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PREDICTION OF OXYGEN CONSUMPTION IN STEELMAKING BASED ON LAOA-TSVR

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To solve the issue of oxygen consumption forecasting, the researchers suggested a twin support vector machine for regression (LAOA-TSVR) prediction model based on an improved arithmetic optimization algorithm. The model has beneficial generalization, high prediction accuracy, and the ability to jump out of the local optimum and other characteristics. The group used the method of mechanism analysis to determine the main influencing factors of oxygen consumption. To confirm the model's prediction effect, it is compared to the Back Propagation, Radial Basis Function, and Twin Support Vector Regression prediction models. The LAOA-TSVR oxygen consumption forecasting prediction model was then tested on actual steel mill production. The test phase consisted of 200 production cycles, and the results revealed that the LAOA-TSVR model had an 85,1 % hit rate for oxygen consumption within 5 m^3/t. The model can suit the actual needs of predicting oxygen consumption in steel.

Keywords: steelmaking, oxygen consumption forecasting, hit rate, industrial test, LAOA-TSVR

INTRODUCTION

Oxygen consumption forecasting is a key component influencing steelmaking costs. At present, the steelmaking process is followed by complicated physical and chemical changes, making oxygen consumption difficult to estimate[1]. Previous researchers proposed a mechanism model based on traditional theory to solve the problem of oxygen consumption prediction in the steelmaking process; however, the steelmaking process is dynamic, and the traditional mechanism model is unable to determine the complex correlation relationship, resulting in less accurate predictions. The group utilize an oxygen consumption prediction model based on classic neural networks as technology advances. However, there are some shortcomings in forecast accuracy and terminal hit rate, and the algorithm is easily trapped in the local minimum.

In order to solve the above problems, the group combined the characteristics of LAOA and TSVR to predict the oxygen consumption in the steel production process based on the actual production data. The LAOA-TSVR algorithm has strong generalization performance, high prediction accuracy, and can jump out of the local optimum. The TSVR algorithm transforms a single large-scale quadratic programming problem into two smaller quadratic programming problems, which significantly shortens the running time and improves the prediction performance. However, twin support vector machine for regression requires random assignment of some parameters [2,3]. If the exhaustive approach is used, it will increase a huge amount of computation is difficult to realize. For this reason, researchers propose to use arithmetic optimization algorithm for parameter optimization, however, the algorithms require additional processing measures to ensure that the solutions satisfying the constraints are searched. In addition, due to the insufficient initial parameter search space, the algorithm may fall into local optimal solutions, leading to inaccurate algorithmic predictions. The improved arithmetic optimization algorithm (LAOA) based on Lévy flight has simple parameter adjustment operations, faster convergence speed, better ability to jump out of local minima, and can well solve the defects of arithmetic optimization algorithm. Therefore, the group combines the LAOA algorithm with the TSVR algorithm and uses its stochastic search to find the optimization of the penalty parameters and kernel function parameters to improve the accuracy of the algorithm [4].

In order to examine the prediction effect of the model, the LAOA-TSVR oxygen consumption forecasting prediction model is compared with the three models of BP, RBF, and TSVR using the obtained actual production data, and it is finally concluded that the prediction accuracy of the LAOA-TSVR oxygen consumption forecasting prediction model is better than the other three models. The LAOA-TSVR based oxygen consumption forecasting prediction model is applied to industrial production, and the test results show that the model meets the actual production requirements.

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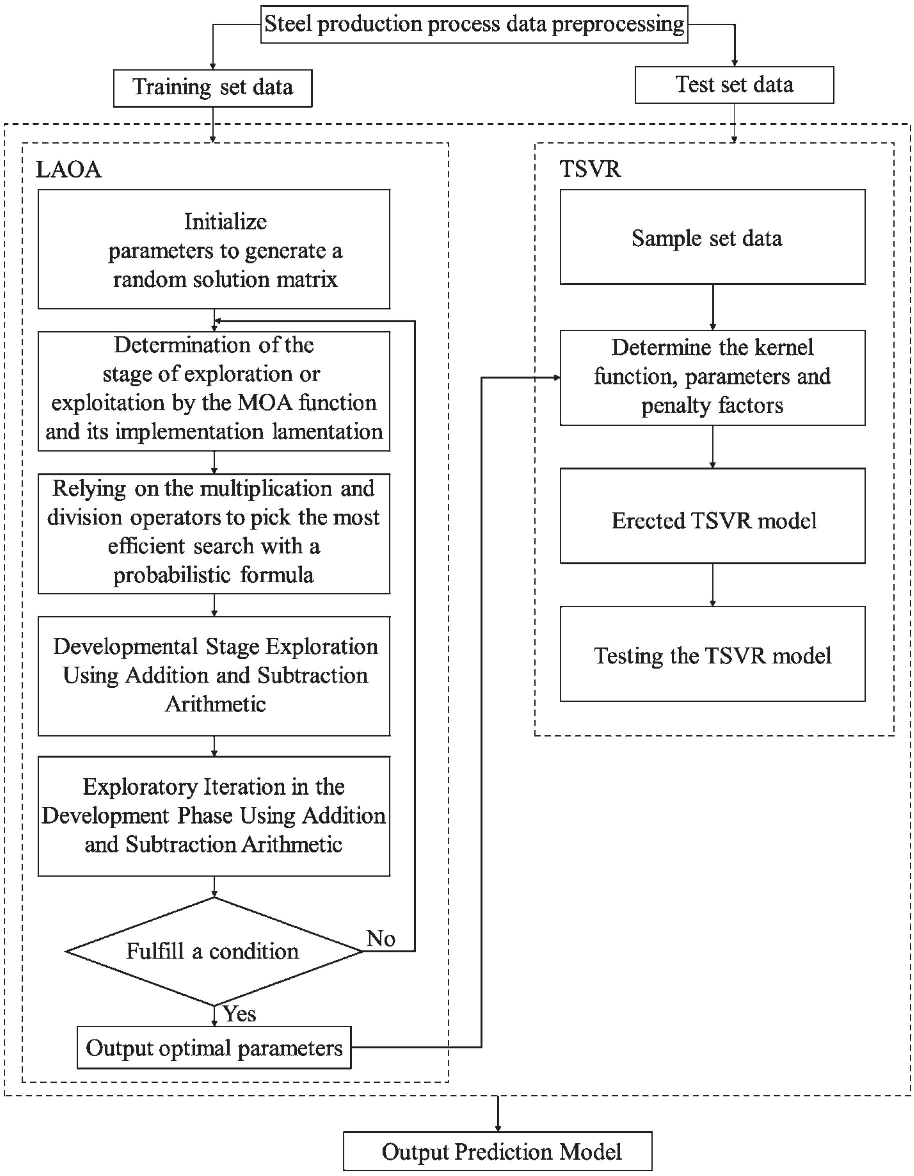

Figure 1 Flowchart of LAOA optimization of TSVR

ESTABLISHMENT OF MODEL

LAOA algorithm is utilized to adjust the penalty parameters and kernel function parameters of TSVR for optimization. The LAOA-TSVR based oxygen consumption forecasting prediction model is established. The flowchart of LAOA optimized TSVR is shown in Figure 1.

ESTABLISHMENT OF LAOA-TSVR MODEL

The group uses Lévy flight to optimize the AOA in a stochastic way with small search and large jumps. The formulas after introducing Lévy flight to improve the AOA are shown in Eq. (1) to Eq. (3):

$$\mathrm{x}_{\mathrm{pause}} = \begin{cases} 2 \cdot \mathrm{MOP} \cdot \mathrm{P} \times \mathrm{x}_{\mathrm{i,j}} \mathrm{r}_4 \leq 0.5 \\ 2 \cdot \mathrm{MOP} \cdot \mathrm{E} + \mathrm{x}_{\mathrm{i,j}} \mathrm{r}_4 > 0.5 \end{cases} \tag{1}$$

Where, r_4, a random number in the interval (0, 1); x_{pause}, the solution generated after the policy update; P and E can be calculated using the following equations:

$$\mathrm{P} = 2a\text{Lévy}(\lambda) - \mathrm{a} \tag{2}$$

$$\mathrm{E} = 2r_2 \tag{3}$$

Where, Lévy(λ), the Lévy distribution with parameter λ; r_2, a random vector in the interval (0,1); A, a variable that decreases linearly from 2 to 0.

The optimal parameters of TSVR are found by optimizing the penalty parameter C of the twin support vector machine for regression and its kernel function parameter "∂" through the LAOA algorithm in the following steps:

Step 1: 1 500 sets of data were normalized and preprocessed, with 1 000 sets serving as the training set and the remaining 500 serving as the test set.

Step 2: Initialize the parameters and generate a set of matrices of random candidate solutions; then, the algorithm explores and develops the current space, using the MOA function to judge and decide the actual execution of the exploration and development phases.

Step 3: The algorithm relies on its multiplication and division operators in the exploration phase to achieve a large range of solution space exploration and uses a probabilistic formulation to update the solution of the optimal policy based on Lévy's rule of flight using Eq.(4).

$$x_{pause} = \begin{Bmatrix} 2 \cdot MOP \cdot P \times x_{i,j} r_4 \leq 0.5 \\ 2 \cdot MOP \cdot E + x_{i,j} r_4 > 0.5 \end{Bmatrix} \tag{4}$$

Step 4: The solution space is fully explored using addition and subtraction operators to find more optimal locations. The development phase can search for the global optimal solution in the middle and late iterations; the main updating equations are shown in Eq. (5), and a small number of multiplication and division operators are also used to update the solution to jump out of the local search for the current approximate global optimal solution until the iteration is closed and the algorithm stops working.

$$x_{i,j}(t+1) = \begin{Bmatrix} best(x_j) - MOP \times (U_j - L_j) \times \mu + L_j, r_3 < 0.5 \\ best(x_j) + MOP \times (U_j - L_j) \times \mu + L_j, r_3 \geq 0.5 \end{Bmatrix} \tag{5}$$

Step 5: The LAOA algorithm calculated parameters are substituted into the TSVR as penalty parameters and kernel function parameters.

OXYGEN CONSUMPTION MODEL

A steel converter as a research object, combined with the oxygen consumption model of the mechanism formula, as shown in Eq. (6) for the mechanism analysis, to assess the impact of the oxygen consumption model of the input. The weight of scrap steel, hot metal weight, carbon content in hot metal, carbon content in target molten steel, temperature of molten iron, silicon content in hot metal are the inputs evaluated by the mechanism equation. The output is the consumption of oxygen.

$$O_2 = \frac{F_e \times F_c \times F_h}{F_h} + \frac{F_e \times F_c \times F_t}{F_t} \tag{6}$$

Where, O_2, oxygen consumption; F_e, the amount of iron; F_c, the carbon content of iron; F_h, the molar mass of the iron reduction reaction; F_t, the molar mass of the iron decarburization reaction.

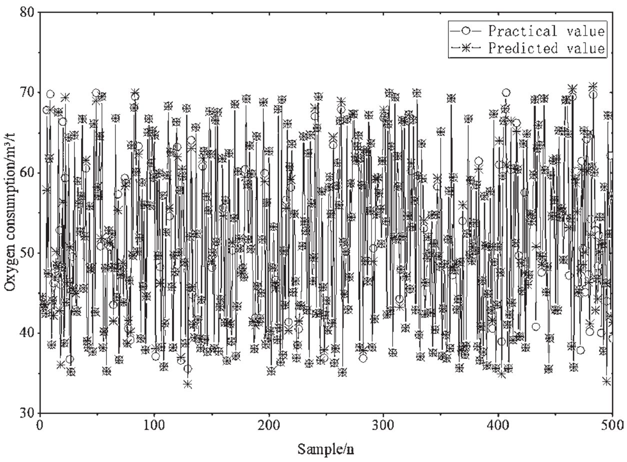

Figure 2 Oxygen consumption model test results

The results of the comparison between the actual and predicted values obtained using the LAOA-TSVR oxygen consumption model are shown in Figure 2.

ANALYSIS OF THE MODEL

Comparison of model prediction effects

In order to verify the prediction accuracy of the LAOA-TSVR based oxygen consumption forecasting prediction model. Four prediction models, BP, RBF, TSVR and LAOA-TSVR, are tested using industrial test data, and the results are shown in Figure 3.

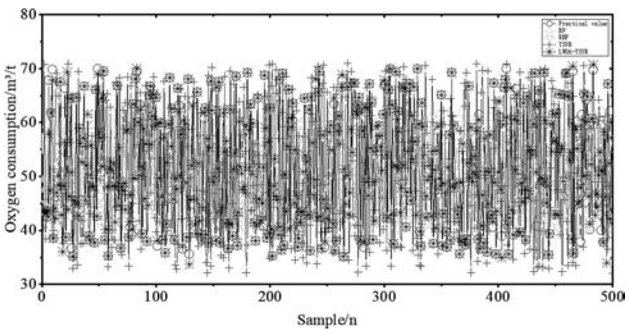

Figure 3 Model predictive effectiveness comparison

Analysis of results of model comparisons

The fitting degree of LAOA-TSVR oxygen consumption forecasting prediction model can be calculated by Eq. (7) and Eq. (8), and the hit rate is calculated by Eq. (9) and Eq. (10). The predictive effectiveness of the model is judged by four technical indicators: SSR/SST value, SSE/SST value, MAE value and HR (hit rate), and the results are shown in Table 1 and Table 2. From the analysis of Figure 3, it can be concluded that the predicted values of the oxygen consumption model for oxygen consumption forecasting are in good agreement with the actual values, and the model has the best fit and analytical properties. From the evaluation indexes in Table 1, it can be seen that the SSR/SST value of the LAOA-TSVR model is closer to 1, and the degree of

Table 1 **Comparison of evaluation indicators for predictive models.**

Model	Oxygen consumption model		
Evaluation indicators	$\frac{SSR}{SST}$	$\frac{SSE}{SST}$	MAE
BP	0,7131	0,2366	16,9001
RBF	0,8462	0,1108	13,4483
TSVR	0,9526	0,0342	10,9102
LAOA-TSVR	0,9874	0,0121	9,2193

Table 2 **Hit rate of each model for oxygen consumption prediction.**

Model	BP	RBF	TSVR	LAOA-TSVR
Hit rate	70,6 %	76,3 %	80,4 %	82,3 %

oscillation between the predicted value and the actual value is close to the same; the SSE/SST value is lower than that of the other three prediction models, and the degree of fit is better. Table 2 can be compared to show that the LAOA-TSVR based oxygen consumption model has a simulation hit rate of 82,3%. The LAOA-TSVR model has the highest hit rate under the same conditions; thus, it can be proved that the prediction accuracy of the LAOA-TSVR model is better than that of other algorithms.

$$SSE / SST = \sum_{n=1}^{m} (y_n - \hat{y}_n)^2 / \sum_{n=1}^{m} (y_n - \overline{y_n})^2 \quad (7)$$

$$SSR / SST = \sum_{n=1}^{m} (\hat{y}_n - \overline{y_n})^2 / \sum_{n=1}^{m} (y_n - \overline{y_n})^2 \quad (8)$$

$$G_s \times \left(100\% - k < G_y < G_s \times \left(100\% + k\right)\right) \quad (9)$$

$$HR = \frac{\left(\left|y_i - \hat{y}_1\right| \le n_e\right)}{n} \times 100\% \quad (10)$$

Where, Gs, the actual value of oxygen consumption; Gy, a forecast of oxygen consumption.

APPLICATION AND VALIDATION

The established LAOA-TSVR oxygen consumption forecasting prediction model was applied to the actual production of a steel converter for testing, the test phase totaled 200 production cycles, and the results are shown in Figure 4. The hit rate of the model on oxygen consumption within ± 5 m^3/t is calculated to be 85,1 %. It can be seen that the prediction accuracy of the LAOA-TSVR oxygen consumption forecasting prediction model meets the requirements in actual production.

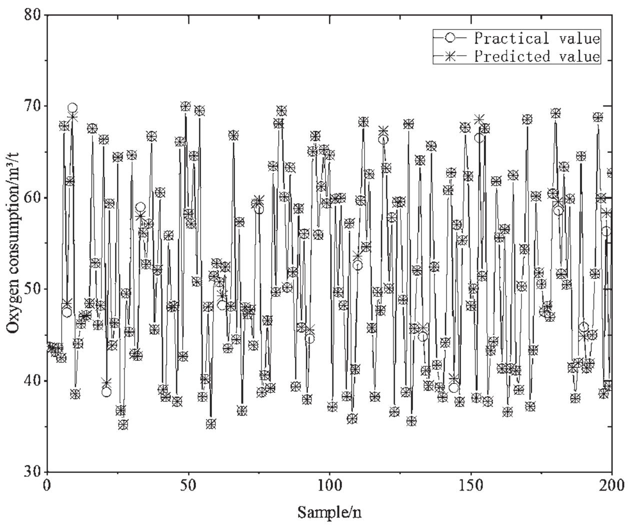

Figure 4 Comparison of actual and predicted values of oxygen consumption models in industrial tests

CONCLUSION

– The constructed LAOA-TSVR oxygen consumption forecasting prediction model is compared with the three prediction models of BP, RBF and TSVR. The results show that LAOA-TSVR oxygen consumption forecasting prediction model has better prediction effect.

– The LAOA-TSVR model applied to the actual production of a steel, a total of 200 production cycle tests, the results revealing that the oxygen consumption model hit rate was 85,1 % within a 5 m^3/t range. The model can well meet the demand for oxygen consumption forecasting prediction in the actual production of a steel.

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REFERENCES

[1] C.Y. Shi, B.S. Wang, S.Y. G, etc. Energy Consumption Prediction of Steelmaking Process Based on Improved Whale Optimization Algorithm and Stochastic Configuration Network [J]. JOM, 10(2023)75,12.

[2] C. Gao, M. G. Shen. End-point prediction of basic oxygen furnace (BOF) steelmaking based on improved twin support vector regression [J]. Metalurgija,1-2(2019)58,4.

[3] C.Y. Shi, S.Y. G, J. Chen, etc. Breakout Prediction Based on Twin Support Vector Machine of Improved Whale Optimization Algorithm. ISIJ International, 63(2023)5, 880–888.

[4] H.P. Fang, X.P. Fu, Z.Y. Zeng, etc. An Improved Arithmetic Optimization Algorithm and Its Application to Determine the Parameters of Support Vector Machine [J]. Mathematics, 16(2022)10,1.

Note: The responsible for English is LI Jun Yuan, Liaoning Institute of Science and Technology, Benxi, China.