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Prediction of Gas Intake of Iron and Steel Enterprises Owned Power Plants Based on HS-RVM Model

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ABSTRACT: To deal with the difficulties in accurate prediction and effective scheduling of the empirical model of gas amount supplied by self-owned power plants in iron and steel enterprises, by analyzing the historical data of gas amount supplied by self-owned power plants, this paper adopts Relevance Vector Machine (RVM) to explore the tendency and rules of gas supply amount change. Meanwhile, Harmony Search (HS) is used to optimize the hyper parameters affecting the performance of RVM prediction model. A HS-RVM prediction model of gas amount supplied by self-owned power plants is constructed. This model is verified based on the actual operating data of power plants. Results have shown that it enjoys better performance than HP-Elman and PSO-SVR models, with the predicted root-mean-square error of 30 (period), 45 (period) and 60 (period) as 1.867%, 1.442% and 1.376% respectively, which meets the gas scheduling and management demand in self-owned power plants of iron and steel enterprises. Wilcoxon sign rank test verifies the effectiveness of this HS-RVM prediction model.

KEYWORDS: Gas; Self-owned power plants; Relevance vector machine; Harmony search; Prediction.

INTRODUCTION

Byproduct gas is an important secondary energy for iron and steel enterprises. Iron and steel enterprise owned power plants are the main buffer user of byproduct gas. It has significance for iron and steel enterprises in improving the utilization ratio of surplus gas, reducing electricity costs, energy conservation and environmental protection as well as enterprise security and the like [1,2].

Self-contained boiler as the main buffer user of steel enterprises can digest and adjust surplus gas, which are blast furnace gas, coke oven gas, converter gas [2]. In the actual production process, the gas supply quantity of owned power plant will have a tremendous impact on the boiler load control of power plant, fuel distribution and pipe network pressure. The steel-making process in iron and steel enterprises is complex and divers, also, the consumption and production of the gas system are very complex. A large number of studies have shown that the gas supply quantity of the owned power plant mostly emerges uncertain, dynamic non-linear characteristic, gas supply quantity of owned power plant is a typical nonlinear system [3]. Therefore, scheduling gas with operating experience often results in lower efficiency of byproduct gas and supply and demand imbalance of gas dispatching. Obviously, the static analysis method can't effectively forecast and schedule gas intake of owned power plant. Prediction for gas intake of owned power plant has raised domestic and foreign scholars' attention.

Current methods to predict and schedule the supply amount of gas of owned power plant are: Auto Regressive Moving Average (ARMA) [4], the improved Elman neural network model [5] and support vector regression (SVR) with parameter optimization [6]. ARMA model is simple and easy to implement, but its prediction accuracy is very limited, so its effective scheduling support for the owned power plant gas needs to be improved. Elman neural network model has a good approximation ability to nonlinear function relationship, but because of its use of empirical risk minimization principle, the fitting process often appeared over learning and less learning, easy to fall into local minimum problems [7]. SVR model is based on structural risk minimization principle and has more excellent outreach capacity and performance [8], but it has too many free parameters and can not give formula to predict the probability [9]. Michael E. Tipping proposed Relevance Vector Machine (RVM) in 2001. It is a machine learning algorithm based on sparse Bayesian framework, which overcomes the shortcomings of SVM and also has the ability to predict

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the probability and few parameters [10]. Document [11] pointed out prediction accuracy of RVM regression model is easy to be impacted by embedding dimension (r) and nuclear parameters (γ), so optimizing *r* and *γ* is important for owned power plant to enhance the accuracy of the gas supply forecasting model and achieve effective gas scheduling. Studies have shown that [12] harmony search algorithm (HS) , Geem et al. [13] proposed, has a better global search performance than genetic algorithms ratio (GA) , particle swarm optimization (PSO) and others. In view of this, according to the non-linear characteristics of the owned power plant gas intake, we use harmony search algorithm to optimize RVM model, then build HS-RVM prediction model with optimized hyper-parameters of owned power plant gas intake. Verify the validity and scientificity of the model relying on the actual production data of a large domestic steel company.

RELEVANCE VECTOR REGRESSION MODEL

RVM model has the same decision-making form with SVM model, for a given gas supply training sample set $\{\boldsymbol{x}_i, t_i\}_{i=1}^{N}$ of an iron and steel enterprise, while the target is assumed to be independent, using the same prediction function formula with SVM (1):

$$t_i = y(\boldsymbol{x}_i, \boldsymbol{W}) + \varepsilon_i \tag{1}$$

In formula (1): $\boldsymbol{W}$ is the weight parameter vector of training sample set, $\boldsymbol{W} = (w_0, w_1, \ldots, w_i)$, the sample noise to gas supply quantity $\varepsilon_i \sim N(0, \sigma^2)$, then $p(t_i \mid \boldsymbol{x}_i)=N(t_i \mid y(\boldsymbol{x}_i, \boldsymbol{W}), \sigma^2)$. The gas supply RVM prediction model can be represented by the formula (2):

$$y(\boldsymbol{x}, \boldsymbol{W}) = \sum_{i=1}^{`} w_i k(\boldsymbol{x}, \boldsymbol{x}_i) + w_0 \tag{2}$$

Where $k(\boldsymbol{x}, \boldsymbol{x}_i)$ is the kernel function of Radial Basis Function (RBF) and N is the number of gas intake training samples. On the basis of Formula (1) and (2), a hyper-parameter $\beta=\sigma^{-2}$ is introduced, and the likelihood function of gas intake training sample set $\{\boldsymbol{x}_i, t_i\}_{i=1}^{N}$ is:

$$p(\boldsymbol{T} \mid \boldsymbol{W}, \beta) = \left(\frac{\beta}{2\pi}\right)^{\frac{-N}{2}} \exp\left(-\frac{\beta}{2}\left\|\boldsymbol{T} - \boldsymbol{\Phi}\boldsymbol{W}\right\|^2\right) \tag{3}$$

Where $\boldsymbol{T} = [t_1, t_2, \ldots, t_N]^{\mathrm{T}}$; $\boldsymbol{\Phi} \in \boldsymbol{R}^{N\times(N+1)}$ is the design matrix. Define $\boldsymbol{\Phi}=[\boldsymbol{\phi}(\boldsymbol{x}_1), \boldsymbol{\phi}(\boldsymbol{x}_2), \ldots, \boldsymbol{\phi}(\boldsymbol{x}_i), \ldots, \boldsymbol{\phi}(\boldsymbol{x}_N)]^{\mathrm{T}}$, then the primary function vector $\boldsymbol{\phi}(\boldsymbol{x}_i)=[1, k(\boldsymbol{x}_i, \boldsymbol{x}_1), \ldots, k(\boldsymbol{x}_i, \boldsymbol{x}_N)]^{\mathrm{T}}$.

The ultimate aim of training gas supply RVM model is to acquire the posterior distribution of W. Suppose $w_j \sim N(0, a_j^{-1})$ (j=0, 1, …, N), the priori condition probability distribution of $\boldsymbol{W}$ is:

$$p(\boldsymbol{W} \mid \boldsymbol{\Lambda}) = \prod_{j=1}^{N} N(w_j \mid 0, \alpha_j^{-1}) \tag{4}$$

Where $\boldsymbol{\Lambda} = [a_0, a_1, \ldots, a_N]^{\mathrm{T}}$, each independent a_j is only related to its corresponding w_j.

According to Bayes Rule, combine equation (4) and (5) to get the posterior distribution of W:

$$p(\boldsymbol{W} \mid \boldsymbol{T}, \boldsymbol{\Lambda}, \beta) = \frac{p(\boldsymbol{T} \mid \boldsymbol{W}, \beta)\, p(\boldsymbol{W} \mid \boldsymbol{\Lambda})}{p(\boldsymbol{T} \mid \boldsymbol{\Lambda}, \beta)} \tag{5}$$

Therefore, the posterior distribution of $\boldsymbol{W}$ can be further expressed by:

$$p(\boldsymbol{T} \mid \boldsymbol{\Lambda}, \beta) = N(\boldsymbol{W} \mid \boldsymbol{U}, \boldsymbol{\Sigma}) \tag{6}$$

The posterior covariance matrix and the mean value are respectively:

$$\begin{cases} \boldsymbol{\Sigma} = \left(\beta \boldsymbol{\Phi}^{\mathrm{T}} \boldsymbol{\Phi} + \boldsymbol{A}\right)^{-1} \\ \boldsymbol{U} = \beta \boldsymbol{\Sigma} \boldsymbol{\Phi}^{\mathrm{T}} \boldsymbol{T} \end{cases} \tag{7}$$

Where $\boldsymbol{A}$ = diag (a_0, a_1, …, a_N).

The optimization of the hyper-parameters is realized by maximizing the marginal likelihood function $p(\boldsymbol{T} | \boldsymbol{\Lambda}, \beta)$. Acquire the negative logarithm of $p(\boldsymbol{T} | \boldsymbol{\Lambda}, \beta)$ to obtain the target function:

$$\begin{cases} \alpha_j^{\text{new}} = \dfrac{\gamma_j}{\mu_j^2} \\ \beta^{\text{new}} = \dfrac{\left(N - \sum_j \gamma_j\right)}{\left\| \boldsymbol{T} - \boldsymbol{\Phi U} \right\|^2} \end{cases} \tag{8}$$

Where μ_i is the *j*-th mean weight of posterior probability, $\gamma_i \equiv 1 - \alpha_i N_{ii}$. N_{ii} is the *j*-th diagonal element in the posterior weight covariance matrix; N is the number of sample data other than the number of primary function.

If given a new gas supply input value x_Δ, corresponding gas intake predictive target value t_Δ. Because of the limiting maximum of α_{MP} and σ_{MP}^2, so the probability distribution of gas intake predictive target output subjects to the Gaussian distribution:

$$p(t_\Delta | t, \alpha_{MP}, \sigma_{MP}^2) = N(t_\Delta | y_\Delta, \sigma_\Delta^2) \tag{9}$$

Where

$$y_\Delta = \mu^{\mathrm{T}} \boldsymbol{\Phi}(x_\Delta) \tag{10}$$

$$\sigma_\Delta^2 = \sigma_{MP}^2 \boldsymbol{\Phi}(x_\Delta)^{\mathrm{T}} \sum \boldsymbol{\Phi}(x_\Delta) \tag{11}$$

And y_Δ is the prediction value of gas intake.

HS-SVM PREDICTION MODEL OF GAS INTAKE

Hyper-parameter Optimization based on HITS Algorithm

Relevance vector machine is a kernel method, so parameter selection of the model is important, including the nuclear parameter (γ) and embedding dimension (r) selection [14]. In this study, HS search algorithm searches the optimal combination of hyper-parameters of gas intake RVM prediction model, to guarantee RVM classification prediction model has the best performance, then improve learning performance of RVM prediction model. Parameter optimization step gas intake RVM prediction based on the HS algorithm are as follows:

***Step l** Parameter Initialization Setting*

Parameters required to be initialized are: harmony memory value ratio (*HMCR*), harmony memory size (*HMS*), pitch trim ratio (*PAR*), pitch adjust bandwidth (*BW*), the maximum evolution iterations $T_{\max}$, hyper-parameters r and the lower and upper limit vector of y are $x^{\min}$ and $x^{\max}$, individual acoustic vector dimension is N.

Step 2 *Harmony Library Initialization*

Use Formula (12) to randomly generate HMS harmony in the solution space, then randomly generate hyper-parameter values x_N^{HMS} and corresponding objective function values $f(x^{HMS})$ and store in the population, that is the initial harmony library, expressed as matrix:

$$x^{(j)} = x^{\min} + rand\left(0,\ 1\right) \times \left(x^{\max} - x^{\min}\right) \tag{12}$$

Rand (0, 1) represents a random numbers between 0 and 1; represents the objective function value under the harmony variable.

$$HM = \left[\begin{array}{c|c} X^1 & f(x^1) \\ X^2 & f(x^2) \\ \vdots & \vdots \\ X^{HMS} & f(x^{HMS}) \end{array}\right] \left[\begin{array}{cccc|c} x_1^1 & x_2^1 & \cdots & x_N^1 & f(x^1) \\ x_1^2 & x_2^2 & \cdots & x_N^2 & f(x^2) \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ x_1^{HMS} & x_2^{HMS} & \cdots & x_N^{HMS} & f(x^{HMS}) \end{array}\right] \tag{13}$$

Each row of the table represents a solution in this harmony library.

Step 3 *New Harmony Generation*

Randomly select a new harmony x_i^{new} from the harmony library according to (14), then do audio trimming to selected harmony according to the *PAR* ratio; if *rand* < *HMCR* is not satisfied, then regenerate a new harmony in variables X_i .

$$x_i^{new} = \begin{cases} x_i^{new} \in \left(x_i^1, x_i^2, \cdots, x_i^{HMS}\right), if\ rand < HMCR \\ x_i^{new} \in X_i, \qquad\qquad\qquad i = 1, 2, \cdots, N \end{cases} \tag{14}$$

PAR takes control of part search process. A smaller *PAR* value can reinforce the searching capability of the algorithm; while a larger *PAR* value is helpful for the harmony algorithm to adjust the searching area around its harmony memory library, which enlarges the searching area to the whole solution space. *BW* is harmony adjustment width. In the earlier stage of HS algorithm, a larger BW value is conducive to acquire an overall optimum solution; at the later period of HS algorithm, a smaller *BW* value helps a fine search partially. Based on the literature [15, 16], the improved strategy of *PAR* and *BW* are expressed by equation (15) and (16) respectively.

$$PAR = PAR_{\min} + \frac{PAR_{\max} - PAR_{\min}}{\frac{\pi}{2}} \arctan(T_d) \tag{15}$$

$$BW = BW_{\max} - \frac{BW_{\max} - BW_{\min}}{T_{\max}} T_d \tag{16}$$

$PAR_{\min}$ and $PAR_{\max}$ are the minimum and maximum value of pitch trim ratio respectively; $BW_{\max}$ and $BW_{\min}$ are the minimum and maximum value of pitch adjust bandwidth respectively. T_d represents the current maximum iterations.

Step 4 *Harmony Memory Updating*

Calculate the fitness of new harmonies generated by Step 3 and update harmony database according to (14) to generate a new generation of harmony library.

$$if\ f\left(x_i^{new}\right) < f\left(x^{new}\right) = \max_{i=1,2,\cdots,HMS} f\left(x_i^{new}\right), then\ x^{new} = x_i^{new} \tag{17}$$

***Step5** Termination Determination*

If the number of iterations reaches $T_{\max}$, the algorithm terminates, output the optimal combination (r, y) of hyper-parameters of gas-intake RVM model. Otherwise, go to Step 3.

***Step 6** HS-SVM Prediction Model Building*

Output optimal output parameter vector, then construct gas intake RVM prediction model with optimized hyper-parameters in accordance with Formula (10).

Gas Intake HS-SVM Prediction Model Construction

In order to ensure sufficient amount of gas production for users and the stability of main pipe network pressure, the owned power plant can use gas. So the factors that affect gas intake of owned power plants are complicated, which is difficult to fully grasp and quantify the factors that impact the amount of byproduct gas emergence and consumption, so gas intake forecasting model of owned power plants can not be directly obtained [6]. Based on the system's point of view, the historical time series of gas intake of owned power plants includes the evolution of the system's effects on the by-product gas emergence and consumption, the mine variation and trends from time series of gas intake. Surplus gas system is typically nonlinear. The evolution of each constituent in the system is determined by other constituents' interrelationship. In the time series of gas supply amount of boilers in self-owned power plants, it covers the long-term evolution information of all variables which affect the constituents, and thereby, the decomposition of these historical data can be used to investigate and predict, which is based on the phase space reconstruction theory, proposed by [5]. Phase space reconstruction is also named as the rebuilding of dynamic system, i.e., the reverse construction of a phase space structure of the source system via one-dimensional time sequences.

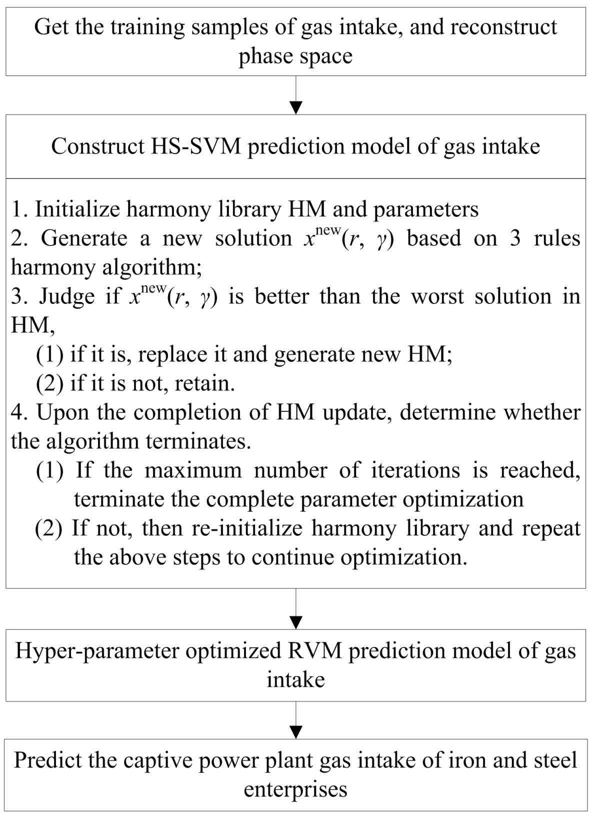

Figure 1. Parameter optimization and HS-RVM prediction model.

Suppose sample data, which change over time and conditions, of gas intake of owned power plan can be written as $\boldsymbol{S}$= [s_1, s_2, …, s_i , …, s_M]. To find the relationship between the input and output variables of gas intake RVM prediction model, phase space reconstruction must be done to gas intake sample data [17, 18]. Phase space reconstruction of gas intake sample is Formula (18), and reconstructed training samples are $\boldsymbol{S}'$.

$$s_i = \xi(s_{i-1},\ s_{i-2},\ \ldots,\ s_{i-r}),\ i = r+1,\ \ldots,\ M \tag{18}$$

Where : r is embedding dimension; $\xi(\cdot)$ is a nonlinear mapping function.

After completion of the sample data space reconstruction, conduct parameter optimization of RVM prediction model, then build the gas intake HS-RVM predictive model, the specific optimization process and model building steps are shown in Figure 1.

By reconstructing phase space of gas intake sample data of owned power plant, and using HS to optimize the hyper-parameters of relevance vector machine, gas intake HS-RVM prediction model with optimized hyper-parameters owned power plant is obtained.

PREDICTION EXAMPLES

Data Sources and Phase Space Reconstruction

Enterprise A is Yunnan's largest joint steel production base, which has a capacity of annual output of 10 million tons of steel production. Choose a gas system of steel company A's branch to be the example, the owned power plant has three boilers, which are all pure gas fired boiler - steam turbine. Randomly select actual value of gas intake boiler from enterprise A's owned power plant. According to the boiler load scheduling period (once per 15 minutes) in the actual production of enterprise A, set the sampling interval of gas intake sample data as 15 minutes. When recording the data, use period to indicate the time interval, i.e., 1 period = 15 min. 360 gas intake data samples of owned power plant were collected this time.

After completing the data collection, in order to meet the requirements of RVM prediction model, carry out space reconstruction on the sample data, select the reconstruction dimension as 30 according to document [6]. After phase space reconstruction, gas intake Samples of Owned power plant is shown in Figure 2.

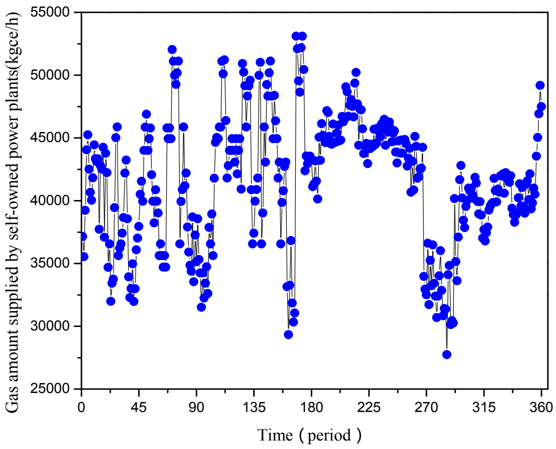

Figure 2. Sample data of gas supply amount in self-owned power plants.

Predictive Analysis of Gas Intake

Aiming at the problem of gas intake prediction accuracy of iron and steel enterprises owned power plant is not high, and difficulty in optimizing the scheduling, HS-RVM predictive model is proposed. In order to ensure the generalization performance of gas intake HS-RVM prediction model, respectively select 11/12, 7/8 and 5/6 of sample size as the training sample, the remaining 30, 45 and 60 sample points as the corresponding test set for performance testing and evaluation of prediction model. Performance indicators to evaluate prediction model are the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). Obviously, the smaller the MSE and RMSE value are, the higher the prediction accuracy of the model is. MAPE and RMSE are calculated as follows.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i' - y_i|}{y_i} \tag{19}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i' - y_i)^2} \tag{20}$$

Where y' is the predicted value of gas intake, y_i is the actual value of gas intake.

On the base of Matlab R2009 software and Libsvm tool, HS-RVM, HP-Elman and PSO-SVR prediction model are constructed, the results is shown in figures 3(a) - (c).

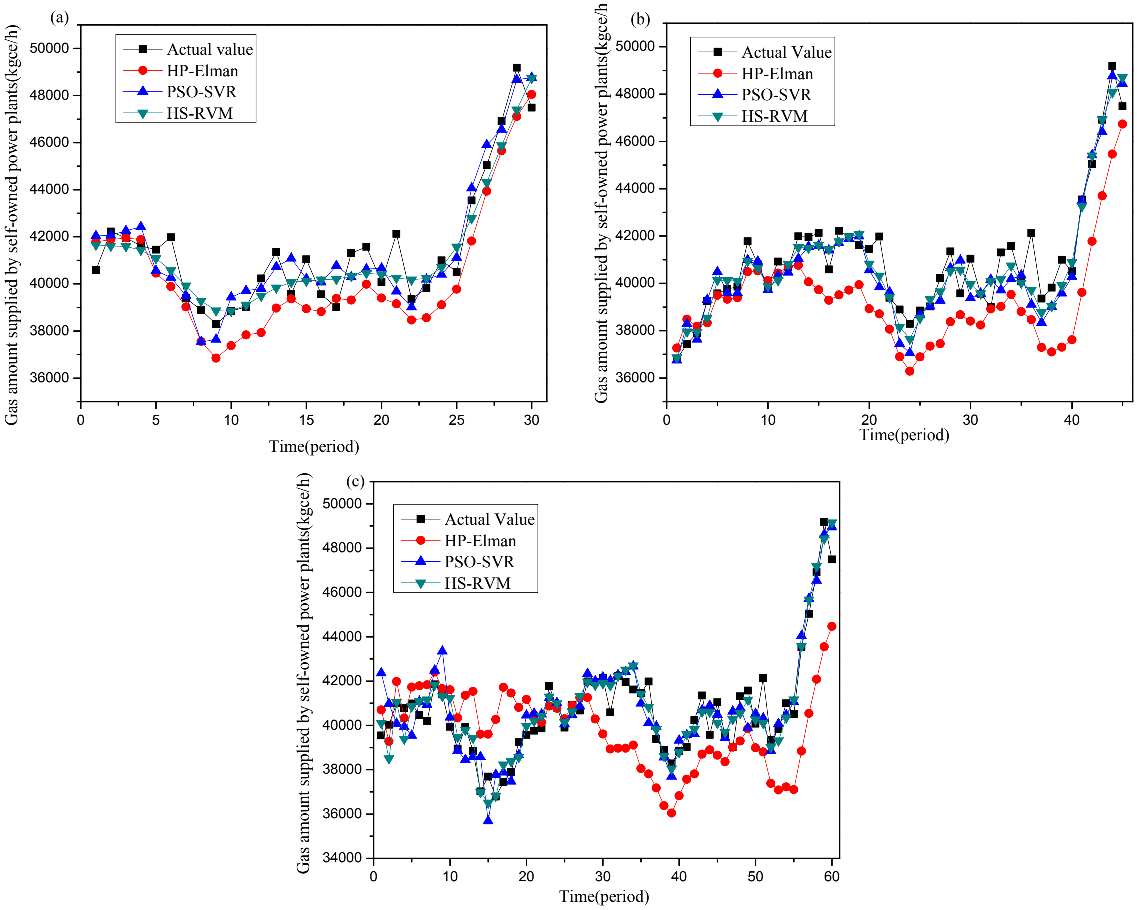

Figure 3. Prediction model of gas amount supplied by self-owned power plants.

Table 1 also evidently show that MAPE, RMPE of LS-RVM prediction model are less than HP-Elman model and PSO-SVR model, therefore, HS-RVM prediction model has the highest prediction accuracy. The accuracy of prediction values of owned power plant gas intake is greatly improved, so it can meet the gas intake forecasting and scheduling needs of enterprise-owned steel plants.

Table 1. Prediction performance comparison among HP-Elman, PSO-SVR and HS-RVM.

The model of gas intake of	MAPE			RMSE		
owned power plant	30 (period)	45 (period)	60 (period)	30 (period)	45 (period)	60 (period)
HP-Elman	0.03015	0.04300	0.04962	1452.7070	2112.9463	2434.2208
PSO-SVR	0.02005	0.01742	0.01895	980.5311	949.1816	960.4107
HS-RVM	**0.01867**	**0.01442**	**0.01376**	**916.3049**	**761.5172**	**725.8754**

Applicability Prediction Test of Model

Verify the practicality model by Wilcoxon unilateral signed-rank test. Using MAPE of 60 points predicted by HS-RVM model, HP-Elman model and PSO-SVR model to calculate rank. The results are shown in Table 2.

Table 2. Wilcoxon sign rank test.

Model	N	rank	sum of rank
HP-Elman	49	36	1602
PSO-SVR	**38**	**35**	**1321**

NOTE: N represents MAPE of HS-SVM model is smaller than the number of HP-Elman model's and PSO-SVR model's.

Wilcoxon unilateral signed-rank test results are consistent with the conclusions of MAPE, which confirms the proposed model has improved the prediction accuracy of existing methods and verifies the outstanding performance of HS-RVM prediction in the prediction of gas intake of owned power plant.

CONCLUSION

To solve the problem that forecasting accuracy and scheduling efficiency of gas intake of iron and steel enterprise owned power plant is not high, we constructed a gas intake steel companies owned power plant HS-RVM mode on the basis of the hyper-parameters of RVM model optimized by HS algorithm. Verify and analyze model relying on actual production data to give following conclusions:

HS-RVM model has good nonlinear recognition performance and can get the change of gas supply of owned power plants, also, the model has good generalization performance. Wilcoxon unilateral signed-rank test verify the model's effectiveness in predicting gas intake of owned power plants;

The examples show that: HS-RVM model has a very high prediction accuracy, 30 (period), 45 (period) and 60 (period). RMSEP of owned power plant gas intake were 1.867%, 1.442% and1.376%, which meet management demand iron and steel enterprises owned power plants, and can help companies save energy.

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