Research Article

Soft Sensor for Oxide Scales on the Steam Side of Superheater Tubes under Uneven Circumferential Load

Qing Wei Li¹ and Gui Huan Yao²

¹Energy and Environment Department, Southeast University, Si Pai Lou No. 2, Xuan Wu District, Nanjing 210096, China

²School of Mechanical and Power Engineering, Nanjing University of Technology, Nanjing, China

Correspondence should be addressed to Qing Wei Li; 230109047@seu.edu.cn

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A soft sensor for oxide scales on the steam side of superheater tubes of utility boiler under uneven circumferential loading is proposed for the first time. First finite volume method is employed to simulate oxide scales growth temperature on the steam side of superheater tube. Then appropriate time and spatial intervals are selected to calculate oxide scales thickness along the circumferential direction. On the basis of the oxide scale thickness, the stress of oxide scales is calculated by the finite element method. At last, the oxide scale thickness and stress sensors are established on support vector machine (SMV) optimized by particle swarm optimization (PSO) with time and circumferential angles as inputs and oxide scale thickness and stress as outputs. Temperature and stress calculation methods are validated by the operation data and experimental data, respectively. The soft sensor is applied to the superheater tubes of some power plant. Results show that the soft sensor can give enough accurate results for oxide scale thickness and stress in reasonable time. The forecasting model provides a convenient way for the research of the oxide scale failure.

1. Introduction

Oxide scale formed on the steam side of superheaters and reheaters of utility boilers in power plant brings many problems like tube clogging, overheating, and erosion of turbine blade [1–3]. It is estimated that 10% of all power plant breakdowns are caused by creep fractures of boiler tubes due to the scales formation [4]. Oxide failure often occurs at boiler's start-up and stop stages. During these stages, large stress in oxide scales would be generated [5]. Many researchers have been devoted to studying the stress generated in oxide scales. For theoretical analysis, Sabau and Wright [6] studied the effects of creep, growth stress, and thermal stress on the internal stress state of the oxide film. Feng et al. [7] corrected the stoney formula for the nonuniform temperature and multilayered oxides to calculate the average stress combined with the deformation curvature of the layers. As for the experiment aspect, Galerie et al. [8] measured the average thermal stress of oxides on ferritic alloy with flat structure in three ways, namely, Raman spectroscopy, X-ray diffraction, and single-sided bending test.

They pointed out that the results measured by Raman spectroscopy were accurate enough without the modifications by the X-ray diffraction and single-sided bending test. Luzin et al. [9] measured the thermal stress in Cu/Al coating systems of the flat structure using neutron diffraction method, which can give results reflecting the distribution along the thickness direction. For numerical aspect, Bian et al. [10] simulated the effects of temperature perturbations of gas and steam on the stress states of tubes and oxides using ANSYS finite element software.

As the load along the circumferential direction of the superheater tube is uneven, the oxide growth temperature is different circumferentially and so is the thickness of the oxide scales. Sabau et al. [11] pointed out that the steam temperature gradually increases along the flow direction of the tube and calculated the growth temperature distribution in the axial direction.

Support vector machine (SVM) introduced by Vapnik is a useful tool for data mining, especially in the fields of pattern recognition and regression. During the past few years, its solid theoretical foundation and good behaviors

FIGURE 1: Geometric model.

have attracted a number of researchers [12, 13]. However, the selection of parameters of SVM is still a problem. Grid search method [14] and optimization methods like particle swarm optimization [15], genetic algorithm [16], and ant colony optimization [17] have been introduced to solve the parameter selection problem.

PSO is an evolutionary computation technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking. It is getting more and more attention as it is simple, fast, and easy to implement [18]. Like other intelligent algorithms, PSO is troubled with prematurity and convergence problem. So some improved PSOs have been proposed [19–21].

It is not convenient to get oxide scales thickness and stress values through theoretical method, experimental method, and simulation method for online application. In this paper, a soft sensor for oxide scales based on SVM optimized by PSO is proposed. The rest of the paper is organized as follow. Section 2 introduces the calculation of the thickness and stress of oxide scales. Then Section 3 provides a soft sensor for oxide scales, after which the temperature and stress calculation method are validated by the operation data and experiment data, respectively. An application is given to show the performance of the soft sensor in Section 5. Finally, Section 6 summarizes the contribution of this paper.

2. Calculation of the Thickness and Stress of Oxide Scales

2.1. Physical Model. The model area is divided into four regions, that is, steam region, scale region, steel region, and gas region from inside to outside, as shown in Figure 1. Define the angle of the windward side as 0° and take counterclockwise as positive.

The steam is fully developed turbulent flow and convection coefficient between steam and oxide scale is expressed as

$$h_s = 0.023 \frac{k_s}{D} (Re_s)^{0.8} (Pr_s)^{0.4}, \quad (1)$$

where Re_s is Reynolds number defined in (2); Pr_s is Prandtl number defined in (3); k_s is thermal conductivity of the steam, $W/(m \cdot K)$; D is the inner diameter of the tube, m:

$$Re_s = \frac{4m_s}{\pi D \mu_s}, \quad (2)$$

where m_s is mass flow rate of the steam, kg/s ; μ_s is steam viscosity, $kg/(m \cdot s)$:

$$Pr_s = \frac{\mu_s C_{p_s}}{k_s}, \quad (3)$$

where C_{p_s} is specific heat of the steam, $J/(kg \cdot K)$.

Heat transfer between gas and steel is forced convection and convection coefficient is given as

$$h_g = 0.33 \frac{12k_g}{d_0} (Re_g)^{0.6} (Pr_g)^{0.33}, \quad (4)$$

where Re_g is Reynolds number that is defined as in (5); Pr_g is Prandtl number that is defined as in (6); k_g is thermal conductivity of flue gas, $W/(m \cdot K)$; d_0 is outer diameter of the tube, m:

$$Re_g = \frac{G d_0}{12 \mu_g}, \quad (5)$$

where μ_g is steam viscosity, $kg/(m \cdot s)$; G is gas mass velocity, kg/s :

$$Pr_g = \frac{\mu_g C_{p_g}}{k_g}, \quad (6)$$

where C_{p_g} is specific heat of the flue gas, $J/(kg \cdot K)$.

The temperature can be solved by the following equation [25]:

$$\rho Cp \left(\frac{\partial T}{\partial \tau} + u \frac{\partial T}{\partial x} + v \frac{\partial T}{\partial y} \right) = \lambda \left(\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} \right), \quad (7)$$

where ρ is the density, kg/m^3 ; Cp is the specific heat, $J/(kg \cdot K)$; τ is time, s; λ is thermal conductivity, $W/(m \cdot K)$; x and y are the space variables, m.

2.2. Mathematical Model of Oxide Thickness Calculation. Oxide scale thickness is the basis of the calculation of stress. For the case where protective oxide scale is formed, the rate of scale growth is controlled by diffusion of ions through the oxide, and the growth of the oxide scales can be described by [5]

$$\begin{aligned} d_{ox}^2 &= 2 \times k_p \times t \\ k_p &= A \times e^{-Q/RT}, \end{aligned} \quad (8)$$

where d_{ox} is the thickness of the oxide scales, μm ; k_p is the oxidation rate, $\mu\text{m}^2/\text{hr}$; t is time, hr ; A is Arrhenius constant, $\mu\text{m}^2/\text{hr}$; Q is activation energy, kJ/mole ; R is universal gas constant, $\text{kJ}/(\text{mole} \cdot \text{K})$; T is absolute growth temperature, K .

Take the temperature between the tube and oxide scales as the growth temperature. The growth temperature changes with the thickness of the oxide scales, so the thickness of the oxide scales should be calculated through [26]

$$\begin{aligned} d_{ox,k}^2 &= d_{ox,k-1}^2 + d(d_{ox}^2) \\ d(d_{ox}^2) &= 2\Delta t k_p(T_{gr}(t_k)), \end{aligned} \quad (9)$$

where $d_{ox,k}$ is the thickness of the oxides at the end of the k th time intervals, μm ; Δt is the time interval, hr ; $T_{gr}(t_k)$ is the growth temperature in the k th interval, K ; $k_p(T_{gr}(t_k))$ is the oxidation rate in the k th interval, $\mu\text{m}^2/\text{hr}$.

2.3. Mathematical Model of the Stress in Oxide Scales. The stress in oxide scales mainly consists of thermal stress, which can be calculated by the following equations [27]:

$$\begin{aligned} \varepsilon_{\text{met}} &= \int_{T_a}^{T_b} \beta_{\text{met}}(T) dT \\ \varepsilon_{\text{oxide}} &= \int_{T_c}^{T_d} \beta_{\text{oxide}}(T) dT, \end{aligned} \quad (10)$$

where ε_{met} and $\varepsilon_{\text{oxide}}$ are the free strain of tube and oxide scale, respectively.

The displacement and stress of tube and oxide scales are calculated according to mechanics of elasticity as follows:

$$\begin{aligned} u_M &= \frac{1 + \nu_M}{r_M} \int_{r_a}^{r_b} (1 + \nu_M) \varepsilon_M r dr + C_M r_M + \frac{D_M}{r_M} \\ \sigma_{r,M} &= E_M \left(\frac{-1}{r_M^2} \int_{r_a}^{r_b} (1 + \nu_M) \varepsilon_M r dr \right. \\ &\quad \left. + \frac{C_M}{1 - \nu_M} - \frac{D_M}{(1 + \nu_M) r_M^2} \right) \\ \sigma_{\varphi,M} &= E_M \left(\frac{1}{r_M^2} \int_{r_a}^{r_b} (1 + \nu_M) \varepsilon_M r dr \right. \\ &\quad \left. - (1 + \nu_M) \varepsilon_M + \frac{C_M}{1 - \nu_M} + \frac{D_M}{(1 + \nu_M) r_M^2} \right) \\ \sigma_{z,M} &= \nu_M (\sigma_{r,M} + \sigma_{\varphi,M}) - E_M \varepsilon_M, \end{aligned} \quad (11)$$

where ε_{met} is the metal free thermal strain; $\varepsilon_{\text{oxide}}$ is the oxide free thermal strain; β_{met} is the linear expansion coefficient of the metal, m/K ; β_{oxide} is the linear expansion coefficient of the oxide scales, m/K ; T_a and T_b are the inside and outside temperature of metal, respectively, K ; T_c and T_d are the inside and outside temperature of oxide scales, respectively, K ; M represents metal or oxide scales; u is the radial displacement, m ; ν is the Poisson ration; r_M is the average radial coordinate, m ; r is the radial argument, m ; r_a and r_b are the inside radius and outside radius, m ; ε_M is the free thermal strain; C_M and D_M are undetermined parameters and are obtained with boundary conditions; $\sigma_{r,M}$ is the radial stress, MPa ; E_M is modulus of elasticity, MPa ; $\sigma_{\varphi,M}$ is circumferential stress, MPa ; $\sigma_{z,M}$ is axial stress, MPa .

The inlet gas temperature and steam temperature are given. The radial boundary stress of the gas side and steam side equals the gas pressure and steam pressure, respectively. The radial stress and temperature are continuous at the interface of tube and oxide scales and the interfaces of different oxide layers.

3. Soft Sensor for the Thickness and Stress of Oxide Scales

Though the stresses can be calculated by simulation method, it is time consuming. Operators are eager to monitor the oxide thickness and stress online. So a soft sensor is proposed.

3.1. Introduction of SVM. Train samples of SVM are $\{(x_1, y_1), \dots, (x_n, y_n)\} \subset R^n \times R$, which are mapped into high-dimensional space through nonlinear function Φ and regressed linearly as follows:

$$f(x) = (w\Phi(x)) + b, \quad (12)$$

where $w \in R^n$; $b \in R$.

The learning process is converted into an optimization problem according to structural risk minimization principle:

$$\begin{aligned} \min \quad & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*), \\ \text{s.t.} \quad & y_i - f(x_i) \leq \varepsilon + \xi_i, \\ & f(x_i) - y_i \leq \varepsilon + \xi_i^*, \\ & \xi_i, \xi_i^* \geq 0, \quad i = 1, 2, \dots, n, \end{aligned} \quad (13)$$

where C is the penalty factor; ξ_i and ξ_i^* are slack variables. Linear insensitive loss function is defined with ε :

$$L^\varepsilon(x, y, f) = \max(0, |y - f(x)| - \varepsilon). \quad (14)$$

FIGURE 2: Soft sensor for oxide scale thickness and stress.

FIGURE 3: The estimated scale thickness and the actual data.

Equation (13) can be transformed into the following form through the dual form of Lagrange polynomial:

$$\begin{aligned}
 \max \quad & \sum_{i=1}^n y_i (\alpha_i^* - \alpha_i) - \varepsilon \sum_{i=1}^n (\alpha_i^* + \alpha_i) \\
 & - \frac{1}{2} \sum_{i,j=1}^n (\alpha_i^* - \alpha_i) (\alpha_j^* - \alpha_j) K(x_i, x_j) \\
 \text{s.t.} \quad & \sum_{i=1}^n \alpha_i^* = \sum_{i=1}^n \alpha_i, \\
 & C \geq \alpha_i^*, \quad \alpha_i \geq 0, \quad i = 1, 2, \dots, n,
 \end{aligned} \tag{15}$$

where α_i^* and α_i are Lagrange multipliers; $K(x_i, x_j)$ is kernel function meeting the conditions of mercer. Radial basis kernel function is selected in this study:

$$K(x_i, x_j) = \exp\left(-\frac{|x_i - x_j|^2}{\sigma^2}\right). \tag{16}$$

TABLE 1: The main parameters for oxide scales [22, 23].

Name	Elasticity modulus/ $\times 10^{11}$ [Pa]	The Poisson ration
Fe-Cr-spinel	2.3	0.31
Magnetite	2.1	0.29
Hematite	2.2	0.19

Due to the sparsity, only some samples' coefficients are not 0 in quadratic programming (15), which are the support vector machines. Assuming the number of support vector machines is g , the regression function can be given as follows:

$$f(x) = \sum_{i=1}^g (\alpha_i^* - \alpha_i) K(x, x_i) + b. \tag{17}$$

3.2. Introduction of PSO. In PSO, each feasible solution of the optimization problem is seen as a "particle" of the solution space. Each particle searches the solution space following the optimal particle of the whole group. Suppose the group searches in a D dimensional solution space. The particle i is expressed as $x(x_{i1}, x_{i2}, \dots, x_{id})$. Particles search for new feasible solutions by constantly adjusting their positions. $P_i(P_{i1}, P_{i2}, \dots, P_{id})$ is the optimal position of particle i . $P_g(P_{g1}, P_{g2}, \dots, P_{gd})$ is the optimal position of the whole group. $V_i(V_{i1}, V_{i2}, \dots, V_{id})$ is position change rate of particle i . Each particle uses the following equations to adjust its velocity and position:

$$\begin{aligned}
 V_{id}^{t+1} &= wV_{id}^t + c_1 \times \text{rand}_1 \times (p_{id} - x_{id}^t) \\
 &+ c_2 \times \text{rand}_2 \times (p_{gd} - x_{id}^t)
 \end{aligned} \tag{18}$$

$$x_{id}^{t+1} = x_{id}^t + V_{id}^t, \quad 1 \leq i \leq N, \quad 1 \leq d \leq D,$$

where w is inertia weight; D is the dimension of the space; N is the particle number in the group; c_1 and c_2 are acceleration coefficients, where c_1 is known as the individual cognitive factor; c_2 is known as social learning factor; rand_1 and rand_2 are two separately generated uniformly distributed random numbers in the range (0, 1).

3.3. Optimization of SVM's Parameters. C and σ have great influence on the learning ability and generalization ability.

TABLE 2: The parameters of TP347 [24].

Temperature [°C]	Elasticity modulus $\times 10^{11}$ [Pa]	The linear expansion coefficient $\times 10^{-6}$ [K ⁻¹]	The Poisson	Conduction coefficient [W/(m·K)]	Arrhenius constant A [$\mu\text{m}^2/\text{h}$]	Activation energy [KJ/mole]
25	2	15.27	0.3	23.2	5×10^9	-171
100	1.96	17.3	0.3	23.2	5×10^9	-171
200	1.88	17.5	0.3	23.2	5×10^9	-171
300	1.81	17.7	0.3	23.2	5×10^9	-171
400	1.72	18.2	0.3	23.2	5×10^9	-171
500	1.63	18.6	0.3	23.2	5×10^9	-171
600	1.56	18.9	0.3	23.2	5×10^9	-171

TABLE 3: Geometrical parameters.

Inner diameter [mm]	Outer diameter [mm]	Axial length [mm]	Length of gas area [mm]	Width of gas area [mm]	Operating time [h]
36.7	44.5	15	1000	500	10000

TABLE 4: Boundary conditions.

	Inlet temperature [°C]	Inlet velocity [m/s]	Outlet pressure [MPa]
Gas	950	9.6	0.09
Steam	560	6.9	25

FIGURE 4: The growth temperature along the tube.

C compromises structural risks and sampling error. σ is decided by the width or the scope of the input space.

In this paper, support vector machine parameters are optimized by PSO. Each particle represents a potential set of C and σ . The fitness function is defined as

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (f(x_i) - y_i)^2, \quad (19)$$

where $f(x_i)$ is the forecasting value and y_i is the actual value.

FIGURE 5: The oxide thickness along the tube.

Initialize PSO and iterate to get proper set of C and σ to minimize the predicting error, namely, the fitness value evaluated by (19), to promote the predicting accuracy.

3.4. Soft Sensor for Thickness and Stress of Oxide Scales. Traditional methods like theoretical method, experimental method, and simulation method cannot provide accurate enough oxide scale thickness and stress in reasonable time. With the development of intelligent algorithms, the soft sensor can be qualified to do this work. In our study, SVM is employed to predict oxide scale thickness and stress.

(1) *Soft Sensor for Oxide Scale Thickness.* Take time and angles as inputs and oxide scale thickness as the output, as shown in Figure 2(a). Train samples and test samples are obtained from simulations. Take 6 out of the samples as train samples and

FIGURE 6: The forecasting results.

FIGURE 7: The optimization progress of SVM parameters (Best $c = 100$ $g = 0.86866$).

the one left is test sample. Leave-one-out method is employed to train SVM parameters [16].

(2) *Soft Sensor for Oxide Scale Stress*. Take time, oxide scale thickness, and angles as inputs and oxide scale stress as the output, as shown in Figure 2(b). Train samples and test samples are obtained from simulations. The first 18 samples

are train samples, while the last 3 samples are test samples. The training method is the same with thickness soft sensor. Leave-one-out method is employed to train SVM parameters.

The steps of constructing the soft sensors are detailed as follows.

Step 1. Collect calculation parameters of oxide scales and superheater tubes.

Step 2. Program thermal calculation procedure according to 73 boiler thermal calculation standards to get the convection coefficient between steam and oxide scales and convection coefficient between gas and substrate and steam temperature and gas temperature.

Step 3. Divide operating time and spatial space into several intervals reasonably considering computational cost and accuracy of the results.

Step 4. Calculate the temperature distribution by finite volume method with the boundaries got in Step 2.

Step 5. Calculate the oxide scale thickness according to (8)-(9) with intervals in Step 3 and temperature distribution in Step 4. Repeat Steps 4 and 5 until all the intervals have been done.

Step 6. Calculate the stress of oxide scales according to (10)-(11) on the platform of ANSYS with given temperature drop and oxide scale thickness in corresponding direction.

FIGURE 8: Forecasting results of radial stresses.

Step 7. Optimize SVM parameters for the oxide scale thickness soft sensor and stress soft sensor with leave-one-out method.

Step 8. Construct thickness soft sensor and stress soft sensor with the data collecting from Steps 5 and 6 and the parameters optimized in Step 7.

4. Verification

4.1. Validation of Oxide Scale Thickness Calculation Method. Two reheater tube samples of power plant in site are taken for validation [28, 29]. Two different cases with different tube diameters from two different locations are used. Operating steam temperature of both tubes is 576°C. The flue gas temperatures were reported ranging from 800 to 900°C. The

estimated scale thickness and the actual data are plotted in Figure 3. It can be seen that the estimated scale thickness is closed to the actual data.

4.2. Validation of Oxide Scale Stress Calculation Method. The average internal stress of oxides on AISI 441 is measured by Raman spectroscopy in [30]. The dimensions of the specimen are 2 mm × 1.5 mm. The thickness of the alloy and oxide scales is 1.2 mm and 0.001 mm, respectively. This literature assumed that the composition of the oxides was chromia only. The specimen was cooled to room temperature after being oxidized at 800°C. The pressure is 1 atm. The average stress of the oxide scales is simulated with finite element method. The simulated result is compressive and the value is 1.126 Gpa. The error is 6.17% compared with 1.2 Gpa provided in [30].

FIGURE 9: Forecasting results of axial stress.

So the results based on (10)-(11) by finite element method are credible.

5. An Application Case

5.1. Description on the Calculation Related Data. The physical parameters of oxide scales and superheater material are listed in Tables 1-2. Geometrical parameters listed in Table 3 are taken from the superheater of some power plant. Take operational parameters as boundary conditions; see Table 4.

5.2. Growth Temperature and Thickness of the Oxide Scales. Growth temperature decreases along the circumferential

direction and changes rapidly at approximately 90°. Reduced gas flow area enhances flow speed, which enlarges the convective heat transfer coefficient. At first, the growth temperature of the oxide scales increases fast as the difference of thermal conductivity between the metal and the oxide scales is large; see Figure 4. The thickness of the oxide scales is given in Figure 5.

5.3. Forecasting of the Oxide Scales Thickness. The predicting results for oxide scale thickness are shown in Figure 6. We can see the forecasting values are closed to the actual values for train samples and test samples in all directions, showing that the results given by oxide scale thickness soft sensor are accurate enough.

FIGURE 10: Forecasting results of circumferential stress.

5.4. Forecasting of the Oxide Scale Stress. Assume that the temperature drop of steam is 100°C while all other parameters remain the same. The stresses are calculated with (10)-(11). The optimization progress of SVM parameters for the radial stress in 0° is shown in Figure 7. The best c and g are found after 38 iterations. The best c and best g are 100 and 0.87, respectively.

Radial stresses, axial stresses, and circumferential stresses in 0° , 90° , and 180° are shown in Figures 8, 9, and 10. The first 18 samples are training samples and the last 3 samples are testing samples. From the figures, it can be seen that the forecasting results provided by soft sensor are accurate enough. The first 3 training samples' forecasting results are not ideal, which is caused by two reasons: the samples are not enough and the stress rises too dramatically.

The corresponding average errors and maximum errors are shown in Tables 5-6. The maximum forecasting error comes from the first training sample. The average forecasting errors are small enough to show the stress level in the oxide scales, which can be further reduced by adding samples in the early stage. To get the stress, the simulation method takes more than 10 minutes; however, the soft sensor only needs few seconds, cutting down the calculation time greatly.

6. Conclusions

The thickness and stress of oxide scales under uneven circumferential loading are calculated by finite volume method and finite element method, which are supplied as the samples. A soft sensor for oxide thickness and stress is proposed for the

TABLE 5: The average forecasting errors for the stress.

	0°	90°	180°
Axial stress average error/[MPa]	1.35	1.41	2.26
Circumferential stress average error/[MPa]	0.40	0.50	0.66
Radial stress average error/[MPa]	0.02	0.02	0.15

TABLE 6: The maximum forecasting errors for the stress.

	0°	90°	180°
Axial stress maximum error/[MPa]	76.85	40.99	24.28
Circumferential stress maximum error/[MPa]	58.38	43.45	41.32
Radial stress maximum error/[MPa]	4.39	4.46	1.99

first time. An application shows that the soft sensor can give enough accurate results for oxide scale thickness and stress while the calculation time is greatly cut down. The soft sensor provides a convenient way to study oxide scale failure. In future, more operating parameters, tube diameters, and tube materials will be studied and incorporated into the predicting model.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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