

Vibration Based Breakdown Prediction for High Speed Centrifuge Systems

Vikram B Baliga¹, Mahesh Rao²

^{1,2} *Department of ECE, MIT, Mysore, Karnataka, India*

Abstract- To understand the health of rotating machineries one of the method used is vibration analysis. Perfectly balanced rotating machineries do not vibrate when running. They vibrate when they are not well-balanced. A breakdown may also occur when they are unbalanced. Hence vibration monitoring and gathering the data can give vital information on the health of the machine. Real-time monitoring of the vibration signal is required to prevent the machine from any kind of breakdown. This kind of analysis requires prior knowledge and data of the machine or the parts under consideration. This paper explains how breakdowns can be predicted using only the vibration data of a machine, whose structural data or parameters are not available. Proposed here is a complete system including hardware with a vibration sensor, to acquire data and a software that not only visualises the vibration in real time, but also can predict the crash and takes action like switching off the machine or alerting the user about it. Here, frequency analysis and simple time domain analysis of the vibration data of a recorded breakdown event is used to predict further breakdowns.

Keywords- breakdown detection; breakdown prediction; vibration monitoring; vibration analysis; high speed centrifuge.

I. INTRODUCTION

Vibration analysis of rotating machinery is a method which can be used to determine faults in the system. Vibration data is analysed in both time and frequency domain to obtain estimate of health. Typically machines are mounted on bearings and it is the lack of balance of these bearings which could result in vibration. Typically these machines run at 800 to 8000 revolutions per minute (rpm), however there are special purpose motors which could be running at higher RPMs like the hard disc motors of computers which could be at 10,000 and above rpm. Some special purpose centrifuge motors could be running at much higher speeds.

Bearing fault detection is one of the most important case where vibration analysis is used. The fundamental frequencies of the bearing which are geometry dependent are calculated and their relative amplitudes are measured to get an estimate of the bearing health as explained in [1] and [2]. Another approach of above method has been explained in [3]. In [4] the statistical properties of the recorded data of the bearings of different types at different speeds are used to train a pattern classifier for classifying the remaining data. In [5], two unique methods of detecting fault in centrifugal pumps are presented. In first method, using Principle Component

Analysis (PCA), different type of faults like impeller failure, seal failure, etc. are identified. In the second an Artificial Immune system is used to predict the remaining life of the machinery when a fault is detected. Feature extraction scheme for vibrational signals, which also involves data compression is explained in [6], where Daubechies' wavelets are used. In [7] wavelet packets are used rather than fundamental wavelets. Wavelet packets are combination of multiple basic wavelets. The usual procedure of wavelet decomposition is then performed on this combination of wavelets.

While fault detection techniques for bearings are based on frequency analysis, fault detection models for centrifugal pumps are also developed in similar manner. A method to determine cracks in the impeller has been explained by determining magnitudes of impeller frequencies and its harmonics in [8] and [9]. Along with frequency measurement method, the current flow through the pump is also used to determine faults as explained in [10]. Many other rotating machines use similar approach. Diagnosis of induction motors using wavelet decomposition method is implemented in [11].

As mentioned above, not just frequency analysis, but analysis in time domain is also used to detect faults. In [12] analysis of time series is performed to determine the health of the experimental structure. Here the system is modelled using AR and ARX models. Using these models along with residual errors in data, good estimate of the structural health is obtained. In [13] using AR and ARX models, finding the location as well as occurrence of the damage in buildings up to 5 floors is implemented.

Another analysis technique is where vibrations of the machine is modelled and an equation that best describes the vibration pattern is determined. These equations are solved using deferential transform method (DTM) to obtain the parameters for safe operation. In cases where DTM is implemented for highly non-linear systems, comparison with well-known numerical methods like Range-Kutta techniques show good results as explained in [14]. In [15], DTM is used on time series of vibration data to solve modelled equations of pipes which convey fluid to determine its status. In [16], DTM is used on vibrations of a rotating centrifugal beam to obtain its prominent frequencies. These obtained frequencies have found to coincide with the natural frequencies of the beam with good accuracy. Thus, by acquiring the vibration data of

machine, DTM can be used to limit parameters like of machine like load, speed, etc. to keep the machine working in safe limits.

A few more techniques implemented are the use of transformations like Hilbert transform as shown in [17] and Morlet transform in [18]; use of fuzzy logic and neural networks for prediction as shown in [19] for centrifugal pumps using velocity and displacement as the features and in [20] as an adaptive kind of neural networks called dynamic evolving neural-fuzzy inference system which learns and alters itself based on previous data sets was used. In [21], multiple bearings were run under measured environment until they failed. The vibration data of these bearings were used as a training set for neural network to predict amount of degradation and remaining life of the bearings.

In [22], Local Mean Decomposition was used on vibration data of shearer used in the coal mines to obtain functions called product functions (PF). These PF's are simple time domain and frequency domain equations which give rather strong information on the data. PF's were used to extract features and perform pattern recognition for shearer cutting status. The pattern recognition was performed using fuzzy C mean clustering.

Vibration data required for the monitoring is acquired using accelerometer. Accelerometers are transducers that measure acceleration of the body they are fixed on. Most common types of accelerometers currently used consist of piezoelectric, capacitive or MEMS components to measure mechanical movements. Proper placement of these sensors play a vital role in vibration monitoring. In [9] and [10] intrusive type of accelerometers are used where a hole is drilled to the body of the machine to mount the sensor. The non-intrusive types used in [2, 8, 11 and 12], require the sensor to be firmly fixed to the body of the machine using adhesives.

Finally, using more than 250 references, [23] classifies and summarises the main methods used for vibration based health monitoring as Natural Frequency Based Methods, Mode Shape Based Methods, Mode Shape Curvature/Strain Mode Shape Based Methods, Dynamically Measured Flexibility Based Methods, Matrix Update Based Methods, Non-linear Methods, Neural Network Based Methods and Other Methods. [24] Mentions in detail, the widely used methods. For rotating machineries like Hydro Turbine Units, Large Francis Turbine Units, Oil Pumps, Reactor Coolant Pump, etc. efficient health monitoring systems are explained in detail including specifications of accelerometers, parameters of the machines and results. Whereas [25] concentrates mainly on cracks in rotating parts of the machinery like rotors, shafts and beams. It describes and compares many previous techniques used to identify the cracks and their severity. It also mentions some theories used in the techniques like the cracked Euler-Bernoulli beam

vibration theory, the continuous cracked beam theory, continuous cracked bar vibration theory, etc. The fundamentals of the theories along with their application in the particular technique to identify the cracks are explained in detail.

II. PROBLEM STATEMENT

The centrifuge systems rotating with very high speed, breakdown because of various factors. Because of their high speed, the damages due to breakdown are huge. A system had to be developed to understand the failure of high speed machines. The system has to be non-intrusive, should constantly monitor and has to provide a means, if possible, to predict the failure.

Vibration is caused by the unbalanced rotor and that causes the majority or all of the breakdown in such systems while operating. This vibration grows in amplitude as it approaches the break down to huge value. Due to this unbalanced load, the torque required to maintain the speed increases and the current consumed by the motor also increases from the steady state value. While breakdowns are indicated by increased current consumption, initial faults and defective parts can be identified by sidebands in the current spectrum as explained in [10]. It shows that defects and breakdowns can be monitored using vibration analysis and/or current signature analysis. This paper concentrates only on vibration analysis to monitor and predict the breakdown.

III. PROPOSED WORK

The system mentioned here consists of a hardware and associated software. The hardware contains a high gravitational force (g) accelerometer interfaced with a microcontroller, which measures and transmits vibration at a rate of 1 kHz. The associated software receives the data from the hardware, plots it in real time and saves it in the computer hard drive. The main objective of the system is to predict when the device under surveillance is going to breakdown and perform controlling actions like switching it off. The breakdown vibration threshold is set to 370 g. That is vibrations, which produce acceleration up to 370 g, are acceptable and are not considered as crash events. A simple method is to keep measuring acceleration and switch off the machine as and when very high vibrations crossing the threshold are encountered. This paper focuses on analysing the vibrations to predict accurately that the vibration is going to increase in near future, which might result in the crash and henceforth switch off the machine before the breakdown event occurs. A solid-state relay (SSR) is used as the output device to which the machine is to be connected. This SSR switches off the machine when the system predicts that a breakdown of machine is going to happen. The technique used to predict is simple frequency and time domain analysis based on a previous data set of the same machine during the occurrence of breakdown. The same hardware was used to record

vibration data when the breakdown took place. Since detection of faulty parts of the machine or identification of source of the breakdown is not the aim of this work, much importance is given to prevention of breakdown. Based on analysis of this data, the prediction system is built which predicts the breakdown based on certain parameters.

IV. EXPERIMENTAL OBSERVATIONS

The above mentioned vibration sensor hardware was attached to the machine and the data was continuously recorded as well as monitored by the associated software for a long period of time. The machine was run until its breakdown. The last 13 seconds of the recorded data before the breakdown is of importance. This data contains acceleration values of the machine when it was running smoothly and when finally the breakdown occurred. The acceleration was recorded in all the 3 axis at a rate of 1000 samples per second. The specifics of the machinery like its structural information or models, or the geometrical data of its load carrying elements like bearings or any other data are unknown or not available. The data recorded from the machine is stored in the PC and analysed in MATLAB. The noise is filtered using 'sym4' wavelet decomposition present in MATLAB. Figure 1 shows the time domain acceleration waveform in the Z axis. The frequency spectrum of the recorded data in Z axis during normal operation is shown in Figure 2.

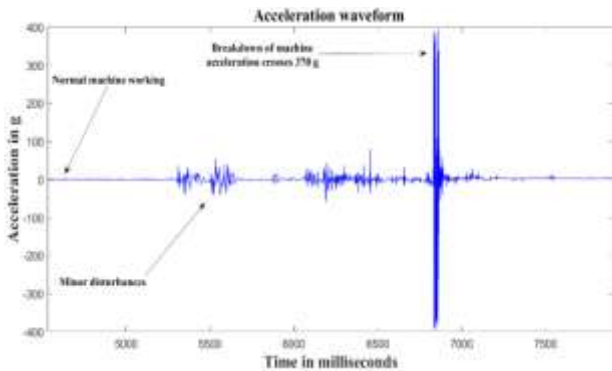


Figure 1. Vibration data in Z axis.

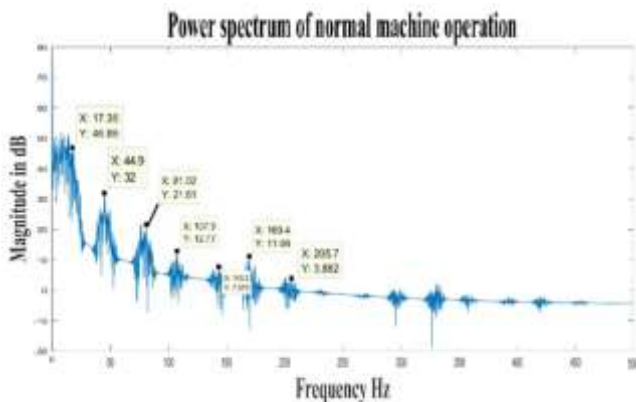


Figure 2. Spectrum of data when machine is operating normally

The spectrum of normal machine operation vibration shows the presence of clusters of frequencies with decreasing amount. These major frequency groups in the 40 dB range are placed alternatively at a distance of 26 Hz and 36 Hz from each other.

The spectrum of the full data including the breakdown event is shown in Figure 3. The spectrum is now made up of wide range of frequencies. Since not much of information can be collected from these spectrums, prediction of data from the frequency domain data is not feasible. Only the breakdown status can be detected using this spectrum.

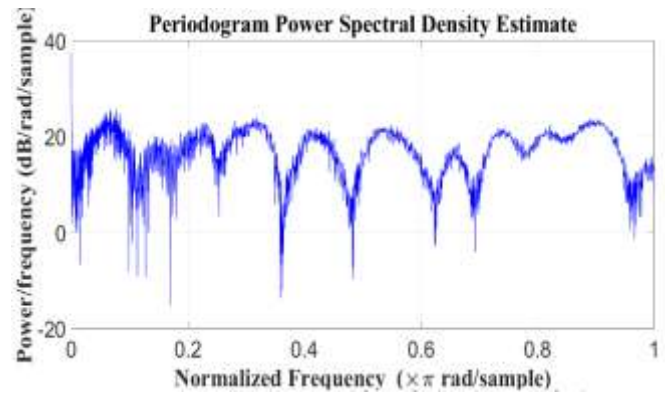


Figure 3. Spectrum of data including the breakdown event

Observing the time domain data, there are several distinct vibration groups as seen from the plot in Figure 1. The first disturbances or obstruction in the rotating machinery cause the first set of vibrations. But the machine stabilises itself and the vibration intensity decreases in 200ms. Similar events take place a few more times before the breakdown of the machine happens. Any vibrations less than the threshold of 370 g are permissible which indicate the machine need not be switched off. In the last part, the vibrations increase above the threshold causing damage and breakdown of the system.

V. METHODOLOGY

Vibration is an oscillatory or a continuous to and fro motion from a base position. Velocity and the direction of velocity of the vibrating body keeps changing rapidly. As there is change in velocity, there is an acceleration in the respective direction. Thus it is intuitive that the amplitude of acceleration signal gives us a fair measure of vibration of the machine. A high frequency acceleration waveform or a waveform with higher number of zero crossing, implies that there is a faster change in the direction of velocity. Which means there is a fast to and fro motion which in turn means the displacement of the body from the base position is lesser. While lower zero crossings in acceleration data means that the change of direction of velocity is slower. Thus the displacement is larger from the base position. Thus, not just the amplitude of the

acceleration signal, but also the frequency of the acceleration signal gives a fair measure of the intensity of the vibration.

As observed from the acceleration data in Figure 4, just before the breakdown event, there is an acceleration in negetivedirection itslef without any zero crossingfor about 18ms. This indicatesthat the velocity is in the same direction for a prolonged period of timeand results in a larger displacement from the base positon.This creates huge imbalanace and results in the machine’s breakdown. Thus low frequency vibration signal or vibration signal with a lower zero crossing rate is found to be the reason for the breakdown of the machine. Along with frequency domain analysis for breakdown detection, time domain analysis is used for breakdown prediction.

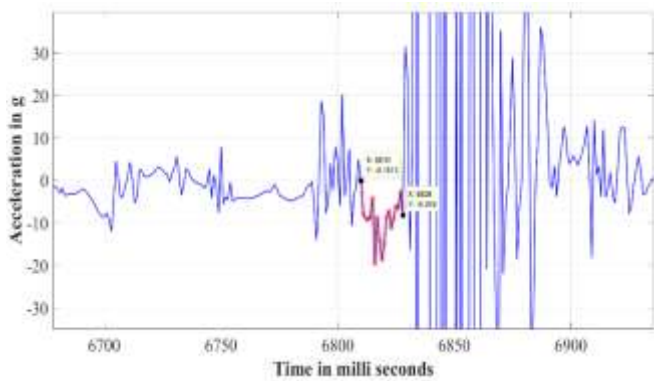


Figure 4. Highlighted portion of prolonged acceleration in a same direction

The parameters selected for prediction of a breakdown are sum of the acceleration and number of zero crossings. The ratio for these paramteters, i.e sum of acceleration or total acceleration over a interval of time divided by number of zero crossings in the same interval, gives a fairly practical estimate of the amount of displacement in the machines vibrational movement. The above mentioned interval must be selected optimumly as too large or a too small interval gives very less or no information at all about the dispalcement.

Here, based on the recorded data,the interval is chosen to be 20ms or 20 samples. Thus parameters are calculated for a period of 20 samples and compared with a threshold based on the given data. Since calculations are easier and faster to perform, values can be calculated before the next 20 samples are received and thus there are no overheads.

The sum , S is given by

$$S(n) = \sum_{k=n-19}^n x(n)$$

The zero crossing, Z is given by

$$Z(n) = \sum_{k=n-19}^n |w(n) - w(n - 1)|$$

Where,

$$w(n) = 1, \text{ if } x(n) > 0, \quad \text{else,} \quad w(n) = 0$$

The ratio, S by Z is calculated and compared with a threshold value. Any value greater than the threshold would indicate higher vibrational displacement that causes the breakdown. This threshold value is to be obtained from the training data sets.

Figure. 5 shows a plot of the ratio for normal operation of the machine. The plot in Figure. 6 is a zoomed in plot of the ration near the disturbance regions. Plot of the ratio along with the vibration data for the both normal operation and the breakdown is shown in Figure. 7. It is seen that this ratio reached a peak only five samples before the acceleration crossed the 370g threshold. Amplitude of no other peaks of the ratio has crossed the amplitude of peak before the breakdown. Thus the amplitude of this peak is taken as the threshold. It can now be said that whenever the ratio approaches the threshold, a breakdown takes place in the next few samples. The accuracy of the prediction is to be increased by performing the same calculations on large number of test data set and obtaining the thresholds. After a good approximate of the threshold is obtained, the above procedure must be implemented in the hardware.

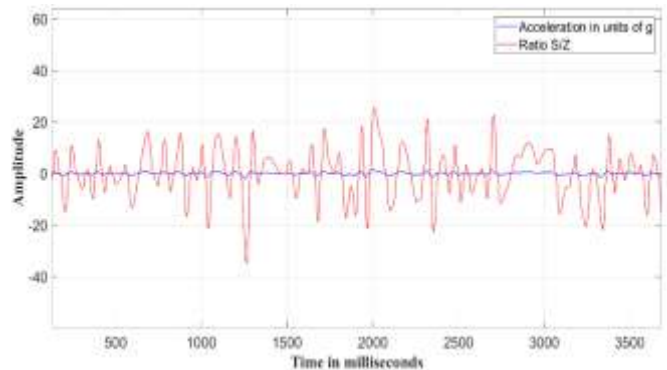


Figure 5. Plot of the ratio along with acceleration for normal machine working

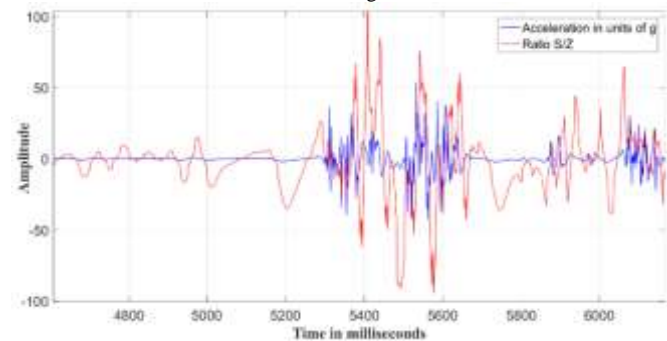


Figure 6. Plot of the ratio along with normal working and disturbances

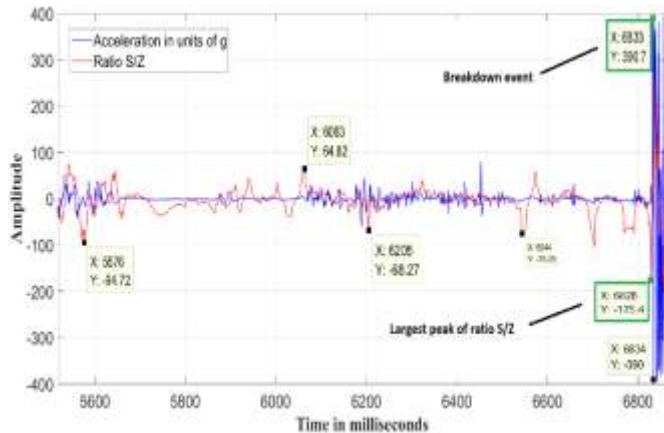


Figure 7. Plot of the ratio at the break down event

The training part is manually performed using the same hardware to acquire breakdown data and store them in the PC. During the training procedure, the microcontroller simply reads and transmits the data to the software in the PC. On obtaining the threshold, the microcontroller is reprogrammed to not only measure and transmit the acceleration, but also calculate the ratio for every 20 samples and compare it with the determined threshold. On crossing the threshold, the SSR will be instantly switched OFF in order to stop the machines operation. As a result, breakdown prediction will be performed completely by the hardware without any dependence on the computer. The hardware can be connected or disconnected from the PC as and when required, while the prediction system will be working uninterruptedly.

VI. CONCLUSION

Even when parameters like fundamental frequencies, the structural model, physical characteristics, etc. of the machine to be monitored are available, other typical methods involve a computationally expensive procedure. These calculations involved in typical methods cannot be easily implemented on readily available general purpose microcontrollers and require a computer preloaded with software or dedicated computational systems. These requirements pose as a disadvantage in the actual machinery sites and such methods cannot be easily implemented in practise for real-time breakdown prediction. Is such an environment, a compact module, independent of any larger machine is a reliable option. The prediction system explained above, can be easily trained, based only on the vibration signals, and implemented in simple embedded circuits. Using this method, breakdowns can also be accurately predicted. Since there are no complex mathematical calculations, the overheads between measuring and evaluating is eliminated and breakdowns are predicted in real-time with a better reliability.

ACKNOWLEDGEMENT

Authors wish to thank Mr. Paramesh Bhat of Aashaya design solutions for his help in the design of the hardware. Without that help, project would not have been successful.

REFERENCES

- [1]. An Overview on Vibration Analysis Techniques for the Diagnosis of Rolling Element Bearing Faults, ShyamPatidar, Pradeep Kumar Soni, IJETT, May 2013
- [2]. Faults Detection and Failures Prediction Using Vibration Analysis Tristan Plante, AshkanNejadpak, and Cai Xia Yang, University of North Dakota, Grand Forks.
- [3]. Automatic Bearing Fault Pattern Recognition using Vibration Signal Analysis, E. Mendel, et al, Federal University of Esp'rito Santo.
- [4]. Statistical analysis of vibration signals for condition monitoring of defects in rolling element bearings, Almeida, Fabiano Ribeiro do Vale, International Congress of Mechanical Engineering, 2005.
- [5]. Fault detection and prediction with application to rotating machinery Gary R. Halligan, International Journal of Advanced Manufacturing Technology, 2009.
- [6]. Wavelet based compression and feature selection for vibration analysis, W. J. Stazewski, Journal of Sound and Vibration ,1998.
- [7]. Wavelet Packet Feature Extraction for Vibration Monitoring Gary G. Yen, IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, 2000.
- [8]. Vibration based fault diagnosis of monoblock centrifugal pump using decision tree N.R. Sakthivel , V. Sugumaran , S. Babudevasenapati 13
- [9]. Centrifugal Pump Impeller Crack Detection Using Vibration Analysis Waleed Abdulkarem, RajakannuAmuthakkannan, and Khalid F. Al-Raheem, International Conference on Research in Science, Engineering and Technology,2014.
- [10]. Fault detection in a centrifugal pump using vibration and motor current signature analysis, Kumar Pradhan, Prasanta, International Journal of Automation and Control,2012.
- [11]. Vibration Signature Analysis for Rotor Broken Bar Diagnosis in Double Cage Induction Motor Drives, Y. Grifli, A. O. Di Tommaso.International Conference on Power Engineering, Energy and Electrical Drives,2013.
- [12]. Damage diagnosis using time series analysis of vibration signals, Hoon Sohn and Charles R Farrar, INSTITUTE OF PHYSICS PUBLISHING,2001
- [13]. Vibration-based damage detection using time series analysis t. Kuroiwa I and h. Iemura, World Conference on Earthquake Engineering, 2008,
- [14]. Analysis of the Response of a Strongly Nonlinear Damped System using a Differential Transformation Technique, Ming-Jyi Jang, National Cheng-Kung University Tainan, Taiwan.
- [15]. Application of the differential transformation method to vibration analysis of pipes conveying fluid, Q. Ni, Z.L. Zhang , L. WanG, Applied Mathematics and Computation, ScienceDirect,2011.
- [16]. Application of differential transformation technique to free vibration analysis of a centrifugally stiffened beam C. Mei, ELSEVIER, Computers and structures, 2008.
- [17]. Vibration Signature analysis of Centrifugal Pump through Pattern Recognition System, Biruduganti Rahul. IJERIT, 2014.
- [18]. DENFIS: Dynamic Evolving Neural-Fuzzy Inference System and Its Application for Time-Series Prediction Nikola K. Kasabov, Senior Member, IEEE, and Qun Song, IEEE TRANSACTIONS ON FUZZY SYSTEMS,2002.

- [19]. Feature extraction based on morlet wavelet and its application for mechanical fault diagnosis, Jing Lin and Liang sheng Qu, Journal of Sound and Vibration, 2000.
- [20]. Non-linear system vibration analysis using Hilbert transform, Michael Feldman, Mechanical Systems and signal processing, Israel Institute of Technology, 1994.
- [21]. Residual Life Predictions From Vibration-Based Degradation Signals: A Neural Network Approach, NagiGebraeel, Mark Lawley, Member, IEEE, R. Liu, and Vijay Parmeshwaran, IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, VOL. 51, NO. 3, JUNE 2004.
- [22]. Vibration-Based Signal Analysis for Shearer Cutting Status Recognition Based on Local Mean Decomposition and Fuzzy C-Means Clustering, Lei Si, Zhongbin Wang, Chao Tan, and Xinhua Liu, Applied Sciences, MDPI, 2017.
- [23]. Vibration Based Condition Monitoring: A Review E. Peter Carden and Paul Fanning, Structural Health Monitoring, Sage Publications, Vol 3(4): 0355–377, 2004.
- [24]. Vibration-Based Condition Monitoring, Y. Wu et al., Vibration of Hydraulic Machinery, Mechanisms and Machine Science 11, Springer Science Business Media Dordrecht, 2013.
- [25]. VIBRATION OF CRACKED STRUCTURES: A STATE OF THE ART REVIEW ANDREW D. DIMAROGONAS, Engineering Fracture Mechanics Vol. 55, No. 5, pp. 831-857, Elsevier Science, 1996.