Research on Fault Diagnosis Method of Wind Turbine Bearing Based on Deep belief Network

Liang Wang¹, *, Yuanyuan Ma² and Xiaoming Rui¹

¹School of Energy, Power and Mechanical Engineering, North China Electric Power University, Beijing, China
²School of Electrical and Electronic Engineering, North China Electric Power University, Beijing, China

*Corresponding author e-mail: wlhuadian@163.com

Abstract. Bearings of wind turbines have become one of the components with high failure rate in wind turbines because of their bad operating environment. In this paper, a fault diagnosis model based on deep belief network is proposed for bearing fault diagnosis of wind turbine. The time-frequency spectrum of wind turbine bearing vibration data after short-time Fourier transform (STFT) is used as the input of fault diagnosis model, and the output is the identification code of various fault types of wind turbine bearing. Compared with the deep belief network diagnosis model based on the time domain signal input to the vibration data of wind turbine bearings, the deep belief network fault diagnosis model based on the short-time Fourier transform of the input signal has higher recognition accuracy. Based on the vibration data of different working conditions and rotating speeds, the model can automatically find fault features and identify the faults of rolling elements, inner rings and outer rings of rolling bearings at different locations, thus avoiding expert experience and feature engineering, making the model more versatile and generalizable and potential for efficient on-site rolling bearing fault diagnosis.

1. Introduction

All manuscripts must be in English, also the table and figure texts, otherwise we cannot publish your paper. Please keep a second copy of your manuscript in your office. When receiving the paper, we assume that the corresponding authors grant us the copyright to use the paper for the book or journal in question. Should authors use tables or figures from other Publications, they must ask the corresponding publishers to grant them the right to publish this material in their paper.

Wind power as a renewable and clean energy is rapidly developing in countries around the world. Bearing as one of the basic components of a wind turbine. As one of the basic components of wind turbines, bearings have the advantages of high efficiency, low frictional resistance, simple assembly and easy lubrication. They are widely used in wind turbine drive chain systems [1]. However, wind turbines are often subject to frequent changes in temperature, air pressure, wind speed and load, which makes the rolling bearing failure rate high, which seriously affects the safe and stable operation of the unit.
At present, a lot of researches have been carried out for wind turbine fault diagnosis at domestic and abroad. For the fault of the transmission chain, vibration state analysis and modal analysis are mainly used. The vibration state detection mainly collects the vibration data of each component of the wind turbine, and comprehensively uses signal analysis methods such as frequency analysis, envelopment analysis and wavelet analysis to find the fault features contained in the vibration signal.

Yang Binyuan proposed to eliminate noise and other disturbances in the vibration signal of wind turbine based on wavelet transform, and use the combination of time domain and frequency domain to diagnose faults. Zhao Hongshan proposed combining MCKD with EMD and using MCKD algorithm to filter noise to reduce the impact on EMD. Chacon et al proposed a wavelet transform denoising method with very low signal-to-noise ratio. The Hilbert transform and autocorrelation function are used to extract the envelope to find the pattern in the signal for fault location of the bearing. Z Feng et al proposed a time-frequency analysis fault diagnosis method based on Kalman filter for the non-stationary failure of wind turbine epicyclic gearboxes. Wang Hongbin proposed a state monitoring method based on deep belief network to monitor the working state of the main bearing in real time. By selecting appropriate modeling variables, the DBN-based main bearing temperature prediction model was established.

Although vibration detection and modal analysis have been applied in the fault diagnosis of wind turbine rolling bearings, due to the complicated operating conditions of wind turbines, the above methods rely too much on expert experience and feature engineering, resulting in poor versatility and generalization. This paper proposes an intelligent diagnosis method based on deep belief network, which can better and more flexibly characterize the running state of wind turbine rolling bearings.

2. DBN

Deep Belief Networks (DBN) is a deep neural network stacked by a series of RBM. Deep Belief Network uses layer-by-layer training to optimize network parameters, the training of the whole network structure includes pre-training and optimization. Firstly, each restricted Boltzmann machine is trained step by step through unsupervised training stage, and the network weights and biases obtained are taken as initial values. Then, in the process of supervised training, the weights of the whole network are fine-tuned by the back propagation algorithm of back propagation neural network to obtain better network performance. It solves the problem that the traditional neural network training method is not suitable for multi-layer network training, effectively avoids the network falling into local optimum, and improves the effectiveness of network convergence. Figure 1 shows the Deep Belief Network structure.
2.1. RBM
Deep Belief Network is a deep network structure formed by multiple restricted Boltzmann machines (RBM) stacking layer by layer. Through deep data mining to extracts important information and key features. RBM includes two layers: hidden layer and visible layer. The hidden layer and the visible layer are connected in two directions. The RBM structure is shown in Figure 2.

Assuming that RBM has i visual nodes and j hidden nodes, if V is all visible layer neurons and H is all hidden layer neurons, \( h_j \) is the j-th hidden layer neuronal state, and \( v_i \) is the i-th visual layer neuronal state, the offset of visual node \( v = (v_1, v_2, ..., v_i) \), the offset of hidden node \( h = (h_1, h_2, ..., h_j) \), then the energy formula of a given RBM structure is:

\[
E(v, h) = -\sum_{i=1}^{l} \sum_{j=1}^{l} w_{ij} v_i h_j - \sum_{i=1}^{l} b_i v_i - \sum_{j=1}^{l} a_j h_j
\]

In the formula: \( w_{ij} \) is the weight between the visible layer \( v_i \) and the hidden layer \( h_j \), \( a_j \) and \( b_i \) is the bias between the visible layer and the hidden layer.

2.2. DBN training
Deep Belief Network is composed of deep neural of multi-layer restricted Boltzmann machine and single-layer backpropagation (BP) neural network. There are connections between layers and layers of neurons, but there are no connections between each neurons in the same layer. Deep Belief Network uses layer by layer greedy learning algorithm to optimize the connection weight of neural network. Its training model steps are divided into pre-training process and fine-tuning process.

2.2.1. pre-training. DBN is stacked by several RBM stacks, and each layer of RBM network is trained unsupervised by learning rules of RBM to ensure that when feature vectors are mapped to different feature spaces, and as much feature information as possible is retained, thus completing the training of the whole model. Each RBM is a two-layer model, each layer is composed of multiple neurons, and there are no prominent links in the same layer. Therefore, the main training parameters considered in the training process of RBM are the weights between layers. In addition, the parameters of RBM also include visible layer offset and hidden layer offset, the training process uses S-shape transformation with logarithmic likelihood function to transform data from one layer to another. Its expression is as follows:

\[
p(S_i = 1) = \frac{1}{1+e^{-\beta S_i - b_i}}
\]

In the expression: \( S_i \) and \( b_i \) are namely the states and the biases of i neurons in the hidden layer; \( S_j \) are the states of the j-th in the visible layer; \( w_{ij} \) are the weights between the visible layer \( v_i \) and the hidden layer \( h_j \).

Initialize the weights and biases of RBM neurons in each layer, and then update the weights after training a batch of data by iteration with input data. The state of neurons in RBM hidden layer is determined by transforming the state of neurons in visible layer into corresponding weights and the deviation of neurons in hidden layer with transformation function.

2.2.2. fine tuning. In the last layer of DBN, BP network is used for reverse fine tuning learning, RBM output eigenvector is used as its input vector, to implement supervised back propagation training.

Each layer of RBM network can only ensure that the weights of its own layer are optimal for the feature vectors of that layer, but not for the whole DBN network. Therefore, the supervised learning process further reduces the training error and improves the classification accuracy of the DBN classification model. The DBN training method is shown in Figure 3.
Figure 3. DBN training method

3. Bearing Fault Diagnosis Based on Deep Belief Network

3.1. Establishment of bearing data samples

At present, the vibration data of each component of the wind turbine is basically in the hands of the manufacturer. The wind farm operation data has only eigenvalues such as the mean value and maximum value of ten minutes, and there is no spectrum feature, which is not suitable for fault diagnosis.

In order to simulate the bearing vibration data of wind turbines under different working conditions, and verify the effectiveness and robustness of the deep neural network model. This paper uses the bearing damage test of the Case Western Reserve University Electrical Engineering Laboratory to disclose the vibration data, and mix the samples of the test bearing under different loads and different damage levels. The sample set is marked according to the fault location. The data of each type of state contains bearing vibration data of different speeds, loads and various fault levels.

The data set uses SKF6205-2RS deep groove ball bearing as the test bearing, and simulates the bearing fault with EDM single point damage. The severity of the fault is simulated by the diameter of the damage. The diameter of the damage is 0.1778 mm, 0.3556 mm, 0.5334 mm, 0.7112 mm. Fault location is inner ring fault, rolling element fault, outer ring fault. The damage point of the outer ring is at the clock: 3 different positions at 3 o'clock, 6 o'clock, and 12 o'clock. An acceleration sensor is placed above the bearing supports to collect the vibration acceleration signal of the faulty bearing. The vibration signal is acquired by a 16-channel data loggers with a sampling frequency of 12 kHz. After the data is collected, the original data is divided at intervals of 0.12s to obtain a sample set with a sample size of 14410 and a dimension of 1000. Figure 4 shows a time domain diagram of the vibration signals for different state categories. After obtaining the vibration data samples of different states, the sample data is subjected to short-time Fourier transform to obtain the time-frequency spectrum of each state sample.
In this paper, the short-time Fourier transform of the sample data requires the use of the specgram function in the Scipy library in Python. Using the Hamming window, the short-time Fourier transform has a length of 100 points, the number of overlapping samples per segment is 64, and the sampling frequency is 1200HZ. Figure 5 shows the amplitude spectrum obtained by performing short-time Fourier transform on various state samples. The abscissa is the time domain and the ordinate is the frequency domain. The spectrum dimension of each sample is $51 \times 26$.

Figure 4. Sample type of rolling bearing

Figure 5. Spectra of a sample of a rolling bearing
3.2. Deep belief network based on time-frequency spectrum input

3.2.1. Bearing fault identification verification. In this paper, the deep confidence network model is used, which is composed of three layers of restricted Boltzmann machines. The number of neurons in each layer is 400, 200, 100 respectively. The activation function uses sigmoid function for a total of 10 batches. The batch size is 32. The input to the deep belief network is the time-frequency spectrum of the bearing vibration signal via the short-time Fourier transform. The training batch is 100 and the size of each batch is 32. The last layer is the output layer, and the bearing vibration signal is output by the Softmax activation function as the state identification code of the six bearings.

Step verification and test steps are as follows:

1) The short-time Fourier transform is performed on the sample data of different categories. The short-time Fourier transform uses the speogram function in the Scipy library in Python. It uses a Hamming window and smoothly moves on the time axis. The transform length is NFFT=100. The number of overlapping samples per segment is noverlap=50, and the sampling frequency is Fs=1200Hz, the spectrum of each sample will be obtained and normalized.

2) Invoking the train_test_split function in Python to divide the sample data into 75% training set and 25% test set.

3) The 75% training data set is input into the deep confidence network for training. The training batch of each layer of the restricted Boltzmann machine is 10, the size of each batch is 32; the training batch of the entire deep belief network is 100, the size of each batch is 32.

4) The 25% test data set was tested and classified, and the test accuracy was 98.81%. The confusion matrix of the classification results is shown in Table 1. The accuracy and recall rate of the six bearing states are shown in Table 2.

| actual sample | normal signal | rolling element fault | inner ring fault | outer ring 3 faults | outer ring 6 faults | outer ring 12 faults |
|---------------|---------------|-----------------------|-----------------|---------------------|---------------------|----------------------|
| normal signal | 506           | 0                     | 0               | 0                   | 0                   | 0                    |
| rolling element fault | 0             | 808                   | 0               | 5                   | 8                   | 0                    |
| inner ring fault | 0             | 5                     | 830             | 5                   | 10                  | 3                    |
| outer ring 3 faults | 0             | 0                     | 0               | 548                 | 5                   | 5                    |
| outer ring 6 faults | 0             | 2                     | 1               | 20                  | 531                 | 0                    |
| outer ring 12 faults | 0             | 0                     | 7               | 2                   | 2                   | 334                  |

Table 1 shows the number of samples corresponding to the actual sample and the diagnostic sample. As shown in Table 4-1, there are 506 normal data, and the same quantity is reached after diagnosis. There are 821 rolling element fault data, 808 data after diagnosis is correctly classified, 5 data errors are classified as outer loop fault of position 3, and 8 data errors are classified as outer loop fault of position 6. There are 853 inner ring fault data, of which 830 are correctly classified, 5 data errors are classified as rolling element faults, 5 data errors are classified as position 3 outer ring faults, and 3 data errors are classified as position 12 outer ring faults. There are 559 outer ring fault data in position 3 and 548 in the classified classification to achieve correct classification. 5 data errors are classified as outer ring faults in position 6, and 5 data errors are classified as outer ring faults in position 12. There are 554 data of outer ring faults in position 6, 531 pieces are correctly classified after diagnosis, 2 data errors are classified as rolling element faults, 1 data error is classified as inner ring faults, and 20 data errors are classified as outer ring faults of position 3. There are 345 outer ring faults in position 12, 334 data are correctly classified after diagnosis, 7 data errors are classified as inner ring faults, 2 data errors are
classified as outer ring faults in position 3, and 2 data errors are classified as Outer ring fault in position 6.

**Table 2.** Accuracy and recall of identification results

|                  | norml signal | rolling element fault | inner ring fault | outer ring 3 faults | outer ring 6 faults | outer ring 12 faults |
|------------------|--------------|------------------------|------------------|---------------------|--------------------|----------------------|
| accuracy rate    | 100%         | 99.14%                 | 99.06%           | 94.81%              | 95.5%              | 97.66%               |
| recall rate      | 100%         | 98.42%                 | 97.3%            | 98.21%              | 95.85%             | 96.81%               |

Model convergence. The change of the correct rate on the training set and the verification set as the number of iterations increases during the training process is shown in Figure 6. During the training process, the model did not have serious over-fitting phenomenon. During the whole training process, in the early stage of training, the correct rate of the verification set was slightly higher than that of the training set. After 20 times, the correct rate of the training set and the verification set was basically reach the same level. The transformation of the loss function with the increase of the number of iterations during the training is shown in Figure 7. It can be seen from the figure that the convergence of the algorithm is better, and it has already converged on the training set for about 20 times. As the number of iterations increases, the fluctuation of the loss function does not change much.

![Figure 6. Correctness Curve of Training Set and Verification Set](image)

![Figure 7. Change Curve of Loss Function](image)
3.3. Deep belief network based on time domain signal input

3.3.1. Bearing fault identification verification. The bearing vibration time domain signal data sample is divided into a 75% training set and a 25% test set. The 75% of the training data set is imported into the deep confidence network for training. Each layer of restricted Boltzmann machine training batch is 10 and the size is 32, the entire deep belief network training batch is 100, the size is 32. The 25% of the test data sets is tested and classified, and the test accuracy is 63.4%. The accuracy and recall rate of the six bearing states are shown in Table 3

|                  | normal signal | rolling element fault | inner ring fault | outer ring 3 faults | outer ring 6 faults | outer ring 12 faults |
|------------------|---------------|-----------------------|-----------------|---------------------|---------------------|----------------------|
| accuracy rate    | 100%          | 65.53%                | 54.63%          | 62.79%              | 50.91%              | 47.54%               |
| recall rate      | 98.7%         | 50.95%                | 56.85%          | 49.7%               | 61.25%              | 41.26%               |

3.3.2. Bearing fault identification verification. The change of the correct rate and the change of the loss function on the training set and the verification set with the increase of the number of iterations during the training process are shown in Figure 8 and Figure 9. During the training process, the training accuracy is much higher than the test accuracy, and the whole model training process not only does not converge, but also has large fluctuations.

![Figure 8. Correctness Curve of Training Set and Verification Set](image8.png)

![Figure 9. Change Curve of Loss Function](image9.png)
4. Conclusion
This paper proposes a fault diagnosis method for wind turbine bearings based on deep confidence network. It uses the excellent feature extraction ability and powerful fine-tuning mechanism of deep confidence network, and the input signal is the time spectrum of short-time Fourier transform. The bearing diagnosis shows high precision. This method not only has excellent diagnostic performance, but also avoids feature engineering and expert experience, and is more versatile.

Acknowledgments
In the process of writing the paper, I thank my teacher, Professor Xiaoming Rui, for giving me great help and support. Whenever I ask my teacher when I encounter difficulties, the teacher will take time out of his busy schedule to guide me and express my sincere gratitude to my teacher, Professor Xiaoming Rui.

References
[1] Feng Z, Chen X, Liang M. Iterative generalized synchrosqueezing transform for fault diagnosis of wind turbine planetary gearbox under nonstationary conditions[J]. Mechanical Systems and Signal Processing, 2015, 52—53: 360—375.
[2] Azevedo H D M D, Araújo A M, Bouchonneau N. A review of wind turbine bearing condition monitoring: State of the art and challenges[J]. Renewable & Sustainable Energy Reviews, 2016, 56:368—379.
[3] Juan Luis Ferrando Chacon, Vassilios Kappatos, Wamadeva Balachandran, Tat-Hean Gan. A novel approach for incipient defect detection in rolling bearings using acoustic emission technique[J]. Applied Acoustics, 2015, 89.
[4] Zhipeng Feng, Sifeng Qin, Ming Liang. Time–frequency analysis based on Vold-Kalman filter and higher order energy separation for fault diagnosis of wind turbine planetary gearbox under nonstationary conditions[J]. Renewable Energy, 2016, 85.
[5] Wang Hongbin, Wang Hong, He Quan, et al. State monitoring method of main bearing of fan based on deep belief network [J]. China Mechanical Engineering, 2018, 29 (8): 948—953.
[6] Niemann H, Kjolstadpoulsen N, Mirzaei M, et al. Fault diagnosis and condition monitoring of wind turbines[J]. International Journal of Adaptive Control & Signal Processing, 2017, 32(2).
[7] Ye Lang. Face recognition based on convolution neural network [D]. Southeast University, 2015