Fault Behaviour Pattern Analysis and Recognition

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***Abstract*— The dynamics of a faulty gearbox that includes the rolling bearings element allows the engineer and the analyst to study the behavior of damaged parts and collect the data so as to analyze the defect. This helps to recognize it without bearing the cost of actual failures in real time. In this case study, a tiny hardware setup has been used for emulating the similar behavior of a gearbox and the same has been used for analysis with k-Means unsupervised machine learning model for in depth diagnostics of the device.**

Keywords— faulty parameters; bearing fault diagnosis; k-means; diagnostics.

I. INTRODUCTION

There are multiple methods in identifying the vibration fault pattern data of the bearing faults. This helps to determine either the normal working condition or abnormal state condition. The abnormal condition further can be classified by in-depth analysis of the faulty pattern so as to determine the type of bearing fault. The methodology of processing a signal can be done in different ways such as (a) time domain, (b) frequency domain and (c) time-frequency methods referenced with [1; 2]. In time domain analysis descriptive statistics such as mean and kurtosis of the time series signals are computed to determine the bearing faults. Applied auto-regressive modeling has been applied along with vibration time series [13] analysis along with neural networks model for bearing fault detection. Whereas in frequency domain, the application of the Fast Fourier Transform (FFT) of the vibration signal is done to process the signal and identify fault frequencies.

A failure pattern of a device is generally investigated more based on its pattern of occurrence. This would help to further derive the root cause of the fault too. In this case, the primary objective is to detect the features and predict the fault in a gearbox. Further, classify the type of defect in depth applying clustering based machine learning algorithm commonly known as K-means.

The failure pattern of the instrument is listed out based on it criticality. In this case study it segregated in to differ the types of faults, so as to identify the root cause of the defect of the fault detected.

II. LITERATURE REVIEW

A rolling-element bearing is generally composed of two rings, between which a set of balls rotate in raceways. In most cases, bearing failures are the result of material fatigue of the bearings too. The repetitive impacts between the components of the bearing and the faulted or fatigue surfaces cause the cracks to gradually propagate and expand, generating an increase in vibrations to the rolling elements.

The condition monitoring based techniques have been widely applied to determine a large variety of faults such as broken rotor bars [6] , windings that have been shorted, bearing faults [8], load faults, etc. Maintaining the Integrity of the Specifications

The pattern of the signal availed on vibration consists of multiple oscillated patterns wherein each pass of the moving component over the fault [9]. The repetition frequency of the impact depends on the position of the fault. The fault could be on the inner race, the outer race or on the rolling element.

Although, condition monitoring techniques such as vibration analysis has been utilized widely for the diagnosis of the bearings, most of the evaluated papers have used the stator current analysis, due to its own advantages.

The methods used for stator current analysis decompose and analyze the signal using multiple techniques such as Fourier analysis, wavelets, and later machine learning analytical models to discriminate the type of faults and get the deeper insight.

Fast-Fourier Transform is an established technique to convert data from the time-domain to frequency-domain for detailed analysis. It is difficult to detect bearing fault frequencies in FFT spectrum of the vibration signal [10]. However, some researchers have applied successfully [11], [12]. Furthermore, envelope analysis spectrum using Hilbert transform can provide better result to locate fault frequencies and its resonances.

III. PROPOSED ARCHITECTURE AND DATA OBSERVATION METHODOLOGY

The architecture of the hardware setup used to emulate the different fault scenarios for the data analysis and processing. Following are the enlisted parameters that are required at different conditions:-

- Rotor Velocity
- Rotor Mass
- Bearing Size
- Load applied on the shaft
- Voltage , Current variations
- Torque

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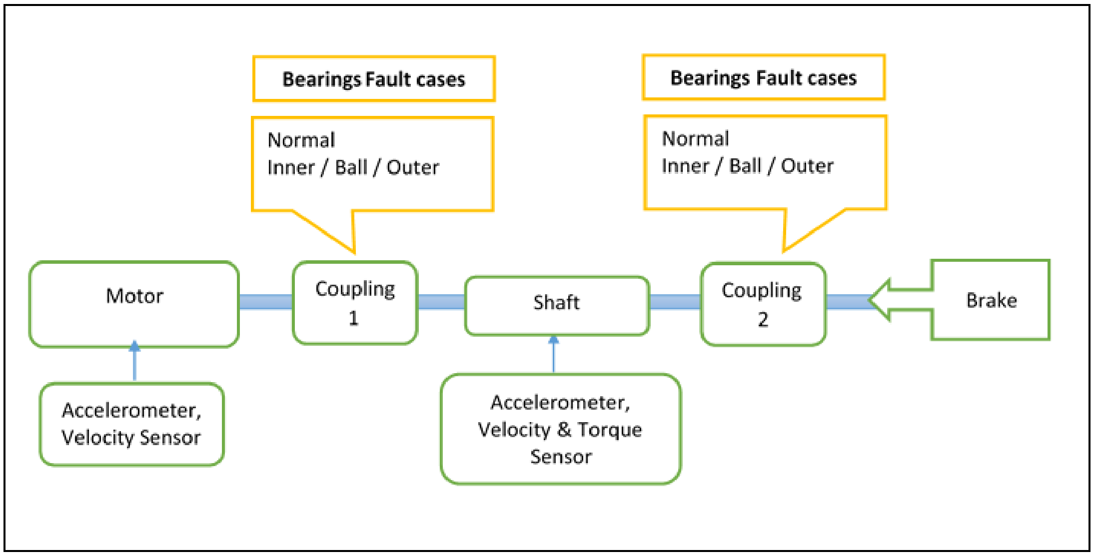

Figure 1:- Architectural layout of the hardware fault simulator for Vibration Analysis

The above figure 1 illustrates the concept of the fault simulator architecture so as to emulate the normal and fault conditions, and take the observations to proceed with fault pattern analysis. The different fault bearings cased were connected via the coupler to the motor shaft.

IV. Evaluation Of Data

A. Signal Processing

The processing of the signal is vital here as the characteristics of the signal cannot be analyzed in the time domain. Hence, this should be applied in such a way that the time history of the signal is retrieved.

The accelerometer sensor ADXL340 [4] measures acceleration i.e. measurement of dynamic acceleration caused due to vibration. The observed output voltages are proportional to the acceleration.

The concept of the Fourier Theorem, states that all signal waveforms, no matter however complex they are, can be expressed as sum of sine waves of varying amplitudes, frequency, and phase. A window of a signal can be considered so as to divide a complex signal waveform into small sections, and perform analysis of the signal using the enveloped sine waveforms.

Envelope Detection is the approach of extracting the modulating signal from an amplitude modulated signal. The repeated impulse type signals during the demodulation of the signal are identified in this detection using Hilbert transform.

Envelope Analysis is the FFT (Fast Fourier Transform) frequency spectrum of the modulating signal. Frequencies within the spectrum Figure 2 shall be correlated with device characteristics, and based on their peak amplitudes the faults are derived.

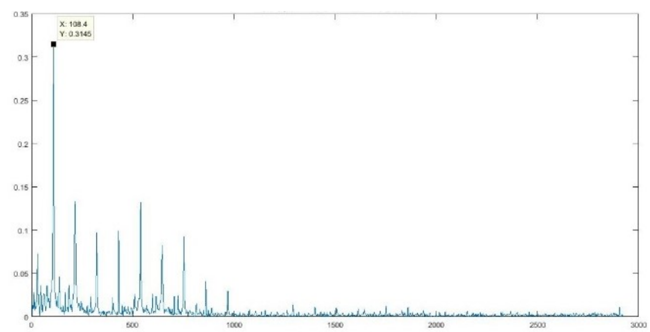

Figure 2: Frequecy spectrum Plot of Hilbert Transform

B. K-Means Clustering Model

In this case study, K-Means has been used as it is one of the popular unsupervised learning model which groups the common features extracted internally and groups them into number of clusters labels specified accordingly.

K-Means finds the best centroids and the data points closer to each of them are grouped as clusters.

1. Initialize **cluster centroids** $\mu_1, \mu_2, \ldots, \mu_k \in \mathbb{R}^n$ randomly.
2. Repeat until convergence: {

   For every i, set
   $$c^{(i)} := \arg\min_j ||x^{(i)} - \mu_j||^2.$$
   For each j, set
   $$\mu_j := \frac{\sum_{i=1}^m 1\{c^{(i)} = j\} x^{(i)}}{\sum_{i=1}^m 1\{c^{(i)} = j\}}.$$
   }

Figure 3:- Psedo code of K-Means Algorithm [2]

The standard k-Means algorithm pseudo code stated by Stanford [2] has been shown in the figure 3.

The Fault Pattern Analysis applying the K-Means Model has been explained using the flowchart shown in the figure 4.

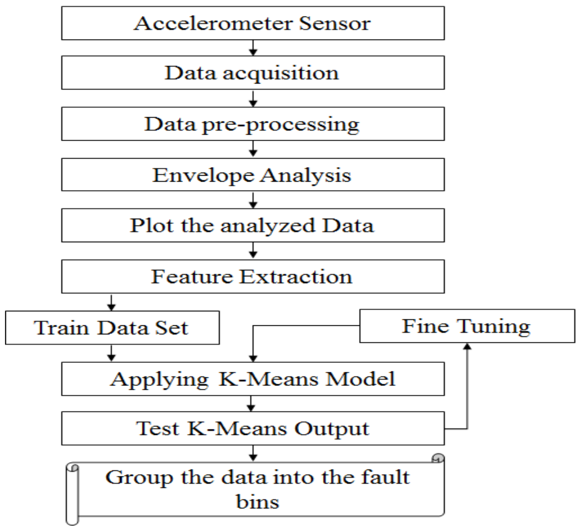

Figure 4:- Flowchart showing the signal data processing applied in this Fault Pattern Analysis

C. *K-Means Evaluated results*

During this analysis, different scenarios of all the fault case patterns have been emulated and evaluated by processing the signal and extracting the key features. This further helps to get the deep insight of the faults and classify them accordingly. The labelled faults grouped as cluster have been enlisted below in Table 1.

TABLE 1. Classification of Fault Labels grouped as cluster in the K-Mean Model

S No	Labelled faults
1	Inner
2	Ball
3	Outer
4	Normal

From the evaluated results few significant categorized results using k-means model have been listed below in Table 2.

TABLE 2. Sample Set of the results evaluated using K-Means Model

Case	Freq.	Amp.	Actual	Predicted
8	76.17188	0.067902	Ball	Ball
21	161.1328	0.146043	Inner	Inner
22	87.89063	0.142216	Inner	Outer
23	158.2031	0.165434	Inner	Inner
29	131.8359	0.054599	Outer	Outer
30	17.57813	0.056189	Outer	Outer
31	17.57813	0.078937	Outer	Outer
32	251.9531	0.049055	Outer	Inner

The prediction accuracy of the model evaluated with the existing data applying k-means model arrived at 82 %.

CONCLUSION

This paper projects the evaluation of the gearbox diagnostics based on fault pattern analysis of the rolling bearings. In this approach, post signal processing categorization of bearing faults has been performed using the K-Means based clustering approach to get the insights of the faults for in depth.

FUTURE ENHANCEMENTS

The initial data signal analysis and feature extraction the K-Means machine learning model has been chosen and applied so as to categorize the type of fault. This shall be further evaluated with other models so as to compare and increase the performance of recognizing the fault patterns of the devices.

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