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A Soft Measure Algorithm for BOF Steelmaking Process

LIU Chang[a, b], *ZHANG Yan-yan*[a, b], *ZHANG Xin-yu*[a]
(a. School of Information Science and Engineering; b. Institute of Industrial Engineering and Logistics Optimization, Northeastern University, Shenyang 110004, China)

Abstract: Based on the analysis of actual industry data, a soft measure modeling method is proposed for basic oxygen furnace (BOF) steelmaking process. The key idea of the proposed method is to achieve the end-point prediction in the BOF steelmaking process. In order to predict the end-point temperature and the end-point carbon content more accurately, an approach combining modified particle swarm optimization with least squares support vector machine (MPSO-LSSVM) is utilized to establish the prediction model. MPSO is used to optimize the parameters of the model, so that the model can have a better adaptability. At the same time, the strategy based on the event driven is adopted, so as to strength the universal capability of the model. Experimental results indicate that the soft measure prediction method is effective, and it can be successfully applied to the actual industry field.

Key words: Basic oxygen furnace (BOF); end-point prediction; LSSVM; MPSO

一种转炉炼钢过程中的软测量方法

刘畅[a, b]，张颜颜[a, b]，张鑫宇[a]
(东北大学 a.信息科学与工程学院；b.工业工程与物流优化研究所，沈阳 110004)

摘　要：基于实际工业数据的分析，针对氧气顶吹转炉炼钢过程，提出一种软测量建模方法。该方法的主要思想是为了实现转炉炼钢过程中的终点预测。为了更准确地预测终点温度和终点碳含量，结合最小二乘支持向量机和改进的粒子群算法被用来建立预测模型。改进的粒子群算法被用来优化模型的参数，使得模型具有一个更好的适应性。同时，采用基于事件驱动的策略，以加强模型的普适性。实验结果表明该软测量方法是有效的，并且能成功地应用于实际工业领域。

关键词：转炉；终点预测；最小二乘支持向量机；改进的粒子群算法
中图分类号：TP29　　　**文献标识码：**A

1 Introduction

Converter steelmaking is a significant link of steel production[1],[2],[3], aiming at smelting steel (mainly carbon content of molten steel), the quality of steel must be conformed to requirements of the molten steel. Therefore, the temperature and composition of molten steel have a very important impact on the smelting control and quality of molten steel in the smelting process. However, the quality information of molten steel is difficult to monitor in converter steelmaking, and then measure information is limited. As the basic of above existing problems, the quality of measurement information may be incomplete, and time may accompany delay. Aware of that, it will be a great challenge for the prediction in converter steelmaking. Therefore, smelting condition needs to be grasped timely and accurately, the strategy of adding oxygen and other materials (including slag and coolant, etc) needs to be adjusted accurately, so that smelting can accurately meet the requirements of steel, the performance of steel has an efficient improvement.

In the steelmaking industries, unmeasured variables can be simultaneously predicted by soft sensor

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作者简介：刘畅(1987-)，男，辽宁沈阳人，博士，主要研究方向为计算智能、数据处理、机器学习研究与应用等；张颜颜(1975-)，女，辽宁丹东人，博士，讲师，主要从事计算智能、机器学习，能源优化等方面的教学与科研工作。

methods. Many researchers have done amount of researches on prediction algorithms to solve these problems[4],[5]. Nowadays, data analytic techniques have a powerful development, including support vector machine (SVM)[6], least squares support vector machine (LSSVM)[7],[8], and some hybrid methods of intelligent optimization[9],[10]. Some novel modeling methods can be used to predict the end-point composition content in converter steelmaking. These prediction models based on new training set are obtained by least square support vector machine. For the unified steelmaking process, Wang[11] put forward a quality control model, and established the black box model of BOF steelmaking in the terminal prediction process. Wang[12] adopted an improved method of input weight based on Support Vector Machine (SVM), and forecasted the endpoint temperature of BOF steelmaking process by the improved algorithm. Han[13] developed a method based on a robust relevance vector machine, and the approach was used to predict the endpoint temperature and the endpoint carbon content in the convert steelmaking process. In recent years, the soft measure model is not only based on above researches, but also combines with other approaches in BOF steelmaking process.

This paper analyzes a large number of actual production data in the process of converter steelmaking, and then adopts the strategy based on the event, but not based on the time, so as to improve the predictive accuracy on the end-point temperature and the end-point carbon content of BOF steelmaking process, and to overcome the disadvantage of traditional soft measure methods. In addition, this paper unitizes a modified PSO to optimize the parameters of LSSVM, and has a better adaptability on the universal problems.

2 Description of BOF Steelmaking Process

BOF steelmaking is a batch process, according to the production process, the traditional BOF steelmaking process is mainly divided into three stages. At the beginning of the converting process, silicon and manganese have a chemical reaction, although carbon content is higher in molten iron, and it is beneficial to oxidation of carbon, but because of the low average temperature of molten pool, the carbon exists in the inert state, and silicon content and manganese content are higher, give priority to oxidization of silicon and manganese. When furnace temperature exceeds 1450℃, the oxidation of carbon is rapidly increasing. Then, the second stage is mainly reaction of carbon and oxygen, due to drastic oxidation of carbon, the temperature has a huge fluctuation. In this stage, the operator mainly should control the change of temperature, so as to make the reaction stable. At the ending stage of smelting, in terms of the speed, reduction of carbon content is very slow. The main task is to adjust the temperature and composition in the ending stage, and get ready to stop smelting steel. Therefore, the converter smelting process has the characteristics including high temperature, a variety of physical and chemical change, fast response, short smelting period, etc. The production process is very complicated. The reaction process of BOF steelmaking is shown in Fig.1.

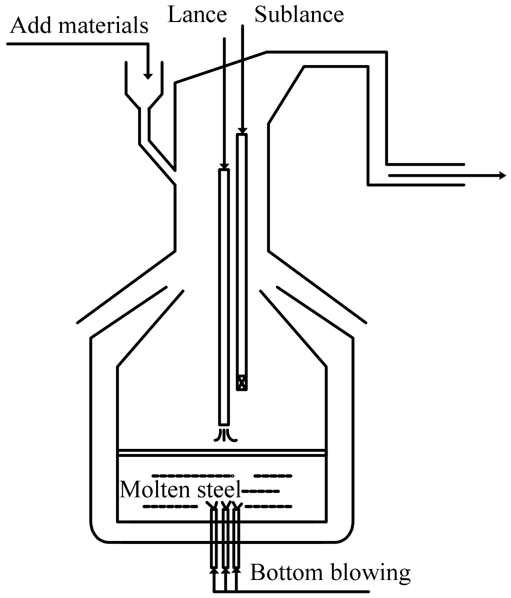

Fig. 1 The reaction process of BOF steelmaking

图 1 转炉炼钢反应过程

In the converter steel-making, it is very significant to accurately predict end-point temperature and end-point carbon content so as to ensure quality of molten steel. However, due to the current measurement technology and tool, it is very difficult for establishing the mechanism model. In order to effectively solve the problem, this paper proposes a prediction method based on soft measure.

3 Prediction Method

This paper regards the modified PSO (MPSO) and

LSSVM as the hybrid algorithm. The MPSO aims at optimizing the parameters of LSSVM, so as to improve the adaptability of soft measure model, and to increase the universal capability of the model for different problems. In addition, this paper adopts the event based idea, to improve the precision of the predictive model.

3.1 The Hybrid Algorithm

In LSSVM model, both the parameter γ and kernel parameter σ^2 play important roles. These parameters will be adjusted by MPSO algorithm. In this paper, the RMSE is used to evaluate the fitness function of particles, the equation is as follows:

$$\mathrm{RMSE}=\sqrt{\frac{1}{l}\sum_{j=1}^{l}e_j^2}=\sqrt{\frac{1}{l}\sum_{j=1}^{l}(y(x_j)-y_j)^2} \tag{1}$$

where the actual value is y_j, and the predictive value is $y(x_j)$. γ and σ^2 are not optimal until the algorithm reaches the predefined number of iteration. The flow chart of MPSO-LSSVM method is shown in Fig.2.

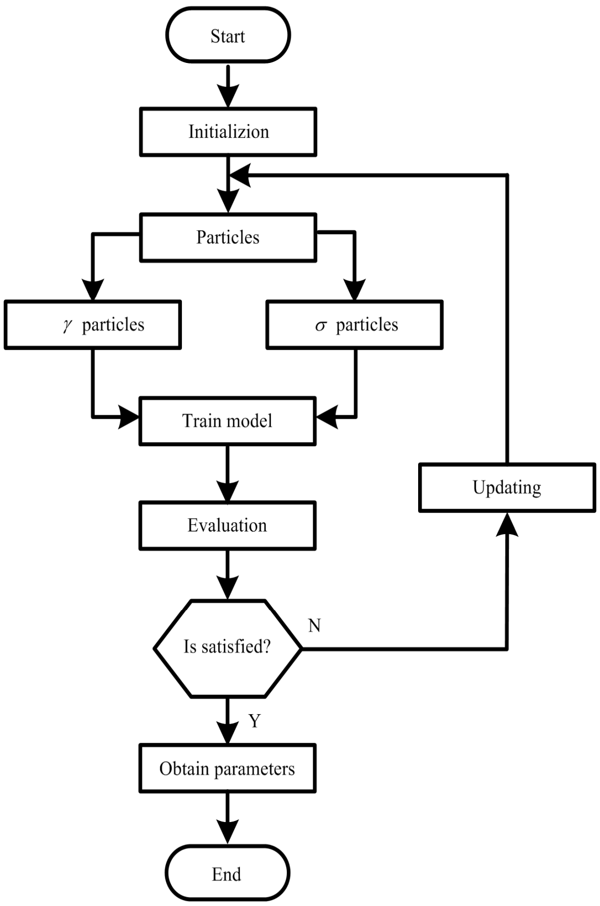

Fig. 2 The flow chart of MPSO-LSSVM method

图 2 MPSO-LSSVM 方法流程图

The training procedure of MPSO-LSSVM is described below:

Step 1 Data set: The training data and the testing data are regarded as training set and testing set respectively.

Step 2 Initialize population: Randomly generate population (include γ and σ^2).

Step 3 Evaluate particles: Each particle is evaluated by the fitness function. The best individual particle and the best global particle are respectively selected from all particles.

Step 4 Termination condition: Set up the maximum iteration and the predefined unchanged iteration, if the stopping criterion satisfies the maximum iteration or the best particle has not been modified for the predefined number of iteration, go to step 6. Otherwise, go to step 5.

Step 5 Update particles: Update the velocity and the position according to Eqs. (12) and (11), and then generate new particles, go to step 3.

Step 6 Stop running: The optimal parameters are obtained.

3.2 LSSVM

Least square support vector machine (LSSVM) is an improved standard support vector machine (SVM), which was developed by Suykens[14]. The most important distinction between SVM and LSSVM is that LSSVM uses a set of linear equations for solving, while SVM mainly relies on the quadratic programming method.

The principle of LSSVM is as follows: Given a training set of l data points $\{(x_i, y_i) \mid i=1,2\cdots,l\}$, where $x_i \in R^N$ is the ith input sample and $y_i \in R$ is the ith output sample, l is the number of training sets. The linear function in high dimensional feature space is shown as (2), where the input data are mapped to the high dimensional feature space.

$$f(x)=w^{\mathrm{T}}\Phi(x)+b \tag{2}$$

The LSSVM can be shown as the constraint optimization problem:

$$\begin{cases}\min\limits_{w,b,e} J(w,e)=\dfrac{1}{2}w^{\mathrm{T}}w+\dfrac{1}{2}\gamma\sum\limits_{i=1}^{l}e_i^2 \\ \text{s.t.}\quad y_i=w^{\mathrm{T}}\Phi(x_i)+b+e_i\end{cases} \tag{3}$$

where $J(w,e)$ is the loss function, $w \in R^{N_c}$ is weight vector, $e_i \in R$ is error variance, b is deviation value, and γ is penalty coefficient.

To solve the problem (3), the following Lagrangian can be formed as:

$$L\left(w,b,e,\alpha\right)=J\left(w,b,e\right)-\sum_{i=1}^{l}\alpha_i\left\{w^{\mathrm{T}}\Phi\left(x_i\right)+b+e_i-y_i\right\} \quad (4)$$

where $\alpha_i \in R$ $(i=1,2,...,l)$ is the Lagrange multiplier. The solution exists in the constrained optimization expression with the following conditions as:

$$\begin{cases}\partial L/\partial w=0\rightarrow w=\sum_{i=1}^{l}\alpha_i\phi\left(x_i\right)\\ \partial L/\partial b=0\rightarrow\sum_{i=1}^{l}\alpha_i=0\\ \partial L/\partial e_i=0\rightarrow\alpha_i=\gamma e_i\\ \partial L/\partial\alpha_i=0\rightarrow w^T\phi\left(x_i\right)+b+e_i=y_i\end{cases} \quad (5)$$

After eliminating variables w, e_i, the following matrix equation can be formulated as:

$$\begin{bmatrix}0 & Z^{\mathrm{T}}\\ Z & \Omega+D\end{bmatrix}\begin{bmatrix}b\\ \alpha\end{bmatrix}=\begin{bmatrix}0\\ y\end{bmatrix} \quad (6)$$

where $\Omega=\begin{bmatrix}\varphi(x_1)\varphi(x_1) & \dots & \varphi(x_1)\varphi(x_l)\\ \vdots & \ddots & \vdots\\ \varphi(x_l)\varphi(x_1) & \cdots & \varphi(x_l)\varphi(x_l)\end{bmatrix}$, $Z=\left[1,...,1\right]^{\mathrm{T}}$, and $D=diag\left(\gamma^{-1},...,\gamma^{-1}\right)$.

According to the Mercer's condition, (6) is equal to the following equation as：

$$\begin{bmatrix}0 & Z^{\mathrm{T}}\\ Z & K+D\end{bmatrix}\begin{bmatrix}b\\ \alpha\end{bmatrix}=\begin{bmatrix}0\\ y\end{bmatrix} \quad (7)$$

where $K=\left\{K_{ij}=K\left(x_i,x_j\right)\right\}_{i,j=1}^{l}$. From the linear equation (7), α_i, b can be obtained, then the LS-SVM regression model can be written as follows:

$$y(x)=\sum_{i=1}^{l}\alpha_iK(x,x_i)+b \quad (8)$$

In the LSSVM model, the penalty parameter γ and the kernel width parameter σ^2 are the key parameters. Because two key parameters have strong impacts on the performance of the LSSVM model. In this paper, we focus on the powerful RBF kernel. In RBF kernel, σ^2 is a bandwidth kernel. The equation is as follows:

$$K(x,x_i)=\exp\left(-\frac{\left\|x-x_i\right\|^2}{\sigma^2}\right) \quad (9)$$

3.3 PSO

Particle swarm optimization (PSO) algorithm is first found by Kennedy[15] and Eberhart[16], the method is from the natural swarm behavior of birds and fish.

In Simple PSO (SPSO) algorithm[17], each particle represents a potential solution in the search space. In order to find the optimal solution, each particle updates its velocity and position according to the following equations:

$$v_{id}(t+1)=wv_{id}(t)+c_1r_1(pbest_d(t)-x_{id}(t))+ c_2r_2(gbest_d(t)-x_{id}(t)) \quad (10)$$

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \quad (11)$$

where the inertial weight is w, the positive acceleration coefficients are c_1 and c_2, c_1 is used to scale the contribution of cognitive, and c_2 is used to scale the social relationship. The range of the velocity is $[-v_{\max},v_{\max}]$, and $v_{\max}$ is a maximum speed value. r_1 and r_2 are uniform random variables in [0,1].

In order to insure the convergence of the algorithm, the constriction factor is added into the formula (10) by Clerc[18], which is regarded as KPSO. The velocity updating formula is as follows:

$$v_{id}(t+1)=k[v_{id}(t)+c_1r_1(pbest_d(t)-x_{id}(t))+ c_2r_2(gbest_d(t)-x_{id}(t))] \quad (12)$$

where $k=2/(2-\varphi-\sqrt{\varphi^2-4\varphi})$, $\varphi=c_1+c_2$ and $\varphi>4$, φ is 4.1, thus k=0.7298.

3.4 MPSO

In order to modify the performance of SPSO algorithm, this paper does some improvements as follows:

1) The guide particle is added to SPSO algorithm, the guide particle is defined as the formula (13);

2) The guide set will store 5-10 best guide particles. If the poor particle solution is not modified for continuous some iterations; MPSO will update the unmodified particle from the guide solution set;

The hybrid algorithm integrates with the inertia weight method and the constriction factor method, and inherits their merits[19], [20].

The updating formula of velocity can be expressed as:

$$v_{id}(t+1)=k(wv_{id}(t)+c_1r_1(pbest_d(t)-x_{id}(t))+ c_2r_2(gbest_d(t)-x_{id}(t)))+c_3r_3(guide_d(t)-x_{id}(t)) \quad (13)$$

$$guide_d=(pbest_d+gbest_d)/2 \quad (14)$$

The inertia weight value is the same in MPSO and SPSO, the constriction factor value is the same in MPSO and KPSO. c_3 is positive acceleration coefficient for scaling the contribution of guide solution. r_3 is uniform random variable in [0,1].

4 Experiments

In order to test the performance of the proposed soft measure method, the experimental data are obtained from the real industrial engineering application. In this paper, the experiment is to predict the end-point temperature and the end-point carbon content in the molten steel. The soft measure method based on data analytics is coded in C++ and run on 3.25GB memory and a Core 2 with 2.83GHz CPU using Windows XP operating system (32-bit).

4.1 Experimental Data and Parameters

In the experiment, the data are collected from the practical iron and steel plant. The flame analyzer and the off gas analyzer were installed for the flue of steel converter. The experiment contains 90 furnaces data.

Experimental parameters[21] are set as follows: the population size is 100, the maximum number of iteration is 50 and the predefined unchanged iteration is 10. The experiment is terminated when the best solution can't be modified for some iterations, or when the predefined maximum iteration is reached. The maximum unimproved iteration is 5 for the poor particles, the size of guide solution set is 5, the inertia weight value is 0.98, the individual cognitive coefficient value is 2.05, the social cognitive coefficient value is 2.05, the learning coefficient value is 2 for guide solution, the range of γ is [0,1 000], the range of σ^2 is [50,100].

For the temperature and carbon content experiments, 20 runs were implemented in order to avoid the influence of fluctuation caused by the random number generator. The below statistic results are average values after 20 experimental runs.

4.2 Evaluation Indicator

To evaluate the performance of the prediction models, three indicators are considered as follows: the maximum error (MAX), the average relative error (ARE) and the root mean square error (RMSE). The performance indicators are described as:

$$\mathrm{MAX} = \max(e_i), \quad i = 1, \ldots, \mathrm{N} \tag{15}$$

$$\mathrm{ARE} = \frac{1}{N}\sum_{i=1}^{N}\left(e_i \big/ y_i\right) \tag{16}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} e_i^2} \tag{17}$$

where e is the error, $\left|y^{predict} - y^{actual}\right| = e$, $y^{predict}$ and y^{actual} are respectively the predicted value and the actual value.

4.3 The End-point Temperature Prediction of BOF Steelmaking

In the end-point temperature experiment, we randomly select 80 furnaces as the training set, and randomly select 10 furnaces as the testing set. The predicted value of MPSO-LSSVM and the actual temperature value can be seen from Fig. 3.

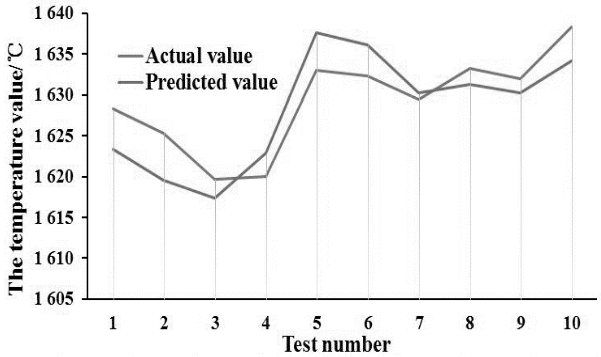

Fig. 3 The end-point profile of temperature between the predicted values and the actual values

图 3 预测值与真实值终点温度曲线

The x axis is the test number; the y axis is the temperature value. In general, the error can be accepted between the predicted values and the actual values. The end-point error profile of temperature between the predicted values and the actual values is shown in Fig. 4.

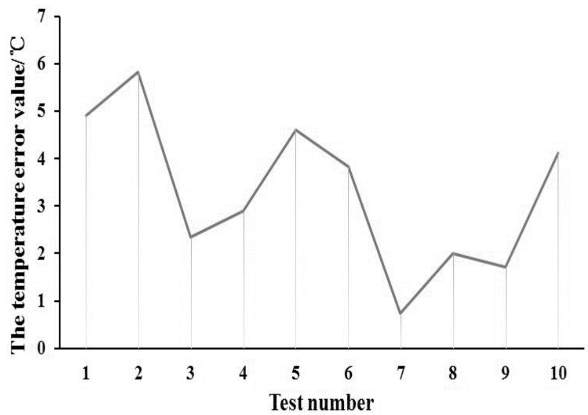

Fig. 4 The end-point error profile of temperature between the predicted values and the actual values

图 4 预测值与真实值终点温度误差曲线

The x axis is the testing number; the y axis is the temperature error between the predicted value and the actual value. The error result illustrates that the proposed algorithm has a strong adaptability.

In order to demonstrate the superiority, this paper compares MPSO-LSSVM with KPSO-LSSVM and SPSO-LSSVM. The ultimate objective function values (OFV) of temperature for three optimization algorithms are shown in Tab. 1.

Tab. 1 OFV results of temperature for different algorithms

表 1 不同算法 OFV 温度结果

	MPSO	KPSO	SPSO
OFV	**0.004 168**	0.004 375	0.004 266

We can find that the convergence value of MPSO is slightly lower, but not very obvious. The comparison results are shown in Tab. 2.

Tab. 2 Temperature test results

表 2 温度测试结果

Algorithm	RMSE	ARE	MAX
MPSO-LSSVM	**3.633 072**	**0.002 022**	**5.813 638**
KPSO-LSSVM	3.638 415	0.002 025	5.834 896
SPSO-LSSVM	3.635 786	0.002 024	5.824 545

The predicted error of MPSO-LSSVM is lower than that of the other two methods. The results show that MPSO-LSSVM has a better performance.

4.4 The End-point Carbon Content Prediction of BOF Steelmaking

The prediction method of carbon content is the same as the temperature prediction method. The comparison results of carbon content between the predicted values and the actual values can be seen from Fig. 5.

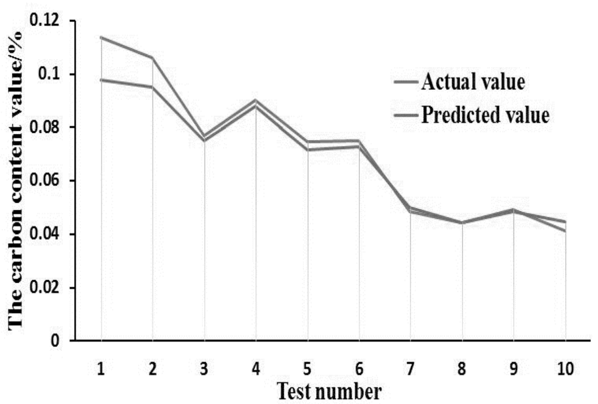

Fig. 5 The end-point profile of carbon content between the predicted values and the actual values

图 5 预测值与真实值终点碳含量曲线

We present the end-point error profile of carbon content between the predicted values and the actual values. The results are shown in Fig. 6.

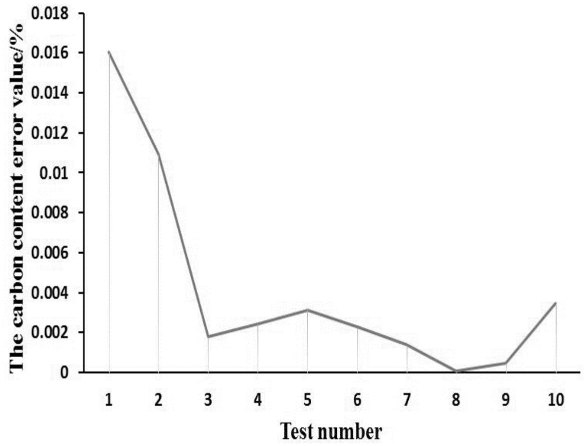

Fig. 6 The end-point error profile of carbon content between the predicted values and the actual values

图 6 预测值与真实值终点碳含量误差曲线

Aware of that, the predicted values are compared with the actual values, the error result is really tiny.

In order to reflect the effectiveness of MPSO-LSSVM, the ultimate objective function values (OFV) of carbon content for three optimization algorithms are shown in Tab. 3.

Tab. 3 OFV results of carbon content

表 3 碳含量 OFV 结果

	MPSO	KPSO	SPSO
OFV	**0.003 833**	0.004 023	0.003 970

From that we can observe that MPSO reveals a smaller FOV. Comparison results from different algorithms are shown in Tab. 4.

Tab. 4 Test results of carbon content

表 4 碳含量测试结果

Algorithm	RMSE	ARE	MAX
MPSO-LSSVM	**0.006 439**	**0.049 057**	**0.016 044**
KPSO-LSSVM	0.006 451	0.049 161	0.016 073
SPSO-LSSVM	0.006 448	0.049 137	0.016 066

We can find the predicted error of MPSO-LSSVM is lower than that of the other two methods. The experimental results demonstrate that the proposed prediction method has a good adaptability.

4.5 Analysis of Parameters for Prediction Algorithm

For the end-point temperature prediction experiment, the optimized parameters of MPSO-LSSVM are obtained as follows: γ = 941.02, σ^2 = 50.02. For the end-point carbon content prediction experiment, the optimized parameters are shown as follows: $\gamma = 990$, $\sigma^2 = 51$. At the same time, in order to show the performance of the optimized parameters, the comparison results between MPSO-LSSVM and Random-LSSVM are shown in Tab. 5 and Tab. 6.

Tab. 5 Comparison results of different parameter settings in temperature prediction experiment

表 5 温度预测实验中不同参数设置比较结果

Algorithm	RMSE	ARE	MAX
MPSO-LSSVM	**3.633 072**	**0.002 022**	**5.813 638**
Random-LSSVM	4.530 716	0.002 466	7.107 568

Tab. 6 Comparison results of different parameter settings in carbon content prediction experiment

表 6 碳含量预测实验中不同参数设置比较结果

Algorithm	RMSE	ARE	MAX
MPSO-LSSVM	**0.006 439**	**0.049 057**	**0.016 044**
Random-LSSVM	0.010 532	0.101 089	0.024 371

The experimental results demonstrate that the optimized method has a better effect.

5 Conclusions

This paper puts forward the prediction model based on the soft measure method, which predicts the end-point temperature and the end-point carbon content in BOF steelmaking process. The proposed method depends on data, and the experimental data are from the real data of BOF steelmaking production. This paper adopts the strategy based on the event, and utilizes MPSO to optimize the parameters of LSSVM. First MPSO-LSSVM is utilized to establish the end-point prediction model. Then, the testing data of 10 furnaces are used to predict the end-point temperature and the end-point carbon content in BOF steelmaking process. Compared with KPSO-LSSVM and SPSO-LSSVM, the results show the proposed end-point prediction method has a very good performance. Finally, through the comparison results of different model parameters, the experimental results demonstrate that the proposed method has a better optimized effect.

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