

Adaptive control of the nitrate level in an activated sludge process

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Abstract In an activated sludge process for nitrogen removal, nitrate may be reduced to nitrogen gas by facultative heterotrophic bacteria in an anoxic environment. In order to guarantee sufficient supplies of readily biodegradable carbon compounds, an external carbon source often needs to be added. In this paper, an automatic control strategy for controlling the nitrate level using an external carbon source is presented. The external carbon source is added in the first anoxic zone to control the nitrate concentration in the last anoxic zone. Key process parameters are estimated on-line for a simplified Activated Sludge Model No 1. The estimated parameters are used for updating a linear quadratic controller. The strategy is illustrated in a simulation study with realistic influent data and is shown to perform very well.

Keywords Activated sludge process; denitrification; estimation; external carbon source; model based control

Introduction

The Activated Sludge Process (ASP) is a commonly used concept for processing biological nitrogen removal in municipal wastewater treatment plants (WWTPs). The degree of nitrogen removal in an ASP is dependent on the efficiency of two biological processes, nitrification and denitrification. In the denitrification, nitrate can be reduced to nitrogen gas by facultative heterotrophic bacteria in an anoxic environment. In this process, an organic carbon source is needed as electron donor and to supply carbon for synthesis of cell components. If the Carbon/Nitrate ratio is too low in the influent water to the anoxic zone, an addition of external carbon source is required (Henze *et al.*, 1995). An important question is how much carbon should be added. A too high carbon dosage is expensive, may increase the carbon load in the effluent, increase the sludge production (Aspegren *et al.*, 1992) and decrease the capacity of the microorganisms to use naturally existing carbon sources (Hallin and Pell, 1996). On the other hand, a too low carbon dosage will leave the denitrification process carbon constrained, and the full capacity for nitrogen removal is not utilized.

Adaptive and model-based approaches for control and estimation of wastewater treatment plants have been frequently reported in the literature. Such an approach is, for example, found in Bastin and Dochain (1990). The IAWQ Activated Sludge Model No.1 (ASM1) described in (Henze *et al.*, 1987) is frequently used for modeling of ASPs. Jeppsson (1996) and Weijers (2000) discuss the need for model reduction together with applications of different reduction techniques to the ASM1. In Lukasse (1999), an adaptive MPC evaluated on an alternating ASP with dissolved oxygen concentration as control input and ammonium and nitrate concentrations as controlled outputs, is presented. The reduced order model used in the control design is based upon ASM1 (Lukasse *et al.*, 1997). In Lindberg (1997) several different controllers for a predenitrifying process are designed.

Some of the reported strategies consider control of the nitrate concentration using the external carbon dosage as an input signal. In Lindberg and Carlsson (1996) a direct adaptive strategy for controlling the nitrate concentration, based on a generalized

minimum-variance (GMV) strategy is evaluated on a predenitrifying pilot plant. A controller design based on the ASM1 is presented in Yuan *et al.* (1997). The choice of optimal set-point for the carbon controller is also considered. A feedforward strategy based on a simple mass balance is presented in Samuelsson and Carlsson (2001). A related strategy is found in Carlsson and Milocco (2001) where a model based feedback-feedforward controller is designed by exact linearization of a simplified ASM1. A cascade control strategy for controlling the nitrate concentration in both the effluent and in the last anoxic compartment is proposed in Cho *et al.* (2002).

In this paper a model based adaptive control strategy is suggested. The model used for controller design rests upon ASM1. By applying some simplifying assumptions, a reduced order time-varying state-space model is employed for describing the dynamic behavior of the nitrate in the anoxic compartment. The time-varying model parameters are updated at each sampling period and estimated from measurements of nitrate concentration and Total Suspended Solids (TSS). The derived state-space model is then used in the design of a Linear Quadratic Gaussian (LQG) controller utilizing both feedback and feedforward from measurable disturbances.

A reduced order state-space model for the anoxic compartment

The ASM1 is a widely used model for simulation of the ASP. Due to its complexity, it is far from trivial to use the ASM1 directly for controller design. In order to design the external carbon flow rate controller, a reduced order state-space model of the ASM1 is presented in this section. The model reduction is based on lumping of components together with some simplifying assumptions, see also Jeppsson (1996). This procedure aims to maintain the basic mechanistic structure and the significant reactions in ASM1. Another reason for lumping components is that several of the components in ASM1 are not measurable.

Initially, one completely mixed anoxic compartment in a denitrifying system will be considered. It is assumed that the compartment has a constant volume V and that the concentration of dissolved oxygen is zero. The dilution rate is $D(t) = Q(t)/V$, where $Q(t)$ is the time-varying inflow to the compartment. The impact of an external carbon source is modelled as an addition of readily biodegradable substrate, $S_{S,C}(t)$. The control variable is considered as the diluted concentration, see also Samuelsson and Carlsson (2001):

$$u(t) = \frac{Q_C(t)}{V} S_{S,C}(t)$$

where $Q_C(t)$ is the flow rate of the external carbon source and $S_{S,C}(t)$ is the COD concentration of the carbon source.

In order to reduce the number of equations in ASM1 and obtain measurable variables, new lumped variables are defined as:

$$X_{TSS}(t) = X_B(t) + X_I(t) + X_S(t) \quad (1)$$

$$X_{COD}(t) = X_{TSS}(t) + S_S(t) + S_I(t) \quad (2)$$

where $X_B(t)$ is the total biomass, $X_S(t)$ is the slowly biodegradable substrate, $S_I(t)$ is the soluble inert organic matter, and $S_S(t)$ is the readily biodegradable substrate. The inert and particulate organic matter as defined in ASM1 are combined into one variable $X_I(t)$. $X_{TSS}(t)$ in (1) can be regarded as the TSS and $X_{COD}(t)$ in (2) as the total COD. From (1)–(2), the sum of $S_S(t)$ and $S_I(t)$ can be calculated as:

$$S_{COD}(t) = X_{COD}(t) - X_{TSS}(t) \quad (3)$$

which may be well approximated as the concentration of soluble COD. The mass balance of the nitrate, $S_{NO}(t)$, and the new variables in (1)–(2) can for one completely mixed anoxic reactor be written as (see Ekman *et al.* (in press) for a derivation):

$$\dot{S}_{NO}(t) = -R(t) + D(t)(S_{NO,in}(t) - S_{NO}(t)) \quad (4)$$

$$\dot{X}_{TSS}(t) = -\alpha Y_H R(t) + D(t)(X_{TSS,in}(t) - X_{TSS}(t)) - H(t) \quad (5)$$

$$\dot{X}_{COD}(t) = -2.86R(t) + D(t)(X_{COD,in}(t) - X_{COD}(t)) + u(t) \quad (6)$$

where variables with the subscript *in* denote influent concentrations to the anoxic zone. $H(t)$ is a hydrolysis term which is assumed to be constant or slowly time-varying, and

$$R(t) = \frac{1 - Y_H}{2.86 Y_H} \hat{\mu}_H \left(\frac{S_S(t)}{K_S + S_S(t)} \right) \left(\frac{S_{NO}(t)}{K_{NO} + S_{NO}(t)} \right) \eta_g X_{B,H}(t) \quad (7)$$

$$\alpha = -\frac{2.86}{1 - Y_H} \quad (8)$$

For an explanation of the different parameters in (7)–(8) and their typical default values, see Henze *et al.* (1987). In the following it is assumed that the yield of the heterotrophic biomass, Y_H , is known.

From now on, the model (4)–(6) is extended to two anoxic compartments with equal volumes V . Subscript *1* and *2* are used to denote components in the first and second compartment respectively. By substituting $S_S(t)$ in the numerator of (7) by $S_{COD}(t)$ in (3), and using the relationship $X_{COD,in}(t) = X_{TSS,in}(t) + S_{COD,in}(t)$, a state-space representation of order six with the following structure is obtained:

$$\dot{z}(t) = F(r_i(t), t)z(t) + B_u u(t) + G_g(t)g(t) + G_v v(t) \quad (9)$$

where the states are $z(t) = [S_{NO,1}(t), S_{NO,2}(t), X_{TSS,1}(t), X_{TSS,2}(t), X_{COD,1}(t), X_{COD,2}(t)]^T$. The vector $g(t)$ denotes measurable disturbances and $v(t)$ denotes non-measurable disturbances:

$$g(t) = \begin{pmatrix} D(t)S_{NO,in}(t) \\ D(t)X_{TSS,in}(t) \\ S_{COD,in}(t) \end{pmatrix} \quad (10)$$

$$v(t) = \begin{pmatrix} H_1(t) \\ H_2(t) \end{pmatrix} \quad (11)$$

The matrix $F(r_i(t), t)$ is dependent on the transformed reaction rate terms $r_1(t)$ and $r_2(t)$ given by:

$$r_i(t) = \frac{R_i(t)}{S_{COD,i}(t)}, \quad i = 1, 2$$

The time-varying $r_i(t)$ is unknown and has to be estimated. The system matrix $F(r_i(t), t)$ and the matrix $[B, G_g(t), G_v]$ are defined in Ekman *et al.* (in press).

Estimation of the reaction rate terms

One approach to estimate the reaction rate terms $r_1(t)$ and $r_2(t)$, is to use an extended Kalman filter (EKF) applied to (9). With an EKF the states and the reaction rate terms can be estimated simultaneously. The state vector in (9) is augmented by the unknown model

parameters, $r_1(t)$ and $r_2(t)$, and by the hydrolysis terms, $H_i(t)$ from (11). The new states are assumed to be Wiener processes, which in discrete-time correspond to random walk processes. The augmented system (9) is sampled and a discrete time EKF is implemented. Estimates of the unknown states, reaction rate terms and the hydrolysis terms can then be obtained. See e.g. Söderström (1994) for a derivation of the EKF algorithm in discrete time.

In the estimation procedure it is assumed that the concentration of nitrate in the last anoxic zone, $S_{NO,2}(t)$, the concentrations of SS in the two anoxic compartments, $X_{TSS,i}(t)$, $i=1, 2$, the dilution rate, $D(t)$ and the influent concentrations, $S_{NO,in}(t)$ and $X_{TSS,in}(t)$, are measured on-line. The convergence of the estimates of $r_i(t)$ and $H_i(t)$ clearly improved with the reasonable assumption that $S_{COD,in}(t)$ can be estimated in twenty-four hour intervals from measurements of the total COD.

A recursive least square (RLS) estimation procedure has also been evaluated, but recent results indicate that the EKF performs better. In the EKF procedure, it is also possible to use sensors of more standard type, which is not the case in the RLS procedure.

Controller design

In the derivation of the LQG controller it is assumed that $D(t)S_{NO,in}(t)$, $S_{NO,2}(t)$, $D(t)X_{TSS,in}(t)$, $X_{TSS,1}(t)$ and $X_{TSS,2}(t)$ in (9) are measurable. It is also assumed that $D(t)S_{COD,in}(t)$ is measured in twenty-four hour intervals. The controller design is based on a reduced order model. The reduced order of the model is obtained by replacing the states $X_{TSS,i}(t)$ and $X_{COD,i}(t)$ in (9) with the new state variables $S_{COD,i}(t) = X_{COD,i}(t) - X_{TSS,i}(t)$. The resulting reduced order state-space representation has the structure:

$$\dot{x}(t) = A(r_i(t), t)x(t) + Bu(t) + G_d d(t) + G_h v(t) \quad (12)$$

where the states are $x(t) = [S_{NO,1}(t), S_{NO,2}(t), S_{COD,1}(t), S_{COD,2}(t)]^T$ and the measurable disturbances are $d(t) = [D(t)S_{NO,in}(t), D(t)S_{COD,in}(t)]^T$. For a derivation of the system matrices in (12), see Ekman *et al.* (in press).

The LQG controller is designed in discrete time. Hence, the first step is to sample the system (12). Here the zero-order hold method is used, see for example Åström and Wittenmark (1997). In order to obtain feedforward action in the LQG controller, the measurable disturbance vector, $d(t)$ is included in the state vector in (12). There exist several different strategies for design of integrating controllers. The approach used here is based on differentiation of the system resulting in an incremental controller.

After rewriting (12) in a discrete-time and differential form with $d(t)$ included in the state vector, a feedforward feedback integrating controller can be designed. The differentiation of the model results in the disappearance of constant process disturbances in the model. Hence, the assumption that the hydrolysis terms are constant results in that $v(t)$ can be omitted from (12) in the controller design. The sampled and differentiated system can now be written as:

$$\begin{pmatrix} \Delta x_n(t+1) \\ y(t+1) \end{pmatrix} = A_d \begin{pmatrix} \Delta x_n(t) \\ y(t) \end{pmatrix} + B_d \Delta u(t) \quad (13)$$

where A_d and B_d are the discrete time system matrices obtained from the zero-order hold sampling, and $y(t) = S_{NO,2}(t)$ is the output signal. Further, $\Delta x_n(t+1) = x_n(t+1) - x_n(t)$, etc. The differentiated state vector is $\Delta x_n(t) = [\Delta x(t) \Delta d(t)]^T$.

The system matrices, A_d and B_d in (13) are updated at each sampling instant using the EKF estimates of $\hat{r}_1(t)$ and $\hat{r}_2(t)$. The states $S_{COD,i}(t)$ are estimated using the relationship:

Furthermore it was assumed that the parameter $S_{COD,in}(t)$ could be measured in twenty-four hour intervals. The data used for estimation and control was sampled with a sampling period of 1 minute without noise and delay on the sensors.

The external carbon source was assumed to be ethanol with $S_{S,C} = 1,200,000$ mg (COD)/l. An upper bound on the external carbon flow rate was introduced and chosen as 5 m^3 ethanol/day. The design variables of the LQG controller were chosen in a way that the controller behaved as fast as possible without exceeding the upper bound on $u(t)$, when influent data from the file dryinfluent was used. The nitrate set-point was 4 mg/l. The penalty matrices in (15) were chosen as $Q_1 = \text{diag}[0, 0, 0, 0, 1, 1, 10]$ and $Q_2 = 100,000$. The initial value of the covariance matrix in the EKF was $P(0) = I$, where I denotes the unit matrix. The design variables in the EKF were chosen as $R_1 = \text{diag}[10, 1, 10, 1, 1, 1, 1, 1, 1, 0.01]$ and $R_2 = 0.01I$.

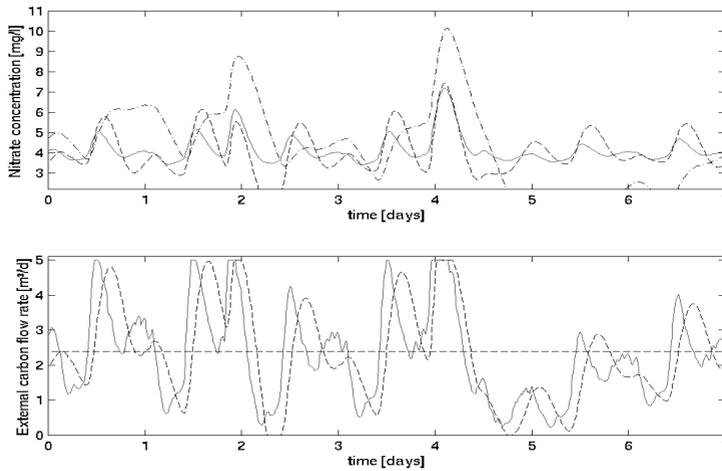


Figure 2 Upper plot: The solid line shows the nitrate concentration in the last anoxic compartment when the LQG controller is used, dashed line shows the nitrate concentration when the PID controller is used, dash-dotted line shows the nitrate concentration when a constant flow rate of external carbon source is added. Lower plot: The external carbon flow rates are shown for the two controllers and the constant flow rate of external carbon source of 2.4 m^3 ethanol/day, respectively

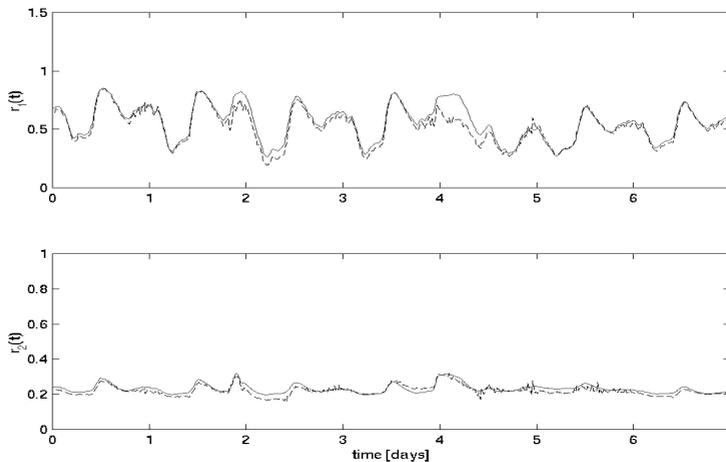


Figure 3 Upper plot: The dashed line shows the EKF estimated value of $r_1(t)$. The solid line shows the true value. Lower plot: The dashed line shows the EKF estimated value of $r_2(t)$. The solid line shows the true value

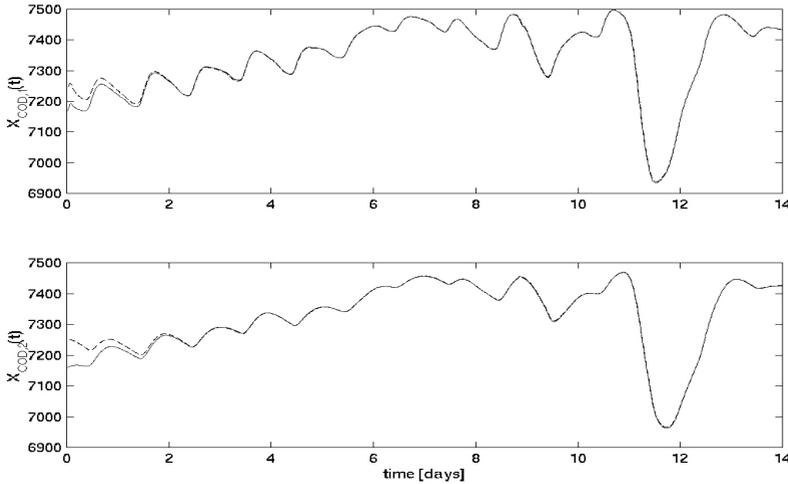


Figure 4 Upper plot: The dashed line shows the EKF estimated value of $X_{COD,1}(t)$. The solid line shows the true value of $X_{COD,1}(t)$. Lower plot: The dashed line shows the EKF estimated value of $X_{COD,2}(t)$. The solid line shows the true value of $X_{COD,2}(t)$

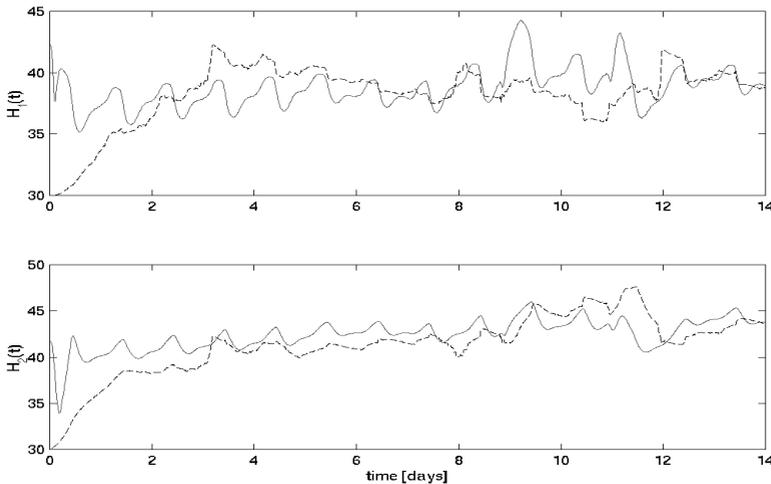


Figure 5 Upper plot: The dashed line shows the EKF estimated value of the hydrolysis term $H_1(t)$. The solid line shows the true value. Lower plot: The dashed line shows the EKF estimated value of the hydrolysis term $H_2(t)$. The solid line shows the true value

For comparison, a traditional PID controller was also implemented. The PID parameters were tuned to make the controller as fast as possible without exceeding the upper bound on $u(t)$ when simulating the file `dryinfluent.mat`. The upper bound on $u(t)$ and the nitrate set-point were the same as for the LQG controller.

Results and discussion

The simulation result for the two different controllers is illustrated in Figure 2. The seven last days of the simulation using data from the `storminfluent.mat` file are shown in the plot. When comparing the feedforward integrating LQG controller designed in this paper to the PID controller, it is seen that the LQG controller gives a faster disturbance rejection than the PID controller. It is worth noticing that none of the controllers are optimally tuned.

Figure 3 illustrates estimation of the reaction rate terms, $r_1(t)$ and $r_2(t)$, during the same

time period as in Figure 2. EKF also performs a good estimate of the total COD, $\hat{X}_{COD,i}(t)$, in the two anoxic compartments, and a satisfactory estimates of the hydrolysis terms, $\hat{H}_i(t)$. This is illustrated in Figure 4 and 5.

Conclusion

In this paper, a model based control strategy for control of the nitrate level in the last anoxic compartment, using an external carbon source is presented. By lumping some states in ASM1 a feasible state-space model for estimation was derived. The model was then used for on-line design of an integrating LQG controller. This strategy can be regarded as an indirect adaptive LQG controller. The controller was evaluated in a simulation study and performed very well despite major process disturbances. Interesting topics for further research are to extend the controller for internal flow rate control and supervisory dissolved oxygen control. Also an evaluation using pilot or full-scale experiments could be done.

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