Real Time Fault Detection Monitoring System of Roller Bearing by Performance Index of SPC

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1. Introduction

Bearing envelope analysis (BEA) [1,2] is a powerful technique for the detection of bearing faults. The improper selection of the envelope window frequency and window bandwidth can render the analysis ineffective. This can reduce the ability to perform condition monitoring to correctly identify a degraded bearing [3,4]. This paper shows an analysis of how the BEA works in the detection of damage occurred in bearings. In the case the description of BEA was given, methods for window selection, such as spectral kurtosis, were described. Finally, statistical process control (SPC) [5,6] enabled us to define monitoring and setting control rules when the system detected an incipient fault.

2. Bearing fault dataset

A bearing fault dataset has been provided to facilitate research into bearing analysis. The dataset comprised data from a bearing test-rig in Fig. 1, such as nominal bearing data, and faults occurred at outer and inner races under various loads.

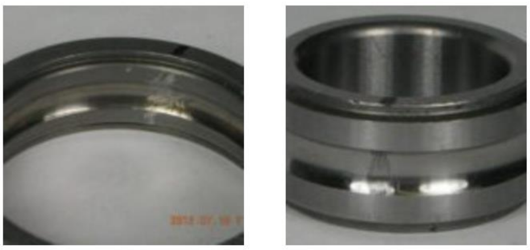

Fig.1 Bearing test-rig for Inner race of roller bearing

The bearing was installed in the test-rig, and the test was carried out with the following parameters:

- Roller diameter: rd = 0.235”
- Pitch diameter: pd = 1.245”
- Number of elements: ne = 8
- Contact angle: ca = 0º
- 3 baseline conditions: 270lbs of load, input shaft rate of 25Hz, sample rate of 97,656sps for 6seconds
- 3 outer race fault conditions: 270lbs of load, input shaft rate of 25Hz, sample rate of 97,656sps for 6seconds
- 7 outer race fault conditions: 25, 50, 100, 150, 200, 250 and 300lbs of loads, input shaft rate 25Hz, sample rate of 48,828sps for 3seconds (bearing resonance was found be less than 20kHz)
- 7 inner race fault conditions: 0, 50, 100, 150, 200, 250 and 300lbs of loads, input shaft rate of 25Hz, sample rate of 48,828sps for 3seconds.

3. Bearing envelope analysis

The BEA was based on demodulation of high frequency resonance associated with bearing element impacts.[1,2] For rolling element bearings, an impact was produced or a fault on a rolling element strikes the inner or outer race, when the rolling elements strike a local fault on the inner or outer race. These impacts modulated a signal at the associated bearing pass frequencies, such as: cage pass frequency (CPF), ball pass frequency of outer race (BPFO), ball pass frequency of inner race (BPFI), and ball fault frequency (BFF). Spectral kurtosis (SK) was a statistical parameter indicating how the impulsiveness of a signal varies with frequency.[3] As noted, faults associated with rolling element bearings gave rise to short impulse. The SK would be larger in frequency bands not only where the fault signal was dominant, but also where the spectrum was dominated by stationary signals. Fig. 2 shows the raw spectrum and the kurtogram.

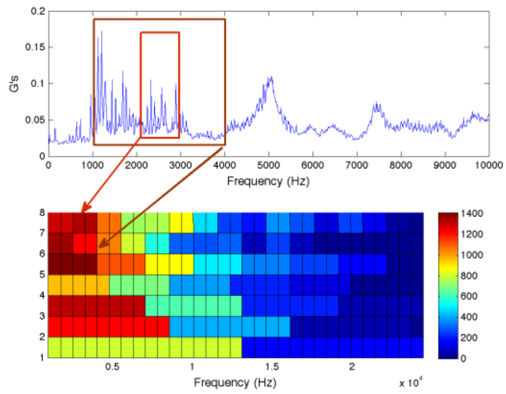

Fig. 2 Spectra and kurtogram

4. Statistical process control

For industrial applications, the automation of the fault detection process is required in order to reduce the need for manual inspection of data. Statistical process control (SPC) provided a platform to achieve this automation.[4,5] The SPC was implemented in two phases. In the first phase, the process was established, and the related variables were defined. Then, the definition of monitoring control rules was followed. Using the process variables to define SPC charts, such as Shewhart, T^2, cumulative sum (CUSUM) and exponentially weighted moving-average (EWMA), gave the output of the process.

When the process deviated from the control rule, an alert was issued.[7] In vibration analysis, the vibration signal, traditionally, was used itself, as the process variables and the control limits were set based on the vibration signal for the EWMA chart. The SPC enabled us to define monitoring and setting control rules, when the system detected an incipient fault. In order to define these process variables, the performance index was used. The EWMA chart was applied to monitor the process. Plotting the EWMA control chart from 42 data points as shown in Fig. 3, it is observed that the process variable at 39th data point deviates the control rules. Consequently, the SPC algorithm can detect the abnormal signal at 39th data point, and determine whether the entire system should be inspected.

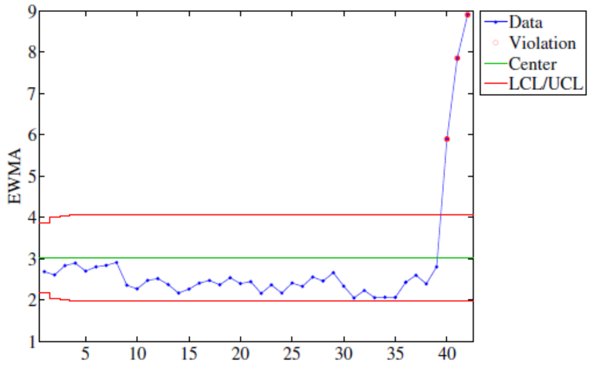

Fig. 3 EWMA control chart

5. CONCLUSION

This paper shows an analysis of how the bearing envelope analysis (BEA) works in the detection of bearing damages, and provides a method of how the automation of the fault detection process can be achieved by the statistical process control (SPC). The obtained results are summarized as follows:

1) Fault features have been extracted from the vibration signals for fault diagnosis of roller bearing by using the BEA via spectral kurtosis (SK).
2) The SPC is a novel way of automating the fault diagnosis of roller bearing because of its ability to generate alarms using online data. It has been shown that this framework is sensitive to fault inception and helps in early prevention.

Acknowledgment

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