Application of MBR Membrane Flux Prediction Based on Elman Neural Network

Chunqing Li and Xinchang Wang

ABSTRACT

In the field of MBR sewage treatment, membrane fouling affects the performance of MBR process. The direct consequence of it is the decline in membrane flux. The prediction of MBR flux is of great significance to the application of MBR. Because the neural network can arbitrarily approximate any continuous function with arbitrary precision, and it can establish a complex nonlinear relationship between input and output model, it is widely used in the field of prediction. We use a feedback type Elman neural network to model the MBR membrane flux, and use this model to predict membrane flux and evaluate the degree of membrane fouling. The results show that the prediction results of membrane flux obtained by Elman neural network prediction model are higher than BP neural network model. The prediction model has a guiding effect on the design and application of MBR system.

INTRODUCTION

Membrane Bio-Reactors is a new type of water treatment technology, which consists of membrane separation unit and biological treatment unit. Membrane fouling affects the performance of the MBR process and therefore results in energy consumption. Membrane flux is an important parameter to characterize membrane fouling. According to the size of membrane flux to determine the extent of membrane fouling, the MBR sewage treatment can maintain a considerable sewage treatment rate.

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Predicting membrane flux by establishing prediction model is an important research field for MBR simulation. The existing MBR membrane flux prediction model is mainly modeled using BP neural network. The Elman neural network used in this paper has the function of associative memory and can guarantee that the network can approximate any continuous function with arbitrary precision. Compared with BP neural network, the prediction accuracy of membrane flux is improved.

ELMAN NEURAL NETWORK STRUCTURE AND LEARNING PRINCIPLE

Elman Neural Network Structure

Elman neural network is a recurrent neural network with local feedback based on the former feedback network[2]. It includes the input layer, the hidden layer, the associative layer and the output layer. The associative layer has the property of storage, and it can save the last operation of the parameters. It is used to feedback to the hidden layer to enhance the ability of the network to process data. As shown in Figure 1, is the Elman neural network structure.

As shown in the figure, $W^{11}$ represents the connection weights from associative to the hidden layer. $W^{12}$ represents the connection weight matrix between the input layer neurons and the hidden layer neurons. $W^{13}$ shows the connection weight matrix between the hidden layer neurons and the output layer neurons. $u(k-1)$ shows the network input. $y(k)$ said the network output. $x_c(k)$ and $x(k)$ ,respectively, say that the carrying layer and the hidden layer of the output. In the carrying layer, $\alpha$ represents the self-linking feedback factor of the neuron in the helper layer.

![Figure 1. Elman neural network structure diagram.](image-url)
ELMAN NEURAL NETWORK LEARNING PROCESS

The mathematical model of the Elman neural network is shown below[3].

\[ x(k) = f(W^{11}x(k) + W^{12}u(k - 1)) \]  \hspace{1cm} (2-1)

\[ x_i(k) = \alpha x_i(k - 1) + x(k - 1) \]  \hspace{1cm} (2-2)

\[ y(k) = g(W^{13}x(k)) \]  \hspace{1cm} (2-3)

Among them, the hidden element neuron excitation function is generally Sigmoid function, with the formula 2-4 said.

\[ f(x) = \frac{1}{1 + e^{-x}} \]  \hspace{1cm} (2-4)

In the Elman neural network, for the sake of convenience, the learning algorithm still uses the gradient descent method similar to the conventional feed-forward neural network to perform the weight correction. The objective function is the error function, and defines the error function as shown below, the desired output of the network is \( y_d(k) \).

ELMAN NEURAL NETWORK ALGORITHM IMPLEMENTATION STEPS

Elman neural network algorithm must first initialize the threshold of each neuron and the weight between the layers; then enter the training sample data, through the formula (2-1, 2-2, 2-3). These calculates the output of the hidden layer, the junction layer, and the output layer neurons, respectively. Calculate the objective function, that is, the error output function composed of the network output and the expected output. The layers of the weight adjustment can be obtained according to the error offset calculation to update network weights. By setting the termination conditions of network training to determine whether the network training is completed, the termination condition can be that the weight updated is below a certain threshold, the error is below a certain threshold or the training reaches the preset number of cycles.
PREDICTION MODEL OF MBR FILM POLLUTION BASED ON ELMAN NEURAL NETWORK

Data Preprocessing

The data obtained after processing through the big data platform is the data to be experimented, which contains six pollution factors: MLSS, operating pressure, total resistance, pH, COD and temperature. The data are different in their dimensions and have more dimensions. They require further processing, including the use of PCA to select the main parameters and normalized operation.

DESIGN OF ELMAN NETWORK STRUCTURE

According to the 3.1, Elman neural network has three input layer nodes. Membrane flux is the desired result, so the output layer node is 1. Selecting the number of hidden layer nodes is more complex. In this paper, Elman neural network with single hidden layer is used. It can use the empirical formula to determine the number of its range of values, the formula is $n_i = \sqrt{n + m + a}$, which can estimate the number of hidden layer nodes. $n_i$ indicates the number of hidden layer nodes. $n$ and $m$ are the number of input and output layer nodes, respectively. $a$ is a constant between 1 and 10. Therefore, the number of hidden nodes is in the 3 to 12. In order to determine the number of hidden nodes, it needs to use the construction method to try to find the best node. By constructing the Elman neural network with different hidden layer nodes, the sample data are used to train and calculate the objective function, finally determine the appropriate number of hidden layer nodes to balance the network prediction accuracy and network convergence speed.

As shown in the following table, after operation, we can obtain the network error with different hidden layer nodes.

From the above results, we can see that when the number of neurons in the hidden layer is 10, the value of the network objective function is the best, that is, the error is the smallest. The three-tier structure of the network has been identified. The amount of information in the neural network exists in the network connection weights, and the connection weights need to be teacher-trained for sample data. Through its continuous optimization and correction, we ultimately get the most appropriate network weights, and network training is completed. Finally, we need to use the test samples to predict and validate the trained network, to calculate the objective function value and analyze the network forecasting effect.
SIMULATION EXPERIMENT AND RESULT ANALYSIS

There are 80 groups of data used in the experiment. After normalization, we randomly selected 70 sets of data as training input samples and the remaining 10 sets of data are used for predictive verification. The effect of the network is analyzed by calculating the error between the network output and the desired output. The experiment is realized by MATLAB. As shown in Figure 2, we use this Elman neural network structure established by MATLAB, and the Figure 3 shows the training performance of the network. We can see that the network tends to be smooth after more than 600 iterations. In the 669th iteration, the mean square error of the network is 0.0019997, reaching a predetermined 0.002. Figure 4 shows the

<table>
<thead>
<tr>
<th>nodes</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network error</td>
<td>0.0774</td>
<td>0.0762</td>
<td>0.0626</td>
<td>0.0679</td>
<td>0.0626</td>
</tr>
<tr>
<td>nodes</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
<td>12</td>
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<tr>
<td>Network error</td>
<td>0.0665</td>
<td>0.0672</td>
<td>0.0509</td>
<td>0.0597</td>
<td>0.0558</td>
</tr>
</tbody>
</table>

Elman neural network prediction fit graph, we can see that the predicted value of the network is basically fitted to the desired output. It is shown that the MBR membrane pollution prediction model established by Elman neural network is basically successful. This design is able to complete the prediction of MBR membrane flux.

Figure 2. Elman neural network structure diagram.
As the Figure 4. said, Elman neural network has a good prediction effect on MBR membrane pollution prediction. It has a higher prediction accuracy, but the individual point of the forecast results is still be a large error. As can be seen from Table 4-1, using the same test sample, the average relative error of the Elman neural network is 0.0586. While the BP neural network has a relative error of 0.0740, the error is reduced. Membrane flux prediction accuracy increases by 26.28%.
TABLE 4-1. COMPARISON OF ELMAN MODEL AND BP MODEL MEMBRANE FLUX.

<table>
<thead>
<tr>
<th>Sample ordinal</th>
<th>Expected value (L / m² h)</th>
<th>Elman Relative error</th>
<th>BP Relative error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>45.5000</td>
<td>0.0050</td>
<td>0.0135</td>
</tr>
<tr>
<td>2</td>
<td>28.9000</td>
<td>0.0073</td>
<td>0.0457</td>
</tr>
<tr>
<td>3</td>
<td>51.8000</td>
<td>0.0557</td>
<td>0.1002</td>
</tr>
<tr>
<td>4</td>
<td>9.4000</td>
<td>0.1888</td>
<td>0.1934</td>
</tr>
<tr>
<td>5</td>
<td>42.2000</td>
<td>0.0100</td>
<td>0.0294</td>
</tr>
<tr>
<td>6</td>
<td>42.3000</td>
<td>0.0812</td>
<td>0.0776</td>
</tr>
<tr>
<td>7</td>
<td>21.7000</td>
<td>0.1690</td>
<td>0.2111</td>
</tr>
<tr>
<td>8</td>
<td>21.6000</td>
<td>0.0360</td>
<td>0.0526</td>
</tr>
<tr>
<td>9</td>
<td>43.4000</td>
<td>0.0146</td>
<td>0.0133</td>
</tr>
<tr>
<td>10</td>
<td>32.5000</td>
<td>0.0183</td>
<td>0.0034</td>
</tr>
<tr>
<td>Average relative error</td>
<td>0.0586</td>
<td>0.0740</td>
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</tr>
</tbody>
</table>

CONCLUSIONS

It can become more time-sensitive for membrane fouling by increasing membrane flux prediction accuracy, and there for that can reduce investment and energy consumption. The existing MBR membrane flux prediction model is mainly established by BP neural network, which is a static pre-feedback neural network, and the prediction results of BP network are not accurate. Compared with BP neural network, Elman neural network is a typical feedback dynamic recursive network. Due to the feedback of the hidden layer nodes, the accuracy and fault tolerance of the network learning are improved for training data. The degree of membrane fouling is represented by membrane flux. The results show that the prediction results of membrane fluxes obtained by using the prediction model are higher than BP neural network model. It can has a significance for the application of membrane bioreactor using the Elman neural network to design the membrane fouling prediction model in the practical application.

ACKNOWLEDGMENT

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REFERENCES