

# Enhancing Rotary Machine Reliability Through Condition-Based Maintenance Optimization

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**Abstract-** Rotary machines possess an inherent characteristic of generating vibrations, leading to the deterioration of critical components, particularly bearings and gears, ultimately failing the system. Vibration analysis is widely acknowledged as the predominant diagnostic technique employed for assessing the state of machinery and informing maintenance strategies. Condition-based maintenance (CBM) is a crucial component of proactive maintenance strategies that optimize machine availability by implementing timely interventions and minimizing costly breakdowns. This research endeavour aims to establish a comprehensive framework that enables evaluating the operational state of rotary machinery and its critical components, specifically emphasizing bearings. The interdependence between maintenance and machine health is evident, as a well-maintained machine requires minimal maintenance, while a machine undergoing deterioration requires immediate intervention. Rotary machines, which hold significant importance in various industrial processes, often face significant obstacles to bearing issues. These challenges lead to considerable disruptions in output and escalate maintenance costs. The current study examines the efficacy of CBM as a potential solution to the aforementioned issues. CBM is a maintenance strategy that utilizes real-time data on machine conditions to make informed decisions regarding maintenance interventions. By leveraging this approach, maintenance activities can be executed at the most opportune time, maximizing efficiency and effectiveness. CBM is a strategic approach that empowers enterprises to proactively mitigate failures, optimize maintenance schedules, and improve overall operational efficiency by accurately estimating the remaining usable life of machine components. This research study contributes to the growing body of knowledge on CBM, offering valuable insights into predictive maintenance and its potential to enhance the reliability and efficiency of rotary machinery.

**Index Terms--** Condition-based maintenance, rotary machine, optimization, reliability.

## I. INTRODUCTION

This section elucidates the significance of upholding mechanical systems, including reciprocating or pivoting components, to mitigate vibrations, a pivotal facet of condition-based maintenance. Academics are motivated to examine and evaluate these factors to optimize operational efficiency, minimize maintenance expenses, enhance structural integrity, and mitigate the risk of catastrophic failures in real time. The predominant factor contributing to vibrations in such systems frequently originates from unbalance or misalignment in the rotating components. The monitoring of vibration, which is characterized by factors such as amplitude, velocity, and acceleration, is conducted in order to ensure the integrity of machinery. Accelerometers are widely employed sensors for the purpose of measuring these characteristics, and alterations in vibration signals serve as indicators of impaired or defective machine components. Predictive maintenance approaches are utilized to anticipate or identify problems and malfunctions by leveraging established patterns of failure, hence facilitating prompt interventions to avert operational disruptions. This study

comprehensively examines different approaches to vibration monitoring and signal processing in condition-based maintenance, specifically targeting gears and bearings. This publication functions as a complete resource for researchers in the specified field, with the primary objective of advancing advanced research subjects related to condition-based maintenance.

### A. Breakdown Maintenance

The maintenance strategy commonly referred to as "run till failure" involves replacing a piece of equipment only after it has experienced a complete breakdown. This particular methodology is employed in scenarios where the malfunctioning of a machine does not result in significant human or financial ramifications. Its purpose is to maximize the duration of operational activity before any necessary shutdowns occur. However, this particular methodology is deemed unfavorable due to its potential safety risks, potential damage to other equipment, and subsequent decrease in overall efficiency. The breakdown maintenance program exhibits several notable factors, including increased expenditures, substantial inventory costs related to spare parts,



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heightened charges for overtime personnel, extended periods of machine downtime, and reduced production availability.

### **B. Preventive Maintenance**

This particular type of maintenance is occasionally denoted as time-based or periodic maintenance. Although it does contribute to a reduction in the occurrence of unexpected malfunctions, it is generally regarded as economically inefficient. The fundamental assumption of this methodology posits that a machine can consistently execute its assigned tasks with efficacy, provided that it has been subjected to appropriate maintenance procedures. Nevertheless, this particular methodology leads to a decrease in overall productivity. It presents a significant potential for introducing flaws, as it is frequently established solely on historical knowledge and expertise. The principal objective of this maintenance procedure is to proactively enhance the operational longevity of the equipment by efficiently overseeing the degradation process to a threshold considered satisfactory. Several components exhibit a relatively stable rate of wear or deterioration over time. However, certain components, such as rolling element bearings, exhibit a notable statistical variation around the mean value. This observed variation yields estimates, such as the aforementioned one, in which the average time until failure surpasses the minimum requirement by two to three.

### **C. Condition-based Monitoring/Maintenance**

To determine the necessary maintenance operations and foresee probable machine breakdowns, condition-based maintenance (CBM) evaluates a machine's current status (machine condition monitoring). To extend machine life, improve efficiency, lower daily operating costs, raise system quality, reduce maintenance efforts, and eliminate human error, CBM stresses completing maintenance only when certain signs point to diminishing performance or impending breakdowns. While CBM is demand-driven maintenance initiated by the system's needs, maintenance refers to a series of procedures to keep a system running. Planned CBM actions are based on condition monitoring (CM) data. A crucial part of CBM, CM makes it possible to maintain machine parts on schedule and foresees when maintenance interventions are most effective. The research investigates numerous condition monitoring indicators for dynamic machine fault analysis [8]. The CBM process entails several processes, such as data collecting to obtain pertinent information, data processing to evaluate and interpret signals, and decision-making to incorporate diagnostic and prognostic methodologies for useful maintenance suggestions. CBM's main objective is to examine real-time data to spot changes in functional parameters and identify abnormalities that can cause failures. Vibration measurements made by non-contact devices have enormous promise for predicting machine failure and maintenance needs [11]. The research provides a novel typology of CBM approaches based on the data kinds and data collecting techniques used, highlighting their pertinent attributes and prerequisites [12]. Prognostics in CBM involves forecasting flaws and degradation before they manifest, while diagnostics concentrate on fault isolation, identification, and diagnosis when abnormalities occur. Model-based, data-driven, and hybrid prognostics are the three

basic types of prognostic approaches [13]. To diagnose and predict CBM patients, the research introduces logical analysis of data (LAD), a novel data processing technique that blends combinatorial and Boolean theories [14].

## **II. LITERATURE REVIEW**

This section delves into the significance of condition monitoring (CM) within the field of mechanical engineering, with a specific focus on bearings and gears. CM offers valuable cost and time savings by reducing the need for scheduled inspections and minimizing downtime. Data analysis during machine operation is highly prioritized, and various vibration parameters are carefully examined to detect defects in rolling element bearings. Ultrasound has proven an effective method for detecting early-stage defects in low-speed bearings. The section also covers fault diagnosis methods for gears, including ferromagnetic analysis and vibration analysis. It highlights the use of artificial neural networks and support vector machines to classify gear faults.

Furthermore, the section explores the impact of speed and load on acoustic emission (AE) in gear monitoring. It proposes methods for predicting the remaining useful life (RUL) by analyzing AE signals. The limitations of AE for defect identification are discussed, with particular emphasis on the influence of temperature on AE activity.

Condition Monitoring (CM) is an emerging technological paradigm that empowers operators to reduce the frequency of scheduled inspections. The decrease in inspection activities leads to notable financial savings, decreased time commitments, and limited operational disturbances. In mechanical engineering, comprehensive examinations of pertinent scholarly works consistently underscore the necessity of discerning and elucidating data alterations that transpire during machinery's operational performance in authentic, real-life situations.

Bearings, integral components of rotary machinery, possess substantial significance owing to the potential adverse ramifications of any shortcomings in these rotating elements. The occurrence of such deficiencies can lead to both transient interruptions and economic setbacks. The diagnostic assessment of bearing faults is a crucial concern encompassing various industries, such as power generation and aerospace [7]. An empirical investigation was conducted to examine the characteristics of vibration signals to detect anomalies in roller bearings. The present study aimed to investigate and juxtapose various parameters, namely Root Mean Square (RMS), peak amplitude, crest factor, and power spectrum characteristics, with the corresponding measurements obtained from healthy bearings of diverse dimensions [8].

Moreover, a comprehensive investigation was undertaken to empirically assess the efficacy of sound pressure microphones in discerning diverse equipment conditions amidst the existence of elevated levels of ambient noise [9]. The results of this study suggest that sound pressure microphones exhibit a comparatively diminished sensitivity towards certain machine diagnostics, such as revolving ball bearings, when compared to alternative techniques like accelerometer measurements.

Furthermore, an all-encompassing conceptual framework has been developed to predict the vibration frequencies and amplitudes characteristic of bearing faults localized in either the outer race, inner race, or one of the rolling elements. The present framework comprehensively encompasses both radial and axial loads. A noteworthy observation was made concerning the influence of shaft speed on statistical characteristics stemming from the susceptibility of bearing housing components to longitudinal vibrations. The elucidation of the mechanisms responsible for generating vibrations and noise in bearings has also been addressed. The wavelet packet transform (WPT) has garnered significant recognition as a valuable technique for precisely analyzing vibration data stemming from faulty bearings [10].

In summary, the authors have conducted a comprehensive investigation into the field of vibration analysis and analytical methodologies related to detecting and characterizing defects in antifriction bearings [11]. Statistical measures, predominantly situated within the temporal domain, can be derived from the noise profiles acquired by using microphones positioned on bearings. The careful analysis of time-series data pertaining to signals can yield substantial quantities of valuable information [12]. The principal methodology involves visually analyzing segments within the time-domain waveform. Moreover, there has been a notable surge in the utilization of advanced time-domain methodologies, such as examining distinct characteristic parameters, which have elicited considerable intrigue. The application of time-domain statistical characteristics has been utilized as significant indicators and threshold criteria for the prompt detection of bearing failures. Expressions 1-6 can be effectively employed to articulate various statistical parameters within the temporal domain.

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

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

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

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

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

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

The squared difference is used to standardize the circumstance. This approach is excellent for spotting spiky or impulsive signals. Use of a Gaussian probability density model to simulate spalling events has shown the importance of form factor, clearance factor,

and impulse indicator in properly mimicking real-world conditions. These properties provide information, especially clearance and impulse indications. For spalling detection, the clearance factor is the most complicated yet reliable signal [13].

Additionally, earlier investigations have illuminated sensor placement's importance [14,15]. Renyi and Honarvar [16, 17] showed that skewness and kurtosis could reveal rolling element-bearing issues. Additional research has shown that statistical characteristics can be used to evaluate vibration and ultrasonic data to discover anomalies in low-speed bearings [18]. Kurtosis and peak factor perform better below 200 rpm. The statistical methodology described has garnered interest in bearing damage monitoring due to its consistent and dependable results even when load and speed factors vary.

This complex and versatile technique can be used for maintenance and quality control [19]. This study addresses vibration feature extraction methods for rotating machinery defect detection [19]. Ball bearings have been studied extensively to improve localized fault detection [20]. Statistical indicators, including kurtosis, skewness, and standard deviation, can identify roller-bearing issues quickly (Reference 21). Soft computing techniques for Condition-Based Maintenance (CBM) are also interesting [21]. In addition, powerful AI algorithms have been applied to identify bearing difficulties across speed and load scenarios [22]. New diagnostic methods use neural networks and transfer learning to detect convolution-bearing flaws [23]. Signal processing methods like variation mode decomposition (VMD) have been extensively studied [24]. The flaw diagnosis approach and combined learning denoising capabilities have been extensively studied [25]. Hasan [26] shows that transfer learning-based systems for defect detection are becoming increasingly popular. Wavelet packet decomposition (WPD) has been studied [27], and empirical wavelet transformation (EWT) has been applied to evaluate rolling bearing early-stage difficulties [28].

### III. METHODOLOGY

Condition-Based Maintenance (CBM) is a maintenance approach based on the notion of doing maintenance activities in response to the unique requirements of a system. This approach involves initiating maintenance actions when the underlying machinery of the system indicates a need for attention. Incorporating data obtained by Condition Monitoring (CM) greatly improves the effectiveness of Condition-Based Maintenance (CBM). Condition monitoring (CM) is a crucial element of condition-based maintenance (CBM), as it assumes a major role in the proactive maintenance of machine components, effectively anticipating and preventing failure. Several indications have been examined in order to facilitate defect diagnosis in dynamic machinery [29-36]. The three fundamental phases comprising the CBM program. Initially, the procedure involves the acquisition of data through gathering relevant information. Data processing encompasses the systematic modification, thorough study, and insightful interpretation of signals with the aim of augmenting comprehension. The third phase, known as decision-making, involves the utilization of diagnostic and prognostic approaches to

generate maintenance suggestions that are efficient and effective. The primary goal of condition-based maintenance (CBM) is to analyze the ongoing data collected on machine deterioration and transfer it to a central processor. This processor then detects any variations in vital parameters and finds abnormalities that may lead to equipment failures. An innovative cognitive behavioural therapy (CBT) scheme has been proposed, which is distinguished by its unique characteristics and requirements. This scheme considers the approach to obtaining baseline patterns and the specific data types. It is important to highlight that a comprehensive condition-based maintenance (CBM) strategy should include two key components: diagnostics and prognostics. Diagnostics are concerned with detecting, distinguishing, and confirming faults when deviations from normal conditions occur.

On the other hand, prognostics is a fast-advancing field that focuses on predicting failures and degradation before they become apparent. The utilization of Logical Analysis of Data (LAD) introduces a novel approach to data processing, which combines combinatorial and Boolean theories. This technique is specifically designed to analyze and predict within the context of Condition-Based Maintenance (CBM).



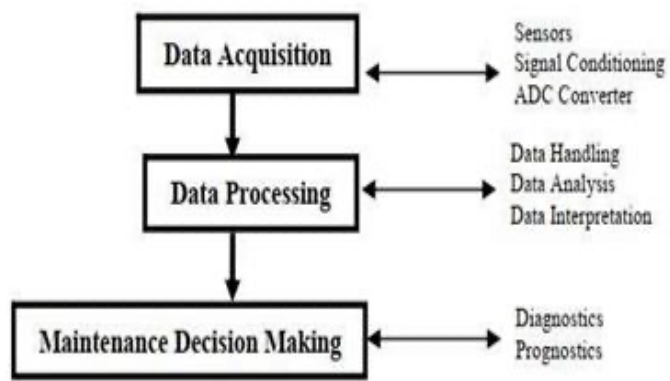
**FIGURE 1.** Experimental Setup for Predictive Maintenance

Vibration testing has emerged as a robust and dependable methodology for determining the functional condition of machines. This technology's non-destructive nature and cost-effective monitoring capabilities have increased significance in industrial settings since it allows for continuous monitoring without causing disruptions to operations. Differences in the functioning of

machines result in the emergence of unique vibration patterns, and the frequency of these vibrations frequently enables the identification of irregularities. Unconventional oscillations are principal indicators of prospective machinery malfunctions, including concerns such as imbalance, misalignment, component disintegration, deteriorating rolling element bearings, and gear impairment. Vibration analysis systems and synthesizers demonstrate a high level of proficiency in promptly identifying a range of concerning circumstances, hence facilitating quick responses by staff [30].

#### IV. EXPERIMENTATION

The experimental configuration employed in this study is depicted in Fig. 1 with a condition-based maintenance phase in Fig. 2, showcasing a versatile testing apparatus that is pivotal in scrutinizing characteristic manifestations of common equipment deficiencies. The adaptable arrangement, characterized by its robust yet flexible structure, facilitates the effortless installation and removal of bearings and gears. The configuration incorporates a variable-frequency drive to ensure a diverse range of velocities. The system comprises three bearings, with two being affixed to a shaft that is interconnected with the motor, while the third bearing is situated within the motor assembly. The vibration data was meticulously acquired by using an Arduino Uno board in conjunction with three SW-420 sensors. Two sensors are strategically placed on the bearing brackets, while the third sensor is securely affixed to the motor casing. For the purpose of experimenting, a singular bearing exhibiting a defect was employed, specifically one that possessed a flawed ball. The experimental trials were conducted at a rotational frequency of 50 Hz, specifically for the bearing defect scenario. Subsequently, the acquired signals underwent a comprehensive analysis utilizing the MATLAB software.



**FIGURE 2.** Condition-Based Maintenance Phases

The signals obtained from deficient and normal situations were carefully plotted on graphs and afterwards subjected to a comprehensive comparison study. The comparison analysis conducted in this study unveiled a significant discrepancy between the two signal sets, facilitating the accurate detection of certain flaws in the bearings. This visual representation may be shown in Fig. 3.

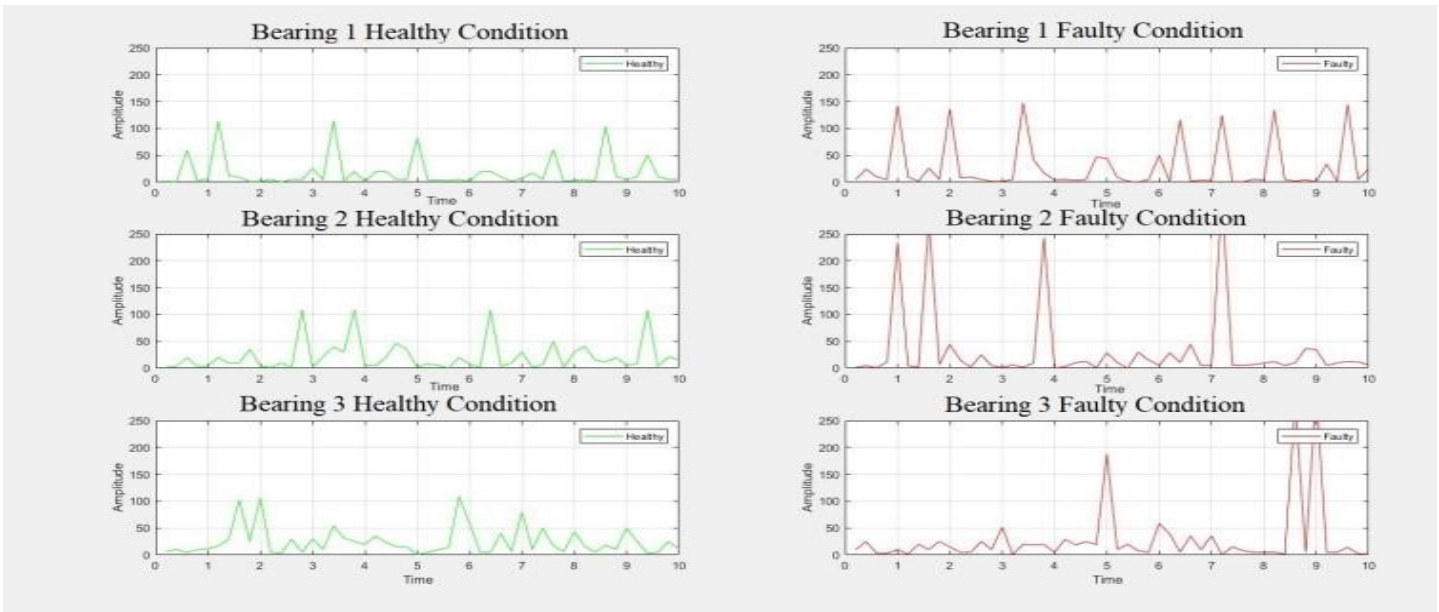


FIGURE 3. Healthy & Faulty bearing graphs

## V. RESULTS

The viability and efficacy of the Condition-Based Maintenance (CBM) methodology, in conjunction with the Remaining Useful Life (RUL) forecast scheme, is highly contingent upon the data derived from rolling element bearings in real-world scenarios. To leverage the potential of this dataset, we effortlessly integrated it into the MATLAB software, establishing the foundation for a complex feature extraction procedure. In this technique, we carefully constructed an ensemble data storage deliberately designed to enable smooth access to data within the Diagnostic Feature Designer, hence optimizing the feature extraction process. The retrieved features mostly consisted of fundamental time-domain characteristics, such as kurtosis, peak amplitude, band power, and Root Mean Square (RMS). A thorough evaluation was undertaken to assess the importance of kurtosis as a key component in identifying bearing problems, resulting in a meticulous ranking of these aspects. The insightful evaluation was effectively demonstrated using the unidirectional Enova curve, as elegantly portrayed in the accompanying diagram in Fig. 4.

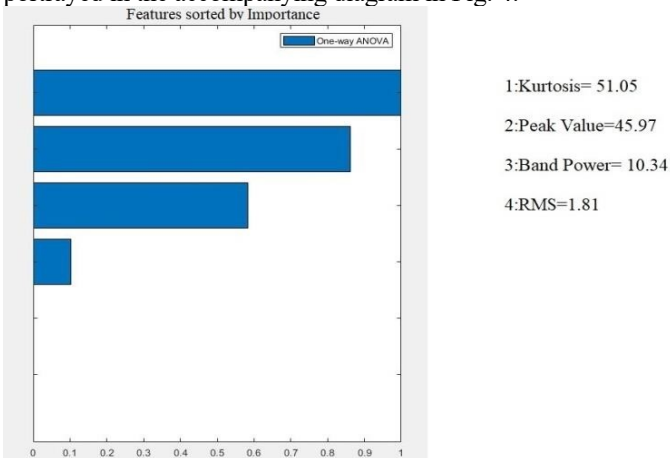


FIGURE 4. Features Ranking

After carefully organizing and evaluating the features, the subsequent essential phase entails their smooth incorporation into the Classification Learner. This step is necessary for training our model, which is responsible for accurately categorizing the condition of the bearing.

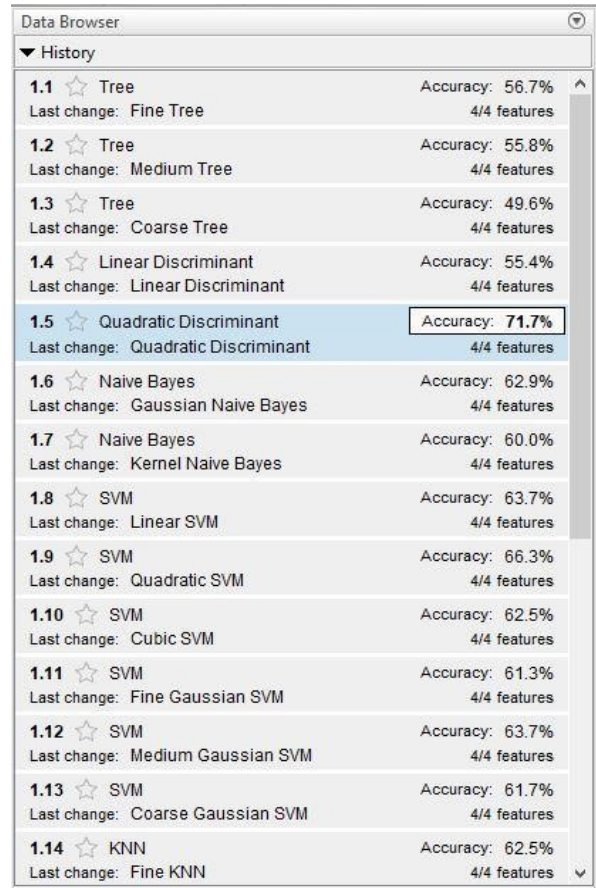


FIGURE 5. Classification learner training Model

The success of this project was supported by the rigorous training of various models using the Classification Learner Application, with each model striving to achieve optimal performance. Within this collection of models, it is worth mentioning that the Quadratic Discriminant Analysis (QDA) model emerged as the most accurate and proficient. This is demonstrated in the informative visual depiction presented in Fig. 5.

To enhance the verification of our model's accuracy, a dual strategy was adopted. The Receiver Operating Characteristic Curve (ROC), as shown in Fig. 6, provided a useful insight into the model's capacity to differentiate and categorize bearing conditions accurately. Furthermore, as depicted in Fig. 7, the Scatter Plot served as an additional means of validation, affirming the model's robustness and accuracy in its prediction capabilities.

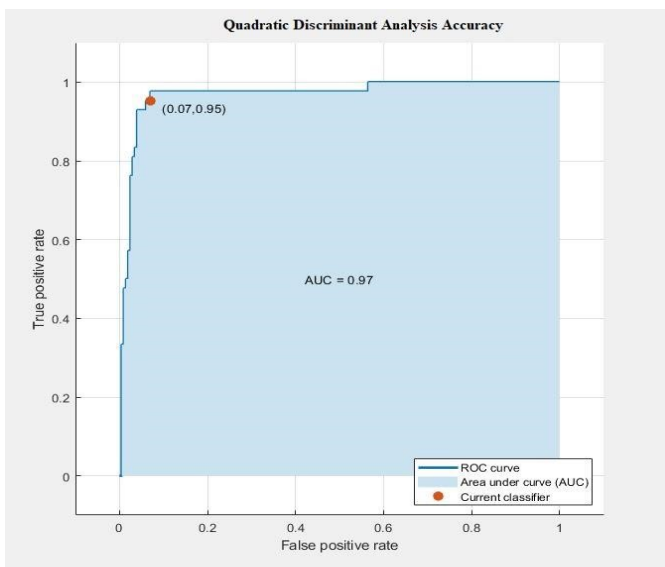


FIGURE 6. Quadratic discriminant analysis ROC Curve

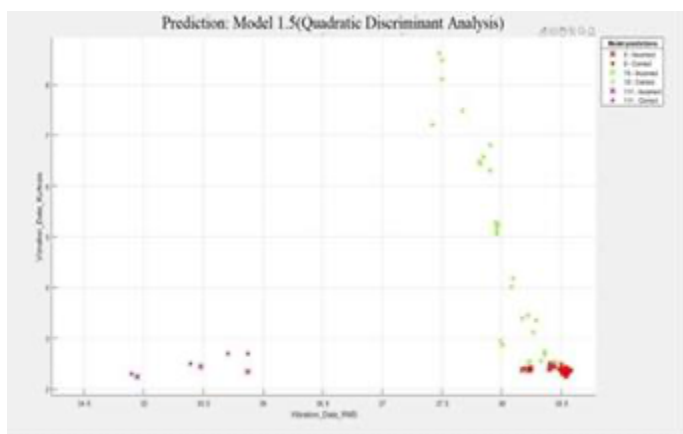


FIGURE 7. Quadratic discriminant analysis Scatter plot

The calculation of the Remaining Useful Life (RUL) is carried out with the assistance of a degradation model, which depicts the deterioration in the system's state over a period of 48 days. Figure 8 depicts the visual representation of the entire scenario. The Remaining Useful Life (RUL) refers to a projected duration during

which an asset is expected to continue functioning by its intended purpose before necessitating replacement, as shown in Fig. 8.

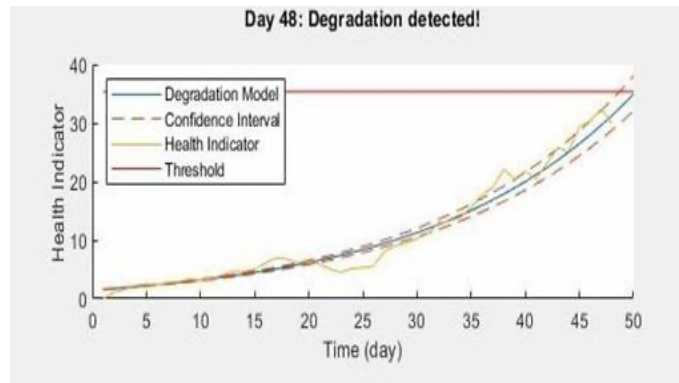


FIGURE 8. Remaining Useful Life

## VI. CONCLUSION

The present study has successfully introduced a novel methodology for condition monitoring, which encompasses a meticulously designed diagnostic system. This system has been specifically developed to identify and proactively indicate potential failures in rolling element bearings. The primary indicator signal utilized in this system is vibration, which is further integrated with a comprehensive time-domain analysis. The data that was obtained underwent a thorough analysis using the MATLAB software. This analysis involved extracting relevant features from the data and ranking them using the Diagnostic Feature Designer tool. The aforementioned ranked features were subsequently utilized in training various models using the Classification Learner Application. This facilitated the process of estimating the Remaining Useful Life (RUL). Our findings yield several noteworthy conclusions. Kurtosis has been identified as the predominant characteristic among the four extracted attributes. In vibration analysis about rotating equipment, considering the significant role played by time domain features is of utmost importance. Quadratic Discriminant Analysis (QDA) emerges as the most precise model compared to its counterparts. Based on the estimation of Remaining Useful Life (RUL), it has been determined that a fault is currently in its early stages, with an approximate duration of 48 days remaining before it fully manifests.

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