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Identification and Prediction of Wastewater Treatment Parameters

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Abstract: In this study, neural networks are extensively used to identify and predict wastewater process parameters. Three methods are implemented to drive the system's operation. In the first one difference neural networks inputs are ignored but considered in the second, an extended Kalman filter implements the third one. High performance is derived from our approach which considers input difference effects and therefore, fits better to overcome the complex wastewater problem.

Key words: Wastewater, identification, prediction EKF and neural networks

INTRODUCTION

Wastewater treatment plant of domestic wastewater is dynamic systems which deal with considerable variation in flux, concentration and composition of pollutants. Mathematical models describing the behavior of microbiological systems are important as they provide a mathematical description of process mechanism strongly required for identification and control of the wastewater process.

The aim of the mathematical modeling is to get the right operations which express and describe the behavior of the study system. Generally models depend on several factors, which take in charge the whole complexity and available information about the process. When given a suitable model, identification and control process system can then be derived.

In 1983, International Water Association (IWA) formed a working group charged to promote and facilitate the practical methods of designing the biological wastewater treatment operations.

As result, the Activated Sludge Model1 (ASM1) has been presented in 1987 (Henze *et al*., 1987). The model used thirteen state variables and described the organic carbon and nitrogen elimination. The same working group extended the model afterwards by adding the biological process of phosphorus elimination, and named this model the Activated Sludge Model 2 (ASM2) (Henze *et al*., 1995). Two new improved versions of ASM2, named ASM2d and ASM3 then appeared (Henze *et al*., 2000).

Identification of non-linear process has always been a problem, as long as the mathematical model structure can hardly be known in advance. Artificial neural networks opened a new horizon in identification and control of highly nonlinear and complex structured systems. This approach can approximate large variety of relationships for identification such as a wastewater treatment plant which possess very strong nonlinear properties.

The prediction operation is used to estimate next right state output. Three approaches are developed in this research. The first approach has been proposed in Sergiu *et al*. (2007) where neural networks input differences are excluded. In our case, the operation uses neural networks and implements input differences and both methods are checked through extended Kalman filter support.

THE WASTEWATER PROCESS MODEL

The mathematical model considered in this study has been proposed in Nedjari *et al*. (1999). This latter supposes the following assumptions:

- The system runs in steady-state regime

(Fin =Fout =F, D=F/V)

- The recycled sludge is proportional to the process flow (F): F_r = r. F, where r is the recycled sludge rate.
- The flow of the sludge removed from the bioreactor (sludge that is in excess) is considered proportional to the process flow (F): $F_\beta = \beta$. F, where is the removed sludge rate.
- There is no substrate or dissolved oxygen in the recycled sludge flow of the bioreactor.
- The output flow of the aerated tank is equal to the sum between the output flow of the clarifier tank (settler) and the recycled sludge flow.

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Figure 1 presents the schematic diagram of the wastewater treatment process. The aeration tank is a biological reactor containing a mixture of liquid and suspended solid. In order to remove the organic substrate from the mixture a microorganism population is grown. The clarifier tank is a gravity settlement tank where the sludge and the clear effluent are separated. A part of the removed sludge is recycled back into the aeration tank and the other part is then removed (Katebi *et al*., 1999).

Under these conditions, the process model is given by the following mass balance equations:

$$\frac{dX}{dt} = \mu(t)X(t) - D(t)(1+r)X(t) + rD(t)X_r(t) \quad (1)$$

$$\frac{dS}{dt} = \frac{\mu(t)}{Y}X(t) - D(t)(1+r)S(t) + rD(t)S_{in} \quad (2)$$

$$\frac{dDO}{dt} = K_0\frac{\mu(t)}{Y}X(t) - D(t)(1+r)DO(t) + \alpha W(DO_{max} - DO(t)) + D(t)DO_{in} \quad (3)$$

$$\frac{dX}{dt} = D(t)(1+r)X(t) + D(t)(\beta + r) + X_r(t) \quad (4)$$

$$\mu(t) = \mu_{max}\frac{S(t)}{K_S + S(t)}\frac{DO(t)}{K_{DO} + DO(t)} \quad (5)$$

Where X(t)-biomass, S(t)-substrate, DO(t)-dissolved oxygen, DO_{max}-maximum dissolved oxygen, $X_r(t)$-recycled biomass, D(t)-dilution rate, S_{in} and Do_{in} Substrate and dissolved oxygen concentrations in the influent,

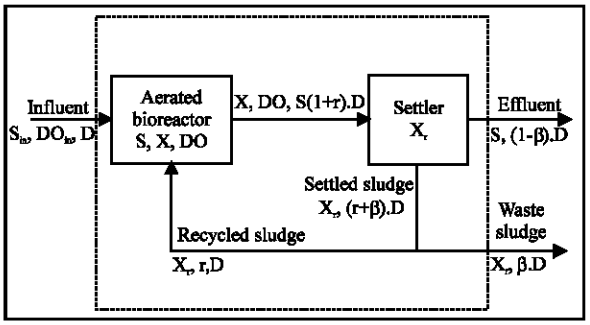

Fig. 1: Wastewater treatment process diagram

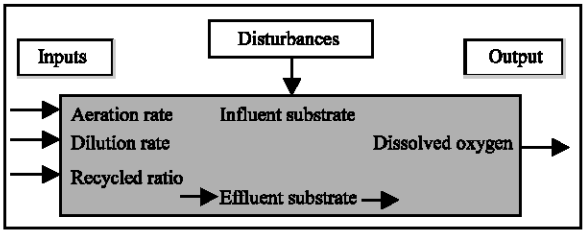

Fig. 2: The systemic diagram of the wastewater treatment process

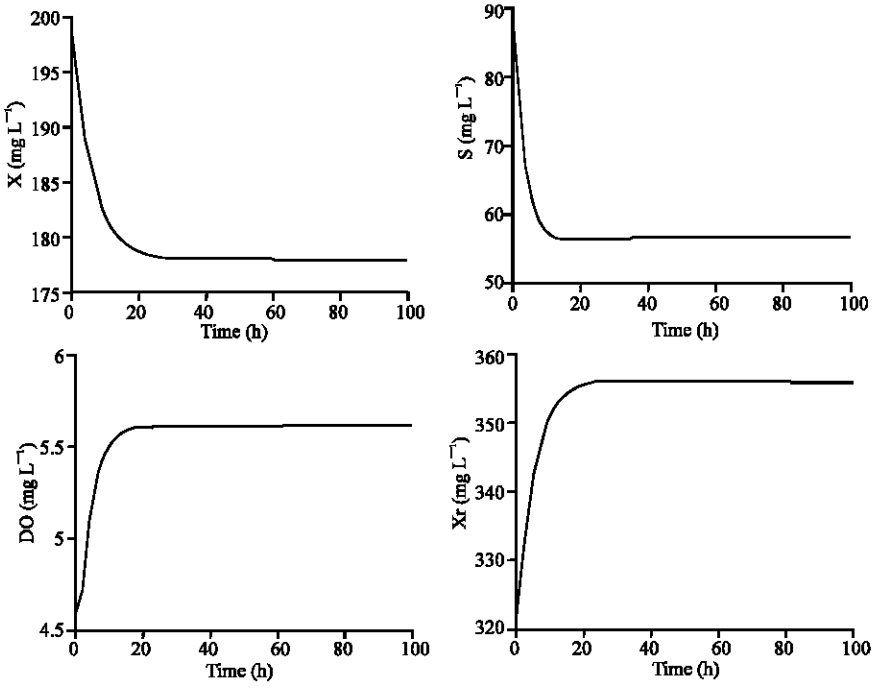

Fig. 3: Open loop system response

Y-biomass yield factor, μ-biomass growth rate, μ_{max}-maximum specific growth rate K_S and K_{DO}-saturation constants, α-oxygen transfer rate, W-aeration rate, K_0-model constant, r and β ratio of recycled and waste flow to the influent. The model coefficients have the following values:

$$Y = 0.65;\ \beta = 0.2;\ \alpha = 0.018;\ K_{DO} = 2\ mg\ L^{-1};\ K_0 = 0.5$$
$$\mu_{max} = 0.15\ mg\ L^{-1};\ K_S = 100\ mg\ L^{-1};$$
$$DO_{max} = 10\ mg\ L^{-1};\ r = 0.6.$$

The systemic diagram of the process is given in Fig. 2.

Figure 3 illustrates the open loop response of the system to a step input $D = 0.1h^{-1}$ ($W = 80\ h^{-1}$). The initial conditions considered in this simulation are:

$$X(0) = 200\ mg\ L^{-1}\ S(0) = 88\ mg\ L^{-1}\ DO(0) = 5\ mg\ L^{-1}$$
$$X_r(0) = 320\ mg\ L^{-1}\ DO_{in} = 0.5\ mg\ L^{-1}\ S_{in} = 200\ mg\ L^{-1}.$$

During normal wastewater treatment process operation, three regimes have been identified: rain ($D = 1/20\ h^{-1}$ $W = 80\ h^{-1}$), normal ($D = 1/35\ h^{-1}$ $W = 60\ h^{-1}$) and drought ($D = 1/50\ h^{-1}$ $W = 20\ h^{-1}$). The first case is characterized by maximum values for the aeration and dilution rates, the second regime considers medium values for W and D. The third case is characterized by small values for the same parameters.

SYSTEM IDENTIFICATION USING NEURAL NETWORKS

The system to be identified can be represented by a transformation operator TP, which maps the compact subset $U \in R^n$ to $Y \in R^m$. The purpose is to find a class T_i such that T_p is represented by T_1 adequately well. The operator T_p is defined by specific input-output pairs that are obtained form the inputs and the outputs of the system to identify (Duder, 1996).

The objective is expressed as follows;

$$\left\| T_i(u) - T_p(u) \right\| \le \varepsilon, u \in U$$

for some desired $\varepsilon > 0$. $T_i(u)$ denotes the identification model output. As can be seen easily, the approach requires the input-state-output representation of the system. Generally, a continuous time dynamical system can be given by:

$$\frac{dx(t)}{dt} = \dot{x}(t) = \Phi[x(t), u(t)] \quad t \in R^+ \qquad (6)$$
$$y(t) = \Psi[x(t)]$$

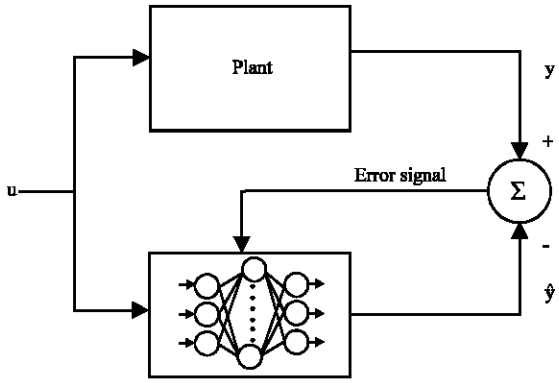

Fig. 4: Neural identification structure

Where:

$$x(t) = [x_1(t)\ x_2(t)\ ...x_n(t)]^T$$
$$u(t) = [u_1(t)\ u_2(t)\ ...u_p(t)]^T$$
$$y(t) = [y_1(t)\ y_2(t)\ ...y_m(t)]^T$$

denoting state, input and output vectors, respectively. In discrete domain, Eq. 6 becomes:

$$x(k+1) = \Phi[x(k), u(k)]$$
$$y(k) = \Psi[x(k)]$$

Even in the cases where Φ and Ψ are not known, neural networks can construct an approximate model which when the same input vector is applied to both the actual plant and the identification model, the difference between the outputs remains within a predefined error level.

System identification structure is illustrated in Fig. 4.

The emphasis on the neural network based identification is determination of an adaptive algorithm that minimizes the difference between the actual plant and the identification model outputs by using a set of training pairs which represent the approximate behavior of the actual plant.

In this study, our simulation results are presented in Fig. 5. The plant consists of a wastewater whose model is expressed by the Eq. 1-4.

Identification model: 6-28-20-4

Inputs:

$$D(k) = 0.05 + 0.05\sin\left(\frac{2\pi k}{100}\right)$$
$$W(k) = 50 + 50\sin\left(\frac{2\pi k}{100}\right)$$

Errors between plant output and identification model output are illustrated in Fig. 6.

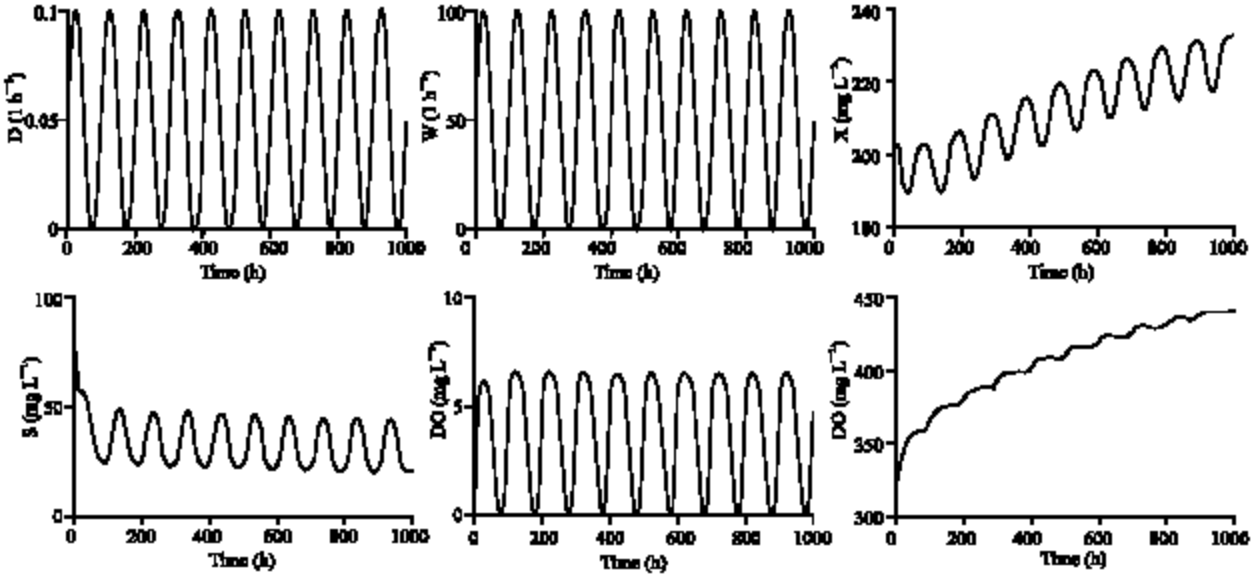

Fig. 5: Actual and identified responses results, solid: Identified outputs, dashed: Actual outputs

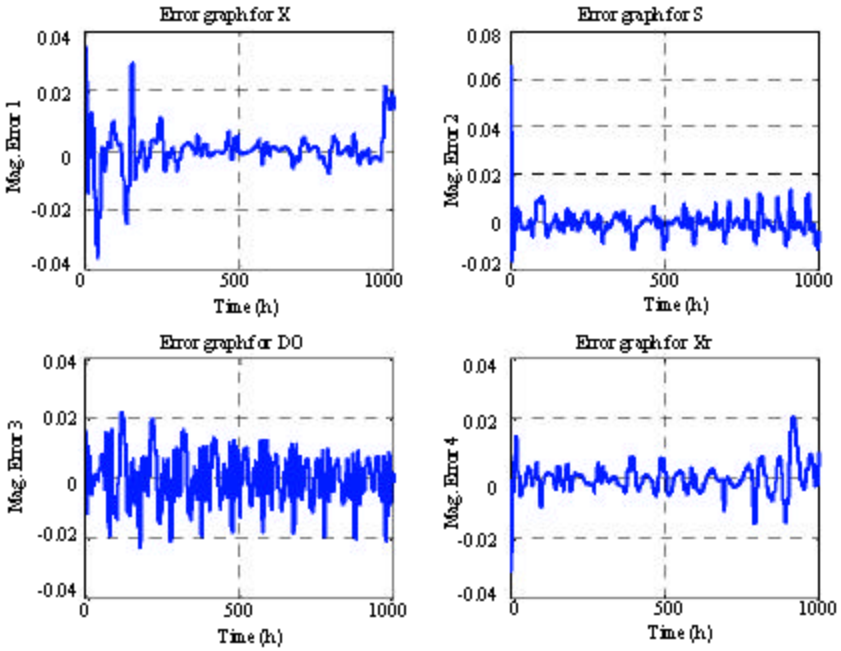

Fig. 6: Errors between actual and identified responses

THE INTERNAL PROCESS MODEL

Artificial neural networks form an important class of nonlinear systems, with many applications in modeling and control. As mathematically proven (Dnder, 1996), any static continuous nonlinear function can be approximated arbitrary well over a compact interval by a multilayer neural network with one or more hidden layers.

First model architecture: The proposed model by Sergiu *et al*. (2007) is illustrated in Fig. 7.

In this contribution a feed forward neural networks is used to model the behavior of the wastewater treatment process. The proposed neural network has three layers. The first two hidden layers contains 15, 7 neurons, respectively. The output layer has only 4 neurons. In order to appropriately capture the

interconnections between all variables, up to four time-delayed inputs and states values have been supplied to the network.

Thus the neural model predicts X(t), S(t), X(t) and DO(t) as functions of:

D(t-1) D(t-2) D(t-3) W(t-1) W(t-2) W(t-3)
X(t-1) X(t-2) X(t-3) X(t-4) S(t-1) S(t-2) S(t-3)
X_r(t-1) X_r(t-2) X_r(t-3) X_r(t-4)
DO(t-1) DO(t-2) DO(t-3)

Data used to train the neural network was obtained by integrating the differential Eq. 1-4, considering randomly varying dilution rates in the interval [0, 0.1] and randomly varying aeration rates in the interval [0, 100]. Before training, the data was scaled the interval [0, 1]. In the same manner, a second data set was generated and used to validate the accuracy of the model.

In Fig. 8, we note the difference which arose between the actual and the neural model and proved by through magnitude errors plotted in Fig. 9.

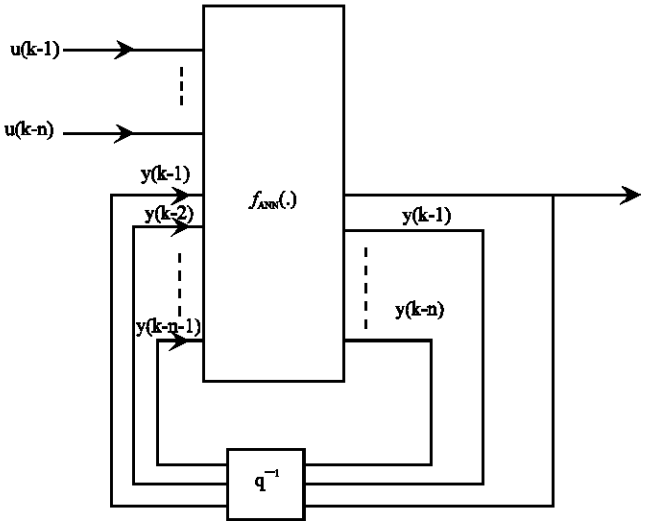

Fig. 7: First model architecture

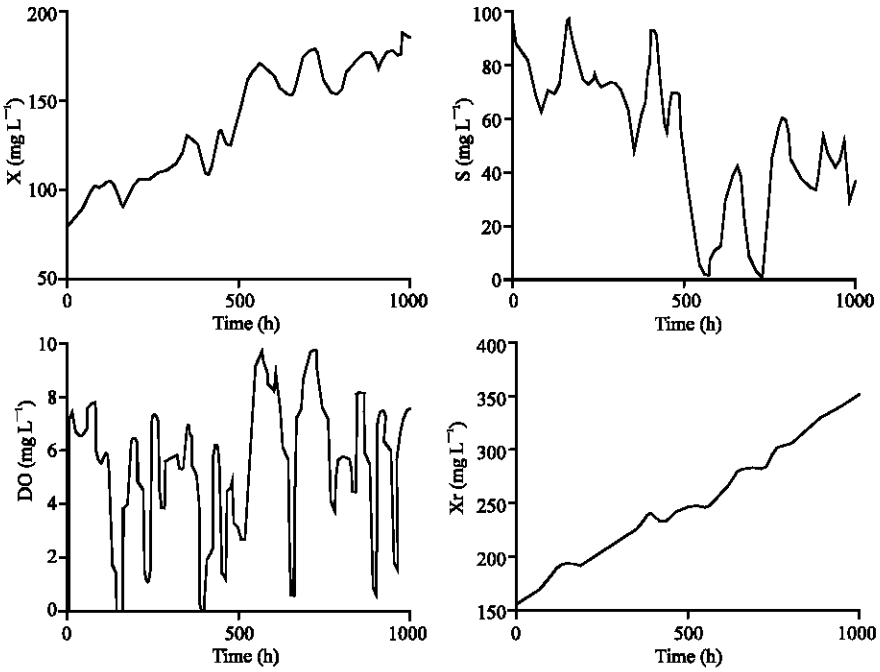

Fig. 8: Actual and predicted outputs, solid: Predicted outputs, dashed: Actual outputs

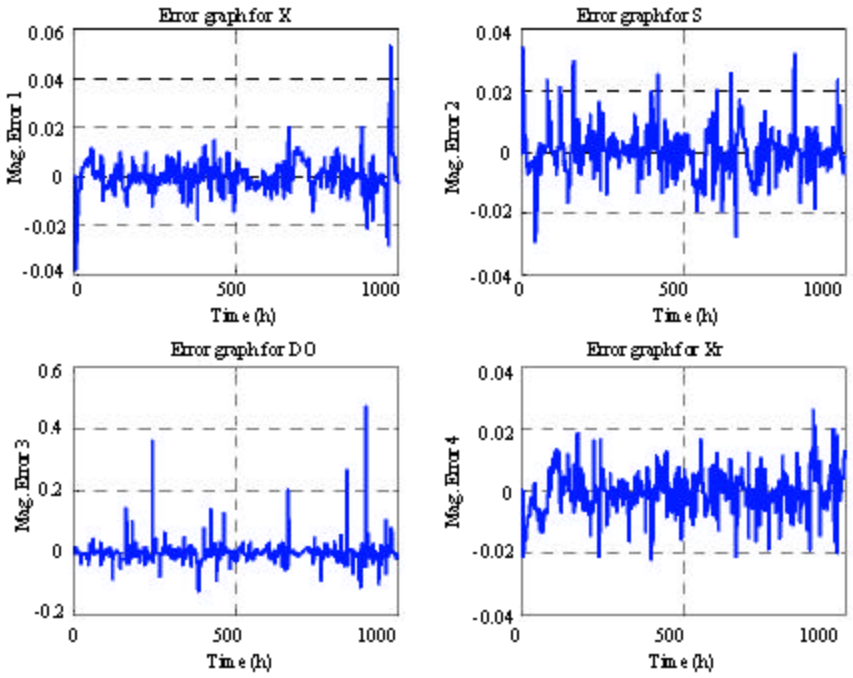

Fig. 9: Errors between actual and predict outputs

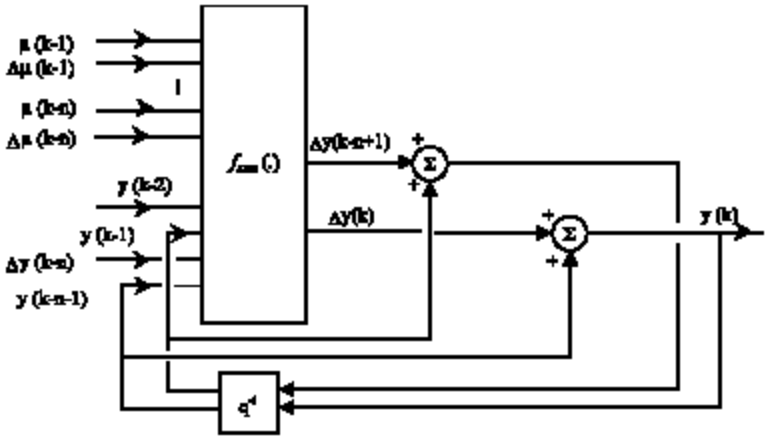

Fig. 10: System architecture proposed

Second model architecture: In this study, we have proposed a new architecture as illustrated in Fig. 10.

This architecture is highly similar to the first one, but in this case the output of neural networks is given rather the difference $\Delta\gamma(\kappa)$.

A thorough study of the present results given in Fig. 11 and 12 show large improvements and so it could be hard to compute any difference between the predicted and actual output.

The neural model predicts $\Delta X(k)$, $\Delta S(k)$, $\Delta DO(k)$ and $\Delta X_r(k)$ as below and expressed in terms of the following inputs:

$X(k-1)\ \Delta X(k-1)\ X(k-2)\ \Delta X(k-2)$,
$S(k-1)\ \Delta S(k-1)\ S(k-2)\ \Delta S(k-2)$,
$DO(k-1)\ \Delta DO(k-1)\ DOX(k-2)\ \Delta DO(k-2)$,
$X_r(k-1)\ \Delta X_r(k-1)\ X_r(k-2)\ \Delta X_r(k-2)$,
$D(k-1)\ \Delta D(k-1)\ D(k-2)\ \Delta D(k-2)$,
$W(k-1)\ \Delta W(k-1)\ W(k-2)\ \Delta W(k-2)$,

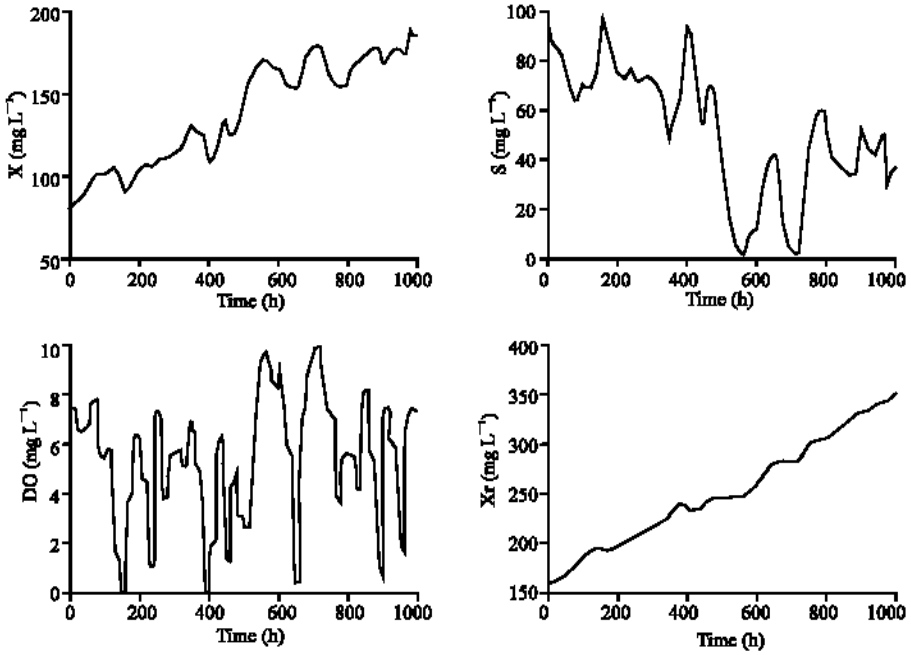

Fig. 11: Actual and predict outputs, solid: Predicted outputs, dashed: Actual outputs

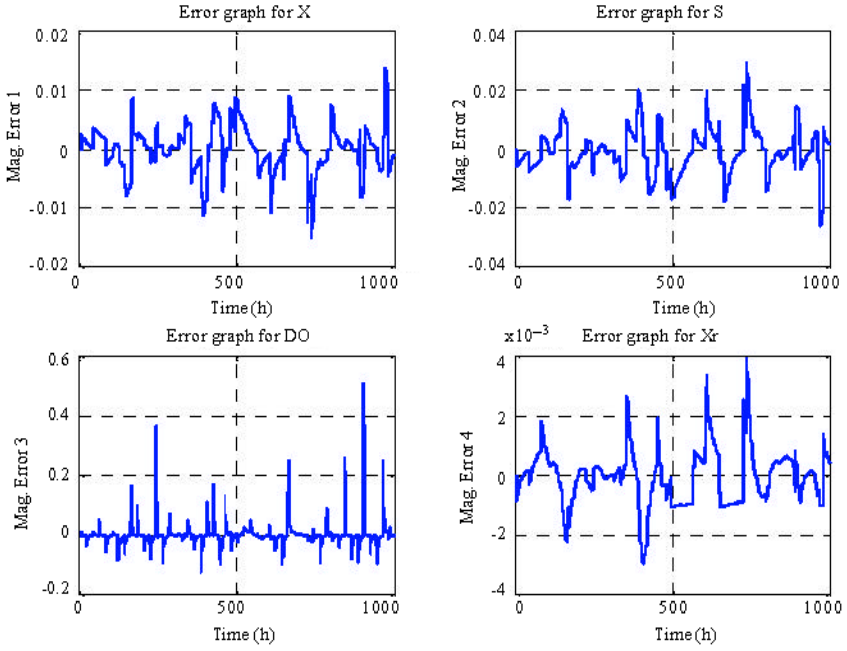

Fig. 12: Errors between actual and predict outputs

THE EXTENDED KALMAN FILTER

In this study, the extended kalman filter is considered as a one step predictor for the dissolved oxygen. Taylor's first approximation is used to linearise system's equations.

In order to implement the continuous time extended Kalman filter, four steps are needed:

- The system equations are expressed as follows:

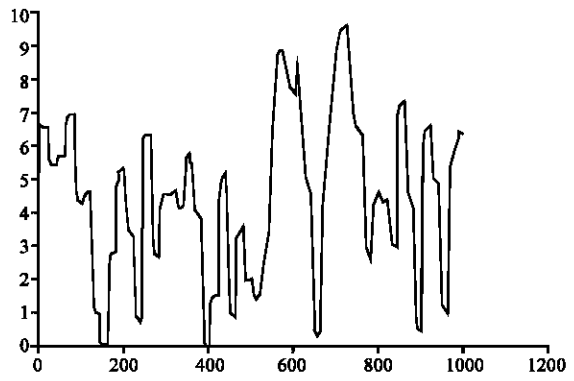

Fig. 13: Measured and predicted dissolved oxygen outputs, solid: Predicted outputs, dashed: Actual outputs

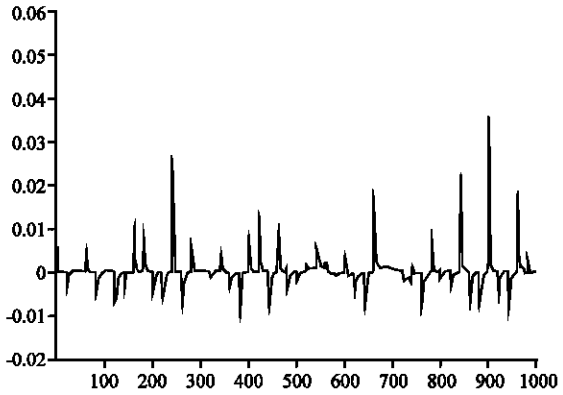

Fig. 14: Error between measured and predicted dissolved oxygen outputs

$$\begin{aligned} \dot{x} &= f(x,u,w,t) \\ y &= h(x, v, t) \\ w &\approx (0, Q) \\ v &\approx (0, R) \end{aligned} \tag{8}$$

- Compute the following partial derivative matrices evaluated at the current state estimate:

$$\begin{aligned} A &= \left.\frac{\partial f}{\partial x}\right|_{\hat{x}} \\ L &= \left.\frac{\partial f}{\partial w}\right|_{\hat{x}} \\ C &= \left.\frac{\partial h}{\partial x}\right|_{\hat{x}} \\ M &= \left.\frac{\partial h}{\partial v}\right|_{\hat{x}} \end{aligned} \tag{9}$$

- Compute the following matrices:

$$\begin{aligned} \tilde{Q} &= LQL^T \\ \tilde{R} &= MRM^T \end{aligned} \tag{10}$$

- Execute the following Kalman filter equations:

$$\begin{aligned} &\hat{x}(0) = E[x(0)] \\ &P(0) = E[(x(0) - \hat{x}(0))\,(x(0) - \hat{x}(0))^T] \\ &\dot{\hat{x}} = f(\hat{x}, u, w_0, t) + K[y - h(\hat{x}, v_0, t)] \\ &K = PC^T \tilde{R}^{-1} \\ &\dot{P} = AP + PA^T + \tilde{Q} - PC^T \tilde{R}^{-1} PC \end{aligned}$$

Where the nominal noise values are given as $w_0 = 0$ and $v_0 = 0$.

In this research:

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Gx + v \end{aligned} \tag{11}$$

The state vector is defined as:

$$x = [X \quad S \quad DO \quad Xr]^T$$

The partial derivative A matrix is obtained as:

$$A = \frac{\partial f}{\partial x} = \begin{bmatrix} \mu(t) - D(t)(1+r) & K_s \dfrac{\mu(t)X(t)}{(Ks + S(t))S(t)} & & \\ -\dfrac{\mu(t)}{Y} & -K_S \dfrac{\mu(t)}{YS(t)} \dfrac{X(t)}{(Ks + S(t))S(t)} - D(t)(1+r) & & \\ -\dfrac{K_0 \mu(t)}{Y} & -\dfrac{K_0 K_s}{Y} \dfrac{\mu(t)X(t)}{(Ks + S(t))S(t)} & & \\ D(t)(1+r) & 0 & & \end{bmatrix}$$

$$\begin{bmatrix} K_{DO} \dfrac{\mu(t)X(t)}{(K_{DO} + DO(t))DO(t)} & rD(t) \\ -\dfrac{K_{DO}\mu(t)X(t)}{Y(K_{DO} + DO(t))DO(t)} & 0 \\ -\alpha W - \dfrac{K_{DO} K_0 \mu(t)X(t)}{Y(K_{DO} + DO(t))DO(t)} - D(t)(1+r) & 0 \\ & -D(t)(\beta + r) \end{bmatrix}$$

Where, $\mu(t)$ is specified by Eq. 5.

The partial derivative B matrix is obtained as:

$$B = \frac{\partial f}{\partial u} = \begin{bmatrix} -(1+r)X(t) + rX_r(t) \\ -(1+r)S(t) + rS_{in} \\ -(1+r)DO(t) + DO_{in} \\ (1+r)X(t) - (\beta + r)X_r(t) \end{bmatrix}$$

And

$G = [0 \quad 0 \quad 1 \quad 0]^T$
$C = 1$
$L = 0$
$M = 1$

Results are presented in Fig. 13 and 14.

CONCLUSION

The complex wastewater problem has been modelled on using neural networks. The proposed technique in this study, allowed correct parameters prediction and thus represents a suitable alternative approach. Our future research focuses on neural fuzzy prediction to take in charge the three main aspect of anaerobic, anoxic and aerobic phenomena.

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