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Nitrate control strategies in an activated sludge wastewater treatment process

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Abstract−We studied nitrate control strategies in an activated sludge wastewater treatment process (WWTP) based on the activated sludge model. Two control strategies, back propagation for proportional-integral-derivative (BP-PID) and adaptive-network based fuzzy inference systems (ANFIS), are applied in the WWTP. The simulation results show that the simple local constant setpoint control has poor control effects on the nitrate concentration control. However, the ANFIS (4*1) controller, which considers not only the local constant setpoint control of the nitrate concentration, but also three important indices in the effluent--ammonia concentration, total suspended sludge concentration and total nitrogen concentration--demonstrates good control performance. The results also prove that ANFIS (4*1) controller has better control performance than that of the controllers PI, BP-PID and ANFIS (2*1), and that the ANFIS (4*1) controller is effective in improving the effluent quality and maintaining the stability of the effluent quality.

Keywords: Nitrate, Control, Wastewater, Simulation, Environment, Numerical Analysis

INTRODUCTION

Eutrophication in receiving waters due to the presence of nutrients including nitrogen is a well recognized environmental problem worldwide, leading to stricter standards for the operation of wastewater treatment plants (WWTPs). Nitrogen removal basically involves the aerobic conversion of ammonia to nitrates (nitrification) and anoxic conversion of nitrate to nitrogen gas (denitrification). Nitrification is performed by nitrifying autotrophic bacteria, which are obligate aerobes, whereas denitrification is conducted by heterotrophic bacteria, which can utilize nitrate in place of oxygen under anaerobic/anoxic conditions. In an activated sludge process with pre-denitrification, as in the COST benchmark simulation model [1], denitrification is a key process for removing nitrate nitrogen. The most effective solutions known to date are to supplement an external carbon source into the anoxic part of the process to enhance denitrification and to control the nitrate recirculation flow rate to provide an appropriate amount of nitrate to the anoxic zones. These methodologies have already been used in many WWTPs [2-8].

Nitrate recirculation flow rate has long been identified as a manipulative variable in pre-denitrification systems. The on-line control possibilities of this variable to improve nitrate removal have been studied by several researchers [6,9,10]. For a pre-denitrification system, controlling the nitrate nitrogen concentration at the end of the anoxic zone at a low set-point minimizes the amount of external carbon required, while maintaining the long-term average effluent nitrate nitrogen concentration at a pre-specified level [11-13]. Limited work has been reported on integrated control of nitrate recirculation and external carbon dosage [4,14].

Aiming at considering the wastewater treatment plant in a large multivariable frame subject to environmental and operational constraints, we have applied model predictive control strategy to the Benchmark Simulation Model 1 (BSM1) wastewater treatment process to maintain the effluent quality within the regulations-specified limits [15,16].

Just like the report by Alex et al. [17], our previous simulation results showed that the traditional proportional-integral-derivative (PID) controller could control the dissolved oxygen concentration effectively, but demonstrated poorly in the control of nitrate concentration. Based on BSM1, this study is to research and evaluate the control strategies for the nitrate concentration in the activated sludge wastewater treatment process. Two control strategies are applied separately: one is the combination of PID algorithm with back propagation network (BP-PID) and another one is the strategy of adaptive-network based fuzzy inference systems (ANFIS). The work focuses on the nitrate concentration control of the second tank in the activated sludge wastewater treatment process.

METHODS

1. Simulation Benchmark

Wastewater treatment plants are large non-linear, long delay time systems, subject to significant perturbations in the flow and load, together with complex physical and biological phenomena. Many control strategies have been proposed in the literature for wastewater treatment plants [18-21]; however, the literatures could not provide a clear basis for comparison of these strategies, because many confounding influences have impacts on the system and the proposed control strategies differ with respect to their objectives and methods. From 1998 to 2004, the development of benchmark tools

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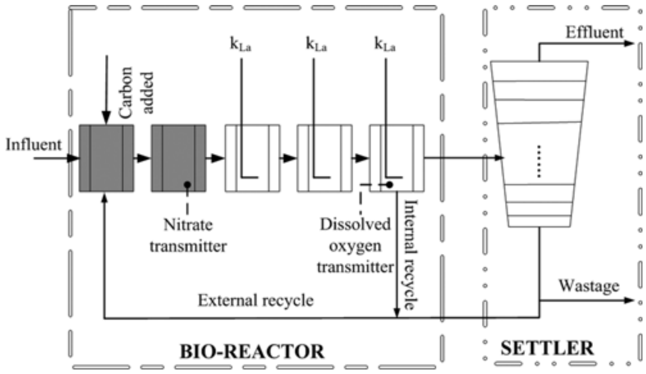

Fig. 1. Schematic representation of the wastewater treatment simulation benchmark.

for simulation-based evaluation of control strategies for activated sludge plants was undertaken in Europe by Working Groups of COST Actions 682 and 624 [17], and was named benchmark simulation model 1 (BSM1). This development work continues under the umbrella of the IWA Task Group on Benchmarking of Control Strategies for WWTPs.

The simulation benchmark plant is composed of five tanks (tanks 1 and 2 are mixed and anoxic, and tanks 3, 4 and 5 are aerobic) in series with a ten-layer secondary settling tank in BSM1. Fig. 1 shows the schematic representation of the layout. In this system, internal recycle flow rate, sludge recycle flow rate and external carbon dosing rate are the frequently investigated manipulated variables. BSM1 advises two controlled variables for the system, the nitrate control in the second tank and the dissolved oxygen (DO) control in the fifth tank [1,22].

Oxygen is supplied for the aerobic reaction in the aerator tank; either overdose or lack of oxygen will lead the sludge environment to be deteriorated. In the case of the lack of oxygen, the mass propagation of filamentous fungus leads to sludge bulking in the aerator tank, and the reduction of bacteria growth rate will make the effluent quality decline. However, an overdose of oxygen destroys flocculants, worsens the settling ability of solid, and increases the energy consumption. The main objective of the DO control is to maintain the DO concentration of the fifth tank in a certain range by the air flow adjusted [23-25]. Based on BSM1, the oxygen mass transfer coefficient (KLa) of the fifth tank is selected as the manipulated variable to keep the DO concentration constant at 2 mg/L. The DO transmitter is supposed to have no time delay and noise. The variation range of KLa is between 0 and 360 d^{-1}.

In the activated sludge wastewater treatment process, since the internal recycle flow brings the dissolved oxygen, carbon source and nitrate to the anoxic tank, the denitrification action, which takes place in the anoxic tank, can be controlled by adjusting the internal recycle flow rate to get better effect of nitrogen removal. In most wastewater treatment plants, in general, the internal recycle flow rate is large. Therefore, the effective control of internal recycle flow rate can reduce energy consumption while ensuring the effluent quality within the limit. Here, based on BSM1, the internal recycle flow rate is selected as the manipulated variable to maintain the nitrate concentration of the second tank be constant at 1 mg/L. The variation range of the internal recycle flow rate is within 0 and 92,230 m^3/d.

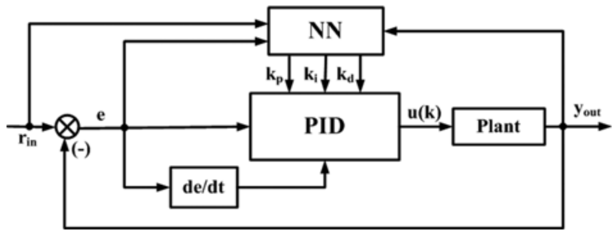

Fig. 2. Schematic representation of the control system with BP-PID controller.

2. Controller Design

2-1. BP-PID Controller Design

Since classical PID parameters cannot be adjusted online, it demonstrates poorly in dynamic systems control, whereas the neural network has the perfect ability of describing any non-linear systems. Therefore, the BP-PID controller, which combines neural network with PID controller, can adjust the PID controller parameters online and achieve effective control results.

Fig. 2 illustrates the schematic representation of the BP-PID controller. The controller contains two parts: the classical PID controller and the neural network (NN). The NN is used for the online adjustment of PID controller parameters. According to the system operating status and the goal of achieving optimization of a performance index, the NN adjusts the weighting coefficients by self-learning ability and obtains the PID controller parameters for the optimal control. The structure of the BP network is given in Fig. 3. The outputs of the NN are three adjustable parameters of PID controller: k_p, k_i, k_d.

Classic incremental digital PID control algorithm is expressed by the following equations:

$$u(k)=u(k-1)+\Delta u(k) \tag{1}$$

$$\Delta u(k)=k_p[e(k)-e(k-1)]+k_i e(k)+k_d[e(k)-2e(k-1)+e(k-2)] \tag{2}$$

Every node in the BP network has an input and output. Like the red node in Fig. 3, its input (u_k) and output (y_k) could be, respectively, expressed as:

$u_k=\sum_{j=1}^{3} w_{ij}x_i$ (w_{ij} is the weight coefficient, x_i is the output of former layer.)

$y_k=\varphi(u_k-\theta_k)$ (θ_k is the threshold, $\varphi()$ is the activation function.)

Therefore, the outputs of BP network depend on the values of the

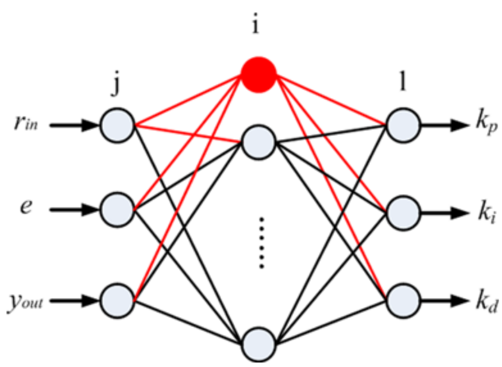

Fig. 3. Structure of the BP network.

weight coefficient w_{ij} and the threshold θ_k, which are the adjusted parameters.

In the present study, the network structure is 3-10-3, where the number of hidden neurons was obtained with the cross-validation method; the activation function of hidden-layer is a sigmoid function whose positive part and negative part are symmetrical: $f(x)=(e^x-e^{-x})/(e^x+e^{-x})$; the activation function of the output layer is a non-negative sigmoid function: $f(x)=e^x/(e^x+e^{-x})$; the performance index function is $E(k)=((r_{in}(k)-y_{out}(k))^2)/2$; the gradient descent method is applied to modify the coefficients of the BP network, which means that the coefficients are adjusted to minimize E(k); the initial values of the coefficients are the random numbers among [−1, 1]; and the formulas to calculate the coefficients of the hidden-layer and output layer are:

$$\Delta w_{ij}^{hidden}(k)=-\eta\frac{\partial E(k)}{\partial w_{ij}^{hidden}}+\alpha\Delta w_{ij}^{hidden}(k-1)\quad (j=1, 2, 3; i=1, 2, \ldots, 10)$$

$$\Delta w_{li}^{output}(k)=-\eta\frac{\partial E(k)}{\partial w_{li}^{output}}+\alpha\Delta w_{li}^{output}(k-1)\quad (l=1, 2, 3)$$

where, $w_{ij}^{hidden}(k)$ is the coefficient of hidden-layer, $w_{li}^{output}(k)$ is the coefficient of output layer, η is the learning rate, and α is the inertial coefficient.

The control algorithm of BP-PID controller is summarized in the following steps:

(1) Starting by k=1;

(2) Taking samples of r_{in} (k) and y_{out} (k), and calculate the error: e (k)=r_{in} (k)−y_{out} (k);

(3) Calculating the inputs and outputs values of the NN;

(4) According to Eq. (2), calculating the output u (k) of the PID controller;

(5) Through the NN self-learning, adjusting weighting coefficients online; achieve the adaptive adjustment of PID controller parameters;

(6) Setting k=k+1, return to step (2).

Based on the above-introduced BP-PID method, the model of BP-PID controller was built with Simulink. In the study, the learning rate η of BP network was 0.27 that was determined according to the literature [26]; the inertial coefficient α was 0.04 that was obtained with the trial-and-error method, and the initial value of weighting coefficient was obtained randomly among [−1, 1].

In the BP-PID controller, the setpoints of nitrate concentration (r_{in}), nitrate concentration deviation (e) and the measured value of nitrate concentration (S_{NO}) are chosen as the controller's input variables; the internal recycle flow rate (Qa) is the output variable (u).

2-2. ANFIS Controller Design

As the fuzzy reasoning does not have the self-learning function, its application is greatly restricted. As a result, the adaptive-network based fuzzy inference system (ANFIS) combines the fuzzy reasoning with the neural network. Jang first introduced the ANFIS method by embedding the fuzzy inference system (FIS) into the framework of adaptive networks [27]. ANFIS not only integrates the advantages of FIS and adaptive networks, but also makes up their deficiencies. The main advantage of ANFIS is that the learning mechanism of the neural network can compensate for the shortcomings of fuzzy control system.

Based on the one-dimensional Sugeno model, ANFIS can approximate any linear or nonlinear functions accurately. Fast convergence,

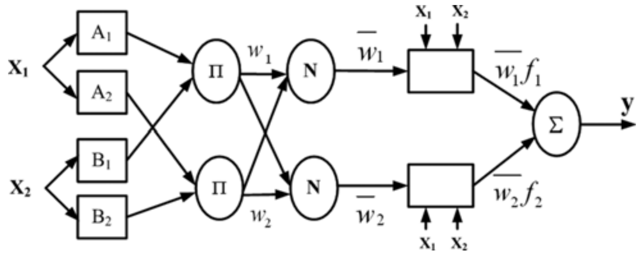

Fig. 4. Configuration of typical adaptive-network based fuzzy inference system (ANFIS).

little errors and fewer training samples are its merits. Fig. 4 shows the architecture of a typical ANFIS with two inputs, two rules and one output for the first-order Sugeno fuzzy model, where each input is assumed to have two associated membership functions (MFs). Nodes in the same layer have the similar functions; each output of the node is expressed by the following equations ($O_{j,i}$ is the output of node):

1st layer:

$$O_{1,i}=\mu_{A_i}(x)\quad (i=1, 2)\quad O_{1,i}=\mu_{B_i}(x)\quad (i=3, 4) \tag{3}$$

2nd layer:

$$O_{2,i}=\mu_{A_i}(x_1)\mu_{B_i}(x_2)\quad (i=1, 2) \tag{4}$$

3rd layer:

$$O_{3,i}=\bar{w}_i=\frac{w_i}{w_1+w_2}\quad (i=1, 2) \tag{5}$$

4th layer:

$$O_{4,i}=\bar{w}_i f_i=\bar{w}_i(p_i x_i+q_i x_2+r_i)\quad (i=1, 2) \tag{6}$$

5th layer:

$$O_{5,i}=\sum_i \bar{w}_i f_i=\frac{\sum_i \bar{w}_i f_i}{\sum_i w_i}\quad (i=1, 2) \tag{7}$$

where x_1 (or x_2) is the input of the system, A_i (or B_i) is the language variable that is associated to the node function, such as 'large' or 'small'. O_{1i} can be regarded as the membership function of the fuzzy set A (A=A_1, A_2, B_1, B_2), which is a bell-shaped function in general.

ANFIS has a hybrid learning rule algorithm which integrates the gradient descent method and the least square method to train parameters. In the forward pass of the algorithm, functional signals go forward until the fourth layer and the consequent parameters are identified by the least squares method to minimize the measured error. In the backward pass, the premise parameters are updated by the gradient descent method [28].

We selected the graphical tool 'anfisedit' in the Matlab fuzzy logic toolbox as the controller design tool and built a two-dimensional fuzzy controller ANFIS (2*1) and a four-dimensional fuzzy controller ANFIS (4*1). The steps of ANFIS controller design are as follows:

Step 1: Determining the input and output variables of controller. In the ANFIS (2*1) controller, the nitrate concentration deviation (e) and the change rate of nitrate concentration deviation (de) are chosen as the controller's input variables, the internal recycle flow rate (Qa) is the output variable (u). In the ANFIS (4*1) controller, the nitrate concentration (S_{NO}) of the second tank and the other three indices of the effluents, which are the ammonia concentration (S_{NH}), total suspended sludge concentration (T_{SS}) and total nitrogen concentration (N_{total}), are four input variables of ANFIS (4*1) controller, and the internal recycle flow rate (Qa) is the output variable of ANFIS (4*1) controller.

Step 2: Data acquisition and loading. First closed-loop steady-state simulation is performed for 100 days, which means simulating under constant input without interference and time lag, and the nitrate concentration (S_{NO}) of the second tank is controlled with the proportional-integral (PI) controller. The values of e, de, S_{NO}, S_{NH}, T_{SS}, N_{total} and Qa are kept recorded during the simulation process. Lastly, the training data and the testing data are extracted from the above acquired data, which are independent sets for each data group. In our study, the controller ANFIS (2*1) uses 272 sets of data in total, which includes 177 sets of training data and 95 sets of testing data; and the controller ANFIS (4*1) utilizes 421 sets of data in total, which contains 281 sets of training data and 140 sets of testing data.

Step 3: Initializing fuzzy inference system (FIS) model. FIS can be generated automatically by grid partition method. Gaussian membership function is selected as the input and output membership function type of initial FIS; the number of membership functions is 3. Therefore, the corresponding rule numbers of controllers ANFIS (2*1) and ANFIS (4*1) are $3^2=9$ and $3^4=81$, respectively; the type of output function is linear.

Step 4: Training FIS model. Hybrid algorithm of the back-propagation method and the least square method are selected to train the network; the error tolerances are 0 and 0.5 for controllers ANFIS (2*1) and ANFIS (4*1) individually; the maximum training time (Epochs) is 50. The training results are shown in Figs. 5 and 6; the errors between the model outputs and the actual outputs no longer reduce after 48 and 36 times training, and their errors are 0.002 and 0.610 with controllers ANFIS (2*1) and ANFIS (4*1), separately.

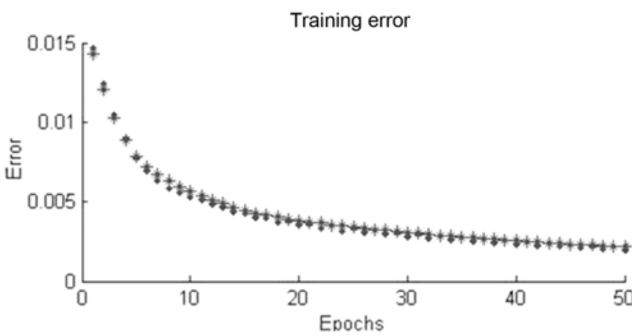

Fig. 5. Training result of the ANFIS (2*1) controller.

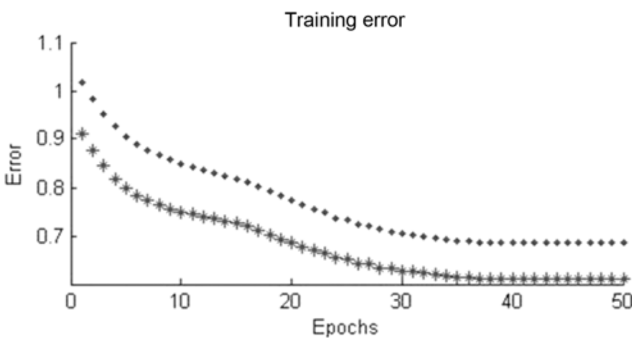

Fig. 6. Training result of the ANFIS (4*1) controller.

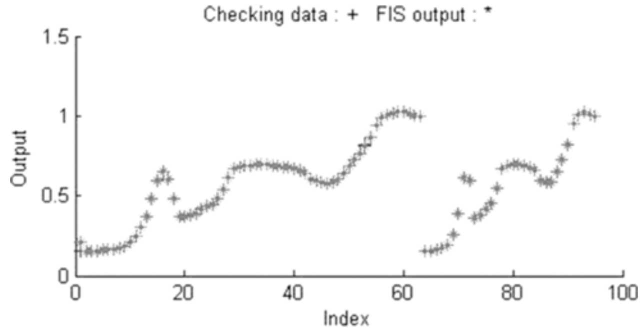

Fig. 7. Checking the training result of ANFIS (2*1) controller.

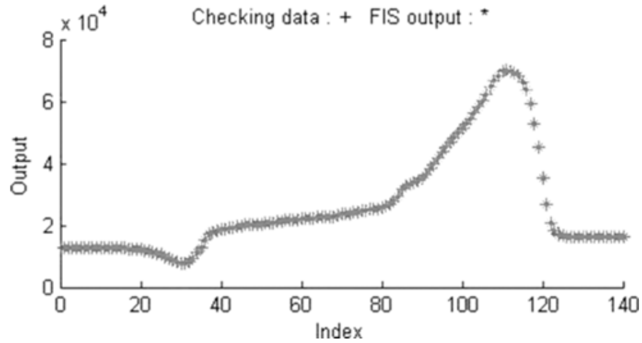

Fig. 8. Checking the training result of ANFIS (4*1) controller.

Step 5: Testing the trained FIS model. Figs. 7 and 8 display the testing results, where the asterisk represents the model trained outputs, and the plus sign stands for the tested data. For the two controllers, the trained outputs are similar to the tested data after training. Compared with the vertical axis scale, the errors between the trained outputs and the tested data in Figs. 7 and 8 are so small that it is difficult to distinguish their difference. The average testing errors for controllers ANFIS (2*1) and ANFIS (4*1) are 0.005 and 0.685, respectively. Therefore, the trained FIS models are effective and can be applied in the simulation.

RESULTS AND DISCUSSION

1. Simulations with Controllers BP-PID, ANFIS (2*1) and ANFIS (4*1)

After closed-loop simulation for 150 days without noise and delay, the system reached the quasi-steady state, followed by 28 days closed-loop simulation with a normally distributed random noise (zero-mean, standard deviation was 0.01 mg/L) and 10 minutes-delay on S_{NO}. The simulated data of the last seven days (from the 21^{st} day to 28^{th} day) were used to assess the control results. During the control process, threshold-crossing phenomena were observed in two important indices of the effluent: ammonia concentration (S_{NH}) and total nitrogen concentration (N_{total}). Because of the limitation of space, only these two indices out of five (S_{NH}, T_{SS}, N_{total}, BOD_5, COD) in the effluent are given in the article.

Figs. 9 and 10 display the simulation results of S_{NH} and N_{total} in the effluent with the actions of controllers PI, BP-PID, ANFIS (2*1) and ANFIS (4*1). According to the BSM1 manual, the limit values in the two figures are the norms which the ammonia concentration

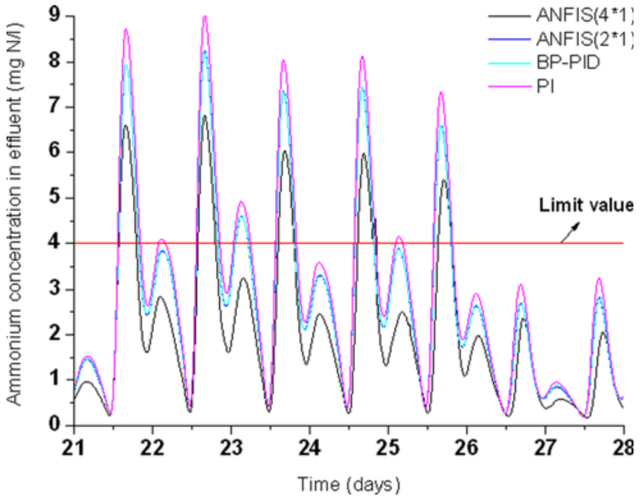

Fig. 9. Variation of ammonia concentration in the effluent with different controllers.

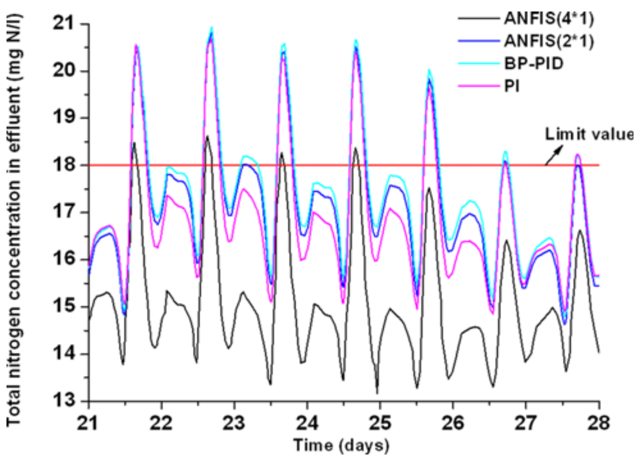

Fig. 10. Variation of total nitrogen concentration in the effluent with different controllers.

and the total nitrogen concentration in the effluent should obey. Fig. 11 shows the control error curve of the nitrate concentration (S_{NO}) in the second tank with the control actions of PI, BP-PID and ANFIS (2*1) controllers. Table 1 gives the main performance evaluation indices and the average values of S_{NH} and N_{total} with the above four controllers. In Table 1, the indices include effluent quality (EQ), aeration energy (AE) and pumping energy (PE). They were calculated according to the formulas in the BSM1 manual [1]; the column

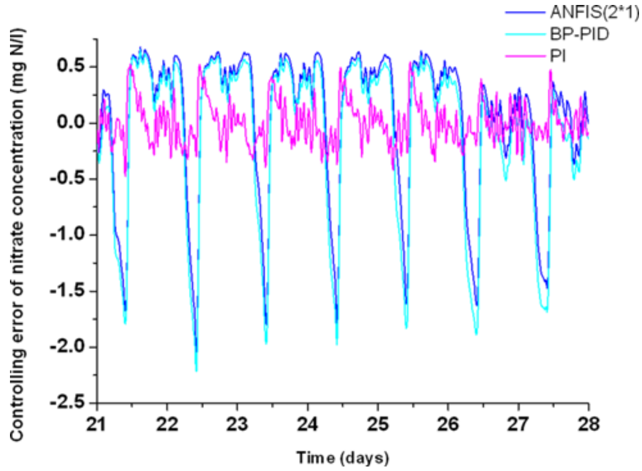

Fig. 11. Control error of the nitrate concentration in the second tank with different controllers.

'%Tvoil' represents the percentage time of the effluent violates the norm, and the data in rows of 'PI' and 'BSM1' are extracted from the BSM1 manual [1].

As can be seen in Figs. 9 and 10, the curves with the controllers BP-PID and ANFIS (2*1) basically overlap, especially for the case of the ammonium concentration (Fig. 9), the data in 'S_{NH}' column of Table 1 also indicate the same result; the average ammonium concentrations in the effluent are 2.73 gN/m^3 and 2.72 gN/m^3 with the controllers BP-PID and ANFIS (2*1), respectively. As we know, the smaller the EQ, the higher the effluent quality, and the higher the energy consumption (AE and PE). In Fig. 11, the nitrate concentrations fluctuates violently with any of the three controllers; all of the three controllers have bad effects on the S_{NO} control. The main reason for their bad control effects may be the inherent time delay in the wastewater treatment process. Before the internal recycle flow rate (Qa) affects the second tank, it must have passed by the first tank, and both of the first two tanks are used for the nitrogen removal; therefore, the reaction of nitrogen removal in the first tank has impacts on the nitrogen removal in the second tank, which means that the S_{NO} control result of the second tank would be affected by the first tank.

Being different from the ANFIS (2*1) controller, ANFIS (4*1) controller considers not only the S_{NO} in the second tank, but also the often out-of-limit indices which includes S_{NH}, T_{SS} and N_{total} in the effluent; hence, the combined control action Qa is performed in accordance with the above four variables. The aim of the controller

Table 1. Main performance indices and the average values of S_{NH} and N_{total} with different control strategies (with dry weather simulation data)

Control strategy	EQ (kg/d)	AE (kWh/d)	PE (kWh/d)	S_{NH} (gN/m^3)	N_{total} (gN/m^3)	%Tvoil	
						N_{total}	S_{NH}
PI	7556	7237	1523	2.99	17.24	17.55	20.53
BP-PID	7640	7229	1441	2.73	17.02	18.6	18.01
ANFIS (2*1)	7724	7227	1373	2.72	17.43	24.85	18.01
ANFIS (4*1)	7068	7253	2164	2.06	15.18	14.88	17.02
BSM1	7596	7246	1473	2.53	17.06	19.22	17.36

ANFIS (4*1) is the global consideration of the effluent quality rather than just the setpoint control of the S_{NO} in the second tank; the internal recycle flow rate Qa is dependent upon the actual values of S_{NO} in the second tank, as well as the values of S_{NH}, T_{SS} and N_{total} in the effluent. That is why the values of S_{NH} and N_{total} with controller ANFIS (4*1) in Figs. 9-10 and Table 1 are obviously smaller than those with controllers BP-PID and ANFIS (2*1). Since the controller ANFIS (4*1) is not designed to be dedicated in the setpoint control of S_{NO} in the second tank; therefore, its control result about S_{NO} in the second tank is not given in Fig. 11.

The detailed comparisons and discussions of the control results with controllers BP-PID, ANFIS (2*1) and ANFIS (4*1) are conducted in the next section.

2. Comparisons of Control Results with Three Controllers

Effluent quality and energy consumption. If we just consider the ecological environmental factors, then the higher effluent quality (EQ) is better, but it may bring high energy consumption (AE and PE). Among the studied controllers PI, BP-PID, ANFIS (2*1) and ANFIS (4*1), the ANFIS (4*1) controller obtains the best effluent quality (7,068 kg/d) with the highest energy consumption (7,253 kWh/d+2,164 kWh/d).

Stability. The stability of a control system can be evaluated by the overrun of contamination concentrations in the effluent. During the simulation, the concentrations of T_{SS}, BOD_5 and COD in the effluents have never overrun, but violations of the ammonia and total nitrogen concentration have been observed; consequently, these are two key factors which should of concern in the study. As can be seen in the simulation results, the concentrations of ammonia and total nitrogen have instantaneous overshoots, but their average concentrations are subject to the norms: 4 mg/L for S_{NH} and 18 mg/L for N_{total}. The less overshoots and the total violation time, the better control effects. Consequently, the simulation results reveal that the ANFIS (4*1) controller is more effective than the controllers BP-PID and ANFIS (2*1) in this aspect. As demonstrated in Figs. 9 and 10, the out-of-limit time of S_{NH} and N_{total} with ANFIS (4*1) controller is smaller than those with controllers BP-PID and ANFIS (2*1), and the data (14.88% for N_{total} and 17.02% for S_{NH}) in the column "%Tvoil" of Table 1 also illustrate the same results, where the violation time of total nitrogen decreases obviously.

Applicability of control strategy. The control results with controllers BP-PID and ANFIS (2*1) indicate that it is not suitable to control the S_{NO} of the second tank by the local constant setpoint control strategies. The major cause maybe the inherent delay in the wastewater treatment process: The first tank is the first reactor which the internal recycle flow rate (Qa) has passed by; the reaction of nitrogen removal in it has impacts on the nitrogen removal in the second tank. Therefore, from the point of view of the global situation, ANFIS (4*1) controller is a good choice. Although it does not demonstrate well in the local constant setpoint control of the S_{NO} of the second tank, it improves the total effluent quality, achieves the lowest effluent concentrations (2.06 gN/m^3 for S_{NH} and 15.18 gN/m^3 for N_{total}), and the least percentage time of the effluent violates the norms (14.88% for N_{total} and 17.02% for S_{NH}).

CONCLUSIONS AND PROSPECTIVE

Based on BSM1, through the control simulations of nitrate concentration in the second tank of activated sludge wastewater treatment process with controllers BP-PID and ANFIS (2*1) separately, it can be found that the simple local constant setpoint control has poor control performance. From a global consideration of the activated sludge wastewater treatment process, the ANFIS (4*1) controller considers not only the constant setpoint control of the S_{NO} in the second tank, but also the other three indices in the effluents, including the ammonia concentration, total suspended sludge concentration and total nitrogen concentration. The simulation results with the dry weather data prove that the control effect with ANFIS (4*1) controller is superior to those with PI, BP-PID and ANFIS (2*1) controllers; the ANFIS (4*1) controller achieves the lowest effluent concentrations, the least percentage time the effluent violates the norms, and the best effluent quality at relatively high aeration energy and pumping energy. The effectiveness of the controller ANFIS (4*1) under the rain and storm weather still needs to be verified.

Although the ANFIS (4*1) controller achieves good effluent quality at the price of relatively high operational energy consumption, from the point of view of global situation, it has the potential to improve the control performance and can be used in practical WWTPs. If the controller ANFIS (4*1) can reduce the operational energy consumption while keeping the present control results, its possibility of being applied in a real WWTP will gain attention. Through the adjustments of the internal parameters of the ANFIS (4*1) controller and the simulations with different weather data (dry, rain and storm), the effectiveness of the ANFIS (4*1) controller can be expected; and this is our ongoing research work where further results are foreseen.

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