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APPLICATION OF PREDICTION MODEL BASED ON RECURRENT NEURAL NETWORK IN MEMBRANE FLUX

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ABSTRACT

In the process of sewage treatments using membrane bio-reactor, solid large particle suspensions and dissolved substances are continuously deposited on the membrane surface, which is a result of the formation of cake layer. As the thickness of cake layer continues to increase, the flux of the membrane continues to decline, which leads to membrane fouling. The degree of pollution directly determines the efficiency of wasted-water treatment, and so monitoring the membrane flux value to determine the degree of membrane contamination is the common method for the sewage treatment factories. In a certain period of time, using the existing membrane flux data to predict the membrane flux in the future, making the decision to clean or change the membrane at the most appropriate moment will save costs and energy. Recurrent neural networks have features that are sensitive to historical data because of their hidden-layer ring structure, which increases the correlation between data. Combined with the particle swarm optimization, it can obtain the characteristics of the global optimal value and optimize the initial weight of the recurrent neural network, which can reduce the number of iterations and obtain prediction results quickly. Based on this, establishing prediction model using particle swarm optimization to optimize recurrent neural networks to determine membrane fouling in this paper. Simulation results show that the prediction model proposed in this paper is better than recurrent neural network and traditional BP neural network.

KEY WORDS: membrane fouling; recurrent neural network; prediction model; particle swarm optimization;

INTRODUCTION:

Membrane bio-reactor is a new type of wasted-water treatment technology that improves the efficiency of the sewage process through the membrane separation or bio-degradation. Solid large particle suspensions and dissolved substances are continuously deposited on the membrane surface which is a result of cake layer under the action of permeate flow and shear stress. As the cake layer continues to accumulate, the membrane's permeability is reduced, and this process is called membrane fouling. Membrane flux has also become one of the important features of membrane fouling. Eliminating membrane fouling can be done by flushing, increasing pressure and replacing membranes. These methods all need to increase costs and energy consumption. Therefore, justifying the membrane flux size and taking corrective measures can achieve cost savings. PSO algorithm as a global optimization algorithm can quickly get the global optimal value. The generated random value as the initial weight of the recurrent neural network can reduce the number of iterations of the RNN. The RNN has a ring structure, and so becomes sensitive to historical data. Moreover, the relevance of individual data is also improved.

Recurrent Neural network:

With the extensive use of deep learning theory, RNN is widely applied to many fields as a basic network. RNN is derived from Hopfield's network. Because the Hopfield network is difficult to achieve, it is gradually replaced by a feed-forward network. The information transmission of traditional neural networks is accomplished through the direct correlation between layer and layer. BP neural network is a typical feed-forward neural network, which consists of an input layer, a hidden layer, and an output layer. The data from the input layer is calculated through the hidden layer using certain neural weights, and then transfer to the output layer. Moreover, BP neural network is very easy to fall into the local optimum due to the limitation of gradient algorithm. The structure of the BP neural network is shown in Fig1.

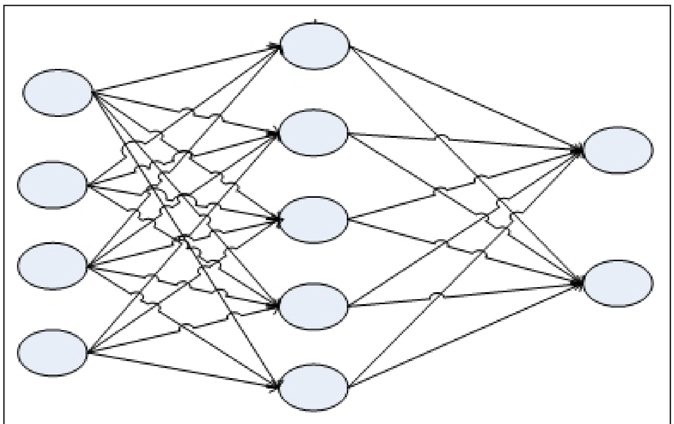

Fig 1

Compared with feed-forward neural network, RNN has more layers for the network structure, because the hidden layer itself through correlated joint form a ring. This is a process that this special structure can save data running at this moment and then combine it to the next moment from the input layer data. So RNN can generate the power of memory for data. RNN can be viewed as a graph model with dynamic depth structure. In other words, with the increase of time, the depth of the network is increasing [4-5]. The RNN structure is shown in Fig 2.

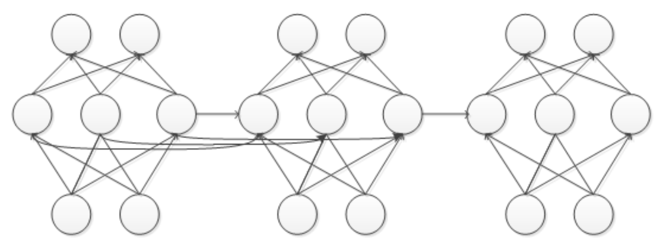

Fig 2. The structure diagram of RNN

For a given input sequence $x=(x_1, x_2,..., x_T)$. The hidden layer sequence calculated by the recurrent neural network is $h=(h_1, h_2,..., h_T)$ .The corresponding output sequence is $y=(y_1, y_2,..., y_T)$.

Its mathematical iterative formula is

$$h_t = \mathrm{sigm}(W^{hx}x_t + W^{hh}h_{t-1} + b_h) \quad (1)$$

$$y_t = W^{yh}h_t + b_o \quad (2)$$

W^{hx} is the weight matrix of the input layer to the hidden layer. W^{hh} is the weight matrix of the hidden layer to the hidden layer. W^{yh} is the weight matrix from the hidden layer to the output layer. b_h and b_o are the bias.

Experimental model:

The data which used in this experiment was from a sewage treatment plant in Shijiazhuang. We totally have 30 groups experimental data where 20 groups act as a training data set and 10 groups act as a test data set. The six main factors affecting membrane fouling are the mixed liquor suspended solids concentration (MLSS), total resistance, operating pressure, chemical oxygen demand (COD), pH and temperature. Based on relevant experience and the limitations of the data obtained, we choose MLSS, total resistance and operating pressure as input parameters for the network. The experimental data sample format is $x=\{16,343.38,2.05\}$. Therefore, in order to ensure the accuracy of the prediction model, we must normalize the data. The network output is membrane flux.

The network depth of the RNN neural network used in this experiment is 2. The number of hidden layer nodes is 9. The number of input layer nodes is 3, and the number of output layer nodes is 1.

Recurrent neural network structure used in the experiment is shown in Fig 3.

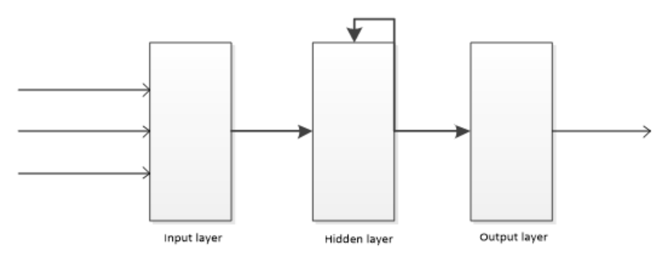

Fig 3. Recursive neural network structure

Particle Swarm Algorithm Process:
The experimental steps of the PSO-Elman algorithm are as follows[8-9].

Step 1. Calculate the nodes' number you need for the network you designed, and then use the real number to code, whose value acts as the weights and thresholds of the network.

Step 2. In the search space which is generated by the particle swarm, and he velocity and position of each particle are randomly got. For the row in the matrix, it represents a weight and threshold distribution of the network.

Step 3. Each individual of the swarm is evaluated by the fitness function. If the current value is better than the best fitness of the record, the algorithm updates the optimal location of the particle. If the fitness of the optimal position in all swarms is better than the fitness of the current recording position, the global optimal position is updated.

Step 4. To repeat Step 2 and Step 3, updating the velocity and position of every particle and then next generation is got.

Step 5. If the program reaches the restrict that is designed before starting the experiment, the algorithm stops. Otherwise jump to Step 3 and Step 4 and then repeat the iterative calculation.

Step 6. The optimal values through the PSO are used to act as the initial weights and thresholds of the RNN.

Step 7. Start the network training.

Model training and prediction:
The prediction model of membrane flux is established by using Matlab. The initial weights of RNN is obtained through the PSO. The parameters of prediction model can be gained by training using the training set.

Experiment 1: Establish a RNN neural network model. The number of training is 1500 and the error is 0.00001. Set up the network according to the parameter setting of 4.1.

Experiment 2: Use the PSO algorithm to arrive at the required 177 optimal values. This value is the initial weight of the RNN neural network. The number of training is 1500 and the error is 0.00001.

Experiment 3: Establish a BP neural network. The number of input layer nodes is 3 (MLSS, total resistance and operating pressure), and the number of output layer nodes is 1 (membrane flux). The number of training is 1500 and the error is 0.00001.

Predictive model results:
The results of the recursive neural network, the recursive neural network after particle swarm optimization and the BP neural network, and the absolute error are shown in the following Table 4-1. And network prediction fit graph is shown in the Fig4.

Table 4-1 Prediction results of neural network model

True value	RNN	Absolute error	PSO-RNN	Absolute error	BP	Absolute error
10.1000	11.9525	0.1834	10.5662	0.0462	10.3645	0.0262
8.4000	12.4435	0.4814	10.2346	0.2184	9.9378	0.1831
14.5000	11.2741	0.2225	14.1803	0.0220	18.1141	0.2492
11.2000	11.7615	0.0501	10.7195	0.0429	10.3664	0.0744
10.5000	12.2381	0.1655	10.9981	0.0474	17.9523	0.7097
11.3000	11.5432	0.0215	11.3178	0.0016	11.3255	0.0023
15.9000	11.1589	0.2982	14.1226	0.1118	15.7687	0.0083
21.6000	11.8877	0.4496	19.7308	0.0865	21.5870	0.0006
9.4000	12.3210	0.3107	10.2733	0.0929	9.9741	0.0611
11.3000	11.5432	0.0215	11.3178	0.0016	11.3255	0.0023
Average value		0.2205		0.0671		0.1317

From the prediction data of each model, it can be known that the relative error of RNN is 0.2205, the relative error of PSO-RNN neural network prediction model is 0.0671, and the prediction model of BP neural network is 0.1317. It can be concluded that the prediction model proposed in this paper is improved compared to the other two models.

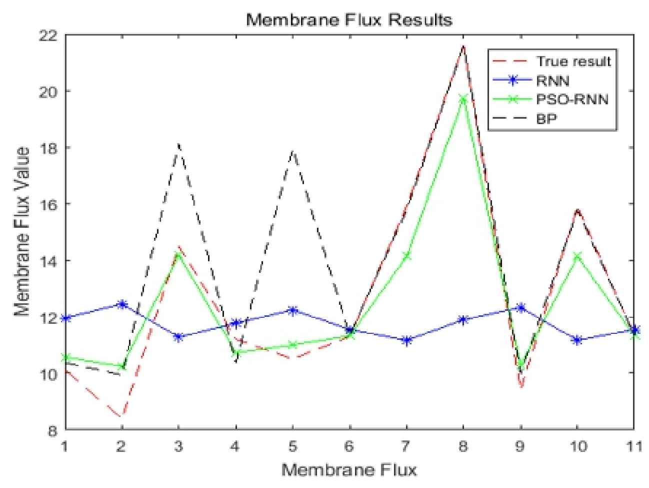

Fig 4. Neural network prediction fit graph

The performance of the experiment was verified as follows, which is shown by Fig5.

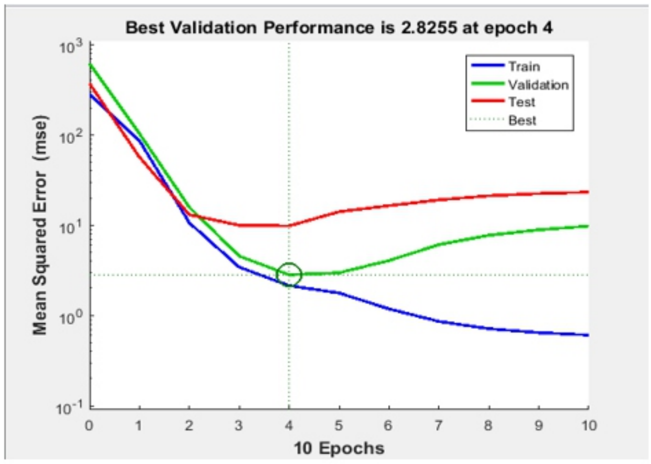

Fig 5. The experiment performance

CONCLUSION:
Membrane fouling reduces the efficiency of sewage treatment, and membrane flux is an important parameter for membrane fouling evaluation. The value which can be obtained by the predict can reflect the extent of usage for the membrane. Then making corresponding decisions, such as cleaning or replacing the membrane to save costs and reduce energy consumption. It can be seen from fig5. Although BP neural network has better results in some areas than other neural network BP neural network and RNN are more easy to be affected by data. Moreover, the PSO-RNN has a better fusion and stability for input data. The improved recurrent neural network proposed in this paper has high prediction accuracy, relatively few iterations and high efficiency. Therefore, it has a reference value for membrane flux prediction to some extent.

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The authors declares that there is no conflict of interest regarding the publication of this paper.

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