and different scales of amplitude (comparison of the reference signal and the output of the plant).

The Fig. 5 shows some additional results of the SMC with I-term.

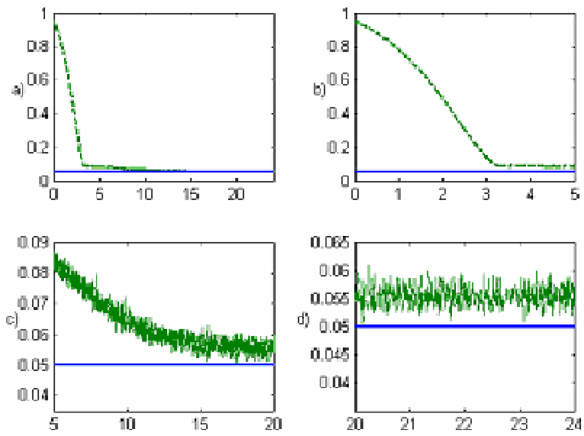

Fig.3. Graphical results of the SMC without I- term for different periods of time and different scales of amplitude (comparison of the reference signal and the output of the plant).

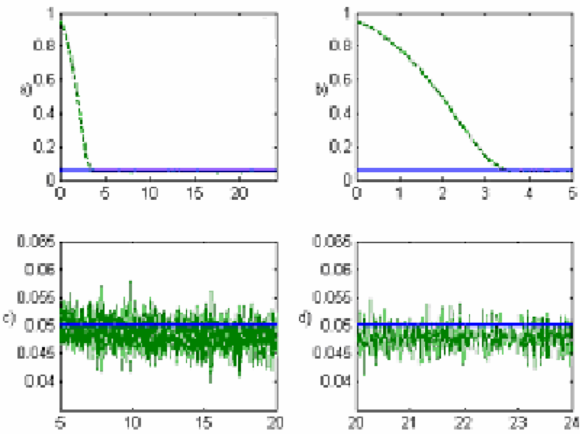

Fig.4. Graphical results of the λ-tracking method of control for different periods of time and different scales of amplitude (comparison of the reference signal and the output of the plant). The application of this control does not need a RNN identifier.

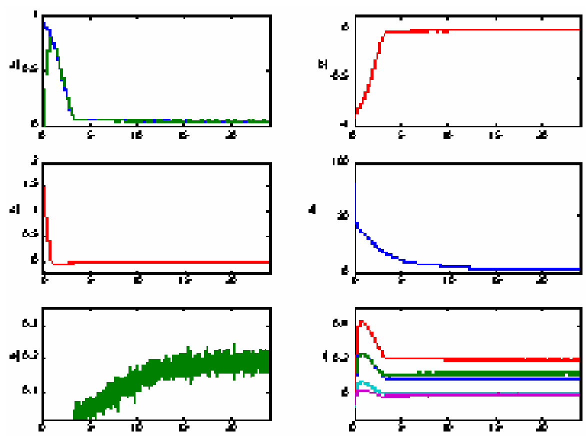

Fig.5. Additional graphical results of the SMC with I- term; a) comparison of the output of the identification RTNN and the output of the plant; b) instantaneous error of control; c) instantaneous error of identification; d) MSE% of control; e) control signal; f) States of the identification RTNN used for control.

The graphics (Fig. 2, 3, 4, a-d) compare the set point reference (Sref=0.05 [g/l]) with the output of the plant for different times of the process evolution and different scales of amplitude. The MSE% of control (Fig. 5, d) at the end of the process (24 hours) reached the value of 2.36 %. The MSE% of plants identification obtained is 0.136%. The control signal, the instantaneous error of identification and control, and the systems states, used for systems control are shown also in the figure Fig. 5, d-h. For sake of comparison, in the Fig. 3, a-d, and Fig. 4, a-d, are given the graphical simulation results applying a proportional SMC and a λ-tracking method of control. The results obtained with the proportional SMC and the λ-tracking method of control (Fig. 3, a-d, and Fig. 4, a-d) show that the offset caused a displacement of the plant output and a substantial increment of the MSE% of control which reached the value of 2.85%, for the proportional SMC and 2.458% for the λ-tracking method of control. The MSE% of identification for the SMC without I-term also augmented to the value of 0.176% due to the noise and offset effects. The graphical results obtained with an I-term SMC exhibits a better performance with respect to the other methods of proportional control. It shows that the I-term SMC could compensate constant offsets and could reduce substantially the noise in the control system, which reduces the MSE% of identification too. So, the obtained simulation results confirmed the good quality of the derived adaptive SMC with neural identifier and I-term.

5. CONCLUSIONS

The paper proposed a new adaptive control system containing a RNN identifier, and a SMC. The SMC is derived defining the sliding surface with respect to the output tracking error and using a nonlinear plant identification, and state estimation RNN, which gives all the necessary state and parameter information to resolve the SMC. Furthermore, the adaptive abilities of the RNN permit the SMC to maintain the sliding regime when the plant parameters changed. To overcome plants perturbations, an integral term is added to the control. The good quality of the proposed control scheme is illustrated by simulation results, obtained with an aerobic continuous stirred tank reactor plant model.

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