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Prediction of Fouling in Condenser Based on Fuzzy Stage Identification and Chebyshev Neural Network

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The prediction of fouling in condenser is heavily influenced by the periodic fouling process and dynamics change of the operational parameters, to deal with this problem, a novel approach based on fuzzy stage identification and Chebyshev neural network is proposed. In the approach, the overall fouling is separated into hard fouling and soft fouling, the variation trends of these two kinds of fouling are approximated by using Chebyshev neural network, respectively, in order to make the prediction model more accurate and robust, a fuzzy stage identification method and adaptive algorithm considering external disturbance are introduced, based on the approach, a prediction model is constructed and experiment on an actual condenser is carried out, the results show the proposed approach is more effective than asymptotic fouling model and adaptive parameter optimization prediction model.

Keywords: Fouling prediction, condenser, fuzzy stage identification, Chebyshev neural network, adaptive algorithm

1. INTRODUCTION

CONDENSER IS one kind of large scale heat exchanger widely used in the power, chemistry, machinery and other industry, it plays the role of condensing vapor into water and improves the efficiency of thermal cycle of the turbo-generator unit, while the condenser is in operation, the cooling water is sent to pass through the thermal tubes of the condenser, this leads to the production of fouling due to the impurity of the cooling water, fouling is a major problem for condenser, it diminishes the heat transfer and leads to the increase of the condensation pressure, thus reduces the efficiency of the thermal cycle, in order to make optimal operation and cleaning schedule of the condenser, it is necessary to predict fouling precisely.

Empirical model [1]-[2], probability model [3]-[4] are traditional fouling prediction model, empirical model, only considering an empirical coefficient parameter which isn't related to the time, to measure the impact of the fouling, can not satisfy the actual needs, not to mention determining the cleaning schedule for the equipments [5], probability model is suitable for simple heat exchanger, concerning to complicated heat exchanger such as condenser, the prediction accuracy will be greatly affected by time-varying parameters and big disturbance in the operating process of the condenser [6].

In recent years, artificial intelligence is reported to use in fouling prediction [7], Enrique Teruel adopts BP network for monitoring and predicting fouling in coal-fired utility boilers [8], Lingfang Sun predicts fouling of heat exchanger based on relevance vector machine [9], Wallhäuer proposes a new approach by using acoustic properties combined with artificial neural network to determine presence of dairy fouling [10], Nebot studies a fuzzy model to predict fouling deposition in condenser considering the effect of water velocity and tube material [11], Zhang Ying proposes locally weighted partial least squares regression algorithm and constructs the adaptive parameter optimization model to achieve fouling prediction in condenser [12], all these methods get better results than traditional empirical model and probability model, but the prediction accuracy still need be improved because they don't concern the periodic fouling process in condenser, which actually has a great influences on the accuracy of fouling prediction.

In this paper, a new approach based on fuzzy stage identification and Chebyshev neural network is proposed to predict fouling in condenser, for the purpose of getting rid of the influence caused by the periodic fouling process and dynamics change of the operational parameters, based on the approach, prediction model is constructed and experiment on an actual condenser is carried out to prove the effectiveness of the proposed approach.

2. THE ANALYSIS OF FOULING PROCESS

The fouling process of condenser is periodic, with the running of condenser, fouling grows in the tubes of condenser. Fouling has two types: one is loose fouling caused by microbial deposition and sedimentation of suspended solid in the cooling water, another is crystallized fouling caused by the crystallization of inorganic salt, actually, fouling is a mixture of both types, when fouling go up to a certain value, the condenser should be cleaned by sponge ball system, which can effectively remove loose fouling in the heating exchanger but can not clear the crystallized fouling thoroughly, therefore, after sponge ball cleaning, the fouling factor is not zero due to the existence of residual fouling which will increase with the time, when the residual fouling is greater than a critical value, the heat exchange performance of the condenser will decrease sharply and sponge ball cleaning will fail, thus, chemical cleaning should be used to make fouling factor falling to zero, so the scaling of condenser is periodic, and the fouling process repeats as follows.

Scaling→Sponge ball cleaning→Scaling→Chemical cleaning→Scaling

The periodic process of fouling in condenser is shown in Fig.1.

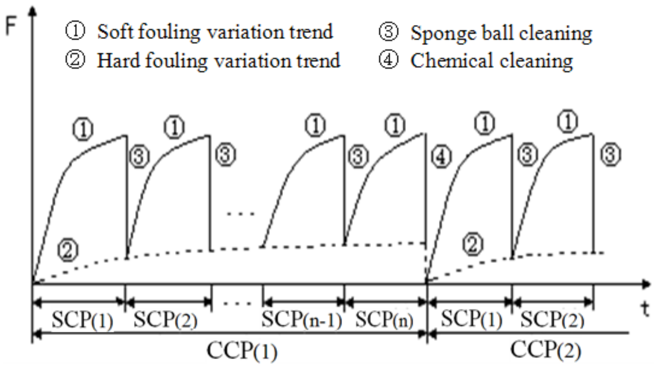

Fig.1. The periodic process of fouling in condenser

where, SCP is the sponge ball cleaning period, CCP is the chemical cleaning period, from the Fig.1., it can be seen the accuracy of fouling prediction precision is heavily influenced by residual fouling, to deal with it, we separate the overall fouling into two parts: hard fouling which is actually the residual fouling and soft fouling, expressed as follows

$$F(t) = F_{fs}(t) + F_{fh}(t) \tag{1}$$

where, F is the overall Fouling factor, F_{fh} is hard fouling factor, F_{fs} is soft fouling factor, Fouling factor is defined as

$$F = \frac{k_i - k_p}{k_i} \tag{2}$$

where k_i is the idea heat transfer coefficient of a clean condenser, k_p is actual heat transfer coefficient of a fouling condenser, so, the prediction of overall fouling turns into the prediction of hard fouling and soft fouling, in this paper, we use Chebyshev neural network to build hard fouling and soft fouling prediction model.

Fouling process mainly consists of four continuous stages which is called starting stage, adhering stage, aging stage and erosion stage, each stage has different characteristics, in order to make precise soft fouling prediction model, it is necessary to identify these four fouling stages.

3. Fouling prediction model

A. *The identification of fouling stage based on fuzzy logic*

Fuzzy model is adopted to identify the four stages of soft fouling, fuzzy variables of fouling factor F are defined in a set {F_1,F_2,F_3}, fuzzy variables of fouling factor change rate FC are defined in another set {FC_1,FC_2,FC_3}. The range of F and FC are defined as follows.

$0 < F \leq 0.05 \in F_1$; $0.05 < F \leq 0.38 \in F_2$; $0.38 < F \in F_3$

$FC \leq 0 \in FC_1$; $0 < FC \leq 0.36 \in FC_2$; $0.36 < FC \in FC_3$

fuzzy variables of stage S are defined in a set { $F_1^{'}, F_2^{'}, F_3^{'}, F_4^{'}$ },where $F_1^{'}, F_2^{'}, F_3^{'}, F_4^{'}$ are the expressions of starting stage, adhering stage, aging stage and erosion stage respectively.

According to fouling characteristics and experience, we get the following rules:

R1: If F is F_1 and FC is FC_2 , Then S= $F_1^{'}$

R2: If F is F_3 and FC is FC_2 , Then S= $F_3^{'}$

R3: If F is F_2 and FC is FC_3 , Then S= $F_2^{'}$

R4: If (F is F_1 and FC is FC_3) or (F is F_2 and FC is FC_2) or (F is F_3 and FC is FC_3), Then S= $F_4^{'}$

R5: $\forall$ F , if FC is FC_1 , Then S= $F_4^{'}$

B. *Chebyshev neural network*

Chebyshev neural network is employed to approximate the soft fouling and hard fouling, due to its excellent generalization performance and dynamic prediction ability [13]-[14], the structure is shown in Fig.2.

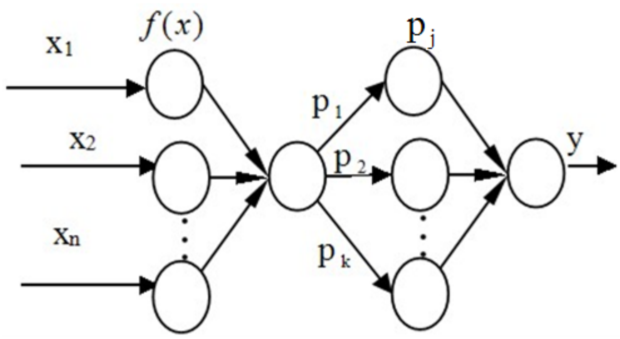

Fig.2. The structure of Chebyshev neural network

Chebyshev neural network is a multi input single output system, all the neural-weights between input-layer and hidden-layer are set to be 1, and the neural-weights between hidden-layer and output-layer are W_j , $(j = 0,1,2,L,n\text{-}1)$, where n is the number of hidden-layer neurons, $f(x)$ is chosen as

$$f(x_i) = 1/(1+e^{-x_i}) \tag{3}$$

p_j is Chebyshev orthogonal polynomial, where,

$$p_1 = 1, p_2 = X, p_j = 2Xp_{j-1} - p_{j-2}, j = 3,4,\cdots,n \tag{4}$$

where, $X = 1/(1+e^{-\sigma \sum f(x_i)})$, σ is a variable parameter which used to change the inclination degree of X .

Input and output sample pairs are defined as $\{(x_l, f(x_l)\}_{l=0}^{m-1}$, m is sample size, the weight vector W from hidden layer to output layer, the output vector of sample $f(x)$ and the practical output vector of the neural network Y are defined as respectively as follows.

$$W=\begin{bmatrix}W_0 & W_1 & \cdots & W_{n-1}\end{bmatrix}^T \in R^{n\times 1} \tag{5}$$

$$f(x)=\begin{bmatrix}f(x_0) & f(x_1) & \cdots & f(x_{m-1})\end{bmatrix}^T \in R^{m\times 1} \tag{6}$$

$$Y=\begin{bmatrix}Y_0 & Y_1 & \cdots & Y_{m-1}\end{bmatrix}^T \in R^{m\times 1} \tag{7}$$

After integration, the input sample motivated matrix of the Chebyshev neural network can be defined as

$$A=\begin{bmatrix} p_0(x_0) & p_1(x_0) & \cdots & p_{n-1}(x_0) \\ p_0(x_1) & p_1(x_1) & \cdots & p_{n-1}(x_1) \\ \vdots & \vdots & \ddots & \vdots \\ p_0(x_{m-1}) & p_1(x_{m-1}) & \cdots & p_{n-1}(x_{m-1}) \end{bmatrix} \in R^{m\times n} \tag{8}$$

The practical output vector is expressed as

$$Y=AW \tag{9}$$

Define error as: $E_l = f(x_l)-Y_l,(l=1,2,\cdots,m)$
where, x_l is desired input, $f(x_l)$ and Y_l are defined respectively as desire output and neural network practical output, m is the number of learning sample.

Error vector is:

$$E=[E_0 \quad E_1 \quad \cdots \quad E_{m-1}]^T = f(x)-Y = f(x)-AW \tag{10}$$

The error performance index can be designed as $\varepsilon = \sum_{l=0}^{m-1} e_l^2$ under scalar meaning, by this way and the two norm definition, we can put forward the following formula

$$\varepsilon=\sum_{l=0}^{m-1}e_l^2=\sum_{l=0}^{m-1}(f(x_l)-\sum_{k=0}^{n-1}W_kP_k(x_l))^2=\left\|f(x)-AW\right\|_2^2 \tag{11}$$

ideally, ε should be zero for $AW=f(x)$, whether $AW=f(x)$ are compatible equations or not, the weight solution of the neural network approximation problem can be expressed as

$$W=A^+f(x) \tag{12}$$

where A^+ is inverse matrix.

In order to determine optimal network structure quickly and effectively, an adaptive algorithm is proposed, which can not only minimize the number of hidden neurons, but also meet the target accuracy.

The adaptive algorithm is described as follows, where m is the number of samples, N is the number of the optimal output hidden neurons, and E >0 is the target precision requirement under the meaning of mean square error, set initial j to be 1.

Step1. Constraint the neuron number n at a certain interval $[p,q]=[2^{j-1},2^j]$, set n=q, and compute the weights and corresponding performance index ε according to the mathematical expression $W=A^+f(x)$.

Step2. If (ε /m)> E , set j=j+1, return to step 1; otherwise, jump to step 3;

Step3. Employ exponential-growth search strategy to calculate the optimal number N, the corresponding weights and error at a certain interval $[p,q]=[2^{j-1}, 2^j]$.

C. The improvement of adaptive algorithm considering external disturbance

The practical system is always running under big disturbance such as a sudden change of the cooling water velocity and load of the generator unit, this disturbance affects the prediction accuracy of Chebyshev neural network greatly, so it is necessary to find method to overcome the external disturbance.

If there is no sudden change of cooling water velocity and load of the generator unit, the fouling factor will not change quickly, based on this, we can set the following thresholds of fouling factor.

ΔF^+: positive maximum change of fouling factor;

ΔF^-: negative maximum change of fouling factor;

F^+: maximum value of fouling factor;

F^-: minimum value of fouling factor;

When fouling factor is too large under normal condition, the prediction value will be processed according to the following rules:

If $\Delta F(k)\ge \Delta F^+$, then $\Delta F(k)=\Delta F^+$;

If $\Delta F(k)\le \Delta F^-$, then $\Delta F(k)=\Delta F^-$;

If $F(k-1)+\Delta F(k)\ge F^+$, then $\Delta F(k)=F^+-F(k-1)$;

If $F(k-1)+\Delta F(k)\le F^-$, then $\Delta F(k)=F^--F(k-1)$.

$\Delta F(k)$ is the value of the backward difference fouling factor in the continuous time sequence, $F(k)$ is the present value of the fouling factor, $F(k-1)$ is the previous value of the fouling factor.

when the cooling water velocity has a big sudden increase, the fouling factor will decrease sharply, to modify the prediction value, the following rules are introduced.

Rule 1: If the cooling water velocity is equal to or greater than a limited value V_{max}, then fouling factor turns into $F(k)=F(k-1)-C$, where C is a constant value and determined by experiment results.

Rule 2: If cooling water velocity is less than the limited value V_{max}, the fouling factor will be processed the same as the condition that cooling water velocity or load has no sudden change.

Combining these rules with the adaptive algorithm, the prediction accuracy can be improved theoretically.

D. *Fouling prediction model*

The structure of fouling prediction model is shown in Fig.3.

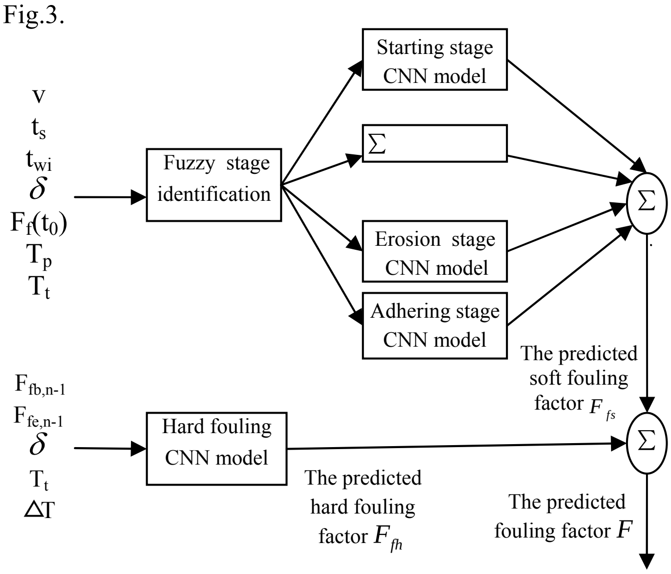

Fig.3. The structure of fouling prediction model

where, CNN is the abbreviation of Chebyshev neural network, v is velocity of cooling water, t_s is condensation temperature, t_{wi} is inlet temperature of cooling water, δ is the cooling water turbidity, $F_f(t_0)$ is the initial fouling factor, T_p is time domain of prediction, $F_{fb,n-1}$ is fouling factor at the beginning of previous sponge ball cleaning period, $F_{fe,n-1}$ is fouling factor at the end of previous sponge ball cleaning period, T_t is the accumulative running time of condenser, and ΔT is condenser running time of previous sponge ball cleaning period, all these parameters are measurable and processed by data acquisition system.

In order to make the fouling prediction more accurate, five CNNs are employed, among them, one is used for hard fouling prediction, the rest four are used to modeling starting stage, adhering stage, aging stage and erosion stage respectively.

4. RESULT AND DISCUSSION

In this section, an experiment on N-3500-2 steam condenser in Xiangtan power plant is conducted to prove the effectiveness of the proposed approach. The experiment system consists of the following main components: PC-type computer with a monitor, data acquisition system and sensors for operation condition parameters measuring.

The data used for prediction model come from various operation conditions. A training set containing 840 data is chosen for Chebyshev neural network modeling, another set containing 260 data is used for model verification.

Fig.4. is stage identification result by fuzzy logic, it can be seen that fouling factor of starting stage, adhering stage and aging stage is respectively at the interval of [0, 0.05], [0.05, 0.38] and [0.38, 0.4], the fouling factor in starting stage grows slowly, increases stably in adhering stage, and presents a saturated state in aging stage. Because the running time of the condenser is only 4 hours in this figure, the erosion stage appears not so obviously.

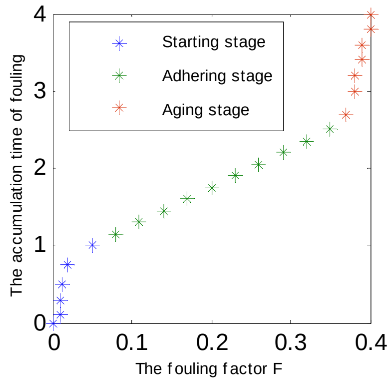

Fig.4. The stage identification based on fuzzy logic

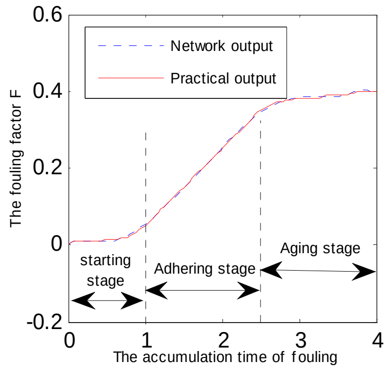

Fig.5. The soft fouling prediction result

Fig.5. is the comparison between the soft fouling prediction value made by proposed model and practical value under the condition of no hard fouling (the condenser has been cleaned by chemical method, so the initial value of hard fouling is zero), from the result, it can be seen the output of the Chebyshev neural network is almost the same as practical one, which proves the correctness of the fuzzy stage identification and effectiveness of neural network approximation.

Fig.6. is the simulation experiment results of hard fouling factor prediction and the overall fouling factor prediction, from the graph, it can be seen that the proposed model approximates the actual fouling variation perfectly.

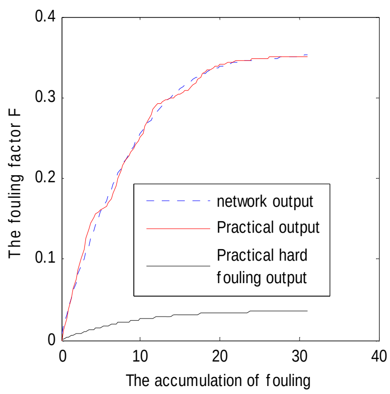

Fig.6. Prediction results of hard fouling and overall fouling

Fig.7. is the output of the proposed model under big external disturbance, at 10th hour, there is 10m/s increase of cooling water velocity and lasts for 1.5 hour, it can be seen that the output of the predictive model traces the practical value accurately, which reflecting the effectiveness of the proposed adaptive anti-disturbance algorithm.

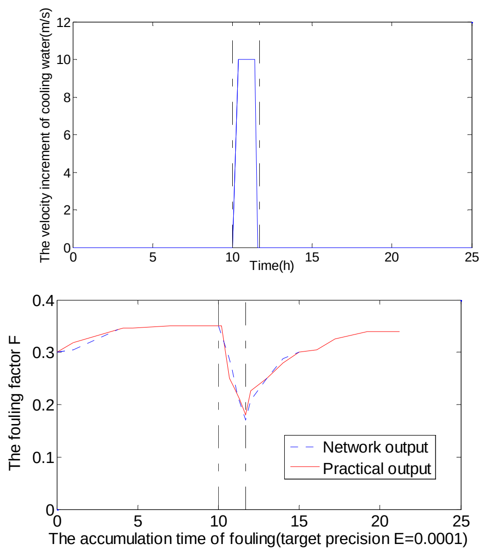

Fig.7. The output of the proposed prediction model under big external disturbance

Fig.8. and Table 1. are the comparison of asymptotic prediction model [15], adaptive parameter optimization prediction model [16] and proposed predictive model. From the figure and table, it can be concluded that proposed prediction model is more accurate than asymptotic prediction model and adaptive parameter optimization prediction model.

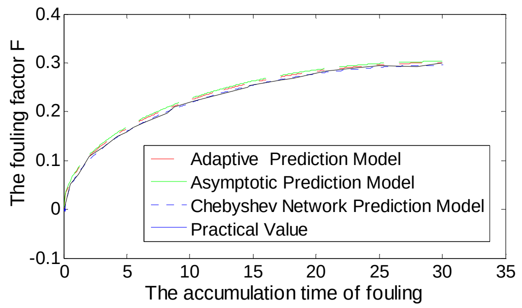

Fig.8. The comparison of the prediction models

Table 1. The comparison of prediction accuracy between proposed model and other ones (%)

	Adaptive prediction model	**Asymptotic predictive model**	**Proposed model**
Fouling prediction accuracy	90.6	87.2	95.5

5. CONCLUSION

A new approach based on fuzzy stage identification and Chebyshev neural network to predict fouling in condenser is proposed in this paper, for the purpose of getting rid of the influence caused by the periodic fouling process and dynamics change of the parameters, based on the approach, prediction model is constructed and experiment on an actual condenser is carried out, the results show the proposed approach is more effective than asymptotic fouling model and adaptive parameter optimization prediction model.

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