Chapter VI
Condition Monitoring Using Computational Intelligence

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ABSTRACT

Condition monitoring techniques are described in this chapter. Two aspects of condition monitoring process are considered: (1) feature extraction; and (2) condition classification. Feature extraction methods described and implemented are fractals, kurtosis, and Mel-frequency cepstral coefficients. Classification methods described and implemented are support vector machines (SVM), hidden Markov models (HMM), Gaussian mixture models (GMM), and extension neural networks (ENN). The effectiveness of these features was tested using SVM, HMM, GMM, and ENN on condition monitoring of bearings and are found to give good results.

INTRODUCTION

Condition monitoring of machines is gaining importance in industry due to the need to increase machine reliability and decrease the possible loss of production due to machine breakdown. By definition, condition monitoring is performed when it is necessary to access the state of a machine and to determine whether it is malfunctioning through reason and observation (William, Davies, & Drake, 1992). Condition monitoring can also be defined as a technique or process of monitoring the operating characteristics of a machine so that changes and trends of the monitored signal can be used to predict the need for maintenance before a breakdown or serious deterioration occurs, or to estimate the current condition of a machine. Condition monitoring has become increasingly important, for example, in manufacturing companies due to an increase in the need for normal undisturbed operation of equipment in manufacturing. An unexpected fault or shutdown can result in a serious accident and financial loss for a company. Manufacturing companies must find ways to avoid failures, minimize downtime, reduce maintenance costs, and lengthen the lifetime of their equipments. With reliable condition monitoring process, machines can be utilized in a more optimal fashion. Time-based maintenance follows a schedule to decide when maintenance is to be conducted. This leads to inefficiencies because either the maintenance may be conducted needlessly early or a failure may happen before scheduled maintenance takes place. Condition monitoring can therefore be used for condition based maintenance, or predictive maintenance.

Rotating machines are used in various industrial applications. One of the most common components in modern rotating machinery is the rolling element bearing. Most machine failures are linked to bearing failure (Lou & Loparo, 2004), which often result in lengthy downtime that have economic consequences. As a result, an increasing volume of condition monitoring data are captured and presented to engineers. This leads to these key problems, such as, the data volume is too large for engineers to deal with and the relationship between the plant item, its health, and the data generated is not always well understood. Therefore, the extraction of meaningful information from data is difficult. Hence, a reliable, fast, and automated diagnostic technique allowing relatively unskilled operators to make important decisions without the need for a condition monitoring specialist to examine the data and diagnose problems is required. The most commonly used condition monitoring system is vibration-based condition monitoring. Vibration monitoring is based on the principle that all systems produce vibration. When a machine is operating properly, vibration is small and constant; however, when faults develop and some of the dynamic processes in the machine change, the vibration spectrum also changes (Marwala, 2001).

The success of a classification system depends very much on the effectiveness of the extracted features. Another crucial step is to establish a reliable and effective condition monitoring classification system. The objective of this chapter is to give a review of three feature selection techniques that have been used recently for bearing fault diagnosis (Nelwamondo, Marwala, & Mahola, 2006) These techniques are: 1) Mel-frequency cepstral coefficients (MFCC), which is a time-frequency domain analysis technique that has been used extensively in speech recognition; 2) kurtosis, which is the time domain analysis method; and 3) Fractal dimension analysis method which is a time domain analysis method that has been applied to problems in image processing. This chapter also evaluates the effectiveness of the extracted feature for bearing fault diagnosis with the support vector machine (SVM), hidden Markov model (HMM), Gaussian mixture model (GMM) and extension neural network (ENN) classifiers. SVM was chosen as it has been applied successfully in many fault diagnosis applications. The inspiration for the use of GMM and HMM is their success in speech recognition, and ENN was chosen because of its success for pattern recognition of partial discharges.

BACKGROUND

As mentioned earlier, the success of a classification system depends on the effectiveness of the extracted observation sequence to represent a particular machine state or condition. During the past decades, considerable research effort has been put into the development of various feature extraction techniques and condition monitoring systems. Feature extraction techniques can be classified into three domains, namely; frequency domain analysis, time-frequency domain analysis, and time domain analysis (Ericsson, Johansson,

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