Fault Pattern Recognition of Axle Box Bearings for High-speed EMU Based on Onboard Real-time Temperature Data

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***Abstract*—Axle box bearing a very vulnerable mechanical component because of its heavy load and unpleasant working environment. Once a fault occurs, it will develop rapidly and seriously threaten the safety of train operation. Therefore, fault pattern recognition of axle box bearing is of great significance. The traditional diagnosis method of axle box bearing is based on vibration signal processing technology and trackside acoustic diagnosis, while the axle box bearing of high-speed EMU in China has not been equipped with acceleration sensors and not every line has been equipped with trackside acoustic diagnosis equipment. Therefore, this paper establishes a fault pattern recognition method based on onboard real-time temperature data of axle box bearing, which can effectively recognize the abnormal condition of a high-speed EMU axle box bearing or an axle box bearing sensor failure.**

Keywords-Axle box bearing; LSTM; Fault pattern recognition; high-speed EMU

ABBREVIATIONS

EMU	Electric Multiple Units
LSTM	Long-term and Short-term Memory
TADS	Trackside Acoustic Device System
ODS	Onboard Detection System
WTDS	Wireless Transmit Device System
RMSE	Root Mean Square Error

NOTATIONS

f_t, i_t, o_t	the output of the forget gate, the input gate, and the output gate at time t
W_f, W_i, W_o, W_c	the weight matrix of the forget gate, the input gate, the output gate, and the candidate memory unit
b_f, b_i, b_o, b_c	the bias of the forget gate, the input gate, the output gate, and the candidate memory unit
x_t	the model input at time t
h_t	the model output at time t
$c`_t$	the candidate memory unit at time t
c_t	the cell state at time t
σ	sigmoid function
tanh	hyperbolic tangent function
I_t	the average temperature of axle box bearings at the same measuring point on the same side of 8 carriages at time t
P_t	the predicted temperature value of 8 boxes bearing at the same measuring point on the same side of 8 carriages at time t.

I. INTRODUCTION

According to statistics, by the end of 2018, China Railway was equipped with 3256 standard high-speed EMU (8 carriages a train), of which 1626 are running at speeds above 300 kilometers per hour, accounting for more than 3/4 of the world's high-speed trains. According to China Railway Corporation, the average running number of EMU in China is more than 4,000 per day. Therefore, there is a great value to study the fault pattern recognition of the high-speed EMU axle box bearing to ensure the safe operation of such a large number of high-speed EMU.

The axle box bearing of high-speed EMU is a very vulnerable mechanical part because of its precise structure, large load, and bad operating environment. Once damaged, traffic safety will be greatly affected, resulting in train speed reduction or even parking. The fault pattern recognition of axle box bearings of high-speed EMU not only can avoid the occurrence of safety accidents, but also reduce unnecessary economic losses.

The fault pattern recognition method of rotating machinery based on vibration data is extrmely mature. If the

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rotating machinery breaks down, the vibration signal will show obvious fault characteristics. The main analysis methods are based on statistical features, time-domain analytical method [1], frequency-domain processing technic [2], time-frequency [3] analysis techniques, and machine learning as well.

The analysis method based on statistical characteristics mainly uses non-dimensional parameters, such as skewness, kurtosis, margin, peak value, waveform, and impulse, etc. Lei Yaguo et al. [4] has made a thorough study on each statistical parameter, pointing out that the characteristics of non-dimensional parameters are that the rotating speed and a load of rotating machinery have better robustness to diagnostic accuracy.

In addition to the most basic statistical parameters, the more complex time-domain analysis method is based on the idea of parameter identification. By fitting time-domain waveforms with time-series models, a parameterized time-series model is established to extract features, such as Autoregressive [5] model. The coefficients of the model are particularly sensitive to the impact components of rotating machinery, so it can be used to characterize the status information of bearing or gear components. As a fault characteristic quantity, the impact energy of rotating components is small and the fault characteristics are not obvious when they work at low speed, which increases the difficulty of fault pattern recognition. Mechefske,C.K et al. [6], [7] put forward an effective diagnosis method based on Autoregressive model and achieved satisfactory results in the recognition of low-speed rolling bearings.

The development of computer hardware and big data makes machine learning to deal with complex problems become possible. Machine learning can solve the problems of nonlinearity and instability in engineering very well. Therefore, more and more application of machine learning in fault diagnosis has been used. Now the methods used in engineering are SVR [8], SVM [9], KNN [10], RNN [11] and so forth. SVM method is especially suitable for small sample classification. After continuous development and improvement, machine learning has been more and more applied to intelligent rolling bearing fault diagnosis. Zhang Wendong et al. [12] transformed the vibration signal of fault bearing into a spectrum, using Fully Convolutional Network not only can realize fault diagnosis of different parts and degrees, but also accelerate the convergence of the model and improve the training speed. The extensive application of intelligent diagnosis technology reduces the dependence on manual work and improves the diagnostic efficiency.

Acoustic emission technology [13] is also used in the condition recognition of rotating machinery. It is mainly used for early fault monitoring of rotating machinery. It can eliminate the influence of speed on the fault characteristics and effectively detect the local defects of rotating parts. Compared with vibration analysis, it is more sensitive to the early failure of rotating parts.

At present, the major fault pattern recognition methods of axle box bearing are based on vibration data [14]-[18] and acoustic emission technology [19], [20]. However, the two methods mentioned above have obvious defects in the fault pattern recognition of high-speed EMU axle box bearings. The method based on vibration signal is very effective, but the axle box bearings of high-speed EMU in China are not equipped with acceleration sensors. For acoustic emission technology, its shortcomings are also obvious. TADS(Trackside Acoustic Device System), not all lines are equipped with this device, it also has limitations.

Temperature is a direct index to fault diagnosis and there are temperature sensors installed on the axle box bearings of EMU in China, temperature sensors are directly attached to the outer ring of the axle box bearing to detect temperature. When the temperature reaches the threshold, the EMU Onboard Detection System (EMU-ODS) alarms. The shortcoming of EMU-ODS is obvious, that is, it can't distinguish whether the axle box bearing is abnormal or the bearing temperature sensor is abnormal, most inportantly, it makes a lot of misjudgments. It will not only increase the labor cost of manual inspection but also increase the inspection time. Therefore, this paper employs a fault pattern recognition method based on LSTM for axle box bearings, which can accurately identify the abnormal types of axle bearings and reduce the labor cost of maintenance. The flow chart of this model can be seen in Fig .1. The contribution of this paper can be summarized as followed:

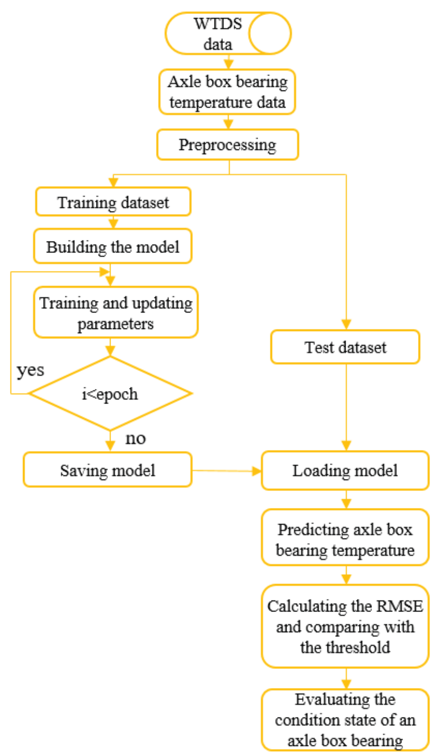

Figure 1. The flow chart of the model

(1)A real-time onboard pattern recognition method for axle box bearings of high-speed EMU based on temperature data is proposed in the absence of accelerometers.

(2)The presented method can efficiently resolve the exist shortcoming of EMU-ODS.

The rest of this paper is scheduled as followed. Section II gives an outline of LSTM. Section III is about expriments and analysis. Section IV gives the model result and makes a simple discussion. Section V draws a conclusion.

II. METHOD

LSTM is the abbreviation of long-term and short-term memory model. LSTM adds input gate, output gate and forget gate as three control units (cell) to RNN model. As information enters the model, cells in LSTM will recognize the information whether accords with the rules, a piece of accordant information will be left behind, and the information that does not accord with the rules will be lost. Based on this criterion, the problem of long-sequence dependence in neural networks can be solved. The structure of the LSTM model is shown in Fig. 2.

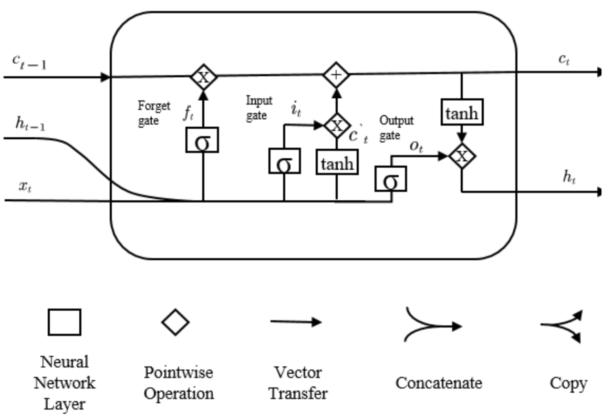

Figure 2. LSTM model structure

LSTM uses some “gates” to alternatively update the state of RNN at each moment. The so-called ‘gate’ structure is a sigmoid neural network and a bit-by-bit multiplication operation. This structure is called gate because the fully connected neural network layer using a sigmoid function as the activation function and the output is between 0 and 1, describing how much information can be input through this structure, so the function of this structure is similar to a door, when the door completely opens (the output of the sigmoid function is 1), all information can be passed; when the door thoroughly closes (the output of the sigmoid function is 0), no information can be passed, the structure shown in Fig. 3.

Forget gate determines which information is removed from the cell state. h_{t-1} is the output at time t-1, x_t is the input at time t. Firstly, a new matrix is formed by splicing columns and stitching them together. Then, take them as an input to an activation function to get an output of 0 to 1. Among them, 0 represents the historical information of the cell completely abandoned, and 1 represents the complete preservation of the historical information of the cell. That is, the forgetting gate determines which of the historical information stored in the cell will be discarded. The formula of the forget gate is shown in (1).

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

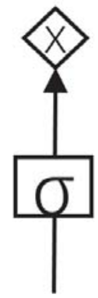

Figure 3. Gate structure

In the formula * is the symbol of matrix multiplication, and “,” in square brackets means that the latter matrix is spliced into columns behind the former matrix, σ which is the activation function. Its output is from 0 to 1. W is the weight matrix, b is the bias matrix, and W and b are obtained through the training of the model.

The input gate determines which information is changed to the cell state. The output of the input gate is shown in (2). $c`_t$ is a candidate memory unit, that is information that needs to be memorized. Its calculation process is shown in (3). In (3), $\tanh$ is an activation function whose output is from -1 to 1.

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i) \tag{2}$$

$$c`_t = \tanh\left(W_{c`} * [h_{t-1}, x_t] + b_{c`}\right) \tag{3}$$

The output gate determines which information in the cell state is used as the output of LSTM. The formula of the output gate is shown in (4), the cell state at the current moment is shown in (5), and the output of LSTM is shown in (6).

$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o) \tag{4}$$

$$c_t = f_t * c_{t-1} + i_t * c`_t \tag{5}$$

$$h_t = o_t * \tanh(c_t) \tag{6}$$

LSTM is a superexcellent variant model of RNN. It succeeds the most characteristics of RNN models and solves the vanishing gradient problem. LSTM is a fabulous solution to deal with time series problems with high correlation.

III. EXPERIMENTS AND ANALYSIS

A. Data description

WTDS is the abbreviation of Wireless Transmit Device System, which is an on-line data acquisition system installed on China's high-speed EMU. Unlike TADS, which is only installed on the trackside of part line, WTDS is installed on every EMU and is an important high-speed EMU detection equipment. The temperature data of axle box bearing comes from WTDS data and samples every minute.

B. Model training and testing

According to the temperature data of actual operation, it is found that the bearing temperature of different carriages at the same time will fluctuate between 0 and 30 degrees in the same place on the same side of different carriage, and the influence of this fluctuation can be eliminated by using the average temperature as an input. Besides, there are many sudden changes in the actual data measured by sensors at a certain point and at a certain time. For example, the same side bearing temperature of eight carriages at the moment is $[80, 80, 81, 81, 82, 82, 83, 120]^T$, of which 120 is the abrupt change temperature of a sensor, but the mean is 86.1, deviation degree is not very large, so the average temperature can be used to eliminate the effect of the mutation of the sensor.

We build a double layers LSTM network and the structure of the model can be seen in Fig. 4 (a). Let $Input = [I_{t-n}, I_{t-n+1}, ..., I_{t-1}]^T$ as the model input and I_t is the average temperature of axle box bearings at the same measuring point on the same side of 8 carriages at time t. Let $Predict = [P_t]^T$ as the model output and P_t as predict the temperature of a box bearing at the same measuring point on the same side of 8 carriages at time t, in other words, bearing temperature at the same position of all 8 carriages use the same predicted temperature value. The detail parameters of this model can be seen in Fig. 4 (b), that is, we use the previous 30 minutes temperature to predict the temperature of this minute. The training data set and test data set of the model are shown in Tab. I.

The fault pattern recognition strategy of the axle box bearing is carried out by calculating the RMSE values of the predicted axle box bearing temperature and the actual temperature intercepted by a sliding window and selecting 3

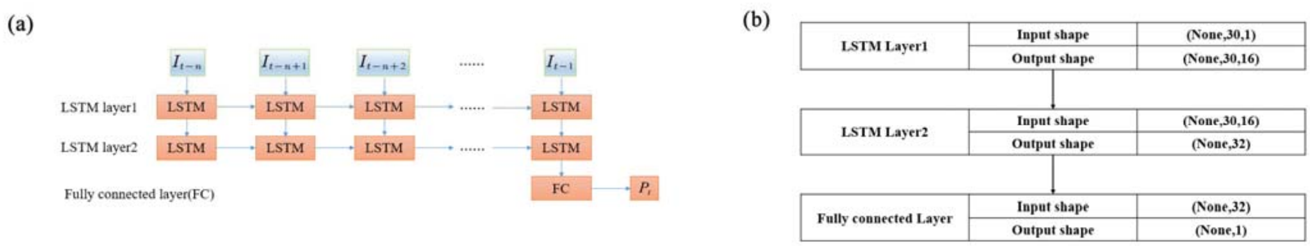

Figure 4. (a) The model structure, (b) The detail parameters of this model

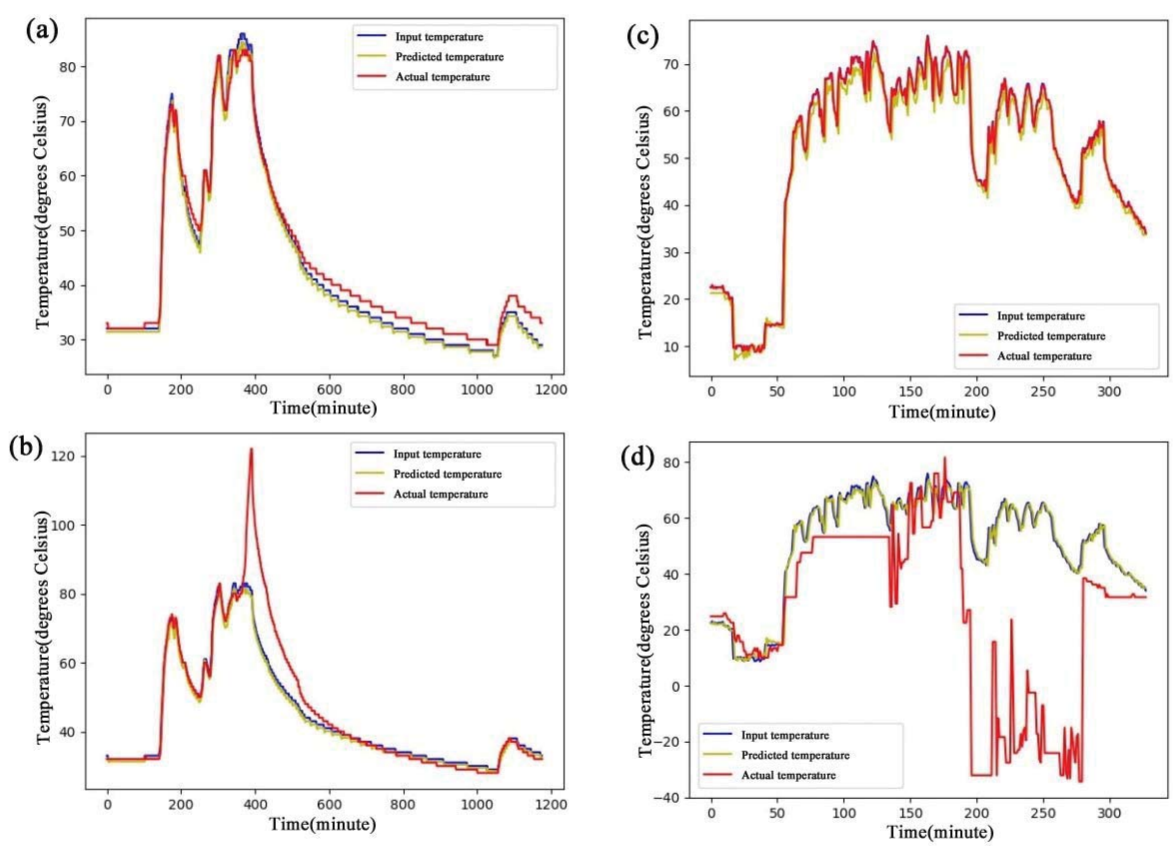

Figure 5. (a) and (c) is normal,(b) axle boxing bearing is abnormal,(d) axle boxing bearing temperature sensor is abnormal.

as the sliding step. If the bearing and temperature sensor is normal, the calculated RMSE is small, otherwise, it is large. Fig. 5 shows the temperature curve of the axle box bearing in different states. In Fig. 5 (b) and (d), the calculated RMSE is abnormal, which is to validate the effectiveness of this model.

TABLE I. The sample size of the training dataset and test dataset

Samples / Types	Training sample size	Test sample size
normal	5600	2400
bearing fault	1680	720
sensor fault	3500	1500

IV. RESULTS AND DISCUSSION

After testing on the test set, statistics show in Tab. II, we can see that when the temperature sensor of axle box bearing

TABLE II. RMSE statistical results for different fault types in the model

RMSE interval / Types	Minimum RMSE	Maximum RMSE
normal	0	11.11
bearing fault	11.11	20.20
sensor fault	20.20	60.60

and axle box bearing is normal, the RMSE of predicted axle box bearing temperature and actual axle box bearing temperature fluctuates between 0 and 11.11; if the axle box bearing temperature sensor is normal but the axle box bearing is abnormal, the RMSE of predicted axle box bearing temperature and actual axle box bearing temperature is fluctuates between 11.11 and 20.20; If the axle box bearings is normal and the axle box bearings temperature sensor is damaged, the predicted temperature of the axle box bearings fluctuates with the RMSE of the actual temperature of the axle box bearings is fluctuates between 20.20 and 60.60. Therefore, the fault pattern recognition of the axle box bearings can be realized by setting the appropriate threshold. We select 11.11 and 20.20 as the threshold and the accurate rate on test dataset is 97.8%.

V. CONCLUSION

The temperature data of axle box bearings in WTDS data can be used to directly recognize the abnormal condition of temperature sensors of axle box bearings and axle box bearings. Therefore, this paper presents a fault pattern recognition method for axle box bearing based on LSTM algorithm. Through model training and model testing, it is proved that the model can effectively detect three states of axle box bearing: normal, abnormal axle box bearing and abnormal temperature sensor. The study is of practical value to guarantee the safe operation of high-speed EMU in China.

ACKNOWLEDGMENT

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