Experimental Study on Dynamic Simulation for Biofouling Resistance Prediction by Least Squares Support Vector Machine

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Abstract

In consideration of influencing factors of biofouling in the cooling water system, a new method of dynamic analog test of cooling water biofouling resistance for shell-tube heat exchanger was presented. The test conditions are as follows: the tube material and process are identical, the water temperature (30°C) and flow rate (0.4m.s⁻¹) both are constant. According to the degree of influence of pH, conductivity, total number of bacteria, dissolved oxygen, TN, NH₃-N on the fouling resistance, this paper selected these water quality factors as the input variable, fouling resistance as the output variable, found a prediction model of cooling water fouling resistance based on Least Squares Support Vector Machine (LS-SVM). Data from another running period was used to verify model prediction accuracy. The mean square error of prediction model is 3.768%; the BP neural network is 9.223%. The results show that the LS-SVM model is pithily, and it has better extensive capability than traditional methods. The new method can be viewed as a new approach to advance the development of cooling water treatment technology and improve the prediction accuracy of the biofouling resistance.

Keywords: biofouling; water quality factors; prediction; least squares support vector machine (LS-SVM)

1. Introduction

The presence of biofouling can reduce device work performance, increase tunnel flow resistance, lower heat-transfer capability and induced surface material corrosion, especially it accompanying grows and acts in synergy with corrosion[¹]. Biofouling and inducing period prediction research, some scholars have made many valuable results. In theory, neural network model and kalman filtering model were compared in Heat exchanger fouling detection methods by Lalot[²], the result shows that neural network model when dealing with fast drifts, and to use the Kalman filter model when dealing with slow drifts. Boffardi and Schweitzer[³] presented a model for predicting the field production tendency of cooling water (fouling or corrosion) by using computer simulation to. Sun Lingfang[⁴] predicted the crystallization fouling by neural networks and intelligent algorithms such as wavelet analysis. In Applications, there are many empirical formula by predicting fouling tendency, including: Langelier index (LSI), Ryznar index (RSI), Puckorius
index (PSI), et al. But these methods are only limited to salt qualitative judgments based on the parameters of pH. Therefore, the study on circulating cooling water of biofouling resistance prediction model and influencing factors are very important to inhibit biofouling and heat exchanger design.

The slime-forming bacteria are selected for research subject in this paper, which is easy to form biofouling in industrial cooling water. Fouling resistance was on-line monitored by the dynamic simulation device. And water quality parameters affected the biofouling forming were off-line detected in the same period. Fouling resistance measured and various water quality parameters were comparative analysis. A prediction model of fouling resistances was established respectively by the least squares support vector machine (LS-SVM) and the BP neural network. The experimental results show that LS-SVM model is higher accuracy.

2. Experimental

A. experimental device

General dynamic simulation monitoring fouling resistance devices (homemade), Orion 5-Star multi-parameter meter kits (USA), UV spectrophotometer.

B. experimental conditions

Bacteria: the slime-forming bacteria obtained from the Songhua River in Jilin City Linjiangmen purified water. Culture medium: peptone 10.0g and NaCl 5.0g dissolved in 1000ml water, adjust the pH to 7.2, steam sterilization: 121±1°C, 15min, the conditions of culture: 29±1°C, 72h. Constant experimental water temperature: 30.0±0.5°C. Flow: 0.40m.s⁻¹. The amount of added bacteria is 1% of water content of dynamic simulation.

C. Measuring principle of biofouling resistance

Tubular heat exchanger inside is usually cooling water and outside is the process media cooled. The heat transfer process of clean tubular heat exchanger is shown in Fig.1 (a), and pollution state is shown in fig.1 (b). Fouling resistance of fluid and heat transfer surface is defined as:

\[ R_f = \frac{1}{U_f} - \frac{1}{U_c} \]  

Where \( R_f \) is fouling resistance under the pollution in m²·k/w; \( U_f \) and \( U_c \) are total heat transfer coefficient of pollution and clean state in w/(m²·k).

![Fig.1 Diagram of water cooler fouling resistance](image)

Related formula of fouling resistance and all thermal resistance is derived according to the definition of Fig.1, and determined as:

\[ R_f = [R_{1f} - R_{ic}] + [R_{2f} - R_{2c}] + R_{f1} + R_{f2} \]  

Where \( R_{1c} \) and \( R_{2c} \) are the convective heat resistance of clean state on both sides; \( R_{1f} \) and \( R_{2f} \) are the convective heat resistance of polluted state on both sides; \( R_{f1} \) and \( R_{f2} \) are fouling layer thermal resistance. \( R_f \) is calculated by the temperature difference of fouling layer on both sides, as shown Eq.(3).
Where $T_{wf}$ is interface temperature between tube wall and fouling layer; $T_s$ is interface temperature between fouling and fluid; $q$ is heat flux. Fouling resistance are calculated by temperature of inflows and outflows, flow rate and tube wall temperature.

3. Features of Cooling Water

Slime-forming bacteria can secrete the colloidal or slime-forming deposition that has a strong adhesion. This substance can adsorb onto the wall, which affects heat transfer and induce surface erosion. Based on the preliminary understanding of the fouling formation and the experimental results, six parameters including pH, conductivity, dissolved oxygen, ammonia- nitrogen, total nitrogen, and total plate count are selected as target parameters to analyze that how the water quality parameters impact the formation of biofouling.

Proton pump, an important component of the biofilm, can discharge protons generate proton motive force during the period of biofouling induction. Proton being squeezed out of the biofilm and have a passive response to proton motive force to regulate cytoplasm pH\cite{3}. Protein has a number of ionizing groups which could affect the conductivity of the solution\cite{6}. The growth rate of the biofouling partly depends on the transport rate of oxygen. So the transport rate of oxygen is an important factor affecting the growth of the biofouling. Due to bacteria growth consume large amounts of nitrogen source material, so causing ammonia nitrogen and total nitrogen decrease. With the bacterial attachment to the wall and bacteria secrete extracellular polymeric substances not only causes reduction of nutrients but also slow down the growth of total plate count.

4. LS-SVM prediction model

A. Algorithm of LS-SVM

SVM is a kind of learning machines based on statistical learning theory. The basic idea of applying SVM to forecasting can be stated briefly as follows: first, map the input vectors into one non-linearly feature space with a higher dimension; then, within the feature space from the first step, seek an optimized linear regression function:

$$f(x) = w^T \cdot \phi(x) + b$$

LS-SVM optimization goals choose quadratic loss function, while the inequality constraints into equality constraints, so optimization problem becomes:

$$\min_{w, b, \xi, \alpha} \frac{1}{2} ||w||^2 + c \sum_{i=1}^{N} \xi_i^2$$

Here, $w$ -weight vector, $b$ -bias term, $c$- penalty factor, $\xi_i$ -loss function.

Constraint condition:

$$f(x_i) = w \cdot \phi(x_i) + b + \xi_i, i = 1, 2, ..., k$$

Lagrange function is constructed as

$$L(a,b,\xi,\alpha) = \frac{1}{2} ||w||^2 + c \sum_{i=1}^{N} \xi_i^2 - \sum_{i=1}^{N} \alpha_i (w \cdot \phi(x_i) + b + \xi_i - f(x_i))$$

Where $\alpha_i$ is Lagrange multipliers, $c > 0$, $a_i$ and $b$ can be calculated based on the Karush–Kuhn–Tucker (KKT) conditions. So LS-SVM model for nonlinear system becomes:

$$f(x) = w \cdot \phi(x) + b = \sum_{i=1}^{N} \alpha_i k(x_i, x) + b, i = 1, 2, ..., k$$

Where $k(x, x_i) = \phi(x)^T \phi(x_i)$ is the kernel function and it satisfies Mercer’s condition.
B. Structure LS-SVM model

The algorithm is a form of SVM based on quadratic loss function, which turns quadratic optimization of SVM into solving linear equations that conducts quickly to solve complex problems and to overcome curse of dimensionality and local minimum.

Based on correlation analysis of microbial growth and water quality parameters, this paper selects six parameters as input that are pH, conductivity, DO, TN, total number of bacteria and NH$_3$-N, and sets fouling resistance as output to establish prediction model by LS-SVM. Factors parameters are as shown in Tab.1. Radial basis function is better than other kernel function on dealing with the nonlinear sample. Complex nonlinear relationship is shown between fouling and water quality parameters. Therefore, this paper selects radial basis function as kernel function and makes use of cross-examination to determine the parameters, regularization parameter $\gamma$ = 698.2939, kernel width Gamma= 1.98451. The above results were compared with regression prediction with single hidden layer BP Neural network (training times is 1000, training targets is 1e$^{-6}$, learning rate is 0.001, hidden layer is 15).

C. Results and discussion

The experimental data in this paper were two operating cycles. The first group was used to establish fouling prediction model. The second group was used to predict inspection. And calculating results were showed in Figure 2.

<table>
<thead>
<tr>
<th></th>
<th>$R_f$ (m$^2$·K/W)</th>
<th>pH</th>
<th>Conductivity (us/cm)</th>
<th>DO (mg/L)</th>
<th>TN (mg/L)</th>
<th>NH$_3$-N (mg/L)</th>
<th>Total bacteria Log(CFU/ml)</th>
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<tbody>
<tr>
<td>The first running cycle</td>
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</table>

The experimental results were compared with regression prediction with single hidden layer BP Neural network (training times is 1000, training targets is 1e$^{-6}$, learning rate is 0.001, hidden layer is 15). The above results were compared with regression prediction with single hidden layer BP Neural network (training times is 1000, training targets is 1e$^{-6}$, learning rate is 0.001, hidden layer is 15).

In order to quantitatively evaluate the accuracy of forecasting methods, mean absolute percentage error (eMAPE) is introduced.

![Fig. 2 Experimental results](image-url)
\[
\varepsilon_{MAPE} = \frac{100\sum_{i=1}^{n}(R_y - \hat{R}_y)/R_y}{n}, n = 8
\]  

Where \( R_y \) is the biofouling value measured, \( \hat{R}_y \) is the predicted value, and \( n \) is the number of data patterns in the data set.

Tab. 2  Error of the two methods

<table>
<thead>
<tr>
<th>Prediction model</th>
<th>( \varepsilon_{MAPE}/% )</th>
</tr>
</thead>
<tbody>
<tr>
<td>LS-SVM</td>
<td>3.768</td>
</tr>
<tr>
<td>BP</td>
<td>9.223</td>
</tr>
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</table>

Tab.2 show that BP neural network model prediction error is larger than LS-SVM. The LS-SVM model not only can predict biofouling and its trend, but also meet the requirement of industry. The results show that LS-SVM model is better than BP neural network in training speed, prediction accuracy and extensive capability.

5. Conclusion

The prediction model of fouling resistances is established by artificial intelligence algorithm (LS-SVM and BP) in the specified temperature and velocity based on analysing dynamic simulation of heat exchanger in mass and heat transfer and fouling forming process, continuous on-line measuring fouling resistances and the change of water parameters. The results show that the LS-SVM is higher precision of prediction than BP neural network.

This paper analyses the influence of water quality parameters to the formation of biofouling and biological growth. The biofouling is predicted by water quality parameters based on LS-SVM, and the mean-square error is less than 5\%, which proved the feasibility that LS-SVM predict biofouling resistances.

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Reference


