https://doi.org/10.1051/e3sconf/202125202023

Investigation on recognition method of acoustic emission signal of the compressor valve based on CNN and LSTM network

Yanfeng Wang[1,2], Jin Wang[1,2], Junwei Sun[1,2*], Enhao Liang[1,2], Tao Wang[3*]

[1] Henan Key Lab of Information-Based Electrical Appliances, Zhengzhou University of Light Industry, Zhengzhou, Henan, 450000, China
[2] School of Electrical and Information Engineering, Zhengzhou University of Light Industry, Zhengzhou, Henan, 450000, China
[3] School of Energy and Power Engineering, Zhengzhou University of Light Industry, Zhengzhou, Henan, 450000, China

Abstract. The valve is one of the important parts of the reciprocating compressor, which directly affects the thermodynamic process and reliability of the compressor. In this paper, acoustic emission (AE) technology is used to predict the dynamic characteristics of valves. The AE signal of the compressor valve is analyzed based on the deep learning method, and the mapping relation between the AE signal and the dynamic characteristics of the valve is obtained. The results show that the prediction accuracy of the models trained by Long Short-Term Memory (LSTM) artificial neural network and Convolutional Neural Network (CNN) is 97% and 95%, respectively, which can accurately predict the dynamic characteristics of the valve. Although the prediction results of CNN are slightly lower than that of LSTM network, the calculation speed of CNN is relatively faster.

1 Introduction

Reciprocating compressors, widely used for gas compression, play a crucial role in industry, including oil refineries, chemical plants, natural gas processing and delivery plants. The reciprocating compressor includes many reciprocating and rotating movements in the working process. There are many vulnerable parts during the process of operation, which makes the condition monitoring and fault diagnosis of the reciprocating compressor very difficult [1,2]. In particular, the failure of the valve is the main reason for the unplanned shutdown of reciprocating compressors [3,4]. Therefore, it is urgent to develop the fault diagnosis technology of the valve.

The failure types of valves include the valve leakage, delayed closing and flutter failure [5]. Based on operating characteristics of reciprocating compressor and fault characteristics of the valves, the monitoring signals and fault diagnosis method selected by different researchers are different [6].

More and more researchers in the field of reciprocating compressor fault diagnosis have turned their attention from low-frequency vibration signals to high-frequency AE signals in recent years. Prateepasen et al. [7] developed a set of portable intelligent equipment for the diagnosis of the valve leakage. The test results proved the leakage rate was reflected by AE signals. Jafari et al. [8] found that there was a linear relationship between the AE signal energy and the leakage rate of the gas valve of the internal combustion engine through theoretical and experimental research. Sharif et al. [9] studied the gas leakage through the control valve by using the AE signal. The reasearch showed that it was easy to obtain the characteristic frequency components related to the leakage from the background noise and its amplitude increased with the increase of the leakage rate. Yuefei Wang et al. [10] proposed a method to diagnose the valve fault by combining AE signal with simulated the valve movement.

Based on the deep learning method, this paper analyzes the AE signal of the reciprocating compressor valve and proposes a fault diagnosis method. The LSTM network and CNN are used to map the relation between the AE signal and dynamic characteristics of the valve. Meanwhile, the experimental verification has been performed. The network model is used to analyze the delay closing characteristic of the valve, which provides theoretical and experimental basis for the fault diagnosis of reciprocating compressors with AE technology.

2 Identification method of the valve dynamic characteristics based on the AE signal

CNN and LSTM network can be applied to the time series analysis of sensor data, as well as the analysis of signal data with fixed length period. On the basis, the mapping relationship between the valve dynamic characteristics and AE signal is analyzed by using CNN [11] and LSTM network [12].

The specific procedures are as follows:

1. Data input： Read the compressor test data, including time, the AE signal, the displacement of air valve and normalize the data. Split the data into the training set and the test set (Train 90%, Test 10%).

2. Convolution operation: The feature map of the previous layer performs a convolution operation with a

*Corresponding author's e-mail: wangtao@zzuli.edu.cn

learnable convolution kernel. The result of the convolution forms neurons of this layer through the output of the activation function, thus forming the feature graph of this layer, also known as the feature extraction layer. The input of each neuron is connected with the local receptive field of the previous layer to extract the local feature. Once the local feature is extracted, its position relationship with other features is determined.

3. Pooling operation: It divides the input signal into non-overlapping regions. For each area, the spatial resolution of the network is reduced by pooling (down sampling) operation. For example, the maximum pooling is to select the maximum value in the region; the average pooling is to calculate the average value in the region. The offset and distortion of the signal can be eliminated through this step.

4. Fully connected operation: The input signal is output as multiple sets of signals after multiple convolution kernel pooling operations. Through the fully connected operation, multiple sets of signals are successively combined into a set of signals.

5. Recognition operation: The above operation process is the characteristic feature learning operation. A layer of network shall be added for classification or regression calculation based on the above operation.

In particular, CNN and LSTM network models will be evaluated after model training. The training time of neural network is obtained by computer statistics. The accuracy of the model is obtained by comparing the predicted value with the experimental value, as shown in equation (1).

$$error = \frac{1}{N}\sqrt{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2} \tag{1}$$

Where N is the number of data points, x_i is the calculated value by the network model, $\hat{x}_i$ is the measured value.

3 Experimental setup

In this paper, the AE signal experimental setup of the valve is established on a single-acting reciprocating air compressor, as shown in Figure 1. The setup is composed of a reciprocating air compressor, an AE sensor, an eddy current displacement sensor, a proximity switch, a data acquisition system and a computer. The test compressor is driven by the motor. Rated discharge pressure is 0.7 MPa, rated flow is 3.0 m3·min-1 and rated speed of the compressor is 1500 r·min^{-1}.

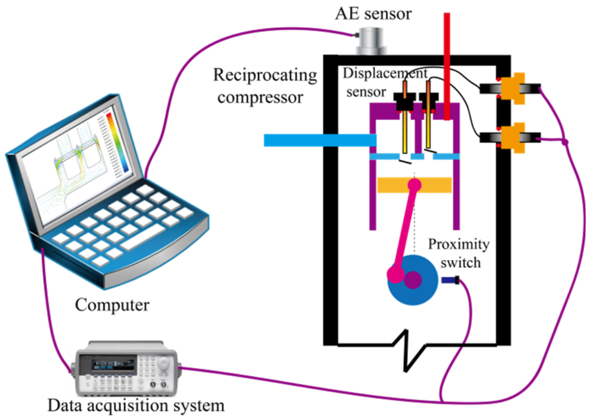

Figure 1. The experimental setup

4 Results and discussion

4.1 Correlation analysis of valve dynamics and AE signals

Figure 2 shows the AE signal excited by the movement of the valve and displacement of the discharge valve with the crankshaft angle during the trouble-free operation of the reciprocating compressor. There are four burst AE signals, namely AE1, AE2, AE3 and AE4. The burst AE signals are generated when the valve hits the lift limiter and valve seat during the opening and closing of the valve.

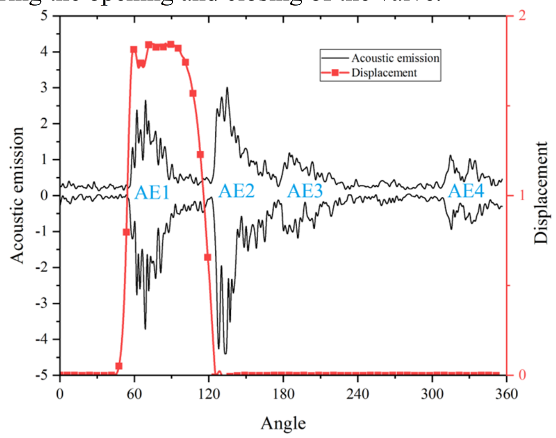

Figure 2. The AE signal excited by the movement of the valve and displacement of discharge valve with crankshaft angle

Combined with the dynamic characteristics of the valve, AE1, AE2, AE3 and AE4 correspond to the discharge valve closing, the suction valve opening, the suction valve closing and the discharge valve opening, respectively. During the operation of the compressor, the piston moves from Bottom Dead Center (BDC) to Top Dead Center TDC (TDC), and the compression process starts. When the pressure in the cylinder is higher than the discharge pressure, the discharge valve opens and the burst AE1 signal is generated when the valve hits the lift limiter. The discharge valve closes at the end of discharge process and the valve hits the seat to excite the burst AE2 signal. When the piston moves from TDC to BDC, the pressure in the cylinder gradually decreases. When the pressure is lower than the suction pressure, the suction valve opens and the valve hits the lift limiter, resulting in the burst AE3 signal. The piston continues to move downward to BDC. When the suction process ends, the valve hits the seat and produces the burst AE4 signal. It can be concluded that according to the position of burst AE signal, the characteristic position of the valve opening and closing can be obtained.

4.2 Verification

In order to map the relation between the AE signal and dynamic characteristics of the valve, this paper uses the LSMT network and CNN to predict the valve displacement. Comparing the error between the prediction valve displacement by the network and the experimental data, the accuracy of the model trained by LSMT network and CNN is 96.14% and 94.49%, respectively, which can accurately predict the dynamic characteristics of the valve. Although the prediction result of CNN is lower than LSTM network, its calculation speed is faster. LSTM network takes 139.33 s and CNN takes 101.65 s.

In order to further verify the effectiveness of the method, the trained LSMT and CNN models are used to predict the opening and closing characteristic angles of discharge valve under variable working conditions. Figure 3, Figure 4 and Figure 5 show the prediction results of the training model under the working conditions of 0.2 MPa, 0.3 MPa and 0.4 MPa, respectively.

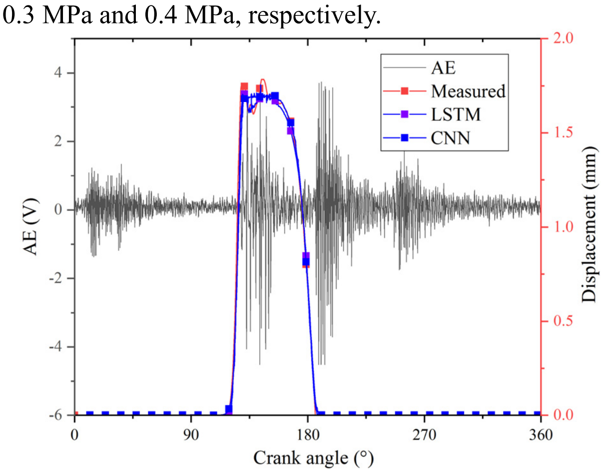

Figure 3. Displacement prediction of the valve under discharge pressure at 0.2 MPa

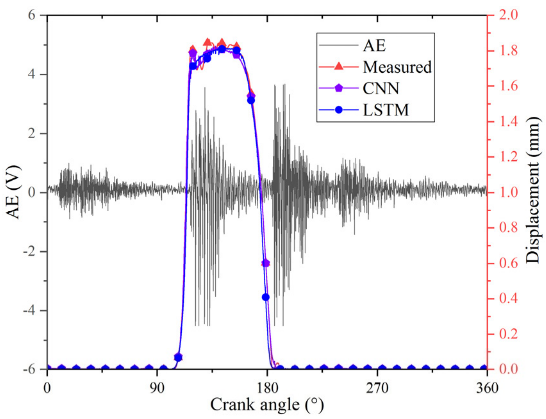

Figure 4. Displacement prediction of the valve under discharge pressure at 0.3 MPa

As shown in the figure, LSMT and CNN model can accurately predict the opening and closing angles of discharge valve. The specific values are shown in the Table 1 and Table 2.

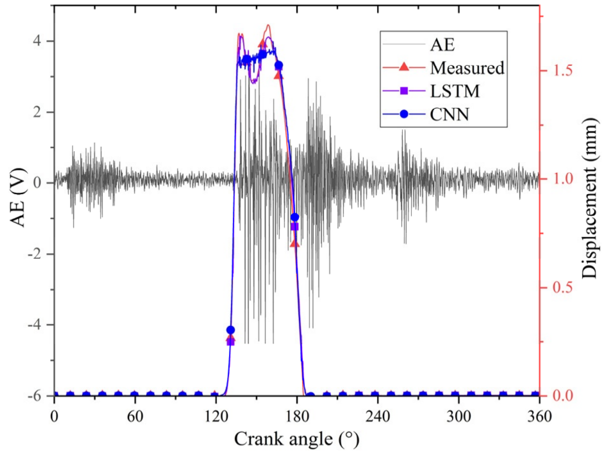

Figure 5. Displacement prediction of the valve under discharge pressure at 0.4 MPa

Table 1. Opening angle of discharge valve under variable working conditions

Method	Opening angle of discharge valve			The average error(%)
	0.2MPa	0.3 MPa	0.4 MPa	
CNN	103.67°	116.19°	124.40°	0.80
LSTM	101.89°	116.66°	126.30°	0.97
Measurement	102.84°	115.23°	125.35°	/

Table 2. Closing angle of discharge valve under variable working conditions

Method	Closing angle of discharge valve			The average error
	0.2MPa	0.3 MPa	0.4 MPa	
CNN	187.09°	187.09°	186.96°	0.50
LSTM	188.64°	187.69 °	187.43°	0.89
Measurement	187.30°	185.66°	185.82°	/

In particular, based on Figure 3, Figure 4 and Figure 5, the LSTM network has a prominent performance in predicting valve flutter, while the model of CNN has a large deviation.

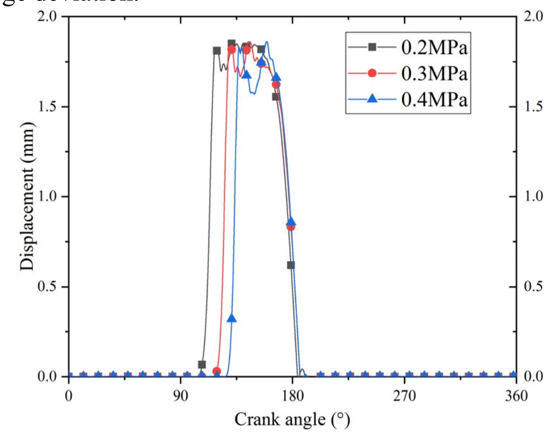

Figure 6. The valve displacement under variable discharge pressure

Furthermore, as shown in Figure 6, when the discharge

https://doi.org/10.1051/e3sconf/202125202023

pressure is 0.2 MPa, 0.3 MPa and 0.4 MPa, the displacement of the discharge valve is compared. Because the spring force is dominant when the valve being closed, the valve is closed at the same angle under three working conditions, and the angle of delayed closing remains constant.

5 Conclusions

The valve is one of the important vulnerable parts of reciprocating compressor, which directly affects the economy and reliability of the compressor. Based on the deep learning method, this paper analyzes the AE signal of the reciprocating compressor valve. The following conclusions can be drawn:

1) The mapping relation between the AE signal and the dynamic characteristics of the valve can be obtained by using the deep learning method. The accuracy of the model trained by LSMT and CNN is 97% and 95% respectively, which can accurately predict the dynamic characteristics of the valve. Although the prediction result of CNN is lower than that of LSTM, its prediction speed is faster.

2) The motion characteristics of the valve predicted by the deep learning method can be used to judge the delay closing fault of the valve.

3) Although the method proposed in this paper can effectively predict the opening and closing angle of compressor air valve, according to the obtained results, the method cannot obtain the valve flutter characteristics.

Acknowledgements

This work was supported in part by the National Key R and D Program of China for International S and T Cooperation Projects (2017YFE0103900), in part by the Joint Funds of the National Natural Science Foundation of China (U1804262).

References

1. Xiao, S.; Nie, A.; Zhang, Z.; Liu, S.; Song, M.; Zhang, H. Fault Diagnosis of a Reciprocating Compressor Air Valve Based on Deep Learning. Appl. Sci. 2020, 10, 6596.
2. Deng, R.; Lin, Y.; Tang, W.; Gu, F.; Ball, A. Object-Based Thermal Image Segmentation for Fault Diagnosis of Reciprocating Compressors. Sensors 2020, 20, 3436.
3. Han, L.; Jiang, K.; Wang, Q.; Wang, X.; Zhou, Y. Quantitative Evaluation on Valve Leakage of Reciprocating Compressor Using System Characteristic Diagnosis Method. Appl. Sci. 2020, 10, 1946.
4. Liu, Z.; Lan, Z.; Guo, J.; Zhang, J.; Xie, Y.; Cao, X.; Duan, Z. A New Hybrid Reciprocating Compressor Model Coupled with Acoustic FEM Characterization and Gas Dynamics. Appl. Sci. 2019, 9, 1179.
5. Liu, Y.; Duan, L.; Yuan, Z.; Wang, N.; Zhao, J. An Intelligent Fault Diagnosis Method for Reciprocating Compressors Based on LMD and SDAE. Sensors 2019, 19, 1041.
6. Zhang, J.; Zhou, C.; Jiang, Z.; Wang, Y.; Sun, X. Optimization Design of Actuator Parameters with Stepless Capacity Control System Considering the Effect of Backflow Clearance. Appl. Sci. 2020, 10, 2703.
7. Prateepasen A, Kaewwaewnoi W, Kaewtrakulpong P. Smart portable noninvasive instrument for detection of internal air leakage of a valve using AE signals[J]. Measurement, 2011, 44 (2): 378-384.
8. Jafari SM, Mehdigholi H, Behzad M. Investigation of the relationship between engine valve leakage and AE measured on the cylinder head ignoring combustion effects[J]. Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering, 2016, 230 (1): 3-9.
9. Sharif MA, Grosvenor RI. Internal valve leakage detection using an AE measurement system[J]. Transactions of the Institute of Measurement and Control, 1998, 20 (5): 233-242.
10. Wang Y, Xue C, Jia X , et al. Fault diagnosis of reciprocating compressor valve with the method integrating acoustic emission signal and simulated valve motion[J]. Mechanical Systems and Signal Processing, 2015, 56-57(5):197-212.
11. Sun, J.; Di, L.; Sun, Z.; Shen, Y.; Lai, Z. County-Level Soybean Yield Prediction Using Deep CNN-LSTM Model. Sensors 2019, 19, 4363.
12. Cui, C.; Zhao, M.; Wong, K. An LSTM-Method-Based Availability Prediction for Optimized Offloading in Mobile Edges. Sensors 2019, 19, 4467.