MODELLING AND CONTROL OF AN N-REMOVING ACTIVATED SLUDGE PROCESS

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Abstract

In this paper an approach to obtain a control strategy for optimal N-removal in alternatingly aerated, continuously mixed, continuously fed activated sludge processes (ASP's) using adaptive Receding Horizon Optimal Control (RHOC) is presented. This control strategy is successfully tested both in simulation and pilot plant experiments. The RHOC approach offers an excellent opportunity to link the higher level of plant economy and the lower level of plant control by expressing the plant economy in the RHOC's cost criterion, including constraints on in- and outputs. Essential for the performance of RHOC controllers is the availability of accurate predictions of near-future NH_4 and NO_x concentrations. A recursive estimator for the model parameters of a grey-box model identified from experimental data is designed to keep the model close to the real process behaviour.

1 Introduction

Recently, the Dutch Water Boards have been faced with the legislatory demand to reduce the yearly averaged total effluent nitrogen to at most 10 mg/l by the year 1999. Usually, wastewater treatment plants (WWTP's) contain aeration tanks for COD-removal and nitrification (see Fig. 1), a first step in the N-removing process. In the Netherlands so-called carrousels, aeration tanks with hydraulic characteristics somewhere between continuously mixed and plug flow, are often found at WWTP sites. The required second step of denitrification can be realised by creating (unaerated) anoxic periods in the aeration tank, as it is usually underloaded.

In current practice the alternation between aerobic and anoxic modes in alternatingly aerated ASP's is often based on timers. The currently available feedback controllers for this type of process normally employ measurements that are only capable of indicating the depletion of NH_4 and NO_x, e.g. Oxygen Reduction Potential (ORP) [1] or Oxygen Uptake Rate (OUR) [2] measurements. Recently, it has also been shown that more advanced operation may improve process performance [3].

The objective of this paper is to develop an aeration strategy for economically optimal N-removal in continuously mixed, continuously fed aeration tanks by means of Adaptive Receding Horizon Optimal Control (ARHOC) using NH_4-N and NO_x-N measurements. The design of an ARHOC strategy is regarded as an intermediate step in the development of such control strategies for full-scale plants with carrousels. The merit of the RHOC approach is that it optimises a cost criterion on-line and straightforwardly handles constraints on both in- and outputs, using model predictions. By expressing the plant economy in the cost criterion a natural relation between plant control and plant economy emerges.

The model-based controller design approach presented in this paper contains the following steps. First dominant patterns in the control input are determined by solving a non-linear optimal control problem given the widely accepted, but complex, Activated Sludge Model (ASM) no. 1 [4]. For practical implementation a receding horizon optimal control strategy, preferably on the basis of a simple prediction model to allow fast computation as well as recursive parameter estimation, has to be designed. Hence, in the second step an identification experiment is performed. The dominant patterns, obtained from the first step, are used to design this experiment with the ultimate goal to identify a possibly simpler non-linear model structure from prior knowledge and experimental data. It is well-known that the nitrification/denitrification process is subject to strong diurnal and seasonal variations and each individual plant has a unique influent characteristic and micro-organism population. Consequently, recursive estimation techniques are used to estimate the unknown, time-varying parameters and to estimate the commonly unknown NH_4-concentration in the influent. On the basis of this time-varying grey-box process model and a given cost criterion, an adaptive RHOC strategy is designed.

In this study the resulting adaptive RHOC controller is tested both in simulation and on a continuously mixed pilot plant, continuously fed with presettled municipal wastewater.

2 Grey-box modelling

According to the ASM no. 1 on a short time scale nitrification/denitrification are mainly affected by the concentrations of NH_4, NO_x, readily biodegradable organic substrate and dissolved oxygen (DO), denoted as S_{NH}, S_{NO}, S_S and S_O . In our application S_O is treated as control input, which in the implementation phase will be used as setpoint for an earlier developed slave DO-controller [5]. To enable the formulation of an optimal control problem the dynamic mass balances of the three other quantities S_{NH}, S_{NO} and S_S are required. These equations can be extracted from the ASM no. 1.

In [6] it is shown, as a solution to a highly non-linear optimal control problem, that a predominantly alternating aeration strategy may well be optimal for these system equations. This result further justified the common practice of an alternating aeration strategy in wastewater treatment plants.

On the basis of this result, identification experiments have been designed and the following model structure has been identified,

$$\frac{d}{dt}\begin{bmatrix} S_{NH} \\ S_{NO} \end{bmatrix} = \frac{-q_{in}}{V}\begin{bmatrix} S_{NH} \\ S_{NO} \end{bmatrix} + \begin{bmatrix} -r_{NH} \\ r_{NH}+r_{NO} \end{bmatrix} u + \begin{bmatrix} \frac{q_{in}}{V} S_{NH,in} \\ -r_{NO} \end{bmatrix} \quad (1)$$

$$r_{NH} = \begin{cases} r_{NH,max} & \text{if} \quad S_{NH} > 0 \\ \frac{q_{in}}{V} S_{NH,in} & \text{if} \quad S_{NH} = 0 \end{cases} \quad (2)$$

$$r_{NO} = \begin{cases} r_{NO,max} & \text{if} \quad S_{NO} > 0 \\ 0 & \text{if} \quad S_{NO} = 0 \end{cases} \quad (3)$$

$$\begin{bmatrix} y_1(k) \\ y_2(k) \end{bmatrix} = \begin{bmatrix} S_{NH}(k-d) \\ S_{NO}(k-d) \end{bmatrix} + \begin{bmatrix} e_1(k) \\ e_2(k) \end{bmatrix} \quad (4)$$

with $u \in \{0, 1\}$, representing an on/off aeration strategy such that $S_O = 0$ or $S_O = S_O^*$, where S_O^* is the non-limiting DO concentration. Here, S_O^* is chosen to be equal to 2 mg/l. In Eqn. 1 the term $q_{in}S_{NH,in}$ represents the reactor's influent load, $r_{NH}\,u$ represents the nitrification and $r_{NO}\,(1–u)$ represents the denitrification process, including the effect of S_S which is not explicitly modelled. Furthermore, the pure time delay induced by the analysers is represented by d in Eqn. 4.

This model is extremely simple in comparison to the generally accepted ASM no. 1. The simplification is justified as basically only four time-varying slopes determine the system behaviour. Due to the alternating process operation simultaneous nitrification/denitrification will only occur during the transient from aerobic to anoxic phases and *vice versa*. These transients typically take a couple of minutes, while one phase lasts at least 20 minutes. So the transients are negligible and it is justified to assume $S_O = S_{O,R}$, the DO setpoint, instead of modelling the region of DO-limited process rates ($0<S_O<2$ mg/l). It was also observed that the region of partially substrate limited process rates is very small. Consequently, the process is hardly operated in this region. Therefore the generally used Monod kinetics can be replaced by hard switching functions, *i.e.* nitrification is maximal if $S_{NH} > 0$ and equal to the influent load if $S_{NH} = 0$ (Eqn. 2), and denitrification is maximal if $S_{NO} > 0$ and zero if $S_{NO} = 0$ (Eqn. 3). The remaining simplifications are the slower or less significant process mechanisms related to growth of biomass. These changes are accounted for by recursive estimation of the model parameters $r_{NH,max}$ and $r_{NO,max}$., the maximum NH_4-N and NO_x-N consumption rate, respectively. Also $S_{NH,in}$, which is not measured usually, is known to exhibit strong variations. Hence, the parameter vector for recursive identification is defined as, $\boldsymbol{\theta} := [S_{NH,in} \quad r_{NH,max} \quad r_{NO,max}]^T$.

3 Receding Horizon Optimal Control

In a first step, non-linear optimal control theory has been used to identify an open-loop optimal control strategy. However, to enable on-line implementation there is a need to introduce feedback, requiring fast computation of the optimal control inputs. Feedback can be simply introduced by employing the Receding Horizon Optimal Control (RHOC) concept (see *e.g.* [7]).

The basic RHOC approach solves at each sampling instant k an optimal control problem with $t_0 = kT$ and $t_f = (k+H)T$ (T = sampling interval, H = prediction horizon) and implements only the optimal control input $u^*(k)$. At k+1 the new output vector $\mathbf{y}(k+1)$, which will deviate from the predicted output $\hat{\mathbf{y}}(k+1\,|\,k)$, is measured and the RHOC problem is solved again, with $t_0 = (k+1)T$, $t_f = (k+H+1)T$ and $\mathbf{y}(k+1)$ as initial condition. The RHOC control algorithm for this specific application is given by

$$\min_u J(u) = \sum_{i=1}^{H} \{ w \cdot |(S_{NH,R} - S_{NH}(k+i))| + |S_{NO,R} - S_{NO}(k+i)| + \lambda \cdot \max\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} S_{NH,min} - S_{NH}(k+i) \\ S_{NO,min} - S_{NO}(k+i) \end{bmatrix} \right) \} \quad (5)$$

subject to initial condition $[S_{NH}(k)\ \ S_{NO}(k)]^T$, the control input constraints

$$u(k+i-1) \in \{0,\ 1\} \qquad i \in [1,\ H] \quad (6)$$

the expected input disturbances $q_{in}(k+i-1)$, $S_{NH,in}(k+i-1)$ with $i=1,..,H$, and the system dynamics:

$$\begin{bmatrix} S_{NH}(k+1) \\ S_{NO}(k+1) \end{bmatrix} = e^{-\frac{q_{in}}{V}T} \begin{bmatrix} S_{NH}(k) \\ S_{NO}(k) \end{bmatrix} + \frac{e^{-\frac{q_{in}}{V}T} - 1}{-\frac{q_{in}}{V}} * \left(\begin{bmatrix} -r_{NH} \\ r_{NH} + r_{NO} \end{bmatrix} u(k) + \begin{bmatrix} \frac{q_{in}}{V} S_{NH,in} \\ -r_{NO} \end{bmatrix} \right) \quad (7)$$

$$r_{NH} = \begin{cases} r_{NH,max} & S_{NH} > 0 \\ \frac{q_{in}}{V} S_{NH,in} & S_{NH} = 0 \end{cases} \quad (8)$$

$$r_{NO} = \begin{cases} r_{NO,max} & S_{NO} > 0 \\ 0 & S_{NO} = 0 \end{cases} \quad (9)$$

$$\begin{bmatrix} y_1(k) \\ y_2(k) \end{bmatrix} = \begin{bmatrix} S_{NH}(k-d) \\ S_{NO}(k-d) \end{bmatrix} \quad (10)$$

where $u = S_{O,R} / S_O^*$. The last term in the cost criterion is added to avoid less effective aerobic and anoxic periods in which substrate limitations may occur in the plant.

Recall that the equivalent discrete-time model (Eqns. 7-10) of the continuous-time model (Eqns. 1-4) is only valid for non-limiting substrate conditions and for $S_{O,R} \in \{0, S_O^*\}$. Due to the discrete control input the RHOC problem can be solved at each sampling instant by enumeration, *i.e.* by just computing the cost criterion value for all 2^H possible control trajectories. The attractive feature of this is that a globally optimal solution of Eqn. 5 is guaranteed. A detailed study of the RHOC controller's behaviour as a function of the tuning parameters T, w, $S_{NH,R}$, $S_{NO,R}$ and H is presented in [6].

In summary, the sampling interval T is selected equal to the pure time delay of 20 min. in the analysers. This value of T may be altered, but there is not much to be gained. Consequently, d in Eqn.10 is set to 1. The weight w acts as a switching function with a threshold

$$w_c = \frac{|r_{NH,\max} + r_{NO,\max}|}{|r_{NH,\max}|} \quad (11)$$

Either S_{NH} or S_{NO} is controlled to its setpoint depending on the value of w, while the other follows as a consequence. If $0<w<w_c$ then S_{NO} is well controlled, if $w>w_c$ then S_{NH} is well controlled. It is most appealing to set both setpoints $S_{NH,R}$ and $S_{NO,R}$ at zero, as this is every operator's ideal. In most cases removal of S_{NH} has priority, so one will choose to control S_{NH} to its setpoint by selecting $w>w_c$. If one wants to adhere to a purely economical tuning one should select $S_{NH,R} = S_{NO,R} = 0$ and w = (costs of effluent S_{NH} minus aeration costs for S_{NH} removal) divided by the costs of effluent S_{NO}. The prediction horizon H is set to only one sampling interval, since it has been shown in [6] and further proven in [8] that larger H yields no improvement at all, while the computational burden increases exponentially with H. The weight λ is chosen such that the last term in the cost criterion prevails over the other two terms: λ = 100 proved sufficient. The lower bounds $S_{NH,min}$ and $S_{NO,min}$ are set at 0.3 mg/l.

4 Adaptive Receding Horizon Optimal Control

The RHOC controller of the preceding section yields optimal N-removal provided that an accurate dynamic process model is available. Due to the time variance in activated sludge processes an accurate model can only be available when recursively estimating the time varying model parameters in $\boldsymbol{\theta}$. Due to space limitations we suffice to say that it has been proven in [9] that stability of the recursive least-squares estimator is guaranteed provided that the aeration does not remain constant for very long periods (over a year).

Adaptive RHOC (ARHOC) is just the combination of the preceding RHOC scheme and a recursive identification scheme. The overall control algorithm performs at sampling instant k the following steps:

1. calculate the one-step ahead prediction: $\hat{\mathbf{y}}(k \mid k-1, \hat{\boldsymbol{\theta}}(k-1))$
2. evolve the recursive least-squares estimator, using the prediction error $\mathbf{y}(k) - \hat{\mathbf{y}}(k \mid k-1, \hat{\boldsymbol{\theta}}(k-1))$ and the time-

varying observation matrix, to obtain estimates of the covariance matrix $\mathbf{P}(k)$ and the parameter vector $\hat{\theta}(k)$

3. reconstruct the state $[S_{NH}(k) \quad S_{NO}(k)]^T$ from Eqns. 7-10 using $\mathbf{y}(k)$, $\hat{\theta}(k)$, $u(k–d)$ and $q_{in}(k–d)$

4. solve the RHOC problem (Eqns. 5-10) using $\hat{\theta}(k)$ and initial condition $[\hat{S}_{NH}(k) \;\; \hat{S}_{NO}(k)]^T$

5. implement the computed optimal control $u^*(k)$

The main difficulty in adaptive control in general is that the controller and the estimator operate together in one closed loop. The overall closed loop behaviour is inherently non-linear in u and $\hat{\theta}$, which makes it generally impossible to get more than a region of stability, *i.e.* local stability results ([10]). Moreover, the information in the measured output signal gradually shifts to high frequencies when the process becomes better controlled. When the parameters are estimated on the basis of this ever poorer information the model actually drifts from process model to noise model. Therefore, special precautions need to be taken to preserve sufficient richness of u. The typical solution is to add a little dither signal to the control input or to the setpoint, from which a logical inconsistency emerges: to enable the control improvement by adaptive control it needs to be deteriorated by adding a dither signal.

This paper's application has some features, which make the use of a dither signal redundant. That is, the control input u can only take two values, which guarantees sufficient richness of the measurements provided that u is switched regularly and T is large enough. If T is large enough the shift of measurement information to high frequencies can be excluded. The highest possible input frequency is reached by switching the value of u at each sampling instant. At this frequency, in case T = 20 min, there still is sufficient information in the measurement outputs to allow for the estimation of reasonable $\hat{\theta}$-trajectories. Obviously the smaller T the larger the percentage of time in which DO is at values between 0 and 2 mg/l. This puts a (not exactly known) lower limit to T, below which the sufficient richness gets lost and $\hat{\theta}$ might drift away indeed. If this behaviour is observed when implementing this adaptive controller, it can be removed by simply increasing T.

On the basis of simulation results of the ARHOC strategy under non-limiting substrate conditions a simple control strategy has been deduced, *i.e.* keep the NH_4 concentrations between two bounds by switching the aeration on/off, as will also be demonstrated by the pilot plant results in the next section.

5 Pilot plant results

Several experiments have been carried out on a pilot scale ASP with continuously mixed aeration tank (V = 475 l, Mixed Liquor Suspended Solids (MLSS) concentration = 2 g/l), continuously fed with presettled municipal wastewater, preceded by a 40 l anoxic tank for predenitrification. The average sludge load during dry weather conditions is roughly 0.2 kg COD/kg MLSS.day. The concentrations S_{NH} and S_{NO} in the aeration tank are measured using SKALAR auto-analysers type SA 9000. The DO concentration S_O is tightly controlled at a setpoint alternating between 0 and 2 mg/l by means of an earlier developed robust model-based predictive controller ([5]). The q_{in} pattern for the experiments is obtained by monitoring the influent flow of the adjacent full-scale WWTP of the town of Bennekom and downscaling this signal to a reasonable level for the pilot plant. In this way a natural relationship between diurnal influent flow and influent pollution variations is guaranteed.

One of the resulting data sets and the accompanying estimates of $\theta(k)$ are shown in Figs. 2 and 3. The gaps in the data, and indicated by a fat overbar in Fig. 2, are due to analyser calibrations. Notice that, as expected from the simulation results, S_{NH} is controlled between bounds (roughly between 4-6 mg/l), except when S_{NO} hits its lower bound (0.3 mg/l) around t = 800 min. In that situation of NO_3-N limitation S_{NH} is reduced further due to the penalty term in the objective functional (Eqn. 5). In the estimated $r_{NO,max}$ (Fig. 3) a slight diurnal cycle is observed, due to the decreased carbon source during the low loaded part of the day (around t = 800 min). In correspondence with earlier experience ([9]) $r_{NH,max}$ is about twice as high as $r_{NO,max}$.

6 Concluding remarks

The presented adaptive RHOC controller showed good performance, both in simulation (not shown here) and in pilot plant application. The control algorithm's stability region is not exactly known, but after many simulations and pilot plant experiments it has been learned how to prevent instability. For instance, after a start-up we first control the plant manually and let the estimator stabilise to prevent negative parameter values. After this the automatic controller is switch on.

The controller is believed to be of direct practical relevance, because the use of an economy-related cost criterion offers a natural way to bridge the gap between the higher level of plant economy and the lower level of plant control. Moreover the use of a recursive estimator for the RHOC's model parameters will fine-tune the controller to the specific plant under control and it will provide additional process information to the operator.

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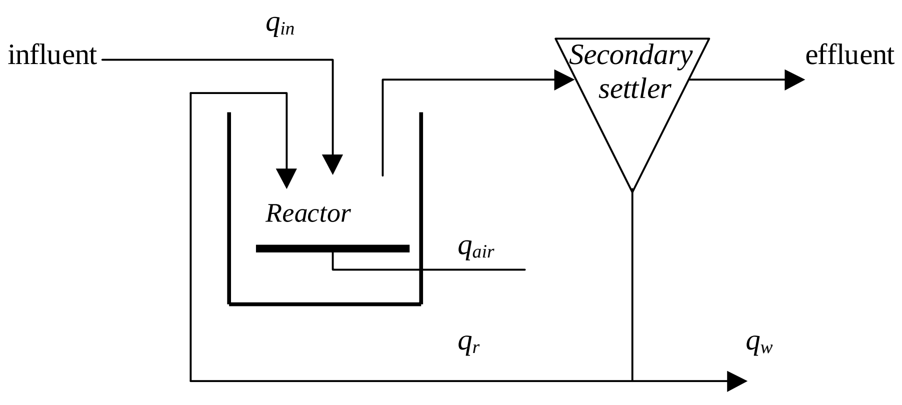

Fig. 1. Schematic representation of the activated sludge pilot plant.

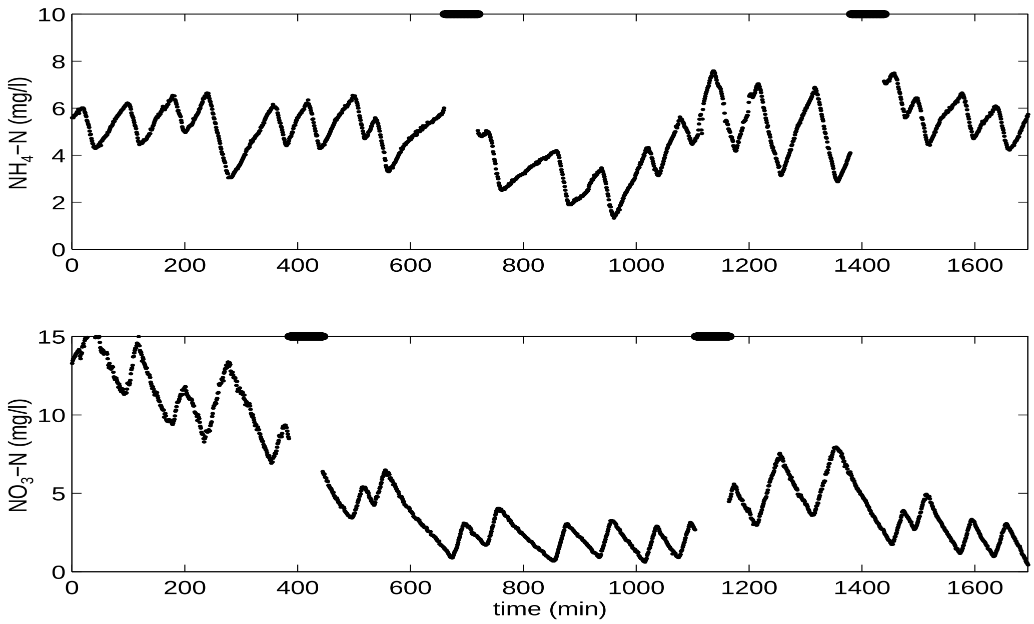

Fig. 2. Controlled NH_4-N and NO_3-N concentrations (fat overbar: periods of analyser calibation).

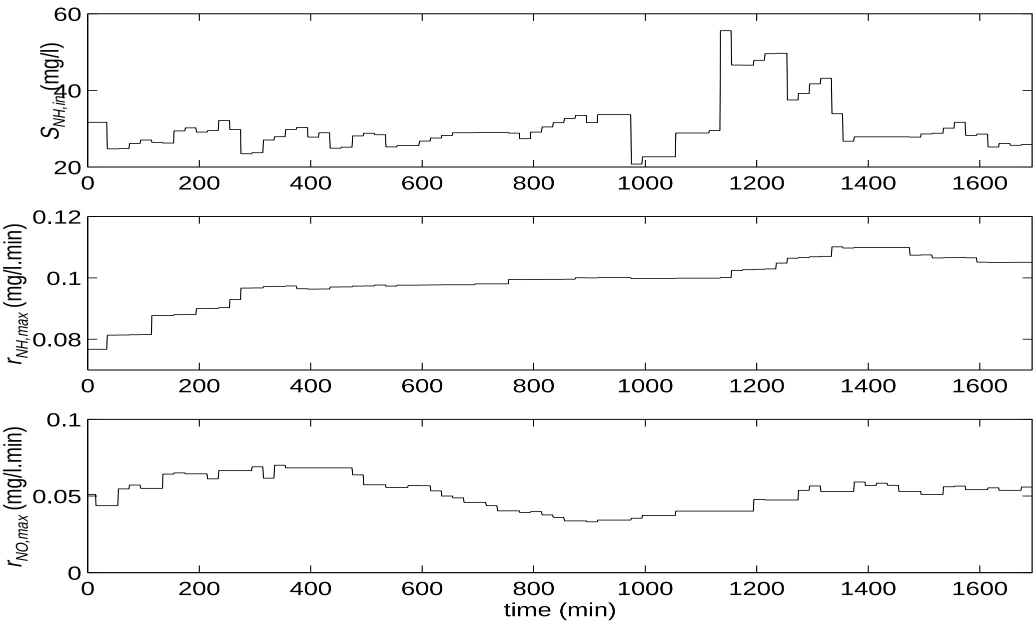

Fig. 3. Recursive estimates of the time-varying model parameters.