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Ladle Refractory Safety Monitoring System Based on Support Vector Regression

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Abstract. Ladle refractories were subject to repeated chemical erosion and physical scouring by various hot fluids such as steel slag, liquid steel, argon and oxygen. Firstly, the heat transfer model of ladle wall was established, the heat transfer of ladle refractory under different corrosion conditions was analyzed. The relationship between the residual thickness of ladle lining refractory and the temperature field of the outer surface of ladle was established. Secondly, a set of infrared thermal imaging ladle outer wall temperature monitoring system was used to measure the ladle outer wall temperature, especially the slag line temperature. The changes of ladle outer surface temperature field under different corrosion conditions and different process conditions were analyzed. Finally, based on the support vector regression (SVR) model, the residual thickness prediction model of ladle refractory was designed. Combined with the ladle surface temperature and steelmaking production process conditions, the residual thickness of ladle refractory corrosion was predicted. The experiment results showed that the prediction accuracy of ladle refractory corrosion reaches 92%, which met the requirements of steelmaking plant for ladle safety monitoring in green and intelligent production.

Keywords. Ladle refractory, infrared thermal imaging, temperature analysis, thickness prediction

1. Introduction

Ladle is a typical high-temperature molten metal storage and transportation container in the field of iron and steel metallurgy. Ladle refractory materials are subject to repeated chemical erosion and physical scouring by a variety of hot fluids such as slag, molten steel, argon and oxygen [1,2]. Improper handling will lead to large-scale production safety accidents such as molten steel leakage [3]. The magnesia carbon brick at the slag line in the refractory of ladle lining is the weak part that is most vulnerable to erosion. The corrosion of magnesia carbon brick is the result of solid liquid gas multiphase thermal fluid chemical and physical coupling [4-6], which is the main cause of steel leakage risk [7,8]. With the advance of intelligent, green and safe production, the service life of ladle is continuously extended, and the leakage prevention monitoring of

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ladle in the production process is extremely urgent. Scholars have carried out various studies on this.

Acoustic emission technology is used to predict the instability of cracks in ladle refractories [9,10]. This method only carries out cold state test in the laboratory and cannot be used in the metallurgical site. Laser ranging can measure the refractory thickness of the ladle [11,12]. This technology can only be used when the ladle is offline, and can't meet the safety monitoring requirements of the whole production process of the ladle. The infrared radiation temperature measurement technology is used to measure the surface temperature of the ladle [13,14]. By setting a safety temperature threshold, the safety status of the ladle can be judged, which can't accurately reflect the corrosion of ladle refractory. Neural network and data analysis safety diagnosis of ladle refractories by using off-line data analysis [15-17], which is difficult to use online. The numerical simulation method is also used to analyze the corrosion of ladle refractory [18-20], but the difference between the numerical simulation and the actual working conditions is that the simulation results can't fully reflect the corrosion of ladle refractory.

In this paper, the heat transfer model of ladle refractory is established, the relationship between ladle surface temperature and corrosion of ladle refractory is analyzed. The relationship between ladle surface temperature field change and corrosion is studied The residual thickness prediction method of ladle refractory based on SVR is proposed, which realizes the on-line monitoring of corrosion of ladle refractory and meets the requirements of safe production in metallurgical enterprises.

2. Research on Radial Heat Transfer Model of Ladle

In order to explore the relationship between the corrosion degree of the ladle lining and the ladle surface temperature, the heat transfer model of the ladle wall is established. Taking the contact heat transfer between the ladle lining refractory and hightemperature molten steel as the main research content. The relationship between the residual thickness of the ladle lining refractory and the temperature field on the outer surface of the ladle is analyzed.

2.1. Establishment of Ladle Heat Transfer Model

According to the iron and steel production process, the temperature of ladle has reached the steady-state heat transfer process from converter to continuous casting platform. Therefore, ignoring the influence of contact thermal resistance between refractory masonry, a two-dimensional heat transfer model is used, and it is assumed that the upper and lower boundaries are infinite planes extending upward or downward. The calculation geometric model is shown in figure 1.



Figure 1. The calculation geometry model of ladle.

The steady-state heat conduction differential equation of ladle lining refractory is as follows:

$$\frac{\partial}{\partial x}\left(\lambda\frac{\partial t}{\partial x}\right) + \frac{\partial}{\partial y}\left(\lambda\frac{\partial t}{\partial y}\right) + \frac{\partial}{\partial z}\left(\lambda\frac{\partial t}{\partial z}\right) = 0 \tag{1}$$

Of which: t is temperature (°C), λ is thermal conductivity ($W/m \cdot °C$), x is coordinates of ladle lining refractory (m).

The empirical formula for the heat transfer coefficient of the first boundary condition is:

$$T(\mathbf{x}, \mathbf{y})|_{\tau} = t(\mathbf{x}, \mathbf{y}) \tag{2}$$

The empirical formula for the heat transfer coefficient of the second boundary condition is:

$$-k\frac{\partial T}{\partial n}|_{\tau} = q(\mathbf{x}, \mathbf{y}, \mathbf{t}) \tag{3}$$

The empirical formula for the heat transfer coefficient of the third boundary condition is:

$$-k\frac{\partial T}{\partial n}|f_{\tau} = h(T - T_{\tau}) \tag{4}$$

Of which: τ is ladle boundary, t(x,y) is temperature function (°C), q(x,y,t) is heat flux function (W/m²), T_f is temperature of fluid medium (°C), h is surface heat transfer coefficient (W/m² · °C).

The refractory in the ladle lining is in contact with the molten steel. The inner wall temperature of the working layer in the ladle lining directly in contact with the molten steel is the first boundary, that is, the approximate inner wall temperature of the working layer is the molten steel temperature. The outer wall of the ladle is in contact with the air in the surrounding environment, and there are two ways to exchange heat between the outer wall of the ladle and the air, one is convective heat transfer, and the other is radiation heat transfer. Therefore, the third kind of boundary conditions for steady-state heat conduction is met.

2.2. Analysis of Ladle Heat Transfer Results

(1) Radial temperature distribution of ladle slag line

Figure 2 shows the radial temperature distribution at 100mm of local corrosion of ladle. It can be seen from figure 2 that the thermal conductivity of carbon magnesium brick and magnesium aluminum carbon brick materials in the ladle working layer is high, and the radial temperature just begins to decline and changes slowly. With the continuous increase of radial distance, it reaches the position of light-weight insulation board material. Due to the low thermal conductivity of the light-weight insulation board, the temperature suddenly drops sharply, and finally it is smoothly transmitted to the ladle shell.



Figure 2. Radial temperature profile of ladle.

(2) Relationship between different ladle lining thickness and surface temperature of ladle

Figure 3 shows the surface temperature of the ladle at the slag line under different degrees of corrosion of refractory. The three curves are the surface temperature values at the center of the slag line, 50mm below the slag line and 200mm below the slag line. It can be seen from figure 3 that with the decrease of the thickness of the working layer of the ladle refractory, the temperature at different positions on the outer surface of the ladle gradually increases. The average refractory decreases by 10mm, and the temperature of the outer surface of the ladle increases by $1.2 \sim 1.8 \,^{\circ}\text{C}$.



Figure 3. Outer surface temperature curves with different ladle refractory thickness.

(3) Relationship between different molten steel temperature and surface temperature of ladle

Figure 4 shows the relationship between the temperature change of molten steel and the surface temperature of the ladle under the condition that the corrosion of ladle refractory is 50mm. With the increase of the temperature of molten steel, the temperature of the outer wall of the ladle will rise accordingly. Due to the good thermal insulation performance of the light-weight insulation board, when the molten steel temperature changes, the rising trend of the ladle outer wall temperature is not obvious. When the molten steel temperature changes about 10 °C, the ladle outer wall temperature changes 1 °C. In the process of steelmaking and refining, the temperature change range of molten steel can reach tens of degrees or even hundreds of degrees. Therefore, the temperature change of ladle surface caused by the temperature change of molten steel must be considered.



Figure 4. Relationship between molten steel temperature and surface temperature of ladle.

3. Acquisition and Analysis of Temperature Field on Ladle Surface

3.1. Acquisition of Temperature Field on Ladle Surface

The heat transfer model analyzes the law of the radial heat transfer of the ladle, and the distribution of the temperature field on the ladle surface needs to be further studied. In this paper, the distribution of the temperature field on the ladle surface is obtained by using the infrared thermal camera. The change of the ladle surface temperature with the corrosion of ladle refractory is discussed.

Four sets of infrared thermal camera are installed at the continuous casting platform of the steel plant. The four thermal cameras respectively obtain thermal images for the ladle outer wall and bottom. The thermal image data is transmitted to the switch through optical fiber, and finally summarized to the server which analyze the ladle thermal image. The installation diagram is shown in figure 5.



Figure 5. Installation diagram of thermal cameras.

The system obtains the infrared thermal image of the ladle online, and locates the weak corrosion area from the infrared thermal image. The actual thermal image of the ladle is shown in figure 6. There is an area at the slag line and the color of this area is brighter from the infrared thermal image. Because the corrosion of ladle refractory at the slag line is thinner, the temperature of this area is higher than other areas of the ladle. This area is also the location where ladle leakage accidents are most likely to occur. Therefore, this paper focuses on the relationship between the temperature change of ladle surface and corrosion of ladle refractory at the slag line of ladle.



(a) NO.9 Ladle infrared thermal image.
(b) NO.13 Ladle infrared thermal image.
Figure 6. Ladle infrared thermal image.

3.2. Analysis of Temperature Field on Outer Wall of Ladle

For the weak area at the slag line on the outer surface of the ladle, when the molten steel temperature in the ladle is approximately the same, the overall temperature of the ladle wall increases gradually with the increase of ladle repair age. The temperature grid diagram of the thermal imager is mapped to two dimensions to generate an isotherm diagram. In this paper, the two-dimensional isothermal diagram generated by the surface temperature at the slag line(as shown in figure 6) of No. 9 ladle with different minor repair ages are shown in the figure 7:



In figure 7, the positive x direction is the direction from ladle bottom to ladle top, and the positive y direction indicates the horizontal direction of ladle wall. It can be seen from the above pictures that the area covered by the yellow isotherm is the weak area near slag line of ladle. With the increase of the ladle repair age, the area covered by the yellow isotherm increases, and the increasing trend of the area is fan-shaped diffusion. The horizontal diffusion rate is faster, and the vertical diffusion is slow. Besides, not only the yellow isotherms, each isotherm will spread in a fan-shaped manner.

As the number of ladle repair ages increases, the isotherm in the weak area of the ladle will spread outward in a fan-shaped manner, the horizontal diffusion rate is large, and the erosion area increases.

It can be seen from the above that the temperature measurement method in the ladle thermal image is adopted. The temperature corresponding to the ladle thermal image under different ladle repair ages can be measured in the same way. The curve between the repair age and the temperature of the outer surface of the ladle slag line can be obtained, as shown in figure 8.



Figure 8. Curve of ladle repair age and ladle outer surface temperature at slag line.

It can be seen from figure 8 that the temperature at the slag line on the outer surface of each ladle does not increase linearly with the increase of ladle minor repair age, but fluctuates up and down, showing a trend of high and low, but generally it is an upward trend. This phenomenon is determined by complex on-site working conditions, such as different ladle baking temperatures, different molten steel temperatures, different molten steel refining times, etc. Therefore, it is not enough to only rely on the ladle surface temperature for corrosion of ladle refractory safety monitoring. It is necessary to comprehensively consider the steelmaking production process conditions and ladle surface temperature to achieve ladle safety monitoring.

4. Prediction and Result Analysis of Residual Thickness of Ladle Refractory Based on SVR

4.1. Prediction of Residual Thickness of Ladle Refractory Based on SVR

In this paper, the Support Vector Regression method is used to design the prediction model of the residual thickness of the ladle refractory. Combined with the steelmaking process parameters and the temperature of the outer wall of the ladle, the residual thickness of the ladle refractory is predicted to ensure the safe production.

According to the analysis of on-site steelmaking process conditions, the corrosion of ladle refractory is related to the ladle repair age, molten steel temperature, refining time and ladle outer wall temperature. Through the research on the corrosion mechanism characteristics of the ladle lining and the ladle thermal images, it can be seen that the corrosion of the working layer at the ladle slag line is the most serious. Most ladle breakout events are related to the working layer at the slag line. Therefore, this paper focuses on the corrosion degree of the refractory at the ladle slag line.

SVR adopts the structural risk minimization criterion and has no limit on data dimension, which can improve the generalization ability of the network. The core idea of SVR is to find an optimal classification surface to minimize the error of all training samples from the optimal classification surface [21]. Suppose there is a training set, and the number of samples is L, $x_i = [x_{i_1}, x_{i_2}..., x_{i_d}]^{v}$, y_i is the corresponding output value. The linear regression function established in the high-dimensional feature space is:

$$y = f(x) = \omega \Phi(x) + b \tag{5}$$

Of which: $x \in R_m$, $y \in R_m$, ω is the m-dimension weight value vector, b is the offset item. $\Phi(x)$ is the non-linear mapping function, because ε insensitive loss function has good sparsity, therefore $|y_i - wx_i - b| \le \varepsilon (i = 1, ..., l)$. If there is fitting error, then the relaxation variable is introduced, and the regression problem of the function can be expressed as

$$\begin{cases} \min \frac{1}{2} \|w\|^{2} + C \sum_{i=l}^{l} (\xi_{l} + \xi_{i}^{*}) \\ y_{i} - w \Phi(x_{i}) - b \leq \varepsilon + \xi_{i} \\ -y_{i} + w \Phi(x_{i}) + b \leq \varepsilon + \xi_{i}^{*} \\ \xi_{i} \geq 0, \xi_{i}^{*} \geq 0 \end{cases}$$
(6)

Of which: C is the penalty factor. Lagrange function is introduced and transformed into dual optimization problem, and kernel function is introduced. Finally, the regression function can be obtained as

$$f(x) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) K(x_i, x) + b^*$$
(7)

Of which: $K(x_i, x_j)$ is the kernel function. It can be seen from the above formula that if the mapping function of the vector or the dimension of the linear space in the function is unknown, the kernel function can also realize the function of prediction. In SVR model, the type of kernel function selection plays an important role. According to the above analysis, this paper selects three types of kernel functions: Linear, Polynomial and Radial Basis Function (RBF), and establishes the prediction model of residual thickness of ladle lining based on SVR respectively. The example analysis and

4.2. Result Analysis of Residual Thickness of Ladle Refractory Based on SVR

result evaluation are carried out through the error evaluation index.

The training data set samples selected for input in this model are shown in the table1, that is, the maximum temperature at the ladle slag line, tapping steel temperature, refining time and ladle repair age measured by the infrared thermal imager.

The quantity of data is 50 groups. When these 50 groups of data are obtained on site, the manual measurement method is adopted at the ladle maintenance station on the steelmaking site to measure the residual thickness of corrosion refractory at the slag line as the actual verification value.

Refining time (min)	Ladle repair age (times)	Tapping steel temperature (°C)	Temperature at ladle slag line (°C)	
55	32	1618	256	
60	20	1596	264	
65	29	1618	267	
70	13	1611	278	
65	29	1606	264	
67	26	1605	266	
68	22	1602	269	
67	6	1602	270	
69	34	1602	271	
56	2	1601	278	
57	21	1600	263	
59	35	1599	264	

Table 1. Model input data.

Select penalty parameter C and insensitive parameter ε of three groups of different parameters. The SVR based residual thickness prediction models of ladle slag line working layer based on Linear, Polynomial and RBF are established respectively, and the regression prediction is carried out to obtain the corresponding residual thickness prediction value of ladle, and the mean square error value is calculated. The model prediction results are shown in table 2.

Model parameter(C,	Kernel	MAE (mm)	MAP (%)	MSE
<i>E</i>)	function			
	Linear	12.4	9	448.2
(3,0.5)	RBF	9.7	7	439.3
	Poly	13.8	10	445.6
	Linear	15.2	11	450.8
(5,1.5)	RBF	11.1	8	447.6
	Poly	12.4	9	449.5
	Linear	16.6	12	450.4
(7,2.0)	RBF	12.4	9	445.6
· · · ·	Poly	19.3	14	448.6

Table 2. Experimental results based on residual thickness prediction of SVR ladle working layer.

Where MAE is the mean absolute error, MAPE is the mean percentage error and MSE is the mean square error. It can be seen from table 2 that the prediction error range of the residual refractory thickness prediction model of ladle based on SVR is 7%-12%. Among them, the average error rate of the ladle refractory layer residual thickness prediction model using RBF kernel function is 8%, which is the lowest compared with 9.7% of the ladle refractory layer residual thickness prediction model using Linear kernel function and 11% of the ladle refractory layer residual thickness prediction model using Polynomial kernel function. Therefore, RBF kernel function is applicable to the ladle lining residual thickness prediction model based on SVR.

Through the steelmaking management system, we can know the refining time, ladle repair age, molten steel temperature of the ladle, combined with the outer surface temperature of the ladle obtained by the infrared thermal camera. These parameters are input into the model to obtain the predicted residual thickness of ladle refractory. When the predicted value is in the safety margin of the ladle refractory of the steelmaking plant, it can be considered that the ladle has no risk of leakage. When the predicted value is greater than the safety margin of ladle refractory in the steelmaking plant, the ladle needs offline maintenance. The residual thickness prediction model of ladle refractory not only prolongs the service life of ladle, but also ensures safety in steelmaking production.

5. Conclusion

In this paper, the safety monitoring problem caused by the corrosion of refractory materials in the ladle at the steelmaking site is studied. The radial heat transfer is analyzed through the ladle heat transfer model, and the relationship between corrosion and temperature change is analyzed through the ladle infrared thermal image. Finally, the prediction model of residual thickness of ladle refractory materials is established to realize the safety monitoring of ladle refractory materials. The conclusions are as follows:

(1) The heat transfer model of ladle wall is established, and the heat transfer of ladle under different conditions is analyzed. The refractory is reduced by 10mm, and the temperature of ladle outer surface is increased by $1.2 \sim 1.8^{\circ}$ C. When the temperature of molten steel changes by about 10°C, the temperature of ladle outer wall changes by 1° C.

(2) The temperature field of the outer wall of the ladle was obtained by the infrared thermal camera. The analysis of the infrared thermal image showed that with the increase of the service life of the ladle, the isothermal region of the slag line in the ladle wall would diffuse outward in a fan-shaped manner, indicating that the corrosion of the refractory materials was intensified.

(3) Based on the SVR residual thickness prediction model of ladle refractory, the residual thickness of ladle refractory is predicted in combination with the number of ladle repair ages, ladle molten steel temperature, refining time and ladle outer wall temperature. The test results show that the prediction accuracy of ladle refractory corrosion reaches 92%, which meets the needs of field application.

References

- [1] Yang SF. Erosion mechanism of slag line brick in large ladle. Wuhan: Wuhan University of Science and Technology, 2007.
- [2] Shen P. Study on interface phenomenon between molten steel slag refractory in metallurgical process. Beijing: Beijing University of Science and Technology, 2017.
- [3] Wang HF. Present situation, damage mechanism and development of RH furnace refractories at PZH Steel. Refractory. 2009; 43(5): 386-388.
- [4] Mahato S, Behera SK. Oxidation resistance and microstructural evolution in MgO-C refractories with expanded graphite. Ceramics International. 2016; 42(6): 7611-7619.
- [5] Vollmann S, Harmuth H. Investigation of refractory corrosion of a gas-stirred steel ladle by simulation. Advances in Science & Technology. 2010; 70: 199-204.
- [6] Eric B, Schmitt N, Hild F. Effect of slag impregnation on thermal degradations in refractories. Journal of the American Ceramic Society. 2010; 90(1): 154-162.
- [7] Bernardo R. Experimental examination of slag/refractory interface. Ironmaking & Steelmaking. 2013; 29(2): 107-113.
- [8] Gu HZ, Huang A and Wang N. Mathematical modelling of erosion of ladle lining with argon blowing at bottom. Journal of Wuhan University of Science and Technology. 2009; 32(5): 487-490.

- [9] Jiang ST, Cai P and Wang X. Damage forecasting of ladle refractory by acoustic emission. Piezoelectric and Acoustooptic. 2010; 32(2): 290-292.
- [10] Liu CM, Shi D and Wang ZG. Acoustic emission damage feature extraction of refractories based on wavelet packet and independent component analysis. Refractory. 2020; 54(3):185-190.
- [11] Liu J, Wu HX and Meng XW. Solution to wall thickness of continuous casting ladle based on laser positioning and ranging. Acta Metrologica Sinica. 2019; 40(4): 557-563.
- [12] Wu XH. Measurement System for ladle's wall thickness based on laser positioning and scanning. Nanchang: East China University of Technology, 2019.
- [13] Biswajit Chakraborty, Billol KUMAR Sinha. Process-integrated steel ladle monitoring, based on infrared imaging-a robust approach to avoid ladle breakout. Quantitative Infrared Thermography Journal. 2019; 19(12): 1639112(1)-1639112(23).
- [14] Guan Rh. The third kind of infrared thermal diagnosis of determining inner wall geometrical shape on the basis of infrared measurement technology. Infrared Technology. 2003; 25(2):54-56.
- [15] Akkurt S. Prediction of the slag corrosion of MgO-C ladle refractories by the use of artificial neural networks. Key Engineering Materials. 2004; 264-268: 1727-1730.
- [16] Venko P, Mincho H, Kosta B. Diagnosis of metallurgical ladle refractory lining based on nonstationary on-line data processing. Bulgarian Academy of Sciences. 2013; 13(2): 122-130.
- [17] Emil M, Venko P. Case-based approach for diagnosis of metallurgical ladle lining. Steel Research International. 2011; 82(12): 1-6.
- [18] Meng QX. Simulation study on the relationship between the thermal image of ladle outer wall and the thickness of lining. Wuhan: Wuhan University of Science and Technology, 2007.
- [19] He DF, Xu AJ and Wu PF. Ladle thermal tracking model in a steelmaking workshop. Journal of Beijing University of Science and Technology, 2011; 33(1): 110-115.
- [20] Olena V, Dieter J. Modelling of temperature distribution in refractory ladle lining for steelmaking. ISIJ International. 2003; 43(8): 1185-1190.
- [21] Liu M, Zhang L. A node data prediction optimization algorithm based on SVR. Electronic Design Engineering. 2018; 26(06):86-89.