Chapter 1

Introduction

‘*People are the quintessential element in all technology. Once we recognize the inescapable human nexus of all technology our attitude toward the reliability problem is fundamentally changed.*’

-Garrett Hardin

We are witnessing an era in which the technology has become an inevitable part of our lives. Even the simplest of tasks, nowadays, are carried out by machines and thus the nexus between humans and machines seems truly inescapable.

Highlights:

- Safety and cost are two important aspects of system reliability. Predictive maintenance increases machine reliability by reducing the downtime when compared with the reactive maintenance.
- Bearings are an important component of rotating machines and majority of failures in such machines occur in bearings.
- Health of bearings can be monitored through vibration or acoustic signals. These signals can be transformed to frequency or time-frequency domain for further processing.
- This thesis contributes in design of a signal processing framework for automatic fault diagnosis under constant as well as variable speed conditions.

In *Industry 4.0* era, the continuous and smooth working of industrial rotating machinery is essential for the operation and maintenance of automated plants. Early fault detection and isolation can improve safety, reliability and efficiency of industrial systems. However, in a highly competitive market, the race for lower time-to-market is pushing design and production deadlines earlier to put the load of most reliability-related activities on maintenance. Increase in production demand has evoked many issues related to reliability and maintenance. As a consequence, the industry is slowly moving from reactive to predictive maintenance. When maintenance is carried out as a reaction to machine failure, it is known as reactive maintenance, whereas, predictive maintenance is based on the current condition of the machine. Reactive maintenance is often linked to larger machine downtime and poses safety concerns as the machine breakdown may cause severe safety hazards. For example, for *Porsche's* 996 variant of its 911 engine, more failures of intermediate shaft bearings were reported, with an estimated failure rate of 8-10%, and if the bearing failure was not identified in time, the complete engine had to be replaced [1]. Several case studies on industrial bearings also show that if the failures are detected earlier, several hours of downtime and huge maintenance costs can be avoided [2–4]. A report published on catastrophic failure of a 150 hp centrifugal pump, in 1988, states that the failure not only caused $1,000,000 of damage and 18 days of lost production, but also initiated fire [5].

Predictive maintenance aims for early detection of faults, followed by specific maintenance and to achieve this, machine condition needs to be continuously monitored through vibration, sound, temperature or current. Over the years, the field of machine condition monitoring has evolved due to technological advancements in various fields. This thesis focuses on the signal processing aspects of bearing fault diagnosis based on vibration and acoustic signals. The motivation behind this research is the fact that bearings are essential component of rotating machines. An estimated 50 million bearings are replaced due to failure every year [6]. A statistical study published by *United States Department of Energy* reports that 76% of wind turbine gearbox failures are caused due to bearings [7] and according to *IEEE-IAS* survey 44% failures in medium-voltage induction motors are bearing related, whereas *Allianze* survey of high-voltage large induction motors shows 13% bearing related failures [8].

For diagnosis of bearing faults, this research is riveted around the signal processing aspects of fractional calculus, which consists of generalizations of well-established integral transforms, like Fourier transform (FT) and Hilbert transform (HT). The cyclostationary nature of bearing signals is also taken into account to develop a windowing based algorithm to exploit the local statistical features related to the sharpness of cumulative distribution function of time-series data. The methodology adapted for this research includes review of relevant literature, identification of gaps in existing research, defining the objectives of this research, study of public datasets and validation using in-house experiments with vibration and sound signals.

1.1 State of the Art

A rolling element bearing consists of five important parts - an inner raceway, an outer raceway, rolling elements, cage and seal. The inner raceway is secured to the rotating shaft while the outer raceway is fixed in a housing. These raceways provide a rotatory path for the rolling elements which are separated from each other by the cage. The rollers and cage assembly is often sealed from the environment using rubber or stainless steel seals. A schematic of a roller bearing is shown in Fig. 1.1. It demonstrates presence of an inner raceway fault. A fault is typically a damaged surface on the raceways or the rolling elements. When the inner race of the bearing rotates with the shaft, the rolling elements come in contact with the fault and this surface-to-fault interaction generates a high frequency shock wave, modulated by the low frequency fault information. This signature is often captured by an accelerometer and further converted to a digital signal using the data acquisition unit.

To separate the low frequency fault information from the high frequency resonance, demodulation is often used for processing of bearing signals. The generalised block diagram of bearing fault diagnosis is shown in Fig. 1.2. There are three important steps

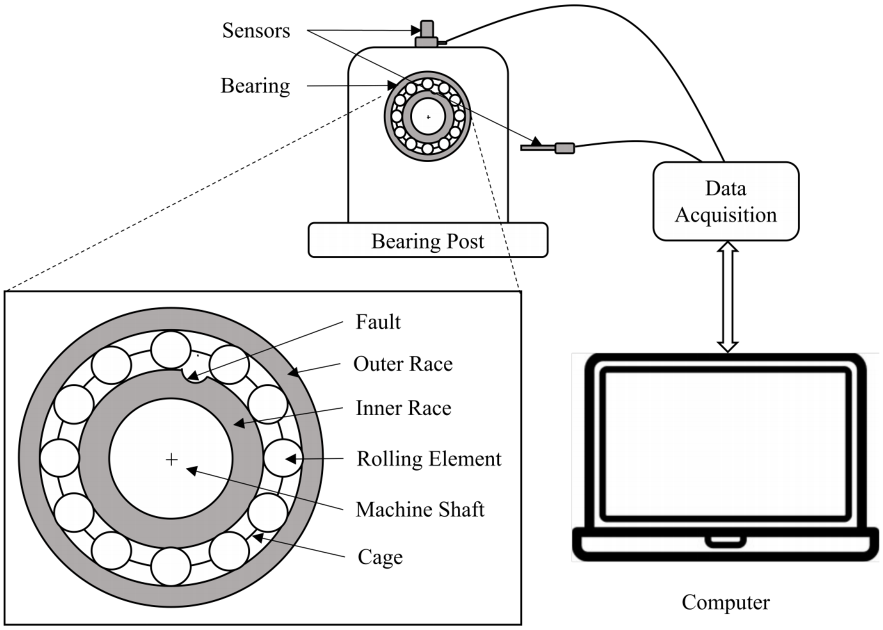

Figure 1.1: Simplified schematic of a bearing condition monitoring system

in this block diagram - Measurement, Signal Processing and Decision Making. The measurement part consists of acquisition of data that captures the health of the machine. The presence of faults can be carried out directly from this time domain data using statistical features and trend analysis. To reveal further critical fault information, like the type of fault, the time domain signal is often transformed using some signal processing method. The information about the fault frequency is often visually inspected to diagnose the faults. Features from both the time domain and the transform domain (frequency or time-frequency) can also be fed to feature extraction and classification algorithms.

The percentage wise split of available literature on state of the art methods is shown in Fig. 1.3. These methods are as follows -

1. **Measurement:** Bearing condition is captured using vibration [9], acoustic emission [10, 11], sound [12], thermal imaging [13] and motor current signals [14]. Out of these, vibration signal is the most widely used.
2. **Signal Processing:** Over the years, several signal processing algorithms are developed and explored for bearing fault diagnosis. These mainly include - wavelet

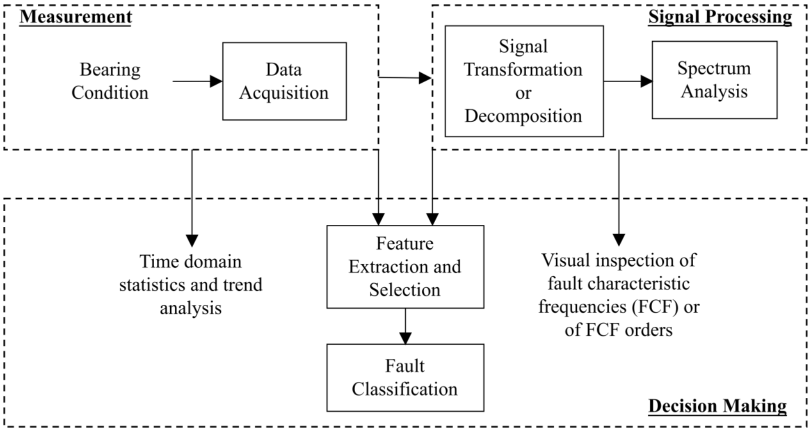

Figure 1.2: Generalised block diagram of bearing fault diagnosis

analysis [15, 16] and kurtogram based techniques [17, 18], empirical mode decomposition [19], variational mode decomposition [20], order tracking [21], fractional signal processing [22] and cyclostationarity analysis [23].

3. **Decision Making:** Bearing condition can be identified from time domain features, frequency domain features or time-frequency domain features [24–26]. Several feature extraction and classification algorithms, like support vector machines [27], principle component analysis [28], artificial neural networks [9], fuzzy inference system [29], are applied to bearing fault classification.

A detailed review of the signal processing methods is given in Chapter 2.

1.2 Research Contribution

This thesis contributes in two areas of active research, as shown in Fig. 1.4. The first area is the processing of vibration and acoustic data for efficient fault diagnosis. The contemporary research is taken a step forward by proposing the application of fractional

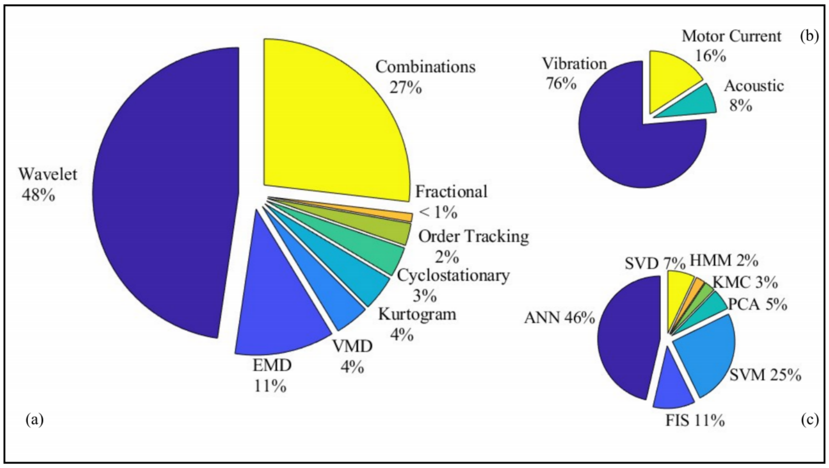

Figure 1.3: Commonly used techniques in bearing fault diagnosis (a) signal processing, (b) measurement, (c) feature extraction and classification (ANN - Artificial Neural Network, FIS - Fuzzy Inference System, SVM - Support Vector Machine, PCA - Principle Component Analysis, KMC - K means Clustering, HMM - Hidden Markov Model, SVD - Singular Value Decomposition). Reference: *Scopus* Database.

Fourier transform[1] based signal enveloping and cumulative distribution sharpness profiling[2] for diagnosis of bearing faults. The second area is the design of a framework for automatic fault diagnosis. In this, a common framework for constant as well as variable speed conditions, based on mutiple time-frequency ridge curves extraction, is developed. Two time-frequency domain fault features - Prominence and Compliance - are proposed for diagnosis of bearing faults. The proposed methods are validated on public datasets and tested on in-house experimental data.

1.3 Thesis Outline

The research is compiled and organised in this thesis as follows -

Chapter 1 lays down the importance of the problem statement and the motivation behind the research.

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[1] This work is published as - A. C. Jahagirdar and K. K. Gupta, "Fractional envelope to enhance spectral features of rolling element bearing faults," in Journal of Mechanical Science and Technology, vol. 34, pp. 573–579, 2020, https://doi.org/10.1007/s12206-020-0105-8

[2] This work is published as - A. C. Jahagirdar and K. K. Gupta, "Cumulative Distribution Sharpness Profiling Based Bearing Fault Diagnosis Framework Under Variable Speed Conditions," in IEEE Sensors Journal, vol. 21, no. 13, pp. 15124-15132, 2021, doi: 10.1109/JSEN.2021.3072368.

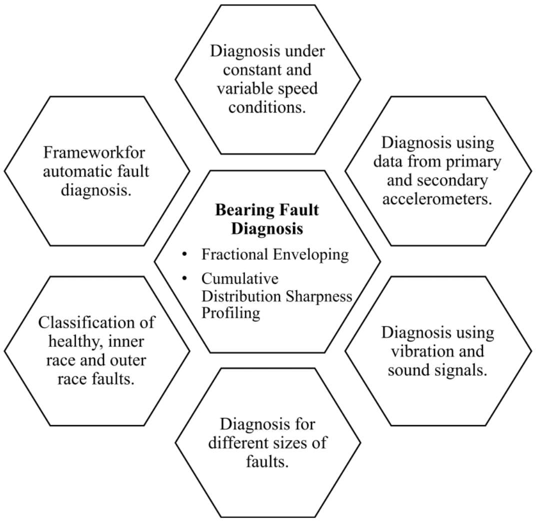

Figure 1.4: Contribution of this research

In Chapter 2, a comprehensive literature review is presented. The review literature is broadly divided as per the type of signal-processing and analysis algorithm used for bearing fault diagnosis. The gaps in the existing research are identified in this chapter.

In Chapter 3, the objectives of this research are defined and the details related to the methodology are explained. This includes information of the computing hardware and software, details of public datasets under study and the procedure of the experiments performed.

In Chapter 4, different methods of calculating the fractional envelope are implemented and investigated. The performance of these methods is, then compared over the range of fractional parameter using bearing fault related features. With some representative cases, it is emphasised that the performance of existing signal processing methods can be improved using fractional enveloping.

In Chapter 5, the cumulative distribution sharpness profiling is proposed for bearing fault diagnosis. First, the theoretical background for the proposed method is established. With evidences from fault cases, it is shown that the bearing fault signal follows Laplace distribution. The proposed algorithm is then explained, followed by the analysis of results.

In Chapter 6, a signal processing framework is designed for automatic fault diagnosis. Two time-frequency domain fault features Prominence and Compliance are proposed for automatic diagnosis of faults. A comparative analysis of the two proposed methods along with some state of the art signal processing methods is carried out for all the datasets under study.

Chapter 7 concludes this thesis with the purpose, important observations, limitations and future scope of the proposed bearing fault diagnosis algorithms.