

SBR SYSTEM FOR PHOSPHORUS REMOVAL: LINEAR MODEL BASED OPTIMIZATION

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ABSTRACT: Using a linear model, an optimization scheme for a sequencing batch reactor (SBR) system for phosphorus removal was investigated. The objective was to minimize energy consumption by reducing the aeration cycle time (t_{air}), while meeting the permit requirement (monthly average PO_4^{3-} of 0.5 mg P/L). Based on the model prediction and error feedback information, the proposed scheme controlled the SBR system well both in the simulation and the real application by adjusting the t_{air} to meet the effluent PO_4^{3-} constraint. Mismatch between the model prediction and the measured data was compensated for. In the simulation, the average aeration cycle time was calculated to be 2.8 h, while in the real system it was 3.5 h. The actual optimized system provided excellent removal of phosphorus, COD, and ammonia with efficiencies of 93% (7.4 to 0.5 mg P/L), 90% (420 to 43 mg COD/L), and 98% (22.1 to 0.4 mg N/L), respectively. However, the effluent nitrate concentrations were relatively high (10 mg N/L), due to a slower endogenous nitrate respiration rate.

INTRODUCTION

Traditional operation of biological wastewater treatment processes often leads to excessive consumption of system resources, including unnecessary energy expenditure. In the case of temporal alternating systems, e.g., a sequencing batch reactor (SBR) system, they are usually operated with fixed time durations that are preset based on an operator's experience. The predetermined cycle time is unable to match the dynamic change associated with influent characteristics, resulting in either too long an aeration time (excessive energy consumption) or an inadequate aeration time. In view of stricter regulations on wastewater treatment effluent and issues of energy savings associated with aeration, process control of biological systems has received considerable attention.

To optimize temporal activated sludge systems, three control schemes have been proposed: on-line sensor, rule based, and model based controls. On-line sensors can be used for monitoring dissolved oxygen (DO), ammonia/nitrate, and phosphate concentrations, as well as pH and ORP (oxidation and reduction potential) in a biological system. A control scheme with a DO sensor along with the oxygen uptake rate (OUR) has been applied to COD (chemical oxygen demand) removal or ammonia oxidation (Suescun et al. 1998). However, since the DO sensor cannot be used for either the anoxic or anaerobic phase, its application is not feasible for SBR systems that have these phases.

There has been noticeable progress in the development of effective sensors for ammonia/nitrate and phosphorus, and several studies utilizing them for process control have been performed (Sorensen et al. 1994; Balslev et al. 1996; Isaacs and Temmink 1996; Thomsen and Kisbye 1996). Since these sensors provide straightforward parameter information about the state of a system, control actions such as air on/off can be easily implemented on an SBR system (Katsogiannis et al. 1999). Unfortunately, a control scheme based on sensors has some disadvantages. The sensors require extensive sample treatment for measurements (Engblom 1998) and frequent cal-

ibration and maintenance result in limited application in real plant operations. Also, high costs for the installation may not be a feasible option in smaller plants (Larose et al. 1997).

Unlike on-line nutrient analyzers, ORP and pH sensors do not require sample pretreatment and only need limited maintenance. The "nitrate knee," an inflection point on the ORP profile indicating the end of denitrification, has been used for the point of adding the external COD for better *P*-release (Wareham et al. 1995) and for initiation of the anaerobic phase (Sasaki et al. 1996). Chang and Hao (1996) have suggested that two inflection points on pH profiles may be utilized to determine the end of phosphate release during the anaerobic cycle (mix stage) and phosphate uptake during the aeration cycle. Unfortunately, a control scheme based on pH or ORP profiles has not been fully explored in biological *P*-removal processes.

A rule-based control system, such as a fuzzy or expert system, has been applied to aeration cycle control in alternating systems for phosphorus (Hamamoto et al. 1997) and nitrogen removal (Cohen et al. 1997; Isaacs and Thornberg 1998). However, these control systems require extensive human knowledge about a particular process of interest, which may not be easily available, particularly for inexperienced operators.

Models have been incorporated into a variety of process control/optimization schemes. Potter et al. (1996) controlled the cycle duration in a Bio-Denipho process for nitrogen removal utilizing ASM1 (Activated Sludge Model No. 1). Zhao et al. (1994) proposed a model-based predictive control scheme, consisting of a simplified process model and an error feedback algorithm, to find optimal cycle times in a Bio-Denipho process. Other researchers incorporated simplified equations from ASM1 into an optimization scheme for optimal air on/off cycle durations in alternating systems (Lukasse et al. 1998; Kim et al. 2000). Demuynck et al. (1994) optimized oxygen and external COD consumption for an SBR system based on the OUR and model prediction.

In this study, a process control scheme for an SBR system for phosphorus removal using an optimizer along with a linear model described in an accompanying paper (Kim et al. 2001) is investigated. The goal of this study is to control and optimize the operation of an SBR system by manipulating aeration cycle time (t_{air}). Because operating costs are directly related to the amount of aeration time, optimal t_{air} values could minimize the energy costs while meeting the PO_4^{3-} discharge permit requirement. A procedure for overcoming mismatch between the model-predicted values and measured data is presented. Additionally, simulation studies with the proposed optimization scheme were initially performed using the industrial standard

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Note. Associate Editor: Robert Arnold. Discussion open until July 1, 2001. Separate discussions should be submitted for the individual papers in this symposium. To extend the closing date one month, a written request must be filed with the ASCE Manager of Journals. The manuscript for this paper was submitted for review and possible publication on February 4, 2000. This paper is part of the *Journal of Environmental Engineering*, Vol. 127, No. 2, February, 2001. ©ASCE, ISSN 0733-9372/01/0002-0105-0111/\$8.00 + \$.50 per page. Paper No. 22188.

model, ASM2 (Activated Sludge Model No. 2 (Gujer et al. 1995), as full plant data.

MATERIALS AND METHODS

An SBR was operated and optimized using a linear model. The SBR system consists of six phases: fill, mix, aerate, idle, settle, and decant. A description of the seeding sludge and the reactor system can be found in an accompanying paper (Kim et al. 2001). The influent composition is also shown in the companion paper (Phase III study).

Optimization Overview

By optimizing “aerate” cycle duration, the energy for aeration can be minimized and the amount of wastewater treated by the system maximized if the cycle times of other phases are fixed. An effluent discharge constraint of 0.5 mg PO₄³⁻ P/L was used during the study. Before the optimization scheme was implemented, the SBR system with a fixed time cycle ratio was run to calibrate the linear model. The optimization routine was then operated to exploit the process model (linear model) to project daily average effluent levels of the PO₄³⁻ and recommended t_{air} value to meet the effluent constraint. The daily P values were determined by averaging the result of each cycle within a day. For almost all cases where a cycle is incomplete within a calendar day (e.g., total cycle time = 8.5 h and each calendar day only contains 2.8 cycles), the daily average result is calculated based on rounding off the cycle fraction (i.e., 3 cycles for the above example).

Assuming that the plant operator would have the laboratory results for both the previous day’s influent compositions and effluent quality, the parameter t_{air} is then set by the optimizer for the current day’s operation. The measured influent parameters were fermentation product (S_A ; in this study, acetate added), soluble COD (S_F) and particulate COD (X_S), ammonia (S_{NH}), nitrate (S_{NO}), and PO₄³⁻ (S_{PO4}). The effluent parameters are total COD and S_{NH} , S_{NO} , and S_{PO4} .

Although the optimization was performed daily, it could be run after each cycle, allowing for more frequent manipulation of the control variable t_{air} .

Linear Model and Optimizer

In this study, the optimization scheme utilizes the linear model presented in the accompanying paper (Kim et al. 2001). The calibrated model is run to predict the values of the 11 variables for today, starting from their initial values obtained from yesterday’s operation, and eventually provides the optimal values for the control variable, t_{air} . The 11 variables are S_A , S_F , and X_S , denitrifying, nitrifying, and phosphorus accumulating bacteria concentration (X_{BH} , X_{BA} , and X_{PAO}), S_{NH} , S_{NO} , S_{PO4} , cell internal storage of PAOs (X_{PHA}), and polyphosphate granule (X_{PP}). Since high DO concentrations were maintained during the aeration cycle, it was assumed in this study that the DO was not a limiting nutrient. Phosphate concentration predicted by the linear model ($P_{predicted}$) was incorporated into an optimization scheme as described in the following:

$$\min \{ \text{cost} \} \quad (1)$$

$$t_{air}$$

subject to: (1) $P_{predicted} \leq P_{max}$; (2) $t_{air} \geq t_1$; and (3) $t_{air} \leq t_2$.

Again, the control variable, t_{air} , is manipulated to minimize aeration cycle time, subject to meeting the allowable effluent constraint. In (1), the operating cost that can be minimized is assumed to be limited to the time that air is on. Other energy costs such as those associated with pumping and mixing are neglected. The first constraint (P_{max}) is the desirable maximum allowable value of the daily average P concentration in the effluent; the same value is for monthly permit requirement.

Thus, the potential violation of the daily value should not present any problems with the normally regulated weekly and monthly average standards. The second constraint (t_1) and the third constraint (t_2) deal with the minimum and maximum “aerate” cycle times, respectively; e.g., $t_1 = 1$ h and $t_2 = 5$ h. If there were no constraint on the minimum air on time, the optimizer would try to drive t_{air} toward 0, and this would eventually result in a washout of the X_{BA} and X_{PAO} . The maximum t_2 is set to ensure that the system will enter the next phase regardless of P level. Note that the cycle times for all other phases are constant, i.e., fill, mix, idle, settle, and decant in the study were fixed at 0.5, 3.0, 1.0, 0.5, and 0.5 h, with a total time of 5.5 h. The method for the optimizer to adjust the mix time will be discussed later.

The linear model prediction used in the optimization scheme given by (1) is illustrated in Fig. 1. Again, the $P_{predicted}$ value is for the daily average of effluent P . Both the $P_{predicted}$ value and the constraint limit (P_{max}) are fed into the optimizer. The optimizer then manipulates t_{air} to solve this optimization problem and to meet the three simple constraints in (1). The approach provided in (1) may not meet precisely the constraint for the real process, because some inaccuracy in the linear model predictions will occur due to the assumptions and simplifications involved in the model development. Also, unexpected and unmeasured local disturbances occur in the real plant. To enable the optimizer to overcome these errors and to control the reactor properly, the error information is fed back into the optimizer. For example, on the first day of the SBR operation, the solution of (1) provides the estimated t_{air1} . When this value is implemented in the reactor, the actual P concentration, measured at the end of the first day, differs from that predicted by the linear model by ΔP

$$\Delta P = P_{measured} - P_{predicted} \quad (2)$$

To counteract this model mismatch, one can subtract ΔP from the value of P_{max} to bring the actual effluent P closer to the objective (0.5 mg/L). For example, if $P_{predicted}$ is 0.45 mg/L, and the actual P is 0.35 mg/L, then the P constraint can be changed to 0.5 mg/L minus the difference of -0.1 mg/L and set at 0.6 mg/L. This method of overcoming the model mismatch was used in a commercial dynamic matrix control (Cutler and Ramaker 1979) and successfully applied to an optimization study of an AAA (alternating aerobic and anoxic) system for N removal (Kim et al. 2000).

To make this feedback robust and to avoid the system responding too sharply to daily parameter fluctuations, the following δ correction was further implemented as an exponentially weighted moving average (McAvoy et al. 1999):

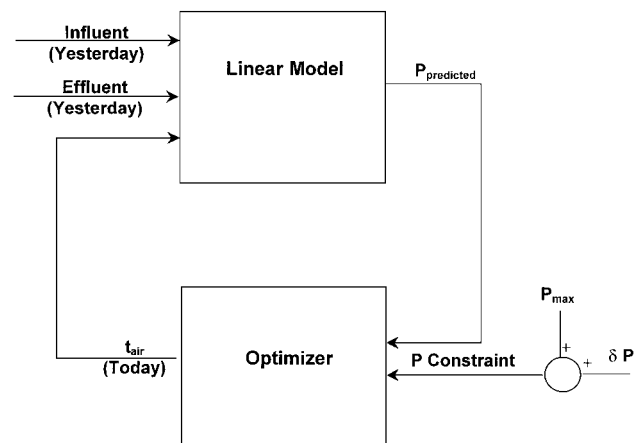


FIG. 1. Schematic Diagram for Optimization Scheme

$$\delta P|_t = \alpha \times \Delta P|_t + \beta \times \{ \alpha \times \Delta P|_{t-1} + \beta \times [\alpha \times \Delta P|_{t-2} + \beta \times (\dots)] \} \quad (3a)$$

$$\delta P|_t = \alpha \times \Delta P|_t + \beta \times \delta P|_{t-1} \quad (3b)$$

where $\delta P|_{t-1}$ = previous day's calculated mismatch value; α and β = weighting factors ($\alpha + \beta = 1$); and $\delta P_0 = 0$. If α is larger than β , the system is more sensitive to the current data. On the other hand, if β is larger than α , the system tends to filter the error from current data and depends more on the past data.

Simulation

Before the optimization scheme was implemented for the control of a real reactor, a simulation study was performed, in which the predicted values from the full ASM2 were used as real plant data. The purpose of the simulation was: (1) to determine if the proposed control scheme is feasible; (2) to provide a better startup strategy for the system; and (3) to obtain appropriate α and β values for the real system. Both the ASM2 and linear model were coded in MATLAB, and the optimization toolbox in MATLAB was used to solve the optimization problem.

The cycle times for the SBR system were initially set at 0.5 h of fill, 3 h of mix, 3 h of aerate, 1 h of idle, 0.5 h of settle, and 0.5 h of decant, with total cycle time = 7.5 h. On the 10th day and thereafter, the aerate cycle times were determined by the optimizer. The lower and upper limits of the aerate cycle times (t_1 and t_2) were set at 1 and 5 h, respectively.

RESULTS AND DISCUSSION

Simulation Study

The calibrated linear model in the accompanying paper (Kim et al. 2001) was initially used for the optimization scheme. The results (Fig. 2) indicate that the optimizer can generally control the system by increasing t_{air} when plant effluent P concentrations (from ASM2) are high, and vice versa.

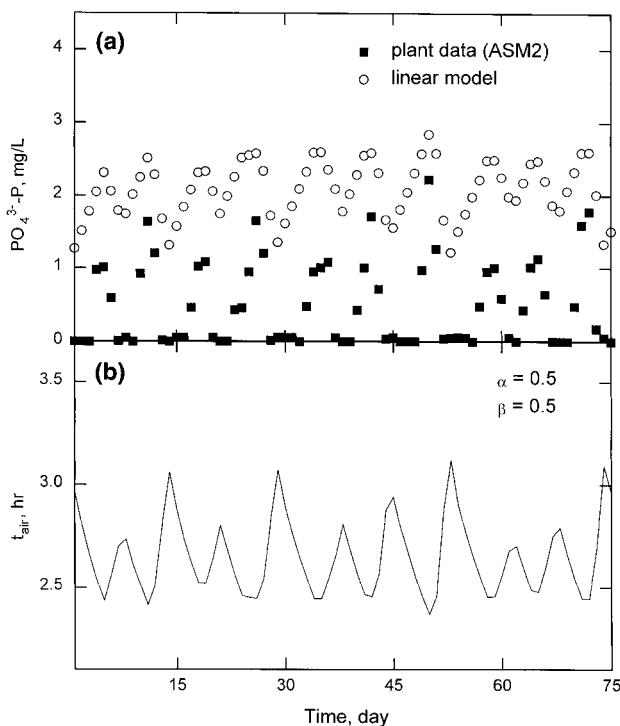


FIG. 2. Simulated Performance of System Based on Optimization Scheme

However, the linear model predicts higher effluent P concentrations, causing a large mismatch. The initial calibration of the linear model was based on the parameter concentration profiles (NH_4^+ , NO_3^- , and PO_4^{3-}) throughout the entire cycle, including the mix, aerate, and idle phases. Since the objective of the control is to reduce the aeration cycle duration after PO_4^{3-} uptake with a lower P constraint (0.5 mg/L), more emphasis of the model calibration should be placed on the aeration cycle, especially at the end of P uptake profiles. When P profiles of the two models at the end of aeration cycle are magnified [Fig. 3(a), insert], a significant mismatch between the models is noticed.

Since the optimizer is sensitive to a large mismatch and may not function properly, both the linear model and ASM2 were recalibrated with typical plots shown in Fig. 3(b). The two models show a similar pattern at the end of the aeration cycle. The parameters for simulation study are presented in Table 1.

The feasibility of applying the optimization scheme was first investigated with the nominal influent composition (Table 2). After 10 days of operation based on a fixed aeration cycle time, the system was simulated using the optimization scheme presented above. To observe the system's response to shock loading, from day 40 to day 59, the influent P level was raised 1.5 times higher. The simulated results with respect to the linear model predicted values and plant data (ASM2) and t_{air} as a function of α and β values are shown in Fig. 4. During the operation with a fixed aeration time, the effluent PO_4^{3-} level was maintained at approximately 0.2 mg P/L. However, once the optimizer started to work, the aeration time was lowered, resulting in higher effluent P levels. The effects of α and β values on the system performance are evident. When α is higher than β [Fig. 4(a)], the system is considerably affected by the recent error, which causes widely scattered effluent P levels. However, when β is higher than α [Fig. 4(c)], the system gives rise to more a stable effluent P level. For example, P reached its highest level of 1.8 mg/L at $\alpha = 0.7$ and $\beta = 0.3$ [Fig. 4(a)], but it increased only to 0.8 mg/L at $\alpha = 0.3$ and $\beta = 0.7$ [Fig. 4(c)] under normal conditions.

Due to the large errors in Fig. 4(a), the effect of shock loading on the system performance is not evident. However,

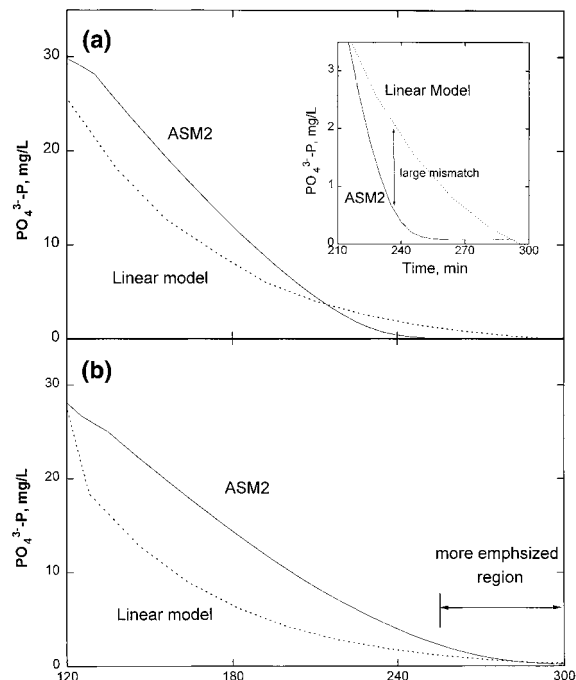


FIG. 3. PO_4^{3-} Profiles of Full ASM2 and Linear Model during Aeration Cycle: (a) Model Parameters from Kim et al. (2001); (b) Model Parameters from Table 1

TABLE 1. Stoichiometric and Kinetic Parameters Used for Calibration for ASM2 and Linear Model (LM) Used in Simulation

Parameters (1)	Default (2)	ASM2 (3)	LM (4)
(a) Hydrolysis			
K_h	3.0	0.5	5.0
η_{NO3}	0.6	0.6	0.4
η_{fe}	0.1	0.4	0.4
K_{O2}	0.2	0.2	—
K_{NO3}	0.5	5	—
K_X	0.1	0.1	—
(b) Heterotrophic organisms			
Y_H	0.63	0.53	0.63
f_{XI}	0.1	0.1	—
μ_H	6.0	3.0	6.0
q_{fe}	3.0	2.0	3.0
η_{NO3}	0.8	0.8	0.8
b_H	0.4	0.2	0.2
K_{O2}	0.2	0.2	—
K_F	4.0	4.0	—
K_{fe}	20	20	—
K_A	4.0	4.0	—
K_{NO3}	0.5	0.5	—
K_{NHA}	0.05	0.05	—
K_p	0.01	0.5	—
K_{alk}	0.1	0.1	—
(c) Phosphorus accumulating organisms			
Y_{PAO}	0.63	0.63	0.63
Y_{PO4}	0.4	0.45	0.6
Y_{PHA}	0.2	0.2	0.2
q_{PP}	1.5	0.8	3.5
q_{PHA}	1.5	4.0	3.0
μ_{PAO}	1.0	1.0	1.0
b_{PAO}	0.2	0.2	0.2
b_{PP}	0.2	0.2	0.2
b_{PHA}	0.2	0.2	0.2
K_{O2}	0.2	0.2	—
K_A	4.0	4.0	—
K_{NHA}	0.05	0.05	—
K_{PS}	0.2	2.0	—
K_p	0.01	0.01	—
K_{alk}	0.1	0.1	—
K_{PP}	0.01	0.01	—
K_{MAX}	0.34	0.14	—
K_{IPP}	0.02	0.035	—
K_{PHA}	0.01	0.01	—
(d) Nitrifiers			
Y_{AUT}	0.24	0.24	0.24
μ_{AUT}	1.0	0.65	1.0
b_{AUT}	0.15	0.15	0.12
K_{O2}	0.5	0.05	—
K_{NHA}	1.0	2.0	—
K_{alk}	0.5	1.0	—
K_p	0.01	0.01	—

Note: Values for J_1 – J_{10} are 0.16, 10, 5, 10, 5, 3, 10, 7.5, 80, and 48, respectively.

TABLE 2. Influent Concentration for SBR System under Simulation

Parameter (1)	Concentration (mg/L) (2)
$S_{A,INF}^a$	120
$S_{F,INF}^a$	70
$X_{S,INF}^a$	120
$S_{NHA,INF}^b$	22
$S_{NO3,INF}^b$	0
$S_{PO4,INF}^c$	6.5

^aConcentration as COD.

^bConcentration as N.

^cConcentration as P.

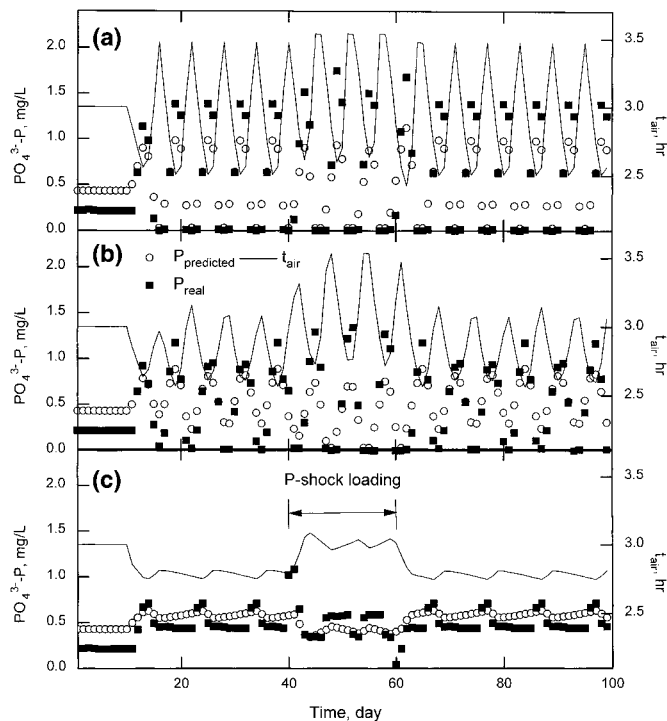


FIG. 4. Simulated Performance of System Based on Optimization Scheme: (a) $\alpha = 0.7$, $\beta = 0.3$; (b) $\alpha = 0.5$, $\beta = 0.5$; (c) $\alpha = 0.3$, $\beta = 0.7$

in Fig. 4(c), the response of the optimizer to the P shock loading is clearly shown. Once the influent P was raised to 9.8 mg/L, the effluent P level increased to 1.0 mg P/L, since the system was operated based on the previous day's influent P information (i.e., 6.5 mg P/L). Due to a large mismatch between model predicted and real P levels [Fig. 4(c)], the system thus increased the aeration cycle time. The same phenomenon is detected when the shock loading is removed from the system. Once the influent P level was lowered to the nominal level, the optimizer reduced aeration cycle time. System performance with different α and β values is summarized in Table 3. Overall, during the 90 days of system operation, the optimal aeration cycle time was found to be 2.8 h, with a monthly average discharge P concentration about 0.5 mg/L when $\alpha = 0.3$ and $\beta = 0.7$.

Although the mismatch between the linear model predictions and the plant data could be compensated with the feedback routine, α and β should be set appropriately for the system to maintain the effluent PO_4^{3-} at the desired level. The simulation suggests that β in (3) should be set higher than α so that the system is not too sensitive to the current day's error.

A realistic case where the influent exhibits varying feed compositions was considered with α and β at 0.3 and 0.7, respectively. The simulation results of adding 10% random noise to each of the six plant influent components are shown in Fig. 5. Although the effluent P profile in Fig. 5(a) indicates more fluctuation than that in Fig. 4(c), the optimizer generally

TABLE 3. Simulation Performance of SBR System under Different Conditions^a

Parameter (1)	$\alpha = 0.7$, $\beta = 0.3$ (2)	$\alpha = 0.5$, $\beta = 0.5$ (3)	$\alpha = 0.3$, $\beta = 0.7$ (4)
Average aeration cycle time, h	2.9	2.8	2.8
Average effluent PO_4^{3-} , mg P/L	0.57	0.5	0.5
Range of effluent PO_4^{3-} , mg P/L	0–1.5	0–1.2	0–1.0

^aBased on 90 days of operation with optimizer; mix cycle time = 3 h.

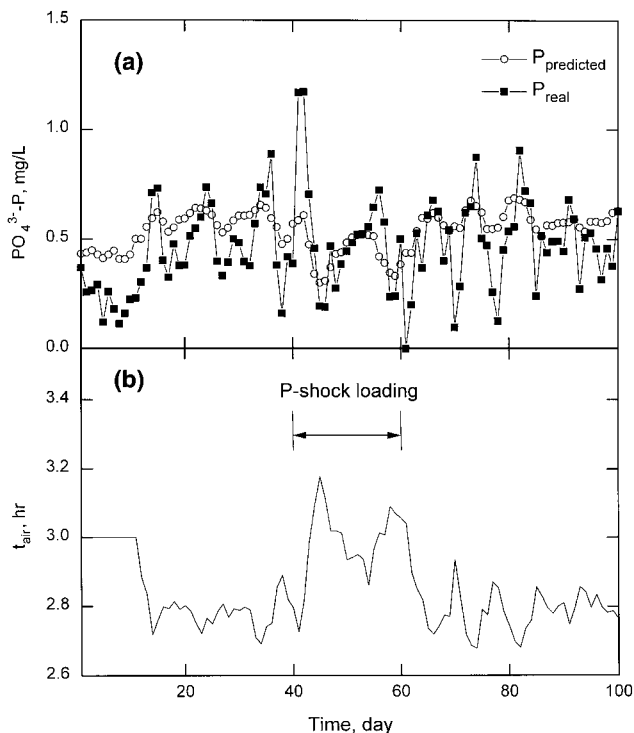


FIG. 5. Simulated Performance of System with Influent Compositions with 10% Disturbances ($\alpha = 0.3$, $\beta = 0.7$)

yields a similar performance. The average total and aeration cycle times were 8.3 and 2.8 h, respectively, with a preset mix cycle time of 3 h. The 30 consecutive days effluent average PO_4^{3-} level was always below 0.5 mg P/L, which meets the permit requirement.

Application to Real System

The aeration cycle time was initially set at 3 h, because the system had previously demonstrated the effluent PO_4^{3-} concentration to be slightly below 0.5 mg P/L within 3 h of aeration stage (Kim et al. 2001). The mix cycle time was again set at 3 h. The lower and upper limits of the aeration cycle times, t_1 and t_2 , were set at 1 and 6 h, respectively. The constraint for effluent PO_4^{3-} (P_{\max}) was also set at 0.5 mg P/L, and α and β was set at 0.3 and 0.7, respectively. Since the calibrated linear model in the accompanying paper predicted the real data well, the parameters used in the accompanying paper (Kim et al. 2001) were used in the current optimization study.

Fig. 6(a) shows the model-predicted values and real effluent PO_4^{3-} data for the entire period of the system operation (27 days). The mismatch between the model predictions and real data is also depicted in Fig. 6(b), along with the aeration cycle time [Fig. 6(c)]. The standard error between the model-predicted data and the actually observed values is about 0.2 mg/L. The error without considering the large ΔP values resulting from the malfunction of the air compressor and the P -shock loading is about 0.1 mg/L. Under normal conditions, the optimizer predicts the real system well, due to the good fit of the linear model used. Again, the optimizer effectively tracks the system. The air compressor malfunctioned at the end of aeration cycle time of the third cycle on day 6, resulting in a much higher effluent PO_4^{3-} concentration (2.4 mg P/L). However, the system was able to control this problem by increasing t_{air} to 5.5 h [Fig. 6(c)]. The capability of the optimizer against shock loading is also demonstrated between day 16 and 18, where the PO_4^{3-} level in the feed solution is increased to 16 mg P/L. Despite the inaccurate prediction by the model, and hence, the large mismatch, the system was able to increase

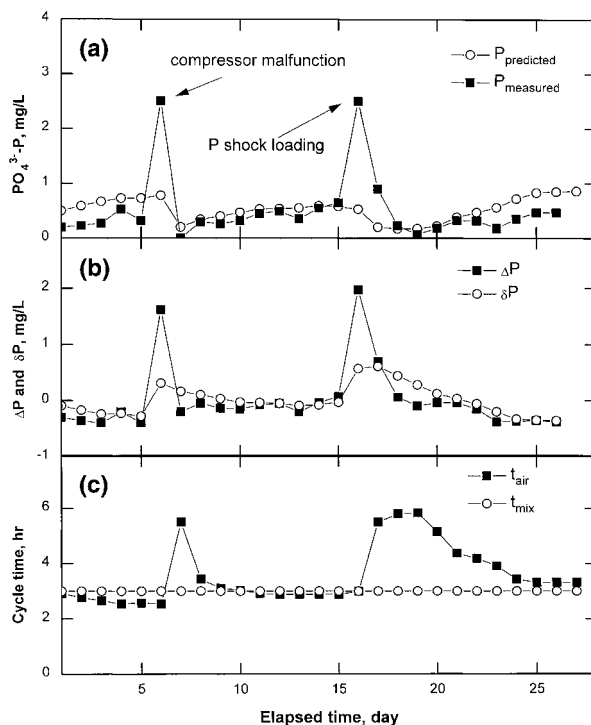


FIG. 6. Optimization Results Based on Model Prediction ($\alpha = 0.3$, $\beta = 0.7$)

aeration time for a few days and then gradually decrease it. Since the control system was designed to weigh the past data more ($\beta = 0.7$), it took a longer time for the system to reach its optimal condition.

Fig. 7 depicts the measured PO_4^{3-} concentration profiles during the aeration cycle on the days before and during the shock loading study. Both profiles show that PO_4^{3-} uptake of the system followed a first-order rate, which is one of the assumptions made in the linear model.

The optimal aeration cycle time to maintain the effluent constraint of 0.5 mg P/L ranges from 2.8 to 3.3 h under normal conditions [Fig. 6(c)]. The average aeration cycle time was calculated to be 3.5 h due to the high values from the compressor malfunction and shock loading. The aeration cycle time for phosphorus uptake was also sufficient to complete

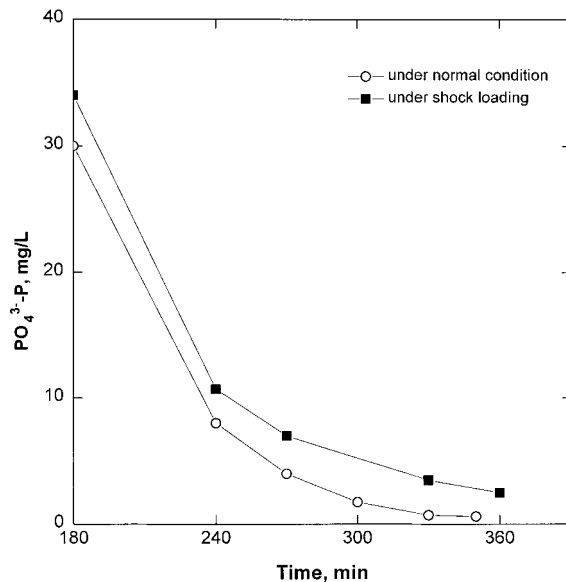


FIG. 7. PO_4^{3-} Uptake Profiles under Normal and Shock Loading Conditions

TABLE 4. Overall Performance of SBR System^a

Parameter (1)	Influent (2)	Effluent (3)	Removal efficiency (%) (4)
Wastewater			
PO ₄ ³⁻ , mg P/L	7.4	0.5	93
COD, mg/L	420	43	90
TN, mg/L	29.5	12.4	58
NH ₄ ⁺ , mg N/L	22.1	0.4	98
NO ₃ ⁻ , mg N/L	—	10.2	
Org N, mg/L	7.6	1.8	76
Reactor			
MLVSS, mg/L		2,120	
Average aerate duration, h		3.5	

^aBased on 27 day operational data; temperature = 25 ± 3°C.

nitrification with an average effluent ammonia concentration of 0.4 mg N/L (data not shown). On the other hand, the denitrification rate during the "idle" period was too slow, resulting in high nitrate levels in the effluent. The performance of COD removal efficiency (90%) was satisfactory. System performance with the optimization scheme is summarized in Table 4.

Control Scheme to Remove Nitrogen and Phosphorus

In the preceding sections, the control scheme to optimize the aeration cycle time was explored, while the mix cycle time was not controlled. The prolonged mix phase causes odor problems and reduces the amount of wastewater to be treated. From the time-dependent concentration profiles, it was found that all the phosphate was released within 1.5 h of the mix time (Kim et al. 2001). Therefore, it is desirable to have a method to optimize the mix cycle time (<1.5 h), still with a complete P release. This may be feasible if the concentration of volatile fatty acids is monitored at the end of the mix cycle and the result is fed into the optimizer, because the phosphate release is only possible when the volatile fatty acids are available.

Even though the system could remove phosphate and ammonia, high levels of nitrate were detected in the effluent, due to the low endogenous nitrate respiration rate during the idle phase. If nitrate were to be removed from the system, not only would the effluent quality be improved but also during the mix cycle the influent acetate would be used only for phosphate release. To remove the nitrate from the system, additional S_F (e.g., methanol) can be added into the reactor during the idle cycle. The addition of methanol during the idle cycle can be programmed and modeled, as in the case of Demuyne et al. (1994).

CONCLUSION

A model that had been developed by linearizing ASM2 was combined with an optimization routine to control an SBR system for phosphorus removal. The optimizer determined t_{air} for the system to minimize energy for aeration, while maintaining the PO₄³⁻ permit requirement. The results reveal that, to overcome the large mismatch from the recent data, the system should be adjusted to rely more on the past data by assigning higher value on β in (3).

A bench-scale SBR system was operated for 27 days using the optimization scheme, with α and β at 0.3 and 0.7, respectively. The mix cycle time was set at 3 h to ensure full phosphate release, although the phosphate release was usually completed in 1.5 h. The optimized aeration time to meet the permit requirement (0.5 mg P/L) under normal conditions ranges be-

tween 2.8 and 3.3 h. The performance of influent ammonia and COD removal was satisfactory, with removal efficiencies of 98% and 90%, respectively, with energy saving about 5–30%. However, the effluent nitrate level was high due to the lack of readily biodegradable COD during the idle cycle.

If a constraint is made for volatile fatty acids during the mix cycle, the mix cycle time can be controlled appropriately, since the PO₄³⁻ release is solely dependent on the amount of the available volatile fatty acids in the system.

ACKNOWLEDGMENT

The financial support from the NSF BBS-9625183 is acknowledged.

APPENDIX. REFERENCES

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