

Research Article

Nonlinear PI Control with Adaptive Interaction Algorithm for Multivariable Wastewater Treatment Process

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The wastewater treatment plant (WWTP) is highly known with the nonlinearity of the control parameters, thus it is difficult to be controlled. In this paper, the enhancement of nonlinear PI controller (ENon-PI) to compensate the nonlinearity of the activated sludge WWTP is proposed. The ENon-PI controller is designed by cascading a sector-bounded nonlinear gain to linear PI controller. The rate variation of the nonlinear gain k_n is automatically updated based on adaptive interaction algorithm. Initiative to simplify the ENon-PI control structure by adapting k_n has been proved by significant improvement under various dynamic influents. More than 30% of integral square error and 14% of integral absolute error are reduced compared to benchmark PI for DO control and nitrate in nitrogen removal control. Better average effluent qualities, less number of effluent violations, and lower aeration energy consumption resulted.

1. Introduction

The wastewater treatment plant (WWTP) is naturally aimed to remove the suspended substances, organic material, and phosphate from the water before releasing it to the recipient. The best technology available was used to control the discharge of pollutants emphasized in biological process, namely, as activated sludge process (ASP). In ASP, the organic materials are oxidized by microorganisms. The organic material is then transformed into carbon dioxide and some incorporate into new cell mass. The new cell mass then forms sludge that contains both living and dead microorganisms and, thus, contains organic material, phosphorous, and nitrogen [1]. Referring to [2], the common problems in WWTP are caused by maintenance issues and poor effluent quality which are due to poor control approaches.

According to [3], aeration process is a crucial part of the whole ASP. It is a nontrivial task to transport the oxygen from the air bubbles to the cells of the microorganisms, thus the process is commonly described by the oxygen mass transfer coefficient (K_{La}). The K_{La} is, in general, nonlinear

and depends on the aeration actuating system and the sludge conditions [4]. Indeed, as referred to in [5], the dissolved oxygen (DO) is stated as a key variable and commonly applied in controlling the ASP. The level of DO in the aerobic reactors has a direct influence on the microorganisms' activities in the activated sludge. The DO level should be sufficiently high so that enough oxygen can be delivered to the microorganisms in the sludge. However, an excessively high DO will require higher airflow rate and thus leads to higher energy consumption and deteriorate the sludge quality. Meanwhile, nitrogen removal in activated sludge requires two-step procedure which takes place simultaneously nitrification and denitrification processes. Nitrification is a process in which ammonium is oxidized to nitrate under aerobic (present oxygen) conditions. The nitrate formed by nitrification process, in turn, is converted into gaseous nitrogen under anoxic (absent oxygen) conditions, that is called denitrification. The improvement of DO concentration in aerated tanks and the nitrogen removal process contribute to big interest of activated sludge control.

The proportional-integral (PI) technique is one of the control strategies that are frequently applied in WWTP. As referred to in [6], each part of PI controller highly contributes in achieving the control target. The proportional part is potential to increase the response speed and control accuracy while the integration part is normally used in eliminating the steady-state error of the system. The performances of several control strategies with PI controller to the WWTP have been discussed in [7, 8]. However, it is hard to achieve high control performance in all operating conditions with a linear PI controller due to different dynamic behaviours of the WWTP control parameters. More retuning task will always be demanded for a fixed-gain PI controller. Therefore, a controller that is potential to maintain a balance of DOs concentrations and nitrogen removal process during the set-point changes is highly demanded. Many approaches have been developed in improving the adaptability and robustness of the controller such as self-tuning method, general predictive control, fuzzy logic, and neural network strategy. However, predictive control technique may require more complex control structure while human knowledge and system's experts are strongly demanded in adaptive fuzzy controller. Besides, the crucial work is concentrated in estimating all of the input-output data within such a complex system and in determining the appropriate structure of the neural network controller.

Under these circumstances, enhanced nonlinear PI (ENon-PI) controller is proposed to compensate the non-linearity of the control parameters hence to improve the performance of the conventional linear PI controller. The design of the ENon-PI controller is basically referred to [9] where the linear fixed-gain PI controller is cascaded to a bounded nonlinear gain. As referred to in [9], the nonlinear gain function has two parameters to be determined in initial simulation such as the range of variation, e_{\max} , and the rate of variation, k_n . Difficulties come to identify the appropriate combination of these parameters especially for a complex nonlinear system. Therefore, modifications to the ENon-PI to automate one of the parameters are obviously proposed. The idea is to automatically update k_n using simple updating algorithm, namely, as adaptive interaction algorithm (AIA). The theoretical of adaptive interaction is previously applied in neural network and PID control as referred to in [10, 11], respectively. AIA is generally a technique in which a system is decomposed into subsystems where an adaptation exists between them. It is believed that the k_n is potential to be updated with respect to proportional control part as referred to in [11].

Two case studies are proposed for control design strategies with respect to dynamic behaviors of the WWTP. Case 1 highlights the improvement of the ASP with respect to DO concentration in all aerated tanks called DO_{345} control while the improvement of nitrogen removal process is aimed in Case 2. Cases 1 and 2 are considered due to different average time constant for DO and nitrate which is in minutes and several hours, respectively. In particular, the WWTP is naturally a multivariable system that is basically described as a system with more than one control loop. Changes in any input will generally affect all the outputs due to interaction between

TABLE 1: List of the acronyms.

Acronyms	Descriptions
AE	Aeration energy
AIA	Adaptive interaction algorithm
ASM1	Activated Sludge Model 1
ASP	Activated sludge process
BSM1	Benchmark Simulation Model No. 1
DO	Dissolved oxygen
DO_q	Dissolved oxygen control of tank q , $q = 3, 4, 5$
DO_{345}	Dissolved oxygen control of tanks 3, 4, and 5
e	Error
e_q	Error of tank DO_q , $q = 3, 4, 5$
ENon-PI	Enhanced nonlinear PI
IAE	Integral of absolute error
ISE	Integral of square error
k_{non}	Nonlinear gain
k_n	Rate variation of nonlinear gain
K_{Laq}	Air flow rate of tank q , $q = 3, 4, 5$
K_p	Proportional gain
K_i	Integral gain
Mean(e)	Absolute error
Max(e)	Maximum absolute deviation from set-point
Q_{intr}	Internal recycle flow rate
Std(e)	Standard deviation of the error
WWTP	Wastewater treatment plant

the inputs and outputs variables. However, a decentralized controller is a simple approach of multivariable controller designs. As a result, the plant to be controlled is essentially a collection of independent subplants where each element in the plant may be designed independently. The proposed ENon-PI is developed in decentralized control structure in both simulation cases. To further extend, the study on how the ENon-PI controller performs under various different dynamic conditions is covered. The proposed ENon-PI controller is then tested to an updated Benchmark Simulation Model No. 1 (BSM1) with more complex sensors and noises as updated in [12].

The paper is organized as follows. The BSM1 is explained in Section 2 while the development of ENon-PI with adaptation algorithm is presented in Section 3. The simulation result and discussion of well-tuned ENon-PI controller are presented in Section 4. Finally, Section 5 concludes the paper. For convenience of discussion, Table 1 lists the acronyms that frequently used in the paper.

2. Benchmark Simulation Model No. 1 (BSM1)

The WWTP used in the simulation is the benchmark plant developed in [12]; referred as BSM1. The plant consists of five tanks where the first two compartments are anoxic zones followed by three aerobic tanks as shown in Figure 1. Each tank is assumed to have constant volume of 1000 m^3 , 1000 m^3 , 1333 m^3 , 1333 m^3 , and 1333 m^3 , respectively.

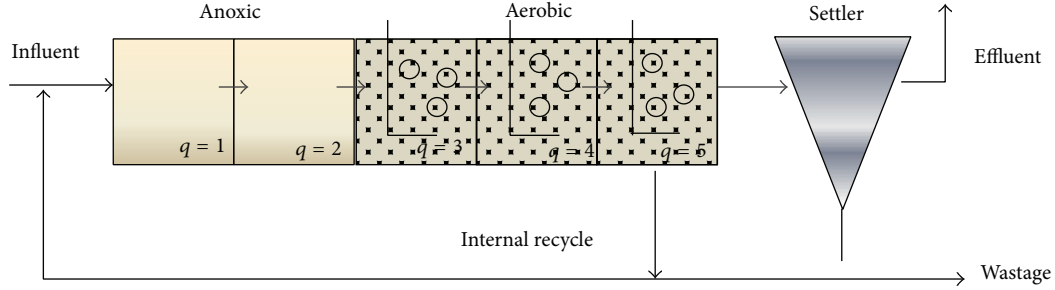


FIGURE 1: The plant layout of the BSM1.

The effluent from the last tank is connected in series to a settler of constant volume of 6000 m^3 . The BSM1 is widely used as a standard model based on the most popular IWA Activated Sludge Model No. 1 (ASM1) proposed in [13]. The ASM1 was developed as to describe the removal of ammonium nitrogen and organic carbon. Meanwhile, the model proposed by [14] was chosen to resemble the behavior of the secondary settler. The BSM1 is default controlled by PI controller where two control loops of nitrate in the second anoxic tank and the DO concentration in the final tank

are emphasized. The performances of the benchmark PI are always used as comparison to the proposed controller. Detail on the model can be referred in [12].

2.1. Influent Load. To investigate the performance of the control strategy in various weather situations, three dynamic input files including dry, rain, and storm events that have realistic variations in the effluent flow rate and composition have been used. The data used for the estimation and control are sampled with a sampling period of 15 minutes given as

$$[\text{time } S_I \text{ SS } X_I \text{ } X_S \text{ } X_{BH} \text{ } X_{BA} \text{ } X_P \text{ } S_O \text{ } S_{NO} \text{ } S_{NH} \text{ } S_{ND} \text{ } X_{ND} \text{ } S_{ALK} \text{ } Q_o]. \quad (1)$$

In any influent: $S_O = 0 \text{ g(-COD) m}^{-3}$; $X_{BA} = 0 \text{ g COD m}^{-3}$; $S_{NO} = 0 \text{ g N m}^{-3}$; $X_P = 0 \text{ g COD m}^{-3}$; $S_{ALK} = 7 \text{ mol m}^{-3}$. The description of influent variables is presented in Table 2.

The dry influent contains two weeks of dynamic dry weather influent data. The rain influent is based on the dry weather file with an added rain event during the second week. Similarly, the storm influent file is also based on the dry weather file but added with two storm events during the second week. There is a constant influent with constant flow and composition that is used during the system simulation under steady state condition. Refer to [12] for detailed explanation.

2.2. Performance Assessment. Two-level performance assessment is highlighted in controlling the WWTP. The local control loop is assessed on the means of absolute error (Mean(|e|)), the integral of absolute error (IAE), the integral of square error (ISE), the maximum absolute deviation from set-point (Max(e)), and the standard deviation of the error (Std(e)) at the first level. Meanwhile, the second level investigates the effect of the control strategy on the plant process operation with respect to economical and quality part. Two measuring assessments are considered in the simulation such as the effluent violations and the aeration energy consumed.

2.2.1. The Effluent Violations. Table 3 indicates the constraints of the effluent water quality. The flow-weighted average effluent concentrations of the following variables must

meet their corresponding limitations. Besides, the effluent violations can be reported through the number of violations and the percentage time plant is in violation. This quantity indicates the frequency of the plant effluent increases above the effluent constraint.

2.2.2. The Aeration Energy. The index of aeration energy (AE) is described as in (2). $K_{Laq}(t)$ is the oxygen transfer coefficient in each tank, q . The AE is calculated for the last 7 days, T of the dynamic test weather conditions with unit of kWhday^{-1} . Consider

$$AE = \frac{S_o^{\text{sat}}}{T \cdot 1.8 \cdot 1000} \int_{7\text{days}}^{14\text{days}} \sum_{k=1}^5 V_q \cdot K_{Laq}(t) dt. \quad (2)$$

3. Development of Enhanced Nonlinear PI Controller

3.1. The Case Study. As mentioned, two case studies are highlighted for control design strategies. The improvement of the ASP with respect to DO concentration in all aerated tanks, tank 3 (DO_3), tank 4 (DO_4), and tank 5, (DO_5) called DO_{345} control is aimed in Case 1. Meanwhile, the improvement of the nitrogen removal process of nitrate and DO_5 control is next highlighted in Case 2.

3.1.1. Case 1: Controlling the Aerated Tanks (DO_{345}). For decentralized control structure, the WWTP is partitioned

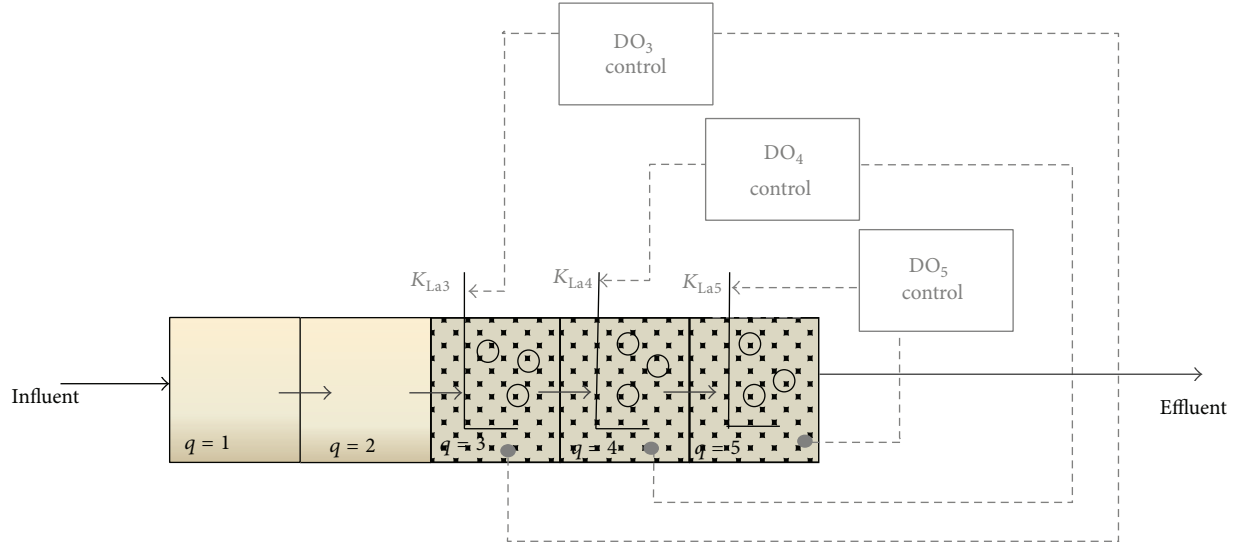


FIGURE 2: ENon-PI control for the last three aerated tanks in Case 1.

TABLE 2: Influent data.

Variables	Descriptions
S_I	Soluble inert organic matter
S_S	Suspended solids
S_O	Dissolve oxygen
S_{NO}	Nitrate
S_{NH}	Ammonium and ammonia nitrogen
S_{ND}	Soluble biodegradable organic nitrogen
S_{ALK}	Alkalinity
X_I	Particulate inert organic matter
X_S	Slowly biodegradable substrate
X_{BH}	Active heterotrophic biomass
X_{BA}	Active autotrophic biomass
X_P	Particulate products arising from biomass decay
X_{ND}	Particulate biodegradable organic nitrogen
Q_o	Input flow rate

TABLE 3: Constraints of the effluent water quality.

Variables	Value
Total nitrogen (N_{tot})	18 g N m ⁻³
Chemical oxygen demand (COD ₅)	100 g COD m ⁻³
Ammonia (S_{NH})	4 g N m ⁻³
Total suspended solids (TSS)	30 g SS m ⁻³
Biochemical oxygen demand (BOD ₅)	10 g BOD m ⁻³

into three SISO subsystems contributing to three ENon-PI controllers. The implementation of DO₃₄₅ control is shown in Figure 2.

3.1.2. Case 2: Controlling the Nitrate-DO₅. For the nitrogen removal process, the ENon-PI controller is set to work correspondingly to the benchmark PI. The implementation of the controller is shown in Figure 3.

3.2. The Controller. For a conventional linear PI controller, the error signal is used to generate the proportional (P) and integral (I) control actions and to be summed in producing the control signal as generally expressed as in

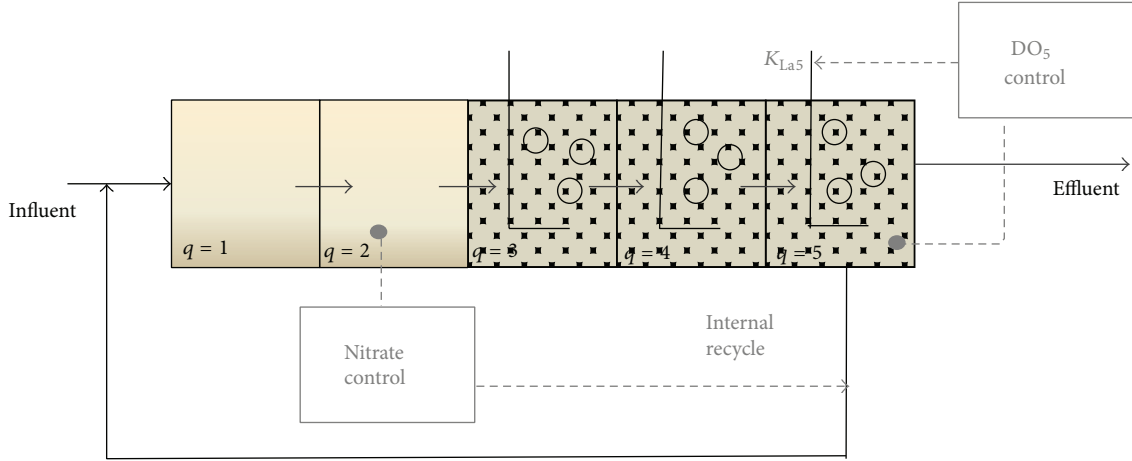
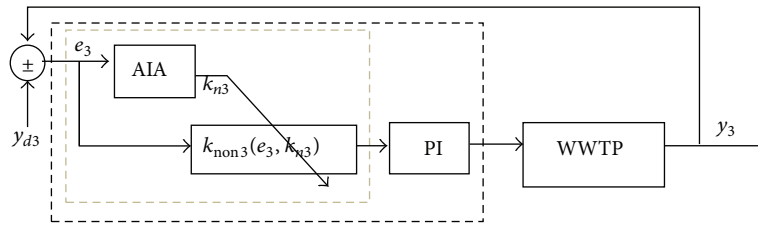
$$u(t) = K_p e(t) + K_i \int_0^t e(t) dt, \quad (3)$$

where K_p and K_i are the proportional and integral coefficients of the PI controller, respectively. However, the fixed-gains of conventional linear PI controller have the limitation in controlling the time-variant characteristics and the process nonlinearities of the WWTP [15]. This problem can be alleviated by employing nonlinear elements in the PI control scheme and thus leads the development of the ENon-PI controller.

As discussed, the ENon-PI is designed by cascading a sector-bounded nonlinear gain to linear PI controller as described in (4). The nonlinear gain, k_{non} is a function of error with respect to the changes of k_n , that acts on the error in producing the scaled error; $f(e) = k_{non}(e, k_n) \cdot e(t)$. The $f(e)$ is then input to the PI controller thus generating the control action as

$$\begin{aligned} u_{ENon-PI}(t) &= \left[k_p e(t) + k_i \int_0^t e(t) dt \right] \cdot f(e) \\ &= \left[k_p e(t) + k_i \int_0^t e(t) dt \right] [k_{non}(e, k_n) \cdot e(t)]. \end{aligned} \quad (4)$$

The k_{non} can be expressed by any nonlinear general function such as sigmoidal function, the hyperbolic function, and the piecewise linear function as explained in [16]. However, the k_{non} used in the simulation are described in (5) and (6).


 FIGURE 3: ENon-PI control for the nitrate-DO₅ in Case 2.

 FIGURE 4: The block diagram of ENon-PI controller for DO₃ control.

Notice that the k_n is automatically updated by the AIA while e_{\max} is the user-defined positive constant. Consider

$$k_{\text{non}}(e, k_n) = \left[\frac{\exp(k_n e) + \exp(k_n e)}{2} \right], \quad (5)$$

where

$$e = \begin{cases} e & |e| \leq e_{\max} \\ \text{sign}(e) \cdot \sqrt{|e_{\max}|} & |e| > e_{\max} \end{cases} \quad (6)$$

3.3. The Algorithm. The work on enhanced nonlinear PID by [9] is extended to adaptively update the k_n . It is believed that the characteristic of k_n is potential to be manipulated based on AIA. As mentioned, the AIA is generally a technique in which a system is decomposed into subsystems where an adaptation exists between them. The k_n is updated with respect to proportional control part as referred to in [11]. The typical decomposition of a system for an adaptive interaction and the detail on AIA can be further referred in [10, 11, 17].

In conjunction to Case 1, DO₃, DO₄, and DO₅ control loops are involved. However, the DO₃ concentration is first considered to present the applied algorithm. The block diagram of ENon-PI of DO₃ control loop is shown in Figure 4. y_{d3} and y_3 are desired and measured outputs that result in the error of DO₃, e_3 . The e_3 is then applied by AIA in updating the k_{n3} for the variation of the $k_{\text{non}3}$. The integration of the

functional of $k_{\text{non}3}$ to the PI controller develops the ENon-PI for DO₃ control.

The aim here is to update k_{n3} of the nonlinear gain for the third tank using the the AIA so that the performance index which is the e_3 as in (7) is minimized. With respect to AIA, it is believed that interaction/adaptation of k_{n3} exists between the proportional gain transfer function of e_3 , A_3 , and the functional of the $k_{\text{non}3}$. The gradient method as given in (8) is then applied. Consider

$$E_3 = e_3^2 = (y_3 - y_{d3})^2, \quad (7)$$

$$\dot{k}_{n3} = -\gamma_3 \frac{dE_3}{dy_3} \circ \dot{F}[x_3] \circ A_3 \quad (8)$$

γ_3 is the adaptation gain while \dot{F} is the Frechet derivative in relation to the plant input, x_3 , and the output, y_3 . The adaptation of k_{n3} is then reduced to

$$\begin{aligned} \dot{k}_{n3} &= 2\gamma_3 (y_3 - y_{d3}) \dot{F}[x_3] \circ A_3 \\ &= 2\gamma_3 e_3 \dot{F}[x_3] \circ A_3. \end{aligned} \quad (9)$$

The functional $F[x_3]$ can be written in the convolution form as in (10). $g_3(t)$ is the impulse response of the linear time invariant system for DO₃ while $*$ denotes convolution.

Therefore, the Frechet derivative can be expressed as in (11). Consider

$$F[x_3] = g_3(t) * x_3(t) = \int_0^t g_3(t-\tau) x_3(\tau) d\tau, \quad (10)$$

$$\dot{F}[x_3] \circ A_3 = \int_0^t g_3(t-\tau) A_3(\tau) d\tau = g_3(t) * A_3(t). \quad (11)$$

However in many practical systems, the Frechet derivative can be approximated as in (12) where A_3 is an arbitrary function and σ_3 is a constant value. Consider

$$\dot{F}[x_3] \circ A_3 = \sigma_3 A_3. \quad (12)$$

This result approximates Frechet tuning algorithm as presented in

$$\dot{k}_{n3} = 2\gamma_3 e_3 \dot{F}[x_3] \circ A_3 = 2\gamma_3 e_3 \sigma_3 A_3. \quad (13)$$

Let the adaptive coefficient, $\eta_3 = 2\gamma_3 \sigma_3$ and $\eta_3 > 0$. The tuning algorithm of k_{n3} thus can be simplified to (14). Therefore, k_{n3} might change and update its responses with time referring to the changes of e_3 in achieving good variation of the k_{non3} . The general function of k_{non} used in the simulation can be referred in (5). Consider

$$\dot{k}_{n3} = \eta_3 e_3 A_3. \quad (14)$$

Taking y_{d4} and y_4 that represent the desired and measured outputs which result the error of DO_4 , e_4 besides A_4 that denotes the proportional gain of tank four, the procedures of (7)–(13) are repeated. This results in an approximate Frechet tuning algorithm for tank four as described in (15). The same goes to DO control of tank five thus contributing to k_{n5} as in (16). Notice that η_3 , η_4 , and η_5 are the adaptation coefficients of k_{n3} , k_{n4} , and k_{n5} in controlling the DO_3 , DO_4 , and DO_5 concentrations, respectively. For simplicity, the proportional gains of A_3 , A_4 , and A_5 are always set to 1

$$\dot{k}_{n4} = \eta_4 e_4 A_4, \quad (15)$$

$$\dot{k}_{n5} = \eta_5 e_5 A_5. \quad (16)$$

In fact, the procedures on (7)–(13) are repeated for nitrate control loop in Case 2. The tuning algorithm of k_{n2} is then described in (17). Meanwhile, similar algorithm presented in (16) is used for DO_5 control. Consider

$$\dot{k}_{n2} = \eta_2 e_2 A_2. \quad (17)$$

4. Results and Discussion

The simulation procedures of BSM1 can be referred to in [12]. In the ideal case, the BSM1 is first simulated for 150 days to attain a quasi-steady-state using the constant influent input. This is done to guarantee that the initial conditions of the states are consistent. It then continued with 14-day simulation of dry influent to set up the plant for the dynamic

benchmark simulation. Finally, the plant is simulated for the next 14 days with the dynamic test input weather with noises present. However, only the data of the last 7 days are evaluated in control assessment. For DO control, the sensor of class A with a measurement range of 0 to 10 g(-COD) m^{-3} and a measurement noise of 0.25 g(-COD) m is used. Meanwhile, a class B0 sensor with a measurement range of 0 to 20 gNm $^{-3}$ and measurement noise of 0.5 gNm $^{-3}$ is applied in nitrate control. Two case studies are considered in the simulation, DO_{345} control and nitrogen removal process control.

4.1. Case 1: Controlling the DO_{345} . The DO concentrations in tank 3, tank 4, and tank 5 are set to 1.5 mg L $^{-1}$, 3 mg L $^{-1}$, and 2 mg L $^{-1}$, respectively, as referred to in [18]. Nevertheless, the previous work develops multivariable PID for COST simulation benchmark [19] instead of updated version [12] that is used in the present simulation. In addition, the oxygen mass transfer coefficient of DO_3 (K_{La3}), the oxygen mass transfer coefficient of DO_4 (K_{La4}), and the oxygen mass transfer coefficient of DO_5 (K_{La5}) are constrained to a maximum of 360 day $^{-1}$. The k_{n3} , k_{n4} , and k_{n5} are automatically updated using AIA as described in (14)–(16). Meanwhile, the adaptive coefficients, η_3 , η_4 , and η_5 are set to 0.09. $e_{max} = 1$ is applied while the proportional gains and the integral time constants of linear PI controllers are set to 25 and 0.0020, respectively.

4.2. Case 2: Controlling the Nitrate- DO_5 . The nitrate- DO_5 control of the nitrogen removal process is considered in the second case. The k_{n2} and k_{n5} are automatically updated using AIA as referred to in (16)–(17). The internal recycle flow rate (Q_{intr}) and the K_{La5} are manipulated. To improve the nitrogen removal, the nitrate concentration is set to 1.0 gm $^{-3}$ with constrained Q_{intr} up to 5 times of stabilized input flow rate, 92230 m 3 day $^{-1}$. The DO_5 level is set to 2.0 gm $^{-3}$ with constrained K_{La5} to a maximum of 360 day $^{-1}$. The η_2 and η_5 are similarly set to 0.09 while the e_{max} and the PI control gains as in Case 1 are maintained in the simulation.

4.3. Discussion. It is aimed to improve the performance for the set-point tracking of the load changes due to daily variations in different influents composition. As mentioned, the effectiveness of the proposed ENon-PI controller is investigated in two-level assessment, the performance of the controller and the performance of activated sludge process compared to benchmark PI.

4.3.1. The Performance of the Controller. The ENon-PI is first assessed by investigating the Mean(|e|), the IAE, the ISE, the Max(e), and the Std(e). As for comparison, the performance of ENon-PI with adaptive k_n is also compared to ENon-PI with fixed k_n . For this purpose, the k_{n3} , k_{n4} , and k_{n5} are set to 0.01 for DO_{345} control. Similarly k_{n5} is used for DO_5 while k_{n2} is set to 0.1 for nitrate in nitrate- DO_5 control. Referring to Table 4, obvious improvement is obtained in Case 1 by ENon-PI controller compared to benchmark PI controller. However, as referred to in Table 5, significant improvement is observed for nitrate compared to DO_5 in Case 2. Difficulties come to

TABLE 4: Comparative of controller performance for Case 1.

		Benchmark PI	Fixed k_n		Adaptive k_n	
				-%		-%
Dry	Mean(e)	0.0840	0.0695	17.3052	0.0688	18.1381
	IAE	0.5883	0.4814	18.1724	0.4813	18.1894
	ISE	0.0840	0.0547	34.8616	0.0547	34.8616
	Max(dev)	0.3963	0.3101	21.7532	0.3058	22.8382
	Std(dev)	0.1095	0.0884	19.2915	0.0884	19.2915
Rain	Mean(e)	0.0795	0.0688	13.4939	0.0666	16.2601
	IAE	0.5567	0.4665	16.2056	0.4665	16.2056
	ISE	0.0747	0.0513	31.3556	0.0512	31.4894
	Max(dev)	0.3851	0.2992	22.2958	0.2868	25.5162
	Std(dev)	0.1033	0.0856	17.1506	0.0855	17.2474
Storm	Mean(e)	0.0809	0.0680	15.8978	0.0672	16.8872
	IAE	0.5660	0.4702	16.9229	0.4701	16.9405
	ISE	0.0789	0.0523	33.6934	0.0522	33.8202
	Max(dev)	0.3792	0.3005	20.7626	0.2970	21.6855
	Std(dev)	0.1062	0.0864	18.6057	0.0864	18.6057

TABLE 5: Comparative of controller performance for Case 2.

		Benchmark PI	Fixed k_n		Adaptive k_n		
				-%		-%	
Dry	Nitrate	Mean(e)	0.2050	0.2049	0.034151	0.1760	14.13377567
		IAE	1.4348	1.2319	14.14134	1.2318	14.14831335
		ISE	0.5690	0.3871	31.96478	0.3862	32.12295903
		Max(dev)	0.9178	0.8138	11.33338	0.8130	11.42053998
		Std(dev)	0.2851	0.2341	17.88558	0.2338	17.99080992
	DO ₅	Mean(e)	0.0840	0.0852	-1.37547	0.0815	3.026985865
		IAE	0.5883	0.5864	0.324659	0.5707	2.993319848
		ISE	0.0840	0.0863	-2.76868	0.0816	2.828222685
		Max(dev)	0.3963	0.4184	-5.57392	0.4396	-10.9232671
		Std(dev)	0.1095	0.1110	-1.3421	0.1095	0.027389756
Rain	Nitrate	Mean(e)	0.2478	0.2068	16.55907	0.2065	16.6801162
		IAE	1.7349	1.4479	16.54274	1.4457	16.66954868
		ISE	0.7944	0.5435	31.58014	0.5411	31.88227
		Max(dev)	0.9213	0.8445	8.340026	0.8431	8.491979074
		Std(dev)	0.3369	0.2783	17.38408	0.2776	17.59187793
	DO ₅	Mean(e)	0.0795	0.0802	-0.83991	0.0762	4.189508625
		IAE	0.5567	0.5514	0.955597	0.5338	4.116970829
		ISE	0.0747	0.0763	-2.0968	0.0700	6.333212905
		Max(dev)	0.3851	0.4060	-5.44085	0.4342	-12.764576
		Std(dev)	0.1033	0.1034	-0.07743	0.0999	3.31010453
Storm	Nitrate	Mean(e)	0.2398	0.2037	15.05067	0.2033	15.21748196
		IAE	1.6785	1.4257	15.06107	1.4229	15.22788204
		ISE	0.7880	0.5454	30.78417	0.5417	31.25372793
		Max(dev)	1.2014	0.9644	19.72699	0.9483	21.0670884
		Std(dev)	0.3355	0.2788	16.89272	0.2779	17.16994068
	DO ₅	Mean(e)	0.0809	0.0818	-1.17001	0.0786	2.787740866
		IAE	0.5660	0.5701	-0.72794	0.5502	2.788084385
		ISE	0.0789	0.0808	-2.43927	0.0763	3.265885694
		Max(dev)	0.3792	0.4137	-9.08659	0.4348	-14.6503533
		Std(dev)	0.1062	0.1075	-1.27179	0.1044	1.648610457

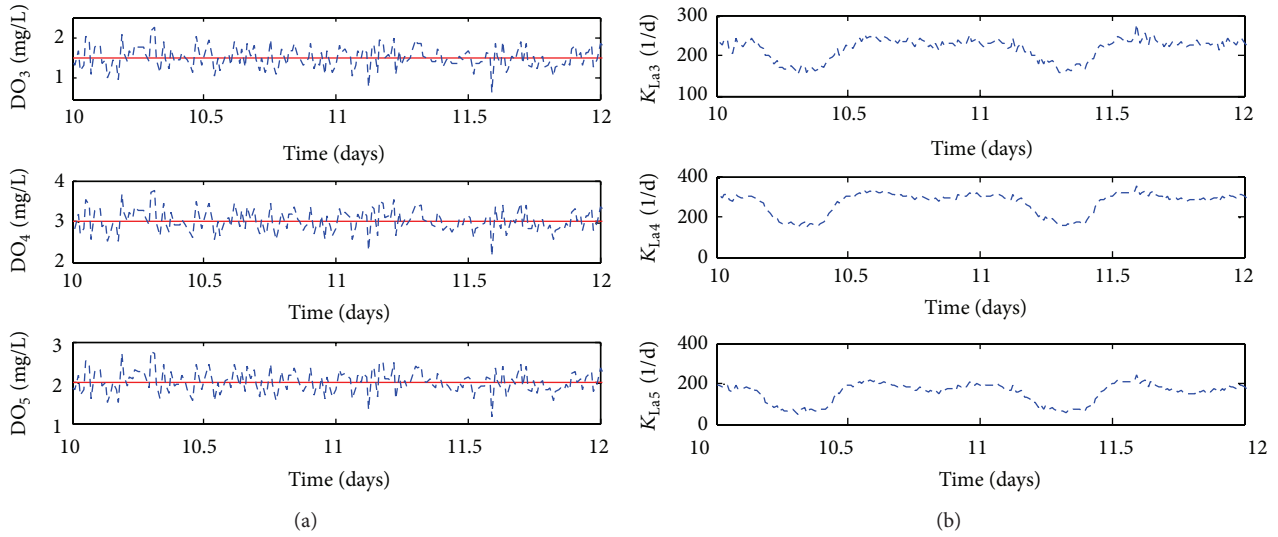


FIGURE 5: Variation of (a) output and (b) input variables under dry influent of Case 1.

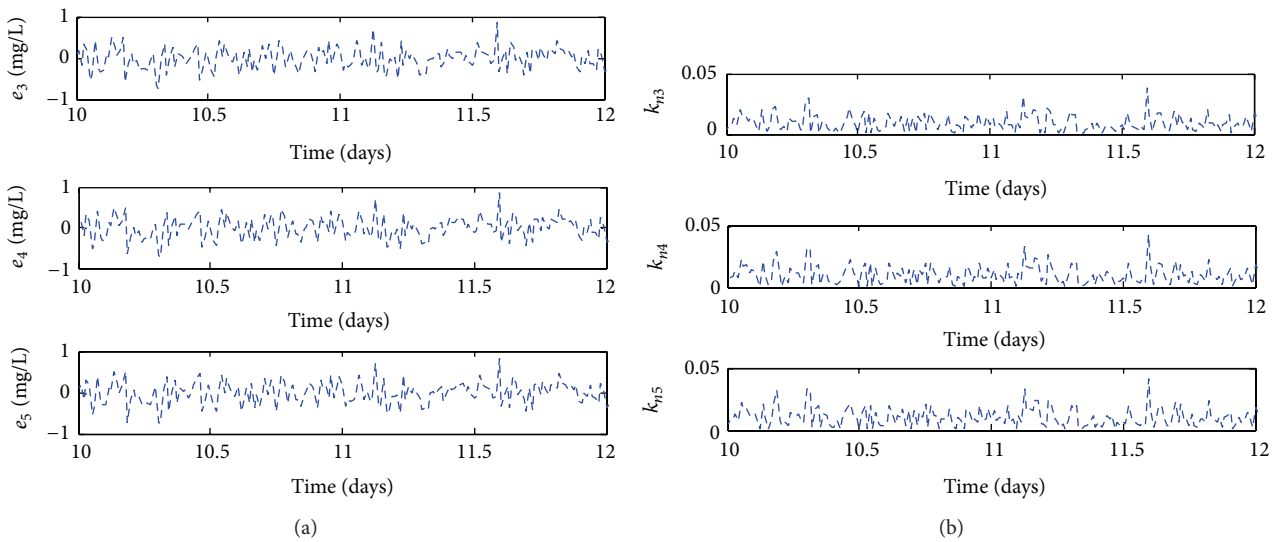


FIGURE 6: Variation of (a) error (b) rate variation under dry influent of Case 1.

control simultaneous nitrate and DO_5 control loops in Case 2 that may due to different dynamic behaviours of the control parameters.

The variation of output and input variables of DO_{345} control in Case 1 under dry input weather by ENon-PI with adaptive k_n is shown in Figure 5. It was seen that the ENon-PI controller with adaptive k_{n3} , k_{n4} , and k_{n5} manages well to keep DO_3 , DO_4 , and DO_5 concentrations around the reference values. Besides, the input variables K_{La3} , K_{La4} , and K_{La5} are always kept under the upper bounds. Meanwhile, Figure 6 shows the variation of the error and the adaptation of the k_n resulted. As observed, higher k_n is demanded for a higher error resulted.

The nitrate- DO_5 control is then simulated with respect to benchmark PI, as applied in [12]. Figure 7 shows the comparative variation of output variables of nitrate and DO_5

under rain input weather. Slight improvements are observed by ENon-PI with adaptive k_{n2} and k_{n5} for nitrate and DO_5 concentrations compared to benchmark PI. Nevertheless, the improvements are obviously better than the fixed k_n . The variations of input variables of nitrate- DO_5 control are next illustrated in Figure 8. Similarly, the Q_{intr} and K_{La5} are always kept under the upper bounds. Meanwhile, the variation of the errors and the adaptation of the rate variation resulted are illustrated in Figure 9.

4.3.2. The Performance of Activated Sludge Process. The second level of controller assessment is to investigate the effect of the ENon-PI control strategy on the process of an activated sludge. Firstly, the performances in average effluent concentrations are compared to benchmark PI and the fixed k_n , as indicated in Tables 6 and 7 for Cases 1 and 2,

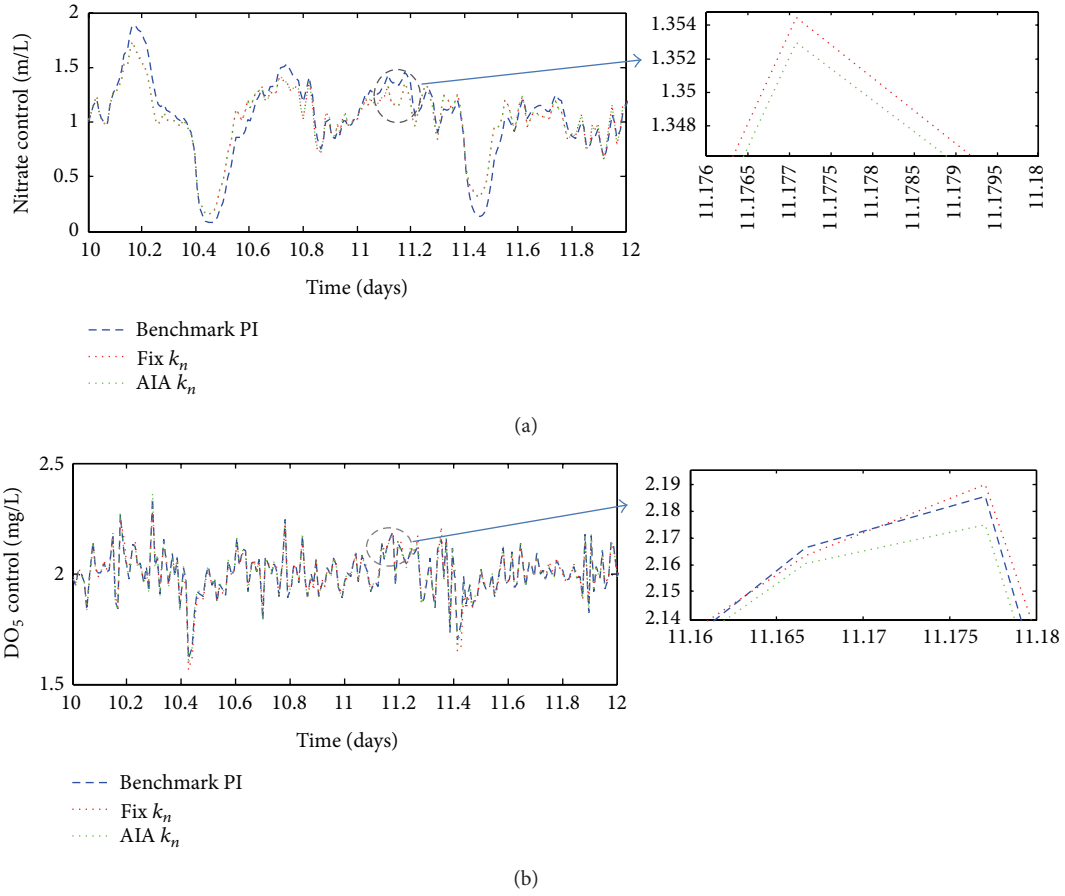


FIGURE 7: Variation of (a) nitrate (b) DO_5 output variables under rain influent of Case 2.

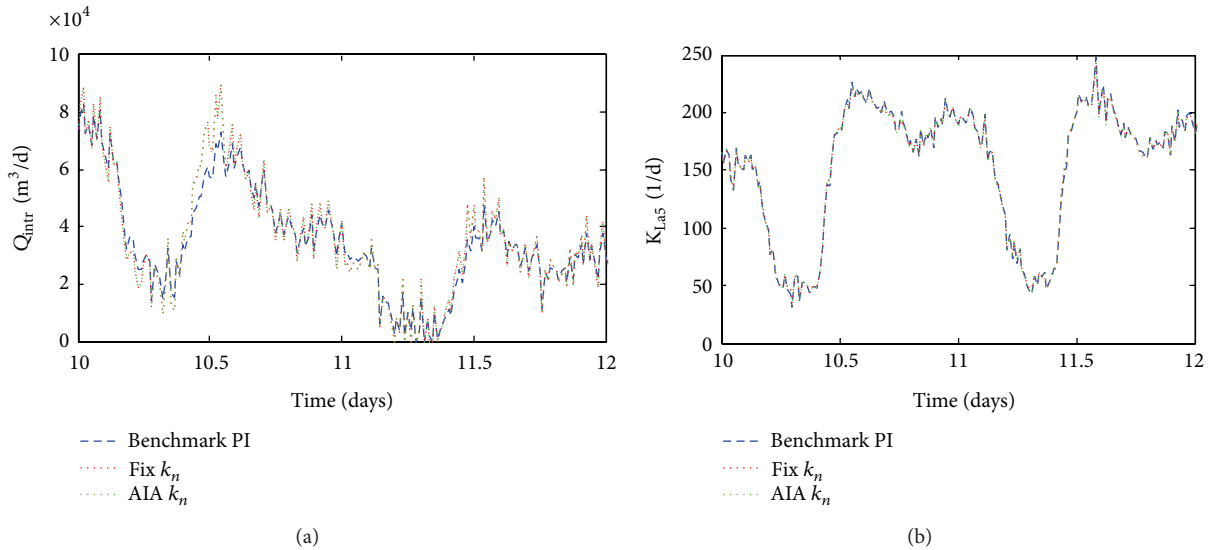


FIGURE 8: Variation of (a) Q_{intr} (b) K_{La5} input variables under rain influent of Case 2.

respectively. Five main process variables including the total S_{NH} , N_{tot} , BOD_5 , COD, and TSS are evaluated. The limit of effluent variables can be referred in Table 3. Overall in Case 1, in spite of total COD concentration, improvement on

average effluents has been observed by ENon-PI compared to benchmark PI. Obvious enhancement on the S_{NH} resulted by ENon-PI with adaptive k_n compared to benchmark PI under three input weathers. In particular, the improvement

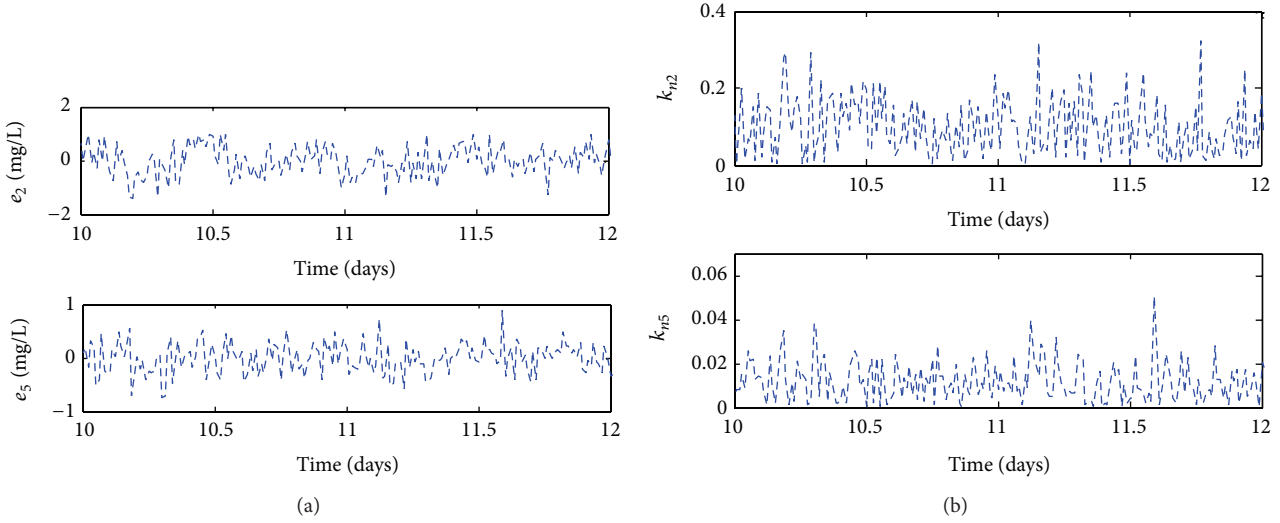


FIGURE 9: Variation of (a) error (b) rate variation under rain influent of Case 2.

TABLE 6: Average effluent concentrations for Case 1.

	Dry			Rain			Storm		
	Benchmark PI	Fixed k_n	Adaptive k_n	Benchmark PI	Fixed k_n	Adaptive k_n	Benchmark PI	Fixed k_n	Adaptive k_n
S_{NH} conc /mg N/L	2.5392	2.3896	2.3881	3.226	3.2041	3.1954	3.0622	3.0395	3.041
TSS conc /mg SS/L	13.0038	13.0038	13.0038	16.1768	16.175	16.1750	15.2737	15.2773	15.2724
N_{tot} conc /mg N/L	16.9245	16.8500	16.8505	16.9245	14.6539	14.6719	15.8676	15.7662	15.7666
Total COD conc/mg COD/L	48.2201	48.2420	48.2427	45.4337	45.4314	45.4479	47.6626	47.6631	47.6639
BOD_5 conc/mg/L	2.7568	2.7615	2.7615	3.4557	3.4548	3.4557	3.2050	3.2049	3.2045

TABLE 7: Average effluent concentrations for Case 2.

	Dry			Rain			Storm		
	Benchmark PI	Fixed k_n	Adaptive k_n	Benchmark PI	Fixed k_n	Adaptive k_n	Benchmark PI	Fixed k_n	Adaptive k_n
S_{NH} conc /mg N/L	2.5392	2.5128	2.5126	3.226	3.2041	3.1954	3.0622	3.0395	3.0390
TSS conc /mg SS/L	13.0038	13.0058	13.0058	16.1768	16.1798	16.1750	15.2737	15.2733	15.2734
N_{tot} conc /mg N/L	16.9245	16.8169	16.8160	16.9245	14.6539	14.6719	15.8676	15.7672	15.7666
Total COD conc/mg COD/L	48.2201	48.2201	48.2201	45.4337	45.4314	45.4479	47.6626	47.6638	47.6639
BOD_5 conc/mg/L	2.7568	2.7560	2.7560	3.4557	3.4548	3.4549	3.2050	3.2049	3.2049

of S_{NH} is maintained by ENon-PI with adaptive k_n in Case 2. Besides, improvement on N_{tot} was recorded under dry and storm influents.

Next, the numbers of time that the effluent limits are not met during simulation obtained by ENon-PI for Case 1 are presented in Tables 8 and 9. The number of violation of N_{tot} is

observed under dry weather while it is extended to TSS under the storm weather. It was proved that the numbers of the effluent increases above the effluent constraints are reduced from 7 to 6 compared to benchmark PI under dry weather. In the meantime, it reduces from 7 to 5 and 2 to 1 for N_{tot} and TSS under storm weather condition, respectively. To clarify,

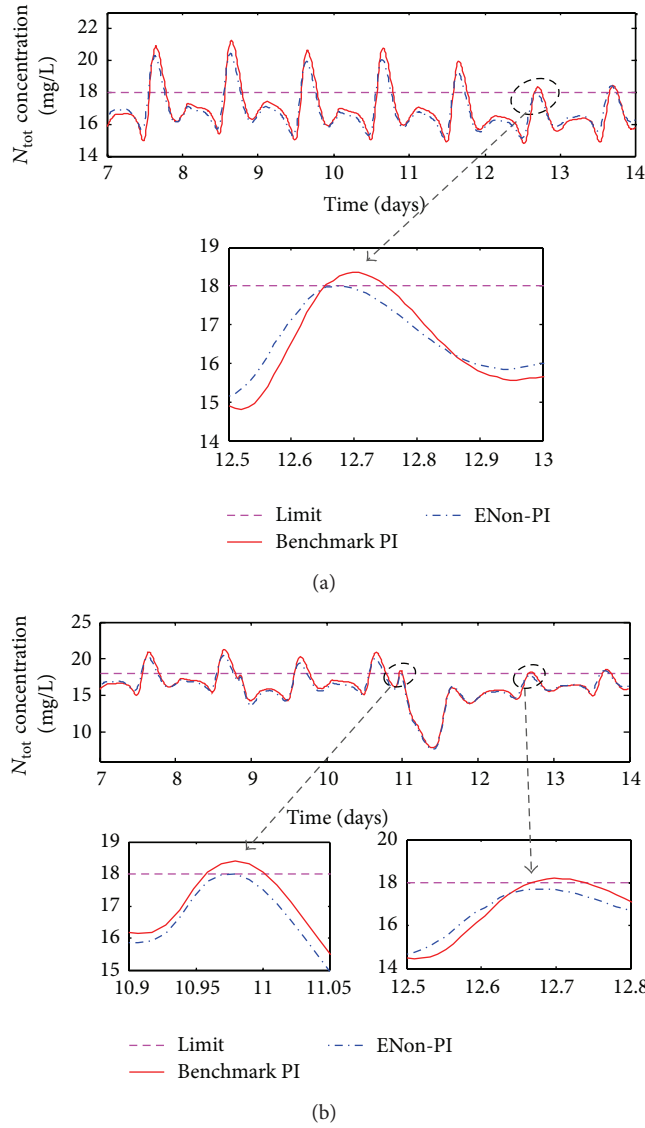


FIGURE 10: Effluent violations of N_{tot} for (a) dry (b) storm influents.

TABLE 8: Effluent violations under dry influent.

	Benchmark PI	ENon-PI
N_{tot} Days	1.2813	1.1042
N_{tot} %	18.3036	15.7738
N_{tot} Occasion	7.0000	6.0000

TABLE 9: Effluent violations under storm influent.

	Benchmark PI	ENon-PI
N_{tot} Days	1.0938	0.9167
N_{tot} %	15.6250	13.0952
N_{tot} Occasion	7.0000	5.0000
TSS Days	0.0208	0.0104
TSS %	0.2976	0.1488
TSS Occasion	2.0000	1.0000

the N_{tot} effluent violation compared to benchmark PI under dry and storm influents is shown in Figure 10.

Next, the average AE consumed in the process of activated sludge is illustrated in Figure 11. As observed in Case 1, the AE is significantly reduced by ENon-PI with adaptive k_n compared to benchmark PI under rain and storm events where the AE is minimized by 140.3118 and 46.7117 kwh per day, respectively. Meanwhile, about 0.5474 kwh per day

of AE is saved with adaptive k_n compared to fixed k_n of ENon-PI controller under storm weather which is the lowest AE consumption in Case 2. In fact, even though slight improvements were recorded by Non-PI in Case 2 but the AE is mostly better than the benchmark PI controller.

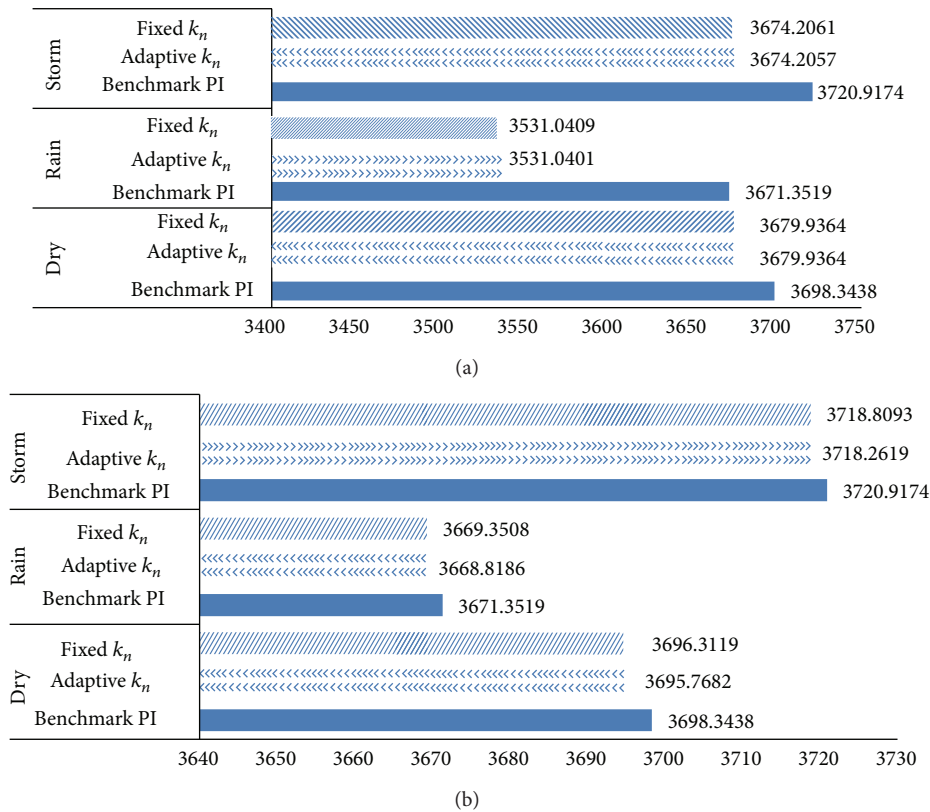


FIGURE 11: Comparative of aeration energy consumed (in kWh per day) for (a) Case 1 and (b) Case 2.

5. Conclusion

The aim of this paper is to design a simple but effective controller so that the performance of activated sludge process DO concentration control (Case 1) and the nitrogen removal (Case 2) of the WWTP are improved. For this work, the enhanced nonlinear PI (ENon-PI) controller is designed in which the conventional fixed-gain PI controller is incorporated with the bounded nonlinear function as to compensate the nonlinearity of the WWTP. The characteristic of the rate variation, k_n , is manipulated and automatically adapted based on adaptive interaction algorithm for a wide range of nonlinear gain.

From simulation, significant improvement is proved for DO_{345} control by ENon-PI compared to benchmark PI. Notice that the Case 1 deals with similar dynamic behaviors of DO concentrations, thus it easier to be controlled. In contrast, difficulties to control the simultaneous nitrate and DO_5 concentrations for Case 2 are undeniable due to different natures of both control parameters. Even though slight improvements were recorded by Non-PI in Case 2 but it is mostly better than the benchmark PI controller.

The effectiveness to simplify the ENon-PI control structure with adaptive k_n has been proved with significant improvement on both case studies. The performance comparison indicates that the proposed ENon-PI yields the most accurate strategy to control the DO concentration and the nitrogen removal process. For DO_{345} control, obvious

improvement resulted where about 34.86%, 31.4894%, and 33.8202% of ISE are reduced compared to benchmark PI under dry, rain, and storm weathers, respectively. Again, more than 30% of ISE is reduced under three dynamic influent weathers for nitrate in nitrogen removal control. Meanwhile, more than 14% of IAE is reduced both simulation cases. Better average effluent concentrations and less number of the effluent violations resulted. Besides, lower average aeration energy is consumed specifically under rain and storm influents for DO_{345} control and in nitrate removal process, respectively. The proposed ENon-PI shows benefit for simple and practical implementation in controlling various dynamic natures of the activated sludge process.

Conflict of Interests

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

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