The Design of Vibration Data Acquisition and Intelligent Fault Diagnostic System for Wind Turbine

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Abstract:
In this paper, a vibration data acquisition and intelligent fault diagnostic system is introduced. Firstly, the vibration data acquisition subsystem based on LabView is described in detail. It consists of a wind turbine and a rotor test bed. There are twelve vibration sensors on wind turbine including axial and radial direction. The vibration data acquisition subsystem is including 16 channels. Software analysis modules can realize real-time data acquisition and analysis, off-line data analysis, trend analysis, fault simulation and graphical result display. The familiar vibration faults, unbalance of rotor and radial rubbing of rotor, are produced and tested artificially. Then, a wavelet neural network (WNN) is used to do vibration trend prediction. The simulation data test result shows that WNN has great advantages in predicting the characteristic vibration parameters of the deterministic trend. Finally, a vibration fault diagnostic expert system prototype for wind turbine is developed using CLIPS expert system tool. Ten rules are collected from literatures and used for rule-based fault diagnosis. From the results of the experiments, the conclusion is obvious that the expert system is effective on wind turbine vibration fault diagnosis. The whole system can be developed in local vibration monitoring and real-time fault diagnosis for wind turbine.

Keywords: Wind turbine, vibration, diagnosis, expert system, artificial neural network

1. Introduction
Wind power, as a kind of clean energy, has get rapid development in recent year. Wind turbines become larger and larger. Due to its severe working condition, there are many failures occurred about wind turbines, especially offshore ones. In order to improve the reliability and safety of wind turbines, reduce unplanned downtime, it is necessary to apply condition-based maintenance (CBM) and repair over the entire lifetime of wind turbine generators. And, Condition monitoring and fault diagnostic system play an important role in CBM.

In this paper, a vibration data acquisition and intelligent fault diagnostic system is introduced. First, structure of the system is presented, as well as the function of the software. LabView, as a fast development tool, is selected to do data collection. Based on the collected data, the condition monitoring system can do real-time monitoring, off-line data analysis, trend analysis and fault simulation. As for trend analysis, a wavelet neural network (WNN) is adopted here. Finally, a prototype vibration fault diagnostic expert system is given using CLIPS expert system tool.

2. The data collection and analysis system

2.1 Hardware structure
The structure of the system is shown in Figure 1.
There are 12 testing points on wind turbine including axial and radial direction as show in Figure 2\(^1, 2\). One part of the data acquisition box is NI data acquisition device including 16 channels signal condition assembly and PCIE-6536 I/O assembly.

2.2 Software function

The condition information of wind turbine is collected through hardware and stored into database instantly. At the meanwhile, the signal is processed to show operation information graphically. The system consists of two modules: real-time monitoring and off-line analysis. The function of real-time analysis module includes time-wave figure, spectrum analysis, and parameter alarmed and so on. Off-line module can do signal trend analysis, fault feature retraction. The system checks the signal's characteristic of time-domain and frequency-domain continually. When some abnormal is found, the system shift to fault diagnosis module automatically. There are several sub-modules in the fault diagnosis module. One of these is Expert System which will be discussed later. Fig.3 shows the software system flowchart.
Experiments have been made on the system. Fig.4. shows the result. The signal is acquired from a fault rotor (unbalance of rotor). The feature of unbalance is clearly showed in the time-wave, spectrum and orbit.

3. Trend prediction using WNN

The output power of the wind turbine in the dynamic stall condition, or vibration of rotor in startup of the wind turbine, may get bigger and bigger continually. So, it is important to make trend prediction for faults find in early stage.

Wavelet transform has become a powerful tool in signal processing due to its good localization characteristics in both time and frequency domain. And wavelet neural networks (WNN) have been studied by many scholars and have shown powerful approximation ability \[5,6\]. It is such a model that the wavelet function replace the role of sigmoid function in the hidden unit, and the wavelet parameters and wavelet shape are adaptively computed to minimize an energy function for finding the optimal representation of the signal.

3.1 Extended RBF WNN \[5,7\]

Here, an extended RBF WNN is adopted to make trend prediction.

One step forward prediction is:
Where \( w_{g,h}(L_2,\ldots) \) are dilation and translation coefficient of wavelet in hidden layer, \( L \) node number of hidden layer, \( m \) number of input nodes, \( \bar{w}_0 \) estimated mean value of time series \( x(t) \), \( \Phi \) wavelet function.

The network is trained by gradient descent algorithm in batch way. Given \( d(t) \) as the desired target output of \( pth \) input pattern, the energy function can be written as:

\[
E_d(t) = \frac{1}{2} \sum_{i=1}^{p} \left[ d(t) - y(t) \right]^2
\]

And the gradient each parameter is:

\[
\frac{\partial E}{\partial w_0} = 2 \sum_{i=1}^{p} \left[ d(t) - y(t) \right] \phi_k(t)
\]

\[
\frac{\partial E}{\partial w_k} = 2 \sum_{i=1}^{p} \left[ d(t) - y(t) \right] \phi_k(t) \phi_k(t)
\]

\[
\frac{\partial E}{\partial a_k} = 2 \sum_{i=1}^{p} \left[ d(t) - y(t) \right] \phi_k(t) \frac{\partial \phi_k(t)}{\partial a_k}
\]

The parameters are updated as follows:

\[
\alpha w_k(t) = \frac{\partial E}{\partial w_k} \quad \alpha a_k(t) = \frac{\partial E}{\partial a_k}
\]

Where \( \alpha \) learning rate and wavelet employed here is morelet wavelet.

### 3.2 Test of RBF-WNN for trend prediction

The experiment is based on a simulated definite trend signal:

\[
x(t) = 0.1 \cos(0.01t^2)
\]

The sample interval is \( \Delta = 1 \). The architecture of both networks is \( mL=8,12 \). The signal is tested by WNN and BP neural network at the same time. The result is shown as follows:

Fig.5. WNN Prediction Result
Note that BP network has better performance in train stage (3.2e-7 vs. 6.1e-11). The experiment results show that WNN has better performance than BP neural network in trend prediction. The reason is the sigmoid activation function in BP. The sigmoid function makes network output change slightly while input change dramatically. In fact, some scholars have tried to modify the activation function in BP network, but the effect is not good enough. Sigmoid activation function is the best one for BP, maybe.

4. Vibration faults diagnostic expert system

Since wind turbine is a complex machine. It requires comprehensive knowledge and experience to make fault diagnosis. It is unrealistic to examine the characteristic of vibration signal manually, in order to diagnose fault. A lot of diagnosis systems have been developed to make fault diagnosis automatically. One of these is Expert System (ES). An ES consists of a knowledge base and a reasoning engine. A typical ES is showed in fig.7.

![Fig.7 Architecture of ES based on rules](image)

Usually, rules are developed by experts previously based on the feature of signal of fault components. In this study, we collect ten rules from literatures, listed in table.1, 2 [4, 11]. Then, a prototype Expert System is developed based on the ten rules.

CLIPS is a powerful and fast development tool for ES. In addition, CLIPS can be called from a procedural language, perform its function, and then return control back to the calling program. This is one of the reasons why we choose it as an ES tool.
Table 1. Vibration faults of wind turbine

<table>
<thead>
<tr>
<th>Fault code</th>
<th>Fault name</th>
<th>Fault code</th>
<th>Fault name</th>
</tr>
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<tbody>
<tr>
<td>VF0</td>
<td>Normal</td>
<td>VF5</td>
<td>Radial rubbing of rotor</td>
</tr>
<tr>
<td>VF1</td>
<td>Unbalance of rotor mass</td>
<td>VF6</td>
<td>Crack of rotor</td>
</tr>
<tr>
<td>VF2</td>
<td>Thermal bend of rotor</td>
<td>VF7</td>
<td>Oil whirl</td>
</tr>
<tr>
<td>VF3</td>
<td>Bearing rigidities (vertical and horizontal) differ greatly</td>
<td>VF8</td>
<td>Oil whip</td>
</tr>
<tr>
<td>VF4</td>
<td>Axial rubbing of rotor</td>
<td>VF9</td>
<td>Misalignment of rotor</td>
</tr>
</tbody>
</table>

Table 2. Spectrum features and process parameters description

<table>
<thead>
<tr>
<th>Spectrum</th>
<th>Description</th>
<th>Spectrum</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>f1</td>
<td>0~0.39X</td>
<td>f5</td>
<td>1X</td>
</tr>
<tr>
<td>f2</td>
<td>0.40-0.49X</td>
<td>f6</td>
<td>2X</td>
</tr>
<tr>
<td>f3</td>
<td>0.5X</td>
<td>f7</td>
<td>3X</td>
</tr>
<tr>
<td>f4</td>
<td>0.5X-1x</td>
<td>f8</td>
<td>&gt;3X</td>
</tr>
<tr>
<td>sc1</td>
<td>vibration direction</td>
<td>sc3</td>
<td>vibration change with speed</td>
</tr>
<tr>
<td>sc2</td>
<td>axis track feature</td>
<td>sc4</td>
<td>time-wave feature</td>
</tr>
</tbody>
</table>

The ES here is a Post System \[^8, 9, 10\]. It is a combination of forward chaining and back chaining rule system, also. The symptom, rules are stored in different knowledge bases in the format of “facts”. Thus, it is convenient to make backward reasoning. Rules are stored as follows:

\[(DiagnosisRule \ (ID \ vf1) \ (if \ symptom\ IDs) \ (then \ fault\ name))\]

The procedure of diagnosis can be separated into four phase: initial phase, data-collection phase, diagnosis phase, and post diagnosis phase. In the first phase, we start the system by providing some necessary facts. Then the system will ask user input some information which may be an estimated fault or some features of fault. Following is the fault diagnosis based on rules under control of inference engine. If the
system can’t tell a fault based on the given information, it will provide user some potential result. Then, the system will ask user to answer a series of questions to find the final result.

After establishment of the system, we use the testing samples to testify the validity of the system. Part features of fault VF1 is inputted into the ES. The system tells that it may be VF1 fault successfully. Then, some questions are asked. Based on the rules and answers, the system gives accurate result: fault VF1. Fig.8 shows the diagnosis process.

Of course, the diagnosis result can only be a reference. Other information such as time-wave characteristic is need for accurate diagnosis.

Expert system benefits from the human knowledge or expertise. CLIPS as an expert system tool can simplify the development of expert system. In the procedure of diagnosis, the expert system can inference based on the human knowledge or expertise. Further, it can inference under the help of field operator. And, the test result of the Expert System shows that CLIPS is a helpful tool in the fault diagnosis. The diagnosis method based on ES is a feasible method.

![Fig.8. Test result of ES](image)

5. Conclusion

In order to make condition monitoring and fault diagnosis, a system is designed for the purpose of data collection and analysis. The system employs NI’s hardware and developed software is based on LabView. Software analysis modules can realize
real-time data acquisition and analysis, off-line data analysis, trend analysis, fault simulation and graphical result display. Some test experiments are done with the systems. The results show that the system works well.

Trend prediction is important for faults find in early stage. A WNN is adopted here to make prediction. It is clearly showed that WNN has greater advantage compare with BP network. And, WNN has the power to make prediction with deterministic trend signals.

For fault diagnosis automatically, we developed a prototype expert system. Ten rules are collected from literatures and text book. Then, a prototype mixed reasoning ES using CLIPS is developed based on the ten rules. The test results prove that ES is one of effective methods for fault diagnosis.

Acknowledgment

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Reference