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Condition Monitoring and Diagnostics for Complex System using Neural Networks

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Abstract: A rule-based expert system is a traditional approach in condition monitoring and diagnostics for complex system. However, the rule-based expert system is not only difficult to be established but also difficult to be renewed along with the changed circumstances. Neural networks provide a data based approach to condition monitoring and diagnostics for complex system such as rotating machinery. By developing associations between neural networks and a rotating machine consisting of gears, bearings and shafts for the first time, a number of advantageous aspects are identified in this study. Fundamental and harmonic frequencies relating to the components, as well as sideband and cepstrum information, were used as input parameters. Outputs of the networks were given as severity levels of system components. Neural networks demonstrated the capability for use in identifying the location and severity of numerous different machinery faults, including multiple component faults. And neural network is not just easy to be established but also easy to be renewed along with the changed circumstances.

Key words: Neural network, complex system, condition monitoring, diagnostics

INTRODUCTION

A rule-based expert system is one of the practical approaches to represent knowledge of faults that has been effectively applied in fault diagnostics. However, fault diagnostics via rule based expert systems, requires a complex database of rules. This would need to be generated through the analysis and experiences of machinery experts familiar with the historical causes and modes of machine failures.

Neural network is an alternative means to present knowledge about multiple fault analysis. It can autonomously store knowledge by learning from historical fault data and has the characteristics of associative memory. Information about faults can be learned by training the network on a set of data such as the state variables for the normal condition and those for identified faulty conditions. Neural network systems are more adapt at many classification and identification tasks than both traditional statistical and expert systems. These tasks require the ability to match large amounts of information simultaneously and then generate categorical outputs. Neural network has the capacity to learn and store information from past operating faults via associative memory and thus has an associative diagnostic ability which may prove superior to conventional methods in fault diagnostics of complex system such as rotating machinery (Hui *et al*., 2013).

In this study, a back propagation neural network is developed, representing a physical model with multiple machinery components-gears, bearings and shafts. A number of experiments were conducted concerning the application of neural networks using vibration frequency spectra and cepstral information in the detection of severity of machinery fault. A general scheme for the diagnostic model is shown in Fig. 1.

VIBRATION ANALYSIS FOR ROTATING MACHINERY

Vibration analysis method: Vibration analysis is among the most powerful tools available for the detection of incipient fault in mechanical systems. First, it has a record of accuracy and reliability. Second, different defects produce different vibration patterns. Third, vibration

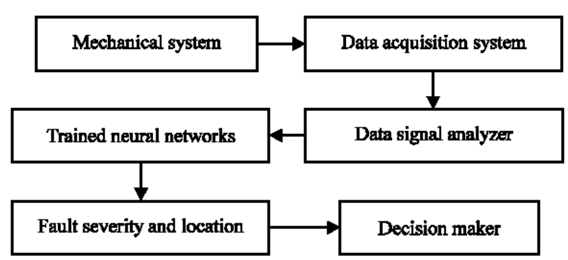

Fig. 1: General scheme of diagnostic model

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monitoring is relatively inexpensive (Liu and Mengel, 1992). Among the methods of vibration analysis in use today and under conditions study are broad band vibration monitoring, time domain analysis and frequency domain analysis. All have varying degrees of utility in machinery condition monitoring and diagnostics.

Since the effectiveness of a neural network is directly to how effectively the chosen inputs define a particular decision space, the selection of the proper vibration parameters for inputs to the neural network is critical. Thus a good understanding of elementary machinery diagnostic techniques is essential.

Vibration of gears: The gear mesh frequency is obtained from the frequency of impacts between the teeth of each gear and is calculated as follows:

$$F_{gm} = N_t F_s \tag{1}$$

where, F_{gm} is the gear mesh frequency, N_t is the number of gear teeth and F_s is the rotational frequency.

Regardless of damage present, this signal and its harmonics always exist. The sidebands are caused by the frequency modulation of the gear meshing due to backlash, eccentricity, loading, bottoming and impacts caused by defects or damage to the gear. These sidebands generally differ from the gear mesh frequency by the rotating frequency of the affected gear and its harmonics. The magnitude of these sidebands tends to increase as damage occurs to the gear.

Cepstral analysis is also a useful tool in gear diagnostics. The effect of the cepstrum is to compress whole families of harmonic frequencies into a single quefrency and perhaps one or two rahmonics, it seems to be an ideal parameter for identifying sideband growth. Thus, the quefrencies associated with sidebands could be employed as alternative inputs to the sidebands obtained from frequency domain.

Vibration of bearings: The frequencies associated with bearing related signals generally depend on the location of the damage, the parameters of the bearings and the shaft rotation speed. In general, fundamental bearing related frequencies can be obtained by calculating the impact frequency for a ball in the bearing: (a) Impacting a fault on the inner or outer race, (b) The impact frequency for a fault located on the ball and (c) The impact frequency for a fault located on the frame. These impact frequencies adhere to the following equation (Yang and Bao, 1993):

$$F_{bo} = (1/2)N_b F_s(1\text{-}d/D\cos a) \tag{2}$$

$$F_{bi} = (1/2)N_b F_s(1+d/D\cos a) \tag{3}$$

$$F_{bb} = (1/2d)DF_s(1\text{-}(d/D\cos a)^2) \tag{4}$$

$$F_{bf} = (1/2)F_s(1\text{-}d/\cos a) \tag{5}$$

where, F_{bo} is the outer race impact frequency, F_{bi} is inner race impact frequency, F_{bb} is the ball impact frequency and F_{bf} is the frame impact frequency. N_b is the number of balls and F_s is the rotating frequency. D is the pitch diameter, d is the ball diameter and a is the contact angle between the ball and inner or outer race.

Vibration of shafts: Shafts generally produce vibration signals at their rotational frequencies and their harmonics. Shafts are also prone to a number of different faults, all of which register at the shaft rotating frequency. In the case of bent shafts and shaft misalignments, the second harmonic is the dominant frequency in 90% of the cases. Imbalances in the shaft and load generate a dominant signal at the shaft rotating frequency but there tends to a phase shift as well. Mechanical looseness can also introduce increases in the shaft rotating frequency but also characteristically involves higher harmonics as well.

EXPERIMENT MODEL AND MONITORING PARAMETERS

Experiment model: In order to explore the behavior of back propagation neural networks in complex system such as a machinery diagnostics environment, a series of experiments were conducted. Here, the rotating machinery for which the diagnostics system was designed is presented in Fig. 2.

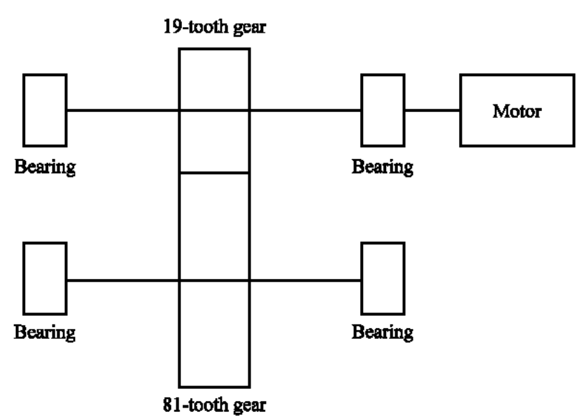

Fig. 2: Medium complexity gear train model

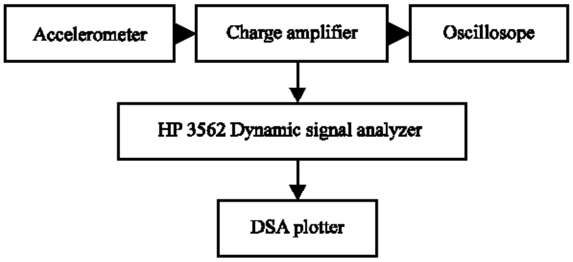

Fig. 3: Arrangement of vibration monitoring equipments

Table 1: Severity level for a fault

dB difference	Criteria	Desired output
0.0-2.5	Normal	0.0
2.5-4.0	Low severity	0.3
4.0-6.0	Moderate severity	0.6
over 6.0	High severity	0.9

It consists of a single reduction gear train consisting of a 19-tooth drive gear (GP) and an 81-tooth driven gear (GD). The gears were both m = 2.5 with 20 degree pressure angle. Each was attached to a 25 mm diameter shaft. Each shaft was supported by two 205 (Chinese National Standard) ball bearings. These bearings were mounted in steel block housings which were in turn bolted onto a 30 mm thick heavy cast iron base. The iron base was fixed to the ground of laboratory to minimize the extraneous vibrations on the system. The drive shaft is driven by a 370 W DC motor.

A schematic of arrangement for vibration monitoring equipment is shown in Fig. 3. The accelerometer was mounted in a radial position directly above the gear train. The heart of the vibration monitoring system was the HP 3562 Dynamic Signal Analyzer (DSA). This is a dual channel FFT analyzer capable of measuring the complete spectrum of vibration parameters, including time domain and statistical parameters as well as the linear and power spectra. It also measures the cepstral values.

Monitoring parameters: The frequency spectrum was used as primary source of diagnostics information. Current readings are compared to an established baseline and a magnitude difference in decibels (dB) is obtained. A general fault condition is deemed to exist when the current amplitude exceeds the baseline by more than 6.0 dB. The severity level is shown in Table 1.

With the physical model operating at 20 Hz, the dB levels at the following frequencies and quefrencies were monitored:

- The dB levels at the gear mesh frequency and the next two harmonics: 380, 760 and 1140 Hz
- The average dB levels of the first three of 4.69 Hz upper and lower sidebands surrounding the gear mesh frequency and its harmonics
- The average dB levels of the first three of 20 Hz upper and lower sidebands surrounding the gear mesh frequency and its harmonics
- The dB levels at cepstral quefrencies associated with the 4.69 and 20 Hz sidebands: That is, 213 and 50 m sec
- The averaged dB levels at the cepstral rahmonics associated with the sidebands where available: That is, 50 m sec and its next rahmonic
- The dB levels of first two harmonics at 20 Hz shaft (driving shaft) bearing inner race defect and outer race defect frequencies: That is, the dB levels at the 108.9 and 217.8 Hz for inner race and the dB levels at the 71.1 and 142.2 Hz for outer race
- The dB levels at the 20 Hz shaft bearing ball defect and frame defect frequencies: That is, 45.4 and 7.9 Hz
- The dB levels of first two harmonics at 4.69 Hz shaft (driven shaft) bearing inner race defect and outer race defect frequencies: that is, the dB levels at the 25.5 and 51.0 Hz for inner race and the dB levels at the 16.7 and 33.4 Hz for outer race
- The dB levels at the 4.69 Hz shaft bearing ball defect and frame defect frequencies: 10.6 and 1.9 Hz
- The dB levels at the shaft rotating frequencies and their next harmonics: That is, 4.69, 9.38, 20 and 40 Hz

NEURAL NETWORKS IN CONDITION MONITORING AND DIAGNOSTICS FOR ROTATING MACHINERY

Neural network architecture: Neural networks were designed to provide machinery diagnostics for the experimental model. All processing elements in the hidden and output layers used the sigmoid transfer function (Yang and Si, 2012).

Three neural networks were explored here. The first one purely employed frequency domain inputs and included four frequencies corresponding to the shafts, twelve bearing frequencies, three gear mesh frequencies and the averages of the first three sidebands on each side of the gear mesh frequencies. This totaled 25 inputs. In the second network, the six sideband average inputs were replaced with three cepstral inputs associated with the gears, totaling 22 inputs. The third network utilized all monitored frequencies and quefrencies for a total of 28 inputs.

Each network has 20 elements in a hidden layer and 12 elements in the output layer. The outputs correspond to machinery components experiencing the faults and consist of the high Speed Shaft (SH), the low speed shaft (SL), the high speed bearing inner race (HBI), the high speed bearing outer race (HBO), the high Speed Bearing ball (HBB), the high speed bearing frame (HBF), the low speed bearing inner race (LBI), the low speed bearing

Table 2: Results of test

	Test		
	Severity error		
Train	Successful diagnosis (%)	Within (15%)	Within (20%)
Experimental data			
Sideband	85.2	52.4	58.7
Cepstral	87.7	61.6	65.3
Combined	91.4	70.9	77.7
Experimental data+10% guass noise			
Sideband	88.6	76.2	79.0
Cepstral	89.7	83.8	86.1
Combined	94.1	86.2	89.5

outer race (LBO), the low speed bearing ball (LBB), the low speed bearing frame (LBF), the 19-tooth drive pinion (GP) and 81-tooth driven gear (GD).

Training neural networks: A database was established for the gear train system with multiple machinery components by observing the vibration signatures at discrete points in the frequency spectrum and cepstrum associated with the machinery components of interest. After establishing a baseline using undamaged components, a total of eighty experimental sets were conducted including various component fault.

From the experiments, half of the preprocessed vectors were used in the training sets while the other half were used in the test sets. The severity criterion used in these sets was based on assessment of the degree of physical damages.

Here, two different types of training sets were utilized for each of the neural networks. The first training set was extracted directly from experimental data. The second set of training data was made by adding 10% Guass noise on the base of the experimental data (Yang and Si, 2011).

RESULTS AND DISCUSSION

Test results are shown in Table 2. The first three networks were trained and tested on experimental data. The sideband averaging network reached a level of 0.058 total errors after 200000 iterations and the cepstral network converged at a level of 0.052 total errors after 200000 iterations. The combined network reached a level of 0.047 total errors after the same iterations. Even though the network were able to correctly diagnose the location in an average of 85.2, 87.7 and 91.4%, respectively, correct diagnosis with 15% severity error were only 52.4, 61.6 and 70.9%, respectively. The networks trained with experimental data performed quite well in finding the location of faults while not well in finding the severity of faults.

Three other networks were trained through the data added 10% Guass noise in the inputs. The networks were able to correctly diagnose the location of faults and kept severity error below 15% in an average of 76.2, 83.8 and 86.2%, respectively. Therefore, the networks trained on noisy inputs performed better compared to the networks trained with experimental data.

CONCLUSION

Neural networks provide a potential approach to machine condition monitoring and diagnostics for complex system such as rotating machinery. Based on results obtained, back propagation neural networks are capable of being successfully trained on either experimental data or the experimental data with 10% Guass noise. Results of the cepstral networks were better than the results of sideband averaging networks. However, the combined network trained on noisy inputs performed the best among all the testing networks.

Neural networks provide an alternative, or complement, to conventional rule based expert systems in machinery condition monitoring and diagnostic applications.

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