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The Combination Prediction of BTP in Sintering Process based on Bayesian Framework and LS-SVM

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Abstract

The sintering process is a complex process with the characteristics of uncertainty, multivariable coupling, time-varying and time-delay. The Burning-Through-Point (BTP), which is a import parameter in sintering process, is affected by many reasons and difficult to be controlled to the required precision by conventional control methods. This paper presents a new time-series forecasting methods, which is called Bayesian Least Squares Support Vector Machines (LS-SVM). The method applies the Bayesian evidence flame work to infer automatically model parameters of LS-SVM regression. ALS-SVM model is proposed on the basis of the Bayesian LS-SVM models. Several intelligent forecasting key techniques of sintered ore's chemical components including algorithms of nonlinear SVM in regression approximation, selection of kernel functions and parameters and standardizing of sample data, Bayesian evidence flame-work are studied; and the control schedules of BTP based on interval optimization are analyzed. At last, a new intelligent forecasting system of BTP are designed and implemented. Experiment results show that the LS-SVM prediction designed within the Bayesian evidence framework consistently yields good generalization performances, which the method of combining Bayesian theory and LS-SVM is faster and more accurate for the BTP in compare with BP neural network and GM (1, 1).

Keywords: *bayesian theory, LS-SVM, BTP, prediction, control*

1. Introduction

The sintering process is an important step in stove smelting. It not only can agglomerate power materials, but also has pretreatment function of burning method for raw materials, so that the target of high productivity, high quality, low cost and longevity can be achieved in stove smelting. The study of sintering process has attracted interest, not only from iron and steel industry, but also from nonferrous industry.

The Burning-Through-Point (BTP) is an important parameter in sintering process. In the iron and steel enterprises, sintered ore is the main raw material for blast furnace. In the sintering process, stability and quality of sinter is a decision factor to production efficiency of blast furnace. The sintering process is a pre-process for blast-furnace materials. The quality of sinter is very important for smooth operation and high productivity of the blast furnace since it improves the permeability and reducibility of the burden material. Burning-Through-Point for judging the quality of sinter important indicator is a measure of good and bad sintered minerals important parameters [1, 2].

The BTP is a very important parameter in the sintering process. The sinter quality can be improved, and the energy consumption can be reduced, if one can accurately predict the BTP value. That means the accurate prediction of BTP can bring significant economic benefits and is of important practical significance. Traditional methods using features such as exhaust gas temperature, negative pressure and exhaust gas composition to predict the BTP [3]. The prediction tools include gray theory, multiple fuzzy linear regression, genetic neural network, artificial neural networks, fuzzy neural network etc. Although artificial neural network based prediction method has achieved a good performance in some very applications, the method has some disadvantages. For example, in the training process, there exist the problems of local minimum, slow convergence, and that the network is difficult to determine the number of

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hidden layer and so on. These shortcomings greatly limit its application [2-5]. Statistical Learning Theory (SLT) is a possible solution to this problem [6]. Support Vector Machine (SVM) is a possible classification and regression tool for our problem. SVM improve its generalization ability using structural risk minimization, and solve the nonlinear, high dimension and local minimum problem with small sample set. It has been applied widely in pattern recognition, signal processing, function approximation and so on [6]. But there is a big problem in the application of SVM that is the presence of redundant information makes the training time of SVM too long and slower the speed when dealing with too large amount of redundant information. The Bayesian theory can deal with inaccurate or incomplete knowledge and redundant information .The Bayesian theory can use the sample information and prior knowledge, and simplify forecasting model, optimization parameters, this paper mainly studies the evidence, under the framework of Bayesian least squares support vector machine algorithms, and applications in order to BTP prediction. simulation study results show that the Bayesian framework for least squares support vector machines than the artificial neural network has better generalization ability, and the program running time of fast and high accuracy [8, 9].

This paper is organized as follows. Section II describes Sintering process and The Analysis of BTP. Section III presents the intelligent forecasting system which consists of LS-SVM and Bayesian framework. In Section IV, numerical simulation is used to demonstrate the effectiveness of the intelligent forecasting system. Section V gives the BTP prediction simulation and analysis. Finally, Section VI gives the conclusion.

2. Sintering Process and the Analysis of BTP

2.1. Sintering Process

Sintering is a method that makes powdered materials (such as fine ore or preparation concentrate) into block mass under conditions involving incomplete fusion by heating to high temperature. Its production is sinter which is irregular and porous. The following parts are usually included in sintering process: acceptance and storage of iron-containing raw materials, fuel and flux; crushing and screening of raw materials, fuel and flux; batching, mix-granulation, feeding, ignition and sintering of mix material; crushing, screening, cooling and size-stabilization of sinter. The flowchart is shown in Figure 1.

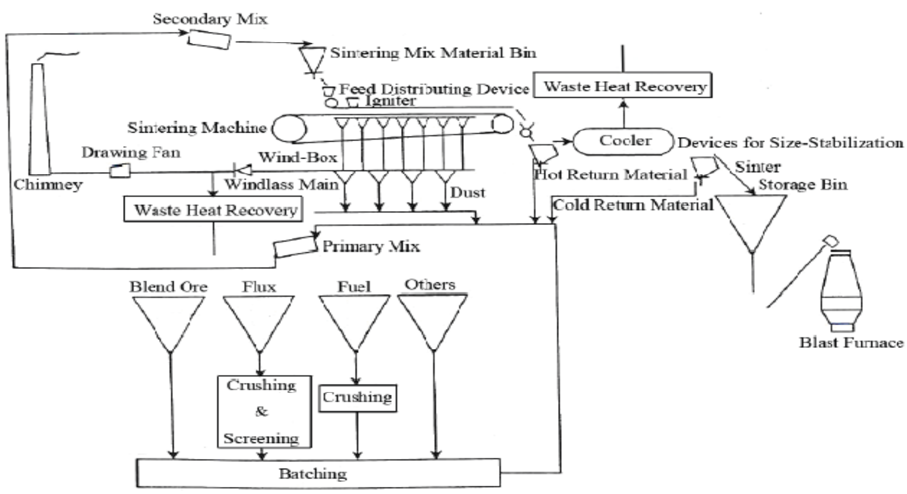

Figure 1. Sintering Process

2.2. The Analysis of BTP

Sintering is the most widely used agglomeration process for iron ores and is a very important chain of iron making. In general, the process of sintering includes three major phases. First, it involves blending all the ores thoroughly according to certain proportions and adding water to the ore mix to produce particles. Second, the actual sintering operation is initiated by the ignition of the cokes as the raw mix passes under gas ignition. Finally, after traveling the length of the strand, the finished sinter is broken up, cooled, and screened. In the recent twenty years, many methods of integrity and fusion have been explored by the metallurgy and automation experts.

The BTP is characterized by the maximum of the exhaust gas temperature, which is measured at six locations towards the end of the strand. It is primarily controlled by variable strand speed. The temperature is measured at a certain point. The method employed here is not to explicitly control the temperature maximum, but to yield the expected BTP by keeping the exhaust temperature distribution on a pre-defined curve. The BTP can not be tested on-line, and the judgment based on the observation data by operators is usually inaccurate. Although many successful at-tempts have been made to model the sintering process, it is very difficult to obtain some important parameters in these models, which indicate the physical properties of the sinter material. Therefore, Soft-sensing method is adopted to solve this problem. Therefore, we make use of support vector machine to solve the problem of the BTP. The model will be built up based on the BTP related variables in real-time. The value of BTP can be calculated according to the temperature curve of waste gas in wind-boxes.

It is generally believed that the temperature of waste gas in wind-boxes is highest when the sinter-mix bed is just burned through. Thermocouples are put along five wind-boxes at discharge end. Quadratic curve is fitted according to three points including the highest temperature. The general expression of quadratic curve is:

$$T_i = aX_i^2 + bX_i + c \text{, (i=1,2,…..,22)} \quad (1)$$

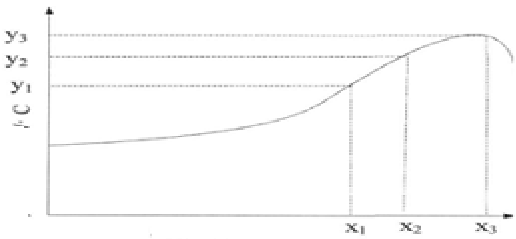

Figure 2. Exhaust Gas Temperature Curve

Where T is temperature of waste gas in wind-boxes, x is number of wind-boxes, A, B, C are coefficients. With the three know values, ((x1, T1), (x2, T2), (x3,T3)), and the highest temperature, using the Equation 1 , the following expression can be obtained:

$$X_{\max} = -\frac{b}{2a}, T_{\max} = aX_{\max}^2 + bX_{\max} + c \quad (2)$$

Burning-Through-Point (BTP) is the position when sinter process is finished and is expressed by corresponding wind-box position when sinter bed is burned through. Accurate control of Burning-Through-Point (BTP) can not only make the sintering process stable but also use the sintering area effectively. The BTP affects the sintering output and quality. It is generally believed that BTP should be at the second wind-box counting from backward. If BTP is ahead of this point, effective grate area of sintering machine will not be fully utilized. On the contrary, if BTP lags behind the point, sinter bed cannot be burned through, this will result in the increase of re-sinter and decrease of sinter rate. BTP may be affected by many factors. Row material parameters, operation parameters and process condition parameters may have a great influence on BTP direct or indirect. Moreover, BTP cannot be measured direct. Up till now, there are no instruments that can be used to measure BTP online. In the paper, the online prediction of BTP based on LS-SVM is analyzed. Mathematical method will be used to solve the problem of online measurement of BTP [10].

In the practical sintering process, BTP is affected by a number of factors, such as the ignition temperature, the material thickness, mixture of water, trolley speed, air volume and mixture back to the impact of mining, sintering charge of negative pressure, lime dosage, fuel consumption, exhaust gas temperature, alkalinity, and mix the influence of particle size [11, 12, 13].

3. Prediction Model based on Bayesian Framework and LS-SVM

3.1. LS-SVM algorithm

The LS-SVM, evolved from the SVM, changes the inequality constraint of a SVM into all equality constraint and forces the sum of squared error (SSE) loss function to become an experience loss function of the training set [8]. Then the problem has become one of solving linear programming problems. This call be specifically described as follows：

Given a training set $\{x_t, y_t\}_{t=1}^{N}$,with $x_t \in R^n$, $\mathrm{y_t} \in \mathrm{R}$, $x_t \in R^n$ is input vector of the first t samples, $\mathrm{y_t} \in \mathrm{R}$ is the desired output value of the first t corresponds to samples, N is the number of samples data, the problem of linear regression is to find a linear function y(x) that models the data. In feature space SVM models take the form:

$$y(x) = \omega^T \varphi(x) + b \tag{3}$$

Where the nonlinear function mapping $\varphi(\cdot): R^{\mathrm{n}} \to R^{n_{\mathrm{h}}}$ maps the high-dimensional space into the feature space.

Having comprehensively considered the complexity of function and fitting error, we can express the regression problem as the constrained optimization problem according to the structural risk minimization principle：

$$\min J(w,e) = \frac{1}{2} w^{\mathrm{T}} w + \gamma \frac{1}{2} \sum_{t=1}^{\mathrm{N}} e_t^2 \tag{4}$$

Subject to the restrictive conditions, $y(x) = w^{\mathrm{T}} \varphi(x_t) + b + e_t$, for t = 1,…, N. Where γ is margin parameter, and e_i is the slack variable for x_i .

In order to solve the above optimization problems, by changing the constrained problem into an unconstrained problem and introducing the Lagrange multipliers, we obtain the objective function：

$$L(w,b,e,\alpha) = J(w,e) - \sum_{\mathrm{t}=1}^{\mathrm{N}} \alpha_{\mathrm{t}} \{ w^{\mathrm{T}} \varphi(x_t) \tag{5}$$

Where α_{t} is Lagrange multipliers. According to the optimal solution of Karush-Kuhn-Tucker (KKT) conditions, take the partial derivatives of (5) with respect to w, b and e, respectively, and 1et them be zero, we obtain the optimal conditions as follows：

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0 \to w = \sum_{t=1}^{N} \alpha_t \varphi(x_t) \\ \dfrac{\partial L}{\partial b} = 0 \to \sum_{t=1}^{N} \alpha_t = 0 \\ \dfrac{\partial L}{\partial e_t} = 0 \to \alpha_t = \gamma e_t \\ \dfrac{\partial L}{\partial \alpha_t} = 0 \to w^T \varphi_t + b + e_t - y_t = 0 \end{cases} \tag{6}$$

After elimination of e_t and w , the equation can be expressed as a linear function group:

$$\begin{bmatrix} 0 & \boldsymbol{1}^T \\ \boldsymbol{1} & \varphi(x_t)^T\varphi(x_t)+\boldsymbol{D} \end{bmatrix}\begin{bmatrix} b \\ \boldsymbol{\alpha} \end{bmatrix}=\begin{bmatrix} 0 \\ \boldsymbol{y} \end{bmatrix} \quad (7)$$

Where $\boldsymbol{y}=[y_1,\cdots,y_N]$, $1=[1,\cdots,1]$, $\boldsymbol{\alpha}=[\alpha_1, \ldots, \alpha_N]$, $\boldsymbol{D}=diag[\gamma_1,\cdots,\gamma_N]$, Select γ > 0, and guarantee matrix $\boldsymbol{\varphi}=\begin{bmatrix} 0 & \boldsymbol{1}^T \\ \boldsymbol{1} & \varphi(x_t)^T\varphi(x_t)+\boldsymbol{D} \end{bmatrix}$ $\begin{bmatrix} \mathrm{b} \\ \boldsymbol{\alpha} \end{bmatrix}=\boldsymbol{\varphi}^{-1}\begin{bmatrix} 0 \\ \boldsymbol{y} \end{bmatrix}$.

Finally, the LS-SVM regression model can be expressed as:

$$y(x)=\sum_{t=1}^{N}\alpha_t \exp\{-\| x-x_t \|_2^2 /2\sigma^2\}+b \quad (8)$$

Where σ is a positive real constant. Note that in the case of RBF kernel function, one has only two additional turning parameters σ and γ, which is less than standard SVM.

This LS-SVM regression leads to solving a set of linear equations, which is for many applications in different areas. Especially, the solution by solving a linear system is instead of quadratic programming. It can decrease the model algorithm complexity and shorten computing time greatly. The LS-SVM algorithm software package is run in MATLAB 7.0.1 software.

3.2. LS-SVM Algorithm of Bayesian Framework

Bayesian framework for least squares support vector machine refers to the theory of using Bayesian methods to find excellent least squares support vector machine, and to determine the regularization parameter and kernel parameter. Bayesian inference of evidence framework will be divided into three criteria for inference, Bayesian evidence framework of the basic idea is to maximize the posterior parameter distribution, and the best parameter values or model is to maximize the posterior parameter distribution of obtained under in the least squares support vector machine, one can infer the criteria parameters and b, the criteria 2 can be estimated regularization parameter, the guidelines can be used to estimate the three nuclear parameters [14-17].

a. Inference of model parameters

Given data points, D= $\{(x_i, y_i)\}_{i=1}^N$ and the hyper-parameters μ 和 ξ of the H , the model parameters ω and b are estimated by minimizing the posterior $p(\omega, b / D, \lg\mu, \lg\xi, H)$. Appling Bayesian rule at the first level, we obtain:

$$p(\omega, b / D, \lg\mu, \lg\xi, H) = \frac{p(D / \omega, b, \lg\mu, \lg\xi, H)\, p(\omega, b / \lg\mu, \lg\xi, H)}{p(D / \lg\mu, \lg\xi, H)} \quad (9)$$

Where $p(D / \omega, b, \lg\mu, \lg\xi, H)$ is likelihood; $p(\omega, b / \lg\mu, \lg\xi, H)$ is the joint priori probability; where $p(D / \lg\mu, \lg\xi, H)$ normalizing constant is independent of ω and b [18].

b. Inference of hyper-parameters.

In the second level of inference, Bayesian' rule is applied to infer the most likely μ and ξ values from the evidence data:

$$p(\lg\mu, \lg\xi / D, H) = \frac{p(D / \lg\mu, \lg\xi, H)\, p(\lg\mu, \lg\xi, H)}{p(D / H)} \propto p(D / \lg\mu, \lg\xi, H) \quad (10)$$

Because the hyper-parameters μ and ξ are scale parameter. We take a uniform distribution in $\log \mu$ and $\log \xi$ for the prior $p(\log \mu, \log \xi / H) = p(\log \mu / H)\, p(\log \xi / H)$ in (12). The evidence p(D/H) is again a normalizing constant, which will be needs in level 3.The probability $p(D / \lg \mu, \lg \xi, H)$ is equal to the evidence in (11) of the previous level [12-16].

c. Inference of Kernel function

We can obtain by choosing a different kernel function or its parameters. For the RBF kernel function, we may obtain different model H by adjusting the core width of the different models available parameters of H, by the level 3:

$$p(H_j / D) = \frac{p(D / H_j)\, p(H_j)}{p(D)} \infty p(D / H_j) \tag{11}$$

Where $p(H_j / D)$ is the likelihood function of the normalizing constant. Level 3 inference ranks the models by examining its posterior $p(H_j / D)$. Assuming uniform prior p(H_j) can be ranked by their evidence $p(H_j / D)$, which can be evaluated using a Gaussian approximation .

All the calculations were performed using MATLAB 7.0 (The Math Works, Natick, USA). The free LS-SVM toolbox (LS-SVM V 1.5, Surykens, Leuven, Belgium) was applied with MATLAB 7.0 to develop the Bayesian LS-SVM models [18, 19].

3.3. Implementation Steps for LS-SVM Algorithm of Bayesian Framework

Prediction model based on LS-SVM time series is regard as a gray box model. The relationship of input and output to the model is a non-linear function which is modeled by the LS-SVM, the least squares support vector machine model parameters regularization and kernel function etc. According to the evidence under the framework of Bayesian deduced, the least squares support vector machine modeling steps: 1) The sample data pre-processing, including a number of abnormal data pre-processing, normalization, so that the input and output data are changed into variables with mean 0, variance 1 of the stationary time series; 2) Select a estimation algorithm for support vector machines; 3) Set the initial parameter values, for least squares support vector machines for training, access to model parameters and b; 4) The use of LS-SVM hyper-parameters inferred iterative method; 5) The use of LS-SVM iterative methods to extrapolate the nuclear parameters; 6) Return to Step 3, using the desired parameters of re-training of support vector machines to select the optimal model and the input; 7) Find a well-established models to predict.

4. BTP Prediction Simulation and Analysis

4.1. Sample Data Processing

We will normalize the collected data to [-1 1], which will help improve the training speed of neural network. In order to allow prediction of a certain super-sector within the framework of the training objectives of the sample set of scale into a 0.1 to 0.9, in the formula one of the following formula:

$$x_{ij}^{'} = \frac{x_{ij} - x_{j\min}}{x_{j\max} - x_{j\min}} \times 0.8 + 0.1 \tag{12}$$

After the neural network computing, do the anti-normalization processing, which will get the actual value of the output value forecasting, using the following formula:

$$x_{ij} = \left(x_{j\max} - x_{j\min}\right) \times \left(x_{ij}^{'} - 0.1\right) + x_{j\min} \tag{13}$$

Where $x_{ij}^{'}$ represents the first i sample and the first j variable data of the standardization; x_{ij} represents the original space vector; $x_{j\max}, x_{j\min}$ respectively represents the maximum and minimum data variable j of the samples. In the sample data, it is inevitable that there are some alies in the samples data, which will affect certain models' performance, even misleading. Therefore, the model data included training samples and test samples are carefully selected.

4.2. Prediction and Analysis of BTP

The length of 360m^2 large sintering machine is 104.5 meters. The effective area of sintering machine is 90 meters. The whole sintering process from the trolley burden distribution to the sinter machine discharge is about 40 minutes. On each side of the trolley has 22 wind-boxes. Normal inflexion point wind-box is the 19th wind-box, its temperature is about 462, BTP is controlled in the position of the 19th wind-box. The 22 thermocouples installed the wind-boxes detect the waste gas temperature. BTP for predictive parameters, the time delay about 12 minutes, which predicts BTP in advance four-steps.

In predictive process, the system collects new parameter, and stores the database while delete the old data, so that it continuously increasing new information, shorten training time, so that the data maintained at around 100 groups (about a sintering cycle, sampling data). according to the training law of LS-SVM, between the training error and testing error are minimized, this mean that no matter how big the sample collection, forecasting accuracy has the great relationship on the recent samples, which requires constant updates. The network over a certain time is necessary to train every two sintering cycles that re-trained to predict the side, they use the new data to update the weights of training networks, they are in different computing modules, they don't affect each other.

Bayesian probability theory provides a integrated framework to find effective models that are well matched to the sampling data and use these models for making optimal decisions. The evidence framework is successful applied to the training of BTP using three levels of Bayesian inference: the model parameters, regularization hyper parameters and network structure are inferred on the three levels respectively. The moderated output is obtained by marginazing the model. We design the LS-SVM time series model in the evidence framework to predict BTP in sintering process. Then we use the inferred hyper-parameters of time series model to construct the LS-SVM volatility model. The LS-SVM model is inferred from 2 and 3 inference, we obtained the Kernel parameters and hyper-parameters.

To demonstrate the effectiveness and accuracy of the proposed forecasting model, GM (1, 1), BP neural network, Bayesian LS-SVM is applied to BTP forecast respectively. The data are collected from sinter plant of Henan province. The three models are used to forecast and analyze BTP during 2008. In order to compare the effectiveness of each model, as well as the difference accuracy of forecasting, while the 48 data were used as testing data set.

In order to compare the difference accuracy of three forecasting model, three evaluation criteria are used. The maximum relative error($E_{\max}$), the root mean square error (RMSE), relative root mean square error (RRMSE), the formula as follow:

$$E_{\max} = \max\left(\frac{y_i - \hat{y}_i}{y_i}\right) \tag{14}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{15}$$

$$RRMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{\left(y_i - \hat{y}_i\right)}{y_i}\right)^2} \tag{16}$$

Where y_i is the actual value, and $\hat{y}_i$ is the predicted value. Where n is the number of samples data used for forecasting.

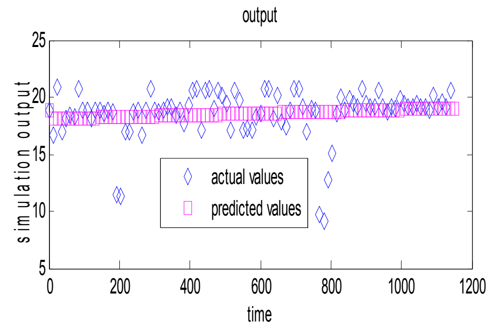

Figure 3. Prediction Diagram of BTP based on Grey Error Residual Model

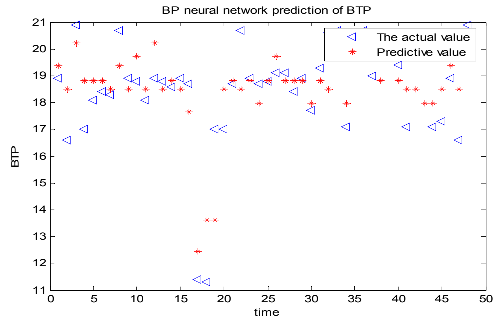

Figure 4. Prediction Diagram of BTP based on BP Neural Network

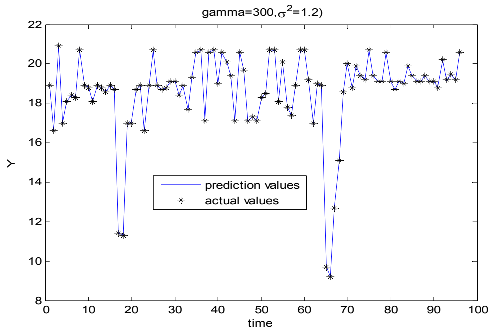

Figure 5. Prediction Diagram of BTP based on Bayesian LS-SVM

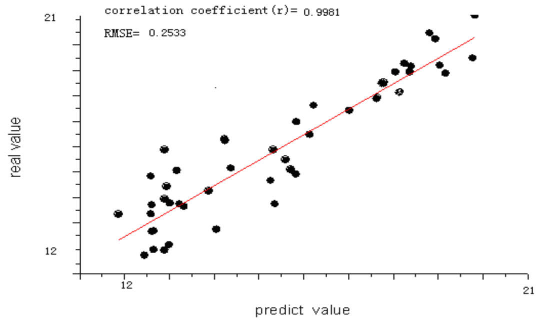

Figure 6. Predicted and Reference Values for BTP by Bayesian LS-SVM Models

To verify the Bayesian LS-SVM model BTP prediction accuracy, this paper employs three kinds of prediction models and simulation. Above all, we adopt three prediction models to train the samples by using GM (1, 1) BP neural network and Bayesian LS-SVM respectively. Some tracing results are shown in Figure 3 and Figure 6

From Figure 3, it can be seen that grey forecasting model has its advantages. The GM (1, 1) model can solve the increase trend forecast problem of BTP and it is mainly applied to the steady system which needs little time and few data. Because the geometry graph of GM (1, 1) model is one smooth curve (a curve of index type), the forecast error is bigger when it is applied to forecast the fluctuation trend.

The model using BP neural network to predict BTP forecast shown in Figure 4, despite its prediction accuracy and prediction error greatly reduced, but there are two fatal flaws: Firstly, model training easily fall into local minimum and cannot extricate themselves; secondly, the generalization ability of the model are relatively poor.

Figure 5 shows that Bayesian support vector machines have good prediction ability and generalization performance. After a three-layer Bayesian inference theory, selection of regularization parameter and kernel function become more appropriate, BTP prediction model have a relatively high prediction accuracy, generalization ability, and the convergence rate is also significantly faster. With stronger generalization ability, the SVM algorithm can successfully solve the learning problem of finite samples, especially the complicated nonlinear mapping problem. It can reach the global optimization avoiding the local optimization, and it is able to forecast the fluctuation trend with obvious advantages which other methods don’t have.

Figure 6 shows the predicted versus actual value. The solid line is the regression line corresponding to the ideal, unity correlation between the predicted and reference values. Figure 5 indicates that BTP could be detected very well by nonlinear regression. Three kinds of model predictions results show Table 1.

Table 1. Prediction Performance of Four Different Algorithms

Model	E_{max}	RMSE	RRMSE
GM(1,1)	18.74	2.1456	2.0148
BPNN	1.237	0.5883	1.612
Bayesian LS-SVM	0.481	0.2889	0.5666

From Table 1, it can be seen that three models present quite satisfactory forecasting results. By comparing the maximum relative error, the maximum relative error of BPNN is smaller than that of GM (1, 1) model. For BPNN, the convergence rate has more precise prediction. Moreover, Bayesian LS-SVM has higher precise prediction than BPNN. Table 1 shows RMSE and RRMSE of the three models. It can be seen that Bayesian LS-SVM has higher forecasting accuracy according to different criteria. For example, RMSE of Bayesian LS-SVM is about 0.36 times of BPNN and 0.1 times of GM (1, 1). In other words, the forecasting accuracy of Bayesian LS-SVM is about 2.7 times of BPNN model and 10 times of GM (1, 1) for BTP. This proves the effectiveness and accuracy of Bayesian LS-SVM algorithm.

In addition, Table 2 shows the computation time required for the prediction phase of the Bayesian LS-SVM and the computation times per prediction step of the GM (1, 1) and BP neural network. Although Bayesian LS-SVM requires longer computation time than the other two methods, increased from 10-4 to 10-3 second, the Bayesian LS-SVM is still able to complete the prediction phase during one sampling interval. The proposed intelligent forecasting system is, therefore, applicable for real-time prediction.

Table 2. Comparison of the Prediction Time of the GM (1, 1), BP Neural Network and Bayesian LS-SVM

Model	GM(1,1)	BP neural network	Bayesian LS-SVM
Computation time per prediction step	4.88e-4	4.13e-4	10.44e-3

5. Construction and Implementation of BTP Control System

The system adopts a powerful object-oriented programming language JAVA as an enterprise class development tool, while back-end database use SQL Server2000 database management system. System makes use of the client and the server that the C/S (Client/Server) structure model and integration framework for information processing within a local area network use C/S mode. The system is devised into two clients, which is placed in sintered main control room and the director rooms, the system users is classified into administrators and ordinary users. Ordinary users is limited to general operations, such as starting the system, viewing the results and forecasting guidance recommendations, etc.; administrators may put up the system parameters change, and add advanced features such as Knowledge Base. System mainly consists of two phases, the first stage inspect and improve the model prediction accuracy and operational guidance recommends accuracy rate; the second stage is to achieve closed-loop control of BTP. Experts in the field is constantly modify the system according to the actual knowledge base, model parameters, and model of continuous adaptive learning, making the system closer to actual production, which can better reflect the actual on-site production. Intelligent optimal control system in the sintering process based on BTP prediction model has been applied in a sintering machine iron and steel enterprises and has achieved good results. The system uses the LS-SVM toolbox in MATLAB7.1, WEB-based working way, J2EE standard, enterprise-level JAVA and XML technology, Internet / Intranet technology and its multi-tier architecture application system, using the Unified Modeling Language UML to build up model and system design. The system is friendly, and easy to operate by the users. What is more the system adopted the self-studying mechanism which can effectively enrich and modify rule databases.

Some practical data are chosen to analyze obtained coordinating models. Time interval of BTP samples is 3.6 minutes. The former figure indicates practical operation and the latter one indicates the coordinating control effects of the proposed method. From the control results of BTP, the fluctuation of BTP has been decreased about 3%, and the effects of BTP control are greatly improved after using the control techniques. The control results of the BTP are improved obviously, and the stabilization of the sintering process is increased by coordinating control of the BTP and the bunker-level through the strand speed.

During the sintering process, due to various reasons, sintered ore constituents, the ratio of sinter and operator experience levels may change, even if the building Bayesian LS-SVM model just started running with very high accuracy, but With the passage of time and changes in the working conditions, there are still predict the state of the model can not adapt to the new situation. Therefore, in order to improve the self-adaptability of predictive models to adapt them to changes in various conditions, must line correction predictive models, the full combination of expert knowledge and real-time updates, to changes in track conditions to improve the model adaptivity.

The prediction model of adaptive mechanisms usually includes three aspects: Firstly, the learning samples continuously update mechanism; secondly, predictive model of self-learning mechanism; At last, online self-correction capability of the model output. Sample constantly updated can improve the reliability of the study samples must establish effective update mechanism to ensure that the the abnormal data excluded, in turn data that truly reflect changes in working conditions with increased sample concentrate. With the forecast model, the ability to learn embodies it tracks changes in working conditions, and automatically adjust the parameters and output in order to achieve a more reasonable and accurate prediction of performance. Reasonable learning mechanisms can greatly improve the real-time accuracy and reliability of the prediction model, is an essential role in the establishment of BTP prediction model. Chosen in the model dimension and new information, the training sample set is added to the latest data, delete the old data, always maintain sample remains unchanged. For the sake of security, of BTP modeling structure with a double model structure, when the condition is stable, the choice of Bayesian LS-SVM model or the modified model, conditions frequent changes in the application of artificial neural network model, two models complement each other independent of each other. The final output of the prediction model results:

$$F(x) = k_1 F_R(x) + (1 - k_1) F_N(x) \tag{17}$$

k_1 is the weight value, and its value can be calculated based on the actual strike.

6. Conclusion

Used in large iron and steel enterprises sintering process, the Bayesian evidence framework model of the least squares support vector machine regression achieved good performance. We conclude the model merits as follows.

1) The BTP is affected by many factors and has complex mechanism.

2) The main advantage of Bayesian LS-SVM theory is to find the regularization parameter and nuclear parameters by using Bayesian inference theory;

3) Experimental results show that the proposed combination of modeling methods for the prediction sintering process BTP provides a new idea has a certain significance in practical applications. At the same time, as the BTP prediction system for the integrated use of sintering theory, modern control theory, artificial intelligence theory, and other fields of knowledge, for improving the level of sintering automation control in China to promote artificial intelligence technology, which is of great theoretical and practical significance.

The experimental results indicate the Bayesian LS-SVM is successful and accurate. In the future the predictor will be generalized into me other engineering field, such as financial series and hydrological series forecasting. .But comparing to previous algorithm, the main disadvantage is its slow speed. Thus, further work shall be done to optimize the inferring speed of Bayesian LS-SVM.

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