Early bearing failure detection

Bearing failure is one of the foremost causes of breakdowns in rotating machinery and such failure can be catastrophic, resulting in costly downtime. One of the key issues in bearing prognostics is to detect the defect at its incipient stage and alert the operator before it develops into a catastrophic failure.

For the sensor-based method, signal de-noising and extraction of the weak signature are crucial to bearing prognostics since the inherent deficiency of the measuring mechanism often introduces a great amount of noise to the signal. In addition, the signature of a defective bearing is spread across a wide frequency band and, hence, can easily become masked by noise and low-frequency effects.

Normally, bearing vibration signals are collected with a vibration sensor installed on the bearing housing where the sensors are often subject to collecting active vibration sources from other mechanical components. The inherent deficiency of the measuring mechanism introduces a great amount of noise to the signal. Therefore, the signature of a defective bearing is spread across a wide frequency band and can easily become masked by noise and low-frequency effects. One of the challenges is to enhance the weak signature at the early stage of defect development. A signal-enhancing method is needed to provide more evident information for bearing performance assessment and prognostics.

The traditional approach for extracting signals from a noisy background is to design an appropriate filter, which removes the noise components and, at the same time, lets the desired signal go through unchanged. Based on noise type and application, different filters can be designed to conduct the de-noising. However, for a situation where the noise type and frequency range are unknown, the traditional filter design could become a computationally intense process.

The wavelet transform has been widely used in signal de-noising due to its extraordinary time-frequency representation capability, which is discussed in detail later in this paper. While most of the signal de-noising approaches intend to detect smooth curves from the noisy raw signals, the vibration signal from mechanical failure, such as gears and bearings, are more impulse-like than smooth. Some researchers have developed a de-noising method based on Morlet wavelet analysis and applied the method to feature extraction of gear vibration signals. These methods seek the optimal wavelet filter that can give out the largest kurtosis value for the transformed signal. However, the defect signature of the bearing is periodic impulses. The periodicity plays an important role in fault identification and should not be ignored in optimal wavelet filter construction.
Another challenge of bearing prognostics is how to effectively evaluate the system performance based on the extracted features. One of the primary difficulties for effective implementation of bearing prognostics is the highly stochastic nature of defect growth. Even though a large variety of features can be extracted to describe the characteristics of signal from different aspects (such as root-mean-square [RMS], kurtosis, crest factor, cepstrum and envelope spectrum), previous work has shown that each feature is only effective for certain defects at certain stages. For example, spikiness of the vibration signals indicated by crest factor and kurtosis implies incipient defects, whereas the high energy level given by the value of RMS indicates severe defects. A good performance assessment method should take advantage of mutual information from multiple features and sensors for system degradation assessment.

**Case Study**

**Weak signature detection for roller element bearing prognostics.**

Most bearing diagnostics research involves studying the defective bearings recovered from the field, where the bearings exhibit mature faults, or from simulated or “seeded” damage. Experiments using defective bearings have less capability to discover natural defect propagation in the early stages. In order to truly reflect the real defect propagation processes, bearing run-to-failure tests were performed under normal load conditions on a specially designed test rig.

The bearing test rig hosts four test bearings on one shaft. Shaft rotation speed was kept constant at 2,000 rpm. A radial load of 6,000 pounds is added to the shaft and bearing by a spring mechanism. A magnetic plug installed in the oil feedback pipe collects debris from the oil as evidence of bearing degradation. The test stops when the accumulated debris adhered to the magnetic plug exceeds a certain level.
Four double-row bearings were installed on one shaft as shown in Figure 1. A high-sensitivity accelerometer was installed on each bearing housing. Four thermocouples were attached to the outer race of each bearing to record bearing temperature for monitoring the lubrication purposes. Several sets of tests ending with various failure modes were carried out. The time domain feature shows that most of the bearing fatigue time is consumed during the period of material accumulative damage, while the period of crack propagation and development is relatively short. This means that if the traditional threshold-based condition monitoring approach is used, the response time available for the maintenance crew to respond prior to catastrophic failure after a defect is detected in such bearings is very short. A prognostic approach that can detect the defect at the early stage is demanded so that enough buffer time is available for maintenance and logistical scheduling.

**Challenges:** Figure 2 presents the vibration waveform collected from Bearing 4 at the last stage of the bearing test.
The signal exhibits strong impulse periodicity because of the impacts generated by a mature outer race defect. However, when examining the historical data and observing the vibration signal three days before the bearing failed, there is no sign of periodic impulse as shown in Figure 3(a). The periodic impulse feature is totally masked by the noise.

**Solutions:** An adaptive wavelet filter is designed to de-noise the raw signal and enhance the degradation detectability. The adaptive wavelet filter is yielded in two steps. At first, the optimal wavelet shape factor is found by the minimal entropy method. Then, optimal scale is identified by maximizing the signal periodicity. Applying the designed wavelet filter to the noisy raw signal, the de-noised signal can be obtained as shown in Figure 3(b).
The periodic impulse feature is clearly discovered, which is strong evidence of bearing outer race degradation. The wavelet filter-based de-noising method successfully enhanced the signal feature and provided potent proof for prognostic decision-making.

**Impacts:** The experimental results verify the effectiveness of the proposed de-noising method and demonstrate its capabilities of detecting defects in its early degradation stage. The weak periodic impulse signature is successfully revealed and enhanced. Detection of the degradation signature at its early stage gives more time for maintenance reaction and business decision-making and also provides proof for prognostics.

**Reference:**