Atomic Spectroscopy

ISSN: 0195-5373
e-ISSN: 2708-521X
Vo. 42 No. 2
Mar./Apr. 2021

www.at-spectrosc.com

Cover Feature:

Junbin Cai, Meirong Dong, Yongsheng Zhang, Yixiang Chen, Hongjie Chen, Youcai Liang, and Jidong Lu
Estimating the Aging Grade of Heat-resistant Steel by Using Portable Laser-induced Breakdown Spectroscopy

Atomic
Spectroscopy
Press

Estimating the Aging Grade of Heat-resistant Steel by Using Portable Laser-induced Breakdown Spectroscopy

Junbin Cai,^{a,b} Meirong Dong,^{a,b,*} Yongsheng Zhang,^{a,b} Yixiang Chen,^{a,b} Hongjie Chen,^{a,b} Youcai Liang,^{a,b} Weijie Li,^c and Jidong Lu^{a,b}

^a School of Electric Power, South China University of Technology, Guangzhou, Guangdong, 510640, P.R. China

^b Guangdong Province Engineering Research Center of High Efficient and Low Pollution Energy Conversion, Guangzhou, Guangdong, 510640, P.R. China

^c WISDRI (Wuhan) Thermal Engineering Co., Ltd, Hubei, Wuhan, 430205, P.R. China

Received: December 19, 2020; Revised: January 5, 2021; Accepted: January 5, 2021; Available online: January 18, 2021.

DOI: 10.46770/AS.2020.217

ABSTRACT: Heat-resistant steel is widely used in the construction of various types of industrial pressure-bearing equipment. In this work, laser-induced breakdown spectroscopy (LIBS) was applied to evaluate the aging grade of actual industrial pipe heating surfaces (made by T91 steel) via a self-developed portable LIBS device. First, the pretreatment effect of wavelet threshold denoising (WTD) and multiple scattering correction (MSC) on the LIBS spectrum is discussed. Based on the K-fold-support vector machine-recursive feature elimination (K-SVM-RFE) and support vector machine (SVM), the aging grade model is established using the spectral data of the T91 artificial specimens and of the industrial pipe slices at different aging grades. The influence of the denoising of WTD and the transformation of MSC in the selection of optimal feature subsets using K-SVM-RFE are discussed along with the model's performance. Second, the spectral characteristics of the actual industrial T91 pipe heating surface of coal-fired boilers are investigated, and the spectral data are screened and standardized. Finally, by using the aging grade model to evaluate the aging grade of the industrial T91 pipe based on the calibrated spectral data, an accuracy of 85.17% was achieved. The results demonstrate that the portable LIBS device and the corresponding hybrid model presented here have strong discrimination and robustness for estimating the aging grade of heat-resistant steel.

INTRODUCTION

Heat-resistant steel is extensively used for high-temperature pressure-bearing equipment in industries such as power plants and chemical plants.^{1,2} The micro-structure of heat-resistant steel changes and its macro-mechanical properties inevitably degrade with prolonged operation of the equipment, causing a degradation of steel performance and operation safety, namely, steel aging.³ Within the aging process, the elemental composition of steel experiences little change, while obvious matrix variations occur due to micro and macro damage.

T91 steel is a relatively new martensitic heat-resistant steel with good oxidation resistance and excellent mechanical properties. For T91 steel, aging means the recrystallization of the lath martensitic

structure, decline of dislocation density in the crystal, coarsening of M₂₃C₆ carbide, and precipitation of the Z (Cr (V, Nb) N) phase, which increases the burst-leak possibility of the water screen tube, super heater, reheater, or economizer, and may lead to unplanned plant shutdowns and operational accidents. Traditionally, metallographic analysis is carried out by cutting specific locations of the pipes to determine the aging grade, which is time-consuming and inconvenient due to the requirement of complex sample pretreatment.⁴ Moreover, such destructive procedures cause irreversible damage to the equipment and increases maintenance costs. Therefore, it is of great importance for proper equipment maintenance and human safety to develop *in situ* and non-destructive techniques for assessing the aging grade of steel.

Laser-induced breakdown spectroscopy (LIBS), which is a rapid detection technology with the advantages of simultaneous multi-elemental analysis, quasi nondestructive ablation, and necessitating little or no sample preparation, has been widely developed and applied in various fields for the elemental quantification of different materials.⁵⁻⁷ The measurement accuracy of LIBS of the elemental composition is limited by the matrix effects caused by the physical and chemical properties of the materials. These would affect the laser ablation process and plasma characteristics, leading to multiple sources of spectral uncertainty and difficulties in data processing and quantitative analysis.^{8,9} On the other hand, the spectral signal and the plasma properties can be used as fingerprints to distinguish the difference of the samples and realize the quantitative analysis of characteristic indicators, such as the compressive strength of concrete,¹⁰ the microstructures of aluminum-lithium alloys,¹¹ the mechanical strain of iron alloys¹² and the corrosion grade of magnesium.¹³

In our previous work, a number of studies were carried out to address the failure characteristics of the metals. It was found that the heat-resistant steel characteristics, such as mechanical properties and phase transformation, can also be assessed by spectral characteristics. Yao et al.¹⁴ found a correlation between the ratios of Fe ionic to atomic lines and the tensile strength in three 12Gr1MoV steel samples with different grades of pearlite spheroidization. Lu et al.¹⁵ reported the relationship between spectral emission intensity ratios at specific plasma regions and aging grades of T91 steel. Li et al.¹⁶ reported an agreement between the emission line intensity ratios (CrI 427.481 nm/FeI 376.554 nm and CrI 428.973 nm/FeI 376.554 nm) and the hardness of T91 steel with different degrees of microstructural aging.

In addition to using the above univariate model for the assessment of the property of steel, samples with a number of spectral features were coupled with the multivariate models, such as the support vector machine (SVM), logistic regression (LGR) and partial least-squares regression (PLSR), to establish a more reliable relationship between measured indicators and spectral characteristics.¹⁷⁻¹⁹ Moreover, to magnify the spectral difference between a different steel matrix and to improve the estimation accuracy, the spectral pretreatment, for example, the wavelet threshold denoising (WTD) and the feature selection methods based on the canonical correlation analysis (CCA), the analysis of variance (ANOVA) or the newly developed layered interval wrapper (LIW) were coupled simultaneously.¹⁹⁻²⁰ On the whole, the developed hybrid modeling methods for evaluation of the properties of heat-resistant steel showed satisfactory accuracy and precision. However, the above achievements are based on the bulky laboratorial-based LIBS equipment using artificial specimens, which have been ground and polished to avoid instrumental measurement effects, *i.e.*, from surface oxides and foreign contaminants.

The aim of this work was to develop a rapid *in situ* techniques for assessing the actual industrial heat-resisting steel heating surface. We developed a portable LIBS device for practical industrial field application. In order to propose an appropriate methodology for estimating the actual heating surface. First, the spectral data of T91 artificial specimens and industrial pipe slices at different aging grades were employed for establishing aging grade model. The performance of the optimize methods used for the T91 aging grade models, such as coupling wavelet threshold denoising (WTD), multiple scattering correction (MSC) or a combination of them both, together with K-fold-support vector machine-recursive feature elimination (K-SVM-RFE), were compared and discussed. Second, the spectral data of actual heating surfaces was screened according to the spectral stability of the T91 matrix elements and modified in accordance with its spectral characteristics. Finally, based on the calibrated spectral data, the actual heating surfaces were evaluated by the established model.

EXPERIMENTAL

Specimens. A reheater pipe and superheater T91 pipe taken from boilers in coal-fired power plants, six industrial T91 specimens cut from various reheaters or superheaters of boilers (two of them cut from the pipe specimens), and 10 artificial T91 specimens with different aging grades were employed as the experimental specimens (Fig. 1a and Fig. 1b).

The preparation details of the artificial specimens have been described in our previous work.¹⁸⁻²⁰ All specimens were analyzed using a metallographic microscope (LEICA DMI5000). The microstructure aging grade of them was evaluated according to China's national standard, then the specimens were graded into five levels qualitatively.⁴ The aging grade information of the specimens is listed in Table 1. Specimens A1-10 represent the artificial specimens, while the six industrial specimens cut from various reheaters or superheaters are labeled with an "I" (specimens I5 and I6 are cut from P1 and P2, respectively), specimens P1-2 are industrial pipe specimens.

LIBS setup. The newly developed portable LIBS device (dimensions: 296 x 126 x 149 mm; weight: 4.5 kg) employed in

Table 1. Detailed Information of T91 Specimens

Specimen	Aging grade	Specimen	Aging grade
A1	1	A10	5
A2	2	I1	1
A3	2	I2	2
A4	2	I3	4
A5	3	I4	5
A6	3	I5	1
A7	3	I6	3
A8	3	P1	1
A9	4	P2	3

Fig. 1 (a) Pretreated T91 specimens, (b) actual industrial T91 pipe, and (c) portable LIBS device for steel aging estimation.

this work is shown in Fig. 1c. It included a laser head, laser controller, spectrometer, and focusing lens, etc. A semiconductor solid-state pulsed laser (Quantel, France), operated at 1064 nm and 4 ns pulse duration, was used as the ablation source. The laser beam was focused with a quartz lens of 50 mm focal length onto the specimen vertically to create the plasma. Plasma emission was collected with a collimating lens and then transmitted by optic fiber to a single-channel spectrometer (Avantes) with a receiving range from 297 nm to 556 nm. The gate width of the spectrometer was 1.1 ms and the resolution 0.14 nm. The delay time between the laser ablation and the scan of the spectrometer was set to 2 μ s. After optimizing the experimental parameters with the target of the best signal-to-noise ratio (SNR) and precision (%RSD) of the emission line intensity, the laser pulse energy was set to 7.5 mJ and the repetition rate to 2 Hz.

For the artificial specimens and the industrial pipe slices, the specimen's surface was sanded and polished to remove the contaminants and the oxide layers. Each specimen was measured at 9 different positions with 30 laser pulses. In the case of the pipe specimens, no surface pretreatment was applied. It was predicted that the first several laser pulses would be affected by the surface that was not pretreated; thus, three positions on each specimen's surface were measured with 400 laser pulses to explore the effect of the actual pipe heating surface on the spectral characteristics and the LIBS measurement.

Analytical methods

1) Wavelet Threshold Denoising. The wavelet threshold denoising (WTD) method, based on the discrete wavelet transform (DWT) function, is an effective noise suppression approach for nonstationary signals which is often used for LIBS spectrum pretreatment.^{21,22} The nonstationary signal $f(t)$ was first translated with wavelet transform (WT) to explore the characteristics in time-domain and frequency-domain.^{23,24} The detailed transformation is expressed as Equation (1):

$$WT(a, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \times \psi\left(\frac{t-\tau}{a}\right) dt \quad (\text{Eq. 1})$$

where $WT(a, \tau)$ is the wavelet coefficient, $\psi(a, \tau)$ is the wavelet-based function, and a and τ are the control parameters for scaling and conversion. The symlets (sym) wavelet-based function, which can avoid distortion when decomposing and reconstructing the signal and has demonstrated superior performance in heat-resistant steel spectra pretreatment, was selected to translate each raw signal into a series of wavelets.^{20,25,26} After the process of wavelet decomposition, the raw spectral signal is transformed to the multi-layer wavelet coefficients $W(a, \tau)$ which are equal to the addition of the pure signal coefficient $s(a, \tau)$ and the noise coefficient $n(a, \tau)$ as expressed in Equation (2):

$$W(a, \tau) = s(a, \tau) + n(a, \tau) \quad (\text{Eq. 2})$$

The emission signal and noise signal with a different amplitude and change rate can be identified by the wavelet coefficient. As usual, the wavelet coefficient threshold λ is defined as triple the standard deviation of white Gaussian noise to separate the informative signal and noise signal. In order to avoid signal oscillation and the pseudo-Gibbs phenomenon, the wavelet coefficients are processed using a soft threshold function.²¹ After adjustment of the wavelet coefficient, the denoised signal can be restructured with the new coefficient matrix.

2) Multiple Scattering Correction. Multiple scattering correction (MSC) is a preprocessing algorithm for correcting the baseline by fitting each spectral line and the average spectrum with a linear regression equation and using the fitting coefficients to carry out correction of the variables in the raw spectrum thereafter. The process of linear regression and correction can be expressed as Equation (3) and Equation (4):

$$\text{Linear regression: } Xi = ai + bim \quad (\text{Eq. 3})$$

$$\text{MSC correction: } XMSC = \frac{Xi - ai}{bi} \quad (\text{Eq. 4})$$

where Xi is a single spectrum, the ai and bi values are the slope and offset coefficients of the linear regression, respectively, m is the average spectrum of the specimens, and $XMSC$ is the spectrum after being pretreated by MSC.²⁷

Fig. 2 Comparison of raw spectrum and denoised spectrum of the I1 specimen.

3) Support Vector Machine and K-fold-Support Vector Machine-Recursive Feature Elimination. Support vector machine (SVM) is a supervised algorithm based on the idea of mapping data to high-dimensional feature space and constructing a maximal margin hyperplane to split the data categories. The function expression of the hyperplane can be described as Equation (5):

$$fp(x) = w^T x + b \quad (\text{Eq. 5})$$

where w is the weight of the support vector, which represents the importance of each feature for the learning machine, and b is a bias value.

LIBS data contain abundant spectral features with irrelevant information about the analyte. Thus, reliable estimation models should be established by selecting informative spectral features to improve model performance and to avoid the curse of dimensionality.²⁸ K-fold-support vector machine-recursive feature elimination (K-SVM-RFE) is an efficient feature selection method for use when appropriate for the SVM model. Aiming at eliminating the irrelevant features, K-fold cross-validation is performed in each iteration, and the weight of features is obtained according to its average contribution to the prediction performance of the SVM model, then the 30% features with the minimum weight is removed. Finally, the optimal feature subset is obtained according to the internal cross-validation accuracy with different subsets. The detailed process of the K-SVM-RFE algorithm is presented in ref 20.

RESULTS AND DISCUSSION

Effect of spectral pretreatment

It is well known that the LIBS signal is comprised of characteristic emission lines, the background signal, and the noise signal. The characteristic emission line and background signal affected by matrix effects could be utilized to evaluate the properties of the materials. However, the noise signal, which is a random and messy

jamming signal, affects proper analysis. The noise signal caused by fluctuations of the optical detector and electronic system could be weakened by WTD. Fig. 2 shows the effectiveness of the denoising pretreatment with WTD. The red lines are the raw spectrum of the I1 specimen, and the black lines are the denoised spectrum. The noise signal with low amplitude and high change rate is corrected, while the characteristic lines of the main elements that change at a low frequency on a large scale are relatively consistent with the original. For example, the wavelengths ranging from 300 to 330 nm, which are mostly noise signals, are efficiently eliminated.

Multiple scattering correction (MSC) is a commonly used data processing method in the current multi-wavelength modeling. The spectral data obtained after the scattering correction can effectively eliminate the influence of scattering and correct the baseline drift caused by the limited resolution of the spectrometer and systematic errors. Taking the representative spectra ranging from 452 to 485 nm from six laser pulses of a single specimen as an example, as shown in Fig. 3a and Fig. 3b, after preprocessing the denoised data by the MSC method, the baselines are corrected, and the spectra have higher similarity and stability.

Establishment of aging grade model

In order to propose an appropriate hybrid model building method for the degeneration assessment of heating pipe surfaces via LIBS, 4320 samples from 16 pretreated specimens with different aging grades (10 artificial specimens and 6 industrial pipe slices, with 270 samples in each specimen from 9 measuring positions) were employed as the analytes. It is worth mentioning that the spectral samples were first normalized by the average spectral intensity of the whole spectrum. From each specimen, 20% of the samples were selected randomly and assigned as the testing set for the external test of the model, and the rest of the samples were used as the training sets. The performance of the models was assessed by the overall accuracy which was calculated as the ratio of the sum of true positives (the number of spectral data correctly classified in the testing set) to the total number of testing spectral data.

Fig. 3 Comparison of (a) denoised spectrum and (b) denoised spectrum preprocessed by MSC of the I1 specimen.

Fig. 4 Accuracy of cross-validation of different feature subsets of the spectra preprocessed by different spectral pretreatment under K-SVM-RFE.

First, the normalized spectra were preprocessed by WTD, MSC or WTD plus MSC, respectively. Then the feature selection based on K-SVM-RFE was applied to the training set. For each spectrum undergoing different spectral pretreatment, there were 2048 features in the spectral band of 297–556 nm. The iteration number of feature selection was set to 16 and the spectral features were eliminated from 2048 to 42. The internal cross-validation result was calculated by the model built within the same training samples at each iteration. The training set data were randomly divided into the training subset and the validation subset for cross-validation according to the ratio of 4:1, namely, K was set to 5. When the cross-validation accuracy reached maximum, the selected current features were considered the optimal subset. As shown in Fig. 4, the optimal feature subsets of the normalized spectra and the normalized spectra only preprocessed by MSC are obtained at iterations five and four, and the size of the feature subsets are 513 and 642, respectively, while the CV results of the spectra that were preprocessed by WTD and WTD plus MSC reached maximum at iterations nine and seven. After the optimal feature subsets were obtained, the testing set screened out the corresponding features through the feature selection results of the training set. Finally, for the effective establishment of the SVM classification model, the kernel function of each model that was used to map the data set and the combination parameters were optimized by the grid-search

Table 2. Performance of the Aging Grade Model Based on Optimal Subsets of the Spectra Preprocessed by Different Spectral Pretreatment

Spectral pretreatment	Size of optimal subset	External test accuracy
Normalization	513	86.81% (750/864)
Normalization and MSC	642	89.00% (769/864)
Normalization and WTD	209	90.97% (786/864)
Normalization, WTD and MSC	328	95.37% (824/864)

method. The aging grade models based on the multivariate SVM method were established using the optimal subsets and model settings, thereby performing external tests on the testing set.

Table 2 shows that the models established with the normalized spectra and transformed by the WTD or MSC methods achieved higher external test accuracy (90.97% and 89.00%) than the model established with the normalized spectra (86.81%). The aging grade model synchronously coupled with WTD and MSC exhibited the highest accuracy (95.37%). It can be seen from the location map of the optimal feature subset (Fig. 5) that the model built with the normalized spectra selects a lot of noisy features, which would affect the constructed relationship between these spectra emissions and the aging grade. Moreover, many wavelengths located at around half maximum of the peaks were selected rather than the peak, which may be attributed to the baseline drift. The determination of the weight coefficients may be arbitrary during the iteration process, which can be easily disturbed by the variables with baseline drift and lead to a flawed feature selection result.²⁹

Feature selection to improve model performance is based on the assumption that the higher the coefficient, the more valuable the variable, but it is seriously affected by the difficulty of building a reliable relationship between variable and coefficients in the selection process. When it comes to the spectra denoised by WTD

Fig. 5 Comparison diagrams of selected feature subsets in the models built with (a) normalized spectral data and the (b) normalized spectral data pretreated by WTD+MSC.

Fig. 6 Comparison of the spectrum of actual pipe specimen (P1) and pipe slice specimen (I5).

Fig. 7 Variation trends of the emission line intensities of T91 matrix element with laser pulse number increasing on actual industrial pipe (P1).

and transformed by MSC, the selection of the optimal subset only retained the profile and peak of the emission line which provided useful information for LIBS data classification.^{30,31} Therefore, the discrimination capacity of the aging estimation model was significantly improved.

Based on the above analysis, a hybrid aging grade model

combined with WTD, MSC, K-SVM-RFE and the multivariate SVM method is proposed for the evaluation of industrial pipes based on all of the spectral data obtained for the pretreated T91 specimens.

Spectral characteristics of actual pipe heating surface

During coal-fired boiler operation, the pipe surface of a heating surface undergoes oxidation in the high-temperature aerobic environment. Fly ash and other coal combustion products may be deposited on the pipe surface, resulting in the growth of a thin layer composed of metal oxides and slagging. Fig. 6 shows the representative spectrum of the actual superheater pipe (P1) and its slice (I5). Ca and Al are common elements of slagging on the heating surface of coal-fired boilers, which can be observed in the spectra of actual pipe specimens.³² The extra iron spectral lines may be attributed to the metal oxide layer. Fig. 7 shows the variations of the matrix element (Fe, Cr, Mn, V) line intensities of T91 with the laser pulse number increasing on the surface of the superheater pipe. In the early 225 shots, the increase of line intensities is obvious, resulting from the consumption of the oxide layer and more abundant ablation on the T91 steel matrix with the increase of pulse number. After that, the line intensities are relatively stable. In the last 75 pulses, the intensities slightly decrease with the increase in pulse number after a brief rise. This is attributed to the evident change of crater depth and shape with the further increase of the pulse number, which is called the crater effect.^{33,34}

Aging grade estimation of actual pipe heating surface

In order to better apply the aging grade model to the evaluation of the actual industrial pipes, the spectral data of the pipe specimens from the first 225 and the last 75 laser pulses were excluded in the subsequent analysis. Thus, we obtained a testing set with 600 samples (a superheater pipe and a reheater pipe, with 300 samples in each specimen from three measuring spots). After preprocessing the normalized testing data by the WTD and MSC methods, 209 spectral features of testing sets were retained based on the results of the feature selection of the aging grade model. Owing to the fact that the feature selection is based on the pretreated specimens, the characteristic spectral lines specific to the actual industrial pipe, such as the emission lines of Ca and Al, are not selected.

Furthermore, the selected features of the pretreated specimens and the actual pipe specimens were compared. Fig. 8 shows the intensities of the representative selected features of the pipe specimens and the average intensities of the optimal subsets of the pretreated T91 specimens. The characteristics of these selected spectral features were different owing to significantly different surface properties as well as element composition and concentrations between the polished specimens and the actual pipe specimens. Several major scale intensity features such as the atomic Fe, Cr, and V emission lines of the pretreated T91 specimens were stronger, while most of the rest of the features,

Fig. 8 Comparison of the intensities of the representative selected features of pipe specimens and the average intensities of the optimal subsets of pretreated T91 specimens.

Table 3 Aging Grade Estimation Result of Pipe Specimens

Specimen	Aging grade	Accuracy rate	Average accuracy
Superheater pipe (P1)	1	86.33% (259/300)	85.17%
Reheater pipe (P2)	3	84.00% (252/300)	

including the ionic Fe, Cr, and Mn emission lines, were weaker than the features of the actual pipe specimens.

Pořizka *et al.*³⁵ proposed that the data standardization process is significant for multivariate data analysis, especially when there is a significant difference between the testing data and the data for the construction of the estimation model. Rescaling each variable not only balances the relative weight of the spectral features, but it also reduces the spectral differences due to the inconsistent ablation behavior between actual surface and polished surface, thereby greatly improving the detection effectiveness.³⁶ Therefore, the testing set was standardized for reliable evaluation. In this study, we proposed a spectral standard method according to the spectral characteristic difference between the actual pipe and the pretreated specimens and applied it to the feature subsets of the pipe.

First, the ionic spectral emission line of Fe II at 522.24 nm, which was the most intense ionic spectral line of the main component element of T91 steel, was selected as the internal standard. The intensity of the spectral features was then divided by the intensity ratio of the FeII 522.24 nm line of the feature subset and the FeII 522.24 nm line of the average optimal subset of the pretreated T91 specimens. The detailed function is expressed as Equation (6):

$$I_{in} = I_j \frac{I_{Fe'}}{I_{Fe}} \quad (\text{Eq. 6})$$

where I_{in} is the feature subset after standardization, I_j is the raw subset, I_{Fe} is the intensity of the FeII 522.24 nm emission

line of the raw subset, and $I_{Fe'}$ is the FeII 522.24 nm emission line intensity of the average optimal subset of the pretreated T91 specimens. After standardization of the selected features of the actual industrial pipe specimens, the estimation of aging grade achieved an accuracy of 85.17% (as shown in Table 3). The established hybrid model presented here has a strong discrimination capacity and robustness (the capability of handling the fluctuations of spectral signals under different measuring conditions).

CONCLUSIONS

This study proposed a hybrid model based on WTD, MSC, K-SVM-RFE and SVM for the estimation of the aging grade of actual industrial pipe heating surface via a newly developed portable LIBS device. It was found that the noise signal and baseline drift of the LIBS spectrum could be corrected effectively with WTD and MSC, which was conducive to the selection of optimal feature subsets using K-SVM-RFE. The aging grade model established with the optimal spectral feature subsets of T91 artificial specimens and industrial pipe slices achieved an accuracy of 95.4% for the external test. Due to the presence of surface oxidation and slagging, the spectrum of the actual industrial T91 pipes showed significantly different spectral characteristics from the artificial specimens versus the industrial pipe slices. Hence the spectral data of the pipe specimens were screened and standardized for improving the representativeness. The assessment of the aging grade was achieved with an accuracy of 85.17%, which verifies the effectiveness of the aging grade model for performing practical measurements. The portable LIBS technology coupled with the spectral pretreatment and the feature selection algorithm has great potential for industrial applications in heat-resistant steel estimation.

AUTHOR INFORMATION

Corresponding Author

* M. R. Dong

Email address: epdongmr@scut.edu.cn

Notes

The authors declare no competing financial interest.

ACKNOWLEDGMENTS

The research was supported by the National Natural Science Foundation of China (No. 51976064), the Guangdong Basic and Applied Basic Research Foundation (2020A1515010646), the Natural Science Foundation of Guangdong Province of China (2017B030311009) and the Fundamental Research Funds for the

Central Universities (2020ZYGXZR027). We also acknowledge the support from the Guangdong Province Key Laboratory of Efficient and Clean Energy Utilization (2013A061401005) and the Key Laboratory of Efficient and Clean Energy Utilization of Guangdong Higher Education Institutes (KLB10004).

REFERENCES

1. S. V. Panin, P. O. Maruschak, I. V. Vlasov and B. B. Ovechkin, *Theor. Appl. Fract. Mech.*, 2016, **83**, 105-113. <https://doi.org/10.1016/j.tafmec.2015.12.008>
2. R. Viswanathan, K. Coleman and U. Rao, *Int. J. Pressure Vessels Pip.*, 2006, **83**, 778-783. <https://doi.org/10.1016/j.ijpvp.2006.08.006>
3. B. Fournier, M. Sauzay, F. Barcelo, E. Rauch, A. Renault, T. Cozzika, L. Dupuy and A. Pineau, *Metall. Mater. Trans. A.*, 2008, **40**, 330-341. <https://doi.org/10.1007/s11661-008-9687-y>
4. DL-T884-2019 Power Plant Metallography Inspection and Assessment Guideline, China, *China Electric Power Press*, 2019. <http://www.doc88.com/p-79229094524928.html>
5. R. Noll, C. Fricke-Begemann, M. Brunk, S. Connemann, C. Meinhardt, M. Scharun, V. Sturm, J. Makowe and C. Gehlen, *Spectrochim. Acta B*, 2014, **93**, 41-51. <https://doi.org/10.1016/j.sab.2014.02.001>
6. F. J. Fortes and J. J. Laserna, *Spectrochim. Acta B*, 2010, **65**, 975-990. <https://doi.org/10.1016/j.sab.2010.11.009>
7. J. L. Gottfried, F. C. De Lucia, Jr., C. A. Munson, and A. W. Miziolek, *Anal Bioanal Chem.*, 2009, **395**, 283-300. <https://doi.org/10.1007/s00216-009-2802-0>
8. J. Vrenegor, R. Noll and V. Sturm, *Spectrochim. Acta B*, 2005, **60**, 1083-1091. <https://doi.org/10.1016/j.sab.2005.05.027>
9. I. Rauschenbach, V. Lazic, S. G. Pavlov, H. W. Hübers and E. K. Jessberger, *Spectrochim. Acta B*, 2008, **63**, 1205-1215. <https://doi.org/10.1016/j.sab.2008.08.006>
10. S. M. Kenichiro Tsuyuki, Nasrullah Idris, Koo Hendrik Kurniawan, Tjung Jie Lie, and Kiichiro Kagawa, *Appl. Spectrosc.*, 2006, **60**, 61-64. <https://doi.org/10.1366/000370206775382668>
11. T. A. Labutin, A. M. Popov, V. N. Lednev and N. B. Zorov, *Spectrochim. Acta B*, 2009, **64**, 938-949. <https://doi.org/10.1016/j.sab.2009.07.033>
12. R. T. E. Cerrai, *Energ. Nucl.*, 1968, **15**, 581-587.
13. P. Pořízka, I. Ročňáková, J. Klus, D. Prochazka, L. Sládková, P. Šperka, Z. Spotz, L. Čelko, K. Novotný and J. Kaiser, *J. Anal. At. Spectrom.*, 2015, **30**, 2099-2106. <https://doi.org/10.1039/c5ja00257e>
14. S. Yao, M. Dong, J. Lu, J. Li and X. Dong, *Laser Phys.*, 2013, **23**, 125702. <https://doi.org/10.1088/1054-660x/23/12/125702>
15. S. Lu, M. Dong, Q. Chen, J. Huang, Y. Yu and J. Lu, *Spectrochim. Acta B*, 2019, **151**, 1-11. <https://doi.org/10.1016/j.sab.2018.11.004>
16. J. Li, J. Lu, Y. Dai, M. Dong, W. Zhong and S. Yao, *Appl. Surf. Sci.*, 2015, **346**, 302-310. <https://doi.org/10.1016/j.sab.2018.11.004>
17. S. Lu, M. Dong, J. Huang, W. Li, J. Lu and J. Li, *Spectrochim. Acta B*, 2018, **140**, 35-43. <https://doi.org/10.1016/j.sab.2017.11.005>
18. S. Lu, S. Shen, J. Huang, M. Dong, J. Lu and W. Li, *Spectrochim. Acta B*, 2018, **150**, 49-58. <https://doi.org/10.1016/j.sab.2018.10.006>
19. J. Huang, M. Dong, S. Lu, W. Li, J. Lu, C. Liu and J. H. Yoo, *J. Anal. At. Spectrom.*, 2018, **33**, 720-729. <https://doi.org/10.1039/c8ja00030a>
20. J. Huang, M. Dong, S. Lu, Y. Yu, C. Liu, J. H. Yoo and J. Lu, *Analyst*, 2019, **144**, 3736-3745. <https://doi.org/10.1039/c9an00370c>
21. H. Duan, S. Ma, L. Han and G. Huang, *Microchem J.*, 2017, **134**, 262-269. <https://doi.org/10.1016/j.microc.2017.06.015>
22. B. Zhang, L. Sun, H. Yu, Y. Xin and Z. Cong, *Spectrochim. Acta B*, 2015, **107**, 32-44. <https://doi.org/10.1016/j.sab.2015.02.015>
23. P. Lu, Z. Zhuo, W. Zhang, J. Tang, H. Tang and J. Lu, *Appl. Optics*, 2020, **59**, 6443-6451. <https://doi.org/10.1364/AO.394746>
24. T. Wang, L. Jiao, C. Yan, Y. He, M. Li, T. Zhang and H. Li, *Chemometrics Intell. Lab. Syst.*, 2019, **194**. <https://doi.org/10.1016/j.chemolab.2019.103854>
25. C. Yan, T. Zhang, Y. Sun, H. Tang and H. Li, *Spectrochim. Acta B*, 2019, **154**, 75-81. <https://doi.org/10.1016/j.sab.2019.02.007>
26. Yuan, T. Wang, Z. Li, Z. Ni, W. Liu, *J. Anal Chim Acta.*, 2014, **807**, 29-35. <https://doi.org/10.1016/j.sab.2019.02.007>
27. Y. Lu, H. Guo, T. Shen, W. Wang, Y. He and F. Liu, *Anal. Methods*, 2019, **11**, 6124-6135. <https://doi.org/10.1016/j.aca.2013.11.027>
28. J. Izetta, P. F. Verdes and P. M. Granitto, *Expert Syst. Appl.*, 2017, **88**, 205-216. <https://doi.org/10.1016/j.eswa.2017.06.043>
29. C. M. Bishop, *Pattern Recognition and Machine Learning*, New York, USA, *Springer*, 2006. <https://doi.org/10.1198/jasa.2008.s236>
30. M. D. Dyar, C. I. Fassett, S. Giguere, K. Lepore, S. Byrne, T. Boucher, C. J. Carey and S. Mahadevan, *Spectrochim. Acta B*, 2016, **123**, 93-104. <https://doi.org/10.1016/j.sab.2016.07.010>
31. L. J. Radziemski, D.A. Cremers, Chichester, *Handbook of Laser-Induced Breakdown Spectroscopy*, John Wiley & Sons Ltd., USA, 2006. <https://doi.org/10.1002/0470093013.ch1>
32. R. Zhu, Y. Liu, Q. Zhang, F. Zhou, F. Jin, W. Yin and X. Zhao, *Optik*, 2018, **169**, 77-84. <https://doi.org/10.1016/j.ijleo.2018.05.035>
33. D. N. Patel, R. P. Singh and R. K. Thareja, *Appl. Surf. Sci.*, 2014, **288**, 550-557. <https://doi.org/10.1016/j.apsusc.2013.10.072>
34. C. G. Corsi M, Hidalgo M, *Appl. Spectrosc.*, 2005, **59**, 853-860. <https://doi.org/10.1366/0003702054411607> · Source: PubMed
35. P. Pořízka, J. Klus, A. Hrdlička, J. Vrábel, P. Škarková, D. Prochazka, J. Novotný, K. Novotný and J. Kaiser, *J. Anal. At. Spectrom.*, 2017, **32**, 277-288. <https://doi.org/10.1039/c6ja00322b>
36. J.P. Castro, E.R. Pereira-Filho, *J. Anal. At. Spectrom.*, 2016, **31**, 2005-2014. <https://doi.org/10.1039/C6JA00224B>