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Optimizing Rotary Machine Reliability through Condition-Based Monitoring and Predictive Maintenance Strategies

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Abstract

Rotary machines have a natural process of creating vibrations, which makes the important parts of the machine worn out, especially bearings and gears which will end up causing failure of the system. It is commonly accepted that Vibration analysis is the most popular diagnostic tool that is currently used to examine the condition of machinery and offer suggestions on maintenance policy. The last element of proactive maintenance strategies is condition-based maintenance (CBM), which maximizes the availability of machines by applying timely interventions and reducing expensive breakdowns. This study project seeks to develop an extensive system that will facilitate the assessment of the working condition of the rotary equipment and the most significant parts of it, particularly focus on bearings. The two are interdependent as a well-maintained machine will need less care and a machine in the process of degradation needs quick action taken. The rotary machines are very important in many industrial pr ocesses and thus find heavy challenges due to bearing problems. The difficulties cause significant disturbances to the production process and increase the cost of maintenance. The paper at hand investigates the effectiveness of CBM as a possible remedy of the abovementioned problems. CBM is a maintenance technique that makes use of real-time machine information to make informed decisions on what to do concerning the maintenance. Through this strategy, maintenance tasks would be implemented at the most appropriate time, which would be the most efficient and effective. CBM is a planning method that enables the businesses to take a proactive initiative to counter the failure, enhance maintenance schedules, and general efficiency of the business by properly estimating the remaining periods of usage of machine parts. The research study is also adding knowledge to the existing knowledge on CBM and it provides useful insights on predictive maintenance, and its potential of improving the reliability and efficiency of rotary machinery.

Keywords: Condition-based maintenance, rotary machine, optimization, reliability.

I. INTRODUCTION

The aspect in this section will explain the importance of supporting the mechanical systems, such as reciprocating or pivoting parts, to ensure the reduction of vibrations, which is a central aspect of condition-based maintenance. Scholars are encouraged to observe and analyze these aspects in order to achieve high operational efficiency, reduce maintenance costs, improve structural integrity and reduce the chances of tragic failures in real time (Hess et al., 2001). Usually the most common cause of the vibrations in such systems is the imbalance or misalignment of the rotating parts. Vibration monitoring is performed to improve machinery integrity by measuring the characteristics of vibration i.e. amplitude, velocity, and acceleration. The most commonly used sensors are accelerators that can be used to measure the following attributes, and a change in the signals of vibrations can be used to signal a failure or faulty part of a machine. The predictive maintenance strategies are applied to forecast or detect issues and failures through the application of the patterns of the failures which have been established and thereby making it easy to take measures beforehand that will prevent contravention of the operations (Goyal, Vanraj, et al., 2017; Hasan et al., 2020). This paper is an in-depth analysis on various methods to vibration test monitoring and signal processing as an element of condition-hoping maintenance particularly to gears and bearings. This journal serves as a tool to a full degree of researchers working in the given field, and the main point of the publication is to promote the high-level research topics concerning condition-based maintenance.

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A. Breakdown Maintenance

The maintenance policy usually known as the run-until-failure policy implies that a certain piece of equipment is replaced once it has been affected by a complete failure. The specified methodology is used in the situations when the failure of a machine does not lead to serious human and financial consequences. It is to increase the time of the activity before the necessary shutdowns take place (Shipley, 1968). Nevertheless, the given methodology turns out to be the most unwanted as it is potentially unsafe and may cause harm to other equipment, as well as result in general decreased efficiency. The breakdown maintenance program has a few significant characteristics that are referred to as higher spending, high inventory at a cost of spares parts, overtime costs, longer time with no production, and less availability of production.

B. Preventive Maintenance

The said form of maintenance is sometimes referred to as time based or periodic maintenance. Nevertheless, it does help in decreasing the number of occurrences of unexpected malfunctions, nevertheless, it is usually considered to be economically inefficient. The basic premise of this methodology is that, it is possible to have a machine that can effectively perform the given tasks as long as it is taken through proper maintenance processes. However, the given methodology results in a drop in the productivity. It leaves a considerable possibility of introducing flaws, as it is often built only on the historical knowledge and experience. The main goal of the maintenance process will be to proactively improve the life cycle of the equipment by effectively monitoring the degradation process to a state that will be satisfactory. A number of parts have quite an unchanging rate of wear or degradation in time. Some of the elements though have significant statistical variation about the mean value like rolling element bearings. The resulting variation provides estimates e.g. as indicated in the above that have the average time until failure exceeding the minimum requirement by two or three times.

C. Condition-based Monitoring/Maintenance

Condition-based maintenance (CBM) is used to assess the current condition of the machine (machine condition monitoring) to ascertain the needed maintenance operations and predict the likely machine breakdowns. CBM emphasizes that doing maintenance should only be performed when there are some indicators of reduced performance or imminent failures of the machinery, in order to increase machine life, increase efficiency, decrease the daily operating costs, increase system quality, decrease maintenance effort, and get rid of human error (Gholap & Jaybhaye, 2020). Unlike CBM where the system triggers the process of maintenance, maintenance is a process of maintaining a system in operation. CBM condition monitoring data are the basis of planned CBM actions. CM is a vital component of CBM, which allows keeping machine parts timely and predetermines the most effective time of carrying out maintenance interventions. The study examines many condition monitoring measures of dynamic machine fault (Goyal & Pabla, 2016). CBM process involves a number of processes that include value such data collecting so as to get relevant data, data processing to assess and interpret signals and decision-making to integrate diagnostic and prognostic procedures to feed in useful maintenance recommendations. The primary goal of CBM is to study real-time data to detect any variation in functional parameters and detect abnormalities, which may lead to failures. Non-contact measures of vibration promise to a huger measure in predicting maintenance requirements and failure of machines (Jiang et al., 2021). The study offers a new typology of CBM methods in accordance with the type of data and data collection methods employed with having considered their relevant characteristics and requirements (Goyal & Pabla, 2016).
Prognostics in CBM (before failure and degradation have occurred) and diagnostics (after abnormalities have occurred) are related to fault isolation, identification and diagnosis. The three fundamental prognostic approaches are model based, data based, and hybrid prognostics (Abbasi et al., 2020). The research aims to diagnose and predict CBM patients and this is achieved through the introduction of logical analysis of data (LAD), a new technique of data processing a combination of both combinatorial and Boolean theories (Acernese et al., 2020).

II. LITERATURE REVIEW

This paper explores the importance of condition monitoring (CM) in the profession of mechanical engineering and particularly those of bearings and gears. CM has an excellent cost and time advantage because it minimizes the workload of scheduled checks, as well as the amount of downtime. The analysis of data during machine working is the priority and many parameters of vibrations are thoroughly analysed to identify the problems with the rolling type elements bearings. Ultrasound has already become a useful tool in identifying defects in the low speed bearings at the early stages of the defect. The fault diagnosis of gears, such as vibration analysis and ferromagnetic analysis is also discussed in the section. It brings to focus the artificial neural networks and support vector machines in classifying gear faults.

Besides, the section addresses how the speed and load affect acoustic emission (AE) in gear monitoring. It suggests the ways of estimating the remaining useful life (RUL) by monitoring AE signals. This is because the shortfalls of AE in identifying defects have been addressed, especially how temperature affects AE performance.

Condition Monitoring (CM) is a new technological paradigm, which enables the operators to minimize the number of planned inspections. The reduction in the inspection tasks prompts significant financial benefits, reduction in time obligations, and minimal operational disruptions. An all-round analysis of relevant academic literature in the field of mechanical engineering always indicates the need to identify and explain data changes that occur in operational performance of machinery in real, life circumstances.

Bearings, which are the essential elements of rotating machines, have a considerable amount of importance due to the possible negative consequences of any failure in rotating devices. Such shortcomings may result in temporary losses as well as in losses to the economy. Diagnostic evaluation of bearing defects is a very important issue that involves different industries including power generation and aerospace (Goyal & Pabla, 2016). To identify the abnormality in roller bearings, an empirical study has been carried out to find out the nature of vibration signal. The aim and scope of the current research study was to compare and contrast different parameters, that is, Root Mean Square (RMS), peak amplitude, crest factor and power spectrum parameters with the relevant measurements in healthy bearings of different dimensions (Goyal, Pabla, et al., 2017).

In addition, an extensive study was conducted with an aim of bewing the effectiveness of sound pressure microphones in identifying various conditions of equipment in the presence of high levels of ambient noise (Qiao et al., 2020). Findings of this research indicate that compared to other methods of machine diagnostics, including accelerometer measurements, sound pressure microphones are relatively insensitive to detection of some machine health indicators that include revolving ball bearings.

A comprehensive conceptual framework, moreover, has been formulated, which can estimate vibration frequencies and amplitudes of bearing faults that are localized in the outer race, in inner race or in one of the rolling elements. Current constructions include in full both radial and axial loads. An interesting observation was done in how the shaft speed affects statistical values that arise due to the vulnerability of the bearing housing elements to longitudinal vibrations. The explanation of the process involved in the formation of the vibrations and noise in bearings has also been discussed. The wavelet packet transform (WPT) has been widely recognized as an important tool in the accurate analysis of vibration signal that is as a result of defective bearings (Wang et al., 2022).

To conclude, the research by the authors is an elaborate study of the literature on the subject of vibration analysis and methods of analysis applied in detecting and characterizing defects in antifriction bearings (Jiang et al., 2021). The noise profiles obtained through the use of microphones on bearings, can give statistical measures that are mostly situated within the temporal domain. The meticulous time-series examination of signal related data can result in large amounts of useful information (Goyal, Vanraj, et al., 2017). The major approach is visual analysis on segments on the time-domain waveform. Besides, the use of advanced time-domain techniques, including the study of individual characteristic parameters has increased remarkably and has provoked significant interest. Use of time-domain statistical characteristics has been made as valuable signals and threshold parameters to extravagant detection of bearing failures. The expressions 1-6 can be successfully applied in the articulation of different statistical parameters of the temporal domain.

$$Peak = (max(y_k) - min(y_k)) \quad (1)$$

$$RMS = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(y_k)^2} \quad (2) \quad (2)$$

$$Crest\ \ Factor = \frac{y_{pk-pk}}{y_{rms}} \quad (3)$$

$$SD = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}(y_k - \bar{y})^2} \quad (4)$$

$$Kurtosis = \frac{N\sum_{k=1}^{N}(y_k-\bar{y})^4}{\left[\sum_{k=1}^{N}(y_k-\bar{y})^2\right]^2} \quad (5)$$

$$Skewnes = \frac{1}{N}\frac{\sum_{k=1}^{N}(y_k-\bar{y})^3}{\sigma^3} \quad (6)$$

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To normalize the circumstance, the squared difference is used. The strategy is outstanding in identifying spiky or impulsive signals. It has been demonstrated that form factor, clearance factor, and impulse indicator are important in using a Gaussian probability density model to simulate spalling events so that they can be representative of the real-world conditions. These properties give information particularly clearance and impulse indications. The clearance factor is the most complicated but dependable signal in case of spalling detection (Abbasi et al., 2020).

Also, previous studies have helped shed light on the relevance of sensor placement (Acernese et al., 2020; Wang et al., 2022). Gholap & Jaybhaye (2020) demonstrated that rolling element- bearing problem could be found by skewness and kurtosis (Gholap & Jaybhaye, 2020). Other studies have indicated that statistical features may be employed to compare vibration and ultrasonic prices with identifying abnormalities in low-speed bearings (Dixit et al., 2021; Habbouche et al., 2022). A peak factor and kurtosis works better at low speeds that are below 200 rpm. Bearing damage monitoring has been of interest to the statistical methodology described since it has a single and reliable result even when the factors of load and speed change.

This multi-modal and multi-purpose method may be applied to the maintenance and quality control. This paper deals with the subject of vibration feature extraction techniques of rotating machinery faults detection (Singh & Verma, 2021). The issue of ball bearings has been researched in order to advance localized fault detection (Adamsab, 2021). Of statistical indicators, kurtosis, skewness, and standard deviation can detect the problems of roller bearings in a brief time (Reference 21). Condition-Based Maintenance (CBM) software methods on the use of soft computing are also a point of interest (Naseer, Khan, Rasool, et al., 2023). As well, strong AI algorithms have been used to determine bearing challenges in both speed and load conditions (Naseer, Khan, Rasool, et al., 2023). The neural networks and transfer learning are also employed in new diagnostic techniques to find convolution-bearing defects in materials (Naseer, Khan, et al., 2023a). Signal processing algorithms such as variation mode decomposition (VMD) have received a significant amount of research (Naseer, Khan, et al., 2023b). Combined learning denoising capabilities and the flaw diagnosis method have had a comprehensive research on them (Altalbe et al., 2023). As demonstrated by Khan (2022), systems based on transfer learning, in regards to defect detection, are gaining more momentum (Khan et al., 2022). A wavelet packet decomposition (WPD) has been investigated and empirical wavelet transformation (EWT) has been used in order to assess therolling bearing early-stage challenges (Naseer, Khan, Rasool, et al., 2023; Syed Mohd Syafiq, 2022).

III. METHODOLOGY

Condition-Based Maintenance (CBM) is a type of maintenance strategy that relies on the concept of performing maintenance processes depending on the specific needs of a system. This strategy is associated with launching the maintenance activities whenever the foundational technology of the system shows that it requires care (Khoualdia et al., 2020). The use of data acquired via Condition Monitoring (CM) will significantly enhance the effectiveness of Condition-Based Maintenance (CBM). Condition monitoring (CM) is a key component to condition-based maintenance (CBM) since it presupposes a significant role in proactive maintenance practices of machine components that would essentially anticipate and prevent failure in advance (Saini & Dhami, 2022). Some of these indications have been analyzed to simplify the process of diagnosing defects in dynamic machinery (Checa et al., 2022; Effiong & Ogunedo, 2023; Kumar et al., 2021)The three basic stages involved in the CBM program. At the beginning, the process entails the acquisition of data by way of data collection of appropriate information. Data processing refers to the systematic alteration, careful analysis, and discerning interpretation of indicators with an intention of enhancing the understanding. The third phase is the decision making phase and this entails the application of diagnostic and prognostic methodology come up with efficient and effective maintenance recommendations. Condition-based maintenance (CBM) aims to process the continuous data that is gathered on machine degradation and pass it on to a central processor (Kumar et al., 2021). This processor will subsequently identify any deviation in vital parameters and locate abnormalities that have potential of creating equipment failure. The unusual cognitive behavioural therapy (CBT) scheme is suggested, and it is characterized by the peculiarities and demands. The scheme takes into consideration the methodology of gaining the baseline patterns and the types of specific data. It should be noted that a comprehensive condition-based maintenance (CBM) strategy must also contain two important segments diagnostic and prognostics. Diagnostics are preoccupied with the process of identifying and differentiating and verifying faults in event of deviations out of normal conditions.

Prognostics, on the other hand, is a rapidly developing outlook that takes an interest in anticipating failures and deterioration even before they happen to be noticed. Opinions expressed with the help of the use of Logical Analysis of Data (LAD) bring a new method of data processing, a mixing between the Combinatorial and Boolean theories. This method is meant to make predictions and analyses with reference to Condition-Based Maintenance (CBM).

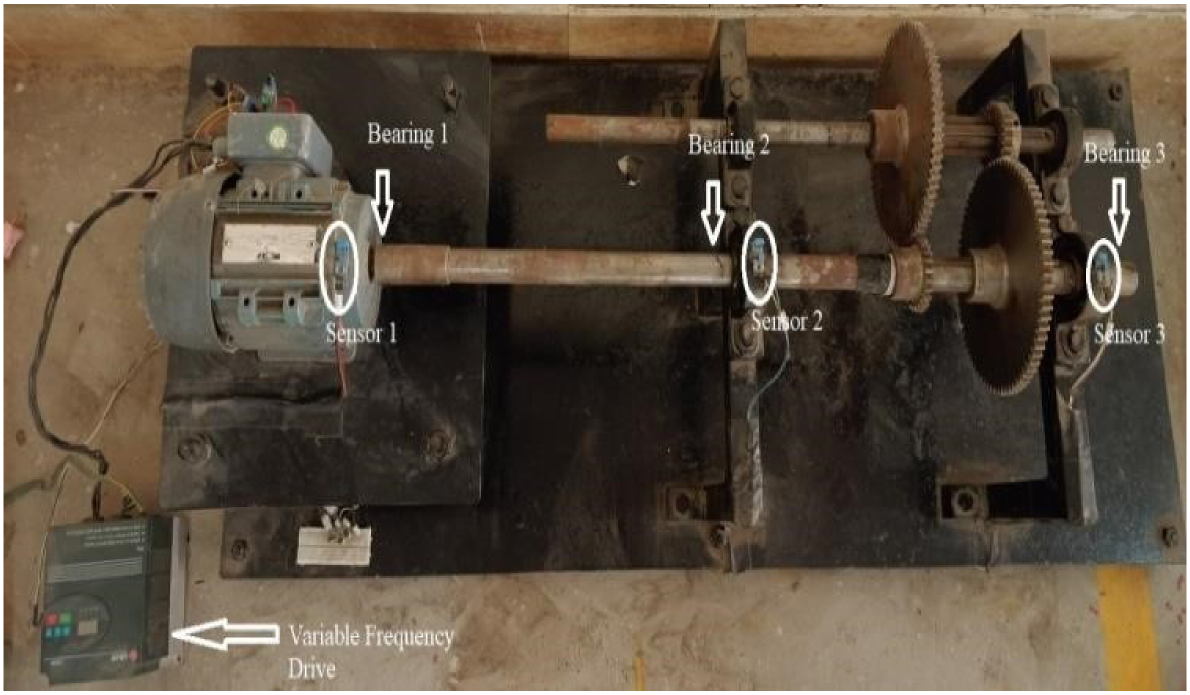

FIGURE 1. Experimental Setup for Predictive Maintenance

Vibration testing has come out as a sound and reliable methodology of finding out the operational status of machines. The cost effective monitoring features and the non-destructive nature of this technology has gained importance in industrial environments as it can be employed in continuous monitoring without disrupting the operations in the industries. The variations in the operation of the machine lead to the formation of distinctive vibration patterns, and the number of vibrations of these patterns often makes it possible to detect abnormalities. Abnormal vibrations are the key predictors of potential malfunctions in the chosen machinery, such as imbalance, misalignment, disintegration of specific components, worsening bearing of rolling components (and gears). Vibration analysis systems and synthesizers have shown a high degree of skill in realizing an array of concerning situations within a short period, therefore, aiding prompt responses by the employees (Hu & Li, 2021).

IV. EXPERIMENTATION

The trials arrangement used in the current study is proved in Fig. 1 with a condition-dependent maintenance phase in Fig. 2 representing an adaptable test system, which is central in examining typical epilogisms of typical equipment failure. The flexible design with its strong yet flexible design enables the easy attachment and detachment of bearings and gears. The design uses a variable-frequency drive in order to guarantee a variety of velocities. The system also has three bearings, two of which appear on a shaft, to which is attached the motor, and through which the third bearing is located in the inner motor assembly. Vibration data was carefully collected with the help of an Arduino Uno board and three sensors of SW-420. The bearing brackets have two sensors and the third sensor is strongly attached to the motor casing. To achieve the purpose of an experiment, one bearing with a defect was used namely one bearing that had a defect in the form of a ball. The bearing defect scenario was tested at 50 Hz by performing the experiment. Then, the obtained signals were thoroughly analyzed using the MATLAB software.

within the context of Condition-Based Maintenance (CBM).

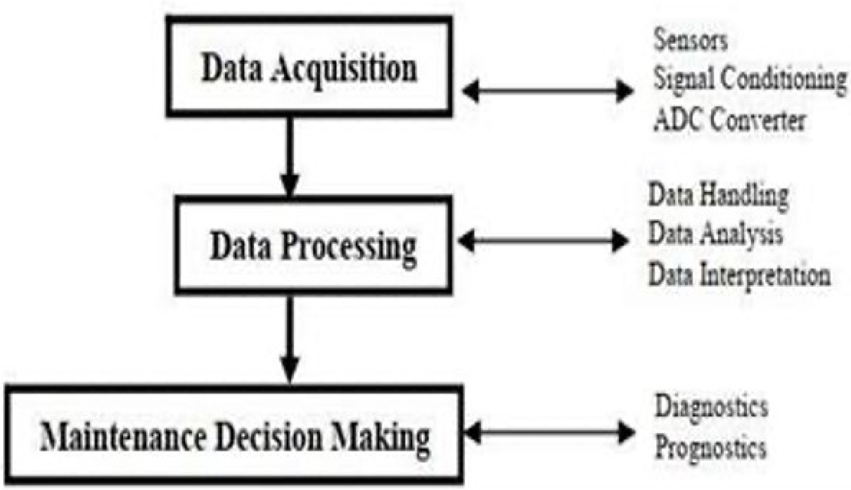

FIGURE 2. Condition-Based Maintenance Phases

The signals received when there is a deficiency case as well as a normal case were put on graphs very meticulously and, they were then systematically studied through comparison. The analysis of comparison made in this work revealed a large inconsistency within the two sets of signals as it enabled the correct identification of some defects in the bearings. Such presentation can be depicted in Fig. 3.

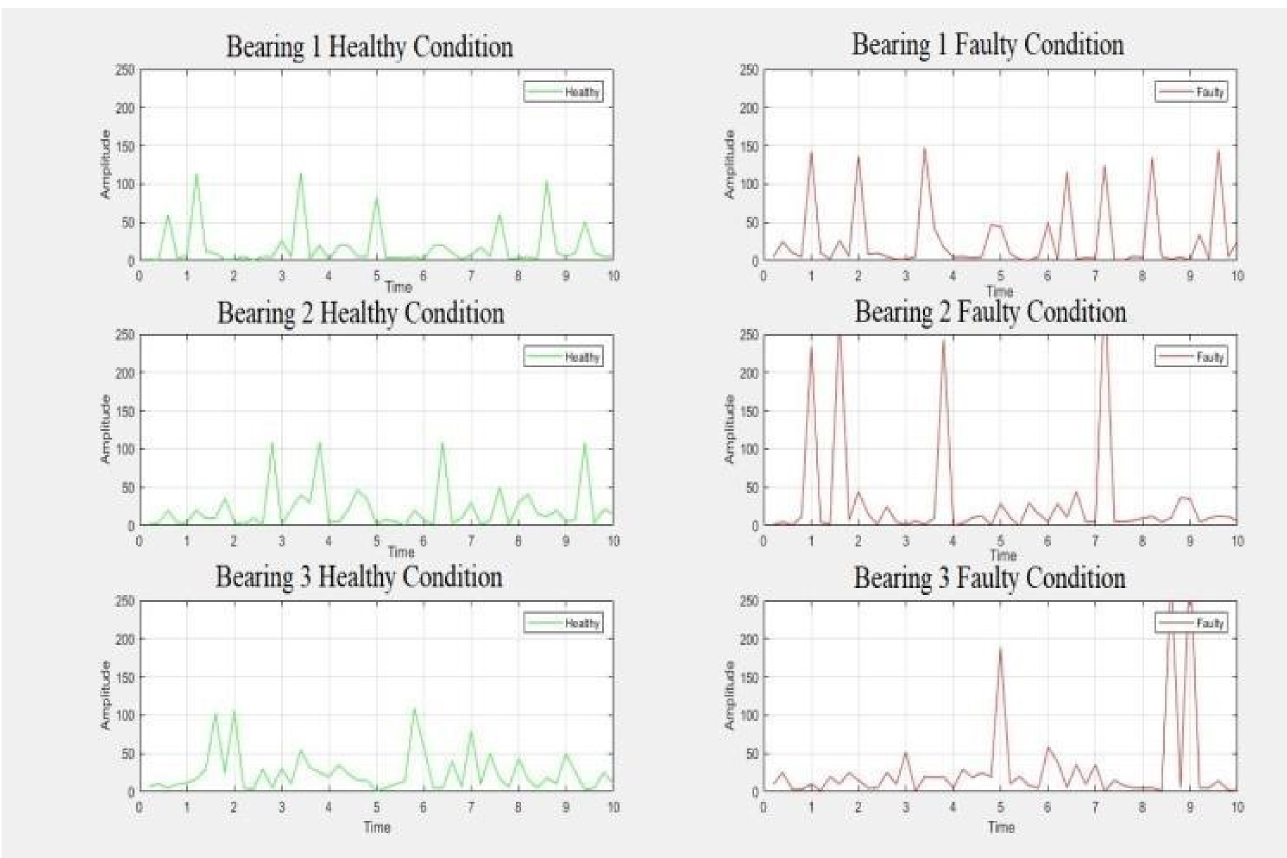

FIGURE 3. Healthy & Faulty bearing graphs

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V. RESULTS

The feasibility and the effectiveness of the Condition-Based Maintenance (CBM) methodology, along with the Remaining Useful Life (RUL) forecast scheme, depends greatly on the data obtained based on the rolling element bearings in actual cases. In order to exploit the possibilities of this dataset, we simply incorporated the fact into the MATLAB program and had the groundwork to an elaborate feature extraction process. Under this method, we have built an ensemble data storage with a deliberate design to achieve the ease of access to data in the Diagnostic Feature Designer in order to streamline features extraction process. The attributes that were retrieved included mostly the basic time-domain attributes, including kurtosis, peak amplitude, band power, and Root Mean Square (RMS). Careful analysis was made to determine the significance of kurtosis as a major constituent of detection of bearing issues, and consequently, an attentive hierarchy of the aspects was prepared. Such a keen judgment was aptly illustrated by the unidirectional Enova curve, which was exquisitely plotted as explained in the attached figure in Fig. 4.

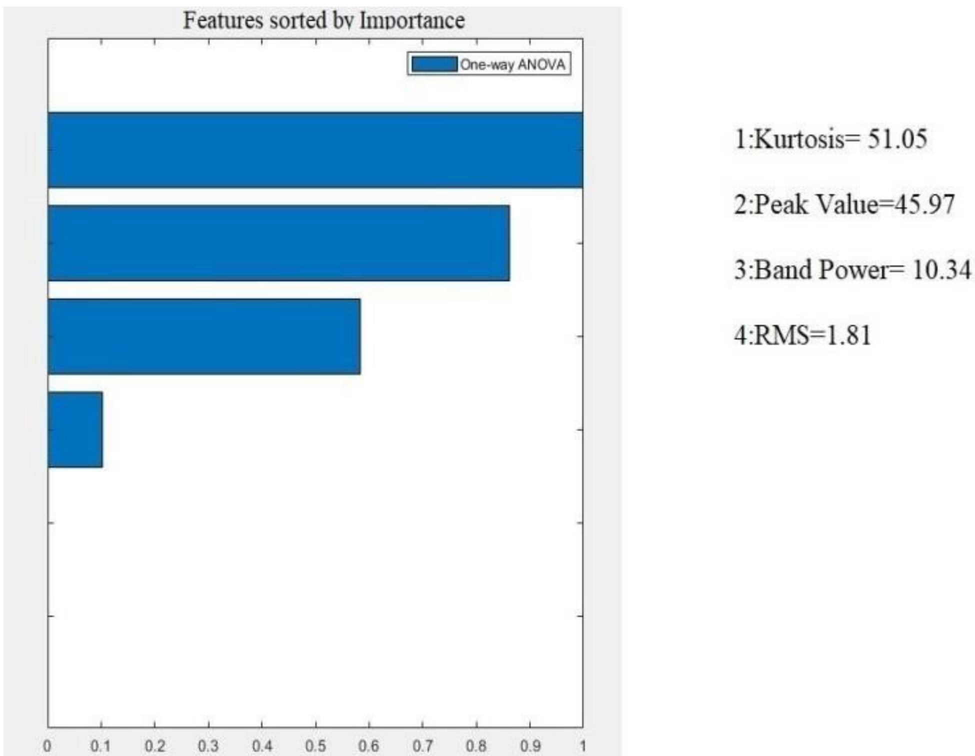

FIGURE 4. Features Ranking

the next necessary step is to have them seamlessly integrated into the Classification Learner. This will be done to train our model, which will do the right classification of the state of the bearing.

It was also important to note that the success of this project was aided by the high training of different models based on the Classification Learner Application where each of the models aimed at delivering the best results. Among these models, one should mention that Quadratic Discriminant Analysis (QDA) model stood out as the most effective and reliable one. This is exhibited in the educative visual representation in Fig. 5.

In order to have increased assistance to verify the accuracy of our model, a two pronged approach was employed. Fig. 6, the Receiver Operating Characteristic Curve, offered a little bit of insight into the ability of the model to discriminate and classify bearing conditions with high accuracy. Moreover, the Scatter Plot as shown in Fig. 7 was also a source of validation and therefore it confirmed to the robustness and reliability of this model in its predictability power.

The Remaining Useful Life (RUL) is computed with the help of the degradation model that illustrates the degradation of the states of the system during 48 days. The

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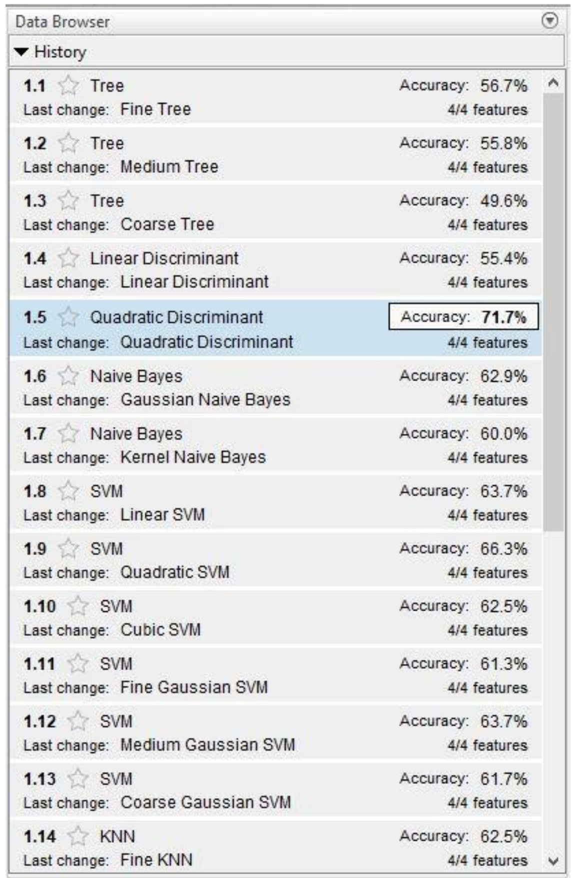

FIGURE 5. Classification learner training Model

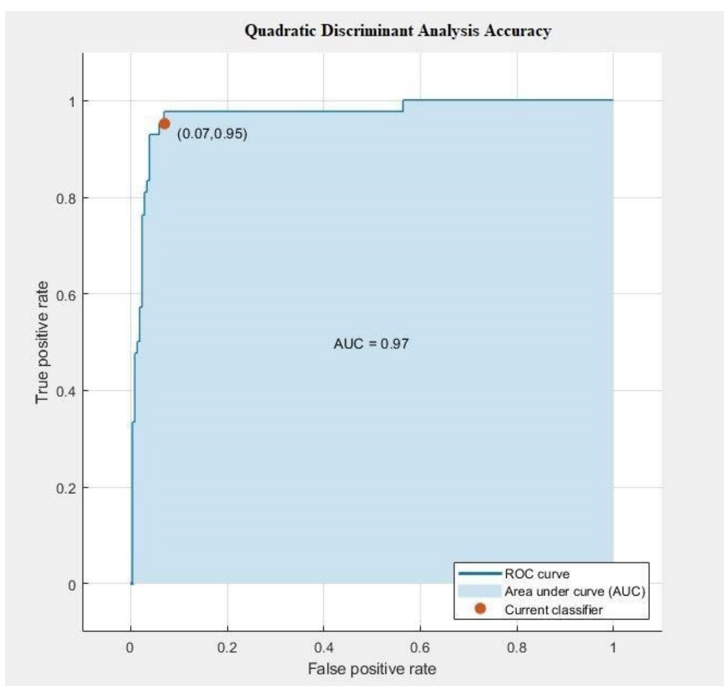

FIGURE 6. Quadratic discriminant analysis ROC Curve

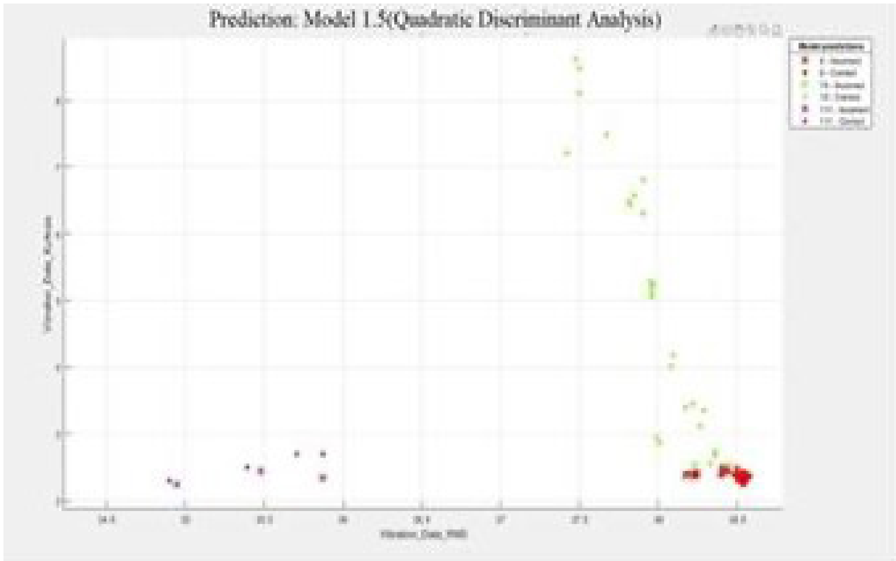

FIGURE 7. Quadratic discriminant analysis Scatter plot

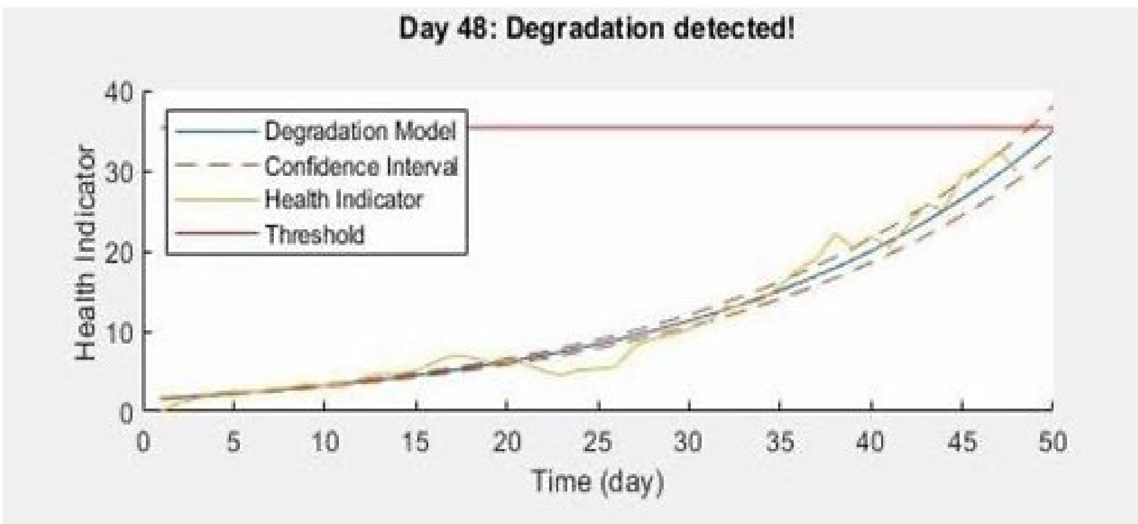

FIGURE 8. Remaining Useful Life

visual illustration of the whole situation is presented in Figure 8. Remaining Useful Life (RUL) is an estimated time period within which an asset, in terms of its purpose, can remain in service before it requires a replacement as indicated in Fig. 8.

VI. CONCLUSION

The current research has managed to propose a new approach to condition monitoring, which implies a carefully elaborated diagnostic system. This system has been arranged in a way that any possible failures in the bearings in the rolling elements are perceived and proactively pointed out. Vibration is the key indicator signal used in this system and it is even combined with a detailed time-domain analysis. The obtained data was then and carefully analyzed with the MATLAB software. This analysis entailed the derivation of relevant features of the data and ranking them through Diagnostic Feature Designer tool. The above ordered features were then employed in training different models through the use of Classification Learner Application. This helped in estimating the Remaining Useful Life (RUL). Some interesting conclusions are obtained in our results. The primary attribute that has been determined as the most common of the four characteristics that have been extracted is kurtosis. When discussing the vibration analysis of rotating equipment, it is of paramount

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importance to take into consideration the role that is played by features of time domain. Compared to others, Quadratic Discriminant Analysis (QDA) becomes the most accurate model. According to the calculation of the Remaining Useful Life (RUL), a fault will be in its initial stages and will last only a few days of approximately 48 days before this time can be completely realized.

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