Prediction of Carbon Content in Fly Ash in Ultra Supercritical Generation Unit with Long Short-term Memory Neural Network

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Abstract. The accurate measurement of carbon content in fly ash is the basis of improving the thermal conversion efficiency of boiler and reducing the coal consumption of power generation. Based on the operation data of 1000MW Ultra-supercritical Unit in a thermal power plant, the input parameters of the model were selected by correlation analysis. The Long Short-Term Memory neural network (LSTM) was used to establish a prediction model with the boiler operation parameters as the input and the carbon content of the boiler fly ash as the output. According to the actual operation data of the unit, the prediction performance of the model was trained and tested. The simulation results show that the average prediction error of the LSTM model is 2.8136\%, and 86\% of the total samples are data with error less than 4.5\%, which means it has high accuracy and strong generalization ability.

1. Introduction

The fly ash carbon content represents the thermal conversion efficiency of coal-fired boiler in power plant, which is an important operating parameter. At present, the measurement methods of carbon content in fly ash are mainly divided into physical measurement and soft measurement. Among them, most physical measurement methods are faced with problems such as delay, accuracy and price, and it is difficult to achieve real-time measurement [1]. Generally, support vector machine is used for soft sensing of carbon content in fly ash, and optimization algorithm and correlation analysis are used to improve the applicability of the model. Wang Wei [2] et al. proposed a LSSVM measurement model based on weighted factors to realize adaptive correction of the model; Jin xiu zhang [3] et al. optimized the input parameters of LSSVM model by using the method of principal component analysis; Zhang Dahai[4] et al. made the sample sparse based on the calculation of sample feature distance, which improved the model accuracy. Ma Hongbo [5] et al. proposed a gsa-lssvm prediction model of carbon content in fly ash based on gravitational search algorithm (GSA); Bian Heying et al. Optimized the main parameters of SVM model by cross validation method [6] and particle swarm optimization [7], and verified the accuracy of the model; he Yao [8] et al. constructed a carbon content measurement model of fly ash by using particle swarm optimization and support vector regression method. The advantage of support vector machine is that it has strong nonlinear mapping ability and definite mathematical theory support, but it will consume a lot of machine memory and operation time when dealing with large-scale samples with multiple features, so it is difficult to guarantee the timeliness. In addition to support vector machine, neural network with high latitude nonlinear fitting ability has also been widely used in predicting...
carbon content of fly ash. For example, Y Qiao [9] proposed a prediction model of carbon content in fly ash based on mutual information selection, which was realized by PLC hardware. ZY Zhang [10] proposed a BP neural network model based on ant colony algorithm optimization to predict the carbon content of fly ash. J Zhao [11] et al. Proposed a BP neural network model of carbon content in fly ash of coal-fired boiler.

Although support vector machine and BP neural network have good nonlinear mapping ability, the object of algorithm research is the operation parameters at a certain time and the fly ash carbon content at the corresponding time. However, the instantaneous fly ash carbon content is the comprehensive result of operation in a period of time. The fitting of the instantaneous operation to the fly ash carbon content is more suitable for the steady-state condition where the input variables do not change, and it is difficult to meet the real-time measurement requirements of the carbon content of fly ash. LSTM neural network is a kind of time-series neural network algorithm. The characteristic of this algorithm is that the output of a certain time is determined by the input changes in the previous period of time, which is consistent with the formation mechanism of carbon content in fly ash. In this paper, firstly, Spearman correlation coefficient is used to analyze the influencing factors of fly ash carbon content, and the main influencing parameters are obtained as the input parameters of the prediction model. The LSTM neural network is trained by the field operation data, and the prediction model of carbon content in fly ash is constructed, which provides an optimization scheme for the real-time measurement of fly ash carbon content.

2. Parameter Selection

2.1. Research Object

The research object of this paper is a 1000MW Ultra-supercritical Unit in a thermal power plant. The boiler of this unit adopts double tangential combustion, single furnace, solid-state slag discharge, one intermediate reheat, all-steel frame suspension structure, π type and semi-open air arrangement. The boiler combustion system is equipped with a direct fired pulverizing system with double in and double out ball mills. The boiler is equipped with 48 once through burners with double tangential firing. Pulverizer A ~ F are arranged from bottom to top.

2.2. Data Filters

The data used in this paper is the actual operation data of 1000MW Ultra-supercritical Unit in a thermal power plant. In this power plant, the carbon content of fly ash is measured by thermogravimetry twice a day. The measured data has high accuracy, but the amount of the data is small. Select the operation data of the unit for one year, refer to the over temperature and environmental protection requirements of the power plant, take the main steam temperature, SO2 emission, NOx emission and other parameters as the screening conditions, and remove the sample data that does not meet the the safety and environmental protection requirements of the power plant. Taking the sampling time of the fly ash carbon content twice in the morning and evening as the node, the first half hour of operation data of the main relevant parameters are taken as the sample data according to the time label. Among them, the main relevant parameter data are directly taken out from the field DCS system, and the fly ash carbon content is input from the field measured data.

2.3. Analysis of factors Influencing Fly Ash Carbon Content

According to the theoretical analysis and field investigation, the main steam temperature, main steam pressure and main steam flow in the steam water system of the boiler and other parameters are selected to analyze the carbon content of ash. The Spearman correlation coefficient is used to calculate the correlation. The formula of the coefficient is as follows:

$$\rho = \frac{\Sigma_i{(x_i - \bar{x})(y_i - \bar{y})}}{\sqrt{\Sigma_i(x_i - \bar{x})^2} \sqrt{\Sigma_i(y_i - \bar{y})^2}}$$

(1)
The correlation analysis and calculation between the carbon content of fly ash and each parameter are carried out, and the results are shown in figure 1. From the results of correlation analysis, the parameters selected in the steam water system have a strong correlation with the carbon content of fly ash. The higher the main steam temperature is, the greater the combustion intensity is, and the better the burnout is, the lower the fly ash carbon content is. Similar to the main steam temperature, the main steam pressure, main steam flow and other state parameters directly related to the boiler combustion state also have a strong correlation with fly ash carbon content.

The oxygen content of the flue gas in the air and flue gas system is an important index to evaluate the combustion situation in the furnace, which indicates the redox atmosphere in the furnace. The total air volume, the differential pressure between the secondary air box and the furnace characterize the total air volume and the secondary air distribution in the furnace, while affecting the combustion atmosphere in the furnace and also the amount of heat brought out by the flue gas. The swing angle of the burner determines the basic shape of the flame in the furnace, and then affects the combustion state and the carbon content of the fly ash. It is necessary to consider the relationship between the primary air temperature and the fly ash carbon content under the condition of considering the influence of coal type. The general trend shows that the higher the primary air temperature is, the less complete the combustion is.

In the pulverizing system, the calorific value represents the heat released by the coal in the furnace, which plays a decisive role in the combustion intensity. But the high calorific value of coal represents the higher degree of coalification of coal and is difficult to fully burn. The coal with higher volatile content has better combustion characteristics and is easy to burn out. Ash does not participate in combustion and will absorb heat in the combustion process, resulting in lower furnace temperature, thus reducing the burn out degree and increasing the fly ash carbon content. The total coal quantity reflects the situation of boiler with load in the overall trend. The larger the total coal quantity is, the higher the combustion intensity is, the better the burnout situation is. To a certain extent, the current of the pulverizer represents the output of the pulverizer, affects the fineness of the pulverized coal, and has a strong correlation with the fly ash carbon content.

3. Prediction Model of Carbon Content in Fly Ash

3.1. Long Short-Term Memory Neural Network

LSTM adds the concepts of forget gate, information addition gate and output gate on the basis of RNN to realize long-term memory function. In the LSTM algorithm, the results of various gating are called
cell memory. The process of cell memory updating is the process of LSTM algorithm training, which is determined by the structure of various gate layers. In the LSTM algorithm, the forget gate is used to decide what information is discarded from the last cell state. In this paper, sigmoid function is selected as the activation function of forget gate \( f_t \), which is recorded as \( \sigma \), then forget gate expression is:

\[
f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)
\]

Where \( W_f \) is the weight of forget gate, \( b_f \) is the offset value, \( h_{t-1} \) is the last hidden state. The information adding gate includes input gate layer \( i_t \) and candidate vector \( \tilde{C}_t \). The input gate layer \( i_t \) determines which information needs to be updated and combines the candidate vector \( \tilde{C}_t \) added to cell state. In this paper, \( \sigma \) is chosen as the activation function of \( i_t \) and tanh as the activation function of \( \tilde{C}_t \), then the corresponding expression is:

\[
i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)
\]

\[
\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)
\]

Using forget gate and information adding gate to update \( \tilde{C}_t \):

\[
C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t
\]

In the output gate includes output \( o_t \) and the hidden state \( h_t \) at the time, the expression is:

\[
o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)
\]

\[
h_t = o_t \cdot \tanh(C_t)
\]

For each time, the back propagation through time (BPTT) is used for the back propagation of the network, assuming that the k-th output parameter of the network at that time is \( y_k \). The actual value of the output parameter is \( y_k \). Then the calculation formula of the total error \( E \) is:

\[
E = \frac{1}{2} \sum_{k=1}^{n} (y_k - o_k)^2
\]

Then, the calculation formula for updating the weights of each layer of LSTM network by gradient descent method is as follows:

\[
W = W - \eta \frac{\partial E}{\partial W}
\]

3.2. Prediction Model of Fly Ash Carbon Content Based on LSTM

TensorFlow-2.2 was used to construct the LSTM network to model the carbon content of fly ash. The actual operation data of 1000MW ultra supercritical unit from January to December 2019 are used for modeling. In the model Sigmoid function is selected as the activation function of forget gate \( f_t \) and input gate layer \( i_t \), and the tanh function is selected as the candidate value vector \( \tilde{C}_t \) and cell state \( C_t \) Activation function for t. The mean square error is chosen as the loss function of the model, and the mean error is chosen as the standard to evaluate the prediction error. The model implementation process is as follows:

1) According to the coupling relationship between various systems of the power plant and the results of field investigation, the parameters related to the carbon content of fly ash are preliminarily selected;
2) Based on the sampling time of fly ash, the operation data of half an hour's main influencing parameters are taken as the time series sample data according to the time tag, and the sample data are screened for stability, environmental protection and safety;
3) Using the grey incidence analysis model, the correlation coefficient between the relevant parameters and the carbon content of fly ash is calculated, and the parameters are screened to obtain the time series sample data of the main parameters affecting the carbon content of fly ash;
4) The measurement model of carbon content in fly ash based on LSTM is constructed by using Python keras neural network library.
① Initialization grid: set the double hidden layer structure, set the loss function, set the activation function of the corresponding layer, initialize the weights of each layer, and set the initial super parameters;
② The time series sample data is processed according to the time tag. The data in the same time period and the corresponding fly ash carbon content are taken as a group of samples. The sample group is divided into training set, verification set and test set according to the proportion of 6:2:2;
③ The training set and verification set are used to train the network, and the grid structure and super parameters are adjusted according to the training results;
④ The validity and accuracy of the model are verified by test set data.

4. Model Effect Verification

4.1. Model Training Results
Take four-fifths plant's operation data in 2019 as the training set for model training. Using cross validation method, the training set is divided into five subsets, each subset is tested once, and the rest is used as training set for cross validation. The model optimizer selects the Adam optimizer with better comprehensive performance. When the learning rate is 0.01, the exponential decay rate of the first-order moment estimation is 0.9, and the exponential decay rate of the second-order moment estimation is 0.99, the model is trained 500 times with the mean square error as the loss function of the model. The results are shown in figure 4. The loss function value decreased rapidly in the initial stage, then continued to decline in the shock, and finally stabilized after 430 times of training. At this time, the mean square error of fly ash carbon content is about $4.7 \times 10^{-4}$, and the average training error is 2.17%, which meets the accuracy requirements of field application.

![Figure 2. Model loss function.](image)

4.2. Model Prediction Effect
Select 50 groups of data randomly from the test data set to verify the prediction effect of the model. The results are shown in figure 5 and figure 6. It can be seen from the figure that the predicted results are in good agreement with the actual measurement results. The relative error of most test groups is within 4%, the maximum error is 6.4415%, the average error is 2.8136%, and the data with error less than 4.5% accounts for 43/50 of the total data. The model has good generalization ability and the prediction effect is ideal.
5. Conclusion
In this paper, a prediction model of fly ash carbon content based on LSTM network is proposed. The input parameters of the model are selected by correlation analysis method, and the prediction model is validated by the operation data collected on site. The simulation results show that the average prediction error of LSTM model is 2.8136%, in which the data with error less than 4.5% accounts for 86% of the total samples. It can predict the fly ash carbon content accurately and has good generalization ability, which provides an effective basis for improving the combustion efficiency of boiler.

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