Intelligent fault diagnosis of wind turbine gearbox based on Long short-term memory networks

Lixiao Cao
School of Instrumentation and optoelectronics Engineering
Beihang University
Beijing, China
caolixiao@buaa.edu.cn

Jingyi Zhang
School of Instrumentation and optoelectronics Engineering
Beihang University
Beijing, China
1095983878@qq.com

JingYue Wang
School of Instrument Science and Opto-electronics Engineering
Beihang University
Beijing, China
wjynnu@163.com

Zheng Qian
School of Instrumentation and optoelectronics Engineering
Beihang University
Beijing, China
qianzheng@buaa.edu.cn

***Abstract*—Gearbox with complex structure is one of the most fragile components of wind turbines. Fault diagnosis of gearbox is crucial to reduce unexpected downtime and economic losses. This paper proposes an intelligent fault diagnosis method based on the Long Short-term Memory (LSTM) networks. Firstly, the multi- accelerometers vibration signals are divided into data segments. Then the common time domain features are extracted from these data segments. After that, these features are fed into the LSTM networks for fault pattern classification. The proposed method has no requirement for well-selected features, and also classifies the fault type accurately. The performance of the proposed method is validated by the multi- accelerometers vibration signals from wind turbine driven test rig. Through comparing with support vector machine (SVM) method, the superiority of the proposed method is verified. Moreover, the impact of different data segments on classification results is analyzed in this paper.**

Keywords—intelligent fault diagnosis, wind turbine gearbox, long short-term memory

I. INTRODUCTION

In response to the problem about energy depletion and environment pollution, wind energy, as a clear and renewable energy, has developed rapidly [1]. However, Due to the time-varying and harsh operating conditions, the damages of wind turbines (WTs) occurs frequently, and the operation and maintenance (O&M) costs remain high [2, 3]. Condition monitoring (CM) and fault diagnosis play a highly significant role in improving the safety and reliability of WTs and reduce the O&M costs for wind farm operators [4, 5]. Gearbox with complex structure is one of the most fragile components of WTs. The gearbox failure accounts for 59% of the total WT failures and causes unexpected downtime as well as economic losses [6]. Therefore, the research of effective CM and fault diagnosis of WT gearbox is significance and critical.

As the vibration signals are a rich source of failure information, the vibration signals are widely employed in most research on fault diagnosis of WT gearbox. The major methods based on vibration signals can be categorized into two classes: traditional methods and intelligent fault diagnosis methods [7, 8]. Traditional methods are based on signal processing methods, which are roughly classified into the following three categories: time-domain analysis, frequency-domain analysis, and time frequency-domain analysis [9]. In traditional methods, the signal processing results under unknown health conditions are compared with those under normal health conditions to identify the fault. There are many papers using these method into fault diagnosis of WT gearbox. The time domain features which are sensitive to the fault, are used to describe condition indicators for gearbox health, such as RMS, Kurtosis, Crest factor etc. Joel et al. [10] used RMS and Peak values of vibration signals as condition indicators for early detection of WT gearbox faults. The frequency analysis methods are used for fault diagnosis in the early researches, such as the Fourier spectrum, Cepstrum analysis etc. As the frequency analysis method is restricted to stationary signals, which is unsuitable for fault diagnosis of WT gearbox [9]. Therefore, many time-frequency analysis methods have been introduced into this area in the last few decades, such as Wavelet analysis [11], Empirical mode decomposition (EMD) [12, 13], and so on. Antoniadou et al. [14] proposed a time-frequency analysis approach for CM wind turbine gearbox based on EMD and the Teager Energy Operator. However, traditional methods depend on high degree of expertise in the specific fields of diagnosis [7, 15]. And it is difficult to exactly to detect the abnormal changes in time domain or frequency domain, especially under strong noise environment [16]. What's more, nowadays, the amount of signals collected by the condition monitoring system is increasing and complex. The traditional methods is not suitable for dealing with massive and complex signals [15]. Therefore, the intelligent fault diagnosis methods attract more and more attention, which are able to improve the drawbacks of the traditional methods.

Generally, the intelligent fault diagnosis method include three main steps: signal acquisition; feature extraction; fault classification [17]. In the step of feature extraction, the fault-sensitive features are extracted and selected from the collected vibration signals based on signal processing technology. The select features have a great influence on the performance of the intelligent fault diagnosis methods. In the step of fault classification, the health conditions are determined based on the extracted features by the intelligent techniques like artificial neural networks (ANN) and support vector machine (SVM). For example, Gao et al. [18] proposed a novel fault diagnosis method based on least squares support vector machine and load mean decomposition multiscale entropy for WTs. However, there are still room for improvements. First, the suitable features are difficult to be selected, because it highly requires extensive domain expertise and prior knowledge. Second, the common machine learning algorithms rely heavily on well-selected features, and also limit on amounts to training data. Deep learning attracts growing attention due to the powerful ability of feature learning and the advantage of dealing with big data. As the operating time is relatively long for gearbox, the temporal dependent nature of faulty is common. However, the standard deep learning methods can only learn short temporal dependent characteristic. LSTM shows great advantage of learning long-term temporal dependency characteristic for sequential data [19]. Lei et al. [7] used LSTM network for fault diagnosis of wind turbine with input of frequency data. Therefore, an intelligent fault diagnosis method based on long short-term Memory (LSTM) is proposed in this paper. And the common statistical features in time domain are used as the inputs of LSTM networks, which there is no need to select suitable features in this study. The SVM is used as comparison.

The rest of the paper is organized as follows. Section II presents the basic theory of LSTM. Section III shows the proposed intelligent fault diagnosis method. In Section IV, the method is demonstrated using vibration datasets from wind turbine driven test rig. Conclusion are drawn in Section V.

II. BASIC THEORY OF LONG SHORT-TERM MEMORY NETWORKS

LSTM Networks, as a type of recurrent neural networks (RNNs), is proposed by Hochreiter and Schmidhuber [20]. LSTM networks are designed to overcome the previously inherent problems of RNNs, such as vanishing and exploding gradients. As the complex repeating module in the network structure, LSTM network can learn long-term time dependence [19]. The main structure of LSTM networks include an input layer, one or more hidden layers, and an output layer. The number of neurons in the input layer is equal to the number of feature space. The number of neurons in the output layer reflects the output space. The main component of LSMT networks is memory cells. The memory cell has three gates to maintain and adjust its cell state: input gate i_t, output gate o_t and forget gate f_t. The structure of a memory cell is shown in Fig1. The updating equations are given as follows [7, 19, 21]:

$$i_t = \mathrm{sigmoid}(W_i x_t + U_i h_{t-1} + b_i) \quad (1)$$

$$f_t = \mathrm{sigmoid}(W_f x_t + U_f h_{t-1} + b_f) \quad (2)$$

$$o_t = \mathrm{sigmoid}(W_o x_t + U_o h_{t-1} + b_o) \quad (3)$$

$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (4)$$

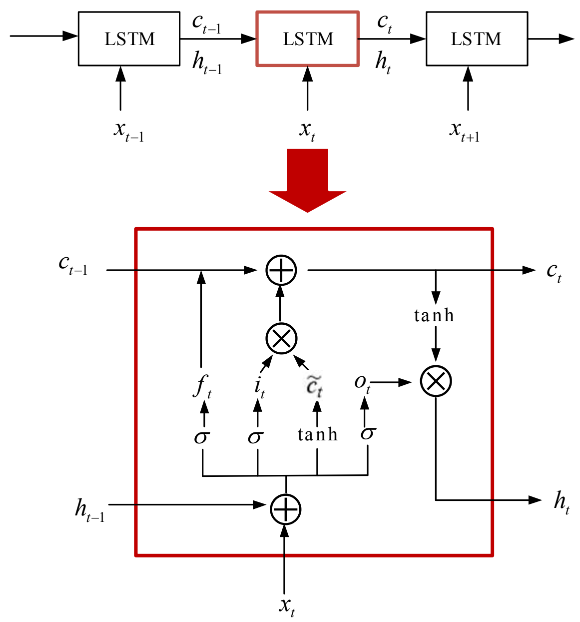


Fig. 1. Structure of LSTM and LSTM memory cell

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (5)$$

$$h_t = o_t \odot \tanh(c_t) \quad (6)$$

Where $x_t \in R^d$ and $h_t \in R^k$ are the input and output of the LSTM unite. $i_t \in R^k$, $f_t \in R^k$, $o_t \in R^k$ are the activation vectors of input gate , forget gate and output gate respectively, all $W \in R^{k\times d}$, $U \in R^{k\times k}$, $b \in R^k$ are learnable parameters and $\odot$ is the element wise multiplication, *sigmoid* is the sigmoid function and tanh is the hyperbolic tangent function.

III. THE PROPOSED FAULT DIAGNOSIS METHOD

The flowchart of the proposed method is shown in Fig. 2, where the SVM is used as comparative method. Vibration data collected from three accelerometers are used in this study. Firstly, the vibration data are divided into several segments. Then, the common statistic time domain features of every data segment are calculated. After that, the model is constructed based on LSTM to diagnosis the health conditions. The common time domain features for vibration signals are shown in Table I. where represent vibration data. In this paper, the ten features are all used to train the model, which avoid choosing the suitable feature selection.

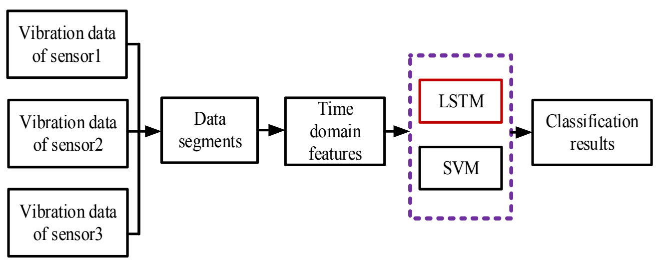


Fig. 2. The flowchart of the proposed method

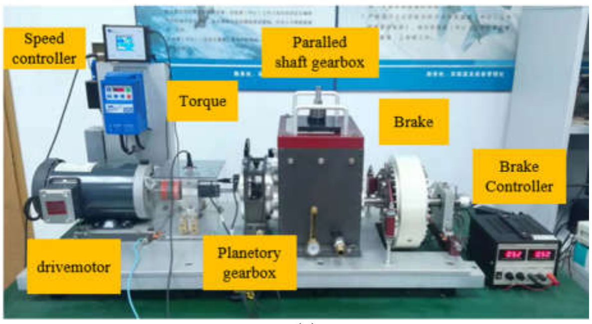
TABLE I. THE COMMON TIME DOMAIN FEATURE

Number	Time domain feature	Calculation formula
1	Mean	$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$
2	RMS	$x_{rms} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$
3	Variance	$\sigma_x^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2$
4	Peak	$x_p = \max(x_i)$
5	Kurtosis	$x_k = \frac{1}{n}\sum_{i=1}^{n} x_i^4 / x_a^2$
6	Skewness	$Sx = \frac{1}{n}\sum_{i=1}^{n}\{x_i^3\}$
7	Peak2Peak	$x_{p2} = \max(x_i) - \min(x_i)$
8	Energy	$E = \sum_{i=1}^{n} x_i^2$
9	Crest factor	$L = x_p / x_r$
10	Shape factor	$K = x_{rms} / \lvert\overline{x}\rvert$

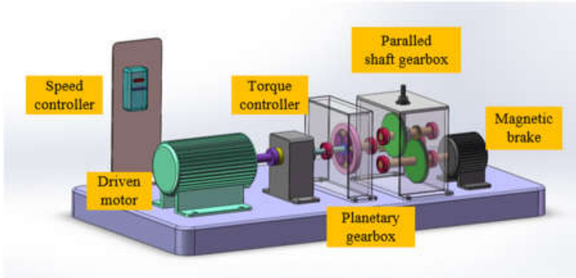
IV. EXPERIMENTAL VALIDATION

A. Description of data from wind turbine driven test rig

The experiments used a wind turbine drivetrain test rig in this paper, which mainly consisted of a driven motor, a torque controller, a one-stage planetary gearbox, a two-stage parallel gearbox and a magnetic brake, as shown in Fig. 3. Vibration signals were collected via three accelerometers (#1, #2, #3). The accelerometers are installed in three directions (horizontal, vertical and radial) in planetary gearbox, which is shown in Figure 4.The sampling frequency is 5120 Hz, and the acquisition time is 60s. The test rig operating condition is at the rotating speed of 35 Hz and the load of 0N.m. In this paper, five health states of sun gear in planetary gearbox were used to validate the diagnostic effect of the LSTM networks, and the details of health states are described in Table II. There are four faulty sun gears and health gear as shown in Fig.5. And the collected vibration signals are shown in Fig.6.



(a)



(b)

Fig.3. (a) Wind turbine driven test rig and (b) its schematic model

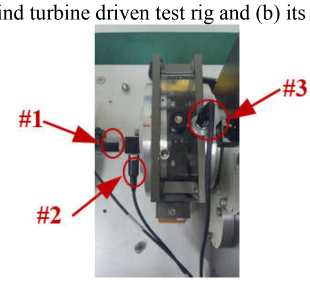


Fig.4.The installed position of accelerometers

TABLE II. THE FIVE HEALTH STATES OF SUN GEAR IN PLANETARY GEARBOX

Health states (sun gear)	Category
Chipped gear	Class 1
Healthy gear	Class 2
Missing gear	Class 3
Root crack gear	Class 4
Surface fault gear	Class 5

Fig.5.The faulty gears

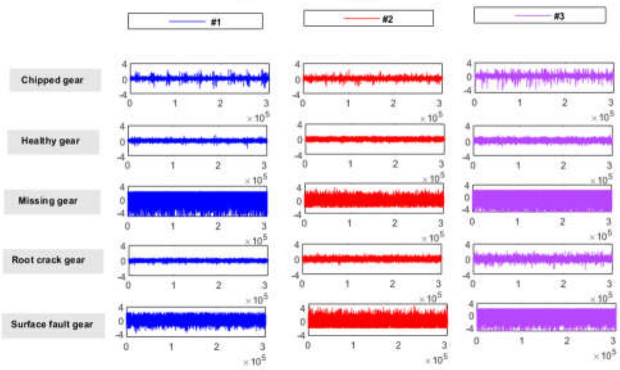


Fig.6.The collected vibration signals of five health states via three accelerometers

TABLE III. THE DETAIL OF TRAINING AND TESTING SETS

Data split	Health states	Size
Train	Class 1/2/3/4/5	10*90/10*90/10*90/10*90/10*90
Test	Class 1/2/3/4/5	10*90/10*90/10*90/10*90/10*90

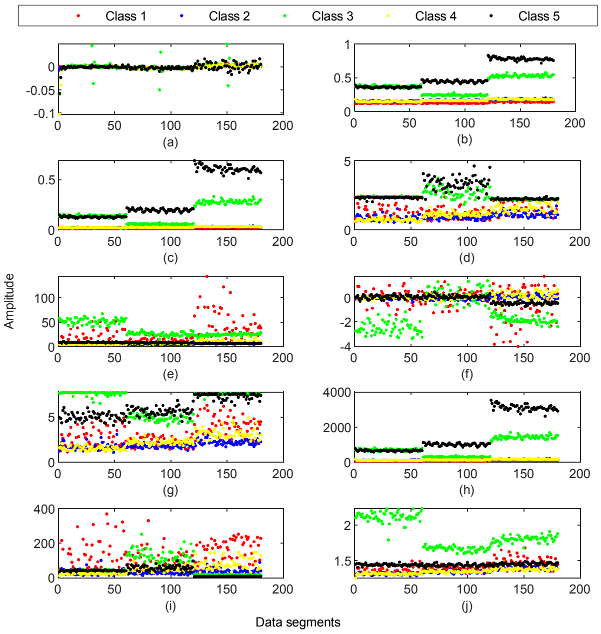


Fig.7. The ten time domain featrues of five health states: (a) Mean (b) RMS (c) Variance (d) Peak (e) Kurosis (f) Skewness (g) Peak2Peak (h) Energy (i) Crest factor (j) Shape factor

TABLE IV. THE MODEL PARAMETERS OF LSTM

Layer	Type	Variable and dimensions
1	Sequence Input	10 dimensions
2	BiLSTM	100 hidden units
3	Fully Connected	5 fully connected layer
4	Softmax	5 outputs
5	Classification Output	crossentropyex

B. *Experimental results and discussion*

- *Fault diagnosis with the proposed method*

As shown in Fig.2, vibration signals of three accelerometers are fused and divided in to data segments. Here, 5120 sample points are selected as a segment. Thus, there are 3*60=180 data segments for every health state and there are 900 segments in total. Then, ten time domain features of every segment are calculated. The features are shown in Fig.7. In this paper, half of the data segments in every health state are randomly selected, the ten time domain features of these segments are as the training set, and the features of rest segments are as the testing set. The details of the training and testing sets are shown in Table III. The model parameters of the LSTM are shown in Table IV.

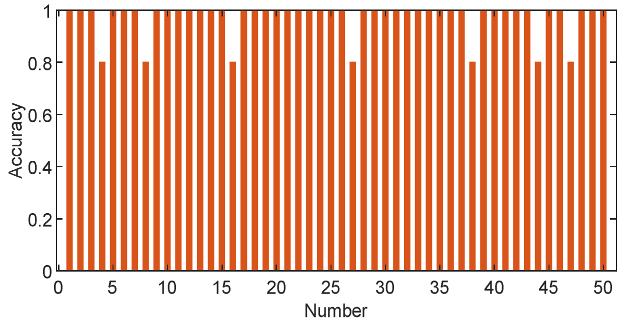


Fig.8. The classification accuracy of the proposed method

To ensure the reliability of the results, the method was repeated 50 times. The classification accuracy of the proposed method is shown in Fig.8. The mean classification accuracy is as high as 97.2%. The results indicate that the proposed method has superior performance in fault diagnosis of gearbox. As comparisons, different numbers of sampling points are also chosen as a data segment to do this research. The detail and classification results are shown in Table V. As the number of points in a segment decreases, the classification accuracy improves slightly, but at the same time, the running time increases.

- *Comparision with SVM method*

The Fig.9 is the classification accuracy of the SVM with input of ten time domain features, and the mean classification accuracy of the SVM is about 20.2%. Therefore, the proposed method has better effectiveness of fault diagnosis than using SVM. As Fig.7and Fig.10 shown, compared with other features, RMS values remain stable in every health state, moreover, there are different RMS values in different states. Thus, RMS of accelerometer #2 is selected as the input of SVM method for fault diagnosis. The classification results show in Fig.11.the mean accuracy is about 84.2%. It demonstrates that SVM relies on well-selected feature heavily.

Above all, compared with SVM method, the proposed method has superior performance on fault diagnosis of gearbox, and has no requirement for well-selected features.

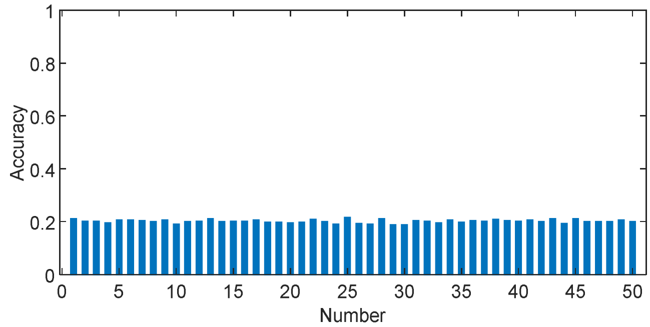


Fig.9. The classification accuracy of the SVM with ten time domain features

TABLE V. THE DETALL AND CLASSIFICATION RESULTS WITH DIFFERENT NUMBER OF SAMPLE POINTS PER SEGMENT

Number of points per segment	Training/testing sets	Mean classification accuracy	Mean running time (s)
1280	Class 1/2/3/4/5 10*360/10*360/10*360/10*360/10*360	0.984	48
2560	Class 1/2/3/4/5 10*180/10*180/10*180/10*180/10*180	0.976	31
5120	Class 1/2/3/4/5 10*90/10*90/10*90/10*90/10*90	0.972	12
10240	Class 1/2/3/4/5 10*45/10*45/10*45/10*45/10*45	0.936	5

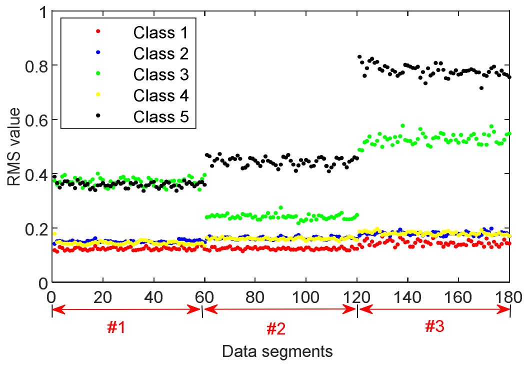


Fig.10. The RMS feature in different health states

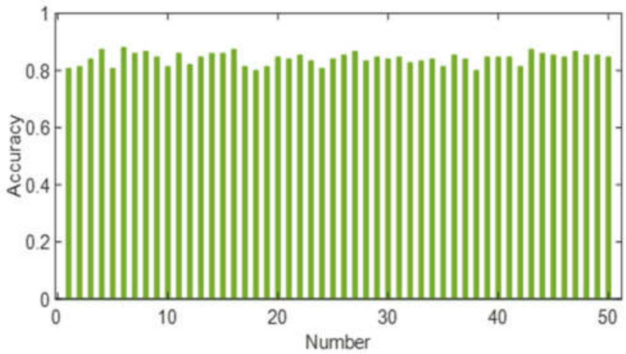


Fig.11. The classification accuracy of the SVM with the RMS feature

V. CONCLUSION

In this paper, an intelligent fault diagnosis method is proposed for wind turbine gearbox based on LSTM networks. The common time domain features are taking as input of LSTM networks instead of selecting suitable feature as the input. The effectiveness of the proposed method is validated by multi-accelerometers vibration data in wind turbine driven test rig. The diagnostic results show that the classification accuracy of the proposed method is much higher than that of the SVM. Thus, the proposed method has superior performance in fault diagnosis and does not rely on well-selected features. Moreover, different numbers of sampling points are chosen as a data segment to do this research. As the number of points in a segment decreases, the classification accuracy may improve slightly, but at the same time, the running time increases. Despite presenting better results, the proposed method also can be improved. Frist, the parameters of LSTM can be optimized. What's more, the LSTM can learn features directly from the raw vibration signals. These will be the future work.

ACKNOWLEDGMENT

This paper is supported by the National Nature Science Foundation of China with grant number 61573046 and the Program for Changjiang Scholars and Innovative Research Team in University (grant number IRT1203).

REFERENCES

[1] Li, Y., S. Liu and L. Shu, Wind turbine fault diagnosis based on Gaussian process classifiers applied to operational data. Renewable Energy, 2019. 134: p. 357-366.

[2] Liu, W.Y., et al., The structure healthy condition monitoring and fault diagnosis methods in wind turbines: A review. Renewable and Sustainable Energy Reviews, 2015. 44: p. 466-472.

[3] Lu, B., et al. A review of recent advances in wind turbine condition monitoring and fault diagnosis. 2009: IEEE.

[4] Gao, Q.W., et al., A novel wind turbine fault diagnosis method based on intergral extension load mean decomposition multiscale entropy and least squares support vector machine. Renewable Energy, 2018. 116: p. 169-175.

[5] Stetco, A., et al., Machine learning methods for wind turbine condition monitoring: A review. Renewable Energy, 2019. 133: p. 620-635.

[6] Wang, L., et al., Wind Turbine Gearbox Failure Identification With Deep Neural Networks. IEEE Transactions on Industrial Informatics, 2017. 13(3): p. 1360-1368.

[7] Lei, J., C. Liu and D. Jiang, Fault diagnosis of wind turbine based on Long Short-term memory networks. Renewable Energy, 2019. 133: p. 422-432.

[8] Lei, Y., 1 - Introduction and background, in Intelligent Fault Diagnosis and Remaining Useful Life Prediction of Rotating Machinery, Y. Lei, Y. Lei^Editors. 2017, Butterworth-Heinemann. p. 1-16.

[9] Lei, Y., 2 - Signal processing and feature extraction, in Intelligent Fault Diagnosis and Remaining Useful Life Prediction of Rotating Machinery, Y. Lei, Y. Lei^Editors. 2017, Butterworth-Heinemann. p. 17-66.

[10] Igba, J., et al., Analysing RMS and peak values of vibration signals for condition monitoring of wind turbine gearboxes. Renewable Energy, 2016. 91: p. 90-106.

[11] Fan, X. and M.J. Zuo, Gearbox fault detection using Hilbert and wavelet packet transform. Mechanical Systems and Signal Processing, 2006. 20(4): p. 966-982.

[12] Chen, J., et al., An integrated method based on CEEMD-SampEn and the correlation analysis algorithm for the fault diagnosis of a gearbox under different working conditions. Mechanical Systems and Signal Processing, 2018. 113: p. 102-111.

[13] Liu, H., et al., Fault diagnosis of gearbox using empirical mode decomposition and multi-fractal detrended cross-correlation analysis. Journal of Sound and Vibration, 2016. 385: p. 350-371.

[14] Antoniadou, I., et al., A time–frequency analysis approach for condition monitoring of a wind turbine gearbox under varying load conditions. Mechanical Systems and Signal Processing, 2015. 64-65: p. 188-216.

[15] Lei, Y., 3 - Individual intelligent method-based fault diagnosis, in Intelligent Fault Diagnosis and Remaining Useful Life Prediction of Rotating Machinery, Y. Lei, Y. Lei^Editors. 2017, Butterworth-Heinemann. p. 67-174.

[16] Chen, R., et al., Intelligent fault diagnosis method of planetary gearboxes based on convolution neural network and discrete wavelet transform. Computers in Industry, 2019. 106: p. 48-59.

[17] Jing, L., et al., A convolutional neural network based feature learning and fault diagnosis method for the condition monitoring of gearbox. Measurement, 2017. 111: p. 1-10.

[18] Gao, Q.W., et al., A novel wind turbine fault diagnosis method based on intergral extension load mean decomposition multiscale entropy and least squares support vector machine. Renewable Energy, 2018. 116: p. 169-175.

[19] Yang, R., et al., Rotating Machinery Fault Diagnosis Using Long-short-term Memory Recurrent Neural Network. IFAC-PapersOnLine, 2018. 51(24): p. 228-232.

[20] S. Hochreiter, J. Schmidhuber, Long Short-term Memory, Springer Berlin Heidelberg, 1997.

[21] Zhang, J., et al., Long short-term memory for machine remaining life prediction. Journal of Manufacturing Systems, 2018. 48: p. 78-86