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MODEL-BASED PREDICTIVE CONTROL OF A PRE-DENITRIFICATION PLANT: A LINEAR STATE-SPACE MODEL APPROACH

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Abstract: This paper focuses on the design of a model-based predictive control (MPC or MBPC) technique to regulate the concentration levels of nitrate in both anoxic and aerobic zones of a pre-denitrifying activated sludge plant, aiming to improve the nitrogen (N)-removal from wastewater. The synthesis of the MPC controller is based on a linear extended state-space model of the process, where an identification horizon is added to include a sequence of past inputs/outputs. This sequence can be used to estimate the model or the updated state of the process, thus eliminating the need for a state observer. The linear state-space model was obtained through subspace identification methods. The controller performance is tested by simulation and the results show the efficiency of the proposed strategy. *Copyright © 2002 IFAC*

Keywords: Waste treatment, Water pollution, Predictive control, Model-based control, Subspace methods, State-space models, Environment engineering.

1. INTRODUCTION

The interest in using the activated sludge (AS) process for biological N-removal has been drastically increasing in the last 5-10 years due to stricter effluent legislation. N-removal from wastewater in an AS plant is performed in two stages: nitrification, in aerobic compartments, where ammonium (NH_4^+) is converted into nitrate (NO_3^-), and denitrification, in anoxic compartments, where NO_3^- is converted into gaseous N, with the use of organic compounds (COD) as reducing agent. In principle, biological N-removal is possible by using the following configurations: pre-denitrification, post-denitrification, simultaneous nitrification-denitrification and alternating nitrification-denitrification. The most common and economic configuration is the pre-denitrification system (Henze, 1991). However, in all cases the AS plants need to be properly operated in order to optimize the N-removal.

In comparison with conventional AS plants (COD removal and, often partly, NH_4^+), N-removal AS plants are more complex. The co-existence of nitrification and denitrification processes is accompanied by new operational problems. Increasing the efficiency of one process will always have negative impacts on the efficiency of the other one. According to Hoen *et al*. (1996), the use of the manipulated variable is useful for controlling N-removal, just if either the nitrification or the denitrification process is not working at full capacity. Hence, automatic control in N-removal plants is important to achieve the adequate balance between nitrification and denitrification processes in the system.

The control of N-removal plants is mainly focused on (NH_4^+), (NO_3^-) and (NH_4^+ plus NO_3^-). This work is related to NO_3^- -removal. In a pre-denitrification

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plant the following approaches are commonly applied to achieve this target:

(1) control of NO_3^- concentration in the aerobic zone by manipulating the internal recycling flow rate (Singman, 1999; Rehnström, 2000; Ekman *et al.*, 2001)
(2) control of NO_3^- concentration in the anoxic zone by manipulating the internal recycling flow rate (Sotomayor *et al.*, 2000; Yuan *et al.*, 2001; Ghavipanjeh *et al.*, 2001)
(3) control of NO_3^- concentration in the anoxic zone by manipulating an external carbon flow rate (Marsili-Libelli and Manzini, 2000; Samuelsson and Carlsson, 2001; Carlsson and Milocco, 2001).

Carlsson and Rehnström (2001) used two single loop controllers to concurrently regulate both approaches (1) and (3). Nevertheless, these approaches (1 to 3) are highly interrelated and for optimal control of the process they should be simultaneously performed in a multivariable control philosophy.

MPC or receding horizon control (RHC) is currently the most widely implemented advanced process control technology for process plants, and they are commonly found in the medium level of a plant-wide control structure. The MPC formulation naturally handles multivariable interactions and constraints. Actually, MPC algorithms compute a sequence of manipulated variable adjustments, in order to optimize the future behavior of a plant through the use of an explicit process model. At each sampling instant, the MPC solves *on-line* a finite-horizon open loop optimal control problem with Bolza objectives, using the current state of the plant as the initial state. The optimization yields an optimal control sequence and the first control action in this sequence is applied to the plant. The entire procedure is repeated at subsequent sampling intervals. This is its main difference from conventional control, which employs a pre-computed control law.

When input and state constraints are not present, infinite-horizon MPC is simply the well-known linear-quadratic control (LQC) problem. Whereas LQC has been mainly developed in academic circles, MPC has arisen out of industrial needs. The first MPC techniques were developed in the late 1970s, because conventional single-loop controllers were unable to satisfy increasingly stringent performance requirements of power plant and petroleum refinery applications. Nowadays they can be found in a large variety of process industries, including chemicals, food processing, automotive, metallurgy, aerospace and pulp and paper (Qin and Badgwell, 1997). The current generation of commercially available MPC technology is based on linear models and, therefore, it is referenced by the generic term linear model predictive control (LMPC). While nonlinear MPC (NMPC) offers the potential for improved process operation, it offers theoretical and practical problems (in design, implementation and maintenance) which are considerably more challenging than those associated with LMPC (Nikolaou, 2001).

In this paper, a MPC based on an extended linear state-space model of the process is developed, aiming to control the NO_3^- concentrations in the anoxic and aerobic zones of an ASP and, therefore, to inferentially control the effluent inorganic nitrogen concentration. The manipulated variables are the internal recycling flow rate and the external carbon flow rate. The state-space model is obtained by using subspace identification methods. Two different control configurations are analyzed: one taking into account the influent flow as a manipulated variable (in a 3x2 system) and another one considering it as being constant (in a 2x2 system). The MPC controller performance is tested by simulation employing the ASWWTP-USP benchmark (Sotomayor *et al.*, 2001a).

2. THE ACTIVATED SLUDGE PLANT

The ASWWTP-USP benchmark is a dynamic simulator of a pre-denitrifying AS plant for the removal of COD and N from domestic effluents, operating at a constant temperature of 15°C and neutral pH. The process layout is shown in figure 1.

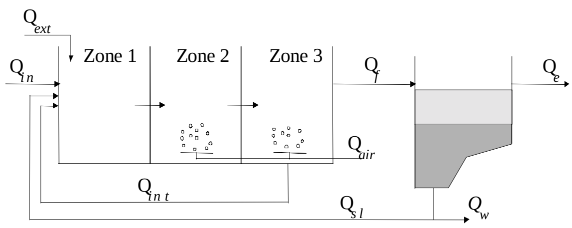

Fig. 1. Layout of the ASWWTP-USP benchmark

The process configuration is formed by a bioreactor composed of an anoxic zone (zone 1 with 13 m^3), two aerobic zones (zone 2 and zone 3 with 18 m^3 and 20 m^3, respectively) and a secondary settler (20 m^3). In nominal steady-state conditions, the influent flow rate Q_{in} is 4.17 m^3/h, with an average proportion of 224 mg COD/l of biodegradable organic matter and 45.88 mg N/l of total N and the hydraulic retention time is 17.0 hours. The internal recycle flow rate is $Q_{\text{int}} = 1.3Q_{in}$, the external sludge recycle flow rate is $Q_{sl} = 0.5Q_{in}$, the wastage flow rate is $Q_w = 25.8$ l/h and the external carbon flow rate is $Q_{ext} = 0$ l/h. An external carbon source is available, in this case, pure methanol as a 33%-solution with a concentration of 80,000 mg COD/l. In the aerobic zones, the DO concentration is controller at 2.0 mg O_2/l by simple PI controllers, whereas in the anoxic zone the DO concentration is assumed as being zero. For a reliable simulation, this benchmark is based on model widely accepted by the international community.

3. A LINEAR STATE-SPACE MODEL OF THE PROCESS

Subspace identification methods is a branch recently developed in system identification, which has attracted much attention, owing to its computational simplicity and effectiveness in identifying dynamic linear state-space multivariable systems. These algorithms are numerically robust and do not involve nonlinear optimization techniques (Favoreel *et al*., 2000).

A comparative study of several subspace identification methods was carried out in Sotomayor *et al*. (2001b), employing the ASWWTP-USP benchmark as a data generator. In this case, the nitrate concentrations in the anoxic zone Sno_1 (mg N/l) and in the last aerobic zone Sno_3 (mg N/l) are selected as outputs. Q_{int} (m^3/h) and Q_{ext} (l/h) are considered as inputs. However, to improve the model Q_{in} (m^3/h), influent readily biodegradable substrate[2] Ss_{in} (mg COD/l) and influent ammonium concentration Snh_{in} (mg N/l) are assumed as measurable disturbances, while influent nitrate concentration Sno_{in} (mg N/l) is assumed as an unmeasurable disturbance. These signals were collected at a sampling rate of 0.16 hours and after they were pre-processed, i.e. normalized and detrended. The resulting subspace state-space model is described by a 3rd-order deterministic strictly proper system, as:

$$\begin{aligned} x_{k+1} &= Ax_k + B\bar{u}_k \\ y_k &= Cx_k \end{aligned} \tag{1}$$

where x is the state vector, $\bar{u}$ is the input vector (including disturbances), y is the output vector, A is the state transition matrix, B is the input matrix and C is the output matrix. The time index k denotes the sampling instant. For this case, the following matrices describe the system (1):

$$A = \begin{bmatrix} 0.9763 & 0.0199 & 03263 \\ 0.0062 & 0.8818 & 0.0907 \\ -0.0024 & 0.0072 & 0.9758 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.0368 & -0.0434 & -0.1537 & -0.0431 & -0.0045 \\ -0.1505 & 0.0234 & 0.0357 & 0.0283 & -0.0044 \\ 0.0167 & -0.0100 & -0.0091 & -0.0003 & 0.0039 \end{bmatrix}$$

$$C = \begin{bmatrix} 0.2259 & -0.4026 & -0.1810 \\ 0.2664 & 0.2876 & -0.4633 \end{bmatrix}$$

This system is asymptotically stable, with (A,C) observable and (A,B) controllable.

[2] Sensors of readily biodegradable substrate are not commercially available nowadays, but it can be inferred from a respirometer or TOC (total organic carbon).

The system (1) can be more suitably written in the following way:

$$\begin{aligned} x_{k+1} &= Ax_k + B_1 u_k + B_2 d_k \\ y_k &= Cx_k \end{aligned} \tag{2}$$

where u is the manipulated variable vector and d is the measurable disturbance vector. In MPC, feedforward disturbances are removed by incorporating their effects into the model. Therefore, aiming to reject disturbance effects and also to incorporate integral error action, these dynamics have to be modeled and then be included in the state vector, forming a new state-space model. This extended subspace state-space model (E3SM) has the following form (Sotomayor *et al*., 2001c):

$$\begin{aligned} \tilde{x}_{k+1} &= \tilde{A}\tilde{x}_k + \tilde{B}u_k \\ y_k &= \tilde{C}\tilde{x}_k \end{aligned} \tag{3}$$

4. MODEL PREDICTIVE CONTROL

The MPC algorithm is based on the fact that E3SM can be applied as a model, which is convenient for prediction and predictive control. This prediction model is independent of the state vector $\tilde{x}$. Hence, there is no need for a state observer (Di Ruscio, 1997). The algorithm presented below will be called 3SMPC (subspace state-space MPC).

4.1 The control problem

A discrete time LQ objective can be written in compact matrix form as follows:

$$\begin{aligned} \Im_k = &\left(y_{k+1/L} - r_{k+1/L}\right)^T Q\left(y_{k+1/L} - r_{k+1/L}\right) + \\ &\Delta u_{k/L}^T R \Delta u_{k/L} + u_{k/L}^T P u_{k/L} \end{aligned} \tag{4}$$

where L is the prediction horizon, $r_{k+1/L}$ is a vector of future references, $y_{k+1/L}$ is a vector of future outputs, $\Delta u_{k/L}$ is a vector of future input changes, and $u_{k/L}$ is a vector of future inputs. Q, R and P are block diagonal weighting matrices. The problem can be formulated as follows:

$$\min_{\Delta u_{k/L}} \quad \Im_k \tag{5}$$

subject to linear constraints on u_k , Δu_k and y_k .

4.2 Prediction model (PM)

The PM is assumed to be of the form:

$$y_{k+1/L} = p_L(k) + F_L \Delta u_{k/L} \tag{6}$$

where $p_L(k)$ is a known vector. It represents the information of the past, which is used to predict the future. This vector is a function of the known number J (identification horizon) and the E3SM matrices. F_L is a constant lower triangular matrix, which is a function of the known E3SM matrices. A simple algorithm to compute $p_L(k)$ and F_L is giben by (Di Ruscio and Foss, 1998):

$$p_L(k) = \mathrm{O}_L \tilde{A}^J \mathrm{O}_J^\dagger y_{k-J+1/J} + P_L u_{k-J+1/J-1}$$
$$F_L = \left[\mathrm{O}_L \tilde{B} \quad H_L^d \right] \qquad (7)$$

with $P_L = \mathrm{O}_L \tilde{A} \Gamma_{J-1}^d - \mathrm{O}_L \tilde{A}^J \mathrm{O}_J^\dagger H_L^d$, where O_L is the extended observability matrix for the pair ($\tilde{A}, \tilde{C}$), with L block rows, $\mathrm{O}_J^\dagger = \left(\mathrm{O}_J^T \mathrm{O}_J\right)^{-1} \mathrm{O}_J^T$ is the Moore-Penrose pseudo-inverse of the extended observability matrix O_J for the pair ($\tilde{A}, \tilde{C}$), with J block rows, Γ_{J-1}^d is the reverse extended controllability matrix for the pair ($\tilde{A}, \tilde{B}$), with J-1 block columns, and the H_L^d is the lower block triangular Toeplitz matrix for the triple ($\tilde{A}, \tilde{B}, \tilde{C}$), with L block rows and L-1 block columns.

4.3 Constraints

The constraints can be written as an equivalent linear inequality of the form:

$$\alpha \cdot \Delta u_{k/L} \leq \beta_k \qquad (8)$$

a) Relationship between $\Delta u_{k/L}$ and $u_{k/L}$:

It is convenient to find the relationship between $\Delta u_{k/L}$ and $u_{k/L}$ in order to formulate the constraints in terms of future deviation variables $\Delta u_{k/L}$ by using:

$$u_{k/L} = S \cdot \Delta u_{k/L} + c \cdot u_{k-1} \qquad (9)$$

where S is a lower block triangular identity matrix and c is a block rows identity matrix, of suitable size.

b) Input amplitude, input change and output constraints:

$$\begin{aligned} S\Delta u_{k/L} &\leq u_{k/L}^{\max} - cu_{k-1} \\ -S\Delta u_{k/L} &\leq -u_{k/L}^{\min} + cu_{k-1} \end{aligned} \qquad (10)$$

$$\begin{aligned} \Delta u_{k/L} &\leq \Delta u_{k/L}^{\max} \\ -\Delta u_{k/L} &\leq -\Delta u_{k/L}^{\min} \end{aligned} \qquad (11)$$

$$\begin{aligned} F_L \Delta u_{k/L} &\leq y_{k/L}^{\max} - p_L(k) \\ -F_L \Delta u_{k/L} &\leq -y_{k/L}^{\min} + p_L(k) \end{aligned} \qquad (12)$$

4.4 Solution by quadratic programming

The objective functional $\Im_k$ may be written in terms of $\Delta u_{k/L}$. The future output $y_{k+1/L}$ can be eliminated from $\Im_k$ by using the PM (6). The input amplitude $u_{k/L}$ can be eliminated from $\Im_k$ by using (9). Therefore, the LQ objective functional becomes:

$$\Im_k = \Delta u_{k/L}^T H \Delta u_{k/L} + 2 f_k^T \Delta u_{k/L} + \Im_k^0 \qquad (13)$$

where:

$$H = R + F_L^T Q F_L + S^T P S$$
$$f_k = F_L^T Q\left(p_L(k) - r_{k+1/L}\right) + S^T P c u_{k-1}$$
$$\Im_k^0 = \left(p_L(k) - r_{k+1/L}\right)^T Q\left(p_L(k) - r_{k+1/L}\right) + u_{k-1}^T c^T P c u_{k-1}$$

H is the Hessian matrix, a constant positive definite matrix. f_k is a time-varying vector, independent of the unknown control deviation variable. $\Im_k^0$ is a known time-varying scalar, independent of the optimization problem.

The problem can be solved by the following QP approach:

$$\min_{\Delta u_{k/L}} \left(\Delta u_{k/L}^T H \Delta u_{k/L} + 2 f_k^T \Delta u_{k/L}\right) \qquad (14)$$

subject to (8). When $\Delta u_{k/L}$ is computed, the control signal to be applied to the process is $u_k = u_{k-1} + \Delta u_k$. (Note that only the first change in $\Delta u_{k/L}$ is used, i.e. a RHC strategy).

5. SIMULATION RESULTS

In order to test the performance of the 3SMPC controller, two different configurations are analyzed, just for set-point changes. It is necessary to state that depending on the use or not of Q_{in} as a manipulated variable, the dimensions of the matrices B_1 and B_2 in (2) change and, therefore, the objective function (14) and the constraints (8) are different for each control configuration. The tuning parameters of the both configurations are not here presented.

5.1 3x2 system

In this configuration, the influent flow is considered as a manipulated variable. In pre-denitrifying processes, the raw sewage is used as carbon source. Therefore, this configuration is applied to make good use of the influent COD concentration. In figures (2) to (4) the responses of the process to set-point changes are shown. It can be observed that the system responds quite well. The effluent inorganic nitrogen concentration (defined as the sum of the effluent ammonium and effluent nitrate concentration) is maintained at low level.

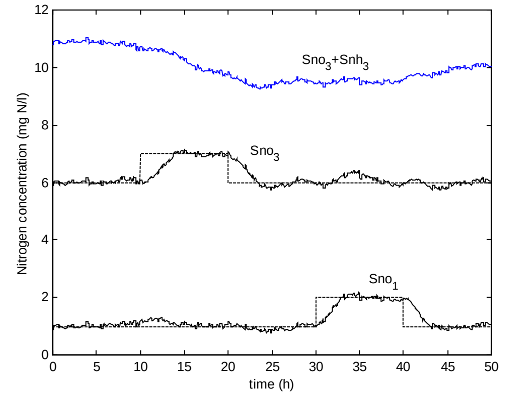

Fig. 2. Response of the process to set-point changes: controlled variables.

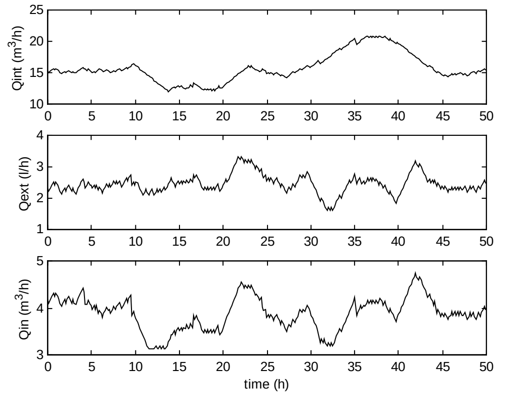

Fig. 3. Response of the process to set-point changes: manipulated variables.

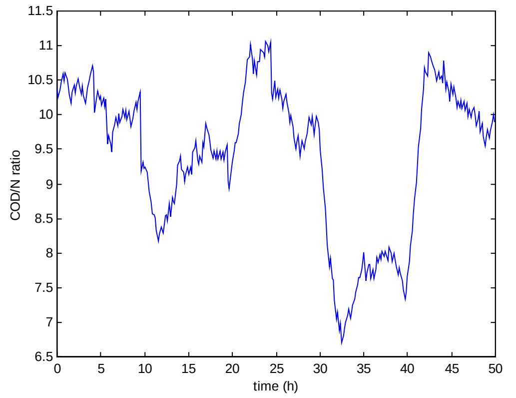

Fig. 4. Response of the process to set-point changes: COD/N ratio in the inlet of bioreactor.

5.2 2x2 system

In this case, the influent flow is kept constant (i.e. previously controlled, e.g. with a PI controller). Figures (5) to (7) show the response of the process to set-point changes. The variables are well-controlled. Nevertheless, a higher control effort is required.

Aiming to compare the performance of both configurations, here it is adopted the integral square error (ISE), which is based on the response system, defined as:

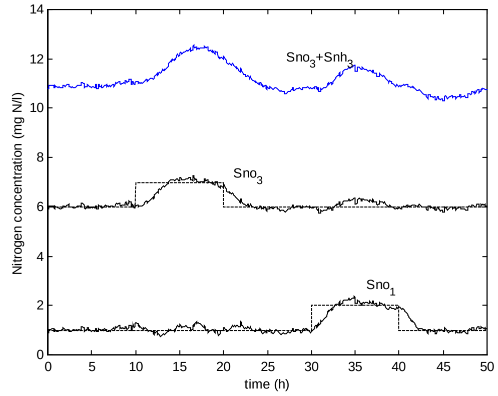

Fig. 5. Response of the process to set-point changes: controlled variables.

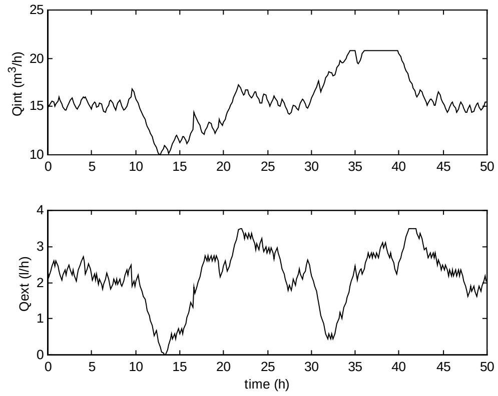

Fig. 6. Response of the process to set-point changes: manipulated variables.

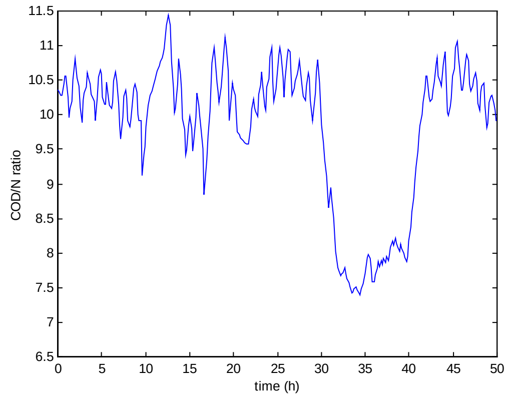

Fig. 7. Response of the process to set-point changes: COD/N ratio in the inlet of bioreactor.

$$ISE = \int (y_k - r_k)^2 \, dt \qquad (15)$$

In table 1, it can be observed that the 2x2 system presents a better performance, i.e. a lower ISE index.

Table 1. Numerical performance comparison for the two control configurations

System	ISE_1 (Sno_1)	ISE_3 (Sno_3)	ISE_T=ISE_1 +ISE_3
3x2	3.15	4.08	7.23
2x2	2.84	3.13	5.97

6. CONCLUSIONS

In this paper, a MPC controller was implemented to improve N-removal capability of AS plants, regulating the nitrate concentration in both zones of the bioreactor: the anoxic and the aerobic ones. In this approach, the effluent nitrate concentration was inferentially controlled. The MPC controller design is based on a general linear state-space model. However, there is no need for a state observer (e.g. Kalman filter).

The control was successful for set-point changes in both control configurations presented. In the 2x2 system, a higher control effort was required in the manipulated variables than in the 3x2 system. The 2x2 system presented a better performance in controlling the nitrate concentrations, but the 3x2 system was better successful in controlling inferentially the effluent inorganic nitrogen concentration, see figure (2) The mean variation of the COD/N ratio for both configurations are practically the same (see figure (4) and figure (7)).

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