Diagnosis Model of Motor Fault of Precooled Air Conditioning Unit
Based on Multivariable LSTM

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Abstract. The motor failure of precooled air conditioning unit (PAU) affects the operation of HVAC system directly. Traditional fault detection methods based on frequency analysis of vibration signals need high sampling frequency. However, in some actual operation and maintenance, the sampling frequency of related data is lower, it is difficult to meet the needs. In this paper, a PAU motor fault diagnosis model is constructed based on long short-term memory neural network (LSTM) combined with in-depth learning technology. The temperature of motor shell is an important symbol of motor fault. Therefore, effective features are extracted by analyzing the data characteristics. LSTM method is used to predict the motor shell temperature, and the motor fault detection and diagnosis are carried out according to the predicted residual threshold. According to the computation, the diagnostic accuracy of fault data is 100%, and the false alarm rate of fault-free data is 0.3%. The results show that the model has stronger generalization ability, higher prediction accuracy.

Introduction

The motor is one of the most critical components in the HVAC system, which is prone to various faults and affects the operation of the HVAC system [1]. Therefore, accurate, effective and reliable motor fault diagnosis has received extensive attention [2].

The most common method of motor fault diagnosis is vibration analysis. Yu et al. [3] obtained time-frequency diagrams based on vibration signals using Short-Time Fourier Transform (STFT), Hilbert-Huang transform (HHT), respectively. They extracted the fault characteristics and classified the faulty motors. However, this method is mostly used when there are few samples, and there are limitations on the application of larger data samples.

In recent years, with the development of big data technology, data-driven methods have been used for motor fault diagnosis. Sun et al. [4] used sparse autoencoder to learn features and achieved better classification performance in asynchronous motor fault diagnosis. Wang et al. [5] used the convolutional neural network to adaptively extract the characteristics of time-frequency maps, which overcomes the engineering experience requirements of feature extraction by traditional diagnostic methods. However, the correlation of time is not considered. LSTM can process data sequences of different lengths, encode time information, and capture long-term correlation [1]. It has been successfully applied to mechanical fault diagnosis tasks [6-7].

In practical applications, due to the cost or technical factors, the data sampling frequency is low, and some high-frequency information of the vibration signal is lost, so that the motor fault diagnosis cannot be performed by using the signal processing technology. Aiming at the above problems, we use a deep learning method to construct a motor fault prediction and diagnosis model based on multivariate LSTM to achieve fast and accurate motor fault diagnosis.
System Analysis

A property company monitors the collected 6-month PAU motor operating status and operating conditions data, including motor casing temperature, motor vibration, three-phase current, voltage and other characteristics of more than 40 characteristics. The sampling frequency is 1/60 hz. Due to the low sampling frequency, the frequency component cannot be analyzed by signal processing technology and the motor fault component cannot be determined.

The representation of motor faults is rather complicated, but the most direct manifestation is the change in motor temperature. Usually, the temperature of the motor rises as the motor starts to run, and reaches a steady state after a while. If the installation is unreasonable or faulty, the temperature of the motor casing will rise and an abnormally high temperature will occur. Diagnosing motor faults based on motor housing temperature is also a method of on-site handling, but most rely on experience to make judgments. Therefore, we perform motor fault detection by abnormal temperature of the motor casing.

It can be seen from Fig. 1 that the temperature of the motor casing gradually changes over a period of time, and the temperature value at the same time is related to the temperature at the historical time. At the same time, it can be seen that the motor casing temperature is similar to the fan bearing temperature, the distribution box temperature and the ambient temperature, which indicates that the motor casing temperature is affected by many factors.

![Figure 1. Trend graph of motor housing temperature and related properties.](image)

In this paper, multiple factors are introduced into the model to establish a multivariate LSTM model, which effectively learns the relationship between the features, predicts the temperature of the motor casing, and diagnoses the fault based on the residual threshold.

LSTM Network

Long short-term memory network (LSTM) is an improved structure of RNN, which is suitable for dealing with the problem of very long time interval and delay in time series prediction. Including input gate $i$, output gate $o$, forgetting gate $f$ and memory unit $C$, it can solve the long short-term dependence problem of sequential data. If the input sequence $X = \{x_{(1)}, x_{(2)}, \cdots, x_{(n)}\}$ is given, where $x_{(t)}$ is a $d$ dimensional vector, the forward calculation formula is expressed as follows:

The value of input gate:

$$i_t = \sigma(w_i x_t + v_i h_{t-1} + b_i)$$

(1)

The value of forgotten gate:

$$f_t = \sigma(w_f x_t + v_f h_{t-1} + b_f)$$

(2)

The value of output gate:
\[ a_t = \delta(w_x x_t + v_h h_{t-1} + b) \]  
(3)

Candidate memory values at the current time:

\[ \tilde{C}_t = \tanh(w_x x_t + v_h h_{t-1} + b_v) \]  
(4)

Current moment memory unit status:

\[ C_t = i_t \ast \tilde{C}_t + f_t \ast C_{t-1} \]  
(5)

Output of LSTM:

\[ h_t = o_t \ast \tanh(C_t) \]  
(6)

Where \( \delta \) is a sigmoid function, \( \ast \) represents the multiplication operation by phase, \( W \in \mathbb{R}^{H \times d} \), \( V \in \mathbb{R}^{H \times H} \), \( b \in \mathbb{R}^{H \times 1} \), \( H \) is the number of hidden layer nodes. The training objectives of the network are:

\[ \arg \min L(W, V, b) = \frac{1}{n} \sum_{t=1}^{n} J(x_t, \hat{x}_t) = \frac{1}{n} \sum_{t=1}^{n} |x_t - \hat{x}_t| \]  
(7)

Case Implementation and Analysis

In this paper, the monitoring data of motor running state of property company for six months are analyzed. We compare the predicted value and the actual value of motor in normal state and fault state. At the same time, we also compare the distribution of residual absolute value in normal state and fault state to set the alarm threshold.

The Specific Process of Motor Fault Diagnosis

**Step 1: Feature Extraction.** The relevant monitoring data was analyzed by using the Pearson correlation coefficient, and the correlation coefficient is shown in Fig. 2. We select the feature with high correlation with the output characteristic motor housing temperature as the input variable. The final selected features are analyzed by fan bearing temperature, distribution box temperature, three-phase current, and three-phase active power.

Figure 2. Correlation coefficient map.
Step 2: Normalized Processing. Since the order of magnitude of each parameter in the sample is very different, in order to reduce the influence of differences between different indicators on the model prediction, the input data is normalized to obtain the standard format data to improve the training rate.

Step 3: Network Parameter Setting and Training. In order to build a suitable LSTM model, we need to determine several parameters, such as the number of network layers, time steps and learning rates. It can be seen from Fig. 3 that as the number of network layers increases from 1 to 5, the average absolute error curve decreases significantly in the first 3 layers and then tends to be stable. As the number of network layers increases, the network model becomes more complex and the computation time increases. Therefore, considering the accuracy and efficiency, we set the number of network layers to 3. The specific parameters are shown in Table 1.

| parameters                        | Value |
|-----------------------------------|-------|
| Enter the dimensions of the data  | 19    |
| Number of network layers          | 3     |
| Learning rate                     | 0.001 |
| Model look back time              | 10    |
| Model forward prediction time     | 5     |
| Batch size                        | 100   |
| Maximum number of iterations      | 200   |
| Abstaining coefficient            | 0.3   |
| Loss function                     | MAE   |

Step 4: Setting Alarm Threshold. The normal value of the absolute value of the prediction residual is fitted, and the mean and standard deviation of the absolute value of the residual are calculated. The warning thresholds determined according to the criterion [8] are shown in Table 2.

| Lower alarm limit  | Lower warning limit | Early warning limit | Upper limit of alarm |
|--------------------|---------------------|---------------------|----------------------|
| $\mu - 3\delta$    | $\mu - 2\delta$    | $\mu + 2\delta$    | $\mu + 3\delta$     |
| -2.2               | -1.31               | 2.22                | 3.1                  |

Results and Analysis

Normal Motor Running State. Under the normal running state of the motor, the temperature of the motor casing is predicted. The prediction curve of the model is shown in Fig. 4. The distribution of the absolute value of the residual is shown in Fig. 4.
Figure 4. (a) Actual and predicted values of the motor casing temperature under normal conditions and the distribution of absolute values of residuals. (b) Actual and predicted values of the motor casing temperature under fault conditions and the distribution of absolute values of residuals.

It can be seen from Fig. 4(a) that the predicted value of the test sample is in good agreement with the actual value when the motor is in normal operation. It can be seen from Fig. 4(a) that the absolute values of the residuals are randomly distributed around 0.5 and fluctuate within the normal control range. Therefore, according to the distribution of the absolute value of the residual, the running state of the motor can be judged, and the result is consistent with the actual running state. It can be seen that the prediction model has a better prediction effect.

Motor Fault Operating State. Motor faults include pulse faults, step faults, drift faults, etc [9], the most typical of which is pulse fault. Therefore, we add the analog pulse fault signal to the real data and then detect it. In the motor fault state, the predicted curve of the model is shown in Fig. 4(b). The predicted and actual values of the motor casing temperature are compared by Fig. 4(b). The results show that the predicted values of the previous test samples agree well with the actual values, which reflects the normal operation of the motor. In addition, the actual values of the motor casing temperature for the last 200 fault samples are higher than the predicted values. Fig. 4(b) shows the distribution of the absolute values of the residuals in the event of a fault. The residuals of the previous test samples fluctuate normally and the fluctuation range is within the normal control range. In addition, in the last 200 fault samples, the absolute value of the residual is relatively small in the initial stage of the fault, and then gradually increases. Exceeding the set threshold form an effective alarm, and it can be judged that the motor is abnormal. In order to further illustrate the validity of the prediction, the quantitative diagnosis results are shown in Table 3. The sensitivity of the model established in this paper to the fault is verified, and the fault of the PAU motor is accurately diagnosed.

|                  | No fault condition | Faulty condition |
|------------------|--------------------|-----------------|
| Prediction accuracy (RMSE) | 0.294 | 2.401 |
| Average error percentage | 1.32% | 7.38% |
| Detection accuracy | 99.7% | 100% |
| False alarm rate | 0.3% | 0 |

Table 3. Diagnostic result.

Conclusion

In this paper, we combines deep learning technology with statistical methods to construct a fault diagnosis model based on multivariate LSTM network. Firstly, feature selection is performed using the Person correlation coefficient to determine the input of the network. Then, the multi-variable LSTM model is used to predict the motor casing temperature and calculate the absolute value of the prediction residual. Finally, the distribution of the absolute value of the predicted residual is analyzed, and the motor fault pre-alarm threshold is set. Our results show that the LSTM model has good predictive performance. The method has a prediction accuracy is 98% and a fault check accuracy is
99.7% for fault-free data, and a check accuracy is 100% for faulty data. This indicates that predicting the motor casing temperature to achieve fault prediction is feasible and effective. This method can find the fault of the PAU motor in time, which has practical significance for ensuring the continuous and safe operation of the HVAC system.

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