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Improving Activated Sludge Wastewater Treatment Process Efficiency Using Predictive Control

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Abstract

This paper investigates the performance of a new predictive control approach used to improve the energy efficiency and effluent quality of a conventional Wastewater Treatment Plant (WWTP). A modified variant of the well-known Generalized Predictive Control (GPC) method has been applied to control the dissolved oxygen concentration in the aerobic bioreactor of a WWTP. The quadratic cost function was modified to a positional implementation that considers control signal weighting and not its increments, in order to minimize the control energy. The Activated Sludge Process (ASP) optimization using the proposed variant of the GPC algorithm provides an improved aeration system efficiency to reduce energy costs. The control strategy is investigated and evaluated by performing simulations and analyzing the results. Both the set point tracking and the regulatory performances have been tested. Moreover, the effects of some tuning parameters are also investigated. The results show that this control strategy can be efficiently used for dissolved oxygen control in WWTP.

Keywords: predictive control, process optimization, process model, wastewater treatment plant, activated sludge treatment

1. Introduction

Wastewater treatment plants are key infrastructures for ensuring a proper protection of our environment. Biological treatment is an important and integral part of any WWTP. The Activated Sludge Process is the most commonly used technology to treat sewage and industrial wastewaters due to its flexibility, high reliability and cost-effectiveness, as well as its capacity of producing high quality effluent. An overview of the activated sludge wastewater treatment process mathematical modeling is presented in [1] and application of ASP models can be found in [2]. The ASPs are difficult to be controlled because of their complex and nonlinear behavior. However, the optimal control of the biological reactors plays an important role in the operation of a WWTP and the efficiency of most WWTP is an important issue still to be improved.

A good control of WWTP processes could lead to better water quality and to an efficient use of energy [3-4]. This research area is a key part of keeping the environment clean and nowadays has received great emphasis due to the strict regulations for the discharged water. Many of the WWTP are operated in a less-than-optimal manner with respect to both treatment and energy efficiency, causing high costs and inefficient operation in order to meet the regulations.

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The dissolved oxygen concentration has a major impact in the activated sludge process. To control the dissolved oxygen concentration, the amount of air provided by the blowers in the aeration tank is modified. The activated sludge process is the most energy consuming processes in the whole WWTP, nearly half of the energy consumed in a WWTP being used in the aeration tank. An over dosage of aeration is unwanted because it brings increased costs and just little or even no gain in the quality of water. For values of dissolved oxygen concentration in the aeration tank above 2 mg/l, the increase of the aeration flow begins to have a lower effect in the quality of effluent and at values of 4-6 mg/l doesn't have any effect. In the absence of adequate control systems, to reduce the effect of disturbances on the flow or load of the effluent, it is sometimes preferred to operate at high concentrations of dissolved oxygen in the aeration tank. Using the blowers in manual operation at constant flow rates during the periods of reduced wastewater intake will produce a loss of energy. Thus, optimizing the aeration process defines an important objective to reduce energy consumption and improve energy efficiency. Several strategies have been proposed for controlling the dissolved oxygen concentration. Some researchers have focused on the importance of well-tuned models and simulation platforms in the process of designing the controllers for the dissolved oxygen concentration [5-6]. Other researchers have focused on designing multiple model controllers instead of nonlinear complex ones [7]. Nevertheless, because of the high nonlinearities of the process, robust controllers are required to maintain an optimum setpoint, regardless of the changes in the operating point. Such control strategies have also been proposed, including adaptive [8-9], predictive [10-11], fuzzy [12] or fractional order $PI^{\mu}D^{\lambda}$ control [13].

Optimizing and maintaining the dissolved oxygen set point define important objectives for researchers in WWTP control. Optimization of the dissolved oxygen set point is not the purpose of this paper. In practice, an appropriate dissolved oxygen set point is determined either manually by experienced operators or automatically through optimization algorithms. In this paper, we assume the appropriate set point is prescribed by the optimizing part of a multilayer hierarchical control structure and the proposed control system will be responsible for forcing the plant to follow this set-point. A modified variant of the well-known Generalized Predictive Control method [14] has been applied to control the dissolved oxygen concentration in the aeration tank of an activated sludge process. The ASP process optimization using the proposed variant of the GPC algorithm provides an improved aeration system efficiency to reduce energy costs. The GPC algorithm is well known and consists of applying a control sequence that minimizes a quadratic cost function defined over a prediction horizon. The consideration of weighting of control increments in the cost function in GPC allows an incremental implementation which ensures offset-free reference tracking and disturbance rejection but does not provide minimization of the control energy. To alleviate the above mentioned limitation, the aim of this paper is to propose a different variant of the quadratic cost function. In order to minimize the control energy, the quadratic cost function was modified to a positional implementation that considers control signal weighting and not its increments. To evaluate the performance of the proposed design for ASP process optimization, simulation results are presented and discussed in detail. The ASP process was first modeled and the models were calibrated and validated based on a combination of laboratory tests and plant operating measured data. The proposed control strategy is investigated and evaluated by performing simulations and analyzing the results. Both the set point tracking and the regulatory performances have been tested. Moreover, the effects of some tuning parameters are also investigated. The results show that this control strategy can be efficiently used for dissolved oxygen control in WWTP.

2. Process Description and Modeling

The activated sludge wastewater treatment processes are very complex, with large, uncontrollable input disturbances, significant nonlinearities and characterized by uncertainties regarding their parameters. The most widely used models to describe these processes is the Activated Sludge Model Nr.1 (ASM1) proposed by the International Water Association (IWA) [15]. Having thirteen state variables and eight dynamic processes, this model is highly complex, but it provides deep insight in the behavior of the process. Since the model also contains a large number of biokinetic and stoichiometries parameters, for control purposes it is necessary to simplify it into a simpler model, especially if a hierarchical control structure is used.

The modelling process and the model calibration are made based on data obtained from a conventional activated sludge system operating under aerobic conditions and whose main purpose is to ensure the removal of colloidal and dissolved carbonaceous organic matter. The residual water that needs to be treated is coming from a factory that processes and is painted cotton, a milk factory and from domestic households.

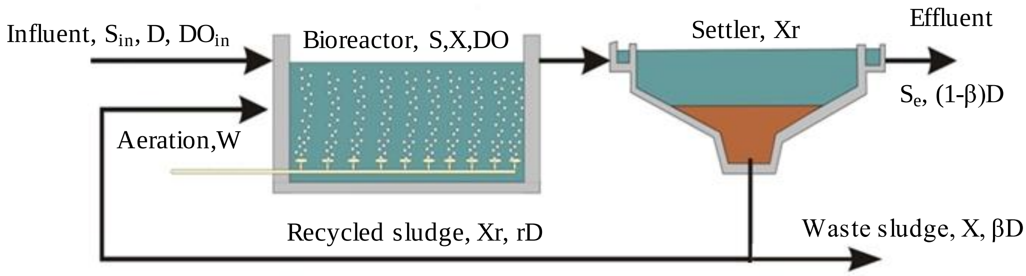

Fig. 1. WWTP's biological treatment process schematic configuration.

The wastewater first enters the aerated bioreactor where the treatment based on ASP takes place. The clear water and the sludge are separated due to gravity in the secondary settler. In order to keep biological sustainability, the active sludge is recirculated and the bioreactor is aerated using an aeration network where air is being blown with fine bubbles.

In our previous work [16-17] we have developed a reduced model to the ASP based wastewater treatment process where the simplest possible case was taken into consideration. Only the removal of organic matter is considered, while biological phosphorus and nitrogen removal is neglected. The following components are treated in the model: one organic matter component, one microorganism component and dissolved oxygen. For the model used in this paper, two processes are considered to take place in the aeration tank: the reduction of organic substance in heterotrophic aerobic bacteria and the reduction of ammonia nitrogen with autotrophic aerobic bacteria. The carbonaceous conversion is integrated in a consistent manner with the transformations of nitrogen. The following components are treated in the model: one organic matter component, two nitrogen components, two microorganism components and dissolved oxygen.

The developed model is based on the following assumptions: the content of the aeration tank is considered perfect stirred; there are no directions in the secondary settler; the biomass concentration in the effluent is negligible; the oxygen concentration and substrate are neglected in the recycled sludge; the active sludge is the only recycled component into the aeration tank.

In this case, there are 6 equations. that can be written for the aeration tank considered as a completely mixed reactor. Eqs. (1-6) correspond to the mass balance Eqs. for:heterotrophic (1) and autotrophic (2) biomass, biodegradable substrate (3), ammonia nitrogen (4), nitrite and nitrate nitrogen (5) and dissolved oxygen(6) concentration.

$$\frac{dX_{B,H}(t)}{dt} = r\cdot D(t)X_{r\,B,H}(t) - D(t)(1+r)\cdot X_{B,H}(t) + [m_H(t)+m_{Ha}(t)-b_H]X_{B,H}(t) \tag{1}$$

$$\frac{dX_{B,A}(t)}{dt} = r\cdot D(t)X_{r\,B,A}(t) - D(t)(1+r)X_{B,A}(t) + [m_A(t)-b_A]X_{B,A}(t) \tag{2}$$

$$\frac{dS_S(t)}{dt} = -\frac{m_H(t)+m_{Ha}(t)}{Y_H}X_{B,H}(t) - D(t)[(1+r)S_S(t)+S_{Sin}(t)] \tag{3}$$

$$\frac{dS_{NO}(t)}{dt} = -\frac{1-YH}{2.86Y_H} m_{Ha}(t) X_{B,H}(t) + \frac{1}{Y_A} m_A(t) X_{B,A}(t) - D(t)[(1+r)S_{NO}(t) + S_{NOin}(t)] \tag{4}$$

$$\frac{dS_{NH}(t)}{dt} = -i_{XB}[m_H(t) + m_{Ha}(t)]X_{BH}(t) - (i_{XB} + \frac{1}{Y_A})m_A(t) X_{BA}(t) - D(t)[(1+r)S_{NH}(t) + S_{NHin}(t)] \tag{5}$$

$$\frac{dDO(t)}{dt} = -\frac{1-Y_H}{Y_H} m_H(t) X_{B,H}(t) - (1 - \frac{4.57}{Y_A}) m_A(t) X_{B,A}(t) - D(t)[(1+r)DO(t) + DO_{in}(t)] + +aW[DO_{max} - DO(t)] \tag{6}$$

The mass balance equations for the recycled biomass are:

$$\frac{dX_{rB,H}(t)}{dt} = D_S(t)(1+r)X_{B,H}(t) - D_S(t)(\beta + r)X_{rB,H}(t) \tag{7}$$

$$\frac{dX_{rB,A}(t)}{dt} = D_S(t)(1+r)X_{B,A}(t) - D_S(t)(\beta + r)X_{rB,A}(t) \tag{8}$$

Under steady state conditions, from mass balance equations in the settling tank the resulting concentrations in the effluent S_{Sef}, S_{NHef} and S_{NOef} are:

$$S_{Sef}(t) = (1+r)\, S_S(t) \tag{9}$$

$$S_{NHef}(t) = (1+r)\, S_{NH}(t) \tag{10}$$

$$\mathrm{S_{NOef}(t) = (1+r)\, S_{NO}(t)} \tag{11}$$

The equations for the heterotrophic growth of the biomass in aerobic (μ_{H}) and anoxic (μ_{Ha}) conditions are:

$$\mu_{\mathrm{H}}(t) = \mu_{\mathrm{Hmax}} \frac{S_S(t)}{K_S + S_S(t)} \cdot \frac{DO(t)}{K_{O,H} + DO(t)} \tag{12}$$

$$\mu_{\mathrm{Ha}}(t) = \mu_{\mathrm{Hmax}} \frac{S_S(t)}{K_S + S_S(t)} \cdot \frac{K_{OH}}{K_{O,H} + DO(t)} \cdot \frac{S_{NO}(t)}{K_{NO} + S_{NO}(t)} \cdot \eta_g \tag{13}$$

While the equation for the growth of autotrophic mass μ_{A} is:

$$\mu_{\mathrm{A}}(\mathrm{t}) = \mu_{\mathrm{Hmax}} \frac{S_{NH}(t)}{K_{NH} + S_{NH}(t)} \cdot \frac{DO(t)}{K_{O,A} + DO(t)} \tag{14}$$

where $X_{B,H}$ and $X_{B,A}$ represent the active heterotrophic and autotrophic biomass concentration, S_S, S_{NH}, S_{NO}, and D_O - concentration of biodegradable organic matter, ammonia nitrogen, nitrite-nitrate, and dissolved oxygen in the aerated bioreactor, S_{Sin}, S_{NHin}, and S_{NOin} - concentrations in the influent, $X_{rB,H}$ and X_{rBA} - recycled heterotrophic and autotrophic biomass concentrations, D and D_S - dilution rates (ratio of influent flow to volume of the aerated bioreactor and settler), W - aeration rate, α - oxygen transfer rate, r - the ratio of recycled sludge flow to influent flow, β - the ratio of waste flow to influent flow, Y_A - autotrophic biomass yield factor, Y_H - heterotrophic biomass yield factor, i_{XB} - conversion coefficient for the nitrogen mass, K_{OH} and K_{OA} - oxygen saturation coefficients at half for heterotrophic/autotrophic biomass, K_{NH} and K_{NO} - ammonia and nitrate saturation coefficients at half for autotrophic biomass, K_S - organic substrate saturation coefficient, η_g - correction coefficient for μ_H in anoxic conditions. This model has 8 state variables: $X_{B,H}$, $X_{B,A}$, $X_{rB,H}$, X_{rBA}, S_S, S_{NH}, S_{NO}, and D_O. The kinetic and stoichiometric parameters values obtained after the model calibration are: b_H=0.034; b_A=0.002; Y_H=0.54; Y_A=0.13; i_{XB}=0.068; α =0.016; D_{Omax}=10; η_g =0.8; μ_{Hmax}=0.127; μ_{Amax}=0.02; K_{OH}=0.2, K_{OA}=0.4; K_S=130; K_{NO}=0.9; K_{NH}=1; β =0.015.

3. Control Strategy

The aeration system, the blower and piping model and the proportional–integral–derivative (PID) control of the air flow is presented in [18-19]. Following this work, this paper investigates the performance of a modified variant of the well-known Generalized Predictive Control (GPC) method to control the dissolved oxygen concentration (DO) in the aerated bioreactor of an activated sludge process, considered as process output variable (Fig. 2). We assume that the appropriate set point for the dissolved oxygen concentration is given and the predictive control system is used to maintain this set point. The aeration air flow (W) is considered as manipulated variable.

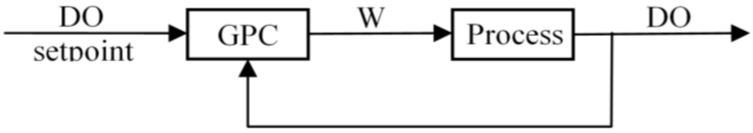

Fig. 2 Predictive control schemes

The Generalized Predictive Controller is one of the most relevant design methods of Model-Based Predictive Control (MBPC). The standard GPC synthesis is based on a linear process model, CARIMA - Controlled Auto-Regressive Integrated Moving-Average, a quadratic cost function and a control law, both using an incremental structure (the actual control signal increment - Δu- is computed) [14]. This incremental implementation ensures offset-free behavior in closed loop control systems.

The activated sludge process is the most energy consuming processes in the whole WWTP, nearly half of the energy consumed in a WWTP being used for the aeration. An important step in developing the proposed control strategy is the reparametrization of the cost function in the predictive algorithm to contain a measure of energy consumed by aeration process. This could exploit the fluctuation of operating conditions by realizing significant energy savings. Since the aeration air flow W is the manipulated variable resulted from the controller output u, to minimize the aeration flow and not its variations the reparametrized cost function of the predictive algorithm has to contain the controller output u, instead of the control output increment Δu. This will lead to a positional implementation based on a positional form for the process model and controller cost function.

Consider the following modified MBPC cost function:

$$J(N_1, N_2, N_u) = E\left\{ \sum_{j=N_1}^{N_2} [y(t+j) - y_r(t+j)]^2 + \sum_{j=1}^{N_u} [\rho[u(t+j-1)]^2 \right\} \tag{15}$$

where: y_r is the future reference sequence, N_1 is the minimum costing horizon, N_2 is the maximum costing horizon, N_u is the control horizon,and ρ is a control-weighting coefficient.

The use of the CARMA process model instead of the CARIMA model :

$$A(q^{-1})y(t) = B(q^{-1})u(t-k) + C(q^{-1})e(t) \tag{16}$$

will lead to a positional form for the controller and therefore the controller will not have an integrator.

For simplicity, in this development $C\ (q^{-1})=1$ is chosen. To derive a j step ahead predictor of the process output $y(t+j)$, on considers the polynomial identity:`

$$1 = E_j(q^{-1})A(q^{-1}) + q^{-j}F_j(q^{-1}) \tag{17}$$

where $E_j(q^{-1})$ and $F_j(q^{-1})$ are polynomials uniquely defined, given $A(q^{-1})$ and the prediction interval j, of degree j and respectively n (n - the process order).

Based on Eq. (16) and Eq. (17) we obtain:

$$y(t+j) = E_j(q^{-1})B(q^{-1})u(t+j-k) + F_j(q^{-1})y(t) + E_j(q^{-1})e(t+j) \tag{18}$$

The optimal predictor, given measured data up to time t (including t) is written as:

$$y(t+j\,|\,t) = G_j(q^{-1})u(t+j-k) + F_j(q^{-1})y(t) + E_j(q^{-1})e(t+j) \tag{19}$$

where

$$G_j(q^{-1}) = E_j(q^{-1}) \cdot B(q^{-1}) \tag{20}$$

For simplicity, in the derivation below, N_1 is set to 1, N_2 to N, N_u to N and k to 1. For j = $1,...,N$, the optimal predictor Eq. (18) can be written::

$$y(t+1) = g_0 \cdot u(t) + [G_1(q^{-1}) - g_0]u(t) + F_1 y(t) + E_1(q^{-1})e(t+1) \tag{21}$$

$$y(t+2) = g_1 \cdot u(t) + g_0 \cdot u(t+1) + [G_2(q^{-1}) - q^{-1}g_1 - g_0]u(t+1) + F_2(q^{-1})y(t) + E_2(q^{-1})e(t+2) \tag{22}$$

$$\begin{aligned} y(t+N) = g_{N-1} \cdot u(t) + ... + g_0 \cdot u(t+N-1) + [G_N(q^{-1}) - q^{-(N-1)}g_{N-1} - ... - g_0]u(t+N-1) \\ + F_N(q^{-1})y(t) + E_N(q^{-1})e(t+N) \end{aligned} \tag{23}$$

On observe that the predictor $y\,(t+j)$, consists of three terms: one including the past known control actions and the filtered measured process outputs, the second depending on future control actions which must be determined and the third, depending on the future noise signals. Let $f(t+j)$ be the component of $y\,(t+j)$, which includes all the known terms at a timely moment:

$$f(t+1) = [G_1(q^{-1}) - g_0]u(t) + F_1 y(t) \tag{24}$$

$$f(t+2) = [G_2(q^{-1}) - q^{-1}g_1 - g_0]u(t+1) + F_2(q^{-1})y(t) \tag{25}$$

$$f(t+N) = [G_N(q^{-1}) - q^{-(N-1)}g_{N-1} - ... - g_0]u(t+N-1) + F_N(q^{-1})y(t) \tag{26}$$

Then Eq. (19) can be rewritten in the vectorial form:

$$y = G \cdot u + f + e \tag{27}$$

where y, u, f and e are vectors of the form:

$$y = [y(t+1), ..., y(t+N)]^T, \quad N \text{ x } 1 \tag{28}$$

$$u = [u(t), ..., u(t+N-1)]^T, \quad N \text{ x } 1 \tag{29}$$

$$f = [f(t+1), ..., f(t+N)]^T, \quad N \text{ x } 1 \tag{30}$$

$$e = [E_1(q^{-1})e(t+1), ..., E_N(q^{-1})e(t+N)]^T, \quad N \text{ x } 1 \tag{31}$$

And the matrix G is then lower triangular of dimension N x N:

$$G = \begin{bmatrix} g_0 & 0 & 0 & \cdots & 0 \\ g_1 & g_0 & 0 & \cdots & 0 \\ g_2 & g_1 & g_0 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ g_{N-1} & g_{N-2} & g_{N-3} & \cdots & g_0 \end{bmatrix} \tag{32}$$

For $N_u < N$ the matrix G is then of dimension N x N_u:

$$G = \begin{bmatrix} g_0 & 0 & 0 & \cdots & 0 \\ g_1 & g_0 & 0 & \cdots & 0 \\ g_2 & g_1 & g_0 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ g_{N-1} & g_{N-2} & g_{N-3} & \cdots & g_{N-Nu} \end{bmatrix} \tag{33}$$

And y, u, f and e are vectors of the form:

$$y = [y(t+1), ..., y(t+N)]^T, \quad N\text{x}1 \tag{34}$$

$$u = [u(t), ..., u(t+N_u-1)]^T, \quad N_u\text{x}1 \tag{35}$$

$$f = [f(t+1), ..., f(t+N)]^T, \quad N\text{x}1 \tag{36}$$

$$e = [E_1(q^{-1})e(t+1), ..., E_N(q^{-1})e(t+N)]^T, N\text{x}1 \tag{37}$$

The cost function becomes:

$$J(1,N,N_u) = E[(y - y_r)^T(y - y_r) + \rho u^T u] = E[(Gu + f + e - y_r)^T(Gu + F + e - y_r) + \rho u^T u] \tag{38}$$

Assuming that $E[e^T u]$=0, $E[e]$=0, and $E[e^T e]$ is not affected by u, the first derivative of the previous equation gives:

$$\frac{\partial J}{\partial u} = 2E[G^T(Gu + f + e - y_r) + \rho Iu] = 2E[(G^T G + \rho I)u + G^T(f - y_r)] \tag{39}$$

For the first derivatal ive equate zero the control vector u is obtained:

$$u = (G^T G + \rho I)^{-1} G^T (y_r - f) \tag{40}$$

Only the first element of u vector, $u(t)$, must be determined and this value represents the current controller output:

$$u(t) = \alpha^T (y_r - f) \tag{41}$$

where $\alpha^T = [\alpha_1 ... \alpha_N]$ is the first row of the $(G^T G+\rho I)^{-1} G^T$ matrix. Note that if the equation for the calculation of the controller output (u) has the same form as that for the incremental GPC algorithm (Δu), the diophantine equation form and calculation of polynomials E_j and G_j is different.

4. Simulation Results

The assessment of the developed control system is done through numerical simulation in Matlab/SIMULINK environment. The nonlinear model of the activated sludge wastewater treatment process given by Eqs. (1)-(14) was used to simulate the process dynamics. In the GPC algorithm the prediction of the process output is based on a linear process model. To obtain the linear state space model and the transfer function from W to DO the model was linearized around an operating point. An eighth order transfer function was obtained. To reduce its order to two, from the linear state space model a balanced state-space realization was first computed and then the smallest 6 diagonal entries of the balanced grammians were eliminated using modred. Similar results were obtained using the input and output data obtained during simulations of the nonlinear model dynamics for small variations around the considered operating point and a Recursive Least Square algorithm to estimate a second order discrete transfer function.

The steady state values of the input variables are: DO=0.064[h^{-1}]; DO_{in0}=0.5[mg/l]; S_{in0}=765[mg/l]; W_0=100[m^3/h] and r_0=0.8. The steady state value for the considered process output is DO_0 =1.36 mg/l. The aeration air flow (W) is considered as the manipulated input, the other inputs being considered as disturbances. The air flow values were limited between W_{min} = 50m^3/h and W_{max} =210m^3/h. The controller design parameters are: N=6, N_u=1, sampling period t_s= 0.01 h. Different aspects, such as setpoint changes and effects of load disturbances, have been analyzed.

In Fig. 3 the setpoint tracking for a step from DO_0 =1.36 mg/l to DO_1 = 2mg/l in DO setpoint at the time moment t=1h is presented. All the process inputs excepting the manipulated input have been considered as constants and equal to their steady state values. Using the original GPC control algorithm that has an incremental form there is no steady state error between the process output (continuous line) and the setpoint. The developed GPC control algorithm has a positional form and the steady state error is increasing with the value of the control-weighting coefficient, ρ(dotted line). However, it can be observed that with the increasing value of this coefficient, the aeration air flow W is decreasing and also the total amount of air consumed to reach the new setpoint.

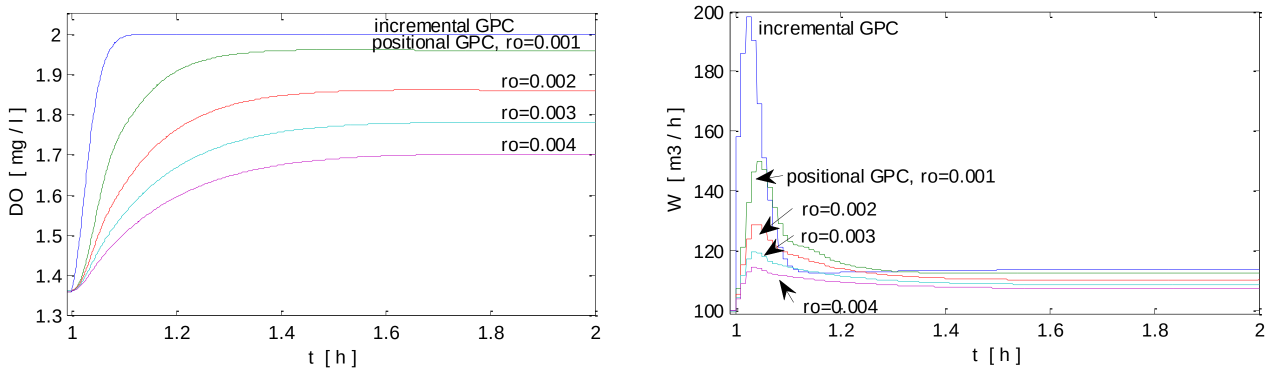

Fig. 3 Setpoint tracking performances for process output (DO) and control output (W). Incremental GPC - continuous line, positional GPC for different values of the control-weighting coefficient (ρ) - dotted line

For the next simulation scenarios a constant setpoint is considered and the regulatory performance during a simulation test when the disturbances presented in Fig. 4 (a step disturbance with an amplitude equal to 10% of the steady state value S_{in0}, from t=10h to t=20h) and Fig. 5 (random disturbances for a large simulation time) are applied on the most significant input for the process output: influent organic matter concentration S_{Sin}.

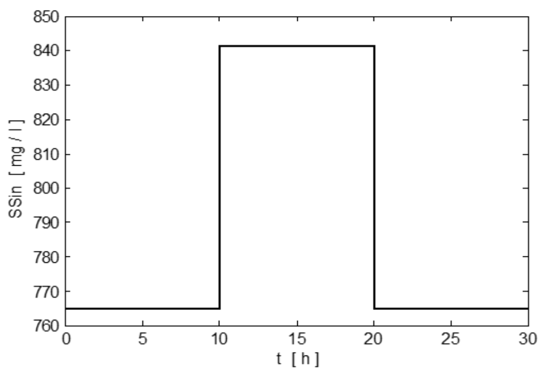

Fig. 4 Regulatory performances. Step SSin input disturbances

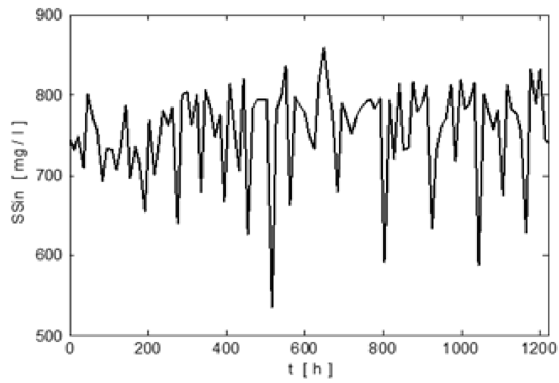

Fig. 5 Regulatory performances. Random SSin input disturbances

Fig. 6 shows the regulatory performance during simulation test when the disturbances presented in Fig. 4 are applied. Using the incremental GPC control algorithm, there is no steady state error between the process output (continuous line) and the setpoint. Using the positional GPC control algorithm the steady state error in the process output is increasing with the value of the control-weighting coefficient, ρ (only the case ρ=0.002 is shown by dotted line in the figure). With the increasing value of this coefficient, the aeration air flow W is decreasing and also the total amount of air consumed to reject the disturbance. As can be seen in the figure representing the control output W, the surplus of air needed to reject the disturbance using a positional GPC control algorithm (dotted line) represents 72% of the surplus of air needed to reject the disturbance using incremental GPC (continuous line). Of course it needs to consider the disadvantage of the steady state error and of the response time.

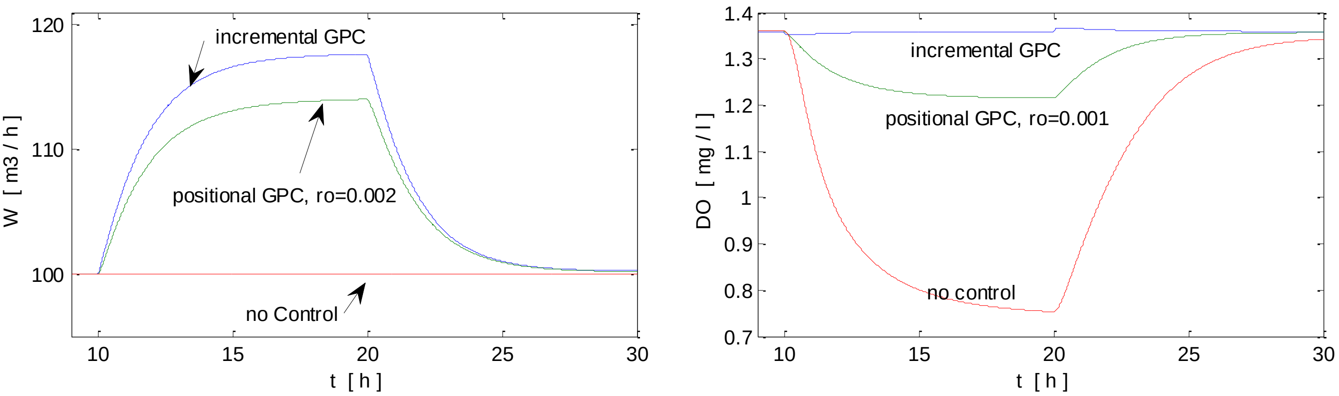

Fig. 6 Regulatory performances for step disturbances presented in Fig. 4, process,output (DO) and control output (W). Incremental GPC - continuous line, positional GPC with ρ=0.002 - dotted line, no control - dashed line.

Fig. 7 shows the regulatory performance during simulation test when the disturbances presented in Fig. 5 are applied. Three cases are presented: (i) control using positional GPC (dotted line), (ii) control using incremental GPC (continuous line) and (iii) no control (dashed line). The DO setpoint is fixed at 2 mg/l and is kept constant during the simulation. The disadvantage of using the positional GPC is the steady state error and the advantage is a low power consumption. Therefore, choosing the control-weighting coefficient value will be based on compromise between performance and power consumption. In the case of Fig. 7, the average amount of air necessary for aeration is 2647 cubic meters daily if incremental GPC control is used. Positional GPC with a value ρ=0.002 leads to an average amount of air necessary for aeration of 2348 cubic meters daily. Considering the percentage, this means 88% of the average amount of air necessary for aeration using incremental GPC, i.e. a 12% reduction in air flow. The blowers operate under a predictable set of laws concerning speed, power and pressure. In accordance with affinity laws, flow is proportional to motor speed; and power is proportional to the cube of motor speed. This means that already minimal reductions in blower air flow can provide savings in energy consumption. Reducing the blower air flow by 12% decreases the power requirement by 32%.

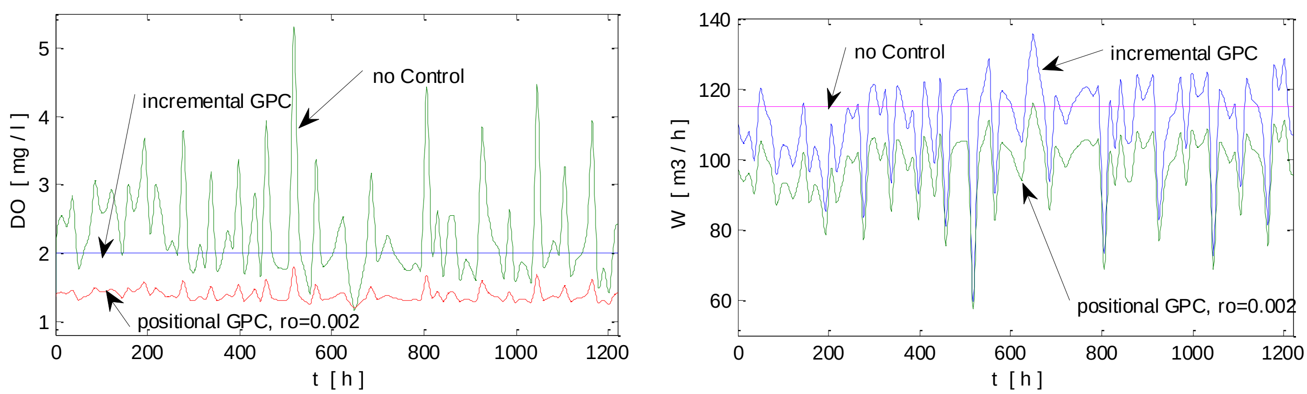

Fig. 7 Regulatory performances for load disturbances presented in Fig. 5, process output (DO) and control output (W). Incremental GPC - continuous line, positional GPC with ρ=0.002 - dotted line, no control - dashed line.

5. Conclusions

The wastewater treatment plants are considered complex processes due to the strong nonlinearities, large variable time constants and continuous perturbations present in the influent. This study evaluates the performance of a positional GPC control algorithm for the dissolved oxygen concentration in the activated sludge process of a WWTP. Both the setpoint tracking and the regulatory performances have been tested and compared with those obtained using the incremental GPC. The design parameters for both controllers are the same and the simulations provide information on the compromise between control performances (steady state error and response time) and savings in energy consumption. The aeration flow and, by default, the blower's speed is allowed to be lowered when the operating conditions of the WWTP permit. The power consumed by blowers is proportional to the cube of air flow. This means that already minimal reductions in blower air flow can provide savings in energy consumption.

Since the presented control system is responsible for forcing the plant to follow the setpoint prescribed by the optimizing part of a multilayer hierarchical control structure, it remains to be analyzed in what degree the overall performances of the hierarchical control system will be affected by the steady state error of this control loop.

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