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OPTIMIZATION AND CONTROL OF ALTERNATING AEROBIC/ANOXIC ACTIVATED SLUDGE OPERATION

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Abstract: Although first principles models of activated sludge waste water processes exist, e.g. the ASM1 model, these models have rarely been used in practice for control or optimization. One problem with such usage is the complexity of the models, and another is their accuracy. This paper discusses the use of a linearized version of the ASM1 model for control and optimization of an alternating aerobic/anoxic activated sludge system. The linear nature of the model facilitates its use for online calculations, and feedback is used to overcome problems of model accuracy. *Copyright © 1999 IFAC*

Keywords: Waste treatment, model based control, optimization, simulation

1. INTRODUCTION

Currently, a variety of activated sludge processes, e.g., the patented Bardenpho, A^2/O, and BioDenipho systems have been employed in waste water treatment plants for nutrient removal. Different environmental conditions are created in these processes to meet the specific requirements of phosphorus release under anaerobic conditions, phosphorus uptake and nitrification under aerobic conditions, and denitrification under anoxic conditions. With proper design and operation, these processes can meet effluent requirements such as total nitrogen (TN) < 8 mg/L and total phosphorus (TP) < 1 mg/L. In general, process control in waste water treatment is in its infancy; computers or computer systems have been used in some plants to monitor dissolved oxygen for process control operation. With dwindling operation budgets and more stringent discharge standards being considered, process optimization through development of a process model and advanced process control becomes more important.

In fact, the area of modeling biological phenomena has received considerable attention lately. An adequate model not only enhances the understanding of these complicated biological processes but also is essential for process design, control, and optimization. To date, the most successful model and the industrial standard is the so-called activated sludge model No. 1 (ASM1), developed in 1986 (Henze et al., 1986) by the Task Group on Mathematical Modeling for Design and Operation of Biological Wastewater Treatment of the International Association on Water Pollution Control and Research, IAWPRC (now IAWQ, International Association on Water Quality). The use of the ASM1 for carbonaceous biological oxygen demand (BOD) removal, nitrification and denitrification in many applications (e.g., Lesouef et al., 1992; Stamou, 1994; Huang and Hao, 1996), including simulation of a

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strategy for start-up nitrification (Finnson, 1993) and computer aided design of a sequencing batch reactor (SBR) (Oles and Wilderer, 1991), has validated its capability to predict process performance under pseudo-steady-state and dynamic conditions. Recently, an upgraded version of the ASM1 (ASM2) has been introduced to further account for biological phosphorus removal (Gujer et al., 1995).

To model biological nutrient removal in complex activated sludge processes, the model structure usually requires a high dimension and the model possesses a large number of kinetic and stoichiometric parameters. For example, a matrix form consisting of 8 process rate equations, 13 dissolved and particulate components, 5 stoichiometric coefficients, 8 kinetic coefficients, and 6 Monod half saturation coefficients are listed in the ASM1. Some components and/or parameters are difficult to estimate, partly due to the limitation of available measurement techniques. Consequently, such models have mostly been used for process design and simulation, and their actual application in process control and operational strategies is rather limited. By contrast, simplified process models are useful to facilitate process control, as demonstrated by several investigators for improving nitrogen removal in waste water treatment systems (e.g., Kabouris and Georgakakos, 1990; Hao and Kim, 1990; Zhao et al., 1994a; 1994b; 1995). However, a simplified model may exhibit poor accuracy due to model simplification and approximation.

The objective of the present study is to use a linearized model developed from the ASM1 model for optimization and control of activated sludge operation, specifically for an alternating aerobic-anoxic (AAA) system. The AAA system has been demonstrated for its capability of removing 60-80% nitrogen (Huang, and Hao 1996), simply by switching air on/off. An optimum O2 on/off control strategy, i.e., total cycle time (t_c) and aeration fraction (f_a), for nitrogen removal in an AAA system is essential for meeting the permit nitrogen requirements and saving energy costs. In this paper the linearized model is used to control/optimize the AAA reactor, and feedback of information from the reactor is used to overcome the problems associated with model inaccuracy.

2 MODELS

The ASM1 represents the state of the art in the modeling of activated sludge processes with carbonaceous BOD removal, nitrification and denitrification. Since its first release in 1987, applications of the model to a number of full-scale activated sludge systems with various process configurations have, for the most part, validated its ability in predicting the process performance under steady-state and dynamic conditions. In fact, the application of the ASM1 in modeling the dynamic behavior of nitrogen species in an AAA system has been previously demonstrated (Huang and Hao, 1996). The present study is concerned with only nitrogen removal, and the ASM1 predictions will serve as "real plant data".

The control approach for the AAA system is based on optimization of the predicted performance of the system, given a set of measurements reflecting the current state (or recent history) and influent composition. However, the equations comprising ASM1 are stiff and require a somewhat large computational effort in order to integrate the full model properly. Thus, despite the success of ASM1 in representing many characteristics of the AAA system, in its original form it is unsuitable for use in a real-time optimization based controller. For controlling the AAA system linearization of the ASM1 model is carried out. The "linear system" used actually consists of two separate linear models (one for each operating phase, "air-on" or "air-off") which are run alternately to simulate AAA process dynamics. Because the AAA system is cyclic, i.e., no steady state is achieved, the linearization of ASM1 is not approached by the traditional means of partial differentiation of the model equations about a steady state; instead, the development of linear models is achieved through simplification of the ASM1 equations.

The numerous unknown parameters of ASM1 were hand tuned to provide qualitative agreement with experimental data obtained on a bench-scale AAA wastewater treatment system (Huang, 1993). An automated approach to parameter estimation was in this case prohibitively time consuming due to the stiffness of the equations and the need to determine the limiting, long term behavior. The linear model is based on the parameter set used for the full ASM1 model, with some further hand tuning. Details of the linear model development are given by Anderson et. al. (1998). Each of the ASM system parameters was chosen within ranges appropriate for a typical system (for some guidelines, see (Henze et al., 1986). The long term dynamic behavior predicted by each model is represented in Fig. 1

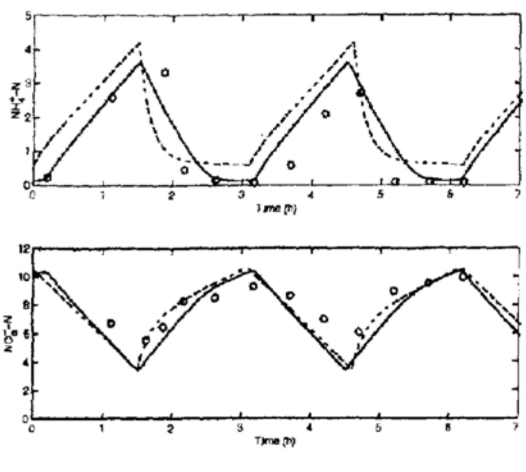

Figure 1. Comparison of Models with Experimental Data

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in which the time series of the full ASM1 model (solid lines) and the linear model (dashed lines) are plotted along with the available experimental data (circles). Time series for ammonia-nitrogen and nitrate-nitrogen are respectively presented in the upper and lower graphs. Good qualitative agreement was obtained between the two models and the bench scale system.

3 USE OF LINEARIZED MODEL FOR OPTIMIZATION AND CONTROL

A major objective in developing hybrid models is to use them for controlling/optimizing activated sludge operation. The operating aeration parameters of the AAA reactor for today, the aeration cycle length t_c, and the fraction of the cycle when aeration is turned on, f_a, have to be determined to control the reactor. The goal is to select the optimal t_c and f_a values which minimize the energy costs, assumed proportional to f_a, while meeting the discharge limits. In practice, the discharge limit is set at a value to be achieved averaged over a month, e.g 10 mg/l. In this paper this limit is specified as a daily limit. Another long term operating goal is to keep the concentration of nitrifying bacteria, Xba, at the necessary concentration for the essential conversion of the ammonia in the influent waste water to nitrate. The nitrate is reduced to gaseous nitrogen during the air-off period, thus eliminating it from the effluent. The plant operator is assumed to set the current day t_c and f_a values each morning, based on the previous day's plant operation results.

It will be assumed that the plant operator has the analytical laboratory results of the previous day's operation available today. These are the influent soluble and particulate chemical oxygen demand (COD), soluble and particulate organic nitrogen, and the ammonia. The AAA reactor state is affected by the hydraulic retention time (HRT), the mean cell retention time (MCRT), t_c and f_a. In this study the HRT and MCRT are assumed constant. It is possible to include the effects of these measurements using the approach given here. The available effluent measurements are the COD, ammonia-nitrogen, nitrate-nitrogen, and organic-nitrogen, and it is assumed that yesterday's values are known today.

As discussed above a linearized model was developed to predict 8 plant values for the day ahead, starting from their initial values. These values are the reactor state, as characterized by the soluble and particulate COD, the nitrifying and de-nitrifying bacteria concentration, the effluent concentration of the three nitrogen species and the particulate nitrogen organic compounds. How to incorporate the predictions of the linearized model into an optimization scheme is discussed next.

For controlling plant effluent there are two variables, t_c and f_a, that can be manipulated in order to minimize energy costs, subject to effluent permit restrictions being met. The control/optimization problem that is solved is:

$$
\begin{aligned}
&\min_{t_c, f_a}\{cost\} \\
&subject\ to \qquad\qquad (1)\\
&\qquad \overline{N}_O \le \overline{N}_{Permit} \\
&\qquad \overline{NH}_4^+ \le \overline{NH}_{4,\max}^+ \\
&\qquad fa * tc \ge 1.0 \\
&\qquad (1 - fa) * tc \ge 1.0
\end{aligned}
$$

where $\overline{N}_{Permit}$ is the permit specification on the average daily TN in the effluent, $\overline{N}_o$ is the actual TN value achieved, and $\overline{NH}_{4,\max}^+$ is the maximum value of the average daily ammonia-nitrogen in the effluent, $\overline{NH}_4^+$. In Eqn. 1 the cost of operation that can be minimized is assumed to be associated only with the time that air is being sparged. Other costs such as those associated with pumping are neglected. The last 2 constraints deal with the minimum air-on and air-off times. Each time period is constrained to be greater than 1 hour, since this time is assumed to be the minimum that can be accepted by the plant so as not to cycle the blowers too frequently. Also, if there were no constraint on the air-on time, the optimizer would drive f_a toward 0., and this could eventually result in a wash out of the Xba bacteria.

The linearized model is used to solve the optimization problem given by Eqn. 1. The optimization scheme is illustrated in Fig. 2.

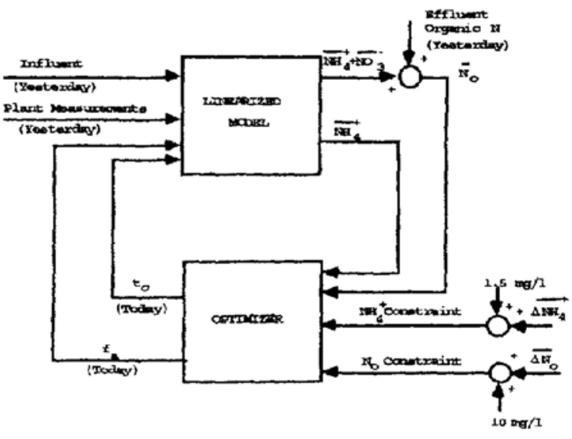

Figure 2 Optimization Scheme

The predictions of the linear model that are used are the daily average ammonia-nitrogen, and the sum of the average daily ammonia-nitrogen and nitrate-nitrogen. The exit organic nitrogen is assumed to be equal to the effluent organic nitrogen measured yesterday, and it is added to the sum to give the predicted average daily total nitrogen in the effluent. For the moment assume that the $\Delta\overline{NH}_4^+$ and $\Delta\overline{N}_o$ terms are 0. The optimizer is fed both the predicted ammonia-nitrogen and the predicted TN values, as

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well as the constraint values for these variables. In the simulations discussed below, the constraint for $\overline{NH}_4^+$ is $\overline{NH}_{4,\max}^+$ =1.5mg/l and that for $\overline{N}_o$ is $\overline{N}_{Permit}$=10mg/l. The optimizer manipulates f_a and tc to solve this optimization problem and to meet the constraints in Eqn. 1. The approach illustrated in Figure 2 will not meet the constraints on the real process precisely, because there will certainly be some inaccuracy in the predictions of the linearized model due to the assumptions and simplifications involved in its development. This inaccuracy is referred to as plant model mismatch. How to overcome this problem, and force the optimizer to exactly track the actual plant $\overline{NH}_4^+$ and $\overline{N}_o$ values is discussed next.

An important issue that needs to be considered in using a linearized model for control is the mismatch that exists between the model and the plant it tries to describe. This mismatch is due to both modeling errors, and the effect of unmeasured disturbances. Feedback of information can be used to deal with this mismatch as follows. Assume that for the initial cycle of the AAA reactor the solution of Equation 1 gives the optimum values t_{c1} and f_{a1}. Further assume that when these values are implemented on the actual reactor, the actual $\overline{NH}_4^+$ which is measured at the end of the first cycle differs from that predicted by the linearized model. Let this difference be $\Delta\overline{NH}_4^+ = \overline{NH}_4^+ - \overline{NH}_{4,Linear}^+$. Then to overcome plant model mismatch one can subtract $\Delta\overline{NH}_4^+$ from $\overline{NH}_{4,\max}^+$ to help bring the actual $\overline{NH}_4^+$ closer to the constraint. For example, if $\overline{NH}_{4,Linear}^+$ is 1.5 mg/l, and $\overline{NH}_4^+$ is 1.7 mg/l, then the $\overline{NH}_4^+$ constraint can be lowered to 1.5 mg/l minus the difference of 0.2 mg/l, and set at 1.3 mg/l. This method of overcoming plant model mismatch is essentially the same as that used in commercially successful dynamic matrix control (Cutler and Ramaker, 1979). An identical approach can be used for the total nitrogen constraint. The use of the Δ corrections to the constraints involves feedback from the plant. To make this feedback robust, and to avoid responding too sharply to daily fluctuations, the Δ corrections are implemented as an exponentially weighted moving average of the current value and yesterday's value. The equations used are:

$$\Delta\overline{NH}_4^+ = .5 * \Delta\overline{NH}_4^+ + .5 * \Delta\overline{NH}_{4,y}^+ \qquad (2)$$

$$\Delta\overline{N}_o = .5 * \Delta\overline{N}_o + .5 * \Delta\overline{N}_{o,y} \qquad (3)$$

where $\Delta\overline{NH}_{4,y}^+$ and $\Delta\overline{N}_{o,y}$ are yesterday's values. As shown below this approach will result in no violation of the desired constraints for $\overline{NH}_4^+$ and $\overline{N}_o$, if the inputs to the reactor remain fixed.

4. RESULTS

In this section the results of using the optimization scheme are presented. Figure 3 gives results for the case where the AAA reactor is initially at steady state, and the operating policy being used is air-on = 1.25 hrs. and air-off = 1.25 hrs. To illustrate how the optimization/control scheme works, no variation in the feed stream is considered initially. As can be seen in Fig. 3a the fixed operating policy is initially achieving an average $\overline{NH}_4^+$ concentration of approximately 1.25 mg/l and in Fig. 3b an average $\overline{N}_O$ concentration of 10.5 mg/l. Since $\overline{NH}_4^+$ is less than 1.5 mg/l too much air is being sparged, and some energy can be saved. On day 5 the optimizer is turned on and it brings the AAA reactor to a new steady state in which $\overline{NH}_4^+$ = 1.5 mg/l. This new policy reduces the average total effluent nitrogen, $\overline{N}_O$, to approximately 6.2 mg/l. The new air-on and air-off policies are shown in Figs. 3c, and 3d. As can be seen between days 5 and 15 the optimizer forces the air-on period to its minimum of 1 hour, and the air-off period is also changed slightly after the transient period between days 5 and 15. The new operating policy results in an energy savings of about 11% compared to the original policy, and it also reduces total effluent nitrogen even though the TN constraint is not active.

On day 15 a 10% step increase in the concentration of all 8 influent species occurs simultaneously. This forcing corresponds to a +10% step load increase to the plant. On day 45 the 10% step is removed. As can be seen the optimization/control approach is able to deal effectively with this upset. The air-on period remains at its lower constraint of 1 hr, while the air-off period is continuously adjusted by the optimizer. Even during this step load upset there is an energy savings over the original fixed operating policy, but it is smaller, namely 6.6%.

Figure 4 illustrates how the Δ correction, discussed above, allows the optimization/control approach to track desired constraints even in the face of plant model mismatch. In Fig. 4a the actual $\overline{NH}_4^+$ concentration is plotted, together with its predictions from the linearized model for the same forcing used for Fig. 3. The linearized model errors reach values of approximately + 0.3 mg/l for $\overline{NH}_4^+$. In spite of these errors the $\overline{NH}_4^+$ concentration is forced to satisfy its constraint value of 1.5 mg/l once transients die out. Figure 4b shows how the negative $\Delta\overline{NH}_4^+$ values added to the constraint change with time. Once these errors reach a value around -0.3 mg/l they remain roughly constant. For the forcing shown in Fig. 4, the constraint on TN is not violated. During the step load period the $\overline{NH}_4^+$ constraint is lowered from 1.5 mg/l to approximately 1.2 mg/l in order to force the actual $\overline{NH}_4^+$ values to be 1.5 mg/l. This lowering of the constraint overcomes the plant model mismatch.

Next, a realistic case where the influent has a time varying feed composition is considered. The results

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of adding 10% random noise to each of the 8 plant influents, starting at day 5 are shown in Figure 5. Figures 5a and 5b give results for the effluent $\overline{nn}_4^+$ and $\overline{n}_O$ respectively. As can be seen the optimization/control approach is able to deal with random feed fluctuations and keep both $\overline{nn}_4^+$ and $\overline{n}_O$ under control. Figures 5c and shows the optimum air-on and air-off policies which result from the approach used in this paper. In this case the air-on period is forced off its constraint of 1 hour for a brief time on several occasions. The optimum policy results in an energy savings of 11% over a fixed policy where the air-on and air-off periods are each 1.25 hours.

5. CONCLUSIONS

This paper has discussed the use of a linearized versions of the ASM1 model for control and optimization of an alternating aerobic/anoxic activated sludge reactor. This reactor uses a cyclic air-on, air-off operating policy, and a different linearized model is used for each operation. To overcome plant model mismatch, an exponentially weighted feedback of information from the plant is employed. An optimization problem is solved daily to determine the air-on and air-off periods that minimize the cost of sparging air. Minimum constraints on the ammonia-nitrogen, total-nitrogen, air-on period, and air-off period are incorporated into the optimization. The control/optimization approach is demonstrated to be effective for both step upsets and random upsets in feed composition. Energy savings in the range of 5 to 10 % are achieved over a fixed operating policy without violation of permit specifications.

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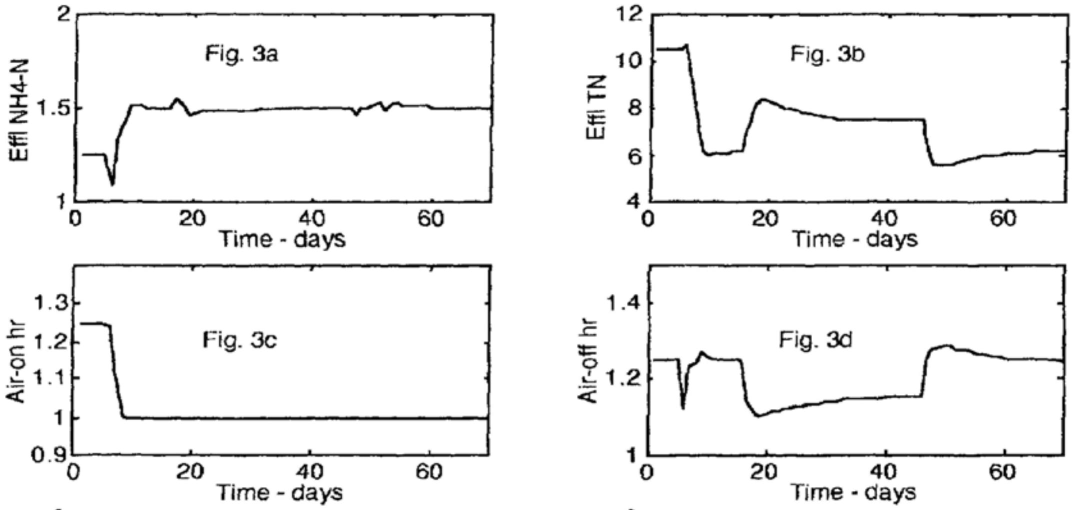

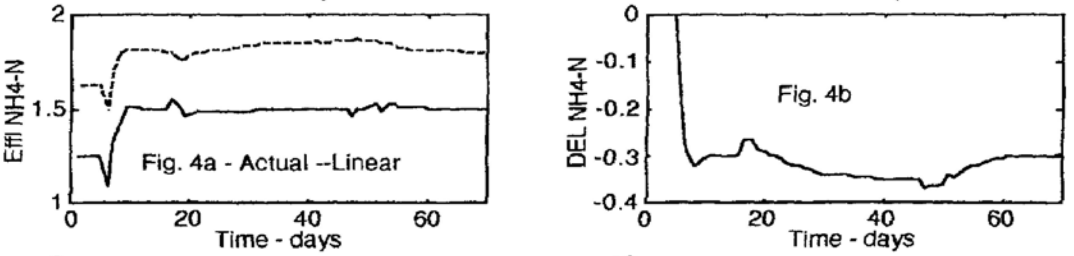

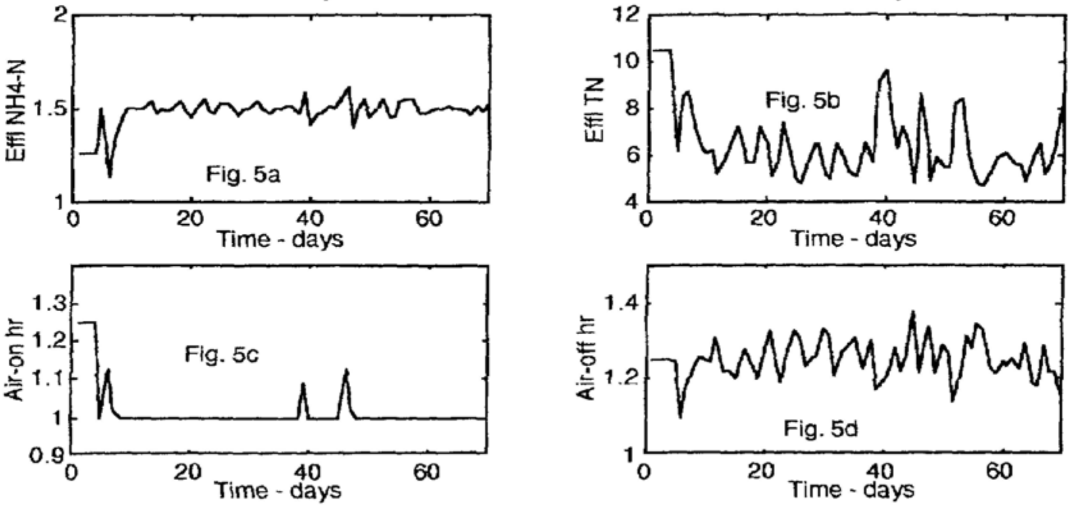

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