Study of Intelligence Diagnosis System for Wind Turbine Gearbox Fault

Xiang Ling, Cui Wei*
Department of Mechanical Engineering, North China Electric Power University, Baoding, China 07100
*Corresponding author, e-mail: zycui08@126.com

Abstract
According to the current application and maintenance situation of gearbox of wind turbine, this paper analyzed the remote fault diagnosis system used for monitoring fault occurrence and diagnosing fault, which is a combination of Expert System and Artificial Neural Networks. A practical fault instance of gearbox of wind turbine is analyzed to define the expert system's knowledge base structure and reasoning method. And verify its feasibility in fault diagnosis by using Matlab language.

Keywords: wind turbine, gearbox, expert systems, fault diagnosis

1. Introduction
With the rapid development of China's economy and its increasing demand for energy, the widespread use of wind energy has been a perfect solution to the energy supply [1]. Wind power is the most promising power generation technology and industry, whose cost can be reduced with the fastest speed. Along with the economic development and the technological progress, wind power is becoming an important alternative energy resource in the world.

The gearbox is an important part of the wind turbine structure. The faults of gearbox will inevitably cause the unit to stop running. Therefore, timely and accurate diagnosis of gearbox faults is extremely valuable. Currently, wind turbine fault diagnosis method mainly depends on the SCADA system which can perform dozens of wind turbine's centralized remote monitoring [2-5]. This system continuously and regularly collect and store operating parameters (such as temperature, wind speed, output power, single-point or two-point vibration, etc.) that can be used for wind turbine transmission systems fault alarm and the reliability assessment of the whole wind turbine.

This article describes a wind turbine gearbox intelligent diagnosis system, which is aimed at fault diagnosis of wind turbine gearbox. This system can be applied to alarm of the operating conditions of wind turbine gearbox and diagnosing fault.

2. The Structure of Expert System
The expert system is one of the active research fields in the application of artificial intelligence [6]. It contains a series of computer programs to analog human expert in the decision-making. The basic structure of the expert system block diagram is shown in Figure 1.

3. The Introduction to the Expert System's Knowledge Base Structure and Reasoning Method
3.1. Knowledge Base Structure
The core of the expert system is knowledge; it determines a good or bad performance of the expert system. The knowledge of fault diagnosis expert system is derived from two aspects: (1) natural language literature, such as professional books, journals and gearbox running historical data; (2) gearbox fault diagnosis expert experience, such as diagnosis features parameter selection and monitoring threshold determination. It is shown in Figure 2 that describes gearbox monitoring and fault diagnosis expert system knowledge structure that contains: gearbox structure knowledge layer, signal characteristics knowledge layer and expert inspired knowledge layer.
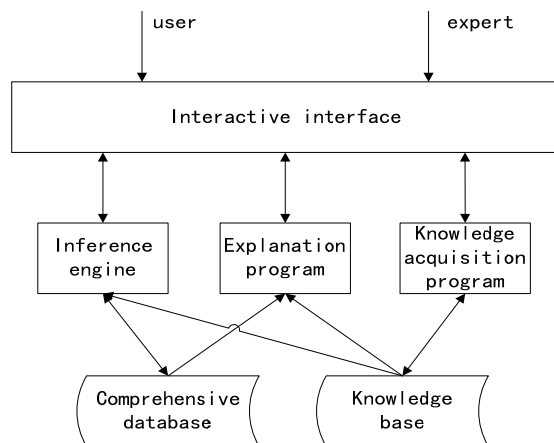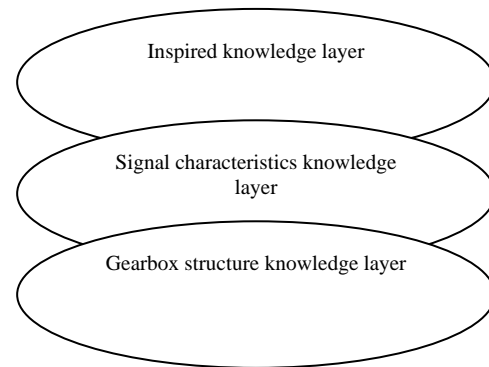
Figure 1. The Basic Structure of the Expert System

Figure 2. Expert System Knowledge Structure

3.2. The Reasoning Methods of the Expert System

The reasoning mechanism comprises a set of computer programs used for coordinating entire expert system. Its reasoning process is applying knowledge. The gearbox fault diagnosis expert system is based on numerical calculation and its reasoning is also based on the numerical calculation. The reasoning mechanism structure is shown in Figure 3.
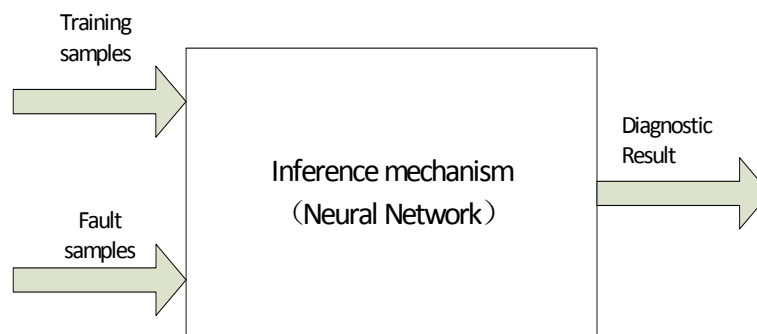

Figure 3.The Structure of Inference Mechanism

After the neural network being trained, it will get the weight values and threshold of each layer. When we input the feature value to be tested, neural network can get the expert diagnostic conclusions. It should be noted that there are large numbers of artificial neural networks of which BP neural network applies to this expert system due to relatively simple network structure and strong pattern recognition capabilities. BP neural network which contains 3 or more than 3 layers can approximate any continuous function in any precision. It has strong nonlinear mapping ability, self-learning ability, self-organizing ability and adaptive ability [8]. Its structure is shown in Figure 4.

The neural network learning process is:

Forward propagation process:

$$y_i = f\left[\sum_{j=1}^{n} w_{ij} x_j - \theta_i\right] \tag{1}$$

Where y_i is the output of each layers, the θ_i is the weight of the i-th layer, the w_{ij} is weight value connecting the j-th node and the i-th node, the F is transfer function.
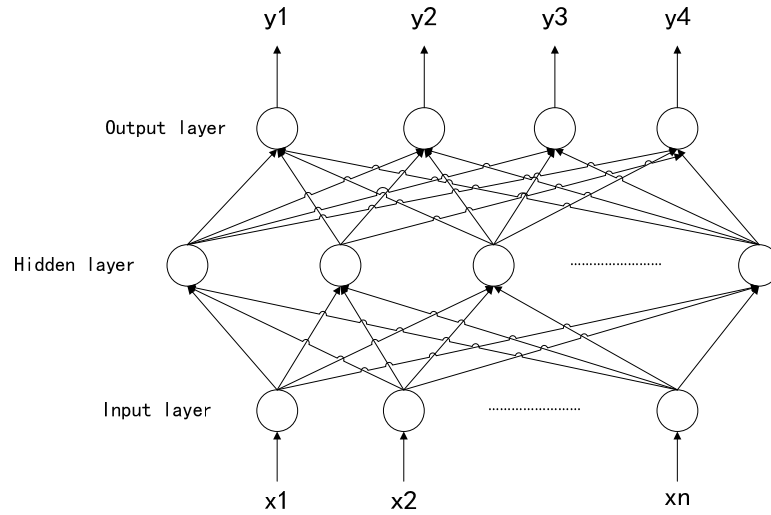
Figure 4. BP Neural Network Model

Error function:

$$E_k = \frac{1}{2}\sum_{j=1}^{n}(y_j^* - y_j)^2 \tag{2}$$

Where y_j^* is the desired output value of the j-th node, the y_j is the actual output value of the j-th node.

Adjust w_{ij} by self-learning to meet $E_k < \varepsilon$. If not, the neural network will make reversed calculation that is called error back propagation process.

$$O_{jk}^1 = f(\sum_{j=1}^{n} w_{ij}^1 x_j) \tag{3}$$

Where O_{jk}^1 is output of j-th node when input k-th sample to hidden layer, x_j is input value of j-th node, w_{ij}^1 is weight value connecting input layer and hidden layer.

$$O_{jk}^2 = f(\sum_{j=1}^{n} w_{ij}^2 O_{jk}^1) \tag{4}$$

Where O_{jk}^2 is output of the j-th node when input k-th sample to input layer, the w_{ij}^2 is weight value connecting input layer and hidden layer.

The correction weight value is:

$$w_{ij}(t+1) = w_{ij}(t) + \mu a_i^k \varepsilon_j^k \tag{5}$$

4. Determination of the Signal Characteristics Knowledge

As we all know, it is the most important part of the gearbox condition monitoring and fault diagnosis expert system to determine the monitoring and fault feature. The main difference between monitoring and fault feature is that monitoring feature value only needs to reflect the abnormal work of the gearbox but fault feature needs to reflect the characteristics of the different fault.

4.1. Determination of the Monitoring Feature based on Kurtosis

Monitoring feature reflects whether the gearbox is normal or not, and it also has the following characteristics: (1) Simple calculation that is aimed to meet the requirements of real-

time monitoring of the expert system. (2) The robustness of the working condition that it is not sensitive to the change in speed and working condition. In this paper, we select kurtosis values as monitoring feature value. Kurtosis index is a dimensionless parameter that is particularly sensitive to impact signal and it has little to do with gearbox's size and rotational speed. It is particularly applicable to the fault of surface damage, especially early fault diagnosis. The formula is:

$$K = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{x_i - \bar{x}}{\sigma_i} \right)^4$$

(6)

Where x_i is signal values, $\bar{x}$ is signal average values, N is sampling length, σ_i is standard deviation.

Calculate the kurtosis values of wind turbine gearbox vibration signal. The calculation results areshown in Table1.

Table1. The Kurtosis Indication Value of Gearbox.

Fault description	1	2	3	4	5	Average
Normal	2.0474	2.1423	1.9865	2.0563	2.1632	2.0791
Gear with face wear	2.5588	3.0892	2.8931	2.9221	3.0594	2.9045
Gear with face pitting	2.9004	3.0458	3.0586	3.0438	3.1139	3.0325
Gear tooth breakage	2.1581	2.2248	2.3254	2.6880	2.4236	2.3640

The average kurtosis indicators of the normal gearbox is 2.0751, but abnormal ones are higher than this value. Therefore, the kurtosis indicators can be used as the monitoring features in this expert system.

4.2. Determination of the Fault Feature Value

It is directly related to the fault identification to select the fault feature that must have good fault separability. Theoretically speaking, the gearbox fault characteristic frequency can be applied to the pattern recognition of fault diagnosis. Such as: the shock pulse will appear whose cycle is the rotational frequency of the gear when the gear teeth has been broken; the rotational frequency and other harmonic frequency vibration amplitude will increase significantly. The spectrum figures of gearbox vibration signal are displayed in the following figure.
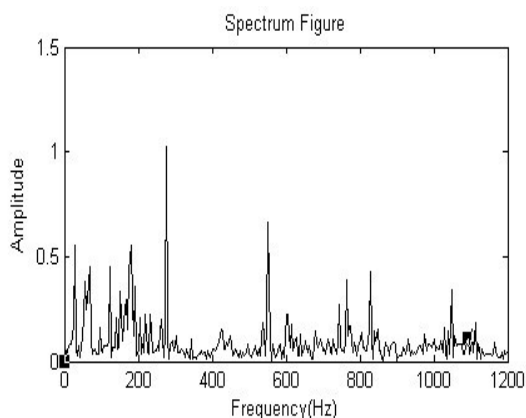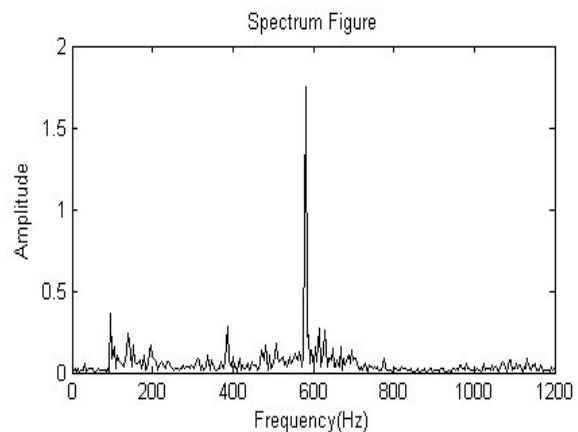

Figure 5. Normal Gearbox

Figure 6. Gear with Face Wear

The vibration signal spectrum structure varies due to the fault state of the gearbox. The energy of the vibration signals of the same frequency band will have a large difference that some band signal energy will be reduced but others may be increased. Therefore, it contains a

wealth of fault information in the frequency band of the vibration signal that can be used for the pattern recognition of the fault. We divide gearbox vibration signal whose frequency is from 0 to 1000 HZ into 10 segments averagely and calculate the energy of each frequency band. Then we get all the energy value normalized.
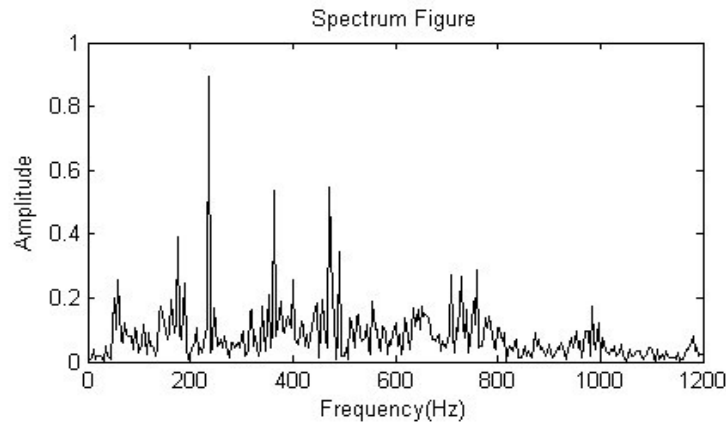

Figure 7. Gear with Face Pitting

$$\mu(x_i) = \frac{x_i - Min(x)}{Max(x) - Min(x)} \qquad i=1,2,3......n \qquad (7)$$

Where the x_i is the vibration energy value of i-th frequency band. The calculation results are shown in Table 2.

Table 2. The Fault Feature Value

Operating condition	1-100 Hz	100-200Hz	200-300Hz	300-400Hz	400-500Hz	500-600Hz	600-700Hz	700-800Hz	800-900Hz	900-1000Hz
Normal	0.0954	0.5864	0.2205	0.2978	0.2601	1.0000	0.5958	0.1526	0	0.026
Face wear	0.6596	1.0000	0.6298	0	0.1626	0.2978	0.3392	0.4137	0.3600	0.1060
Face pitting	0.1915	0.6486	0.5020	0.7948	1.0000	0.3771	0.5884	0.7816	0	0.1219

The normalized value can be taken as the fault feature value. The Figures 8-10 are spectral energy ratio diagrams. Obviously, they can show distinction among the different gearbox faults clearly.
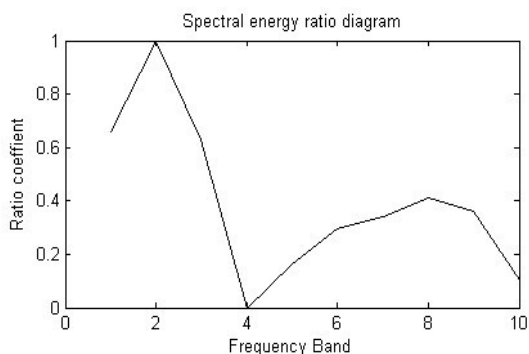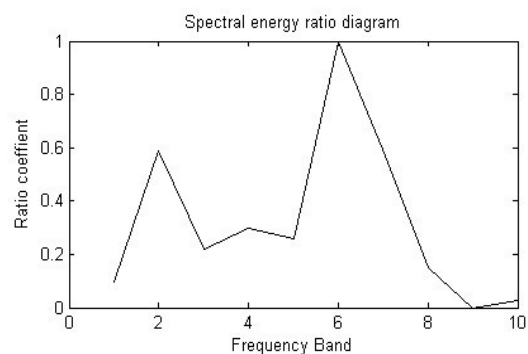

Figure 8. Normal Gearbox
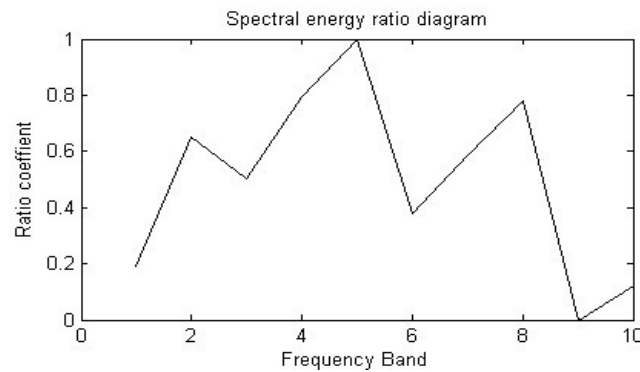

Figure 9. Gear with Face Wear

Figure 10. Gear with Face Pitting

5. Simulation of Intelligent Fault Diagnosis

According to the expert system inference process in former section, combining the fault of the gearbox, the simulation processes are given as,

Step 1, Select the simulated signal

Calculate the Kurtosis Value of wind turbine gearbox. Extract three groups of signal in these signals that the Kurtosis of one group is less than normal value and the others are greater than normal value.

Step 2, Extract characteristic parameters

Extract the fault characteristic parameters from the signals of first step.

Step 3, Train the neural network

Train the neural network whose input node is ten and the output node is three, and its hidden layer nodes are got by empirical formula: $K > \sqrt{m + n} + a$

Where K represents the number of nodes of the hidden layer, m represents the number of output node, n represents the number of input node.

The transfer function of the hidden layer neurons is "tansig" of S-type tangent function, the output layer neuron transfer function is "logsig" of S-type logarithmic function. The training function adopt trainim function, training times are 1000, the learning efficiency is 0.1.

Step 4, Fault diagnosis simulation

The extracted characteristic parameters of Step 2 are input neural network to simulate fault diagnosis. The simulation results are shown in Table 3.

Table 3. The Contrast between Ideal Outputs and Simulation Results

	Ideal outputs			Simulation results			Operating condition
1	1	0	0	0.8905	0.0587	0.0092	Normal
2	0	1	0	0.0103	0.9517	0.0024	Gear with face wear
3	0	0	1	0.0042	0.0476	0.9167	Gear with face pitting

6. Conclusion

In this paper, a fault diagnosis system of wind turbine gearbox based on expert system and artificial neural networks is analyzed. Expert system, which is the best fully-fledged discipline in the field of artificial intelligence, has a low efficiency in reasoning. The artificial neural networks reasoning algorithm, which is used for reasoning mechanism of expert system, is applied to handle the fuzziness and concurrency of fault and inadequate and uncertain information. Utilization of the artificial neural networks' processing ability, visualized graph description and simple matrix operation are applied to realize complicated reasoning process, thus making the diagnostic reasoning decision-making process visualized and simplify. Finally, a practical fault instance of gearbox of wind turbine power is simulated whose diagnostic results verify the feasibility and validity of the neural networks reasoning algorithm.

References
[1] Hongche Guo, Gangqiang Li. *Analysis of Gearbox Fault Diagnosis System of Wind Turbine based on Fuzzy Petri Nets.* International Conference on Fuzzy Systems and Knowledge Discovery. 2012: 540-544.
[2] Amirat Y, Benbouzid M, Al-Ahmar E, Bensaker B, Turri S. A brief status on condition monitoring and fault diagnosis in wind energy conversion systems Renew. *Sust. Energ. Rev.* 2009; 13(9): 2629-2636.
[3] Hameed Z, Hong Y, Cho Y, Ahn S, Song C. Condition monitoring and fault detection of wind turbines and related algorithms: A review Renew. *Sust. Energ. Rev.* 2009; 13(1): 1-39.
[4] Barszcz T, Randall R. Application of spectral kurtosis for detection of a tooth crack in the planetary gear of a wind turbine Mech. *Syst. Signal Pr.* 2009; 23(4): 1352-1365.
[5] XL An, DX Jiang, SH Li, J Chen. *Fault diagnosis of direct-drive wind turbine based on support vector machine.* The 9th International Conference on Damage Assessment of Structures. 2009.
[6] Huang xiquan Yao zhuting. The Study on Expert System about State Monitoring and Fault Diagnosis of the Gearbox. North University of China. 2006.
[7] Xiukun Wei. Lihua Liu. Fault Detection of Large Scale Wind Turbine Systems. The 5th International Conference on Computer Science & Education. 2010: 1299-1304.
[8] N Saravanan, VNS Kumar Siddabattuni, KI Ramachandran. Fault diagnosis of spur bevel gear box using artificial neural network (ANN) and proximal support vector machine. *Journal of Applied Soft Computing.* 2010: 344–360.
[9] Wei X, Verhaegen M. *Sensor Fault Diagnosis of Wind Turbines for Fault Tolerant.* Proceedings of the 17th World Congress the International Federation of Automatic Control, Seoul, Korea. 2008.
[10] Na Chen, Shaopu Yang, Cunzhi Pan. Application of Fault Detection based on Hybrid Intelligent Methods. *TELKOMNIKA*. 2012: 2020-2026.
[11] Selvam K. *Individual Pitch Control for Large scale wind turbines, a Multivariable Control Approach.* Technical Report ECN-E07-053, ECN Petten. Netherlands. 2007.
[12] Verbruggen TW. Wind Turbine Operation and Maintenance based on Condition Monitoring. Technical Report, ECN-C–03-047. *The Energy Center of the Netherlands.* 2003.
[13] Xuexia Liu. Study on Knowledge -based Intelligent Fault Diagnosis of Hydraulic System, *TELKOMNIKA*. 2012: 2041-2046.
[14] Verdult V. Feasibility Study on the Application of Model-Based Fault Detection and Controller Reconfiguration for Wind Turbines. Technical Report, Delft University of Technology. 2002.