A Novel Approach for Fault Detection in Bearings of Rotary Machineries at Variable Load Conditions

by

©A F M Mursalin

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Abstract

This thesis proposes a novel approach for machine fault detection from vibration data collected at variable load conditions of a system. Although load variation is a common phenomena in real industry, most of the traditional fault detection techniques fails to take this load variability into account while analyzing vibration data. Plant loads and machine rpm change have a significant influence on the vibration data and to address this fact accurately, a multivariate technique combining Multiscale PCA (MSPCA) and Multiway PCA (MPCA) is presented here. The methodology takes the powerful data signature extraction feature of Wavelet Transform (WT) and strong fault detection ability of PCA and integrate them with the multiple conditions monitoring ability of MPCA. Another significant feature of this proposed multiscale MPCA technique is that it combines the process variables with the vibration analysis. An advanced simulation system of bearing fault at variable loads is presented and the methodology is used on the acquired simulated data. The results are presented along with a comparison with a conventional technique. The efficacy of the proposed methodology is demonstrated on a DC motor experimental setup.

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Chapter 1

Introduction

1.1 Overview

Rotating machineries (e.g., compressors, turbines) are important assets in process industries. Conditional monitoring and fault diagnosis can save maintenance costs of these machines and significant benefits to most processing and manufacturing operations. Machine condition monitoring and fault diagnostics can be defined as the field of technical activity in which selected physical parameters, associated with machinery operation, are observed for the purpose of determining machinery integrity [1]. Reduced costs of instrumentation, improved capability of instrumentation, improved data storage, and faster and more effective data analysis has made condition monitoring system cost-effective [2].

Vibration analysis is a powerful diagnostic tool in condition monitoring. Maintenance of major rotating equipment is quite impossible without effective vibration analysis [3]. Vibration monitoring means analysis of the signals acquired by data collectors from the vibrations generated by virtually all dynamic systems e.g., rotating machinery. Individual rotating equipment produce unique vibration patterns, or signatures, which can indicate their condition or change in their normal condition.

Early fault detection using vibration monitoring is one of the most effective condition monitoring based preventive maintenance strategy in process industry. Bearing fault diagnostic procedure consists of three main steps: data acquisition, data processing and maintenance decision making [4]. Data acquisition is the primary step and vital for vibration monitoring techniques. Among various type of transducers, Piezoelectric accelerometers are the most popular to measure acceleration, velocity or displacement. Generally, single axis and tri-axial accelerometers are used to collect vibration signals from rotating machinery, i.e., bearings. A data acquisition board (DAq) is used to collect and transform these data into standard form to present in time domain, frequency domain or time-frequency domain for diagnosis. The main purposes of data processing techniques are to extract of significant vibration signature from extreme noisy vibration signals. Then, different fault detection techniques are applied to identify fault and to take maintenance decision. In most of fault detection techniques, it is often assumed that process conditions do not change, which is not true for most practical cases.

Plant loads and rotating machine conditions are not stationary. Plant operating conditions changes for various reasons such as insufficient feed, lack of efficiency of the machines, methods of operation, make the rotating machineries operate at different loads and different rpm (rotation per minute). Therefore, these non-stationary conditions of the system cause variation in vibration signals. While the plant runs at different loads, it is quite impractical to apply fault detection algorithm developed for stationary system. This kind of application may cause misinterpretation of collected data and results in either a false alarm or no alarm when there is a need for one. Addressing variable conditions in vibration analysis and relating the changing variables effectively with the vibration monitoring technique is not only a critical safety issue but also save a lot of costs in condition based maintenance (CBM) by taking decision in complex situations. Based on this important fact, the purpose of this research is developed. This research makes a significant attempt to relate the changing process conditions with the vibration signals with a aim to produce effective fault detection.

1.2 Objectives

The main goal of this thesis is to develop an effective vibration monitoring system for fault detection of rolling element bearings of large rotating machines operating uder variable process conditions. Based on this target, the following objectives are set.

- To study the effect of process conditions changes on vibration signals and fault detection methods.
- To develop a fault detection method based upon multivariate statistical techniques that is able to take into account process variation.
- To augment vibration data with process data and develop a methodology to analyze the combined data matrix for better fault detection ability under non-stationary process conditions.
- To develop a test set-up for simulating bearing faults under load change scenerios and use it for validating the proposed fault detection method.

1.3 Novelty and contribution

The main contributions of this thesis is stated below.

- A novel multivariate technique based on Multiscale PCA (MSPCA) and Multiway PCA (MPCA) to detect fault in rolling element bearings in variable process condition has been developed. The methodology uses the MSPCA to filter out the noise of the system and extract the significant fault finger prints from vibration signals and combines MPCA to analyze different sets of vibration data collected under variable process conditions.

- A technique of fusing process variables with vibration signals is proposed. This data augmentation technique has improved the effectiveness of the fault detection method under non-stationary conditions significantly.
- An experimental setup has been developed that is able to simulate bearing faults under variable process conditions. The developed methodologies have been tested and validated on this setup.

1.4 Organization

The thesis consists of two journal manuscripts. Both manuscripts have been submitted to journal for publication and currently under review.

Chapter 1 begins with an overview of condition monitoring of bearings of large rotary machines in industry, and the importance of vibration based condition monitoring schemes. After that, one of the major limitations of conventional monitoring approaches is discussed. The objective of the thesis is explained and the novelty and the contributions are listed.

Chapter 2 presents the literature review. This section gives an overview of various methods used by the researchers over past years. This includes the significant breakthroughs in earlier attempts in the frequency domain analysis, advanced artificial intelligence methods and complex multivariate methods. This section also discusses recent works on fault diagnosis of bearings under non-stationary operating conditions.

Chapter 3 introduces the application of MPCA for fault detection of bearings. An advanced model of bearing fault simulation at different loads is developed. The proposed technique is applied to simulated data and to demonstrate its effectiveness. Subsequently, these results are also compared with an established method. This chapter is submitted for publication in the *Mechanical Systems and Signal Processing (MSSP)* journal and currently under consideration.

Chapter 4 introduces a significant improvement of the method described in chapter three. The vibration data is augmented with corresponding process variables and subsequently a methodology is developed to analyze the augmented data matrix. Detailed description of an experimental setup simulating bearing faults under variable load conditions is stated in this chapter. The efficiency of the proposed multiscale MPCA has been demonstrated on this experimental setup. The results acquired from this experimental evaluation are explained and compared with previous results described in chapter three and a conventional method. This chapter is submitted for publication in the *Mechanical Systems and Signal Processing (MSSP* journal and currently under review.

Chapter 5 finishes the thesis with conclusions and discussions of future scope of work.

Chapter 2

Literature review

A rolling element bearing is an integral part of many rotary machines and it directly influences the operation of the entire process. Unexpected failures of bearings cause fatal breakdown of machines and could lead to significant economic losses. Therefore, fault diagnosis of the rolling element bearing has been extensively studied in past years. The literature on bearing fault diagnosis is diverse, primarily due to the wide variety of techniques. Hundreds of papers in this area, including theories and practical applications, appear every year in academic journals, conference proceedings and technical reports. In this literature review section, the most significant ones that have been done in past years, are highlighted in three different sections. The first section is about basic techniques of fault detection using vibration analysis. The second describes advanced artificial intelligence methods. The third emphasizes on the latest and more complex techniques in this area. Additionally, a separate section is added, with emphasis on the recent studies on load variation fact influencing bearing vibration analysis.

Frequency domain analysis contains introductory discussion of the techniques used for vibration analysis. Starting with Fourier transform, this sections describes the early development in vibration analysis pointing out basic techniques such as Fast Fourier transform (FFT), Wavelet Transform (WT), Wigner-Ville Distribution (WVD), Hilbert Transform (HT)etc.

Artificial intelligence methods represents various complex methods including Artificial Neural Network (ANN), Support Vector Machine(SVM), Cluster analysis, Principal component analysis (PCA)etc., which have been engaged for fault detection in vibration analysis by researchers over the course of time.

Complex multivariate analysis consists of vivid illustration of composite techniques such as combination of multiscale and multivariate Principal Component Analysis (MSPCA) with Ensemble Empirical Mode Decomposition (EEMD), Kernel Principal Component Analysis with EEMD , wavelet combined with different statistical procedure. This section emphasizes on multivariate analysis while the prior sections define univariate methods.

Effect of load Variation expresses the idea of the change of vibration patterns in different loads in the rotating machine. Few researchers have identified and taken the fact of load change into account.

2.1 Frequency Domain analysis

Frequency domain analysis is the most widely used and perhaps the basic tool to extract machine information from raw vibration signals. It is generally accepted that the vibration signal is noisy and bears lot of information for the users that cannot be extracted until it has been transformed into some usable format. There are two components to a vibration signal: *i*) how fast the machine moves known as frequency and *ii*) how much it moves also known as amplitude[5]. Any time domain signal can be represented in form of a series of sines and cosines with particular frequencies and amplitudes using Fourier analysis. Typically with this reversible transformation users can monitor the amplitudes in different frequencies in defined states of a machine. An alternative representation of

Fourier transformation, Fast Fourier Transform(FFT), is the most widely used basic tool for vibration analysis. This classical method gives signal strength at different frequencies, which allows the observer to detect different faults in the rotating machine.

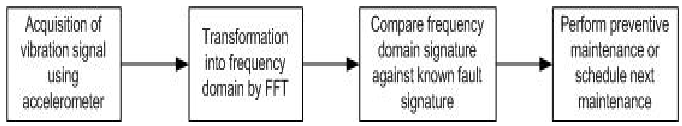

Figure 2.1: Vibration monitoring scheme based on FFT

McFadden and Smith [6], [7] developed the models for high frequency vibration produced by a single point defect on the inner race of the rolling element bearing under redial load and proposed a fault detection method based on FFT analysis. Wu et al. [8] investigated bearing fault such as crack location and depth using FFT. In their research, they used equation of motion, energy expression and lagrange's equation to produce equation of rotor for vibration. They simulated the crack signal and transformed it to frequency domain using FFT analysis. They showed that amplitude changes in different frequencies for faulty vibration signals and this amplitude change is different depending upon the location and size of the crack. Based on this fact, they revealed the crack location and depth by graphically plotting amplitude ratio with probe-crack location ratio. The methodology did not take noise into account for vibration signals, which is very common for a typical vibration signal. Moreover, this study failed to show any practical application for vibration analysis.Önel et al. [9] studied a new technique combining vibration and motor stator current in frequency domain for fault detection in rolling element bearing. They illustrated that air flux density changes between the air gap among the rolling element and inner or outer race of the bearing. This air flux variation affected the stator current harmonics and can be a indication of bearing fault. The authors made an experiment where they took vibration measurement of bearing and at the same time acquired the current measurement. After that, they had transformed using FFT both vibration and current signal in frequency domain to identify the Characteristic Defect Frequency (CDF) for inner, outer or cage fault frequency. They took healthy as well as faulty bearing measurements and compared them graphically. However, they admitted that the stator current analysis could not be a stand alone strong identifier of CDF detection but it could be an additional tool along with vibration spectra in frequency domain to determine a fault in bearings.

Rai et al. [10] proposed a unique methodology combining Hilbert-Huang transform (HHT) with FFT analysis. They suggested that only HHT is vulnerable to subjective error in calculation, where as only FFT is unable to analyze amplitude variations and non linear trends in vibration. In their proposed technique, vibration signals transformed to Intrinsic Mode Functions (IMFs) by Empirical Mode Decomposition (EMD) and then FFT analysis was employed to the IMFs to detect CDF from vibration spectra. They made a practical application of their technique on a test rig and detected the CDFs. Nevertheless, because of the poor performance in analyzing the non-stationary signals, FFT loses its interest among the researchers as a central appliance for fault detection of bearings [11]. Briefly speaking, during machine fault, it is a common phenomena that signals having no constant frequency spectrum but change their frequency content over time. Essentially, conventional Fourier transform is unable to detect the frequency change associated with a particular instant of time of these so called non-stationary signals. Conclusively, FFT bears significant importance to the primary users of vibration analysis, despite of its potential drawback.

To overcome the shortcomings of the Fast Fourier transform and at the same time, thirst for more accurate approximate techniques, researcher sought to discover more sophisticated time frequency domain analysis. Short time Fourier transform or small windowed

Fourier transform made it possible for the users to explain a signal from two dimension-time and frequency simultaneously. While the normal procedure was to observe the vibration signal in time domain, it is very difficult to identify process characteristics or process finger prints to scrutinize signals in one dimension without any prior knowledge of the spectral content. Therefore, Short Time Fourier Transform (STFT) examines the signal frequency in small constant width window that allows the users to look at the non-stationary signal more closely. Although STFT may be regarded as the gateway to time frequency domain analysis, it is unable to change small time window size when examining a sharp transient shift in signal frequency.

On the other hand, Wavelet theory, which is comparatively new discovery for researchers, includes the feature of zooming in short lived high frequency and zooming out long lived low frequency to the existing STFT tool resulting in a powerful and sophisticated technique. Generally speaking, wavelet is multi-scale decomposition process that not only analyzes the signal step by step in each scale instead of some pre-defined scales but also reduces the bandwidth through reduction in mean frequency. Because of its adaptability and flexibility, Wavelet has gained popularity among researchers who, in turn, made it their fundamental estimation technique for fault detection.

Lin et al. [12] presented an advanced de-noising method based on the Morlet wavelet for mechanical fault diagnosis. In their proposed methodology they overcame the prerequisite requirement of mother wavelet being orthogonal. They selected the β value from the β vs. Wavelet entropy relationship and introduced a constant which influenced the soft-thresholding and could able to extract features even in low SNR (signal to noise ratio). Although it was a univariate method, they successfully identified the fault impulse at designated frequency which was confirmed theoretically both in rolling bearings and a gearbox. Prabhakar et al. [13] used the Discrete Wavelet Transform (DWT) for detecting single and multiple faults in the ball bearings. Purushotham et al. [14], later, proposed

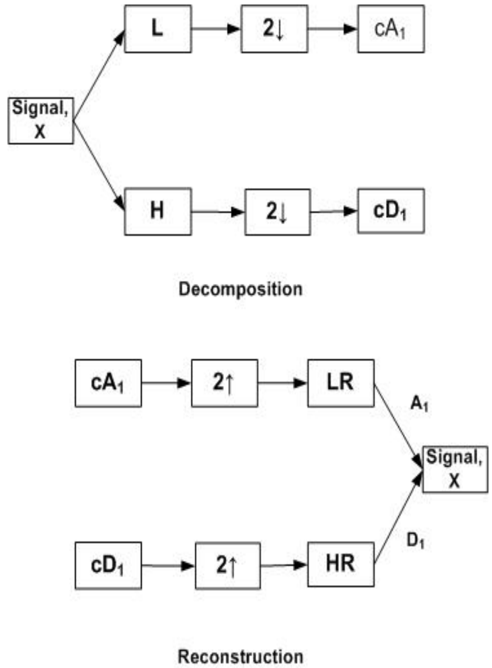

Figure 2.2: Basic steps of decomposition and reconstruction in wavelet transform

an improved methodology of pattern recognition for bearing fault monitoring combining DWT with hidden Markov Models (HMMs). On the other hand, Bozchalooi and Liang [15] suggested a Wavelet filter-based denoising method to detect outer race, inner race and rolling element faults in bearings. The algorithm introduced scale and shape factor selection method for wavelet feature extraction from signals preprocessed using spectral subtraction.

Around the 90s, another important means of detecting fault in rolling element bearing, HT was emerged in envelope analysis arena. Originating from Fourier transform, it has few advantages compared to the former in frequency domain. Randall et al. [16] investigated bearing fault with the help of HT from simulated as well as actual bearing fault signals. In this study, a hard threshold technique was applied to low frequency components while the higher ones were processed with squared envelope analysis based on HT. The method engaged HT as a noise demasking filter to extract the significant frequency portions.

Another popular time-frequency domain analysis is Wigner-Ville distribution (WVD). Bayder et al. [17] employed WVD in detecting faults in gearbox and argued that it was better in handling acoustic data compared to vibration data. The research successfully detected early fault condition using acoustic data, although the study admitted that WVD is a linear representation of data, which means it has some disadvantages in handling non-linear data.

Kim et al. [18] took a practical initiative to detect crack on rolling bearings. In their proposed methodology, they came up with a diagnosis system that combined FFT, STFT, WVD and WT for comparison and applied it in real time bearing fault in a experiment. They induced cracks in the bearings during speed up and speed down of the process. Next, they investigated the findings of the vibration signals following the above four techniques and pointed out abnormal condition such as crack by making a contrast between the faulty signals and the normal signals. However, their research lacked of uniqueness and was unable to provide sufficient information on different fault vibration signals.

2.2 Artificial intelligence methods

Artificial neural network approach (ANN) has been increasingly applied to bearing fault diagnosis for the past few years and has shown some improved performance over conventional approaches [19]. Artificial neural networks (ANNs) implement algorithms that attempt to achieve a neurological related performance, such as learning from experience, making generalizations from similar situations and judging states where poor results are achieved in the past [20]. An ANN is a computational model, consists of processing elements connected in a complex layer structure that enables the model to approximate a complex non-linear function with multi-input and multi-output. A processing element comprises a node and a weight. The ANN learns the unknown function by adjusting its weights and with observation of input and output. This process in usually called training of an ANN. Among various models, Feed Forward Neural Network (FFNN) structure is the most widely used neural network structure in machine fault diagnosis. A special FFNN, multilayer perception with back propagation (BP) training algorithm, is the most commonly used neural network model for pattern recognition and classification and hence, machine fault diagnosis as well [4]. Samanta et al. [19] investigated bearing fault using ANN training with BP algorithm. In this study, characteristics features of time domain such as root mean square, skewness, variance, kurtosis, and normalized sixth central moment from vibration signals of the rotary machine were used in nodes for input layer. The output layer of the ANN consists of two binary nodes indicating normal and faulty conditions, while there were two hidden layers with different number of nodes used in between input and output layers. The BP neural networks, however, have two main limitations such as (1) difficulty in determining the network structure and number of nodes and (2) slow convergence of the training process [4]. Support vector machine (SVM) is a relatively new computational learning technique based on the statistical learning theory and can serve expertise system (ES) as an application of artificial intelligence (AI) in maintenance. In machine condition and fault diagnosis problems, SVM that based on the structural risk minimization (SRM) principal rooted in the statistical learning theory, is employed for recognizing special patterns from acquired signals. Those patterns are classified according to the fault occurrence in the machine. Generally, SVM takes large numbers of samples as an input to a hyperplane where it classifies them as positive and negative parts. At the same time, it maximizes the margin between two sections by support vectors, which are simply the data points nearest to the linear margins [21]. In this way, SVM can act as a perfect classifier and is applied to bearing fault detection by numerous researchers. Jack and Nandi [22] performed fault detection of roller bearing using SVM and ANN. They used vibration data taken from a small test rig and simulate four bearing fault condition: inner race fault, outer race fault, cage fault, and rolling element fault. They defined and calculated statistical features based on moments and cumulants and selected the optimal feature using genetic algorithm (GA). In the classification process, they employed SVM using redial basis function (RBF) kernel with a constant kernel parameter.

The model based approach is another means of fault diagnosis procedure. This approach utilizes an explicit mathematical model of the monitored machine. Wang et al. [23] used the Kalman smoothing algorithm to develop a parametric model of non-stationary so as to obtain high resolution time-frequency spectrum. The authors applied a singular value decomposition (SVD) method for feature vector extraction and used an RBF neural network for the decision making of different fault cases. Model based approaches can be more effective than other model-free approaches if a correct and accurate model is built. However, this kind of approach may not be feasible for complex system, as it would be difficult to build a mathematical model for such systems [4].

2.3 Complex multivariate analysis

Statistical process control (SPC), a conventional approach, was originated in quality control theory and well developed and widely used in fault detection and diagnostics. The principal of SPC is to measure the deviation of the current signal from a reference signal representing normal conditions to see whether the current signal is within the control limit or not. Fugate et al. [24] used statistical parameters such as mean and variance in autoregressive modelling to define control limit and statistical pattern recognition to detect fault, based on vibration data.

Cluster analysis, a multivariate statistical analysis method, is a statistical classification approach that groups signals into different fault categories on the basis of the similarity of the characteristics or features they possess. It seeks to minimize within-group variance and maximize between-group variance. The result of cluster analysis is a number of heterogeneous groups with homogeneous contents: there are substantial differences between the groups, but the signals within a single group are similar [4]. Lei et al. [25] utilized cluster analysis, combined with Fuzzy *c*-means (FCM) algorithm, for fault diagnosis in bearings. In that study, two stages of feature selection and weighing technique were introduced prior to improved FCM cluster algorithm to investigate damage in different cases of bearing faults, severity, and fault conditions.

Principal component analysis (PCA) based monitoring schemes are one of the most widely used multivariate data-driven statistical techniques for process monitoring, since they can handle high dimensional, noisy, and highly linearly correlated data by projecting them onto a lower dimensional subspace, which contains most of the variance of the original data. Although this dimensionality reduction technique was first proposed by Pearson [26] and later developed by Hotelling [27], researchers applied PCA as a multivariate process control (SPC) only in the past few decades. It is well known that conventional PCA schemes are not capable for monitoring non-stationary wide dynamic range systems, i.e., systems generating data which present a convolved picture of many events occupying different regions in the time-frequency plane. The reason is that PCA schemes operates on a single scale. However, by performing a PCA monitoring approach on different time scales, a model with increased sensitivity that facilitates the extraction of important system condition information from multiscale process data, can be obtained. This is actually the core idea behind PCA-based multiscale monitoring approaches where the roll of decomposing signals into various time scales is assigned to multiresolution analysis, while PCA is used to monitor them. Kosanovich et al. [28] was the first researcher to develop the idea of combing PCA and one of the most popular multiresolution analyses WT for monitoring purposes. Later, Bakshi [29] presented the multiscale principal component analysis (MSPCA) and demonstrated its great potential in monitoring multivariate processes. Figure 2.3 depicts this technique. The method became firmly estab-

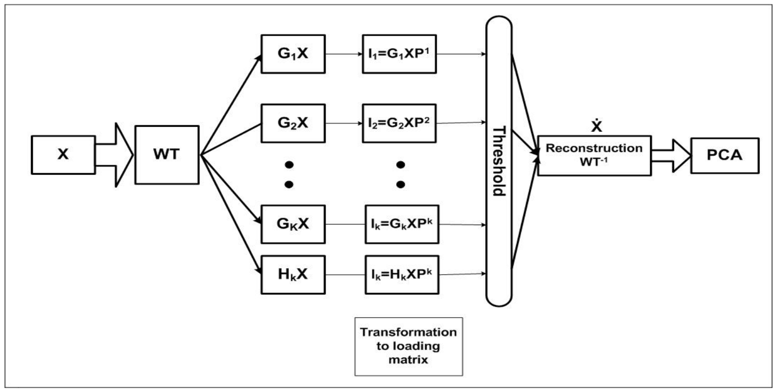

Figure 2.3: Multiscale Principal Component Analysis (MSPCA)

lished and was, with several modifications and extensions, used as the basis structure in various research tasks. Kano et al. [30], for example, borrowed the MSPCA concept and replaced the conventional PCA monitoring scheme with the method called moving PCA, which originates from the idea that a change of operation condition, i.e., the change f correlation among process variables, can be detected by monitoring directions of principal components. Lee et al. [31] used an adaptive multiway PCA model with recursive updating of the covariance matrices instead of the conventional PCA, with the goal of making the statistical model follow evolution of the process. They also proposed the fault identification method to identify major sources of process disturbances. Going beyond fault detection of the original MSPCA was also researched by Misra et al. [32], who proposed a multiscale fault identification approach based on contribution plots with the goal to perform early fault diagnosis. Žvokelj et al. [33] proposed a modified technique EEMD-KPCA based on the MSPCA methodology for bearing fault diagnosis. The study adopted the MSPCA and replaced WT with empirical mean decomposition (EMD) for significant feature extraction for vibration signals and later used kernel PCA (KPCA) for monitoring purposes. Figure 2.4 presents the entire technique.

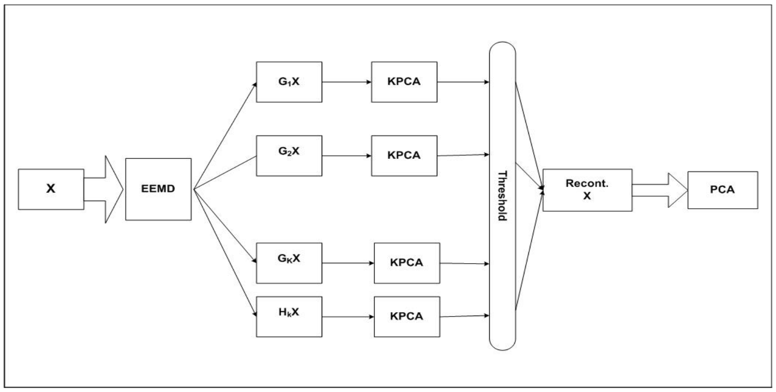

Figure 2.4: EEMD-KPCA methodology

2.4 Effect of load variation

With the advancement of technology in recent days, researchers tend to monitor complex situations in process industry. Reasons such as insufficient feed supply, machine incapability, environmental effects etc., could become vital for deviation in plant loads in heavy industry. These factors cause a major variation in rotating machine's speed and load. Therefore, vibrations of bearings of these machines get affected and are required careful observation. To address these situations, researchers are trying to develop advance monitoring technique for accurate fault diagnosis under variable conditions. Villa et al. [34] developed a diagnosis algorithm based on a linear regression technique using vibration data under non-stationary load and speed conditions of wind turbine bearings. This algorithm presented a linear model that takes into account speed, load and fault level. After building non-faulty situation, the model incorporated new data and fault was detected based on the variance of the fault levels in the linear models of the calculated variables.However, the model was based on a linear assumption, while vibration data is generally non-linear by nature. In addition, Zimroz et al. [35] suggested an advance technique of bearing fault detection at non stationary operating conditions based on regression analysis. The authors took long term segments for the selected vibration based feature and chosen reference data and built a linear model based on regression analysis. The authors successfully showed the variance of vibration characteristics at at variable operating condition, however the technique could develop ambiguity in the detection of fault as there was an absence of any threshold value for the parameters in case of fault condition identification. Yang et al. [36] proposed a fault diagnosis approach based on a variable predictive model classifier discriminate (VPMCD)-a pattern recognition technique, order tracking analysis and local mean decomposition analysis (LMD) targeting the characteristics of rolling element bearing vibration signals in variable rotation speed conditions. The proposed algorithm re-sampled the vibration signals using order tracking technique to remove influence of speed variation. Later, spectral peak values obtained using LMD and spectral analysis on the re-sampled signals. Finally, the VPMCD technique is applied for fault diagnosis.Although this method classified the different faults of bearing successfully, It could not able to relate the operating variables in the fault analysis.

Chapter 3

Detection of Fault in a Rotating Machine Using Multiway PCA

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Preface

A version of this paper has been submitted in the Journal *Mechanical Systems and Signal Processing (MSSP)* for publication and is currently under review. The lead author A F M Mursalin performed necessary literature review for background information, developed the multisacle MPCA technique, conducted the simulation and fault detection analysis and prepared draft of the paper. Co-authors Drs. Imtiaz and Khan introduced the conceptual framework of the work, supervised the work, provided continuous technical guidance and editing of the manuscript.

Abstract

A variety of frequency domain methods and multivariate statistical techniques are used to analyze vibration data. However, it is still not understood how load variation affects these monitoring schemes. This research takes into account the effect of load variation on vibration pattern. We propose a new method based on wavelet analysis and multi-way principal component analysis to detect abnormalities in the equipment. The proposed method uses multivariate vibration data measured at different locations in the equipment. It pools batches of vibration data collected at different times under different load conditions. This results in a three-dimensional data matrix. The noisy vibration data are filtered by applying PCA on wavelet coefficients at different frequency levels. A novel unfolding technique is used to convert the three-dimensional data matrix to a two-dimensional data matrix where each batch of data considered as an object. Subsequently PCA is carried out to detect the fault. The advantage of the model is that it compares the vibration data against a band of normal vibration data collected under different load conditions. It is better able to distinguish between load changes and equipment fault by analysing vibration data. The effectiveness of the proposed method is demonstrated on bearing fault detection using numerical simulation case studies.

3.1 Introduction

Rotating machineries (e.g., compressors, turbines) are important assets in process industries. Most of this equipment contains bearings, gearboxes and other rotating components are more prone to faults. These faults, which in turn, cause machine breakdowns and may cause casualties to personnel along with extensive economic loss. Early fault detection of these rolling elements has been basis of research for several decades to ensure safe and smooth operation in the process industry. Condition monitoring (i.e., vi-

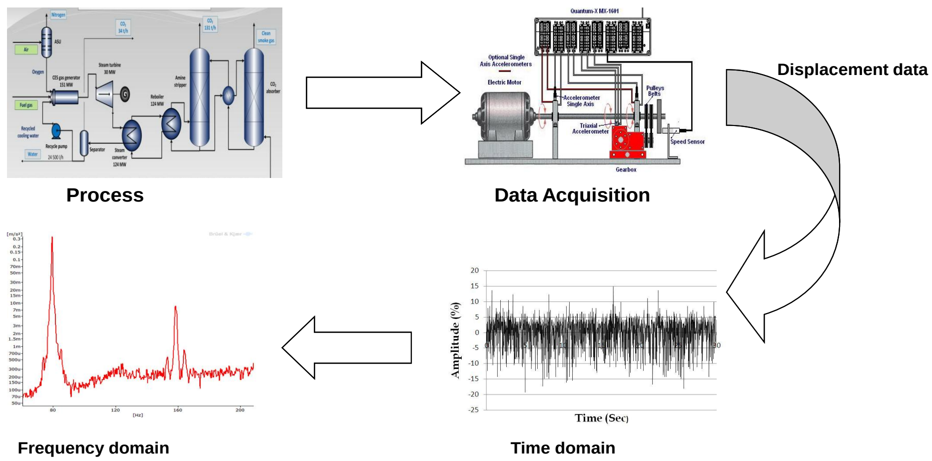

Figure 3.1: Vibration analysis in details

bration monitoring) is widely used; it is a powerful technique that extracts vibration "signatures" for fault diagnosis in rotating machines. Vibration created by displacement is measured using sensors (single-axis or tri-axial accelerometers) placed around the bearings. Signals from the sensors are collected using data acquisition system and presented in amplitude vs. time format. The signals are transformed into suitable frequency or time-frequency domains to detect any anomaly or fault in the bearing [4]. Figure 3.1 shows the steps of vibration data acquisition and processing.

Multiple sensors are often placed at different axial locations to acquire a complete vibration pattern. These high-dimensional datasets acquired from the sensors require multivariate statistical data processing in order to fully capture the benefits of multiple sensors. One effective analysis technique is to apply multivariate dimension reduction approaches. It is easy to interpret low-dimension featured space and identify characteristic behaviour; it might also be possible to visualize which makes the monitoring system simpler[28]. Since vibration data are noisy and multiscale in nature, multiscale analysis and denoising are required to extract the true process fingerprints. One method now being widely used for analyzing vibration data is multiscale principal component analysis (MSPCA). Bakshi [29] originally proposed MSPCA in which WT is integrated with PCA. MSPCA is capable of detecting process faults from extremely noisy data. Researchers are now increasingly using multivariate statistical methods for analysing vibration data.For example, Z̃vokelj et al. [33] investigated large size low speed bearing faults using kernel PCA in conjunction with empirical decomposition method. Based on MSPCA theory, the authors used empirical decomposition method to extract the significant features from vibration signals and detected faulty bearing condition on T^2-plot with help of kernel PCA. Apart from that, Jack and Nandi [22] used support vector machine (SVM) combined with artificial neural network (ANN) for detecting different kinds of faults in rolling element bearing. They used vibration data taken from small test rig and simulated four bearing fault condition: inner race fault, outer race fault, cage fault, and rolling element fault. They defined and calculated statistical features based on moments and cumulants and selected the optimal feature using genetic algorithm (GA). In the classification process, they employed SVM using redial basis function (RBF) kernel with constant kernel parameter. Lei et al. [25] utilized cluster analysis combined with Fuzzy *c*-means (FCM) algorithm for fault diagnosis in bearings. In that study, two stage of feature selection and weighing technique were introduced prior to improved FCM cluster algorithm to investigate damage in different cases of bearing fault, severity, and fault conditions. However, none of the above methods took into consideration the effect of load change in vibration pattern. Unless the analytical method takes into account effect of load change on vibration, faults may appear at different process conditions that affect vibration of machine may mask the faults within the process change.

In this paper we specifically focus on the changes in the vibration data due to change in machine loads and its impact on these diagnostic tools. In a real industrial scenario, for various reasons(e.g., insufficient supply of raw material, process equipment deficiency), process plants change their loads quite frequently. Because of load changes, the vibration patterns of rotating machines vary quite drastically. Figure 3.2 shows radial vibration signals from sensors placed at different locations of a natural gas compressor. The data shows that average plant load was around 90% from September, 2009 to December, 2009 when the vibration range was between 17 to 23 microns, whereas change of plant load to an average 85% from April, 2010 to September, 2010 influenced vibration significantly and reduced the average displacement to 15 micron. Even though there was no fault in the compressor bearings, the vibration pattern changed drastically when the plant load changed. Unless the load changes in the system are accounted for, the monitoring tools may detect these load change events as fault [7], [35]. To address this load change phenomenon, we propose a fault detection method based on wavelet filtering of MSPCA and multiway PCA (MPCA). MPCA was originally proposed to monitor batch processes [21]. The proposed method combines the denoising capability of wavelet filtering of MSPCA and the ability of MPCA to detect fault under varying process conditions.

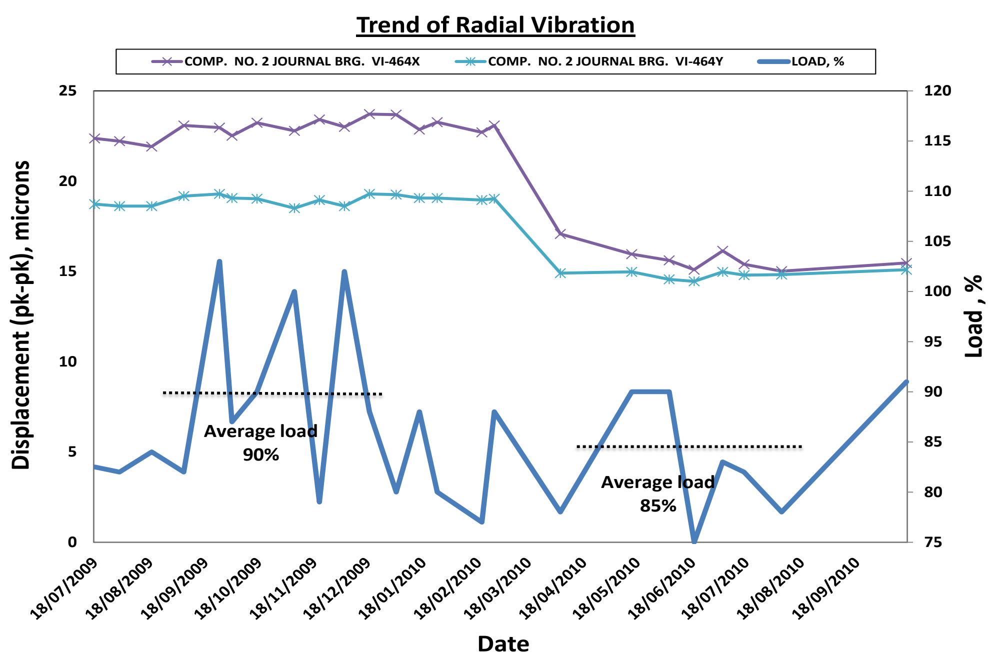

Figure 3.2: Vibration amplitude of a natural gas compressor change due to load change in a fertilizer industry

The paper is organized as follows: Section 2 highlights preprocessing techniques to extract process information. Section 3 summarizes key facts and describes the proposed methodology in detail. Section 4 addresses the effectiveness of the proposed method for the load effect of bearing and fault detection, with a brief comparison to the existing approaches based on synthetic signals. Section 5 presents the conclusion of this paper.

3.2 Preprocessing of data

Preprocessing of data is extremely important when the data are acquired from a noisy environment. In the proposed methodology, data preprocessing plays an important part. First, all the data were converted to positive values. Then multiplicative signal correction (MSC) was applied. MSC is a powerful preprocessing technique that removes additive and multiplicative effects in data and performs higher order and complex baseline removal in order to model the data easily [15]. For example, consider $\mathbf{x}$ as a column vector to be standardized and $\mathbf{r}$ as a column vector corresponding to reference data (often this is the mean spectrum of the calibration data set). The vectors are most often mean-centered according to Equations (3.1) and (3.2),

$$\mathbf{x}_c = \mathbf{x} - \bar{x}\mathbf{1} \tag{3.1}$$

$$\mathbf{r}_c = \mathbf{r} - \bar{r}\mathbf{1} \tag{3.2}$$

where $\mathbf{x}_c$ and $\mathbf{r}_c$ are the mean-centered vectors, $\bar{x}$ and $\bar{r}$ are the respective means, and $\mathbf{1}$ is a vector of ones. The unknown multiplicative factor b is defined using equations (3.3) and (3.4).

$$\mathbf{r}_c b = \mathbf{x}_c \tag{3.3}$$

$$b = (\mathbf{r}_c^T \mathbf{r}_c)^{-1} \mathbf{r}_c^T \mathbf{x}_c \tag{3.4}$$

therefore, the corrected form $\hat{\mathbf{x}}$ is given by Equation 3.5 [16].

$$\hat{\mathbf{x}} = \mathbf{x}_c / b + \bar{r}\mathbf{1} \tag{3.5}$$

In all calculations, the median was used instead of mean in order to make the method robust to outliers. Finally, data was autoscaled in order to have unit variance for each signal.

3.3 Multiscale PCA combined with Multiway PCA

The proposed methodology consists of two parts: first, multiscale PCA is applied to denoise the signals and extract the fault signature from extremely noisy vibration data. Second, multiway PCA is used to detect fault under varying process conditions (e.g., loads, RPM). Below we describe these two key steps. The overall methodology is shown in Figure 3.7.

3.3.1 Denoising using multiscale PCA

Bakshi [29] first introduced the idea of multiscale principal component analysis that integrated the power of wavelet filtering with PCA. Wavelet analysis is a time-frequency domain method that has special advantages in analyzing non stationary signals and extracts signal fingerprints which are the hidden time-frequency structure in noisy signals [17]. Discrete wavelet transform (DWT) is considered efficient to analyze vibration signals for computational advantage.
The DWT for a given function *f(t)* is given by [18]

$$f(t) = \sum_{i,j} a_{i,j} \psi_{i,j}(t) \tag{3.6}$$

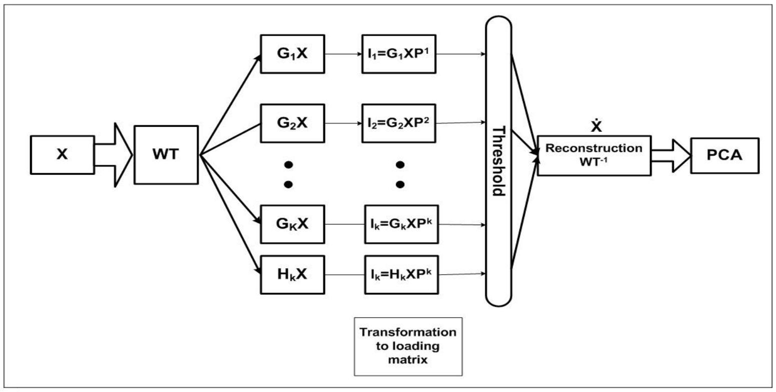

Figure 3.3: Multiscale Principal Component Analysis (MSPCA) method

where the two-dimensional set of coefficients $a_{i,j}$ is called the discrete wavelet transform (DWT) coefficients of $f(t)$ defined by

$$a_{i,j} = \int f(t)\psi_{i,j}dt \tag{3.7}$$

and $\psi_{i,j}(t)$ is called generating wavelet or mother wavelet defined by Equation 3.8

$$\psi_{i,j}(t) = 2^{\frac{j}{2}}\psi(2^j t - k) \qquad j,k \in Z \tag{3.8}$$

In discrete case, filters of different cut-off frequencies analyse the signal at different scales. In MSPCA, as shown in Figure 3.3, each variable $x_j(t)$ of signal data X is decomposed into a given number of frequency bands K using WT. According to the multiresolution theory proposed by Mallet [19], any signal $x_j(t) \in L^2(R)$ can be approximated by successively projecting it down onto a set of orthonormal scaling functions to obtain "Approximation" and onto the wavelet (mother) functions to obtain "Details" from a signal [19]. The original signal passes through low-pass filter **H** and high-pass filter **G** and is decomposed into different frequency bands. The signal output in each filtering operation is decimated by two[29].The operation[17] is shown in the Figure 3.4.

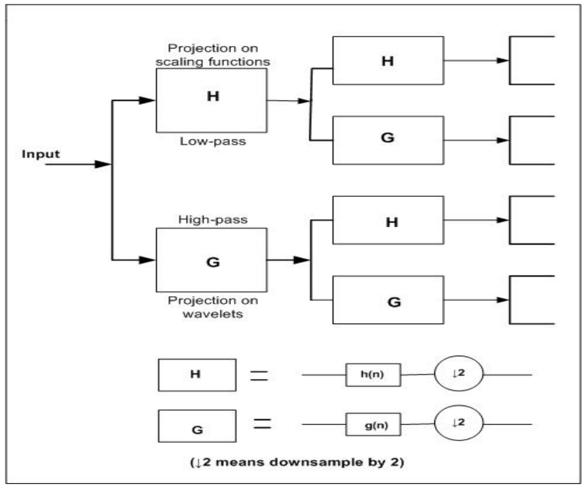

Figure 3.4: Wavelet decomposition

The coefficients at different scales can be obtained as

$$a_k = \mathbf{H}a_{k-1}, \qquad d_k = \mathbf{G}a_{k-1} \tag{3.9}$$

where a_k is the vector scaling function coefficients and d_k the vector wavelet coefficients at scale k. Bakshi (1998)[29] represented the equation in terms of the original measured digital signal x_j as

$$a_k = \mathbf{H}_k x_j, \qquad d_k = \mathbf{G}_k x_j \tag{3.10}$$

where $\mathbf{H}_k$ denotes application of $\mathbf{H}$ filter k times and $\mathbf{G}_k$ signifies the application of $\mathbf{H}$ filter $(k-1)$ times and the $\mathbf{G}$ filter once. After decomposing the signal in k different frequency scale, PCA is applied on coefficients at each scale. T^2 and Q statistics are used to determine whether a certain scale holds fingerprints or significant information. In each scale, only coefficients that exceeds the T^2 and Q statistics are retained. Thus the filtering is carried out in the decomposed coefficient space. Subsequently the retained coefficients from all the scales are combined and the signal is reconstructed by applying inverse wavelet transform.

3.3.2 Multiway PCA

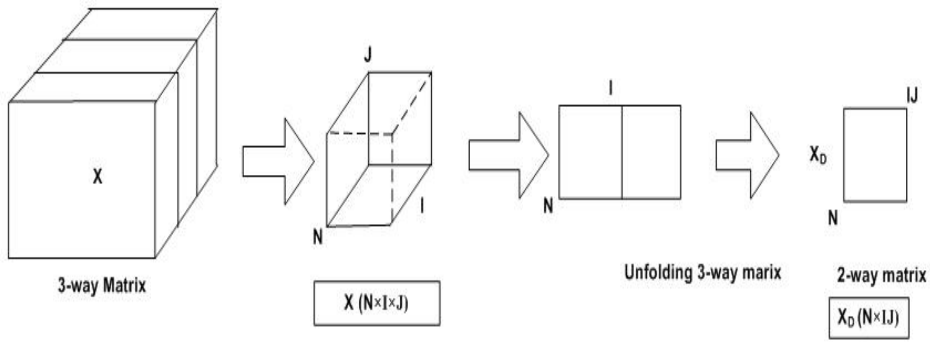

Figure 3.5: Unfolding of 3-way data matrix to 2 dimensional data matrix

Multiway PCA is an extension PCA to handle data in three-dimensional arrays[20]. Condition monitoring data are collected in batches at points in time when the process may be operating under different load conditions. With MPCA, one studies the difference between different batches of data. A band of fault-free operations is defined based on vibration data collected for different load conditions and no equipment fault. It allows one to compare each set of data against a group of good sets of data to classify it as good or bad as shown in Figure 3.6 [21]. Vibration data collected for different load conditions gives a three-dimensional data matrix containing I vibration measurements at J points in time for N different load conditions. In MPCA , the three-way matrix $X_{(N\times I\times J)}$ can be unfolded in six different ways. This results in the following two-dimensional matrices: $A_{(NI\times J)}$, $B_{(JI\times N)}$, $C_{(IJ\times N)}$, $D_{(N\times IJ)}$, $E_{(I\times JN)}$and $F_{(J\times IN)}$. Generally, for monitoring and analysis, matrix D is the most meaningful way of unfolding. It appends data collected from different sensors in the row directions and creates one vector. Thus each set of data for a specific load is considered as an object. MPCA decomposes X into a summation of the product of t score vectors (t) and p-loading matrices (P), plus a residual matrix (E)

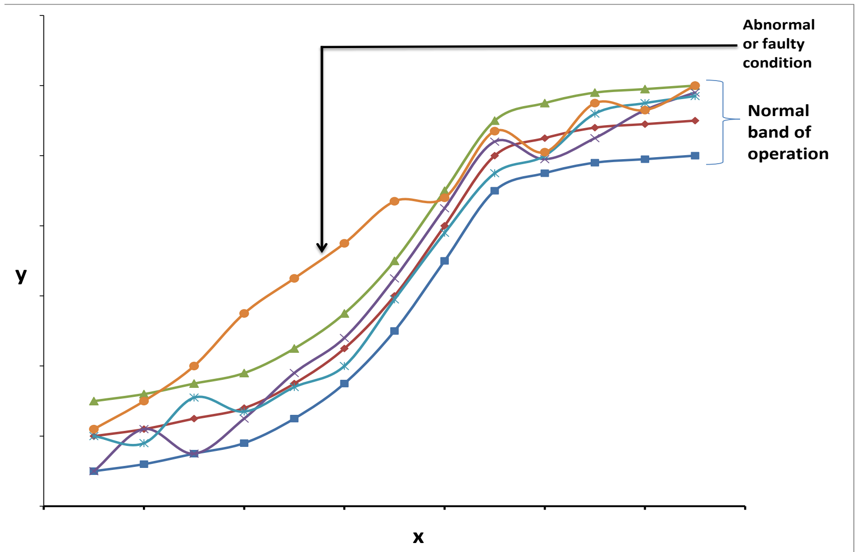

Figure 3.6: Multiway PCA methodology

that is minimized through a least square method.

$$X = \sum_{r=1}^{R} t_r \otimes P_r + E \tag{3.11}$$

where r is the number of principal components used in the analysis. This decomposition represents the data with respect to both variables and time in low-dimensional score spaces. These spaces account for variability over the conditions at all points in time. Each p-loading matrix summarizes major time variation of the variables about their average trajectories over all the conditions. As a result, MPCA can actually utilize the magnitude of the deviation of the each variable from its mean trajectory and at the same time correlate among them [21].

3.3.3 Fault detection using T^2 statistics

Statistical test such as Hotelling's T^2 on the principal plane, is carried out for fault detection. The Hotelling's T^2 and the corresponding limit T^2_{lim} are given in Equations (3.12) and (3.13) respectively[22].

$$T_i^2 = (\mathbf{x}_i - m)^T \mathbf{S}^{-1} (\mathbf{x}_i - m) \tag{3.12}$$

$$T_{lim}^2 = \frac{a \cdot (I-1) \cdot (I+1)}{I \cdot (I-a)} \cdot F_{a,I-a,\alpha} \tag{3.13}$$

where $\mathbf{x}_i$ is the row of the matrix $\mathbf{X}_{I\times J}$, m is the mean value of column $\mathbf{x}_j$ in the matrix $\mathbf{X}$, S is the covariance matrix of data matrix $\mathbf{X}$, $\mathbf{a}$ is the number of selected principal components, $\mathbf{I}$ is the number of samples or measurements and $\mathbf{F}_{a,I-a,\alpha}$ represents F-distribution with a and $(I-a)$ degrees of freedom and level of significance. T^2-statistics is the sum of normalized squared scores; it can represent the normal behaviour of the process as it remains unaffected by inaccuracies of smaller eigenvalues.

3.3.4 Methodology of Multiscale-MPCA analysis of vibration data

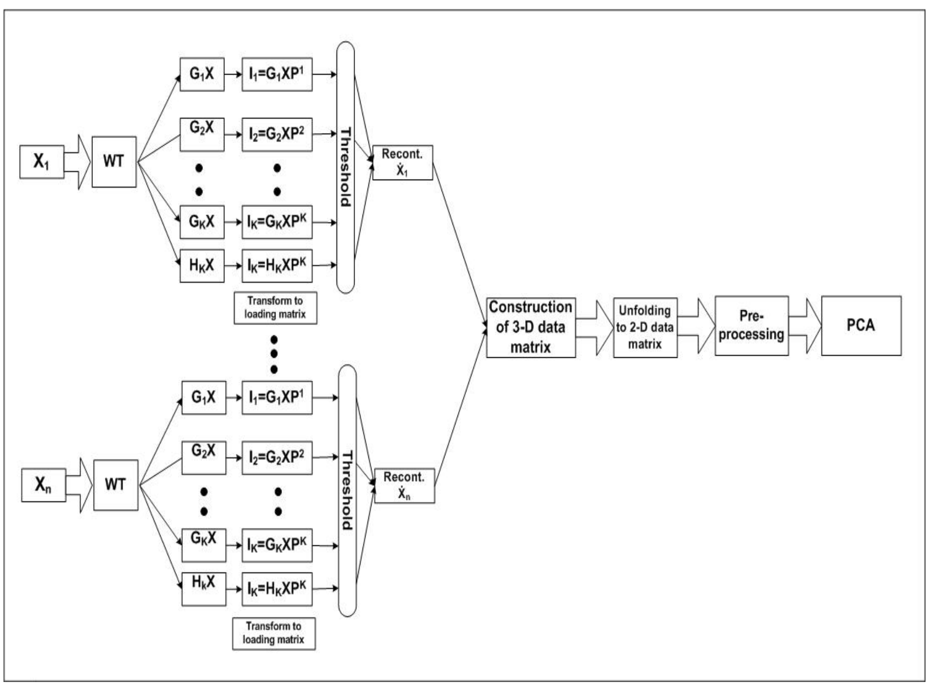

Figure 3.7: Proposed Multiscale MPCA model construction

Consider data matrix $\mathbf{X}_i [i = 1,2,3,...,n]$ represents batches of vibration data. Each data matrix $\mathbf{X}_i$ contains measured vibration signals from sensors $x_j(t)$ at an axial location around the bearing. These different batches of data are not necessarily collected under identical conditions. A realistic scenario for a rotating machine would be that load and RPM of the machine may be different for these different batches of data. Wavelet transformation (WT) is applied to decompose each variable $x_j(t)$ into different frequency scales. Following this, uniscale PCA models are applied to coefficients of each of the scales. The purpose of uniscale PCA is to denoise the signals. A signal $x_j \quad \{j = 1,2,3,...,J\}$, i.e., a column in the matrix $\mathbf{X}_{I\times J}$ is reconstructed by multiplying individual scales $c_{jk}(t)$ with the relevance factor κ_k and adding them together as in the following equation:

$$\hat{x}_j(t) = \sum_{K=1}^{K} \kappa_k(t).c_{jk}(t) \tag{3.14}$$

where the relevance factor $\kappa_k(t)$ is defined by

$$\kappa_k(t) = \begin{cases} 1 & \text{if} \quad SF_{K,norm}(t) \geq 1, \\ [SF_{K,norm}(t)]^{\mu} & otherwise \end{cases} \tag{3.15}$$

$SF_{K,norm}(t)$ is defined as

$$SF_{K,norm}(t) = \frac{T^2{}_k}{T^2{}_{k,lim}} \quad \text{or} \quad \frac{Q_k}{Q_{k,lim}} \tag{3.16}$$

It can be seen that only those decomposed wavelet coefficients on each scale k have been used whose $T^2{}_k$ or Q_k value exceeds the corresponding confidence limits $T^2{}_{k,lim}$ or $Q_{k,lim}$. The value below confidence limit is assumed to be mostly contribution of noise has been revised accordingly by the reduction factor μ. The reduction factor μ is the key element of the noise "thresholding." As the the value of the reduction factor increases or tends to go towards ∞, any value that crosses the confidence limit is kept, whereas all values below the limit become zero; this is called "hard-thresholding." The reconstruction process acts as a perfect multivariate multiscale filtering technique for removing noise. The other datasets $\widehat{\mathbf{X}}_2, \widehat{\mathbf{X}}_3, \ldots, \widehat{\mathbf{X}}_N$ can be built in a similar way. Once the sufficient data matrices have been collected, they are arranged in a three-way matrix $\widetilde{X}(N \times I \times J)$. The three-way data matrix $\widetilde{X}(N \times I \times J)$ is unfolded to $\widehat{X}_D(N \times IJ)$, where each row represents a batch of vibration data. Before applying PCA on the unfolded matrix $\widehat{X}_D$, data are preprocessed as described in Section 3.2. Then PCA is carried out on the preprocessed matrix and T^2-statistics or Q-statistics are monitored. Each batch of data is represented as a point on the T^2 and SPE plot. Any non-faulty data should remain below the limits. Any data set that has correlation significantly different from other data sets will exceed the threshold and be regarded as a faulty data set. As new data sets become available, those are incorporated with existing data sets. if the relevant T^2 or Q value exceeds the threshold, the data set is regarded as abnormal, indicating a fault in that particular machine.

3.3.5 Steps for the proposed Multiscale-MPCA methodology

The proposed Multiscale PCA combined with multiway PCA (Multiscale-MPCA) methodology consists of two parts : (1) reference model building, and (2) testing of new data sets. These two steps of the methodology are described below.

3.3.5.1 Reference Model building

1. No-fault vibration data set X_I^R is collected at any particular load condition.

2. After mean centering and scaling to unit variance, each column $x_j^R(t)$ of the matrix X_I^R is decomposed using wavelet transformation to K different frequency scales.

3. Coefficients of all variables for each scale are arranged in a matrix $C_k^R = [c_{1k}, c_{2k}, \ldots, c_{jk}, \ldots, c_{Jk}]$.

PCA is applied on the coefficient matrix.

4. Using the equations (3.14), (3.15), and (3.16), the reconstruction of the signals is done and is kept in matrix $\widehat{X}_1^R$.

5. Several datasets are collected for different load conditions and the reconstructed matrices $\widehat{X}_1^R, ..., \widehat{X}_N^R$ are collected in a three-way matrix $\widehat{X}^R(N \times I \times J)$.

6. The three-way matrix $\widehat{X}^R(N \times I \times J)$ is unfolded into a two-way matrix $\widehat{X}^R(N \times IJ)$ using the unfolding technique described in Figure 3.5.

7. The data in the matrix are preprocessed. Data are first transformed to their absolute values, then normalized by MSC (median), and finally autoscaled.

8. A PCA model is built using the unfolded and denoised two-way matrix using a few dominant principal components and T^2 and Q- statistics of datasets $(1, 2, .., N)$, and the confidence limits of T_α^2-statistics or Q_α-statistics for normal operation are calculated.

3.3.5.2 Monitoring system operation

The monitoring operation is similar to reference model building as graphically shown in Figure 3.7. The steps are as follows:

1. Vibration signals, $X_{I\times J}^M$, are collected from the monitoring system.

2. Using steps (2), (3), and (4) described in previous section, new dataset is constructed and stored in the matrix $\widehat{X}^M$.

3. The newly reconstructed matrix is added as an additional dataset with the previously built three-way matrix $\widehat{X}^R$ in reference model building step to construct a combined three-way matrix $\widehat{X}^C$.

4. The three-way combined data matrix $\widehat{X}^C$ is unfolded to two-way data matrix and pre-processing is done. PCA is applied on the combined preprocessed two-way matrix. T^2 and Q values are calculated. Then in similar way, the T^2 and Q values are plotted with limits calculated from reference model. The last value in the T^2-plot represents newly collected dataset X^M; if it exceeds the limit of either T^2 or Q, that is an indication of fault.

3.4 Application of wavelet analysis combined with Multi-way PCA for fault detection in bearings

3.4.1 Simulation of bearing fault signal

Various models of rolling element vibration with fault are described in literature [17]. In our simulation we used the technique proposed by Cong et al.(2013) [29] to simulate bearing faults. A rotor bearing system consists of the rotor, supporting bearings, and motor. The model is based on rotor dynamic forces. The bearing load is the main controller of rotor dynamic forces that can be analyzed and combined with an impulse signal model for fault signal generation. The bearing load can be divided into two components: the constant load (system gravity) and the alternate load (inertia force). Also the total forces working on bearing are divided into forces acting on two directions, F_x and F_y, given by following equations:

$$F_x = F_m sin\theta \tag{3.17}$$

$$F_y = G + F_m cos\theta \tag{3.18}$$

$$F_m = me\omega^2 \tag{3.19}$$

where F_m is rotating inertia force, $G = mg$ acts as a constant load working in a downward direction, m is the mass of the load, e is the distance from its geometric centre to the mass centre of the loading disk, ω is rotational acceleration, g represents the gravitational acceleration $\theta = 2\pi f_r t$ where f_r is rotational frequency. Combining equations (3.17) to (3.19), we find expressions that describe vibration behaviour under fluctuating load conditions.

$$F_x = me\omega^2 sin\theta \tag{3.20}$$

$$F_y = mg + me\omega^2 cos\theta \tag{3.21}$$

Following the technique proposed by Cong et al. (2013), we present the following equation for vibration signal where fault is at the outer race of the bearing,

$$x(t) = \sum_{i=1}^{N} [A_M + A_T cos(2\pi f_r t + \Psi + \phi_j)] \cdot s(t - iT_0 - \tau_i) + n(t) \tag{3.22}$$

where N is the number of simulated impulses, and i is the sequence number of the impulses, and $n(t)$ is additive white noise which accommodates the effect of other vibrations in the systems. A_M and A_T represent amplitudes caused by the constant (or determinant) load and variable (or alternate) load respectively. f_r is the rotational frequency. ϕ_j is used to simulate the effect of sensor locations. Four vibration sensors are placed at an angle of 90^o relative to each other around the fixed outer bearing ring,

$$\phi_j = \frac{(j-1)\pi}{2} \quad \text{for } j = 1,2,3,4 \tag{3.23}$$

where $s(t)$ is the decaying oscillating component. T_0 is the time period of repeated impulses and τ_i accounts for the uncertainties in the time period. The decaying oscillating waveform can be expressed as

$$s(t) = e^{-Bt} cos(2\pi f_n t) \tag{3.24}$$

where f_n is system natural frequency and B is the decay parameter. In the case of a faulty signal, the oscillation component is delayed and t is the naturally changed to $(t - iT - \tau_i)$. Ψ accounts for fault amplitude around fault location. McFadden et al. (1983) concluded that the amplitude of the faulty impulses is a direct effect of the instantaneous bearing load and according to Stribeck equation the load distribution can be determined [6]:

$$L(\Psi) = \begin{cases} L_{max}[1 - (1/2\varepsilon)(1 - cos\Psi]^p & \text{for} \quad |\Psi| < \frac{\pi}{2}, \\ 0 \quad \text{elsewhere} \end{cases} \tag{3.25}$$

where L_{max} is the maximum load intensity, ε is the load distribution factor ($\varepsilon < 0.5$), $|\Psi|$ is the extent of the load zone, and p is the bearing type factor, such as $p = \frac{3}{2}$ for ball bearing and $p = \frac{10}{9}$ for roller bearing.

3.4.1.1 Simulation details with parameters

The numerical values assigned for simulation are given in Table 3.1. The signal was simulated for a period of $0.4s$ with sampling frequency $0.0001s$ to simulate an appropriate number of discrete signals for calculation. Figure 3.8a shows normal vibration without any fault containing mostly white Gaussian noise, while Figure 3.8b represents simulated vibration generated with fault combined with Gaussian noise magnitude of -15 db (SNR) after scaling signals to mean centering and unit variance. As can be seen from Figure 3.8, to the naked eye, there is hardly any difference between the normal vibration signal and the faulty signal.

Parameters	Value
Constant load, A_M	2.5-8.5
Alternate load, A_T	0.5
Rotational frequency, f_r	12.57
Fault amplitude, ψ	2.5-4.5
Decay parameter, B	600
Time period, T	$1e^{-5}$
Natural frequency, f_n	$(2 \times \pi \times T)$
Jitters, τ_i	0.00005
SNR for Gaussian white noise	-15 dB

Table 3.1: Values of the parameters used for simulating normal and faulty vibration signals

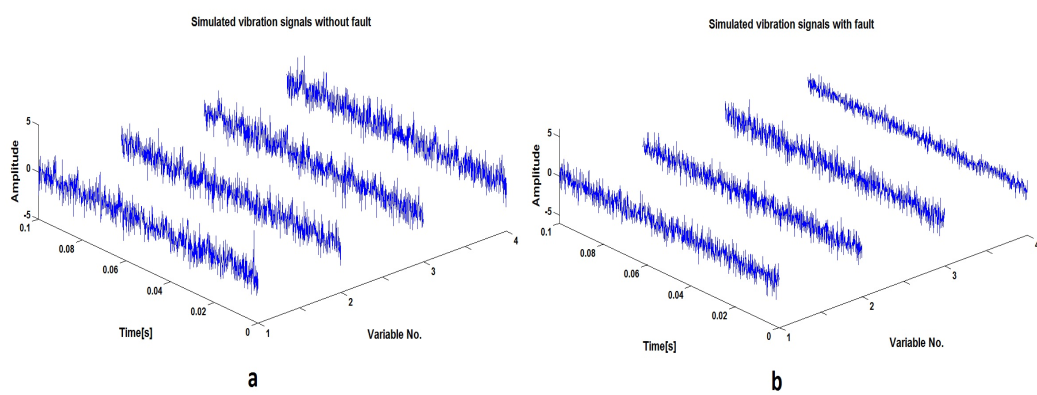

Figure 3.8: (a) normal simulated scaled vibration signals and (b) fault-induced simulated scaled vibration signals

3.4.2 Monitoring performance

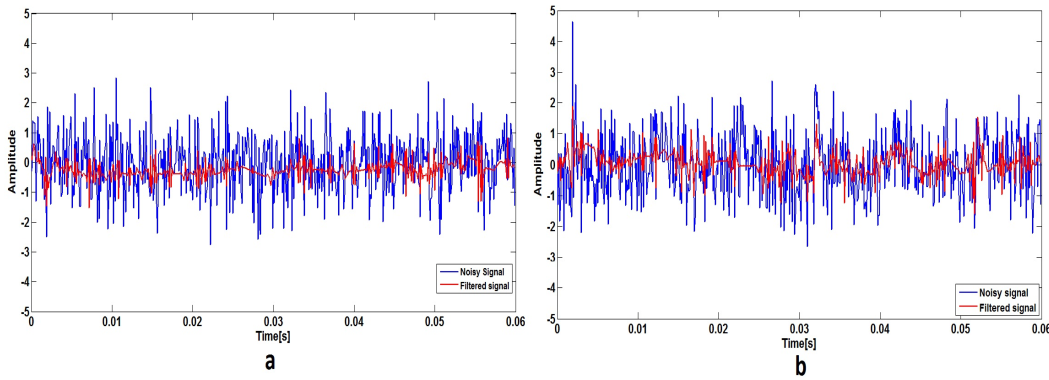

Figure 3.9: (a) Raw and filtered vibration signal with constant load 2.5 of amplitude and (b) raw and filtered vibration signal with constant load 7.5 of amplitude

First we show the effect of load variation on MS-PCA. Figure 3.10a represents T^2 statistics for a constant load. The values remain within the control limit as there was no fault induced. On the other hand, in Figure 3.10b, which represents the T^2 statistics values for a different load condition, the magnitude of T^2 values clearly exceeds the control limit and identifies the data as faulty. In reality, no fault was introduced in data except that the magnitude of load was changed. This clearly demonstrates that the existing MSPCA methodology fails to identify a load variation effect, and the methodology for analyzing vibration data with a variable load needs further improvement.

As discussed in the previous section, we generated vibration signals for different loads with fault and without fault. We applied the proposed methodology to these synthetic signals. We used a reverse biorthogonal (rbio 5.5) wavelet packet for signal decomposition [28]. The decomposition level of 11 was found to be appropriate to extract a vibration signature. At each level, we used one PC because the signals are different realizations of the same vibration measurement. The reshape parameter, μ, is set to $10,000$ because the larger factor will convert the values below the limit, close to zero and make the extraction of significant data more efficient. In Figure 3.9, two different load con-

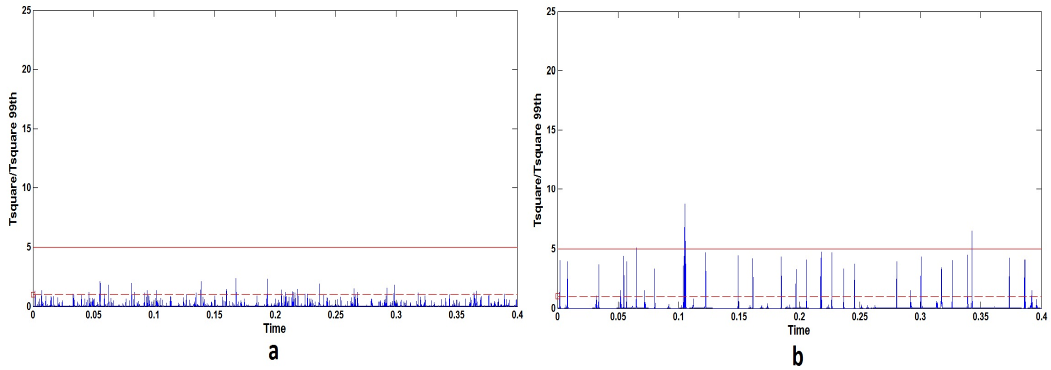

Figure 3.10: MS-PCA results for load change effect (a) T^2 statistics of normal vibration and (b) T^2 statistics of normal vibration with variation in loads

ditions are presented. Figure 3.9a shows the vibration signals generated at a constant load 2.5 whereas in Figure 3.9b the constant load was changed to 7.5. Similarly, we have simulated vibration signals for seven different load conditions and put them in a three-way matrix. In next step, the three-way matrix was unfolded to a two-way matrix as discussed in Section 4.3.2. At this point, the dimensions of the 2-way matrix were 16384×7. The data in the matrix were converted to their absolute values and normalized by MSC and autoscaled. Preprocessing plays an important part in this methodology. Preprocessing helps to remove the non-linear trends in data and puts all variables in the same scale. Figure 3.11a shows results without preprocessing where the 8th data set was collected from a faulty bearing, but the T^2-plot was not able to detect it. Figure 3.11b shows results from the preprocessed datasets which clearly show that the 8th data set is faulty, as it exceeds the threshold in the T^2-plot. PCA is performed on the preprocessed two-way data matrix and T^2 statistics were calculated for each batch of data. While performing the Multiway-PCA, one PC was used because these four accelerometers are somewhat redundant sensors measuring the same vibration signal. Therefore, these four variables are highly correlated and a single PC should be sufficient to explain the variability. Figure 3.12 shows the fault detection results for the proposed Multiscale-MPCA

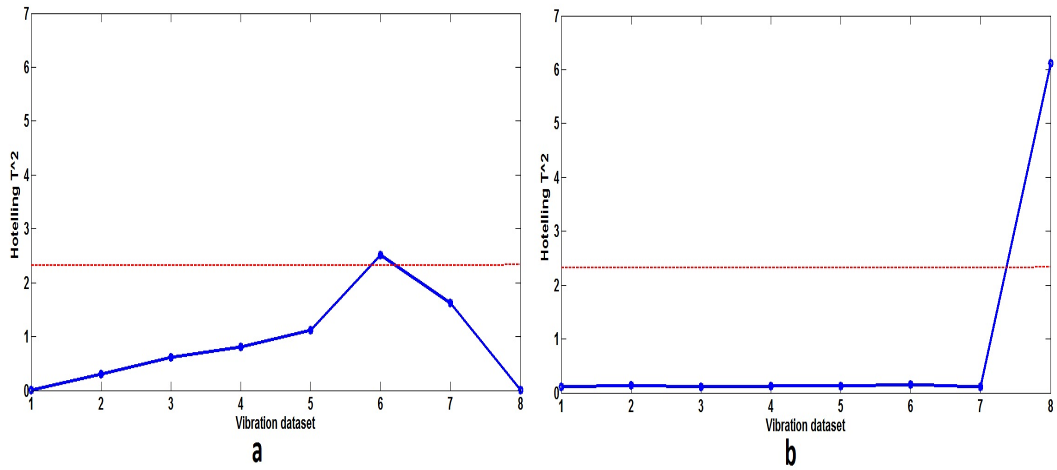

Figure 3.11: Importance of preprocessing on the MSPCA-MPCA methodology (a) T^2 statistics of faulty vibration with variation in loads without preprocessing and (b) T^2 statistics of faulty vibration with variation in loads with preprocessing

methodology. Each sample along the x-axis represents a load condition. Figure 3.12a shows normal conditions change, although the T^2 statistics values are fluctuating due to the change in load, they remain within the threshold (i.e., below 2.5 of T^2 plot). As soon as we introduced a faulty dataset in the analysis, the T^2 value (Figure 3.12b) exceeded the control limit by large margin, clearly showing the presence of fault in that particular data set.

The proposed method is applied to seven faulty data sets of varying magnitude and it is able to detect faults for each of the cases, resulting in 100% success for detecting fault in the bearings under different load conditions.

3.5 Conclusion

A multivariate statistical technique based on MSPCA and MPCA is proposed to detect fault in rolling element bearings operating under variable load conditions. Multiscale PCA is integrated in the methodology to extract important vibration finger prints from

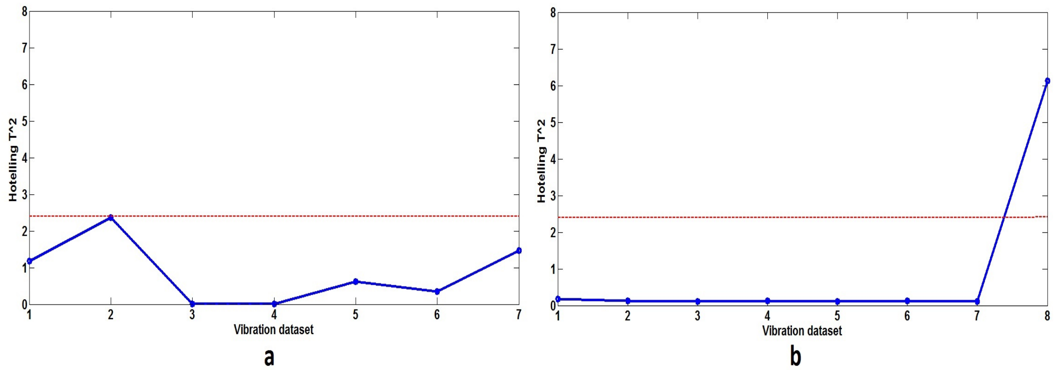

Figure 3.12: Fault identification by the proposed Multiscale-MPCA methodology (a) T^2 statistics of normal vibration with variation in loads and (b) T^2 statistics of faulty vibration with variation in loads (fault at load 3.5)

extremely noisy data. On the other hand, multiway PCA converts each set of multivariate data collected at a particular load to an object. The method compares any new vibration data set against several sets of data collected at different load conditions. An updated bearing fault signal method is used to simulate different load conditions alternating constant load on the rotor. The proposed method showed good fault detection ability in a simulation study when other methods, such as MSPCA, gave false detection.

Acknowledgements

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Chapter 4

Augmentation of process variables with vibration signals for bearing fault detection

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Preface

A version of this paper has been submitted in the Journal *Mechanical Systems and Signal Processing (MSSP)* for publication and is currently under review. The lead author A F M Mursalin performed necessary literature review for background information, developed the multisacle MPCA technique augmented with process variables, conducted the associated experimental tests and prepared draft of the paper. Co-authors Drs. Imtiaz and Khan introduced the conceptual framework of the work, supervised the work, provided

continuous technical guidance and editing of the manuscript.

Abstract

A monitoring scheme is developed to detect faults in machines operating under variable loads using vibration pattern. The new method is based on wavelet and Multiway Principal Component Analysis (MPCA) to detect abnormalities in the equipment. The main features of this method are that it augment vibration data with process data and use a characteristics unfolding to convert a three dimensional data (time × multiple sensors × variable load) into a two dimensional data matrix. Subsequently, PCA is carried out and T^2-statistics is used to detect equipment fault. The method compares any new set of vibration data against a band of normal vibration data collected under different load conditions. As such, it has more power to discern between load changes and equipment fault compared to other methods (e.g., Multiscale Principal Component Analysis (MSPCA)). The effectiveness of the proposed method is demonstrated on an experimental DC motor system. The proposed method shows superior fault detection performance compared with multivariate technique like MSPCA.

4.1 Introduction

Condition monitoring is an important maintenance strategy adopted in process industry to prevent economic loss and other consequences for the machine operators. Review shows that 65.9% failure cases occur due to maintenance deficiencies [1]. Vibration based condition monitoring is a very popular technique for rotating equipemnts.

The aim of this research is to propose a novel approach to detect faults in rolling element bearings under varying operating conditions, such as load and speed. Generally, extremely noisy vibration signals are transformed from time domain into the frequency domain using Fast Fourier Transformation (FFT) to detect faults. McFadden and Smith made an earlier attempt to detect single point defect on the inner race of the rolling element bearing in vibration based fault detection history. Later, researchers like Lin et al. [12] and Purushotham et al. [14] developed fault detection techniques based on Wavelet Transformation (WT) because of its strong denoising characteristics. These techniques are not able to accommodate multiple variables, however they are considered as the primary steps for the detection of faults in bearings based on vibration data.

To improve data fidelity, multiple sensors are often placed at different locations of rotary machines, which results in high dimensional data space and makes detection and diagnosing of faults challenging. The PCA based monitoring scheme has become a perfect solution to address this problem. Conventional PCA has the ability to handle linearly correlated noisy data by projecting them onto a lower dimensional subspace containing most of the variance of original data. However, it can be inadequate for non linear data because of its underlying linear assumption. Researcher have been using variations of PCA for fault detection purposes. For example, Fugate et al. [24] proposed a method to detect vibration damage using PCA for feature extraction from Auto Regressive(AR) model. W. Sun et al. [5] used PCA with a decision tree for fault diagnosis in rotary machine, where PCA is used for feature reduction after preprocessing and feature extraction from time and frequency domain separately. Trendafilova et al. [6] suggested a modified PCA approach combined with a pattern recognition procedure for detection and identification of ball bearing faults. These researchers, however, do not address any relation between the variable process conditions information in their diagnosis techniques.

Generally, in the case of monitoring a complex non stationary dynamic system, a multiresolution decomposition technique is required to supply refined data towards a PCA-based monitoring scheme. I.e., a system generates data where process fingerprints hidden in different regions of the time-frequency plane. Wavelet transform (WT) has these particular abilities and is widely used for the waveform data analysis in the fault diagnostics of bearings by researchers such as Nikolaou et al. [7] and Prabhakar et al. [13]. Bakshi [29] presented the Multi-scale PCA (MSPCA) method combining PCA and WT and demonstrates its great potential for monitoring multivariate processes. Based on this approach, Zvokelj et al. [33] developed a technique where the kernel PCA and empirical mode decomposition method (EMD) are applied for the fault diagnosis of large bearings operating at low speed. The actual conditions in industry can be more complex as bearing vibration data depends on the varied load and speed of the system [10]. For example, Figure 4.1 presents radial vibration signals from sensors placed at different locations of a natural gas compressor. The data shows that the average plant load was around 90% from September 2009 to December 2009 when the vibration range was between 17 to 23 microns. Subsequently, a change of plant load to an 85% average from April 2010 to September 2010 influenced vibration significantly and reduced the average displacement to 15 microns. To monitor bearing, the load variation should be taken into consideration. Otherwise, there may be a false indication of bearing fault occurring, which costs money for unnecessary maintenance. In general, an appropriate multivariate monitoring technique that can relate the process deviation to vibration analysis is needed for greater accuracy in bearing fault diagnosis in heavy industry.

Considering process complexity and with the help of the advancement of technology, researchers have started to investigate fault detection of bearings under different process conditions. Villa et al. [34] proposed a method based on linear regression analysis to detect fault under non-stationary conditions of speed and load. They used a linear model consisting of speed, load and a qualitative variable chosen as the fault level and predicted fault based on the analysis of variance of the last parameter. However, the model was based on a linear assumption, while vibration data is generally non-linear by nature. In addition, Zimroz et al. [35] suggested an advance technique of bearing fault de-

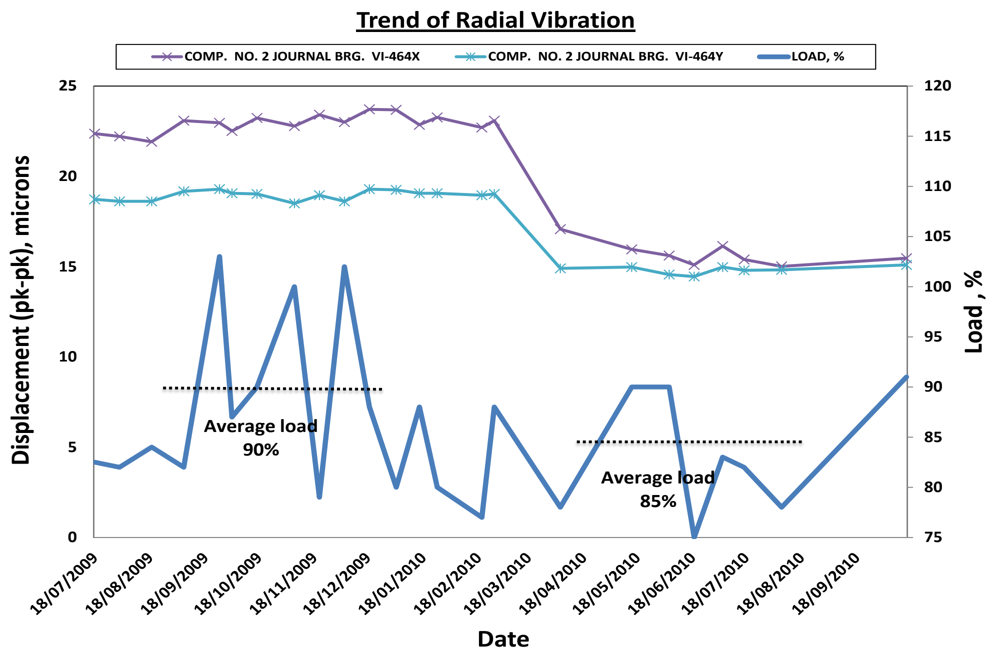

Figure 4.1: Vibration amplitude of a natural gas compressor change due to load change in a fertilizer industry

tection at non stationary operating conditions based on regression analysis. The authors took long term segments for the selected vibration based feature and chosen reference data and built a linear model based on regression analysis. The authors successfully showed the variance of vibration characteristics at variable operating condition. However, the technique could be ambiguous in detecting fault as there was an absence of any threshold value for the parameters in case of fault condition identification. Yang et al. [36] used a model based pattern recognition technique for fault diagnosis of roller bearings under variable speed conditions. Although this method classified the different faults of bearing successfully, It could not be able to relate the operating variables in the fault analysis. In this paper, a novel non-linear data driven approach based on MSPCA and Multiway PCA (MPCA) is proposed to detect fault in the rolling element bearing under different process conditions. Essentially, MPCA is widely used for monitoring batch processing systems and it is strongly capable of addressing different process conditions and reducing the data dimensionality for fault diagnosis [14]. The uniqueness of this study is that it has fused the process information with the vibration data analysis and the approach is tested on an experimental DC-motor system.

The paper is organized in six sections. Section 2 highlights preprocessing techniques to extract process information. Section 3 summarizes important facts and descriptions regarding proposed methodology in detail. In Section 4, details of an experiment conducted to show the efficiency of the proposed methodology is presented. Section 5 discusses the effectiveness of the proposed method for load effect of bearing and fault detection with a brief comparison with the existing approaches based on experimental study signals. Finally, conclusions are presented in Section 6.

4.2 Preprocessing of data

Preprocessing of data is extremely important when the data are acquired from a noisy environment. First, all the data were converted to positive values. Then multiplicative signal correction (MSC) was applied. MSC is a powerful preprocessing technique that removes additive and multiplicative effects in data and performs higher order and complex baseline removal to model the data easily. It actually generates classical least squares (CLS) and inverse least squares (ILS) formulations [15]. For example, consider **x** as a column vector to be standardized and **r** as a column vector corresponding to reference data (often this is the mean spectrum of the calibration data set). The vectors are most often mean-centered according to Equations (4.1) and (4.2),

$$\mathbf{x}_c = \mathbf{x} - \bar{x}\mathbf{1} \tag{4.1}$$

$$\mathbf{r}_c = \mathbf{r} - \bar{r}\mathbf{1} \tag{4.2}$$

where $\mathbf{x}_c$ and $\mathbf{r}_c$ are the mean-centered vectors, $\bar{x}$ and $\bar{r}$ are the respective means, and $\mathbf{1}$ is a vector of ones. The unknown multiplicative factor b is defined using equations (4.3) and (4.4).

$$\mathbf{r}_c b = \mathbf{x}_c \tag{4.3}$$

$$b = (\mathbf{r}_c^T \mathbf{r}_c)^{-1} \mathbf{r}_c^T \mathbf{x}_c \tag{4.4}$$

therefore, the corrected form $\hat{\mathbf{x}}$ is given by Equation 4.5 [16].

$$\hat{\mathbf{x}} = \mathbf{x}_c / b + \bar{r}\mathbf{1} \tag{4.5}$$

In all calculations, the median was used instead of mean in order to make the method robust to outliers. Finally, the data was autoscaled in order to have unit variance for each signal.

4.3 Multiscale PCA combined with Multiway PCA

The proposed methodology consists of two parts: first, multiscale PCA is applied to denoise the signals and extract the fault signature from extremely noisy vibration data. Second, multiway PCA is used to detect fault under varying process conditions (e.g., loads, rpm). The overall methodology is shown in Figure 4.6. Below we describe the individual steps.

4.3.1 Denoising using multiscale PCA

Bakshi [29] first introduced the idea of multiscale principal component analysis that integrated the power of Wavelet filtering with PCA. Wavelet theory is a time-frequency domain method that has special advantages in analyzing non stationary signals and extracts signal fingerprints which are the hidden time-frequency structure in noisy signals[17]. Discrete wavelet transform (DWT) is considered efficient to analyze vibration signals for computational advantage.

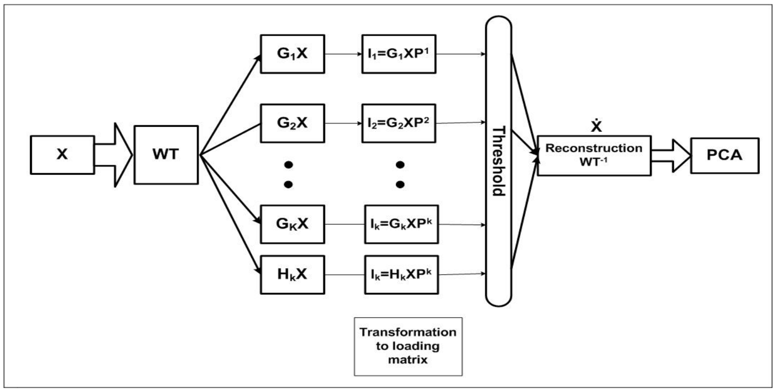

Figure 4.2: Multiscale Principal Component Analysis (MSPCA) method

The DWT for a given function *f(t)* is given by [18]

$$f(t) = \sum_{i,j} a_{i,j} \psi_{i,j}(t) \tag{4.6}$$

where the two-dimensional set of coefficients $a_{i,j}$ is called the discrete wavelet transform (DWT) coefficients of $f(t)$ defined by

$$a_{i,j} = \int f(t) \psi_{i,j} dt \tag{4.7}$$

and $\psi_{i,j}(t)$ is called generating wavelet or mother wavelet defined by Equation 4.8

$$\psi_{i,j}(t) = 2^{\frac{j}{2}} \psi(2^j t - k) \qquad j, k \in Z \tag{4.8}$$

In discrete case, filters of different cut-off frequencies analyse the signal at different scales. In MSPCA, as shown in Figure 4.2, each variable $x_j(t)$ of signal data X is decomposed into a given number of frequency bands K using WT. According to the multiresolution theory proposed by Mallet [19], any signal $x_j(t) \in L^2(R)$ can be approximated by successively projecting it down onto a set of orthonormal scaling functions to obtain "Approximation" and onto the wavelet (mother) functions to obtain "Details" from a signal [19]. The original signal passes through low-pass filter **H** and high-pass filter **G** and is decomposed into different frequency bands. The signal output in each filtering operation is decimated by two[29].The operation[17] is shown in the Figure 4.3.

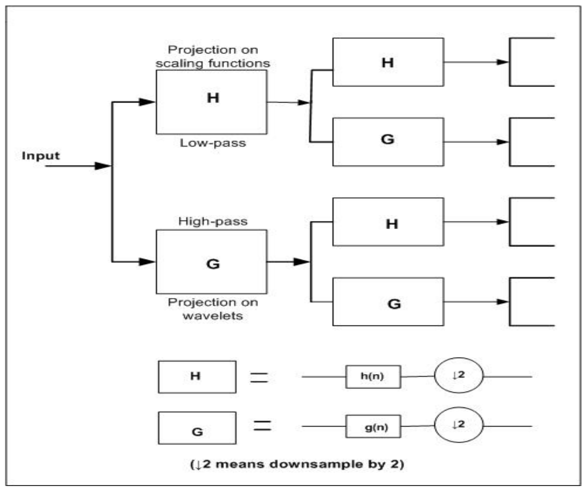

Figure 4.3: Wavelet decomposition

The coefficients at different scales can be obtained as

$$a_k = \mathbf{H} a_{k-1}, \qquad d_k = \mathbf{G} a_{k-1} \tag{4.9}$$

where a_k is the vector scaling function coefficients and d_k the vector wavelet coefficients at scale k. Bakshi (1998)[29] represented the equation in terms of the original measured digital signal x_j as

$$a_k = \mathbf{H}_k x_j, \qquad d_k = \mathbf{G}_k x_j \tag{4.10}$$

where $\mathbf{H}_k$ denotes application of $\mathbf{H}$ filter k times and $\mathbf{G}_k$ signifies the application of $\mathbf{H}$ filter $(k-1)$ times and the $\mathbf{G}$ filter once. After decomposing the signal in k different frequency scale, PCA is applied on coefficients at each scale. T^2 and Q statistics are used to determine whether a certain scale holds fingerprints or significant information. In each scale, only coefficients that exceeds the T^2 and Q statistics are retained. Thus the filtering is carried out in the decomposed coefficient space. Subsequently the retained coefficients from all the scales are combined and the signal is reconstructed by applying inverse wavelet transform.

4.3.2 Multiway PCA

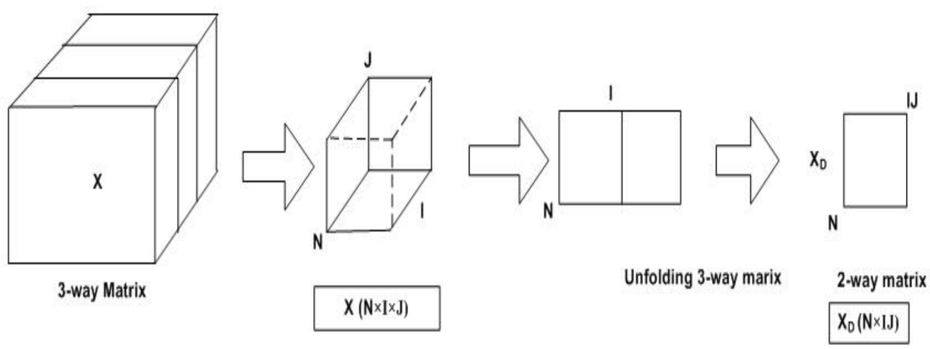

Figure 4.4: Unfolding of 3-way data matrix to 2 dimensional data matrix

Multiway PCA is an extension PCA to handle data in three-dimensional arrays[20]. Condition monitoring data are collected in batches at points in time when the process may be operating under different load conditions. With MPCA, one could study the difference between different batches of data. A band of fault-free operations is defined based on vibration data collected for different load conditions and no equipment fault. It allows one to compare each set of data against a group of good sets of data to classify it: good or bad, shown in Figure 4.5 [21]. Vibration data collected for different load conditions gives a three-dimensional data matrix containing I vibration measurements at J

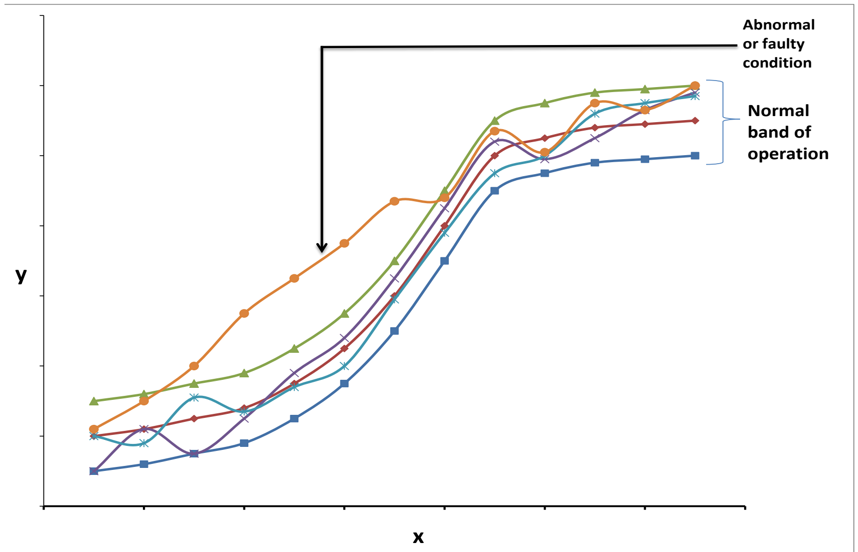

Figure 4.5: Multiway PCA methodology

points in time for N different load conditions. In MPCA, the three-way matrix $X_{(N\times I\times J)}$ can be unfolded in six different ways. This results in the following two-dimensional matrices: $A_{(NI\times J)}$, $B_{(JI\times N)}$, $C_{(IJ\times N)}$, $D_{(N\times IJ)}$, $E_{(I\times JN)}$and $F_{(J\times IN)}$. Generally, for monitoring and analysis, matrix D is the most meaningful way of unfolding. It appends data collected from different sensors in the row directions and creates one vector. Thus, each set of data for a specific load is considered as an object. MPCA decomposes X into a summation of the product of t score vectors (t) and p-loading matrices (P), plus a residual matrix (E) that is minimized through a least square method.

$$X = \sum_{r=1}^{R} t_r \otimes P_r + E \tag{4.11}$$

where r is the number of principal components used in the analysis. This decomposition represents the data with respect to both variables and time in low-dimensional score spaces. These spaces account for variability over the conditions at all points in time. Each p-loading matrix summarizes major time variation of the variables about their average trajectories over all the conditions. As a result, MPCA can actually utilize the magnitude of the deviation of the each variable from its mean trajectory and at the same time correlate among them [21].

4.3.3 Fault detection using T^2 statistics

A statistical test such as Hotelling's T^2 on the principal plane, is carried out for fault detection. The Hotelling's T^2 and the corresponding limit T^2_{lim} are given in Equations (4.12) and (4.13) respectively[22].

$$T_i^2 = (\mathbf{x}_i - m)^T \mathbf{S}^{-1} (\mathbf{x}_i - m) \tag{4.12}$$

$$T^2_{lim} = \frac{a \cdot (I-1) \cdot (I+1)}{I \cdot (I-a)} \cdot F_{a,I-a,\alpha} \tag{4.13}$$

where $\mathbf{x}_i$ is the row of the matrix $\mathbf{X}_{I \times J}$, m is the mean value of column $\mathbf{x}_j$ in the matrix $\mathbf{X}$, S is the covariance matrix of data matrix $\mathbf{X}$, $\mathbf{a}$ is the number of selected principal components, $\mathbf{I}$ is the number of samples or measurements and $\mathbf{F}_{a,I-a,\alpha}$ represents F-distribution with a and $(I-a)$ degrees of freedom and level of significance. T^2-statistics is the sum of normalized squared scores; it can represent the normal behaviour of the process as it remains unaffected by inaccuracies of smaller eigenvalues.

4.3.4 Methodology for analysis of vibration and process data

Application of multiscale PCA and multiway PCA for vibration data analysis was described [10]. In this present paper, we further advanced the methodology to analyze vibration signals augmented with process variables. The proposed methodology is shown in Figure 4.6.

Consider data matrix $\mathbf{X}_i [i = 1,2,3,...,n]$ are batches of vibration data. Each data matrix

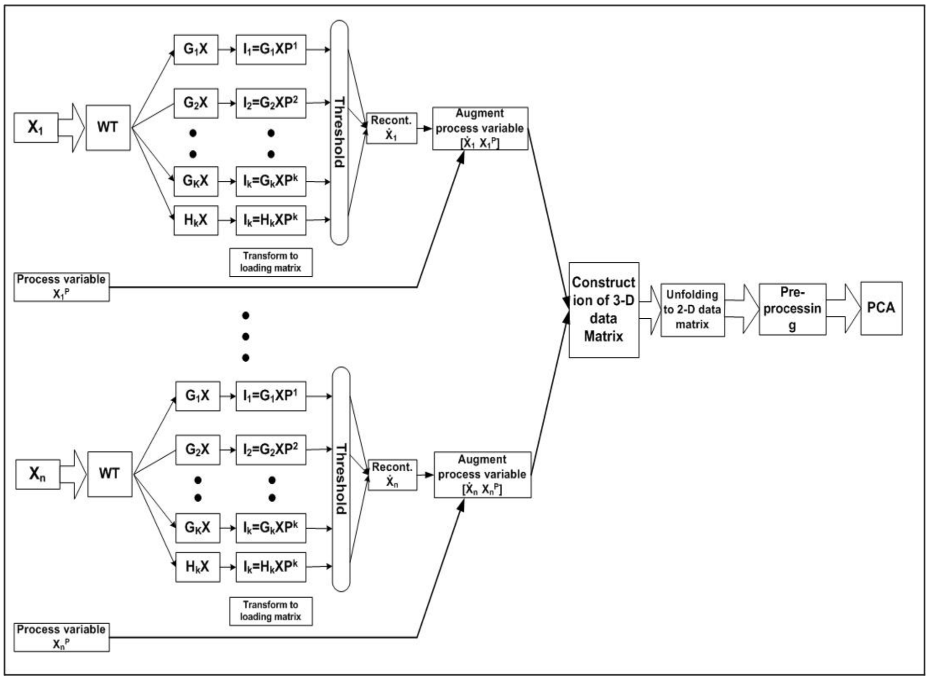

Figure 4.6: Proposed multiscale MPCA augmented with process variables model

$\mathbf{X}_i$ contains measured vibration signal from sensors $x_j(t)$ at an axial location around the bearing. These different batches of data are not necessarily collected under identical conditions. A realistic scenario for a rotating machine would be that load and rpm of the machine may be different for these different batches of data. Wavelet transformation (WT) is applied to decompose each variable $x_j(t)$ into different frequency scales. Following this, uniscale PCA models are applied to coefficients of each of the scales. The purpose of uniscale PCA is to denoise the signals. A signal $x_j \quad \{j = 1, 2, 3, ..., J\}$, i.e. a column in the matrix $\mathbf{X}_{I \times J}$, is reconstructed by multiplying individual scales $c_{jk}(t)$ with the relevance factor κ_k and adding together as in the following equation

$$\widehat{x}_j(t) = \sum_{K=1}^{K} \kappa_k(t).c_{jk}(t) \tag{4.14}$$

where the relevance factor $\kappa_k(t)$ is defined by

$$\kappa_k(t) = \begin{cases} 1 & \text{if} \quad SF_{K,norm}(t) \geq 1, \\ [SF_{K,norm}(t)]^{\mu} & otherwise \end{cases} \tag{4.15}$$

$SF_{K,norm}(t)$ is defined as

$$SF_{K,norm}(t) = \frac{T^2{}_k}{T^2{}_{k,lim}} \quad \text{or} \quad \frac{Q_k}{Q_{k,lim}} \tag{4.16}$$

It can be seen that only those decomposed wavelet coefficients on each scale k have been used whose $T^2{}_k$ or Q_k value exceeds the corresponding confidence limits $T^2{}_{k,lim}$ or $Q_{k,lim}$. The value below confidence limits is assumed to be contribution of noise has been revised accordingly by the reduction factor μ. The reduction factor μ is the key element of the noise "thresholding". As the value of reduction factor increases or tends to ∞, any value that crosses the confidence limit is kept, whereas all values below the limit become zero and this is called "hard-thresholding." The reconstruction process acts as a perfect multivariate multiscale filtering technique for removing noise.

At this point, augmentation of process variables technique is applied. Process variables, such as loads of the process, rpm of the rotary machines, and flow towards the rotary machines, is regarded significant process variables as they have direct influence on the vibration signals of the rolling element bearings. The proposed study put forward the idea of relating the process variable with vibration analysis technique for accurate fault detection purpose. In this study, load and rpm are used as process variable. After having filtered signals, the significant process information corresponding particular process condition i.e., load or rpm or both of them, x^P is added to corresponding data matrix as an additional variable in an form, $\widehat{\mathbf{X}}_1^A = [\widehat{x} \;\; x^P]$. The other datasets $\widehat{\mathbf{X}}_2^A, \widehat{\mathbf{X}}_3^A, ..., \widehat{\mathbf{X}}_N^A$ can be built in a similar way.

Once the sufficient data matrices have been collected, they are arranged in a 3-way matrix $\widetilde{X}^A(N \times I \times J)$. The three way data matrix $\widetilde{X}^A(N \times I \times J)$ is unfolded to $\widehat{X}_D(N \times IJ)$ where each row represents a batch of vibration data. Before applying PCA on the unfolded matrix $\widehat{X}_D$, data are preprocessed as described in Section 4.2. Then PCA is carried out on the preprocessed matrix and T^2-statistics or Q-statistics are monitored. Each batch of data is represented as a point on the T^2 and SPE plot. Any non-faulty data should remain below the limits. Any data set that has correlation significantly different than other data sets will exceed the threshold and regarded as a faulty data set. As new data sets become available, those are incorporated with existing data sets. If the relevant T^2 or Q value exceeds the threshold, the data set is regarded as abnormal indicating fault in that particular machine.

4.3.5 Steps for the proposed MSPCA-MPCA methodology

The proposed multiscale PCA combined with multiway PCA (MSPCA-MPCA) methodology consists of two parts : (1) reference model building, (2) testing of new data sets. These two steps of the methodology are described below.

4.3.5.1 Reference Model building

1. No fault vibration data set X_I^R at any particular load condition is collected.

2. After mean centering and scaling to unit variance, each column $x_j^R(t)$ of the matrix X_I^R is decomposed using wavelet transformation to K different frequency scales.

3. Coefficients of all variables for each scale are arranged in a matrix $C_k^R = [c_{1k}, c_{2k}, ..., c_{jk}, ..., c_{Jk}]$. PCA is applied on the coefficient matrix.

4. Using the equations (4.14) , (4.15) and (4.16), the reconstruction of the signals is done and is kept in matrix $\widehat{X}_1^R$.

5. Particular process information, x^P which acts as additional variable is added to the corresponding matrix $\widehat{X}_1^A = [\widehat{x}_1^R \;\; x^P]$.

6. Several datasets are collected for different load conditions and the reconstructed matrices $\widehat{X}_1^A, ..., \widehat{X}_N^A$ are collected in a three-way matrix $\widehat{X}^A(N \times I \times J)$.

7. The three way matrix $\widehat{X}^A(N \times I \times J)$ is unfolded into a two way matrix $\widehat{X}^A(N \times IJ)$ using unfolding technique described in Figure 4.4.

8. The data in the matrix are preprocessed. First, data are transformed to their absolute values and then normalized by MSC (median) and finally auto scaled.

9. A PCA model is built using the unfolded and denoised two-way matrix using few dominant principal components and T^2 and Q- statistics of datasets $(1, 2, .., N)$ and the confidence limits of T_α^2-statistics or Q_α-statistics for normal operation are calculated.

4.3.5.2 Monitoring system operation

The monitoring operation is similar to reference model building as graphically shown in Figure 4.6. The steps are as follows:

1. Collect the vibration signals, $X_{I \times J}^C$ from the monitoring system.

2. Using steps (2), (3), (4), (5) described in previous section, new dataset is constructed and stored in the matrix $\widehat{X}^C$.

3. The new reconstructed matrix is added as an additional dataset with the previously built three-way matrix in reference model building (step 6), it is combined to develop a new three-way augmented matrix.

4. PCA is applied on the new preprocessed and unfolded two-way matrix. T^2 and Q values are calculated. Then in similar way, the T^2 and Q values are plotted with limits calculated from reference model. The last value is newly collected dataset, if it exceeds the average limit of either T^2 or Q, that is an indication of fault.

4.4 Experimental details

A DC-motor with four discrete loads and variable rpm was designed for experimental testing and validation of the method. Faults were introduced to the bearings. The proposed condition monitoring technique was applied to data acquired from faulty and non-faulty bearings. Experimental set-up and the fault detection results are discussed in the following sections.

4.4.1 Experimental procedure

A DC motor was used to turn a flywheel which is considered as the load in the experiment. The flywheel is connected to the motor using a rotor which rests on two rolling bearings. Figure 4.7**b** shows the experimental set-up. A power converter is used to supply DC current from AC current source. The converter has the ability to supply different voltage which is specifically used for controlling of motor rpm. The motor rpm was measured using an external tachometer. Three different flywheels weighing 3 kg, 5 kg, 12 kg were used in different combination to create different load conditions for the system. Four single axis accelerometers with special noise free coaxial cables were vertically mounted on the bearing house of the two bearings. Their locations were chosen such that the sensors were orthonormal to each other. The signals acquired by these piezoelectric accelerometers were collected in portable computer via 16-bit data acquisition board. Vibration data are measured in displacement with G unit[1].The data collection sample rate was 398 Hz, each sample interval 0.002513 seconds. The main focus of the experiment was to simulate several different process conditions and study their effect on vibration data. Three different flywheels were used in different combinations and motor rpm was set to different levels in order to simulate different process conditions. These

Table 4.1: Specification of different components of the experimental set-up

Item	Specification
Motor	3 HP, 3 phase DC motor. Model:M-253AS-DBZ, type: M-1607
Converter	0-150V-25A converter (type: 103-52). Input:120-208 V, 25 A DC. Output:0-150 V, 35 A
Tachometer	General purpose tachometer from Tenma, model-72-6633
Loads	3 flywheel used as load. Large (diameter-0.762 m, width-0.0127 m)-12 kg, medium (diameter-0.254 m, width-0.0127 m)-5 kg, small (diameter-0.2032 m, width-0.0127 m)-3 kg
Bearing	Model SKF YAR 205-100-2F, ID-25 mm, center height 28.3 mm, Basic load limit 10800 N (dynamic), 7800 N (static), fatigue limit 232 N, Bearing mass 0.17 kg
Accelerometers	4 single axis ICP industrial accelerometers, model: 603C01
Data acquisition system	USB powered module for vibration analysis with 4 simultaneous 16 bit IEPE input channels, model-DT9839E

sets of experiments constitute the normal dataset i.e., no bearing fault. Subsequently we repeated these experiments with faulty bearings.

Bearing fault is defined as any force opposing the particular equipment from free rotation. There are mainly four types of bearing faults are evident: ball damage, inner race defect, outer race defect, cage damage [23]. In this study, we simulated cage fault which can lead to catastrophic consequences [24]. Cage failure can be caused by various rea-

[1] 1 G = 9.80665 m/sec^2 used for vibration measurement

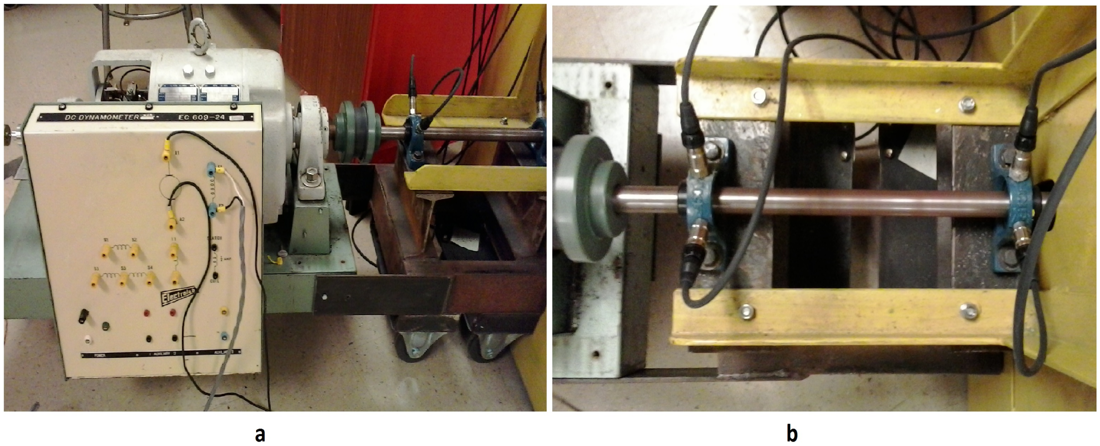

Figure 4.7: Experimental setup for verifying proposed methodology

sons: vibration, wear, excessive speed, blockage [25], [26]. In our experimental study, the cages of the rolling bearings were hammered severely to produce significant cage damage [27]. Figure 4.8 shows the damaged bearing with cage fault. Detailed experimental

Figure 4.8: Faulty bearing with cage fault

design is given in Table 4.2.

Experiment No.	1	2	3	4	5	6	7	8	9	10	11	12
Load (kg)	3			8			12			17		
rpm	1200	1600	2100	1200	1600	2100	1200	1600	2100	1200	1600	2100
No fault bearing	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Faulty bearing		✓	✓			✓		✓		✓		✓

Table 4.2: Design of experiments with rolling bearings

4.5 Results

By varying flywheel weight and rpm several real life load change scenarios were simulated that a process plant might experience. The proposed methodology was applied to investigate whether it can detect the fault. The detection results of multiscale MPCA methodology are compared with multiscale MPCA methodology without augmenting process information and MSPCA method.

4.5.1 Constant rpm and variable load

The first set of experiments were conducted to evaluate the effect of load variation on fault diagnosis method at constant rpm. First MSPCA technique was applied to a condition where rpm was constant at 1200 rpm but load was varied. Figure 4.9**a** shows T^2-statistics where load was at 8 kg. The flywheel weight was changed to 12 kg simulating a process load change scenario. Figure 4.9**b** shows T^2-statistics for the changed load. Clearly the method is sensitive to load change and T^2-values exceeded the threshold. The proposed multiscale MPCA method was applied to similar datasets where rpm was kept constant at 1200 and loads were varied to 3, 8, 12, 17 kg. Figure 4.10**a** represents T^2-statistics of all normal load conditions (3, 8, 12, 17 kg) at 1200 rpm and the corresponding control limit. A bearing fault was introduced to 17 kg load and 1200 rpm case. The T^2-statistics for this case is shown in Figure 4.10**b** where the fault is clearly identified successfully by following multiscale-MPCA technique as the T^2-statistics for the faulty dataset exceeded the normal limit to a great extent.

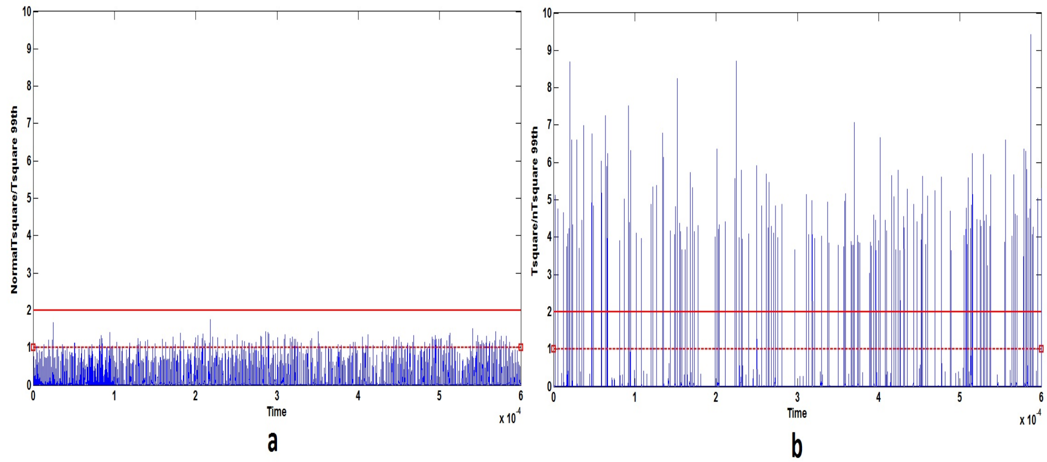

Figure 4.9: Effect of variation in load using MSPCA

In order to generalize, a total of twelve experiments were conducted by varying load and rpm and the proposed multiscale MPCA methodology was able to detect fault in 8 cases out of 12 which means it was 66.67% successful for fault detection under variable load with constant rpm condition. Also, there was no false detection.

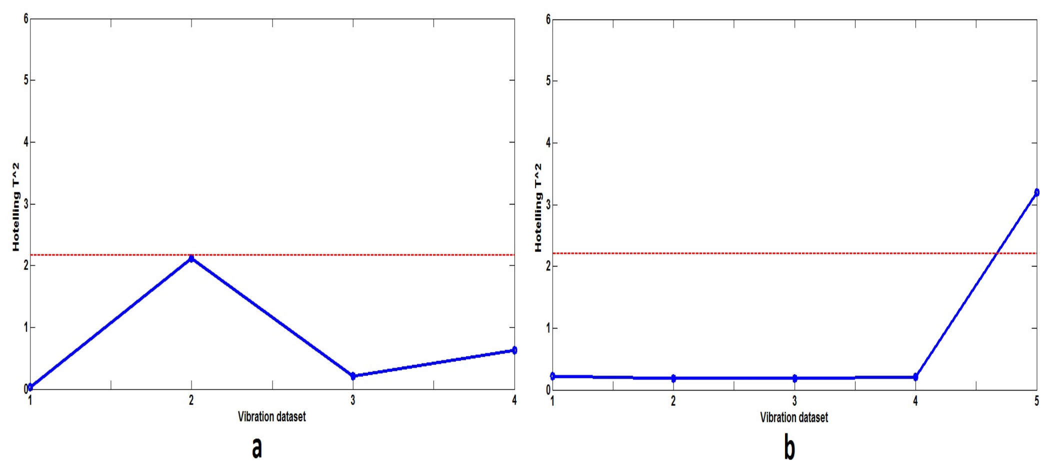

Figure 4.10: Effect of variation in load (constant rpm) using multiscale MPCA

Next, we augmented process variables namely load and rpm with vibration data and results were analyzed using multiscale MPCA. In Figure 4.11**a**, the normal values of T^2-plot is shown for all four load conditions (3, 8, 12, 17 kg) at constant rpm 2100, which gives

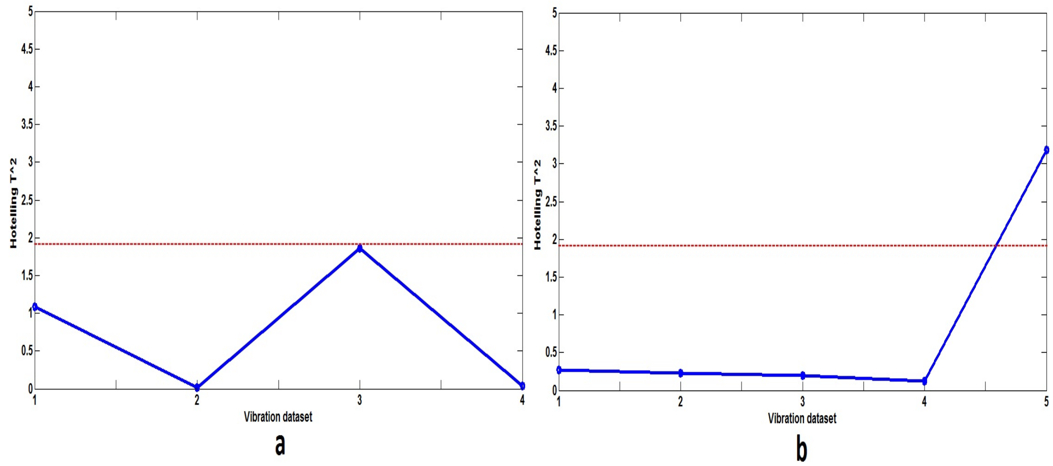

Figure 4.11: Effect of variation in loads with constant rpm using multiscale MPCA

the normal control limit . Figure 4.11**b** shows the T^2-plot with 5th dataset coming from a faulty bearing. The multiscale MPCA method rightly detected as faulty dataset. In a similar way, 12 sets of faulty data at various rpm were tested using proposed methodology. Therefore, it detected fault in 11 cases out of total 12 cases resulting in 91 % success rate. Thus the success rate is increased from 66 % to 91 % because of augmenting process data.

4.5.2 Constant load and variable rpm

Next, we observe the effect of change of rpm on bearing fault detection. For this purpose, the DC motor was run at several rpms i.e., 800, 1000, 1300, 1600, 1900, 2200, 2400 at a constant load of 12 kg. The datasets are collected at these conditions and analyzed. Figure 4.12 presents outcome of MSPCA technique on T^2-plot, where Figure 4.12**a** rpm was at at 1300, whereas 4.12**b** represents rpm 1900 at a load of 12 kg. In the latter, however, it is quite clear that MSPCA considers rpm change a faulty condition because T^2-values exceeds the control limit value. Next, we tested multiscale MPCA without incorporating process information. Figure 4.13**a** shows T^2statistics plot of datasets collected at rpm

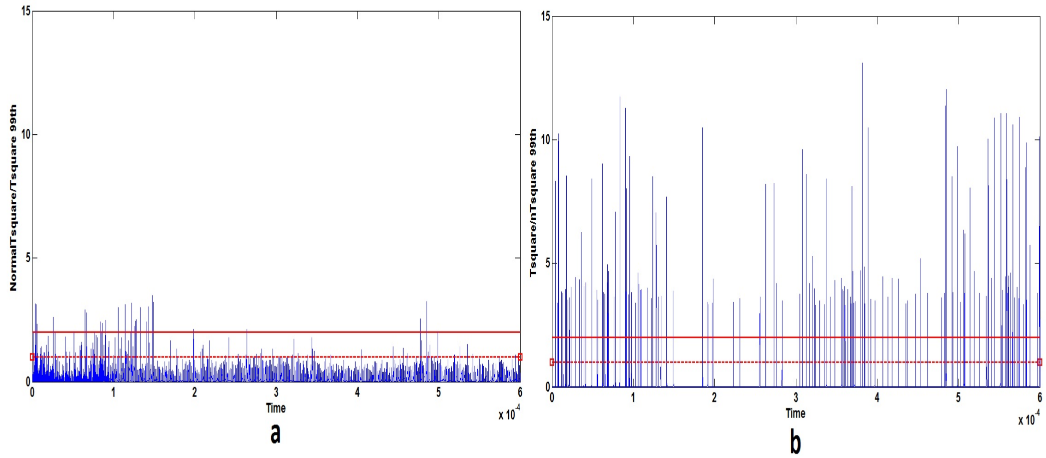

Figure 4.12: Effect of variation in rpm at constant load using MSPCA

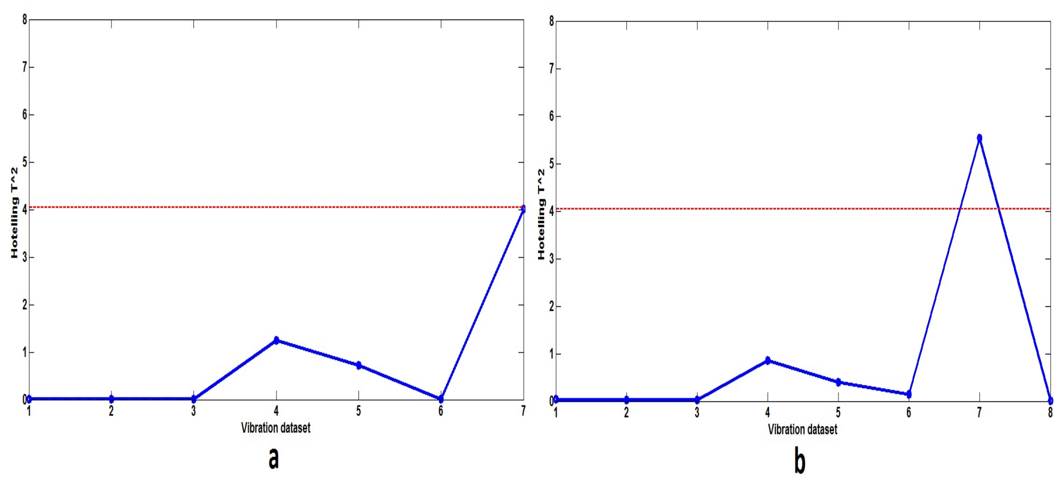

Figure 4.13: Effect of variation in rpm at constant load using multiscale MPCA

800, 1000, 1300, 1600, 1900, 2200, 2400 and at a constant load of 12 kg. In Figure 4.13**b**, it is seen that proposed multiscale MPCA technique detects the 7th dataset faulty and considers the 8th dataset normal, whereas the 8th dataset was actually faulty taken at rpm 2100. As discussed earlier, the proposed methodology fails to detect faults under variable rpm conditions along with two other cases resulting in zero success for this particular scenario.

The methodology including the process information showed significant improvement resulting in 66.67% success in case of fault detection. The reference model is built from vibration datasets acquired from the test setup with constant load of 12 kg and rpms were at 800, 1000, 1300, 1900, 2100, 2400. In addition to the vibration signals, the corresponding rpm signals were also included with the datasets.

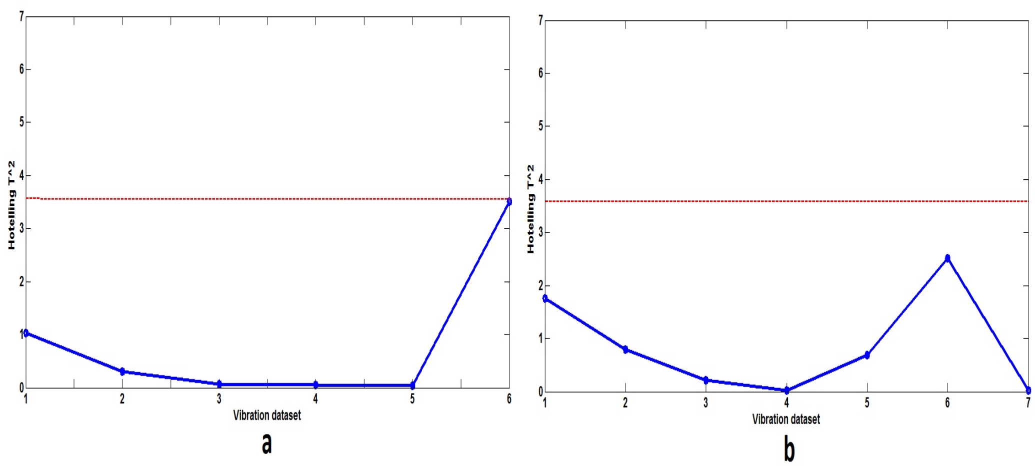

Figure 4.14: Effect of variation in rpm with constant load using multiscale MPCA with process information

Figure 4.14**a** shows the T^2-plot for normal datasets when motor rpm was changing but load was at a constant value. We wanted to investigate if including of process variables helps to detect the fault successfully and robust to false alarm. In order to do that, we included a normal dataset acquired from 12 kg load and 1600 rpm with our reference datasets. Figure 4.14**b** shows the proposed methodology successfully detected the new dataset as normal as new T^2-value did not exceed the control limit set by normal reference model. Next, the proposed approach with process information is tested with

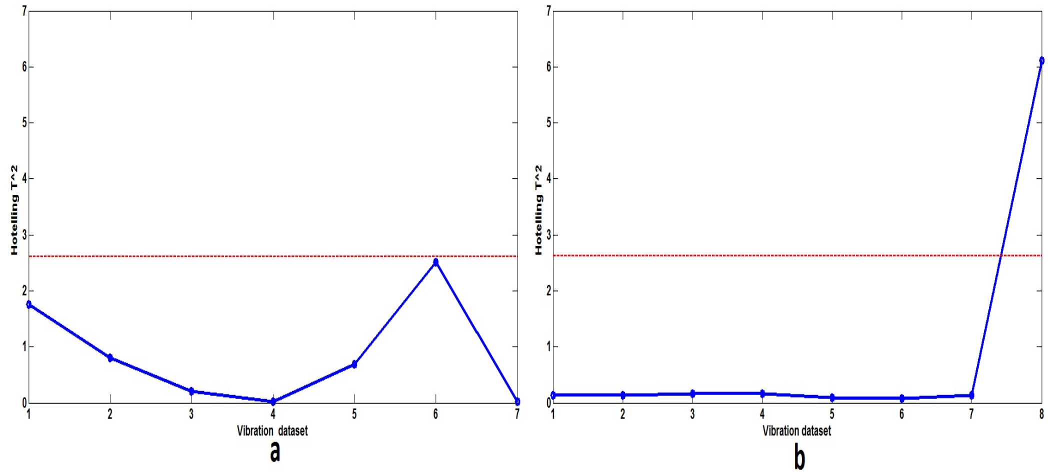

Figure 4.15: Fault detection in variable rpms with constant load using multiscale MPCA with process information

faulty dataset. Figure 4.15**a** presents the T^2-plot along with normal control limit for normal datasets of rpm's-800, 1000, 1300, 1600, 1900, 2200, 2400 at constant load of total 12 kg. Next, we included a faulty dataset along with the seven datasets. Proposed multiscale MPCA detects the 8th dataset as faulty as it exceeds the limit in T^2-plot in Figure 4.15**b**. The 8th dataset is extracted from bearing with damage cage at rpm 1600 and load of 12 kg. Three faulty datasets were tested with the normal model and subsequently, the algorithm detected fault successfully 2 times out of 3.

4.5.3 Variable load and rpm

Variable load and rpm is a more common scenario in process industries. The proposed methodology is applied for data analysis along with MSPCA technique for comparison. First, MSPCA was applied to vibrational datasets changing load and rpm. T^2-plot of dataset representing rpm 1600 and load of total 8 kg following MS-PCA approach is shown in Figure 4.16**a**. Then using the control limit and model determined from nor-

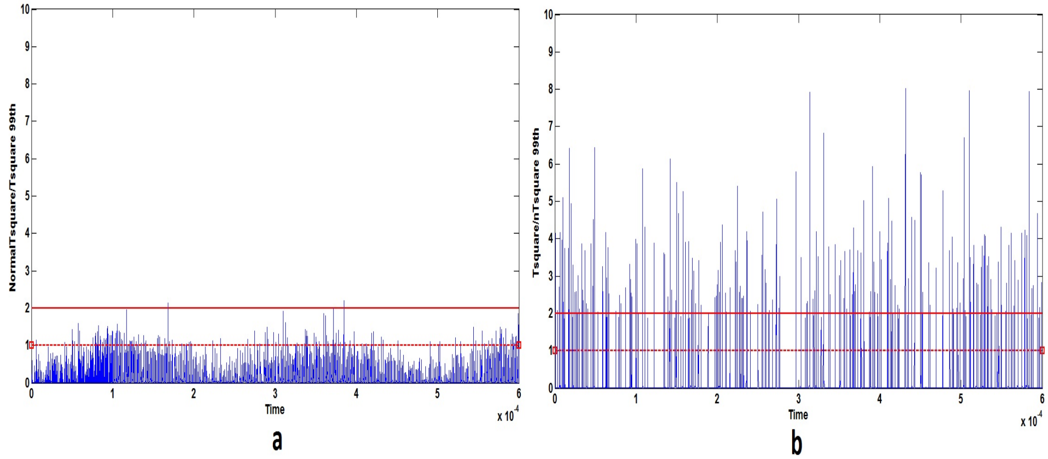

Figure 4.16: Effect of variation in both rpm and load using MS-PCA

mal dataset, another dataset collected at a different load and rpm i.e., 1200 rpm and 12 kg load, was projected using MSPCA. The applied method refers to rpm 1200 and 12 kg of load condition as faulty on T^2-plot as most of the T^2 values exceed the normal limit in Figure 4.16**b**. Thus it can be concluded that MS-PCA approach may not be appropriate to detect equipment fault under variable process conditions. By setting load at four levels: 3, 8, 12, 17 kg and rpm at three levels: 1200, 1600, 2100, a total of eleven datasets were collected for normal conditions. After combining these, the reference model is built and control limit is determined. Then the model was tested for thirteen different fault conditions for fault detection purpose. Our proposed multiscale MPCA methodology successfully detected the bearing fault in spite of load and rpm variation. Figure 4.17**a** presents T^2-plot of 12 normal datasets as mentioned earlier. When, the dataset from a faulty bearing is included in the data analysis process, it is detected as faulty as T^2 value exceeds the normal limit in Figure 4.17**b**. Similarly, eleven other faulty cases were taken tested, the proposed method was able to detect faults in all cases except one resulting 91.67% success in detection and no false detection.

Next, we included the rpm and load with vibration data and used multiscale MPCA to detect bearing fault.The normal model is built of these datasets and the T^2-plot along

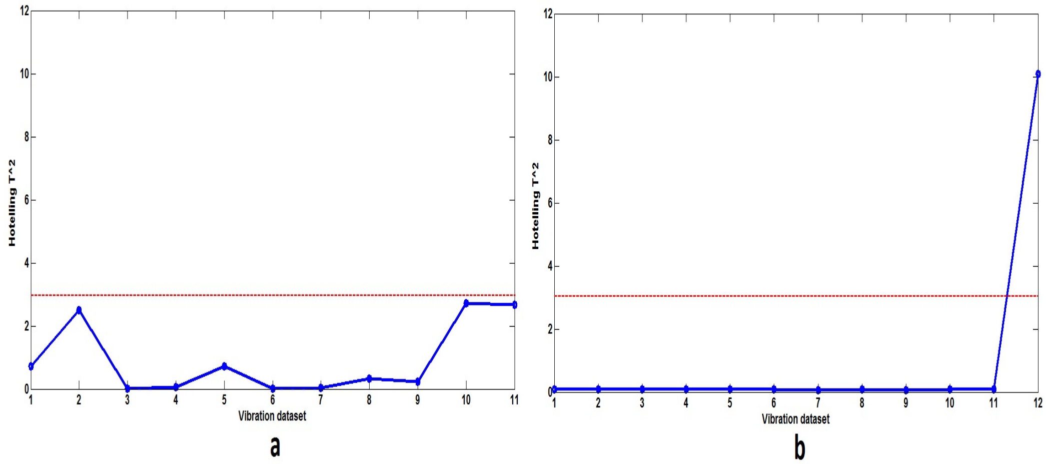

Figure 4.17: Effect of variation in both rpm and load using multiscale MPCA

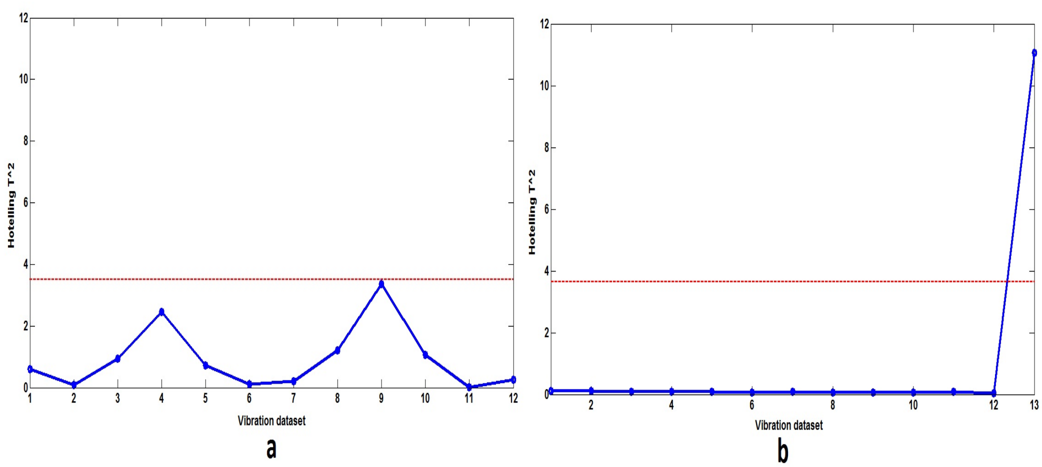

Figure 4.18: Effect of variation in both rpm and load using multiscale MPCA with process information

with the normal control limit is shown in Figure 4.18**a**. In Figure 4.18**b**, a faulty dataset at rpm 1600 and load of 8 kg is introduced with the normal datasets. The T^2-value of the faulty dataset exceeds the threshold by big margin leading to the successful detection of the bearing fault. A total of thirteen faulty datasets were tested and the methodology detected faults successfully for all thirteen cases with no false detection resulting in 100 % success rate.

4.6 Conclusion

The present work investigated the characteristics of vibration signals in rolling element bearings under variable load and speed conditions and its impact on fault detection techniques. A novel approach based on MSPCA and MPCA is proposed for fault detection under the varying load and speed of rotary machine. The fundamental idea of this proposed methodology is that it combines the vibration data with process data and simultaneously transforms the data for monitoring purpose using unique unfolding technique. This approach was demonstrated on a DC motor system with varying load and speed conditions. The proposed method showed good fault detection ability compared to other conventional methods such as MSPCA, under variable systems of load and rpm mentioning potential use of such technique in industrial environment and unique characteristics such as success rate, no false detection etc.

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Chapter 5

Conclusion and recommendation

5.1 Conclusions

This thesis investigates the effect of process variation on vibration data. It was experimentally observed that change of machine load or rpm has significant effect on vibration signal. Most of the traditional signal processing methods including multivariate statistical method such as MSPCA gives false alarm when process conditions (i.e.,load, rpm) varies. Putting focus on this problem, this research develops a multivariate technique combining powerful filtering feature of MSPCA with MPCA. MPCA is a powerful multivariate technique that allows to analyze batches of vibration data collected under different operating conditions collectively. The method was tested using simulated data. It successfully delineated between load change and bearing fault. However, the method was sensitive to rpm changes and wrongly identified any rpm change as bearing fault. The method was further advanced by augmenting process variables (e.g., load, rpm) with vibration data. The augmented data was analyzed using proposed multiscale MPCA method. The efficiency of the methodology was demonstrated on a DC motor-flywheel system with variable rpm and variable loads. The proposed method showed superior performance in bearing fault detection under variable loads and rpm. The methodology showed strong fault detection capability by combining the process variables with vibration data when the conventional technique fails. At the end, it becomes a strong tool for vibration based condition monitoring by proven applicability both in simulated cases as well as in experimental study.

5.2 Recommendations

We have the following recommendations for future work.

- The proposed method was validated using simulated and experimental trial. However, it remains to see how the methodology will perform in industrial scenario. Field data collected from the industry should be used for validating the method.

- While this research focus on the detection of the bearing fault under non-stationary process conditions, it did not deal with estimating fault magnitude. Multivariate statistical techniques, such as SPC (Li et al. [37]) could be used for estimating fault magnitude and subsequently it can be used for estimating remaining useful life for equipment.

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