Research on Multi-step Mixed Prediction Model of Coal Gasifier Furnace Temperature Based on Machine Learning

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Abstract: In order to ensure the safe and stable operation of the coal gasifier, it is particularly important to study a new and reliable method for predicting the temperature of the gasifier. In this paper, the coal gasifier furnace temperature prediction is transformed into a time series prediction problem, and according to the non-linear characteristics of the gasifier furnace temperature data set, the LSTM (Long Short-Term Memory) model in the machine learning algorithm is selected for the gasifier furnace. Then use the PSO (Particle Swarm optimization) algorithm to optimize the hyperparameters of the model. The results show that the LSTM model is feasible but the accuracy is slightly lacking. The prediction accuracy based on the POS-LSTM model is significantly improved. It is of great significance to accurately predict the temperature of the gasifier.

1. Introduction

In recent years, with the rapid development of coal chemical industry, coal chemical industry accidents continue to emerge, and the safety situation is very severe. As the source of coal chemical industry and the core of energy conversion in the whole plant, the safe operation of coal gasifiers must be ensured. If the temperature is too high, it will cause serious damage to the refractory bricks and process burners, and at the same time will reduce the gas production rate; if the temperature is too low, the gas production rate and effective gas content will be reduced, and it will also affect the liquid discharge of coal ash. Therefore, the furnace temperature of the gasifier must be kept within a certain range, otherwise it may cause production accidents. In order to ensure the safe and stable operation of the coal gasifier, it is particularly important to study a new and reliable method for predicting the temperature of the gasifier[1]

2. Data preprocessing

This paper adopts the real-time operation data of a multi-nozzle opposed coal water slurry gasification device in an enterprise. The data acquisition time is 23:36 minutes and 0 seconds on September 20, 2019 to 5:36 minutes and 0 seconds on September 22, 2019. The data is recorded every 1 minute, collecting 1800 data, that is, running data for 30 consecutive hours. Each record collected includes the current time of var1 oxygen branch pressure (E tube, unit MPa), var2 oxygen branch pressure (G tube, unit MPa), var3 oxygen coal ratio (E tube, unit %), var4 oxygen coal ratio (G tube, unit %), var5CO content (unit VOL %), var6CO2 content (unit VOL %), var7H2 content (unit VOL %), var8CH4 content (unit PPM) and var9 furnace temperature (unit °C). The collected data are shown in Table 1.

In this paper, the 1800 data sets collected are divided into training set, validation set and test set...
according to 80%, 10% and 10%. Abnormal data are processed by three criteria, because the collected data are all numerical data and have strong timing. Therefore, this paper uses the average value of corresponding feature sequence to replace the missing data after elimination.

The maximum value normalization method is used to normalize the collected data, perform linear transformation on the original data, achieve equal scale scaling, and map the results to the range of [0,1]. Table 2 shows the data set after data normalization (only the first three are shown).

Table 1. Data collection table of gasifier operation process parameters.

| serial | var1  | var2  | var3  | var4  | var5  | var6  | var7  | var8  | var9  |
|--------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 1      | 7.14  | 7.12  | 467.7 | 471.6 | 47.2  | 16.3  | 35.0  | 1156  | 1194  |
| 2      | 7.14  | 7.12  | 463.3 | 473   | 47.2  | 16.3  | 35.0  | 1227.1| 1193  |
| ...    | ...   | ...   | ...   | ...   | ...   | ...   | ...   | ...   | ...   |
| 1800   | 7.16  | 7.16  | 465.5 | 470.0 | 47.1  | 16.1  | 34.4  | 1336.2| 1183  |

Table 2. Normalization of the most value of the operating parameters of the gasifier.

| serial | var1  | var2  | var3  | var4  | var5  | var6  | var7  | var8  | var9  |
|--------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 1      | 0.33333| 0.55556| 0.23372| 0.57360| 0.50000| 0.66667| 0.85714| 0.40503| 0.65217|
| 2      | 0.33333| 0.55556| 0.06513| 0.64467| 0.50000| 0.66667| 0.85714| 0.49405| 0.60870|
| 3      | 0.33333| 0.44444| 0.41762| 0.60914| 0.66667| 0.66667| 0.85714| 0.50757| 0.60870|

In order to realize the multi-step prediction of gasifier temperature, it is necessary to find out the relationship between input data and output problem. Therefore, it is necessary to separate the hidden output data from the original data. In this paper, the input is the observed value of each parameter index including a total of x steps at time t before time t, and the output is the predicted temperature of gasifier in the next five time steps of t+1, t+2, t+3, t+4 and t+5. The furnace temperature time series are respectively moved backward by 1-5 time steps, and then filled into five columns to form the output data. The input format of the model is [sample number, input time step, characteristics], and the output format is [sample number, output time step][2].

After the model training, it is necessary to evaluate the model according to the appropriate model evaluation index to judge the performance and prediction of the model. The model evaluation indexes selected in this paper are mean absolute error (MAE), root mean square error (RMSE), and determination coefficient (R²). MAE is sensitive to the accumulation of small errors, RMSE is sensitive to large errors, and R² can reflect the degree of interpretation of the predicted value to the actual value. The smaller the values of MAE and RMSE, the closer the predicted value of gasifier temperature to the actual value, and the closer the value of R² to 1, indicating that the better the interpretation of the predicted value to the actual value, the better the performance of the model[3].

3. Multi-step prediction model of gasifier temperature based on LSTM network

Using the hyper-parameters and models of LSTM network that have been determined previously, and using RMSE of validation set as the model loss function, the future five-step prediction analysis of the selected gasifier temperature is carried out to verify the prediction effect of LSTM single method. The multi-step prediction model of gasifier temperature trained in LSTM network

LSTM (Long Short-Term Memory) is proposed by Hochreiter S[4]. LSTM is a special RNN, which can learn long-term dependencies. The construction of LSTM network model needs to determine the model super parameters first. Whether the selection of super parameters is reasonable or not directly affects the overall performance of the model. Some scholars have proposed that the input time step of the model may have an impact on the performance of the time series prediction model[5]. Therefore, the input time step of the model is taken into account in the optimization parameters of the model. In this paper, the super parameters are shown in Table 3.
Table 3. BP neural network model hyperparameters.

| time stepping | hidden_size | batch_size | num_layers | epochs | learning_rate |
|---------------|-------------|------------|------------|--------|---------------|
| 7             | 64          | 32         | 1          | 35     | 0.008         |

Among them, the time step length refers to the input step length of the model, which is generally \((\text{input dimension} + \text{output dimension}) / 2\). In this paper, a total of seven steps \((t-6, t-5, \ldots, t)\) are input to predict the gasifier temperature. hidden_size refers to the number of hidden layer neurons; batch_size refers to the batch size; num_layers refers to the hidden layers; epochs refers to the maximum number of iterations; learning_rate refers to the learning rate; the loss function is defined as the root mean square error of validation set (RMSE)\[^6\].

This paper chooses the Tanh function as the activation function of each connection layer of the LSTM network \[^7\]. Using the hyperparameters and models of the LSTM network that have been determined in the previous article, and using the verification set root mean square error RMSE as the model loss function, the selected gasifier temperature is predicted and analyzed in the next five steps. After the model training is completed, use Test set to test model prediction performance. Model test set actual-predicted fitting effect is shown in Figure 1~5, \(y_{\text{true}}(x)\) is the actual value of the furnace temperature at time \(x\), \(y_{\text{pred}}(x)\) is the prediction of furnace temperature at time \(x\) value (°C).

![Figure 1. LSTM model one-step sequence prediction curve in the future.](image1)

![Figure 2. LSTM model two-step sequence prediction curve in the future.](image2)

![Figure 3. LSTM model three-step sequence prediction curve in the future.](image3)

![Figure 4. LSTM model four-step sequence prediction curve in the future.](image4)

![Figure 5. LSTM model five-step sequence prediction curve in the future.](image5)
Table 4 records the calculation results of the error evaluation indicators MAE, RMSE, $R^2$ based on the LSTM network gasifier furnace temperature multi-step prediction model test set.

| sequence | MAE  | RMSE | $R^2$ |
|----------|------|------|-------|
| $t+1$    | 0.570| 0.756| 0.927 |
| $t+2$    | 0.702| 0.897| 0.897 |
| $t+3$    | 0.867| 1.092| 0.848 |
| $t+4$    | 1.051| 1.294| 0.786 |
| $t+5$    | 1.226| 1.492| 0.716 |
| average  | 0.883| 1.106| 0.835 |

Through the prediction curve and prediction error of the five-step prediction model for gasifier furnace temperature based on the LSTM neural network, it can be seen that as the time step increases, the model prediction error will also increase, and the model performance will decrease, that is, predict the future The error at one moment is much smaller than the fifth moment.

4. Multi-step mixed prediction model of gasifier temperature based on PSO algorithm

This paper uses the PSO algorithm to optimize the hyperparameters of the LSTM network model. It is hoped that better hyperparameters can be used to improve the prediction accuracy and performance of the model. The hyperparameter solution space of the LSTM model and the optimal solution of the PSO output are set as shown in Table 5.

| time stepping | hidden_size | batch_size | num_layers | epochs | learning_rate |
|---------------|-------------|------------|------------|--------|---------------|
| [1,15]        | [32,128]    | [32,128]   | [1,5]      | [10,50]| [0.0005,0.01]|   

The optimal hyperparameters of the LSTM neural network output by the PSO algorithm are substituted into the model, and the selected gasifier temperature is predicted and analyzed in the next five steps. The test set is used to test the prediction performance of the model. The actual-predicted fitting effect of the model test set is shown in the figure. As shown in 6~10, $y_{true}(x)$ is the actual value of the furnace temperature at time $x$, and $y_{pred}(x)$ is the predicted value of the furnace temperature ($^\circ C$) at time $x$.

![Figure 6. PSO-LSTM model one-step sequence prediction in the future.](image)

![Figure 7. PSO-LSTM model two-step sequence prediction curve in the future.](image)
Table 6 records the calculation results of error evaluation indexes MAE, RMSE, $R^2$ based on the PSO-LSTM model gasifier furnace temperature multi-step prediction model test set.

| sequence | MAE  | RMSE | $R^2$ |
|----------|------|------|-------|
| t+1      | 0.515| 0.763| 0.926 |
| t+2      | 0.566| 0.783| 0.922 |
| t+3      | 0.617| 0.820| 0.914 |
| t+4      | 0.664| 0.865| 0.904 |
| t+5      | 0.707| 0.916| 0.893 |
| average  | 0.613| 0.829| 0.912 |

The comparison diagram of prediction error between LSTM model and PSO-LSTM model is shown in Figure 11.
5. Conclusion
It can be seen from Figure 11 that as the time step increases, the prediction error of the PSO-LSTM model will also increase, but the error change between each time step is significantly smaller than that of the LSTM model, indicating that the PSO-LSTM model predicting the performance is more stable than the LSTM model. Moreover, the MAE and RMSE of the PSO-LSTM model at all times are smaller than the LSTM model, and $R^2$ is closer to 1, indicating that the PSO-LSTM model has a better prediction effect and higher prediction accuracy. It can be seen from Table 3-8 that compared with the average value of each error evaluation index of the LSTM model, the MAE of the PSO-LSTM model is reduced by 30.6%, the RMSE is reduced by 25%, and the $R^2$ is increased by 9.2%, indicating that the overall performance of the PSO-LSTM model is excellent. It is based on the LSTM model, and can realize the forecast demand to realize the gasification furnace temperature forecast.

References
[1] Zou Jie,Yi Zhijing. (2018) TexacoAnalysis of furnace temperature monitoring means of coal water slurry gasifier. [J]. Guangzhou chemical industry, 37(07): 186-188.
[2] Feng Wang. Ou Yang. Ruibo Zhang. Lei Shi. (2016) Method for assigning safety integrity level (SIL) during design of safety instrumented systems (SIS) from database [J]. Journal of Loss Prevention in the Process Industries, 44: 212-222.
[3] Chen Cunyin. (2013) Design method and application of integrity level of safety instrument system in petrochemical Plant [D]. Beijing: Beijing University of Chemical Technology.
[4] Hochreiter S, Schmidhuber J. (1997) Long Short-Term Memory [J]. Neural computation, 9(8): 1735-1780.
[5] Da yingyun. (2015). Water quality prediction Technology based on machine learning Theory [D]. Zhejiang: Zhejiang Normal University.
[6] Jeffrey L. Elman. (1990) Finding structure in time [J]. No longer published by Elsevier, 14(2): 179-211.
[7] Tommaso B Enrico F, (2019) Gian Antonio Susto. Machine Learning approaches for Anomaly Detection in Multiphase Flow Meters[J]. IFAC PapersOnLine, 52(11): 212-217.