Research on Prediction of Vertical Water Wall Temperature of Power Station Boiler Based on Deep Learning and Expert Experience

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Abstract. Based on deep learning and expert experience to predict the temperature of the vertical water wall of a power station boiler, the research is based on real-time or offline data collected by the power station boiler, and the data is processed through expert experience and algorithms to divide the data set. Based on three deep learning algorithms, an algorithm learning machine is established. Through this learning machine and expert experience, the temperature of the vertical water wall of the power station boiler is predicted. At the same time, this paper also realizes rolling real-time prediction of vertical water wall temperature. The results show that the model can accurately predict the temperature of the vertical water wall, thereby providing reference guidance for the operation of power station boilers.

Keywords. predict temperature; deep learning; vertical water wall; power station boiler

1. Introduction

The main safety problem faced by the water wall during the operation of power station boilers is over-temperature operation.\footnote{1} Long-term over-temperature operation of the water wall can easily cause the water wall to burst, which seriously affects the safe operation of the boiler.\footnote{2} Predicting the boiler water wall temperature is helpful to ensure the long-term safe and stable operation of the water wall, avoiding the over-temperature operation of the water wall to reduce its service life, preventing the water wall from bursting due to over-temperature operation, and avoiding the huge economic loss caused by the shutdown of the unit.\footnote{3}

At present, there are few researches on the prediction of vertical water wall temperature, so the research method proposed in this paper has certain significance.\footnote{4} This paper mainly puts forward several methods to predict the temperature of vertical water wall, and finds a good method to predict the temperature of vertical water wall by comparing the evaluation indexes, so as to provide advice and guidance for boiler operation.\footnote{5}

This article first introduces the processing of a large amount of collected data through mathematical methods and expert experience. Secondly, this article establishes an algorithm learning machine for three deep learning algorithms to train the data set, by comparing evaluation indicators the best prediction method is found. Next, a rolling real-time method of predicting the temperature of a vertical water wall is introduced in this paper. Through verification, the above method can accurately predict...
the temperature of the vertical water wall, and then guidance for the operation of power station boilers are provided.

2. Data processing
The data collected in the power plant is large in quantity, high in dimension, and redundant. Before forecasting, the data must be integrated and processed, and the required data must be extracted for subsequent model construction and analysis. [6]

2.1. Data filtering
One-year operating data of a power plant are collected. The characteristic variables that affect the temperature of the vertical water wall are selected through expert experience. According to the data collected in this article, there are a total of 856 characteristic variables. After being screened by experts, 49 such as main feed water flow, total coal volume, total air volume flow, air temperature, mixture temperature of each mill separator, and mixed air temperature of each mill inlet are selected. [7] These characteristic variables affect the temperature of the vertical water wall. The research object of this paper is the temperature of the 102nd vertical water wall tube.

2.2. Data cleaning
For the above data, first all non-numerical variable features are deleted, and all the features at the same time according to time are integrated. [8] Through statistical analysis, it is found that there are missing values, inconsistencies, and abnormal data in the data. The main feed water flow is selected as an example. The timing diagram is shown in Figure 1. The data value of the main feed water flow is deleted and interpolated. The processed result is shown in Figure 2. The horizontal axis is the data point, and the vertical axis is the main feed water flow after treatment.

2.3. Data specification
Since different evaluation indicators have different dimensions, in order to eliminate the differences in dimensions and value ranges between indicators, data normalization is required to process the data. 49 variables that have an effect on the temperature of the vertical water wall are taken as characteristic variables, and the temperature of the 102nd vertical water wall is taken as the target variable. 80% of all data are randomly take as the training set, and the remaining 20% as the test set.

3. Deep learning integrated machine prediction
The three algorithms of BP neural network, deep belief neural network, and deep neural network are integrated into an algorithm learning machine, and the vertical water wall temperature is predicted by this learning machine. [9] For the index of vertical water wall temperature, there are 49 characteristic variables and one target variable.
3.1. BP neural network
The structure of the BP neural network is shown in Figure 3. The neural network has three layers, including 49 variables in the input layer and 1 variable in the output layer. The activation function of this network is the sigmoid function.

![Figure 3. BP neural network structure diagram.](image)

![Figure 4. DNN network structure diagram](image)

![Figure 5. DBN network structure diagram](image)

After setting the number of iterations to 150, the initial learning rate to 0.05, and the network error value to 0.001, the weights and thresholds are updated. Until the output error is within the specified range, the training of the BP neural network on the data set can be completed.

3.2. DNN
The structure of the DNN network is shown in the Figure 4. The network has seven layers, including one input layer, 49 variables, five hidden layers, and one output layer. The activation function of this network is the relu function.

In this DNN structure, the hidden layer nodes are all 25, the number of samples for each gradient update is 49, and the network error value is 0.05.

3.3. DBN
The structure of the DBN network is shown in the Figure 5. There is one input layer, 49 variables, 50 hidden layers, and one output layer.

In this DNN structure, the hidden layer nodes are all 100, the learning rate is 0.01, the number of iterations is 60, and the number of reverse iterations is 30.

3.4. Algorithmic learning machine prediction
A program is written to integrate the three algorithms of BP neural network, DNN, and DBN into a neural network learning machine. The temperature of the 102nd vertical water wall tube is predicted. The training data are trained through the neural network learning machine to form three different networks. The input data of the validation set are passed through these three types of networks to obtain the prediction results. By comparing the average absolute error, root mean square error and other evaluation indicators, the final prediction algorithm is chosen.

4. Rolling real-time forecast
When the influence of human factors is not considered, the historical temperature of the vertical water wall has a certain influence on the future development, so the temperature of the vertical water wall can be regarded as a sequence related to time. The time series analysis can be applied to predict the temperature in the short term in the future.

According to the time series analysis process, the time series need to be tested. The specific process is as follows.

From the processed data, the vertical water wall temperature for 50 consecutive time points are selected. A timing diagram of this sequence is drawn. As shown below in Figure 6. The horizontal axis is time, and the vertical axis is the temperature of the vertical water wall.
The autocorrelation diagram of the sequence is shown in Figure 7. It can be seen from the figure that the sequence has a strong short-term correlation.

![Figure 6. Sequence diagram.](image1)

![Figure 7. Autocorrelation graph.](image2)

The white noise test shows that the original sequence is a stationary non-white noise sequence. ARMA model is used for modeling. The Bayesian information criterion BIC is used to determine the order, it can be obtained that the minimum p value of BIC is 0, and the q value is 1. After determining the prediction model and parameters, the model is tested and the vertical water wall temperature is predicted. 10 minutes are treated as a time interval. The vertical water wall temperature is predicted immediately in every 10 minutes to achieve rolling real-time prediction.

5. Result analysis

Footnotes should be avoided whenever possible. If required they should be used only for brief notes that do not fit conveniently into the text.

5.1. Prediction results of deep learning integrated machine

The input parameters of the model are mainly feed water flow, total coal flow, total air flow, air temperature mixture temperature of each mill separator, mixed air temperature of each mill inlet, etc. The temperature of the 102nd vertical water wall tube is used as an output parameter to build a model. After the data set passes through the three neural network algorithms of BP neural network, DNN, and DBN, the results obtained are shown in the Figure 8-10.

![Figure 8. BP neural network prediction results.](image3)

![Figure 9. DBN network prediction results.](image4)

![Figure 10. DNN network prediction results.](image5)

The specific value of the error is shown in the table. According to the figures and the table, DNN has the highest accuracy rate, and MAE, MSE, RMSE error are the smallest, so the DNN prediction result can be used as the final output.

| Algorithm | Accuracy | MAE  | MSE  | RMSE |
|-----------|----------|------|------|------|
| BP        | 65.84%   | 5.59 | 21.65| 4.65 |
5.2. Rolling real-time prediction results

After determining the time series prediction model and parameters, the model is tested and the vertical water wall temperature is predicted. The vertical water wall temperature is predicted in every ten minutes to achieve rolling real-time prediction. The prediction result is shown in the Figure 11.

![Figure 11. Rolling real-time prediction results.](image)

It can be seen from the figure that this prediction method has a better prediction trend for the vertical water wall temperature, that is, the actual value and the predicted value have the same development trend. And the deviation range is also within the acceptable range. It shows that this method has high desirability.

6. Conclusion

Based on the neural network learning machine and expert experience method has a higher ability to predict the temperature of the vertical water wall of the power station boiler. For the data used in this article, among the three neural network algorithms of BP neural network, DNN, DBN, the DNN evaluation index is the best, which is the best solution for prediction. The rolling real-time prediction of vertical water wall temperature provides early warning of vertical water wall temperature. If over-temperature occurs, it can be alerted in advance to reduce losses and provide guidance for the safe operation of power plants.

From the above analysis results, it can be seen that DNN can be used as a long-term forecast with input data, and the time series analysis results can be used as a rolling real-time short-term forecast.

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