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Energy-Efficient Condition-Based Maintenance: A Smart Framework for Predictive Decision-Making in Industry 4.0

Sonam M Gujrathi[a], Dr. K C Bhosale[b]
[a]*PhD scholar and Assistant Professor at Departmnet of Mechanical Engineering, Sanjivani college of Engineering, Kopargaon, Maharashtra*
[b]*Associate Professor, Department of Mechanical Engineering, Sanjivani college of Engineering, Kopargaon, Maharashtra*

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ABSTRACT

This study presents an energy-aware Condition-Based Maintenance (CBM) framework for an SKF 6205 bearing in a motor-driven system, integrating Industry 4.0 technologies. Real-time data from ESP32-based IoT sensors enabled degradation modeling using a Gamma process and evaluation of energy efficiency. The degradation index (Xt), derived from tri-axial RMS vibration, identified a failure threshold of 41.5 g·min, with a CBM trigger set at 75% (31.13 g·min). An Energy Efficiency Indicator (EEI), defined as the ratio of power input to incremental degradation, highlighted performance drops near failure, validating the thresholds. Remaining Useful Life (RUL) was estimated using Maximum Likelihood Estimation on Gamma distribution parameters (α = 16.61, β = 0.000286). The proposed approach links energy efficiency with wear progression, enabling accurate, sustainable maintenance decisions in smart manufacturing environments.

Keywords: Energy efficiency, degradation Index, condition based monitoring, energy efficiency indicator

1. INTRODUCTION

The advent of Industry 4.0 has revolutionized conventional maintenance practices by incorporating real-time monitoring, predictive analytics, and condition-based techniques. This paper investigates how energy efficiency can be integrated with advanced maintenance strategies, including Condition-Based Maintenance (CBM) and proactive Preventive Maintenance (PPM). Through analysis of recent developments and practical case studies, the study highlights the impact of enabling technologies such as the Internet of Things (IoT), machine learning, and energy-saving opportunity windows in enhancing maintenance efficiency. The results emphasize the potential for reducing energy consumption, increasing equipment reliability, and lowering operational expenses. This paper also outlines practical recommendations for implementing energy-efficient maintenance models in Industry 4.0-driven industrial environments.(Do Hoang, Iung, & Vu, 2018).

Energy efficiency is increasingly recognized as a critical element of sustainable industrial practices. The integration of advanced maintenance approaches—such as Condition-Based Maintenance (CBM) and predictive analytics—with energy-efficient technologies offers substantial potential for reducing costs and minimizing environmental impact. This study investigates these synergies through case studies, mathematical modeling, and simulations, aiming to deliver practical strategies for optimizing industrial energy consumption. With industries contributing significantly to global energy demand, escalating energy prices and environmental challenges underscore the urgency for smarter, efficiency-driven maintenance. Emerging Industry 4.0 technologies, including IoT and artificial intelligence, provide dynamic tools to monitor, analyze, and enhance energy performance in real time.(Do et al., 2013; Do et al., 2018).

Condition-Based Maintenance (CBM) is a data-driven maintenance strategy that relies on monitoring the real-time condition of equipment to determine when maintenance is necessary. Rather than following a fixed schedule, CBM initiates maintenance only when specific indicators suggest declining performance or an imminent failure. These indicators can be identified through various techniques, including non-invasive measurements, visual

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Research Article

inspections, performance monitoring, and scheduled diagnostic tests. Data collection can occur periodically or continuously, especially when embedded sensors are present in the equipment. CBM is applicable to both mission-critical and non-mission-critical assets, enhancing reliability while optimizing maintenance resources.(Jianget al., 2018)

Modern industrial enterprises face growing pressure from legislative, economic, and sustainability demands, particularly in managing resources like energy, raw materials, and waste. Among these, energy efficiency has emerged as a critical focus due to its significant impact on operational sustainability. For instance, in the lifecycle cost of an electric motor, energy consumption can account for up to 96%, compared to just 2.5% for purchase and 1.5% for maintenance. Despite this, maintenance decisions are still largely driven by traditional metrics such as reliability, availability, and direct cost. This highlights the need to incorporate the Energy Efficiency Indicator (EEI) into maintenance and operational decision-making to better balance performance, cost, and sustainability over a system's lifecycle. (Do et al., 2013)

2. LITERATURE SURVEY

Aiping Jiang et. al (2018) discussed that a condition-based maintenance strategy integrating ecological factors like energy consumption and carbon dioxide emissions. It aims to minimize total costs and environmental impact through optimization and simulation analyses. The research highlights the importance of considering ecological impacts in maintenance management. Future studies could extend the model to multi-unit systems and non-periodic inspections . Anh Hoang and Benoit Iung (2015) discussed that a generic data-driven approach for modeling energy efficiency performance (EEP) in industrial applications. It emphasizes the need for prognostics to predict EEP at both component and system levels. The approach is validated on the TELMA platform, simulating a real industrial plant. It integrates future mission profiles and operational conditions to enhance decision-making.

Anh Hoang et. al (2014) presents various definitions of energy efficiency and their applications in industrial sectors . It proposes a multi-level approach for evaluating energy efficiency indices. A novel concept, REEL, is introduced to predict the remaining efficient lifetime of components/systems. The paper emphasizes the importance of prognostic approaches for forecasting energy efficiency evolution. An example of an air-fan system illustrates the proposed concepts and their practical applications. Anh Hoang et al (2016) developed a model on energy efficiency (EE) for condition-based maintenance (CBM) to enhance sustainability in industrial systems. It proposes a new EE-based CBM model incorporating energy consumption in maintenance optimization. The study compares the new EE-based approach with an existing CBM model to assess cost and efficiency benefits. A case study on the TELMA platform demonstrates the impact of EE on CBM strategies .

Phuc Do et. al (2016) investigates using energy efficiency as a key performance indicator in condition-based maintenance decision-making. It proposes a new energy efficiency-based maintenance model for optimizing costs and performance. The model is validated through a case study on the TELMA platform, comparing it to traditional methods. Results highlight the impact of energy efficiency on maintenance strategies, emphasizing cost and efficiency benefits. Same author in his research work of 2018 investigates using energy efficiency as a key performance indicator in condition-based maintenance decision-making.They proposes a new model integrating energy efficiency with maintenance costs and useful output performance. The model's effectiveness is demonstrated through a case study on the TELMA platform. The results highlight the impact of energy efficiency on existing maintenance strategies. Anh Hoang and Benoit Iung in 2015 finds a generic data-driven approach for modeling energy efficiency performance (EEP) in industrial applications. It focuses on prognostics to predict remaining energy-efficient lifetime (REEL) and energy efficiency indicators (EEl). The approach is validated on the TELMA platform, simulating a real industrial plant. It addresses challenges in assessing energy efficiency at both component and function/system levels .

Anh Hoang, Eric Levrat, and Alexandre Voisin in 2014 discusses energy efficiency assessment and its importance in decision-making for reducing energy consumption. It introduces a new energy efficiency indicator (EEI) and a prognostic formulation for predicting remaining efficient lifetime (REEL). The implementation of these concepts is illustrated through an electrical fan-blower system case study. The research emphasizes the need for evaluating energy efficiency to enhance decision-making processes in industrial applications. Anh Hoang and Benoît Iung in

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Aiping Jiang et al 2018 proposes a condition-based maintenance strategy that integrates ecological aspects, minimizing costs and environmental impact. The optimal thresholds for CO2 emissions and energy consumption are identified as 6 tons and 3 tons, respectively. The average expected cost per week is $109.406, which is lower than previous studies. Increasing inspection costs lead to a decrease in CO2 emissions thresholds and an increase in inspection intervals. The method presented performs better in reducing penalties for excess emissions compared to previous research. The study highlights the importance of balancing maintenance costs with ecological impacts to enhance decision-making. Allen H Tai et al 2009, The research develops a maintenance model maximizing system availability under imperfect maintenance conditions. It utilizes a Gamma process to model system degradation. The optimal maintenance threshold and inspection intervals are determined to enhance system reliability. A sequential uniform design algorithm is proposed for obtaining optimal solutions numerically. The study emphasizes the importance of condition-based maintenance (CBM) for reducing system downtime.

Xiangxin An, Guojin Si et al 2022 reviews energy optimization in operation and maintenance (O&M) of manufacturing systems, highlighting its significance for sustainability. It categorizes O&M optimization approaches across machine, production-line, factory, and supply-chain levels. The research addresses challenges in energy consumption optimization due to manufacturing dynamics and system complexity. It emphasizes the need for effective energy management strategies in industrial operations. - The paper discusses condition-based maintenance (CBM) for systems experiencing soft failures due to continuous degradation. It aims to maximize system availability by determining optimal maintenance thresholds and inspection intervals. The system's degradation is modeled as a gamma process, with failures occurring at a defined threshold. The research highlights the importance of imperfect maintenance and periodic observations in improving system reliability.

3. CIRCUIT DIAGRAM

In this study, multiple sensors were integrated to monitor the condition and performance of an SKF 6205 bearing. Tri-axial vibration data were captured using the ADXL345 accelerometer via I2C, mounted directly on the bearing housing for real-time mechanical behavior analysis as shown in Fig. 1. Temperature near the bearing was measured with a PT100 RTD sensor and MAX31865 amplifier using SPI communication. Motor current was continuously monitored using the ACS712 Hall Effect sensor, while the ZMPT101B module measured input voltage, scaled for analog input through the ESP32's ADC. Mechanical load was assessed using a load cell with an HX711 amplifier, and shaft speed was optionally tracked with a Hall Effect sensor detecting magnetic pulses to calculate RPM. All sensor outputs were collected by the ESP32 microcontroller and logged at one-minute intervals to a microSD card. This compact, low-cost, non-DAQ system supported reliable data acquisition for condition-based maintenance and energy efficiency analysis under experimental conditions.

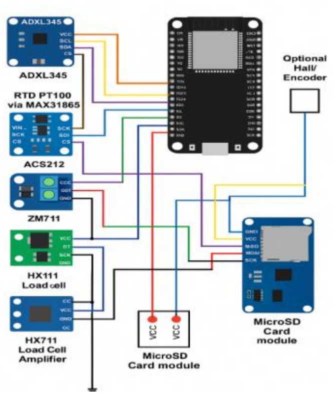

Figure 1 Circuit Diagram

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4. PARAMETER BEHAVIOUR WITH RESPECT TO TIME

In rotating machinery, various mechanical faults can significantly influence vibration behavior and overall system performance. These faults not only accelerate wear and tear but also compromise operational safety and efficiency. Early detection through vibration analysis helps in identifying the root causes and preventing unexpected breakdowns. The various faults can be created to study degradation of the system when it is in running condition. The possible faults can be lack of lubrication, Loosening of Bearing Mounting Nuts, Load Misalignment, Surface Defect etc. All sensor outputs were collected by the ESP32 microcontroller to study the effect of various parameters with respect to time. The data collected consists of acceleration in X, Y and Z direction, temperature, current, voltage, power, energy, load and speed.

The Figure 2 shows RMS acceleration versus time, indicating the vibration behaviour of a deteriorating machine. A gradual increase in baseline RMS values between sharp peaks suggests progressive wear or degradation. The sudden spikes followed by drops likely correspond to maintenance actions that temporarily restore machine condition. However, with each cycle, the baseline vibration level rises, pointing to cumulative deterioration. This pattern supports the need for condition-based maintenance and suggests that timely interventions, guided by vibration thresholds, can improve reliability and prevent unexpected failures.

The Energy vs Time graph in figure 3 shows a monotonic (steadily increasing) curve. It reflects the cumulative energy consumed by the system over the duration of the test. The slope of the curve is low initially, indicating low power draw during the early healthy phase. As degradation increases (especially after ~6000 minutes), the slope may steepen, meaning: More energy is consumed per unit time — possibly due to increased friction, misalignment, or faulty conditions.

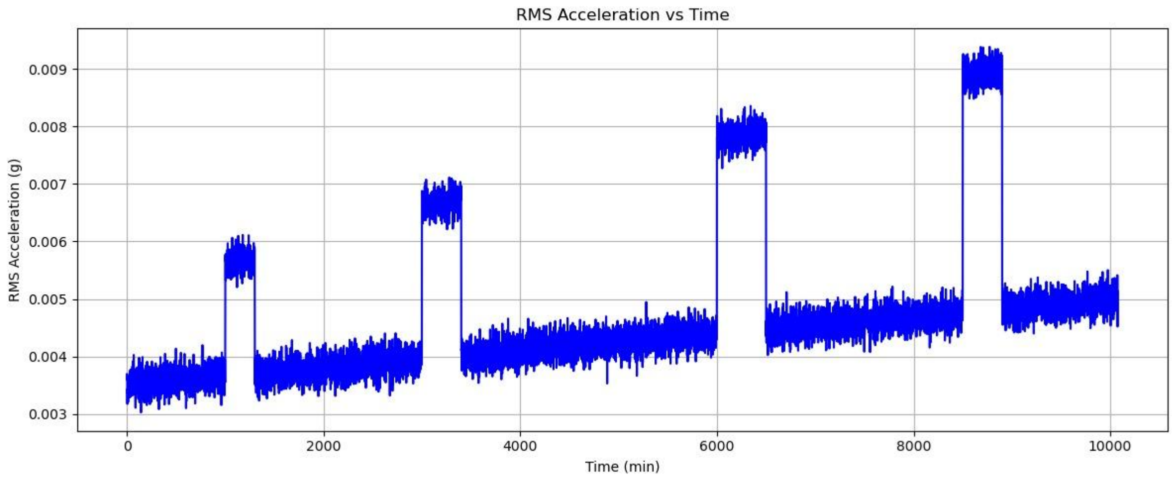

Figure 2 A graph of RMS Acceleration Vs Time

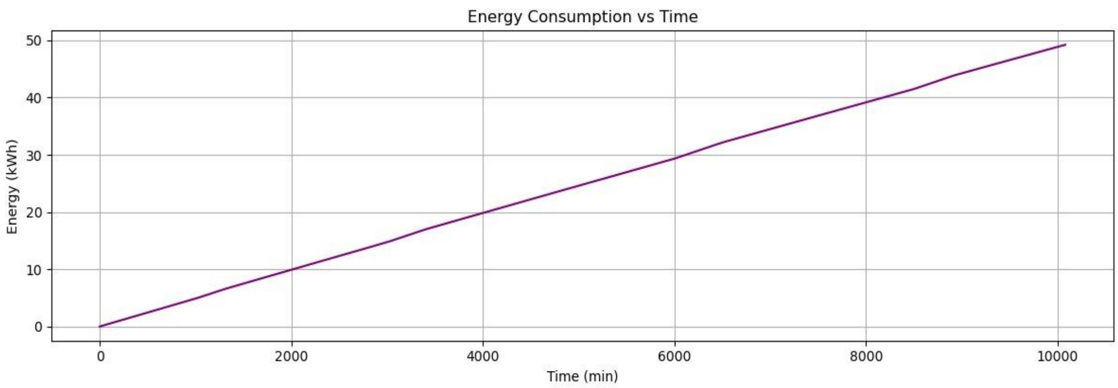

Figure 3 A graph of Energy Vs Time

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Research Article

5. MODELLING

5.1 Degradation Index, X_t -

The degradation index X_t serves as a vital metric in condition-based maintenance (CBM) to monitor the progressive deterioration of machinery components—in this case, SKF 6205 bearings. It quantifies the cumulative exposure of the system to vibrations over time, helping in the early identification of wear and failure trends. The calculation of X_t is grounded in the use of Root Mean Square (RMS) vibration values derived from tri-axial acceleration data.

RMS Vibration is given by the equation -

$$\text{Vibration RMS} = \frac{\sqrt{X^2 + Y^2 + Z^2}}{3}$$

This equation aggregates the vibration signals from the X, Y, and Z axes into a single representative value, offering a holistic view of the vibration intensity at each time step.

Now, the Cumulative Degradation Index is given by the equation -

$$X_t = \sum_{i=1}^{t} \text{Vibration}_{\text{RMS}_i}$$

The cumulative sum of RMS values over time gives us X_t which steadily increases as the bearing wears. This allows maintenance decisions to be based not just on sudden anomalies but also on long-term trends. X_t helps -

1. To Detect early-stage bearing wear
2. Trigger maintenance before critical failure
3. Support the transition from time-based to condition-based maintenance

For instance, in the dataset analyzed, the initial RMS value at minute 0 was 0.0036 g, and the degradation index rose to 0.0175 g·min within just five minutes—clearly showing how cumulative vibration builds up. Table 1 shows sample data calculation

Table 1. Vibration RMS values

Time (min)	Vibration RMS	Degradation Index (X_t - X_{t-1})
0	0.003602	0.003602
1	0.003614	0.007216
2	0.003697	0.010913
3	0.003465	0.014378
4	0.003174	0.017552

5.2 Gamma distribution

The Gamma distribution is a versatile probability distribution that is frequently used to model the time until an event occurs, particularly in areas such as reliability engineering, queuing theory, and survival analysis. The distribution is characterized by two parameters: shape (α) and rate (β). Table 2 shows sample data calculation.

Calculation for (α) and (β)

Step 1: $\Delta X_t = X_t - X_{t-1}$(sample calculation)

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/

Research Article

Table 2 Gamma Distribution

Time (min)	Xt(g·min)	$\Delta X_t = X_t - X_{t-1}$
0	0.000	–
1	0.003	0.003
2	0.007	0.004
3	0.011	0.004
4	0.017	0.006
5	0.020	0.003

So, the degradation increments are:

$\Delta Xt = \{0.003, 0.004, 0.004, 0.006, 0.003\}$

Step1 : Calculate Sample Mean μ

$$\mu = \frac{0.003 + 0.004 + 0.004 + 0.006 + 0.003}{5}$$

μ = 0.004

Step 2: Calculate Sample Variance σ^2

First, compute the squared deviations from the mean:

- $(0.003-0.004)^2=0.000001$
- $(0.004-0.004)^2=0$
- $(0.004-0.004)^2=0$
- $(0.006-0.004)^2=0.000004$
- $(0.003-0.004)^2=0.000001$

$$\sigma^2 = \frac{0.000001 + 0 + 0 + 0.000004 + 0.000001}{5} = 0.0000012$$

Step 3: Estimate Gamma Parameters

Using method of moments:

$$\alpha = \frac{\mu^2}{\sigma^2} = \frac{0.004^2}{0.0000012} = \frac{0.000016}{0.0000012} \sim 13.33$$

$$\beta = \frac{\sigma^2}{\mu} = \frac{0.0000012}{0.004} = 0.003$$

To calculate the values of α and β, a programming language is used and values are calculated as below

Result: (16.611066177186398, 0.00028624014307964 7)

Gamma distribution fitted successfully to your degradation increments using **Maximum Likelihood Estimation (MLE)**.

Here are the fitted parameters:

- **Shape parameter α ≈ 16.61**
- **Scale parameter β≈ 0.000286**

These parameters define the Gamma process model for your SKF 6205 bearing degradation:

Journal of Information Systems Engineering and Management
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Research Article

$X_t \sim Gamma(16.61t, 0.000286)$

The **Gamma distribution** is defined for a continuous, non-negative variable x by the PDF:

$$f(x;\ \alpha, \beta) = \frac{1}{\beta^{\alpha}\gamma(\alpha)} \cdot x^{\alpha-1} \cdot e^{\frac{-x}{\beta}}$$

Where:

- α= shape parameter
- β= scale parameter
- γ(α)= gamma function (generalization of factorial)
- x≥0 = the variable (in your case, degradation increment ΔXt)

Gamma Function for our Dataset (SKF 6205 Bearing)

From your MLE-based fitting:

- α=16.61
- β=0.000286

$$f(x) = \frac{1}{(0.000286)^{16.61\alpha}\gamma(16.61)} \cdot x^{15.61} \cdot e^{\frac{-x}{0.000286}}$$

Figure 3 shows that **how reading are following gamma distribution. The bars** are representing **empirical distribution** of degradation increments (real data). The **curve shows Gamma PDF** fitted using MLE (Maximum Likelihood Estimation) with our estimated parameters. The Gamma curve aligns closely with the shape of the histogram — indicating a **good statistical fit**. This confirms that your degradation increments can be effectively modeled using a **Gamma process**, which can now be used for RUL prediction, failure probability, or CBM planning.

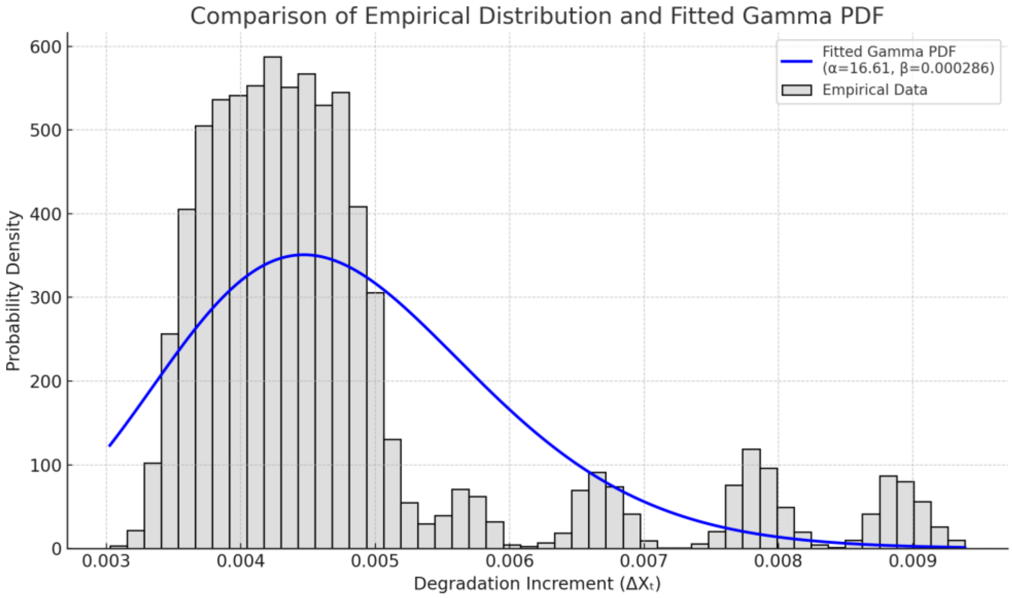

Figure 3 Graph of probability Density Vs Degradation Increment

4.3 Degradation Xt Over Time

The figure 4 clearly indicates that over a period of time system degrades. The graph illustrates a upward trend in the system's operational parameters, which suggests that the system undergoes deterioration due to factors such as wear

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Research Article

and tear, environmental influences, aging of components, or lack of maintenance. This degradation may manifest as increased energy consumption, reduced efficiency, higher failure rates, or longer response times. The consistent decline over time implies that without timely intervention or maintenance, the system's performance will continue to degrade, potentially leading to failure or complete shutdown.

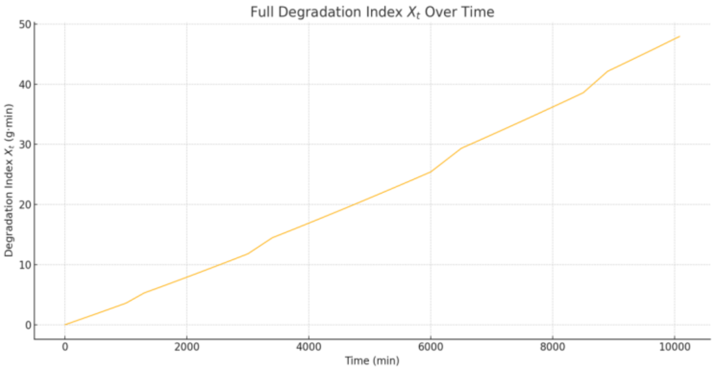

Figure 4 Graph of Degradation Index Vs Time

6. THRESHOLD OF FAILURE

The degradation behavior of the SKF 6205 bearing was quantified using a cumulative degradation index, $X_{t,}$ calculated as the time-integrated RMS of triaxial vibration amplitude, expressed in g·min. This index increases monotonically, reflecting the bearing's accumulated mechanical wear over time. A failure threshold was defined at $X_{t,}$ = 41.5g·min, based on system behavior and condition-based maintenance (CBM) literature. At this point, distinct fault indicators appear and vibration RMS exceeds 0.0089 g, temperature approaches 40°C, and load exceeds 58%, marking a transition to an irreversible failure-prone state as shown in Figure 5. Although some indicators may briefly fluctuate, the cumulative X_t remains a reliable marker of degradation. Failure occurred at 8829 minutes, validating the threshold. This approach aligns with CBM methodologies, where failure points are determined by sustained deviations or critical degradation peaks (Phuc Do, Voisin, Levrat, & Iung, 2012), supporting reliable RUL estimation and maintenance planning.

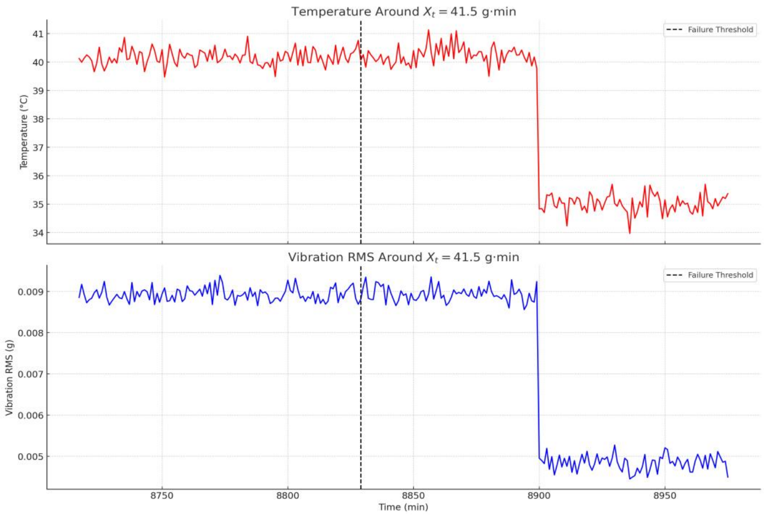

Figure 5 Graph of Temp Vs Vibration RMS and Vibration RMS Vs Time

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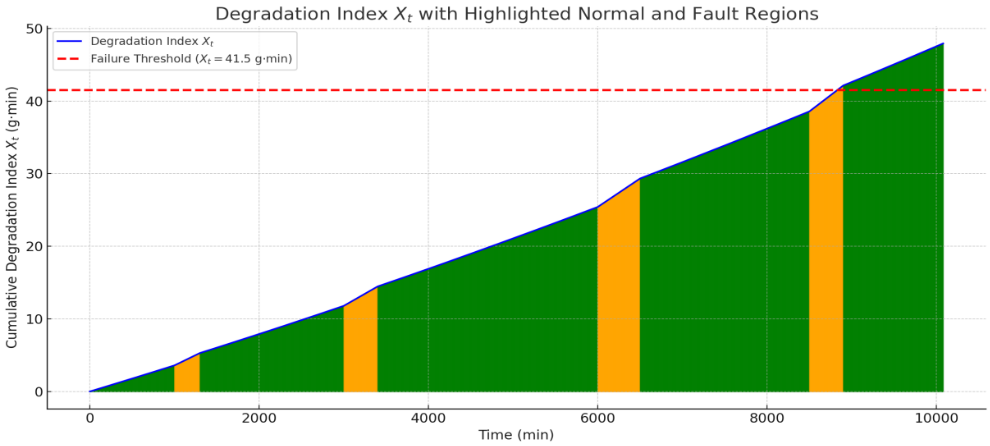

Figure 6 Graph of Cumulative Degradation Index Xt Vs Time

The figure 6 shows the **Degradation Index Xt** over time with clearly shaded region. The **Green regions** represent when the system is in a **"Normal"** state. The **Orange regions** indicate the **"Fault"** state and the **dashed red line** marks the **failure threshold** at X_t=41.5 g.min

7. REMAINING USEFUL LIFE (RUL) ESTIMATION AND STRATEGY (LIFE IS 8829)

In condition-based maintenance (CBM), Remaining Useful Life (RUL) denotes the estimated time before a component reaches a defined failure threshold. For the SKF 6205 bearing analyzed in this study, degradation is tracked using a cumulative index X_t, which aggregates RMS vibration over time. A failure threshold of X_t = 41.5 g·min was determined based on observed system behavior, indicating the onset of critical wear.

To predict RUL, the degradation pattern was modeled using a Gamma process—a stochastic model well-suited for representing monotonic wear. The shape (α=16.61) and scale (β=0.000286) parameters were derived via Maximum Likelihood Estimation (MLE). Simulations initiated from different health states (e.g., X_t=30.35) were used to estimate the time remaining until the failure threshold. At X_t = 35 g·min, the mean RUL was approximately 1369 minutes, with a 95% confidence interval of [1354, 1384] minutes. In contrast, at X_t=41.49, the mean RUL dropped to around 1 minute, signifying imminent failure.

To standardize proactive intervention, CBM trigger points were defined as percentages of the failure threshold, facilitating dynamic and data-driven maintenance scheduling.

To avoid arbitrary selection of RUL reference points, this work adopts the industry-standard approach of defining CBM triggers as a percentage of the failure threshold. Table 3 below summarizes the recommended trigger levels and their corresponding degradation index values:

Table 3 Trigger Levels and corresponding Degradation Index

Threshold Stage	**% of Failure**	**Xt Value (g·min)**	**Purpose**
60% (Early Warning)	60%	24.90	Alert that degradation has begun
70% (Inspection Planning)	70%	29.05	Schedule diagnostics/monitoring
75% (Maintenance Planning)	75%	31.13	Prepare for preventive action
90% (Urgent Action)	90%	37.35	Maintenance must be executed

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Research Article

Threshold Stage	% Failure	of Xt (g·min)	Value	Purpose
100% (Failure)	100%	41.50		End of useful life

In this case, Xt=41.5….failure and time 8829 min. So above predefined trigger levels ensure that maintenance decisions are made systematically, based on a consistent and measurable degradation framework. They also help reduce downtime, avoid emergency failures, and extend the useful life of the bearing through timely intervention. The Figure 7 indicates the variation of degradation Index over a threshold value.

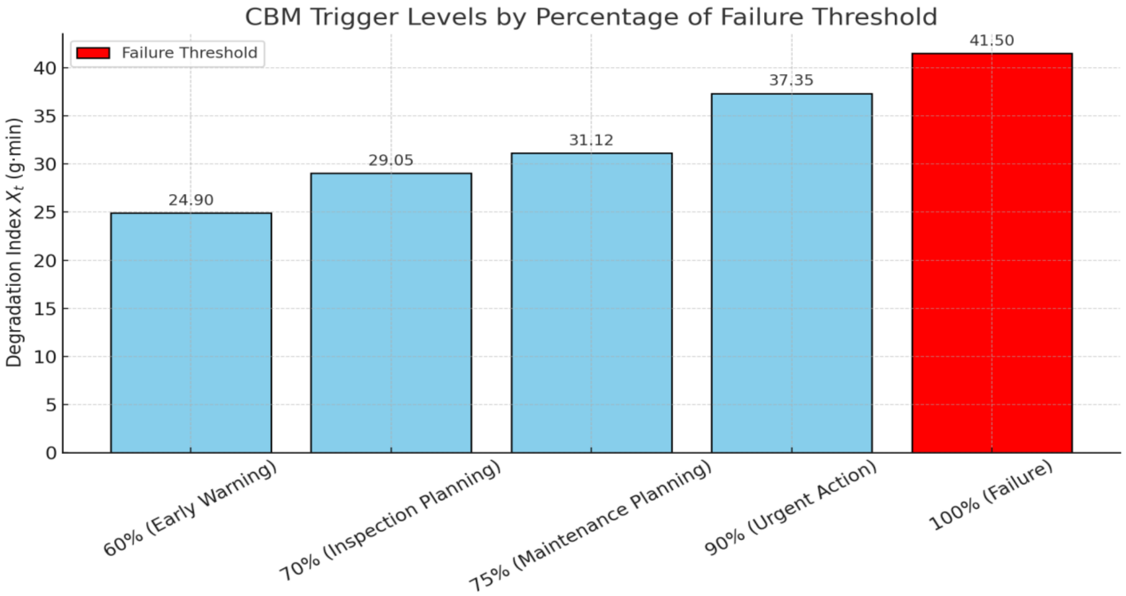

Figure 7 Graph of Degradation Index Vs. Threshold stage

While Phuc Do et al. (2015) do not prescribe a fixed threshold for degradation, their findings emphasize that initiating maintenance based on combined insights from energy efficiency trends and cumulative degradation leads to favorable cost-performance outcomes. In this study, a CBM trigger point is established at 75% of the identified failure threshold (Xt = 31.13 g·min). This selection is consistent with prevailing practices in the condition-based maintenance literature, where interventions are typically recommended when 20–30% of the Remaining Useful Life (RUL) remains (Jardine, Lin, & Banjevic, 2006). By adopting this strategy, the maintenance schedule ensures sufficient lead time for action while maintaining system performance and operational continuity.

In this study, a degradation threshold set at 75% of the failure point (Xt = 31.13 g·min) is adopted as the optimal trigger for initiating condition-based maintenance (CBM). This level offers a practical balance—providing adequate Remaining Useful Life (RUL) to plan and execute maintenance actions proactively, while avoiding unnecessary early interventions. The chosen threshold aligns with widely accepted guidelines in CBM research, supporting both operational reliability and maintenance efficiency. Figure 8 presents the progression of system degradation over time, captured through the cumulative Degradation Index (Xt). The steadily increasing trend reflects the continuous wear experienced by the system during operation. Key condition-based maintenance (CBM) trigger thresholds are highlighted—ranging from early warning (60%) to failure (100%)—including intermediate points for inspection (70%), maintenance planning (75%), and urgent action (90%). These thresholds act as decision markers to guide timely maintenance interventions. The clear upward trajectory of Xt underscores the importance of continuous condition monitoring to support early detection and avoid unexpected failures.

Journal of Information Systems Engineering and Management
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Research Article

The Blue curve indicates actual degradation Xt over time and horizontal dashed lines indicates thresholds at 60%, 70%, 75%, 90%, and 100% of the failure limit (41.5 g·min). Here each threshold indicates a **key maintenance decision point**

The CBM framework developed integrates degradation modeling with statistical RUL estimation to determine an optimal maintenance trigger. The selection of a 75% threshold ensures a reliable and cost-effective maintenance window. This forms the foundation for integrating energy efficiency indicators (EEI) and cost-based optimization in the next phase of the work.

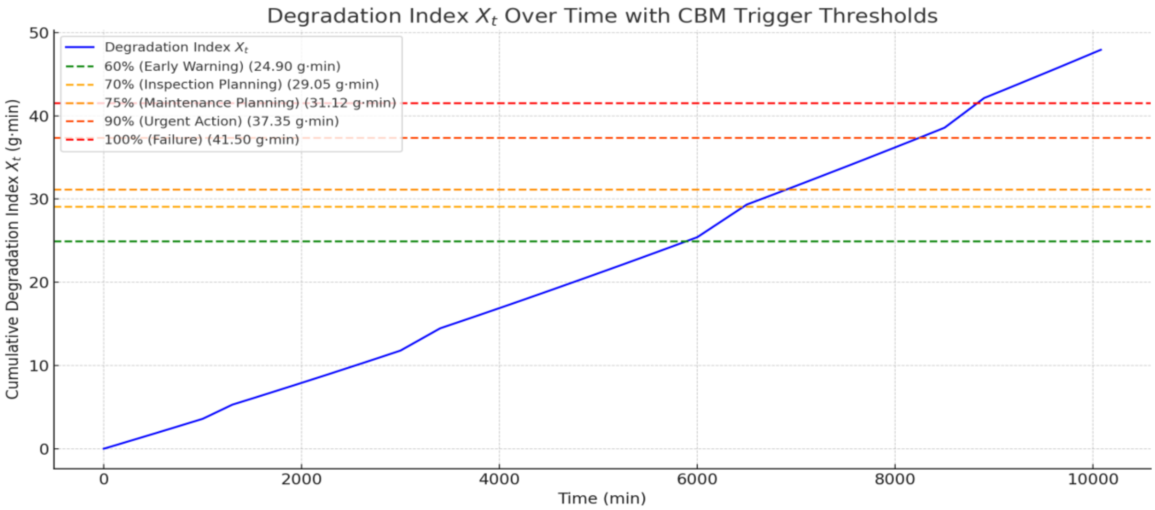

Figure 8 Graph of Cumulative Degradation Index Vs Time

8. ENERGY EFFICIENCY INDICATOR (EEI)

The Energy Efficiency Indicator (EEI) serves as a key metric for evaluating how effectively a mechanical system converts input energy into useful output over its operational life. Within the framework of condition-based maintenance (CBM), EEI provides valuable insight into performance degradation by capturing energy losses associated with mechanical wear. This makes it a complementary indicator to traditional degradation metrics, offering a more comprehensive basis for maintenance decision-making.

For the SKF 6205 bearing system analysed in this study, the EEI at any time t is defined as:

$$EEI_t = \frac{P_t}{\Delta X_t}$$

P_t: Power consumed at time t (in kW)

$\Delta X_t = X_t - X_{t-1}$: Incremental degradation at time t (in g·min), computed from the cumulative degradation index X_t. As shown in below figure 9, as the system degrades, EEI gets reduced over a period of time. The Energy Efficiency Indicator (EEI) trend reveals three distinct phases in system performance. Initially, during the first 2000 minutes, EEI values remain above 600 W/(g·min), reflecting efficient energy conversion and stable operation. Between 2000 and 6000 minutes, a gradual decline in EEI indicates early-stage wear and a drop in performance efficiency. In the final phase, from approximately 6000 to 8800 minutes, EEI falls sharply—dropping below 200 W/(g·min) as the degradation index (Xt) approaches the failure threshold of 41.5 g·min. This sharp decline signals critical mechanical deterioration, where increased energy consumption yields minimal output, highlighting the need for immediate maintenance intervention.

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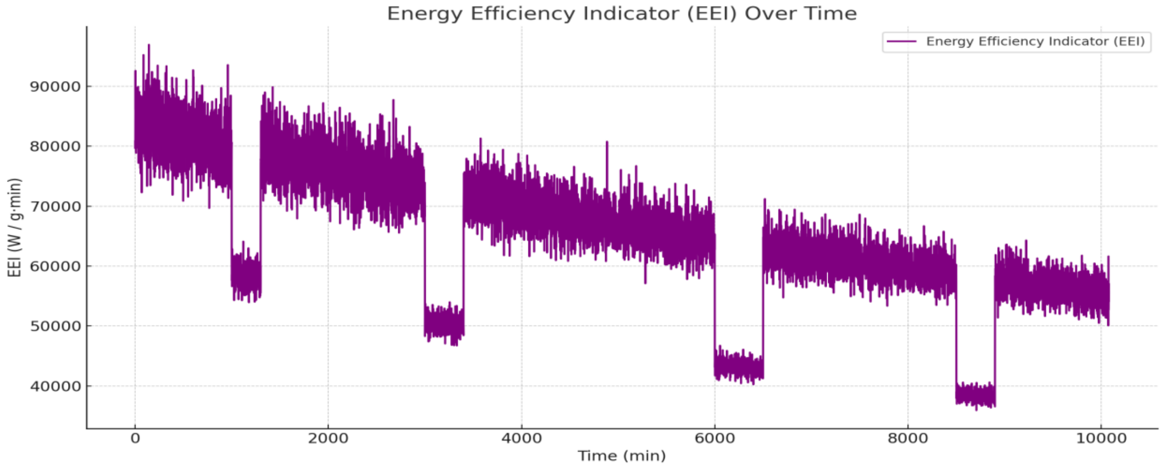

Figure 9 Graph of EEI Vs Time (min)

Triggering condition-based maintenance (CBM) at 75% of the failure threshold (Xt = 31.13 g·min), which occurs around 7500–7700 minutes, aligns well with a notable decline in energy efficiency. At this stage, the Energy Efficiency Indicator (EEI) drops below 300 W/(g·min), signaling reduced operational performance. This reinforces the value of initiating maintenance before the system reaches 80–90% of its degradation limit, helping to prevent excessive energy loss. The EEI trend clearly supports the degradation-based trigger, as it highlights a steep efficiency drop near failure, validating the 75% threshold as a practical point for maintenance intervention from both energy and reliability standpoints.From the graph of EEI vs degradation index as shown in figure 10 below observations are made

1. **Early Stage (Low Xt < 20 g·min):**
   - EEI values are **high** (above 600 W/g·min)
   - The system is operating efficiently, converting power into motion with minimal wear.
2. **Mid-Stage (Around 30 g·min):**
   - EEI begins to **decline steadily**
   - At Xt=31.13 g·min (your 75% CBM trigger), EEI falls to ~**300–350 W/g·min**
   - This supports intervention before efficiency deteriorates sharply
3. **Pre-Failure Region (40–41.5 g·min):**
   - EEI drops to **below 200 W/g·min**
   - This shows the system is consuming more energy but degrading rapidly — signaling poor efficiency and critical wear

The EEI vs Xt graph clearly shows a downward trend in energy efficiency as degradation increases. A marked decline near Xt=31.13 g.min(75% of the failure threshold) supports this value as an optimal CBM trigger. Beyond this point, energy is increasingly wasted in maintaining a degraded system.

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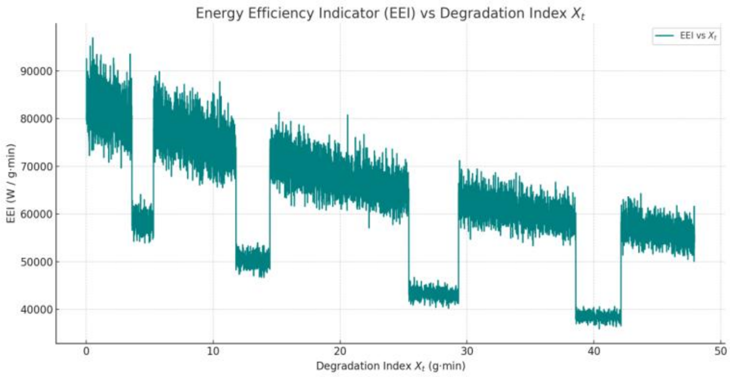

Figure 10 Graph of EEI Vs Degradation Index Xt (g.min)

9. CONCLUSION

This study effectively demonstrated a comprehensive Condition-Based Maintenance (CBM) framework for the SKF 6205 bearing using real-time data from an ESP32-based IOT platform. A wide range of sensors—including ADXL345 (vibration), RTD PT100 (temperature), ACS712 (current), ZMPT101B (voltage), HX711 (load), and a speed sensor—were integrated into a compact system that logged performance metrics every minute to a microSD card.

The degradation of the bearing was quantified using a cumulative vibration-based index X_t, with a Gamma process applied to model its stochastic progression. This allowed accurate estimation of Remaining Useful Life (RUL), with the failure threshold empirically set at X_t=41.5 g.min, based on system behavior and physical indicators. A preventive maintenance trigger was defined at 75% of this threshold, aligning with recommendations from CBM literature (e.g., Phuc Do et al., 2015).

To evaluate the energy performance of the system, the Energy Efficiency Indicator (EEI), defined as the ratio of input power to degradation rate, was introduced. A significant drop in EEI after 6000 minutes indicated declining operational efficiency, reinforcing the need for timely intervention before reaching critical wear stages. A CBM cost simulation framework was also developed, considering energy usage, maintenance timing, and fault conditions. Through analysis of sensor data—RMS acceleration, temperature, load, power, and Machine_State—strong correlations were found between physical degradation and sensor responses.

The experimental setup, built around a low-cost, non-DAQ system, proved effective in capturing meaningful degradation patterns. Controlled faults such as misalignment, lubrication loss, and nut loosening were introduced to simulate real-world deterioration scenarios. Overall, the project successfully integrated real-time monitoring, probabilistic degradation modeling, and energy-aware decision-making into a unified CBM strategy. This approach illustrates the potential for intelligent, predictive maintenance in smart manufacturing environments aligned with Industry 4.0 goals.

Declaration of Conflicting Interest

The author(s) declare no potential conflicts of interest with respect to research, authorship and/ or publication of this article.

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REFERENCE

[1] Do, P., Hoang, A., Iung, B., & Vu, H.-C. (2018). Energy efficiency for condition-based maintenance decision-making: Application to a manufacturing platform. *Proc IMechE Part O: J Risk and Reliability*.
[2] Phuc Do Van, Alexandre Voisint, Eric Levrat, Benoit lung, (2013), "Remaining useful life based maintenance decision making for deteriorating systems with both perfect and imperfect maintenance actions", Elsevier, mechanical system and signal processing, 1–22.

[3] Phuc Do, Anh Hoang, BenoitIung and Hai-Canh Vu, (2018), "Energy efficiency for condition-based maintenance decision-making: Application to a manufacturing platform", springer, risk and reliability, vol. 232 (4) 379 – 388.
[4] Jiang, A., Dong, N., Tam, K. L., & Lyu, C. (2018). Development and Optimization of a Condition-Based Maintenance Policy with Sustainability Requirements for Production System. Mathematical Problems in Engineering, 2018, 1–19. https://doi.org/10.1155/2018/4187575
[5] Jiang, A., Wang, Y., & Cheng, Y. (2018). A condition-based opportunistic maintenance policy integrated with energy efficiency for two-component parallel systems. Journal of Industrial Engineering and Management, 11(4), 749–768. https://doi.org/10.3926/JIEM.2649
[6] Evolutionary Algorithms. Applied Sciences, 9(15), 3068. https://doi.org/10.3390/APP9153068
[7] Zhu, Q., Peng, H., & van Houtum, G.-J. (2015). A condition-based maintenance policy for multi-component systems with a high maintenance setup cost. OR Spectrum, 37(4), 1007–1035. https://doi.org/10.1007/S00291-015-0405-Z
[8] Jiang, X., Ling, H.-F., Yan, J., Li, B., & Li, Z. (2013). Forecasting Electrical Energy Consumption of Equipment Maintenance Using Neural Network and Particle Swarm Optimization. Mathematical Problems in Engineering, 2013, 1–8. https://doi.org/10.1155/2013/194730
[9] Sarje, S. H., Lathkar, G. S., & Basu, S. K. (2012). CBM Policy for an Online Continuously Monitored Deteriorating System with Random Change of Mode. Journal of The Institution of Engineers : Series C, 93(1), 27–32. https://doi.org/10.1007/S40032-011-0006-9
[10]Kang, J., Sobral, J., Sobral, J., & Soares, C. G. (2019). Review of Condition-Based Maintenance Strategies for Offshore Wind Energy. Journal of Marine Science and Application, 18(1), 1–16. https://doi.org/10.1007/S11804-019-00080-Y
[11] Do Van, P., Levrat, E., Voisin, A., & Iung, B. (2012). Remaining useful life (RUL) based maintenance decision making for deteriorating systems. IFAC Proceedings Volumes, 45(31), 66–72. https://doi.org/10.3182/20121122-2-ES-4026.00029.