Hindawi Publishing Corporation
Mathematical Problems in Engineering
Volume 2015, Article ID 178953, 9 pages
http://dx.doi.org/10.1155/2015/178953

Research Article

Linear Active Disturbance Rejection Control of Dissolved Oxygen Concentration Based on Benchmark Simulation Model Number 1

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Received 20 October 2014; Accepted 12 December 2014

Academic Editor: Wudhichai Assawinchaichote

In wastewater treatment plants (WWTPs), the dissolved oxygen is the key variable to be controlled in bioreactors. In this paper, linear active disturbance rejection control (LADRC) is utilized to track the dissolved oxygen concentration based on benchmark simulation model number 1 (BSM1). Optimal LADRC parameters tuning approach for wastewater treatment processes is obtained by analyzing and simulations on BSM1. Moreover, by analyzing the estimation capacity of linear extended state observer (LESO) in the control of dissolved oxygen, the parameter range of LESO is acquired, which is a valuable guidance for parameter tuning in simulation and even in practice. The simulation results show that LADRC can overcome the disturbance existing in the control of wastewater and improve the tracking accuracy of dissolved oxygen. LADRC provides another practical solution to the control of WWTPs.

1. Introduction

Wastewater treatment plants (WWTPs) are a class of nonlinear, uncertain, and time-delay systems. Influent flow rate, contaminant concentrations, amount of pollutants, and other uncertain factors make the control of wastewater a big challenge. Additionally, an increasing discharge standard of sewage drives people to propose more efficient and practical approaches to improve the control of wastewater.

For the control and simulation of WWTPs, in general, a mathematical model describing the biochemical process is of necessity. Benchmark simulation model number 1 (BSM1) has been proposed by Working Groups of COST Actions 682 and 624 [1, 2]. It is a benchmark model for WWTPs with realism and accepted standards. It defines the plant layout, simulation, influent loads, test procedures, and evaluation criteria [3–5], and the model could well simulate the main process of wastewater treatment and any control strategy could be tested and compared on BSM1. It is a better way to make a simulation study on the control of wastewater treatment process on BSM1.

On BSM1, many manipulated variables, such as the dissolved oxygen concentration, ammonia concentration, internal recycle flow rate, and external carbon dosing rate [1, 2], are involved. BSM1 mainly simulates the activated sludge process. Dissolved oxygen level, a key factor of activated sludge process, plays a significant role in the behavior of the heterotrophic and autotrophic microorganisms living in the activated sludge. Proper level of the dissolved oxygen should be supplied for organic matter degradation and nitration; however, excessive dissolved oxygen will increase the pollution concentration and decrease the denitrification process [6–9]. In other words, wastewater effluent quality depends greatly on the level of dissolved oxygen. Additionally, effective control of the dissolved oxygen level could reduce the operational cost of the wastewater treatment [10]. Therefore, the control of dissolved oxygen concentration is important, effective, and widely studied in WWTPS.

PID is firstly involved in WWTPs for the control of dissolved oxygen and it is still widely used in practice [11–14]. Only 3 parameters and the simple structure make the controller easily applied in many occasions. In order to make the dissolved oxygen concentration stably near the expectations, reject disturbances in WWTPs and make the effluent satisfied with the requirements; the proportion parameter of the controller has to keep large. However, large proportional

parameter easily results in high frequency oscillations, which also increase the costs or even destabilize the closed-loop system. Additionally, all kinds of disturbances existing will degrade the performance of the closed-loop systems. In the last decades, various control algorithms have been proposed to control the dissolved oxygen, such as model predictive control (MPC) [7, 10, 15, 16], fuzzy control [6, 17], and neural network control [8, 9, 18, 19]. The MPC has been widely applied in industrial processes, especially the fruitful linear MPC business software packages. However, WWTPs are typical nonlinear systems, and few successful MPC applications exist in nonlinear systems [20]. Moreover, no clear physical interpretation and high amount of computation always hinder MPC's applications [20]. Similarly, the fuzzy rules and nonlinear mapping network also require a lot of data for training in fuzzy control and neural networks. In addition, fuzzy rules, the number of nodes of neural networks, and the weight value of neural networks are difficult to get for achieving good performance.

As a matter of fact, the control of dissolved oxygen in WWTPs is a typical nonlinear and strong couplings process. It is affected by other variables, such as nitrate and nitrite nitrogen, ammonia nitrogen, and the internal effluent. If all factors affecting the control effect of dissolved oxygen can be viewed as disturbances, the core of dissolved oxygen control is the problem of disturbance rejection.

Linear active disturbance rejection controller (LADRC) is a promising way to solve the disturbance rejection problem. In LADRC structure, the external unknown disturbance and the internal uncertainty dynamics are treated as only a generalized disturbance, which can be estimated and compensated by designing an extended state observer in real time. Therefore, the closed-loop system has great disturbance rejection ability. Professor Han firstly proposed active disturbance rejection control (ADRC), which is taking full advantage of control errors to suppress the control errors [21–23], and it is composed of tracking differentiator (TD), extended state observer (ESO), and nonlinear PID. However, there are 12 parameters in ADRC, which results in a difficult tuning process. With an attempt to simplify the tuning process and make ADRC more practical, LADRC is proposed with linearizing the ESO and TD by Gao in 2003. By this simplification, LADRC only has 3 parameters for tuning [24]. LADRC has lots of successful applications [25–28]. Simulation and experimental results prove that LADRC has nice performance and strong robustness to disturbances. In WWTPs, the variables except the dissolved oxygen can be regarded as the internal uncertain dynamics, while the influent can be regarded as the external unknown disturbance, which could be estimated and compensated by the linear extended state observer (LESO). Therefore, LADRC may have good effect in the control of dissolved oxygen. However, the ability of LADRC to overcome the disturbance of WWTPs and how to choose proper LADRC parameters for the control of dissolved oxygen are unclear. Both of them are worth making a further research in theory and practice for WWTPs. For this purpose, some theoretical analysis and simulation researches are fulfilled.

This paper is organized as follows. Section 2 presents the basic structure of BSM1, the dissolved oxygen control strategy, and the design approaches of LADRC. Section 3 presents the results of simulation, the steps of parameters tuning, and related analysis. Finally, conclusions are given in Section 4.

2. Benchmark Simulation Model Number 1 and Its Control Strategy

2.1. The BSM1 Introduction. BSM1 layout can be divided into two parts, which includes 5 activated sludge reactors and a secondary settler. General structure of BSM1 is shown in Figure 1. Five activated sludge reactors are called bioreactors which are composed of 2 anoxic tanks (Units 1 and 2) and 3 aerobic tanks (Units 3–5). The activated sludge model number 1 (ASM1) has been selected to describe the biological phenomena taking place in biological reactors [29, 30]. Thus, the model includes oxidizing reactions, nitrification, and denitrification for removing biological nitrogen. Behind the reactors, there is a secondary settler, which is composed of 10 layers. The 6th layer is the feed layer, through which the wastewater is from the bioreactors to the secondary settler. At last the treated wastewater comes out of the 10th layer and parts of the sludge from the 1st layer go back to Unit 1 through the external recycle. In the secondary settler, there is no biochemical reaction, just physical deposition. The double-exponential settling velocity function has been selected to describe the secondary settler [31, 32].

In ASM1, there are 13 state variables (including 6 particulate components and 7 soluble components), 8 basic processes, 5 stoichiometric parameters, and 14 kinetic parameters. All the variables, processes, and parameters describe the oxidizing reactions, nitration reactions, and denitrification reactions. Reactions in each bioreactor about 13 state variables follow mass balancing:

$$\frac{dZ_k}{dt} = \frac{1}{V_k}\left(Q_{k-1}Z_{k-1} - r_i V_k - Q_k Z_k\right), \tag{1}$$

where k is the bioreactor number, Z_k is the state variables, Q_k is the influent, V_k is the volume of the bioreactor, r_i is the observed conversion rates, and i is from 1 to 13. r_i is the core parameter in ASM1, which reflects the relationship among variables. BSM1 is built with Matlab/Simulink, including 5 bioreactors, a secondary settler, and a time-delay unit. The simulation data of dry weather, rainy weather, and stormy weather on benchmark of WWTPs on 14 days is provided to test the model. Only the dry weather data present in Figure 2 is used in this paper, because the data of dry weather, rainy weather, and stormy weather is the same except the last 2 two days.

The flow-weighted average values of the effluent concentrations, such as chemical oxygen demand (COD), biochemical oxygen demand (BOD), ammonium (S_{NH}), total nitrogen (TN), and total suspended solids (TSS) [1, 2], should be within the limits given in Table 1. The quality of processed

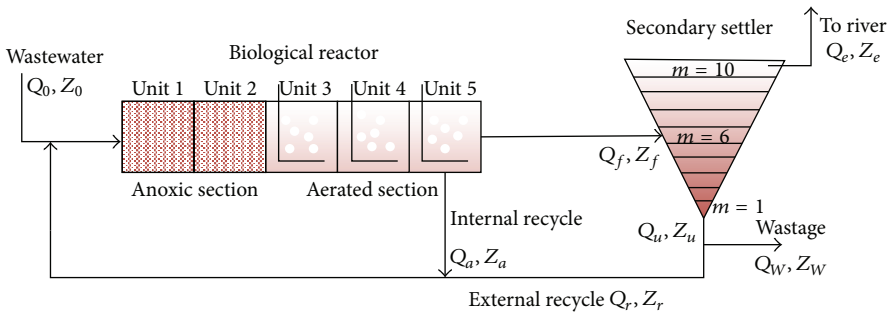

Figure 1: General overview of the BSM1 plant.

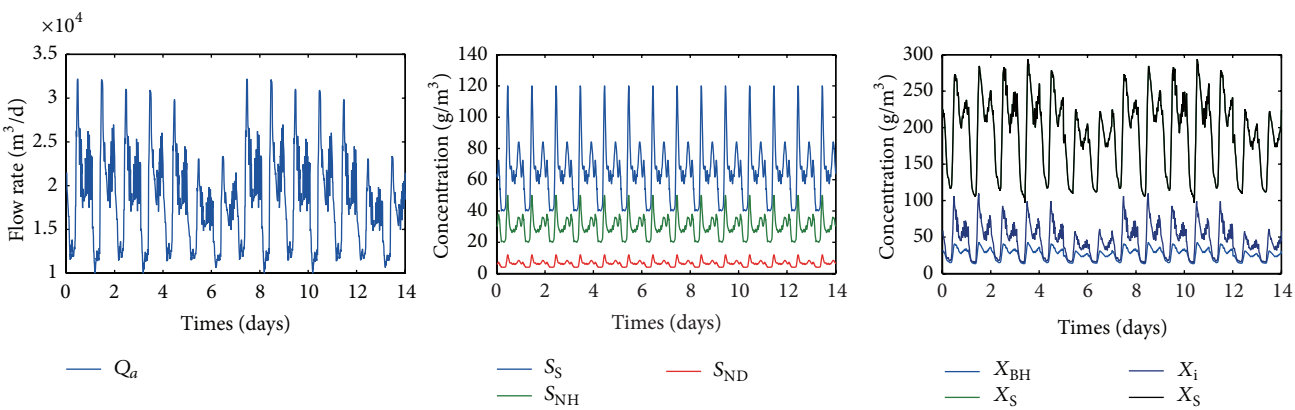

Figure 2: Dry weather influent.

Table 1: Effluent quality limits.

The variable limits	Value
Chemical oxygen demand (COD)	18 gN/m^3
Biochemical oxygen demand (BOD)	100 gCOD/m^3
Ammonium (S_{NH})	4 gN/m^3
Total nitrogen (TN).	30 gSS/m^3
Total suspended solids (TSS)	100 gBOD/m^3

wastewater called effluent quality (EQ) from the 10th layer can be described by [31]

$$\mathrm{EQ} = \frac{1}{7000}\int_{7\,\mathrm{days}}^{14\,\mathrm{days}} \left[2\mathrm{TSS}(t) + \mathrm{COD}(t) + 30\mathrm{TN}(t) - 20S_{\mathrm{NO}}(t) + 2\mathrm{BOD}(t)\right] \cdot Q_e(t)\,dt, \tag{2}$$

where S_{NO} is the nitrate and nitrite nitrogen. Accordingly, the influent quality (IQ) can be calculated as

$$\mathrm{IQ} = \frac{1}{7000}\int_{7\,\mathrm{days}}^{14\,\mathrm{days}} \left[2\mathrm{TSS}(t) + \mathrm{COD}(t) + 30\mathrm{TN}(t) - 20S_{\mathrm{NO}}(t) + 2\mathrm{BOD}(t)\right] \cdot Q_0(t)\,dt. \tag{3}$$

2.2. Control Strategy. In BSM1, the control of nitration reactions and denitrification reactions is important. Two factors affect the reactions. The first is the concentration of dissolved oxygen for the activated sludge process, because adequate oxygen level is good for the growth of autotrophic bacteria to reduce ammonia nitrogen to be nitrate. The other factor is the level of nitrite and nitrate in anoxic tanks. Primary control objectives have been given in Table 2 and Figure 3 shows the control structure of BSM1.

Based on ASM1, the dissolved oxygen concentration in aerated sections is the key factor, which affects the process of the biochemical reactions. The dissolved oxygen concentration is manipulated by the oxygen transfer coefficient, which determines the reaction rate of the whole 13 state variables. Excessive dissolved oxygen concentration leads to increase of COD and BOD of the wastewater. On the contrary, if the dissolved oxygen concentration is relatively low, the nitration reaction is inhibited and the removal of ammonia nitrogen in the wastewater will be incomplete. The TN and S_{NH} cannot meet the effluent requirement. Moreover, in aerated sections, keeping the proper dissolved oxygen concentration in Unit 5 is of great importance. First, the effluent quality on 7 soluble components depends on the wastewater from Unit 5, and they will not be changed in secondary settler. Second, parts of the excessive dissolved oxygen from Unit 5 to anoxic sections through the internal recycle constrain the denitrification reactions, so the control of feedback influent (Q_a) will keep the dissolved oxygen in a proper value in the internal recycle.

Table 2: Control variables and their limitations.

Control handle	Limits	Controlled variables	Set point
Fixed oxygen transfer coefficient (K_La_5)	0~360	Dissolved oxygen (S_O)	2 g(-COD)/m^3
Feedback influent (Q_a)	0~92230	Nitrite and nitrate (S_{NO})	1 g/m^3

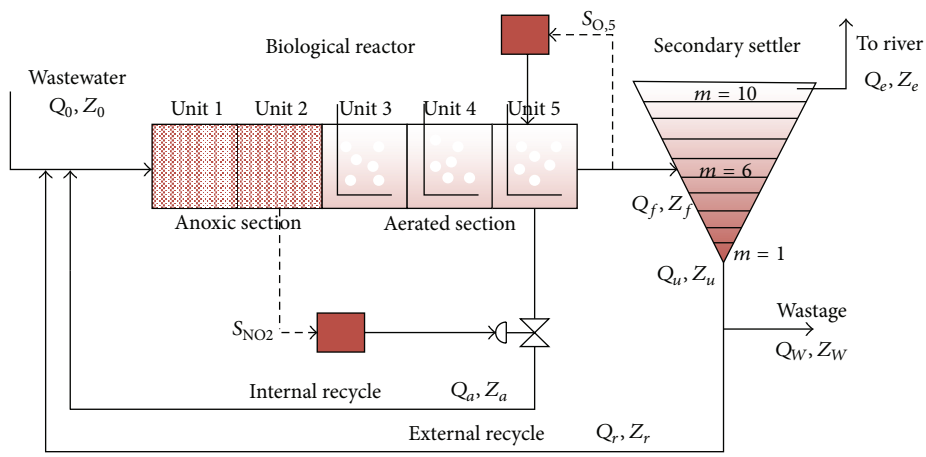

Figure 3: Control strategies of BSM1.

In addition, controlling the oxygen transfer coefficient in Units 3–5 is less efficient to control the oxygen transfer coefficient in Unit 5 and make the oxygen transfer coefficient in Units 3 and 4 fixed. Therefore, the proper dissolved oxygen concentration in Unit 5 is the key factor in the whole BSM1 system.

Equation (1) covers 13 state variables that meet mass balancing. However, considering the influence of the oxygen transfer coefficient (K_La_5), the equation of the oxygen ($S_{O,5}$) in Unit 5 is

$$\frac{dS_{O,5}}{dt} = \frac{Q_4 S_{O,4}}{V_5} - \frac{Q_5 S_{O,5}}{V_5} + u(t) + r_8, \tag{4}$$

where V_5 is the volume of Unit 5, Q_4 is the fluent of Unit 4, Q_5 is fluent of Unit 5, r_8 is the observed conversion rates of the oxygen, and $u(t)$ is the oxygen transfer coefficient.

2.3. Designing the LADRC. In BSM1, (4) can be written as a first order plant

$$\dot{x}_1 = f_0(x_1) + b_0 u(t) + f(t), \tag{5}$$

where

$$x_1 = S_{O,5}, \qquad f_0(x_1) = -\frac{Q_5 S_{O,5}}{V_5}, \qquad f(t) = \frac{Q_4 S_{O,4}}{V_5} + r_8. \tag{6}$$

Let

$$m = -\frac{Q_5}{V_5}, \qquad f_0(x_1) = m S_{O,5} = m x_1. \tag{7}$$

Here, $f(t)$ is referred to as the external unknown disturbance and the internal uncertain dynamics. b_0 is the compensating factor of the plant. Let $x_2 = f(t)$, and then (5) can be written as

$$\dot{x}_1 = f_0(x_1) + b_0 u(t) + f(t), \qquad \dot{x}_2 = \chi(t), \qquad y = x_1, \tag{8}$$

where

$$\chi(t) = \frac{df(t)}{dt}. \tag{9}$$

The state space model (8) can be written as a compact form

$$\dot{x} = Ax + Bu(t) + Eh, \qquad y = Cx, \tag{10}$$

where

$$A = \begin{bmatrix} m & 1 \\ 0 & 0 \end{bmatrix}, \qquad B = \begin{bmatrix} b_0 \\ 0 \end{bmatrix}, \qquad E = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \qquad C = \begin{bmatrix} 1 & 0 \end{bmatrix}. \tag{11}$$

The linear extended state observer (LESO) is designed as

$$\dot{z} = Az + Bu(t) + L(y - \hat{y}), \qquad \hat{y} = Cz, \tag{12}$$

where $\hat{y}$ is the estimate of y. L can be obtained using the pole placement technique, and let

$$L = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix}. \tag{13}$$

The two observer poles should be placed at ω_o:

$$|\lambda I - (A - LC)| = (\lambda + \omega_o)^2. \tag{14}$$

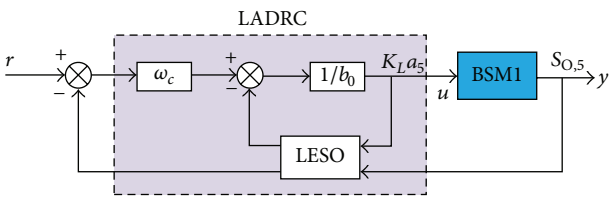

Figure 4: Control scheme of dissolved oxygen on BSM1.

Then, β_1 and β_2 can be placed at $2\omega_o + m$ and ω_o^2. Therefore, LESO is

$$\dot{z} = \begin{bmatrix} -2\omega_o & 1 \\ -\omega_o^2 & 0 \end{bmatrix} z + \begin{bmatrix} b_0 \\ 0 \end{bmatrix} u(t) + \begin{bmatrix} 2\omega_o + m \\ \omega_o^2 \end{bmatrix} y. \quad (15)$$

The PD controller is

$$u(t) = \frac{(r - z_1) k_d - z_2}{b_0}, \quad (16)$$

where the gain k_d can be defined as the function of closed-loop natural frequency ω_c [24]. The control scheme of dissolved oxygen in BSM1 by LADRC is given in Figure 4.

3. Simulation Results and Discussions

3.1. LADRC Parameter Tuning. In (15) and (16), 3 parameters, ω_o, ω_c, and b_0, are tunable parameters of LADRC. Integral of absolute error (IAE), integral of squared error (ISE), and variance of error (VAR) are calculated to evaluate the control of LADRC on BSM1 [2]. The optimal LADRC tuning steps are given below.

Step 1. In (4) and (5), b_0 can be set to be 1 (if the plant is unknown, b_0 could be acquired by simulation).

Step 2. A common rule is to choose $\omega_o = 3 \sim 5\omega_c$ [24]. Based on this rule, we may get a set of ω_c and ω_o that can stabilize the systems.

(a) Fixing ω_c, increasing and decreasing ω_o, we can find several groups of stable parameters named class A.

(b) Fixing ω_o, increasing and decreasing ω_c, we can find another class B.

(c) Comparing A and B, we may find the relationship between ω_o and ω_c.

(d) Changing both ω_c and ω_o on this relationship, we may find other groups of stable parameters.

Step 3. By comparison with the value of IAE, ISE, and VAR, optimal parameters can be found easily.

According to the steps described above, several groups of simulation are performed, and several results can be found.

(1) Dissolved oxygen concentration in Unit 5 could keep near 2g(-COD)/m^3 (see Figure 5(a)) when nearly $\omega_o + \omega_c = 1000$, $\omega_c > 40$, and $\omega_o < 900$.

(2) If $\omega_o < 200$, the concentration of the dissolved oxygen fluctuates greatly (see Figure 5(b)).

(3) If $\omega_o \geq 900$, the disturbance is larger than the controlled signal. Performance of the closed-loop system degrades (see Figure 5(c)).

(4) If ω_o is decreased, ω_c must be increased to keep the performance (see Table 3).

Parts of simulation results are present in Figure 5. The performance of closed-loop system and the EQ values are shown in Table 3. Comparing groups a ~ j, one may find that as long as the dissolved oxygen concentration in Unit 5 keeps near 2g(-COD)/m^3, the EQ values are almost the same.

In Table 3, the optimal parameters are shown in group e. In fact, the performances of the groups c ~ h look the same in Figure 5. When the parameters are chosen as group e, the variation of $S_{O,5}$ and K_La_5 is shown in Figure 6, which gives out the comparison with virtual reference feedback tuning (VRFT) [19]. The change of wastewater quality is given in Table 4. Apparently, the wastewater quality has been improved greatly.

3.2. Analysis of LADRC Parameters to BSM1. In Section 2.3, LADRC is designed based on BSM1. LESO is the key part of LADRC, which can actively estimate two states, y and $f(t)$. The estimation errors e_1 and e_2 can be defined by

$$\begin{aligned} e_1 &= z_1 - y = z_1 - x_1, \\ e_2 &= z_2 - f(t) = z_2 - x_2. \end{aligned} \quad (17)$$

According to (12) and (13), LESO can be rewritten as

$$\begin{aligned} \dot{z}_1 &= mz_1 + z_2 - \beta_1 (z_1 - y) + b_0 u(t) \\ &= mz_1 + z_2 - \beta_1 e_1 + b_0 u(t), \\ \dot{z}_2 &= -\beta_2 e_1. \end{aligned} \quad (18)$$

Then, the differential errors are

$$\dot{e}_1 = e_2 - (\beta_1 - m) e_1, \qquad \dot{e}_2 = -\chi(t) - \beta_2 e_1. \quad (19)$$

When the states go into steady, that is $\dot{e}_1$ and $\dot{e}_2$ are almost zero, we have,

$$e_2 - (\beta_1 - m) e_1 = 0, \qquad -\chi(t) - \beta_2 e_1 = 0. \quad (20)$$

The errors are obtained as

$$e_1 = -\frac{\chi(t)}{\beta_2}, \qquad e_2 = (\beta_1 - m) e_1 \quad (21)$$

which can be rewritten as

$$e_1 = -\frac{\chi(t)}{\omega_o^2}, \qquad e_2 = 2\omega_o^2 e_1, \quad (22)$$

where $\beta_1 = 2\omega_o + m$ and $\beta_2 = \omega_o^2$. If $\omega_o^2 \gg -\chi(t)$, e_1 will tend to zero and e_2 will also tend to zero. In other words, LESO could

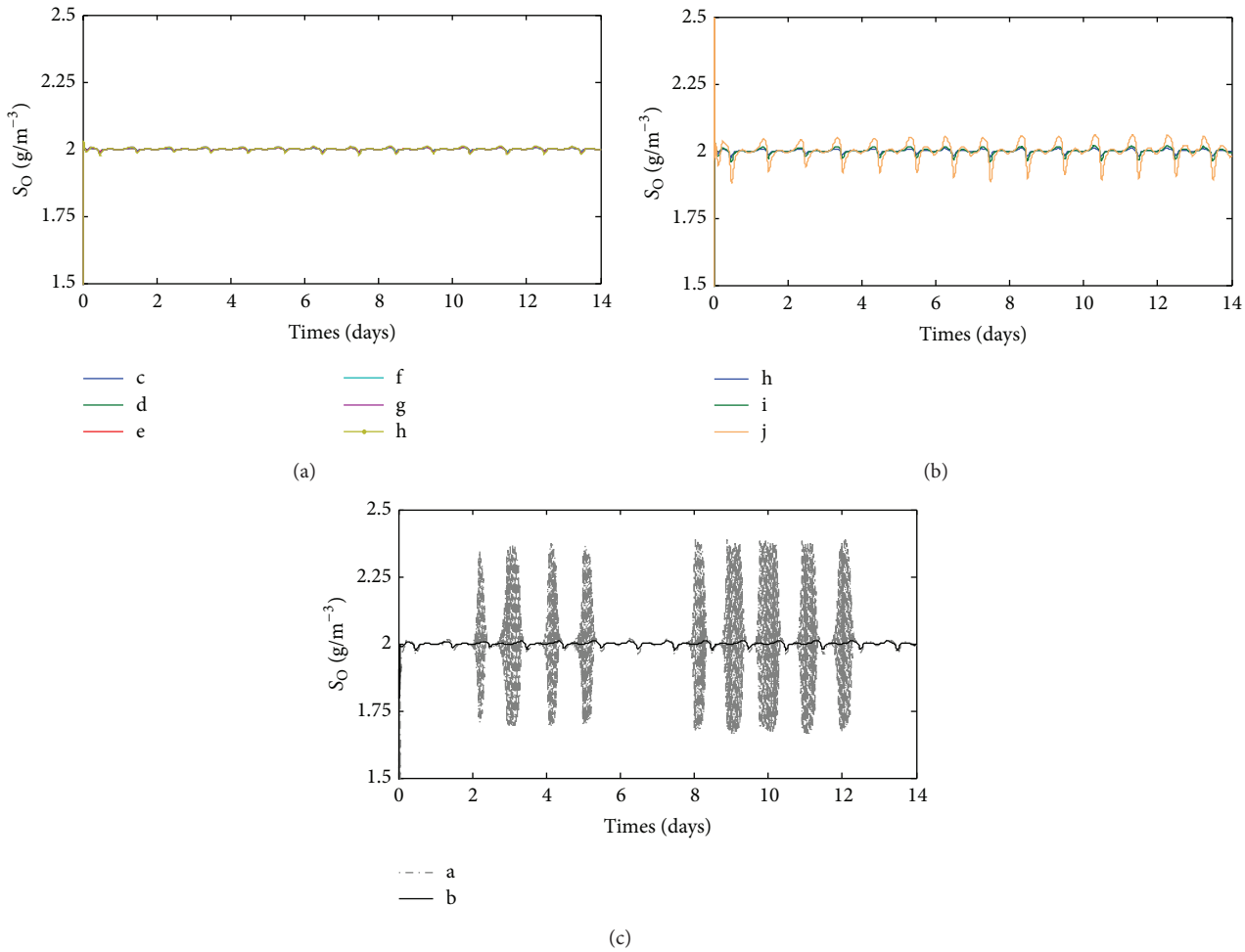

Figure 5: Comparison of the dissolved oxygen concentration in Unit 5 for different LADRC parameters.

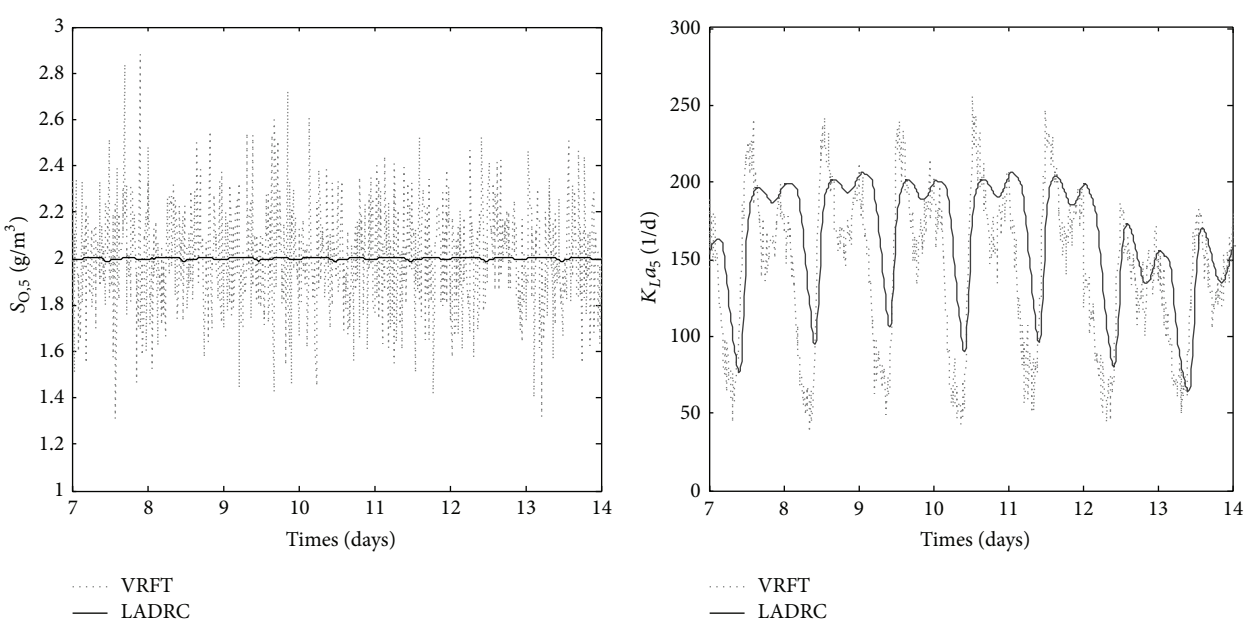

Figure 6: Comparison of $S_{O,5}$ and K_La_5 for VRFT and LADRC.

Table 3: Performance indexes of the closed-loop system.

	b_0	ω_c	ω_o	IAE	ISE	VAR	EQ
a	1	50	950	0.818	0.198	0.01080	6155.0
b	1	100	900	0.085	0.242	0.001700	6153.9
c	1	200	800	0.051	0.012	0.00089	6153.7
d	1	300	700	0.056	0.007	0.00050	6154.1
e	1	400	600	0.037	0.006	0.00039	6154.1
f	1	500	500	0.385	0.004	0.00030	6153.9
g	1	600	400	0.454	0.004	0.00028	6154.1
h	1	700	300	0.615	0.005	0.00028	6154.2
i	1	800	200	0.107	0.006	0.00035	6153.9
j	1	900	100	0.328	0.023	0.00110	6154.8

Table 4: Comparison of influent and effluent.

Standers	Influent	Effluent
NT	51.47	17.39
COD	360.04	46.58
S_{NH}	30.14	2.61
BOD	183.51	2.58
TSS	198.60	11.73
IQ/EQ	52089	6154.12

estimate the y and $f(t)$ effectively. From Section 2.3, $f(t)$ can be described by

$$f(t) = \frac{Q_4 S_{O,4}}{V_5} + r_8 = \frac{Q_4 S_{O,4}}{V_5} - \frac{1 - Y_H}{Y_H}\rho_1 - \frac{4.75 - Y_A}{Y_A}\rho_3, \tag{23}$$

where Y_H and Y_A are the parameters of BSM1, ρ_1 is the basic process of aerobic growth of heterotrophs, and ρ_3 is the basic process of aerobic growth of autotrophs:

$$\rho_1 = \frac{4S_{S,5}}{S_{S,5} + 10}\frac{S_{O,5}}{S_{O,5} + 0.2}X_{BH,5}$$
$$\rho_3 = \frac{0.5S_{NH,5}}{S_{NH,5} + 1}\frac{S_{O,5}}{S_{O,5} + 0.4}X_{BA,5}, \tag{24}$$

where $S_{S,5}$ is the readily biodegradable substrate in Unit 5, $X_{BH,5}$ is the active heterotrophic biomass in Unit 5, $S_{NH,5}$ is the nitrogen in Unit 5, and $X_{BA,5}$ is the active autotrophic biomass. Then the differential of $f(t)$ is

$$\chi(t) = \frac{df(t)}{dt} = \frac{Q_4}{V_5}\frac{dS_{O,4}}{dt} - \frac{1 - Y_H}{Y_H}\frac{d\rho_1}{dt} - \frac{4.75 - Y_A}{Y_A}\frac{d\rho_3}{dt}, \tag{25}$$

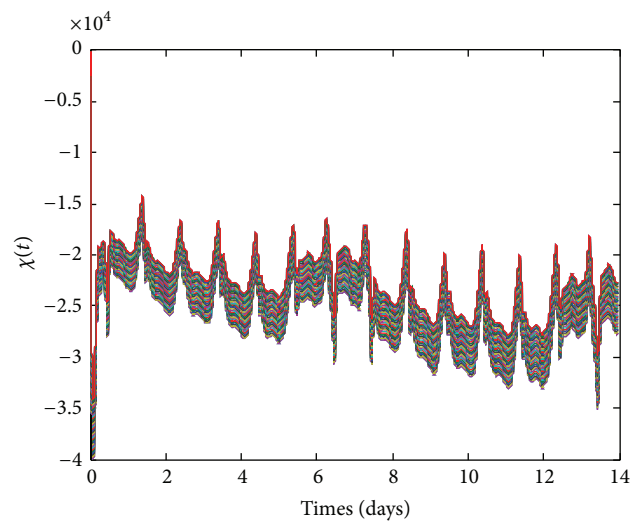

Figure 7: Estimate of $\chi(t)$.

where

$$\frac{d\rho_1}{dt} = \frac{4S_{O,5}}{S_{O,5} + 0.2}\left[\frac{10X_{BH,5}(dS_{S,5}/dt)}{(S_{S,5} + 10)^2} + \frac{S_{S,5}}{S_{S,5} + 10}\frac{dX_{BH,5}}{dt}\right],$$
$$\frac{d\rho_3}{dt} = \frac{0.5S_{O,5}}{S_{O,5} + 0.4}\left[\frac{X_{BA,5}(dS_{NH,5}/dt)}{(S_{NH,5} + 1)^2} + \frac{S_{NH,5}}{S_{NH,5} + 1}\frac{dX_{BA,5}}{dt}\right]. \tag{26}$$

ρ_1 and ρ_3 include the controlled state variable $S_{O,5}$. For the wastewater process being a large time-delay system, it is reasonable to let $S_{O,5}$ in $\chi(t)$ be a small variable in $[2 - \Delta, 2 + \Delta]$, where Δ leads to zero. At the same time, another variable could be estimated by a 14-day period of stabilization in closed-loop using dry weather inputs [4]. Through the simulation and calculation, $\chi(t)$ is described in Figure 7 with Δ about 0.2.

If the parameter ω_o meets $\omega_o^2 \gg -\chi(t)$, ω_o should exceed 160. In Section 3.1, if the parameter $\omega_o < 200$, the fluctuate of the dissolved oxygen concentration becomes large. Therefore, the optimal parameters are $\omega_o = 600$ and $\omega_c = 400$. This ω_o^2

is nearly 14 times the $-\chi(t)$. This also confirms the data given in Table 3 and the analysis above.

4. Conclusions

In this paper, the control of dissolved oxygen in WWTPs is considered. The process of wastewater treatment is full of nonlinear, uncertain, and strong couplings. A robuster and more practical control strategy is in great need. As a result of the simple structure, nice disturbance rejection performance, and easy tuning approach, LADRC is employed.

For the control of dissolved oxygen in WWTPs, optimal LADRC parameters tuning approach is obtained by simulations. Estimation capacity of the linear extended state observer is analyzed, which also provides a valuable guidance to choose parameters of LADRC for the control of dissolved oxygen. Simulation results confirm that LADRC is able to get a nice performance.

Although the study is performed by simulation, it can be viewed as an essential step before implementing LADRC in a real plant, since BSM1 is a common framework to test control strategies for WWTPs. LADRC will probably be a more practical and promising solution to the control of wastewater treatment processes.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This work is supported by National Natural Science Foundation of China (51179002), Beijing Natural Science Foundation (4112017), the Importation and Development of High-Caliber Talents Project of Beijing Municipal Institutions (YETP1449).

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