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Single Spectrum End Point Predict of BOF with SVM

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***Abstract*—**SVM (Support Vector Machine) is a new method in the artificial neural network (ANN). In the steel making, how to use computer to predict the end point of BOF accuracy is a great problem. A lot of method and theory have been claimed, but most of the results is not satisfied. Now the hot topic in the BOF end point predicting is to use optical way the predict the end point in the BOF. And we found that there exist some regular in the characteristic curve of the flame from the mouse of pudding. And we can use SVM to predict end point of the BOF, just single spectrum intensity should be required as the input parameter. Moreover, its compatibility for the input space is better than the BP network.

***Keywords*—**SVM, predict, BOF, single spectrum intensity.

I. Introduction

BOF is an important step in the industry of steel making, which decided the quality of the steel products. Now a new way in the BOF is collecting the information in the blame of furnace to predict the end point of BOF [1]. Bethlehem Corp. has developed an optical detector, which can measure the contain of the carbon in the melt steel by the intensity of the flame. But only the capability of the furnace must be satisfied over 200t [2]. Another technology can solve this problem. They use telescope and fiber to establish a collection system to gather the information of the blame, and use the BP algorithm to get the end point of BOF. But the BP is not a suitable algorithm in this complicated process. Because the BOF is too complicated to be denoted by a fixed function. The BP algorithm is deeply cling to the training data, so if the training data cannot contain all the condition of BOF, then the predicting result will present a large error [3-4]. So the statistics learning is put forward, which called support vector machine. SVM has such advantage: at first, it aims at the finite number of samples, secondly, its result is the optimal solution of the full district, moreover, if the training data is multi-dimension, it will not make the algorithm being complicated [5]. As these superiorities, we could use SVM to take place of BP in the BOF end point predicting. And we only choose the intensity of the flame as the input parameter to get the relative exact result. Moreover, if a new sample is added as a training point, it will not act on the predicting results only if the sample is supporting vector, which could be adjusted by changing parameter of the core function.

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II. Principle and Experiment

A. SVM Regression Principle

Fig. 1 shows the structure of the SVM network. In the SVM, we care the structural risk of the system, which is different with other artificial neural network. The structural risk $R(\omega)$ can be given as [6]:

$$R(\omega) = R_{emp}(\omega) + \sqrt{\frac{h(\ln(2l/h)+1)-\ln(\eta/4)}{l}} \tag{1}$$

Where h is the VC dimension of a function set, l is the number of samples, $R_{emp}(\omega)$ is the expert risk, η is a parameter, and $0 \le \eta \le 1$.

What we can get from the mouse of pudding is the intensity of the flame and the image information of the flame. And it is can be treated as a time series. So SVM is used to be a time series prediction system.

In this case, we should mapping the input vector to the feature space, and in which, we make a optimize function [7].

$$f(x) = W^T g(x) + b \tag{2}$$

Where W is a weight vector, $g(x)$ is the function which mapping the data x to the feature space, b is a coefficient of the SVM.

We introduce the Lagrange multiplier α_i, α_i^*, η_i, η_i^*, the problem is transfer to seek a optimal solution of the function:

$$\begin{aligned}\min Q(W,b,\xi,\xi^*,\alpha,\alpha^*,\eta,\eta^*) &= \frac{1}{2}\|W\|^2 + C\sum_{i=1}^{M}(\xi_i+\xi_i^*) \\ &- \sum_{i=1}^{M}\alpha_i\left[\varepsilon+\xi_i-y_i+W^T g(x)+b\right] \\ &- \sum_{i=1}^{M}\alpha_i^*\left[\varepsilon+\xi_i^*+y_i-W^T g(x)-b\right] - \sum_{i=1}^{M}(\eta_i\xi_i+\eta_i^*\xi_i^*)\end{aligned} \tag{3}$$

Finally, we can get the regression function as:

$$f(x) = \sum_{i=1}^{M}(\alpha_i-\alpha_i^*)g^T(x_i)g(x)+b \tag{4}$$

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Also we can use the kernel function $K(x_i, x)$ to instead the mapping function $g(x)$. The kernel function must contend the Mercer condition, that is:

$$K(x_i, x) = g^T(x_i)g(x) \tag{5}$$

So the regression function can be written as:

$$f(x) = \sum_{i=1}^{M} (\alpha_i - \alpha_i^*) K(x_i, x) + b \tag{6}$$

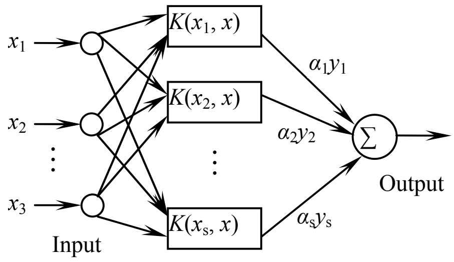

Fig. 1 SVM network

B. SVM Creating

In the BOF, the worker controls the volume of oxygen according the intensity of the flame. The volume of oxygen per second is used to control the reaction rate of carbon and oxygen. That means the content of carbon in the molten iron in the furnace could be estimated by the intensity of the flame. According the blackbody radiation theory[8]:

$$M(\lambda, T) = \alpha(\lambda, T) M_e(\lambda, T) \tag{7}$$

Where, λ is the wavelength of the flame, T is the temperature of the molten iron. $M(\lambda, T)$ is the flux of the flame, $M_e(\lambda, T)$ is the flux of the ideal blackbody. $\alpha(\lambda, T)$ is the absorption rate.

The ideal blackbody radiation flux is nothing to do with the material. It is only depended on the wavelength and temperature. But the content of carbon could be estimated by the radiation flux. So we could make a conclusion that $\alpha(\lambda, T)$ has another parameter which is the content of carbon in the molten iron.

The worker controls the oxygen chamber to adjust the volume of oxygen. If the rate of input oxygen is changed, the intensity of the flame should change. So in the practice manipulation, the intensity of the flame is a basic parameter in the BOF. Every change in the intensity could be treated as a step of the worker's manipulation. And the end point of BOF can be predicted if we know how the worker controls the oxygen chamber. Therefore, we suppose that the intensity of light could be describe how the worker manipulates the oxygen chamber and could be describe the content of carbon in the molten iron. So we compose the system of the arithmetic showed as Fig. 2. And the light intensity transformation must be accord red such law showed as Fig. 3.

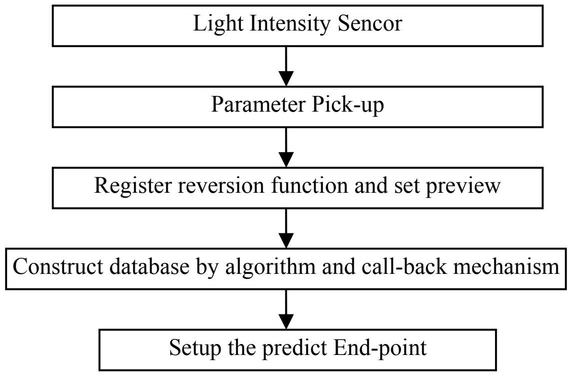

Fig. 2 Systems Composing

Usually, the process of BOF will last about 800 seconds. So we choose the mean intensity of every 100 seconds as a input parameter of SVM. The number of parameter is 7. For example x_1 is the mean intensity of 1s to 100s. That is the input of SVM is $X = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7\}$. And the output of SVM is the end point T.

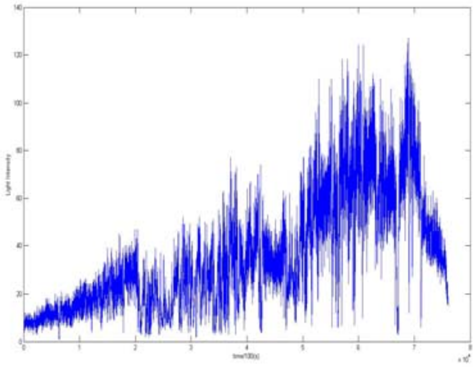

Fig. 3 The light intensity of BOF

So the problem is to find a function $f(\bullet)$ to predict endpoint according the parameter we choose above.

$$T = f(X) = \sum_{i=1}^{M} (\alpha_i - \alpha_i^*) K(X_i, X) + b \tag{8}$$

C. Experiment

We choose 41 BOF as training sample and choose five BOFs as test. The result is showed as below:

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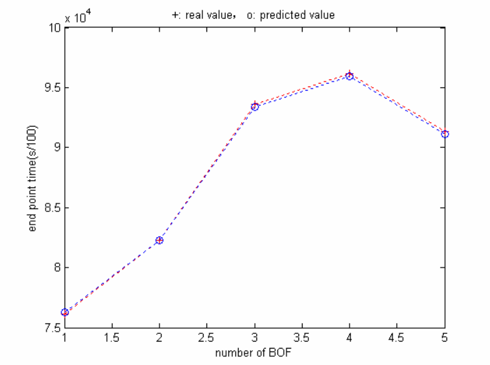

Fig. 4 Predict result with 41 training data

And the error between the real value and predicted value is showed as:

TABLE I
ERROR STATISTICS

Pudding Number	*1*	*2*	*3*	*4*	*5*
Error	-136.60	-16.26	205.79	256.56	161.147

If we add 4 new BOF as training data and the test BOF is the same as the above, that means the number of training data is added to 45, the predicting result will almost still be as same as the result above.

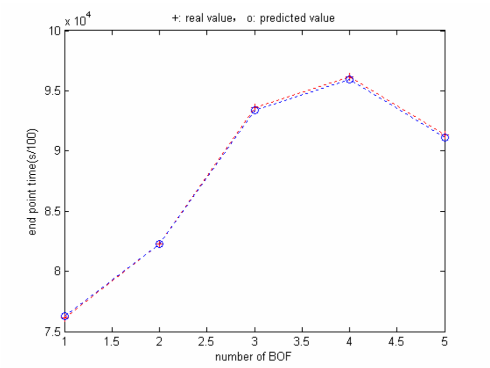

Fig. 5 Predict result with 45 training data

TABLE II
ERROR STATISTICS

Pudding Number	*1*	*2*	*3*	*4*	*5*
Error	-96.33	24.01	240.07	269.83	201.43

We can see there is little difference between group 1 data and group 2 data. That means SVM can find whether the training data is suitable for the common regulation. The prediction result will not change if the training data has added. So in the application, we will not need to change de model parameter for the training data has added. The system could add more training data without any adjust in the model parameter.

III. CONCLUSION

As we all know, in the learning system, more training data it has, more accuracy result it should be. SVM could be added training data automatically. On the other hand, we can see the predict result is so precise, that means in the process of BOF, the change of light intensity determined the end point of BOF. What we really care is not the time ending point of BOF, but the carbon containing. However, we could calculate the carbon containing by the light intensity of single spectrum. From the research, we can use SVM to research the multi-spectrum of BOF's flame.

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REFERENCES

[1] Feng Jie, Zhang Hongwen, *BOF steelmaking[M]*. Beijing: Metallurgical Industry Press, 2006. 332–338.
[2] Sharan A., *Light sensors for BOF carbon control in low cabon heats[C]*. Steelmaking Conference Proceedings, 1998, 81: 337–345.
[3] Hong-yuan Wen, Qi Zhao, Yan-ru Chen, Mu-chun Zhou, Meng Zhang, Ling-fei Xu., *IBasic-Oxygen-Furnane Endpoint Forecating Model Based on Radiation and Modified Neural Network[J]*. ACTA Opitca sinica. 2008, 28(11): 2131–2135.
[4] Hong-yuan Wen, Qi Zhao, Yan-ru Chen, Mu-chun Zhou, Meng Zhang, Ling-fei Xu., *TConerter End-point Prediction Model Using Spectrum Image Analysis and Improved Neural Network Algorithm[J]*. Optica Applicata, 2008, 38(4): 693–704.
[5] C. Cortes, V.Vapnik. *Support vecter networks[J]*. Machine Learning, 1995(20): 273-297.
[6] Nello Cristianini, John Shawe-Taylor, An Introduction to Support Vector Machines[M], London: Cambridge University Press, 2006: 54-59.
[7] Wang Weiwei. *Time Series Prediction Based on SVM and GA[J]*. The Eighth International Conference on Electronic Measurement and Instruments,2007,2:307-310.
[8] Weiping Wang, Chengxian Guan, Zhongqing Chen. *HF-NQO-100 model oxygen concentration cell[J]*. Proc. SPIE 4077, 304-308 (2000).

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