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Decentralized Adaptive PI with Adaptive Interaction Algorithm of Wastewater Treatment Plant

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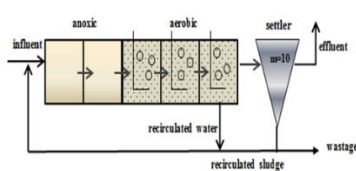
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Graphical abstract

Abstract

Wastewater treatment plant (WWTP) is highly known with the variation and uncertainty of the parameters, making them a challenge to be tuned and controlled. In this paper, an adaptive decentralized PI controller is developed for nonlinear activated sludge WWTP. The work is highlighted in auto-tuning the PI control parameters in satisfying straighten effluent quality and hence optimizing the nitrogen removal. The PI controller parameters are obtained by using simple updating algorithm developed based on adaptive interaction theory. The error function is minimized directly by approximate Frechet tuning algorithm without explicit estimation of the model. The effectiveness of the proposed controller is then validated by comparing the performance of activated sludge process to the benchmark PI under three different weather conditions with realistic variations in influent flow rate and composition. The algorithm is effectively applied in activated sludge system with improved dynamic performances in effluent quality index and energy consumed of Benchmark Simulation Model No.1.

Keywords: Adaptive decentralized PI; adaptive interaction algorithm

Abstrak

Loji rawatan air (WWTP) adalah sangat dikenali dengan perubahan dan ketidakpastian parameter, menjadikan ia satu cabaran untuk ditala dan dikawal. Di dalam kertas kerja ini, penyahpusatan suai pengawal PI dibangunkan untuk enapcemar teraktif WWTP tidak linear. Kerja-kerja ditumpukan dalam automatik-talaan parameter untuk pengawal PI bagi memenuhi kawalan kualiti kumbahan yang ketat seterusnya mengoptimum pembuangan nitrogen. Parameter pengawal PI diperolehi dengan menggunakan algoritma kemaskini yang mudah berdasarkan teori suai saling tindak. Fungsi ralat diminimumkan secara terus oleh algoritma penghampiran talaan Frechet tanpa perlu membuat anggaran model. Kecekapan pengawal yang dicadangkan kemudian disahkan dengan membandingkan prestasi proses enapcemar teraktif dengan tanda asas PI di bawah tiga keadaan cuaca yang berbeza dengan perubahan sebenar dalam kadar aliran influen dan komposisi. Algoritma ini digunakan dengan berkesan dalam sistem enapcemar teraktif dengan penambahbaikan prestasi dinamik dalam indek mutu kumbahan dan tenaga yang digunakan oleh Benchmark Simulation Model No.1.

Kata kunci: Penyahpusatan kawalan suai PI; algoritma suai saling tindak

▪1.0 INTRODUCTION

Most of industrial systems are nonlinear multivariable dynamics with input-output interactions. Difficulties caused by the interactions of control parameters are always encountered in controller design. This leads the system to be decomposed into a number of equivalent single loops that becomes one of the most widely used strategies in industrial process control. With decentralized controller, the complex structure in decoupling controller, integrity and robustness issues as stated in [1] are avoided. Besides, fewer tuning parameters and the easiness to handle the loop failures are the most attractive advantages of such systems.

Meanwhile, wastewater treatment plants (WWTP) are subject to large disturbances in flows and loads together with uncertainties concerning the composition of the influent wastewater. The plants typically aim to remove suspended substances, organic material and phosphate from the water before releasing it to the recipient. The best technology available used to control the discharge of pollutants emphasized in biological process. Activated sludge process (ASP) becomes a common concepts for biological process in which organic matters are oxidized by microorganisms. Nitrogen removal in ASP requires a two-step procedure which takes place simultaneously; that is nitrification and denitrification. Nitrification is a process in which ammonium is oxidized to nitrate under aerobic conditions. The nitrate formed by the nitrification process, in turn, is converted into gaseous nitrogen under anoxic conditions, that called as denitrification [2]. Obviously, a multistep configuration is generally needed in

order to perform an efficient nitrogen removal. However, the dynamic behavior of the biological nitrogen removal is highly nonlinear and time varying thus makes complex relationship between the control inputs and outputs variables. Therefore, it is a big interest to control the nitrogen removal for the process's improvements. The Benchmark Simulation Model No.1 (BSM1) is widely used as a standard model [3, 4] based on the most popular Activated Sludge Model No.1 (ASM1) proposed in [5] and Takacs settler model [6]. The purpose of BSM1 is to provide a platform-independent simulation environment which defines the plant layout, a detailed description of the influent disturbances, simulation models and parameters besides evaluation criteria of control strategies.

Indeed, a PID technique is one of the control strategies that are frequently applied in WWTP due to its simplicity, robustness and near to optimal control performances. The controller attempts to minimize the error by adjusting the process control inputs. However, as discussed in [7] most of the controller parameters are adjusted using a trial and error methods. Difficulties come in handling the interactions between different loops that are usually asked for iterative cycle that make the parameters to be changed often. According to [8], a good tuning of decentralized PI controllers for multivariable process is still relatively complex and definitely asks for critical tuning procedures. [9] has propose an auto-tuning PID controller for the dissolve oxygen (DO) concentration in a coke wastewater treatment bioreactor. Closed-loop identification by initiating set point step changes online is used. The integral of the time weighted absolute error (ITAE) disturbance rejection rule is then applied in estimating the optimal PID parameters. An adaptive genetic algorithm (AGA) form of self-tuning PID controller in ASP has been proposed by [10]. The process models are developed through mass-balance equations which are simulated and a simplified first order plus dead time (FOPDT) model is obtained. The PID controller parameters are then been optimized by AGA.

In conjunction to auto-tuning work on BSM1, a self–organizing radial basis function model predictive control (SORBF-MPC) method has been proposed in [11] in controlling the dissolve oxygen (DO) concentration where the SORBF can vary its structure dynamically in maintaining the prediction accuracy. Meanwhile, [12] has proposed an adaptive fuzzy control using Lyapunov synthesis approach with a parameter projection algorithm strategy while genetic algorithm optimized fuzzy logic controller has been applied in [13]. Alternatively, a multivariate virtual reference feedback tuning (VRFT) has been presented in [7] where open-loop input and output data are directly used in finding the controller parameters. It is outlined that more retuning task due to the changes of process dynamics will always been asked for a fixed conventional PID controller while the SORBF-MPC may ask for more complex control structure with MPC control strategy. Meanwhile, human knowledge and experts are strongly demanded in an adaptive fuzzy controller while the quality of VRFT technique is definitely depends on the information in the data. Besides, model-based adaptive control approach can be difficult and costly to be implemented due to the challenges in developing the process model. Under these circumstances, an adaptive PI controller with much more simpler implementation and tuning dealings is proposed in controlling both nitrate and DO concentrations.

The choice of the control algorithm is very important in ensuring good performance of adaptive controller. The present work proposes a model reference free adaptive decentralized PI controller. The algorithm is based on adaptive interaction theory proposed in (Brandt & Lin, 1999). It is one of direct adaptation method for online tuning of the PID parameters. Thus, the controller parameters are updated directly without explicit estimation of the parameters of the plant model. An adaptive interaction algorithm is proved to adapt and control different types of systems; stable, unstable, linear to nonlinear

and time variant systems besides easy in derivation and implementation. Besides, the stability of the algorithm was proved by Lyapunov stability theory [14]. A simple and effective ways in performing the gradient descent in the parameter space are explored. The algorithm was successfully tested in simulating SISO system such as in reducing the combustion engine crankshaft speed pulsation as discussed in [14]. Conversely, the proposed algorithm is suggested to be applied in multi-input multi-output (MIMO) system of WWTP.

According to adaptive interaction algorithm, the system is decomposed into three subsystems consisting of proportional control, integral control and the controlled plant. The controller parameters of K_p and K_i are viewed as the interactions between these subsystems. With self-tuning algorithm, the system to be controlled might change its response to the input with time in achieving good output responses. The challenges in tuning control parameters are stressed in satisfying straighten effluent quality and hence optimizing the nitrogen removal. The plant performance criteria considering the effluent violations and improvement in ASP are investigated and compared to updated BSM1 as referred in [3].

The paper is organized as follows. The BSM1 is briefly explained in Section 2. The adaptive interaction theory is discussed in Section 3 while the development of adaptive decentralized PI in BSM1 is described in Section 4. Subsequently, the performances of the well-tuned controller are thereafter presented in Section 5. Finally, Section 6 concludes the paper. For convenience of discussion, Table 1 lists the acronyms used in present work.

Table 1 List of acronyms

Acronyms	Descriptions
AE	aeration energy
ASM1	Activated Sludge Model 1
ASP	activated sludge process
BOD_5	biological oxygen demand over a 5-day period
BSM1	Benchmark Simulation Model No. 1
DO	dissolved oxygen
DO_5	dissolved oxygen tank 5
K_{La5}	air flow rate tank 5
K_p	proportional gain
K_i	integral gain
MIMO	multi input multi output
P	proportional
I	integral
PI	proportional integral
PID	proportional integral derivative
PE	pumping energy
Q_{intr}	internal recycle flow rate
SISO	single input single output
S_{NO2}	nitrate tank 2
WWTP	wastewater treatment plant

■2.0 BENCHMARK SIMULATION MODEL NO. 1 (BSM1)

The WWTP simulation benchmark was developed by the COST action 624 & 682 research group [4]. The simulation case study concentrates on biological WWTP and the optimization of the design and operation based on dynamic process models. ASP becomes a common concepts for biological process in which organic matters are oxidized by microorganism. The plant layout of BSM1 is as shown in Figure 1. The bioreactor consists of five reactors where the first two compartment are anoxic zones (denitrification) and followed by three aerobic ones (nitrification) and a secondary settler. The biological reactor volume and the settler volume are both equal to 6,000 m^3. The wastage flow rate is equal to 385 m^3/day. Meanwhile, the secondary settler is modeled as a m=10 layers non-reactive unit. In default benchmark control strategy, DO and nitrate concentrations are used as measurement signals

with control handle of air flow rate, K_{La} and internal recirculation flow rate, Q_{intr} respectively. K_{La}, is set to 240 day^{-1} in the last two aerobic tanks while the K_{La} at the last compartment is manipulated in keeping the DO concentration at 2 mgl^{-1}. Meanwhile the Q_{intr} is manipulated in maintaining the nitrate at 1 mgl^{-1}. The performance of the plant is benchmarked and used for comparing with different control strategies. More details on BSM1 can be referred in [3].
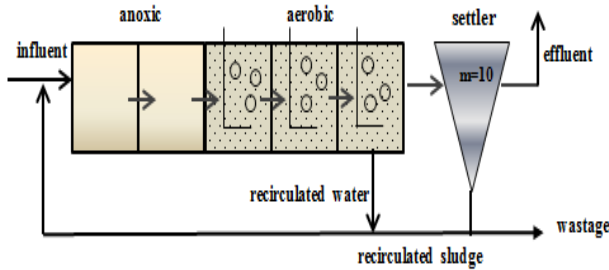

Figure 1 The plant layout of the BSM1

2.1 Influent Load

To investigate the performance of the control strategy in various weather situations, three dynamic inputs files include dry, rain and storm events that has realistic variations in influent flow rate and composition have been used. The data used for the estimation and control is sampled with a sampling period of 15 minutes given in the following order:

[time S_I SS X_I X_S X_{BH} X_{BA} X_P S_O S_{NO} S_{NH} S_{ND} X_{ND} S_{ALK} Q_o]
In any influent: S_O = 0g (-COD) m^3; X_{BA}= 0 g COD m^{-3}; S_{NO} =0 g N m^{-3}; X_P= 0 g COD m^{-3}; S_{ALK} = 7 mol m^{-3}.

The dry influent contains two weeks of dynamic dry weather influent data. Meanwhile, 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 has instead two storm events added during the second week. As an example, a dry influent weather can be seen as in Figure 2. More details on influent weather conditions can be referred in [3, 4]. Despite, there is a constant influent with constant flow and composition that is used in simulating the system under steady state condition.
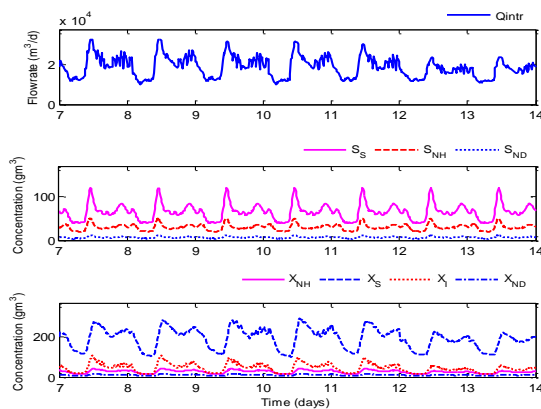

Figure 2 Dry influent weather

2.2 Performance Assessment

The effect of the proposed adaptive PI controller on plant performance is assessed by effluent violations and the

performance in ASP. Referring to effluent violations, constraints with respect to five effluent components include total ammonia (S_{NH}), total nitrogen (N_{tot}), the biological oxygen demand over a 5-day period (BOD_5), total chemical oxygen demand (COD) and total soluble substrate (TSS) are defined as in Table 2. The flow-weighted average effluent concentrations of the following variables must meet their corresponding limitations. Subsequently, the plant performances of ASP concerning on effluent quality index, aeration and pumping energy acquired in the simulation are evaluated. Again, details on the plant performances can be referred in [3, 4].

Table 2 Maximum limit values for effluent violations

Variables	Value
N_{tot}	18 g N m^{-3}
COD	100 g COD m^{-3}
S_{NH}	4 g N m^{-3}
TSS	30 g SS m^{-3}
BOD_5	10 g BOD m^{-3}

■3.0 ADAPTIVE INTERACTION THEORY

Evidently, the conventional PID controller remains the most popular method and widely used in industrial control application. However, a well-tuned PID controller works excellently in obtaining optimal control targets. The present work proposes a model reference free adaptive decentralized PI controller based on adaptive interaction algorithm as proposed in [14-16].

An adaptive interaction considers a complex system with N subsystems called devices with each device $n \in N := \{1, 2, ... N\}$ having an integrable input and output signals. The dynamics of each device is described by a causal functional as

$$F_n : x_n \to y_n, \quad n \in N \qquad (1)$$

X_n and Y_n represent the input and output spaces, so that the output, $y_n(t)$ of the nth device relates to its input, $x_n(t)$ by:

$$y_n(t) = (F_n \circ x_n)(t) = F_n[x_n(t)], \quad n \in N \qquad (2)$$

where o denotes the functional composition.

Two assumptions were made; Frechet derivative is exists and each device is a SISO system [17]. However, partition into several SISO systems can be done for a MIMO system; that is suggested in the present simulation. The goal of the adaptive interaction algorithm is to adapt the connection parameters α_c so that the performance index is minimized. Meanwhile, a typical decomposition of a system for an adaptive interaction can be further referred in [17]. The input to a device is a linear combination of the output of the other devices via connections in I_n and possibly an external input signal $u_n(t)$ as

$$x_n(t) = u_n(t) + \sum_{c \in I_n} \alpha_c y_{pre_c}(t), \quad n \in N \qquad (3)$$

where α_c represents the connection weights.

Then, the dynamic response is given by:

$$y_n(t) = F_n[u_n(t) + \sum_{c \in I_n} \alpha_c y_{pre_c}(t)], \quad n \in N \quad (4)$$

F_n is then denotes by Frechet derivative as indicated in (5) thus yields the connection parameters, α_c as in (6).

$$\lim_{\|\Delta\| \to 0} \frac{\left\| F[x_1 + \Delta] - F[x_1] - \dot{F}[x_1]\Delta \right\|}{\|\Delta\|} = 0 \tag{5}$$

$$\dot{\alpha} = \left(\sum_{S \in 0\,post_c} \alpha_s \dot{\alpha}_s \frac{\dfrac{dE}{dy_{post_s}} \circ \dot{F}_{post_s}[x_{post_s}]}{\dfrac{dE}{dy_{post_s}} \circ \dot{F}_{post_s}[x_{post_s}] \circ y_{post_c}} - \gamma \frac{\partial E}{\partial y_{post_c}} \right) \circ \dot{F}_{post_c}[x_{post_c}] \circ y_{pre_c}, c \in C \tag{6}$$

It is outlined that equation (6) has a unique solution so that the performance index, E will decrease monotonically with time. Eq. (7) is always been satisfied with adaptive constant $\gamma > 0$; thus can be further expressed as in (8).

$$\dot{\alpha} = -\gamma \frac{dE}{d\alpha_c}, \quad c \in C \tag{7}$$

$$\dot{\alpha} = -\gamma \frac{dE}{dy_{post_c}} \circ \dot{F}_{post_c}[x_{post_c}] \circ y_{pre_c} \tag{8}$$

Therefore, an adaptive connection for PI controller can be referred as

$$\alpha_c := \{K_p, K_i\} \tag{9}$$

Referring to [15, 18] for a PI control system, the system is decomposed into three devices represent the proportional control part, integral control part and the control plant. The block diagram of adaptive tuning algorithm applied can be referred in Figure 3.
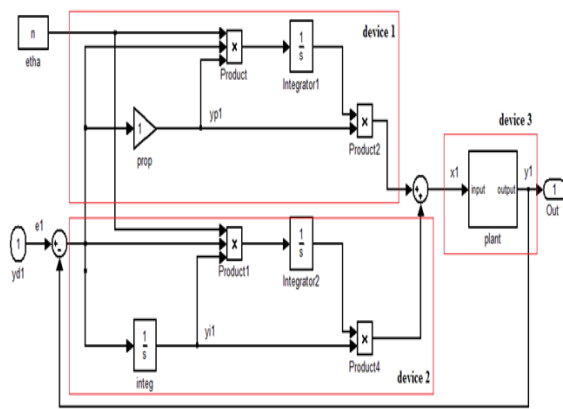

Figure 3 Adaptive PI tuning state block diagram

■4.0 DEVELOPMENT OF ADAPTIVE DECENTRALIZED PI CONTROLLER

The simplest case of multivariable control is when the system is decomposed to SISO subsystems and the design of controllers is based on SISO controllers. With decentralized techniques, a multivariable system with *n* inputs and *n* output variables is treated as *n* subsystems. Meanwhile, for a PI controller, the error signal e(t) is used to generate the proportional (P) and integral (I) control actions with the resulting signals weighted and summed to form the control signal u(t) applied to the plant model. The mathematical description of the PI controller can be expressed as

$$u(t) = K_p\, e(t) + K_i \int_0^t e(t)dt \tag{10}$$

where e(t) is deviation of the control input, u(t) is the control input variable while K_p and K_i are the proportional and integral coefficient of the controller.

The adaptive PI controller is proposed to work correspondingly to default benchmark PI where two control loops are considered. The first loop involves in controlling the nitrate level in the second anoxic compartment, S_{NO2} by manipulating the Q_{intr} while the second control loop is set to control the dissolve oxygen level in the final compartment, DO_5 by manipulating the oxygen transfer coefficient of tank 5, KLa_5. For a process with 2 inputs and 2 outputs, 2 diagonal controllers need to be designed. Therefore, the WWTP is partitioned into two SISO subsystems contributing to two decentralized PI controllers. The implementation of adaptive decentralized PI can be simplified as in Figure 4. Notice that the parameters of K_p and K_i for both PI controllers are not fixed but will automatically adjusted using the adaptive interaction algorithm.
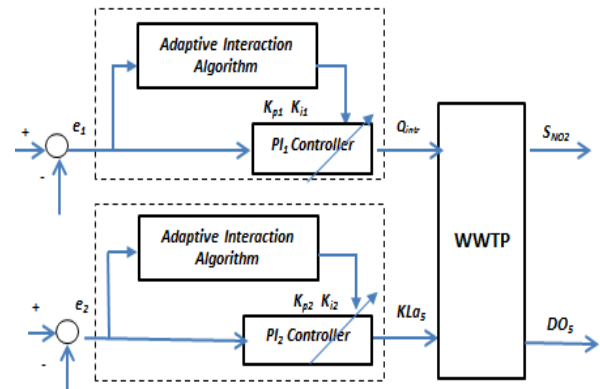

Figure 4 The implementation of adaptive decentralized PI

To develop the algorithm, the control loop of second anoxic compartment is first concerned. y_{p1} and y_{i1} indicate the output of the proportional and the integral transfer function of the first two devices. Meanwhile, y_{d1} and y_1 are the desired and measured output of the S_{NO2}, respectively. The error function, E_1 is described as

$$E_1 = e_1^2 = (y_1 - y_{d1})^2 \tag{11}$$

The gradient method is then been applied to both of the P and I control parameters, K_{p1} and K_{i1} in minimizing the error function.

$$\dot{K}_{p1} = -\gamma_1 \frac{dE_1}{dy_1} \circ \dot{F}[x_1] \circ y_{p1} \tag{12}$$

$$\dot{K}_{i1} = -\gamma_1 \frac{dE_1}{dy_1} \circ \dot{F}[x_1] \circ y_{i1}$$

γ_1 is the adaptation gain while $\dot{F}$ is the Frechet derivative in relation to the plant input, x_1 and the output, y_1 The adaptation algorithm is then reduces to

$$\dot{K}_{p1} = 2\gamma_1(y_1 - y_{d1})\dot{F}[x_1] \circ y_{p1} \tag{13}$$
$$= 2\gamma_1 e_1 \dot{F}[x_1] \circ y_{p1}$$

$$\dot{K}_{i1} = 2\gamma_1(y_1 - y_{d1})\dot{F}[x_1] \circ y_{i1} \tag{14}$$
$$= 2\gamma_1 e_1 \dot{F}[x_1] \circ y_{i1}$$

It was observed that all the tuning parameters, K_{p1} and K_{i1} are depending to the error, e_1, the Frechet derivative $\dot{F}[x_1]$ and the output of the P and I devices, y_{p1} and y_{i1}. Basically, the Frechet derivative of F at x_1 is defined by

$$\dot{F}[x_1] \circ y_1 = \int_0^t f_x(x_1(\tau),\tau)\, y_1(\tau)d\tau \qquad (15)$$

where $f_x = \dfrac{\partial f}{\partial x}$

In the convolution form, the functional $F[x_1]$ can be written as

$$F[x_1] = g_1(t) * x_1(t) = \int_0^t g_1(t-\tau)\, x_1(\tau)d\tau \quad (16)$$

where $g_1(t)$ is the impulse response of the linear time invariant system for S_{NO2} while * denotes convolution. Hence, the Frechet derivative can be expressed as

$$\dot{F}[x_1] \circ y_1 = \int_0^t g_1(t-\tau)\, y_1(\tau)d\tau = g_1(t) * y_1(t) \qquad (17)$$

However in many practical systems, the Frechet derivative can be approximated as in (18); where h is an arbitrary function and σ is a constant value.

$$\dot{F}[x_1] \circ h = \sigma h \qquad (18)$$

This result approximate Frechet tuning algorithm as presented in (19).

$$\dot{K}_{p1} = 2\gamma_1 e_1 \dot{F}[x_1] \circ y_{p1} = 2\gamma_1 e_1 \sigma_1 y_{p1}$$

$$\dot{K}_{i1} = 2\gamma_1 e_1 \dot{F}[x_1] \circ y_{i1} = 2\gamma_1 e_1 \sigma_1 y_{i1} \qquad (19)$$

Let $\eta_1 = 2\gamma_1 \sigma_1$ and $\eta_1 > 0$, the tuning algorithm is then simplified to

$$\dot{K}_{p1} = \eta_1 e_1 y_{p1}$$

$$\dot{K}_{i1} = \eta_1 e_1 y_{i1} \qquad (20)$$

The numerical solutions of (20) give the parameters of the adaptive controller online at every time t. With adaptive interaction algorithm, the WWTP might change its response to the input with time in achieving good output responses. By taking y_{p2} and y_{i2} that represent the output of the proportional and the integral transfer function besides y_{d2} and y_2 that indicates the desired and measured output of DO_5, the procedures on (11) till (19) are repeated. This extends to approximate Frechet tuning algorithm for tank 5, described by

$$\dot{K}_{p2} = \eta_2 e_2 y_{p2}$$

$$\dot{K}_{i2} = \eta_2 e_2 y_{i2} \qquad (21)$$

η_1 and η_2 are the adaptation coefficients of PI_1 and PI_2 in controlling the S_{NO2} and DO_5 concentrations, respectively.

■ **5.0 RESULT AND DISCUSSION**

To improve the nitrogen removal, the S_{NO2} level is set to 1.0 gm^{-3} with constrained Q_{intr} up to 5 times of stabilized input flow rate. The DO_5 level is set to 2.0 gm^{-3} with constrained K_{La5} to a

maximum of 360 day^{-1}. A full ASM1 was used to model the process. It is noted that the time constants for S_{NO2} and DO_5 are of the order of hours and minutes, respectively. The performance of the proposed adaptive PI is generally affected by the adaptation coefficients, η_1 and η_2 that are strongly influences the pace of adaptation. The best, η_1 and η_2 were tuned to 0.09, respectively. The simulation starts in steady state condition under constant influent flow rate. It then continued by the varying influent flow of weather conditions in dynamic input simulation.

Initially, the tracking performance in dry weather condition with ideal sensors and actuators is investigated. The plant is simulated for 5 days and the set-point changes are set at day-3 for both S_{NO2} and DO_5. Notice how the controller tries to compensate for the set-point changes through the system as shown in Figure 5. It was proved that both adaptive PI controllers are potential to track the desired input concentrations effectively.

The simulation in noisy environment is followed next. Referring to [3], the plant is first simulated for 500 days to achieve quasi steady-state using the constant influent input in ideal case; so that the initial conditions of the states are consistent. It then continued by 14 days simulation with dry influent to set up the plant for the dynamic benchmark simulations. Finally, the plant is simulated in next 14 days with the dynamic test input weather with noises present; 0.5 g Nm^{-3} and 0.25 g $(-COD)$ m^{-3} for S_{NO2} and DO_5, respectively. However, only the data of the last 7 days is applied in evaluating the controller. It is a great interest to study how the controllers perform under three different dynamic conditions.

In achieving good dynamic responses, the PI controller parameters K_p and K_i are automatically adjusted using adaptive interaction algorithm as described in (20) and (21). The performance of the input and output controlled are plotted in Figure 6. It was observed that the S_{NO2} and DO_5 concentrations are manage to keep the preferred reference values using adaptive PI controller. Besides, both input variables are always kept under the upper bound.
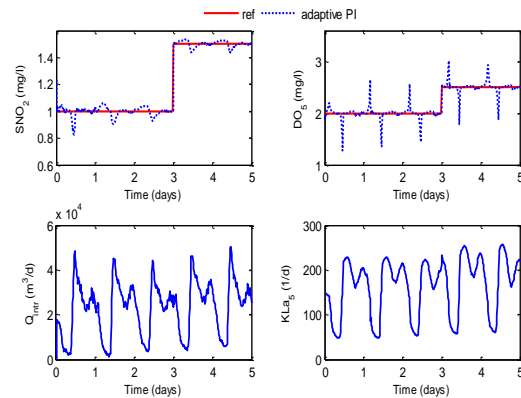
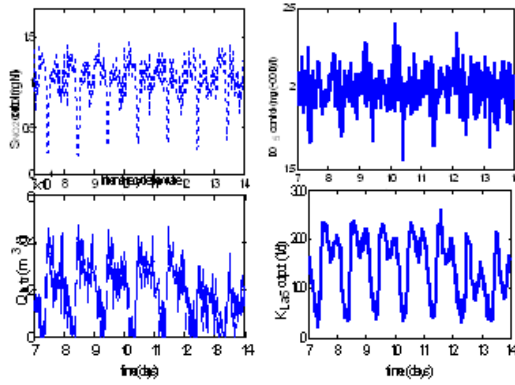**Figure 5** Tracking control performance under dry weather

Figure 6 The performance of the input and output controlled under dry weather

The dynamic responses of average effluent concentrations, S_{NH} and N_{tot} for dry weather influent are presented in Figure 7. The effluent threshold values and the effluents resulted by adaptive PI are marked by solid straight lines and dotted line, respectively. There is an improvement on both effluent components compared to benchmark PI. It same goes to rain and storm weather influents as shown in Figure 8.
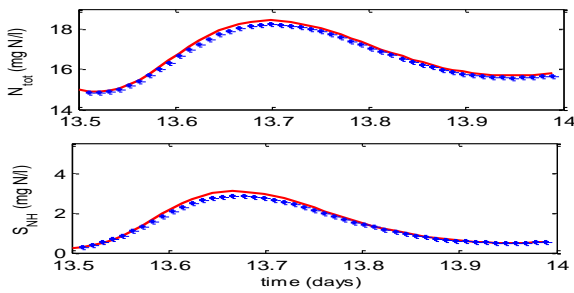

Figure 7 Comparison on total nitrogen and total ammonia concentrations under dry weather
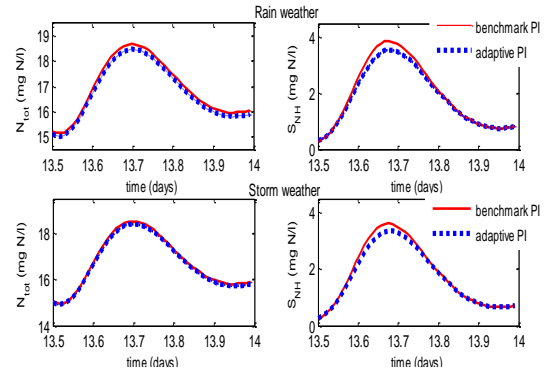

Figure 8 Comparison of total nitrogen and total ammonia concentrations under rain and storm weathers

To further extend, the resulted plant performance in effluent violations by adaptive decentralized PI is compared to benchmark PI, as indicated in Table 3. The maximum values of average effluent concentrations are satisfied. There is an improvement in S_{NH}, N_{tot} and BOD_5 with 7.381% , 0.246% , 0.03% decrement compared to benchmark PI under dry weather, respectively. The best effluent concentration is achieved when the controller is employed in the rainy condition where all components are lower than benchmark PI values. Meanwhile, there is slight reduction in average S_{NH} and TSS is achieved under storm weather; where both effluent components are slightly reduced by 0.0107 mg/l and 0.0001 mg/l, respectively. With respect to the plant performance in ASP as presented in Table 4, the effluent quality index is obviously reduced to 6094.9356 from 6123.0182 kg pollution unit per day, representing lower levies or fines to be paid due to the discharge of pollutions under dry weather condition. Notice that under all three dynamic conditions, lower aeration and pumping energy are acquired by adaptive PI.

The results suggest that the enhancement of nitrogen removal's process can be achieved in terms of effluent concentrations and energy savings in ASP with a properly tuned of the controller. Even though there is just a slightly improvements and most of the effluent concentrations obtained is closely similar with respect to benchmark PI, but the adaptive PI provides an easier implementation and tuning technique. Thus, the decentralized PI with approximate Frechet tuning algorithm offers an alternative of decentralized control strategy and tuning method for nonlinear multivariable plant. Besides, the control scheme applied is robust to WWTP changes since no knowledge of the controlled plant is required in the algorithm.

Table 3 Comparison of the effluent violations

		S_{NH} (mg/l)	TSS (mg/l)	N_{tot} (mg/l)	COD (mg/l)	BOD_5 (mg/l)
	Limit	4	30	18	100	10
Dry influent	**Benchmark PI**	**2.5392**	**13.0038**	**16.9245**	**48.2201**	**2.7568**
	Adaptive PI	2.4994	13.0086	16.8828	48.2242	2.7565
Rain influent	**Benchmark PI**	**3.2254**	**16.1768**	**16.9245**	**45.4598**	**3.4633**
	Adaptive PI	3.1371	16.1762	15.2718	45.4531	3.4597
Storm influent	**Benchmark PI**	**3.0622**	**15.2737**	**15.8676**	**47.6626**	**3.205**
	Adaptive PI	3.0515	15.2736	16.1669	47.6708	3.2058

Table 4 Performance of the activated sludge process

	Controllers	Effluent Quality (kg poll. unit/day)	Aeration energy (kWh/day)	Pumping energy (kWh/day)
Dry influent	**Benchmark PI**	**6123.0182**	**3698.3438**	**241.0305**
	Adaptive PI	6094.9356	3675.0026	239.5244
Rain influent	**Benchmark PI**	**8184.7263**	**3671.3519**	**285.264**
	Adaptive PI	8276.1387	3669.7661	246.1352
Storm influent	**Benchmark PI**	**7220.7241**	**3720.9173**	**265.1984**
	Adaptive PI	7283.2003	3695.0435	245.4554

■4.0 CONCLUSION

The work has investigated the design of an adaptive decentralized PI controller for an activated sludge WWTP. The plant is partitioned into two SISO subsystems contributing to two decentralized PI controllers. The approximate Frechet tuning algorithm provides an easy-way of tuning the PI parameters in minimizing the error function is applied. With the algorithm, difficulties in retuning the controller parameters due to the changes of process dynamics and the challenges in developing the process model are solved. The updating algorithm is simple to be implemented in practice and robust to WWTP changes.

The effect of the proposed controller is validated by comparing the plant performance obtained to the benchmark PI using three different weather conditions. It was demonstrated that the application of adaptive decentralized PI with adaptive interaction algorithm perform well in multivariable WWTP. An improvement in effluent violations, aeration and pumping energy saving are resulted and hence leads the improvement of the nitrogen removal of WWTP.

References

[1] Luyben, W. L. 1986. Simple Method for Tuning SISO Controllers in Multivariable Systems. *Ind. Eng. Chem. ProcessDes. Dev.*

[2] Samuelsson, P., B. Halvarsson, and B. Carlsson. 2005. Interaction Analysis and Control Structure Selection in a Wastewater Treatment Plant Model. *IEEE Transactions on Control System Technology.*

[3] Alex, J. , L. Benedetti, J. Copp, K. Gernaey, U. Jeppsson, I. Nopens, *et al.* 2008. Benchmark Simulation Model No. 1 (BSM1).

[4] Copp, J. B. 2002. COST Action 624: The COST Simulation Benchmark. Description and Simulation Manual: Office for Official Publications of the European Communities.

[5] Henze, M., C. P. L. G. Jr., W. Gujer, G. V. R. Marais, and T. Matsuo. 1987. Activated Sludge Model No.1.

[6] Takács, I., G. G. Patry, and D. Nolasco. 1991. A dynamic model of thc clarification-thickening process. *Water Research.* 25: 1263–1271.

[7] Rojas, J. D., X. Flores-Alsina, U. Jeppsson, and R. Vilanova. 2012. Application of Multivariate Virtual Reference Feedback Tuning for Wastewater Treatment Plant Control. *Control Engineering Practice.* 20: 499–510.

[8] Pomerleau, D. and A. Pomerleau. 2001. Guidelines for the Tuning and the Evaluation of Decentralized and Decoupling Controllers for Process with Recirculation. *ISA Transactions.* 47(40): 341–35.

[9] Yoo, C. K., J. H. Cho, H. J. Kwak, S. K. Choi, H. D. Chun, and I. Lee. 2001. Closed Loop Identification and Control Application for Dissolved Oxygen Concentration in a Full-Scale Coke Wastewater Treatment Plant. *Water Sciene and Technology.* 43: 207–214.

[10] Zhang, P., M. Yuan, and H. Wang. 2006. Self-Tuning PID Based on Adaptive Genetic Algorithms with the Application of Activated Sludge Aeration Process. *6th World Congress on Intelligent Control and Automation.*

[11] Hong-Gui, H., Q. Jun-Fei, and C. Qi-Li. 2012. Model Predictive Control of Dissolved Oxygen Concentration Based on a Self-Organizing RBF Neural Network. *Control Engineering Practice.* 20: 465–476.

[12] Belchiora, C. A. C., R. A. M. Araújoa, and J. A. C. Landeck. 2012. Dissolved Oxygen Control of the Activated Sludge Wastewater Treatment Process Using Stable Adaptive Fuzzy Control. *Computers and Chemical Engineering.* 37: 152–162.

[13] Rocca, J. 2012. GA Optimized Fuzzy Logic Controller for the Dissolved Oxygen Concentration in a Wastewater Bioreactor. Master of Applied Science in Engineering, University of Guelph.

[14] Badreddine, B. M., A. Zaremba, J. Sun, and F. Lin. 2001. Active Damping of Engine Idle Speed Oscillation by Applying Adaptive PID Control. The British Library.

[15] Lin, F., R. D. Brant, and G. Saikalis. 2001. Self-tuning of PID Controllers By Adaptive Interaction. *American Control Conference.*

[16] G. Saikalis and F. Lin. *Adaptive Neural Network Control By Adaptative Interaction.*

[17] Brandt, R. D. and F. Lin. 1999. Adaptive Interaction and Its Application to Neural Networks. *Information Sciences.* 121: 201–215.

[18] Badreddine, B. M. and F. Lin. 2001. Adaptive PID Controller For Stable Unstable Linear and Non-Linear Systems. *IEEE International Conference on Control Applications.*