Disturbance rejection control for a wastewater treatment process by a learning approach

Wei Wei¹,²,³, Nan Chen¹,²,³, Zaiwen Liu¹,²,³ and Min Zuo¹,²,³

Abstract
Nonlinearities, uncertainties and external disturbances commonly exist in a wastewater treatment process (WWTP). Those issues present great challenges to the control of the dissolved oxygen (DO) concentration in a WWTP. In this paper, an active disturbance rejection control (ADRC) is utilized to estimate the total disturbance and drive the DO concentration to track the set-value. Simultaneously, an iterative learning strategy is employed to adjust the parameters of an extended state observer (ESO) to improve the accuracy of the estimation and reduce the dependence on experience in determining parameters. By combining the advantages of the ADRC and the iterative learning strategy, an iterative learning based active disturbance rejection control (ILADRC) is constructed, and the close-loop stability is analyzed. The benchmark simulation model No.1 (BSM1) is utilized to confirm the ILADRC. Numerical results show that the ILADRC is more effective in the DO concentration control.

Keywords
wastewater, active disturbance rejection control, iterative learning, DO concentration, BSM1

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Introduction
With the development of human society, freshwater becomes one of the most significant problems that we face due to the increasing demand and serious pollution.¹ The water crisis significantly affects several industries or even countries.² Therefore, the wastewater treatment attracts much attention. In early years, wastewater treatment processes (WWTPs) mainly relied on the manual control, the efficiency was low and the effluent quality could not satisfy higher effluent standards.³ Thus, automatic control system has been applied in WWTPs.

Dissolved oxygen (DO) concentration directly affect the effluent quality, it has been commonly recognized as a key variable in a WWTP. Therefore, the control of DO concentration has been becoming a hot topic in the automatic control of a WWTP. However, kinds of control methods fail to regulate DO at a desired level due to WWTPs’ unique features, such as the varying rate of inflow, unstable compositions and concentrations, and unknown biochemical reactions, by comparison with other process industries.³⁻⁴ Much effort has been paid to address those challenges. PID control, a commonly used approach, has also been widely utilized in the DO concentration control.⁵ However, the performance of the PID control degrades significantly for strong nonlinearities and disturbances in WWTPs.⁵ To improve the tracking performance, a feedback linearization-based PI controller was designed.⁶ Drawback of the feedback linearization method is that the robustness cannot be guaranteed for the existing uncertainties.⁷ Nowadays, model predictive control (MPC) has a wide variety of applications.⁸ In Zeng and Liu,⁹ a centralized economic model predictive control (EMPC) was applied to a WWTP, the simulation results show that it can reduce operating cost and improve the effluent quality simultaneously. However, computational complexity resulting from solving the optimization problem and the relatively poor fault tolerance of a centralized control challenge its implementation.¹⁰ Belchior¹¹ proposed a stable adaptive fuzzy control for a WWTP to control the DO. The algorithm...
achieved a promising result. However, traditional fuzzy control is largely dependent on input dimensions. If more input dimensions are defined, more fuzzy rules are necessary, and more computation complexity is involved. In Bo and Zhang, an echo state networks based online adaptive dynamic programming was taken to control the DO concentration. Its design mainly depends on the online data, and minor prior knowledge is required.

It should be noted that the key point of the DO control in a WWTP is how to deal with the uncertainties, unknown dynamics, and disturbances. To estimate those undesired factors, various disturbance observer-based methods have been designed. Lin proposed an adaptive neural control, it combined a nonlinear disturbance observer for a WWTP. Satisfactory performance was achieved. An active disturbance rejection control (ADRC) was employed to control the DO concentration. The extended state observer (ESO) estimated the system states and total disturbance. Simulation results showed that the ADRC can achieve satisfied performance on DO concentration control. Based on the ESO, system can be dynamically transformed to be a linear system with connected integrators form. Then, a controller based on the idea of the U-model control is designed to control the DO concentration. It does achieve faster and more robust response.

Actually, for the convenience in realizing, the effectiveness in dealing with strong disturbances and uncertainties, and the satisfied performance, ADRC has been applied in many fields. In this paper, we also focus on the ADRC. However, to some extent, determining parameters of an ESO depends on engineers’ experience. To make the ESO be more accurate in estimating and reducing the dependence on experience to fix the parameters, a P type iterative learning algorithm is utilized, and the iterative learning based ADRC (ILADRC) is designed in the DO concentration control. Main advantage of the ILADRC is that the ESO in the ILADRC can acquire better estimation performance by an iterative learning approach. Simultaneously, it reduces the requirement of an engineer’s experience.

The rest of this paper is organized as follows. Section II describes the model and control difficulties of a WWTP. Section III is controller design and stability analysis. Simulation results are shown in Section IV. Finally, a conclusion is drawn in Section V.

System description and control problem statement
System description
Benchmark simulation model no.1 (BSM1) is a benchmark simulation model for a WWTP. It contains influent data of dry, rain and storm weather, and it provides a set of standard evaluation criteria for different control strategies. Layout of the BSM1 is presented in Figure 1. It consists of two parts. One is the biological reactor and the other is a secondary clarifier. The biological reactor comprises two anoxic tanks ($V_1 = V_2 = 1000 \text{m}^3$) and three aerobic tanks ($V_3 = V_4 = V_5 = 1333 \text{m}^3$). Biological and physical phenomena in tanks are described by activated sludge model no.1 (ASM1). The secondary clarifier is modeled as a 10 layers non-reactive unit.

Control problem statement
DO concentration in the fifth tank is a key parameter, which affects the growth of microorganisms and the effluent quality. Keeping it in a desirable level is critical for a WWTP. However, the DO concentration in the fifth tank is affected by various uncertainties, such as the time-varying influent components, concentrations, and inflow rates. Meanwhile, in practice, both parameters and dynamics of a WWTP are partially known or even completely unknown. Besides that, most issues are usually coupled with each other, and most of them are not available. In other words, disturbances, uncertain dynamics, and strong couplings are difficulties in
Iterative learning based active disturbance rejection control

Structure of the ILADRC

ADRC can estimate and cancel out the total disturbance in real time to guarantee the closed-loop system performance. Thus, an accurate mathematical model is not necessary. However, the parameters of an ESO determines its estimation ability greatly. To reduce the dependence on engineers’ experience in tuning parameters and improve ESO’s estimation ability, an iterative learning based ESO is designed. The structure of the ILADRC is given in Figure 2.

Here \( r \) is the set-value, \( u \) is the control signal, and \( y \) is the system output.

The ESO is designed as:

\[
\begin{align*}
\dot{z}_1 &= z_2 + \beta_1 (y - z_1) + b_0 u \\
\dot{z}_2 &= \beta_2 (y - z_1)
\end{align*}
\]  

where \( b_0, \beta_1, \beta_2 \) are adjustable gains of an ESO, \( y \) is the system output, \( u \) is the control signal, \( z_1 \) is the estimation of \( y \), and \( z_2 \) is the estimation of the total disturbance.

The control law is

\[
\begin{align*}
u &= (u_0 - z_2)/b_0 \\
u_0 &= k_p (r - z_1)
\end{align*}
\]

where \( k_p \) is an adjustable control gain.

In this paper, to decrease the estimation error of an ESO and reduce the dependence on experience in determining an ESO’s parameters, a P type iterative learning algorithm is utilized to adjust the parameters of an ESO, and it is designed as:

\[
\begin{align*}
b_{0[k+1]}(t) &= b_{0k}(t) + k_l \cdot e_k(t) \\
\omega_{nk}[k+1] &= \omega_{nk}(t) + k_l \cdot e_k(t)
\end{align*}
\]

where \( k \) is the current iteration number, \( e_k(t) \) is the estimation error of the \( k \)th iteration, \( e_k(t) = y(t) - z_{1k}(t) \), \( \omega_{nk}(t) \) is the observer bandwidth, and \( k_l \) is a learning gain.

According to the bandwidth-parameterization approach,\(^2^4\) one has \( \beta_1 = 2\omega_{on}, \beta_2 = \omega_{on}^2 \). Here, \( \omega_{on} \) is the bandwidth after iterating \( n \) times.

**Remark 1.** If the learning gains equations (4) and (5) are selected properly, estimation errors will be bounded (It can be seen from simulation results in section IV). For a strict formulation, a projection mechanism is introduced to the iterative learning algorithm

\[
\begin{align*}
b_{0[k+1]}(t) &= \text{sat}[b_{0k}(t) + k_l e_k(t)] \\
\omega_{nk}[k+1] &= \text{sat}(\omega_{nk}(t) + k_l e_k(t))
\end{align*}
\]

The bound of \( \text{sat}(\cdot) \) should be chosen as large as possible to ensure the actually generated parameters would be within it. Then, we can say the generated parameters are always bounded. After the algorithm iterating \( n \) times, much smaller estimation errors can be obtained by the iterative learning based ESO.

**Remark 2.** The estimation error directly reflects whether an ESO works as desired. Thus, based on the estimation error, a P type iterative learning algorithm is designed to adjust the parameters of an ESO, and the ESO adjusts its bandwidths to estimate the total disturbance more accurately.

**Stability analysis**

Consider a first-order system

\[
y = f + b_0 u
\]

where \( f \) represents the total disturbance, \( b_0 \) is a non-zero constant, \( u \) is the control input, \( y \) is the controlled system output.

Let \( x_1 = y, x_2 = f \) and \( \dot{f} = h \), system equation (6) can be rewritten as

\[
\dot{X} = AX + B_1 u + B_2 h(X, w)
\]

where \( X = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, B_1 = \begin{bmatrix} b_0 \\ 0 \end{bmatrix}, B_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}. \)

Similarly, the ESO (1) can be rewritten as

\[
\dot{\hat{X}} = A \hat{X} + B_1 u + \beta(X - \hat{X})
\]

where \( \hat{X} = [\hat{x}_1, \hat{x}_2]^T \) is the observation vector, \( \hat{x}_1, \hat{x}_2 \) are observation values of \( y \) and \( f \), respectively, \( \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} \) is a gain matrix.

Next, convergence of the iterative learning based ESO and the close-loop stability of ILADRC are analyzed.
Convergence of the iterative learning based ESO. Subtracting equations (8) from (7), one has

$$
\dot{\hat{X}} = \hat{X} - \dot{\hat{X}} = (A - B)(X - \hat{X}) + B_2 h(X, w) 
$$

where \( \hat{X} = [\hat{x}_1, \hat{x}_2]^{T} = [x_1 - \hat{x}_1, x_2 - \hat{x}_2]^{T} \) is an estimation error vector.

Let \( e_j = \hat{x}_j/\omega_{on}^{-1} \), \( j = 1, 2 \), then, the estimation error system equation (9) can be rewritten as

$$
\dot{e} = \omega_{on} A_2 e + B \frac{h(X, w)}{\omega_{on}} 
$$

where \( e = \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} \), \( A_2 = \begin{bmatrix} -2 & 1 \\ -1 & 0 \end{bmatrix} \), \( B = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \).

Here, \( \omega_{on} \) is the bandwidth after iterating \( n \) times, and according to Remark 1, \( \omega_{on} \) is always bounded.

**Remark 3.** Due to the power of an engineering system is always limited, it is reasonable to assume that the change rate of the total disturbance is bounded.

Then, Theorem 1 is obtained.

**Theorem 1.** When \( h(X, w) \) is bounded, that is, there exists a positive constant \( M_1 \) such that \( |h(X, w)| \leq M_1 \), then the estimation error of an iterative learning based ESO is also bounded.

**Proof.** Solving equation (10), one has

$$
e(t) = e^{\omega_{on} A_2 t} e(0) + \int_{0}^{t} e^{\omega_{on} A_2 (t - \tau)} B \frac{h(X(\tau), w)}{\omega_{on}} \, d\tau 
$$

Let

$$
P(t) = \int_{0}^{t} e^{\omega_{on} A_2 (t - \tau)} B \frac{h(X(\tau), w)}{\omega_{on}} \, d\tau
$$

For \( j = 1, 2 \), one has

$$
|p_j| \leq \frac{\int_{0}^{t} \left| e^{\omega_{on} A_2 (t - \tau)} B \right| \frac{|h(X(\tau), w)|}{\omega_{on}} \, d\tau}{M_1} \leq \frac{M_1}{\omega_{on}^2} \left| (A_2^{-1} B) \right| + \left| (A_2^{-1} e^{\omega_{on} A_2 t} B) \right|
$$

For \( A_2 \) and \( B \) defined in equation (10), one has

$$
A_2^{-1} = \begin{bmatrix} 0 & -1 \\ 1 & -2 \end{bmatrix}
$$

System matrix \( A_2 \) is Hurwitz, then there exists a finite time \( T_1 > 0 \) such that

$$
\left| e^{\omega_{on} A_2 t} \right| \leq \frac{1}{\omega_{on}^2}
$$

for all \( t \geq T_1, j, k = 1, 2 \).

Thus

$$
\left| e^{\omega_{on} A_2 t} B \right| \leq \frac{1}{\omega_{on}^2}
$$

for all \( t \geq T_1, j = 1, 2 \).

Let \( A_2^{-1} = \begin{bmatrix} s_{11} & s_{12} \\ s_{21} & s_{22} \end{bmatrix} \) and \( e^{\omega_{on} A_2 t} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix} \), one has

$$
\left| (A_2^{-1} e^{\omega_{on} A_2 t} B) \right| = \begin{cases} 
|s_{11} d_{12} + s_{12} d_{22}|, & j = 1 \\
|s_{21} d_{12} + s_{22} d_{22}|, & j = 2 
\end{cases} 
$$

Therefore

$$
|p_j| \leq \frac{2 M_1}{\omega_{on}} + \frac{3 M_1}{\omega_{on}^2}
$$

for all \( t \geq T_1, j = 1, 2 \).

Let \( e_{sum}(0) = |e_1(0)| + |e_2(0)| \), then it follows that

$$
\left| e^{\omega_{on} A_2 t} e_{sum}(0) \right| \leq \frac{M_1}{\omega_{on}^2} \left| e_{sum}(0) \right|
$$

From equation (11), one has

$$
|p_j| \leq \frac{\|e_i(0)\| + |e_j(0)|}{\omega_{on}^2}
$$

Let \( \tilde{x}_{sum}(0) = |\tilde{x}_1(0)| + |\tilde{x}_2(0)| \), and taking \( e_j = \tilde{x}_j/\omega_{on}^{-1} \), equations (18) and (20) into consideration, one has

$$
\left| \tilde{x}_j \right| \leq \frac{\tilde{x}_{sum}(0)}{\omega_{on}^2} + \frac{2 M_1}{\omega_{on}^3} + \frac{3 M_1}{\omega_{on}^4} = M_2
$$

for all \( t \geq T_1, j = 1, 2 \).

Thus, when \( h(X, w) \) is bounded, the estimation errors of an iterative learning based ESO are also bounded, and the bounds are proportional to \( \omega_{on}^{-1} \).

**Close-loop stability of the ILADRC.** Control law of the ILADRC is

$$
u = k_p (r - \tilde{x}_1) + (f - \tilde{x}_2) \frac{b_0}{b_0}
$$

Substitute equations (22) into (6), one has

$$
\dot{\tilde{y}} = k_p (r - \tilde{x}_1) + (f - \tilde{x}_2) + \dot{r}
$$
Theorem 2. When $|h(X, \omega)| \leq M_1$ and there exists a tunable control gain $k_p > 0$, the tracking error of the ILADRC is bounded, and the closed-loop system is bounded input and bounded output (BIBO) stable.

Proof. Solving equation (25), one has

$$\dot{\xi} = e^{-k_p \xi}(0) + \int_0^t e^{-k_p (t-\tau)} A_3 \hat{X} d\tau$$

(26)

According to equation (25) and Theorem 1, one has

$$|A_3 \hat{X}| = |k_p \hat{x}_1 - \hat{x}_2| \leq (1 + k_p) M_1 \triangleq \gamma$$

(27)

Let

$$\phi(t) = \int_0^t e^{-k_p (t-\tau)} A_3 \hat{X} d\tau$$

(28)

Then

$$|\phi(t)| = \int_0^t |e^{-k_p (t-\tau)} A_3 \hat{X}| d\tau \leq \int_0^t e^{-k_p (t-\tau)} \gamma d\tau \leq \frac{1}{k_p} \gamma$$

(29)

According to Gao,\(^24\) one has $k_p = \omega_c$, $\omega_c$ is the controller bandwidth. Then, there exists a finite time $T_2$, such that

$$|e^{-k_p \tau}| \leq \frac{1}{\omega_c^2}$$

(30)

$$|e^{-k_p \xi}(0)| \leq \frac{\xi(0)}{\omega_c^2}$$

(31)

for all $t \geq T_2$.

Let $T_3 = \max\{T_1, T_2\}$, one has

$$|e^{-k_p \tau}| \leq \frac{\gamma}{\omega_c^2}$$

(32)

for all $t \geq T_3$.

Then

$$\frac{1}{k_p} e^{-k_p \gamma} \leq \frac{\gamma}{\omega_c^2}$$

(33)

for all $t \geq T_3$.

From equations (29) and (33), one has

$$|\phi(t)| \leq \frac{\gamma}{\omega_c^2} + \frac{\gamma}{\omega_c^2}$$

(34)

for all $t \geq T_3$.

From equation (26), one has

$$|\xi(t)| = |e^{-k_p \xi}(0)| + |\phi(t)|$$

(35)

Then,

$$|\xi(t)| \leq \frac{\xi(0)}{\omega_c^2} + \frac{\gamma}{\omega_c^2} + \frac{\gamma}{\omega_c^2} = M_3$$

(36)

Based on Theorem 1 and Theorem 2, one can find that, if estimation errors of an ESO are bounded, tracking errors of the closed-loop system will also be bounded. Then, for a bounded set-value $r$, the system output $y$ is also bounded. In other words, the closed-loop system is bounded input and bounded output (BIBO) stable.

Therefore, by choosing proper parameters, the iterative learning based ESO is bounded, and the closed-loop system is also stable.

### Simulation results

In this section, the iterative learning based ADRC is designed, and it is verified on the BSM1 under dry, rain and storm weather. The aim is to make the DO concentration in the fifth reactor ($SO_3$) at 2 mg/L by manipulating the oxygen transfer coefficient ($K_{La}$). To confirm the ILADRC, the ADRC is taken to make a comparison. All experiments are based on the same numerical environments. Parameters of the ADRC and the ILADRC are listed in Table 1.

The performance is evaluated by the integral of absolute error (IAE), integral of squared error (ISE) and the maximal deviation from the set-value (DEVmax). IAE, ISE, and DEVmax can be calculated as

$$IAE = \int_0^{T} |\xi| dt$$

(37)
ISE = \int_{t_1}^{t_2} \xi^2 dt \quad (38)

Dev_{max} = \max\{|\xi|\} \quad (39)

where \(\xi = r - y\) is the tracking error.

For the ILADRC, in each experiment, initial learning gain \(k_i\) is determined by try and error, and they are listed in Table 1. To obtain a better learning gain, Monte Carlo experiments are carried out. To ensure the learning gains \(k_i\) s in Monte Carlo experiments are selected properly, they randomly vary in \(\pm 20\%\) of their initial values. In other words, in dry and stormy days \(k_i \in [12.8, 19.2]\), and in rainy days \(k_i \in [13.6, 20.4]\). 30 Monte Carlo experiments are carried out, and 30 \(k_i\) s are obtained. For each \(k_i\), 30 iterations have been executed, and 30 IAE values can be obtained. Then, a root mean square error (RMSE) can be calculated based on the 30 IAE values. Thus, for each \(k_i\), there is one RMSE. 30 RMSE values can be received from 30 times Monte Carlo tests. Relationships between the learning gain \(k_i\) s and RMSE values are given in Figures 3, 8 and 13. From those figures, one can find a clear picture that, when \(k_i\) increases, the RMSE values decreases. \(k_i\) equals 19.0118, 20.2000, and 18.9395, the RMSEs are minimum. Thus, \(k_i\) s are chosen to be 19.0118, 20.2000, and 18.9395 in dry, rainy and stormy days’ simulations.

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} IAE_i^2} \quad (40)
\]

Based on \(k_i\) s, bandwidths \(\omega_0s\) and \(b_0s\) of the ILADRC can be obtained. The \(\omega_0s\) and \(b_0s\) after 30 times iterations are listed in Table 2. Other parameters are the same with those given in Table 1.

### Remark 4.
Generally, the learning gain \(k_i\) can be determined by experience. However, to fix the learning gain via a scientific approach, or to get rid of the subjective experience, here, the Monte-Carlo method is utilized. The gains are generated in a random way from a certain range, and objective numerical simulations are performed to evaluate the gains. It overcomes the subjectivity and blindness of the parameter selection.

### Remark 5.
More times of the Monte Carlo tests should be taken so that the gains can be chosen more objective. Here, by compromising the computational complexity and the numerical results, 30 times Monte Carlo tests are performed.

### Remark 6.
The iteration times of each Monte Carlo test are determined by try and error. It should guarantee the convergence of the estimation errors.

### Remark 7.
Initial parameters of the ESOs in both ADRC and ILADRC are the same, and they are determined by try and error.

Figure 4 shows the tendency of IAE values when \(k_i = 19.0118\). In this case, outputs of the ILADRC are given in Figure 5. Simultaneously, outputs of the ADRC are also shown in Figure 5. From Figure 5, it is

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**Table 2. Main parameters of the ILADRC after 30 times iterations.**

| Controllers  | \(\omega_0\) | \(b_0\) |
|--------------|-------------|--------|
| ILADRC (dry) | 499.7357    | 0.7357 |
| ILADRC (rain)| 499.8096    | 0.8096 |
| ILADRC (storm)| 499.7775   | 0.7775 |
easy to find that the ILADRC achieves better tracking performance in dry days. Figures 6 and 7 are tracking errors and estimation errors of the ADRC and the ILADRC. The median of both tracking error and estimation error equal zero, it means the average level of those errors is zero. The distance of upper and lower quartiles in the boxplot reflects the varying degree of the tracking and/or estimation errors. Higher the boxplot, larger fluctuations of the errors. Figures 6 and 7 show that, by comparison with the ADRC, both tracking errors and estimation errors of the ILADRC have fewer changes and closer to the median. Fewer outliers of the ILADRC also means ILADRC is more effective. Performance values listed in Table 3 confirm the fact discussed above in a quantitative way.

Figure 8 shows the relationship between the learning gains \( k_l s \) and RMSEs. It can be found that, when the learning gain \( k_l = 20.2000 \), the RMSE value is minimum.

Figure 9 presents the IAE values of the estimation errors. System outputs of the ADRC and the ILADRC are shown in Figure 10. From Figure 10, it is easy to see that better tracking performance is obtained by the ILADRC in rain weather. Figures 11 and 12 are tracking errors and estimation errors of the ADRC and the ILADRC. Both tracking and estimation errors of the ILADRC are smaller than the ones of the ADRC. Performance values are shown in Table 3.

Figure 13 shows the relationship between learning gains \( k_l s \) and RMSEs in stormy days. When \( k_l = 18.9395 \), RMSE is minimum.

Figure 14 is the IAE values of the estimation errors. It illustrates that the learning process is convergent. System outputs of the ADRC and the ILADRC are shown in Figure 15. It indicates that ILADRC has better tracking performance. Figures 16 and 17 show that

|          | IAE  | ISE  | DEV\(^{\text{max}}\)  |
|----------|------|------|------------------------|
| Dry      |      |      |                        |
| ADRC     | 0.0206 | 1.3552 \( \times 10^{-4} \) | 0.016                  |
| ILADRC   | 0.0151 | 7.3339 \( \times 10^{-5} \) | 0.012                  |
| Improvements | 26.70% | 45.85% | 25%                  |
| Rain     |      |      |                        |
| ADRC     | 0.0187 | 1.0903 \( \times 10^{-4} \) | 0.016                  |
| ILADRC   | 0.0152 | 7.1548 \( \times 10^{-5} \) | 0.013                  |
| Improvements | 18.72% | 34.38% | 19%                  |
| Storm    |      |      |                        |
| ADRC     | 0.0201 | 1.2351 \( \times 10^{-4} \) | 0.016                  |
| ILADRC   | 0.0156 | 7.4772 \( \times 10^{-5} \) | 0.013                  |
| Improvements | 22.39% | 39.46% | 25%     |
the average level of the tracking errors and estimation errors are close to zero. In addition, from the distance of upper and lower quartiles in boxplots, one can see that the tracking errors and estimation errors of the ILADRC system are closer to zero. Performance comparisons in storm weather are also given in Table 3.

In Table 3, the improvements signify that the ILADRC is superior to the ADRC from the perspective of IAE, ISE and DEV$^{max}$. For example, in dry days, ISE values of the ILADRC are improved by 45.85% by comparison with the ADRC. Data listed in Table 3 confirm the advantage of the iterative learning based ESO.

From the simulation results in dry, rain and storm weather, it is obvious that, because of an iterative learning ESO, the ILADRC tracks the set-value more accurately. It demonstrates that, compared with a conventional ESO, an iterative learning ESO can estimate the total disturbance more effectively. Simultaneously,
when choosing the parameters, the iterative learning based ESO is less dependent on the experience of an engineer. It helps improve the estimation and control performance of the ADRC.

Conclusion

A WWTP is a time-varying system with strong nonlinearities and couplings. In addition, kinds of uncertainties and disturbances are also existing. Therefore, it is impossible to establish an accurate model for the control of a WWTP. In this paper, an iterative learning based ADRC is designed for the DO control in a WWTP. The iterative learning method is utilized to optimize the parameters of an ESO. Compared with the conventional ESO whose parameters are fixed, the iterative learning based ESO achieves a more accurate estimation. Then, the close-loop DO concentration control of a WWTP is more satisfied. Advantages of the iterative learning based ESO and the ILADRC show that it may be a promising way to control the DO in a WWTP. However, it should be verified in a real wastewater treatment process and it is our future work.

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ORCID iD

Min Zuo https://orcid.org/0000-0003-3336-2940

References

1. Prasse C, Stalter D, Schulte-Oehlmann U, et al. Spoilt for choice: a critical review on the chemical and biological assessment of current wastewater treatment technologies. Water Res 2015; 87(1): 237–270.
2. Collins A, Schwab K, Samans R, et al. The global risks report 2018. Geneva: World Economic Forum, 2018.
3. Olsson G. ICA and me—a subjective review. Water Res 2012; 46(6): 1585–1624.
4. Bo YC and Qiao JF. Heuristic dynamic programming using echo state network for multivariable tracking control of wastewater treatment process. Asian J Control 2015; 17(5): 1654–1666.
5. Iratni A and Chang NB. Advances in control technologies for wastewater treatment processes: status, challenges, and perspectives. IEEE/CAA J Automatica Sinica 2019; 6(2): 4–30.
6. Lindberg CF and Carlsson B. Nonlinear and set-point control of the dissolved oxygen concentration in an activated sludge process. Water Sci Technol 1996; 34(3–4): 135–142.
7. Munoz C, Young H, Antileo C, et al. Sliding mode control of dissolved oxygen in an integrated nitrogen removal process in a sequencing batch reactor (SBR). Water Sci Technol 2009; 60(10): 2545–2553.
8. Holenda B, Domokos E, Redey A, et al. Dissolved oxygen control of the activated sludge wastewater treatment process using model predictive control. Comput Chem Eng 2008; 32: 1270–1278.
9. Zeng J and Liu J. Economic model predictive control of wastewater treatment processes. Ind Eng Chem Res 2015; 54(21): 5710–5721.
10. Zhang A, Yin X, Liu S, et al. Distributed economic model predictive control of wastewater treatment plants. Chem Eng Res Des 2019; 141(1): 144–155.
11. Belchior CAC, Araujo RAM and Landeck JAC. Dissolved oxygen control of the activated sludge wastewater treatment process using stable adaptive fuzzy control. Comput Chem Eng 2012; 37(2): 152–162.
12. Xu JC, Yang CL and Qiao JF. A novel dissolve oxygen control method based on fuzzy neural network. In: Proceedings of the 36th Chinese Control Conference, Dalian, China, 26–28 July 2017, pp. 4363–4368. New York: IEEE.
13. Bo YC and Zhang X. Online adaptive dynamic programming based on echo state networks for dissolved oxygen control. *Appl Soft Comput* 2018; 62(1): 830–839.

14. Lin MJ and Luo F. Adaptive neural control of the dissolved oxygen concentration in WWTPs based on disturbance observer. *Neurocomputing* 2016; 185(4): 133–141.

15. Wei W, Zuo M, Li W, et al. Control of dissolved oxygen for a wastewater treatment process by active disturbance rejection control approach. *Control Theory Appl* 2018; 35(1): 24–30 (in Chinese).

16. Wei W, Chen N, Zhang ZY, et al. U-model-based active disturbance rejection control for the dissolved oxygen in a wastewater treatment process. *Math Probl Eng* 2020; 3507910, 1–14.

17. Cheng Y, Chen ZQ, Sun MW, et al. Cascade active disturbance rejection control of a high-purity distillation column with measurement noise. *Ind Eng Chem Res* 2018; 57(13): 4623–4631.

18. Chen WH, Yang J, Guo L, et al. Disturbance-observer-based control and related methods-an overview. *IEEE Trans Ind Electron* 2016; 63(2): 1083–1095.

19. Wu Z, He T, Li D, et al. Superheated steam temperature control based on modified active disturbance rejection control. *Control Eng Pract* 2019; 83: 83–97.

20. Shen D, Zhang W, Wang YQ, et al. On almost sure and mean square convergence of P-type ILC under randomly varying iteration lengths. *Automatica* 2016; 63: 359–365.

21. Wei W, Wei XF, Xia PF, et al. Seizure control by a learning type active disturbance rejection approach. *IEEE Access* 2019; 7(1): 164792–164802.

22. Alex J, Benedetti L, Copp J, et al. Benchmark simulation model no. 1 (bsm1). Lund University, Sweden, 2008.

23. Han HG, Qiao JF and Chen QL. Model predictive control of dissolved oxygen concentration based on a self-organizing RBF neural network. *Control Eng Pract*, 2012; 20(4): 465–476.

24. Gao QZ. Scaling and bandwidth-parameterization based controller tuning. In: *Proceedings of the 2003 American Control Conference*, Denver, CO, 4–6 June 2003, pp. 4989–4996. New York: IEEE.