Discrete-Time Recurrent High Order Neural Observer for Activated Sludge Wastewater Treatment

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

***Abstract*—** This paper presents a recurrent neural observer to estimate substrate and biomass concentrations in an activated sludge wastewater treatment. The observer is based on a discrete-time high order neural network (RHONN) trained on-line with an extended Kalman filter (EKF)-based algorithm. This observer is then associated with a hybrid intelligent system to control the substrate/biomass concentration ratio. The neural observer performance is illustrated via simulations.

I. Introduction

Recently, the use of wastewater treatment plants (WWTPs) has increased due to environmental issues. Controlling a WWTP is not a simple task, and several techniques has been proposed [6], [9]. The application of these strategies requires sensors allowing the measurements of the process main variables; these sensors could be very expensive and require elaborated maintenance procedures.

Due to these facts, state estimation applied to WWTP and to biological processes has received special attention by many authors, who have obtained interesting results in different directions and for different purposes. Most of the existing results need the use of a special nonlinear transformation [16]. Other kind of observers are those called robust, which have good performance under uncertainties although their design is too complex and has very restrictive conditions [17].

The main problem of all the approaches mentioned above is the requirement to know at least partially the plant dynamic model. However, other kinds of observers have been recently proposed: neural observers [1], [3], [11], [14] which do not need this requirement.

In this paper, we use a recurrent high order neural observer (RHONO) [3], based on RHONN [5] which is applied to a WWTP in order to estimate the substrate and biomass concentrations. The neural network learning uses an extended Kalman filter algorithm [2]. Moreover, we propose to associate this observer to a hybrid intelligent control in order to ensure effluent quality even in presence of external disturbances.

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II. Process Description

The process of a typical aerobic treatment plant corresponds to the benchmark of the European group COST 624 [8]; the diagram of the aerobic treatment plant 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.

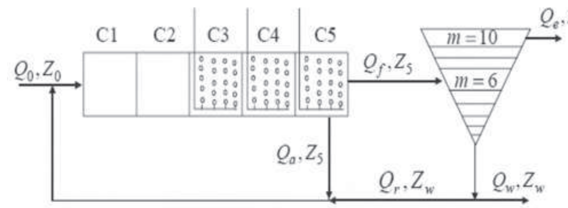

Fig.1. Activated Sludge Wastewater Process Scheme.

The first two compartments of the bioreactor are non-aerated and there denitrification takes place; 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 [13]. The main 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 five sections of the bioreactor and the 10 layers of the settler. Benchmark simulations are implemented with the simulator provided by [8].

III. Discrete-Time Recurrent High Order Neural Network

Let consider a MIMO nonlinear system

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$$x_i(k+1) = F(x(k), u(k)) \quad (1)$$

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

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

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

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

with $d_{ji}(k)$ nonnegative integers and y_i defined as follows:

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

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

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

We consider now the problem to approximate the general-time nonlinear system (1), by the following discrete-time RHONN [11]:

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

where χ_i is the ith plant state, ϵ_z is the bounded approximation error, which can be reduced by increasing the number of adjustable weights [5]. Assume that there exists 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. Let us define its estimate as w_i and the estimation error as

$$\widetilde{w}_i(k) = w_i^* - w_i(k) \quad (7)$$

IV. THE EKF TRAINING ALGORITHM

The well known Kalman filter is a set of mathematical equations that provides an efficient computational (recursive) solution of the least-squares method, which estimates the state of a linear system with additive state and output white noises [18]. 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 predictions error. In this work, we use, an EKF-based training algorithm described by

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

with

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

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:

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

where i=1,…,n and j=1,…,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 [18]. To obtain H in (10) is not an easy task. In this case $\hat{y}(k) = x_i(k)$, so by the chain rule, we have

$$\frac{\partial \hat{y}(k)}{\partial w_{ij}(k)} = \frac{\partial \hat{y}(k)}{\partial x_i(k)} \frac{\partial x_i(k)}{\partial w_{ij}(k)} \quad (11)$$

V. DISCRETE TIME NEURAL OBSERVERS

In this section, we briefly present the neural observer, proposed in [3]. We consider the state of a discrete-time nonlinear system, which is assumed to be observable, given by

$$x(k+1) = F(x(k),u(k)) + d(k)$$
$$y(k) = Cx(k) \tag{12}$$

where $x \in \Re^n$ is the state vector of the system, $u \in \Re^m$ is the input vector, $y(k) \in \Re^p$ is the output vector, $C \in \Re^{p\times n}$ is a known output matrix, $d(k) \in \Re^n$ is a disturbance vector and $F(\bullet)$ is a smooth vector field and $F_i(\bullet)$ its entries; hence (12) can be rewritten as:

$$x(k+1) = [x_1(k) \dots x_i(k) \dots x_n(k)]^T$$
$$d(k) = [d_1(k) \dots d_i(k) \dots d_n(k)]^T \tag{13}$$
$$x_i(k+1) = F_i(x(k),u(k)) + d_i(k), \quad i = 1,\dots,n$$
$$y(k) = Cx(k)$$

For system (13), a Luenberger neural observer (RHONO) is proposed in [3], with the following structure:

$$\hat{x}(k) = [\hat{x}_1(k) \dots \hat{x}_i(k) \dots \hat{x}_n(k)]^T$$
$$\hat{x}_i(k+1) = F_i(\hat{x}(k),u(k)) + L_i e(k) \tag{14}$$
$$\hat{y}(k) = C\hat{x}(k), \qquad i = 1,\dots,n$$

with $L_i \in \Re^p$, w_i and z_i as in (2); the weight vectors are updated on-line with a decoupled EKF (8)-(11). The output error is defined by

$$e(k) = y(k) - \tilde{y}(k) \tag{15}$$

and the state estimation error as

$$\tilde{x}(k) = x(k) - \hat{x}(k) \tag{16}$$

Hence the dynamic of (16) can be expressed as

$$\begin{aligned}\tilde{x}(k+1) &= x_i(k+1) - \hat{x}_i(k+1) \\ &= w_i^{*T} z_i(x(k),u(k)) + \in_{z_i} + d_i(k) \\ &\quad - w_i^T z_i(\hat{x}(k),u(k)) - L_i e(k) \\ &= \tilde{w}_i z_i(\hat{x}(k),u(k)) + \in_{z_i} + d_i(k) - L_i e(k)\end{aligned} \tag{17}$$

Considering (14) and (15)

$$e(k) = C\tilde{x}(k) \tag{18}$$

Then the error of (9) can be rewritten as

$$\tilde{x}(k+1) = \tilde{w}_i z_i(\hat{x}(k),u(k)) + \in'_{z_i} - L_i C\tilde{x}(k) \tag{19}$$

where $\epsilon'_{zi} = \epsilon_{zi} + d_i(k)$. On the other hand the dynamics of (9) is

$$\tilde{w}_i(k+1) = w_i^* - w_i(k+1) = \tilde{w}_i(k) - \eta_i K_i(k) e(k) \tag{20}$$

For a detailed explanation of the synthesis and analysis of the neural observer see [3].

VI. Observer Application

To this end, the neural observer is applied to a WWTP discussed in section II, whose nonlinear dynamics is considered unknown. To estimate substrate and biomass concentrations with oxygen concentration measurement in the fifth compartment of the bioreactor, we use the RHONO (14) with n=3. The neural network used is given by

$$\begin{aligned}\hat{x}_1(k+1) &= w_{11}S(\hat{x}_1) + w_{12}S(\hat{x}_1)S(\hat{x}_2)S(\hat{x}_3) + w_{13}S^2(\hat{x}_3) \\ &\quad + w_{14}S^2(\hat{x}_1)S^3(\hat{x}_2)S(\hat{x}_3) + w_{15}S(u_1) \\ \hat{x}_2(k+1) &= w_{21}S(\hat{x}_2) + w_{22}S(\hat{x}_1)S(\hat{x}_2)S(\hat{x}_3) \\ &\quad + w_{23}S(\hat{x}_2)S(\hat{x}_3) + w_{24}S^2(\hat{x}_2)S(\hat{x}_3) + w_{25}S(u_1) \\ \hat{x}_3(k+1) &= w_{31}S^3(\hat{x}_3) + w_{32}S(\hat{x}_1)S^2(\hat{x}_3) + w_{33}(\hat{x}_2)S(\hat{x}_3) \\ &\quad + w_{34}S(\hat{x}_3) + w_{35}S(u_2) \\ \hat{y} &= \hat{x}_3\end{aligned}$$

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, and u_2 is the control action of oxygen in the fifth compartment of the bioreactor, which in this paper is constant (open-loop).

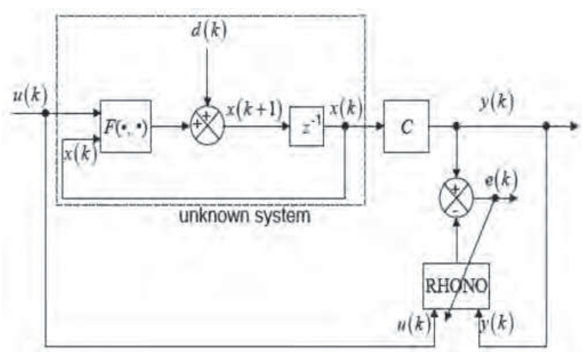

Fig.2. Observation scheme.

The training is performed on-line, using a parallel configuration as displayed in Fig.2. All the NN states are initialized randomly. The covariance matrices are initialized as diagonal, with nonzero elements as: $P_i(0)$ = 800000, $Q_i(0)$ = 200 and $R_i(0)$ = 4000, (i=1,2,3), respectively.

VII. Simulation Results

The simulations are implemented using a Matlab/ Simulink™; two different scenarios are considered: the first four days a constant disturbance is included; then, for the next five days a variable disturbance is inserted, see Fig 3.

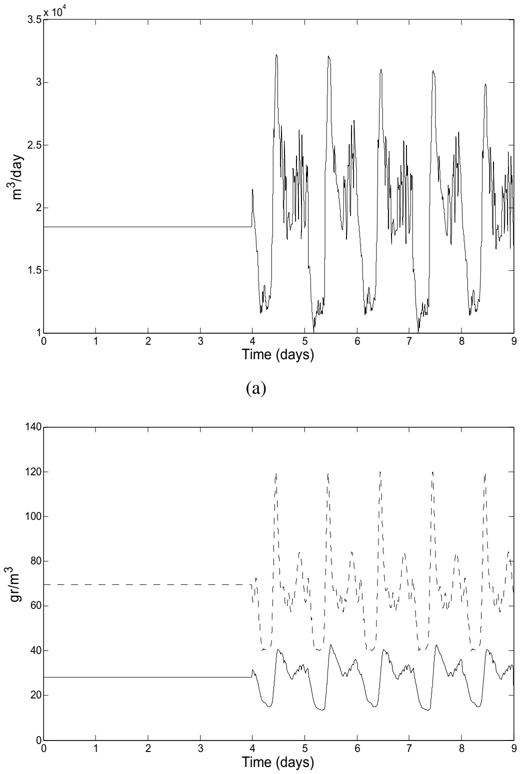

Fig.3. External Disturbance: (a) Volumetric flux influent. (b) Fast biodegradable substrate (solid line) and heterotropic biomass concentrations influent (dashed line).

As can be seen in Fig. 4, there is exact convergence for the state variable (S_o) as expected, whereas for the other state variables good estimations are obtained, see Fig.5.

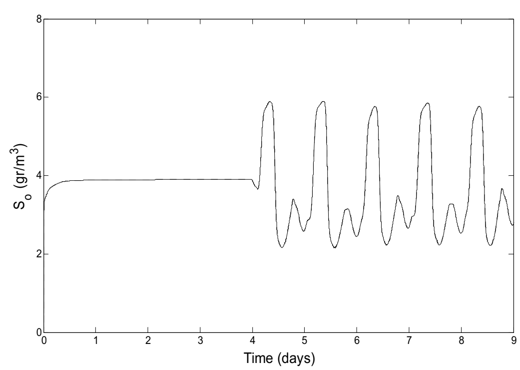

Fig.4. Oxygen concentrations (solid line) and their respective estimates (dashed line).

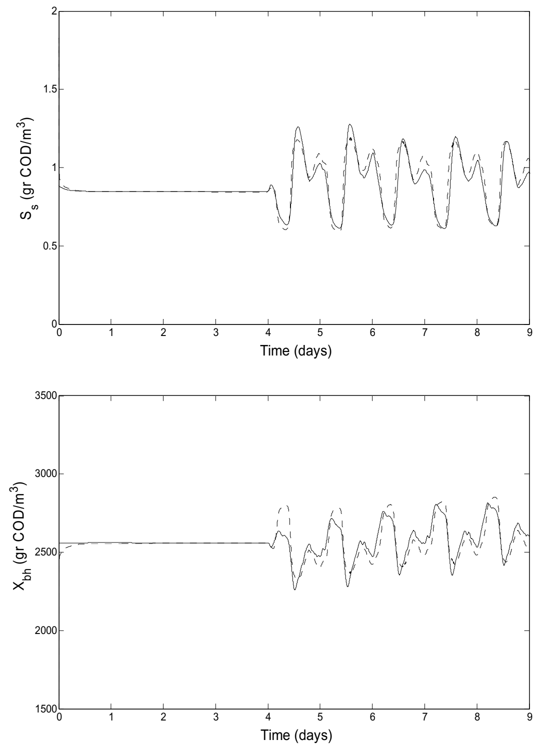

Fig.5. Fast biodegradable substrate, heterotropic biomass and oxygen concentrations (solid line) and their respective estimates (dashed line).

Additionally, it is possible to verify that, for the first four days, when the disturbance is constant, the estimation is almost exact. The next five days when a variable disturbance is introduced to the system, we can notice that the estimation of the fast biodegradable substrate concentration is very close to the respective state variable. On the other hand, the estimation of the heterotrophic biomass concentration is good for the first 4 days.

VIII. Hybrid Intelligent System

In this section, 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 observer. This strategy is based on the following reasoning: if there is an excessive amount of biomass concentration, then the suspended solids increase; if on the contrary, the biomass concentration is low and substrate concentration is high, influent pollution cannot be treated. Both cases degrade treated water quality. For these reasons, we propose a relation RT, which has to be kept constant;

$$RT = \frac{S_s}{X_{bh}} \tag{21}$$

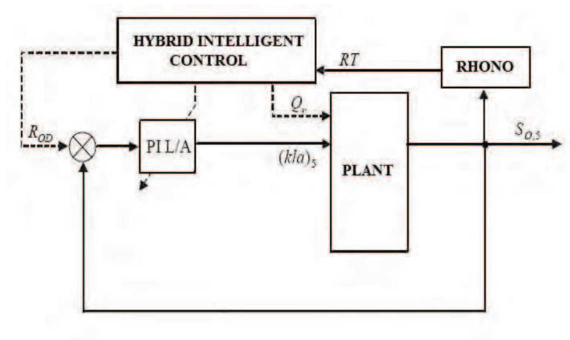

Fig.6. Hybrid intelligent control scheme.

The hybrid intelligent control is based on *RT* tracking, using the scheme shown in Fig. 6. In this scheme, a PI L/A controller, see Fig.7, is considered to control S_o using as manipulated variable *kla* (aeration constant); for a detailed explanation see [6].

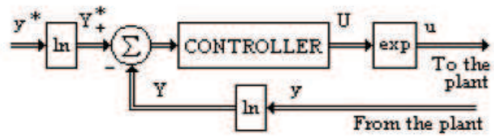

Fig.7. L/A controller.

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

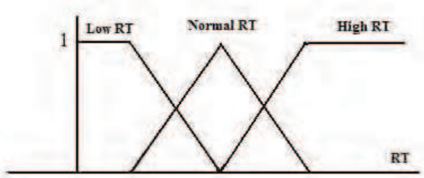

Fig.8. Input membership functions.

The respective rules are:

If RT is low then $Q_r= Q_{rl}$ and $R_{OD}=R_l$, $K_i=k_{il}$ and $K_p=k_{pl}$

If RT is normal then $Q_r= Q_{rn}$ and $R_{OD}=R_n$, $K_i=k_{ir}$ and $K_p=k_p$

If RT is high then $Q_r= Q_{rh}$ and $R_{OD}=R_h$, $K_i=k_{ih}$ and $K_p=k_{ph}$

where, K_i is the integral gain of the controller, and K_p is the proportional gain of the controller.

IX. Conclusions

In this paper, the estimation of concentrations of fast biodegradable substrate and heterotropic biomass in a WWTP has been developed, using a RHONO and considering only on-line measurements of the dissolved oxygen; this observer is trained with an EKF-based algorithm, which is implemented on-line as a parallel configuration. Simulations results show the effectiveness of the observer in spite of the presence of input disturbances. The proposed hybrid intelligent control gives promising guidelines to tackle in the future the problem of WWTP control.

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References

[1] A.S. Poznyak, E.N. Sanchez and W. Yu, *Differential Neural Networks for Robust Nonlinear Control*, Word Scientific, Singapore, 2001.

[2] E.N. Sanchez, A.Y. Alanis and G. Chen, "Recurrent neural networks trained with Kalman filtering for discrete chaos reconstruction", *Proceedings of Asia-Pacific Workshop on Chaos Control and Synchronization*, Melbourne, Australia, July 2004.

[3] E.N. Sanchez, A. Y. Alanis, and A. G. Loukianov, *Discrete-Time Recurrent High Order Neural Observer for Induction Motors*, in "Foundations of Fuzzy Logic and Soft computing" Eds. P. Melin, et al., Springer-Verlag, Berlin Heidelberg, Germany, 2007.

[4] E.N. Sanchez, J.F. Beteau and S. Carlos, "Hierarchical fuzzy control for a wastewater treatment plant", *IEEE conference on Systems*, *Man and Cybernetics*, Tucson, USA, Oct. 2001.

[5] G.A. Rovithakis and M.A. Christodoulou, *Adaptive Control with Recurrent High-Order Neural Network*, Springer-Verlag, New York, USA, 2000.

[6] G. Vera, E.N. Sanchez, J.F. Béteau and C. Cadet, "Intelligent control of an activated sludge wastewater treatment plant", *American Control Conference ACC03*, Denver, USA, June 2003.

[7] I. Takács, G.G. Patry and D. Nolassco, "A dynamic model of the clarification thickening process", *Water Research*, Vol.25, 1991.

[8] J. Alex, J. F. Beteau, et al., "The COST simulation benchmark: description and simulator manual", Benchmark for evaluating control strategies in wastewater treatment plants, *European Control Conference*, Karlsruhe, Germany, BM20, 2000.

[9] M.A. Brdys, M. Grochowski, T. Gminski, K. Konarczak and M. Drewa, "Hierarchical predictive control of integrated wastewater treatment systems", *Control Engineering Practice*, January 2007.

[10] K. Passino and S. Yurkovich, *Fuzzy Control*, Addison Wesley Longman, INC., New York, USA, 1998.

[11] L. J. Ricalde and E.N. Sanchez, "Inverse optimal nonlinear high order Recurrent Neural observer", *International Joint Conference on Neural Networks IJCNN 05*, Montreal, Canada, August, 2005.

[12] M. Hamed, M. G. Khalafallah and E. A. Hassanien, "Prediction of wastewater treatment plant performance using artificial neural networks", *Environmental Modeling & Software*, Vol.19, 2004.

[13] M. Henze, Jr. Gredy, W. Gujer, G. Marais, and T. Matsuo, "Activated sludge model nº 1", *IAWQ Scientific and Technical Report nº1*, London, England, 1986.

[14] R. Marino, "Observers for single output nonlinear systems", *IEEE Transactions on Automatic Control*, Vol.35, pp. 1054-1058, September 1990.

[15] R. M. Tong, M. Beck, and A. Latten, "Fuzzy control of activated sludge wastewater treatment process", *Automatica*, Vol. 16, 1980.

[16] T. Lopez, A. Pulis, and R. Baratti, "On-line monitoring of a biological reactor for wastewater treatment", *Revista Mexicana de Ingeniería Química*, 3 (1), 51-63, 2004.

[17] V. Alcaraz and V. Gonzalez, *Robust Nonlinear Observers for Bioprocesses: Application to Wastewater Treatment*, Springer-Verlag, Berlin Heidelberg, 2007.

[18] Y. Song and J. W. Grizzle, "The extended Kalman Filter as a Local Asymptotic Observer for Discrete-Time Nonlinear Systems", *Journal of Mathematical Systems, Estimation and Control*, Vol. 5, No.1, pp. 59-78, Boston, USA, 1995.