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Classification Of Rotating Machinery Fault Using Vibration Signal

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CLASSIFICATION OF ROTATING MACHINERY FAULT USING VIBRATION SIGNAL

by

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This thesis, submitted by Santosh Paudyal in partial fulfillment of the requirements for the degree of Master of Science from University of North Dakota has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved

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July 2019

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ABBREVIATIONS

FFT- Fast Fourier Transform

CWT-Continuous Wavelet Transform

KNN- k-Nearest Neighbor

PCA- Principal Component Analysis

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ABSTRACT

Rotating machinery are critical instruments in the manufacturing sectors that are continually operated to fulfill their productivity objective. To reduce the risk of catastrophic failure and unwanted breakdown, it is crucial to ensure that these machines operate within their quality standards. Waste is undesirable to such sectors that directly affect manufacturing price. Maintenance intervention must be efficient, else it is deemed as waste. It is estimated that businesses are losing billions of dollars worldwide due to inadequate maintenance and poor management. It is, therefore, crucial to carry out effective maintenance actions. Since condition-based monitoring method recommends maintenance only when necessary, this approach can avoid unnecessary plan maintenance costs. Condition-based approach, along with the different faults detecting and correcting approach can become handy for the smooth operation of the machine in the industries. Out of various approaches, the vibration parameters based condition monitoring approach has been proposed in this work. The significance of the proposed method is that it can correctly identify and classify the condition of the equipment as normal, misaligned, unbalanced, and cracked. Using the information of local harmonic acceleration amplitude, instead of harmonic acceleration amplitude, fault detecting, and classifying method is proposed. Then, the phase plane diagram-based fault classification technique is also proposed using the information of all the accelerometer data. Similarly, the Fuzzy Logic method is also used for fault detection and classification purpose. The obtained results signify the effectiveness of these proposed methods.

Chapter I

1. Introduction

1.1. Background Information and Motivation

Rotating machinery have found their application in the field of turbine, generator, and gearboxes-based industries. Failure in these critical elements will hinder the productivity and effectiveness of the businesses. The factors that could affect the machine performance is more likely to be because of the change in shaft relative position and uneven mass distribution. Presence of these factors generates undesirable stresses which could cause cracking and fatigue in the machine. The factors mentioned above adversely impact critical components of the machine, such as bearings, seals, gears and couplings. If the shaft's position deviates from its rotation axis, we call it a fault of misalignment. Similarly, if the center of mass alignment with the rotational axis is influenced by an uneven distribution of mass, it is called an unbalanced fault. These are the most prevalent fault types in the industries. So, these faults must be prevented on time by constantly tracking and maintaining the system.

Three maintenance technique are commonly implemented in industrial sectors, namely corrective maintenance, preventive maintenance, and predictive maintenance. Machine health surveillance is essential in order to prevent catastrophic failure. Several writers have suggested various kinds of condition-based surveillance method to track the system online in real-time, making system maintenance effective. The machine's condition can be monitored effectively using multiple parametric data of the rotating machine such as vibration, temperature, pressure, and acoustics. Despite different techniques of identifying faults, difficulties are still prevailing to classify faults in earlier stages. While some of the techniques have demonstrated the adequate potential for classification of faults, they are complicated and time-consuming. Therefore, a straightforward and economical technique that can be readily interpreted and developed is required to save the industry's resources and economy.

The primary objective of this study is to identify various kinds of rotating equipment fault. Different characteristics of the fault are investigated and assessed using the vibration signal to identify the fault. After the evaluation of the signal, the useful features are obtained and used to develop different types of condition monitoring techniques.

Since time-domain data mostly provides data about instability in vibration amplitude, this data provides insight into machine experiencing problems but is not relevant if we need to figure out what causes it to function ineffectively. We need frequency data to find out the causes of the machine faults and to distinguish the faults. In this study, the phase plane method has been developed, which will use the time domain data from the four-accelerometer to classify different machinery fault. This method proved useful in classifying the various fault based on their phase plane diagram, where each type of fault showed significant differences in the phase plane shape. Also, using the local maximum acceleration-based amplitude of the different faults, K- Nearest Neighbor algorithm was developed that could efficiently classify rotating equipment faults. The fuzzy logic method was also implemented to check its fault classification capabilities.

1.2 Condition Based Monitoring and Its Necessity

It is desirable to have a minimal level of vibration in the rotating machinery. However, improper design and malfunction in the machine amplify vibration level. If the machines are adequately designed, the level of vibration produced by them is minimal. As the machines are operated continually for more extended periods, they go through wear, fatigue, and deformation. Once the machine experiences these impacts, the shaft is likely to be misaligned, and the rotor becomes unbalanced. These faulty scenarios than not only amplify the vibration level but also supplement the dynamic load on bearings. If the machines continue to operate with these impacts, it will gradually begin to deteriorate and may fail catastrophically [1]. The catastrophic failure in the machine will not only halt the operation of the machine but will also increase the breakdown, decrease productivity, and economically impact the industries. Although the catastrophic failure is challenging to avoid, we can at least minimize by observing the machine operating condition which can be done by observing the machine properties such as vibration, sound, and temperature. These processes where the machine conditions are observed based on the machine parameters like vibration, sound, and temperature to avoid any catastrophic failure during the operation can be termed as condition monitoring [2] [3]. It is crucial to analyze the modes when dealing with the rotating machinery because of their ability to increase the vibration. The vibration caused by the rotation should also be studied extensively as these vibrations tend to amplify without the resonance [4].

As previously mentioned, rotating machinery must be closely monitored using condition monitoring techniques to warranty its continuous operation. Since condition monitoring can be carried out based on various machine parameters, several monitoring methods have been used by the industries. Acoustic emission, vibration-based analysis, and infrared thermography-based monitoring techniques are the most popular and commonly used condition monitoring techniques in the industry [1]. Maintenance costs are regarded as a major expense because of their contribution to the general manufacturing of the products. The equipment requires to be correctly maintained for the manufacturing of the goods, which includes part replacement, maintenance labor cost and downtime. Overall maintenance costs vary from industry to industry depending on the type of industry and the percentage of maintenance costs can be between 15 to 60 percent of the cost of manufacturing goods. Maintenance requires to be efficiently performed to make it worth otherwise, it can be counted as an undesirable waste. It is found that an estimated $60 billion is lost owing to inadequate maintenance and poor management, which has a significant impact on the worldwide competing industries [5]. These reports emphasize the significance of efficient strategy and management for maintenance in the industries. This makes condition monitoring an essential tool since a failure to detect machine degradation has an adverse effect on the monetary side. As the identification of failures and their translation have been made easier with the accessibility of art and resources of condition monitoring, it has found for a wide application in the monitoring of machinery [6].

1.3 Condition Monitoring Types

1.3.1 Acoustic Emission Based Monitoring Method

As previously mentioned, acoustic emission is one of the industry's conventional surveillance methods for identifying abnormal behavior of machines. Whenever there is displacement in the material internal structure strain energy briskly get discharged, which as a result, generates the elastic stress known as acoustic emission (AE) [7]. The AE signal-based monitoring technique was proposed by Elijah and Erdal to monitor the cutting tool as these signals constitute high frequency separating from noise and other unnecessary sources. The information from the signal sources relating to chip formation and tool wear, chipping and breakage, formed chip is useful in condition monitoring of the cutting tool. They used pattern recognition technique and discriminant function for the sources mentioned above, utilizing the spectral component to extract the feature and make classification [8]. Acoustic emission saw its enormous rise in the manufacturing industries for the monitoring of the system because of the sensitivity to the process criterion [9]. If we combine both vibration and acoustic technique, the result will get better by saving time and number of workforce required [2].

1.3.2 Infrared Thermography Based Monitoring Method

Infrared thermography is a nondestructive technology that is capable of sensing and displaying the temperature of machinery components remotely. Using the information of temperature distribution, fault related to the machinery can be identified [10]. It was seen that IR technology was capable of sensing the temperature of the skin and could be used for detecting and diagnosing of the vasospastic disorder. This method was successful in validating the detection of rheumatology patients during the 1900’s [11]. This technology has found wider application in the field of monitoring the machinery [12] [13] and evaluating the fatigue limit of the materials [14] [15]. The capabilities of the IR method in comparison to the vibration monitoring were shown by Lim et al. [16] where the fault identification accuracy was found comparable to the one using the vibration monitoring. The advancement in the cameras, along with the easy interpretability of the data makes it more user-friendly compared to other techniques [2].

1.3.3 Lubricant Analysis Based Monitoring Method

Lubricant analysis is another common monitoring technique where the assessment of machine is made based on the lubricant samples used. For this method, samples are examined outside of the machine tested mostly in the laboratory. This technique can identify the root cause and even detect tiny particles that may influence the future [2]. Although the lubricant analysis is one of the common tools for tracking machines, it has limitations too. The restriction of this method is on condition monitoring of electrical devices as it will not be able to deal with these systems. JS Stecki used Ferrographic oil analysis to predict the failure of jet engines. This technique was capable of detecting wear particle of all sizes that could provide meaningful information on the characteristics of the wear particles present in the sample oil used [17]. Flanagan et al. [18] used the lubricant of steam turbine generator to analyze the presence of wear in the system. If lubricant based analysis is combined with acoustic emission and vibration analysis technique, the detection capabilities get more powerful and efficient [19]

1.3.4 Statistical Analysis Based Monitoring Method

Another important condition monitoring tool that addresses a large number of data sets as temperature data, vibration data, and acoustic signal data is statistical-based analysis. It is possible to apply a statistical method based on the extracted information to classify the machinery's fault and condition. The different statistical methods are used for fault detection based on the size of the data set. Poyhonen et al. used Support Vector Machine (SVM) to classify the fault after making the comparison between Power Spectrum density with Higher Order Spectra (HOS), Cepstrum Analysis and AR modeling [20]. Lachouri et al. used Multi-Scale Principal Component Analysis (PCA) so that the cross and auto-correlation can be selected via PCA and wavelet analysis respectively; the multiscale Squared Prediction Error (SPE) was then used to identify the faulty condition of the bearing system [21]. Jiang et al. used the phase space to reconstruct the vibration signal, using the Phase-PCA based method, the system condition was identified based on the T2 and SPE value [22]. Harlişca et al. proposed a cheap and user-friendly method for detecting bearing faults at inceptive stage using statistical processing [23]. Hu et al. used the Ensemble Empirical Mode Decomposition (EEMD) to decompose the vibration signal into Intrinsic Mode Functions IMF in order to extract the first five features from IMF, and once the features were extracted, the SVM was used for the classifying the source data acquired through the sensor [24]. Li et al. used the Independent Component Analysis (ICA) to extract the feature and using the reference as the input they used self-organizing-map (SOM) based neural network to not only detect the fault but also identify the extent of the fault [25].

1.3.5 Vibration Analysis Based Monitoring Method

Analysis of vibration is regarded as one of the most efficient monitoring technology. When monitoring the rotating vibration analysis of the equipment, it can be regarded as an optimal tool as roughly all machines vibrate during their operation. Since the distinct fault generates distinct power at distinct frequencies, vibration assessment is a robust technique that uses spectrum processing to provide this data in detail [2]. This technique can quickly detect abrupt changes in the system's conduct. Since it can handle short-term and long-term surveillance by periodically or permanently mounting the sensor, they are regarded as a flexible surveillance system. The added advantages for these systems are that vibration signal can be easily processed using most of the major signal processing methodology available these days [26]. Vibration analysis has been used successfully to identify the fault and its types. Using the vibration signal different types of fault corresponding to the bearing failure, unbalanced caused by mass, misalignment of the shaft, gearbox failure has been successfully identified. The condition of the machine can be identified using the vibration signal as it could classify and detect the abnormality in the system [27] [28] [29]. In this study, Vibration analysis will be used for classifying the fault of rotating machinery because of its advantages over the other methods which were discussed earlier.

1.3.6 Machine Learning-Based Monitoring Method

The science of machine learning allows the system to understand the program through the information sets supplied. Since they tend to be feasible and economical, they are widely used in a broad range of areas such as data mining, computer vision, and pattern recognition [30]. Recently, several machine-based learning techniques were suggested to identify the fault and showed strong capacities to detect the fault. Samanta used Artificial Neural Network (ANN) and Support Vector Machine (SVM) to identify bearing failure. The time-domain signal was used for features; the signal was optimized using a genetic algorithm to extract the features. ANN and SVM were used as a classifier for detecting the bearing fault [31]. Similarly, Jia et al. used the deep learning method for diagnosing the rotating machinery fault where the frequency spectrum was used for training deep learning. Since the features used were of the frequency spectrum, this method could work with the system that has a periodical vibrational motion [32]

1.4 Thesis Orientation

The remainder of the thesis chapter will focus on a different model used for identifying and classifying vibration fault. Chapter II outlines how the raw vibration signal extracted from the experimental setup is processed for meaningful information. It also provides information on how different fault conditions are simulated using Machinery Fault Simulator. Chapter 3 focuses on how the technique of phase plane classification and detection of vibration failure are implemented. Implementation of fuzzy logic-based fault classification is addressed in Chapter 4. In addition, Chapter 5 discusses using the K-Nearest Neighbor model to use the Local Maximum Acceleration-based fault detection model. Finally, the conclusion of the research and future work will be discussed in Chapter 6.

Chapter II

2. Data Analysis and Methodology

2.1 Overview

This chapter focuses on providing a brief outline on how the systems are monitored using the raw vibration signal. Since the extracted data contains raw information, they need to be processed further using signal processing to get more meaningful information. This chapter will provide further information on how an experiment was carried out using the Machinery setup. It will also provide an idea of what kind of setup is chosen for acquiring and analyzing data. Moreover, the information on the selection of transducer and signal processing technique for the experiment is also mentioned. Different methodology that has been used for the research is also discussed.

2.2 Methodology

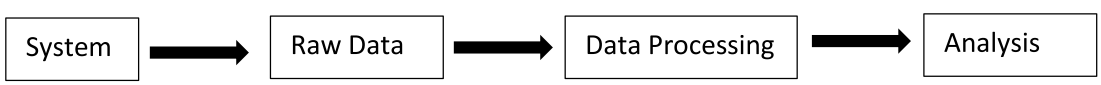

Figure 2. 1 Block diagram data analysis.

As discussed earlier, almost all machines vibrate and these vibrational behaviors tend to be different when there is deterioration in the machines. If the signal behavior is understood upon studying the vibration of the machinery at different working conditions, then the fault classification becomes easier. With the advancement in technology and availability of the transducers, the vibration signal can be easily extracted from the machinery. Once the vibration signal is extracted, we can analyze their energies at different frequency using the spectrum analysis. Since every fault has its own energy for different frequency, the fault classification using a vibration signal with signal processing method becomes easier. First step would be acquiring the signal for which we need to mount the transducer in the system. As there are different types of transducer available in the market, we need to decide the transducer based on our application and economy.

We must mainly consider in selecting proper transducer and ideal signal processing methodology based on the application and the system whose parameter is to be measured.

2.2.1 Transducer Selection

Table 2. 1 Comparison of the readings of the transducers **[33]**

Parameter	Displacement	Velocity	Acceleration
Frequency (Hz)	0-30	5-2,000	>50

Due to the wider frequency response spectrum of the accelerometer, it is solid and stable over the temperature range. The velocity and displacement data can also be incorporated so that the accelerometer was selected as a transducer for the study.

2.2.2 Signal Processing Techniques

Signal processing is a widely used tool in the past decades to detect the fault present in rotating machinery. The signal intensification method and signal handling methods were used to obtain helpful data from the raw vibration signal or fault features. Signal analysis using the Fast Fourier Transform is one of the widely used traditional tools to study the spectrum and certain frequency elements that are of concern to us in order to extract the characteristic features. These methods are based on the frequency analysis that has some limitation on the side. As it assumes the signal being linear and stationary, they are unable to deal with the time localized transient events which are of the non-stationary nature. Hence, we are unable to get the information of the vibration in time domain, making us difficult to find when the machine fault occurs [34] [35]. To overcome these limitations, the time – frequency analysis approach got started. The time–frequency analysis techniques such as Short-Term Fourier Transform (STFT) [36], Wigner-Ville Distribution (WVD) [37] [38] showed the capabilities of the handling the non-stationary signals but they also have some limitations as STFT can only deal with the transient signal which dynamics changes slowly as they are based on the signal segmentation. WVD which are not based on the segmentation do overcome the limitation of the STFT, but they also have a limitation as the inference term formed by the transformation makes it harder to understand the estimated distribution. The signal based on the Wavelets came into the practice to overcome these difficulties known as Wavelet Transform (WT) [39] [40], which depicted the signal in time scale rather than time-frequency representation. The development of the wavelet Transform has led to the technique of continuous Wavelet Transform (CWT) [41] and discrete Wavelet Transform (DWT). These techniques have been successful in dealing with the fault detection of non-stationary signals. In this work, FFT and CWT have been used for the processing of the vibration data. FFT has been used for the feature extraction purpose for the fuzzy logic-based method for classifying unbalanced and misalignment condition present in the machinery.

2.2.3 Experimental Setup

Machinery Fault Simulator (MFS) as seen in Figure 2.2, was used for simulating the different working condition of the machine. This is a powerful simulating tool capable of simulating numerous machinery fault condition.

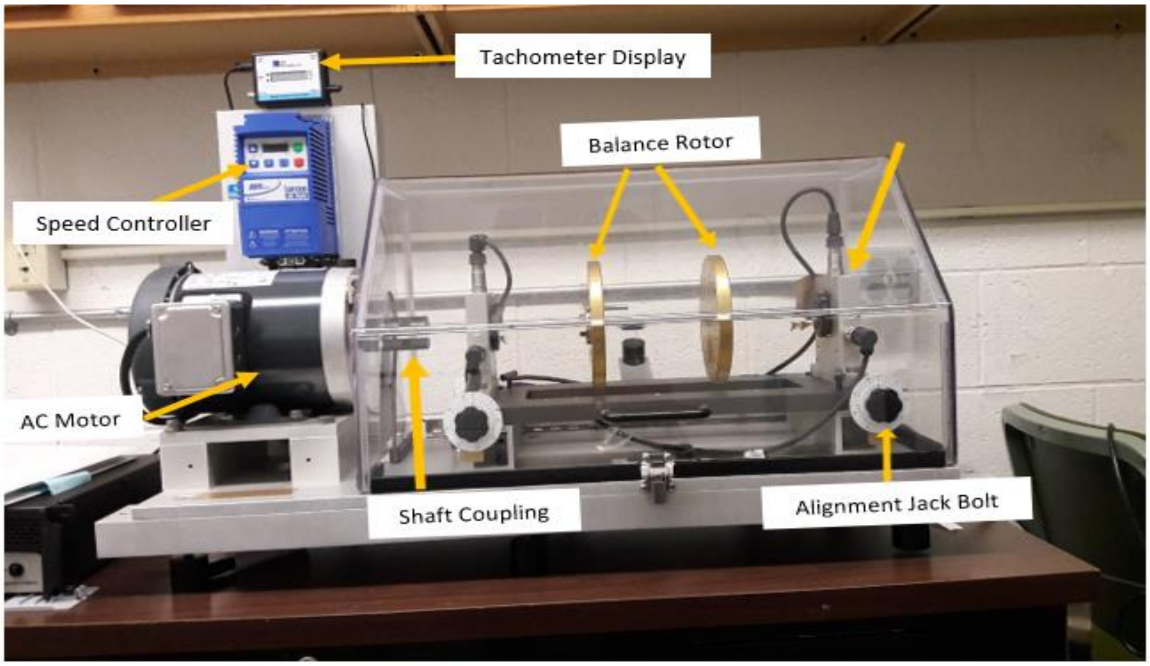

Figure 2. 2 Machinery fault simulator setup

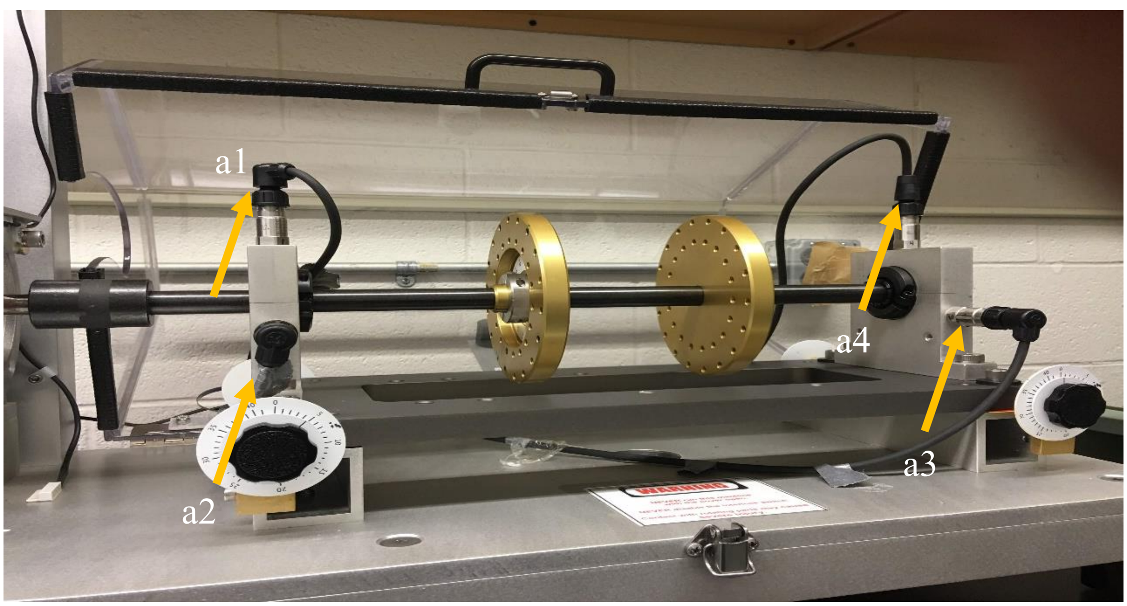

Figure 2. 3 Accelerometer positioning

The experimental setup consists of the following major components

A. Hardware

- 3 Phase Induction Motor
- GS1 AC Drive
- Accelerometers
- Sensor Signal Conditioner
- BNC – 2144 Adapter
- NI PXIe 1073 DSA

B. Software

- NI Sound and Vibration Assistant
- MATLAB R2016a

As the study mostly focused on the detection of fault related to unbalanced mass, misalignment, and cracked shaft these faults were simulated for this study purpose using the experimental setups. The unbalanced mass condition was generated by adding the mass in the threaded holes of the rotors. The screw of 10.2 g and inserted it inside one of the 36 threaded holes of the 6-inch Aluminum rotor as shown in figure 2.4. The mass was added to one of the rotors during this study.

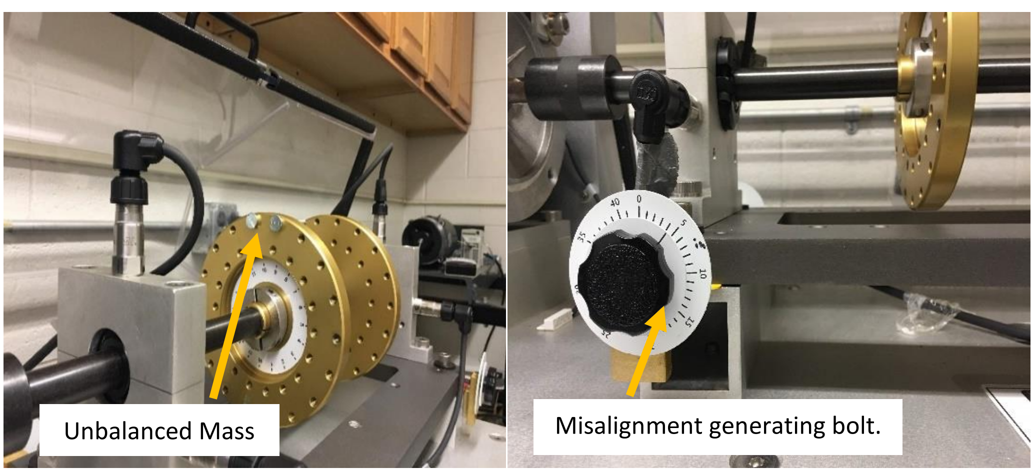

Figure 2. 4 Unbalanced and misaligned condition simulation.

Similarly using the Alignment Jack Bolt, the misalignment condition was generated. Using the Alignment Jack bolt, the system can be misaligned to the desirable milli-inch (mils) as seen in the dial indicator. Using the misalignment generating bolt the angular misalignment condition is simulated in the system by 5 mils and 10 mils.

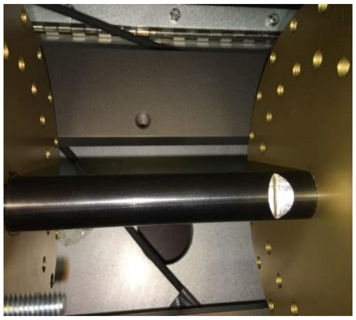

Figure 2. 5 Cracked shaft

For cracked shaft simulation, a cracked shaft of 5.8 with v notch crack", as shown in Figure 2.5 was used. Accelerometers placed on the bearing housing are used for extracting the analog signal using the Data Acquisition Board and adapter, as shown in Figure 2.6 and Figure 2.7. The vibration data are analyzed and processed using the NI Sound and Vibration Software and MATLAB software.

Figure 2. 6 Data acquisition device

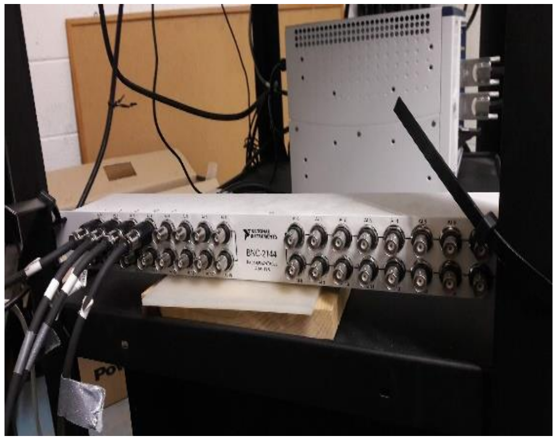

Figure 2. 7 Adapter

2.2.4 Methods Used for Classifying the Vibration Fault

Fuzzy Inference system has been used to classify the fault and its severity in which the amplitude and frequencies are taken as the input for developing a fuzzy inference system. With the formulation of rule based on the triangular membership function, the model is developed which will provide an output on the condition of the machine and severity level in the case of fault presence. Further Phase plane diagram-based method is proposed for the classification of the fault and its type based on the unique characteristics shown by the different faulty condition along with the healthy condition. Here, the vibration response of all the 4-accelerometers attached to the bearing housing are plotted against each other and their behavior are noted. The flow diagram used for the data analysis is shown in the below figure 2.8

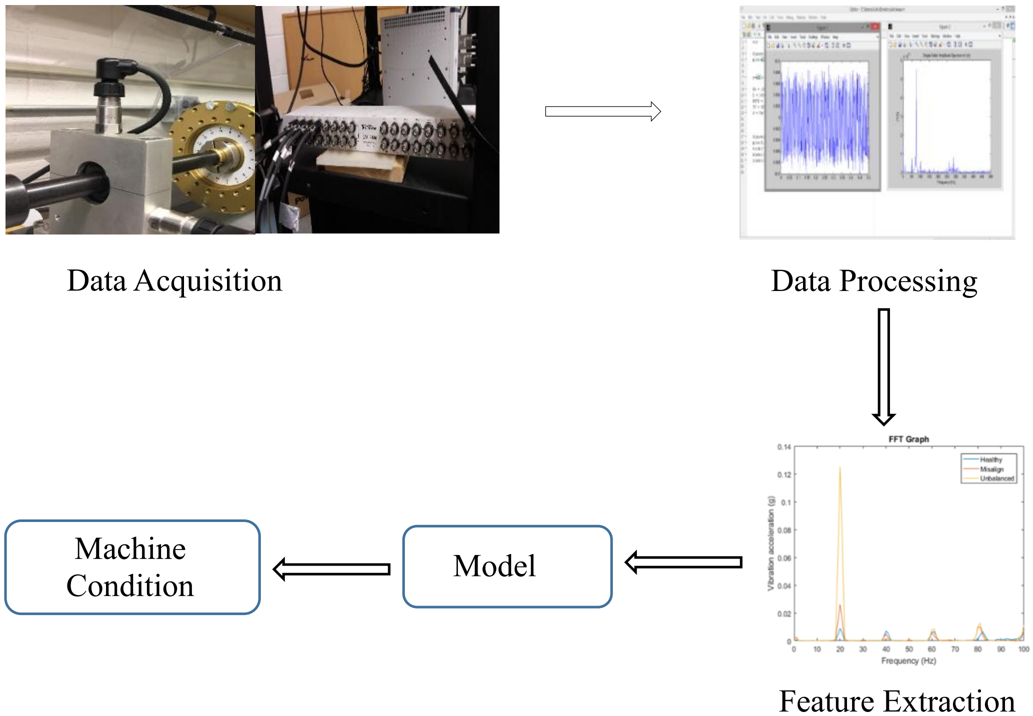

Figure 2. 8 Process flow diagram for monitoring machine condition.

First, for the vibration analysis data needs to be acquired using the machinery setup. After acquiring data, they are processed using the MATLAB software. The features for different condition of the machinery are extracted using the signal processing technique, which will be used as baseline for identifying the condition of the machinery. Once the data are processed and features are extracted model for detecting and classifying the faults are developed. Using the developed model as Fuzzy Logic, Phase plane, and KNN the condition of machine is identified. For the Fuzzy Logic, and KNN features can be extracted using FFT and CWT while for the Phase plane-based method, the pattern of data is observed by plotting the data from each accelerometer against each other.

Chapter III

3. Phase Plane Diagram Based Method for Fault Classification

3.1 Overview

Through this chapter, a novel method for detecting and classifying fault related to misalignment, cracked shaft, and unbalanced mass will be presented. This simple and user-friendly tool using the four-accelerometer data can classify the fault as all these operating conditions of the machine shows distinctive characteristic.

3.2 Phase Plane Diagram

Phase plane diagram is the simple representation of the vibration signal measured from all the accelerometer plotted against each other. Vibration data acquired from the accelerometer a1, a2, a3, and a4 located along horizontal and vertical directions are cross-compared using this method. For this study purpose the data from these accelerometers will be represented as shown in the table 3.1 below.

Table 3. 1 Position and representation of the accelerometer

Accelerometer	Position	Representation
1	Vertical Left	VL
2	Horizontal Left	HL
3	Horizontal Right	HR
4	Vertical Right	VR

3.2.1 Phase Plane Diagram for Healthy and Misaligned Data

The vibration signal data of all four accelerometers were plotted against each other for three different data sets. The operating speed of the machinery was 20 Hz while for the misaligned condition the misalignment levels were 5 mils and 10 mils respectively. Once they were plotted, they were cross-compared. The plot is illustrated in Figure 3.1 from Healthy data set and can be seen that the plane drawn are represented in the Horizontal shape for all the six plots.

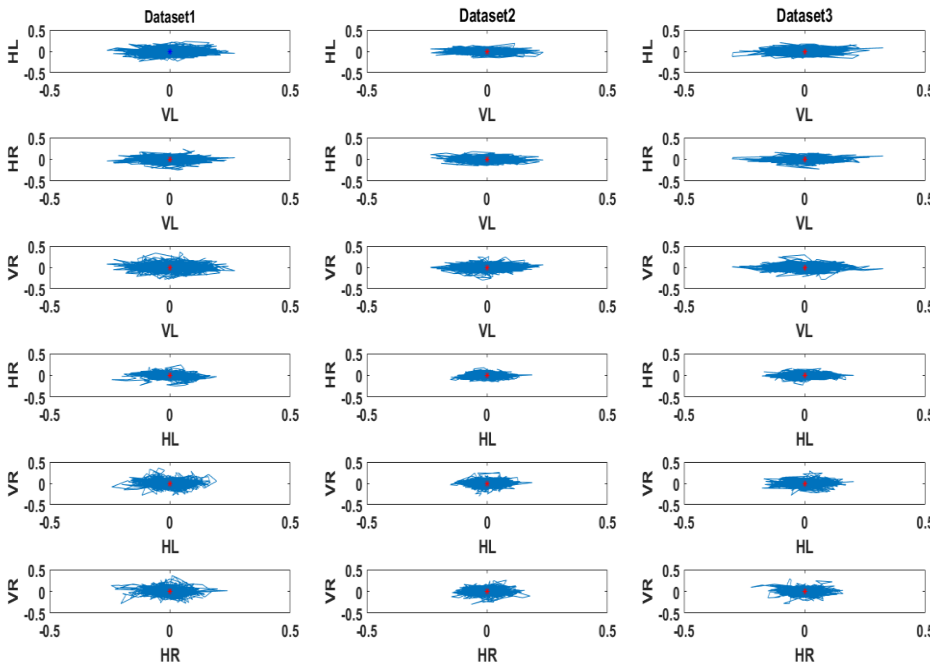

Figure 3. 1 Healthy dataset phase plane diagram (20 Hz)

Now, it was also interesting to see how the phase plane diagram represents when the system is subjected to 5mils (5 milli inch) angular misalignment and operated at 20 Hz.

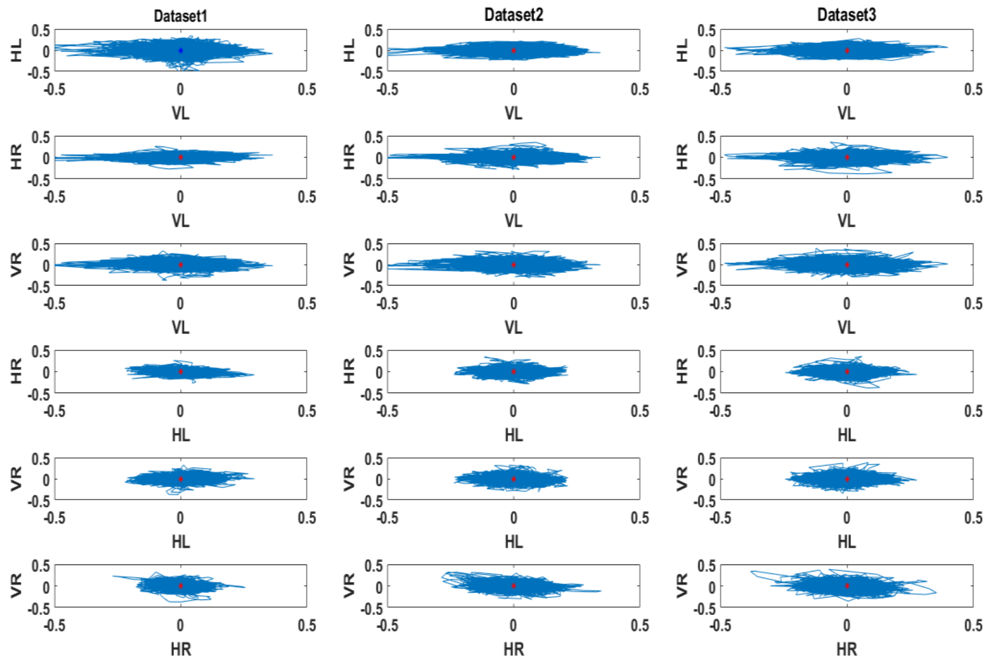

Figure 3. 2 Misaligned dataset phase plane diagram (5 mils, 20Hz)

For better illustration and understanding response of vertical right accelerometer and horizontal right accelerometer are plotted for healthy and 5mils misaligned data. As seen in Figure 3.3 misaligned response is a bit rotated in comparison to the healthy responses. So, it can be said that both machine condition shows characteristic behavior in terms of the shape formed when the vibration response of 2 different accelerometers positioned at different location is plotted.

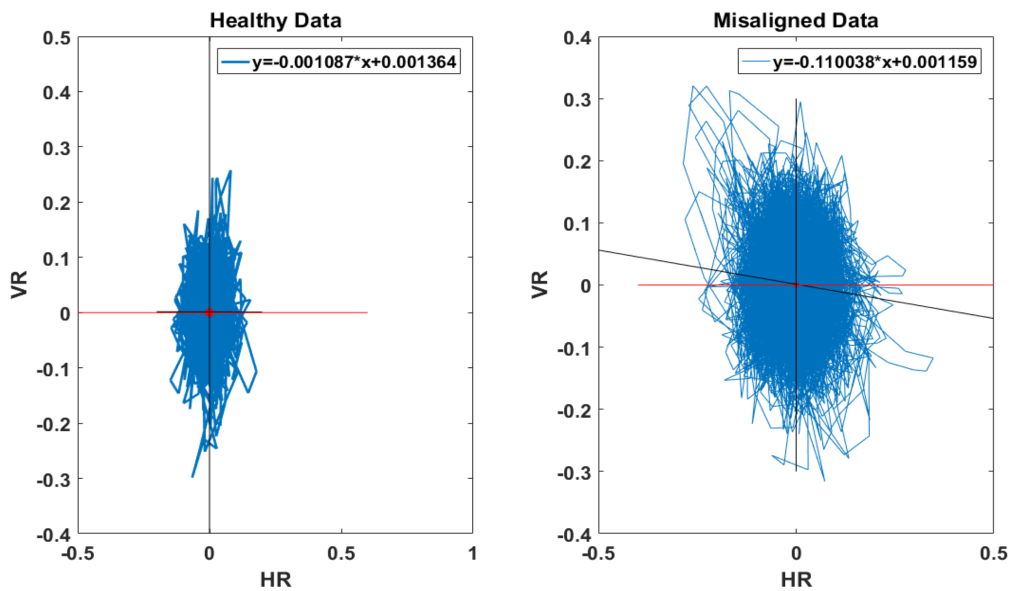

Figure 3. 3 Healthy vs misaligned (5 mils) comparison

When the phase plane diagram for the healthy and misaligned data are plotted individually, there appears to be a considerable difference in the phase plane shape. The phase plane plot of the vertical right and horizontal right from figure 3.3 shows the shift in the phase shape from its reference line. There is not a huge difference in the shape of healthy and misaligned data but there are considerable differences.

3.2.2 Phase Plane Diagram for Unbalanced Data

Similarly, it was checked what difference it makes when the condition of the machine is switched to the unbalanced state. Looking at the figure 3.4, it can be noticed that the shape of the plane diagram shows differences in the shape formation.

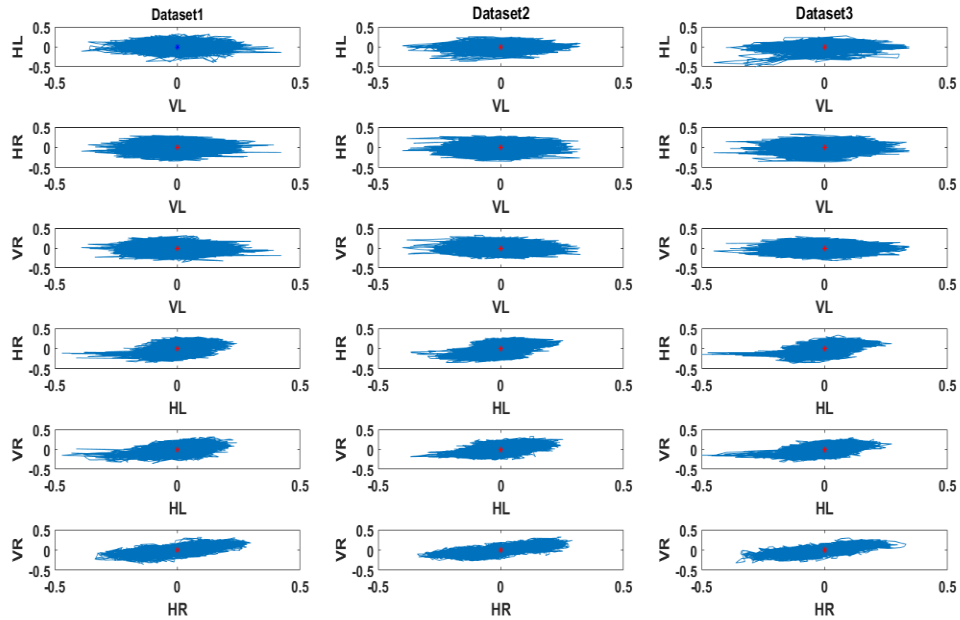

Figure 3. 4 Unbalanced dataset phase plane diagram (20 Hz)

Further, the most significant shape was plotted which is for vertical right vs horizontal right to make better illustration that can be seen in Figure 3.5.

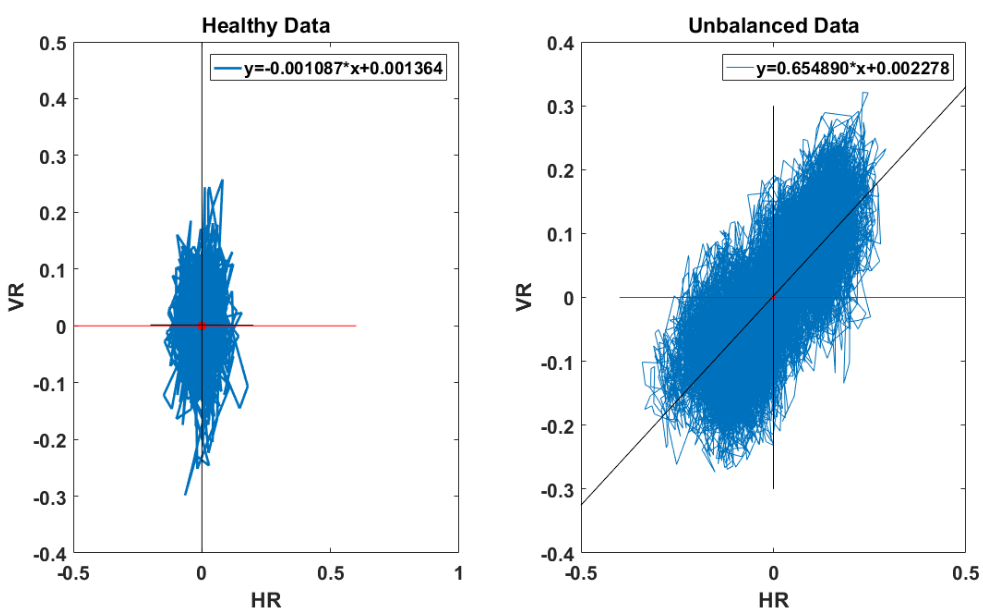

Figure 3. 5 Healthy vs unbalanced comparison

Whenever there is a presence of the unbalanced mass cross response between the accelerometer positioned at the horizontal left, and horizontal right are distinctive in shape. The shape rotates on the right side or there is rotational movement. It can be noticed that unbalanced condition has a significant effect on the response than the misaligned condition this could be because of the misalignment generated at the left end of the machinery.

3.2.3 Phase Plane Diagram for Cracked Shaft Data

Further, the phase plane diagram for the condition with cracked shaft is plotted to see the behavior or the characteristics of this condition. Like the above-mentioned condition 3, data sets of cracked condition machine operating at 20 Hz is plotted. As seen in Figure 3.6 it can be observed that the shape of the plot for the cracked data set is entirely different when the accelerometer data of (HR, HL), (VR, HL) and (HR, VR) are plotted. The shape of cracked data is rotated as compared to the healthy data set. The HR accelerometer data is plotted against VR data for further illustration and clarity in Figure 3.7.

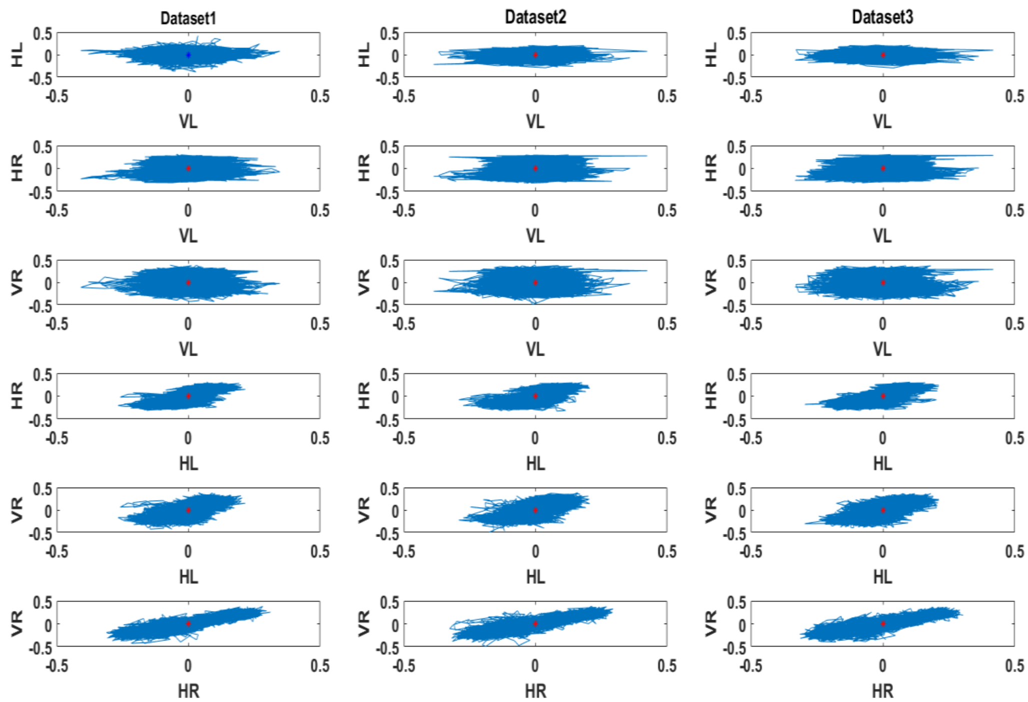

Figure 3. 6 Cracked dataset phase plane diagram (20 Hz)

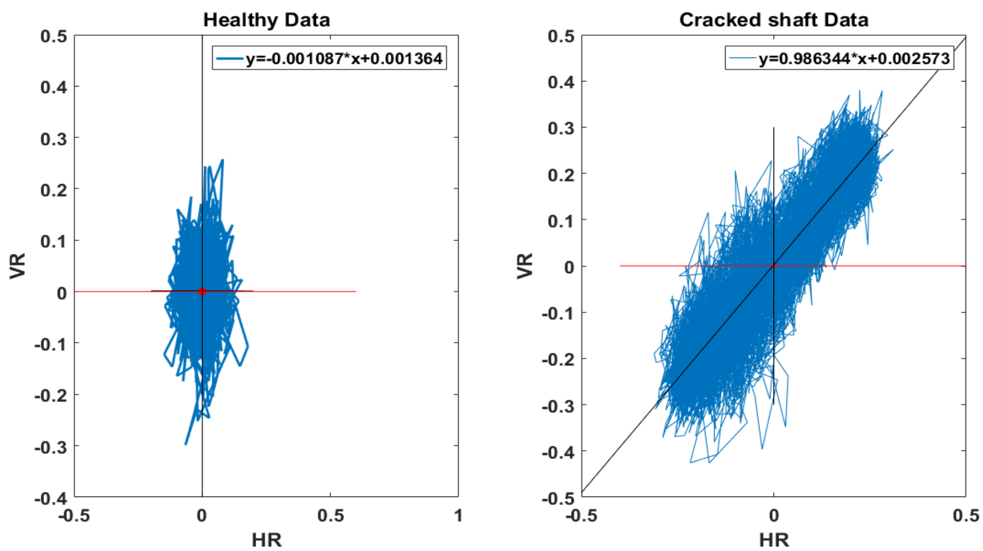

Figure 3. 7 Healthy vs cracked shaft comparison

There are considerable differences in the phase plane shape of the healthy and cracked shaft. When the vertical right vs horizontal right phase plane is plotted for both healthy and cracked shaft, they can be identified using the information of their phase plane shape. There is significant shift in the shape of the vertical right vs horizontal right plot when the system has cracked shaft condition. The distribution of data and chaotic behavior of the machine under different operating condition makes data distribution and phase plane diagram distinctive.

Chapter Summary

With the data from all four accelerometers that were recording the horizontal and vertical vibration motion of the machinery are analyzed and plotted against each other to see if they show any distinctive pattern. The phase plane diagram of these accelerometers when plotted showed a distinctive pattern where different fault condition showed different behavior. Using the phase plane diagram, we were able to find the fault pattern of the different operating condition of the rotating machinery. Healthy, misaligned, unbalanced, and cracked shaft condition were distinctive when the accelerometer data of (HR, HL), (VR, HL), and (HR, VR) were plotted. These phase plane diagram can be used as a baseline for identifying the working condition of the machine. This method is simple and economical to be implemented so it can be a great asset to the industry. Further, the reason behind the differences in these particular directions of vibration is to be studied and analyzed.

Chapter IV

4. Fuzzy Logic-Based Fault Classification Method

4.1 Introduction

In this chapter, the effectiveness of fuzzy logic in classifying the vibration fault present in the rotating machinery will be discussed. This economical and straightforward tool which is easy to develop and interpret was used to classify the unbalanced and misalignment fault present in the machinery.

Traditional logic is based on the Boolean logic that satisfies the principle of bivalence where the logic is based on either true or false simply represented as 1 and 0. Fuzzy logic, on the other hand, is a multivalued logic based on the degree of multiple truths expressed on the closed interval [0, 1] by the values.

In Fuzzy Logic, the 0 and 1 are associated with traditional False and True Value, respectively. Fuzzy logic represents the variation of truth's degree in terms of the value (0, 1). There are numerous ways to express the Fuzzy operation but for our easiness, it will be discussed in an uncomplicated way. For the given fuzzy values of x and y the following operations can be defined [42].

$$(\boldsymbol{x\ and\ y}) = \mathbf{min}(\boldsymbol{x}, \boldsymbol{y}) \tag{4.1}$$

$$(\boldsymbol{x\ or\ y}) = \mathbf{max}(\boldsymbol{x}, \boldsymbol{y}) \tag{4.2}$$

$$(\boldsymbol{not\ x}) = \mathbf{1} - \boldsymbol{x} \tag{4.3}$$

$$(\boldsymbol{x\ implies\ y}) = \mathbf{max}(\boldsymbol{x}, \mathbf{1} - \boldsymbol{y}) \tag{4.4}$$

If the above definition is considered as traditional logic, then the Truth and False value would be expressed as 1 and 0, respectively. If we have to define the Fuzzy set, we try to represent it as a universe of discourse where the function S represents the membership function of the fuzzy set [42]

$$\boldsymbol{\mu S}: \boldsymbol{U} \to [\mathbf{0}, \mathbf{1}] \tag{4.5}$$

Since the universal set of real numbers R is restricted, so the membership function is represented as:

$$\boldsymbol{\mu S}: \boldsymbol{R} \to [\mathbf{0}, \mathbf{1}] \tag{4.6}$$

The finite set are then restricted to the fuzzy subsets. The Fuzzy set S operator (∈) can be defined as: [42]

$$(\boldsymbol{x} \in \boldsymbol{S}) = \boldsymbol{\mu S}(\boldsymbol{x}) \tag{4.7}$$

Hence, the set of fuzzy S returns the true and false value. If the right- hand side is a fuzzy set, then the value returned is no longer a Boolean operator. If we have two fuzzy sets T and S, we define the membership functions of S ∪ T, S ∩ T and S´ as:

$$\mu(S \cup T)(x) = (\mu S(x) \text{ or } \mu T(x)) = \max(\mu S(x), \mu T(x)) \tag{4.8}$$

$$\mu(S \cap T)(x) = (\mu S(x) \text{ and } \mu T(x)) = \min(\mu S(x), \mu T(x)) \tag{4.9}$$

$$\boldsymbol{\mu S'(x) = not\ \mu S(x) = 1 - \mu S(x)} \tag{4.10}$$

$$\boldsymbol{\mu(S\ implies\ T)(x)=(\mu S(x)\ implies\ \mu T(x)} \tag{4.11}$$

$$\boldsymbol{\mu(S \setminus T)(x) = max(0, \mu S(x) - \mu T(x))} \tag{4.12}$$

$$\boldsymbol{S \subseteq T\ if\ \mu S(x) \leq \mu T(x) for\ all\ x \in U}\ \textbf{[42]} \tag{4.13}$$

At first, the data for the misalignment, unbalanced, and healthy condition were analyzed using the FFT and CWT. They were mainly used for finding the characteristics features of each operating condition of the machine. To see the behavior of the machine when subjected to healthy, misaligned, and unbalanced condition, the vibration response of the machine at the first, second, third, and fourth harmonics were observed. Vibration data of the machine operating at 20 Hz when it was healthy, unbalanced, and angularly misaligned were taken and graphed using FFT and CWT to see their characteristics. As seen in Figure 4.1 and 4.2 once can see that they show differences in the first harmonics (20 Hz) or 1x rotating speed of the machinery.

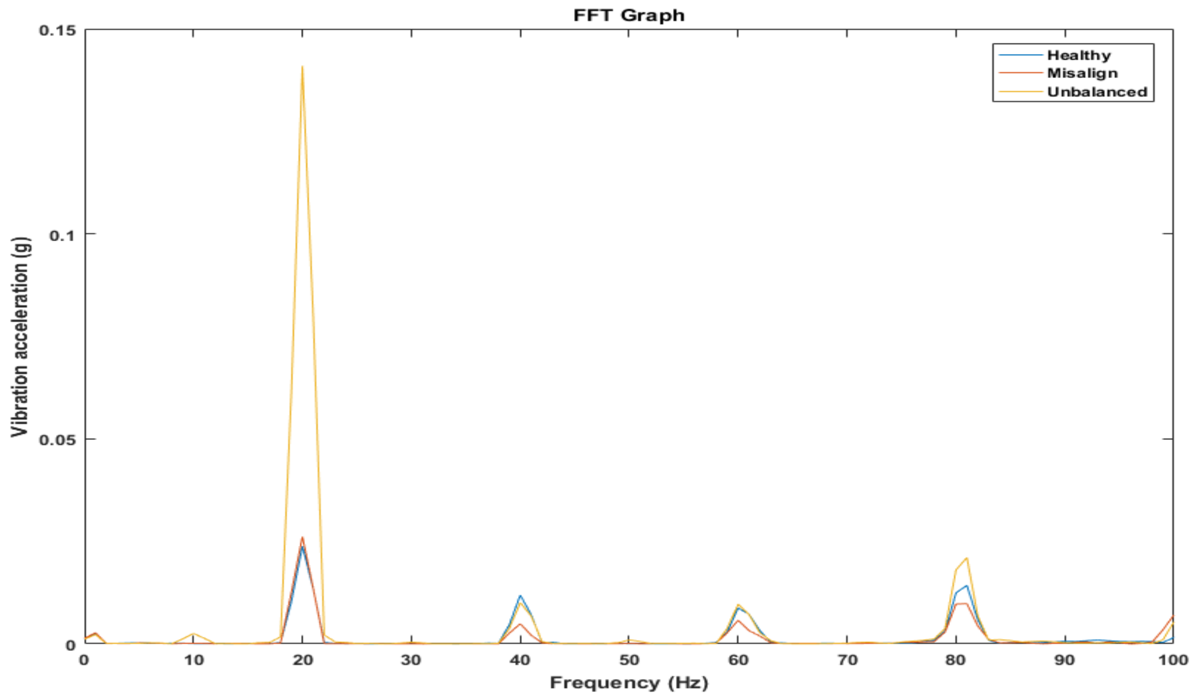

Figure 4. 1 FFT graph for healthy, misaligned and unbalanced data

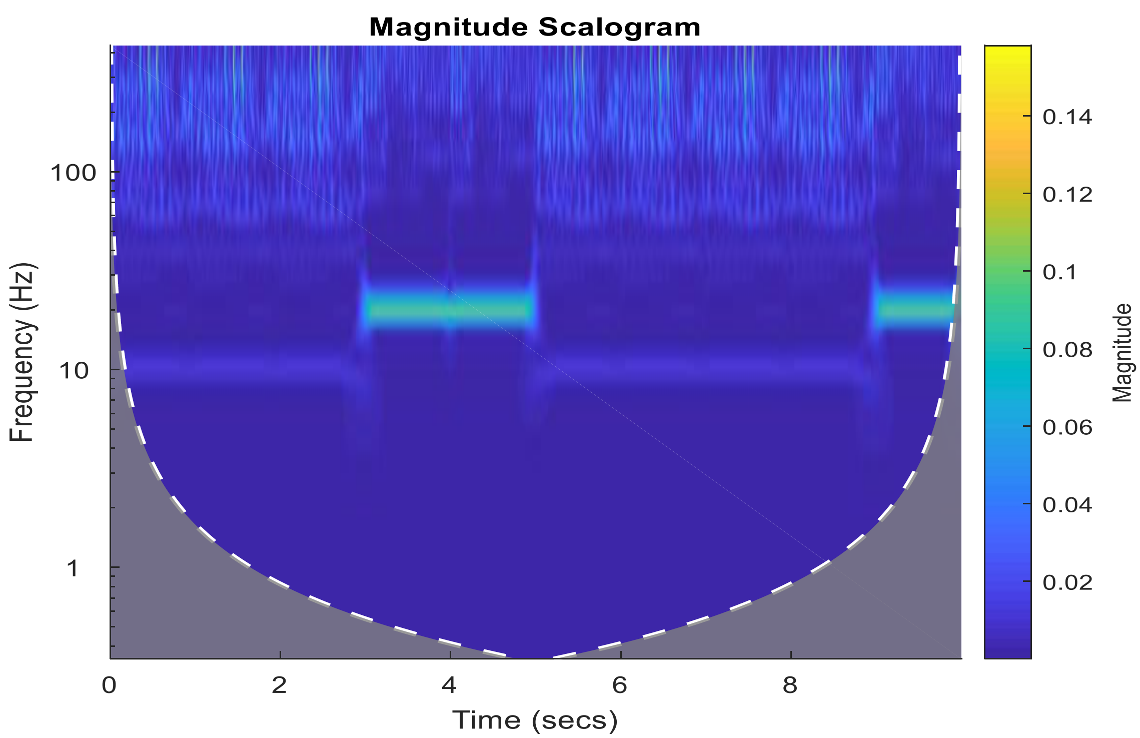

Figure 4. 2 CWT graph for healthy and unbalanced data

The triangular membership function is used for mapping the input points to the respective membership value (0-1). If X represents the universe of discourse and x represents its element, then the fuzzy set A in x can be defined as the ordered pair sets [43].

$$\boldsymbol{A} = \{\boldsymbol{x}, \mu_{\boldsymbol{A}}(\boldsymbol{x}) |\ \boldsymbol{x} \in \boldsymbol{X}\} \tag{4.14}$$

where $\mu_A(x)$ is the membership function.

The triangular membership function used for defining the membership function of the input can be defined mathematically as below:

$$\mathbf{f}(\mathbf{x}; \mathbf{a}, \mathbf{b}\ \mathbf{c}) = \begin{cases} \mathbf{0} & \boldsymbol{x} \le \boldsymbol{a} \\ \frac{\boldsymbol{x}-\boldsymbol{a}}{\boldsymbol{b}-\boldsymbol{a}} & \boldsymbol{a} \le \boldsymbol{x} \le \boldsymbol{b} \\ \frac{\boldsymbol{c}-\boldsymbol{x}}{\boldsymbol{c}-\boldsymbol{b}} & \boldsymbol{b} \le \boldsymbol{x} \le \boldsymbol{c} \\ \mathbf{0} & \boldsymbol{x} \ge \boldsymbol{c} \end{cases} \tag{4.15}$$

where a, b, and c are the scalar parameter on which triangular curve is dependent. Once the membership function for the input parameters are defined the 9 rule sets are defined based upon which the Fuzzy Interface will provide its output. These rules are used to evaluate the condition of the machine

After the vibration data is measured using the accelerometer signal under the normal and faulty conditions then the spectrum pattern is obtained by using the FFT. The healthy and faulty data sets obtained are then further analyzed to extract the features. These features are used as a baseline to classify the faults using the fuzzy System. The fuzzy system takes vibration amplitude and frequency as its input variables while the output for the system will be as healthy and faulty. The block diagram for the fuzzy inference system is seen below in the Figure 4.3

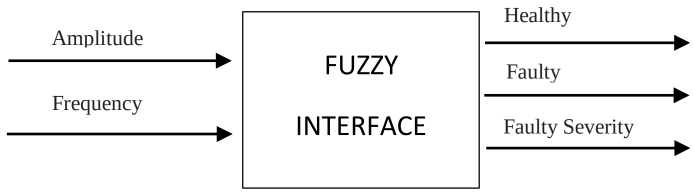

Figure 4. 3 Fuzzy system processing block diagram

The crisp input is first changed into the fuzzy input using the triangular membership function after that the fuzzy rules are developed based on the input variable data set using the MATLAB interface. After the fuzzy rules are developed the output is assigned membership function which is further fuzzified to provide crisp output. After the fuzzy logic-based system is developed, several healthy and unhealthy data sets are tested for the effectiveness of the proposed method.

4.2 Features for Fuzzy Logic Based Fault Detection Model

The machine operating at 20 Hz (1200 RPM) vibration data obtained from the Machinery Fault Simulator (MFS) was used for analyzing the spectrum patterns of normal and faulty conditions using the FFT. The features for both the healthy and faulty condition are extracted using the frequency and amplitude as an input while output will be the condition of machine and severity of the fault.

The simulated data extracted from MFS were analyzed for extracting the features for Fuzzy based fault detection system. As the first harmonics (20Hz) and second harmonics (40 Hz) for the faulty condition were distinctive from the healthy condition, they were taken as input data for the fuzzy system which were further categorized to low, medium, and high value. The amplitude (g) of the first and second harmonics were extracted from 20 combining data sets of healthy and faulty data which were then used as the features to separate these condition as shown in Tables 4.1 and 4.2 below.

First, the features were extracted for healthy and unbalanced Data. The features selected were the amplitude of the first and second harmonics calculated in terms of g.

Table 4. 1 Features of healthy and unbalanced data

S.N	1st Harmonics	2nd Harmonics	Machine Status
1	0.010364	0.006439	Healthy
2	0.010168	0.006362	Healthy
3	0.009664	0.005858	Healthy
4	0.009762	0.008135	Healthy
5	0.009259	0.005932	Healthy
6	0.008918	0.006652	Healthy
7	0.009079	0.007359	Healthy
8	0.00904	0.008271	Healthy
9	0.008911	0.006928	Healthy
10	0.008933	0.00826	Healthy
11	0.128761	0.003766	Unbalanced
12	0.127431	0.002573	Unbalanced
13	0.127759	0.004255	Unbalanced
14	0.12657	0.001911	Unbalanced
15	0.125938	0.003444	Unbalanced
16	0.125597	0.003682	Unbalanced
17	0.125143	0.002388	Unbalanced
18	0.124651	0.002035	Unbalanced
19	0.124536	0.002566	Unbalanced
20	0.12474	0.00262	Unbalanced

As seen in the above Table 4.2, the features from the 20 data sets are selected and there seems to be the significant difference in the 1st and 2nd harmonic amplitudes when the operating condition of the machinery is abnormal compared to normal and further, the 1st harmonic amplitude for the Unbalanced condition if greater than that of Normal operating condition. Similarly, the system was subjected to the misaligned condition and features of the 1st and 2nd harmonics were calculated as shown in the Table 4.2 below

Table 4. 2 Features of healthy and misaligned data

S.N	1st Harmonics	2nd Harmonics	Machine Status
1	0.027	0.0042	Misaligned
2	0.0269	0.0069	Misaligned
3	0.0267	0.0063	Misaligned
4	0.0269	0.0042	Misaligned
5	0.0268	0.0038	Misaligned
6	0.0268	0.0057	Misaligned
7	0.0266	0.0051	Misaligned
8	0.0265	0.0051	Misaligned
9	0.0266	0.0057	Misaligned
10	0.0263	0.0049	Misaligned
11	0.010364	0.006439	Healthy
12	0.010168	0.006362	Healthy
13	0.009664	0.005858	Healthy
14	0.009762	0.008135	Healthy
15	0.009259	0.005962	Healthy
16	0.008918	0.006652	Healthy
17	0.009079	0.007359	Healthy
18	0.00904	0.008271	Healthy
19	0.008911	0.006928	Healthy
20	0.008933	0.00826	Healthy

After feature extraction, the Fuzzy Logic tool box was used to generate the Fuzzy Interface System (FIS) to classify the fault. After developing the fuzzy-based fault detection interface based on the 9 rules, the test data set of both healthy and unbalanced condition were tested for its effectiveness. The machine is in faulty or unhealthy condition if the FIS value is greater than 0.5 and larger the value of FIS, greater is the severity.

4.3 Results

Using the fuzzy logic toolbox of MATLAB (version: R 2016a) fault classification model was developed. The acceleration amplitude (g) and the frequency were chosen as input for the proposed fuzzy model. Then triangular membership function was used for assigning the membership value for the three operating conditions of the machinery. The membership value was chosen as low, medium and high based on the acceleration amplitude operating conditions. After assigning the membership function, the nine fuzzy rules were used for classifying and identifying the severity of the machine operating condition. Based upon the membership function and rules, the fuzzy model could give output as Healthy, Unbalanced and Misaligned. Also, the FIS value would provide an insight on the severity level of the machine operating condition.

First healthy and unbalanced unknown data set were tested using the proposed fuzzy logic model. It could easily classify the normal and misaligned working condition of the machinery. As seen in the Table 4.3, healthy and unbalanced condition are classified accurately.

Table 4. 3 Features of healthy and unbalanced data

S.N	1st Harmonics	2nd Harmonics	Machine Status	FIS Results
1	0.008197	0.006302	Healthy	0.3667
2	0.00898	0.007254	Healthy	0.35813
3	0.008437	0.006239	Healthy	0.36376
4	0.008695	0.006407	Healthy	0.37254
5	0.008426	0.00721	Healthy	0.35962
6	0.008559	0.008009	Healthy	0.33352
7	0.008612	0.006933	Healthy	0.37363
8	0.008192	0.008138	Healthy	0.33159
9	0.008332	0.006184	Healthy	0.36103
10	0.008084	0.006698	Healthy	0.38629
11	0.125155	0.001756	Unbalanced	0.6615
12	0.124891	0.002249	Unbalanced	0.66113
13	0.124458	0.003556	Unbalanced	0.61689
14	0.124739	0.002312	Unbalanced	0.66091
15	0.124596	0.001919	Unbalanced	0.6607
16	0.124661	0.002661	Unbalanced	0.65448
17	0.124384	0.001273	Unbalanced	0.65836
18	0.124487	0.002994	Unbalanced	0.64053
19	0.124164	0.002527	Unbalanced	0.65907
20	0.12413	0.002591	Unbalanced	0.65696

Based on the threshold of 0.5, FIS above 0.5 is identified as an unbalanced condition while below 0.5 is identified as a normal operating condition. Also, based on the FIS value, the severity of the machine can be identified. The greater the FIS value higher the severity of the machinery. Since the unbalanced operating condition is more severe compared to healthy operating condition, the FIS value is relatively higher for it. As can be seen from Table 4.3, the Fuzzy inference system could distinguish between the unbalanced and healthy operating condition of the machine based on the threshold of FIS value. As the unbalanced condition is more severe than the healthy operating condition, the severity results obtained from the FIS validates the statement. This simple technique can be thus utilized to detect the unbalanced fault.

Similarly, the fuzzy model was tested for the classification capabilities of misalignment and healthy operating condition. Twenty unknown data set were tested using the proposed fuzzy model. As seen in Table 4.4, the model could classify the normal and misaligned operating condition of the machine with distinction. Similar to the proposed model for unbalanced condition, it could identify the machine operating condition severity. Based on the threshold of 0.5 FIS above 0.5 is identified as a misaligned condition while below 0.5 is identified as a normal operating condition. The severity can be identified based on the FIS value, where greater the FIS value higher the severity.

Table 4. 4 Features of healthy and misaligned data

S.N	1st Harmonics	2nd Harmonics	Machine Status	FIS Results
1	0.0262	0.0049	Misaligned	0.62861
2	0.0264	0.0066	Misaligned	0.64666
3	0.0264	0.0046	Misaligned	0.62144
4	0.0263	0.0072	Misaligned	0.61734
5	0.0265	0.0052	Misaligned	0.6451
6	0.0265	0.0048	Misaligned	0.62085
7	0.0266	0.0054	Misaligned	0.64875
8	0.0265	0.0065	Misaligned	0.6477
9	0.0266	0.0046	Misaligned	0.62085
10	0.0268	0.006	Misaligned	0.65057
11	0.009	0.0073	Healthy	0.4133
12	0.0084	0.0062	Healthy	0.36489
13	0.0087	0.0064	Healthy	0.37211
14	0.0084	0.0072	Healthy	0.40525
15	0.0086	0.008	Healthy	0.36824
16	0.0086	0.0069	Healthy	0.40317
17	0.0082	0.0081	Healthy	0.35856
18	0.0082	0.0063	Healthy	0.35869
19	0.0083	0.0062	Healthy	0.36211
20	0.0081	0.0067	Healthy	0.37648

Using the features of first and second harmonics, the unbalanced and misalignment fault can be distinguished with healthy operating machine condition. The proposed method was developed separately for classifying healthy condition with the misaligned and unbalanced condition. In the future, these three faults can be incorporate together and classified along with their severity level.

Chapter Summary

In this chapter, the fault detection method for rotating machinery was purposed. Initially the most important features are identified using the FFT or CWT. The FFT is chosen. The features selected were the amplitude of the first and second harmonics for the normal and abnormal working conditions. After selecting the features, the fuzzy inference system was modeled using the MATLAB (version: R 2016a). The triangular membership function was chosen for mapping the degree of membership. After developing the Fuzzy system, they were tested on the extracted features. The fuzzy logic-based method showed good fault detection capabilities. It could not only easily identify healthy, unbalanced, and misaligned condition of the machinery, but also the severity of the machine based on the FIS level. As this method is easy to interpret and develop, it could be a useful tool in the industry.

Chapter V

5. Local Maximum Acceleration Based Rotating Machinery Fault Classification Using KNN

5.1 Introduction

Industries such as process, oil, and gas have widely deployed rotating machinery. To operate continuously at the optimum level, these industries need rotating machinery. These machines overall performance depends largely on the condition of their components such as bearings, seals, gearboxes, pumps, compressors, motors, and generators. Absence of a practical monitoring approach could cause a machine, and its part to fail catastrophically. Industries aim not only to minimize the failure rate of machines but also to optimize their maintenance resource. Taking maintenance action only when there is an abnormality in the operation of the machinery helps industries to get rid of additional cost incurred due to irrelevant schedule maintenance. CBM is considered as one of the most comprehensive monitoring and maintenance approaches because of its ability to optimize maintenance resources, minimize the risk of catastrophic failure, and improve machine reliability [34]. The CBM technique is based on various machine parameters such as temperature, vibration, and sound to determine the operating condition of the machine [2]. Vibration parameter based monitoring has proven to be a strong tool for identifying and detecting different fault such as bearing failure, misalignment, and unbalance in the rotating machinery [44] [45]. Since most rotating machines vibrate during their operation and different faults produce distinctive energy at a particular frequency, vibration-based monitoring can be considered as an ideal tool for detecting and identifying the machines faults [2]. Usually, the vibration-analysis is based on time and frequency domain methods. For analyzing vibration signal in time domain amplitude is taken as a function of time while for frequency domain analysis amplitude is considered as a function of frequency. The most common vibration fault like bearing failure can be predicted and detected using the vibration signal [46].

Machine learning (ML) is the science that empowers the intelligence of a machine to learn program by using example data and prior understanding [47]. ML is gaining popularity these days because of their agility to adapt to unfamiliar scenarios and capability of solving the complicated tasks that are difficult to be solved using mathematical modeling [48]. ML approaches such as Artificial Neural Network (ANN), Support Vector Machine (SVM), Deep Learning, Hidden Markov Model (HMM) has successfully identified faults in rotating machinery and their capabilities are still yet to exploit in various rotating machinery applications [49] [50] [32]. Pandya et al. used a modified KNN algorithm built on asymmetric proximity function (APF) to classify rolling element bearing fault. They used acoustic emission data for fault classification of rolling element bearing, and the result showed very good accuracy of 96.67% [51]. Lei and Zuo used weighted K-Nearest Neighbor to identify the crack level of gears. To detect gear damage and characterize gear condition, the time and frequency domain features of gear subjected to different load and rotor speed were used. The identification of the crack level of gears using this approach was found to be satisfactory [52]. Using the acceleration amplitude of 1x to 6x rotational speed as a feature, Nejadpak and Yang proposed a KNN based algorithm. This method showed satisfactory fault classification capability with an accuracy of 95% [53]. By analyzing the operating frequencies and their harmonics, various machine malfunctions caused by rotor imbalance and shaft misalignment are predicted and detected. It has been observed from the earlier literature work that operating frequencies and their harmonics have been used primarily to detect, classify, and predict machine faults. At these frequencies and their harmonics, preeminent differences are expected to occur. Although dominant differences may be observed at one time (1x) operating speed, it may not be accurate with other harmonic speed. The study then tried to check whether these dominant peaks or dominant acceleration amplitude are exactly located at the operational frequencies and their harmonics. So, the acceleration amplitude of harmonic frequencies and local maximum acceleration amplitude were determined. Finally, these amplitudes of acceleration were compared to test their similarity. It was found that besides a few amplitudes of acceleration rest others were not the same. It was evidential that acceleration amplitude of the harmonic frequencies and the maximum local acceleration were not identical. It could be misleading to use acceleration amplitude features at operating speed and its harmonics only, so the maximum local acceleration amplitude and acceleration amplitude at operating speed were selected as a vibration feature for the proposed KNN classifier.

5.2 Methodology

KNN is a simple supervised learning algorithm used for separating the data points into different classes. This nonparametric classification algorithm assigns the non-descriptive test samples to the particular class based on the measurement of the distance to the nearest training samples [54]. Easy interpretability without training requirement makes this method straightforward. The effectiveness of the algorithm is based on the suitable selection of the nearest neighbors.

The training data set can be represented as $T = \{(x_1, y_1), \ldots, (x_n, y_n)\}$. Here, x_i is *the n-*dimensional feature vector and y_i the corresponding class level. The binary classes are labeled as 0 or 1. KNN constructs a logical sub-region $R(x) \subseteq \Re^d$ from the training set at the estimation point *x*. The region is predicted based on the following criterion [55]

$$\boldsymbol{R}(\boldsymbol{x}) = \left\{\widehat{\boldsymbol{x}} \middle| \boldsymbol{D}(\boldsymbol{x}, \widehat{\boldsymbol{x}}\,) \leq \; \boldsymbol{d}_{(\boldsymbol{k})}\right\} \tag{5.1}$$

Where $D(x, \hat{x}\,)$ is a distance metric, and $d(k)$ is the kth order statistic of $\{D(x, \hat{x})\}_1^n$. The number of samples in R(x) is denoted by $k\ [y]$. The posterior probability $p(y \mid x)$ of x is obtained as:

$$\boldsymbol{p}(\boldsymbol{y} \mid \boldsymbol{x}) = \frac{\boldsymbol{p}(\boldsymbol{x} \mid \boldsymbol{y})\boldsymbol{p}(\boldsymbol{y})}{\boldsymbol{p}(\boldsymbol{x})} \cong \frac{\boldsymbol{k}[\boldsymbol{y}]}{\boldsymbol{k}} \qquad 5.2$$

The decision $g(x)$ is obtained from the highest $k[y]$ value

$$\boldsymbol{g}(\boldsymbol{x}) = \begin{cases} \mathbf{1}, & \boldsymbol{k}[\boldsymbol{y} = \mathbf{1}] \geq \boldsymbol{k}[\boldsymbol{y} = \mathbf{0}], \\ \mathbf{0}, & \boldsymbol{k}[\boldsymbol{y} = \mathbf{0}] \geq \boldsymbol{k}[\boldsymbol{y} = \mathbf{1}]. \end{cases} \qquad 5.3$$

The KNN algorithm allocates a class from the decision with maximum posterior probability. The decision rule for binary classification $y_i \in \{0, 1\}$ can be simplified as $\boldsymbol{g}(\boldsymbol{x}) = \boldsymbol{sgn}\left(\boldsymbol{ave}_{\boldsymbol{x}_i \in \boldsymbol{R}(x)} \boldsymbol{y}_i\right)$

The KNN algorithm was used for classifying misalignment, and unbalanced fault as they are the most common cause of the rotating machinery failure. The local maximum acceleration amplitude and its location were initially identified for healthy, misaligned and unbalanced conditions. For the above-mentioned operating conditions, their local maximum acceleration amplitude information was extracted. These extracted characteristics were chosen as vibration features for the proposed KNN classification. The Euclidean distance function was used to calculate the distance of the test sample from a training sample. The number of k was selected as three based on the number of classes and the training set. Since the KNN result depends on the selected value of k, Euclidean distance is built in the same class to compensate for the error caused by the incorrect selection of k.

The characteristics of the normal, misaligned and unbalanced condition were analyzed using Fast Fourier Transform (FFT) in the MATLAB (version: R2016a) after acquiring the signal from the Machinery Fault Simulator (MFS). Also, to extract substantial information, the local maxima for the different operating conditions were identified and graphed. Several data sets were studied for the comparative study of healthy, misaligned and unbalanced condition to gather more information about the most common and dominant local maxima.

5.3 Experimental Setup

MFS was used to simulate three different operating conditions of the rotating machinery. The setup consisted of the three phase four pole AC driven induction motor. Accelerometers placed on the bearing housing were used by BNC–2144 Adapter and NI PXIe 1073 DSA Data Acquisition Board to extract the analog vibration signal. The speed controller controlled the speed of the engine or shaft. The system further consisted of an amplifier and analog to digital converter (ADC). The adjustable alignment jack bolt was used to align the shaft while the balanced rotor disk was used to simulate unbalanced machinery condition

Figure 5. 1 Unbalanced fault simulation

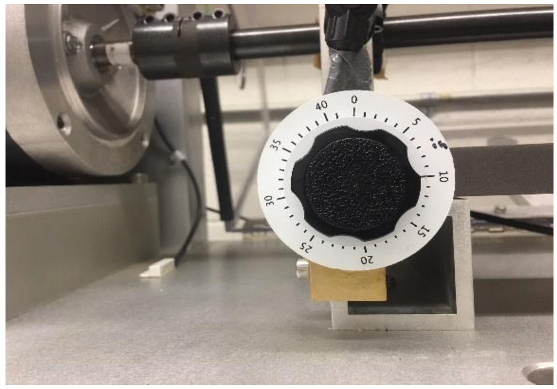

Figure 5. 2 Misalignment fault simulation

As illustrated in Figure 5.1 two screws of 10.2-gram were added in the threaded hole of the left side rotor for simulating an unbalanced operating condition. Additional mass in the form of screws was removed from the rotor disk to simulate normal operating condition. Before extracting healthy operating condition data, the shaft was also aligned perfectly. The system was set to operate at various motor speeds by changing the frequency to 10 Hz, 15 Hz, 20 Hz, and 25 Hz successively. The signals were extracted and further processed using MATLAB (version: R2016a) and NI Sound and Vibration Assistant Software after recording data. Hanning window was selected during data acquisition to minimize the leakage in the non-periodic signal. Similarly, as shown in Figure 5.2, the alignment jack bolt was used to misalign the shaft angularly to 10 milli inches.

5.4 Local Maxima Detection Using the Signal Analysis

As mentioned earlier, different fault conditions of machinery can be detected and predicted using the information of energy produced at specific frequencies. Therefore, it is crucial to have information related to frequency and energy content to monitor machinery operating status. The spectrum acceleration curve was thus designed to study the relationship of energy produced by the different frequencies when the system was subjected to different working conditions. This acceleration amplitude curve is shown in Figure 5.3.

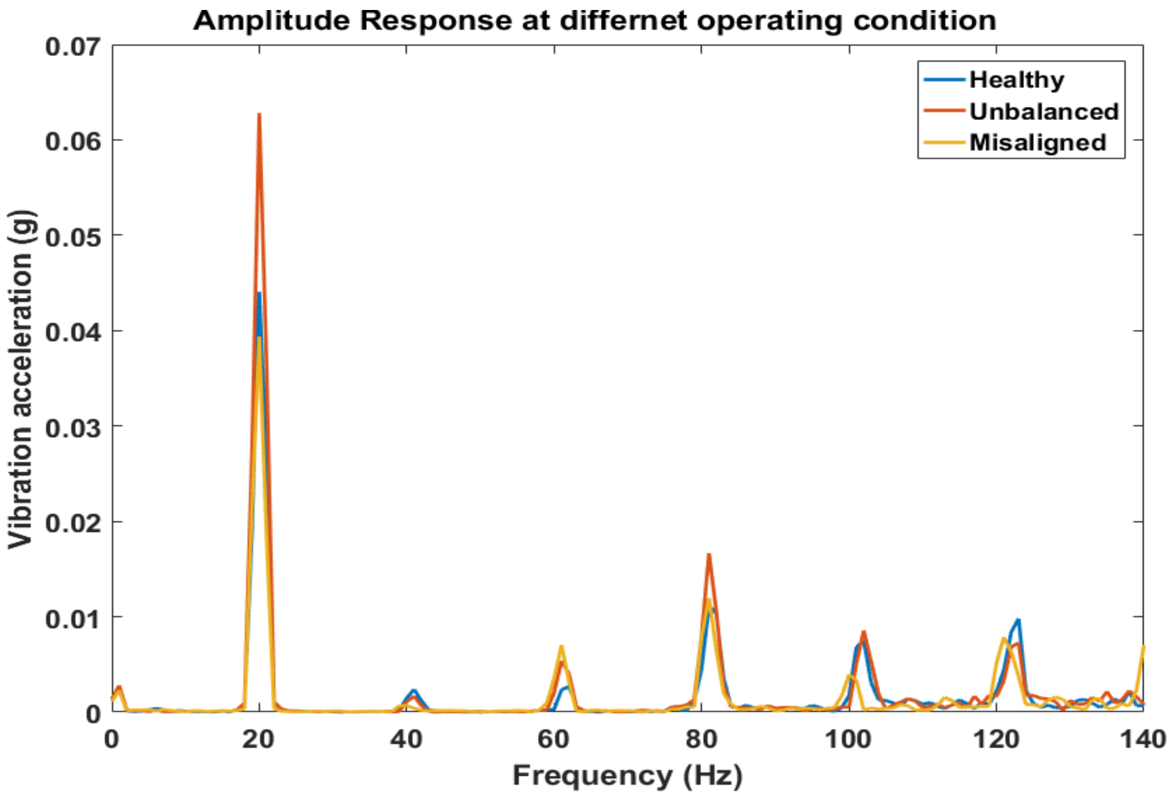

Figure 5. 3 Comparison of the different operating conditions of machinery

From Figure 5.3 it can be observed that unbalanced and healthy operating conditions are comparable at the exact speed of operation (1X, 20Hz). The acceleration amplitude for unbalanced, healthy, and misaligned operating conditions is higher and dominant at 1X of the rotating frequency condition.

Initially a spectrum of vibration response under the healthy operating condition as shown in Figure 5.4 was generated.

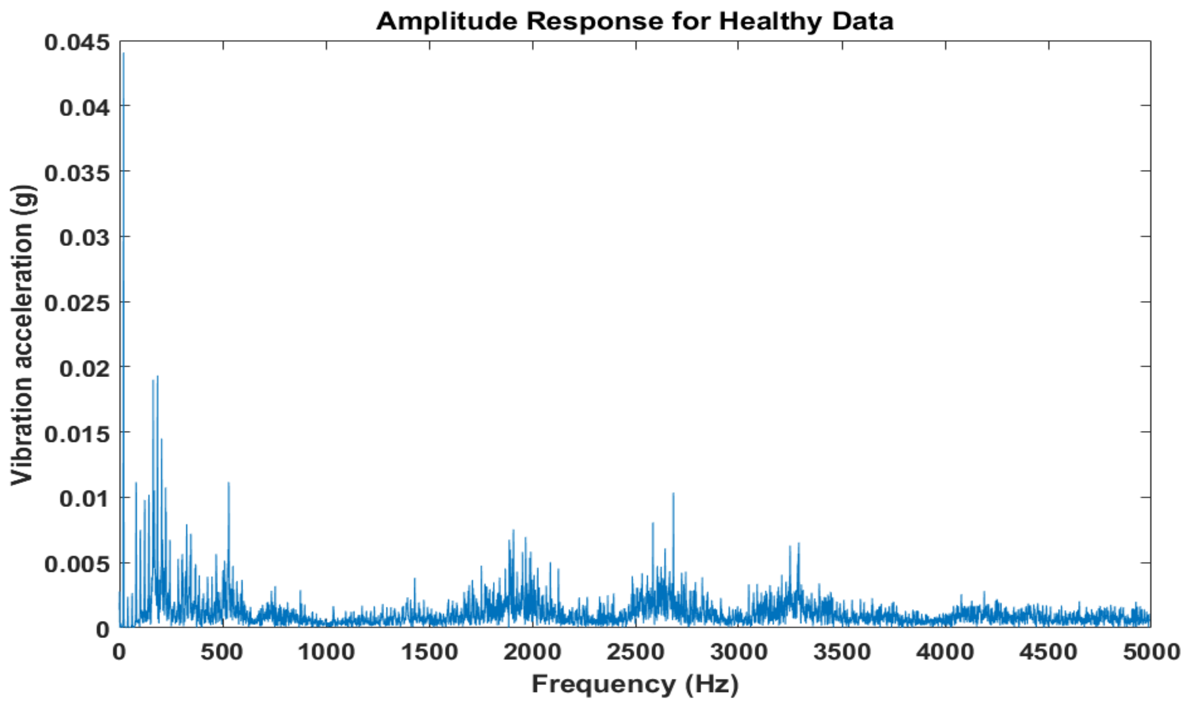

Figure 5. 4 Amplitude response for healthy data

The several dominating peaks are observed from Figure 5.4. However, it is challenging to determine the exact locations of these peaks. Then the graph was narrowed down with the information about the first 20 harmonic speed for better visualization and analysis. The graph contained the data of nX speed where n is the order of harmonic speed ranging from 1 to 20 while X is the system operating speed (20 Hz). The acceleration amplitude of nX harmonic speed was plotted using the MATLAB peak finding functions which can be seen as a red star in Figure 5.5.

It was observed that 1X is the location of the dominant peak. Other peaks appear around harmonics of operating speed but not at them exactly. A MATLAB program was developed to find all local maximum accelerations around 1 to 20 times operating speed. It also showed that finding peaks or finding acceleration from the exact value of 1 to 20 times operating speed can provide misleading information on the selection of functions for KNN analysis.

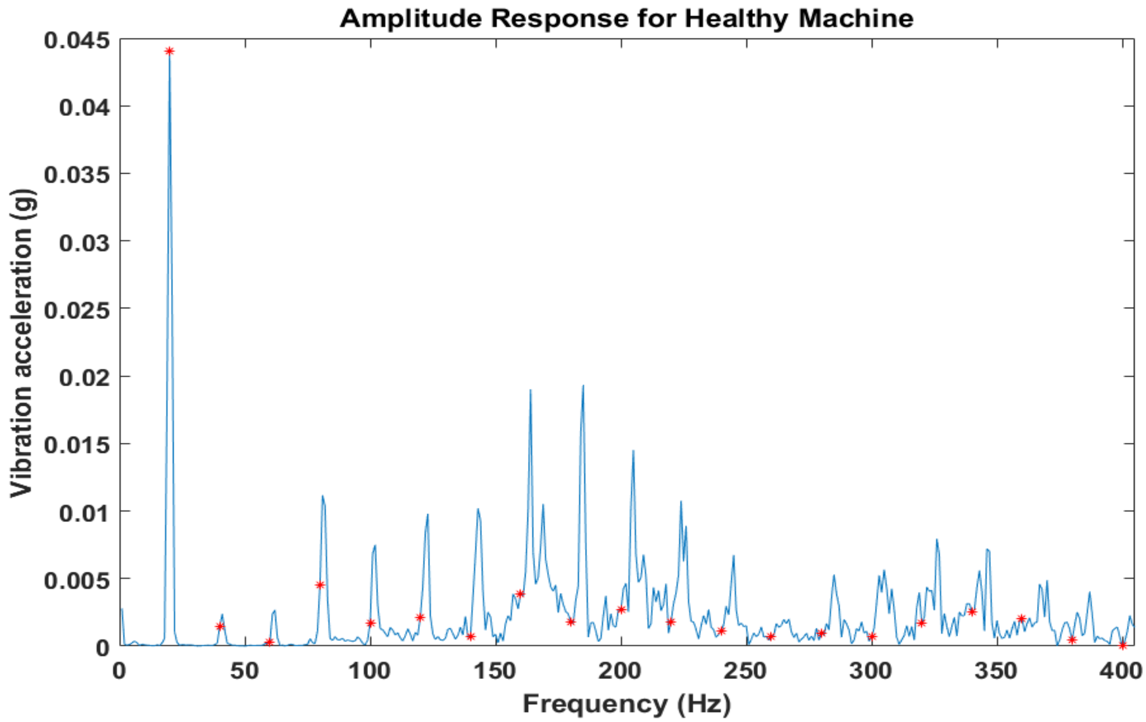

Figure 5. 5 Acceleration amplitude at the multi times operating speed.

A healthy operating condition analysis showed that smaller peaks are not always located at nX speed. Since it was challenging to track the exact location of smaller peaks using the above-discussed MATLAB graph, the program to accurately locate the first 20 local maximum amplitude was developed. The optimum speed range had to be selected at first in order to include the information of all the maximum local acceleration amplitude. To compare the peaks around the harmonic speed, it was decided to select the harmonic speed range of ±10 Hz. This program would evaluate the peaks placed between ±10 Hz from nX harmonics. For simplicity let's say if we had to find the local maximum amplitude around 2X (where X is 20) harmonic speed, then the local peaks ranging from harmonic speed 30 to 50 will be compared and then the most significant peak would be identified. After identifying the first 20 local maximum acceleration amplitudes, they were then paired with their corresponding speed. These resulted pairs were then plotted as the blue circle in a narrowed vibration response graph as seen in Figure 5.6.

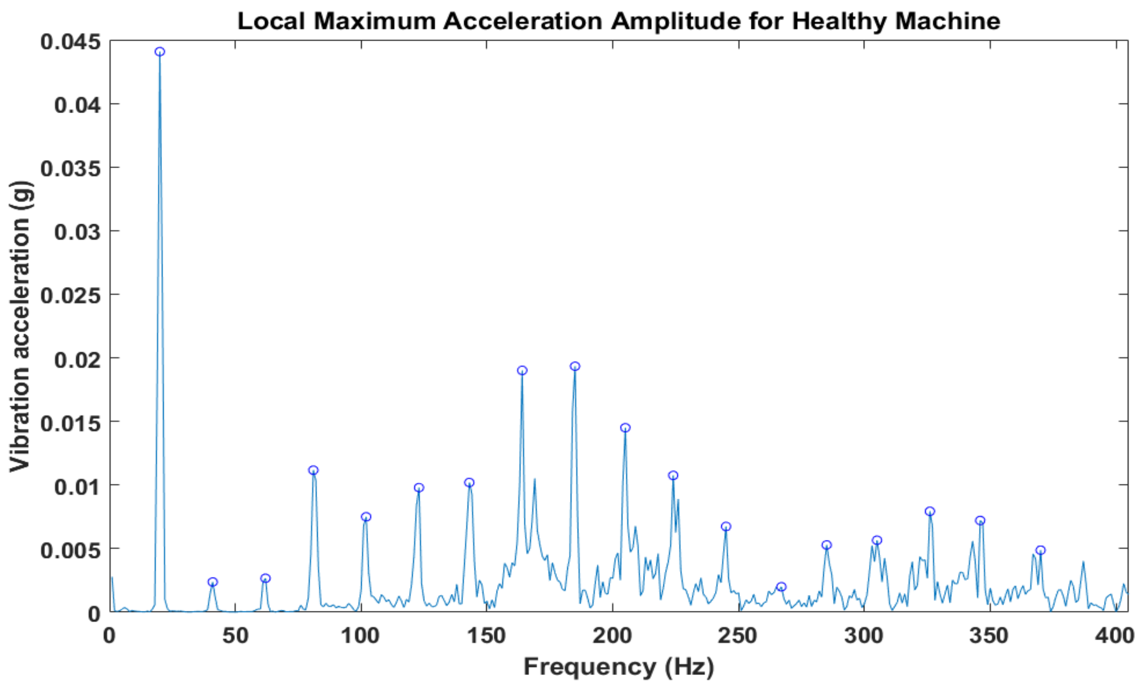

Figure 5. 6 Local maximum acceleration amplitude plot for healthy data

As seen from the Figure the local maximum peak is taken into the account which are closer to the harmonic speed. These local maximum acceleration amplitudes are calculated based on the selected ranges of the acceleration between the ±10 around the periphery of the harmonic speed. The ranges were selected based on the ability to detect all the local maximum amplitude.

As shown in Figure 5.6 all peak amplitudes were accurately detected. Comparing the Figures 5.5 and 5.6, it can be concluded that apart from a few peaks, most of the peaks are not precisely at Harmonic speed.

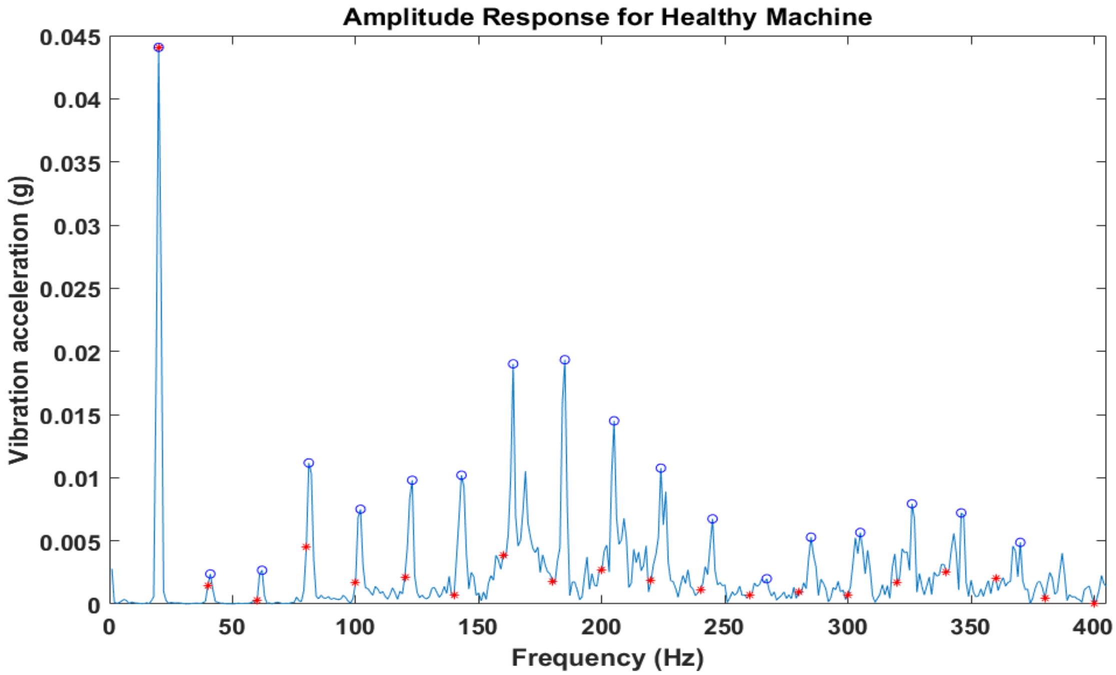

Figure 5. 7 Comparison of the acceleration amplitude for Healthy condition

The graph presented above in Figure 5.7 provides a clear idea on how the local maximum acceleration is distinctive to the one corresponding at the harmonic speed. As seen, there are greater differences in the acceleration amplitude value of the harmonic speed and the corresponding acceleration amplitude of the local speed that are closer to the harmonic speed. Thus, the study tried to concentrate on these local acceleration amplitude value beside the one with the largest peak for the further analysis and feature selection.

It was to be seen whether a similar trend is shown by the system when it is not working in the normal operating condition. Using the data set of unbalanced and misaligned machine condition similar graph described above were generated to see how closely the trend was related. From Figures 5.8 and 5.9, it was observed that the trend and behavior was similar to the healthy condition. For the visualization, we can have a closer look at the below Figures 5.8 and 5.9. Besides coinciding of few amplitudes' majorities of other local maximum amplitude and harmonic amplitudes are distinctively different for the unbalanced and misaligned condition. Thus, the focused shifted towards finding the order pattern for the dominant local amplitudes and their corresponding speed and use these values and information for the KNN algorithm.

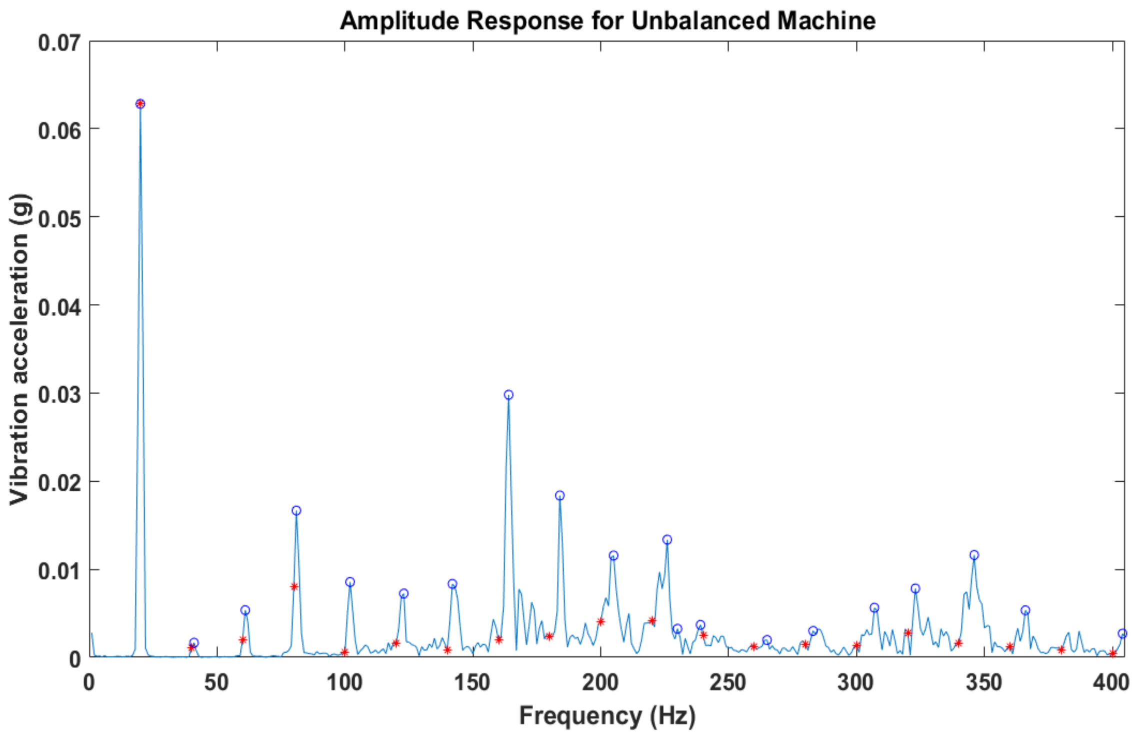

Figure 5. 8 Comparison of the local and maximum acceleration amplitude for unbalanced condition

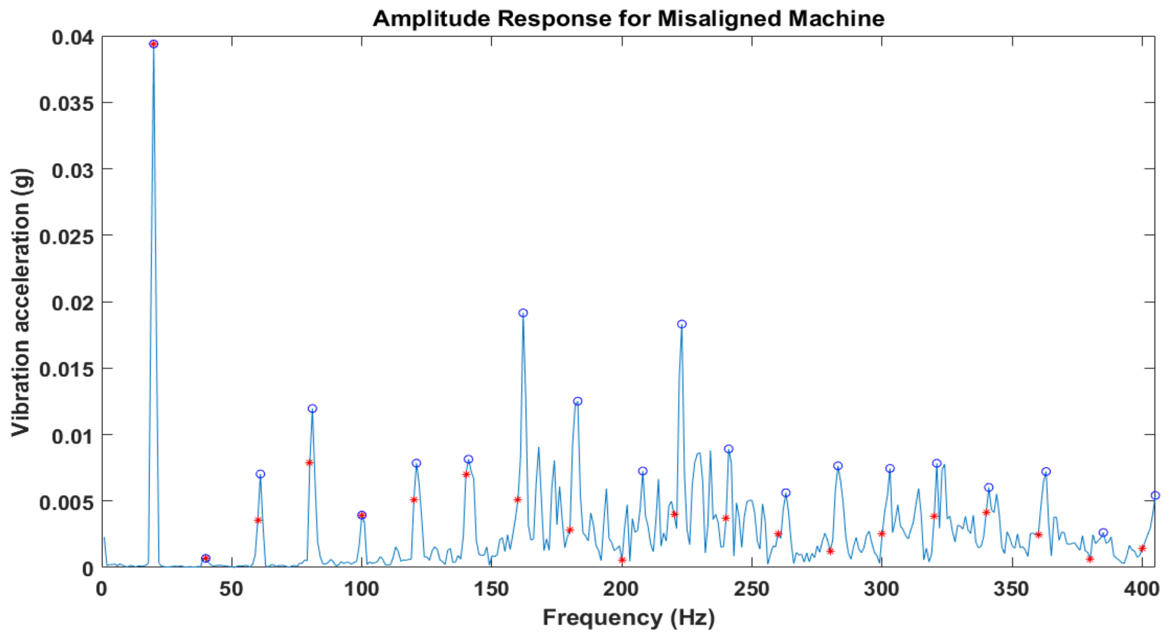

Figure 5. 9 Comparison of the local and maximum acceleration amplitude for misaligned condition

Further using other data samples, the study tried to find the dominant local maximum acceleration amplitude and their corresponding speed.

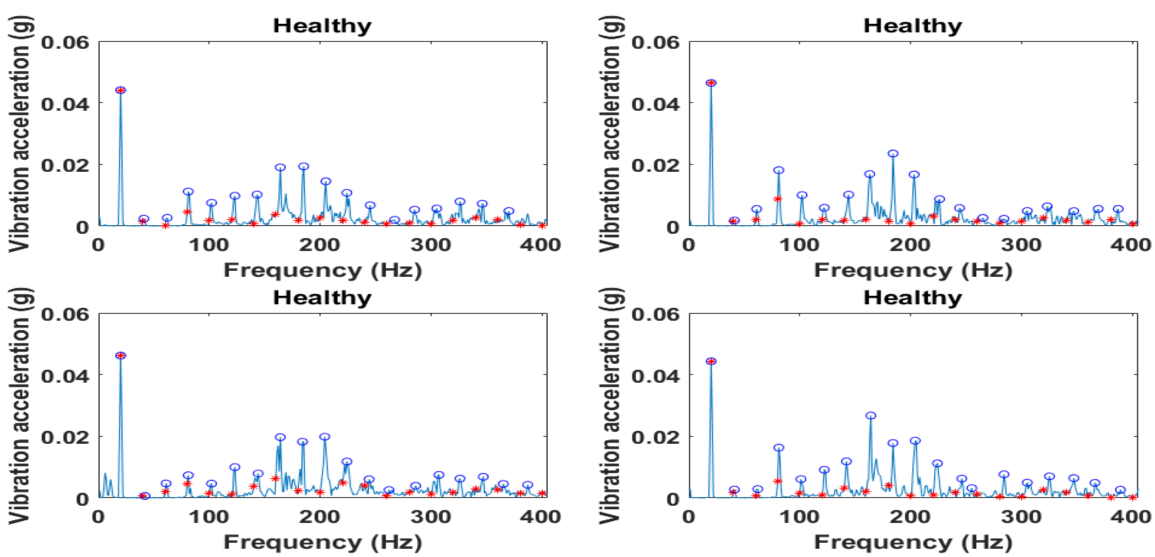

Figure 5. 10 Comparison of the acceleration amplitude for healthy data sets.

It can be seen from the comparison of acceleration amplitude in Figure 5.10 for healthy data, that besides a few amplitudes coinciding most of them are occurring at a different speed. Using different data set of the healthy operating condition study tried to find out the most dominating local acceleration amplitude and their corresponding speed. It was found that the local maximum amplitude corresponding to their speed was closer to the following harmonic speed in the descending order as 1x,9x,8x,10x,11x,4x,7x,6x ,16x.

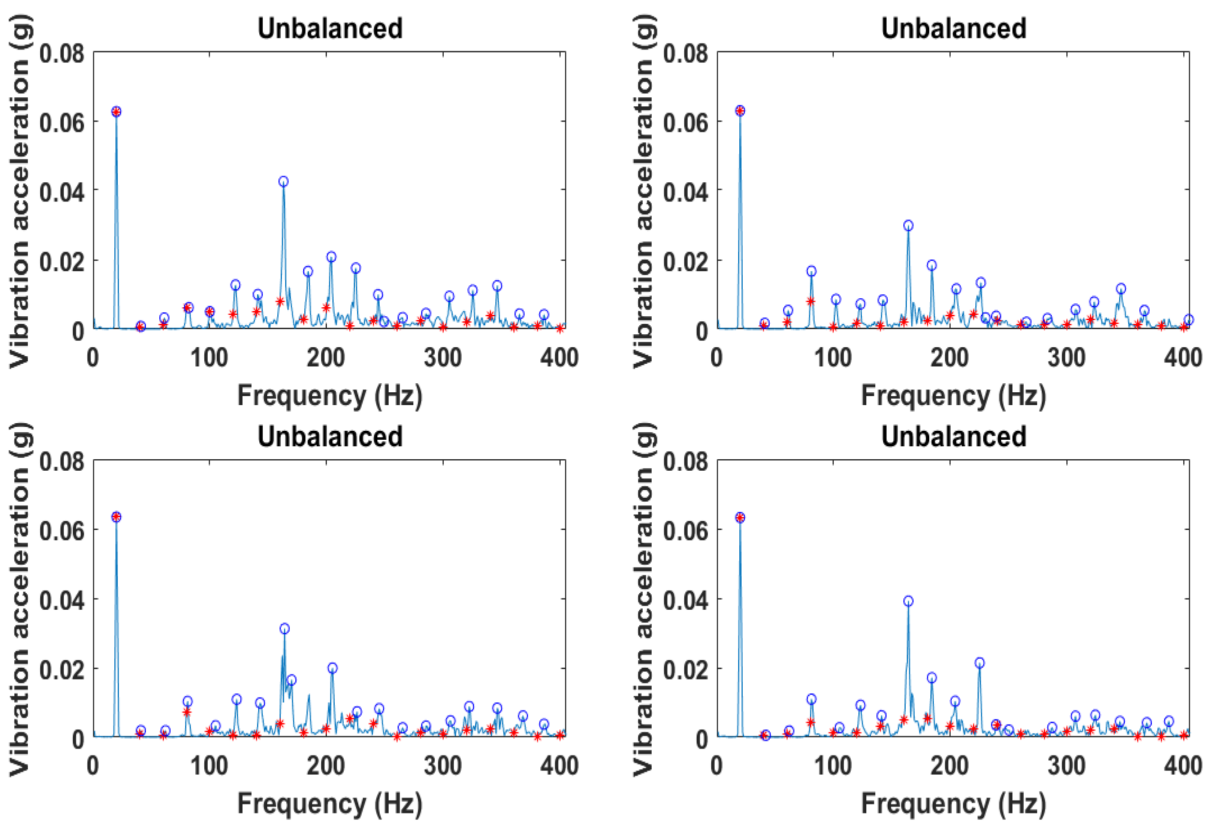

Figure 5. 11 Comparison of the acceleration amplitude for unbalanced data sets.

Similarly, from Figure 5.11 we can see that there are differences in the amplitude acceleration and local maximum one besides a few coinciding amplitudes. These Unbalanced operating condition data set showed that the maximum amplitude is not always occurring at multi times of operating speed. Looking at the pattern, the descending order of the local maximum amplitude closer to the harmonic speed were as 1x, 8x,9x, 10x, 16x.11x,4x,6x.

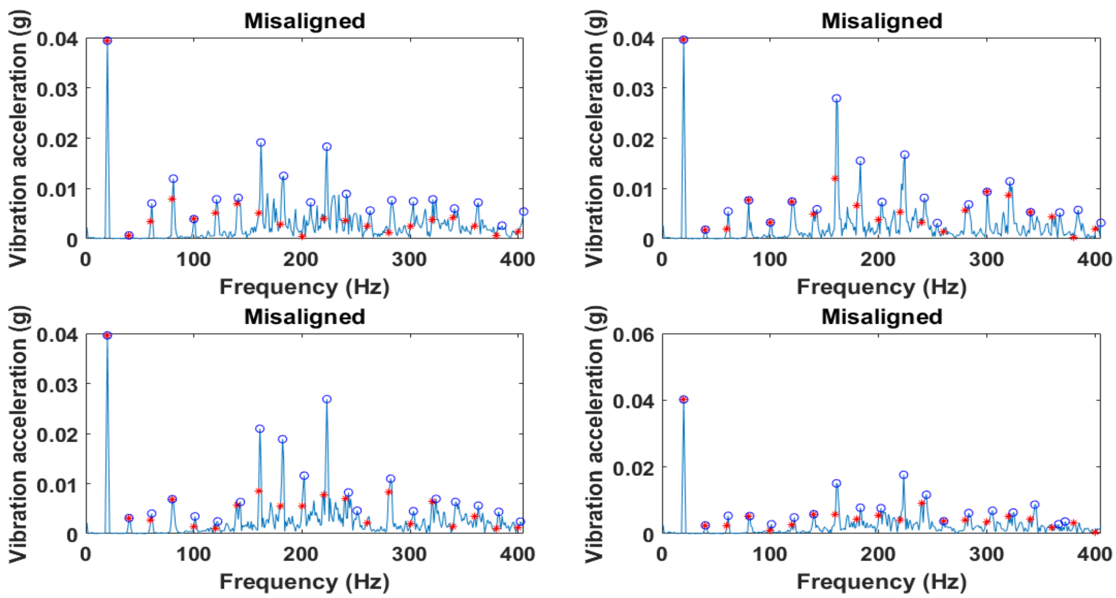

Figure 5. 12 Comparison of the acceleration amplitude for misaligned data sets.

The pattern was like one of Healthy and Unbalanced data set for the misaligned operating condition. The dominating local maximum amplitude closer to the harmonic speed were as 1x,8x,11x,9x,16x,10x,4x.

After the analysis first six common dominant order for all three-operating condition of the machinery were found as 1x, 8x, 9x, 11x, 16x, and 10x RPM. Therefore, the above six dominant orders were selected as six features for KNN algorithm features

5.5 Results

The features based on the order of the dominant local maximum acceleration amplitude were further studied to see the most significant one. 1x RPM and 16x RPM were found to be the most significant features when compared to the 95% confidence interval using

Tukey's method. The selected features were then used to generate training data for the proposed KNN classifier. Euclidean distance function was used as a distance metric for the classifier. Using the training data set the Euclidean distance of the testing data sets were calculated. The number of nearest neighbor K was chosen as 3. The classes closer to the minimum distance were ranked in ascending order after calculating the Euclidean distance. The test data set class label is then classified based on its closest neighbor's majority class. The model was tested using the unknown operating condition data set where it demonstrated excellent fault classification capabilities. It showed satisfactory accuracy of over 96%. Since the proposed method concentrate on identifying the local dominant peaks and its corresponding harmonic speed rather than concentrating on just harmonic amplitude and its corresponding speed, the identification, and classification of the different operating condition becomes more efficient. Tables 5.1 and 5.2 show the result of the classification for the proposed KNN method.

Table 5. 1 Unknown Testing Data Sets

Testing Dataset	Feature1 1x RPM	Feature2 8x RPM	Feature3 9x RPM	Feature4 11x RPM	Feature5 10x RPM	Feature6 16x RPM	Situation
1	0.045027	0.021722	0.01227	0.009155	0.013987	0.009374	Unknown
2	0.043975	0.008434	0.024332	0.007996	0.010282	0.009226	Unknown
3	0.044651	0.022586	0.010738	0.01473	0.01525	0.008634	Unknown
4	0.063556	0.042059	0.020411	0.009278	0.008583	0.00876	Unknown
5	0.063247	0.028454	0.012991	0.019314	0.012181	0.004144	Unknown
6	0.063155	0.01924	0.018068	0.011175	0.008922	0.007019	Unknown
7	0.039874	0.016669	0.011933	0.025645	0.010187	0.009802	Unknown
8	0.040065	0.01151	0.012123	0.010416	0.008755	0.009174	Unknown
9	0.040579	0.013342	0.0142	0.01036	0.007299	0.013818	Unknown

Table 5. 2 KNN Fault Classification Based on the Local Harmonic Amplitude

Feature1 1x RPM	Feature2 8x RPM	Feature3 9x RPM	Feature4 11x RPM	Feature5 10x RPM	Feature6 16x RPM	Rank	Euclidean Distance	Category
0.044069	0.019011	0.019337	0.010756	0.014503	0.007936	5	0.004867133	Healthy
0.046403	0.016859	0.023506	0.008721	0.016715	0.006386	12	0.006984217	Healthy
0.046179	0.019703	0.018243	0.011807	0.019856	0.006263	11	0.006436746	Healthy
0.044328	0.026735	0.017797	0.011218	0.018571	0.007009	8	0.005336826	Healthy
0.043794	0.027905	0.017037	0.01423	0.009442	0.008671	4	0.004168619	Healthy
0.045027	0.02629	0.0215	0.014755	0.007172	0.006369	10	0.006261113	Healthy
0.062562	0.04247	0.016599	0.017554	0.020773	0.011169	13	0.014872686	Unbalanced
0.062815	0.029798	0.018373	0.01336	0.011563	0.00782	14	0.015505756	Unbalanced
0.063347	0.031236	0.016461	0.00731	0.019909	0.008812	15	0.015654394	Unbalanced
0.063189	0.039176	0.017107	0.021397	0.010365	0.006347	16	0.016000239	Unbalanced
0.063668	0.029883	0.019234	0.020621	0.015014	0.004562	18	0.01676255	Unbalanced
0.063265	0.031205	0.019234	0.016034	0.020179	0.005897	17	0.016197614	Unbalanced
0.039384	0.019155	0.012509	0.018313	0.007255	0.007836	3	0.004126924	Misaligned
0.039585	0.027924	0.01551	0.016732	0.007296	0.01142	2	0.001789946	Misaligned
0.039598	0.020953	0.018866	0.02686	0.011592	0.006948	6	0.004883526	Misaligned
0.040194	0.015063	0.007774	0.01763	0.007633	0.006339	9	0.005419133	Misaligned
0.039581	0.006451	0.013812	0.013578	0.006263	0.01396	1	0.000687263	Misaligned
0.040428	0.018695	0.015676	0.014285	0.006702	0.00593	7	0.005312943	Misaligned

Table 5. 3 Testing Data with the unknown operating condition

Feature1 1x RPM	Feature2 8x RPM	Feature3 9x RPM	Feature4 11x RPM	Feature5 10x RPM	Feature6 16x RPM
0.040579	0.013342	0.0142	0.01036	0.007299	0.013818

Table 5. 4 Result of the KNN testing

Test Data	**K=1**	**K=2**	**K=3**
1	Misaligned	Misaligned	Misaligned

Result: Machine is operating in *Misaligned* condition

As can be seen from the above table, this method showed good fault classification capabilities. This method can be used for the classification of the fault in the industries for better accuracy and predictability.

Chapter Summary

Even though the first order frequency shows peak amplitude it is not always the case with the other remaining order to have similar peaks, the other smaller peaks usually does not always occur at the multi times operating frequency instead they occur at the frequency closer to these frequencies. These maximum peaks were referred as the local maximum. By focusing on the local maximum acceleration amplitude rather than amplitude at the harmonic speed a KNN based algorithm was developed which could classify the operating status of the rotating machinery correctly using the features of the local maximum acceleration around the harmonic speed.

Chapter VI

6. Conclusion and Future Work

6.1 Conclusion

Industries deploying rotating machinery aim to operate them smoothly so that their revenue generation is not hampered. It can be said that these industries look for safe, reliable and cost efficient operation to match their organizational goals. Efficient monitoring of these machinery with a reliable diagnostic tool can ensure industries to meet their above mentioned desirability. Vibration analysis is one of the most popular conditions monitoring approach used in modern day industries, it uses vibration signal to monitor the operating condition of the machinery. Since these are signal based monitoring approach, there need to be an adequate understanding of the signal for efficient monitoring. One should have a better understanding of utilizing the time and frequency related information to detect and identify different machine fault. On the other hand, one should have familiarity with the complexity of vibration analysis for these industries need an expert or professional analyst to carry out vibration analysis. So the industries are looking for the cost-effective, easily interpretable and efficient vibration monitoring tool. Most of the time, focus has been laid on the time domain signal to detect the fault while frequency domain information is used for identifying the fault type. Similarly, the multi times operating speed's amplitude is considered for developing a vibration-based condition monitoring tool. The aim of this research project is to develop efficient, economical, and straightforward monitoring tools that could utilize time domain signal to identify not only the fault but also classify the fault type. Similarly, the local maximum acceleration-based fault detection is proposed further.

The vibration signal of the machinery system is extracted by simulating it to different operating condition as healthy, misaligned, unbalanced and cracked shaft. Once these data are acquired they are processed using the signal processing tool like FFT and CWT for understanding the characteristic features of each operating condition, once these are known fault classification and detection tool are developed. Phase plane diagram-based tool utilizes the signal from all the 4 accelerometers to classify the fault while the KNN method based on the local maximum acceleration uses the frequency information for classifying the fault. Similarly, fuzzy logic based method is proposed for classifying the fault and identifying the severity of machine condition. The proposed method showed greater accuracy and efficiency in identifying and classifying the machine condition. So they can be implemented in the industries for the monitoring purpose.

6.2 Future Work

The proposed methodology can be incorporated with Artificial Intelligence System for not only detecting and classifying fault but also diagnosing or correcting it. This work also forms a solid basis for stability analysis in rotating machinery using CAD/CAE based approach. Thus, it is important to investigate on how stiffness and damping coefficients affect rotor systems. Various numerical methods can be used for such analysis and a simple fuzzy based system could be developed to validate the results. Furthermore, for the reliability of the proposed methods, data will be acquired in real environmental conditions from operating machines with larger sample size instead simulating in a laboratory setting.

Chapter VII

7. Appendices

7.1 Appendix A

MATLAB program for local and harmonic maximum acceleration amplitude detection

```
clc;
clear all;
close all;
%%At first we will be importing the excel file of our accelerometer
data
data1=xlsread('20f3','spectrum - PXI1Slot4_ai2','A11:B1009');
% data1=xlsread('20t2','Acceleration - PXI1Slot4_ai2','A9:C20008')
%Now we will be selecting the variables based on the data column
VarNameM1_1 = data1(:,1);
VarNameM1_2 = data1(:,2);
% Now we will be finding the indices(frequency) for the maximum value
of
% amplitude for all the six data set, M1max will store data of the maxm
% val
[M1max,IDM1] = max(VarNameM1_2)
for i=1:4;
% Now we will find all the local maxima around the harmonics
[M1(i), IDM1_a(i)]= max(VarNameM1_2(i*IDM1-5:i*IDM1+5))  % Here we are
calulating the local maxima besides the harmonics
% Find all local maximum accelerations at exact harmonics
M1_test(i)= max(VarNameM1_2(i*IDM1))
 % Find difference of local maximum accelerations
    D1(i) = M1(i)-M1_test(i)
    % Find exact harmonics
Frequency1(i) = VarNameM1_1(i*IDM1)
end

%Print results for Right, Wrong and Difference of acceleration at
Harmonics

Data1 = [M1;M1_test;D1]
[M1_New,Order1] = sort(M1,'descend')

%% Plot
% figure(1)
% plot(VarNameM1_1(1:90), VarNameM1_2(1:90), Frequency1,M1,'r*')
% xlabel('Frequency (Hz)')
% ylabel('Vibration acceleration (g)')
% title('Misallignment1 Values at Harmonics')

hold on
plot(VarNameM1_1(1:90), VarNameM1_2(1:90), Frequency1,M1,'r*',
Frequency1,M1_test,'bo')
```

```
xlabel('Frequency (Hz)')
ylabel('Vibration acceleration (g)')
title('Misallignment1 Values at Harmonics')
```

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