Korean J. Chem. Eng., **21**(1), 14-19 (2004)

Nonlinear Model-based Dissolved Oxygen Control in a Biological Wastewater Treatment Process

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(*Received 23 May 2003 • accepted 25 July 2003*)

Abstract−The dissolved oxygen (DO) concentration has been an important process parameter in the biological wastewater treatment process (WWTP). In this paper, we propose a nonlinear control scheme to maintain the dissolved oxygen level of an activated sludge system. Without any linearization or model reduction, it can directly incorporate the nonlinear DO process model with on-line estimation of the respiration rate (R) and the oxygen transfer rate (K_La). Simulation results show that it outperforms a control performance of the PID controller. Since it incorporates the process disturbance and nonlinearity in the controller design, the suggested method can efficiently deal with the operating condition changes that occur frequently in the wastewater treatment process.

Key words: Biological Wastewater Treatment Process (WWTP), Dissolved Oxygen (DO) Concentration, Generic Model Control (GMC), Model-based Control, Nonlinear Process Control, Respiration Rate

INTRODUCTION

The dissolved oxygen (DO) concentration in a mixed liquor is an important process parameter in the biological wastewater treatment process because of the economic reasons and the process performance. The proper DO control can give an improved process performance and provide an economic incentive to minimize the excess oxygen consumption by supplying the necessary air to meet the time-varying oxygen demand of the mixed liquor. However, the principal difficulties in the control of biological process control are the variability of the kinetic parameters and the limited availability of on-line information; hence, an adaptive and nonlinear controller is the best choice for the biological process control.

To overcome these problems, several adaptive control strategies have been suggested recently for the DO control in the aeration basin [Holmberg et al., 1989; Carlsson, 1992; Lindberg and Carlsson, 1996; Lindberg, 1997; Olsson and Newell, 1999]. Also, several methodologies have been developed for estimation of R(t) and K_La based on simple measurements of the DO sensor and airflow rate in the real aeration basin. Holmberg et al. [1989] posed a recursive estimation method which added the excitation of the process by including a small relay. Carlsson [1993] developed a novel method to estimate the respiration rate using a constrained piecewise linear model. Lindberg [1997] developed a nonlinear controller which estimated the oxygen transfer rate during the identification step. Marsili-Libelli and Voggi [1997] introduced and summarized various estimation methods about the respirometric activities in the bioprocess, and Yoo et al. [2001] applied a closed loop identification and control method to a full-scale coke WWTP. Yoo and Lee [2003] compared several process identification methods for DO dynamics and compared the novel estimation methods for oxygen transfer rate and respiration rate and applied a supervisory control algorithm in the full-scale WWTP.

Despite the relatively simple but nonlinear dynamics of the DO process, DO estimation and DO control may not be sufficiently satisfied by the operator in the biological treatment process. This means that a good control performance for all the operating conditions cannot be expected to be achieved with a conventional linear controller.

This paper proposes a new nonlinear control strategy by considering important operating conditions. The key idea of this paper is to take the oxygen transfer rate and the respiration rate of the DO nonlinear process model into account in the controller design step. For this purpose, we propose the oxygen transfer rate and the respiration rate by the Kalman filter algorithm. And then the model-based nonlinear controller is designed based on the obtained parameters.

METHODS

In the first section, we describe the DO control system in the biological WWTP. The second subsection introduces an estimator design method for the oxygen transfer rate and the respiration rate. The last subsection illustrates a nonlinear model-based DO control.

1. General Dissolved Oxygen Control System

The concentration of dissolved oxygen (DO) in the mixed liquor in biological treatment systems has proved to be an important process parameter. The proper DO control can improve the process performance, and gives economic incentive which minimizes excess oxygenation by supplying only the amount of air necessary. In this paper, we focus on the DO dynamics in the aeration tank, which relates a biomass activity to the air supply and the input organic load according to the mass balance equation:

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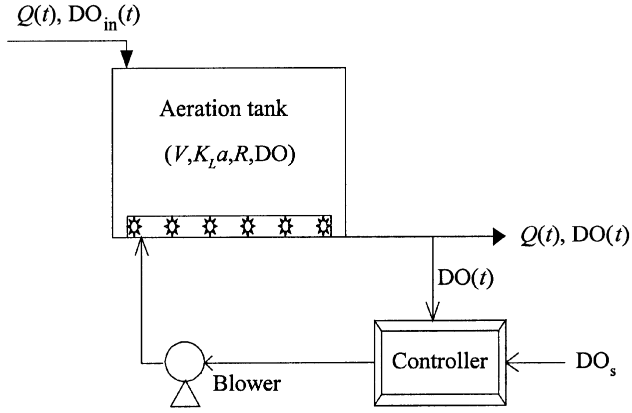

Fig. 1. Dissolved oxygen control system strategy.

$$\frac{dy(t)}{dt}=\frac{Q(t)}{V}(y_{in}(t)-y(t))+K_La(u(t))(y_{sat}-y(t))-R(t) \tag{1}$$

where y(t) is the DO concentration in the aeration basin, $y_{in}(t)$ is the DO concentration of the input flow, y_{sat} is the saturated DO concentration, Q(t) is the influent wastewater flow rate, V is the aerator volume, $K_La(u(t))$ is the oxygen transfer rate, u(t) is the airflow rate into the aeration tank, and R(t) is the respiration rate. The parameters, K_La and R(t), vary with time, which causes the DO concentration to vary with time.

Fig. 1(a) illustrates the general DO control system structure in the wastewater treatment plant. If a DO concentration below the set point of DO controller (y_s) is detected, the controller increases the amount of air blown into the aeration tank. When a higher DO concentration above the set point is detected, the controller decreases the amount of air to maintain the DO at a specific concentration. Despite the relatively simple dynamics of the DO process, there are a number of factors that complicate the control of the DO concentration: influent flow variation, organic load fluctuation, nonlinearity, sensor noises and so on. Daily variations in the influent load lead to continuous changes in the respiration rate and oxygen transfer rate, which make the DO dynamics time-varying. This means that it may be difficult to achieve good control and estimation performance for all operating conditions by using a conventional method.

The respiration rate has been selected as a meaningful biological indicator, as it yields the rate at which the microorganisms utilize oxygen in carrying out their metabolic activities. This variable provides information about the current state of the biological reactions and can be used in connection with a number of control strategies to adjust the process operation as stable as possible [Marsili-Libelli and Vaggi, 1997]. Estimates of the oxygen transfer rate $K_La(u)$ and the respiration rate R(t) in the biological wastewater treatment plant are needed in order to monitor the biological activity and assess the performance of the process control system. In addition, estimates of these rates are required to construct a nonlinear controller that controls the DO concentration more effectively. So we need both controller's performance and estimation performance of key parameters in these biological processes. Knowledge of these variables is therefore of interest in both the process diagnosis and the process control. In particular, the respiration rate is the key variable characterizing the DO process and the associated removal and degradation of biodegradable matter. In fact, the respiration rate is the true indicator of biologically degradable load. Furthermore, a rapid decrease of the respiration rate can be used as a warning that toxic matter has entered the plant. The entry of toxic matter into a plant causes the microorganisms to slow their activity or die, leading to a decrease in the respiration rate [Lindberg, 1997].

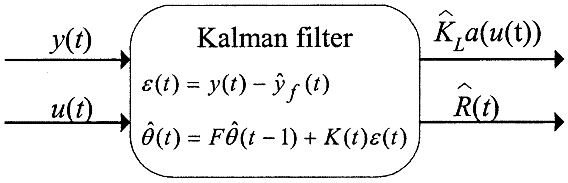

Fig. 2. Estimator of $K_La(u(t))$ and R(t).

2. Estimation of the Oxygen Transfer Rate and the Respiration Rate

The estimation of the oxygen transfer rate ($K_La[u(t)]$) and the respiration rate (R(t)) is needed to construct a nonlinear controller for controlling the DO concentration more effectively. Several recursive approaches were proposed in order to estimate $K_La[u(t)]$ and R(t) from the measurement of DO and airflow rate [Holmberg et al., 1989; Carlsson, 1993; Marsili-Libelli and Voggi, 1997]. Here we used Lindberg's method [1997]. A schematic figure of the estimator is shown in Fig. 2.

Because the respiration rate is affected by microbial activity, influent characteristics, influent loads, flow rate etc., it is not possible to decide its mathematical formulation and specific form, that is, a kind of stochastic process. The respiration rate in many biological treatment processes which treat domestic wastewater exhibits sinusoidal behavior due to large diurnal fluctuations in the flow rate and the composition of the feed stream; and the respiration rate in industrial WWTPS shows a step-like behavior. Several models for modeling the respiration rate as a stochastic process, such as random walk model, a filtered random walk model, and an integrated random walk model, are suggested [Olsson and Newell, 1999]. In this paper, the respiration rate is modeled as a filtered random walk based on a deviation variable,

$$R(t)=\frac{1}{(1-q^{-1})(1-fq^{-1})}e_r(t) \tag{2}$$

where f is a filter pole between 0.9 and 1, $e_r(t)$ is zero mean white noise, and q is backward shift operator. Here, we consider the respiration rate as a filtered random walk model among stochastic processes. The filtered random walk model can give better tracking performance of the respiration rate than a random walk model in the presence of measurement noises [Lindberg, 1997].

The exponential oxygen transfer rate model, K_La, can be a good choice, because it can be given a similar shape of the K_La function, which is natural in a physical sensor (the oxygen transfer deteriorates for high airflows). Further, only two parameters are necessary to estimate and it is easy to invert the K_La function. An exponential model of the oxygen transfer rate is modeled suggested by Lindberg [1997],

$$K_La(u(t))=k_1(1-e^{-k_2u(t)/a}) \tag{3}$$

where a is a scaling factor and k_1 and k_2 are parameters in the exponential K_La model. The parameters of k_1 and k_2 can be measured during the laboratory batch experiment under an assumption of a fixed airflow rate gives a fixed K_La.

The Kalman filter equations are as follows [Ljung, 1987].

$$\varepsilon(t)=y_f(t)-\hat{y}_f(t|t-1;\ \hat{\theta}(t-1))$$
$$\hat{\theta}(t)=F\hat{\theta}(t-1)+K(t)\varepsilon(t)$$
$$K(t)=\frac{FP(t-1)\varphi(t)}{1+\varphi^T(t)P(t-1)\varphi(t)}$$
$$P(t)=FP(t-1)F^T-\frac{FP(t-1)\varphi(t)\psi^T(t)P(t-1)F^T}{1+\varphi^T(t)P(t-1)\varphi(t)}+R_1$$
$$F=\begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1+f & -f\\ 0 & 0 & 1 & 0\end{bmatrix} \tag{4}$$

where $\varepsilon(t)$ is the predictor error, $y_f(t)$ is the filtered DO signal, and $\hat{y}_f(t)$ is the predictor. The parameter vector θ is defined as θ=[θ= $[\hat{k}_1\ \hat{k}_2\ \hat{R}(t)\ \hat{R}(t-1)]^T$, where the $\hat{k}_1$ and $\hat{k}_2$ are the estimated value of exponential K_La model, and the respiration rate; $\hat{R}(t)$, is the estimated value of respiration rate. The covariance matrix R_1 is a 4 by 4 diagonal matrix, $R_1=\mathrm{diag}(\gamma_1, \gamma_1, \gamma_2, 0)$ which should have appropriate values. The parameter γ_1 is a small number which reflects the slow variation in the K_La parameters. The much faster variation in the respiration rate is turned into a larger value of γ_2. A too small value of γ_2 may give (a larger) bias in the estimate, since the Kalman filter will not be able to the follow the variations in the true respiration rate. On the other hand, a too large value of γ_2 results in unnecessary large variations (due to measurement noise) of the estimated respiration rate [Lindberg, 1997].

The regressor $\varphi(t)$ is given by

$$\varphi(t)=h^*[(y_{sat}-y_f(t-1))[1-e^{-\hat{k}_2u(t)/a}\ k_1u(t)e^{-\hat{k}_2u(t)/a}]\ -1\ 0]^T$$
$$h^*=\frac{-1}{K_La(u)+Q/V}(e^{-(K_La(u)+Q/V)h}-1) \tag{5}$$

where h is a sampling time. The predictor $\hat{y}_f(t)$ is given by

$$\hat{y}_f(t|t-1)=y_f(t-1)+h^*\left\{\frac{Q(t-1)}{V}[y_{in}(t-1)-y_f(t-1)]\right.$$
$$\left.+K_La[u(t-1)][y_{sat}-y_f(t-1)]-\hat{R}(t-1)\right\} \tag{6}$$

3. Nonlinear Model-based Dissolved Oxygen Control

In this paper, we propose an adaptive model-based DO control that combines the adaptive estimation of the respiration rate and the oxygen transfer rate by the Kalman filter algorithm and the fundamental dynamics of the DO process. In the present study, the Kalman filter method is used to estimate the respiration rate and the oxygen transfer rate adaptively. And generic model control (GMC) is used to utilize the nonlinear dynamics of the DO process in the control algorithm [Lee and Sullivan, 1988]. In GMC, nonlinear process models can be imbedded directly into the controller without any linearization. GMC is a very simple, robust and nonlinear control algorithm in single-input and single-output (SISO) processes.

The main idea behind GMC is to find values of the manipulated input variable which forces the model output to follow a desired trajectory. The considered model is given by the following differential equation.

$$y(t)=f(y, x, u, t, \theta) \tag{7}$$

where Eq. (7) is a deterministic model, f is a known (nonlinear) function, y is the process output, x is the state variable, u is the input, and θ is a vector of model parameter. In order to avoid problems with an unstable predictor, it is assumed that the autonomous system $y(t)=f(y, x, 0, t, \theta)$ is asymptotically stable in the operating region. GMC is based on solving f in Eq. (7) with respect to input u, and then it is assumed that u appears directly in the equation of the derivative of output.

The commonly used state space model for a control affine system is given by

$$x=\tilde{f}(x)+\tilde{g}(x)u \tag{8}$$
$$y=\tilde{h}(x) \tag{9}$$

Eqs. (8) and (9) can be brought into the form of Eq. (7) by introducing the Lie derivatives $L_{\tilde{f}}\tilde{h}=\tilde{f}^T(\partial\tilde{h}/\partial x)$ and $L_{\tilde{g}}\tilde{h}=\tilde{g}^T(\partial\tilde{h}/\partial x)$. Then, $y=L_{\tilde{f}}\tilde{h}+L_{\tilde{g}}\tilde{h}u$ is obtained. The requirement that the input appears directly in the model equation for y implies that $L_{\tilde{g}}\tilde{h}\neq 0$, that is, the relative degree of the system is one. Also, it is assumed that Eq. (7) has stable zero dynamics. The assumptions of an asymptotically stable autonomous model and stable zero dynamics may impose restrictions on the set of model, that is, it must be restricted to a set where these assumptions are satisfied.

The desired trajectory r^* used in the GMC is given by

$$r^*=K_1[y_s-y(t)]+K_2\int_0^t[y_s-y(t)]dt=PI \tag{10}$$

where y_s is a set point, K_1 and K_2 are GMC control loop constants, which can be determined from the following equation.

$$K_1=\frac{2\xi_i}{\tau_i},\ K_2=\frac{1}{\tau_i^2} \tag{11}$$

where, ξ_i and τ_i determine the shape and speed of the desired closed-loop trajectory. The reference trajectory of Eq. (10) has a pseudo-second-order response for a step set point change.

Our goal is that the actual process output approaches a set point with a desired trajectory. Then, combining Eqs. (7) and (10) leads to the following implicit control law, that is, GMC.

$$f(y,x,u,t,\theta)=K_1(y_s-y)+K_2\int_0^t(y_s-y)dt \tag{12}$$

To find the value of the input variable, Eq. (12) is solved with respect to u. In the GMC, a nonlinear process model can be imbedded into the controller directly without any linearization. However, there always exists a model parameter mismatch between the process and process model [Signal and Lee, 1992; Erik, 1996]. Then, we may encounter a problem involving unmeasured state variables in solving Eq. (12).

Therefore, a nonlinear model-based control is introduced in this paper in order to correct the process/model mismatch and to estimate the unmeasured state variables. With the available process input and output measurements, the model-based control updates the estimated parameter vector θ. Then the updated model is used by GMC for the control input. Fig. 3 shows the structure of the proposed model-based control scheme. Although the proposed control tuning parameters are constant, the updated model can compensate the process/model mismatch because of its model-based characteristics.

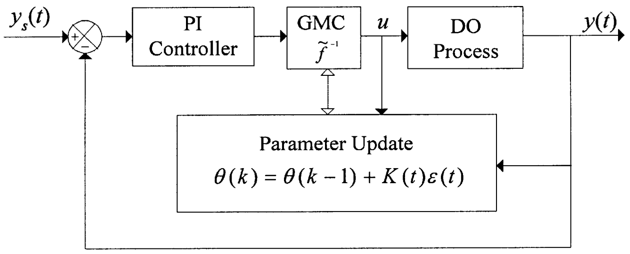

Fig. 3. The proposed nonlinear model-based control strategy.

The suggested method for DO control is as follows.

DO Process:

$$\frac{dy(t)}{dt}=\frac{Q(t)}{V}[y_{in}(t)-y(t)]+K_La[u(t)][y_{sat}-y(t)]-R(t) \tag{13}$$

DO model:

$$\frac{dy(t)}{dt}=\frac{Q(t)}{V}[y_{in}(t)-y(t)]+\hat{K}_La[u(t)][y_{sat}-y(t)]-\hat{R}(t) \tag{14}$$

Desired trajectory:

$$\frac{dy_{desired}(t)}{dt}=K_1[y_s-y(t)]+K_2\int_0^t[y_s-y(t)]dt=PI \tag{15}$$

Here, we made a desired trajectory as a Proportional-Integral controller (PI) without a state observer. $\hat{K}_La(u(t))$ and $\hat{R}(t)$ are estimated from the previous mentioned Kalman filter estimation algorithm. Using Eq. (14) and setting $(dy(t)/dt)=PI$, we can derive the following equation in order to obtain the control input u(t).

$$\hat{K}_La(u(t))=\frac{PI+\hat{R}(t)+Q(t)/V\cdot y(t)-Q(t)/V\cdot y_{in}(t)}{y_{sat}-y(t)} \tag{16}$$

Using a nonlinear model $(\hat{K}_La(u(t))=\hat{k}_1(1-\exp(-\hat{k}_2u(t)/a)))$, u (t) can be obtained easily by

$$u(t)=\frac{-a}{\hat{k}_2}\cdot\ln\left[1-\frac{PI+\hat{R}(t)-Q(t)/V(y_{in}(t)-y(t))}{\hat{k}_1(y_{sat}-y(t))}\right] \tag{17}$$

In Eq. (17), the control input, u(t) is explicitly shown as only a function of the estimated values $(\hat{K}_La(u(t))$ and $\hat{R}(t))$ and the measured process values (Q, y(t), $y_{in}(t)$, and y_{sat}) without any state observer. The control input u(t) has a nonlinear gain and all values in numerator except PI are the sum of the bias of steady state term and feed-forward term of the respiration rate which estimate the respiration rate $\hat{R}(t)$ and adjust the DO controller to compensate for the effect of the variable respiration rate. Since we can make a model of the oxygen transfer rate $(K_La(u(t)))$ and respiration rate (R(t)) in the short estimation phase, we can easily compute the control action from Eq. (17). The proposed nonlinear control law has no offset and robustness against the modeling error since it contains the integral action by the external input in the structure itself. Moreover, the suggested control strategy has a special robustness to the disturbance of DO process and the respiration rate since it contains the estimated respiration rate in the controller structure. As an ideal case, if the estimated values are equal to the true ones, $\hat{K}_La(t)=K_La$ and $\hat{R}(t)=R(t)$, the proposed control algorithm makes the offset free. Combining the control input, Eq. (17) and the DO dynamics, Eq. (1), gives the following error equation.

$$\frac{de(t)}{dt}=-K_1e(t)-K_2\int_0^t e(t)dt=-PI$$

$$e(t)=y_s(t)-y(t) \tag{18}$$

Thus, the error signal e(t) approaches zero exponentially. Moreover, it is especially robust to disturbances in the DO process (i.e., respiration rate) because it contains the estimated respiration and oxygen transfer rates in the controller structure.

In general, the oxygen transfer rate K_La is known to vary much more slowly (in a matter of days) than the respiration rate R(t) which is directly related to the biological activity and hence can vary in a matter of minutes. So, we can assume that the oxygen transfer rate, K_La, is constant during the normal operation. If we assume K_La to be non time varying, the estimation procedure can be separated into two steps [Carlsson, 1993]. In the first step, the nonlinear parameters of the oxygen transfer model, k_1 and k_2, and the respiration rate R(t) can be estimated during high excitation of the airflow rate, where the high excitation of the airflow rate is required in both frequency and amplitude. The estimation procedure is performed on a relatively short data set, that is, typically a few hundred data points. This makes it possible to update the model parameters of the exponential oxygen transfer rate model (k_1 and k_2) and the respiration rate R(t). In the second step, which occurs when the estimated parameters in the K_La model, $\hat{k}_1$ and $\hat{k}_2$, have settled, the high excitation of the airflow rate can be switched off, that is, normal operation of DO control system is applied. Then, the estimated values of K_La and R models is used to the nonlinear controller design. Under the closed-loop control, the respiration rate can be estimated by setting all ele-

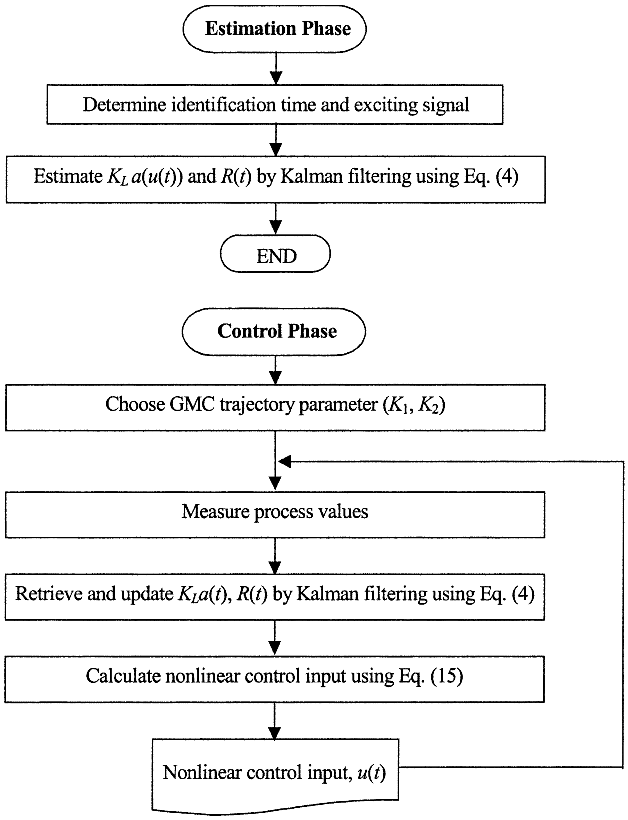

Fig. 4. Flowchart of the proposed identification and control algorithm.

ments in the covariance matrix (P) to reset in the estimation stage, except for the (3, 3) element which is only related to the respiration rate; and a tuning parameter for the respiration rate tracking (a large value gives fast but noisy tracking, while a small value gives less noise but a slow tracking) In Fig. 4, we represent the procedure of the estimation sequence and the proposed nonlinear control law.

RESULTS AND DISCUSSION

In this paper, the following DO process is simulated.

$$\frac{dy(t)}{dt}=\frac{Q(t)}{V}[y_{in}(t)-y(t)]+K_La(u(t))(y_{sat}-y(t))-R(t) \quad (19)$$

where Q(t)=1,000 *l*/h, V=630 *l*, y_{sat}=10 mg/*l*, y_{in}(t)=0 mg/*l*, R(t)=20+15 sin(6t) mg/*l*/h, and $K_La(u(t))=5\tan^{-1}(20u(t)/1{,}000)\ h^{-1}$. The sampling time is 10 seconds and we added the zero mean white measurement noise. In this simulation, we also considered the time delay that always exists in the real biological treatment process, where the time delay was ten times the sampling time, that is, 100 secs.

In Fig. 5, the estimation performances of K_La and R(t) during the estimation phase are shown. We used the following parameters in this paper, f=0.97, $R_1(3, 3)=0.1$, $\theta(0)=[1\ 1\ 0\ 0]^T$, and P(0)=diag(10^3, 10^3, 10^3, 10^3). The estimated respiration rate has just a small time delay and the estimated K_La is close to the true value. The estimated respiration rate can also be useful for the determination of a suitable DO set point. It is important that the input signal should be sufficiently exciting, both in amplitude and in frequency to obtain good estimation result, especially with the measurement noise corrupted data.

Fig. 6 compares the control performances of the PID controller and the proposed controller. Here, the PID tuning parameters are tuned appropriately by adjusting the gain of the controllers by Lindberg's pole placement tuning rule [Lindberg, 1997]. The tuning parameters of the suggested nonlinear controller are tuned by Lee's reference trajectory shape [Lee and Sulivan, 1988]. In spite of the time-varying behavior of R(t) and K_La, the proposed controller gives good control performance, as shown in Fig. 6. However, the PID controller shows somewhat of a tracking error between set point and DO concentration because the DO dynamics are influenced by the continuously time-varying influent load and respiration rate.

The second simulation proves the proposed controller's performance when the respiration rate varies in both amplitude and frequency. The respiration rate varies as R(t)=20+15 sin(6t) mg/*l*/h at first, R(t)=20+15 sin(12t) mg/*l*/h after 3 hours and R(t)=10+15 sin(3t) mg/*l*/h after 6 hours. Fig. 7 shows the control performances of the PID controller and the proposed controller during the several load changes. The tuning parameters are the same as the previous example. In spite of the respiration rate's variation in both amplitude and frequency, the proposed controller shows superior control performances to the conventional PID controller. This means that the suggested nonlinear model-based DO controller can effectively treat the operating condition changes that frequently break out in the biological wastewater treatment process.

However, the PID controller shows a large offset since it is a linear controller and its tuning parameter is fixed. If the linear controller were tuned for high performance during a low load, a slow

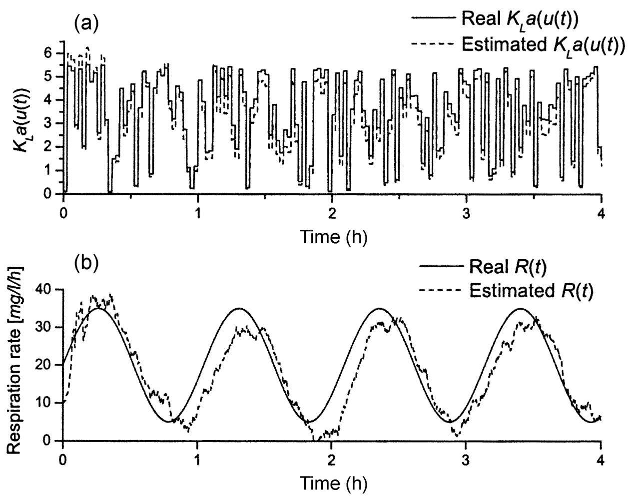

Fig. 5. Estimation performances of K_La(u(t)) and R(t) using the Kalman filter. (a) K_La (b) Respiration rate.

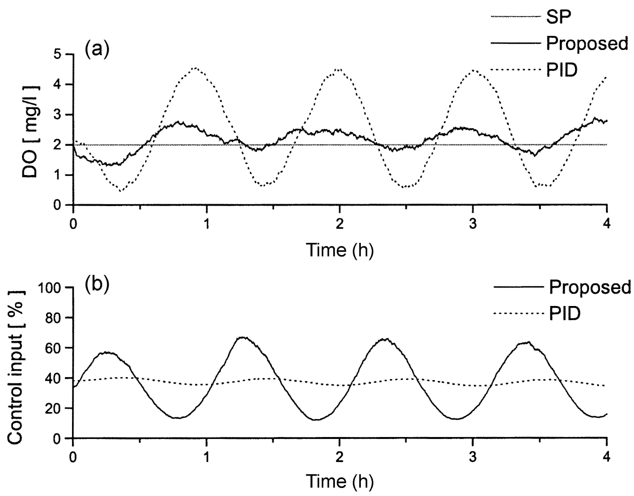

Fig. 6. Control comparisons of the PID and the proposed method with a sinusoidal variation of the respiration rate.

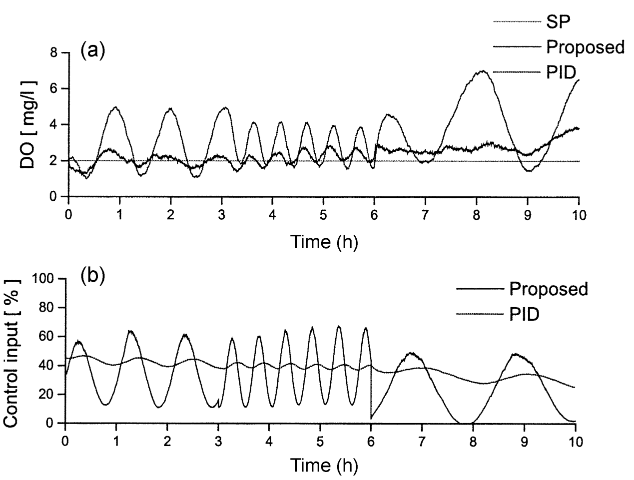

Fig. 7. Control comparisons of the PID and the proposed control with operation range changes.

closed loop response would be obtained for a high load or vice versa.

CONCLUSION

A nonlinear model-based control algorithm for the dissolved oxygen control is proposed. The nonlinear oxygen transfer rate and the time varying respiration rate are estimated by using the Kalman filter. And then, the suggested idea incorporates the obtained nonlinear DO process model into the controller design directly. From the simulation results, the proposed controller shows an enhanced control performance than the PID controller because it includes the nonlinear and time varying characteristics explicitly in the controller design step. In particular, the proposed model-based DO controller can efficiently cope with the operating condition changes that occur frequently in the wastewater treatment process.

ACKNOWLEDGMENT

This work was supported by the Post-doctoral Fellowship Program of Korea Science & Engineering Foundation (KOSEF) and a Visiting Postdoctoral Fellowship of Fund for the Belgium Scientific Research-Flanders (FWO).

NOMENCLATURE

a : scaling factor
DO : dissolved oxygen concentration [mg/*l*]
DO_s : dissolved oxygen set point [mg/*l*]
$e_r(t)$: zero mean white noise
f : filter constant
GMC : generic model control
$K_La(u(t))$: oxygen transfer rate
k_1 : exponential model parameters of $K_La(u(t))$
k_2 : exponential model parameters of $K_La(u(t))$
K_1 : GMC controller constants
K_2 : GMC controller constants
PI : Proportional-Integral
PID : Proportional-Integral-Derivative
Q(t) : wastewater flow rate
q^{-1} : difference operator
R(t) : respiration rate [mg/*l*/h]
r^* : desired trajectory
u(t) : air flow rate into the aeration tank
V : volume of the aerator
y(t) : dissolved oxygen concentration in the aerator [mg/*l*]
$y_{desired}(t)$: desired dissolve oxygen concentration [mg/*l*]
$y_{in}(t)$: dissolved oxygen concentration of the input flow [mg/*l*]
y_s : set point
y_{sat} : saturated concentration of dissolved oxygen [mg/*l*]

Greek Letter

θ : parameter vector

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