Time domain analysis in condition monitoring- a review

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Abstract

Rotating components are important element in any machine as most of the failures are happening due to rotating components. Therefore, rotating components needs to be inspected for their faults regularly to verify its health so that shutdown of the machine should not occur during its repair. This chapter aims to review the time-domain techniques used in the detection of rotating components faults. After the review of the various time-domain techniques, the techniques were compared to draw the advantage of using them in vibration analysis. The main advantage of using vibration analysis techniques is that one needs not to dis-mental the rotating components for the purpose of inspection. The chapter is mainly structured in two parts. In the first part the advantage of using vibration based technique are discussed and in the next part various time domain techniques are discussed along with their advantages.

Keywords: Condition monitoring, vibration analysis, rotating machinery

1. Introduction

In practice, after deciding the type of sensor to be used with its location of mounting and the parameter to be monitored [Lifshits et al., 1986], the waveforms of vibration/acoustic signals from rotating machinery are often recorded. Apart from containing the information relating to machine condition, the background noise is also present in the recorded signal. Further processing of the signal is necessary to elicit information particularly relevant to faults in rotating components. The signals can be processed using different techniques based on time domain, frequency domain or multi-resolution analysis [Yiakopoulos et al., 2011]. Each different technique gives some typical information about the condition of the machinery. If fault detection is the objective, then the speed and reliability of the processing technique are important, if fault diagnosis and measurement is objective, the accuracy of the method is essential. Many studies have been carried out to find the most effective technique for the analysis, monitoring and diagnostics of machines [Miaoa and Makis, 2007].

In the following section, the three broad categories of signal processing such as time domain, frequency domain and time-frequency domain techniques are described.

2. Time domain techniques

In time domain techniques, vibration signal is represented in amplitude versus time plot [Eshleman, 1983]. Instrument working on time domain technique is as simple as an oscilloscope. A typical time domain plot is shown in Figure 1.3.

Although, the time domain plot often shows the nature of the mechanical problem better than the frequency domain but in the cases of complex machine

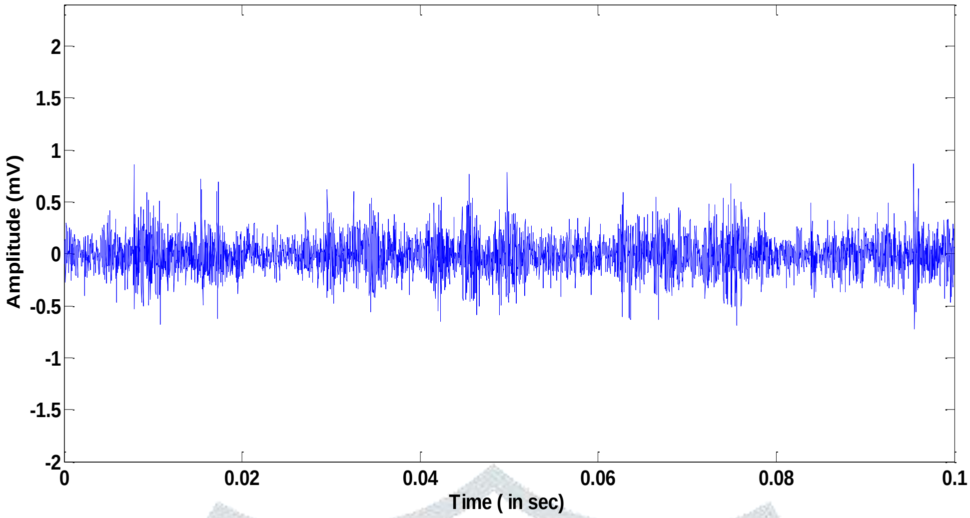

Figure 1.3: A typical time domain signal for defect free bearing.

systems, when the vibration/acoustic signature may combine several other signals with different frequencies, amplitudes and phases, it results in ambiguity in identifying defect. The amplitude vs time waveform is characterized by the statistical parameters explained below.

2.1 Overall root mean square (RMS) level

Root mean square value of a vibration/acoustic signal is a measure of the overall power content present in the signal [Barkov et al., 1995]. The mathematical expression used to calculate RMS is as follows

$$RMS = \sqrt{\frac{\sum_{k=1}^{n} x_k^2}{n}} \qquad (1.1)$$

where x_k denotes the amplitude of signal and n is the number of data points.

This feature gives good results in tracking the overall noise level in the signal present but does not give any information about when the component is going to fail. Apart from that, it has limitation to extract precise information from the data. For example, the measurement of a damaged bearing must be made from the bearing housing support which is affected by the transmission path to the sensor. Due to defect there is some change in RMS level of measurement but unless the problem is severe (at the time of failure), the overall RMS level measurements may not change significantly.

2.2 Peak level detection

The peak level indicator is basically the maximum value of amplitude present in the amplitude-time waveform of the signal [Safizadeh, 1992]. For a new defect free machine there is a baseline peak level and any variations from this level would be indicative of a change in machine condition. Operational standards are developed for recommending vibration boundary levels for satisfactory running conditions. The change in the amount of impulse may be due to the occurrence of impacts that can be monitored effectively by use of this statistical parameter. However, in isolation, this method is not reliable since resonant behaviour often dominates the vibration signal.

2.3 Crest factor

The ratio of the peak level to the root mean square level of the signal is called the crest factor [Kiral and Karagulle, 2003]. The crest factor could be used as an indicator of bearing condition [Weichbordt and Bowden, 1970]. Periodic peaks occur in the signal due to a localized fault. For sharp edged severe faults, the waveform becomes more impulsive with higher peak levels. The crest factor limits are as follows: 2 to 3 indicates a normal bearing, 3 to 8 indicates fault initiation and 8 to 10 indicates fault growth. But for distributed defects, root mean square level is significantly increased leading to reduction in the crest factor value which misrepresents the condition of fault. Also due to background noise the root mean square level in the signal increases and the value of crest factor decreases.

2.4 Standard deviation (σ)

Standard deviation shows the variation or dispersion of data from its mean value [Jena et al., 2012]. Standard deviation (σ) can be calculated by the following expression:

$$\sigma = \sqrt{\frac{\sum_{k=1}^{n}(x_k - \bar{x})^2}{n}} \tag{1.2}$$

where, $\bar{x}$ denotes the average value of amplitude of the signal. The other symbols used have already been defined.

2.5 Skewness

Skewness is a measure of the lack of symmetry [Sugumaran et al., 2008]. A distribution or data set is symmetric if it looks the same to the left and right of the center point. Mathematically it can be expressed as:

$$Skewness = \frac{n}{(n-1)(n-2)} \frac{\sum_{k=1}^{n}(x_k - \bar{x})^3}{\sigma^3} \tag{1.3}$$

Symbols used have already been defined.

The skewness for a normal distribution is zero and hence any symmetric data should have a skewness near zero. Negative values for the skewness indicate data that are skewed left and positive values for the skewness indicate data that are skewed right. By skewed left, we mean that the left tail is long relative to the right tail and skewed right means that the right tail is long relative to the left tail. It generally gives the good indication for the cases having the local defect.

2.6 Kurtosis

Kurtosis is a statistical parameter to analyze the distribution of the vibratory amplitudes contained in a time domain signal and is often used as an indicator of impulsiveness by measuring peak and tails [Sugumaran et al., 2008]. The kurtosis factor K_u is expressed as below:

$$K_u = \frac{\frac{1}{n}\sum_{k=1}^{n}\left[x_k - \bar{x}\right]^4}{\left[\frac{1}{n}\sum_{k=1}^{n}\left[x_k - \bar{x}\right]^2\right]^2} \quad (1.4)$$

A bearing in good condition has a Gaussian distribution function and the Kurtosis value of its signal is equal to three, but a damaged bearing has a Kurtosis value which will be greater than three [Tandon and Choudhury, 1999]. Advantage of using this method is that the Kurtosis value is able to identify defects in bearing at different speeds. But for modulated signals this technique may lead to inaccurate predictions.

The parameters described above can give information about the overall condition of the machine but fail to identify the location, type and severity of defect in the complex machine.

3. Conclusion

Attention has to be paid to the vibration analysis-based techniques for detecting faults in rotating components. Therefore, they need to be reviewed properly before taking decision that which technique has to be implemented. The main advantage of using appropriate technique is to detect the defect at incipient stage and hence, avoiding the shutdown of the machine. This chapter presented most common time-domain techniques used in the detection of rotating components faults. The techniques were compared to draw justification for their appropriateness of the condition where they have to be used. The time domain techniques are widely used where defects are non-localized This chapter will help the readers to learn that how to make use of time-domain based techniques as a predictive maintenance tool.

References

[1] Lifshits, A, Simmons, H.R., Smalley, A.J. 1986. More comprehensive vibration limit for Rotating Machinery. *Journal of Engineering for Gas Turbines and Power*. 108: 583

[2] Yiakopoulos, C.T., Gryllias, K.C. and Antoniadis, I.A. 2011. Rolling element bearing fault detection in industrial environments basedon a K-means clustering approach. *Expert Systems with Applications.* 38: 2888-2911

[3] Miaoa, Q. and Makis, V. 2007. Condition monitoring and classification of rotating machinery using wavelets and hidden Markov models. *Mechanical Systems and Signal Processing* 21 : 840-855

[4] Eshleman, R.L. 1983. Machinery diagnostics and your FFT. *Sound and Vibration*. 17 : 12-18

[5] Barkov, A., Barkova, N. and Mitchell, J. S. 1995. Condition Assessment and Life Prediction of Rolling Element Bearing- Part 1. *Journal of Sound and Vibration*. 29: 10-17

[6] Safizadeh, M.S. 1992. Vibrational Diagnosis of Rotating Machinery in Time-Frequency Plane, PhD. Thesis, Ecole Polytechnique of Montreal, Quebec, Canada

[7] Kiral, Z. and Karagulle, H. 2003. Simulation and analysis of vibration signals generated by rolling element bearing with defects. *Tribology International*. 36: 667–678

[8] Weichbordt, B. and Bowden, F.J. 1970. Instrumentation for predicting bearing damage. G.E.C. Technical Report RADC-TR-69-437

[9] Jena, D.P., Singh, M. and Kumar, R. 2012. Radial ball bearing inner race defect width measurement using analytical wavelet transform of acoustic and vibration signal. *Measurement Science Review*. 12: 141-148

[10] Sugumaran V., Sabareesh, G.R. and Ramachandran, K.I. 2008. Fault diagnostics of roller bearing using kernel based neighborhood score multi-class support vector machine. *Expert Systems with Applications.* 34: 3090–3098

[11] Tandon, N. and Choudhury, A. 1999. A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings. *Tribology International*. 32: 469–480