Prediction Model of Wear Amount of Work Roll and Replacement Moment in Finishing Rolling Based on Lévy's Improved Arithmetic Optimization Algorithm Twin Support Vector Regression

CHUNYANG SHI, YIKUN WANG, JIANJUN HU, LEI ZHANG, and PEILIN TAO

For the control of the wear amount of work rolls and replacement moment in finishing rolling, most of the traditional models are unable to accurately predict the optimal finishing wear amount and replacement moment of work roll in advance, which may lead to the disruption of the production rhythm, and even cause product quality defects. This research describes a Lévy's improved arithmetic optimization algorithm twin support vector regression (LAOA-TSVR) prediction model for wear amount of work roll and replacement moment in a finishing mill. Firstly, the research group initially employed real production data from a hot strip finishing mill to identify influential factors of wear amount of work roll through correlation analysis using SPSS. Subsequently, to validate its predictive performance, the model was compared against three classical algorithms: Back Propagation (BP), Radial Basis Function (RBF), and Support Vector Machine (SVM), confirming LAOA-TSVR's superior accuracy. Finally, the model underwent practical production testing with a dataset totaling 200 sets. The findings reveal that the model attains a 95.2 pct hit rate for predicting wear amount of work roll within $\pm$ 0.5 pct. Likewise, it achieves a 98.3 pct hit rate for predicting the replacement moment of work roll for finishing mill.

I. INTRODUCTION

As rivalry in steel production heats up, steel manufacturing technology is continually evolving. Steel production methods are now more focused on efficiency, energy-saving, environmental friendliness, and high-quality, high-precision manufacturing.[1–3] Excessive wear on the work rolls alters the shape of the roll gap, directly impacting strip shape and, consequently, strip quality. Quantitatively controlling the wear amount of work roll is challenging in current production.

Conducting a comprehensive analysis of wear amount of work roll and developing a high-precision prediction model for wear amount of work roll and replacement moment in finishing rolling contributes to enhancing automatic control of thickness and shape for hot strip finishing mill. By identifying the optimal replacement moment for work rolls, production costs of hot strip finishing mill can be reduced, maximizing work roll utilization and ensuring smooth production while enhancing product quality.[4–6] Therefore, it is crucial to investigate the wear patterns of work roll for finishing mill and develop a reliable prediction model to enhance finishing plate shape, product quality, and production efficiency, mitigate rolling accidents, and decrease steel cost per ton.

Intelligent steel rolling is currently a hot topic in the field of science and engineering research, but few researchers and scholars have studied and explored the hot rolling finishing process prediction model, and many researchers are still using traditional modeling methods such as random forests.[7,8] Traditional optimization methods have several shortcomings when working with complex problems involving high dimensions and multiple multimodality. These shortcomings include the limited consideration of influencing factors in traditional machine learning models, a susceptibility to getting stuck in locally optimal solutions, the risk of overfitting when dealing with large datasets, and problems related to sample imbalance.[9–11] As a result, researchers suggested a time series model to predict the

CHUNYANG SHI, YIKUN WANG, LEI ZHANG, and PEILIN TAO are with the School of Electrical and Automation Engineering, Liaoning Institute of Science and Technology, Benxi 117004, P.R. China. Contact e-mail: scy9090@126.com JIANJUN HU is with the Bensteel Group Beiying Steel Rolling Mill, Benxi 117000, P.R. China.

wear amount of work rollers based on recurrent neural networks, but the method suffers from problematic defects such as training complexity, gradient vanishing and gradient explosion, and interpretability.[12–14] With technological advancements, researchers have devised genetic algorithm models that optimize issue solutions by imitating the biological evolution process. However, defining the parameters for this method is complicated, the algorithm has large iteration times, and the interpretability is poor. These issues cause deficiencies in predicting accuracy, endpoint hit rates, and model calculation time.[15–17]

To address the aforementioned shortcomings, the group proposed a prediction model for ending wear amount of work roll based on LAOA-TSVR algorithm. Due to the multiple factors influencing wear amount of work roll in the finishing mill, the research group used SPSS to conduct a correlation analysis of the parameters in the finishing process, resulting in the model's input variables. TSVR computation requires random assignment of values to specific parameters. This increases computational load, reduces operational efficiency, and may affect prediction accuracy.[18,19] To overcome this issue, the research group used the AOA technique for parameter optimization. However, the AOA method still has limitations, such as limited exploration capabilities and a tendency to prematurely converge to non-optimal solution.[20] To solve this, the research group developed the Lévy algorithm to improve the AOA algorithm (LAOA), giving it benefits such as easier parameter modification, an extended exploration range, fast convergence, and a strong capacity to jump out of local minima. Eventually, the group merged LAOA and TSVR and used stochastic search to optimize the kernel function, adjustment parameters, and penalty factor tuning, improving the model's computing speed, exploration capabilities, and prediction accuracy on the original premise.[21–23] According to the production process standards of a hot strip finishing mill, work rolls need to be replaced when their wear exceeds 6mm (Refer to the industrial trials section for details). The research group combined this criterion with the wear amount of work roll predictive model to forecast the replacement moment in finishing rolling. Finally, the model was tested in an industrial trial, and the findings revealed that it had a greater prediction accuracy. This model provides realistic assistance for predicting wear amount of work roll and roll replacement moment in a steel mill's actual production process.

II. INDUSTRIAL TRIALS

Figure 1 depicted the process flow of the trial procedure. The research group acquired essential data from the real-time data report of a hot strip finishing mill as input volume data for creating the LAOA-TSVR model and saved these data in the model's database, which was used as the model's training and test sets. The

F7 work roll of a hot strip finishing mill unit, which was a 4-roll mill with a mechanism depicted in Figure 2(a), was chosen as the subject of study in the industrial test technique. These work rolls were made of infinite chilled cast iron. The material for rolled strip steel was Q235B, with an initial work roll diameter of 600mm. Industrial trial data required for the rolling process were collected using relevant rolling line detection equipment. This mainly included roll gap, strip threading speed, rolling length, side guide opening, roll diameter, rolling force, roll contact length, reduction amount, strip width, exit strip width, rolling speed, and working temperature. According to the production process requirements of a hot strip finishing mill, when the wear amount of the F7 work rolls exceeded 6mm, it was necessary to be replaced promptly. The wear amount of work roll was measured using the #1 grinder equipment (Type: ProfiGrind2500-25x600), the structure of which was shown in Figure 2(b). And the wear value of the work roll was taken as the output of the model.

III. DATA PROCESSING

A. Correlation Analysis

Collected the roll diameter replacement data of the F7 rolling mill in a hot strip finishing mill, coupled with production data. Firstly, any outliers should be removed from the data. Then, 1500 samples should be chosen for the training set and 500 for the test set. To gather model input variables throughout the modeling phase, a correlation study of 1000 sets of production data was performed using SPSS. The obtained correlation coefficients were shown in Figure 3. The final list of primary input variables influencing wear amount of work roll prediction includes rolling speed, strip threading speed, working temperature, roll gap, rolling length, side guide opening, roll diameter, roll contact length, rolling force, reduction amount, strip width, and exit strip width. The correlation coefficient results were presented in Table I.

B. The normalization of input data

Since different parameters have different physical meanings and different scales, in order to ensure the comparability of the sample data, improve the reliability of the wear prediction model of the work roll and the convergence speed, the chosen data must be normalized before training. The data are normalized to the [0,1] interval according to their highest and minimum values. The method for data normalization is Eq. [1].

$$X_{\mathrm{p}} = \frac{(X - X_{\min})}{X_{\max} - X_{\min}} \quad [1]$$

where: X_{p}, represents the standardized sample value; $X_{\max}$, represents the maximum value of the sample data; $X_{\min}$, represents the minimum value of the sample data.
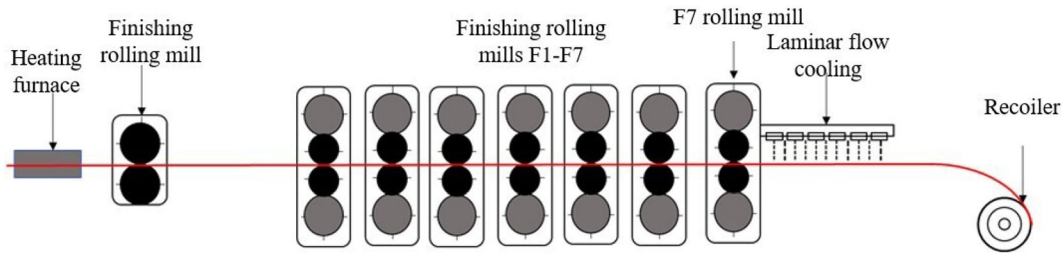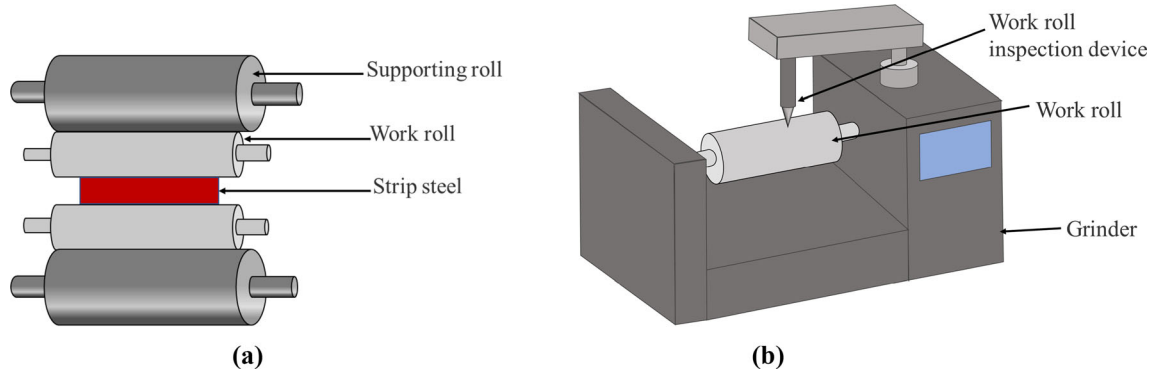
Fig. 1—Hot rolling process diagram.

Fig. 2—The devices used in the industrial trials (*a*) F7 rolling mill structure (*b*) grinder equipment.

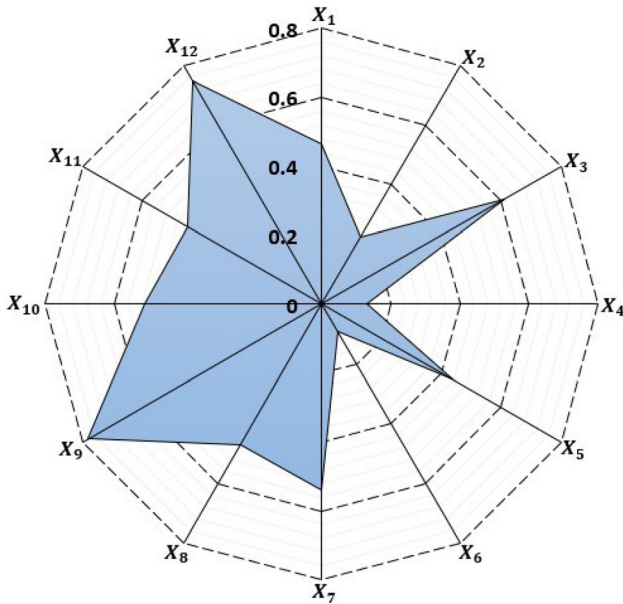

Fig. 3—Data correlation analysis chart.

IV. MODEL BUILDING

This article discusses the LAOA algorithm is mainly used to optimize the main kernel function, adjustment parameters, and penalty factors in TSVR, taking the best prediction accuracy as the goal of parameter optimization, generating new solutions by using arithmetic operations, and evaluating the fitness of each solution and selecting the optimal solution until the stopping condition is satisfied, so as to find the optimal model parameters and establish the prediction model of wear amount of work roll and replacement moment in finishing rolling based on LAOA-TSVR. The progression of LAOA-TSVR hybrid intelligent algorithm is shown in Figure 4.

A. *Establishment of LAOA Model*

The Lévy algorithm is used to improve the weights and thresholds of the AOA algorithm, and the revised algorithm has the advantages of faster convergence, faster running speed, larger searching range, and simpler to jump out of the local optimum, *etc*. The three steps of the AOA algorithm and the optimization of the Lévy algorithm are as follows:

To facilitate algorithm exploration and selection during the development phase, AOA defines a search control coefficient, *i.e.*, the Mathematical Optimization Accelerator (MOA), as shown in Eq. [2].

$$MOA(t) = Min + t \times \frac{(Max - Min)}{T} \qquad [2]$$

where: Max, the maximum value of the accelerator 1; Min, the minimum value of the accelerator 0.2; *t*, the current number of iterations; *T*, the maximum number of iterations.

When the random number $r_1 > MOA(t)$, the algorithm expands the search space to avoid local extremes, otherwise local exploitation is performed to improve the accuracy of the solution.

Based on the high dispersion property of the domain resulting from multiplication and division operations, the AOA algorithm utilizes multiplication and division search strategies to randomly explore a wider search area, with the position update equation as shown in Eq. [3].

$$X(t+1) = \begin{cases} X_{\text{best}}(t) \div (MOP + \varepsilon) \times ((UB - LB) \times \mu + LB), & r_2 < 0.5 \\ X_{\text{best}}(t) \div MOP \times ((UB - LB) \times \mu + LB), & r_2 \geq 0.5 \end{cases} \quad [3]$$

where: $X(t+1)$, the solution at the $t + 1$th iteration; $X_{\text{best}}(t)$, the population's best individual up to the current iteration; r_2, random number between 0 and 1; ε, the local minimum; μ, control parameter with a value of 0.5.

Based on the high-density value domain characteristics of the results of addition and subtraction operations, the AOA algorithm applies addition and subtraction search strategies to perform deep exploration of the search space, thereby enhancing solution accuracy, as shown in Eq. [4].

$$X(t+1) = \begin{cases} X_{\text{best}}(t) - MOP \times ((UB - LB) \times \mu + LB), & r_3 < 0.5 \\ X_{\text{best}}(t) + MOP \times ((UB - LB) \times \mu + LB), & r_3 \geq 0.5 \end{cases} \quad [4]$$

where: r_3, random number between 0 and 1; $X_{\text{best}}(t)$, best(t) represents the population's best individual up to the current iteration; UB, the upper limit for the relevant variable values; LB, the lower limit for the relevant variable values.

In Eqs. [3] and [4], MOP stands for Mathematical Optimization Probability, and its calculation formula is as shown in Eq. [5].

$$\text{MOP}(t) = 1 - \left(\frac{t}{T}\right)^{\frac{1}{\alpha}} \quad [5]$$

where, α, define the sensitivity parameter for development accuracy, which is set to 5 in this case.

Applying Lévy flight to the update of solution positions, the algorithm performs another Lévy flight update of individual positions after the initial update. This helps in escaping local optima and expanding the search capability. The method of position update is as follows:

$$X(t + 1) = X(t) + \alpha \oplus L\acute{e}vy(\lambda) \quad [6]$$

where: α, is the step scaling factor; $L\acute{e}vy(\lambda)$, indicating that it follows a Lévy distribution with a parameter of λ, and the formula is:

$$L\acute{e}vy \sim u = t^{-\lambda} \quad [7]$$

Due to the complexity of Lévy flight, the Mantegna algorithm is employed to simulate it, with its mathematical representation as follows:

$$s = \frac{\mu}{|v|^{\frac{1}{\beta}}} \quad [8]$$

where u and v follow a normal distribution with parameters σ_μ and σ_v:

$$\mu \sim N\left(0, \sigma_\mu^2\right) \quad [9]$$

$$v \sim N\left(0, \sigma_v^2\right) \quad [10]$$

$$\sigma_\mu = \left\{\frac{\Gamma(1 + \beta)\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right)\beta 2^{\left(\frac{\beta-1}{2}\right)}}\right\} \quad [11]$$

$$\sigma_v = 1 \quad [12]$$

In order to seek a reasonable computational load, a constant of 1.5 is taken for β, at which point σ_μ is a constant 0.6966.

B. Establishment of TSVR model

The TSVR algorithm aims to derive two regression functions by solving two quadratic programming problems to optimize the objective function. Suppose the training sample is an n-dimensional vector and the number of training samples is p. Let the matrix $A = [x_1, \cdots, x_p]^T \in R^{p \times n}$ be the input training sample, the vector $Y = [y_1, \cdots, y_p]^T \in R^p$ be the output training sample, and the vector e be a 1 vector of the appropriate dimension.

Prediction of the wear amount of work roll is a multiple-input single-output nonlinear system. It is necessary to introduce the kernel function $K = (x^T, A^T) = \exp\left(-\frac{\|x^T - x_i{}^T\|^2}{2\sigma^2}\right), \sigma > 0$, is the width of Gaussian kernel function. The sample is mapped to the high-dimensional space, and linear regression is performed through the high-dimensional feature space to obtain the regression function $g(x) = K = (x^T, A^T)\omega + b$ where ω is the weight vector and b is the bias.

By introducing Lagrange multipliers α and β vectors and combining them with the Karush–Kuhn–Tucker (KKT) conditions, we can obtain the dual problem of the objective function, as shown in Eqs. [13] and [14].

$$\max -\frac{1}{2}\alpha^T H (H^T H)^{-1} H^T \alpha + f^T H (H^T H)^{-1} H^T \alpha - f^T \alpha, 0 \leq \alpha \leq C_1 e \quad [13]$$

$$\max -\frac{1}{2}\beta^T H (H^T H)^{-1} H^T \beta + h^T H (H^T H)^{-1} H^T \beta + h^T \beta, 0 \leq \beta \leq C_2 e \quad [14]$$

where: $C_1 > 0$, adjustment parameter; $C_2 > 0$, adjustment parameter; $H = [K(A, A^T)e]$; $f = Y - e\varepsilon_1$; $h = Y + e\varepsilon_2$; $\varepsilon_1, \varepsilon_2 \geq 0$, for adjustment parameters.

Table I. Data Correlation Analysis Table

Dependent Variable	Variable	Correlation Coefficient
Wear Amount of Work Roll	rolling speed	0.466
	strip threading speed	0.226
	working temperature	0.612
	roll gap	0.132
	rolling length	0.436
	side guide opening	0.092
	roll diameter	0.539
	roll contact length	0.471
	rolling force	0.783
	reduction amount	0.513
	strip width	0.449
	exit strip width	0.748

C. Establishment of LAOA-TSVR Model

The detailed procedure of optimizing the TSVR algorithm for LAOA is as follows:

Step 1: Obtain data related to wear amount of work roll, preprocess the data, and generate the training set and sample set;

Step 2: Initialize decision variable parameters and generate the initial solution;

Step 3: Utilizing the algorithm's addition, subtraction, multiplication, and division search strategies, update the solution's position, evaluate the new solution on the objective function, and search for nearby potential optimal solutions;

Step 4: Evaluate the fitness of the current solution to check if it meets the criteria for the optimal solution. If it does, output the optimal parameters. If not, continue to refine the solution using the search strategy that includes addition, subtraction, multiplication, and division, until the termination criteria are met;

Step 5: Insert the optimal parameters into the weight and bias vectors to compute ω and b. Next, apply these values to the regression function $g(x)$ to develop the predictive model for estimating the wear of finishing work rolls and the timing for their replacement.

V. MODEL PREDICTION RESULT

The LAOA-TSVR algorithm prediction model was used to generate final prediction results. Real values from the training and test sets were compared with the corresponding predicted values. The outcomes are presented in Figures 5, 6, 7, and 8.

VI. MODEL COMPARISON AND RESULTS ANALYSIS

To evaluate the prediction effectiveness of the model against traditional algorithms, we employed BP, RBF, SVM, and LAOA-TSVR models. We compared models using metrics such as fluctuation degree (SSR/SST), fitting degree (SSE/SST), root mean square error (RMSE), mean absolute error (MAE), and hit rate (HR). The parameter settings are as follows: BP (learning rate: 0.05, max training iterations: 1000, required accuracy: 1e-5, min error: 0.005), RBF (hidden nodes: 10, max iterations: 1e4, precision: 0.001, alpha: 0.01), SVM (error penalty: $c = 1.0$, kernel: rbf, degree: 3, gamma: auto, coef0: 0, stop precision: 1e-3), and LAOA-TSVR (lambda: 1.5, search solutions: 10, max iterations: 1000). Predicted and actual values from the BP, RBF, SVM, and LAOA-TSVR models were analyzed to assess convergence speed. The results are depicted in Figures 9 and 10.

When the SSR/SST value of a model approaches 1, it indicates a better fit between its projected and real values; a smaller SSE/SST value corresponds to lower RMSE and MAE, indicating higher prediction accuracy. Table II reveals that the SSR/SST values of the BP, RBF, SVM, and LAOA-TSVR prediction models increase in the order of SSR/SST, while SSE/SST, RMSE, and MAE decrease in the order of SSE/SST. Thus, LAOA-TSVR demonstrates a superior degree of fit compared to the other three algorithms. The wear amount prediction model for work rolls developed by LAOA-TSVR exhibits the lowest relative error and outperforms the other algorithms. As depicted in Figure 10, the iteration curve of LAOA-TSVR flattens first, indicating a faster convergence speed compared to the other three models. In summary, based on the data from Table II, it can be concluded that the LAOA-TSVR prediction model outperforms the other algorithms.

To assess the prediction performance of the model, we used the HR (hit rate) analysis. In the analysis of the prediction model, if the wear amount of work roll meets the requirements as specified in Eq. [15], it is considered a successful prediction. The corresponding formula for calculating the hit rate is shown in Eq. [16].
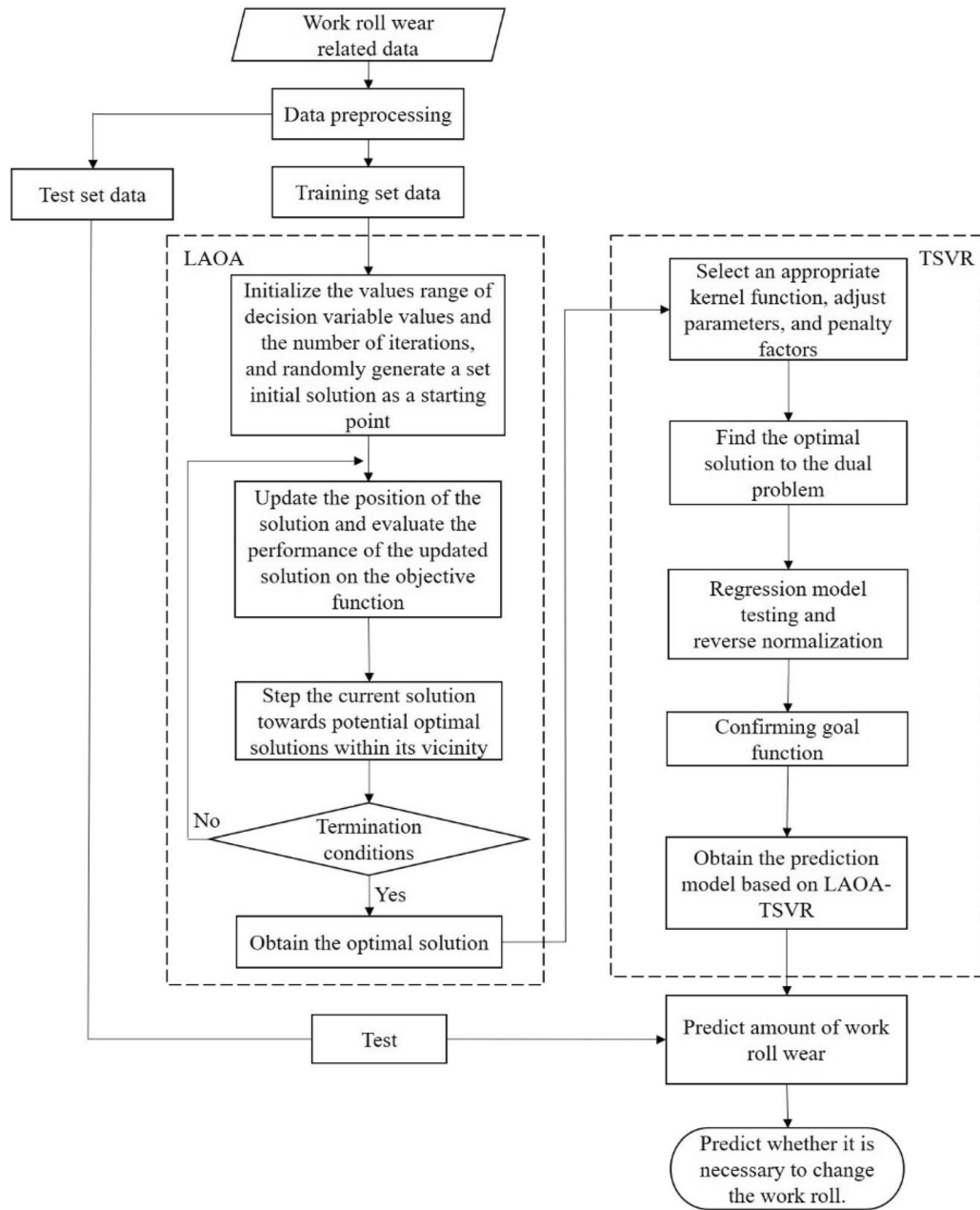
Fig. 4—Flowchart of LAOA optimization of TSVR.

$$P_S \times (100\,\text{pct} - k) < P_y < P_S \times (100\,\text{pct} + k) \qquad [15]$$

where: P_S, the measured wear amount of the work rolls; P_y, the predicted wear amount of the work rolls; k, with an accuracy rate of 0.5 pct.

$$\text{HR} = \frac{\left(\left|y_i - \overset{\triangle}{y_i}\right| \le n_e\right)}{n} \times 100\,\text{pct} \qquad [16]$$

Table III presents the hit rates of the four prediction models. From Table III, it is evident that for the prediction of wear amount of work roll within a range of ± 0.5 pct, the hit rates for BP, RBF, SVM, and LAOA-TSVR models are 77.3, 86.5, 90.6, and 96.2 pct, respectively. The hit rates for roll replacement moment prediction are as follows: 79.5, 87.1, 91.7, and 94.5 pct, respectively.

In summary, comparing the hit rates and SSE/SST, SSR/SST of the four models BP, RBF, SVM, and LAOA-TSVR, the LAOA-TSVR model exhibits superior predictive performance examination indexes and the highest endpoint hit rate, thus confirming its superior prediction effectiveness.
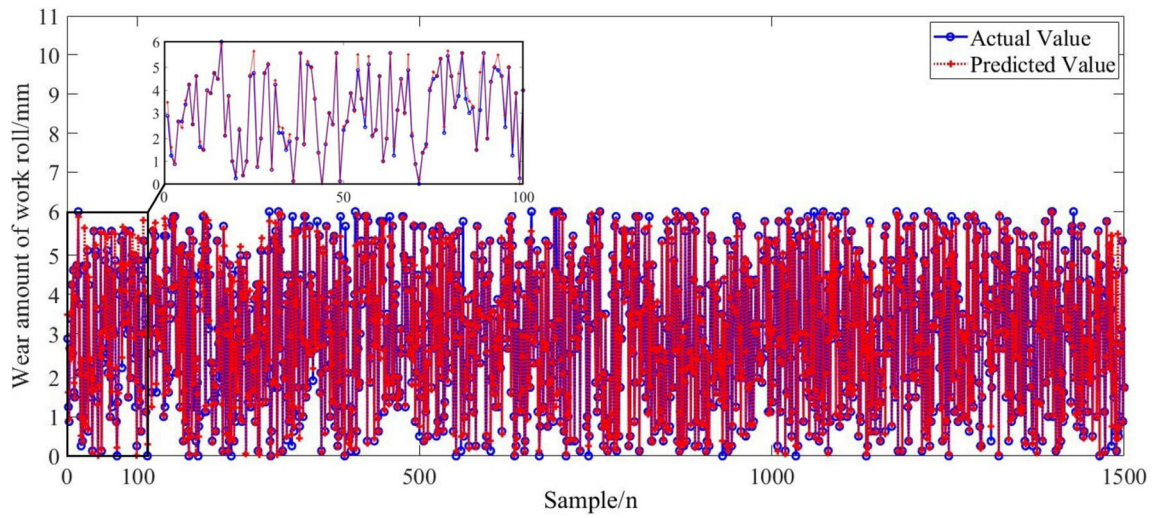
Fig. 5—Prediction results for the wear amount of work rolls in the training set.
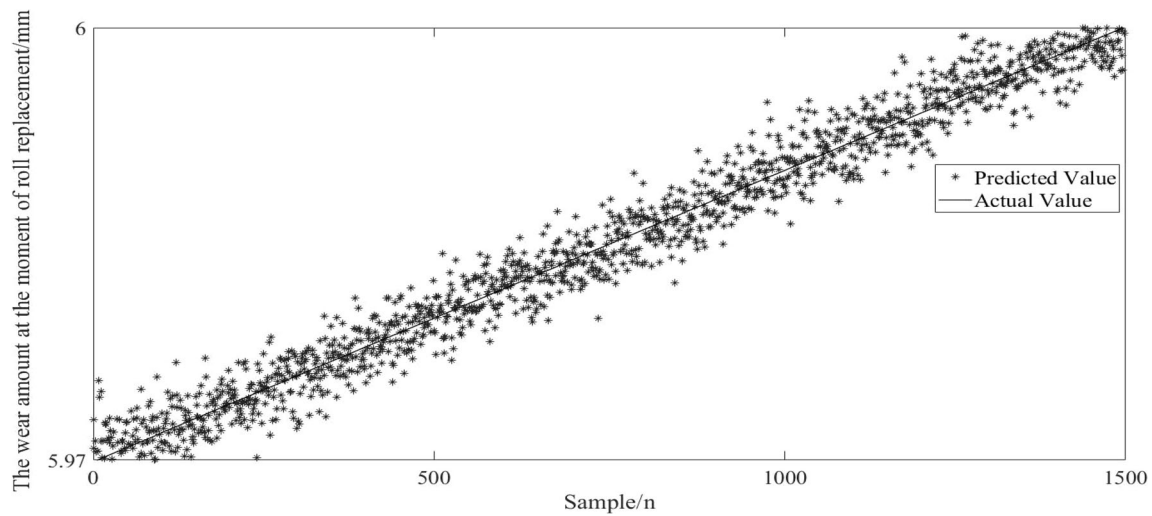

Fig. 6—Prediction results for the replacement moment during finishing rolling in the training set.
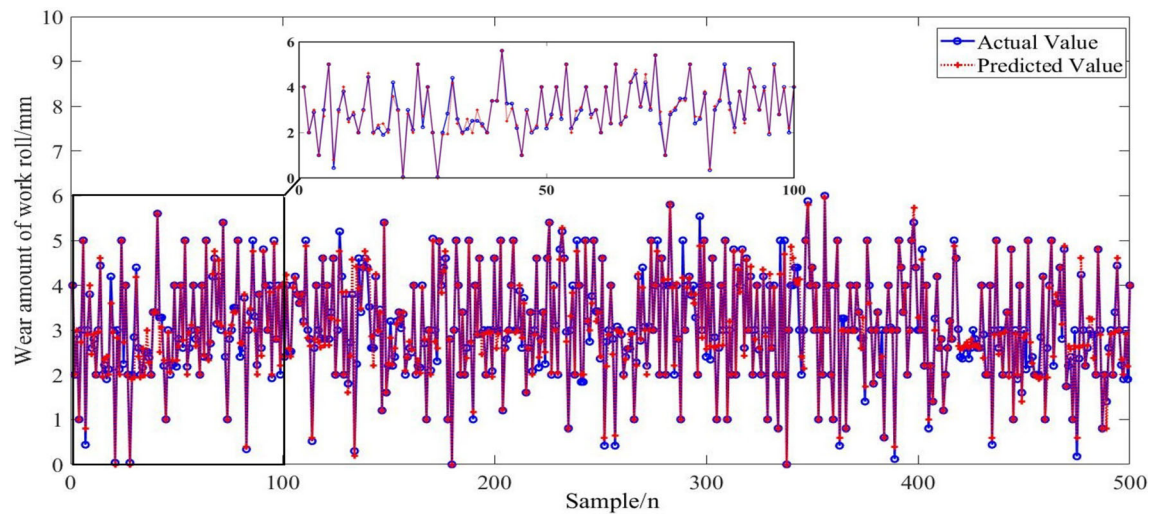

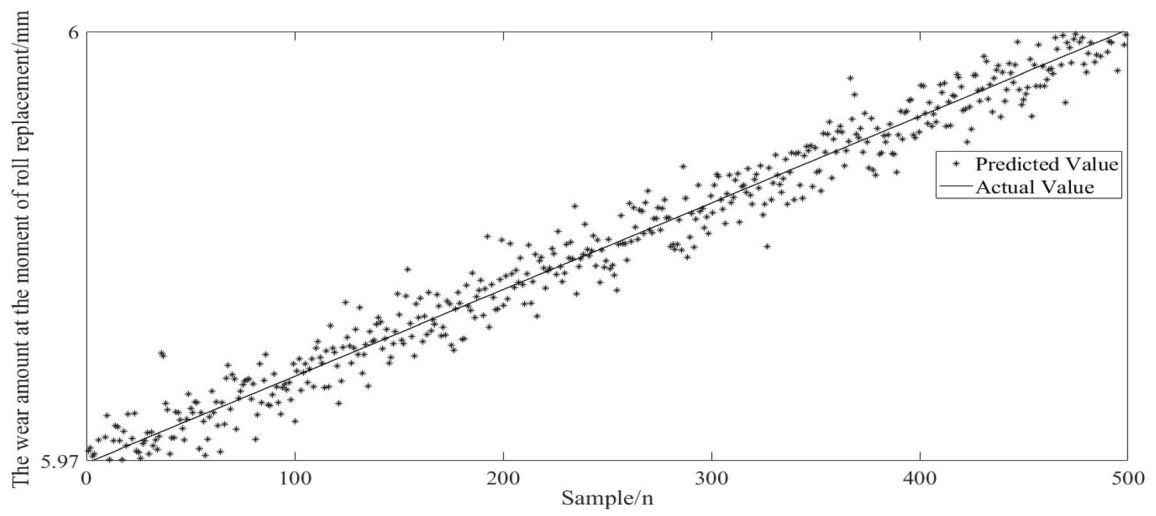Fig. 7—Prediction results for the wear amount of work rolls in the test set.

Fig. 8—Prediction results for the replacement moment during finishing rolling in the test set.
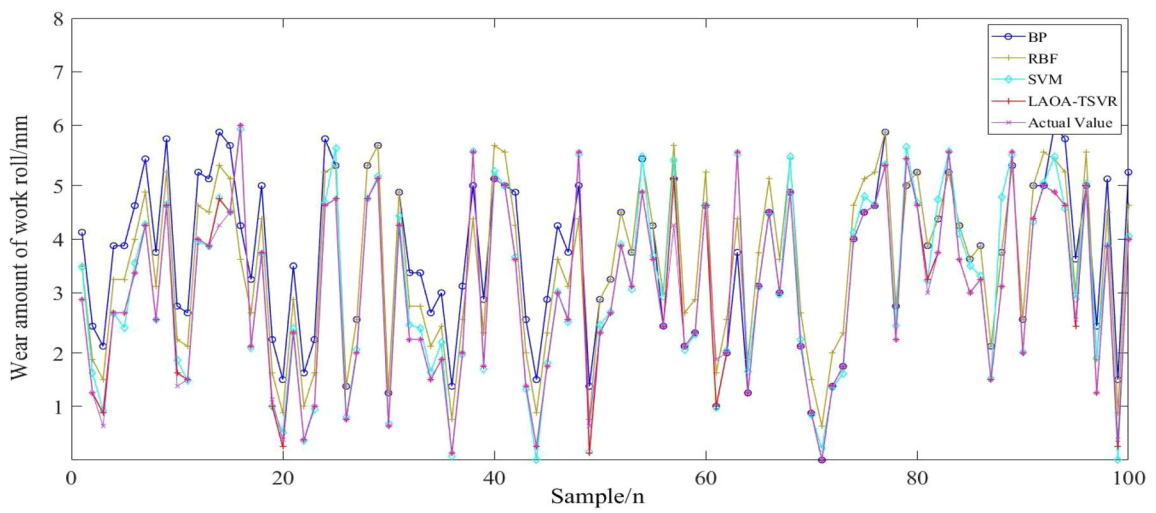

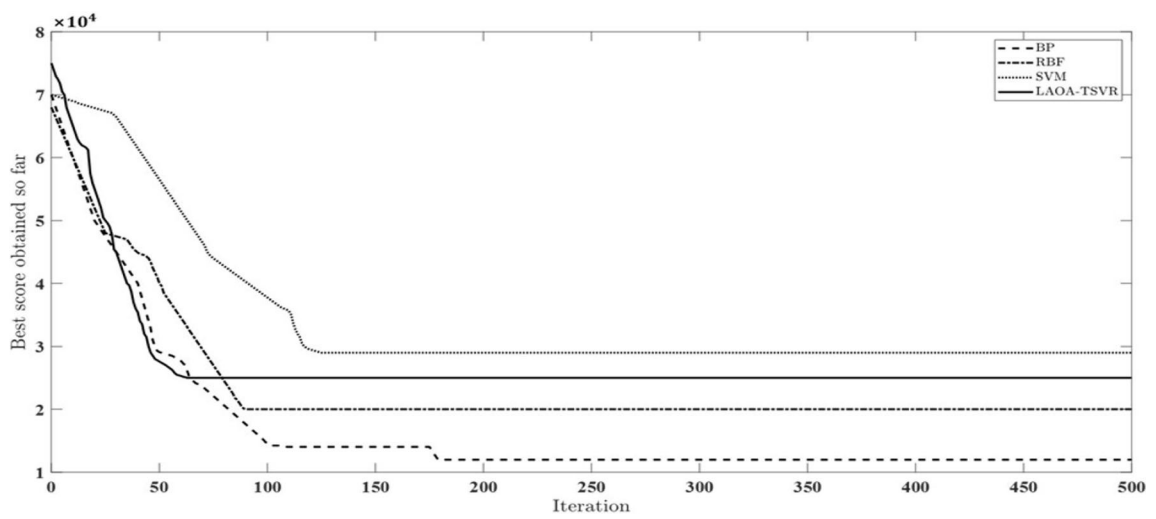Fig. 9—Comparison of predictive effects of different models.

Fig. 10—Comparison of convergence speed of four algorithms.

Table II. Comparison of Prediction Performance of Four Models

Models	Index	BP	RBF	TSVR	LAOA-TSVR
Wear Amount of Work Roll	RMSE	0.4060	0.3993	0.3930	0.3864
	MAE	0.1649	0.1595	0.1545	0.1493
	SSE/SST	0.3742	0.2279	0.1573	0.0343
	SSR/SST	0.6258	0.7721	0.8427	0.9657
Replacement Moment in Finishing Rolling	RMSE	0.3914	0.3845	0.3746	0.3695
	MAE	0.1532	0.1479	0.1403	0.1365
	SSE/SST	0.4502	0.3173	0.1945	0.0751
	SSR/SST	0.5498	0.6827	0.8055	0.9249

Table III. Predicted Hit Rate

	Model			
Prediction of Wear Amount of Work Roll	BP (Pct)	RBF (Pct)	SVM (Pct)	LAOA-TSVR (Pct)
The Hit Rates for Wear Amount of Work Roll Within a Range of ±0.5 Pct	77.3	86.5	90.6	96.2
The Hit Rates for Roll Replacement Moment Prediction	79.5	87.1	91.7	94.5

VII. INDUSTRIAL PRODUCTION VERIFICATION

To verify the practical application effect of the LAOA-TSVR forecasting model, the model is applied to a hot strip finishing mill to carry out actual industrial tests, a total of 200 sets of data, when the wear amount of work roll exceeds 6mm of the diameter of the work rolls need to be changed in a timely manner, which is defined as the moment of changing rolls. The acquired data were preprocessed and substituted into the model, and the model prediction effect is displayed in Figures 11 and 12. The hit rate of LAOA-TSVR model in forecasting the wear amount of work roll within the range of ± 0.5 pct is 95.2 pct, and its accuracy in predicting the moment of replacement moment is 98.3 pct. In this can be seen in the complex hot rolling conditions, indicating that the model prediction effect is better, to meet the actual production needs of a steel mill.

To verify the practical application effect of the LAOA-TSVR forecasting model, the model underwent actual industrial trials in a hot strip finishing mill, where 200 sets of data were collected. When the wear amount of work roll exceeds 6mm of the diameter, indicating the need for timely replacement, defined as the roll changing moment. The acquired data underwent preprocessing and were then inputted into the model, with the prediction results displayed in Figures 11 and 12. The LAOA-TSVR model achieves a hit rate of 95.2 pct in forecasting the wear amount of work roll within the range of ± 0.5 pct, and an accuracy of 98.3 pct in predicting the moment of replacement. This demonstrates that under complex work rolls application conditions, the model exhibits superior prediction effectiveness, meeting the actual production requirements of a hot strip finishing mill.

VIII. CONCLUSION

This article proposes a prediction model based on the LAOA-TSVR algorithm for predicting wear amount of work roll and replacement moment in finishing rolling. The model offers advantages such as high prediction accuracy, fast convergence speed, strong fitting ability, and robust generalization capability. By optimizing TSVR with LAOA for kernel functions, parameter tuning, and penalty factors, the model's computational speed, exploratory ability, and prediction accuracy are enhanced compared to the original version.

The LAOA-TSVR model is characterized by a unique extreme point. Compared with the traditional algorithmic model, the LAOA-TSVR model can better avoid falling into the local optimum and deal with the nonlinear regression problem, and more accurately predict the amount of wear of the work roll and replacement moment in finishing rolling.

The industrial production verification results demonstrate that the LAOA-TSVR model accurately predicts the wear amount of work rolls within a range of ±0.5 pct, achieving a high hit rate of 95.2 pct. Furthermore, it achieves an outstanding hit rate of 98.3 pct in predicting the moment for roll replacement, surpassing other algorithmic models. These findings indicate that the LAOA-TSVR model meets the demand for precise prediction of wear amount of work roll and replacement moment in finishing rolling, providing valuable theoretical guidance for predicting wear amount and replacement moment of work roll in the hot strip finishing process.

After comparing the predictive performance of four algorithms (BP, RBF, SVM, and LAOA-TSVR), the findings highlight the LAOA-TSVR model as the optimal choice based on its evaluation using RMSE and MAE indexes. It demonstrates the smallest relative
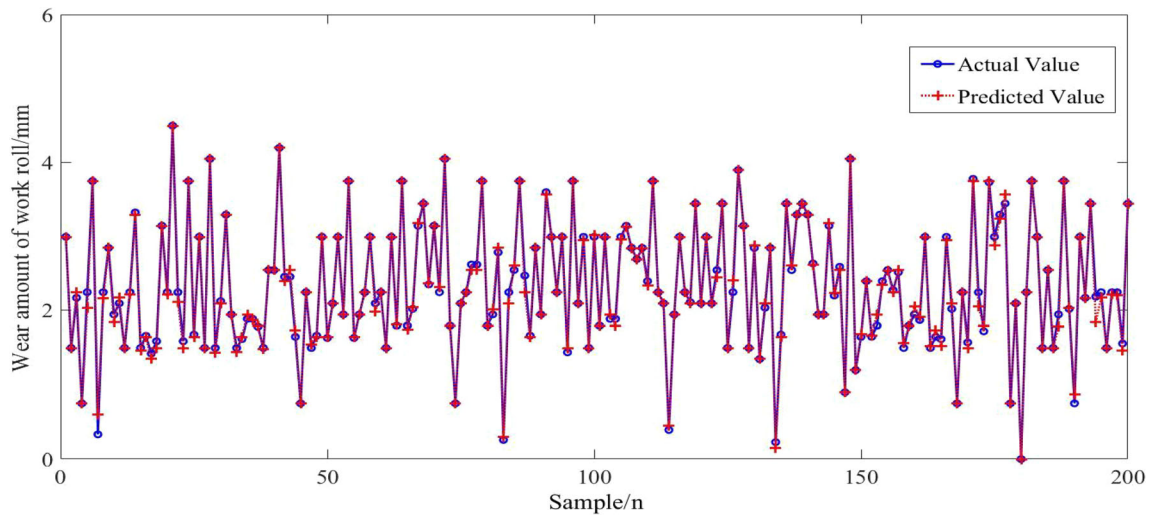
Fig. 11—Predictive effect of LAOA-TSVR model in predicting wear amount of work roll in practical applications.
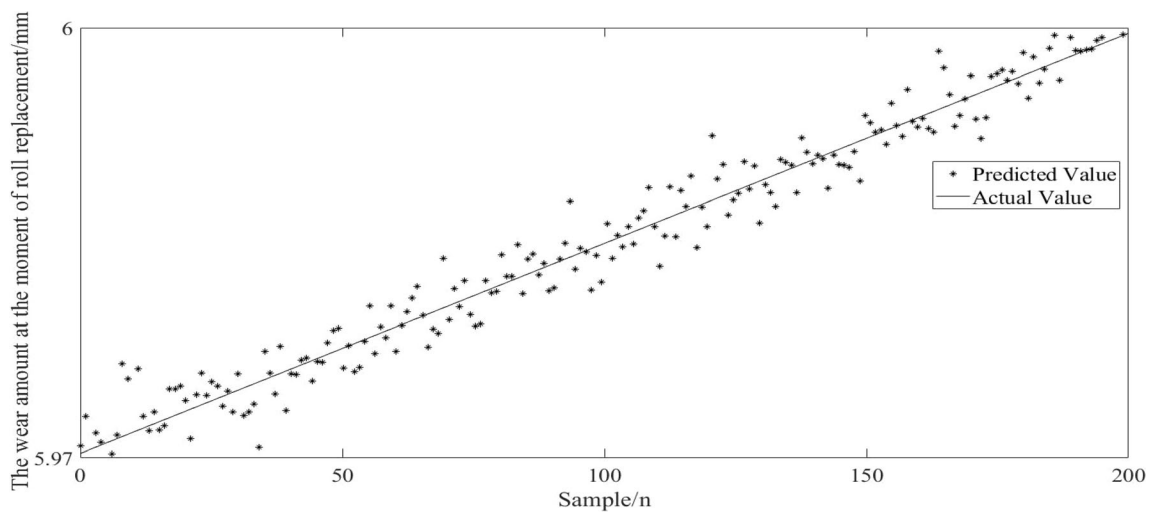

Fig. 12—Predicted effect of the replacement moment in finishing rolling.

error, superior tracking capability, and the highest accuracy among the regression models. These results confirm the strong generalization ability and effectiveness of the LAOA-TSVR prediction model. This can be applied to the different rolling processes *via* transfer learning in the future.

CONFLICT OF INTEREST

No potential conflict of interest was reported by the author(s).

REFERENCES

1. Q. Dong, Z. Wang, Yi. He, L. Zhang, F. Shang, and Z. Li: *Ironmak. Steelmak.*, 2023, vol. 50, pp. 67–74.
2. Z. Liu, Y. Guan, and F. Wang: *IOP Conf. Ser.*, 2017, vol. 207, p. 012022.
3. S. Jian, H. Anrui, Y. Quan, and G. Hongwei: *China Mech. Eng.*, 2009, vol. 20, p. 266.
4. Z. Xi, A. He, Q. Yang, X. Lai, H. Huang, and L. Zhao: *J. Univ. Sci. Technol. Beijing*, 2004, vol. 11, pp. 94–96.
5. S.M. Byon and Y. Lee: *Proc. Inst. Mech. Eng. B*, 2008, vol. 222, pp. 875–85.

6. G. Song, X. Wang, and Q. Yang: *Int. J. Adv. Manuf. Technol.*, 2018, vol. 97, pp. 2675–86.
7. L. Sun, Q. Zhang, X. Chen, Wu. Binghuo, Yu. Zhihua, and L. Li: *J. Univ. Sci. Technol. Beijing*, 2002, vol. 9, pp. 224–27.
8. G.Y. Deng, Q. Zhu, K. Tieu, H.T. Zhu, M. Reid, A.A. Saleh, L.H. Su, T.D. Ta, J. Zhang, and C. Lu: *J. Mater. Process. Technol.*, 2017, vol. 240, pp. 200–08.
9. S.-E. Lundberg and T. Gustafsson: *J. Mater. Process. Technol.*, 1994, vol. 42, pp. 239–91.
10. X.-D. Wang, Q. Yang, A.-R. He, and R.-Z. Wang: *Ironmak. Steelmak*, 2007, vol. 34, pp. 303–11.
11. S. John, S. Sikdar, A. Mukhopadhyay, and A. Pandit: *Ironmak. Steelmak.*, 2006, vol. 33, pp. 169–75.
12. C. Shi, S. Guo, J. Chen, R. Zhong, B. Wang, P. Sun, and Z. Ma: *ISIJ Int.*, 2023, vol. 63, pp. 880–88.
13. C. Shi, S. Guo, B. Wang, Z. Ma, C. L. Wu, and P. Sun: *Ironmak. Steelmak.*, 2023, pp. 1–10.
14. C. Shi, R. Zhong, P. Sun, Z. Ma, B. Wang, X. Yin, and S. Guo: *Metall. Res. Technol.*, 2023, vol. 120, p. 404.
15. A.F. Kamaruzaman, A.M. Zain, S.M. Yusuf, and A. Udin: *Appl. Mech. Mater.* 2013, vol. 421, pp. 496–501.
16. H. Haklı and H. Uğuz: *Appl. Soft Comput.*, 2014, vol. 23, pp. 333–45.
17. S. Khatir, S. Tiachacht, C. Le Thanh, E. Ghandourah, and S. Mirjalili: *Compos. Struct.*, 2021, vol. 273, p. 114287.
18. M. Wang, S. Li, C. Gao, and Y. Fan: *Iron Steel*, 2020, vol. 55, pp. 53–57.
19. T.S.V.R.X. Peng: *Neural Netw.*, 2010, vol. 23, pp. 365–72.
20. L. Abualigah, A. Diabat, S. Mirjalili, M. Abd Elaziz, and A. Gandomi: Comput. Methods Appl. Mech. Eng. 2021, vol. 376, p. 113609.
21. A. Rajasekhar, A. Abraham, and M. Pant: Levy mutated artificial bee colony algorithm for global optimization. in *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics*, Anchorage, Alaska, 2011. IEEE, 2011, pp. 655–62.
22. W. Zhang, Q. Zhou, C. Jiao, and T. Xu: A class-integrated test sequence generation method based on Gray Wolf arithmetic hybrid optimization algorithm. *ComputerScience*, 2023, pp. 1–13.
23. S. Chauhan and G. Vashishtha: Mutation-based arithmetic optimization algorithm for global optimization. in *2021 International Conference on Intelligent Technologies (CONIT)*, Hubli, 2021, pp. 1–6.