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Fault diagnosis system of wind turbine gearbox based on GRNN and fault tree analysis[1]

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Abstract. The gearbox fault diagnosis system based on General Regression Neural Network (GRNN) and fault tree analysis method are studied. We collected the fault information accumulated during the maintenance procedure of gearbox, drew the fault tree, and put forward the gearbox diagnosis method that integrates the fault diagnosis expert system based on fault tree diagnosis and GRNN-based fault diagnosis system. Moreover, we analyzed the vibration signal without faults, gear wearing and teeth-breaking within time and frequency domains, we extracted five characteristic parameter as the input of GRNN and train of the network, established the recognition model of gearbox fault situation based on GRNN, and detected the diagnosis model of GRNN with the reserved signals. The diagnosis result was in conformity with the practical operation, so that the research and development of the gearbox fault diagnosis system has been realized through integrating GRNN model and NET development platform. This fault diagnosis system can recognize different conditions accurately and effectively, then diagnose them quickly and put forward expert solutions.

Key words. GRNN, fault tree analysis, wind turbine gearbox, fault diagnosis.

1. Introduction

Owing to the rapid development of wind turbine industry, fault diagnosis of wind turbine gearbox has always been addressed by the analysis of maintenance staff relying on their experience [1, 2]. The time required for this process is long and the accuracy is low [3]. During the process, the time for addressing the fault accounts for 70 %–90 % of the whole process, whereas the time for maintenance accounts for only 10 %–30 %.

The structure of wind turbine gearbox is complicated, with many subjects involved, so that it is difficult to conduct fault reasoning. Therefore, to relieve the burden of operating and maintenance crew, it is quite necessary to improve the ac-

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curacy and rapidity of analysis and judgment, as well as to develop a fault diagnosis system that special to the gearbox. Given this, fault diagnosis expert system can be applied to the wind turbine gearbox to diagnose the fault in time and propose reasonable solutions. We also study the experience from other wind turbine enterprises and try to apply fault diagnosis expert system to the design of gearbox fault diagnosis system. We diagnose the fault of gearbox by integrating the fault tree analysis method with GRNN.

2. Literature review

The fault diagnosis technology of wind turbine gearbox comes from the mechanical fault diagnosis technology, and it will be connected with artificial intelligence technology more and more closely. The present research on the gearbox fault is mainly to detect the operation of the rotor of the wind turbine. The diagnosis is achieved by analysis of the vibration signal spectrum [4]. Howlet et al. [5] proposed a fault diagnosis system of velocity transducers. The signal processing of this system adopts the methods of momentum regression for neural networks and multi-signals processing as well as Fourier variation method. It has been put into use. Moreover, Amirat et al. [6] summarized the monitoring technologies of wind turbine. Zaher et al. [7], through comparing the different research data from three countries, keep the opinion that the most important part of the wind turbine generator system is the gearbox, and also put forward that the operating condition can be accessed by the condition monitoring technologies. Moreover, there are some researches at home that analyze the vibration signals of the main axis and gearbox of wind turbine with the methods like wavelet transform and frequency spectrum analysis. They compare the spectrum under normal and abnormal situations, find out the change of the frequency spectrum and then address the reason and position of the fault [8]. As a result, we try to apply expert system and neural network to the fault diagnosis of wind turbine gearbox.

3. Research method

3.1. Fault tree analysis

The fault tree analysis is an interpretation method that refines the reasons for the system fault in dendritic graph progressively [9]. The fault tree analysis method analyzes the possible factors of system fault, draws the fault tree, and refines the fault events in a dendritic shape. Thus, it addresses the reasons and the probability of occurrence, and calculates the importance of each factor leading to system fault [10–11].

Fault tree model sets the most undesirable event in the system as the top event, all possible reasons for the top event as intermediate event, and all possible reasons for the intermediate event as basis event. Logic gate is adopted to show the connection of different events. A schematic diagram is shown in Fig. 1.

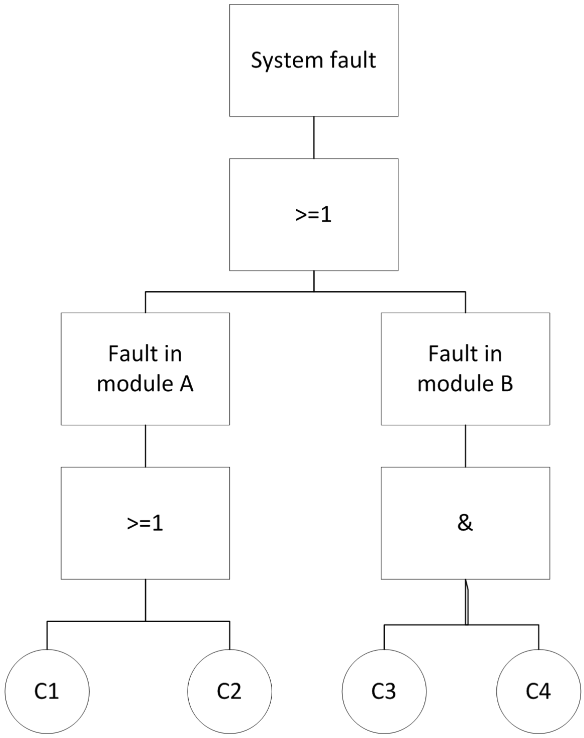

Fig. 1. Schematic diagram of fault tree

In Fig. 1, the top event is system fault, which was caused by the intermediate events (faults in module A or B). Meanwhile, fault in module A was caused by the failure of basis event C1 or C2, while fault in module B was caused by the simultaneous failure of basis event C3 and C4.

In general, most gearbox faults happened in the gears, bearings, shafts and components like cases [12]. Looking at the previous analysis, we can see that the establishment of fault tree can be classified to the establishing of top event (T), intermediate event (M) and basis event (C), as well as the construction of the fault tree. Construction of the fault tree is one of the core parts of fault tree analysis method. Fault in any part of the gearbox may lead to the fault in the system, so the logic relation among different faults refers to the word “or”. The fault tree constructed can be seen in Fig. 2.

In Fig. 2, the top event T refers to the fault in gearbox, intermediate event M1 refers to gear fault, M2–bearing fault, M3–shaft fault, M4–case fault, M5–fastener fault, M6–oil seal fault, and basis event C1–fatigue fracture, C2–overload fracture, $\cdots$, C32–rubber aging. Since there exist various basic events, the rest are omitted here.

We add corresponding weight and solution to every basis event of the fault tree. The total weight of all basis events is equal to to 1. Then the expanded fault tree

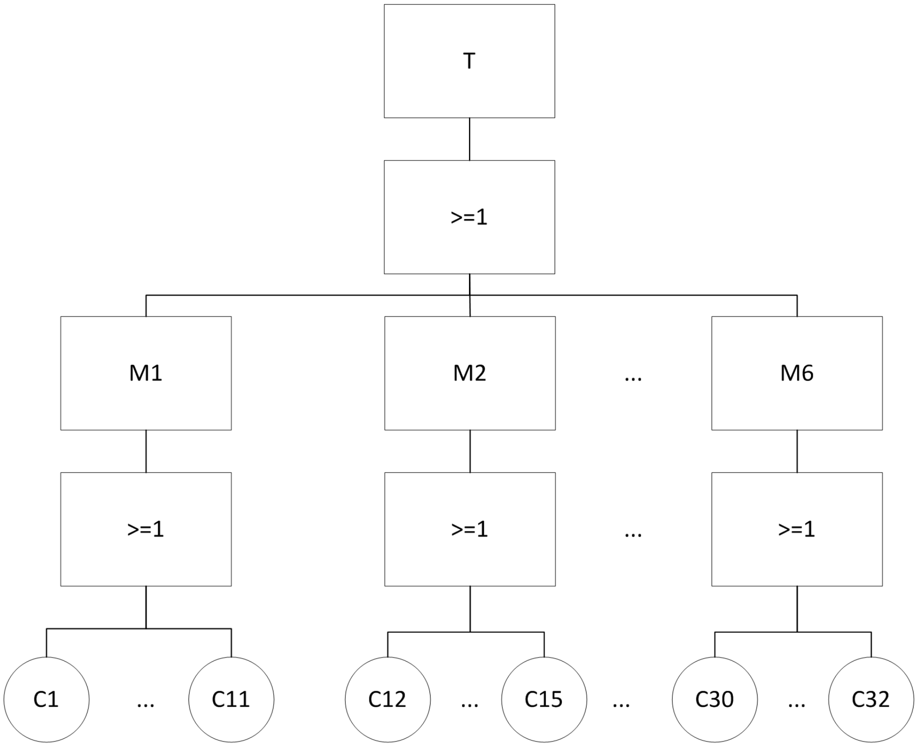

Fig. 2. Fault tree diagram of wind turbine gearbox

can not only help to address the positions of and reasons for the faults, but also figure out the referred solution from the system.

Qualitative analysis of fault tree analysis method aims at searching the minimum cut-set of fault tree, that is the reason for the fault of top event [13]. There are two major methods to search the minimum cut-set: ascending method and descending method [14]. The latter method is adopted this time. The descending method, starting from the top event, supersedes every event with the lower level event from top to bottom, records the events in portrait format when encountering with "or" gate, and records in landscape format when facing "and" gate. The rest can be done in the same manner until all the logical gates were transformed to basis events. Thus, all the cut-set of fault tree are addressed [15].

Given the characteristics of the gearbox, all the cut-set in this research are the minimum cut-sets, denoted as C1, C2, ..., C32. All the minimum cut-sets are independent from each other. If there is any fault in a certain one, the top event related to it will occur, that is, the gearbox will exhibit a fault [16].

The quantitative analysis aims at working out the incidence of the top event and importance of the basis event, which refers to the influence of the basis event occurrence on the top event. The analysis on the probability of top event follows.

When the logical gate refers to "or" gate, the occurrence probability of the top event is:

$$p(x) = \bigcup_{i=1}^{n} p(x_i) = 1 - \prod_{i=1}^{n} [1 - p(x_i)] \,. \tag{1}$$

When the logical gate refers to "and" gate, the occurrence probability of the top event is:

$$p(x) = \bigcap_{i=1}^{n} p(x_i) = \prod_{i=1}^{n} p(x_i) \,. \tag{2}$$

In both above formulae, $p(x)$ is the occurrence probability of the top event, $p(x_i)$ is the probability of the minimum cut-set that ranks as the place of i, while n refers to the total amount of minimum cut-sets. The importance can be expressed as follows:

$$I_i(x) = \frac{\partial p(x)}{\partial p(x_i)}, \ (i = 1, 2, \cdots, n) \,. \tag{3}$$

In this formula, $I_i(x)$ is the probability importance of the basis event which ranks at the ith position. The higher is the value, the greater is its influence on the occurrence of the top event.

When users check the gearbox, they can input the obtained fault phenomenon in the system to search or check them directly. The module of the diagnosis process is shown in Fig. 3. Obtaining of knowledge refers to a transferring process of accessing the professional knowledge from the knowledge source, and then transforming them to the knowledge base. In general, the obtaining methods of knowledge involve three methods, as artificial obtaining, semi-automatized obtaining, and mechanical obtaining.

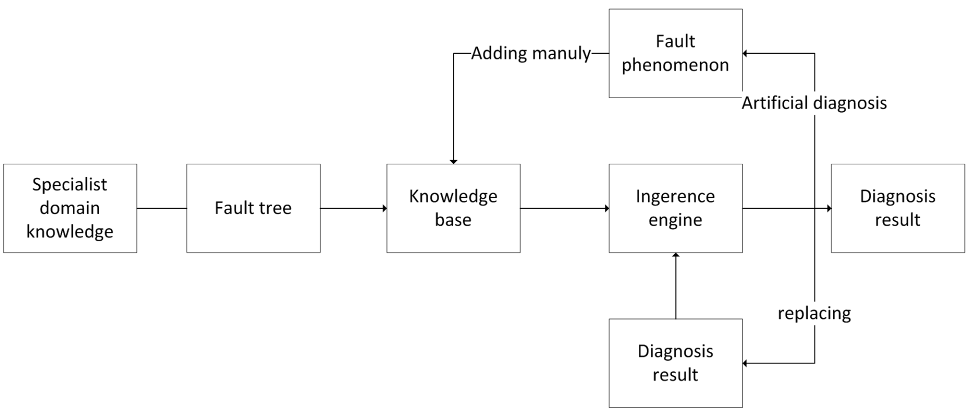

Fig. 3. Diagnosis module

3.2. Fault diagnosis strategy based on GRNN

During the operation of mechanical equipment, their vibration signals vary rapidly, involving many condition information of their operating. When there is any fault in the equipment, the vibration condition changes, and the vibration signals may include fault information [17–18].

During the process of signals collection, the selection of the measurement point is very important. The principle of this selection is to get as much vibration signals and less loss of vibration transferring path as possible. Yet, as to the gearbox, the measurement point should be placed at the position where damping is low and rigidity is high. The place near the bearing pedestal is good to choose the measurement point.

Any artificial neural network cannot have recognition ability unless learning to do it [19]. So some data samples are needed to train the neural network, and these samples refer to the interpretation on the characteristics of the extracted vibration signals. We will conduct research from aspects of time domain as well as frequency domain.

Extracting signal features within time domain is convenient. The statistical indicators of time domain can be classified as unit characteristic values and unitless characteristic values [20]. A unit characteristic value includes peak value, peak-to-peak value, mean, variance, etc. A unitless characteristic value includes average amplitude, waveform index, peak index, impulsion index and so on. However, in unitless characteristic value, tolerance index, kurtosis index, peak index and impulsion index can indicate the value of impact energy properly, referring to good evaluation index to diagnose faults. Given this, these four indexes are chosen within the time domain to carry out a characteristic extraction on vibration signals.

If $\{x_n | n = 1, 2, 3, \cdots, N\}$ is used to show a discrete time sequence, then the unit parameter and the four consequent unitless characteristic values can be shown in Table 1:

Table 1. Unit and unitless characteristic values

Unit characteristic value		Unitless characteristic value	
Peak value	$X_{\max} = \lvert x(n)\rvert_{\max}$	Tolerance index	$CL_{\mathrm{f}} = \frac{X_{\max}}{X_{\mathrm{r}}}$
Average value	$\mu = \frac{1}{N}\sum_{n=1}^{N} x(n)$	Kurtosis index	$K_{\mathrm{v}} = \frac{\beta}{\sigma^4}$ (σ−standard deviation)
Variance	$\sigma^2 = \frac{1}{N-1}\sum_{n=1}^{N}(x(n)-\mu)^2$	Peak index	$C_{\mathrm{f}} = \frac{X_{\max}}{D}$ (usually between 3–6)
Root-mean-square value	$D = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x^2(n)}$	Impulsion index	$I_{\mathrm{f}} = \frac{X_{\max}}{\mu}$
Root-square magnitude	$X_{\mathrm{r}} = \left[\frac{1}{N}\sum_{n=1}^{N}\sqrt{\lvert x(n)\rvert}\right]^2$		
Kurtosis	$\beta = \frac{1}{N}\sum_{n=1}^{N}(x(n)-\mu)^4$		

If the gear or bearing is damaged, there will arise impact signals, and the peak value will increase evidently to 10 or more. Along with the expansion of the fault, the peak index will decrease gradually, so changes of the peak index can be used as an early warning for the infancy fault of the gearbox. If the information involved in time signals belongs to numerous components, the waveform index, impulsion index, tolerance index and other unitless indexes can be used to conduct fault diagnosis [21]. The kurtosis index, tolerance index and impulsion index are relatively sensitive to damages like shock pulse; their values will increase obviously, especially at the onset of fault. But when increasing to a certain value, they will start to decrease in turn along with the expansion of fault, which shows that they are highly sensitive to the early fault but their stability is low.

During the process of signal analysis, the time-domain signal has limitations in analyzing complex signals. As a result, time-domain signals are often transformed to those of frequency domain through mathematical methods to obtain more information from the signals. As to the distributing characteristics of signals in frequency domain, information entropy can be adopted as signal signature parameter. We extract the characteristics of information entropy from the signals within frequency domain based on power spectrum analysis.

If $\{x_n | n = 1, 2, 3, \cdots, N\}$ is used to show the discrete time sequence, the power spectrum is [22]:

$$S(w) = \frac{1}{2\pi N} \left|x(w)\right|^2 . \tag{4}$$

In this formula, $x(w)$ is the Fourier transform of sequence $\{x_n\}$. Through dispersing the Fourier transform, we can draw the spectrum $X(k)$ and power spectrum $S_k,\ k = 1, 2, \cdots, N$. We can derive

$$\sum_{i=1}^{N} \left|x(n)\right|^2 = \sum_{i=1}^{N} \left|S(k)\right|^2 . \tag{5}$$

The power spectrum entropy H_{f} can be defined as:

$$H_{\mathrm{f}} = -\sum_{k=1}^{N} p_k \ln p_k , \tag{6}$$

where p_k is the percentage of kth power spectrum to the whole spectrum, and

$$p_k = \frac{S_k}{\sum_{k=1}^{N} S_k} .$$

The power spectrum entropy indicates the spectral structure of vibration signals. The simpler is the frequency structure of the signals, the lower is the power spectrum entropy, and also the less is the complexity and uncertainty of the signals. In turn, the uncertainty will be increasingly high. As a result, the power spectrum entropy can indicate the distribution complexity of vibration energy on the whole frequency [23].

Now, we start building the fault diagnosis module based on GRNN. If the joint probability density function of random vector x and random variable y is $f(x,y)$, the regression of y to x can be expressed as [24]

$$E(y/x) = \hat{y}(x) = \frac{\int_{-\infty}^{\infty} y f(x,y)\,\mathrm{d}y}{\int_{-\infty}^{\infty} f(x,y)\,\mathrm{d}y}\,. \tag{7}$$

In formula (7), the estimation of $f(x,y)$ can be accessed by estimating the training data with the application of the Parzen's nonparametric estimation operator. The nonparametric estimation is

$$\hat{\mathrm{f}}(x,y) = \frac{1}{(2\pi)^{\frac{m+1}{2}}\sigma^{m+1}} \cdot \frac{1}{n}\sum_{i=1}^{n} \mathrm{e}^{-d(x,x_i)}\mathrm{e}^{-d(y,y_i)}\,, \tag{8}$$

where

$$d(x,x_i) = \frac{(x-x_i)^{\mathrm{T}}(x-x_i)}{2\sigma^2}, \quad d(y,y_i) = \frac{(y-y_i)^2}{2\sigma^2}\,.$$

In this formula, x_i is the observation vector of x and y_i is the observation value of y. Symbol m denotes the dimensionality of x, σ is the smoothing factor and n is the number of samples. Symbol $\hat{f}(x,y)$ is used to replace $f(x,y)$. substituting it to formula (7), and taking into account that $\int_{-\infty}^{\infty} z\mathrm{e}^{-z^2}\,\mathrm{d}z = 0$, we can see that

$$\hat{y}(x) = \frac{\sum_{i=1}^{n} y_i \mathrm{e}^{-d(x,x_i)}}{\sum_{i=1}^{n} \mathrm{e}^{-d(x,x_i)}}\,. \tag{9}$$

The estimated value $\hat{y}(x)$ is the weighted average of all y_i. Each weighted factor of y_i is the index of squared Euclidean distance between sample x_i and x. Through formula (9), we can see that $\hat{y}(x)$ is within the variation range of y_i, which is the sample observation value of y [25].

Construct now a general regression neural network according to formula (9), whose structure is expressed in Fig. 4. It includes 4 layers of neurons.

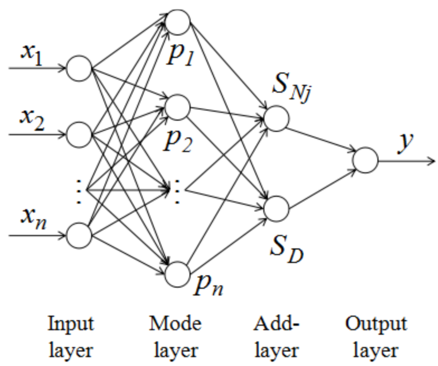

Fig. 4. Structure diagram of GRNN

From the previous analysis, we select the tolerance index, kurtosis index, peak index, impulsion index and power spectrum entropy as the input and output parameters. The settings are as follows:

Normality: Output $Y = (1, 0, 0)$. Abrasion: Output $Y = (0, 1, 0)$. Gear teeth breakage: $Y = (0, 0, 1)$.

The fault diagnosis module based on GRNN is depicted in Fig. 5

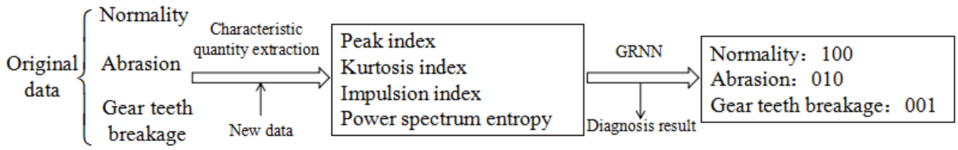

Fig. 5. Fault diagnosis module based on GRNN

4. Experimental results and discussion

4.1. Test on fault diagnosis model

During the training of neural network, the input information data should be within range $[0, 1]$, so the input data used in the neural network should be transformed through normalization processing. The corresponding formula is [26]

$$x_{io} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}. \tag{10}$$

In this formula, x_{io} is the ith characteristic parameter after normalization processing, symbol x_i is ith characteristic parameter of the original input data, $x_{\min}$ is the minimum characteristic parameter, and $x_{\max}$ is the maximum characteristic parameter.

General regression neural network will conduct the module recognition on the gearbox with three fault conditions: fault-free, abrasion and gear teeth breakage. The output mode is $y = (a, b, c)$. The ideal output result is that there is one "1", and two "0"s among these three parameters. However, the real outcome is certainly a little different from the ideal outcome. So we need to judge the simulation result. We judge it with the threshold condition of 0.9 in this research, in the following way: if $0.9 \leq a \leq 1$, it is judged as fault-free, if $0.9 \leq b \leq 1$, it is judged as abrasion of gear surface, and if $0.9 \leq c \leq 1$, it is judged as gear broken. If there is an exception, the case is not evaluated.

There are 25 groups of data under these signal samples of 3 fault conditions, among which 10 data groups are fault-free, 10 are abrasion and 5 are gear broken. To prove the validity of this module, we randomly choose one sample among those three to detect module, and the rest samples are used as module-building, i.e. network training. After modulating and observing the diagnosis outcome for many times, we can see that the training effect is the best when the distributing density is 0.14. The results of the training process are summarized in Table 2:

Table 2. Training diagram of general regression neural network

Fault type	Sample number	Tolerance index	Kurtosis index	Peak index	Impulsion index	Power spectrum entropy
Fault-free	1	4.5363	2.5926	3.1438	3.8794	3.7556
	2	4.8814	2.6627	3.2776	4.1243	3.9353
	3	4.2038	2.5822	2.9482	3.6025	3.2745
	4	4.2392	2.3255	2.9264	3.6123	3.2972
	5	3.4127	1.6478	2.3685	2.9245	3.3713
	6	4.7188	2.9606	3.1489	3.9878	3.5716
	7	3.8659	2.1607	2.7261	3.3114	3.3946
	8	3.7938	1.9976	2.6339	3.2534	3.9537
	9	4.6521	2.3712	3.2262	3.9764	3.8014
Gear abrasion	11	2.5653	1.2408	1.9142	2.2726	2.9810
	12	3.6127	1.6156	2.2588	2.9465	3.3054
	13	6.0127	2.7246	3.4326	4.7176	3.1076
	14	4.5746	2.3827	3.1072	3.8765	3.4056
	15	3.7716	1.7365	2.5217	3.1726	3.3845
	16	3.1975	1.4945	2.2947	2.7775	3.1727
	17	4.1426	2.5217	2.8128	3.5056	3.3903
	18	3.9175	1.7203	2.5718	3.2642	3.1054
	19	4.1517	2.1987	2.7653	3.4956	3.0656
Gear broken	21	6.3805	2.9665	3.6652	5.0627	4.3424
	22	8.7954	4.7965	6.1554	7.6534	4.9945
	23	7.9436	4.1823	5.3335	6.7365	4.3347
	24	9.8745	4.9345	6.2114	8.1767	6.3665

To detect the fault diagnosis ability of general regression neural network, the network that has been trained needs to be tested. The reserved 3 groups of sample data were used to do module detection. The comparative condition of predicted and real results is shown in Table 3.

Analyzing the data in Table 3 we can see that the fault diagnosis based on GRNN has a high recognition rate on three typical fault modes, all of which are above 90 %. It satisfies the threshold conditions set before, and thus, the validity of this module can be declared as verified.

Table 3. Detection result of fault diagnosis module based on GRNN

Fault type	Normality	Abrasion	Teeth breakage
Testing sample	Sample 11	Sample 27	Sample 31
Fault number	100	010	001
Diagnosis result	0.9987, 0.0003, 0.0000	0.0012, 0.9994, 0.0000	0.0000, 0.0004, 0.9996

4.2. The design and implementation of fault diagnosis system

Based on analysis on the gearbox fault, we developed an expert system of gearbox fault diagnosis facing with Web. The system is designed in three levels: page for fault conditions, page for fault reasons and page for solutions. The default page of the system is the one for fault conditions, see Fig. 6.

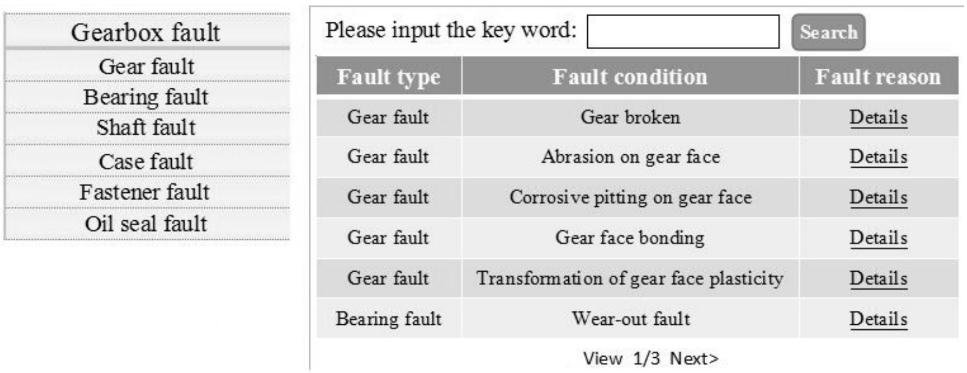

Fig. 6. Expert system of gearbox fault diagnosis

We developed this system on .NET platform, integrating C programming language. The overall framework of the system is: the left side is the menu of fault types, the right side is the list for fault conditions. Below the page of fault conditions, users can search information page by page, and also can input key words in the box to search what they need. Click the "View detail" in the list of search results, the possible reasons correspondent to various fault conditions can be achieved. Users can also click the correspondent menu of fault conditions, and have access to the list of relative reasons where possible reasons are listed. The list of search result is ranked according to the weight of reasons, those with the higher weight are ranked at a higher position on the list to attract the attention of the maintenance staff immediately.

After having knowledge of fault reasons, users only need to click the "View detail" on the solutions list to obtain the expert solutions. The maintenance staff can choose relative fault solutions considering the practical fault condition and concerning their own knowledge.

5. Conclusion

Gearbox is an important part of the wind turbine generator system, whose fault will influence the stability and security of the whole wind turbine generator system. We developed a fault diagnosis system based GRNN and fault tree analysis, and applied it to the gearbox of wind turbine. The results show that this system can shorten the time of diagnosing fault, and put forward expert solutions rapidly, thus the gearbox fault can be diagnosed and maintained accurately and effectively.

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