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DESIGN OF URBAN SLUDGE EMISSION REDUCTION OPTIMISATION STRATEGY BASED ON FUZZY NEURAL NETWORK

Abstract: Urban sewage sludge treatment is important for sustainable utilisation and virtuous cycle of freshwater resources. However, with the improvement of sewage discharge standards, ensuring stable operation of sewage sludge treatment plants is becoming an urgent problem to be solved in the sewage treatment industry. This paper proposes a FNN control framework based on different working conditions to optimise the whole process of municipal sewage sludge treatment and discharge. The framework first divides the working conditions according to the weather, forming a separate feature and an input vector together with the typical indicators of other sewage treatment plants. Then the FNN is used to complete the control and optimisation of various indicators, achieving the dual objectives of reducing energy consumption and optimising water quality. Finally, the model is tested for the tracking index of sewage flow. The results demonstrate that the FNN control method used has significantly lower MAE than the single method in the two indexes of energy consumption and water quality evaluation. This provides new ideas for the optimisation of urban sewage sludge treatment process in the future. Overall, the paper effectively highlights the importance of urban sewage sludge treatment and presents a well-designed FNN control framework for optimising the treatment process. Additionally, the paper could benefit from further elaboration on the significance of the results obtained, and suggestions for future research in this area.

Keywords: fuzzy neural network, sewage emission, environment protection, wastewater treatment process

Introduction

Water resources are the source of human life and the foundation of scientific and technological progress and sustainable development of human society. In the process of sewage treatment by activated sludge method, the reaction tank needs to be aerated and the reaction liquid needs to be continuously stirred, and the air is added to the reaction tank to provide the oxygen required for microbial biochemical reaction. In the whole sewage treatment process, the consumption of electric energy accounts for about 70 % of the total operation cost of the sewage treatment plant [1, 2]. With the increase of the number of effluent indicators and the improvement of requirements, urban sewage treatment plants need to continuously increase the amount of aeration, extend the aeration time, and increase the sludge return flow to ensure that the effluent quality meets the standard. High energy consumption has become the bottleneck restricting the development of urban sewage treatment industry, and also poses a serious challenge to the national energy and resource

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security. Therefore, to ensure the sustainable development of the sewage treatment industry, the key is to further tap the energy saving potential of the sewage treatment process and implement optimal control. The sewage treatment process involves dozens of microbial populations and hundreds of biochemical reaction processes, with many processes, large time lag, strong uncertainty and other characteristics. It is a system with complex detection, difficult modelling and unstable operation. It is a difficult problem in the current control field to ensure that its sewage discharge meets the standard and stable operation [3].

An important feature of the urban sewage treatment process is that there are many operating procedures and conditions, the sewage quality and inflow fluctuate significantly, and the model is difficult to establish. Therefore, the sewage treatment process is a system with complex detection, difficult modelling, and unstable operation [4]. The research on its optimal control method and the design of the optimal control system are difficult problems in the current control field. Another important feature of urban sewage treatment process is that the process data is rich in information, the system is relatively closed, and the degree of intelligentisation is relatively low [5]. According to the historical data of urban sewage treatment plants, combined with the historical weather and other conditions, this paper will optimise the inflow of sewage treatment and the process of relevant links, so as to achieve the objectives of energy emission reduction and water quality optimisation. The specific contributions of this paper are as follows:

1. Divide the working conditions according to the weather data to form the sewage discharge characteristics under typical working conditions.
2. The Mean Absolute Error (MAE) analysis of energy consumption index and water purification index under different working conditions is completed by using fuzzy neural network (FNN), which proves the superiority of the method proposed.
3. In the actual test, the control index of sewage flow was tracked, and the results showed that this method was better than other control methods, which provided a new idea for sewage purification and management in the future.

Related works of sewage treatment process control

The urban sewage treatment process contains complex nonlinear biochemical reactions, and the influent water quality is affected by seasonal, environmental and other factors, with serious uncertainty. Its optimal control is facing great challenges [6]. In the early stage of the development of the sewage treatment industry, the sewage treatment plant mainly used traditional control methods to control the sewage treatment process, including proportional integral (PI) and proportional integral derivative (PID) control [7]. For the control of dissolved oxygen (DO) concentration in sewage treatment process, Han et al. [8] designed a PI control method based on fuzzy reasoning mechanism. This control method adaptively adjusts the parameters of the PI controller, realises the tracking control of DO concentration, and can effectively improve the control accuracy of sewage treatment process. To improve the nitrogen removal efficiency of sewage treatment, Samsudin et al. [9] proposed a PI control method based on adaptive interactive algorithm theory. This control method adaptively adjusts the parameters of PI controller during the nitrogen removal process of activated sludge sewage treatment, effectively improving the effluent quality. The control effect of PI controller and PID controller is largely affected by the parameter setting. Scholars have studied the parameter self-adjusting strategy for the stability of the controller [10], the control lag problem and the control performance problem [11]. Ye et al. [12] proposed an adaptive PID control method, which uses fuzzy set theory to dynamically adjust the parameters of PID controller, effectively improving the control accuracy of DO concentration. The sewage treatment process has nonlinear characteristics, and the treatment process is not easy to quantify, making it difficult to significantly improve the control accuracy of PI controller and PID controller [13].

The combination of artificial neural network methods and human cognitive methods provides a superior solution for addressing the issue of sewage sludge discharge. Currently, research is focused on optimising the purification and discharge of sewage sludge under different working conditions, as well as achieving dual optimisation of energy and water purification effectiveness. To this end, this paper utilises FNN to leverage the nonlinear characteristics of neural networks and the cognitive advantages of fuzzy methods, in order to enhance the overall optimisation performance of the model.

Establishment of optimisation model for sewage emission reduction

The working condition division

For the optimisation of municipal sewage sludge emission reduction, it is of great significance to adjust the water purification and the flow of each part in real time according to the weather conditions, and make full use of the rainwater scouring and purification functions for the overall optimisation of emission reduction.

The data of three typical operating conditions, sunny day, rainy day and rainstorm weather, are used to describe in detail the influent flow, soluble and insoluble component concentrations under the three typical operating conditions. The characteristics of different weather are shown in Table 1 [14].

Table 1

The working condition under different condition

Weather	Characteristic
Sunny day	There is no interference from any external environmental changes, the sewage treatment system operates stably, and the biochemical Normal reaction process
Rainy day	In rainy days, the inflow flow and pollutant concentration are generally less at night than in the daytime, and at weekends Less regular than the middle of the week
Rainstorm	In rainstorm, the inflow flow and pollutant concentration still follow the rule that night is less than day, and weekend is less than week. However, the influent flow increased sharply, and the concentration of soluble components decreased significantly on the day of rain, and returned to normal after rain

Due to the lag of the weather, in addition to the classification of the weather conditions according to the relevant weather conditions, the overall situation of the weather within a few days has also been taken into account when building the model. During the data training, the data of the previous week and the next week under different conditions, a total of 14 days, are used as input to complete the training and optimisation of the model.

Fuzzy control theory

In daily life, we usually do not distinguish transactions by strict standards, but use some vague and abstract adjectives. These descriptions without clear boundaries can be translated into vague language in specific ways [15]. In the control process, method that uses a series of rules to define the range of variables and describe the properties of variables is called fuzzy control. Compared with digital expression, data expressed in fuzzy language can contain more information and convey richer content. Fuzzy control divides variables into different "domains". By comparing the relationship between different variable domains, appropriate output values are formed to control the system in a timely and efficient manner.

Fuzzification is to transform the input quantity with clear boundary into fuzzy quantity that can be input in the fuzzy inference machine according to the corresponding membership function. Generally speaking, according to different actual requirements, different systems with different accuracy requirements can have different domain division. The membership function mainly includes three types, namely, triangular membership function, Gaussian membership function and trapezoidal membership function.

Optimisation of sewage discharge based on fuzzy neural network

For the algorithm of fuzzy neural network, it is mainly to use BP neural network to train the variable parameters of the control system, and then select the optimal parameter value. The parameter training is mainly based on gradient descent algorithm, including forward propagation and back propagation. The forward propagation is to send the input data to the output layer after the output of the multi-layer neural network is processed by fuzzy processing and other multiple processes, and finally get the actual output value. The reverse propagation process is to modify and optimise each parameter variable value layer by layer according to the error between the set expected and the real. The transmission process of each layer of forward propagation has been introduced. Next, we will mainly analyse the process of reverse propagation. The first consideration is the selection of error function. Generally, square error is used to judge the deviation between the actual value and the set value. Suppose there are n groups of data, and the input of the *j-th* neuron of a layer is $x_j(n)$, output value is $y_j(n)$, according to the weight value $W_{ji}(n)$ can be obtained by weighted cumulative summation of each neuron in the front layer:

$$x_j(n) = \sum_{1}^{k} W_{ji}(n) y_i(n) \tag{1}$$

where $W_{ji}(n)$ represents the weight between the *i* neuron and the current *j* neuron; common activation functions include sigmod function, etc.:

$$y_j(n) = f_j\big(x_j(n)\big) \tag{2}$$

According to the selection of error function, the actual output of the *j-th* neuron in the output layer and the expected output value $d_j(n)$. The difference can be obtained as:

$$e_j(n) = d_j(n) - y_j(n) \tag{3}$$

When there are *m* neurons in the output layer, the total square error is:

$$E(n) = \frac{1}{2} \sum_{j \in m} e_j^2(n) \tag{4}$$

In order to be accurate, the error of each sample needs to be averaged. When the total number of samples is *N*, the objective function can be obtained:

$$E_{av}(n) = \frac{1}{N}\sum_{n=1}^{N} E(n) \tag{5}$$

In this paper, it is mainly considered that the input state of the water treatment plant mainly includes the following eight components: sewage flow, component flow, component volume, component concentration, influent component concentration, influent flow, internal return flow and sludge discharge. In the model training, the average of every 14 days is used as a model calculation cycle to form an input vector. At the same time, the model is trained according to the historical data of weather conditions, and the FNN is used to optimise the sewage sludge treatment effect. The overall process is shown in Figure 1.

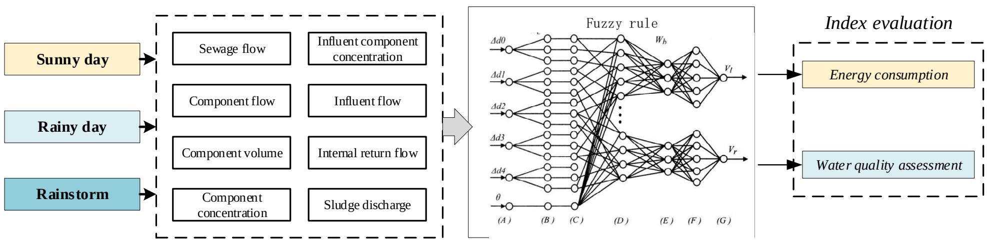

Fig. 1. Framework for the sewage purification process using the fuzzy neural network

Experiment result and analysis

Model training comparison and the index evaluation

In the experiment process, the model is trained separately according to the eight components and weather data described in previous section to complete the establishment of the model. In the selection of data, we selected the data of the past three years for model training. In the training, we selected the data of seven days before and after the data of the day, that is, half a month, as the input to complete the model training, so the dimension of each input vector in the model is 120, and then input the weather data as a separate vector. In this paper, to evaluate the model performance, we select the model data optimised by experts, that is, fine-tuned model data, as the benchmark for data comparison. To better illustrate the optimisation results under the two indicators, this paper has carried out different methods, and the results are shown in the next subsection.

The control result compared with the traditional methods

In evaluation process, we selected the MAE index, which is widely used in machine learning, as the evaluation index. The specific calculation method is shown in equation:

$$\mathrm{MAE} = \frac{1}{n}\sum_{k=1}^{n} |(a_1 - p_1)| + \cdots + |(a_n - p_n)| \tag{6}$$

where a_1, a_2, … a_n indicates actual value, p_1, p_2, … p_n indicates predicted value. The prediction accuracy of the model can be well reflected by calculating the mean absolute error between the predicted value and the actual value. The prediction results of different methods are shown in Tables 2 and 3.

Table 2

The MAE for different methods without weather input

Models	**Evaluation**	
	Energy consumption [-]	**Water quality assessment [-]**
NN	6.487	7.864
Fuzzy	5.792	5.498
PID	9.479	10.672
Fuzzy NN	3.975	3.993

Table 3

The MAE for different methods with weather input

Models	**Evaluation**	
	Energy consumption [-]	**Water quality assessment [-]**
NN	5.769	6.754
Fuzzy	5.287	4.967
PID	7.865	8.763
Fuzzy NN	3.357	3.187

Table 2 shows the result of directly inputting 8 variables into the model, that is, the weather conditions are not inputted as a kind of separate data. It is not difficult to see from the comparison between Table 2 and Table 3 that the model training with weather as a single feature in the framework proposed can greatly improve the training accuracy of the model, that is, MAE can be effectively reduced on both indicators. From Table 3 alone, it can be found that the MAE of the FNN framework proposed are significantly better than the NN and fuzzy control methods alone, and far better than the traditional PID control methods. Therefore, taking weather conditions as characteristics and combining with Fuzzy NN can effectively improve the efficiency of sewage sludge treatment process, reduce energy consumption and ensure that water quality meets the standard.

Discussion

Urban sewage sludge discharge involves a variety of factors, such as policy, weather and the working conditions of the water purification plant, which will affect the sewage sludge discharge results. Therefore, it is necessary to optimise the water purification process according to the working conditions. This paper divides the working conditions according to the weather conditions in the region, completes the data induction and feature classification, and then carries out model training according to the characteristics of the traditional water purification process, thus improving the control ability and accuracy of the model [16]. The FNN algorithm is used to realise the optimisation of sewage sludge discharge process. The fuzzy rules set by experts can be fully used for model training. The network has good fault-tolerance and stability. In addition to its stable performance in MAE, it performs well in a scalar tracking process, which provides a new idea for the future sewage sludge discharge optimisation.

The optimisation of sewage sludge discharge through FNN algorithm can reduce energy consumption to achieve green development on the basis of ensuring water quality, but more policy guidance and measure optimisation are needed to achieve pollution-free development. First of all, for urban domestic sewage, reduce the total amount of pollution discharge in a large area and treat it according to the source of sewage to avoid secondary pollution [17]. Secondly, with the development of new energy technologies, we should adjust the energy structure and make full use of solar energy, wind energy and tidal energy to ensure green emissions. Finally, complete the upgrading of industrial structure, eliminate backward productivity, and provide corresponding compensation and upgrading and transformation schemes for the factories with enlarged emissions and low output, so as to achieve the reduction of emissions [18].

Conclusion

This paper studies the optimisation of the current urban sewage sludge treatment strategy, and proposes a FNN optimisation control framework that integrates the characteristics of weather conditions. The framework extracts weather conditions as input features based on historical data, and integrates 8 indicators such as sewage flow, which are common in sewage treatment process, to achieve full use of data features. Then the FNN method is used to optimise the drainage process. In the MAE comparison of energy consumption and water quality, the result is significantly better than the control result of a single method. Although this paper has achieved some research results in the process of optimal scheduling of sewage sludge discharge, due to the data collection capacity, this paper only divides the working conditions into three weather conditions, and fails to complete the analysis of other external factors. Therefore, expanding the data range and optimising the characteristics of the model are the focus of the next step.

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