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Research Article

Machine Learning-Based Multi-Fault Diagnosis of Deep Groove Ball Bearings Using Vibration Signal Analysis under Variable Speed Conditions

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Abstract

The most common type of rolling element bearing used in the power and chemical industry, in addition to being used in the automotive industry, is called a deep groove ball bearing (DGBB). These bearings will help machines to operate in a smooth manner with as little noise and friction, but over time they will be affected by high load and contact stresses caused by the motion of the bearings and the loads on those bearing, thus making them very vulnerable to failure as a result of high stresses and fatigue from having a load on the bearing. Even though it may be difficult to detect a minor defect in the bearing by visual inspection, it is very important to discover and repair any defects in a DGBB before they cause a major failure of the bearing and lead to a substantial amount of cost associated with repairing the machine. Using vibration analysis as a technique to identify fault conditions within a bearing has been utilized for many years. There are many patterns of characteristic vibrations generated due to bearing faults in the inner race, outer race or rolling elements of the bearing prior to full bearing failure. Characteristic patterns of vibration can provide valuable information on the condition of a bearing. Vibration signals are frequently analysed using a Fast Fourier Transform (FFT) analyser to convert the time response of these vibration signals into frequency response. The frequency spectrum provides an avenue for determining the existence of faults and their location based upon the fact that each fault type produces vibrations at a distinct frequency or characteristic frequency. By examining the frequency spectrum, one may thus establish frequencies associated with various fault conditions for a bearing.

In this study, vibration signals from a healthy (non-defective) bearing were first recorded. After that, different types of defects were intentionally introduced into various components of the bearing. The analysis clearly showed that each defect generated excitation in the system at its own frequency, resulting in peaks in the FFT spectrum for each defect. Additionally, machine learning algorithm was performed to validate how vibration parameters change with increasing speed. It was observed that parameters like unbalance and misalignment become more noticeable as the speed increases.

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KEYWORDS: FFT analyser, Condition monitoring, Machine Learning, Fault detection.

1. INTRODUCTION

Bearings account for the majority of maintenance capital expenditures in any manufacturing or processing facility that uses rotating machinery. Whenever an overhaul is done on a piece of equipment, sales reps representing one of the leading bearing manufacturers have a goal to sell you replacement bearings. Nine times out of ten, the bearings are replaced regardless of the cause of the machine's failure, and they are frequently held accountable [1]. However, a variety of issues might lead to the bearing failure, such as a machine operating at a crucial speed when imbalanced or misaligned; Due to its ease of measurement, vibration-based methods for detecting and identifying bearing damage are more popular. After collecting the measured data, there are three different ways to process it: time domain, frequency domain, and time-frequency domain. These processes are used to provide information about what type of bearing damage has occurred, and how much possible future damage will result from the defect (4). The yearly maintenance expense for a medium-sized industry is two to three corers. When equipment is not properly maintained, it breaks down and causes various losses including manufacturing loss, accident-related loss, loss of replacement parts, etc. These losses cost more than three corers. The main element of the majority of condition-based maintenance programs is typically vibration monitoring. Additional monitoring and diagnostic methods must be included in the maintenance schedule. Some of these methods include vibration analysis, corrosion analysis, lubrication analysis, monitoring process variables, and checking visually [2].

2. CONDITION MONITORING OF BALL BEARINGS

Faults in bearings can happen early if the bearing is not loaded correctly or if it's misaligned or if it's running too fast. Sometimes faults just happen as the bearing gets worn out over time. Machines had their bearings and related parts replaced regularly during routine maintenance, regardless of whether the bearing or part had worn out or not. This was done to prevent bearing failure, which would cause the machine to stop at a time and be more expensive to fix. Nowadays people are starting to monitor the condition of bearings continuously. By doing this, they can identify wear and tear before the bearing is completely worn out; therefore, it is best to replace a bearing before it completely fails. A range of issues may present themselves at the ring where the ball rolls, on the ball, or with the mechanism holding the ball in place. When this happens, vibrations are created when the faulty part hits parts of the bearing. The frequency of these vibrations depends on how the faulty part hits other parts. These frequencies are also called frequencies [5].

1. The bearing has parts that can get damaged.
2. Defects can occur on the bearing.
3. Defects make the bearing vibrate.
4. The vibrations have a frequency.
5. This frequency is based on how the defect hits other parts.

The frequencies that are special to a bearing can be calculated easily. However finding a fault in a bearing is not that simple. There are things that can make it complicated. Some of the frequencies of a bearing may be very close to the frequencies that happen when the bearing is rotating. As the bearing wears out the frequencies change more. Sometimes we see frequencies of the fault and these frequencies can have their own side frequencies. These higher frequencies can be so strong that they overwhelm all the frequencies. Also, tiny particles of wear can move around the bearing. Make more faults in other places. This makes the bearing vibrate a lot at different frequencies. So, it becomes hard to find the frequencies they're special to a particular fault. To assess the state of the bearing, we will first need a set of measurements of vibration as a reference point. These measurements are like a baseline. We need these measurements to be sure about what the frequencies mean. What is causing them? If the surface of the bearing is not perfectly smooth it can make high frequency vibrations. So it is not an idea to just use frequency analysis to find faults in a bearing. It is also important to analyze the results obtained by frequency analysis against time domain analysis and vice versa.

Generally, to diagnose a fault in a roller bearing we do the following things:

1. We collect the vibration signal from the roller bearing that has a fault
2. We find the features of the fault
3. Utilizing these characteristics to assess the state of the bearing and determine the source of the problem. We have to do these steps to find the fault, in the roller bearing.

3. FFT ANALYSER

As shown in Figure 4.2 an FFT spectrum analyser (like a digital oscilloscope) transforms the incoming signal into information at a very fast pace. The incoming digital signal is then transformed into a frequency spectrum (i.e., beside each of the characteristics of each defect) through the execution of a series of mathematical algorithms, referred to as Fast Fourier Transform (FFT). These FFT algorithms utilise the principles of Fourier analysis, with the resulting frequency spectrum reflecting the frequencies present in the input signal [2].Here is the fascinating part the original digital signal data was collected by taking "samples" of the waveform at a high sampling rate. According to Fourier's principle, any signal can be described as a summation of sine waveforms, with sine waveforms of varying frequencies. If the signal is periodic - repeating at regular intervals-there should be a dominant frequency component. The spectrum analyser allows you to observe which frequencies were present in the original signal reflected on the graph [3].

4. EXPERIMENTAL SETUP

4.1 Test Rig

The test rig shown below in Figure 4.1 consists of a Crompton Greaves AC 3-Ph. Induction Motor (RPM - 1500) connected to Hypothec (0.5 HP) via a coupling with rubber bushes for vibration dampening, this shaft has an extension of one meter and is 20 mm in Diameter (1"). We are depending on the installation of two splined discs (total 15 N) that are going to transfer a horizontal force for taking no-load measurements into our test spindle shaft. We'll also install two deep groove ball bearings at either side of the shaft. The shaft itself will be supported by a support we'll manufacture as a split housing allowing for easy disassembly/reassembly while removing the bearings. A pulley is connected to the shaft for connecting a

Dynamometer (This connection is made using a B-22 belt).

Figure 4.1 Experimental setup

4.2 Instrumentation*:*

The axial accelerometer was mounted on the machine (as shown in Figure 4.4) and had a 5 mV /g sensitivity. The vibration signal was then sent to the Fast Fourier Transform. The tachometer (as shown in Figure 4.3) was used to measure the speed of the machine shaft. The results of the Fast Fourier Transform were provided to us through the Adash VA4-PRO 4400 (as shown in Figure 4.2) and allowed us to produce a graph that includes both the time domain and frequency domain. The graphs were accessed through the DDS software (installed on the PC) and presented the data obtained from the Fast Fourier Transform of the vibration signal [1].

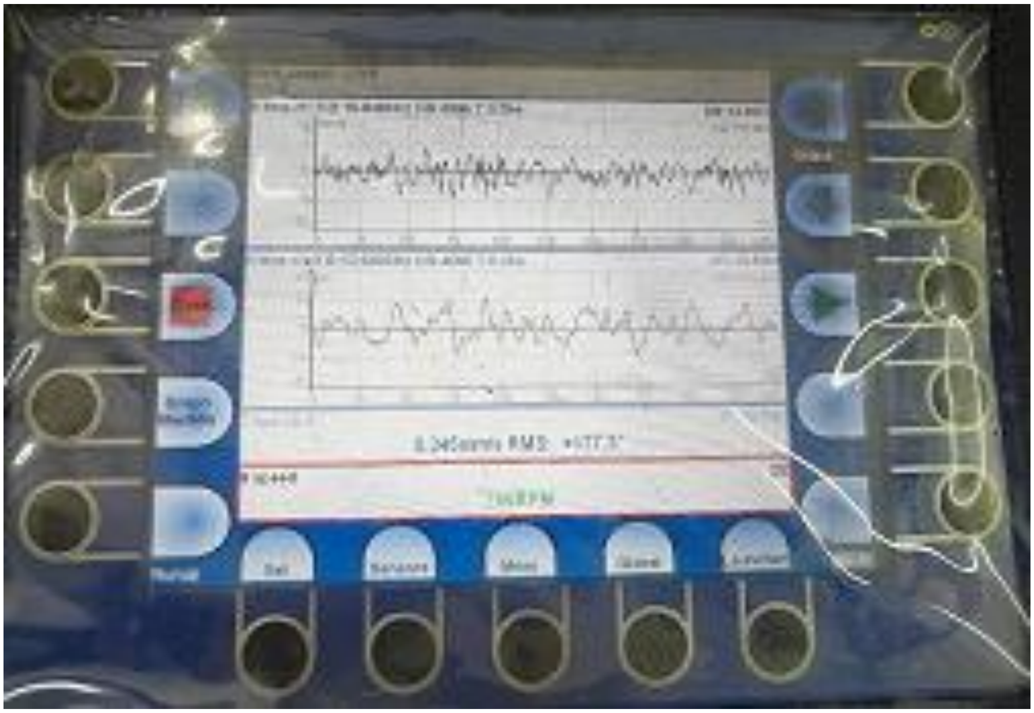

Figure 4.2 FFT analyser

Figure 4.3 Laser Tachometer

Figure 4.4 Accelerometer

4.3Measurement Condition:

The motor was tested at speeds. 500, 750, 1000, 1250, Rpm. We looked at the vibrations. We used six bearings. The one closest to the motor was always a bearing. The other bearing was changed times. We tried defects on this bearing. Like problems with the inner race, outer race, inner-outer race, outer race at 90 degree and ball defect. We also tried combining defects. Like two problems with the race or one problem with the outer race and one with the inner race. We got graphs, for velocity and frequency by mixing and matching the bearings and speeds. The defects we tried are shown in the following figures.

Figure 4.5 Outer race defect (0.7mm hole)

Figure 4.6 Inner race defect (0.7 mm hole)

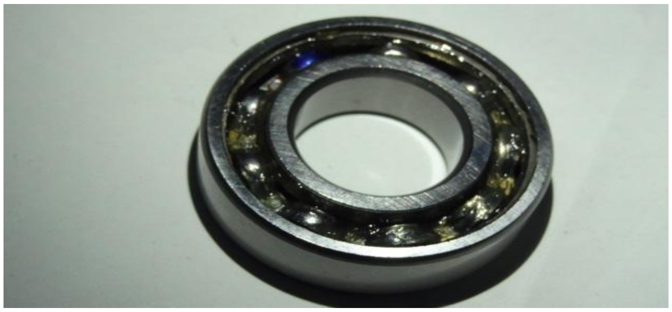

Figure 4.7 Ball defect (0.7 mm hole)

Figure 4.8 Inner-outer defects (0.7 mm holes)

Figure 4.9 Two-outer race defects at 90 degree (0.7 mm holes)

5. TIME DOMAIN ANALYSIS

Time-domain analysis is one of the simplest and most widely used methods for condition monitoring of Deep Groove Ball Bearings (DGBBs). In this method, vibration signals are analysed directly in the time form without converting them into frequency components. The main advantage of this approach is its simplicity, low computational cost, and suitability for real-time monitoring systems [1].In time-domain analysis, vibration signals collected from bearings are treated as a sequence of data points over time. Any change in bearing condition such as inner race fault, outer race fault, or rolling element defect directly affects the vibration pattern. These changes can be observed using simple statistical features. Researchers have shown that statistical time-domain features such as Root Mean Square (RMS), variance, standard deviation, skewness, kurtosis, crest factor, and peak-to-peak value are very effective for detecting bearing faults. RMS and kurtosis are some of the most widely used statistics for evaluating vibration signals due to them sensitivity to detecting an increased level of vibration due to a defect [2]. A vibration signal's RMS value will provide a measure of the total energy within that vibration signal; on the other hand, the kurtosis of a vibration signal will identify impulsive fault-like behaviours such as bearing cracks or surface faults. Both of these features can be readily computed and provide insight into the machine's health [3].Time-based features have been found to effectively separate both healthy and faulty bearings under different operating conditions (i.e. load and speed).This makes the use of time-based analysis forms of analysis very attractive for use in industry, especially when real-time decision-making processes are being employed [4].Another benefit of using time-based methods is that they do not require the use of complicated signal-processing techniques (i.e. FFTs or wavelets).

5.1. Healthy Bearing

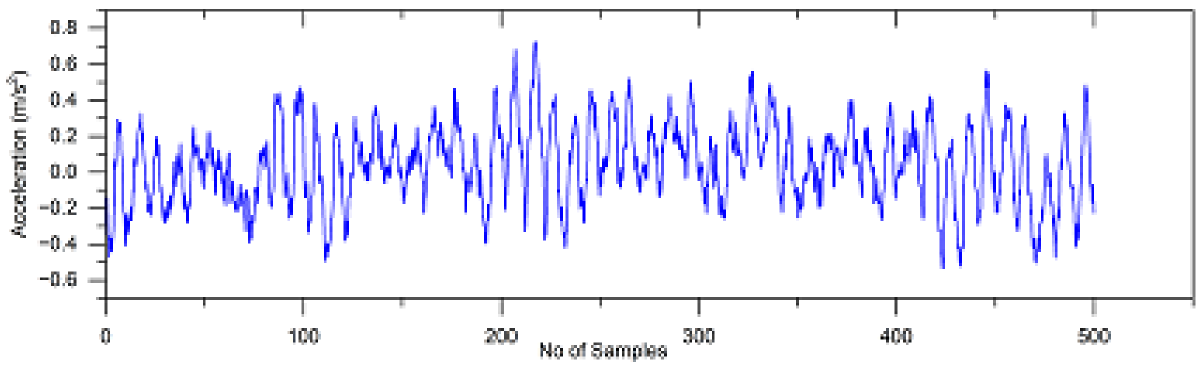

Figure 5.1 Healthy Bearing at 500 RPM

The vibration waveform at 500 RPM indicates that the bearing is in good working order and operating normally, based upon its smoothness, low-amplitude and uniform peak-to-peak values. There are no noticeable deviations from an unbroken line, as there are no sudden changes in amplitude and no large spikes present within the waveform. All of this confirms the continued health of this particular bearing, with no major issues whatsoever.

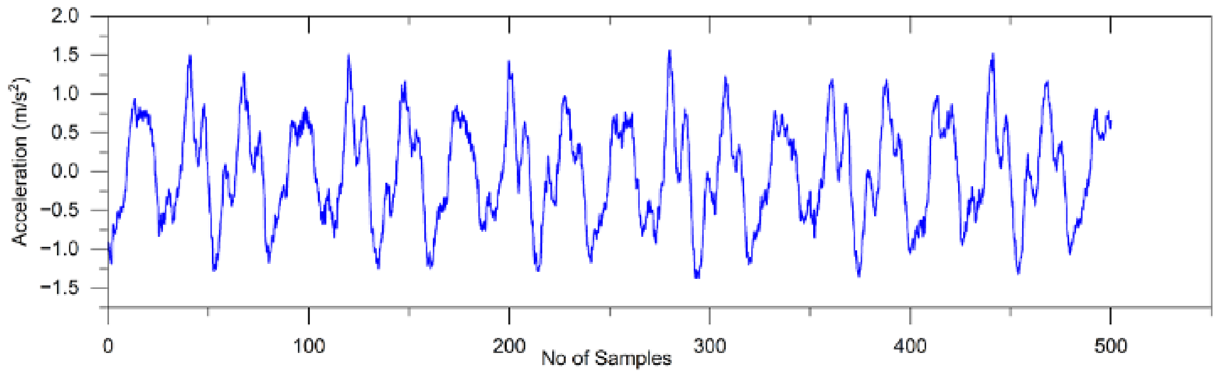

Figure 5.2 Healthy Bearing at 750 RPM

At 750 RPM, the amplitude of the vibration signal has increased slightly over the 500 RPM reading. It still is relatively stable; however, you can see that the amplitudes are now showing some slight amplitude variances between each peak, and some small peaks are also starting to show up. This is due to increased velocity resulting in higher dynamic forces, but there are no distinct, sudden impulsive spikes present, indicating the bearing is functioning normally without significant malfunction.

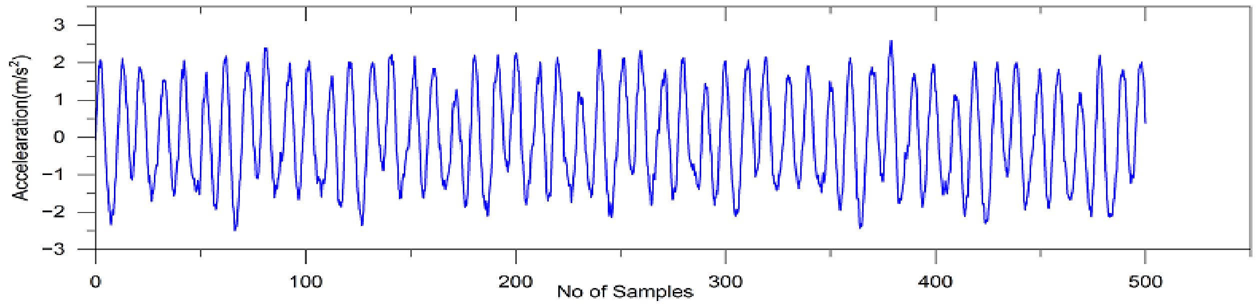

Figure 5.3 Healthy Bearing at 1000 RPM

In the 1000 RPM plot, as you increase your rotational speed, the amplitude and complexity of your vibration signals will also increase. Increased rotational speed causes the overall vibration level to increase substantially. Although the overall vibration signal increases and appears more erratic there are no noticeable impulsive peaks or irregular patterns indicating that the bearing itself is functioning normally but is under greater stress than what is normal.

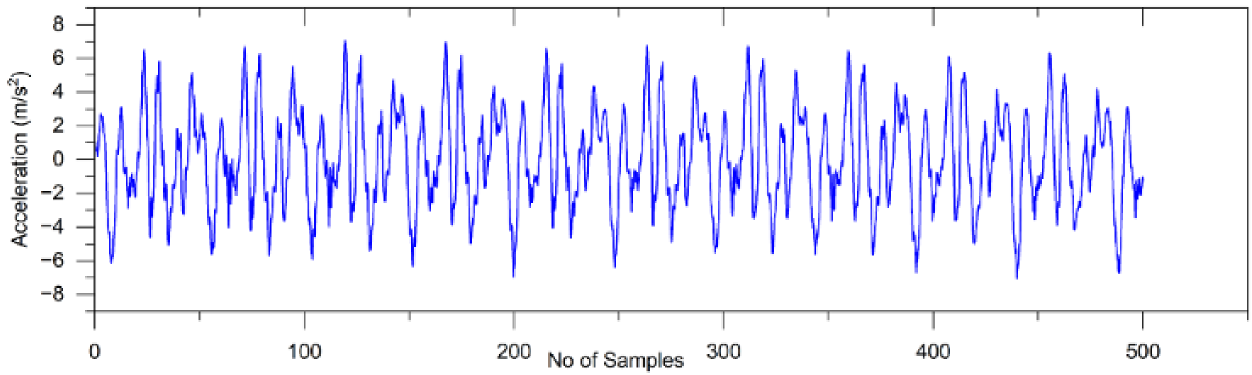

Figure 5.4 Healthy Bearing at 1250 RPM

At 1250 RPM, the vibration signal shows higher amplitude and more complex waveform patterns. Higher amplitude oscillations with small irregularities present indicate that there is an increase in dynamic force acting on the system - likely due to speed, a small amount of unbalance, or a slight misalignment of components connected to the system. There does not appear to be excessive impulsive peaks; therefore, it is safe to assume that your bearing is still within acceptable limits; however, you should continuously monitor it closely.

RESULT AND DISCUSSION

The increase from 500 RPM to 1250 RPM will produce an increase in vibration amplitude and complexity of the vibration signal. This is typical of rotating machines. In addition, the fact that none of the plots show any large spikes or irregular impacts indicates that the bearing appears to be functioning normally without any significant defects.

5.2. Outer –Race Defect

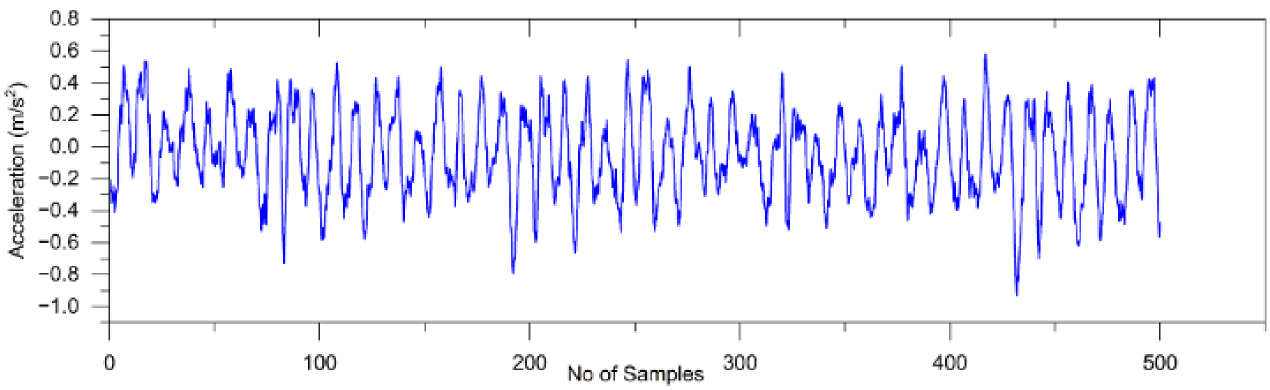

Figure 5.5 Outer-Race defect at 500 RPM

The above plot (at 500RPM) shows accelerations changing little and having large amounts of change over time implies that this is an environment with small movement changes and reasonable levels of motion stability. The accelerations will change frequently, so there will be non-positive and positive accelerations.

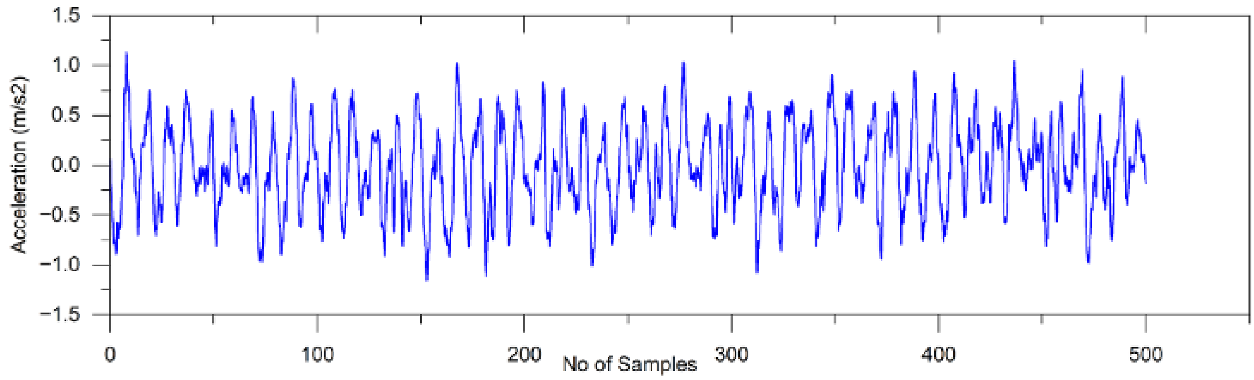

Figure 5.6 Outer-Race defect at 750 RPM

In the above plot (at 750 RPM As we go from the first to second graph the acceleration shows an increase in number of high vs low point fluctuations. With this increase in acceleration peak and trough difference, it indicates that the unit is going through greater variations such as increased motion fluctuation peaks and troughs. Therefore, the unit will have a more 'jittery' nature.

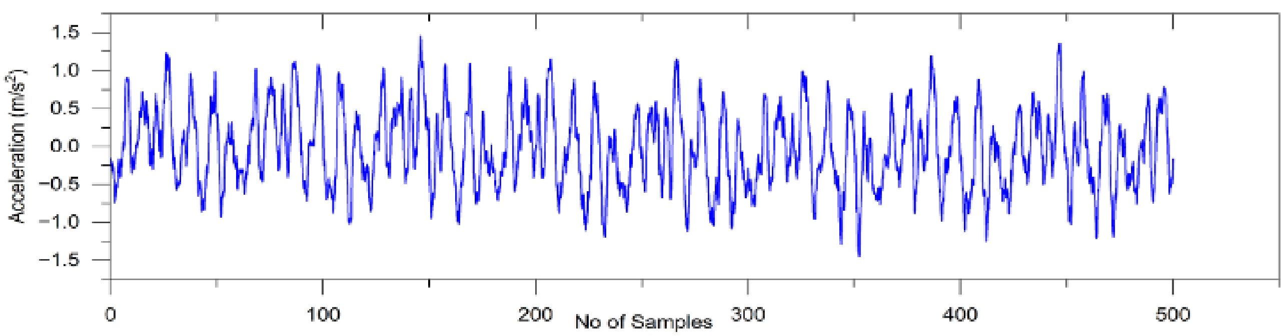

Figure 5.7 Outer-Race defect at 1000 RPM

At 1000 RPM the fluctuation points of acceleration in this graph show not only some acceleration points with fluctuations, but an overall increase in irregularity (i.e., larger peaks and deep troughs), as well as greater intensity (possibly because of outside forces acting on the system), and/or an increase in the amount of acceleration and motion being added to the system due, in part, to additional complexities influencing the dynamics of motion of objects.

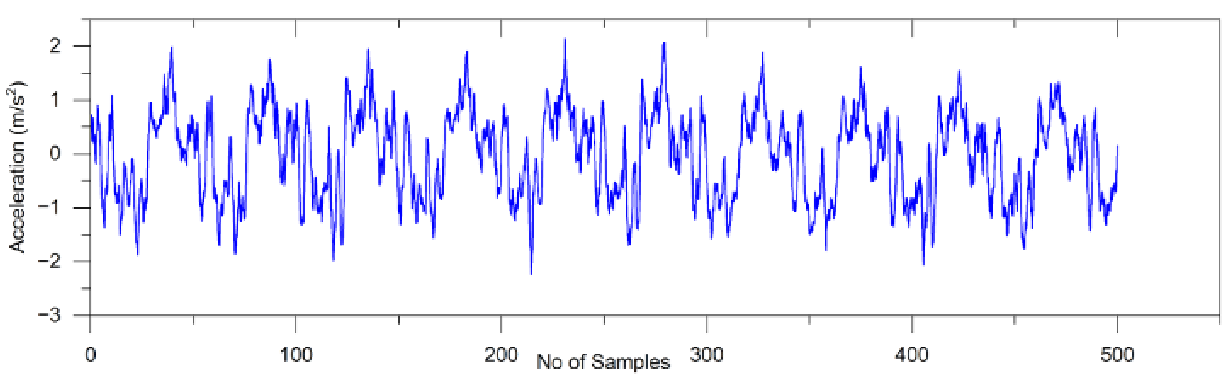

Figure 5.8 Outer-Race defect at 1250 RPM

At 1250 RPM, the plot again indicates very high levels of extreme behavior compared to other individuals. Acceleration values vary tremendously, showing large peaks and very deep troughs. The pattern appears much more chaotic and much less predictable, which means that the system is very dynamic and exhibits rapid changes in movement at this level.

RESULT AND DISCUSSION

As the speed increases from 500 RPM to 1250 RPM, the increase in the amplitude of vibrations and complexity of the signal is considerable. The bipolar plots exhibit greater intensity in their fluctuation patterns, irregularities/cycles through time, and sharper peaks than would be expected under normal circumstances. This behavior is typical when there is a defect in the outer race (e.g., a dented outer ring) because the rolling elements repeatedly hit the damaged surface and generate periodic impacts. Additionally, the presence of spikes on spectrums and the increase in severity of vibration at higher speeds indicate that the bearing has an outer race fault.

5.3. Inner-Race Defect

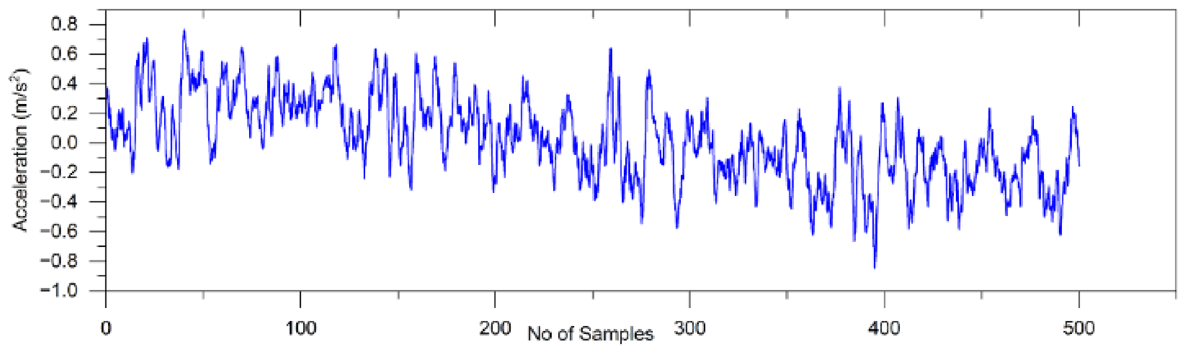

Figure 5.9 Inner-Race defect at 500 RPM

In the plot with an initial speed of 500 RPM, there appears to be non-linear accelerations in a moderate range. There are numerous peaks, but the average height of these peaks does not change significantly. Increasing sample sizes tend to show a slight downward trend in acceleration, implying that the system is losing momentum as time progresses.

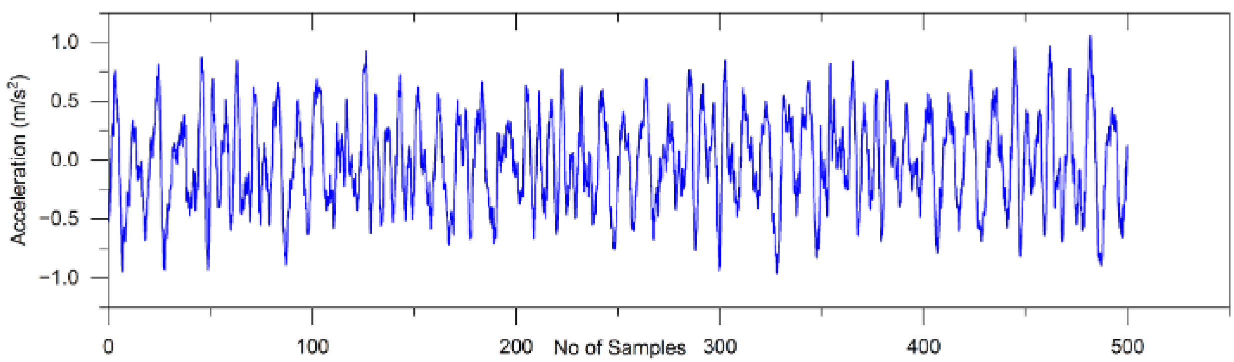

Figure 5.10 Inner-Race defect at 750 RPM

The trends represented in the second graph demonstrate increased fluctuation in acceleration levels. Peaks appear considerably taller, and falls are quite deeper than those seen in the first plot. Acceleration appears to be significantly more active/energetic in general and is exhibiting a less-damped response than in the first plot, resulting in more frequent and rapid changes throughout the entire period represented by the two plots.

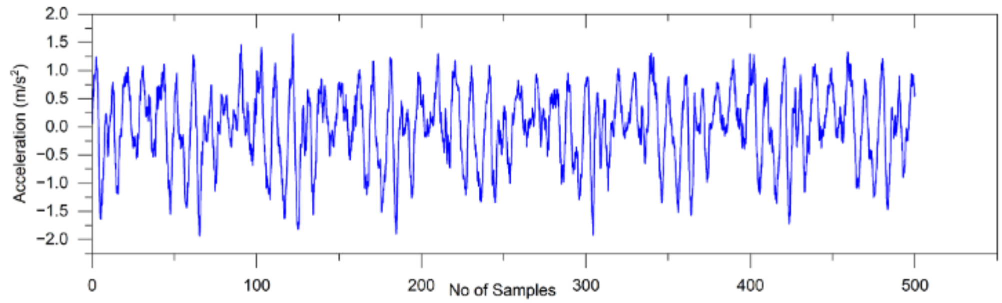

Figure 5.11 Inner-Race defect at 1000 RPM

An increase to 1000 (RPM), indicates very large fluctuations in the magnitude of acceleration. It also appears that the same signal has a wide range of high and low values, and is exhibiting very random behaviour.

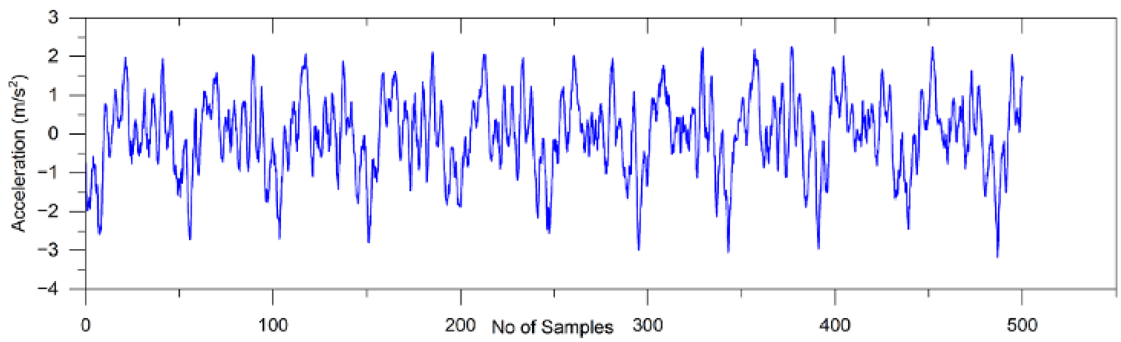

Figure 5.12 Inner-Race defect at 1250 RPM

At 1250 RPM, the results indicate that extreme values will be seen in the acceleration behaviour. The values of acceleration are at their highest and lowest range, as well as the behavior's displayed are chaotic in nature. The nature and behaviour of the motion appear highly dynamic due to large, sudden changes; therefore, the behavior of the system will be much more unstable than at 1000 RPM, and significantly more variable, due to the effect of variable input parameters.

RESULT AND DISCUSSION

When changing the speed of the motor from 500RPM to 1250RPM there is a noticeable change in both the vibration amplitude and the complexity of the vibration signal. On the charts below, the amplitude increases significantly, there are more pronounced variations in the vibration signal, there are more uneven patterns in the vibration signal, and there are many more sharply defined peaks than measured under normal operating conditions. Additionally, repeating patterns in the vibration signals are characteristic of an inner race failure of a bearing, wherein the damaged area rotates with the shaft and continuously impacts the rolling elements throughout the entire recovery operation. The result is that the frequency of impact occurrence and therefore the density and irregularity of the vibration signal is greater than that of a normal operating condition. Therefore, this steady increase in vibration energy level coupled with these repeating peaks strongly suggests that the bearing has an inner race fault.

5.4. Inner-Outer Race defect

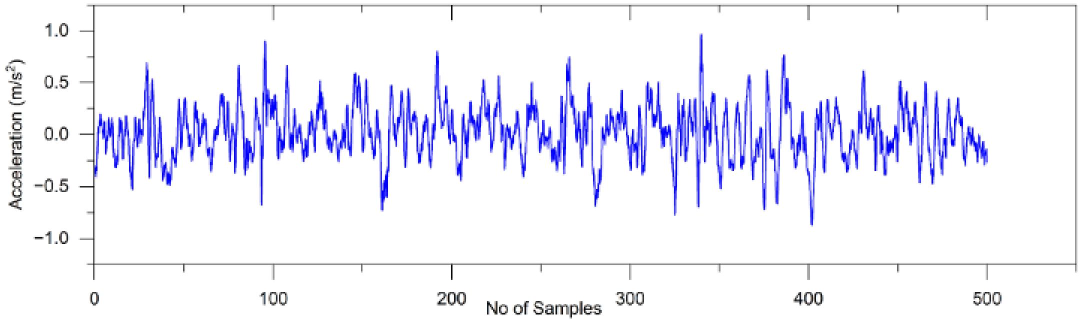

Figure 5.13 Inner-Outer Race defect at 500 RPM

The acceleration values at 500 RPM have a slight trend of slow, steady increase over time on the plot. There are no major jumps in acceleration values, and most values are near zero, indicating a constant state with minimal disturbances.

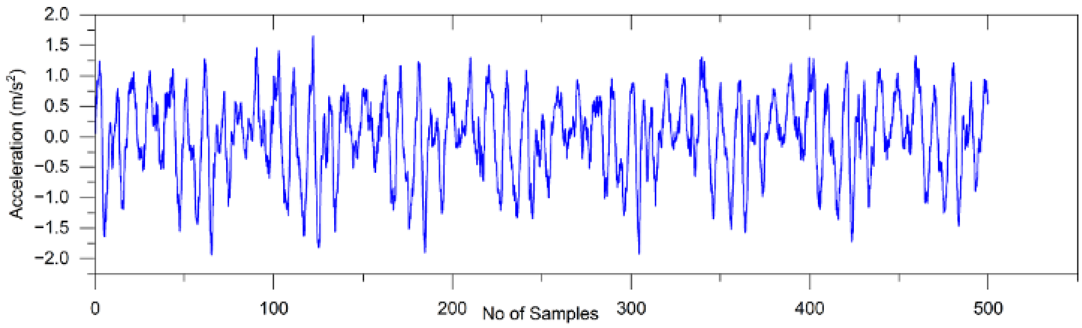

Figure 5.14 Inner-Outer Race defect at 750 RPM

The acceleration values continue to exhibit a general trend of increasing speed in this second plot, but the magnitude of fluctuations in the acceleration values is greater than in the first plot. In this case, larger fluctuations and more frequent spikes in acceleration indicate that the signal is much more active and energized than was seen in the previous plot.

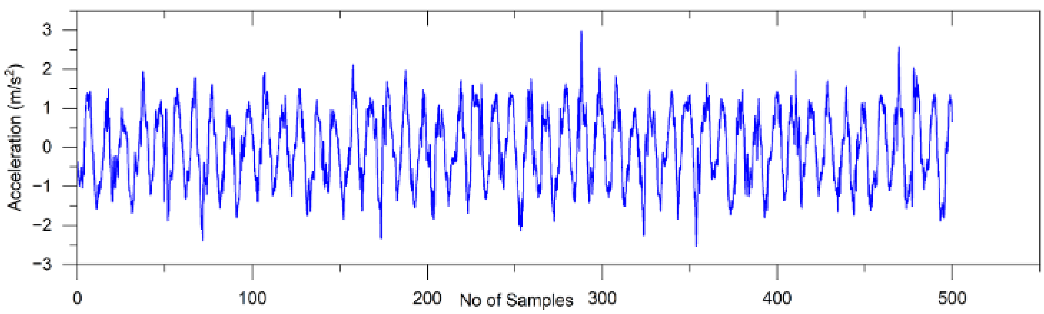

Figure 5.15 Inner-Outer Race defect at 1000 RPM

The above graph shows much larger and more pronounced changes in acceleration than the previous graph; each peak higher, and each valley (drops) deeper, and therefore has a more pronounced wave-like shape. This implies that the movement is becoming more dynamic and regular, while exhibiting clearer cycles of movement.

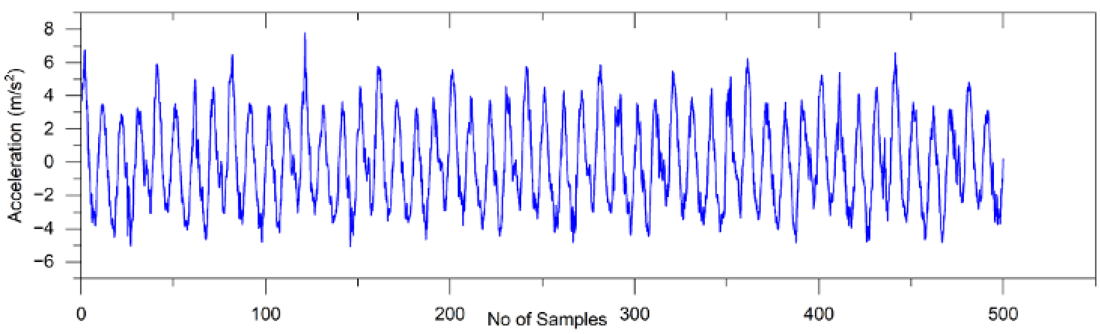

Figure 5.16 Inner-Outer Race defect at 1250 RPM

The data points in the second graph exhibit even larger swings in acceleration, with little variation between those moving towards a positive value and towards a negative value, suggesting an active and forceful system, resulting in very quickly changing and significant movement.

RESULT AND DISCUSSION

The amplitude and complexity of the vibration signal increase markedly as the speed rises from 500 RPM to 1250 RPM. The type of vibration signal seen here is typical of having both inner and outer raceway defects present. In this case, impacts from multiple contact points create an increased chaotic nature of the signal, with both an inner race that is rotating and an outer race that is stationary creating repeated spikes in the same way that increasing levels of vibration intensity occur when increasing speed show evidence of abnormal operation as a result of defects present in both the inner and outer raceways of the same bearing.

5.5. Outer-race defect at 90^0 or Double Outer-Race

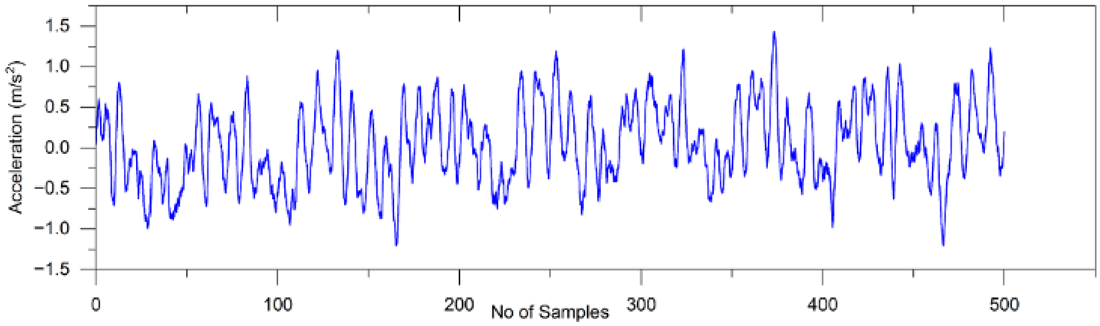

Figure 5.17 Double Outer-Race defect at 500 RPM

The graph shows acceleration changing at 500 RPM in a relatively smooth and average manner. Although there are clear highs and lows where the acceleration signal alternates, it appears to be relatively stable within certain limits. This shows that the system has periodic activity, but not excessive movement of this nature.

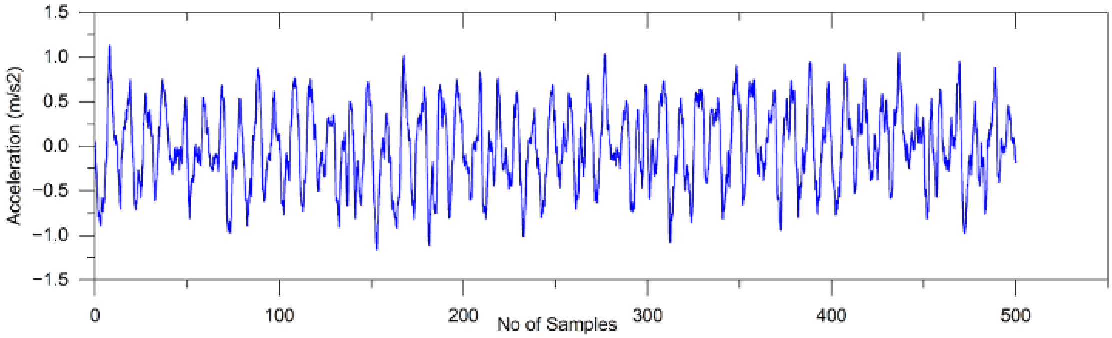

Figure 5.18 Double Outer-Race defect at 750 RPM

In contrast to the previous graph, acceleration differences appear to be larger in this graph. Here again the same point is made that the system has moved further and faster in both directions, thereby creating a more energetic and less stable configuration.

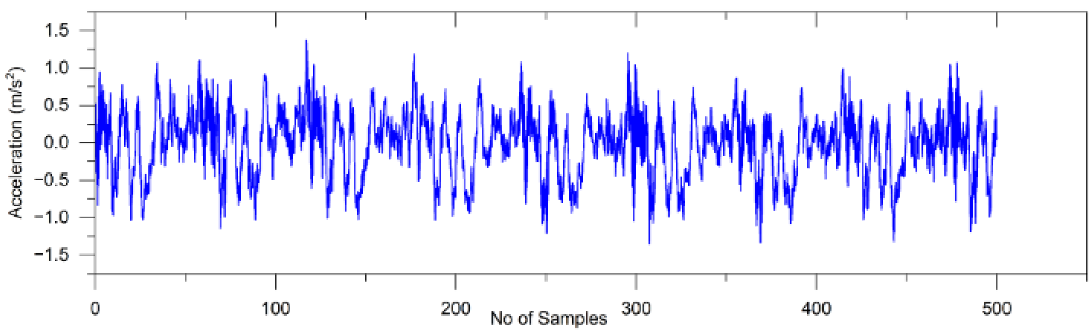

Figure 5.19 Double Outer-Race defect at 1000 RPM

The above plot (as the graph is not shown here) demonstrates the greatest amount of motion variance (meaning that the top speed and lowest speed have an extremely large variance between them).

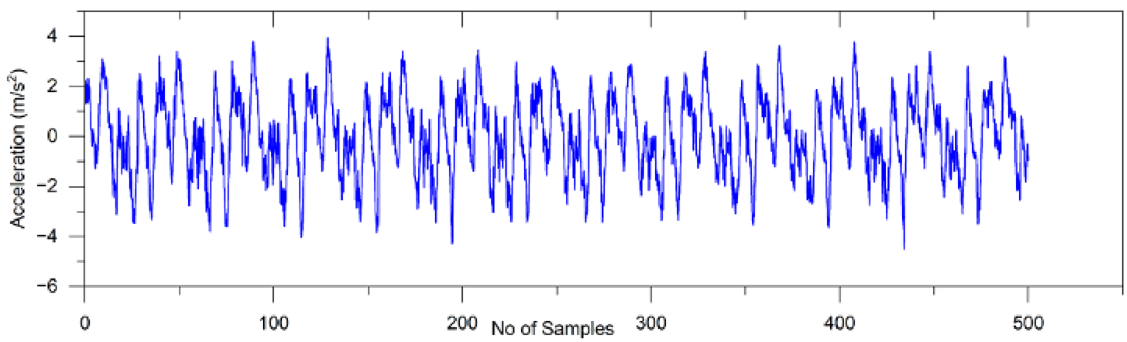

Figure 5.20 Double Outer-Race defect at 1250 RPM

The final plot demonstrates extremely high variations in acceleration as a result of the high number of changes that occur in the system over time. There appears to be less smoothness in the pattern created by high and low acceleration, therefore, indicating more energy in the system as well as decreased stability.

RESULT AND DISCUSSION

As speed increases from 500 RPM to 1250 RPM, the vibrations increase both in amplitude and complexity. In the plots, at increasing RPM, the fluctuations of the baseline/RMS level become more pronounced along with a higher occurrence of repeating peaks. This type of vibration pattern is characteristic of an outer race defect at a known location (e.g., 90 degrees). This repeating impact creates periodic spikes in the signal. As speed increases, the impacts become more frequent and larger, making the repeating peak pattern more visible. The existence of repeating peaks and an increase in vibration clearly represent an abnormal condition and provide strong evidence of an outer race defect at the 90-degree location of the bearing.

5.6. Ball Defect

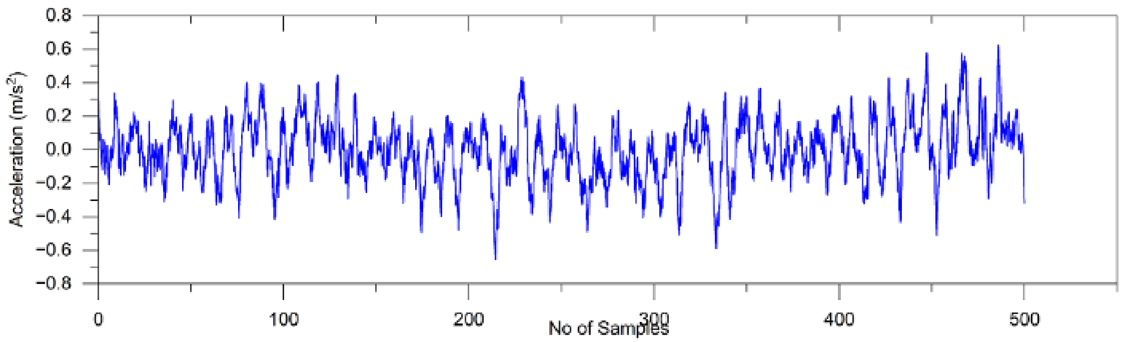

Figure 5.21 Ball defect at 500 RPM

In the initial graph, the acceleration has been steadily changing gradually over time. Most of the time, the signal is near zero, but there are occasional moderate spikes and valleys. Overall, it appears very stable and smooth, indicating that the motion is generally calm with some slight changes

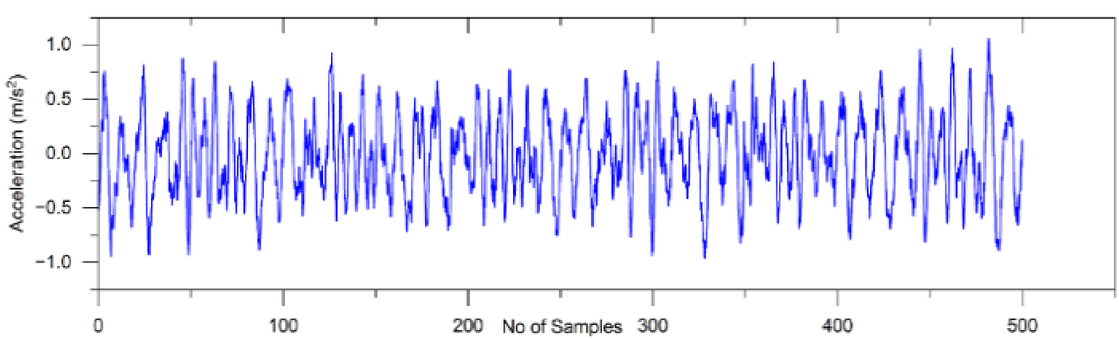

Figure 5.22 Ball defect at 750 RPM

Comparison of second versus first plots shows significantly enhanced amplitude and frequency of fluctuations. Active, energetic waveform with less smoothness; rapid changes through time.

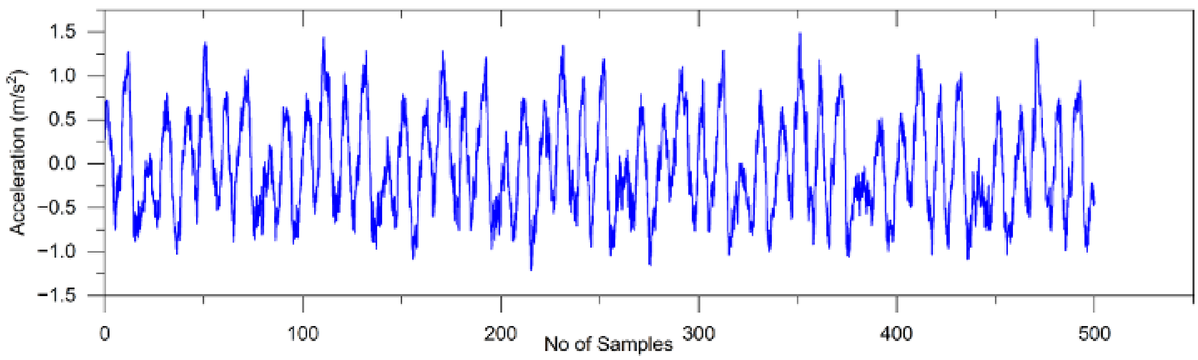

Figure 5.23 Ball defect at 1000 RPM

Comparison of third vs second plots shows dramatic increase in amplitude and regularity of fluctuated motion. The signal clearly oscillates up/down within a defined pattern; this indicates very active, rhythmic oscillation. More pronounced motion, more consistent patterns.

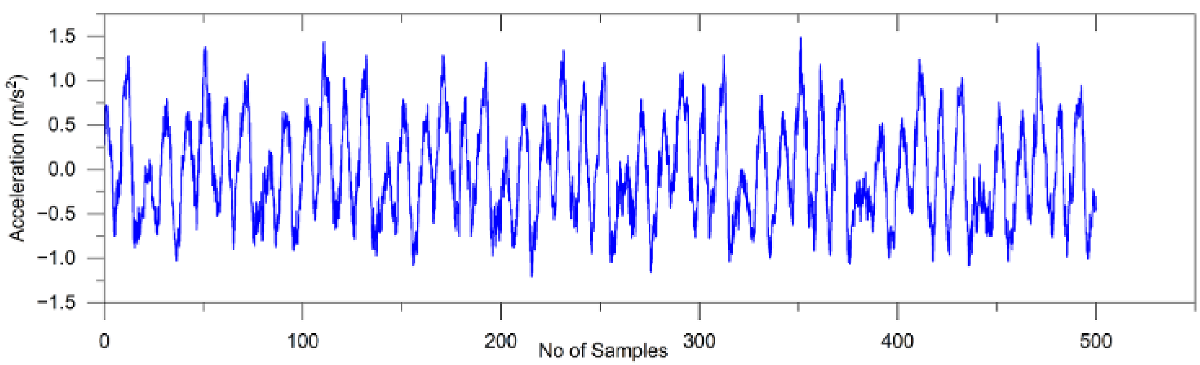

Figure 5.24 Ball defect at 1250 RPM

Fourth plot shows oscillation patterns similar to those of second plot, but continues steady amplitude around a mean value. Also indicates continuing increases and decreases of acceleration in an established, regular pattern. This indicates that the system has reached a steady state of activity characterized by high levels of energy but stable and repetitive behavior; thus, this could be classified as an inertial system.

6. RESULT AND DISCUSSION

As speed varies between 500 RPM & 1250 RPM, the amplitude, size and complexity of the signal dramatically increase. The plots show irregular bounding as well as very large intermittent spikes throughout the signal. The presence of these spikes, as well as the uniform increase in vibration throughout the speed range indicates the presence of a ball defect, or defect to the rolling elements of the bearing itself. Because ball bearings are constantly moving while they rotate and change contact points from inner to outer rings during roll cycle; the impact of each ball cannot produce perfectly consistent spacing and/or magnitude of each electrical pulse. Therefore, the signal is somewhat irregular in appearance and harder to predict than if there were no spacing and/or magnitude variation. When speeds increase, the frequency of impact and/or magnitude of impact to the inner and/or outer rings increases as well, thus producing more denser and complex signals. As illustrated by the continuous irregular patterns in the signal and the subsequent continuous increase in the overall amount of vibration caused by the rolling elements; the bearing is producing an acoustical or mechanical abnormality demonstrating that the balls are faulty.

7. MACHINE LEARNING IN BEARING CONDITION MONITORING

The main aim of machine learning in the field of monitoring the condition of bearings is to provide an automated method of determining whether or not a bearing is in a healthy state. This means to be able to classify the bear to be either – normal or with faults; these include an outer race defect, inner race defect, ball defect or a combination of 2 or more of these defects. The general process for condition monitoring through the use of machine learning is to collect a set of data regarding the condition of the bearings from an initial data acquisition phase [6].When acquiring this data, sensors (such as accelerometers) are installed on the machine (usually the housing of the bearing) that will continuously monitor the vibrations of the bearing and record vibrational data when the machine runs at multiple different speeds such as 500 RPM, 750 RPM, 1000 RPM and 1250 RPM. Raw vibration data collected from the bearings will possess many different types of noise, interruption, unfavorable impact, and noise caused by the environment. The raw data (vibration signals) that is collected typically has a very high noise level and due to the noise interfering with the vibration signatures will require several different types of filters to be applied for signal smoothing, denoising, normalization and segmentation [7].For the purpose of providing the data to the machine learning model, the vibration signals will be separated into smaller windows/samples so that each individual sample may be used to provide a unique instance of training data to the machine learning models [8].

The third and most important step is featuring extraction. Instead of directly giving the raw signal to the model, useful statistical information is extracted from the signal. These features help the model understand the fault pattern more clearly.

RMS (Root Mean Square), Mean, Standard deviation, Kurtosis, Skewness, Peak value, Crest factor and Variance are some of the most widely used time-related features that describe how a vibration signal behaves in relation to its amplitude/peaks/spread. Typically, when a bearing is defective, the RMS values will be higher, which indicates that there are many repeated impacts and elevated kurtosis values [9].

Similarly, frequency-domain features are extracted using FFT (Fast Fourier Transform). This helps in identifying defect frequencies such as:

- BPFO → Ball Pass Frequency Outer race
- BPFI → Ball Pass Frequency Inner race
- BSF → Ball Spin Frequency
- FTF → Fundamental Train Frequency

These frequencies are very useful because each bearing fault type produces its own characteristic frequency signature.

Once features have been extracted, the next step in the process is feature selection and/or dimensionality reduction (DR). Numerous features can often be extracted, but do not necessarily have to provide useful or valuable information; as such, dimensional reduction techniques such as PCA (Principal Component Analysis) may be used to accomplish DR by eliminating the less important features from the analysis. This allows for an increase in the speed of computation time and the accuracy of models to be developed. Once a feature set has been developed; it is input into various machine learning algorithms for the purposes of classification [10].

Commonly used classification algorithms for bearing fault diagnosis include:

1. Support Vector Machine (SVM)
2. Random Forest
3. K-Nearest Neighbors (KNN)
4. Decision Tree
5. Logistic Regression
6. Artificial Neural Network (ANN)

SVM and Random Forests have become common reference techniques in the work of this study. This is due to their capability of modelling both simple and complicated vibration characteristics and patterns. An example of an application for the two techniques would be training a machine learning model to classify vibration signals into classes; for example, health bearing, outer race defect, inner race defect and ball defect or combination thereof. During the process of training ('learning'), the machine learning model will learn how to associate extracted feature(s) from vibration data with fault condition(s). After training has been completed, models testing will occur using unseen data, in order to determine performance of the models. The performance metrics used for evaluating how accurately the models identify fault(s) on bearings are: Accuracy, Precision, Recall, F1 score, and Confusion Matrix. In addition to SVM and Random Forests, other new technologies (i.e. deep learning) such as CNN, LSTM and Transformer type models are being utilized within recently published research due to their ability to directly learn features from raw vibration data (or signal). Automatic learning of features improves the accuracy of the fault detection process, particularly for complicated defect(s) and machine speed that is not constant during operation.

8. CONCLUSION

This research has developed a system that uses machine learning to monitor the condition of Deep Groove Ball Bearings (DGBB). There were three major phases to the method: feature extraction, feature selection, and classification. After collecting vibration data from healthy and defective bearings at different operating speeds and conditions, the objective was to find the right combination of features and machine learning models to accurately identify faulty bearings. Various types of defects (inner race, outer race, ball defects, and combined faults) were examined to observe their respective vibration patterns as well. Testing of the model on blind/unseen datasets has shown that the system can be used reliably in real-world situations. Overall, the machine learning process provides a smart way to detect the fault early in a Bearing, thus improving the machine's performance and reducing unexpected breakdowns. Thus, the ML method described is similar to an intelligent diagnostic tool that learns how to identify faults in bearings from previous vibration data and can automatically identify faults in real-time. As such, this will lead to earlier detection of faults, predictive maintenance, reduced downtime, and increased reliability.

A vibration signal pattern can easily be identified from a standard bearing because of the smoothness and regularity of it due to the rolling elements travelling smoothly over both races without any damage interfering with their motion. The result is that the machine exhibits quietness and low noise or vibration due to this factor. In contrast, a defective bearing will show a variety of different vibration characteristics depending on the type of defect present. For example, with an inner race defect, since the damaged area rotates with the shaft, the resulting vibration signal would be much more irregular in nature and would have a denser distribution of amplitude than that of a normal bearing - exhibiting peaks distributed throughout the signal. For instances of outer race defects, since the fault is located in a fixed position, the resulting vibration signals would display distinct peaks occurring at periodic intervals as the rolling elements of the bearings travel across the defect. Finally, ball defects would result in vibration signals that are much more random and exhibit different timing relationships with each race, resulting in intermittent amplitude peaks occurring as the balls travel over each race in succession.

In summary, the differences between normal and defective bearings with respect to their vibration signals provide sufficient information to perform successful fault identification using vibration analysis and machine learning methods for early detection and prevention of costly failures.

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