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Study on Modelling and Neural Network Control Algorithm in Sewage Treatment Process

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ABSTRACT

With the development of industries, the problem of environmental pollution caused by the massive discharge of sewage is becoming more and more serious, which has gained increasing attention of people. In order to solve the problem of drastic change of water quality and dissolved oxygen concentration in wastewater discharge, activated sludge method was used to deal with the discharge of wastewater and the neural network control algorithm was used to model and control the wastewater treatment process in this study. Besides, the neural network predictive control algorithm was proposed to control the concentration of nitrate nitrogen. Through the simulation of the sewage treatment process, it is found that the method can quickly and accurately achieve the desired requirements of the nitrate nitrogen and realize the effective sewage treatment.

INTRODUCTION

Since the 21st century, the discharge of a large amount of industrial wastewater and domestic sewage has caused serious environmental pollution and shortage of water resources. Hence, the purification and recycling of sewage water is very important for industrial production and people's daily life. Abrahams et al. (2017) designed the principle of perpetuity to create a water purification and harvesting system that can collect wastewater and convert it to productive wetlands, eliminate the need for non-renewable energy in water purification and make biodiversity, flood resilience and yield increase. Pronk et al. (2015) studied the aerobic granular sludge technology to treat domestic sewage. Experiments showed that the maximum volumetric conversion rate of phosphorus and nitrogen was greatly increased while the energy consumption was reduced, suggesting that the technology could realize effective sewage treatment. In this paper, the process of wastewater treatment with this method was studied and modelled, and a neutral network control algorithm was proposed to control dissolved oxygen and nitrate nitrogen in wastewater. The simulation software was used to simulate the wastewater treatment process and the results showed that this method could effectively treat sewage and provide reference for the development of sewage treatment.

MODELLING OF SEWAGE TREATMENT PROCESS

BSM1 is a good biochemical simulation model for the treatment of wastewater with activated sludge process, in which many biochemical reaction equations and biochemical reaction parameters as well as evaluation criteria of controller and control performance are involved (Crisan et al. 2015). BSM1 model is simple and practical in the process simulation of sewage treatment. Different control strategies can be applied to this model, and then the same performance evaluation criterion can be used to evaluate the advantages and disadvantages of the control strategy.

BSM1 model is mainly composed of 1 secondary sedimentation tank and 5 activated sludge reaction tanks (of which 2 are anoxic tanks and 3 are aerobic tanks). The BSM1 sewage treatment process model is shown in Fig. 1.

As there are many impurities, sand and trace elements in the actual sewage treatment process, we only consider the components with large content. The components in the sewage treatment process are divided into the following 13 species: soluble inert organic matter W_I, mechanism to be biodegraded W_W, particulate inert organic matter M_I, slow biodegradable mechanism M_S, active heterotrophic organism $M_{B,H}$, active autotrophic organism $M_{B,A}$, granular products of biological corruption M_P, dissolved oxygen DO, nitrate nitrogen W_{NO}, ammonia nitrogen W_{NH}, soluble biodegradable organic matter W_{ND}, granular biodegradable organic nitrogen M_{ND} and alkalinity W_{ALK}.

Activated sludge sewage treatment process is a biochemical reaction process, during which various biochemical reactions occur, including carbon oxidation process, pre-denitrification process and nitrification process (Hoang et al. 2015).

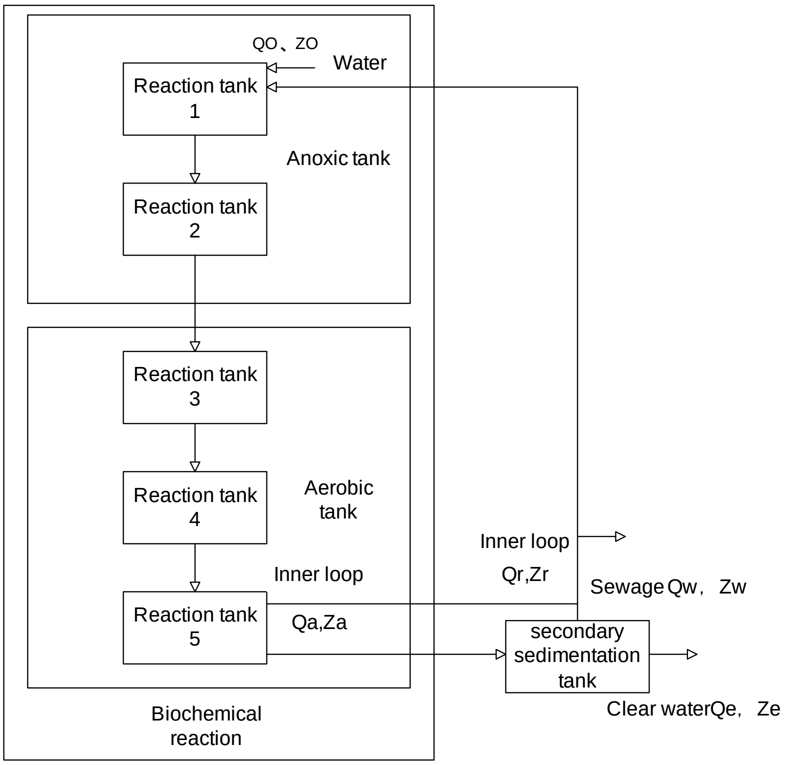

Fig. 1: BSM1 model.

Biochemical pool reaction: The biochemical reaction in the biochemical reaction pool is simulated by the ASM1 model (Mohamadi et al. 2015). The biochemical reactions in the sewage treatment process can be divided into eight processes, including microbial growth, attenuation and hydrolysis process, which can be expressed in the following equations:

The aerobic growth rate of heterotrophic bacteria g = 1 is:

$$v_1 = \mu_H\left(\frac{W_W}{K_W + W_W}\right)\left(\frac{W_O}{H_{O,H} + W_O}\right)M_{B,H} \qquad ...(1)$$

The anoxia growth rate of heterotrophic bacteria g = 2 is:

$$v_2 = \mu_H\left(\frac{W_W}{K_W + W_W}\right)\left(\frac{K_{O,H}}{K_{O,H} + W_O}\right)\left(\frac{W_{NO}}{K_{NO} + W_{NO}}\right)\sigma_i M_{B,H} \qquad ...(2)$$

The aerobic growth rate of autotrophic bacterium g = 3 is:

$$v_3 = \mu_A\left(\frac{W_{NH}}{K_{NH} + W_{NH}}\right)\left(\frac{W_O}{K_{O,A} + S_O}\right)M_{B,A} \qquad ...(3)$$

The decay rate of heterotrophic bacterium g = 4 is:

$$v_4 = b_H M_{B,A} \qquad ...(4)$$

The decay rate of autotrophic bacterium g = 5 is:

$$v_5 = b_A M_{B,A} \qquad ...(5)$$

The ammonia reaction rate of soluble organic nitrogen is:

$$v_6 = k_a W_{ND} M_{B,H} \qquad ...(6)$$

The hydrolysis rate of slow biodegradable organic matter is:

$$v_7 = k_h \frac{M_W / M_{B,H}}{K_M + (M_S / X_{B,H})}\left[\sigma_h\left(\frac{W_O}{K_{O,H} + W_O}\right) + \sigma_h\left(\frac{K_{O,H}}{K_{O,H} + W_O}\right)\left(\frac{W_{ND}}{K_{NO} + W_{NO}}\right)\right]M_{B,H} \qquad ...(7)$$

The hydrolysis rate of slow biodegradable organic nitrogen is:

$$v_8 = t_7 (M_{ND} / M_W) \qquad ...(8)$$

Where, $K_{O,H}$ refers to the aerobic respiration saturation coefficient of heterotrophic bacterium, K_{NO} refers to the nitrate nitrogen respiration saturation coefficient of heterotrophic bacterium, σ_i refers to the heterotrophic bacteria

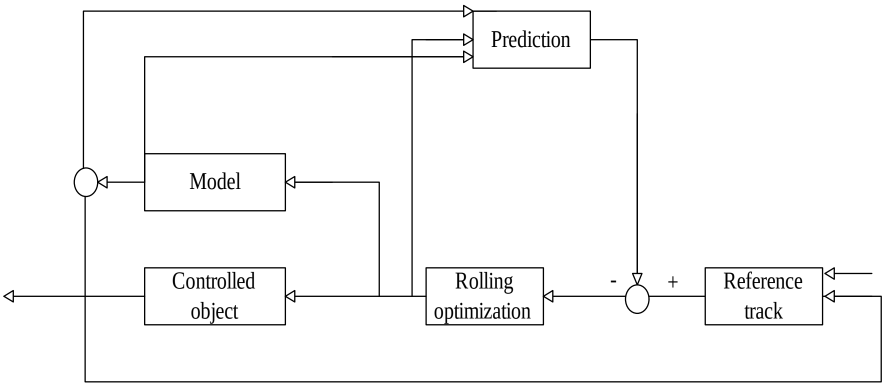

Fig. 2: Predictive control structure.

growth correction factor under hypoxic conditions, σ_h refers to the hydrolysis correction factor in hypoxic environment, M_W refers to the heterotrophic bacteria growth and substrate utilization saturation coefficient and μ_A refers to the maximum ratio increase rate of autotrophic bacterium.

The material balance equation for each component is as follows:

The equation for reaction pool k = 1 is:

$$\frac{dZ_1}{dt} = \frac{1}{V_1}(Q_a Z_a + Q_r Z_r + Q_0 Z_0 + r_1 V_1 - Q_1 Z_1) \quad ...(9)$$

$$Q_1 = Q_a + Q_r + Q_0 \quad ...(10)$$

The equation for reaction pool k=2, 3, 4, 5 is:

$$\frac{dZ_k}{dt} = \frac{1}{V_k}(Q_{k-1} Z_{k-1} + r_k V_k - Q_k Z_k) \quad ...(11)$$

$$Q_k = Q_{k-1} \quad ...(12)$$

Q_a refers to internal quantity of reflux, Q_r refers to external quantity of reflux, Q_0 refers to the quantity of reflux entering water, Z_0 refers to concentration of water components, Z_a refers to concentration of components in the internal reflux nitrifying solution and Z_r refers to concentration of components in the sludge reflux.

Secondary sedimentation tank: Second sedimentation tank has 10 layers and the sixth layer is the water entering layer, without biochemical reactions (Malczewska et al. 2017). It has a cross-sectional area of 750 m^2 and a volume of 3750 m^3, with a height of each layer of 0.5 m. There are many insoluble suspended particles in the sewage in the sink pool, which will go down by the effect of gravity. The rate formula is as follows:

$$v_S = \min\{v_0', v_0[e^{-\theta_h(M-M_{\min})} - e^{-\theta_p(M-M_{\min})}]\} \quad ...(13)$$

Where, $M_{\min} = f_{nW} M_f$, v_0' refers to the maximum precipitation velocity, v_0 refers to the maximum filtration precipitation speed, θ_h and θ_p refer to precipitation parameters in the obstruction zone and the condensation zone and f_{nW} refers to the non-sediment fraction.

The mass average equation of the sludge in each layer of the secondary settling tank is as follows:

When the number of water entering layer is c = 6:

$$\frac{dM_c}{dt} = \frac{\frac{Q_l M_l}{A} + G_{clear,c+1} - (v_{up} - v_{do})M_c - \min(G_{w,c}, G_{w,c-1})}{Z_c} \quad ...(14)$$

When c = 1:

$$\frac{dM_1}{dt} = \frac{v_{do}(M_2 - M_1) + \min(G_{s,2} - G_{s,1})}{Z_1} \quad ...(15)$$

When c = 10:

$$\frac{dM_{10}}{dt} = \frac{v_{up}(M_9 - M_{10}) + G_{clear,10}}{Z_{10}} \quad ...(16)$$

When c = 2, 3, 4, 5:

$$\frac{dM_c}{dt} = \frac{\frac{Q_l M_l}{A} + G_{clear,c+1} - (v_{up} - v_{do})M_c - \min(G_{w,c}, G_{w,c-1})}{Z_c} \quad ...(17)$$

When c = 7, 8, 9:

$$\frac{dM_c}{dt} = \frac{v_{up}(M_{c-1} - M_c) + G_{clear,c+1}, G_{clear,c}}{Z_c} \quad ...(18)$$

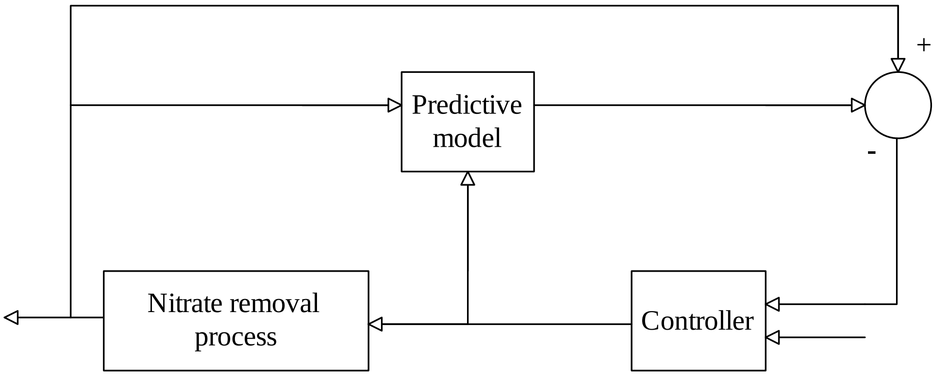

Fig. 3: Predictive control structure of wastewater treatment process.

NITRATE NITROGEN CONTROLLER BASED ON NEURAL NETWORK CONTROL ALGORITHM

According to the above model needs, this paper uses a predictive control method to establish a neural network to control the W_w concentration in the first reaction tank.

Predictive control principle: Predictive control is a new type of computer-based control algorithm used in industry. It mainly includes prediction model, rolling optimization and feedback correction (Aras et al. 2015). The structure of predictive control is as follows:

Prediction model (Fig. 2) is a control method based on neural network model, which can predict future output data through historical input and output data and future input data (Ma et al. 2017). The model is used to predict future behaviour, through which the future control strategy can be designed based on the predicted output.

There is a great difference between predictive control and traditional control because that predictive control can achieve the rolling optimization within a limited period of time (Raszmann et al. 2017). At each sampling, optimizing performance metrics can only optimize the limited time ahead for this moment, and optimization must move forward in the next moment. Therefore, the optimization in predictive control is not completed in one time, but is accomplished by rolling.

Neural network predictive control algorithm is a closed-loop control algorithm. In the process of optimization, all optimization strategies need to be calculated using the prediction model (Zhakatayev et al. 2017). In order to prevent the prediction model from mismatch and interference, it is necessary to detect the actual output at the next moment after the control effect is achieved, record the data, and correct and optimize it with the model.

Prediction model of neural network control algorithm: The prediction model of neural network control algorithm is built based on the neural network modelling capability. The performance indicators are used to determine the control information for each time period and the historical input and output information is used to express the future output information through the neural network prediction model, with the equation as follows:

$$y_\alpha(\beta+1) = f_{NN}\left[\omega(\beta-d),\cdots\omega(\beta-d-\alpha-1),\ y(\beta),\cdots,y(\beta-n-1)\right] \quad ...(19)$$

Where, d refers to system delay, α refers to the selected number of historical control information, n refers to the selected historical output information and β refers to number of iterations.

Calculation method of neural network control: In predictive control, each control function is accomplished by optimizing a performance index. The performance indicators selected in this paper are as below:

$$T = \left[r(\beta+d) - y_p(\beta+d)\right]^2 + \varepsilon\left[\omega(\beta) - \omega(\beta-1)\right]^2 \quad ...(20)$$

Where, $r(\beta+d)$ refers to the reference value of future output, $y_p(\beta+d)$ refers to the predicted value of future output and $\omega(\beta-1)$ refers to the control effect of the previous moment. Hence, the control function $\omega(\beta)$ that needs to be input at this moment is obtained by solving the minimum for j.

$$\omega(\beta) = \omega(\beta-1) + \frac{1}{\varepsilon}\left[r(\beta+d) - y_p(\beta+d)\right]\frac{\partial y_p(\beta+d)}{\partial\omega(\beta)} \quad ...(21)$$

$$y_p(\beta+d) = y_\alpha(\beta+d) + e(\beta+d-1) \quad ...(22)$$

Where, $y_p(\beta+d)$ refers to the predicted correction value and $y_\alpha(\beta+d)$ refers to the predicted value of the model

Table 1: The total nitrogen content of the two controllers in the BSM1 model.

	BSM1	Traditional controller	Neural network prediction controller
Mean concentration of nitrate nitrogen (mg/L)	3.10	1.25	0.91
Mean value of total nitrogen content (mg/L)	1029.33	735.12	729.3

Table 2: Control effect of the two controllers.

	Neural network predictive controller	Traditional controller
Stability	4.88×10^{-3}	1.26×10^{-2}
Integrated absolute error	5.04×10^{-2}	8.15×10^{-2}
Maximum error	1.46×10^{-1}	3.76×10^{-1}
Aeration consumption	-8.7%	-12.6%

which can be solved with the prediction model. When solving $\omega(\beta)$, the value of $\omega(\beta)$ is required. Therefore, the $\omega(\beta)$ in the equation should be separated.

As the neural network structure of the neural network control algorithm is complicated and $\omega(\beta)$ is difficult to be separated, special algorithm is required. In this study, we adopt the optimization seeking method.

The optimization method is a method of one-dimensional search on the $\omega(\beta)$ value space. According to the rules, select two points in the value space to be brought into the calculation, and determine the value space through whether there is an optimal value in the value space (Shrestha et al. 2017). This step is repeated until the space is small enough and the median value in the space is selected to be the optimal output of $\omega(\beta)$.

Controller design: In the practical application of the controller, we also need to design its control strategy and assign the reasonable output and input to the corresponding locations. The input signals of the PID controller based on neural network are $\Delta\omega(\beta)$, $\Delta\omega(\beta-1)$, $W_{NO}(\beta-1)$ and $W_{NO}(\beta)$. Where, $\Delta\omega(\beta)$ refers to the increment of the control effect in this period, $\Delta\omega(\beta-1)$ refers to the increment of the control effect in last period, $W_{NO}(\beta)$ refers to the concentration of nitrate nitrogen in sewage in this period and $W_{NO}(\beta-1)$ refers to the concentration of nitrate nitrogen in sewage in last period. The predicted NO concentration in the nth period is expressed by $W_{NO}(n)$.

In addition, we added the gradient descent method to the prediction output and actual output of the network neural to correct the error value (Li et al. 2017). After the prediction of the NO concentration, the error compensation is made according to the prediction error of the previous time, and the value after compensation is taken as the actual prediction value. Then the actual predicted value is substituted into the above formula by the controller to calculate the performance index value so as to minimize the value of J in the above formula to determine the best control signal and introduce this new control function into the system. The design structure of the controller is shown in Fig. 3.

RESULTS

Effluent nitrate nitrogen content: Both the controller designed in this paper and the traditional controller are tested. A fixed value of the water inflow and was set and the average nitrate nitrogen concentration in the wastewater was calculated every 15 minutes. Both the controllers were applied to the BSM1 model, which calculated the mean value of the total nitrogen content. The experiment lasted six days and the results are presented in Table 1.

As given in Table 1, after using neural network prediction controller, the average concentration of nitrate nitrogen was lower than that of traditional controller. In addition, due to the hydrolysis of the nitrogenous material and the conversion of ammonia nitrogen to nitrate nitrogen in the BSM1 model, the nitrate nitrogen content increased a lot, suggesting that good effluent quality could be obtained after using the controller in the sewage treatment process.

Effluent control effect: In order to further test the control effect of the controllers, we performed set value optimization and tracking control on them, with the results given in Table 2.

As shown in Table 2, the stability of the neural network prediction controller was higher than the traditional controller. The integrated absolute error and maximum error as well as the aeration consumption of the neural network prediction controller were smaller than the traditional controller. Therefore, the controller designed in this paper had better control effect, and its decoupling ability was better than that of traditional controller.

DISCUSSION AND CONCLUSION

In recent years, the discharge of sewage has caused a great burden on the environment, and research on wastewater treatment technology has become very important. Centered on sewage treatment technology, this paper described the activated sludge method, established a model of activated sludge method, and put forward a neural network control algorithm, designed a neural network predictive controller, studied the role of the controller in removing nitrate nitrogen in wastewater. The results showed that the controller had better stability, less error and less energy consumption, but better effluent water quality compared with the traditional controller and could meet the requirements of sewage treatment.

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