STM JOURNALS

Trends in
Mechanical Engineering & Technology

https://journals.stmjournals.com/tmet

ISSN: 2231-1793 (Online)
ISSN: 2347-9965 (Print)
Volume 15, Issue 2, 2025
May–August
DOI (Journal): 10.37591/TMET

Case Study TMET

Feature Extraction and Analysis of Bearing Faults: A Review

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Abstract

One of the most important steps in identifying bearing problems is feature extraction. In order to provide a more meaningful dataset, it entails locating and extracting pertinent features from raw bearing vibration signals. Tasks involving categorization and prediction can then make use of these attributes. In many practical applications, such as monitoring rotating machinery or electronic components, the raw signals collected (e.g., vibration, current, temperature) are often complex, high-dimensional, and noisy. Feature extraction helps reduce this complexity by isolating key characteristics such as statistical parameters, frequency components, or time-frequency patterns that are sensitive to faults. These extracted features enhance the capability of diagnostic models to detect, classify, and predict faults with greater accuracy and reliability. Moreover, by concentrating on the most relevant aspects of the data, feature extraction improves computational efficiency, making real-time monitoring and automated fault detection more practical. It also aids in distinguishing between different fault types and severities, which is essential for effective condition-based maintenance. In the experimental set up, there are four test bearings placed on a single shaft. First of all, data is fetched from all the four bearings and then various features, Max, Min, Mean, Standard deviation, RMS, Skewness, Kurtosis, Crest factor, and Form factor are calculated for all the four bearings and then a comparison is made among all of these features. All these features can be further used for fault classification.

Keywords: Fault diagnosis, feature extraction, bearing, test rig, vibration

INTRODUCTION

Most of the bearing diagnostics research points on finding damaged bearings that have been found from the field where they have shown major flaws or from the damage that have been created. Scratching, drilling and adding particles to the lubricant are the common methods to create simulated defects. Defective bearing experiments are not able to find natural defect spread. Rotating machinery forms the backbone of modern industry, finding application in sectors ranging from manufacturing and transportation to energy production and aerospace. Within these systems, rolling element bearings are essential components designed to reduce friction between moving parts, support rotating shafts, and ensure smooth mechanical operation. Given their widespread usage and critical functional role, the operational health of bearings is paramount. Any degradation or failure can lead to reduced system performance, increased energy consumption, unplanned downtime, or even catastrophic mechanical breakdowns. As such, the early detection and accurate diagnosis of bearing faults are fundamental to industrial maintenance strategies and reliability engineering [1].

Bearing faults generally manifest in the form of localized defects, including cracks or pits, on different bearing elements such as the inner race, outer race, rolling elements (balls or rollers), and the cage. These faults can result from various sources including poor lubrication, contamination, improper installation, material fatigue, or manufacturing

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Received Date: May 20, 2025
Accepted Date: June 10, 2025
Published Date: June 20, 2025

Citation: Varun Sharma. Feature Extraction and Analysis of Bearing Faults: A Review. Trends in Mechanical Engineering & Technology. 2025; 15(2): 20–28p.

defects. If not identified promptly, even small defects can propagate due to cyclic stresses, leading to the eventual failure of the bearing and the machinery it supports. Consequently, condition monitoring and fault diagnosis of bearings have attracted significant research attention, aiming to develop robust, accurate, and real-time diagnostic systems [2].

A vital step in the fault diagnosis process is feature extraction, which involves transforming raw sensor signals, typically vibration, acoustic, or temperature data, into meaningful, discriminative attributes that can effectively characterize the health condition of a bearing. The quality of the extracted features directly influences the performance of the diagnostic system, particularly when these features serve as inputs to classification algorithms such as support vector machines, decision trees, or deep learning models. Poor feature selection can result in misclassification, delayed detection, or reduced sensitivity to incipient faults [3].

Traditionally, vibration analysis has been the most prevalent technique for bearing fault detection due to its sensitivity to mechanical changes and ease of acquisition through accelerometers. Vibration signals carry rich information about the dynamic behavior of machinery and are particularly effective at revealing periodic impulses caused by localized bearing defects. However, these signals are often non-stationary and contaminated by noise, making direct interpretation or simple statistical analysis insufficient. This challenge necessitates the use of advanced signal processing techniques for effective feature extraction [4].

Time-domain features, such as root mean square (RMS), kurtosis, skewness, crest factor, and peak-to-peak value, are among the simplest and most commonly used indicators. These features provide useful information about the overall amplitude and statistical properties of the vibration signals. While effective for detecting significant changes in machine behavior, time-domain features often lack sensitivity to subtle fault signatures and may fail to capture frequency-specific characteristics of faults.

To address these limitations, frequency-domain analysis methods such as the Fast Fourier Transform (FFT) are employed. These techniques decompose signals into their frequency components, allowing for the identification of characteristic fault frequencies associated with specific bearing components. For example, inner race faults typically exhibit energy at specific frequencies known as bearing fault characteristic frequencies (BFCFs), which are determined by bearing geometry and rotational speed. Frequency-domain features enhance the diagnostic process by enabling targeted analysis of these fault-related frequencies. However, they also suffer from drawbacks, particularly in handling non-stationary signals where transient behaviors or time-varying features are present [5].

In recent years, time-frequency analysis techniques have emerged as powerful tools for bearing fault diagnosis. Methods such as the Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and more specifically, the Continuous Wavelet Transform (CWT), provide a joint representation of signals in both time and frequency domains. These methods are capable of capturing localized, transient, and non-stationary behavior in vibration signals, which are characteristic of early-stage bearing faults. The CWT, for example, allows for the decomposition of signals using wavelets at various scales, offering multi-resolution analysis that is particularly suited for identifying impulsive events associated with defects [6].

Feature extraction using time-frequency techniques often results in a large number of features, necessitating further feature selection and dimensionality reduction strategies. Techniques such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and t-Distributed Stochastic Neighbor Embedding (t-SNE) are commonly used to retain the most informative features while reducing computational complexity and enhancing interpretability. Moreover, statistical and machine learning-based feature ranking methods can help prioritize features based on their relevance to fault classification tasks [7].

The extracted features serve as inputs to diagnostic algorithms, which may include classical machine learning models or modern deep learning approaches. Supervised learning models like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests (RF) have demonstrated strong performance when trained on well-curated feature sets. In parallel, deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) offer the advantage of automatic feature learning, especially when applied to time-frequency representations like scalograms or spectrograms derived from CWT or STFT [8].

An emerging trend in this domain involves the integration of image-based representations of vibration signals with deep learning architectures. For instance, converting CWT scalograms of vibration signals into 2D images allows the use of CNNs to extract hierarchical features that are highly effective for fault classification. This image-based approach has shown great promise in enhancing diagnostic accuracy and reducing the dependency on handcrafted features [9]. Despite significant progress, several challenges remain in the field of bearing fault diagnosis. These include the generalization of diagnostic models to unseen operating conditions, robustness to noise and signal variability, scarcity of labeled fault data, and the need for real-time implementation in industrial environments. Addressing these challenges requires continued research into more adaptive and resilient feature extraction methods, as well as the development of comprehensive datasets and benchmarks [10].

In conclusion, the process of feature extraction and analysis lies at the core of effective bearing fault diagnosis. By transforming complex, noisy, and high-dimensional vibration signals into informative representations, it enables the detection, classification, and understanding of various fault conditions. The continued evolution of signal processing techniques, combined with advances in machine learning and deep learning, holds the promise of more intelligent, accurate, and automated diagnostic systems. As industries move toward predictive maintenance and smart manufacturing, the role of feature extraction in bearing fault analysis will become increasingly crucial, supporting safer, more efficient, and cost-effective operations [11].

EXPERIMENTAL SET UP

Four test bearings are placed on a single shaft in the test set. An AC motor is connected via rub belts which is used to power the shaft. 2000 rpm is the steady rotation speed. A spring system adds 6000 lb of radial load to the shaft and bearing. Each bearing is greased with force. The temperature and flow of the lubricant is important in an oil circulation system.

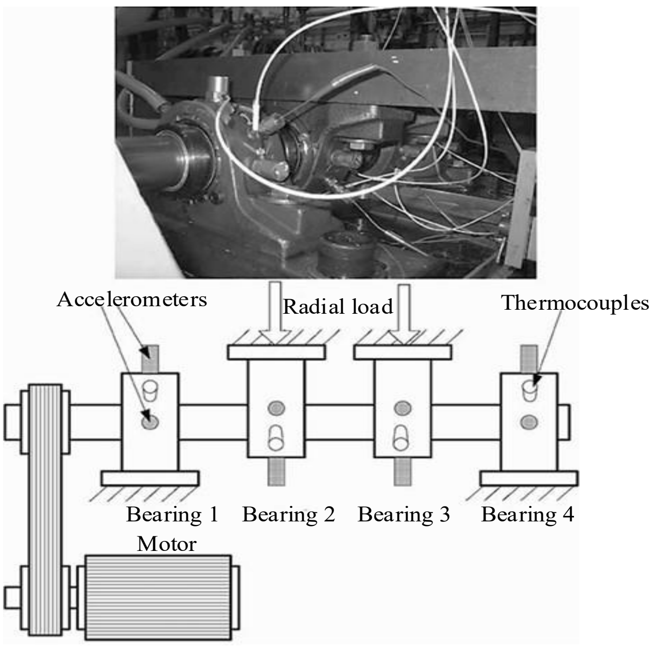
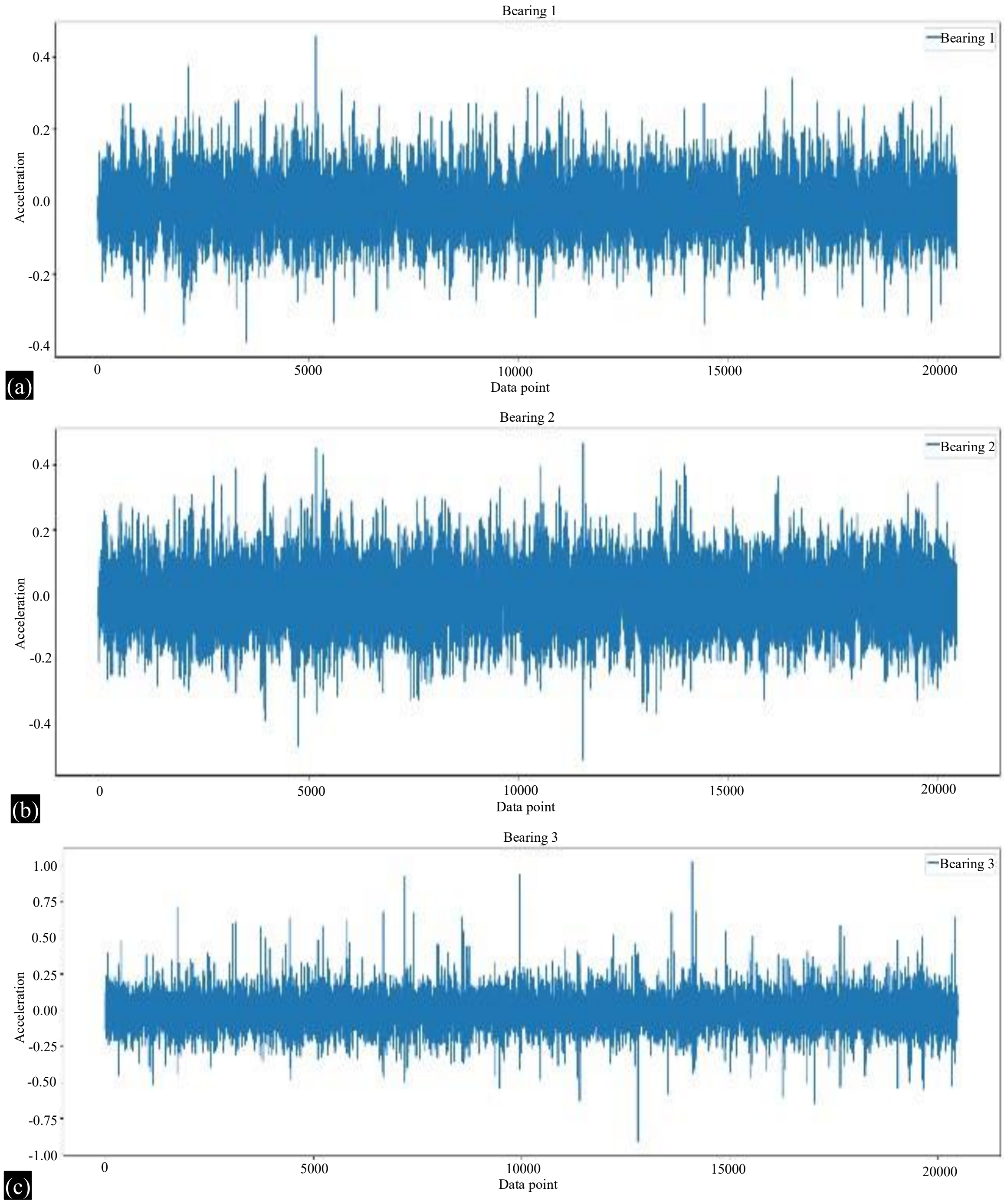


Figure 1. Bearing test rig.

Waste from the oil is gathered from a magnetic plug. When accumulated trash connected to the magnetic field reaches a particular threshold an electric switch closes and test ends. From Figure 1, single shaft has four Rexnord ZA-2115 double row bearings placed on it. Tapered contact angle is 15. 171. Pitch diameter and roller diameter are 2.815 and 0.331 in respectively. Each row has 16 rollers. Every bearing sheltering was equipped with a PCB 353B33 High Sensitivity Quartz ICP Accelerometer. Every bearing's outer race has four thermocouples. A National Instruments DAQCard-6062E data acquisition card is used to collect vibration data every 20 min. 20480 points data length and 20 kHz is the sampling rate. Data collection is done using LabVIEW software [1].

FEATURE EXTRACTION

Data is fetched for all four bearings; and vibrations produced in four bearings are showed in Figure 2.



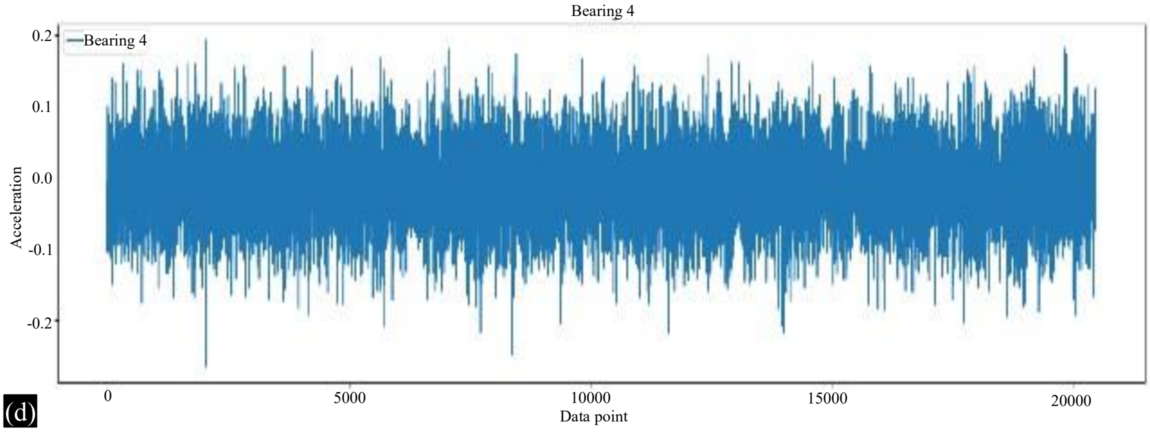
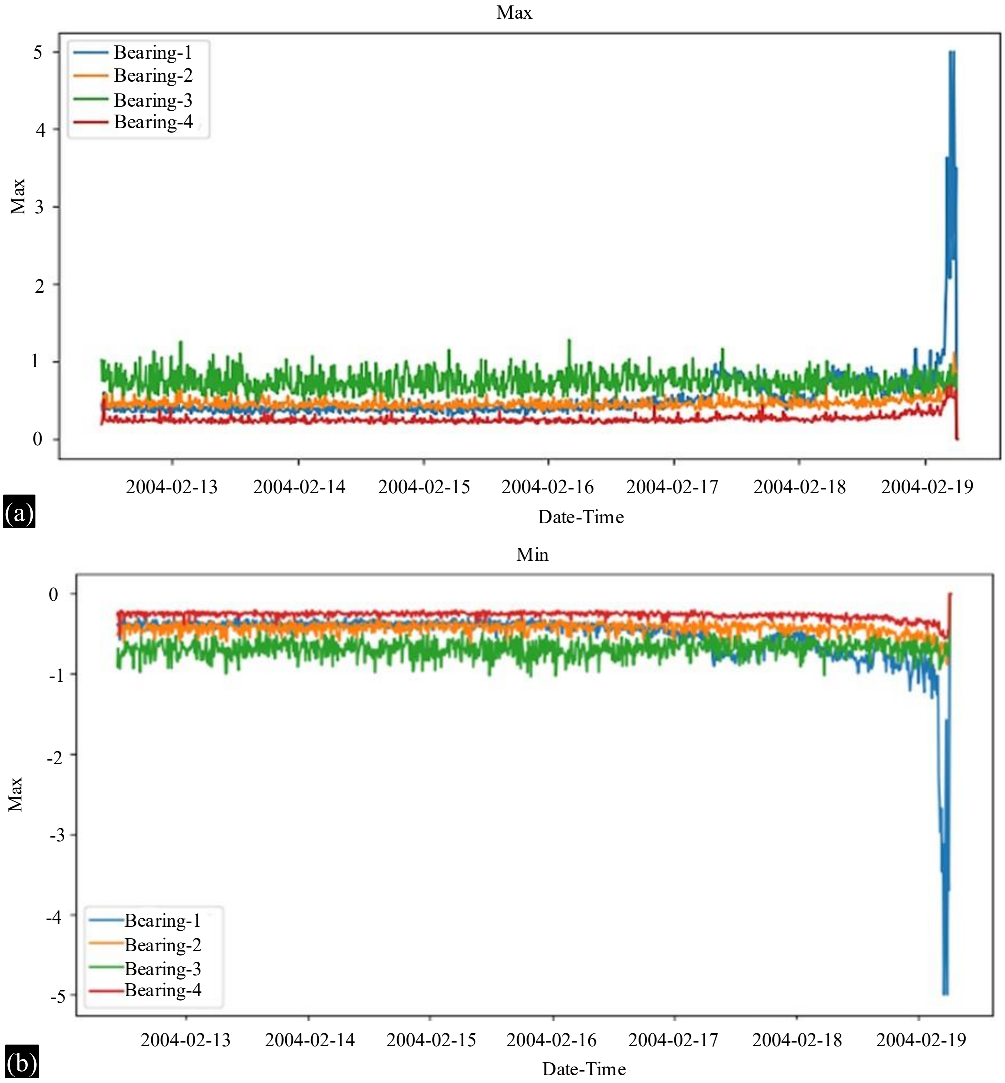


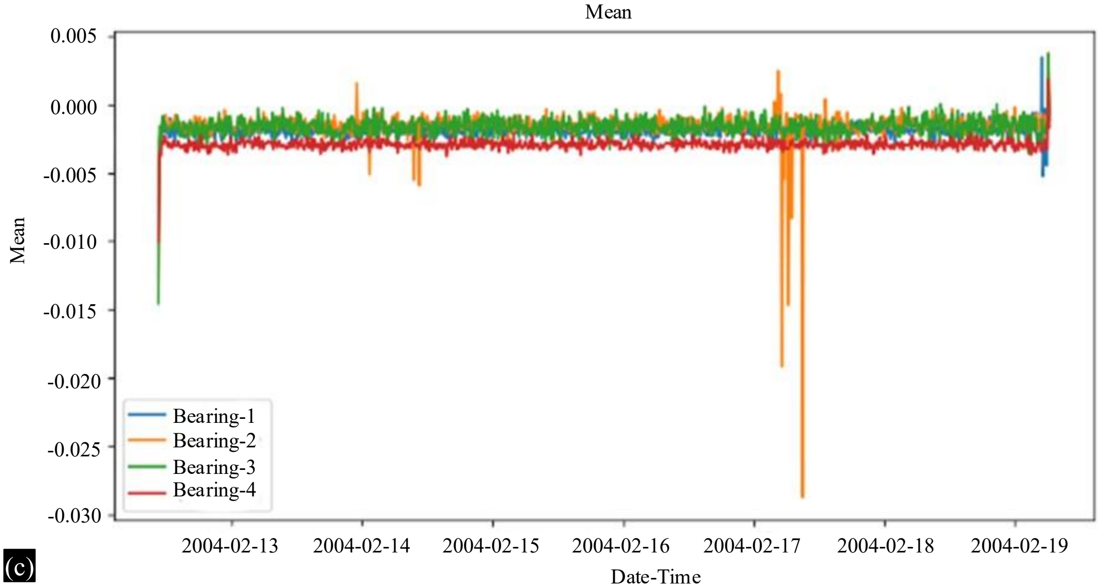
Figure 2. (a–d) Vibrations produced in four bearings.

Features for all four bearings: Max., Min., Mean, Standard deviation, RMS, Skewness, Kurtosis, Crest factor, and Form factor, are computed following the retrieval of vibration data.

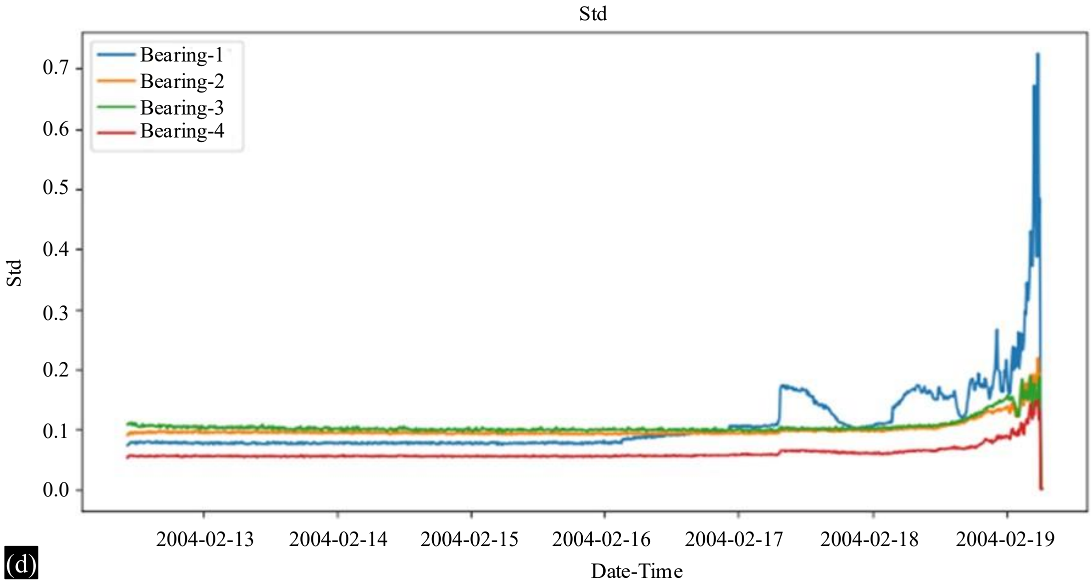
RESULTS COMPARISON

Comparison of features for all four bearings showed in Figure 3.

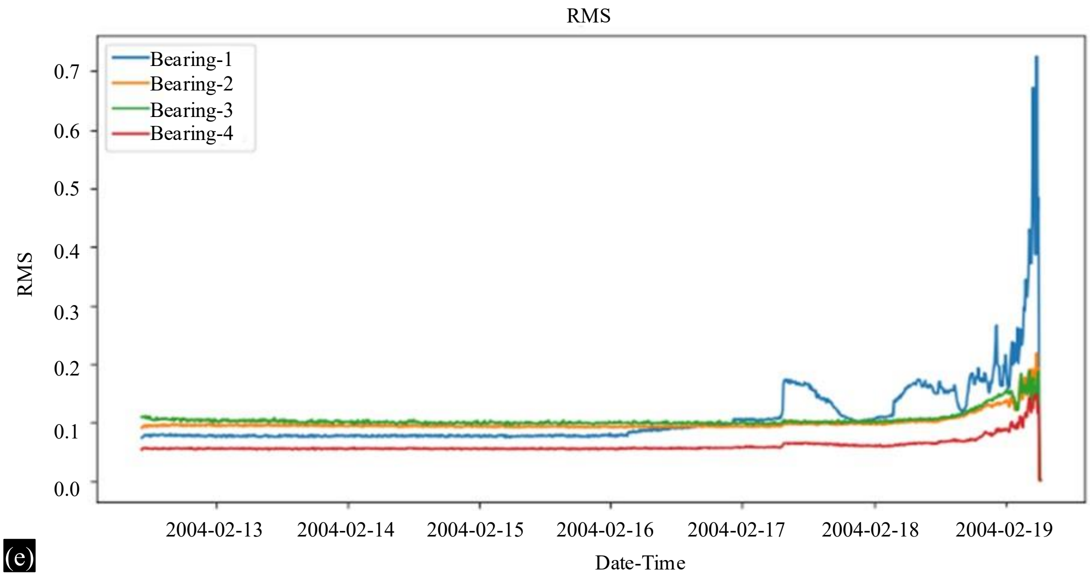



Mean
0.005
0.000
-0.005
-0.010
-0.015
-0.020
-0.025
-0.030
Mean
Bearing-1
Bearing-2
Bearing-3
Bearing-4
2004-02-13
2004-02-14
2004-02-15
2004-02-16
2004-02-17
2004-02-18
2004-02-19
Date-Time

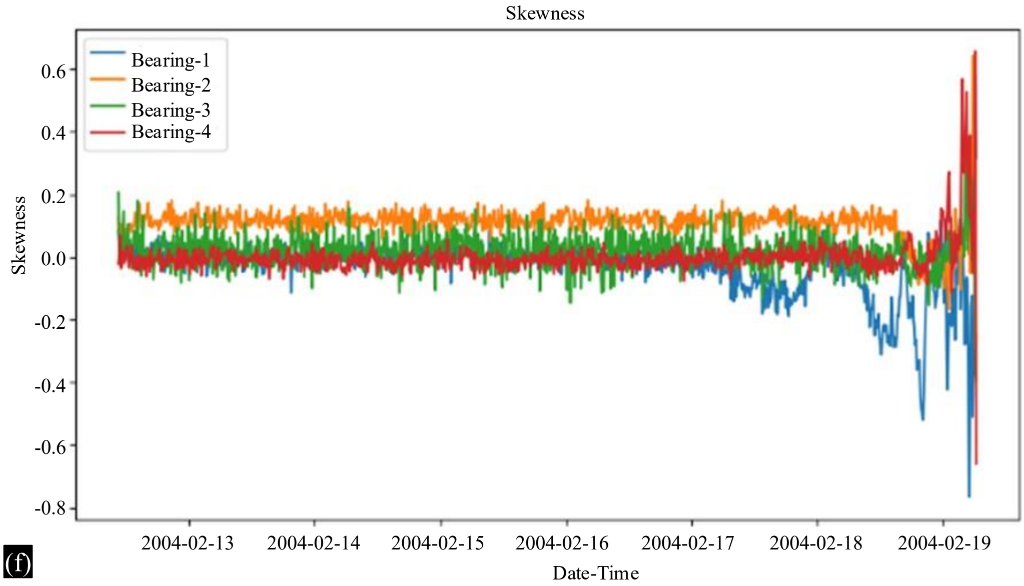
(c)


Std
Bearing-1
Bearing-2
Bearing-3
Bearing-4
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Std
2004-02-13
2004-02-14
2004-02-15
2004-02-16
2004-02-17
2004-02-18
2004-02-19
Date-Time

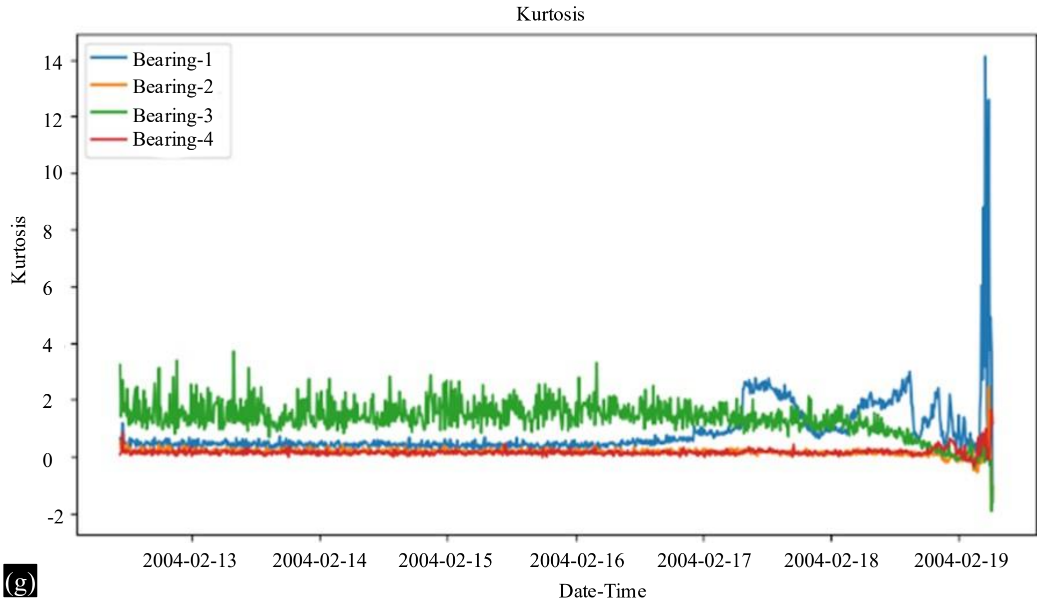
(d)


RMS
Bearing-1
Bearing-2
Bearing-3
Bearing-4
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
RMS
2004-02-13
2004-02-14
2004-02-15
2004-02-16
2004-02-17
2004-02-18
2004-02-19
Date-Time

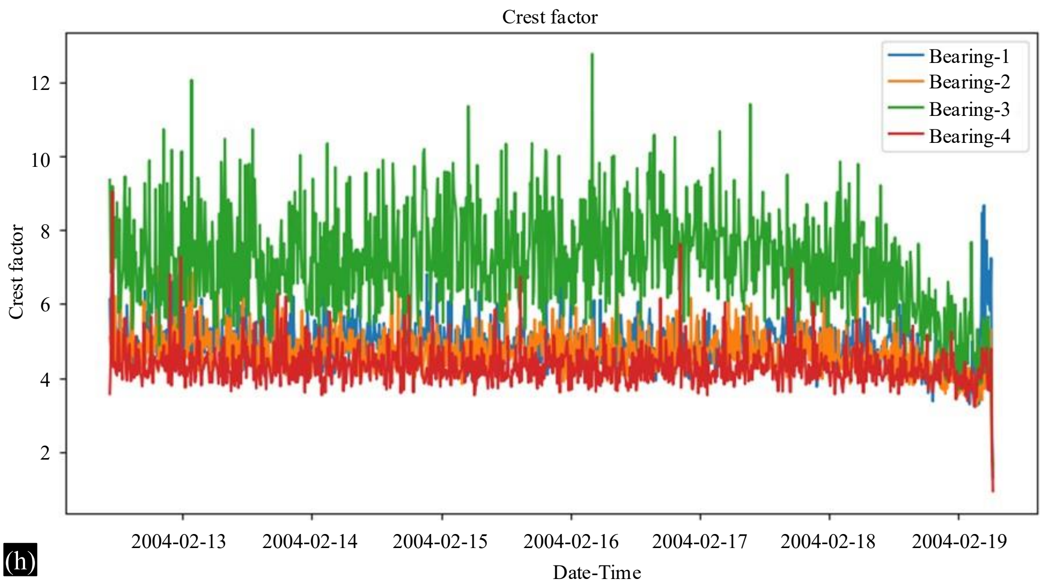
(e)


Skewness
Bearing-1
Bearing-2
Bearing-3
Bearing-4
Skewness
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
2004-02-13
2004-02-14
2004-02-15
2004-02-16
2004-02-17
2004-02-18
2004-02-19
Date-Time

(f)


Kurtosis
Bearing-1
Bearing-2
Bearing-3
Bearing-4
Kurtosis
14
12
10
8
6
4
2
0
-2
2004-02-13
2004-02-14
2004-02-15
2004-02-16
2004-02-17
2004-02-18
2004-02-19
Date-Time

(g)


Crest factor
Bearing-1
Bearing-2
Bearing-3
Bearing-4
Crest factor
12
10
8
6
4
2
2004-02-13
2004-02-14
2004-02-15
2004-02-16
2004-02-17
2004-02-18
2004-02-19
Date-Time

(h)

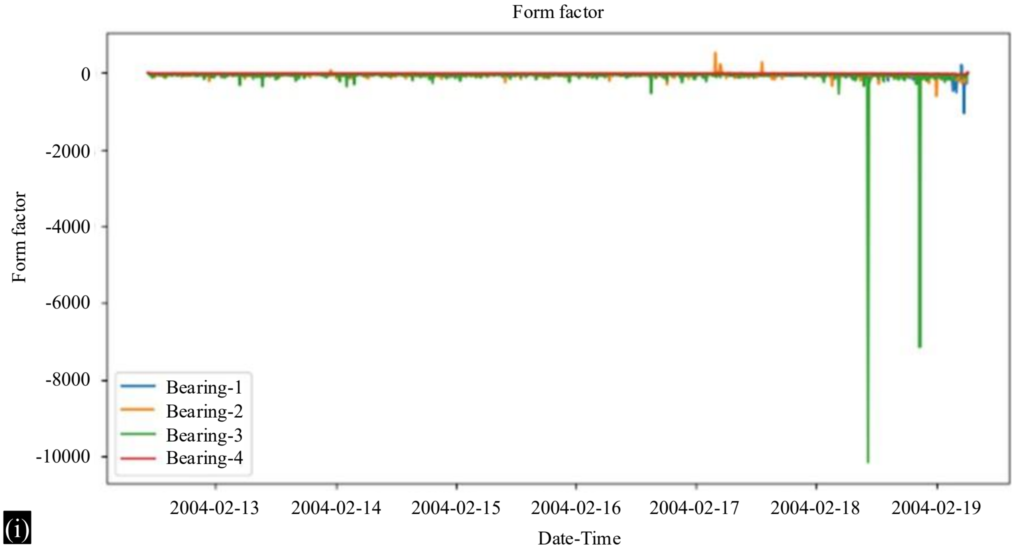


Figure 3. (a–i) Comparison of features for all four bearings.

CONCLUSION

It is visible that bearing-1 shows maximum variations for maximum and minimum values. Mean value is almost same for all the bearings and variation in bearing-2 is large. Standard deviation and RMS is maximum for bearing-1 but does not fall to lowest. In skewness, bearing-2 has the max. value and in kurtosis bearing-3 has the max value. Bearing-3 has the largest crest factor. Form factor is almost same for all the bearings and bearing-3 is showing minimum low. All these features can be further used for fault classification.

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