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Indirect Control of Substrate Concentration for a Wastewater Treatment Process by Dissolved Oxygen Tracking

C. Vlad*, M. Sbarciog, M. Barbu*, S. Caraman*, A. Vande Wouwer****

** Dunărea de Jos University of Galaţi, 47, Domnească, 800008-Galaţi Romania (Tel: 0040-336-130-108; e-mail: ciprian.vlad@ugal.ro; marian.barbu@ugal.ro; sergiu.caraman@ugal.ro)*
***Mons University, Automatic Control Laboratory, Boulevard Dolez, 31, 7000 Mons, Belgium (e-mail: MihaelaIuliana.Sbarciog@Umons.ac.be; Alain.VandeWouwer@umons.ac.be)*

Abstract: Two control strategies, relying on different principles, are used in this paper for improving the performance of an Activated Sludge Process (ASP): gain scheduling PI control (GS-PI) and model predictive control (MPC). Among the numerous existing control strategy, PI control and MPC control are the most frequently ones used successfully in industrial applications. The ASP is described by a nonlinear multivariable model with two inputs and two outputs. The main objective is to obtain a substrate concentration in the effluent within the standard limits established by legislation on wastewater treatment, especially the strict EU Guideline Urban Wastewater Directive 91/271/EEC. This goal is achieved by controlling the dissolved oxygen (DO) concentration to setpoint values established by preliminary tests. Simulations are carried out on the nonlinear model to show the effectiveness of GS-PI and MPC control methods. The contribution of the paper can be summarized to the fact that the effluent substrate concentration is controlled through two different methods without using measurements of the substrate, but only measurements of the DO concentration. This is more reliable and less expensive. Additionally, the performance of wastewater treatment process is analyzed in terms of energy efficiency. This is done by considering the volume of treated water in relation to the consumed electricity.

Keywords: Wastewater Treatment, Scheduling Algorithms, Predictive Control, Dissolved Oxygen Control, Activated Sludge Process.

1. INTRODUCTION

The activated sludge process (ASP) is a widely used system for biological wastewater treatment. Its control has been the subject of a large number of research studies. The control of such systems is motivated by the fact that ASPs are very complex, with significant nonlinearities and characterized by many uncertainties. In addition, many wastewater treatment plants are not fully equipped with measurement devices. Nevertheless, they have to be operated continuously, to meet strict regulations. One of such regulation, imposed by European Union (EU Guideline Urban Wastewater Directive 91/271/EEC), is to maintain the effluent substrate concentration below standard limits (20 mg/l).

When investigating the WWTP in terms of efficiency, two operational parameters are found to have the biggest influence. The operation of the process has to satisfy the aforementioned effluent requirements and the operational costs have to be kept as low as possible. The latter generally include the cost for the energy consumed by the aeration pumps and the pumping of the recycled sludge. According to Zhao, H. et al. (1995), aeration energy is up to 50–60% of the global operational cost.

To achieve a good operation of the process, many control strategies that may use various types of models are considered in the literature for ASP processes. Among them intelligent structures like fuzzy, neural-fuzzy systems (e.g. Boger, Z. (1992), King, R.E. and Stathaki, A. (2004), Du, Y.G. et al. (1999)), model based predictive control (e.g. Sanches, A. and Katebi, M.R. (2003), Caraman, S. et al. (2007)) and advanced multivariable techniques (e.g. Cosmescu, A. and Dumitrache, I. (2003), Caraman, S. et al. (2005)) are used.

Since the on-line monitoring of some parameters (i.e. ammonia, nitrate) is difficult, some indirect measurements (i.e. oxidation-reduction potential (ORP), pH, dissolved oxygen (DO)) are commonly used to control ASPs (Fuerhacker, M. et al. (2000)). The level of the dissolved oxygen concentration in the aerobic reactors has a significant influence on the behaviour and activity of the heterotrophic and autotrophic microorganisms from the activated sludge. For that reason, the DO control is the most widely-spread in real-life applications (e.g. Lindberg, C.F. and Carlsson, B. (1996), Chotkowski, W. et al. (2005), Sanches, A. and Katebi, M.R. (2003)). It should be sufficiently high to supply enough oxygen to the microorganisms in the sludge, but not excessively high, because it is directly related to the amount of consumed electrical energy and to the sludge quality.

PI control is used by Rojas, J.D. et al. (2011) and Vilanova, R. et al. (2009) for ASP processes. Decentralized control strategies have been designed for the multivariable process, in which the dilution rate is manipulated to control the substrate concentration and the aeration rate is manipulated to control the dissolved oxygen concentration. It is assumed that both dissolved oxygen and substrate concentrations are measurable. Han, Y. et al. (2008) develop a softly switched Takagi-Sugeno fuzzy PI control system for dissolved oxygen concentration tracking. The controller calculates the reference for the aeration control system, while dilution rate, influent substrate concentration and influent dissolved oxygen concentration are considered plant disturbances that can significantly vary in time. In Holenda, B. et al. (2008) model predictive control (MPC) is applied to control the dissolved oxygen concentration in the aerobic reactor of a wastewater treatment plant (WWTP). The control variable in this case is the oxygen mass transfer coefficient, K_{La}.

In academic literature, MPC control of ASPs has been widespread in simulation (e.g. Piotrowski, R. et al. (2008), Shen, W. et al (2009)). Recently O'Brien, M. et al. (2011) have reported a practical implementation.

Several previous works have dealt with minimizing the energy consumption while satisfying effluent quality standards (e.g. Anderson, J.S. et al. (2000) and Heduit, A. et al. (1990)).

In Fikar, M. et al. (2005) an optimal sequence of aeration/non-aeration times was determined such that for a typical diurnal pattern of disturbances, the effluent constraints are fulfilled and the energy consumption is minimized. In this case, the ASM1 model has been used.

An optimization procedure for minimizing the pollution load in the receiving water body, rather than the operational cost, using a complete model of the treatment process has been presented in Holenda, B. et al. (2007). The results showed that an optimal solution can be efficiently found where both pollution load and energy consumption savings can reach up to 10% compared to traditional control strategies.

The present work uses a simplified but realistic model of the wastewater treatment plant, see Nejjari, F. et al. (1999). Taking into account the expertise of the wastewater treatment plant operator and the level of the influent, several levels of aeration rate were established. Thus, the aeration rate is the variable that changes the operation point of the process. Due to system nonlinearities several PI linear controllers were designed through pole placement method. The PI controllers are to be used with gain scheduling method (GS) on the nonlinear process. The level of the aeration rate changes the operating points and the gain scheduling controller parameters. The second method used in this paper is model-based predictive control (MPC). In this case a nonlinear model of the process is used to obtain and validate the control solution.

The control purpose in this work is to obtain a substrate concentration in the effluent within the standard limits established by legislation on wastewater treatment, especially the strict EU Guideline Urban Wastewater Directive 91/271/EEC (below 20 mg/l). This goal is achieved by controlling the dissolved oxygen (DO) concentration, considering the dilution rate, D, as control input. Another aspect investigated in this paper is the efficiency of the wastewater treatment process considered as the volume of treated wastewater in relation to the electricity consumed by aeration pumps.

The paper is organized as follows. Section 2 presents the process description. The third section deals with theoretical considerations regarding the control methods used in this paper, while the simulation results are described in the Section 4. Finally, conclusions are drawn.

2. ACTIVATED SLUDGE PROCESS (ASP) DESCRIPTION

The mathematical model considered in this paper has been proposed by Nejjari, F. et al. (1999). It is a simplified but realistic, highly non-linear, multivariable model of the wastewater treatment process (WWTP), given by the mass balance equations of four state variables (biomass, substrate, dissolved oxygen and recycled biomass):

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

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

$$\begin{aligned}\frac{dDO}{dt} = &-\frac{K_0\mu(t)X(t)}{Y} - D(t)(1+r)DO(t) + K_{La}(DO_{\max} - \\ &- DO(t)) + D(t)DO_{in}\end{aligned} \tag{3}$$

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

with

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

$$K_{La} = \alpha W(t); D(t) = \frac{Q_{in}}{V_a}; r = \frac{Q_r}{Q_{in}}; \beta = \frac{Q_w}{Q_{in}} \tag{6}$$

where $X(t)$ – biomass concentration [mg/l], $S(t)$ – substrate concentration [mg/l], $DO(t)$ – dissolved oxygen concentration [mg/l], DO_{max} - maximum dissolved oxygen concentration [mg/l], $X_r(t)$ - recycled biomass concentration [mg/l], $D(t)$ - dilution rate [h^{-1}], S_{in} and DO_{in} - substrate and dissolved oxygen concentrations in the influent [mg/l], Y - biomass yield factor, μ - biomass growth rate [h^{-1}], μ_{max} - maximum specific growth rate [h^{-1}], K_S and K_{DO} - saturation constants [mg/l], K_{La} - oxygen mass transfer coefficient, α – oxygen transfer rate, W - aeration rate [m^3/h], K_0 - model constant, r and β - ratio of recycled and waste flow to the influent, Q_{in}, Q_r, Q_w are the influent, recycle and waste flow rates, respectively. V_a represents the aerator volume. For a complete reference of the WWTP model, equations and assumption see Nejjari, F. et al. (1999).

The schematic layout of the wastewater treatment process is represented in Figure 1. The *Aeration Tank* is a biological reactor containing a mixture of liquid and suspended solids, where microorganisms act on the organic substrate in order to remove it from the mixture. In the *Settler Tank* the solids are separated from the wastewater. A part of the removed sludge is recycled back to the aeration tank while the other part is removed from the system.

The model coefficients have the following values: Y=0.65; μ_{max}=0.15 h^{-1}; K_S=100 mg/l; K_0=0.5; α=0.018; DO_{max}=10 mg/l; β=0.2; K_{DO}=2 mg/l; r=0.6. The influent concentrations are set to S_{in} = 200 mg/l and DO_{in} = 0.5 mg/l.

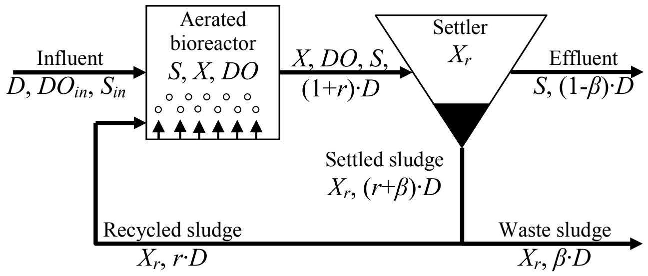


Fig. 1. Diagram of the activated sludge process

3. CONTROL PROBLEM

Most of the wastewater treatment plants do not have systems for on-line measurement of organic substrate concentration but they always have dissolved oxygen sensors. This is due to the fact that on-line measurement devices for organic substrate are very expensive and less reliable. Thus, direct control of the dissolved oxygen concentration in the aeration tank is one of the most encountered control approaches for WWTP. Controlling the dissolved oxygen concentration ensures the necessary conditions for maximizing the efficiency of the aerobic processes, thus leading to a good quality of the effluent.

This paper considers the case when only dissolved oxygen, DO [mg/l], from the aerated tank is measured. The dilution rate, D [h^{-1}] is used as manipulated variable. The effluent quality is given by the level of organic substrate concentration. The latter is considered as qualitative variable.

During operation, situations occur when the water must stay only a short period of time in the tank. In this case, the dilution rate is high and its inverse, which is the water retention time in the aerated tank, is low. Thus, a large quantity of water is treated. To have an effluent level within limits, a high aeration rate is needed. This ensures favorable conditions for the sludge development and for organic substrate consumption. Hence, an operating regime requiring the treatment of a large volume of water, which implies a high input flow in the aerated tank, is characterized by high levels of dilution and aeration rates.

Caraman, S. et al. (2007) and Barbu, M. (2007) considered only three working regimes: high flow regime (D=1/20 h^{-1}, W=80 m^3/h), normal flow regime (D=1/35 h^{-1}, W=60 m^3/h) and low flow regime (D=1/50 h^{-1}, W=20 m^3/h). In reality, intermediate regimes are also met. Hence, in order to obtain a small water retention time, which means low electrical energy consumption by the aeration pumps of the bioreactor, acceptable limits for dilution rate between 0.02 and 0.04 h^{-1} and for organic substrate concentration between 4 and 18 mg/l were imposed.

3.1 Gain scheduling PI control

Adaptive controllers have the ability of adjusting to changes in process dynamics. This is the case of gain scheduling controllers, where process dynamics can be associated with the values of some process variables that can be measured. If the dynamic characteristics of the process can be inferred from measurable variables, the controller parameters can be computed from these variables. The control scheme of the dissolved oxygen concentration is presented in Figure 2. At the entrance of the wastewater treatment plants there are always tanks which equalize variations of water collected from the system. These variations have a diurnal component, caused by domestic water consumption, and a random component, caused by rainfall. Depending on the water level from this tank one can choose the aeration rate level, W.

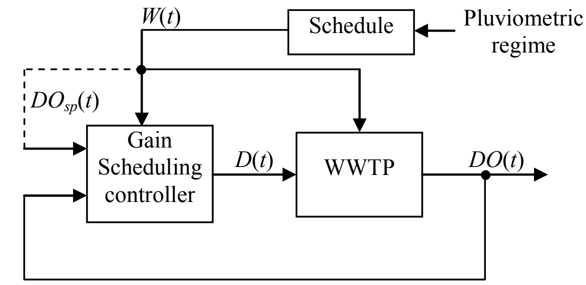


Fig. 2. Gain scheduling scheme for dissolved oxygen control

Due to the strong nonlinear character of the process, one PI controller cannot successfully meet good performance requirements. Since the operating points of the working domain, with limits taken from Caraman, S. et al. (2007), depend on the value of the decision variable W, seven points were considered to cover the working domain (W= [20:10:80] m^3/h). In all these points, a linearized model having the input D and the output DO was obtained. Modal analysis shows that a first order system with the transfer function given by (7) can approximate rather accurately the wastewater treatment process:

$$H(s) = \frac{K}{Ts+1} \tag{7}$$

where K is the static gain and T is the time constant.

In order to prove this statement, a process linearization with *linmod* function in the operating point corresponding to the normal flow regime (characterized by D=1/35 h^{-1} and W=60 m^3/h) is performed. The initial conditions considered in the simulation are: X(0)=210 mg/l, S(0)=27 mg/l, DO(0)=6.87 mg/l, X_r(0)=400 mg/l, DO_{in}=0.5 mg/l and S_{in}=200 mg/l.

The transfer function obtained through linearization is given by (8) and the reduced one is given by (9).

$$H_P(s) = \frac{-10.49s^3\text{-}19.8s^2\text{-}1.316s\text{-}0.003589}{s^4\text{+}1.579\,s^3\text{+}0.3954s^2\text{+}0.02037s\text{+}5.439\text{e-}5} \qquad (8)$$

$$H_{P_{sim}}(s) = \frac{-14.9677}{s\text{+}0.2268} \qquad (9)$$

Figure 3 presents the frequency characteristics of the two transfer functions. One can see that at low frequency values the two characteristics are almost superposed.

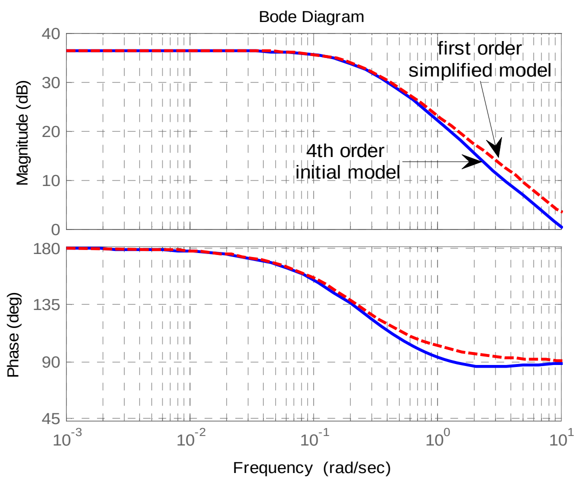


Fig. 3. Modal analysis of the linearized dynamics between *D* and *DO*

The closed-loop transfer function for the dissolved oxygen control is calculated using the simplified expression of the process (7) and a PI controller with proportional gain K_p and integral time T_i. This is given by:

$$H_o(s) = \frac{KK_p(T_i s+1)}{T_i T s^2 + (KK_p T_i + T_i)s + KK_p} \qquad (10)$$

To compensate the effect of the zero in (10), which may cause large overshoot to the closed-loop system dynamics, a prefilter for the *DO* setpoint was introduced in the structure of the dissolved oxygen control loop. The prefilter has the transfer function

$$F(s) = \frac{1}{T_i s+1} \qquad (11)$$

Hence, the closed-loop transfer function becomes:

$$H_{o\_BOx}(s) = \frac{KK_p}{T_i T s^2 + (KK_p T_i + T_i)s + KK_p} \qquad (12)$$

where K_p is the proportional gain, T_i is the integral time.

Further on, the PI controller design was made by pole placement method. Since the transfer function of closed-loop system (12) is of second order, it can be rewritten as

$$H_o(s) = \frac{\omega_n^2}{s^2 + 2\xi\omega_n s + \omega_n^2} \qquad (13)$$

where ω_n is the undamped natural frequency and ξ is the damping ratio.

By identifying the denominator parameters of the transfer functions (12) and (13) it results:

$$\omega_n^2 = \frac{KK_p}{TT_i};\; 2\xi\omega_n = \frac{KK_p+1}{T} \qquad (14)$$

Imposing requirements on the settling time, t_r, and the percentage overshoot (%OS) and knowing that

$$\xi = \frac{-\ln(\%OS)}{\sqrt{\pi^2 + \ln^2(\%OS)}} \qquad (15)$$

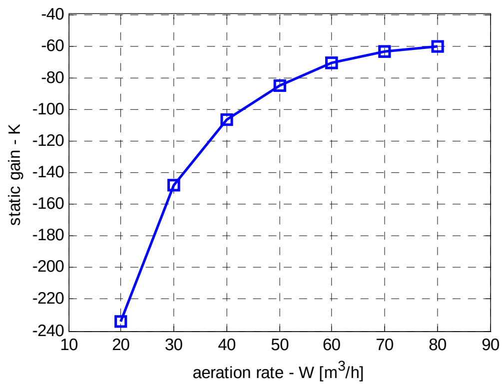
and

$$\omega_n = \frac{4}{t_r \xi} \qquad (16)$$

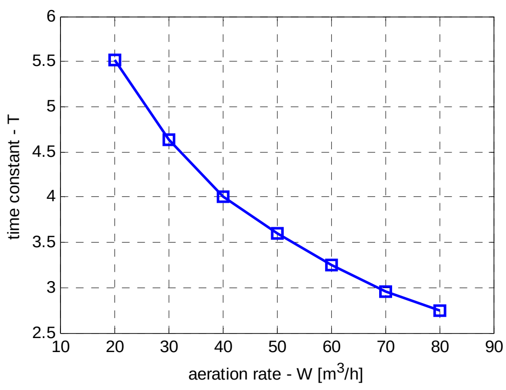
the PI controller parameters are obtained, as follows:

$$K_p = \frac{8T - t_r}{Kt_r} \text{ and } T_i = \frac{t_r \xi^2 (8T - t_r)}{16T} \qquad (17)$$

This procedure has been used for all chosen operating points. The imposed performance requirements are: overshoot = 5 % and t_r = 6 h. The values of the static gain, *K*, and the time constant, *T*, corresponding to the linearized model of the process with input *D* and output *DO*, in the analyzed operating points, are represented with square markers in Figure 4.



a)



b)

Fig. 4. Parameters values of the linearized model of the wastewater treatment process: a) static gain; b) time constant

The multimodel control is obtained by aggregating the seven pairs of control parameters. The control input that is applied to the process at each time instant results from switching the linear controllers designed for each operating point. Switching the controller parameters is based on the schedule variable value *W*, which is correlated with the operation point of the process.

The gain scheduling control structure has proved to be useful in many situations, although it certainly has drawbacks. One of them consists in the fact that the controller parameters have to be determined for different operating conditions, covering all possible operating regimes, which requires a long commissioning time.

3.2 Model predictive control

MPC (Model Predictive Control) refers to a family of control algorithms which make use of a process model to incorporate the predicted future behavior of the process into the controller design procedure. The key elements of MPC are: the model used for prediction, the online optimization and the feedback compensation for model mismatch (e.g. Camacho, E.F. and Bordons, C. (1999)). There are no special demands on the form of model, the computational tool for online optimization and the form of feedback compensation (e.g. Zheng (2010)).

The block diagram of the MPC control loop is illustrated in Figure 5 and the working principle is as follows: an appropriate model is used to predict the process output, $DO(t+k/t)$, k=1...N_2, over a future time interval known as *prediction horizon*, N_2. A sequence of control actions, $D(t+k/t)$, k=0… N_u-1, over the *control horizon*, N_u, is calculated by minimizing a specified cost function, possibly subjected to constraints. The first control component of the sequence, $D(t/t)$, is applied to the real process, all the other elements of the control vector are discarded and the calculations are repeated for the subsequent sampling instants. In order to account for the plant-model mismatch, a prediction error, $d(t)$, that is calculated based on $DO(t)$, measured from the real plant, and model output, $DO_m(t)$, is used to update the future predictions.

Commonly in MPC, the cost index considers the summed squares of the predicted output deviations from the setpoint and penalties on the manipulated variable:

$$J = \sum_{k=1}^{N_2} \left(DO_{sp}(t+k/t) - DO(t+k/t) \right)^2 + \alpha \sum_{k=0}^{N_u-1} \left(\Delta D(t+k/t) \right)^2 \qquad (18)$$

where

$$\Delta D(t+k/t) = D(t+k/t) - D(t+k-1/t) \qquad (19)$$

In this paper the same nonlinear mathematical model described by the equations (1) – (4), is used for both the process and the model. This means that the output predictions are calculated by recursion of the equations (1) – (4). In these simulations a fast control is pursued, which can be generally achieved for a small prediction horizon, and less attention was paid to the magnitude of control input variations, thus the weighting coefficient α was set to zero. The following controller parameters were used: N_2=5, N_u=1. The optimal dilution rate, which forces the dissolved oxygen concentration to follow the setpoint is the solution of a nonlinear optimization problem, which minimizes the cost index (18). The optimal solution can be found by using nonlinear optimization functions such as *fmincon* in Matlab or by sequential quadratic programming which is less computationally intensive.

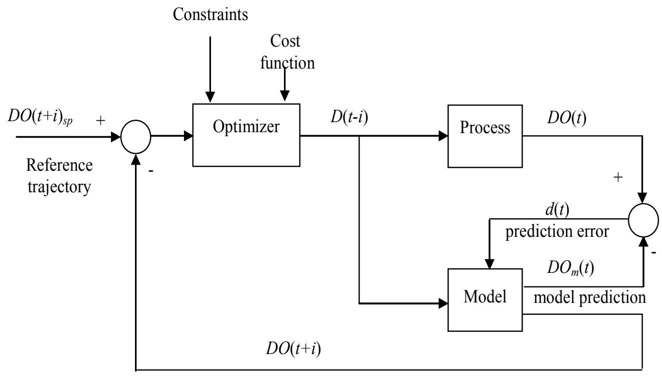


Fig. 5. MPC block diagram

4. SIMULATION RESULTS

Figure 6 presents results of the simulations carried out using the two analized methods. In this case, the evolution of the main variables are obtained when a constant dissolved oxygen setpoint (DO_{sp}=6.5) is imposed. From Figure 6 one can see that the substrate concentration in the effluent exceeds the maximum allowable value. The manipulated variable D, has values between 0.01÷0.06 h^{-1}, which correspond to a water retention time between 100 and 16.67 hours. Retention times bigger than 50 hours, imply high energy consumption by the aeration pumps. Also, in case of gain scheduling method, large variations of dilution rate during the transient periods are obtained (see Figure 6(d)).

An efficient WWTP treats the water at a certain rate, meaning that the flow of water entering the system is almost constant throughout the operation. To obtain small changes on the dilution rate and at the same time allowable variations for the effluent substrate concentration, a variable setpoint for the *DO* concentration, depending on the schedule variable *W,* must be imposed. Small variations in the input flow do not hamper the smooth running of the aerated bioreactor processes, especially the phenomena of decantation in the settler.

The variable setpoint for the dissolved oxygen concentration control loop has the values given in Table 1.

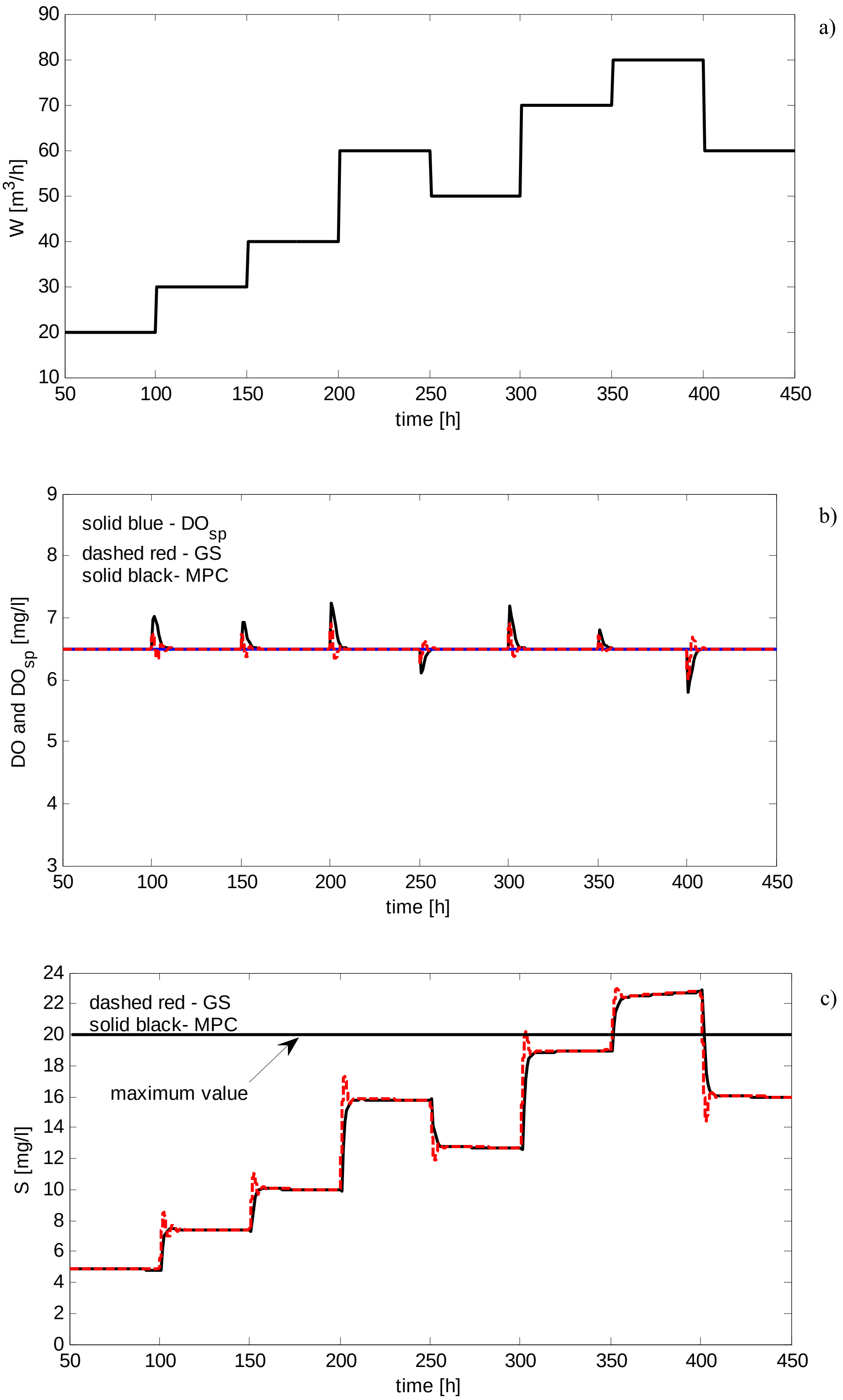
Table 1. *DO* setpoint values

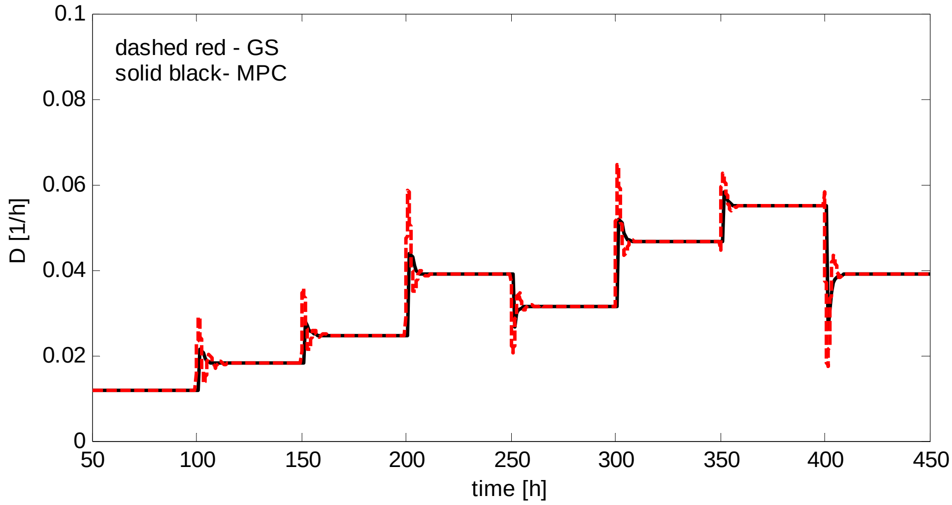
W [m^3/h]	20	30	40	50	60	70	80
DO_{sp} [mg/l]	4.25	4.75	5.25	5.75	6.25	6.75	7.25

Based on the values given in Table 1, an equation relating the variable dissolved oxygen setpoint to the aeration rate is obtained through a polynomial regression.

$$DO_{sp}(W) = 0.05 \cdot W + 3.25 \qquad (20).$$

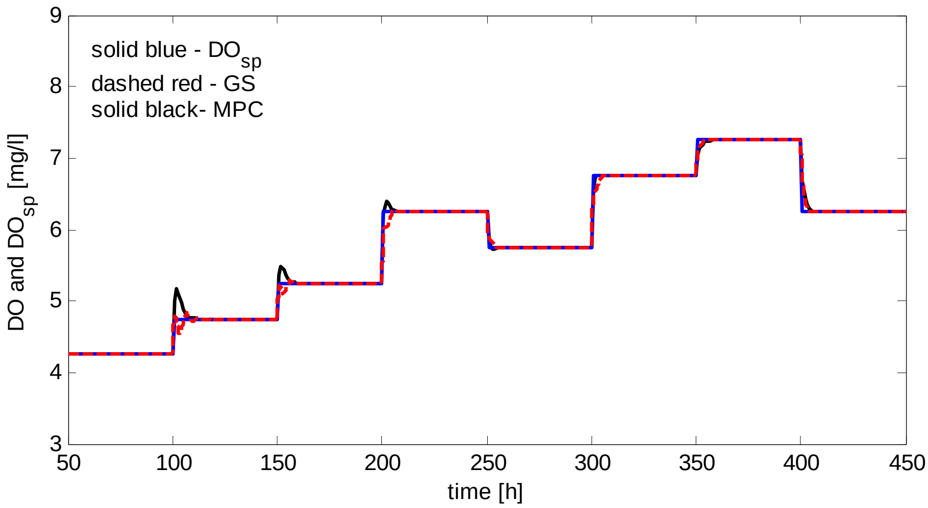
Figure 7 presents the closed loop response when both control methods, GS and MPC, are used. For this simulation, the same profile of the aeration rate as in Figure 6(a) was used. Analyzing these results, one may notice that a working regime, characterized by small variations (around 0.04 h^{-1}) in the dilution rate is obtained. Also, the effluent substrate concentration is below the maximum limit (20 mg/l).





d)

Fig. 6. Simulation results for constant DO setpoint (6.5 mg/l) obtained with the two methods: GS and MPC: a) aeration rate, b) dissolved oxygen, c) substrate, d) dilution rate



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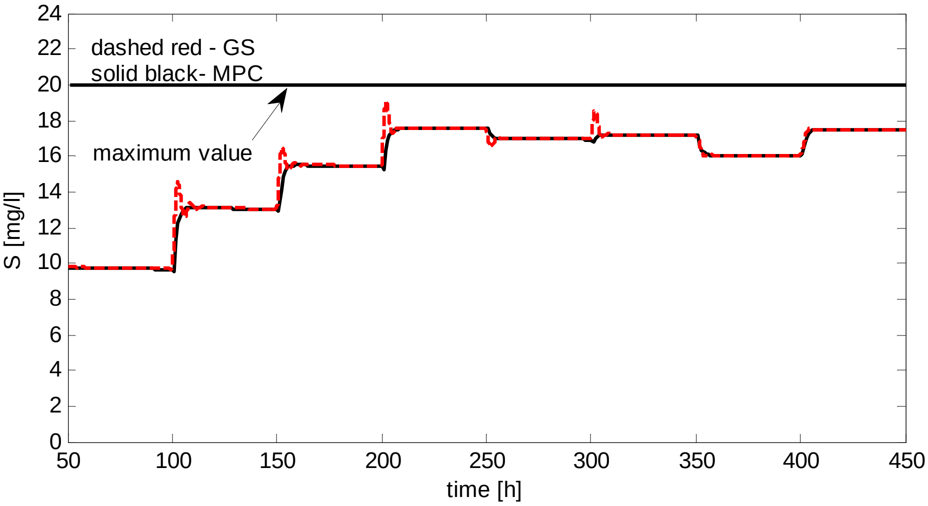

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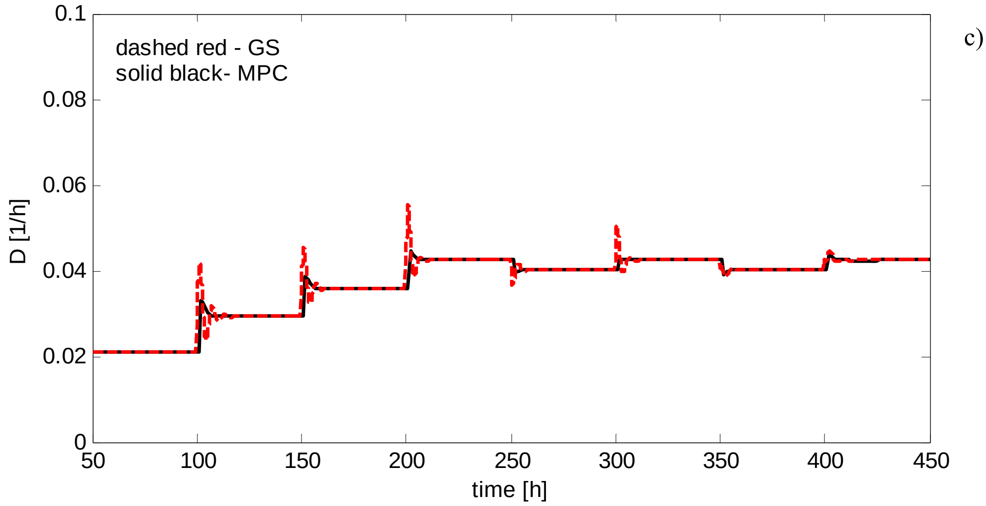


Fig. 7. Simulation results for variable *DO* setpoint obtained with the two methods: GS and MPC: a) dissolved oxygen, b) substrate, c) dilution rate

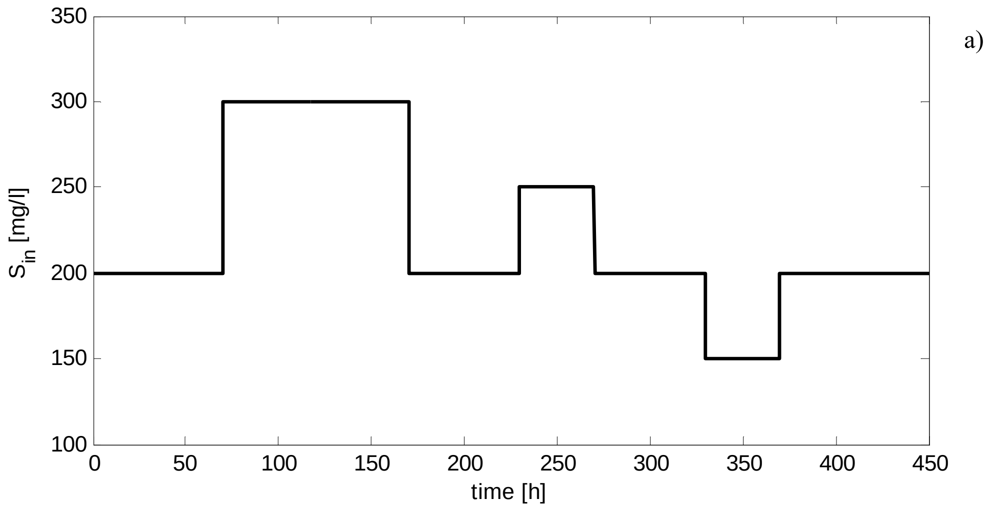
Further on, the behavior of the two control methods with respect to disturbance rejection was checked. The main disturbance of the WWTP that influences the effluent quality is the concentration of the substrate in the influent, S_{in}. Figure 8(a) presents its variation. In this case, the same aeration rate profile was used, as in Figure 6(a). The results from Figure 8 show that both control structures used in this paper rejects the disturbance generated by the variation of S_{in} while *DO* follows the setpoint with small variations when the disturbance occurs. The evolution of the qualitative variable is kept below the maximum admissible value despite the fact that perturbations up to 50% of the influent substrate concentration were encountered.

Next, the wastewater treatment process performances in terms of energy efficiency are presented. Since the considered aeration rate profile is identical for both investigated methods, the power consumption is the same at the aeration pumps. The wastewater treatment process efficiency is seen in terms of the amount of water treated with the same energy.

Consequently, the numerical computation of the dilution rate integral using *trapz* function in Matlab allows to determine the results shown in Table 2. Comparing these results one can see that higher ratio of the treated wastewater volume and aerator volume is obtained in the case of variable setpoint for the dissolved oxygen loop.

Table 2. Results regarding the efficiency of the wastewater treatment process with constant and variable DO setpoint

	Treated wastewater volume/aerator volume	
Method	Constant DO setpoint	Variable DO setpoint
GS-PI	13.876	15.781
MPC	13.802	15.681



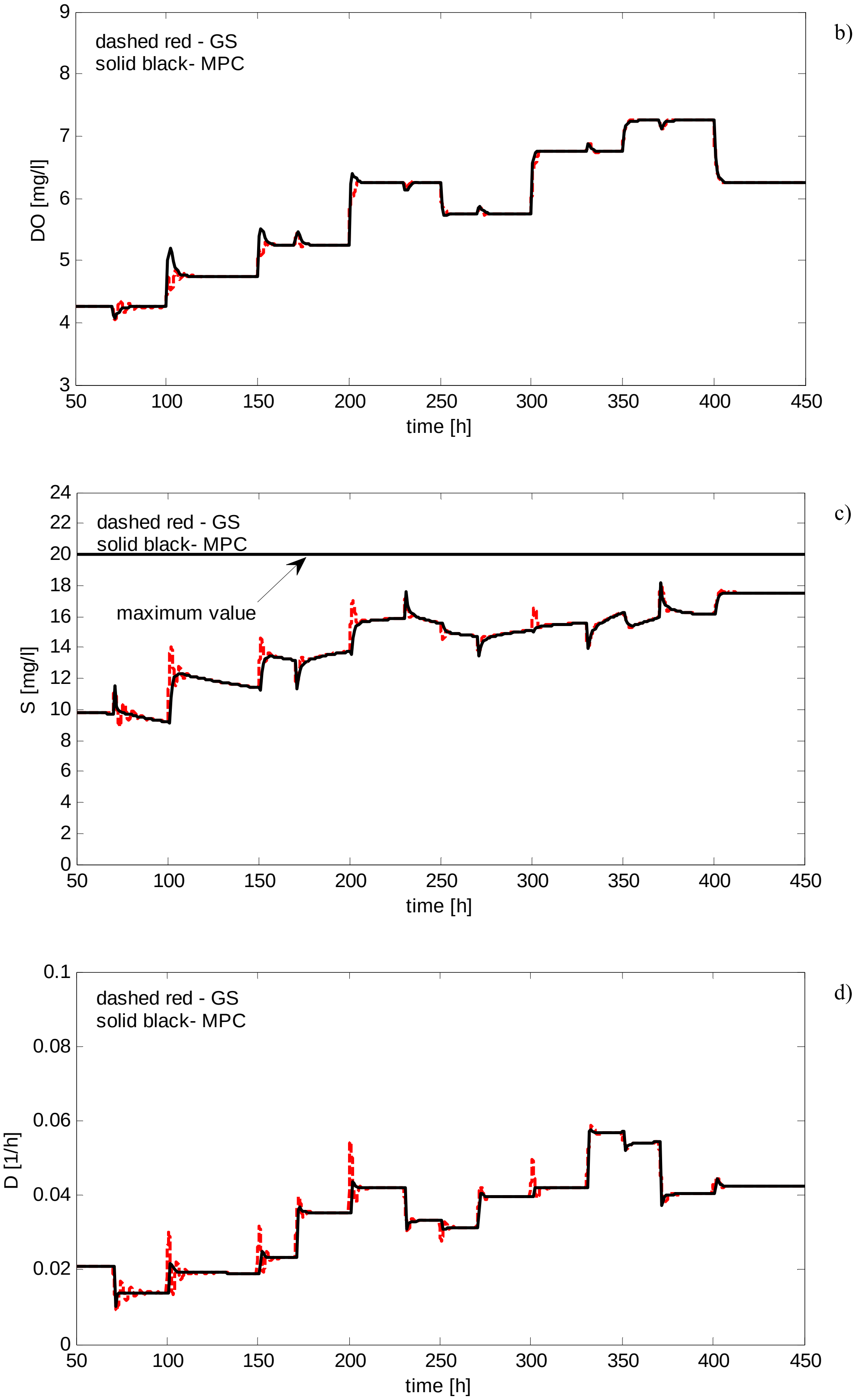


Fig. 8. Simulation results for variable *DO* setpoint and substrate concentration in influent (S_{in}) obtained with the two methods: GS and MPC: a) influent substrate concentration variation, b) dissolved oxygen, c) substrate, d) dilution rate

The evolutions of the treated wastewater volume and aerator volume ratio illustrated in Figure 9 reinforce the results from Table 2. Throughout the simulation higher efficiency is obtained when using a variable setpoint for the dissolved oxygen loop. Basically, for a 1000 m^3 aerator, a difference of 1905 m^3 of treated wastewater is obtained in the variable setpoint case than in the constant setpoint case.

Comparing the results presented in this work from the multicriteria perspective (good dynamics when changing the operating points, effluent substrate concentration within the limits allowed by law and volume of wastewater treated with the same amount of electricity consumed by the aeration pumps) one may conclude that using a variable setpoint for the DO loop leads to improved performances.

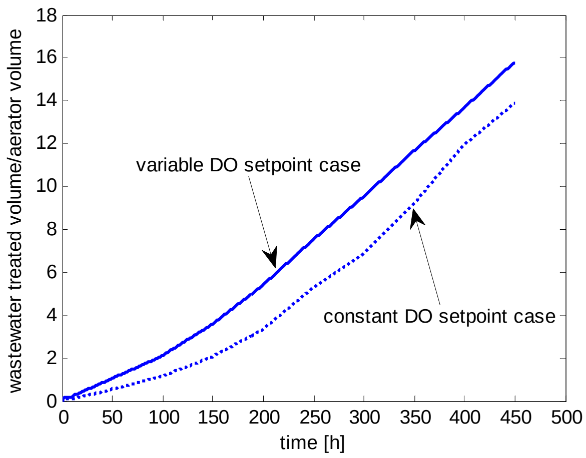


Fig. 9. Wastewater treatment process efficiency (the amount of treated wastewater with the same electrical power consumption) with gain scheduling method for constant DO setpoint case (dotted line) and variable DO setpoint case (solid line)

5. CONCLUSIONS

In this paper, two of the mostly used in industry control strategies have been implemented to control the dissolved oxygen concentration in an activated sludge process: gain scheduling PI control and predictive control. Three issues are emphasized in this paper. The first one refers to the dynamical performances of the closed-loop, the second one regards the behavior of the two control methods to the disturbance rejection and the last one deals with the efficiency of the wastewater treatment process in two situations: with constant and variable setpoint for the dissolved oxygen control loop.

Based on the steady-state analysis, a variable setpoint for the dissolved oxygen concentration has been designed. In this case, the control variable (D) takes values corresponding to acceptable water retention times, which do not require large electrical energy consumption. By modifying the aeration rate (W) and the dissolved oxygen concentration setpoint an effluent with an almost constant quality and flow has been obtained. The substrate concentration in the effluent remains below the maximum values imposed by law (20 mg/l), for both methods: gain scheduling and predictive control.

The gain scheduling controller has been designed based on a family of linear PI controllers, using the aeration rate as scheduling variable. The linear PI controllers have been tuned to fulfill the performance requirements in each of the analyzed operating points. For the MPC control, the fourth order nonlinear model has been used to calculate the predictions and sequential quadratic programming has been employed to solve the on-line optimization problem. Both methods need only measurements of the oxygen concentration which can be easily obtained. The substrate concentration in the effluent is indirectly controlled, thus no measurements of the effluent substrate concentration are needed.

The wastewater treatment process efficiency has been considered in terms of the wastewater volume treated with the same electrical energy consumed by the aeration pumps. In all the simulations two cases were considered: constant and variable setpoint for the dissolved oxygen control loop. The best results were obtained with variable setpoint.

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