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An Adaptive Sliding Mode Control with *I*-term 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 Controller (SMC), and an I-term controller. 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. So to compensate constant process disturbances, an I-term controller is used. Comparative simulation results obtained with a fed-batch fermentation plant model confirmed the good quality of the proposed control scheme.*

Keywords: *Recurrent neural network identifier, states and parameters estimation, indirect adaptive control, sliding mode control, feed-batch fermentation bioprocess.*

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 U t k i n [1]. In [2], a sliding mode control is designed via Lyapunov approach. The main definitions for the discrete-time sliding mode control (DTSMC), are given in [3, 4], and the designed control is bounded in an admissible domain. In [5], the DTSMC has been applied for two-mass mechanical system where a full order observer is used to estimate the necessary state variables. In [6], 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 like [7] 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, [8], who updated the weights of an adaline Feddforward Neural Network (FFNN) by means of a SMC. In [9] 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 [3], the chattering is eliminated substituting the sign function by saturation or dead-zone one, (see also [6]). In [10], a SMC of nonlinear systems is proposed using Neural Network (NN). Here the NN of peceptron 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 [11], 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 [12], 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 [13], 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 [14], 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 [15], 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 [16] 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, [9], 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, [16]. 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), [17], 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. So to compensate constant process disturbances, an *I*-term controller is added. The paper is organized as follows: Part 2 give a short description of the RNN topology and learning; Part 3 derive the sliding mode control algorithm; Part 4 described the SMC with *I*-term, Part 5 give graphical simulation results with nonlinear plant; Part 6 represents the concluding remarks.

2. Recurrent Neural Network topology and learning

In [17, 18], a discrete-time model of *Recurrent Trainable Neural Network* (RTNN), and a dynamic *Backpropagation* (BP) weight updating rule, are given. The RTNN is given by

(1) $$X(k+1) = AX(k)+BU(k),$$

(2) $$Z(k)=\theta\,[X(k)],$$

(3) $$Y(k) = \theta\,[CZ(k)],$$

(4) $$A = \text{block-diag}\,(A_i);\ |A_i| < 0,$$

where $X(k)$ is an N-state vector of the system; $U(k)$ is a M-input vector; $Y(k)$ is a L-output vector; $Z(k)$ is an auxiliary vector variable with dimension L; $\theta(.)$ is a vector-valued activation function with appropriate dimension; A is a $N \times N$ weight-state diagonal matrix with elements A_i; 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 *controllability*, *observability* and *stability* of this model are discussed and proved in [17]. Parameters of that model are the weight matrices A, B, C and the state vector $X(k)$. The equation (4) is a stability preserving condition. The BP learning is given by:

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

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 model weights C_{ij}, A_{ij}, B_{ij}, are given as follows:

(6) $$\Delta C_{ij}(k) = [T_j(k) - Y_j(k)]\ \theta_j'\,[Y_j(k)]\ Z_i(k),$$

(7) $$R_1 = C_i(k)\ [T(k) - Y(k)]\ \theta_j'\,[Z_j(k)],$$

(8) $$\Delta A_{ij}(k) = R_1\,X_i(k-1),$$

(9) $$\Delta B_{ij}(k) = R_1\,U_i(k),$$

where T is a target vector with dimension L and $[T - Y]$ is an output error vector also with the same dimension; 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 T normalization.

3. Sliding mode control system design

Let us suppose that the studied nonlinear plant possess the following structure:

(10) $$X_p(k+1) = F\,[X_p(k), U(k), Q(k)],$$

(11) $$Y_p(k) = \varphi\,[X_p(k)],$$

where $X_p(k)$, $Y_p(k)$, $U(k)$, $Q(k)$ are plant state, output, input and disturbance vector variables with dimensions N_p, L and M, where $L=M$ is supposed; F and φ are smooth, odd, bounded nonlinear functions. The linearization of the activation functions of the learned identification RTNN model, which approximates the plant (see equations (1)-(3)), leads to the following approximated linear local plant model:

(12) $$X(k+1) = AX(k)+BU(k),$$

(13) $$Y(k) = CX(k),$$

where $L = M$, is supposed. Let us define the following sliding surface with respect to the output tracking error:

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

where: $S(.)$ is the sliding surface error function; $E(.)$ is the system output tracking error; γ_i are parameters of the desired error function; P is the order of the error function. The additional inequality in (14) is a stability condition, required for the sliding surface error function. The tracking error is defined as

(15) $$E(k) = R(k) - Y(k),$$

where $R(k)$ is an L-dimensional reference vector and $Y(k)$ is an output vector with the same dimension.

Block-diagram of the SMC closed-loop system with RTNN identifier is shown on Fig. 1. 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 assure that the output tracking error reaches zero in P steps, where $P<N$. So, the control objective is fulfilled if:

(16) $$S(k+1)=0.$$

The iteration of the error (15) gives

(17) $$E(k+1) = R(k+1) - Y(k+1).$$

Now, let us iterate (13) and substitute (12) in it so as to obtain the input/output local plant model, which yields:

(18) $$Y(k+1) = CX(k+1) = C[AX(k) + BU(k)].$$

From (14), (16) and (17), it is easy to obtain

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

The substitution of (18) in (19) gives

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

As the local approximation plant model (12), (13), is controllable, observable and stable, [17], the matrix A is diagonal, and $L=M$, the matrix product (CB) is

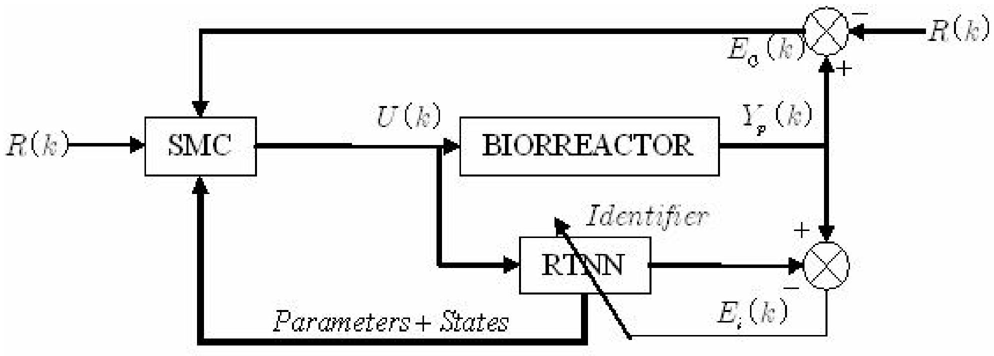

Fig. 1. Block-diagram of the closed-loop system containing neural identifier and sliding mode controller

nonsingular, and the plant states $X(k)$ are smooth non-increasing functions. Now, from (20) it is possible to obtain the equivalent control capable to lead the system to the sliding surface which yields:

$$U_{eq}(k) = (CB)^{-1}[-CAX(k) + R(k+1) + \sum_{i=1}^{P} \gamma_i E(k-i+1)]. \quad (21)$$

Following [16], the SMC avoiding chattering is taken, using a saturation function inside a bounded control level U_0, taking into account plant uncertainties. So the SMC obtains the form:

$$U(k) = \begin{cases} U_{eq}(k), & \text{if } \|U_{eq}(k)\| < U_0, \\ -U_0\, U_{eq}(k)/\|U_{eq}(k)\|, & \text{if } \|U_{eq}(k)\| \geq U_0. \end{cases} \quad (22)$$

The proposed SMC copes with the characteristics of the wide class of plant model reduction neural control with reference model, defined by N a r e n d r a and P a r t h a s a r a t h y, [20], and represents an indirect adaptive neural control, given by B a r u c h [18].

4. Sliding mode control system with *I*-term

Let us suppose that the studied nonlinear plant is Bounded – Input – Bounded – Output (BIBO) stable one, given by the equations (10), (11). The block diagram of the control scheme is shown on Fig. 2. 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 ($E_i \to 0$, $k \to \infty$). If we supposed $U_0 = 1$ and linearized the saturation function in (22), we could state $U^* = U_{eq}$.

This identification error could be considered acceptable if it reached a value below of 2% and it is considered as part of the process disturbance. The linearization of the activation functions of the learned identification RTNN model, which approximates the plant (see equations (1)-(3)), leads to linear local plant model (12), (13) adding the disturbance term, which yields:

$$X(k+1) = AX(k) + B[U(k) + Q(k)], \quad (23)$$

$$Y(k) = CX(k). \quad (24)$$

The systems control $U(k)$ have two parts:

$$U(k) = U^*(k) + U_I(k), \quad (25)$$

where $U^*(k)$ is the dynamic compensation control part, based on SMC, which could be taken in its simple form (21), as stated above; $U_I(k)$ is the *I*-term control part, which is:

$$U_I(k+1) = U_I(k) + T_0 K_I E_c(k), \quad (26)$$

where T_0 is a period of discretization; K_I is a diagonal $(L\times L)$ *I*-term gain matrix.
The identification and control errors $E_I(k)$, $E_c(k)$, are:

$$E_I(k) = Y_p(k) - Y(k); \; E_c(k) = R(k) - Y_p(k). \quad (27)$$

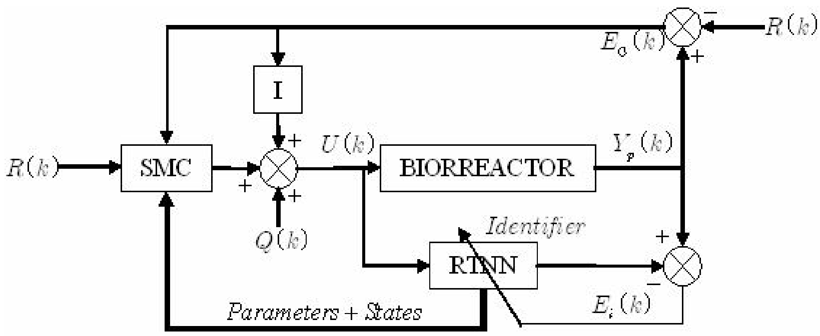

Fig. 2. Block-diagram of the adaptive SMC system, with a neural identifier and an *I*-action

The RTNN identifier is proved to be convergent, (see B a r u c h *et al.* [17]). 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 (21), in (25), and then – the obtained control signal $U(k)$ – in the linear model (23), (24) give us, after some mathematical manipulations, an expression for the error dynamics:

(28) $$E_c(k+1) = -\gamma E_c(k) - (CB)U_I(k) - (CB)Q(k).$$

The equations (26) and (28) could be rewritten in operators form and the closed-loop systems error dynamics could be derived as:

(29) $$U_I(z) = (z-1)^{-1} T_0 K_I E_c(z),$$

(30) $$(zI + \gamma) E_c = -(CB)\, U_I(z) - (CB)\, Q(z),$$

(31) $$[(z-1)(zI + \gamma) + T_0 (CB) K_I]\, E_c(z) = -(z-1)(CB)\, Q(z).$$

As it could be seen from the equation (31), 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 disturbance term which reduces substantially that error, especially for constant process disturbance, and accelerates the RTNN learning.

5. Simulation results

In this section, the quality of the derived SMC will be illustrated by a fed-batch fermentation of *Bt.* process control.

List of symbols used:

$u(t)$ – Nutrient feeding rate at a t time, l / h;
S_f – Substrate concentration in the feeding g / l;
$S(t)$ – Substrate concentration in the culture, g / l;
$X(t)$ – Biomass concentration in the culture, g / l;
$V(t)$ – Culture volume into the bioreactor at t, l.

The fed-batch fermentation model described a microorganism *Bt.* cultivation in a sterile reactor, [19], maintained under operational conditions, adequate for microorganism growth at a desired specific growth rate. The operational conditions considered are: temperature of 30 ?C, pH of 7.1 and dissolved oxygen in a concentration greater than 40%. The nutrients are supply during the exponential phase of *Bt*. growth. So, to derive the model, some suppositions are taken into account. They are: 1) yield coefficient is constant during all the fermentation (*Y*); 2) the substrate consumption for the maintenance cells is negligible; 3) the increased volume in the bioreactor is equal to the nutrient volume fed; 4) cell dead is considered negligible during the fermentation.

Sketch of the Fed-batch bioreactor is shown on Fig.3. The model is based on the derivation of the Mass balance equations of the bioreactor, [19], which are as follows:

- evolution of the culture volume

(32) $$\frac{dV}{dt} = u\,(t);$$

- evolution of the total microorganism mass in the bioreactor

(33) $$\frac{d\left(VX\right)}{dt} = \mu\left(S\left(t\right)\right)X\left(t\right)V\left(t\right);$$

- evolution of the limiting substrate in the bioreactor

(34) $$\frac{d\left(SV\right)}{dt} = u\left(t\right)S_f - \frac{\mu\left(S\left(t\right)\right)X\left(t\right)V\left(t\right)}{Y};$$

- the specific growth rate $\mu(S(t))$ is described by the Monod equation, [19]

(35) $$\mu(S(t)) = \frac{\mu_{\max} S(t)}{K_{\mathrm{M}} + S(t)},$$

where $\mu_{\max}$ is the maximal growth rate; K_{M} is a Michaelis–Menten constant. The derivation of (33) and (34) gives:

(36) $$\dot{V}(t) = u(t),$$

(37) $$\dot{X}(t) = X(t)\left(\mu(s(t)) - \frac{u(t)}{V(t)}\right),$$

(38) $$\dot{S}(t) = \frac{u(t)}{V(t)}(S_f - s(t)) - \frac{\mu(s(t))X(t)}{Y},$$

where $V(t)$: $\Re_{\geq 0} \rightarrow \Re_{>0}$ is a growth function, representing the culture volume in the bioreactor at t (t is the current time); $u(t)$: $\Re_{\geq 0} \rightarrow \Re_{>0}$ is the input to the bioreactor at t; $S_f > 0$ is the substrate concentration in u(t) at t; $S(t)$ is the substrate concentration in the culture at t; $X(t)$ is the cell concentration in the culture at t; finally, $Y > 0$ and $\mu(t, S)$: $\Re_{\geq 0} \times \Re_{\geq 0} \rightarrow \Re_{\geq 0}$ are continuous functions for $\mu(t, 0) = 0\ \forall\ t \geq 0$. The initial conditions of the state variables and the constant parameters are: $V(0) = 3.0$; $X(0) = 3.58$ g/l; $S(0) = 15.6$ g/l; $S_f = 34.97$ g/l; $\mu_{\max} = 1.216$; $K_{\mathrm{M}} = 5$; $Y = 7.5$.

The nonlinear mathematical model of the fed-batch fermentation of *Bt*. bioprocess, derived, is validated with experimental data, produced in optimal operating

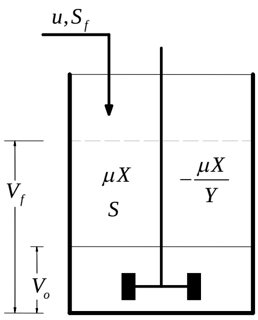

Fig. 3. Sketch of the fed-batch bioreactor of the fermentation process of *Bt*

conditions, [19]. The results, obtained, are presented in Figs. 4, 5 for an optimal nutrient rate. The results represented the case of SMC control without process noise (the ideal case). The figure shows two cycles of the *Bt*. fermentation, being of duration of 21 hours. The process terminated with the break in the nutrient feeding. The neural control is trained with the output of the fed-batch fermentation model, represented by equations (36), (37), (38) for different values of nutrient feeding rate in the interval [0.1; 0.7] l/h. The nutrient concentration in the feeding rate is constant. In order to avoid saturation of SMC and the RTNN during the learning, the plant output is multiplied by the scaling constant $k_0 = 0.0025$. The identification RTNN has topology (1-5-1). The values of learning parameters are $\eta = 0.1$, α=0.01. The SMC parameters (see equations (21), (22)) are $U_0 = 1$, $P = 1$, and $\gamma = 0.9$. The graphics of Fig. 4a gives a comparison between the desired reference signal and the output of the plant. The

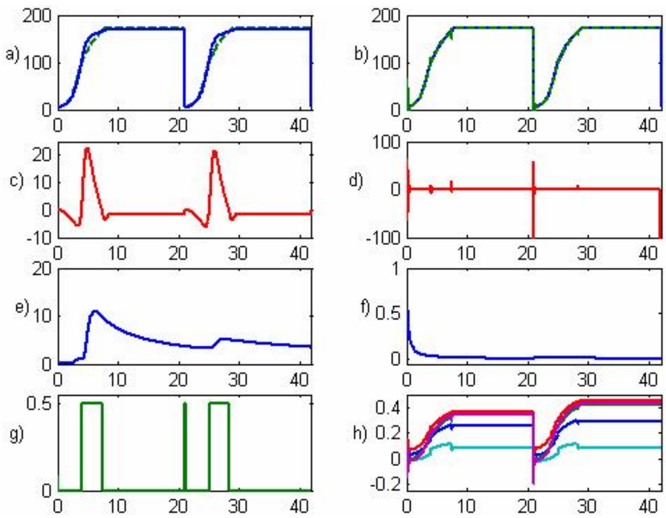

Fig. 4. Simulation results of the discrete-time adaptive SMC of a fed-batch fermentation process: a) comparison of the reference signal with the plant output; b) comparison of the output of the plant with the output of the identification RTNN; c) instantaneous error of control; d) instantaneous error of identification; e) mean square error of control; f) Mean square error of identification; g) control signal; h) systems states, estimated by the identification RTNN

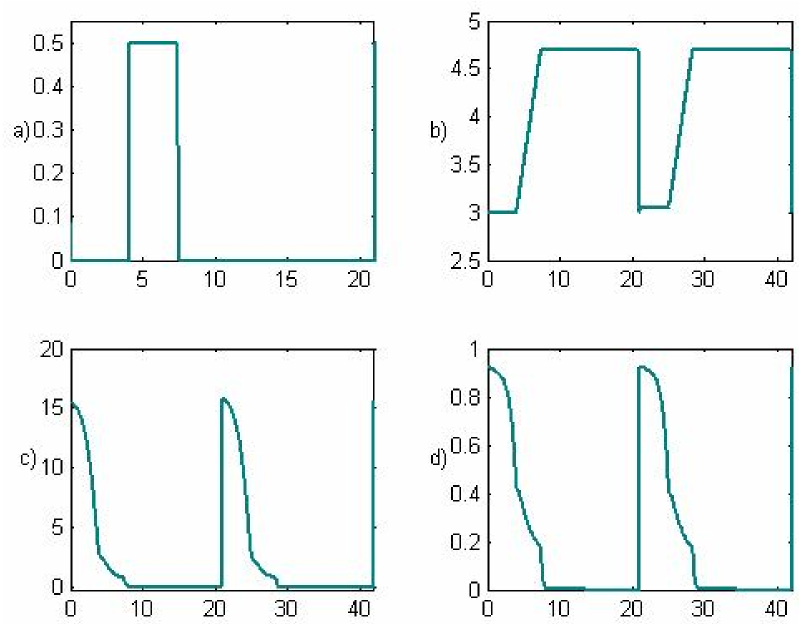

Fig. 5. Additional simulation results of the discrete-time adaptive sliding mode control application: a) control signal; b) evolution of the culture volume into the bioreactor; c) evolution of the limiting substrate in the bioreactor; d) evolution of the specific growth rate $\mu S(t)$)

equations of the bioprocess model did not represent micro-organisms death, so the graphics of this part are complemented with semi-square pulses. The graphics, given on Fig. 4b, represented comparison between the output of the plant and the output of the identification RTNN. The graphics of Fig. 4c, and d, represented the instantaneous error of control and identification, respectively.

The graphics of Fig. 4e and f, gives us the Means Squared Error (MSE%) of control and identification, which are 4% and 2.5%, respectively. The control action, given on Fig. 4g, was carried out during 8 hours in the exponential growth phase. After this time, the control signal is equal to zero and the behaviour of the plant's output is unknown. The last graphics (Fig. 4h) shows the five states, estimated by the identification RTNN, and used for feedback control. Some additional process information is given on Fig. 5, where Fig. 5a repeats the control signal for one cycle of fermentation. Fig. 5b shows the evolution of the culture volume into the bioreactor. Fig. 5c gives the evolution of the limiting substrate in the bioreactor. Fig. 5d shows the evolution of the specific growth rate $\mu(S(t))$.

Simulation results of the fermentation plant governed by 10% constant process noise controlled by a SMC with integral term are given on Fig. 6. For sake of comparison on Fig. 7 are shown the same results but for system without integral term. The results show that the constant process noise affects the system output for SMC without integral term and does not affect the system with *I*-term, which behaved like the ideal case of Fig. 4. The obtained simulation results confirmed the good quality of the derived adaptive SMC with *I*-term.

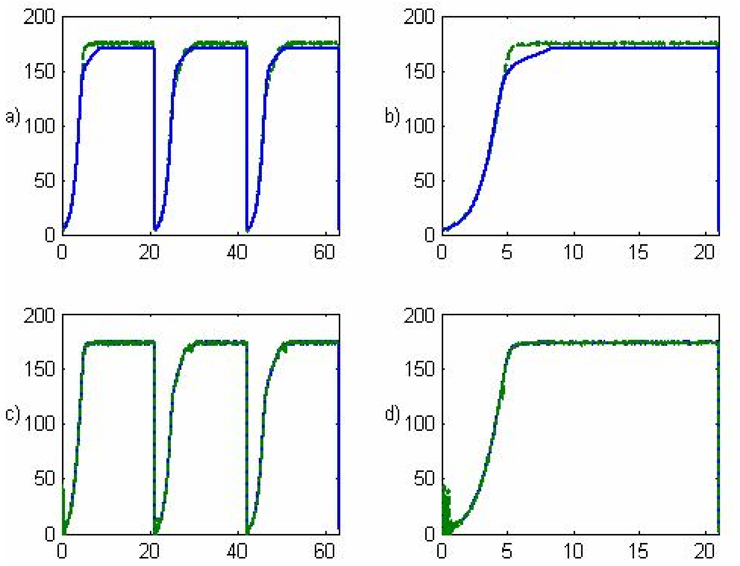

Fig. 6. Simulation results of the discrete-time adaptive SMC with *I*-term and 10% constant process noise, applied for a fed-batch fermentation process; a) comparison of the reference signal with the plant output for three cycles; b) detailed view of a) for one cycle; c) comparison of the output of the plant with the output of the identification RTNN; d) detailed view of b) for one cycle

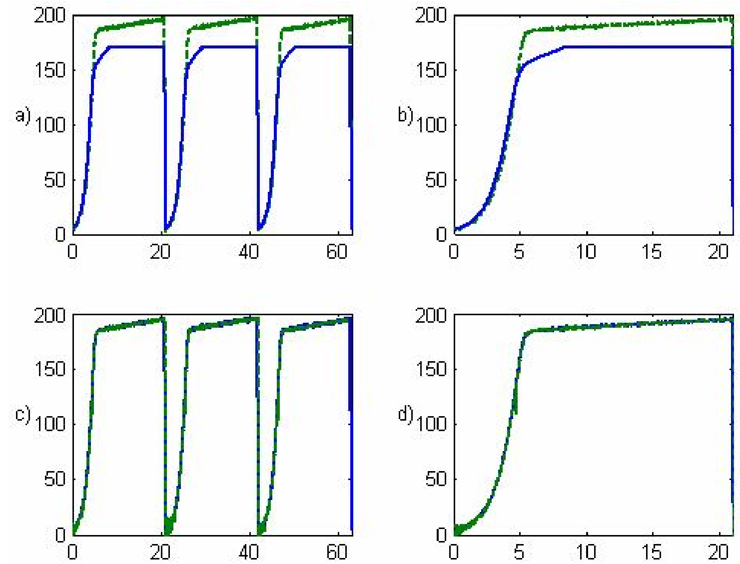

Fig. 7. Simulation results of the discrete-time adaptive SMC without *I*-term and with 10% constant process noise, applied for a fed-batch fermentation process: a) comparison of the reference signal with the plant output for three cycles; b) detailed view of a) for one cycle; c) comparison of the output of the plant with the output of the identification RTNN; d) detailed view of b) for one cycle

6. Conclusions

A new Recurrent Trainable Neural Network model and a dynamic Backpropagation-like learning algorithm are applied in an indirect adaptive neural control scheme of a fed-batch fermentation of *Bt*. The control scheme, proposed, contains identification RTNNs and a sliding mode controller. 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 plants parameters changed. An extension of the SMC scheme incorporates an *I*-term to the control law, permitting to reduce a process noise. A nonlinear mathematical model of a feed-batch fermentation process of *Bt.* is derived and validated with experimental data. Simulation results using this model and applying the adaptive SMC with and without *I*-term are obtained. The identification results reproduced the exponential and the lag phase of the experimental data with a MS approximation error of 2.5%. The obtained closed-loop MS control error of noisy plant is below 4% which is a satisfactory result. The results show that the proposed SMC with *I*-term could completely remove a constant process noise.

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