J. Cent. South Univ. (2021) 28: 2333−2344
DOI: https://doi.org/10.1007/s11771-021-4773-z

Springer

Application of SVM and PCA-CS algorithms for prediction of strip crown in hot strip rolling

JI Ya-feng(姬亚锋)[1], SONG Le-bao(宋乐宝)[1], SUN Jie(孙杰)[2],
PENG Wen(彭文)[2], LI Hua-ying(李华英)[3], MA Li-feng(马立峰)[1]

1. School of Mechanical Engineering, Taiyuan University of Science and Technology, Taiyuan 030024, China;
2. State Key Laboratory of Rolling and Automation, Northeastern University, Shenyang 110819, China;
3. School of Materials Science and Engineering, Taiyuan University of Science and Technology, Taiyuan 030024, China

Abstract: To make up the poor quality defects of traditional control methods and meet the growing requirements of accuracy for strip crown, an optimized model based on support vector machine (SVM) is put forward firstly to enhance the quality of product in hot strip rolling. Meanwhile, for enriching data information and ensuring data quality, experimental data were collected from a hot-rolled plant to set up prediction models, as well as the prediction performance of models was evaluated by calculating multiple indicators. Furthermore, the traditional SVM model and the combined prediction models with particle swarm optimization (PSO) algorithm and the principal component analysis combined with cuckoo search (PCA-CS) optimization strategies are presented to make a comparison. Besides, the prediction performance comparisons of the three models are discussed. Finally, the experimental results revealed that the PCA-CS-SVM model has the highest prediction accuracy and the fastest convergence speed. Furthermore, the root mean squared error (RMSE) of PCA-CS-SVM model is 2.04 μm, and 98.15% of prediction data have an absolute error of less than 4.5 μm. Especially, the results also proved that PCA-CS-SVM model not only satisfies precision requirement but also has certain guiding significance for the actual production of hot strip rolling.

Key words: strip crown; support vector machine; principal component analysis; cuckoo search algorithm; particle swarm optimization algorithm

Cite this article as: JI Ya-feng, SONG Le-bao, SUN Jie, PENG Wen, LI Hua-ying, MA Li-feng. Application of SVM and PCA-CS algorithms for prediction of strip crown in hot strip rolling [J]. Journal of Central South University, 2021, 28(8): 2333−2344. DOI: https://doi.org/10.1007/s11771-021-4773-z.

1 Introduction

The production of hot-rolled strip occupies an important position in the industrial system, and due to its excellent performance, the hot-rolled strip has been widely applied in various aspects of the industry, agriculture, defense and daily life. However, the quality problems of the strip crown may adversely affect the users and the poor quality of final product may lead to some serious consequences. For example, the deviations of strip crown may cause not only insignificant process disruptions and many issues but also the shape

Foundation item: Project(52005358) supported by the National Natural Science Foundation of China; Project(2018YFB1307902) supported by the National Key R&D Program of China; Project(201901D111243) supported by the Natural Science Foundation of Shanxi Province, China; Project(2019-KF-25-05) supported by the Natural Science Foundation of Liaoning Province, China
Received date: 2020-08-14; **Accepted date:** 2021-01-07
Corresponding author: JI Ya-feng, PhD, Associate Professor; Tel: +86-18735126590; E-mail: jyf0109@126.com; ORCID: https://orcid.org/0000-0002-4101-3217

defects and the product failures, so ensuring product quality and improving shape accuracy are always a challenging task [1]. Therefore, hot strip rolling process is of great significance in the fields of manufacturing and processing; moreover, the quality of hot strip crown is particularly critical.

In addition, the production process of hot strip rolling is a large system with complicated mechanism and many system parameters, and there is a strong coupling among the parameters. Consequently, it is unusually complex to set up an accurate mathematical model. The simplified mathematical model was usually adopted in the current strip crown control methods, and the production data are used to modify the model in long-term production. SUN et al [2] presented a profile distribution model based on dynamic programming, in which the major parameters are computed by the finite element method and through a regression strategy to keep bending force and shift position within an appropriate scope. HE et al [3] put forward a method of skew rolling; meanwhile, the finite element method was used to simulate the deformation of strips. These methods are effective in modeling process, but each process control parameter is not optimal obviously, which affects the further improvement of the strip crown forecast and control accuracy. So far, many studies have been made to further comprehend the strip crown control capacity of hot rolling mills in the rolling procedure [4]. ZAMANIAN et al [5] designed a new mill for the product of a strip with zero strip crown. ZHAO et al [6] proposed a high-precision shape model for hot strip rolling. A feedback control of the contour shape in hot-rolled was shown by SCHAUSBERGER et al [7]. The product of strips with uniform thickness has great significance in rolling industries, but it is daunting to accomplish existing technical matters, such as pair cross mill and high-crown control mill.

The past several decades have witnessed an expeditious development of big data and intelligent control techniques, and an increasing number of researches have begun to use data analysis technologies [8] and artificial intelligence methods in the study of strip crown control algorithms. A significant amount of researches were conducted to forecast. For example, DING et al [9] proposed a load distribution optimization based on max-min ant colony algorithm during the rolling process. BOUKHALFA et al [10] used the fuzzy-PSO method to reduce the high torque ripple of motor and shorten the rise time, avoiding interference that affects the drive performance. Besides, a way of surface defect classification in large-scale strip steel image collection based on hybrid chromosome genetic algorithm was proposed by HU et al [11]. WANG et al [12] utilized the adaptive mutation PSO algorithm and SVM to forecast the strip crown during the process of hot-rolling. Furthermore, LOTFAN et al [13] presented a parametric modeling of carbon nanotubes by estimating nonlocal constant using the signals-ARMA (autoregressive moving average) and ANN (artificial neural network) based approach. An empirical mode decomposition based on ensemble deep learning for load demand time series forecasting was proposed by QIU et al [14]. The neural network-based methods [15−17] are widely used in many fields and achieved a good application effect.

As known to all, the strip crown of hot rolling is a non-linear problem and the mechanism is extraordinarily complicated for the variations of rolling force, roll speed and other major parameters and variables during the rolling procedures. ANN, as a kind of typical machine learning method, based on the principle of empirical risk minimization, due to its strong non-linearity and capacity of adaptive information processing, is one of the most fashionable machine learning algorithms currently. However, the performance of neural networks is highly dependent on data samples, and its approximation and generalization capabilities of network models are closely related to the typicality of learning samples. SVM, as another prevalent machine learning algorithm, based on statistical learning theory and structural risk minimization, is able to achieve a stronger generalization capability with fewer support vectors [18]. SHEN et al [19] developed a new model by combining SVM with small experimental data and an advanced material was designed successfully. A temperature rise parameter identification model of the main motor of the hot rolling mill was established by SVM method, and the feasibility of the model was verified by actual data [20]. Therefore, based on industrial big data, artificial intelligence high-precision strip crown prediction model undoubtedly has a broad theoretical significance and practical application value.

2 Hot rolling technology

In this work, the experimental dataset consists of seven 4-high stand finishing mills in a hot rolling manufactory. Parameters of the continuous variable crown (CVC) mill are listed in Table 1 and its structure configuration is shown in Figure 1.

Table 1 Parameters of CVC mill

Parameter	Value
Maximum rolling force/kN	50000
Maximum bending force/kN	1200
Maximum rolling speed/(m·s^{-1})	21
Roll shifting/mm	320
Strip thickness/mm	1.2−12.7
Strip width/mm	700−1450
Work roll diameter/mm	630−700

Strip shape includes crown and flatness, and the profile is described as crown and flatness is depicted differential elongation [21]. It is generally considered that the thickness changes between the left and right marking points of hot-rolled strip are parabolic, so the profile is used to represent shape characteristics of the cross-section. Additionally, as shown in Figure 2, the absolute strip crown is defined as the difference between the thickness at average of the thickness of the marked points at 40 mm from edge of the band on both sides.

$$C_R = h_c - \frac{h_{ds} + h_{os}}{2} \tag{1}$$

where C_R is the strip crown; h_{ds}, h_{os} and h_c are the thickness of drive side, operator side and center of the strip, respectively.

The factors influencing the strip crown during the rolling process may refer to two aspects, the rolled product and rolling conditions. However, the current precision requirements of strip crown control may no longer be met, relying on traditional analytical methods and control theories, which are mainly manifested in three points. First, the simplified conditions in the modeling process have greatly restricted the further improvement of the accuracy of strip crown model. Second, the complexity of the site condition and the difficulty of measuring some special variables directly and in real-time also increase the difficulties for raising the precision. Third, the difficulty of feedback control is also a key factor hindering the improvement of strip crown accuracy. In engineering, different specifications and grades correspond to different models, and it is rather complex to build a reasonable model that is suitable for various circumstances and situations. Besides, the parameters such as stress distribution, thermal expansion and roll wear are complicated to calculate and measure directly. Therefore, the characteristics of the selected parameters shown in Table 2 are easy to obtain with relatively small errors. Using data detection devices to directly obtain data can maximize the value of the original data. The systematic errors of calculation model caused by the simplification of various models (e.g., rolling force model, temperature model and thermo-mechanical coupling model) are avoided.

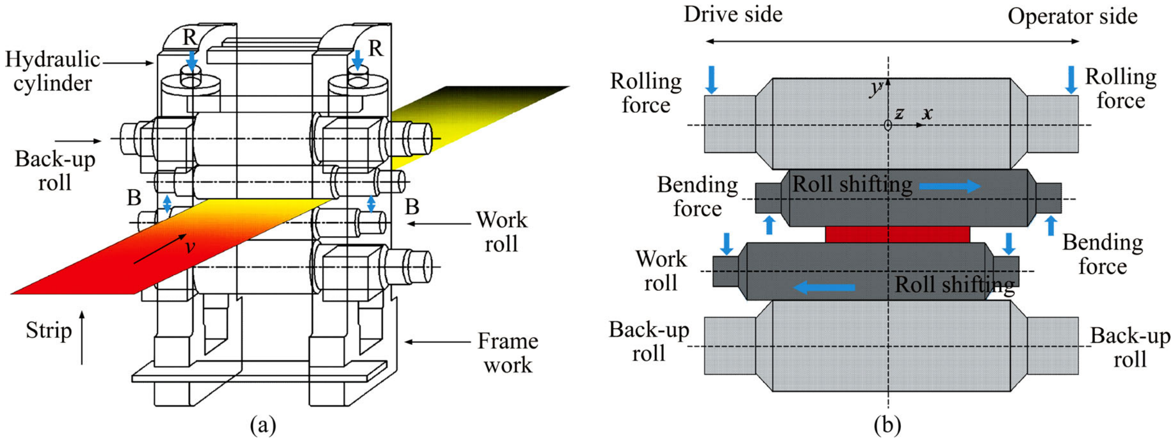


Figure 1 Structure diagram of a CVC mill: (a) Rolling mill structure; (b) Working principle of the roll

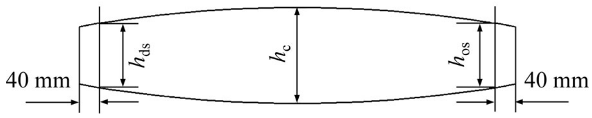


Figure 2 Cross-sectional shape of hot strip rolling

Table 2 Parameters of inputs and output for SVM model

No.	Parameter	Unit
1−7	Rolling force at F1−F7	kN
8−14	Rolling speed at F1−F7	m/s
15−21	Bending force at F1−F7	kN
22−28	Rolling gap values at F1−F7	mm
29−35	Roll shifting at F1−F7	mm
36−37	Exit thickness and width at F7	mm
38	Entrance temperature	°C
39	Finishing temperature	°C
40	Strip crown at F7	μm

F_i is the i-th stand (i=1−7).

3 Theory of SVM and parameter optimization strategy

3.1 Theory of SVM

Most of the practical engineering issues about classification or regression, in fact, are always non-linear, so the ideal classification surface also should be non-linear. For classification problems, the SVM puts efforts to look for a hyperplane between two different types of data in the feature space [22]. As for the regression problems, the method for SVM is to map the training data from original pattern to a high-dimensional space through a non-linear transformation of a specific function, and generally, given a set of non-linear samples data $[x_i, y_j] \subset R^n \times R$ (i, j=1, 2, ⋯, m), where x is input value and y is corresponding objective value.

The SVM regression function is defined as:

$$f(x) = \omega^{\mathrm{T}} x + d \tag{2}$$

The objective function can be gained:

$$\Phi(\omega) = \min\left\{\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m} L(f(x_i), y_i)\right\} \tag{3}$$

where ω and d are the regression factors; C is the regularization parameter; $L(\cdot)$ is the ε-insensitive loss function.

$$L(f(x_i) - y_i) = \begin{cases} 0, & |f(x_i) - y_i| \le \varepsilon \\ |f(x_i) - y_i| - \varepsilon & |f(x_i) - y_i| > \varepsilon \end{cases} \tag{4}$$

Assuming that the non-linear mapping is: $x \to \varphi(x)$, at this time, the objective function becomes:

$$Q(\alpha) = \sum_{k=1}^{n} \alpha_k - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} \alpha_i \alpha_j y_i y_j \langle \varphi(x_i), \varphi(x_j) \rangle \tag{5}$$

where α_i and α_j are the Lagrange multipliers.

Additionally, the radial basis function is expressed as follows:

$$K(x_i, x_j) = \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right) \tag{6}$$

where σ is a constant.

Finally, the decision function of SVM regression model will be defined:

$$f(x) = \sum_{i=1}^{m} (\alpha_i - \alpha_i^*) \langle \varphi(x_i), \varphi(x) \rangle + d$$
$$= \sum_{i=1}^{m} (\alpha_i - \alpha_i^*) K(x_i, x) + d \tag{7}$$

where K is the kernel function; $\varphi(x)$ is the non-linear mapping function.

3.2 Strategy of parameter optimization

3.2.1 PSO

The PSO is one of the representative swarm intelligence optimization algorithms to deal with multi-objective optimization problems and an evolutionary computation technique. It originated from the research of bird predation behavior. The fundamental principle of PSO is through cooperation and information sharing among individuals in group to search for an optimal solution. Due to its simplicity, operation easiness and non-necessity for adjustments for parameters, the PSO algorithm has been widely applied in solving practical optimization issues. The basic PSO algorithm diagram is shown in Figure 3 and

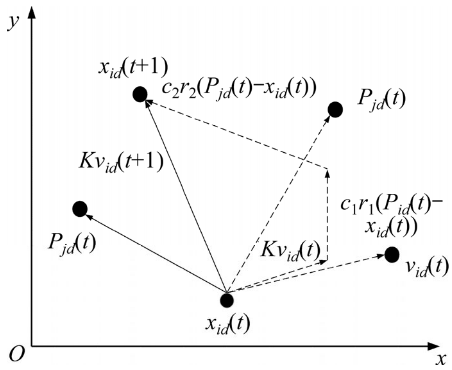


Figure 3 Schematic of PSO algorithm

the particle updates its speed and position by following formulas:

$$v_{id}(t+1)=K(v_{id}(t)+c_1r_1(P_{id}(t)-x_{id}(t)+c_1r_2(P_{jd}(t)-x_{id}(t))) \tag{8}$$

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \tag{9}$$

where v and x represent speed and position of the particle, respectively; i and d are the i-th particle and the d-th dimension, respectively; t is the number of iterations; ω means inertia weight; c_1 and c_2 are learning factors; P_{id} is individual extreme coordinate of the particle in the d-th dimension; P_{jd} is global extreme coordinate of the particle swarm in the j-th dimension.

3.2.2 CS

The CS optimization algorithm is an emerging heuristic algorithm which was firstly put forward by YANG [23]. As an effective swarm optimization algorithm, CS has been developed by simulating breed behavior of cuckoos. It is a population based search procedure which is used as an optimization method and tool, in solving complicated and non-linear issues. Simultaneously, CS also adopts the relevant Levy flight search mechanism (i.e., a global random search mode), which can effectively solve the global optimization problem. Moreover, the algorithm can be enhanced by the Levy flight rather than a simple isotropic random walk. Comparing with other heuristic searches, e.g., GA (genetic algorithm) and PSO, the main advantages of CS algorithm are needing fewer parameters, having simpler operation, easier implementation, more excellent random search paths and stronger generation ability, and able to converge to the global optimal. The main idea of CS is based on two strategies: the nest parasitism of cuckoos and the Levi's flight mechanism. Through the way of Levi's flight mechanism to search for an optimal host nest to hatch their eggs, an efficient optimization model can be built as:

$$X_{t+1}=X_t+\beta\times L(\lambda) \tag{10}$$

where t represents the number of generations; β is generated from −1 to 1. The step length calculation formula is:

$$\beta=\beta_0(x_t-x_{\text{best}}) \tag{11}$$

where β_0 is a constant; x_{best} represents current optimal solution; $L(\lambda)$ obeys the probability distribution of Levy $L\sim u=t^{-\lambda}$, and adopts the formula $\alpha\times u/|v|^{\frac{1}{\beta}}$ to generate Levy random numbers; u and v all meet the normal distribution, $\alpha=\left\{\dfrac{\Gamma(1+\beta)\sin(\pi\times\beta/2)}{\Gamma[(1+\beta)/2]\times\beta\times 2^{\frac{\beta-1}{2}}}\right\}^{\frac{1}{\beta}}$.

3.2.3 PCA

The principal component analysis (PCA), as a multivariate statistical technique, has great advantages in reducing dimensions of big data and extracting features from the original data. Specific implementation methods refer to Ref. [24]. The schematic diagram of PCA is shown in Figure 4 where the original data space [X_1, X_2] forms a new data space [l_1, l_2] by PCA. The direction of l_1 represents the direction in which the variance of the data changes the most and explains the most of changes in the data. While the direction of l_2 represents the secondary part of the data and the noise part of system. In Figure 4, the sample points of the original data space (x_{i1}, x_{i2}) are projected into the new data space (t_{i1}, t_{i2}), and the new coordinates of the sample points can be obtained by using the projection value. The change of the sample points in the direction l_1 is greater than the change in the direction l_2, reflecting the characteristics of the sample points more truly than the distribution of the original data space.

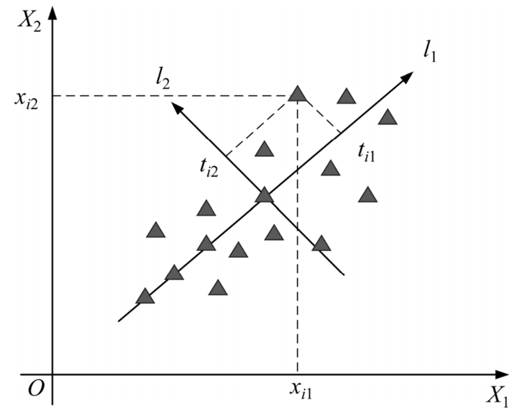


Figure 4 Schematic diagram of PCA

4 Experiment

4.1 Analysis of experimental data

A great number of data samples were collected from a hot-rolled manufactory to build SVM-based models and the framework of strip crown prediction is shown in Figure 5.

To utmost recover the facticity of the information of sample data and accomplish a reliable experimental result, the sample data handling is fundamental instead of directly using. Besides, all the experimental data come from a hot strip rolling plant and part of the data are listed in Table 3. In truth, the original data always contain lots of noise and outliers, which may bring about misleading prediction results. Therefore, the predicted values based on the prediction model have a great relationship with the quality of the measured data.

In Figure 6, a three-dimensional visual map of the experimental data shows distinct distributions of those variables and parameters which impact the hot strip crown. The values of strip crown increase from 10 μm to 70 μm, and with the change of horizontal and vertical coordinates, it presents a messy distribution. That is to say, not only these generous sample points, but also its tremendous disorder, can partly demonstrates that the strip crown prediction models established using this dataset will have a strong robustness in practical hot strip rolling production.

There is no doubt that the large amount of raw data collected from a hot-rolled plant certainly contain a lot of noise and abnormal points. Therefore, on the basis of Pauta criterion, to eliminate the outliers and noise in the sample data and recover the original information in the sample data is a key step to guarantee the facticity of experimental results. The formula of criterion is

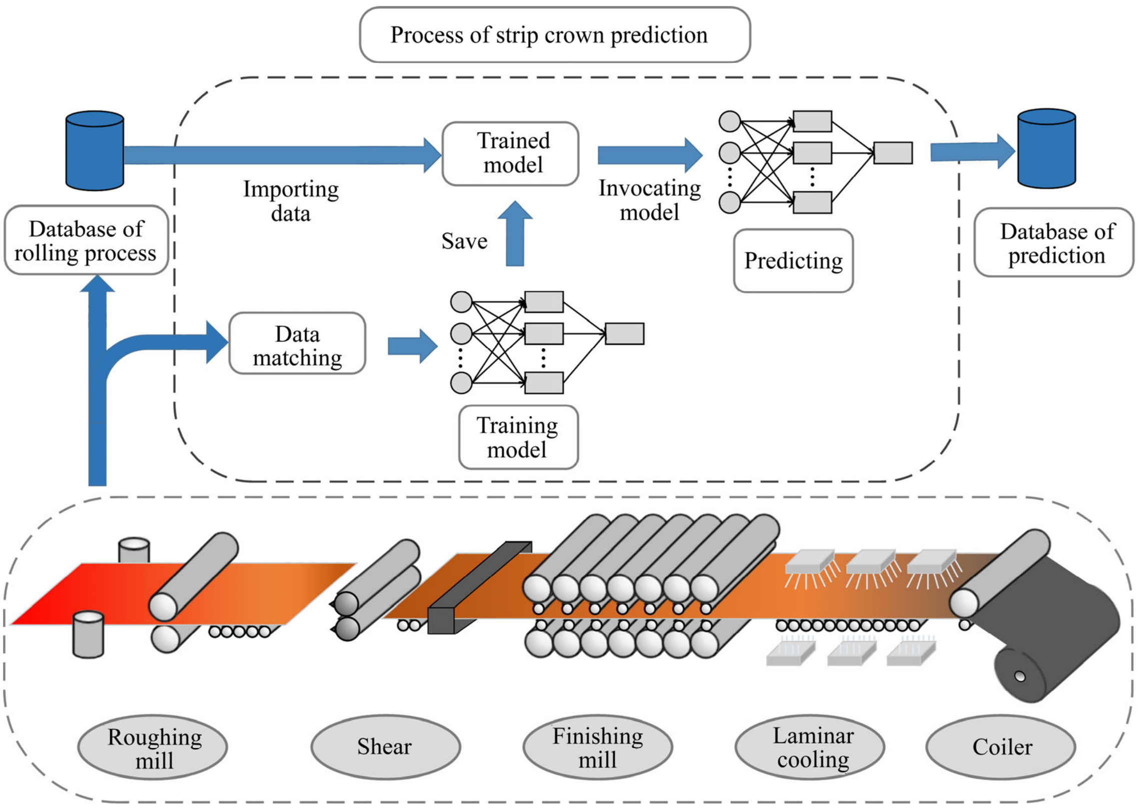


Figure 5 Framework of strip crown prediction

Table 3 Experimental data

No.	Rolling force/kN	Bending force/kN	Roll shifting/mm	Thickness/mm	Width/mm	Finishing temperature/°C	Strip crown/μm
1	16576	870	−53.82	5.59	880	879.06	52.46
2	24612	826	−37.31	3.87	862	868.75	49.05
3	19259	1206	63.08	3.00	867	866.88	53.33
4	17420	866	42.68	2.53	871	867.81	41.98
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
2700	17429	838	111.91	1.80	870	860.63	25.11
2701	17859	880	77.83	1.79	869	879.34	22.68

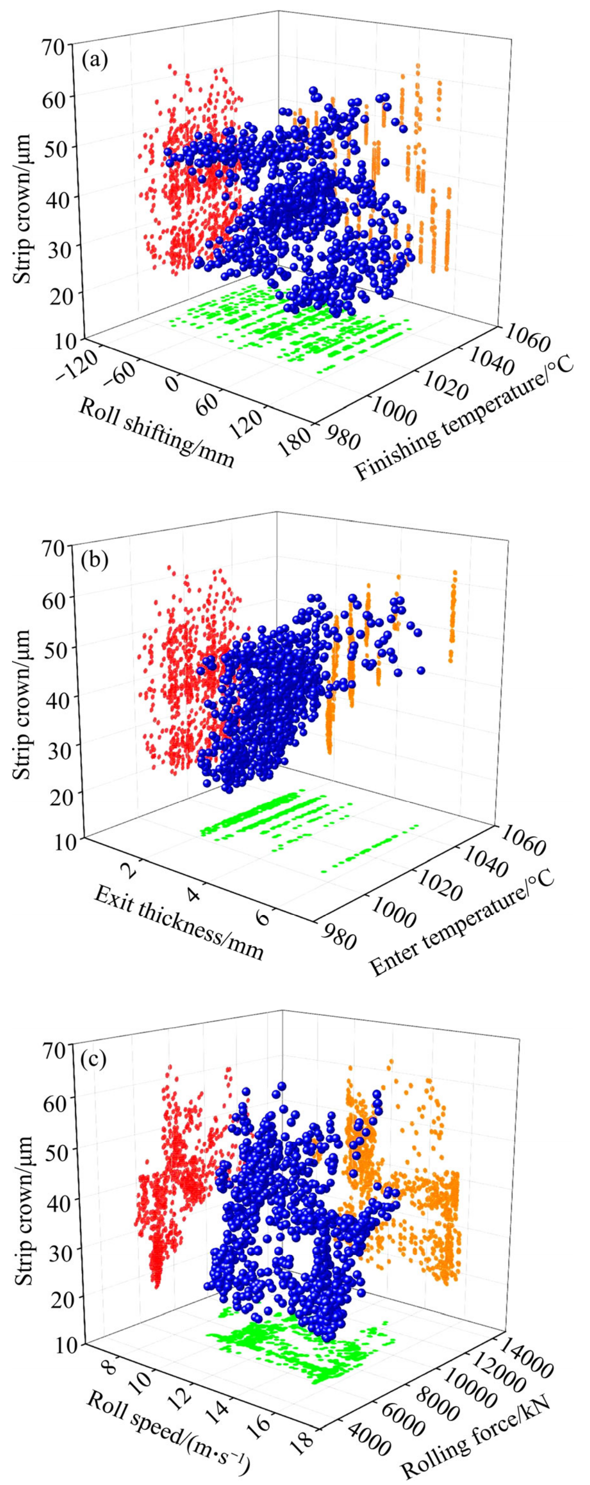


Figure 6 3D visualization diagrams of experimental data

defined as follows:

$$|x_i-\bar{x}|>3S_x \tag{12}$$

where $S_x=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2}$ $\left(\bar{x}=\frac{1}{n}\sum_{i=1}^{n}x_i\right)$ (13)

and $\bar{x}$ is the mean of x_i and S_x is the standard deviation.

Moreover, in order to remove the noise and abnormal points, the data also need to smooth by the five-spot triple smoothing method. As a result, a total of 106 sample points are detected and eliminated, and 2701 sample data are selected for further experiment program.

Besides, to avoid the influence caused by different dimensions, these sample points have to be normalized through a min-max scaling and the specific method is as follows:

$$x\rightarrow y=\frac{x-x_{\min}}{x_{\max}-x_{\min}} \tag{14}$$

where y, x, $x_{\min}$ and $x_{\max}$ are the normalized data, original data, minimal and maximal data, respectively.

4.2 Establishment of predictive models

4.2.1 SVM model

During the establishment of the SVM model, there are two crucial and sensitive parameters (the penalty factor c and the kernel function variable g) supposed to be searched and adjusted to achieve an ideal accuracy. It is a complicated process to accurately determine the sensitive parameters. Either too large or too small parameters will affect the performance of SVM. However, there is no universally accepted uniform method for the selection of the parameters optimization of SVM. Cross validation (CV), a kind of statistical analysis technique, is used to demonstrate and verify the capability of classification or regression problems.

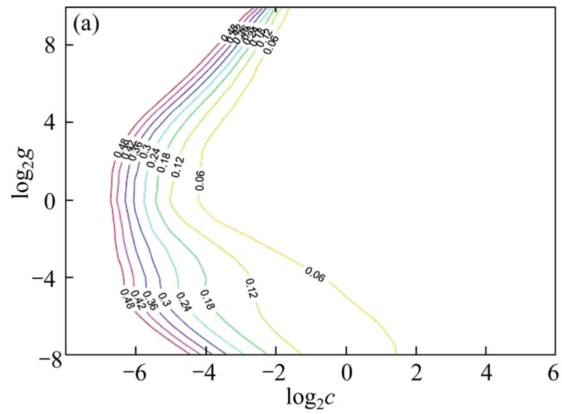
Additionally, to comprehensively and synthetically appraise the capability of the prediction models, two crucial criteria, the MSE and R^2, are used:

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}\left(x_{ti}-x_i\right)^2 \tag{15}$$

$$R^2=\frac{\sum_{i=1}^{n}\left(x_i-\bar{x}_i\right)^2-\sum_{i=1}^{n}\left(x_{ti}-x_i\right)^2}{\sum_{i=1}^{n}\left(x_i-\bar{x}_i\right)^2} \tag{16}$$

where x_i, x_{ti} and $\bar{x}_i$ are measured values, predicted values and average values, respectively.

In Figure 7, the contour lines and 3D views indicate the accuracy and mean squared error of the CV algorithm searching for the parameters of SVM model.



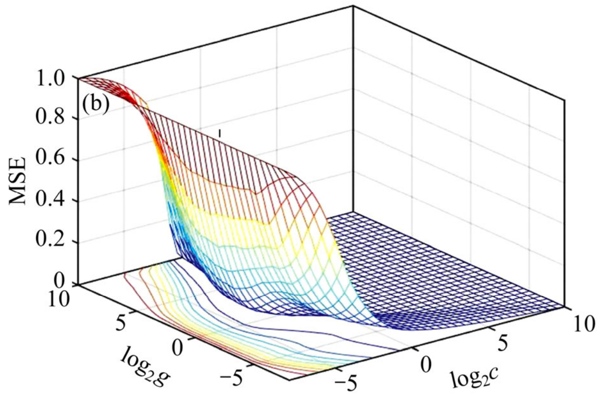


Figure 7 Selection of parameters ($c\&g$): (a) Contour map; (b) 3D views

4.2.2 PSO-SVM model

Compared with the CV method, the PSO-SVM does not need to select the range of optimization parameters multiple times, while possessing faster convergence speed and better optimization capacity. In most cases, the PSO can converge to an optimal solution faster than CV method. The step of using PSO algorithm for optimizing SVM parameters is depicted as follows:

Step 1: Load the whole processed experimental data and divide it into two parts: one is the training set (70%) and the other is the testing set (30%). All of the training samples (1801) are used as training the models of SVM and the remaining data (900) are applied as testing the predictive capability of established models.

Step 2: Search for the best ($c\&g$) combination by the PSO algorithm and repeat the process until it approaches the condition of stopping.

Step 3: Output the best combination searched by the PSO algorithm.

Step 4: Establish the SVM regression model using the optimal ($c\&g$) combination parameters.

Step 5: Calculate the criteria of prediction model and evaluate its performance.

4.2.3 PCA-CS-SVM model

During the process of hot-rolling, strip crown is affected by many factors, such as mill parameters, strip parameters and dynamic parameters of stand. The input features in this paper are up to 39 dimensions. To prevent the data distribution on each element dimension from becoming sparse because the high dimension is catastrophic for machine learning, PCA technique can be used to extract and determine the main information in multidimensional data. Therefore, obtaining the valid information instead of high-dimensional data is beneficial to simplify the calculating model and greatly improve the training speed. In this work, the cumulative contribution rate is 99% to ensure that the most of data information can be contained in compound variables. The data extraction result is shown in Figure 8.

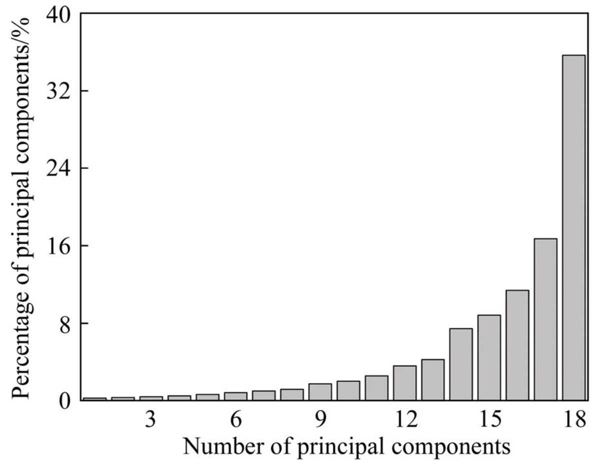


Figure 8 Result of dimensionality reduction processing by PCA method

PSO algorithm is based upon the population instead of the gradient information, so it has the ability to search the optimal solution in the global solution space; meanwhile, the PSO algorithm also has disadvantages with premature convergence, low search precision and efficiency during the later iterations [25]. However, the CS, an effective algorithm, is considered an optimization tool in handling complicated and non-linear issues. Besides, data-driven methods and data mining techniques can be used effectively to mine the potential information in data. By projecting the data to reduce dimensionality, the effective information in data is extracted, and the internal laws among the variables are found to establish effective nonlinear models. The PCA is applied to reducing the dimensionality of the process data in this paper, which not only fully excavates and utilizes potential information in data, but also greatly improves the convergence speed of models.

The steps of the algorithm process for optimizing SVM parameters using PCA-CS method are similar to those of PSO-SVM model. The workflow of optimizing the SVM parameters by using PCA-CS algorithm is illustrated in Figure 9.

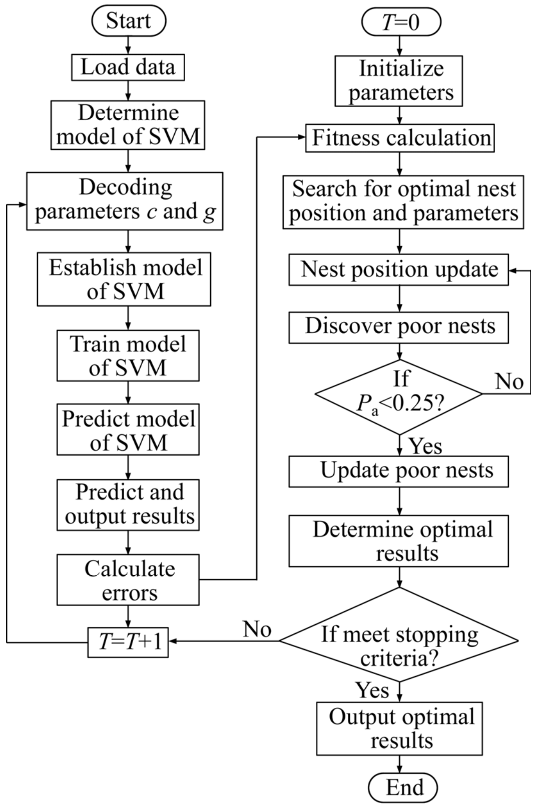


Figure 9 Workflow of optimizing SVM parameters by using PCA-CS method

5 Experimental results and discussions

Figure 10 shows the comparison of the iteration time of these three strip crown prediction models. The comparison result shows that the iteration time of the PCA-CS-SVM model is the shortest. Table 4 lists iteration time and iteration speed of three models.

It can be clearly seen from Table 4 that the iteration time of the PCA-CS-SVM model is the shortest, which is about 1 min; while the iteration time of the SVM model is the longest with 3 min approximately, and its iteration speed is the slowest. Therefore, the PCA-CS-SVM method proposed in this paper is the most reasonable and has the fastest convergence speed.

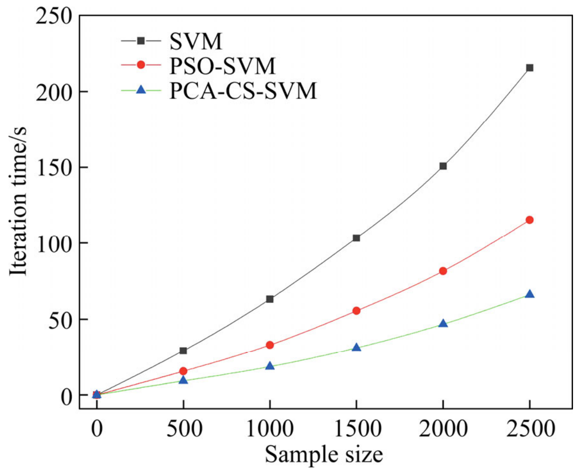


Figure 10 Comparison of iteration time of three models

Table 4 Comparison of iteration time and iteration speed of three models

Model	Iteration time/s	Iteration speed/s^{-1}
SVM	187.59	0.27
PSO-SVM	101.73	0.50
PCA-CS-SVM	58.89	0.88

Moreover, to pursue perfect experimental results as many as possible, MAE (mean absolute error), MAPE (mean absolute percentage error) and RMSE (root mean squared error) are employed to measure the performance of established strip crown prediction models. Simultaneously, MSE (mean square error) and R^2 (square correlation coefficient) are adopted to comprehensively evaluate the prediction accuracy as well. The mathematical formulas are listed as follows:

$$\mathrm{MAE}=\frac{1}{n}\sum_{i=1}^{n}\left|x_{ti}-x_i\right| \tag{17}$$

$$\mathrm{MAPE}=\frac{100}{n}\sum_{i=1}^{n}\left(\frac{x_{ti}-x_i}{x_i}\right) \tag{18}$$

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_{ti}-x_i\right)^2} \tag{19}$$

where x_i is the measured values; x_{ti} is the predicted values.

The evaluate results of prediction model of SVM, PSO-SVM, and PCA-CS-SVM are shown in Figure 11. From Figure 11, we can see that the strip crown predictive capacity of PCA-CS-SVM is preferably higher and it has the best performance, of which R^2 is 0.9550. Moreover, from SVM to

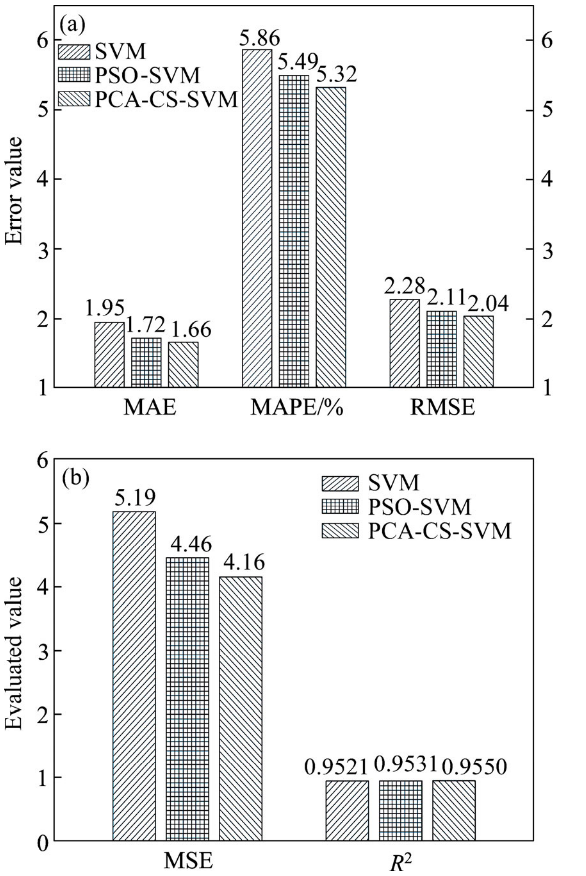


Figure 11 Comparison of prediction performance of proposed three models

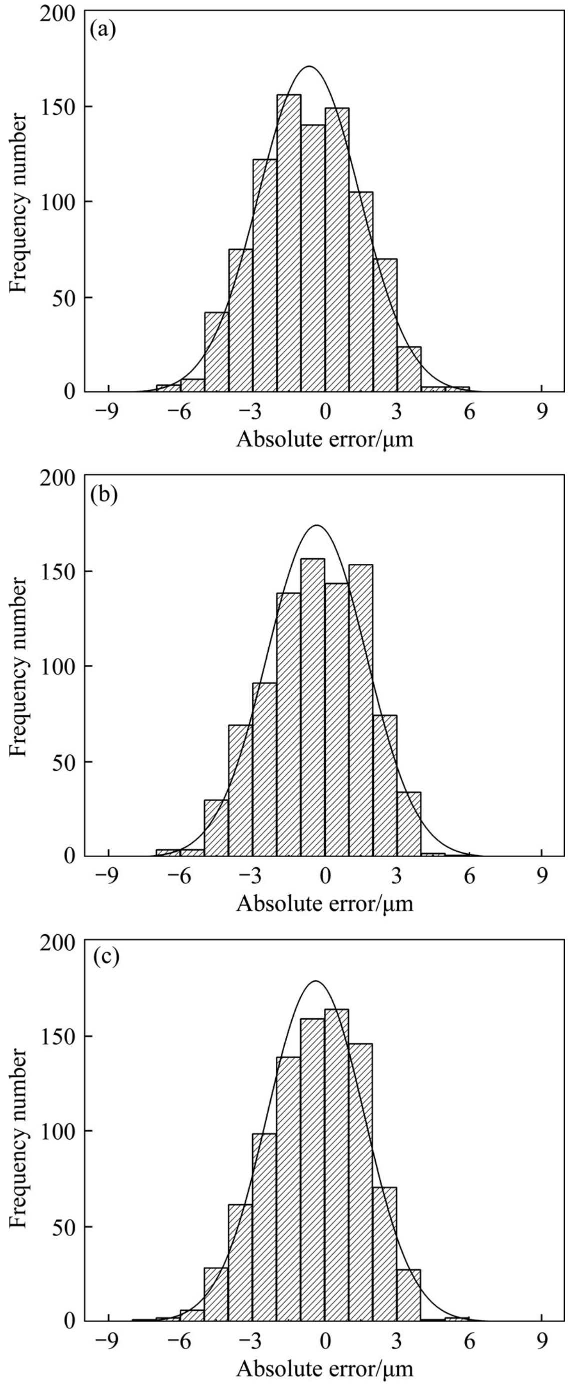


Figure 12 Absolute error frequency distribution for prediction results of proposed three models: (a) SVM; (b) PSO-SVM; (c) PCA-CS-SVM

PCA-CS-SVM, the values of MAE, MAPE, and RMSE decline distinctly in Figure 11.

Figure 12 shows the absolute error frequency number distribution for strip crown prediction results of proposed model comparison for the SVM, PSO-SVM, and PCA-CS-SVM. Apparently, the model of PCA-CS-SVM has the highest prediction accuracy with 98.15% of the predicted data, and the absolute error is below 4.5 μm.

6 Conclusions

1) Among the three strip crown prediction models proposed in this paper, the PCA-CS-SVM shows the best prediction performance. The main advantages of the CS algorithm, compared with PSO algorithm, are fewer parameters, simpler operation, easier implementation, more excellent random search paths, stronger optimization ability, and able to converge to the global optimal.

2) In handling complicated, non-linear and non-convex optimization issues, the PCA-CS-SVM has the faster convergence speed and higher prediction accuracy compared with SVM and PSO-SVM methods.

3) Compared with SVM and PSO-SVM, the prediction performance of PCA-CS-SVM model has been clearly showed in results. Among the three methods, PCA-CS-SVM has the highest prediction accuracy, in which 98.15% of the predict data have an absolute error of less than 4.5 μm, which has

certain guiding significance for the actual processing of hot strip rolling production.

Contributors

The overarching research goals were developed by JI Ya-feng and SUN Jie. JI Ya-feng provided the hot rolling data. SONG Le-bao and JI Ya-feng edited the initial draft of the manuscript. PENG Wen, LI Hua-ying and MA Li-feng analyzed the measured data and reviewed and edited the draft of manuscript. SONG Le-bao and SUN Jie analyzed the calculated results. All authors replied to reviewers' comments and revised the final version.

Conflict of interest

JI Ya-feng, SONG Le-bao, SUN Jie, PENG Wen, LI Hua-ying and MA Li-feng declare that they have no conflict of interest.

References

[1] DENG Ji-fei, SUN Jie, PENG Wen, HU Yao-hui, ZHANG Dian-hua. Application of neural networks for predicting hot-rolled strip crown [J]. Applied Soft Computing, 2019, 78: 119−131. DOI: 10.1016/j.asoc.2019.02.030.

[2] SUN W Q, LI B, SHAO J. Research on crown & flatness allocation strategy of hot rolling mills [J]. International Journal of Simulation Modelling, 2016, 15(2): 327−340. DOI: 10.2507/ijsimm15(2)co6.

[3] HE You-liang, HILINSKI E J. Skew rolling and its effect on the deformation textures of non-oriented electrical steels [J]. Journal of Materials Processing Technology, 2017, 242: 182−195. DOI: 10.1016/j.jmatprotec.2016.11.033.

[4] LI Hong-bo, ZHAO Zhen-wei, ZHANG Jie, KONG Ning, BAO Ren-ren, JIA Sheng-hui, HE Fei. Analysis of flatness control capability based on the effect function and roll contour optimization for 6-h CVC cold rolling mill [J]. The International Journal of Advanced Manufacturing Technology, 2019, 100(9−12): 2387−2399. DOI: 10.1007/s00170-018-2838-4.

[5] ZAMANIAN A, NAM S Y, HWANG S M. A new mill design for the production of a strip with zero strip crown [J]. Steel Research International, 2019, 90(11): 1900252. DOI: 10.1002/srin.201900252.

[6] ZHAO Jian-wei, WANG Xiao-chen, YANG Quan, WANG Qiu-na, LIU Chao, SONG Guang-yi. High precision shape model and presetting strategy for strip hot rolling [J]. Journal of Materials Processing Technology, 2019, 265: 99−111. DOI: 10.1016/j.jmatprotec.2018.10.005.

[7] SCHAUSBERGER F, STEINBOECK A, KUGI A. Feedback control of the contour shape in heavy-plate hot rolling [J]. IEEE Transactions on Control Systems Technology, 2018, 26(3): 842−856. DOI: 10.1109/TCST.2017.2695168.

[8] TAO Liang, GUO Jian-chun, ZHAO Zhi-hong, YIN Qi-wu. Refracturing candidate selection for MFHWs in tight oil and gas reservoirs using hybrid method with data analysis techniques and fuzzy clustering [J]. Journal of Central South University, 2020, 27(1): 277−287. DOI: 10.1007/s11771-020-4295-0.

[9] DING Jing-guo, MA Geng-sheng, PENG Wen. Load distribution optimization based on max-Min ant colony algorithm in hot strip rolling process [J]. Metallurgist, 2018, 62(7): 837−846. DOI: 10.1007/s11015-018-0727-6.

[10] BOUKHALFA G, BELKACEM S, CHIKHI A, BENAGGOUNE S. Genetic algorithm and particle swarm optimization tuned fuzzy PID controller on direct torque control of dual star induction motor [J]. Journal of Central South University, 2019, 26(7): 1886−1896. DOI: 10.1007/s11771-019-4142-3.

[11] HU Hui-jun, LIU Ya, LIU Mao-fu, NIE Li-qiang. Surface defect classification in large-scale strip steel image collection via hybrid chromosome genetic algorithm [J]. Neurocomputing, 2016, 181: 86−95. DOI: 10.1016/j.neucom.2015.05.134.

[12] WANG Zhen-hua, LIU Yuan-ming, GONG Dian-yao, ZHANG Dian-hua. A new predictive model for strip crown in hot rolling by using the hybrid AMPSO-SVR-based approach [J]. Steel Research International, 2018, 89(7): 1800003. DOI: 10.1002/srin.201800003.

[13] LOTFAN S, FATHI R. Parametric modeling of carbon nanotubes and estimating nonlocal constant using simulated vibration signals-ARMA and ANN based approach [J]. Journal of Central South University, 2018, 25(3): 461−472. DOI: 10.1007/s11771-018-3750-7.

[14] QIU Xue-heng, REN Ye, SUGANTHAN P N, AMARATUNGA G A J. Empirical mode decomposition based ensemble deep learning for load demand time series forecasting [J]. Applied Soft Computing, 2017, 54: 246−255. DOI: 10.1016/j.asoc.2017.01.015.

[15] LI Yue-lin, LIU Bo-fu, WU Gang, LIU Zhi-qiang, DING Jing-feng, ABUBAKAR S. Intelligent prediction on air intake flow of spark ignition engine by a chaos radial basis function neural network [J]. Journal of Central South University, 2020, 27(9): 2687−2695. DOI: 10.1007/s11771-020-4491-y.

[16] MAHMOOD A, TANG Xiao-wei, QIU Jiang-nan, GU Wen-jing, FEEZAN A. A hybrid approach for evaluating CPT-based seismic soil liquefaction potential using Bayesian belief networks [J]. Journal of Central South University, 2020, 27(2): 500−516. DOI: 10.1007/s11771-020-4312-3.

[17] QURESHI A S, KHAN A, ZAMEER A, USMAN A. Wind power prediction using deep neural network based meta regression and transfer learning [J]. Applied Soft Computing, 2017, 58: 742−755. DOI: 10.1016/j.asoc.2017.05.031.

[18] WANG Zhen-hua, GONG Dian-yao, LI Xu, LI Guang-tao, ZHANG Dian-hua. Prediction of bending force in the hot strip rolling process using artificial neural network and genetic algorithm (ANN-GA) [J]. The International Journal of Advanced Manufacturing Technology, 2017, 93(9−12): 3325−3338. DOI: 10.1007/s00170-017-0711-5.

[19] SHEN Chun-guang, WANG Chen-chong, WEI Xiao-lu, LI Yong, van der ZWAAG S, XU Wei. Physical metallurgy-guided machine learning and artificial intelligent

design of ultrahigh-strength stainless steel [J]. Acta Materialia, 2019, 179: 201−214. DOI: 10.1016/j.actamat.2019.08.033.

[20] GAO Yi, CAI Ping, CHEN Feng, QIN Ru. Study on temperature rise modeling of main motor of hot rolling mill based on support vector machines [J]. Applied Mechanics and Materials, 2017, 870: 427−431. DOI: 10.4028/www.scientific.net/amm.870.427.

[21] PENG Kai-xiang, ZHONG Hao, ZHAO Liang, XUE Kai, JI Yi-dao. Strip shape modeling and its setup strategy in hot strip mill process [J]. The International Journal of Advanced Manufacturing Technology, 2014, 72(5−8): 589−605. DOI: 10.1007/s00170-014-5649-2.

[22] LI Xiao-feng, WU Shi-jing, LI Xiao-yong, YUAN Hao, ZHAO Deng. Particle swarm optimization-support vector machine model for machinery fault diagnoses in high-voltage circuit breakers [J]. Chinese Journal of Mechanical Engineering, 2020, 33(1): 1−10. DOI: 10.1186/s10033-019-0428-5.

[23] CHANDRASEKARAN K, SIMON S P. Multi-objective scheduling problem: Hybrid approach using fuzzy assisted cuckoo search algorithm [J]. Swarm and Evolutionary Computation, 2012, 5: 1−16. DOI: 10.1016/j.swevo.2012.01.001.

[24] MALVONI M, DE GIORGI M G, CONGEDO P M. Photovoltaic forecast based on hybrid PCA-LSSVM using dimensionality reducted data [J]. Neurocomputing, 2016, 211: 72−83. DOI: 10.1016/j.neucom.2016.01.104.

[25] MA Chi, ZHAO Liang, MEI Xue-song, SHI Hu, YANG Jun. Thermal error compensation of high-speed spindle system based on a modified BP neural network [J]. The International Journal of Advanced Manufacturing Technology, 2017, 89(9−12): 3071−3085. DOI: 10.1007/s00170-016-9254-4.

(Edited by YANG Hua)

中文导读

基于 SVM 和 PCA-CS 算法的热轧带钢板凸度预测

摘要：为了弥补传统控制方法的缺陷，满足日益增长的板凸度精度要求，提出了一种基于支持向量机(SVM)的优化模型，以提高热轧带钢产品的质量。为了丰富数据信息并保证数据质量，建立预测模型的实验数据均来自于某热轧厂，并通过计算多项评价指标来评估模型的预测性能。建立主成分分析结合布谷鸟搜索(PCA-CS)算法优化的预测模型，并与粒子群优化算法(PSO)优化的模型及传统 SVM 模型进行对比，分析并讨论了这三种模型的预测性能。实验结果表明，PCA-CS-SVM 模型具有最高的预测精度和最快的收敛速度，模型的均方根误差(RMSE)为 2.04 μm，且 98.15%的预测数据的绝对误差小于 4.5 μm。结果证明，PCA-CS-SVM 模型不仅能够满足板凸度精度要求，而且对热轧带钢的实际生产具有一定指导意义。

关键词：板凸度；支持向量机；主成分分析；布谷鸟搜索算法；粒子群优化算法