Sewage Treatment Control Method Based on Genetic-SOFNN

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Abstract. In the sewage treatment process, the dissolved oxygen concentration is a very important control target, but it is difficult to be controlled. To solve this problem, a self-organizing fuzzy neural network controller based on genetic ideas (G-SOFNN) is proposed. In the controller structure reduction process, the deleted neuron information is merged with the remaining neurons to reduce the interference set. During the controller structure increasing phase, the information of new neurons is initialized to avoid overlapping of information. Then, the controller parameters are trained by the projection algorithm to improve the control precision. Experiments illustrate that the proposed method can accurately control the concentration of dissolved oxygen in the sewage treatment process.

Keywords: Sewage treatment · Fuzzy neural network · Tracking control · Projection gradient learning

1 Introduction

Water pollution is one of the most serious urban environmental problems. In treating urban sewage, the activated sludge process is the most commonly used method, whose principle is to react microorganisms and organic substances in activated sludge to oxidize and decompose organic matter. While due to the complex nonlinear dynamics of the wastewater treatment process, it is very difficult to control the process [1].

In the sewage treatment process, the dissolved oxygen concentration is an important control target [2,3], since the value of the dissolved oxygen affects the activity of the microorganisms in the activated sludge. Recently, the traditional PID control method can not achieve the required control accuracy [4,5]. Therefore, some experts use the neural network as the intelligent controller to improve the control precision. For example, Han et al. implemented intelligent predictive control to improve the control accuracy of dissolved oxygen concentration [7]. Spall et al. used dynamic performance indicators to adjust the structure of the neural network, and accurately controlled the return flow of sewage [8].

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Qiao et al. designed the fuzzy neural network (FNN) structure as the controller to control the dissolved oxygen concentration [9].

The structure of the FNN plays a vital role in the process of solving the control problems. Therefore, experts have proposed their own methods for the adjustment of neural network structure [10,11]. Wu et al. proposed a FNN structure adjustment method based on the pre-rule extraction, which was verified in the classification problem [12]. Xu et al. adjusted the structure of the FNN network by incorporating the importance of neurons and the intensity of activation, and achieved good results in wastewater treatment [13]. But there are some problems in these methods: Firstly, in the process of structural deletion, these methods cannot guarantee the uselessness of the information contained in the deleted neuron and rule. Secondly, in the increasing phase, the added neuron and rule should ensure its information be different from original information.

Based on above problems, this paper combines the idea of genetic inheritance into the network structure adjustment process. In the structural deletion phase, the depleted neurons are merged with the remaining neurons, and the information is preserved while the structure is reduced. In the increasing phase, the new neurons are combined with mutation operators for parameter initialization to reduce the coincidence of information. Finally, through the projection algorithm to train parameters of the network, which can avoid falling into local optimum. Simulation results show that the sewage treatment controller can accurately track the dissolved oxygen concentration.

The sections of the article are arranged as follows: Sect. 2 introduces the control variables in the sewage treatment process and the structural composition of the fuzzy controller. Section 3 introduces the process of combining genetic ideas into self-organizing fuzzy controller. Section 4 proves the control effect of the proposed method by the experiments with BSM1. Section 5 is the conclusion.

2 FNN Controller Method for Sewage Treatment

The activated sludge process is the most widely used sewage treatment method, in which a series of microbial biochemical reactions occur in the aeration tank. The BSM1 model is a wastewater treatment imitation benchmark model jointly developed by the International Water Association and the European Union's Science and Technology Cooperation Organization [14,15]. The overall layout of the BSM1 model is shown in Fig. 1.

In the BSM1 model, the controller realizes the tracking control of the dissolved oxygen concentration in the fifth zone by controlling the oxygen transfer coefficient of the fifth unit. Therefore, the output of the controller is the amount of change in the oxygen transfer coefficient of the fifth zone, which is transferred to the BSM1 to complete the control of the dissolved oxygen concentration.

By incorporating the nonlinear dynamic characteristics and large time lag in the sewage treatment process, the overall controller design is shown in Fig. 2, and the controller used in this paper is based on fuzzy neural network. The input can be expressed as $\dot{x} = (e, de/dt)$, where e is the error between the set value and the true value, de/dt is the amount of error change.

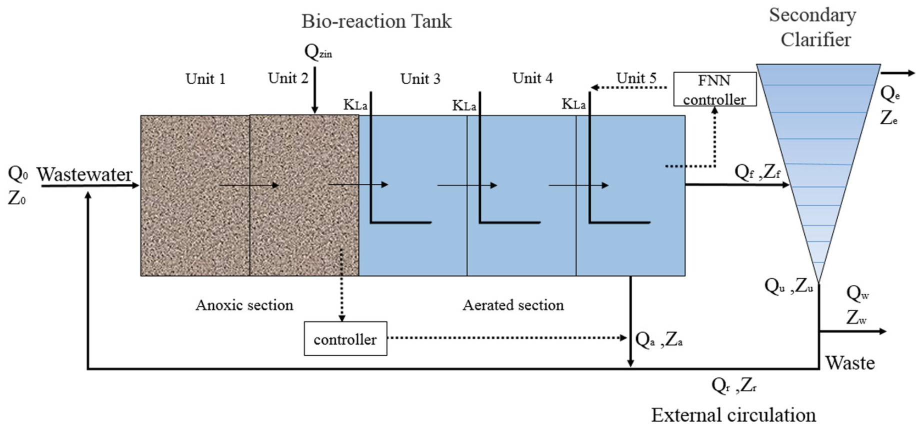

Fig. 1. BSM1 model of FNN dissolved controller for oxygen concentration.

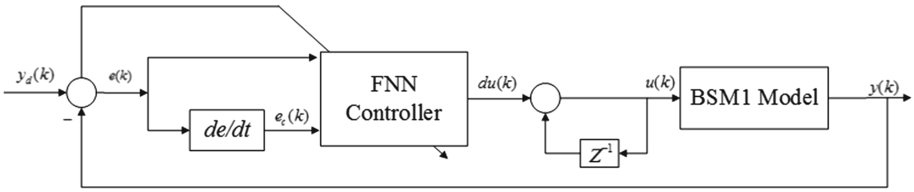

Fig. 2. The model of controller.

The fuzzy neural network structures are shown in the Fig. 3, which are mainly divided into input layer, membership layer, fuzzy rule layer, normalization layer and output layer. The input and output relationships with each layer are as follows:

The membership layer can be expressed as:

$$\mu_n^m = exp\frac{-(x_n - c_n^m)^2}{\delta_m^2} \tag{1}$$

In Eq. (1), μ_n^m indicates the output of this layer of neurons, x_n represents input, c_n^m represents the center, and δ_m represents the width.

The fuzzy rule layer can be expressed as:

$$b_m = \prod_{j=1}^{m} \omega_{nm}\mu_n^m \tag{2}$$

where b_m represents the output of the layer, ω_{nm} represents the connection weight of the membership layer and the fuzzy rule layer.

The normalization layer can be expressed as:

$$a_m = \frac{b_m}{\sum_{j=1}^{m} b_m} \tag{3}$$

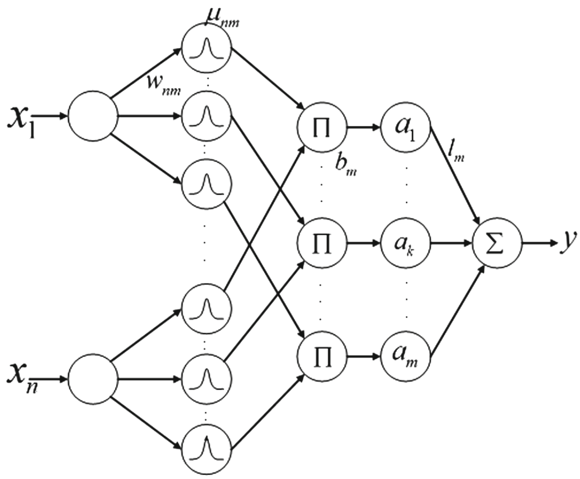

Fig. 3. The structure of FNN.

Finally, the output layer can be expressed as:

$$y = \sum_{j=1}^{m} l_m a_m \tag{4}$$

where l_m represents the connection weight of the normalization layer and output layer.

The structure of FNN is fuzzied by Gaussian functions. The characteristics of the input data are extracted at the fuzzy rule layer. The final output layer is used to implement defuzzification and sharpening.

3 G-SOFNN Adjustment Method

To change the structure of fuzzy neural networks, many experts have proposed some structure adjustment methods [9–13,16,17]. The most widely used method is to increase or decrease the network structure by calculating the intensity of fuzzy rules or neurons. However, the network deletion threshold (I_{cth}) and increase threshold (I_{dth}) are depended on human experience. In the deletion phase, the uselessness of the information contained in neurons and rules cannot be guaranteed. While in the increasing phase, the added neurons and rules should also have great difference between its information and the original, to avoid overlapping information. Therefore, this paper proposes a self-organizing fuzzy neural network by incorporating the genetic operators (G-SOFNN).

3.1 Deletion Phase

In the genetic algorithm, the genetic variation in biology is cited, thus good results are obtained in the optimization algorithm. In this paper, the idea of genetic variation will also be introduced in the proposed structural algorithm. In the neuron reduction phase, the neuron reduction is based on the comparison of the threshold with the minimum activation intensity. According to the genetic inheritance methods, the information of the deleted neuron will be added as part of the gene to the remaining neurons. There are two steps during this period: Firstly, calculate the shortest euclidean distance between each neuron and the depleted neurons by Eq. (5) to obtain the neurons. And then, according to Eqs. (6)–(8), the information of the neurons with the shortest distance and the new parameters are obtained.

Euclidean distance is calculated as below:

$$d(x, y) = \sqrt{(x_1 - y_1)^2 + \cdots + (x_n - y_n)^2} \tag{5}$$

Center is updated as below:

$$C_{new} = I_{cth} \cdot C_k + (1 - I_{cth}) \cdot C_d \tag{6}$$

Weight is updated as below:

$$w_{new} = I_{cth} \cdot w_k + (1 - I_{cth}) \cdot w_d \tag{7}$$

Width is updated as below:

$$\delta_{new} = I_{cth} \cdot \delta_k + (1 - I_{cth}) \cdot \delta_d \tag{8}$$

where C_d, w_d, and δ_d represent the center, width, and weight of the deleted neurons, respectively, C_k, w_k, and δ_k represent the center, width, and weight of the fused neurons, respectively.

3.2 Increasing Phase

In the increasing phase, if the maximum value of all neuron activation intensities is less than the set growth threshold, it indicates that the current rules cannot effectively cover the new data, and it is necessary to increase the neurons to meet the requirements of the current control environment. However, the new data (center, weight, width) initialization process of the added neurons need to be differentiated from the original neurons, so that the added neurons can cover the information of the new data as much as possible. Therefore, the maximum activation intensity of neurons should be maximized variation when new neurons are generated.

In this period, we defined the mutation operator according to I_{cth} and I_{gth}, as shown in Eq. (9). Then, the center, width and weight of the new neuron are calculated according to the mutation operator, as shown in Eqs. (10)–(12).

The mutation operator is calculated as below:

$$\eta = \frac{I_{cth}}{I_{cth} + I_{gth}} \tag{9}$$

The new center is calculated as below:

$$C_{new} = \eta \cdot (C_1 + \cdots + C_k) \tag{10}$$

The new weight is calculated as below:

$$w_{new} = \eta \cdot (w_1 + \cdots + w_k) \tag{11}$$

The new width is calculated as below:

$$\delta_{new} = \eta \cdot (\delta_1 + \cdots + \delta_k) \tag{12}$$

where I_{cth} represents deletion threshold, I_{gth} represents increase threshold, C_k, w_k and δ_k represent the center, weight and width of the k-th existing neuron, respectively.

3.3 Learning Algorithm

In the network parameter adjustment process, the gradient projection is used. The method can avoid the solution in the parameter adjustment process. The adjustment process of the weight is as shown in Eq. (13).

$$w_i = \begin{cases} l_{rw} \cdot e \times b_m & if(\left\|w_i^2\right\| < h)or(\left\|w_i^2\right\| = h\ and\ b_m w_i \geq 0) \\ \frac{-l_{rw} \cdot e \times b_m + l_{rw} \cdot e \times b_m w_i^T}{\left\|w_i^2\right\|} & if(\left\|w_i^2\right\| = h_w\ and\ b_m w_i < 0) \end{cases} \tag{13}$$

The l_{rw} in the formula represents the learning rate, e is input error, b_m represents the output of the fuzzy rule layer, and h_w represents associated parameter bounds.

The update formula for the *center* and *width* is based on the gradient descent, the adjustment process is as follows:

$$c_t = c_{t-1} + \eta \frac{\omega_i}{\delta_i^2} \sum_{j=1}^{n} \beta_i e_i \phi_i(x_j)(x_j - c_i) \tag{14}$$

$$\delta_t = \delta_{t-1} + \eta \frac{\omega_i}{\delta_i^3} \sum_{j=1}^{n} \beta_i e_i \phi_i(x_j)||x_j - c_i||^2 \tag{15}$$

where η_i is the learning rate, β_i is the forgetting factor, e_i is the error signal between the network output and the real value, and $\phi_i(x_j)$ is the output of the first hidden node to x_j.

4 Experiments

In order to verify the proposed method, we designed the following experiment: Firstly, the method proposed in the paper controls the dissolved oxygen in BSM1 under dry weather (dissolved oxygen concentration set value $2\,\mathrm{mg} \cdot \mathrm{l}^{-1}$) will be compared with PID controller and SOFNN controller. The results of the comparison are shown in the Fig. 4. At the same time, we also show the changes of the fuzzy neural network controller structure of G-SOFNN under three different weathers in Fig. 5.

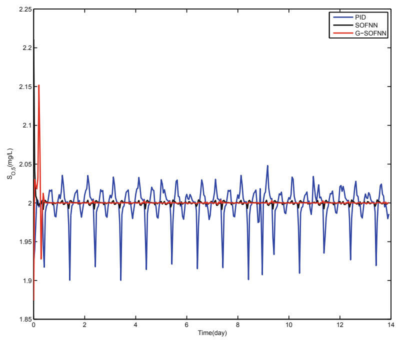

Fig. 4. Control comparison of DO.

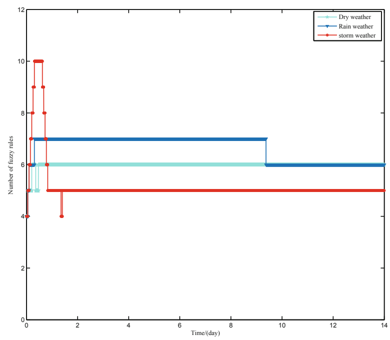

Fig. 5. Rule change process.

According to Fig. 4, it takes a period of time to adapt the environment to the fuzzy neural network. In the period when PID and SOFNN and G-SOFNN are stable, it is obvious that the tracking effect of the PID controller is the worst, and the SOFNN controller is slightly better, G-SOFNN has the higher precision and ability to track dissolved oxygen concentration.

It can be seen from the Fig. 5 that under different weather conditions, the G-SOFNN method can adapt the current sewage environment in a short time. Although there is a process of change in the middle, the structure of the controller can be quickly adjusted to steady state, which also shows the stronger adaptive ability of the controller.

Then, we compared three indicators including integral absolute error (IAE), intergral square error (ISE) and maximum error (Dev^{max}) in rain weather and storm weather as shown in Table 1. The calculation process of the three indicators are as shown in Eqs. (16)–(18), respectively.

$$IAE = 1\frac{1}{t_f - t_0}\int_{t_0}^{t_f} |e_i|\,dt \tag{16}$$

$$ISE = 1\frac{1}{t_f - t_0}\int_{t_0}^{t_f} e_i^2 dt \tag{17}$$

$$Dev^{max} = max|e_i(t)| \tag{18}$$

where e_i refers to the difference between the dissolved oxygen concentration tracking set value and the actual value in BSM1, and $e_i(t)$ represents the systematic error value at time t.

Table 1. The control performance comparison under different weathers condition.

Methods	Rain weather			Storm weather		
	IAE	ISE	Dev^{max}	IAE	ISE	Dev^{max}
PID	4.536	0.153	0.099	4.848	0.181	0.095
SOFNN	0.858	0.005	0.018	0.984	0.012	0.092
G-SOFNN	0.156	0.003	0.008	0.453	0.031	0.016

The results of three algorithms are given in the Table 1. It is obvious that our algorithm obtains the best control effect compared to other algorithms. Also, the performance of the G-SOFNN algorithm is optimal in the comparison algorithm, which prove the effectiveness of genetic variation based methods.

5 Conclusions

In order to accurately track the dissolved oxygen concentration in the sewage environment, a self-organizing fuzzy neural network control method based on genetic operation is designed in this paper. First of all, in the deletion process of FNN, the genetics of the depleted neurons are genetically inherited. Furthermore, projection algorithm is used to train the FNN parameters online to prevent the network from falling into optimum and improves control accuracy. Moreover, through the tracking experiment of dissolved oxygen concentration in BSM1, it is proved that the proposed method can achieve high-precision control effect.

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