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Prediction of Chemical Oxygen Demand Emissions in Wastewater Treatment Plant Based on Improved Artificial Neural Network Model

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With the increasingly serious pollution of water resources, China's awareness of water resources protection is becoming stronger and stronger, and a series of effective measures have been taken. The water quality monitoring technology can detect and analyze the water quality timely, so as to obtain accurate detection results. However, due to the limitations of the current measurement methods and measuring instruments, some parameters are difficult to be measured in time, thus affecting the control effect of water quality parameters in wastewater treatment. To solve this problem, this paper tries to use the strong nonlinear identification ability of neural network to realize soft sensing of chemical oxygen demand. Firstly, the self-adaption method is used to change the learning rate of BP algorithm to control the gradient descent speed of BP neural network in learning, and then to improve the convergence characteristics of standard BP algorithm. Learning rate adjustment process is based on certain principles, so it can ensure that the learning rate can maintain a larger value, but also ensure the stability in the learning process. In order to find out the water quality parameters which have great influence on the treatment effect, 8 water quality parameters are selected as the auxiliary variables, and the chemical oxygen demand (COD) parameters are treated as the main variables after the treatment of the sewage treatment system. The results show that the BP neural network model has high prediction accuracy, fast convergence speed, good generalization ability. It can accurately predict the COD value in the sewage treatment process, and better reflect the change law of COD and influence factors.

1. Introduction

With the increasingly serious pollution of water resources, China's awareness of water resources protection is becoming stronger and stronger, and a series of effective measures have been taken. The water quality monitoring technology can detect and analyze the water quality timely, so as to obtain accurate detection results. This method is one of the effective methods to protect water resources in our country. Scholars at home and abroad have also made corresponding research on this issue. Qi et al., (2004) propose a soft sensor method based on radial basis function (RBF) neural network, train and simulate the RBF neural network by using a large amount of measured data, and prove the effectiveness of the soft sensing model based on RBF neural network through experiments. Qiao et al., (2014) use the COD, solid suspended solids (SS), pH and dissolved oxygen (DO) as input variables, use the improved T-S fuzzy neural network model to predict the effluent BOD, and achieve good results. Tian et al., (1998) compare the ozone biological activated carbon system model of BP and RBP artificial neural network. The research shows that the model of water treatment system based on BP artificial neural network has good generalization ability. Tian et al., (2009) use mathematical statistics methods to study the relationship between COD, pH and nitrogen substrate concentration, the results show a good linear relationship between COD and pH and NH4+ concentration. Bao and Xu (2011) have the established stepwise regression analysis model, ARMA model, neural network model based on time series analysis and neural network model based on regression analysis. Through comparison,

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the neural network model based on time series analysis is chosen as the prediction model of effluent COD in wastewater treatment plant.

2. Principles and grades of wastewater treatment

The sewage treatment process is divided into three levels. The primary treatment includes the structure of grid, grit chamber and primary sedimentation tank, and use these remove coarse particles and suspended solids. The principle of treatment is to achieve solid-liquid separation, so as to separate pollutants from sewage, which is a commonly used sewage treatment method. Biochemical treatment of sewage belongs to the two stage treatment. It can be used to remove non-suspended solids and dissolved biodegradable organic compounds. At present, most municipal wastewater treatment plants adopt activated sludge process. The principle of biological treatment is to complete the decomposition of organism and the synthesis of organism through biological action, especially the microorganism action. The three-stage treatment is the advanced treatment of water, it is the wastewater treatment process after the two stage treatment, and it is the highest treatment measure of the sewage. After removing nitrogen and phosphorus, the activated carbon adsorption method is used to remove the residual pollutants in the water, and ozone or chlorine is used to kill bacteria and viruses, and then the treated water is sent into the channel. The main structure of the sewage treatment plant in the enterprise is shown in Figure 1:

Figure 1: The main structure of sewage treatment plant in Enterprises

3. Improved artificial neural network model for predicting chemical oxygen demand

The neural network model is put forward in the study of the structure of the human brain nervous system. The mathematical expressions of synapses in biological neurons can be represented by weights, and the symbols of weights represent the excitation and inhibition of synapses. The magnitude of the weights represents the difference in the connection strength between synapses. Unlike biological neural networks, neural networks also require an incentive function. In order to obtain the desired results, it is necessary to use this function to regulate the output of neurons in a certain range. The operation model of the neural network is finally determined as shown in Figure 2:

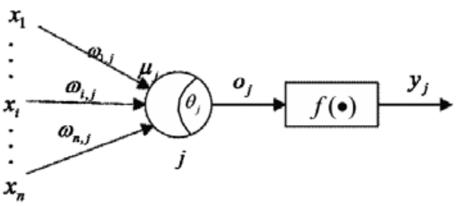

Figure 2 : Artificial neural network structure

In Figure 2, x_i(i=1,2,…,N) is the input signal of neuron j, and W_{ij} is the weight of connection between neurons i and j . u_j is the output value of input signal after linear combination, θ_j is the threshold of neuron j, f(·) is the transfer excitation function, and y_j is output value of the neuron j. The relation between input and output of neurons can be expressed as:

$$u_j = \sum_{i=0}^{N} \omega_{ij} x_i \tag{1}$$

$$y_j = f(x) = wx + b = f(\sum_{i=0}^{N} \omega_{ij} x_i + \theta_j) \tag{2}$$

The input of each node in the hidden layer is:

$$net_j = \sum_i \omega_{ij} x_i \tag{3}$$

The output of each node in the hidden layer is:

$$y_j = f(net_j) = f(\sum_{i=0}^{N} \omega_{ij} x_i) = 1 \Big/ (1 + e^{-net_j}) \tag{4}$$

The output of each node in the output layer is:

$$o_l = f(net_l) = f(\sum_{i=0}^{N} v_{lj} y_j) = 1 \Big/ (1 + e^{-net_l}) \tag{5}$$

At this point, both the hidden layer nodes and the output layer nodes use the Sigmoid function. The activation function can be continuously derivable, and the derivative of the activation function has:

$$E = \frac{1}{2}\sum_l (t_l - o_l)^2 = \frac{1}{2}\sum_l [t_l - f(\sum_j v_{lj} y_j)]^2 = \frac{1}{2}\sum_l \{t_l - f(\sum_j v_{lj} f(\sum_{i=0} \omega_{ij} x_i))]\}^2 \tag{6}$$

Then the weight iteration formula between the input layer and the hidden layer is:

$$\omega_{ij}(k+1) = \omega_{ij}(k) + \Delta\omega_{ij} = \omega_{ij}(k) + \eta \xi_j x_i \tag{7}$$

The iterative formula of weight between hidden layer and output layer is:

$$v_{lj}(k+1) = v_{lj}(k) + \Delta v_{lj} = v_{lj}(k) + \eta \xi_l y_j \tag{8}$$

In this paper, an adaptive method is used to change the learning rate of BP algorithm to control the gradient descent speed of BP neural network in learning, and then to improve the convergence of standard BP algorithm. Learning rate adjustment process is based on certain principles, so it can ensure that the learning rate can maintain a larger value, but also ensure the stability in the learning process. The adaptive adjustment formula of learning rate is as follows:

$$\eta(n+1) = \begin{cases} a\eta(n) & E(n+1) > 1.04E(n) \\ b\eta(n) & E(n+1) < E(n) \\ \eta(n) & otherwise \end{cases} \tag{9}$$

Among them, a<1, b>1, E is error function. The method of adaptive learning rate can be used for dynamic network processing, which can not only make the learning rate reasonable value, but also accelerate the convergence speed of BP neural network algorithm, at the same time, it can guarantee the stability of BP neural network and the convergence of BP algorithm

4. Simulation experiment and result analysis

4.1 The experimental data

Through the detailed analysis of the sewage treatment process, we choose the variables which are correlated with the dominant variables as auxiliary variables. The selection of auxiliary variables includes the number of variables, the type of variables and the location of test points. These three aspects are interrelated, and are determined by the specific process. At the same time, a series of constraints, such as reliability, feasibility, economy and maintainability, should be taken into consideration in practical engineering. City sewage treatment process is a complex process of multi variable and nonlinear, and many factors influence the effect of sewage treatment. In order to find out the water quality parameters that greatly influence on the treatment effect, we use the total nitrogen (TN), ammonia nitrogen (NH3-N), suspended solids (SS), the concentration of dissolved oxygen (DO), pH , nitrate nitrogen (NO3-N), nitrite nitrogen (NO2-N) and temperature (T) as auxiliary variables, and use the chemical oxygen demand (COD) as the main variable parameters.

Next, we introduce the criteria for water quality assessment and the significance of several major impact factors.
First of all, we need to understand the relationship between the water quality rating standards and the chemical factors, as shown in Table 1:

Table 1: Limited value of water quality evaluation index

Chemical index	Class I	Class II	Class III	Class IV	Class V
PH	6~9				
DO	≥7.5	≥6	≥5	≥3	≥2
CODMn	≤2	≤4	≤6	≤10	≤15
NH3-N	≤0.15	≤0.5	≤1.0	≤1.5	≤2.0

Secondly, we give a brief introduction to several major factors that affect water quality:
(1) Water temperature (T)
The results shows that the microbial activity decreased sharply and the purification efficiency decreased greatly when the water temperature is higher than that of the activated sludge process. For different types of microbial flora, the most suitable water temperature is not the same.
(2) Dissolved oxygen concentration (DO)
Dissolved oxygen concentration is a common control variable in municipal wastewater treatment. The degradation of organic compounds by activated sludge process is an aerobic process, and different aerobic purification processes have different requirements for dissolved oxygen.
(3) Chemical oxygen demand (COD)
It represents the amount of oxygen required for the oxidation of organic and inorganic substances under the action of strong oxidants. The value of COD contains the amount of organic and inorganic substance that can not be decomposed by bacteria in sewage. There is a certain relationship between COD value and BOD value, which can be used as an alternative to BOD value in wastewater treatment and control.

Table 2: The sample data set of Sewage treatment plant

Number	SS (mg/L)	pH	Total nitrogen (mg/L)	dissolvedoxygen(mg/L)	ammonia nitrogen (mg/L)	nitrite nitrogen (mg/L)	nitrate nitrogen (mg/L)	T	CODMn(mg/L)
1	2.6	107.4	7.92	1.08	13	0.12	0.014	5.57	0.158
2	8.2	78	8.15	1.75	12	0.1	0.0051	3.88	0.136
3	9.6	39.4	8.09	2.61	11.6	0.2	0.023	4.32	0.828
4	15.1	85	8.65	1.9	0.37	0.16	0.014	10.36	0.379
5	20.8	96	7.97	2.47	8.7	0.057	0.008	4.91	1.43
6	23.2	30.2	8.09	2.33	7.66	0	0.006	4.24	1.271
7	26.4	32.2	8.39	1.75	7.92	0.119	0.004	3.88	0.799
8	29.2	19.2	8.76	0.88	7.13	0	0	5.37	0.194
9	25.2	33.2	8.21	1.08	7.34	0.202	0.004	3.63	0.092
10	17.8	40.8	8.17	0.877	9.22	0.02	0.006	3.08	0.411
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
497	0	49	0	1.84	8.43	0.064	0.007	3.32	0.885
498	26.8	27.6	8.4	2.08	8.67	0.028	0.004	2.67	0.703
499	24	5	8	1.54	8.01	0.071	0.011	3.03	0.672
500	24.2	9.6	7.9	1.2	8.15	0.01	0.007	2.77	0.444

(4) Suspended solids (SS)
According to their existing state, the pollutants in sewage are divided into suspended substance, dissolved substance and so on. The suspended solids can-not settle freely because of Brown motion in the water, which makes the water turbid. In wastewater treatment, the removal rate of suspended solids is an important index to measure the effect of sedimentation.
(5) Ammonia nitrogen (NH3-N)

Ammonia nitrogen mainly refers to the nitrogen existing in the form of ammonia ion or free ammonia, and total nitrogen also includes organic nitrogen and nitrate nitrogen. These two indexes indicate the amount of NH4+, NH3 and total nitrogen in sewage, which has guiding effect on the selection of treatment methods.
Next, we collect data of a sewage treatment plant in real time, and obtain 500 groups of data.
Among them, the first 450 groups of data as the training sample of BP neural network, the last 50 groups of data as BP neural network test samples, so the error between the predicted and measured values of the BP neural network model is studied and analyzed. Due to the limited space, part of the sample data is shown in Table 2.

4.2 The experiment steps and the result analysis

After we obtain the sample data, we need to standardize and normalize the data, and then set the parameters of the improved BP model:
BP neural network is established in this paper. There are 12 hidden layer neurons and 4 output neurons. The results of the training model are shown below:

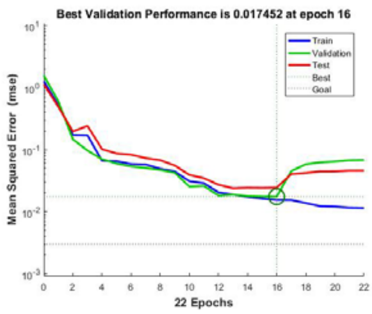

Figure 3: Training error curve of improved BP neural network

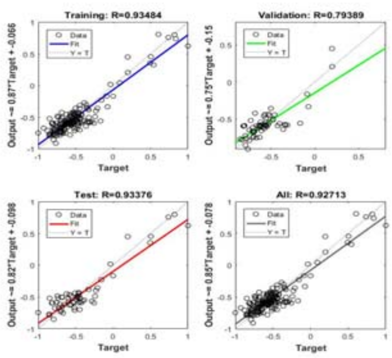

Figure 4: Regression result of neural network

As can be seen from Figure 3, using 8 measurable sewage indexes as inputs of BP neural network, and COD as output, a soft sensing model of sewage treatment is established. The convergence speed of the improved BP neural network algorithm is very fast, and it converges to the error target value about 16 times. The learning speed of the algorithm is faster than that of the standard BP neural network, thus improving the estimation efficiency of the soft sensing model of the sewage index. The test set is measured by the established model, and the test results of the BP neural network proposed in this paper are shown in Figure 5. As can be seen from Figure 4, the error between the target and the training (test) data target will become smaller and smaller when the training is carried out. At the beginning, the error between the validation and the target of validation will also become smaller. Then, with the increase of training, the error of test will continue to be smaller, and the error of validation will increase. When the error of validation continues to rise 6 times (the default setting), the training stops, because there will be a phenomenon of overfitting. The results of the model training are better, the curves of the four graphs are basically on the diagonal, and the values of R are close to 1, which will improve the accuracy of our subsequent prediction work.

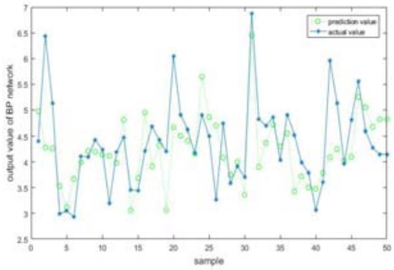

Figure 5: Comparison of measured values and actual values of improved BP neural network

As can be seen from figure 5, the neural network model established in this paper is close to the actual measured value of COD, and the running time is short. The main reason is that the neural network not only has the advantage of accelerating learning, but also has the nonlinear and local search ability of BP neural network. The measurement accuracy of the model is much higher than that of the standard BP neural network, and it can jump out of the local optimal solution and overcome the standard defects. It is very meaningful to accurately predict the numerical value of COD. The higher the chemical oxygen demand is, the more serious the organic pollution in the water source is. The sources of organic pollution may be pesticides, chemical plants, and organic fertilizers and so on. After accurate observation and prediction, we can effectively avoid the destruction of the ecosystem in the river, and avoid the absorption of these toxins by aquatic organisms, thus protecting the health of human beings.

5. Conclusions

With the rapid development of industry and society, urban sewage treatment has become an important research topic in the field of environmental protection. In the process of sewage treatment by activated sludge, chemical oxygen demand, biochemical oxygen demand, nitrogen content and other parameters are the key indicators to evaluate the performance of sewage treatment, and also an important parameter to measure the quality of sewage. Due to the limitations of the current measurement methods and measuring instruments, some parameters are difficult to obtain in time, thus affecting the control effect of water quality parameters in wastewater treatment. To solve this problem, this paper tries to use the strong nonlinear identification ability of neural network to realize soft sensing of chemical oxygen demand. The experimental results are satisfactory and can be used for reference in actual production.

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