

Predictive Control of a Wastewater Treatment Process

Sergiu Caraman, Mihaela Sbarciog, Marian Barbu

Abstract: The paper deals with the design of a predictive controller for a wastewater treatment process. In the considered process, the wastewater is treated in order to obtain an effluent having the substrate concentration within the standard limits established by law (below 20 mg/l). This goal is achieved by controlling the concentration of dissolved oxygen to a certain value. The predictive controller uses a neural network as internal model of the process and alters the dilution rate in order to fulfill the control objective. This control strategy offers various possibilities for the control law adjustment by means of the following parameters: the prediction horizon, the control horizon, the weights of the error and the command. The predictive control structure has been tested in three functioning regimes, considered essential due to the frequency of their occurrence in current practice.

Keywords: predictive control, wastewater treatment, neural network, bioreactor

1 Introduction

The issue of wastewater treatment belongs to a larger area, namely the environment protection. The environment protection generally and biological wastewater treatments particularly is essential for the life of the human communities and received lately a lot of attention from specialized international organizations. In this context, European laws envisage a series of specific orientations for treating and maintaining the water quality within legal limits (eg. surface water directives, 75/440/EEC and 79/869/EEC, drinking water directives 80/778/EEC/15July1980 and 98/83/EEC/3 November 1998, urban wastewater treatment directive 91/271/EEC etc.).

Complementary to what has been already stated, the wastewater treatment processes are very complex, non-linear and characterized by many uncertainties w.r.t. the influent parameters, the structure and the coefficients of the model. Moreover, many wastewater treatment plants do not have measurement and control equipments. Therefore, there is a need in designing control strategies for the good operation of the process, strategies that may consider various types of models.

Process modelling: there has been a long transition between adopting the procedure of wastewater treatment using active sludge and setting up the theoretical framework to closely describe the procedure. The delay was mainly caused by the conflicting hypotheses related to the explanation of process mechanisms and their difficult translation into mathematical models [3, 7].

In 1983, International Water Association (IWA) formed a working group destined to promote and facilitate the practical methods of designing and operating the biological wastewater treatment systems. As a result, the Activated Sludge Model 1 (ASM1) has been presented in 1987 (see [8]). The model used 13 state variables and described the elimination of organic carbon and nitrogen. 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) [9]. Two other improved versions of ASM2, named ASM2d and ASM3 appeared [10]. The major shortcoming of ASM1 is its complexity, which makes it difficult to be used in a control system. A simplified alternative of the ASM1 model was obtained by taking into consideration the significant variables on a medium time-scale (a few hours to several days). This is why the variables with a slow evolution were considered constant and those having a fast evolution were neglected [13]. These simplifications allowed the usage of ASM1 model in designing control laws. Lately, IWA established two major research areas:

- Modelling of different industrial wastewater treatment processes: cellulose and paper industry, agricultural farms, spun glass industry, etc. The research team tries to model each process, depending on the substances involved in the process. Contrary to the case of domestic wastewater treatment which is made naturally by the microorganisms, the industrial wastewater treatment is done by cultivation of microorganisms, sometimes genetically modified, which consume a certain organic substrate [17, 5].
- Conditioning the excess of active sludge in order to use it in other industrial activities, especially as a fertilizer in agriculture [16, 20].

Process control: the wastewater treatment systems are complex, non-linear processes, with multiple inputs and outputs (multivariable), which determine equivocal information about the influent's characteristics, the model's structure and parameters. Two approaches can be distinguished in choosing the control structure for such a process: the first one is process-driven and the second one is model-based. The first approach deals with the separate control of the most important variables. Within this category, the well-known problem of controlling the dissolved oxygen level is one of the most important issues for a good operation of the wastewater treatment plants. Thus, a good level of dissolved oxygen allows the optimal growth of microorganisms used in the process [12]. Recently, the control of nitrogen and phosphor level received also a lot of attention [21]. The second approach has been improved a number of times. These improvements are related to the type of the mathematical model used, as it is the case for state estimators. Using simplified models allowed the application of advanced control techniques (e.g. precise linearizing or adaptive control, robust control techniques etc.) [19]. However, when using more complex models, such as the ASM1 model, the issue of automatic control became very complicated and the established results were less numerous. For the ASM1 model classic control techniques are usually used (PI, PID controllers), arranged hierarchically, in a three-level structure [2]: at the higher level, a stable trajectory for the process is calculated for a certain period of time; the medium level deals with the trajectory optimization for the dissolved oxygen, the flow of the recycled active sludge and the recycled inflow for nitrogen removal; at the lower level, the control of dissolved oxygen concentration is achieved, based on the medium level reference. A well-suited approach for this type of process is the control based on artificial intelligence strategies. Thus the intelligent control exploits the knowledge and experience accumulated from managing the process and puts it across the control structures like expert, fuzzy, neuro-fuzzy systems [1, 15, 18].

The present study considers a simplified model of the biological wastewater treatment plant [19]. The process is controlled using a model-based predictive control (MPC) strategy. The predictive controller uses a neural network as internal model of the process. This offers various possibilities for the control law adjustment by means of the following parameters: the prediction horizon, the control horizon, the weights of the error and the command. The control purpose is to maintain the substrate concentration below an admissible limit, which is indirectly achieved by controlling the dissolved oxygen concentration, considering as control input the dilution rate D . The predictive control structure has been tested during several functioning regimes, which are essential due to their frequent occurrence in current practice.

The paper is structured as follows: the second section describes the process components and the mathematical model of the plant, the third section introduces theoretical considerations about the control structure used in the paper, while the fourth section refers to the neural network used as internal model of the predictive controller. The fifth section presents the simulation results of the proposed control structure and the last section is dedicated to conclusions.

2 The model of the wastewater treatment process

The mathematical model considered in this paper has been proposed in [19]. The model is based on the following assumptions:

- the system runs in steady-state regime ($F_{in} = F_{out} = F$, $D = F/V$);
- the recycled sludge is proportional to the process flow (F): $F_r = r \cdot F$, 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): $F_\beta = \beta \cdot F$, where β 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.

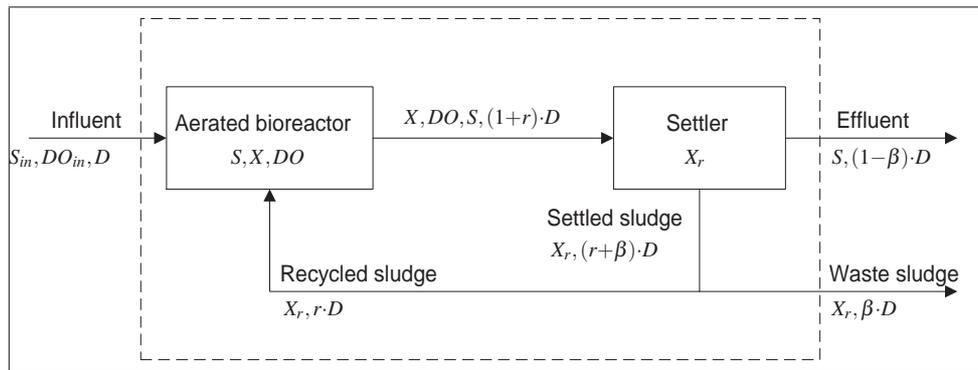


Figure 1: The schematic representation of the wastewater treatment process

Figure 1 presents the schematic representation of the wastewater treatment process. The *Aeration Tank* is a biological reactor containing a mixture of liquid and suspended solid, where a microorganism population is grown in order to remove the organic substrate from the mixture. 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 to the aeration tank and the other part removed [14].

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

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

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

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

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

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

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, 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: $Y = 0.65$; $\beta = 0.2$; $\alpha = 0.018$; $K_{DO} = 2 \text{ mg/l}$; $K_0 = 0.5$ $\mu_{max} = 0.15 \text{ mg/l}$; $k_S = 100 \text{ mg/l}$; $DO_{max} = 10 \text{ mg/l}$; $r = 0.6$.

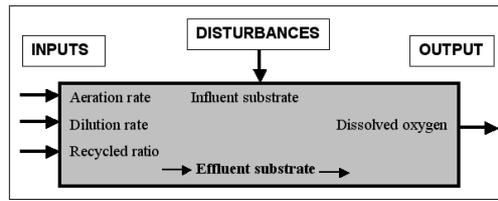


Figure 2: The systemic diagram of the wastewater treatment process

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

Figure 3 illustrates the open loop response of the system for a step input $D = 0.1 \text{ h}^{-1}$ ($W = 80 \text{ h}^{-1}$). The initial conditions considered in this simulation are: $X(0) = 200 \text{ mg/l}$, $S(0) = 88 \text{ mg/l}$, $DO(0) = 5 \text{ mg/l}$, $Xr(0) = 320 \text{ mg/l}$, $DO_{in} = 0.5 \text{ mg/l}$, $S_{in} = 200 \text{ mg/l}$.

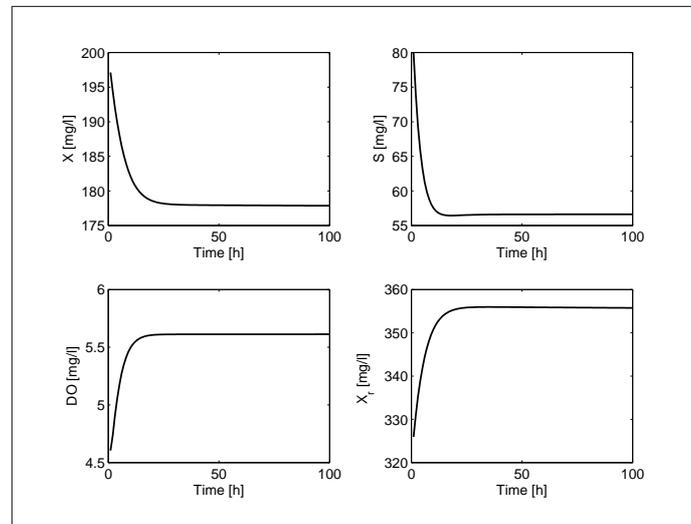


Figure 3: Open loop system response

During the normal functioning of the wastewater treatment process, three regimes have been identified: *rain* ($D = 1/20 \text{ h}^{-1}$, $W = 80 \text{ h}^{-1}$), *normal* ($D = 1/35 \text{ h}^{-1}$, $W = 60 \text{ h}^{-1}$) and *drought* ($D = 1/50 \text{ h}^{-1}$, $W = 20 \text{ h}^{-1}$). The first case is characterized by maximum values for the aeration and dilution rates, the second regime considers medium values for W and D and the third case is characterized by small values for the same parameters. In this study special attention has been paid to the predictive controller, such that it provides good performances for all the three functioning regimes.

3 Predictive control

Predictive control algorithms belong to the class of model-based control strategies, using a process model to incorporate the predicted future behavior of the process into the controller design procedure [6]. Independent of the type of model used and of the cost index minimized, the principle of MPC is the same. At each sampling instant t [4]:

- use the process model to predict the future output of the process over the *prediction horizon* N_2 , $\{y(t+k/t), k = 1 \dots N_2\}$, based on past inputs and outputs and *postulated* future inputs;
- minimize the cost index, taking into account possible constraints on input, output and states, in order to determine the optimal control sequence $\{u(t+k/t), k = 0 \dots N_u - 1\}$, where N_u is the *control horizon*;

- use the receding-horizon control mechanism that introduces feedback into the optimization problem by applying to the process the first optimal control action and discarding the consequent ones.

As it is straightforward from the description above (the model is the central element of the entire strategy), the success of MPC strategy is highly dependent on a reliable process model, that is a model which approximates well the process dynamics. A lot of research has been carried out up to now in the area of MPC based on linear models, however many of the real-life processes are characterized by complex non-linearities, the necessity of having a non-linear model of the process becoming straightforward. Therefore, emphasis is placed nowadays on using nonlinear models in the framework of predictive control that would lead to improved control performances.

The concept of the predictive control algorithm used in this work is illustrated in figure 4.

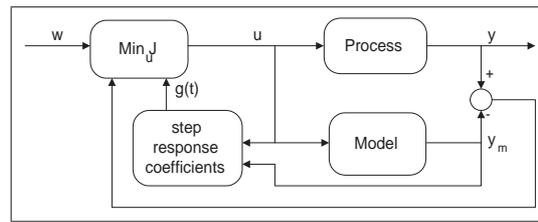


Figure 4: Predictive control structure

At each sampling instant t , the increment of the control input $\Delta u(t)$ is calculated by minimizing the cost function

$$J = \sum_{k=1}^{N_2} \delta^2(k) [w(t+k/t) - y(t+k/t)]^2 + \sum_{k=0}^{N_u-1} \lambda^2(k) [\Delta u(t+k/t)]^2 \quad (6)$$

where $w(t+k/t)$ is the setpoint prediction, $\delta(k)$ and $\lambda(k)$ are respectively the weighting coefficients of the prediction errors and of the control input increments. In order to calculate the output prediction, the step response of the model must be determined. To this end, it is necessary to admit that the model can be linearized around the current operating point. Then

$$y(t+k/t) = y_{free}(t+k/t) + y_{forced}(t+k/t) \quad (7)$$

where $\{y_{free}(t+k/t), k=1 \dots N_2\}$ is the model output produced by the control input sequence $\{u(t+k/t) = u(t-1), k=0 \dots N_2-1\}$ and

$$y_{forced}(t+k/t) = \sum_{i=1}^k g_i \Delta u(t+k-i/t) \quad (8)$$

with $\{g_i, i=1 \dots N_2\}$ the unit step response coefficients. In matrix notation, equation (7) becomes

$$Y = GU + Y_{free} \quad (9)$$

where

$$Y = [y(t+1/t) \quad \dots \quad y(t+N_2/t)]^T \quad (10)$$

$$U = [\Delta u(t/t) \quad \dots \quad \Delta u(t+N_u-1/t)]^T \quad (11)$$

$$Y_{free} = [y_{free}(t+1/t) \quad \dots \quad y_{free}(t+N_2/t)]^T \quad (12)$$

$$G = \begin{bmatrix} g_1 & 0 & \dots & 0 \\ g_2 & g_1 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ g_{N_2} & g_{N_2-1} & \dots & g_{N_2-N_u-1} \end{bmatrix} \quad (13)$$

Using the model (9) in (6), a quadratic relation with respect to U is obtained:

$$J = [\Delta \cdot W - \Delta(G \cdot U + Y_{free})]^T [\Delta \cdot W - \Delta(G \cdot U + Y_{free})] + (\Lambda \cdot U)^T (\Lambda \cdot U) \quad (14)$$

where

$$W = [w(t+1/t) \quad \dots \quad w(t+N_2/t)]^T \quad (15)$$

$$\Delta = \text{diag} [\delta(1) \quad \dots \quad \delta(N_2)] \quad (16)$$

$$\Lambda = \text{diag} [\lambda(0) \quad \dots \quad \lambda(N_u - 1)] \quad (17)$$

Only the first component of the vector U , $\Delta u(t/t) = \Delta u(t)$, is used. At the next sampling instant the whole procedure is repeated.

4 The internal model of the process

Artificial neural networks form an important class of nonlinear systems, with many applications in modeling and control. As mathematically proven (see [11]), 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.

In this contribution a feedforward neural network is used to model the behavior of the wastewater treatment process. The proposed neural network has three layers: the first one contains 15 neurons, the second one 7 neurons and the output layer 4 neurons. To appropriately capture the interconnections between all variables, up to four time-delayed values of the inputs and states were supplied to the network. The neural model predicts $X(t)$, $S(t)$, $X_r(t)$ and $DO(t)$ as functions of:

$$\begin{aligned} & D(t-1), \quad D(t-2), \quad D(t-3), \quad W(t-1), \quad W(t-2), \quad W(t-3) \\ & X(t-1), \quad X(t-2), \quad X(t-3), \quad X(t-4), \quad S(t-1), \quad S(t-2), \quad S(t-3) \\ & X_r(t-1), \quad X_r(t-2), \quad X_r(t-3), \quad X_r(t-4), \quad DO(t-1), \quad DO(t-2), \quad DO(t-3) \end{aligned}$$

The data used to train the neural network was obtained by integrating the differential equations (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 to the interval $[0, 1]$. In the same manner, a second data set was generated and used to validate the accuracy of the model.

As figure 5 shows, there is hardly any difference between the measured values from the process and the ones predicted by the neural network for the dissolved oxygen and substrate concentrations. There is a noticeable shift between the biomass calculated based on the differential equations of the process and the biomass predicted by the neural network, but this is not going to affect the performance of the predictive controller since the neural network is used to predict the dissolved oxygen level.

5 Simulation results

Figure 6 illustrates the control principle. The predictive controller calculates the dilution rate, which forces the dissolved oxygen concentration to follow the setpoint. Controlling the concentration of dissolved oxygen has a benefic effect on the substrate concentration, which is brought within the limits imposed by the law (below 20mg/l).

Various configurations of the predictive controller parameters can be chosen in order to fulfill the control requirements. In these simulations a fast control was pursued, which can be generally achieved for a small prediction horizon, and less attention was paid to the magnitude of control input variations. The controller parameters were: $N_2 = 5$, $N_u = 1$, $\Delta = I_5$, $\lambda = 0$.

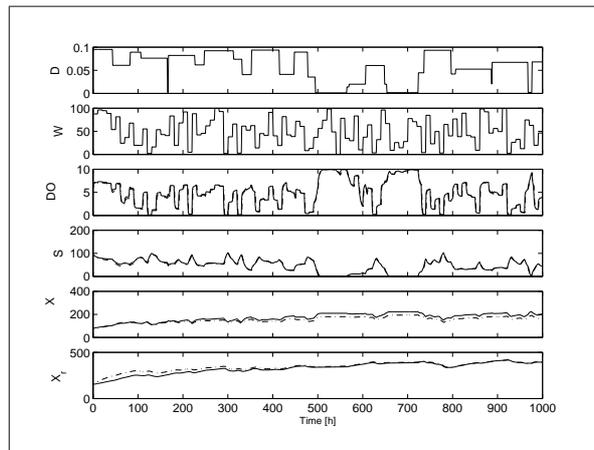


Figure 5: Validation of the neural network model: process - continuous line, model - dash-dotted line

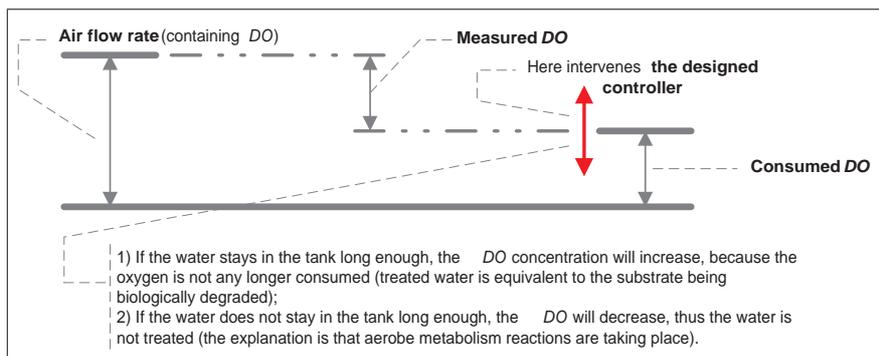


Figure 6: The principle of the dissolved oxygen concentration control

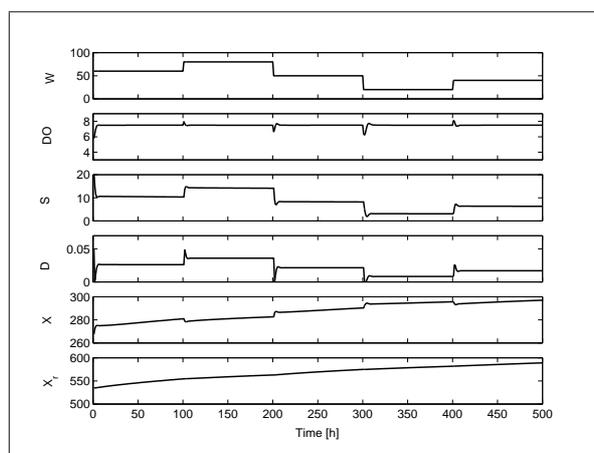


Figure 7: Simulation results for DO constant setpoint (7.5)

The results of the dissolved oxygen concentration control are presented in figures 7, 8 and 9. Figure 7 considers a constant dissolved oxygen setpoint (7.5), while figure 8 shows the case when the dissolved oxygen setpoint is variable. In both cases, the aeration rate W varies such that the process covers all three functioning regimes (rain, normal and drought).

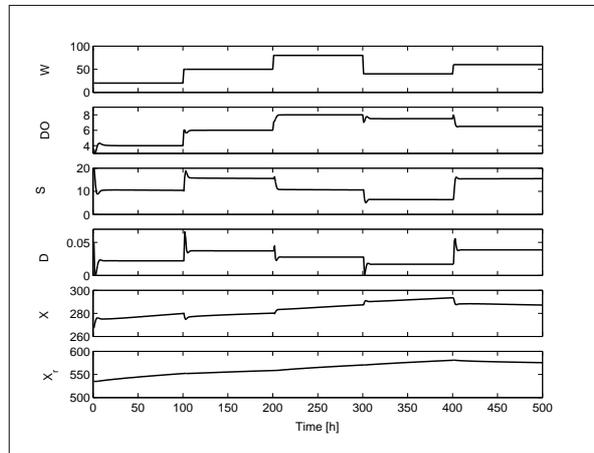


Figure 8: Simulation results for DO variable setpoint

Figure 9 considers a constant dissolved oxygen setpoint but a variable concentration of the substrate in the influent. At time $t = 150h$, S_{in} was changed from 200 mg/l to 300 mg/l and was kept constant to the new value until $t = 250h$, when it was changed to 150 mg/l. The controller adjusts the dilution rate and DO is brought back to the setpoint value.

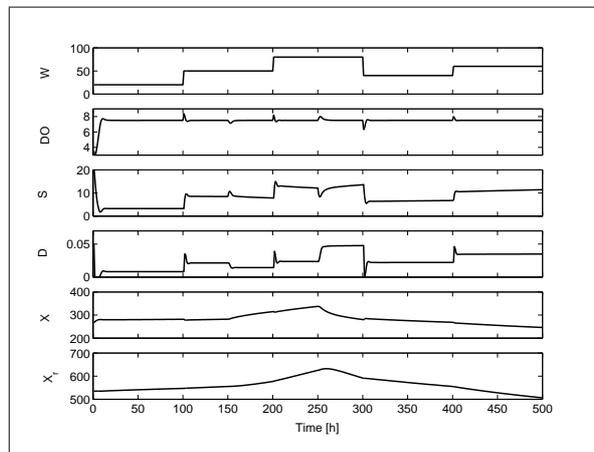


Figure 9: Variable substrate concentration in influent

6 Conclusions

Wastewater treatment is a complex process, which needs control for a good operation. This paper introduces a predictive controller for such a system and evaluates the control performances.

The success of the MPC strategy is highly dependent on a reliable process model, that is a model which approximates well the process dynamics. Taking into account the complexity of the wastewater treatment process, a neural network has been chosen as internal model for the predictive controller.

The simulation results show a good performance of the control loop. The controller manipulates the dilution rate and forces the dissolved oxygen concentration to follow the imposed setpoint. This has a benefic effect on the substrate concentration, which is maintained within the limits established by law. The control is effective for various operational regimes, defined by the aeration rate. Moreover, it is able to reject disturbances that might appear on the substrate concentration in the inflow.

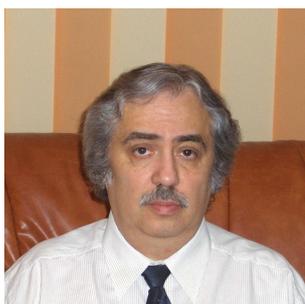
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