Application of GA Based Fuzzy Neural Networks for Measuring Fouling in Condenser

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Abstract **- A novel approach for online measurement of fouling in condenser is proposed in this paper. In the approach, terminal temperature difference is chosen to reflect fouling state, B-spline membership fuzzy neural network is employed to approximate off-design condition terminal temperature difference, which separates the influence imposed by fouling on terminal temperature difference from other factors. Since the selection of the weighting factors, the knot positions and the control points of the B-spline membership fuzzy-neural networks is crucial to obtaining good approximation for complex nonlinear systems, a genetic algorithm with an efficient search strategy is developed to optimize these variables. Based on the approach, an experimental system is developed and experiment on an actual condenser is carried out. The results show the approach measures the fouling correctly, and is more effective than thermal resistance method or heat transfer coefficient method under the condition of blocked tubes or excessive amount of air in condenser.**

Index Terms - Novel approach; Fouling measurement; Fuzzy neural network; B-spline membership functions; Genetic algorithm

I. INTRODUCTION

A condenser is a kind of large scale heat exchanger used in power plant and chemistry plant. It plays the role of condensing the vapour into water and improves the efficiency of the thermal cycle of the turbo-generator unit. When 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 condensers, it diminishes the heat transfer and leads to the increase of the condensation pressure, thus reducing the efficiency of the cycle. So, the condenser needs cleaning. In order to make optimal cleaning schedule, it is necessary to measure fouling precisely.

Up to now, Thermal resistance method and heat transfer coefficient method are the most common used methods for online measurement of fouling[1],[2], but they are not always effective over the full range of operating conditions. Thermal resistance method can not achieve precise measurement under the condition of blocked tubes and heat transfer coefficient method is not accurate when excessive amount of air in condenser occurs [3],[4].

In this paper, a novel approach based on fuzzy neural network for online measurement of fouling in condenser is proposed. In the approach, terminal temperature difference is chosen to reflect fouling state, B-spline membership fuzzy neural network is employed to approximate off-design condition terminal temperature difference, which separates the influence imposed by fouling on terminal temperature difference from other factors. In order to improve the approximation of fuzzy neural network, genetic algorithm (GA) is proposed to optimize network parameters. Based on the approach, an experimental system is developed and experiment on an actual steam condenser under various conditions is carried out. The results show the approach is more effective than thermal resistance method or heat transfer coefficient method.

II. MEASURE APPROACH

Terminal temperature difference is chosen to reflect fouling state, it is defined as

$$\delta_t = t_s - t_{wo} \tag{1}$$

where, δ_t is terminal temperature difference, t_s is condensation temperature, t_{wo} is outlet cooling water temperature. Analyzing the process of heat transfer, δ_t can be expressed as

$$\delta_t = f(D_c, D_w, C, \varepsilon, t_{wi}) \tag{2}$$

where, D_c is flow volume of vapour, D_w is flow volume of cooling water, C is fouling factor, ε is the amount of non-condensible gas (air) in condenser and t_{wi} is inlet cooling water temperature.

From Eq.2, it is known that δ_t does not only have strong relation with fouling factor but also with many condition parameters, Therefore, the key point for precise fouling measurement is to separate the influences of both the fouling and condition parameters on terminal temperature difference.

Provided the condenser is cleaned throughout, under a certain operation condition, we have δ_{td} which is called the measurement value of terminal temperature difference under cleaning state of condenser. Changing the operation condition, we have another measurement value δ_{tf} . Obviously, the difference $\Delta\delta$ between δ_{tf} and δ_{td} is caused by both the fouling and the variation of condition parameters.

$$\Delta\delta = \Delta\delta_c + \Delta\delta_g \tag{3}$$

Where, $\Delta\delta_c$ is the variation of terminal temperature difference caused by fouling. $\Delta\delta_g$ is the variation of terminal temperature difference caused by the variation of condition parameters.

Fouling factor C is defined as

$$C = \frac{\Delta\delta_c}{\delta_{td}} = \frac{\Delta\delta - \Delta\delta_g}{\delta_{td}} \tag{4}$$

If $\Delta\delta_g$ is known, the Fouling factor C can be figured out by Eq.4. However, $\Delta\delta_g = f(\Delta D_c, \Delta D_{w,} \Delta t_{wi}, \Delta\varepsilon)$ expresses a complicated nonlinear heat transfer process, the exact mathematics model is difficult to acquire.

A fuzzy neural network can be considered as a universal approximator [5],[6]. It is especially suitable to model nonlinear dynamic system and has the ability to achieve complicated mappings. So, we employ it to map the nonlinear relationship $\Delta\delta_g$ and therefore achieve precise fouling online measurement.

III. GA BASED FUZZY NEURAL NETWORK MODELING

A. Fuzzy neural network

$\Delta\delta_g = f(\Delta D_c, \Delta D_{w,} \Delta t_{wi}, \Delta\varepsilon)$ can be approximated by Fuzzy neural network. The configuration of fuzzy-neural networks is shown in Fig.1.

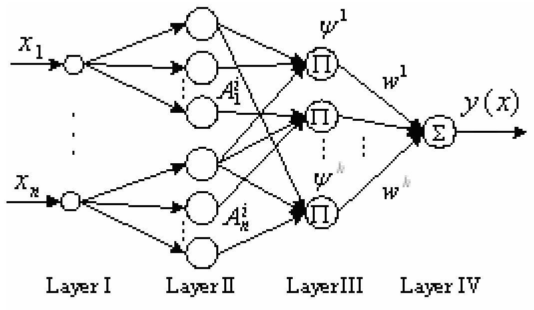

Fig.1 The configuration of fuzzy-neural networks

The network has a total of four layers. Nodes at layer I are input nodes that represent input linguistic variables. Nodes at layer II are term nodes which act as membership functions to represent the terms of the respective linguistic variables. Each node at layer III is a fuzzy rule. Layer IV is the output layer. The ith fuzzy rule is written as**:**

If x_1 is A_1^i and … and x_n is A_n^i

Then y is B^i (5)

where, $A_1^i, \ldots, A_n^i$ and B^i are fuzzy sets. By using product inference engine, the output of the network can be expressed as

$$y(x) = \frac{\sum_{i}^{h} w^i \left(\prod_{j=1}^{n} \mu_{A_j^i}(x_j)\right)}{\sum_{i=1}^{h} \left(\prod_{j=1}^{n} \mu_{A_j^i}(x_j)\right)} \tag{6}$$

where, $\mu_{A_j^i}$ is the membership function value of the fuzzy variable x_j, h is the number of the nodes at layer III, which also is the number of the total IF-THEN rules. w^i are adjustable weighting factors.

B. B-spline membership function

Fuzzy neural network can be expressed as a linear combination of basis function, an appropriate choice of basis functions is B-spline function, a B-spline function is a piecewise polynomial [7].

Let $T = \{t_0, t_1, \cdots, t_{r+\alpha}\}$ be the knot vector, where t_k are knots with $t_0 \le t_1 \le \cdots \le t_{r+\alpha}$. The kth B-spline basis function of order α , denoted by $N_{k,\alpha}$, is defined as

$$N_{k,1} = \begin{cases} 1 & if \quad t_k \le t \le t_{k+1} \\ 0 & otherwise \end{cases} \tag{7}$$

$$\begin{aligned} N_{k,\alpha}(t) &= (\frac{t - t_k}{t_{k+\alpha-1} - t_k}) N_{k,\alpha-1}(t) \\ &+ (\frac{t_{k+\alpha} - t}{t_{k+\alpha} - t_{k+1}}) N_{k+1,\alpha-1}(t) \end{aligned} \tag{8}$$

For $r+1$ control points, the B-spline function $s(t)$ is defined as

$$s(t) = \sum_{k=0}^{r} c_k N_{k,\alpha}(t) \tag{9}$$

The B-spline membership function $\mu_A(x_j)$ is defined as

$$\mu_A(x_j) = \sum_{k=0}^{r} c_k N_{k,\alpha}(t) \tag{10}$$

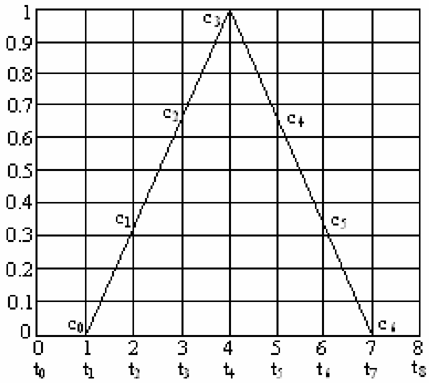

Fig.2 B-spline membership function

Fig.2 illustrates the B-spline membership function which has 7 control points, 9 knot points and order 2.

C. Genetic algorithm

When the B-spline membership fuzzy neural networks are used for complex nonlinear system modeling, there are some problems, such as how to select the appropriate knot positions, and how to choose control points optimally. These problems are significantly important in achieving good approximation. The unsuitable knot positions and the unsuitable control points often cause the poor performance of B-spline membership fuzzy-neural networks [8]. So far, there is less theory about how both knot points and control points can be chosen optimally. Since the weighting factors, the knot positions, and the control points are considered to be variables, it becomes a highly nonlinear optimization problem.

In this paper, we investigate the optimization problem of B-spline membership fuzzy-neural networks by using a genetic algorithm (GA). The GA solves two parameter search problems. The first is to obtain the weighting factors of fuzzy-neural networks. The second is to construct B-spline functions, including the knot positions, and a set of control points.

Assuming the ith rule and jth B-spline membership function $\mu_{A_j^l}(x_j)$ has r+1 control points. Then, the adjusted variables include the weighting factors w^p, p=1,2,…,h, the control points c_{kj}, k=0,1,…,r, j=1,2,…,n, and the knot points t_{qj}, q=0,1,…, $r+\alpha$, j=1,2,…,n. Note that because the equality $t_{qj}=t_{(q+1)j}$ is allowed, the redundant knots will be avoided. Hence, the objective of the search algorithm is to minimize the error function E(w,c,t), which is defined as

$$E^2(w,c,t) = \frac{1}{m} \sum_{i=1}^{m} (y_l - y_l^*)^2 \tag{11}$$

$$\text{Where} \quad \begin{aligned} c &= \{c_{kj} \mid k = 0,1,\cdots,r, j = 1,2,\cdots,n\} \\ t &= \{t_{qi} \mid q = 0,1,\cdots,r+\alpha, j = 1,2,\cdots,n\} \\ w &= \{w^p \mid p = 1,2,\cdots,h\} \end{aligned} \tag{12}$$

m is the number of training data pairs, y_l and y_l^* represent the outputs and the desired outputs respectively.

Define a chromosome as

$$z^l = [w^T c^T t^T] = [z_1^l z_2^l \cdots z_{k-1}^l z_k^l] \quad (13)$$

where a set of the weighting factors w range from within the interval $D_1 = [w_{\min}, w_{\max}] \subseteq R$, a set of control points c range from within the interval $D_2 = [c-\eta, c+\eta] \subseteq R$, $\eta \geq 0$ and a set of knot points t range from within the interval $D_3 = [t-\varepsilon, t+\varepsilon] \subseteq R$, $\varepsilon \geq 0$. The t and c are the initial values of the knot points and the control points. Define a fitness function as

$$f = \frac{1}{1 + E^2(w, c, t)} \quad (14)$$

The initialization procedure begins with the initialization of the chromosomes in the population. Each chromosome is coded as an adjustable vector with floating point type components. During the initialization step, the initial values of chromosomes are randomly created in some intervals. During the selection process, the population is first sorted by ranking the fitness of chromosomes. In particular, the first chromosome of the sorted population has the highest fitness value (or smallest error). Then, based on the sorted population, the selection process retain a best individual in the current generation unchanged for the next generation. After the selection process, the crossover procedure selects randomly subparts from two parent chromosomes and creates a new offspring chromosome. During the mutation process, certain components in some randomly selected chromosomes may be randomly replaced by new components. Moreover, some chromosomes with worse fitness values may be completely replaced, and the probability of the complete replacement is based on the sorted population.

The proposed GA is performed as follows.

```
Genetic_Algorithm()
{
Initialize the Population_of_Chromosomes;
Calculate the Fitness_Function;
While (not terminate-condition)
{
Perform Selection with Sorting;
Perform Crossover According to the Sorted
Population;
Perfom Mutation According to the Sorted
Population ;
Calculate the Fitness_Function;
}
```

IV. EXPERIMENT RESULTS

A. Experiment system description

In this section, an experiment on N-3500-2 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 and micro-processing system and sensors for operation condition parameters measuring.

The data used for fuzzy neural network modeling came from various operation conditions. A training set containing 716 data is chosen for modeling, another set containing 260 data for model verification. The average error and maximum error are adopted to evaluate the model performance. Through above mentioned algorithm, The average error and maximum error for fuzzy neural network modeling are 0.0031, 0.0104 respectively, The average error and maximum error for model verification are 0.0027, 0.0095 respectively. After the fuzzy neural network constructed well, it can be used for online measurement.

B. Fouling online measurement

Fouling measuring experiment consists of two parts:

(1) Cleaning the condenser throughout, and then measuring the fouling increasing after cleaning finished.

(2) Re-cleaning the condenser and measuring the fouling decreasing.

The variation of specific thermal consumption ΔHR is chosen to evaluate the correctness of the fouling measurement. The curves of fouling variation and ΔHR under a certain operating condition are shown in Fig.3, where, δ_{td} =6.1°C.

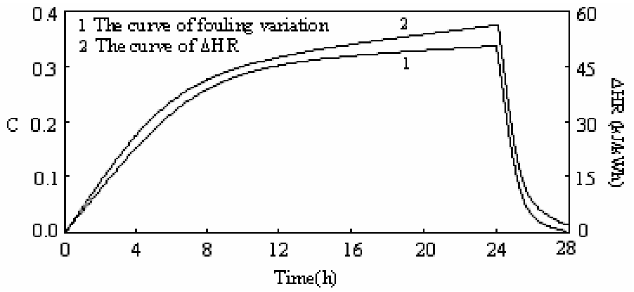

Fig.3 The curves of fouling variation and ΔHR

In Fig.3, in the period of T=0-24h, no cleaning takes place. In the period of T=24-28h, condenser cleaning is in operation. The results show that the variation of fouling factor complies with the variation of ΔHR. This proves that the measurement is credible.

C. Comparison with thermal resistance method

If the thermal tubes with thermal couplers are blocked, the thermal resistance method can not achieve precise measurement, the result is shown in Table 1, where, C_r is the fouling factor made by thermal resistance method.

TABLE 1

FOULING STATE IN CONDENSER UNDER THE CONDITION OF TWO BLOCKED TUBES WITH THERMAL COUPLERS

Time h	D_c t/h	t_{wi} ℃	t_{wo} ℃	t_s ℃	δ_{tf} ℃	C	C_r
0.0	135.0	11.3	23.0	29.6	6.6	0.002	0.216
0.5	135.0	11.3	22.9	29.6	6.7	0.031	0.234
1.0	135.0	11.0	22.6	29.5	6.9	0.048	0.242
1.5	135.0	10.8	22.4	29.4	7.0	0.067	0.248
2.0	135.0	10.9	22.4	29.5	7.1	0.082	0.257

When the blocked tubes occured, for a clean condenser, the fouling factor is 0.216 by thermal resistance method, this is a wrong measurement. The proposed approach is not affected by blocked tubes and gives the correct result.

D. Comparison with heat transfer coefficient method

If there is excessive amount of air in condenser, the measurement made by heat transfer coefficient method will be strongly affected. The result is shown in Table 2. C_h is the fouling factor made by heat transfer coefficient method.

When the condenser has excessive amount of air, for a clean condenser, the fouling factor is 0.166 by heat transfer coefficient method. The proposed approach is not subjected to this influence and gives the correct measurement.

TABLE 2

FOULING STATE IN CONDENSER UNDER THE CONDITION OF EXCESSIVE AMOUNT OF AIR

Time h	D_c t/h	t_{wi} ℃	t_{wo} ℃	ε %	t_s ℃	δ_{tf} ℃	C	C_h
0	128.2	15.7	27.2	0.045	34.3	7.1	0.004	0.166
1	128.2	15.5	27.0	0.045	34.2	7.2	0.029	0.185
2	128.2	15.2	26.6	0.045	34.1	7.5	0.071	0.21
3	129.1	14.7	26.0	0.041	33.8	7.8	0.119	0.235
4	129.1	14.5	25.8	0.041	34.0	8.2	0.158	0.254

V. CONCLUSION

In this paper, a novel approach based on GA based fuzzy neural network is proposed to make online measurement of fouling in condenser. It gives correct measurement and is more effective than thermal resistance method or heat transfer coefficient method. It can be seen as a powerful tool for fouling measuring in condenser.

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