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Hybrid Intelligent Control Scheme for Activated Sludge Wastewater Treatment

E. N. Sanchez, E. A. Hernandez, C. Cadet, J. F. Beteau

***Abstract*— This paper presents a neural network identification scheme to estimate substrate, biomass and dissolved oxygen concentrations in an activated sludge wastewater treatment. This scheme is based on a discrete-time high order neural network (RHONN) trained on-line with an extended Kalman filter (EKF)-based algorithm. Then, the identification scheme is associated with a fuzzy control to regulate the ratio between substrate and biomass concentrations. Obtained simulation results are very encouraging.

I. Introduction

Identification and control are an essential part for wastewater treatment plants (WWTPs), which have been object of attention since the last decades, due to environmental issues. A WWTP based on activated sludge technology, is commonly used for treatment of urban and industrial wastewater. This kind of plant is capable of treating wastewater such that the quality of the effluent can be reached. Controlling this process is a difficult job, and a WWTP requires several strategies in order to guarantee good operating conditions. Control strategies using a variety of techniques have been proposed by different authors [1], [2], [4], [7]. Some of these approaches give importance to effluent quality while the other ones prioritize energy minimization [8]. Moreover, efficient control systems of a WWTP require a very structured knowledge, represented in term of differential equations. This mathematical description of the dynamic system is known as the model. Basically, there are two ways to obtain a model; it can be derived from physics laws in a deductive manner, or it can be inferred from a set of data collected during a practical experiment. The second method, referred as system identification, is a useful short cut for deriving mathematical models. Neural network identification is an outstanding tool, which approximates the performance of the plant using artificial neural networks [11].

In this work, a WWTP is identified by means of a recurrent high order neural network, which is trained with an extended Kalman filter algorithm [6]. In order to ensure effluent quality, the ratio between substrate and biomass is defined as a relation and is used by the intelligent controller. The hybrid intelligent system, using the proposed fuzzy control and a neural network identifier, set references for the oxygen concentration and for the recycling rate. The intelligent control and identification performances are illustrated via simulations.

E. N. Sanchez, CINVESTAV, Unidad Guadalajara, Apartado Postal 31-438, Plaza la Luna, Jal. C.P. 45090, e-mail: sanchez@gdl.cinvestav.mx

E. A. Hernandez, CINVESTAV, Unidad Guadalajara, Apartado Postal 31-438, Plaza la Luna, Jal. C.P. 45090, e-mail: avargas@gdl.cinvestav.mx

C. Cadet, Institute National Polytechnique de Grenoble, GIPSA-lab Department of control systems BP 46-38402 St-Martin d´Hères Cedex, France, e-mail: Catherine.Cadet@inpg.fr

J. F. Beteau, Institute National Polytechnique de Grenoble, GIPSA-lab Department of control systems BP 46-38402 St-Martin d´Hères Cedex, France, e-mail: Jean-Francois.Beteau@inpg.fr

II. Process Description

A typical activated sludge treatment plant constitutes the benchmark of the European group COST 624 [1], which is presented in Fig. 1. The two main parts are: the bioreactor which usually can be modeled by five perfectly mixed tanks, and the settler, modeled with 10 layers.

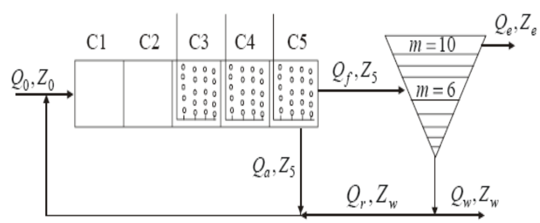

Fig.1. Activated Sludge Wastewater Process Scheme.

The first two compartments of the bioreactor are where denitrification takes place, and are non-aerated; the next three compartments (nitrification process) are aerated. Q_0 and Z_0 are respectively the flow rate and the concentrations of the plant influent (disturbances); Q_f and Z_5 are the flow rate and concentration at the bioreactor output; Q_e and Z_e are the flow rate and concentration of the plant effluent; Q_w and Z_w are the flow rate and concentration of the sludge wastage; Q_r is the external recycle flow rate and Q_a is the internal recycle flow rate. All the flow rates used in the model are in m^3/day. The process model uses 13 state variables according with ASM1 [9]. The main state variables are

S_S Fast biodegradable substrate.
X_{BH} Active heterotropic biomass.
X_{BA} Active autotrofic biomass.
S_O Dissolved oxygen.
S_{NO} Nitrate and nitrite nitrogen.
S_{NH} Amoniacal nitrogen.

The global mathematical model for this process requires 145 nonlinear differential equations, obtained by calculating mass balances for the bioreactor five sections and the settler ten layers. Benchmark simulations are implemented with the simulator provided by [1].

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III. Discrete-Time Recurrent High Order Neural Network Identifier

A. Neural Network Identification

Let consider a discrete MIMO nonlinear system

$$x_i(k+1) = F(x(k), u(k)) \tag{1}$$

where $x \in \Re^n$, $u \in \Re^m$ and $F \in \Re^n \times \Re^m \rightarrow \Re^n$ is a nonlinear function. A discrete-time recurrent high order neural network (RHONN) can be presented as:

$$x_i(k+1) = w_i^T z_i(x(k), u(k)), \ i = 1, \ldots, n \tag{2}$$

where x_i ($i = 1,2,\ldots,n$) is the state of the ith neuron, L_i is the respective number of higher-order connections, n is the state estimation, $\{I_1, I_2, \ldots, I_{Li}\}$ is a collection of non-ordered subsets of $\{1,2,\ldots,n\}$, w_i ($i = 1,2,\ldots,n$) is the respective on-line adapted weight vector, and $z_i(x(k),u(k))$ is given by

$$z_i(x(k),u(k)) = \begin{bmatrix} z_{i_1} \\ z_{i_2} \\ \vdots \\ z_{i_{Li}} \end{bmatrix} = \begin{bmatrix} \Pi_{j \in I_1} y_i^{di_j(1)} \\ \Pi_{j \in I_2} y_i^{di_j(2)} \\ \vdots \\ \Pi_{j \in I_{L_i}} y_i^{di_j(L_i)} \end{bmatrix} \tag{3}$$

$d_j(k)$ being nonnegative integers and y_i is defined as follows:

$$y_i = \begin{bmatrix} y_{i_1} \\ \vdots \\ y_{i_1} \\ y_{i_{n+1}} \\ \vdots \\ y_{i_{n+m}} \end{bmatrix} = \begin{bmatrix} S(x_1) \\ \vdots \\ S(x_n) \\ u_1 \\ \vdots \\ u_m \end{bmatrix} \tag{4}$$

In (4), $u = [u_1,u_2,\ldots,u_m]^T$ is the input vector to the neural network (NN), and $S(\bullet)$ is defined by

$$S(x) = \frac{1}{1+\exp(-\beta x)} + \in \tag{5}$$

We consider now the problem to approximate the nonlinear system (1), by the following discrete-time RHONN series-parallel representation:

$$\chi_i(k+1) = w_i^{*T} z_i(x(k), u(k)) + \in_{z_i}, \ i = 1, \ldots, n \tag{6}$$

where χ_i is the ith plant state, ϵ_z is a bounded approximation error, which can be reduced by increasing the number of adjustable weights [12]. Due to Theorem 1, stated below assume that there exists the ideal weight vector w_i^*, such that $\|\epsilon_z\|$ can be minimized on a compact set $\Omega_{Z_i} \subset \Re^{L_i}$. In general, it is assumed that this vector exists and is constant but unknown, see [6] for the details. Let us define its estimate as w_i and the estimation error as

$$\tilde{w}_i(k) = w_i^* - w_i(k) \tag{7}$$

Theorem 1: The RHONN (2) trained with the EKF algorithm to identify the nonlinear plant (1), ensures that the identification error is semiglobally uniformly ultimately bounded (SGUUB); moreover, the RHONN weights remain bounded. For the proof, see [6].

B. The EKF Training algorithm

For KF-based neural network training, the network weights become the states to be estimated. In this case, the error between the neural network output and the measured plant output can be considered as additive white noise. Due to the fact that the neural network mapping is nonlinear, an EKF-type is required. The training goal is to find the optimal weight values which minimize the prediction error [6], [13]. In this work, we use an EKF-based training algorithm described by

$$\begin{aligned} w_i(k+1) &= w_i(k) + \eta_i K_i(k) e_i(K) \\ K_i(k) &= P_i(k) H_i(k) M_i(k) \qquad i = 1, \ldots, n \\ P_i(k+1) &= P_i(k) - K_i(k) H_i^T(k) P_i(k) + Q_i(k) \end{aligned} \tag{8}$$

with

$$\begin{aligned} M_i(k) &= [R_i(k) + H_i^T(k) P_i(k) H_i(k)]^{-1} \\ e_i(k) &= y(k) - \hat{y}(k) \end{aligned} \tag{9}$$

where $e(k) \in \Re^p$ is the observation error and $P_i(k) \in \Re^{L_i \times L_i}$ is the weight estimation error covariance matrix at step k, $w_i \in \Re^{L_i}$ is the weight (state) vector, L_i is the respective number neural network weights, $y \in \Re^p$ is the plant output, $\tilde{y} \in \Re^p$ is the NN output, n is the number of states, $K_i \in \Re^{L_i \times p}$ is the Kalman gain matrix, $Q_i \in \Re^{L_i \times L_i}$ is the NN weight estimation noise covariance matrix, $R_i \in \Re^{p \times p}$ is the error noise covariance, and $H_i \in \Re^{L_i \times p}$ is a matrix, in which each entry (H_{ij}) is the derivative of the *i-th* neural output with respect to *ij-th* NN weight, (w_{ij}), given as follows:

$$H_{ij}(k) = \left[\frac{\partial \hat{y}(k)}{\partial w_{ij}(k)} \right]^T \tag{10}$$

where $i=1,\ldots,n$ and $j=1,\ldots,L_i$. Usually P_i and Q_i are initialized as diagonal matrices, with entries $P_i(0)$ and $Q_i(0)$, respectively. It is important to remark that $H_i(k)$, $K_i(k)$ and $P_i(k)$ for the EKF are bounded; for a detailed explanation of this fact see [13].

C. Wastewater Application

To estimate substrate, biomass and oxygen concentrations, the RHONN (6) with n=3 is used as given by

$$\hat{x}_1(k+1) = w_{11}S(x_1)^4 + w_{12}S(x_1)^2 S(x_2)S(x_3) + w_{13}S(x_3) + w_{14}S(u_1)$$

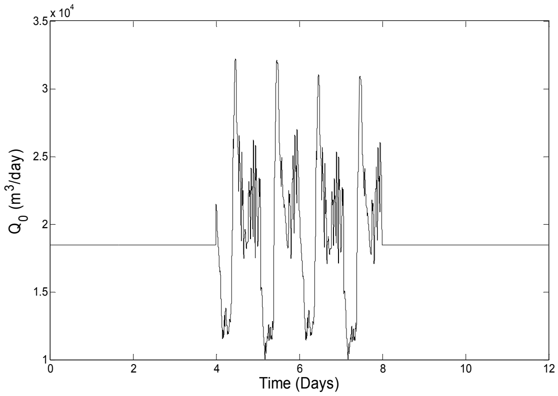
$$\hat{x}_2(k+1) = w_{21}S(x_2)^5 + w_{22}S(x_1)^2 S(x_2)S(x_3)^3 + w_{23}S(x_2) + w_{24}u_2$$

$$\hat{x}_3(k+1) = w_{31}S^2(x_3) + w_{32}S(x_1)S^2(x_2)S(x_3)^3 + w_{33}S(x_3) + w_{34}S(u_3)$$

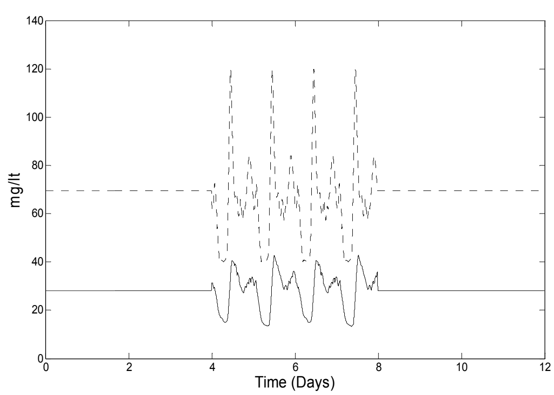
where $\hat{x}_1$, $\hat{x}_2$ and $\hat{x}_3$ are the estimation of the fast biodegradable substrate S_S, active heterotropic biomass X_{BH} and oxygen S_O, respectively. The input u_1 is the flow rate of the plant influent Q_0, u_2 is the external recycle flow rate Q_r, and u_3 is the control action of oxygen in the fifth compartment of the bioreactor. The training is performed on-line, using a series-parallel configuration. All the NN states are initialized randomly. The covariance matrices are initialized as diagonal, with nonzero elements as: $P_i(0) = 60000$, $Q_i(0) = 2500$ and $R_i(0) = 4400$, (i=1,2,3), respectively.

D. *Simulation Results*

For simulation, the scenario considered is: the first four days a constant disturbance is included; for the next three days a time variable disturbance is inserted, and finally, for the last four days a constant disturbance is considered, see Fig.2.



(a)



(b)

Fig.2. External Disturbance: (a) Volumetric flux influent. (b) Fast biodegradable substrate (solid line) and heterotropic biomass concentrations influent (dashed line).

As can be seen in Fig. 3, there is almost exact convergence for the three state variables, which are very close to the respective state variable.

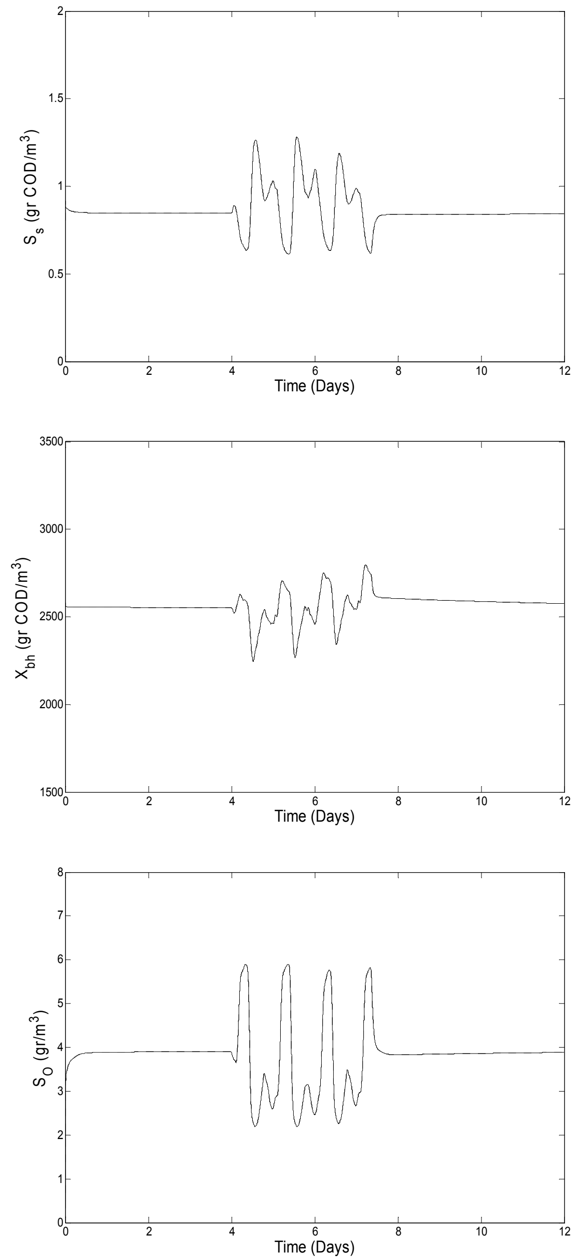


Fig.3. Fast biodegradable substrate, heterotropic biomass and oxygen concentration concentrations (solid line) and the respective identification (dashed line).

IV. CONTROL STRATEGY

A. *L/A Structure*

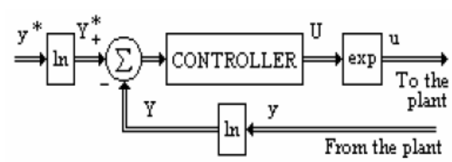


Fig.4. *L/A* controller.

This structure is discussed in [14] and portrayed in Fig.4, which is called *L/A* because two transformations are used; the first one is based on the logarithmic (*L*) function and the second one on the antilogarithmic (*A*) function, as follows:

Logarithm

$$\begin{aligned} Y(t) &= ln\ y(t) \\ Y^*(t) &= ln\ y^*(t) \\ U(t) &= ln\ u(t) \end{aligned} \tag{11}$$

Antilogarithm

$$\begin{aligned} y(t) &= exp Y(t) \\ y^*(t) &= exp\ \ Y^*(t) \\ u(t) &= exp U(t) \end{aligned} \tag{12}$$

where $y(t)$ is the output, $y^*(t)$ is the set point, and $u(t)$ is the control action. These transformations allow to select any conventional control law and to obtain an *L/A* equivalent. In [2], a PI is defined as follows

$$U_k = U_{k-1} + K_1(Y_{k-1} - Y_k) + K_2(Y^*_{k-1} - Y_k) \tag{13}$$

with K_1 and K_2 the integral and proportional gains respectively. The *L/A* equivalent of this control law is:

$$u_k = u_{k-1}\left(\frac{y_{k-1}}{y_k}\right)^{K_1}\left(\frac{y^*_k}{y_k}\right)^{K_2} \tag{14}$$

The control law (14) offers different advantages, such as: to take into account the physical process constraints (such as positivity), and to eliminate the requirement to know the process mathematical model.

B. *Fuzzy Supervisory Control*

The Takagi –Sugeno system is a special case of "functional fuzzy systems":

$$\begin{aligned} &\text{If } u_i \text{ is } A_1^j \text{ and } u_2 \text{ is } A_2^j \text{ and, ..., and } u_n \text{ is } A_n^j \\ &\text{then } b_i = g_i(.) \end{aligned} \tag{15}$$

where "." represents the arguments of the function g_i and the b_i are not output membership function centers. The premise of this rule is defined with linguistic terms like for the standard fuzzy system. The consequent is different, instead of linguistic terms with an associated membership function, we use a function b_i=g(.), which does not have an associated membership function. The choice of this function depends on the application being considered. Virtually any function can be used (e.g. a linear equation, neural network mapping or another fuzzy system), which makes the functional fuzzy system very general.

The functional fuzzy system can use an appropriate logical operation for representing the premise (e.g., minimum or product) and defuzzification may be obtained using

$$y = \frac{\sum_{i=1}^{R} b_i \mu_i}{\sum_{i-1}^{R} \mu_i} \tag{16}$$

where μ_i is the membership value defined as

$$\mu_i(u_1, u_2, ..., u_n) = \mu_{A_1^j}(u_1) * \mu_{A_1^k}(u_2) * ... * \mu_{A_n^l}(u_n)$$

One way to view the functional fuzzy system is as a nonlinear interpolation between the mappings that are defined by consequents of the rules. When the consequent function are dynamic system then the functional fuzzy system is named as Takagi-Sugeno one [10], such as

$$b_i = g_i(.) = a_{i,0} + a_{i,1}u_1 + ... + a_{i,n}u_n$$

where $a_{i,j}$ are real numbers.

C. *Hybrid Intelligent System*

To this end, we propose the development of a hybrid intelligent control system for WWTP. For this strategy, we use fast biodegradable substrate and heterotropic biomass concentrations, estimated by the proposed neural identification scheme.

This strategy is based on the following reasoning: if on one hand, there is an excessive amount of biomass concentration, then the suspended solids increase. If on the other hand, the biomass concentration is low and substrate concentration is high, influent pollution cannot be treated. Both cases lead to operational problems. For these reasons, we propose a relation *RT*, which has to be constant;

$$RT = \frac{X_{BH}}{S_s} \tag{17}$$

The hybrid intelligent control is based on *RT* tracking, using the scheme shown in Fig. 5.

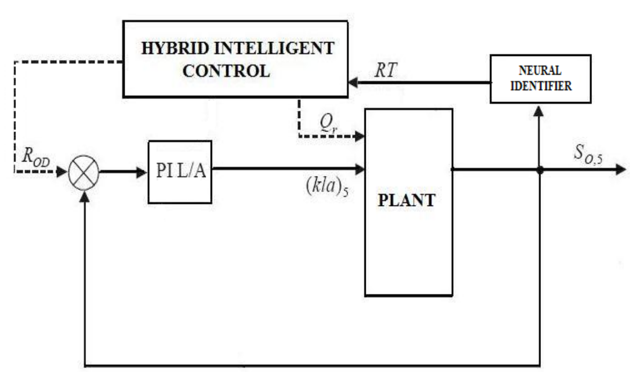


Fig.5. Hybrid intelligent control scheme.

This scheme uses a PI L/A controller to control S_o using as manipulated variable *kla* (aeration constant); for a detailed explanation see [2].

The structure of the hybrid intelligent control uses a fuzzy Takagi Sugeno supervisor to modify the oxygen set point (R_{OD}) of the L/A controller and the external recycle flow rate Q_r. The respective fuzzy sets are defined as

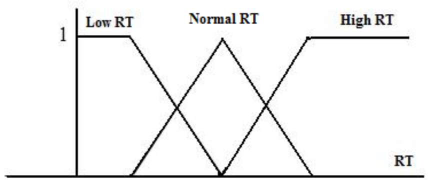


Fig.6. Input membership functions.

The respective rules are:

If RT is low then $Q_r = Q_{rl}$ and $R_{OD} = R_l$

If RT is normal then $Q_r = Q_{rn}$ and $R_{OD} = R_n$

If RT is high then $Q_r = Q_{rh}$ and $R_{OD} = R_h$

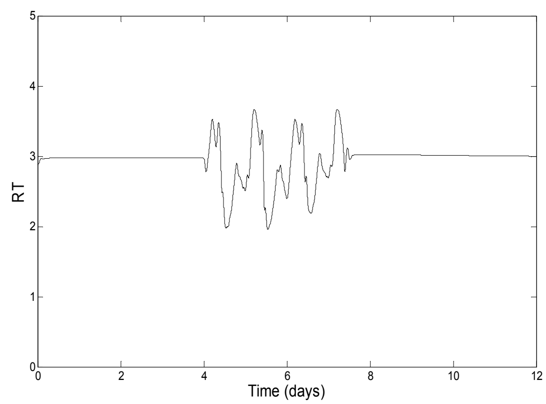


Fig.7. RT control using intelligent control.

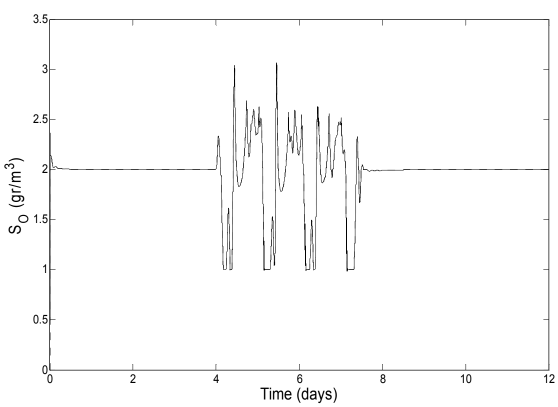


Fig.8. Controlled oxygen concentration.

Fig.7 and Fig.8 display how the proposed hybrid intelligent control keeps both outputs: the oxygen (S_o) and the ratio RT at the designed values when there is a constant external disturbance. When this disturbance is time-varying, the control is still able to keep these outputs around the desired values.

Fig.9 presents the time-evolution for the identification of fast biodegradable and heterotrophic biomass concentration. This identification performs adequately. The conditions for a well behaved identifier performance are given in [6].

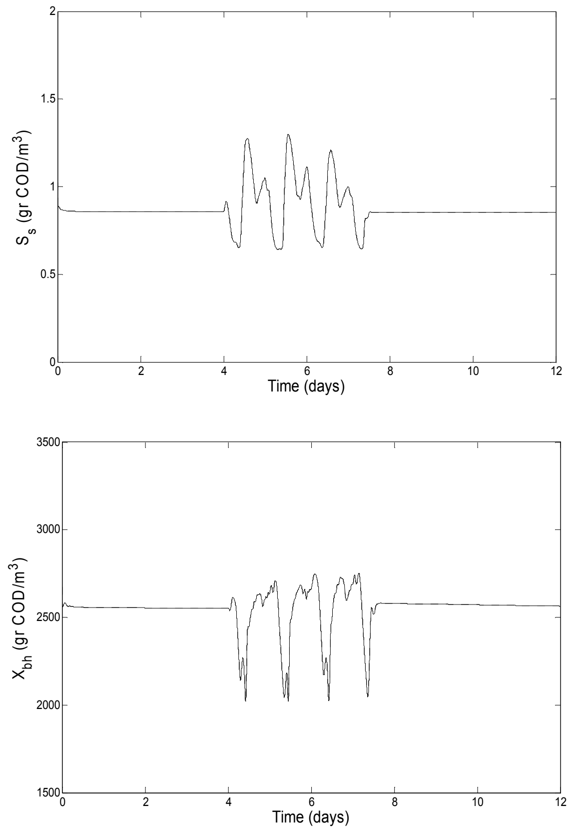


Fig.9. Controlled fast biodegradable, heterotrophic biomass concentration.

V. Conclusions

In this paper, a RHONN identification scheme for concentrations of fast biodegradable substrate, heterotropic biomass and dissolved oxygen in a WWTP has been developed; the training of the neural networks is performed on-line using an extended Kalman filter in a series-parallel configuration. Simulations results show the effectiveness of the RHONN in spite of the presence of external disturbances. The proposed hybrid intelligent control gives promising guidelines to tackle the problem of WWTP control. In addition, the combination of neural networks and fuzzy controller reveal an important tool to control other complex process.

As future work, the real-time implementation of the proposed control scheme, using a recurrent high order neural observer will be explored.

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