Prediction Model of Blast Furnace Molten Iron Temperature Based on Time Series Data

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The thermal controlling for a blast furnace is very important. But it is hard to measure the thermal state inside the blast furnace. The molten iron temperature can be measuring and corresponds with the heat of the blast furnace. From when the ores are feed in to the molten iron, the process needs 6~8 hours. The molten iron temperature is a lagging indicator and difficult to predict by physical model. This experiment proposes an AI model training by two time series models, long short-term memory (LSTM) / Gated Recurrent Unit (GRU), to predict the molten iron temperature with in two hours. Before training the AI model, there are 66 features selected from a total 2600 features by dynamic time warping (DTW). The 66 features have different response times that were analyzed to find their critical response time within 8 hours of every feature via the feature importance method of the xgboost (XGB). The trained AI models with the 66 features and the critical response times can predict the molten iron temperature in 2 hours. The mean absolute errors of the two models of the LSTM and GRU are 25 and 20.5. The trained model of the GRU is better than the LSTM.

Keywords: Molten Iron Temperature, DTW, LSTM, GRU

1. INTRODUCTION

The molten iron temperature is an important parameter of the thermal balance of the blast furnace. Control of molten iron temperature is important to realize an efficient and stable operation of the blast furnace. From when the coke and iron ores are feed into the molten iron, the process leads to a long response time of approximately 6~8 hours. The molten iron temperature is a lagging indicator from when the temperature is detected, and the temperature is difficult to predict by physical model because of the complicated process dynamics. In recent years, the AI technology has developed rapidly and can replace a complicated physical model. In this research, machine learning of the AI technology is introduced for training the model, and the model is used to predict the molten iron temperature.

Before training the AI model, the features and training data have to be prepared. There are 2600 features that were collected from the blast furnace and less features would have an effect on the molten iron temperature. It is important to find the critical features for training the prediction model. Most data of the blast furnace are time series data but the molten iron temperature is discontinued data. The molten iron temperature of the blast furnace is manually measured, and the measurement time is not fixed. It is difficult to use commonly correlation analysis such as pearson or spearman to compare the correlations of the features and molten iron temperature. Dynamic time warping (DTW) is one of the algorithms for measuring similarity between two sequences(1). It minimizes the effects of shifting and distortion in time by allowing elastic transformation of time series in order to detect similar shapes with different phases like the data of the features and the molten iron temperature.

A recurrent neural network (RNN) is an extension of a conventional feedforward neural network, which is able to handle a contextual sequence input. Unfortunately, it is difficult to train RNNs to capture long-term dependencies(2). Two models were presented to solve the problem called long short-term memory (LSTM) and gated recurrent unit (GRU)(2,3). The models have been shown to perform well in tasks that require capturing long-term dependencies. The data of the features and the molten iron temperature are long-term dependencies. In this paper we developed an AI model predicted system with LSTM and GRU for predicting molten iron temperature and applied the prediction services to the cloud server.

2. EXPERIMENTAL METHOD

The model development process is shown in figure 1. Firstly, from the many features of the blast furnace's critical features that have a higher correlation with the molten iron temperature were found. Secondly was to analyze and find the critical response time within the 8 hours that affect the molten iron temperature in two hours. Thirdly was model training. Finally, the molten iron temperature prediction service of the trained model was published on the cloud server.

The blast furnace has collected about 2600 features, but not all data have an effect on the molten iron temperature. The numbers of data between the features and molten iron temperature are mismatched and difficult to calculate the correlation. The DTW method was used to calculate the correlation between the features and molten iron temperature in this case. The algorithm calculates both warping path values and the distance between the two series with mismatched numbers of the two series. Suppose two series of one feature and the molten iron temperature are Q and C. The lengths of Q and C are m and n. The path W is a matrix that define the distances between Q and C.

$$W = W_1, W_2, \ldots, W_k,\ \max(m,n) \leq k < m+n-1 \ \ldots\ldots (1)$$

The warping path W can be represented as figure 2. An optimal warping path is the correlation coefficient.

The critical response times are analyzed between each time point of the features and the molten iron temperature by feature importance analysis. The feature importance was directly established by the xgboost model, and then performed a time point importance analysis based on the model. The feature importance was calculated and the times which the feature was selected was the division point. The more times a feature is selected, the more important it represents.

In this work, the AI model was trained with two methods, LSTM and GRU. The structure of the LSTM is shown in figure 3. Unlike in the RNN which simply computes a weighted sum of the input signal and applies a nonlinear function, the LSTM unit maintains two states, c^t (cell state) and h^t(hidden state). The h^t is the hidden layer parameter calculated from the previous state h^{t-1} and the feature x^t is from the current input. The c^{t-1} is the information passed from the previous state. The forget gate of the model disregards the unimportant information of c^{t-1}. Then the other information of the c^{t-1} are calculated with h^{t-1} and the feature x^t of the current input to obtain the target value y^t. Then the cell pass c^t and h^t to the next time point for calculation.

The GRU structure is shown in figure 4. Like RNN, there is a current input feature x^t and a hidden layer parameter state h^{t-1} passed from the previous node. Combining x^t and h^{t-1} can obtain the current output y^t, and pass h^t to the next cell. The difference is the GRU adds a gate to control the memory of h^{t-1}.

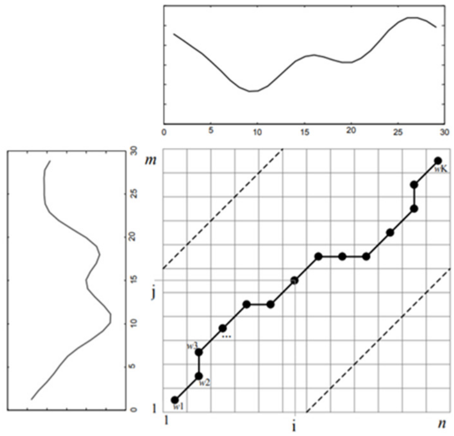

Fig.2. The warping path of the two series data.

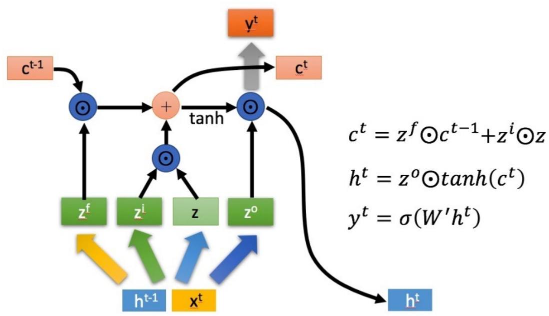

Fig.3. Illustration of LSTM.

Fig.1. The flow chart of the prediction service.

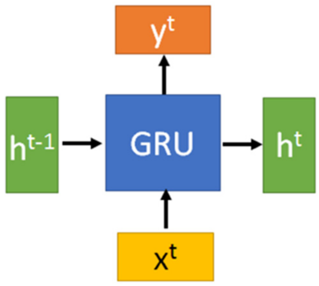

Fig.4. Illustration of GRU.

3. RESULTS AND DISCUSSION

In this paper, all data was obtained from CSC NO.2 blast furnace. The training data was collected over a period starting from January 2020 to April 2020 and the testing data from May 2020. In order to verify the correlation between the data of the features and the molten iron temperature, the DTW method is used to analyze the correlation. Before DTW, all data will be normalized to 0~1 to ensure that the data range is consistent. DTW correlation coefficient is a relative value, and a reference value must be used to separate the critical features. Si content has a great influence on the molten iron temperature. Therefore, the Si content is used as the selection boundary. The correlation coefficient of the Si content by the DTW result is 52, and the features with the correlation coefficient lower than 52 are selected. Finally, a total of 66 features are selected. Critical times are analyzed by the feature importance of XGB. It is to analyze every time point at 480 minutes of each features with the molten iron temperature and the critical times of the features being found. Table 1 is the correlation coefficient and critical time of the features. The correlation coefficient and critical time of the features are shown as table 1. The training data of the features were made by critical time. Figure 5 is the data format. The data of each feature are based on the critical time which were during the previous 8 hours, and the data within 30 minutes before and after the critical times were taken.

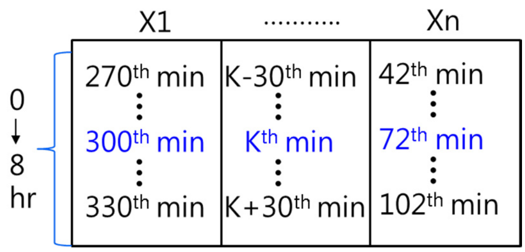

Fig.5. The data format of the training data.

The AI model was trained with two methods, LSTM and GRU. The input of the LSTM model has 66 features,

Table 1 The correlation coefficient and critical time of the features. (correlation coefficient, δ, and critical time, t/min)

The operation of blast furnace			The top of blast furnace		
Feature name	δ	t	Feature name	δ	t
•CO%	2.0	375	•pressure	7.6	386
•CO%	2.3	330	•temperature	24	449
•H_2%	8.0	404	PCI		
•Gas utilization	1.4	212			
•Coke rate	1.7	458	Feature name	δ	t
•Fuel rate	1.7	59	•coke injection (ton/hr)	9.8	315
•Thermal rate	3.2	430	•coke injection (g)	9.0	372
•Heat loss-B05	37	213	•coke injection (ton)	7.7	457
•Heat loss-S7	43	274	•hot air pressure	6.7	141
•Heat loss-SUB	35	262	Blast furnace		
•Heat loss-tuyere	6.2	238			
•content of S	52	390	Feature name	δ	t
•content of Si	52	182			
•content of Ti	48	406			
•PCI rate	8.7	355			
•Tiny coke rate	4.3	425	•iron level(east)	3.8	445
•SOLU	23	266	•iron level(west)	3.6	432
•Thermal efficient-12hr	5.1	72	•hot flow rate	13	300
•Thermal efficient -18hr	3.9	341			
•Thermal efficient	2.7	392			

the hidden layer has 66 nodes, and the output is the molten iron temperature. The molten iron temperature is discontinuous. The molten iron temperature information cannot be transmitted to the next step, and the 'return_sequences' must be set to false. Figure 6 is the predicted result of the LSTM model. The blast furnace scheduled maintenance was from 5/6 to 5/7 with no data collection. The mean absolute error(MAE) is 25°C. The prediction was inaccurate after the scheduled maintenance because of the molten iron temperature varied widely.

The training condition of the GRU model was the same. Figure 7 is the predicted result of the GRU model. The mean absolute error(MAE) is 20.5°C. The trend of the prediction was conformed to the molten iron temperature. The predictability of the GRU model is better than the LSTM model in this situation.

The molten iron temperature predicted service was established on the cloud platform. Operators can use the service at the iron making platform of China Steel Corporation. Figure 8 is the HMI of the predicted service. The service supplies three functions. 1. Molten iron temperature prediction service: The top of the page is the molten iron temperature predicted curve. The red line is

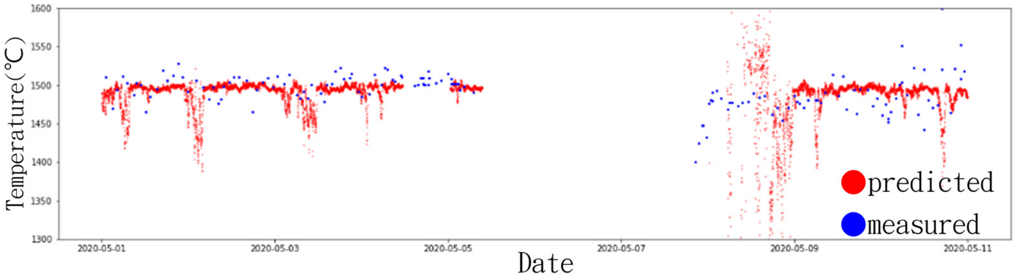

Fig.6. The predicted result of the LSTM model.

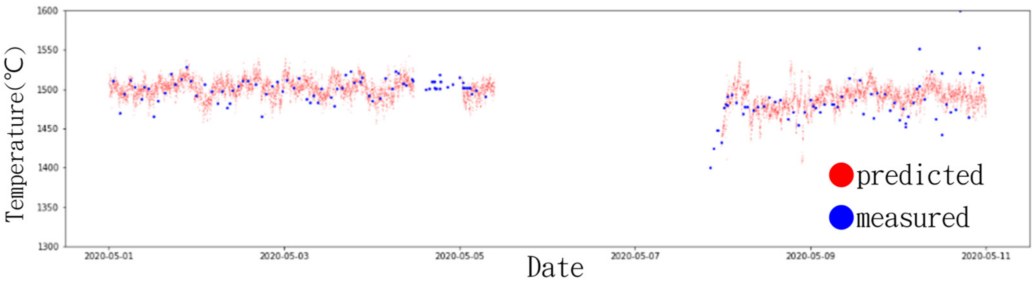

Fig.7. The predicted result of the GRU model.

Fig.8. The HMI of the predicted service on the cloud platform.

the predicted temperature in the next two hours. The red dot and blue dot are the measured molten iron temperature at the east and west tap-holes. 2. The data display service: The left side of the page is a list of important features. Operators can view the values of the important features. 3. The curves comparison service: The bottom of the page can display the curve of the important features. Operators can choose the important features, and the curve will be displayed in the two graphs make it convenient to compare the value changes of the features.

4. CONCLUSIONS

1. Analyzing time series data of features and discontinuous data of the molten iron temperature. There are 66 features successfully selected from 2600 features. The critical response times of the feature were found too. The training data format was established. In the future, this format can quickly establish the dataset for the molten iron temperature predicted model.
2. The molten iron temperature predicted model was established by LSTM and GRU. The MAE of the LSTM model is 25 and the GRU model is 20.5. Comparing the predicted temperature at 5/7 after the scheduled maintenance, the predicted trend of the GRU model were conformed to the molten iron temperature. The predictability of the GRU model is better than the LSTM model at the situation. The LSTM model has poor prediction accuracy when the temperature changes widely.
3. The predicted service was established on the cloud platform. Operators can use the service on the cloud platform without being restricted by hardware. The service supplies three functions. 1. Molten iron temperature prediction service. 2. The data display service. And 3. The curves comparison service.

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