Decentralized Adaptive PI with Adaptive Interaction Algorithm of Wastewater Treatment Plant

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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

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 anaerobic 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 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 efficient 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>
<thead>
<tr>
<th>Acronyms</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>AE</td>
<td>aeration energy</td>
</tr>
<tr>
<td>ASM1</td>
<td>Activated Sludge Model 1</td>
</tr>
<tr>
<td>ASP</td>
<td>activated sludge process</td>
</tr>
<tr>
<td>BOD$_5$</td>
<td>biological oxygen demand over a 5-day period</td>
</tr>
<tr>
<td>BSM1</td>
<td>Benchmark Simulation Model No. 1</td>
</tr>
<tr>
<td>DO</td>
<td>dissolved oxygen</td>
</tr>
<tr>
<td>DO$_5$</td>
<td>dissolved oxygen tank 5</td>
</tr>
<tr>
<td>$K_{ir}$</td>
<td>air flow rate tank 5</td>
</tr>
<tr>
<td>$K_p$</td>
<td>proportional gain</td>
</tr>
<tr>
<td>K</td>
<td>integral gain</td>
</tr>
<tr>
<td>MIMO</td>
<td>multi input multi output</td>
</tr>
<tr>
<td>P</td>
<td>proportional</td>
</tr>
<tr>
<td>I</td>
<td>integral</td>
</tr>
<tr>
<td>PI</td>
<td>proportional integral</td>
</tr>
<tr>
<td>PID</td>
<td>proportional integral derivative</td>
</tr>
<tr>
<td>PE</td>
<td>pumping energy</td>
</tr>
<tr>
<td>$Q_{rec}$</td>
<td>internal recycle flow rate</td>
</tr>
<tr>
<td>SISO</td>
<td>single input single output</td>
</tr>
<tr>
<td>S$_{tank}$</td>
<td>nitrate tank 2</td>
</tr>
<tr>
<td>WWTP</td>
<td>wastewater treatment plant</td>
</tr>
</tbody>
</table>

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

\[\text{Figure 1} \text{ The plant layout of the BSM1}\]

2.1 Influent Load

To investigate the performance of the control strategy in various weather situations, three dynamic input files include dry, rain and storm events that have 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:

\[[\text{time } S_1 \text{ SS } X_1 \text{ XS } X_{BH} \text{ XBA } X_P \text{ SO } S_{NO} \text{ SSOH } S_{ND} \text{ SALK } Q_{in}]\]

In any influent: \(S_0 = 0 \text{ g } (-\text{COD}) \text{ m}^3\), \(X_{in} = 0 \text{ g } \text{COD} \text{ m}^3\), \(S_{NO} = 0 \text{ g } \text{N} \text{ m}^3\), \(S_{SOH} = 0 \text{ g } \text{COD} \text{ m}^3\), \(S_{ALK} = 7 \text{ mol} \text{ m}^3\).

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.

\[\text{Figure 2} \text{ Dry influent weather}\]

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\(_{NA}\)), total nitrogen (N\(_{na}\)), the biological oxygen demand over a 5-day period (BODs), 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].

\[\text{Table 2} \text{ Maximum limit values for effluent violations}\]

<table>
<thead>
<tr>
<th>Variables</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>N(_{na})</td>
<td>18 g N \text{ m}^3</td>
</tr>
<tr>
<td>COD</td>
<td>100 g \text{COD} \text{ m}^3</td>
</tr>
<tr>
<td>S(_{NO})</td>
<td>4 g N \text{ m}^3</td>
</tr>
<tr>
<td>TSS</td>
<td>30 g SS \text{m}^3</td>
</tr>
<tr>
<td>BOD(_o)</td>
<td>10 g BOD \text{ m}^3</td>
</tr>
</tbody>
</table>

\[\text{3.0 ADAPTIVE INTERACTION THEORY}\]

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 \(n \in N := \{1, 2, \ldots, N\}\) having an integrable input and output signals. The dynamics of each device is described by a causal functional as:

\[F_n : x_n \rightarrow y_n, \quad n \in N\]

\[X_n \text{ and } Y_n \text{ represent the input and output spaces, so that the output, } y_n(t) \text{ of the } n^\text{th} \text{ device relates to its input, } x_n(t) \text{ by:}\]

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

where \(\circ\) 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 \(\alpha_c\) 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 \(I_s\) and possibly an external input signal \(u_n(t)\) as:

\[x_n(t) = u_n(t) + \sum_{c \in I_s} \alpha_c y_{pre}(t), \quad n \in N\]

where \(\alpha_c\) represents the connection weights.

Then, the dynamic response is given by:

\[y_n(t) = F_n[u_n(t) + \sum_{c \in I_s} \alpha_c y_{pre}(t)], \quad n \in N\]

\(F_s\) is then denotes by Frechet derivative as indicated in (5) thus yields the connection parameters, \(\alpha_c\) as in (6).
The performance index, $E$, will decrease monotonically with time. Eq. (7) is always satisfied with adaptive constant $\gamma > 0$; thus can be further expressed as in (8).

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

(7)

$$\alpha = -\gamma \frac{dE}{dy_{post}} F_{post} [x_{post}] \circ y_{pre_c}$$

(8)

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

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

(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.

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

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

(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 $Q_{an}$ while the second control loop is set to control the dissolve oxygen level in the final compartment, $DO_2$ by manipulating the oxygen transfer coefficient of tank 5, $K_{La}$. 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.

To develop the algorithm, the control loop of second anoxic compartment is first concerned. $y_{i1}$ and $y_{i2}$ indicate the output of the proportional and the integral transfer function of the first two devices. Meanwhile, $y_{i1}$ and $y_{i2}$ are the desired and measured output of the $S_{NO2}$, respectively. The error function, $E_1$ is described as

$$E_1 = E_1^2 = (y_{i1} - y_{d1})^2$$

(11)

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

$$\dot{K}_{pi} = -\gamma_i \frac{dE_1}{dy_{i1}} F [x_i] \circ y_{p1}$$

(12)

$$\dot{K}_{ii} = -\gamma_i \frac{dE_1}{dy_{i1}} F [x_i] \circ y_{i1}$$

(13)

$\gamma_i$ is the adaptation gain while $F$ is the Frechet derivative in relation to the plant input, $x_i$ and the output, $y_i$. The adaptation algorithm is then reduces to

$$\dot{K}_{pi} = 2\gamma_i (y_{i1} - y_{d1}) F [x_i] \circ y_{p1}$$

$$\dot{K}_{ii} = 2\gamma_i (y_{i1} - y_{d1}) F [x_i] \circ y_{i1}$$

Figure 4 The implementation of adaptive decentralized PI control
It was observed that all the tuning parameters, $K_p$ and $K_i$, are depending to the error, $e_t$, the Frechet derivative $\dot{F}[x_i]$ and the output of the $P$ and $I$ devices, $y_{p1}$ and $y_{i1}$. Basically, the Frechet derivative of $F$ at $x_i$ is defined by

$$\dot{F}[x_i]o y_i = \int_0^t f_s(x_i(\tau), \tau) y_i(\tau) d\tau$$

(15)

where $f_s = \frac{\partial F}{\partial x}$.

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

$$F[x_i] = g_1(t) \ast x_i(t) = \int_0^t g_1(t-\tau) x_i(\tau) d\tau$$  

(16)

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

$$\dot{F}[x_i]o y_i = \int_0^t g_1(t-\tau) y_i(\tau) d\tau = g_1(t) \ast y_i(t)$$

(17)

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

$$\dot{F}[x_i]o h = \sigma h$$

(18)

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

$$K_{p1} = 2\gamma_1 \sigma \cdot x_1, y_{p1}$$

$$K_{i1} = 2\gamma_1 \sigma \cdot y_{i1}$$

(19)

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

$$K_{p1} = \eta_1 \sigma \cdot x_1, y_{p1}$$

$$K_{i1} = \eta_1 \sigma \cdot y_{i1}$$

(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 $y_{02}$ and $y_2$ that represent the output of the proportional and the integral transfer function besides $y_{i2}$ 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

$$K_{p2} = \eta_2 \sigma \cdot x_1, y_{p2}$$

$$K_{i2} = \eta_2 \sigma \cdot y_{i2}$$

(21)

$\eta_1$ and $\eta_2$ are the adaptation coefficients of $P1$ and $I1$ 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 $Q_{infl}$ 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, $\eta_1$ and $\eta_2$ that are strongly influences the pace of adaptation. The best, $\eta_1$ and $\eta_2$ 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](image-url)
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.

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 BODs 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

<table>
<thead>
<tr>
<th></th>
<th>$S_{NH}$ (mg/l)</th>
<th>TSS (mg/l)</th>
<th>$N_{tot}$ (mg/l)</th>
<th>COD (mg/l)</th>
<th>BODs (mg/l)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Limit</td>
<td>4</td>
<td>30</td>
<td>18</td>
<td>100</td>
<td>10</td>
</tr>
<tr>
<td><strong>Dry influent</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benchmark PI</td>
<td>2.5392</td>
<td>13.0038</td>
<td>16.9245</td>
<td>48.2201</td>
<td>2.7568</td>
</tr>
<tr>
<td><strong>Rain influent</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benchmark PI</td>
<td>3.2254</td>
<td>16.1768</td>
<td>16.9245</td>
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<td>3.4633</td>
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<tr>
<td>Adaptive PI</td>
<td>3.1371</td>
<td>16.1762</td>
<td>15.2718</td>
<td>45.4531</td>
<td>3.4597</td>
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<tr>
<td><strong>Storm influent</strong></td>
<td></td>
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<tr>
<td>Benchmark PI</td>
<td>3.0622</td>
<td>15.2737</td>
<td>15.8676</td>
<td>47.6626</td>
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<td>3.0515</td>
<td>15.2736</td>
<td>16.1669</td>
<td>47.6708</td>
<td>3.2058</td>
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</table>
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.

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References


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<thead>
<tr>
<th>Controllers</th>
<th>Effluent Quality (kg poll. unit/day)</th>
<th>Aeration energy (kWh/day)</th>
<th>Pumping energy (kWh/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry influent</td>
<td>Benchmark PI</td>
<td>6123.0182</td>
<td>3698.3438</td>
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<td></td>
<td>Adaptive PI</td>
<td>6094.9356</td>
<td>3675.0026</td>
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<tr>
<td>Rain influent</td>
<td>Benchmark PI</td>
<td>8184.7263</td>
<td>3671.3519</td>
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<tr>
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<td>Adaptive PI</td>
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<td>Storm influent</td>
<td>Benchmark PI</td>
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<td>3720.9173</td>
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<tr>
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<td>Adaptive PI</td>
<td>7283.2003</td>
<td>3695.0435</td>
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</tbody>
</table>