2004 8th International Conference on
Control, Automation, Robotics and Vision
Kunming, China, 6-9th December 2004

Development of a Distributed Bearing Health Monitoring and Assessing System

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Abstract

Rolling element bearings are widely used components in industrial equipments and their failure may result in severe damage of critical processes. Bearing plants are required to provide estimated performance data to their customers. These statistically based data are usually got through various testing experiments with product samples via bearing test rig. However, it is usually hard to get convincible results from traditional method due to the limitation of monitoring device and analysis methods. This paper designs an intelligent system for a bearing testing and inspection center of a bearing plant to monitor the health status and assess the performance of bearings being tested. The system has a distributed infrastructure and can continually collect testing data, analyze vibration signals, extract features of bearing fault, diagnose bearing faults and further assess the quality of the bearings. Fuzzy logic, wavelet neural network and dynamic wavelet neural network are employed as diagnostic/prognostic algorithm.

1 Introduction

Rolling element bearings are important components of almost all forms of rotating machinery. Bearing failures are account for a large percentage of breakdowns in rotating machinery [5]. Therefore, the quality and performance of bearings is concerned by both customers and producers. Before bearings are sold to customers, bearing plants need to do various experiments to assess bearing performance and inspect if there is any disfigurement in their products. Engineers of the factory also intend to analyze the factors that affect the quality and lifetime of their bearings from these experiments. However, in some plants, most bearing testing rigs only have simple monitoring or analyze device and can not provide enough information for performance assessment. To solve the problem, this paper designs a distributed system for a bearing test and inspection center of a bearing plant to monitor the testing process online. It can continually collect data, do signal processing, vibration analysis, fault diagnosis and prognosis, etc. By the intelligent diagnosis and prognosis ability, this system can give the performance assessment of the bearings being tested. Through the data storage function, the system can eventually build up a bearing experiment database and data warehouse for data mining and further research.

A number of approaches to the fault diagnostic/prognostic problem of bearings have been reported in the technical literature. These methods including probabilistic analysis methods [6]-[7], frequency domain analysis methods [6]-[9] , time domain analysis [6] and finite element analysis methods [10] .Among these methods, the frequency analysis approach is the most popular one. This popularity is most probably due to the availability of Fourier transform technique, as characteristics of vibration signals are more easily noticed in the frequency domain rather than in the time domain. The frequency analysis technique involves frequency analysis of the vibration signal and further processing of the resulting spectrum to obtain clearly defined diagnosis information [11], [12]. Among the methods that use frequency analysis are the bearing defect frequencies analysis method [11], [12], high-frequency shock pulse and friction forces method [11], [12], and enveloped spectrum method [11], [12]. In the category of time-domain analysis technique there are the time-series averaging method [12], the signal enveloping method [12], the Kurtosis method [12], and the spike energy method [12].

In this paper, Fuzzy logic, wavelet neural network and dynamic wavelet neural network are employed as diagnostic/prognostic algorithm.

It is generally possible to break down the sensor values into two categories: low-bandwidth data, such as temperature data, stress data, *etc.*, and high-bandwidth data, such as vibration data, acoustic data, *etc.* The data from the first category may vary slowly while those from the second category may change rapidly. The fuzzy logic classifier operates on the incoming low-bandwidth sensor data, while the WNN classifies the fault modes with high-bandwidth data.

2 System structure

The bearing testing and inspection center has more than 80 bearing test rigs(BTR) belong to different model and suitable for testing different type of bearings. Each rig is equipped with such sensors as accelerometer, temperature sensor, speedometer and load pressure sensor. A PC based industrial computer with diagnostic /prognostic software acts as the monitoring device (Test monitoring Unit, TMU). While testing, the TMUs continuously collect sensor data including motor speed, bearing temperature, load pressure and vibration data and use these collected data as inputs to do fault diagnosis and prognosis. Other parameters such as test type, bearing model, bearing batch No., Testing date and time, etc. are also recorded.

Operating stations (OS) site in the operator's room are connected to TMUs by industrial Ethernet and thus construct a distributed infrastructure. The system also has a database server for data storage. Figure 1 depicted the structure of the system.

Except for data display function, OSs also have software for analyzing the diagnostic results that TMUs give out and do data mining work via historical database.

Web enabled function of the system make the test data, including current results from experiments in progress, can be accessed by remote computer,. The system structure is depicted in figure 1

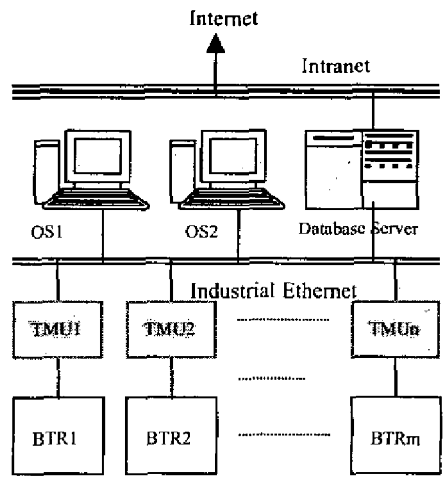

Figure 1 System Structure

3 Diagnostic/Prognostic Algorithms

The software on TMUs is composed of several modules, including data acquisition module, feature extractor module, diagnostic module and prognostic module, etc. The data acquisition module continuously collects data from sensors and the feature extractor module extracts features from these raw data. Then Diagnostic algorithms

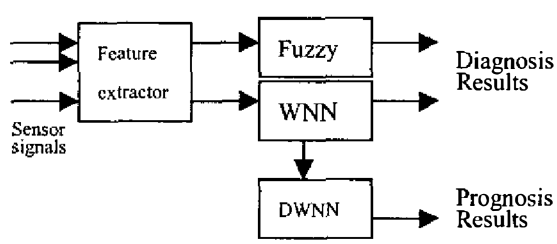

Figure 2 Diagnosis/Prognosis Algorithm

identify the fault modes, and accordingly prognostic module prognoses the remaining lifetime of tested bearings. The structure of the diagnosis/prognosis algorithm is depicted in figure 2.

3.1 Feature Extractor

Measurements of the bearing testing process can be divided into two broad categories: low-bandwidth measurement and high-bandwidth measurements. The former, such as temperature, pressure, *etc.* may propagate slowly and data can be sampled at relatively slow rates without loss of historical significance. On the other hand, the latter, such as vibrations, or acoustic signals, require fast sampling rates in order to capture a reasonable signature of the failure mode.

Bearing faults can not be readily identified by simply monitoring these raw sensor data. Raw data must be transformed into features, which contain meaningful information in a compressed form. Features, such as mean, variance, standard deviation, *etc.*, are extracted from raw data and constitute the first level of the feature vector. "Features of features" are also extracted, and form higher levels of the feature vector. Such derived features as the slope of the mean value, kurtosis, *etc.*, are assisting to improve the classification task and increase the signal-to-noise ratio [1].

3.2 Diagnostician

To detect and classify the bearing faults, two different methods are implemented. The first one is based on a fuzzy logic paradigm while the second uses a wavelet neural network construct.

3.2.1 The Fuzzy Diagnostic Module

The fuzzy diagnostic module is utilized to detect process fault modes from feature data, i.e. faults, resulting from low-bandwidth events and exhibiting low-frequency signatures. An initiation event begins the fuzzy diagnostic module calculations if receives feature inputs from the feature extractor and reports to the operator any indications that a fault mode may have occurred,

The fuzzy logic system structure is composed of four blocks: fuzzification, the fuzzy inference engine, the fuzzy rule base, and defuzzification.

3.2.2 The Wavelet Neural Network Module

The WNN (figure 3) is used also as one component of the classifier. The WNN belongs to a new class of neural networks with unique capabilities in addressing identification and classification problems. Wavelets are a class of basic elements with oscillations of effectively finite-duration that makes them look like "little waves". The self-similar, multiple resolution nature of wavelets offers a natural framework for the analysis of physical signals and images. On the other hand, artificial neural networks constitute a powerful class of nonlinear function approximants for model-free estimation. A common ground between these two technologies may be coherently exploited by introducing a WNN.. WNN may be optimized with respect to structure (number of nodes) and their parameters using a Genetic Algorithm as the optimization tool. The WNN is trained, thus, as a

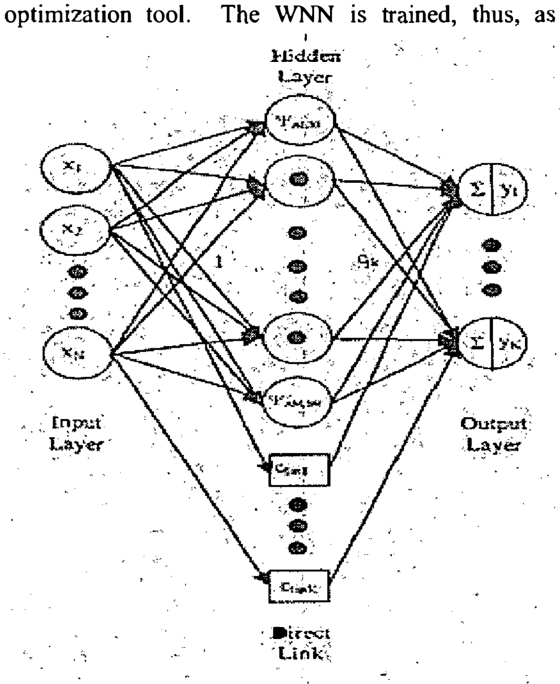

Figure 3. WNN Structure.

two-step process: the structure and the parameters of the network are determined iteratively until a performance metric is satisfied.

3.2.3 Prognosticator

In bearing testing process, the system require to record the vibration data at some key point before the bearing failure occurs and the prognostic module can provide the reference time for this purpose. The prognostic module can get the estimated remaining lifetime of tested bearings. This can also be useful information for bearing quality and performance analysis. The additional benefit of prognostication of the lifetime of bearings is that it can also provide useful information to customers who want to use the information in their own monitoring process while bearings running in their equipments. The prognostic algorithm is based on "dynamic wavelet neural network", known as DWNN [4].

The DWNN is based on a static "virtual sensor" and a predictor. The static virtual sensor relates known measurements to failure measurements, such as from the acceleration magnitude of the vibration to the fatigue size, which is difficult to be acuired while the bearing is running. The predictor attempts to project the current state of the faulted component into the future thus revealing the time evolution of the fault mode and allowing the estimation of the component's remaining useful lifetime. The components upon a dynamic wavelet neural network model acting as the mapping tool. The structure of DWNN is depicted in figure 4.

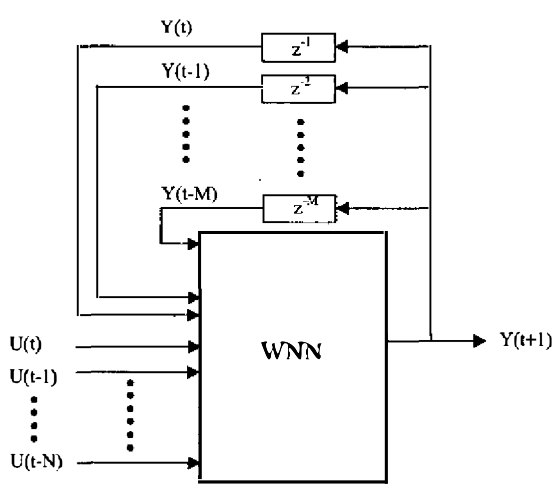

Figure 4. DWNN structure.

4 Software implementation

The system provides users a friendly interface for the operators operating and monitoring the testing process. It can display all sensor and feature data as real time values and historical records. Operators can start, pause or stop a test process of any testing rig. As soon as a bearing experiment is started, the experiment data will be continuously saved to database, including motor speed, load pressure, bearing temperature and vibration data, etc. Other information such as the starting date and time of the experiment, bearing type, etc. are also stored in database. Incase any fault is found by the diagnostician, a flashing alarm message will be displayed on the screen and a sound alarm will also give out to notify the operator. A central database access management module has been developed to serve the crucial role of storing and accessing raw data, fault features, diagnostic and prognostic results. Modules on TMUs are built into a COM/DCOM infrastructure in order to be accessed and used in an open and flexible manner accommodating a variety of development languages. The data exchange between modules is event-based and does not require an overall scheduler to manage all the modules. And the communication between TMUs and OSs are via TCP/IP protocol.

5 Application Notes

For training the neural network, both data of good bearings and data of bearings with some specific defects need to be collected. Good bearing data can be got from the early period of a testing. To get data of bearings with specific defect, sample bearings with specific defect selected from past test were reinstalled to the testing rig and then data can be got by restarting a test. These data were used for training the wavelet neural network of the diagnostician. Data for training the prognosticator can be got from bearings with seeded crack of different size. Install these bearings on the testing rig in an ascending order and repeat the test, vibration data of different crack size in an ascending order will be collected and used to train the DWNN[13].

The system has already been implemented in a bearing testing and inspection center of a bearing plant in China and the fault diagnosis and prognosis algorithm are being tested and improved while the paper is being written..

6 Conclusions

A distributed bearing testing and inspection center monitoring system is designed in this paper and is being used in a bearing plant. It provides a new methodology to test and assess bearing quality and performance. Fuzzy logic, wavelet neural network and dynamic neural network are employed as bearing fault diagnosis and prognosis algorithm. Testing results show that the system is helpful to the bearing quality and performance assessment.

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Acknowledgement

The Project is Sponsored by the Scientific Research Foundation for the Returned Overseas Chinese Scholars, State Education Ministry.