Research on the Fouling Prediction of Heat exchanger Based on Wavelet Neural Network

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***Abstract*—The application of wavelet neural network based on Levenberg-Marquardt Optimization to predict heat exchanger fouling is reported in this paper. We construct a 6-6-1 network according to the fouling monitor principle and parameters, the modeling of the wavelet neural network programmed with MATLAB, and trained with Levenberg-Marquarde Optimization algorithm, all training data came from the Automatic Dynamic Simulator of Fouling and input the network after normalized processing and reclassification. Simulations show that the relative error of fouling prediction is less than 0.71 percent, and wavelet neural network can be used to predict heat exchanger fouling, and has the rapid convergence rate and perfect prediction precision, the Levenberg-Marquarde Optimization algorithm can also improve convergence rate of wavelet neural network to a certain extent.**

***Keywords*—fouling prediction, wavelet neural network, Levenberg-Marquardt Optimization**

I. INTRODUCTION

Fouling generally exists in the nature and all kinds of industry process, especially in the heat transfer process. The harm is very huge, only in national industry, it causes losses to reach as high as the industrial production resultant 0.3 percent[1]. So many researches have been done in the past years, however, the formation of fouling is a complicated physical and chemical process, which is influenced by many factors, and progress in the scaling prediction isn't outstanding based on the exact and sufficient understanding of formation mechanics. Neural network has great capabilities in self-learning, parallel processing and solving nonlinear problem, so prediction indirectly with neural network is the new way which we could take. Qi Lianhui and Zhang Jiahua[2] created a BP network which used in water quality forecast and fouling judgment. Fu Yarong, Wang Kaibing, et al[3] adapted BP network for fouling forecast and judgment in the oil field ground collection pipeline, they avoid embarking from the fouling influencing factor and the difficulty in construction mathematical model, then the forecasting result and the actual result have obtained good tallying in certain precision scope. In view of power plant coal boiler's fouling, Enrique Teruel, Cristobal Cortes, etc[4] adapted BP network for on-line fouling monitor and forecast to make certain achievements as well. However, the models that using the BP network to forecast fouling have some defects such as lower precision, slower network convergence speed, unstable performance and so on. In view of the good time-frequency localized property of the wavelet analysis, we construct the wavelet neural network (WNN) and make an attempt to predict the heat exchanger fouling with it.

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II. THE BASIC PRINCIPLE OF WAVELET NEURAL NETWORK

A. *Structure of wavelet neural network*

In 1992, Zhang Qinhua[5], who worked in IRISA, a famous Gallo information science institution, first put forward a new neural network named wavelet neural network, which was combined by both wavelet transformation and common neural network. This new kind of network has many merits such as high speed of convergence, sufficient theory rules of the network's establishment. Nowadays, two kinds of adapting wavelet neural network, put forward by Szu and Telfer, based on continuous wavelet transformation, are widely used, and with the common three layers structure of MISO neutral network.

Wavelet functions $\psi(x)$ were chosen to instead of hidden layer node functions, and the function which can meet the following qualification is called wavelet function:

$$C_\Psi = \int_{-\infty}^{+\infty} \frac{\left|\hat{\psi}(w)\right|^2}{|w|} dw < \infty \tag{1}$$

$\psi(x) \in L^2(R)$, and $\hat{\psi}(w)$ is $\psi(x)'s$ Fourier transformation. If we add continuous translation parameters $a_k \in R$ and scale parameters $b_k \in R$ to wavelet function, we can get a group of wavelet function with common features:

$$\psi^k{}_{a,b}(x) = \frac{1}{\sqrt{|a_k|}}\psi(\frac{x-b_k}{a_k}) \quad (2)$$

For any function, $f(x) \in L^2(R)$, it's wavelet transformation is as follows:

$$W_f(a,b) = |a|^{-1/2}\int_{-\infty}^{+\infty} f(x)\psi^*(\frac{x-b_k}{a_k})dx \quad (3)$$

Where, ψ^* is the complex conjugate function of ψ' . After a serial of deducing, we can get:

$$f(x) = \sum w_k \psi^*(\frac{x-b_k}{a_k}) \quad (4)$$

Then $\psi^*\left(x-b_k \big/ a_k\right)$ was chosen to be as the function of hidden layer node, and if a_k and b_k is given, then the function of hidden nodes can be confirmed. So WNN is regarded as a modified form of RBF network.

B. Levenberg-Marquardt algorithm

Many algorithms can be chosen to adjust the parameters of wavelet network, in this paper, Levenberg-Marquarde Optimization is taken, which contains merits of both steepest descent method and Newton's method. Compared with other algorithms, it has better stability of network and higher speed of convergence, and so on.

Given *n* is the number of input nodes, *m* is connotative nodes, *N* is output nodes, and *P* is the number of the sample. If input of the *p*th sample is $X^p = \{x_j^p\}, (j = 1, 2, ..., n)$, the output of network is $Y^p = \{y_i^p\}, (i = 1, 2, ...N)$, and the actual value is $D^p = \{D_i^p\}, (p = 1, 2, ...P)$. If w_{kj} is the joint weight value from the *j*th input node to the *k*th hidden node, the output of the *k*th hidden node is $\psi((\sum_{j=1}^{n} w_{kj}x_j^p - b_k)/a_k)$. And if w_{ik} is the joint weight value from the *i*th output node to the *k*th hidden node, the current network output is:

$$Y_i^p = \sum_{k=1}^{m} w_{ik}\psi(\frac{\sum_{j=1}^{n} w_{kj}x_j^p - b_k}{a_k}) \quad (5)$$

And the error function of network is:

$$E = \frac{1}{2}\sum_{p=1}^{P}\sum_{i=1}^{N}(Y_i^p - D_i^p)^2 = \frac{1}{2}\sum_{i=1}^{N} e^2(x) \quad (6)$$

or

$$E = \frac{1}{2}\sum_{i=1}^{N} e^2(x) = \frac{1}{2}e^T(x) \bullet e(x) \quad (7)$$

Where x is a vector containing w_{kj}, w_{ik}, b_k, and a_k , and it can be denoted as:

$$x = (w_{kj}, w_{ik}, b_k, a_k) \quad (8)$$

According to the L-M algorithm, the parameters of network can be adjusted to the following forms:

$$\nabla E(x) = \sum_{i=1}^{N} e_i(x)\frac{\partial e_i(x)}{\partial x} = J^T(x)e(x) \quad (9)$$

$$\Delta x = -\left[J^T(x)J(x) + \mu I\right]^{-1} + J(x)e(x) \quad (10)$$

$$x^{k+1} = x^k + \Delta x^k \quad (11)$$

Where $J(x)$ is a Jacobin matrix, $\mu \in R$ is a positive constant, and I is an identity matrix.

III. FOULING PREDICTION BASED ON WAVELET NEURAL NETWORK

A. Data Acquisition

All of experiment data were collected from the Automatic Dynamic Simulator of Fouling (ADSF)[6] illustrated in Fig 1. It consisted of three parts: double tube simulation heat exchanger, water circulation system and monitoring equipment. In the fouling experiments, one tube of heat exchanger worked as a testing loop through which working fluid treated with ion-rod water treater flowed(we can call it "clean tube"). The other worked as reference loop in the same working conditions except for non-treated fluid flowing (we can call it "fouling tube"). Measured signals were gathered by data acquisition system and sent to computer. With the monitor model, fouling resistance and the anti-fouling efficiency could be calculated and displayed on-line. A more detailed description about ADSF can be found in [7].

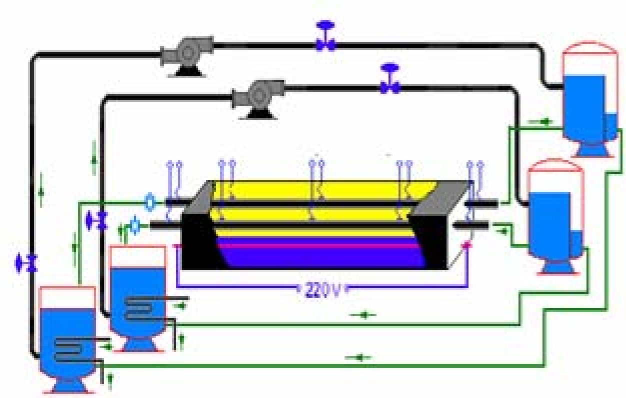

Fig 1. Schematic plan of ADSF

In this paper, "fouling tube" is the prediction research object. We select the fouling thermal resistance as a way to detect the fouling degree, and six measuring parameters influenced fouling, i.e. input temperature of working fluid, output temperature of working fluid, flow velocity of working fluid and three temperatures of heat exchanger tube wall, form as the input of WNN. So the structure of this wavelet neural network used in this paper is net 6-6-1, and collected 228 groups of data form this experiment to study.

B. Data Pre-processing

In order to accelerate the rate of convergence and avoid the possibility of coupling among different inputs, it is necessary to do this pre-processing work before we input these data to the network.

First, we should pick out the data with distinct errors. According to experience, fouling thermal resistance increases as time goes by. So, if the data we collected suddenly increase or decrease, we should rejected those data point. In the end we have screened out 160 groups of samples.

Secondly, these data should be normalized, and all data would be transformed to the range [-1,1]. There are two methods we can use for normalization: One is that all input data stand in the same order of magnitude (like this paper). All the data should be normalized according to the following formula. But if they stand in different orders, we can not operate like this, details refer to literature [8].

$$x_{\mathrm{mid}} = (x_{\max} + x_{\min})/2 \tag{12}$$

$$\overline{x_i} = (x_i - x_{\mathrm{mid}})/0.5(x_{\max} - x_{\min}) \tag{13}$$

At last, according to ergodicity principle, first we divide these 160 groups of data samples into 2 parts: 80 odd groups and 80 even groups, and then we divide the even group mentioned above into another 2 groups: 40 odd groups and 40 even groups. In order to cover all kinds of experiment conditions as many as possible, we select the odd groups in the first division and the even groups in the second division to compose learning samples. And the reminders were simulation samples.

C. Modeling and Training

As the establishment of wavelet network is not provided by MATLAB neutral network toolbox, we use MATLAB to establish the wavelet network by programming.

At the beginning, initial parameters of network should be set, such as numbers of connotative nodes, joint weight value w_{ik} and w_{kj} , scale parameter b_k , translation parameter a_k .By experience, we set the initial number of connotative nodes as 6, but in fact we didn't find it affect network performance remarkably. And we set the initial value b_k , a_k and the network joint weight value w_{ik} , w_{kj} in the range [0,1], which obey the normal distribution.

Secondly, setting the performance index of network as follows: the max number of learning is 1000, and the error should be controlled in range of [-0.1%, 0.1%].

At last, beginning to learn according to the following steps after we have set initial learning parameters: β (mostly is 10), μ (mostly is 0.01).

(1)Setting k=0 and $\mu = \mu_0$;

(2)Calculate the output of network, error function $E^k(x)$ and Jacobin matrix $J^k(x)$;

(3)Calculate the adjusting value Δx^k of parameters of network in terms of formula (2);

(4) If $E^k(x)<\varepsilon$, turn to step (5). Else set k=k+1, update w_{ik} , w_{kj} , b_k , a_k and set $x^{k+1} = x^k + \Delta x^k$, recalculate the error parameter $E^{k+1}(x)$ by x^{k+1} . If $E^{k+1}(x) < E^k(x)$, then x^{k+1} is accepted, $\mu = \mu / \beta$ and turn to step (2). Else the updating x^k will be rejected, $x^{k+1} = x^k$ and let $\mu = \mu\beta$, then turn to step (3);

(5) End.

Network is established and learned by the steps above. And the errors will gradually achieve the aim index. After 50 times of learning, the network gets to the convergence (see Fig.2). As shown in the Fig.2, during the process of the convergence of network, there is no evident vibration. It shows a favorable convergence performance of WNN.

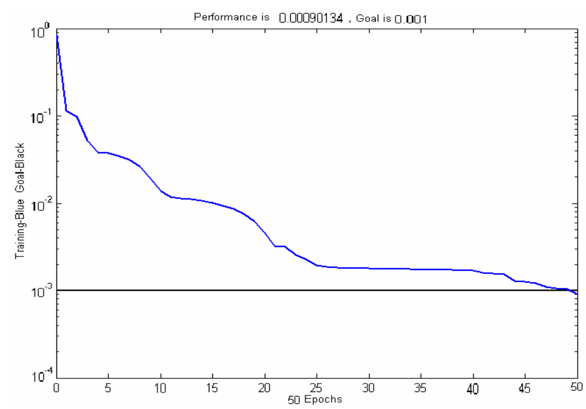

Fig 2. Convergence figure of error function

D. Results and Discussion

Input the 40 groups of simulation samples to the network, and use wavelet network with the proper error qualifications to simulate, and then compared with the measure data, we can get the absolute error and relative error between the prediction data and the measure data, shown as Table 1.

Table 1. Error between the prediction data and the measure data

Normalized measure value (m^2K/kJ)	Normalized prediction value (m^2K/kJ)	Absolute error (m^2K/kJ)	Relative error (%)
-0.75453	-0.75416	0.00037	0. 04
0.87226	0.87262	0.00036	0. 04
-0.19216	-0.1919	0.00026	0. 14
-0.44773	-0.4483	-0.00057	0. 13
0.44014	0.4394	-0.00074	0. 16

0.58429	0.58533	0.00104	0.18
0.36002	0.36259	0.00257	0.71
0.12034	0.12046	0.00012	0. 01
0.61228	0.61366	0.00138	0.23

According to Fig. 2 and table 1, we can conclude that wavelet network has satisfied rapidity of convergence and accuracy of prediction and the relative error is less than 0.71 percent, i.e., the wavelet neural network can be used to predict heat exchanger fouling. But this does not mean that if we choose L-M algorithm, the improvement of performance of WNN speed of convergence will be achieved every times. The reason is that most wavelet functions in whole number field have many zero points, which means the network will not be convergent at that time[9]. If the right initial parameters were chosen, the performance of the network will be promoted remarkably by using LM algorithm.

IV. CONCLUSION

The result shows that the wavelet neural network can be used to predict heat exchanger fouling, and has the rapid convergence rate and satisfied prediction precision, the Levenberg-Marquarde Optimization algorithm can also improve convergence rate of wavelet neural network to a certain extent. The research provided a new method for fouling prediction.

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