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PREDICTION OF THE OUTLET TEMPERATURE OF THE CONVERTER DRY-TYPE DUST REMOVAL EVAPORATIVE COOLER BASED ON LAOA-SCN

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In the converter dry-type dust removal system, controlling the outlet temperature directly impacts the efficiency of flue gas treatment. To ensure high-precision control of the outlet temperature, this study utilized improved Arithmetic Optimization Algorithm for Optimizing Stochastic Configuration Networks. This resulted in the establishment of the outlet temperature prediction model, LAOA-SCN, for the converter dry-type dust removal evaporative cooler. To assess the predictive performance of model, a comparative analysis was conducted with algorithms such as Back Propagation (BP), Radial Basis Function (RBF), and Twin Support Vector Regression (TSVR). Finally, the model was applied to practical production verification, confirming its high prediction accuracy. This underscores its potential to provide theoretical guidance for the control of outlet temperature in converter dry-type dust removal evaporative coolers.

Keywords: steel; converter; outlet temperature; dust removal; LAOA-SCN

INTRODUCTION

The converter is a crucial component of a steelmaking plant, but the dust generated during its production process significantly impacts the environment. To mitigate this effect, the efficient purification of flue gas has become a key task. Conventional wet de-dusting methods suffer from high water requirements and deficiencies. As a result, dry and semi-dry dust removal processes have gradually gained popularity both domestically and internationally. Dry dust removal technology, due to its efficient dust removal, low energy consumption, and avoidance of secondary pollution, has become a highly regarded approach. With increasingly stringent environmental policies, more and more steel companies are adopting dry dust removal technology to replace traditional wet methods [1].

Evaporative coolers, serving as the primary equipment for dry dust removal, play a critical role. The precise control of the outlet temperature in the evaporative cooler significantly impacts the dust content in the flue gas and the overall operational status of the system [2]. With the advancement of information technology, researchers have utilized intelligent algorithms to establish models for predicting and achieving precise control of the outlet temperature of evaporative coolers, yielding certain achievements. However, due to the complexity of predicting outlet temperature involving multiple inputs and a single output, as well as other data-related challenges, models built using traditional algorithms still exhibit shortcomings in terms of prediction accuracy and hit rate [3]. To solve the above problems, the group proposed an improved arithmetic optimization algorithm to optimize the intelligent hybrid algorithm for stochastic configuration network (LAOA-SCN) [4,5].

To assess the predictive performance of this model, a comparison was made with traditional algorithms such as BP, RBF, and TSVR. The evaluation of the four algorithm models was conducted using measures such as fluctuation degree (SSR/SST), fitting degree (SSE/SST), root mean square error (RMSE), mean absolute error (MAE), and hit rate (HR). Finally, the model is applied to industrial tests, and the results show that the model has a more excellent prediction ability, and the establishment of the model provides theoretical guidance for the control of the outlet temperature of the evaporative cooler of the converter dry de-dusting system in the actual production process of iron and steel enterprises.

DATA PROCESSING

After removing abnormal production data from the production data, 2 000 sets of data were randomly extracted from the database, of which 1 500 sets of samples were used as the training set for exit temperature prediction; 500 sets of samples were used as the test set for exit temperature prediction. The group used SPSS to correlate the influencing factors and obtained the correlation coefficients between the outlet temperature of the evaporative cooler and the screened influencing fac-

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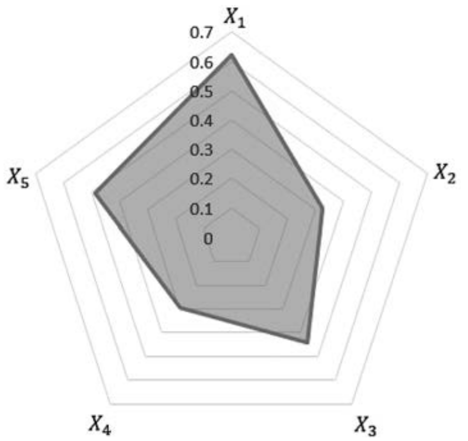

Figure 1 Correlation coefficient of influencing factors

tors as shown in Figure 1, and determined that the main input variables for the outlet temperature prediction are the inlet temperature X_1, flue gas flow rate X_2, flue gas flow rate X_3, valve opening X_4, and the amount of water added X_5.

Normalization of variable data. Since different parameters have different physical meanings and different units of measurement, the selected data must be normalized before training to ensure the comparability of the sample data and improve the reliability of the export temperature prediction model and the convergence speed. Normalize the data to the [-1,1] range based on its maximum and minimum values. The formula for data normalization is given by Equation (1).

$$X_p = \frac{(X - X_{\min})}{X_{\max} - X_{\min}} \tag{1}$$

Where: X_p sample value after normalization; X_{max} maximum value of sample data; X_{min} minimum value of sample data.

LAOA-SCN MODEL BUILDING

The SCN algorithm can automatically configure the number of hidden nodes. Starting from a small network, the input weights and thresholds are randomly selected, and the number of neuron nodes in the hidden layer is gradually increased, and the LAOA is used to optimize the output weights and thresholds until the training accuracy of the network meets the termination conditions. The established mathematical model is as follows:

To facilitate algorithm exploration and the selection and switching during the development stage, AOA defines a search control coefficient, namely the Mathematical Optimization Accelerator (MOA), as shown in Equation (2)

$$MOA(t) = Min + t \times (Max - Min)/T \tag{2}$$

Where,

Max represents the maximum value of the gas pedal 1;

Min the minimum value of the gas pedal 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, it performs local development to improve the accuracy of the solution.

$$X(t+1) = \begin{cases} X_{best}(t) \div (MOP + \epsilon) \times ((UB - LB) \times \mu + LB), r_2 < 0,5 \\ X_{best}(t) \div MOP \times ((UB - LB) \times \mu + LB), r_2 \geq 0,5 \end{cases} \tag{3}$$

Where,

$X(t+1)$ the solution at the t+1st iteration; $X_{best}(t)$ the optimal individual of the population up to the current iteration;

r_2 a random number between 0 and 1;

ϵ a random number between 0 and 1;

μ a control parameter that takes the value of 0,5.

$$X(t+1) = \begin{cases} X_{best}(t) - MOP \times ((UB - LB) \times \mu + LB), r_3 < 0,5 \\ X_{best}(t) + MOP \times ((UB - LB) \times \mu + LB), r_3 \geq 0,5 \end{cases} \tag{4}$$

Where,

r_3 a random number between 0 and 1; $X_{best}(t)$ the optimal individual of the population as of the current iteration;

UB the upper limit of the values taken by the individual correlation variables;

LB the lower limit of the values taken by the individual correlation variables.

$$MOP(t) = 1 - t^{\frac{1}{\alpha}} / T^{\frac{1}{\alpha}} \tag{5}$$

Where, α is the sensitive parameter defining the development accuracy, and its value is set to 5.

$$X(t+1) = X(t) + \alpha \oplus Lévy(\lambda) \tag{6}$$

Where, α is the step scaling factor;

Lévy(λ), denotes that it obeys the Lévy distribution with parameter λ, i.e.:

$$Lévy \sim u = t^{-\lambda} \tag{7}$$

Inserting the optimized parameters into the SCN algorithm, the mathematical model of the SCN is established as follows:

Step 1: Given the objective function f: $R^M \to R^O$, After adding nodes for the n-1 time, the output of the current network is:

$$f_n(x) = \sum_{l=1}^{n} \beta_l g_l \left(w_l^T x + b_l\right) \tag{8}$$

Here $w_l = [w_{l1}, \ldots, w_{lM}]^T, \beta_l = [\beta_{l1}, \ldots, \beta_{lo}]^T$, the residual at this time:

$$\mathrm{e}_{n-1} = f - f_{n-1} = \left[\mathrm{e}_{n-1,1}, \cdots \mathrm{e}_{n,m}\right] \tag{9}$$

Step 2: Whenever a new hidden node is added, the input weight vector w_n and the deviation vector b_n will be randomly generated. where the randomly generated a pair of w_n, b_n satisfies the following inequalities:

$$\sum_{q=1}^{m} < \mathrm{e}_{n-1,q}, g_n^{*2} \geq g_n^{*2} \delta_n \tag{10}$$

Where,

$$g_n^* = g_n \left(w_n^T x + b_n\right) \tag{11}$$

$$\delta_n = (1 - r - u_n) \mathrm{e}_{n-1}^2 \tag{12}$$

$$\mu_n = (1-r)/(n+1) \tag{13}$$

$$0 < r < 1 \tag{14}$$

Step 3: Calculate output weights:

$$\beta_{n,q} = \frac{e_{n-1,q}, g_n}{g_n^{\ 2}}, q = 1,2,\ldots m \tag{15}$$

Step 4: Calculate whether the error e_n is less than the pre-defined error criterion: if it is satisfied, the SCN model training is complete, otherwise, continue to add intermediate nodes according to **Step 2** until the error criterion is satisfied.

PREDICTION MODEL

Utilizing the LAOA algorithm to optimize the input weights and biases of the SCN algorithm. Firstly, read the actual production data and normalize it. Secondly, use the optimal solution to train and validate the regression model. Finally, perform inverse normalization on the regression production data to obtain the outlet temperature forecasting model.

To verify the prediction effect of the model, the LAOA-SCN prediction model was utilized to compare the true value with the predicted value by calculating its results. Finally, the prediction results and errors of the LAOA-SCN prediction model were obtained as shown in Figure 2 and Figure 3.

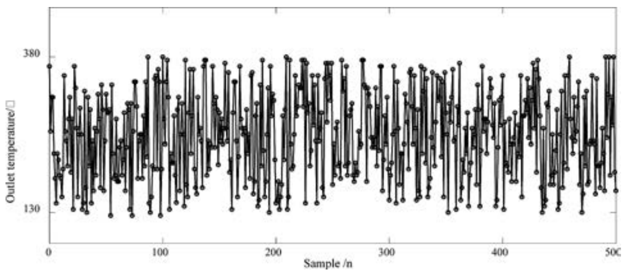

Figure 2 Prediction effect diagram of model

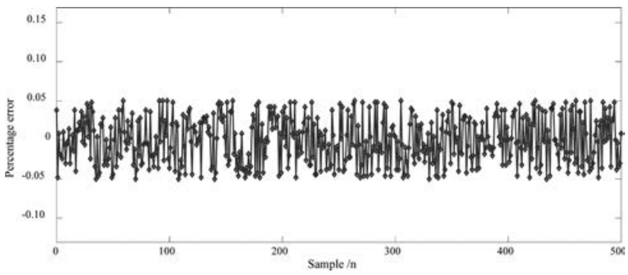

Figure 3 Error plots for the prediction model

From Figure 2, it can be seen that the predicted and real values of the model have a high degree of fit, and from Figure 3, it can be seen that within the error range of ± 5 %, the model has a high prediction accuracy and a small error, and it can meet the requirements for the prediction accuracy of the outlet temperature of the evaporative cooler of the converter dry de-dusting system.

MODEL COMPARISON

To examine the prediction effectiveness of the model compared to the traditional algorithms, BP, RBF, TSVR, and LAOA-SCN models were used for prediction, respectively. Comparisons were made using SSR/SST, SSE/SST, RMSE, MAE and HR methods, and the predictions derived from the models were compared with the actual values as shown in Figure 4.

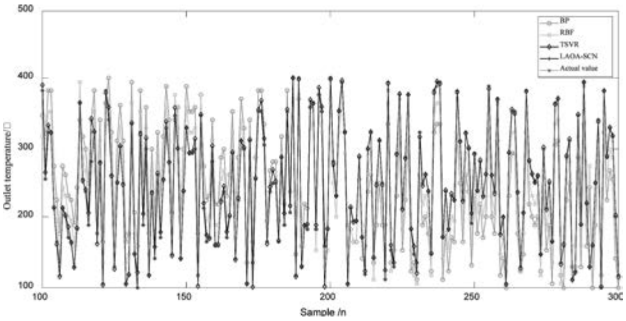

Figure 4 Comparative chart of the predictive effectiveness of the four models

The closer the SSR/SST value is to 1 and the smaller the SSE/SST value is, the better the model's predicted and true values are fitted; the smaller the RMSE and MAE are, the higher the model's prediction accuracy is. From Table 1, it can be seen that the SSR/SST of BP, RBF, TSVR, and LAOA-SCN prediction models are increasing in the order of SSE/SST, SSE/SST, HR and decreasing in the order of RMSE and MAE. Therefore, LAOA-SCN has a better model fit compared to the other three algorithms.

Table 1 **Comparison of predictive performance of four models**

Index	BP	RBF	TSVR	LAOA-SCN
RMSE	0,397	0,381	0,378	0,363
MAE	0,158	0,145	0,142	0,131
SSE/SST	0,337	0,259	0,144	0,038
SSR/SST	0,663	0,741	0,856	0,962
HR	76,3 %	81,5 %	86,6 %	90,4 %

In summary, by comparing the hit rate and SSE/SST, SSR/SST of the four models of BP, RBF, TSVR, and LAOA-SCN, the LAOA-SCN model has the best predictive performance evaluation indexes and a higher end-point hit rate, which verifies that the LAOA-SCN prediction model has a better prediction effect.

APPLICATION AND VALIDATION

The LAOA-SCN model was applied to actual production verification, and 300 sets of real production data were collected. The model's prediction results are shown in Figure 5 Within a ±5% error range, the hit rate of outlet temperature prediction is 85,3 %. The model demonstrates a fast convergence speed and high predic-

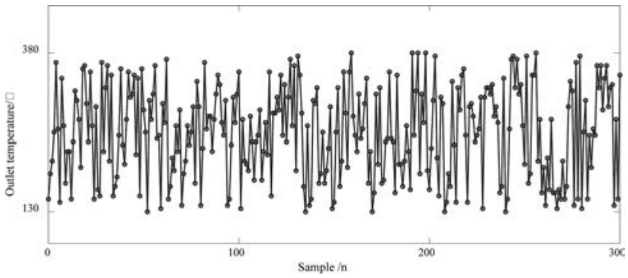

Figure 5 Prediction effect diagram of LAOA-SCN model in real production validation

tion accuracy, indicating good predictive performance. This satisfies the practical production requirements for predicting the outlet temperature of the evaporative cooler in the industrial converter dust removal system.

CONCLUSION

This study proposes a hybrid intelligent algorithm prediction model LAOA-SCN based on improved arithmetic optimization algorithm for optimizing stochastic configuration network is proposed, and after comparing with the traditional algorithmic model, the prediction model is higher than the traditional algorithmic model in each performance index. The LAOA-SCN evaporative cooler outlet temperature prediction model is applied to industrial actual production. The prediction hit rate of the model within ± 5 % error range is 85,3 %, which realizes the high-precision prediction of the outlet temperature of the evaporative cooler of the industrial converter dry de-dusting system, and provides a theoretical basis for the control of the outlet temperature of the evaporative cooler.

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