Research Article

Feature-Based Fault Detection and Degradation Analysis of Ball Bearings under Run-to-Failure Conditions

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Abstract
Reliable fault detection and degradation assessment of rolling element bearings are crucial for condition-based maintenance of rotating machinery. This paper presents a feature-based approach for fault detection and degradation analysis of ball bearings operating under run-to-failure conditions. Vibration signals measured along two orthogonal directions were processed to extract RMS features. It captures directional vibration behavior, and a combined RMS-based degradation index was constructed, providing a representation of bearing health. Statistical thresholds were established from the healthy operating region, and a persistence-based detection criterion was applied to identify fault onset while avoiding false alarms caused by transient fluctuations. The results show that RMS vibration features are sensitive to early mechanical degradation. It exhibits a sustained increase before bearing failure. Directional analysis shows clear vibration responses along different axes, which supports using a combined degradation index for dependable fault detection. Temperature analysis shows a delayed response compared to vibration indicators. A significant temperature rise happens in the later stage of bearing life, confirming the level of degradation. This proposed method offers a clear and effective way to detect bearing faults when running to failure and serves as a practical foundation for future studies on predicting remaining useful life.

Keywords: Bearing fault diagnosis, Condition-based maintenance, Degradation monitoring, Run-to-failure, Vibration signal analysis

1 Introduction

Ball bearings are critical components in rotating machines. Their failure can lead to sudden downtime, a threat to safety, and economic losses. The result shows that reliable fault detection and remaining useful life (RUL) estimation of bearings is necessary in condition-based maintenance. Studies show that early fault detection with accurate degradation analysis can improve system reliability and planning of maintenance [1]. Recent reviews further highlight the growing importance of RUL prediction techniques. It also highlights the increasing integration of data-driven approaches in prognostics and health management systems [2].

Characterizing the evolution of degradation using appropriate health indicators is a key idea behind RUL estimation. Degradation based approach aims to track the gradual decrease of system performance. This relates it to the remaining operational life [3]. Several frameworks have been proposed that integrate degradation monitoring, defect identification, and RUL estimation. It unifies structure, emphasizing the importance of interpretable and physically meaningful health indicators for reliable predictions [4]. These studies underline the effectiveness of RUL prediction. It strongly depends on the quality of the degradation representation extracted from sensor data. Model based approaches are widely used for bearing RUL estimation, particularly those based on Kalman filtering techniques. Extended Kalman filters are applied to track bearing degradation by combining dynamic system models with measurement data. It enables recursive estimation of RUL under uncertainty [5]. Time-varying Kalman filter formulations have further improved prediction accuracy. It is done by adapting model parameters to evolving degradation characteristics [6]. While these methods offer strong theoretical foundations, their performance often relies on accurate system modeling. It may be sensitive to modeling assumptions and noise.

To overcome these limitations, machine learning (ML) based methods are increasingly adopted for bearing RUL prediction. The classical ML techniques, like support vector machines (SVM) combine with degradation tracking models, which demonstrate an improved flexibility. This helps in capturing nonlinear degradation trends [7]. More recently, deep learning (DL) approaches gained attention due to their ability to automatically learn complex representations from sensor data. Deep neural networks, recurrent neural networks, and convolutional neural networks are successfully applied for bearing RUL prediction. It helps in achieving promising results under various operating conditions [8–11]. Advanced architectures incorporating attention mechanisms. With further enhanced prediction performance, it emphasizes informative temporal features during degradation progression [12]. Despite their accuracy, many DL methods operate as black-box models. It offered limited interpretability with respect to fault initiation and physical degradation stages.

Vibration and temperature measurements are widely adopted among the various sensing modalities used for bearing condition monitoring. Vibration signals are highly sensitive to surface defects, spalling, and dynamic changes in bearing components. It makes them effective for early fault detection. In contrast, temperature reflects frictional losses, lubrication degradation, and severe contact deterioration. It typically exhibits a delayed response compared to vibration [13]. For improved fault diagnosis performance, recent studies combine vibration and temperature features. It indicates that temperature can serve as a complementary indicator that validates late-stage degradation identified through vibration analysis [14].

The availability of high-quality run-to-failure datasets is essential for developing predictive methods. Recently released datasets contain synchronized vibration and temperature measurements collected until bearing failure. It provides valuable opportunities to study degradation behavior across the entire bearing life [15]. However, many existing studies using such datasets focus primarily on prediction accuracy [16]. This uses complex models with limited emphasis on interpretable, feature-based fault detection and degradation analysis. There remains a need for systematic investigation of how simple yet informative features, such as RMS vibration and temperature, evolve under run-to-failure conditions. The features contribute to robust fault detection prior to failure. This study addresses this gap by presenting a feature-based fault detection and degradation analysis framework. The framework uses RMS vibration and temperature features. It provides an interpretable foundation for future RUL prediction studies.

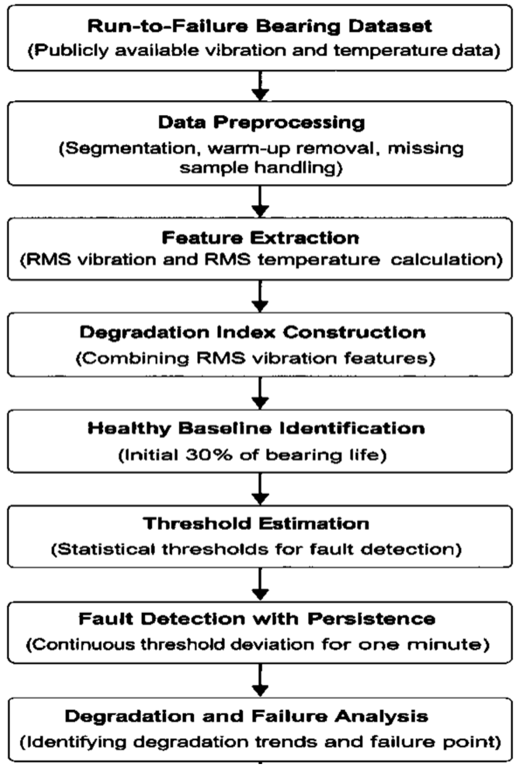

Figure 1: Block Diagram of Proposed Methodology.

Though RMS features and statistical thresholding are widely used in bearing monitoring, prior studies emphasize prediction accuracy via complex machine learning models. In contrast, this work investigates degradation evolution using physically interpretable RMS features under full run-to-failure conditions. The novelty lies in the fusion of orthogonal vibration components into a unified degradation index, robust median-based baseline modeling, integration of persistence-based fault validation, and experimental analysis of vibration–temperature coupling.

2 Materials and Methods

2.1 *Process and Dataset Description*

The present study utilizes a publicly available run-to-failure ball bearing dataset. The dataset contains synchronized vibration and temperature measurements. This has been widely adopted for bearing prognostics and health management research [15].

The data was obtained using an accelerated life test. This was carried out under controlled laboratory settings. The bearing experienced combined axial and radial loading, with the rotational speed maintained at approximately 1770–1780 RPM throughout the test duration. The test was stopped after a total of 128 hours. This was when levels of both vibration and temperature exceeded set safety standards.

The vibration signals are collected by two accelerometers fixed to the bearing housing in cross directions, which are named the x-direction and y-direction of vibration. In addition to vibration characteristics, measurement of the temperature of the bearing is conducted by a K-type thermocouple fixed to the surface of the bearing housing. The vibration and temperature signals are recorded at a sampling rate of 25.6 kHz and are stored as four-channel comma-separated value files at one-hour intervals for vibration in the x-direction, vibration in the y-direction, the temperature of the bearing, and environmental temperature.

It should be noted that the data set covers the entire life span of the bearings, from a healthy operational regime right up to complete failure, slowly. Further examination of the bearings after the test proved the occurrence of spalling as well as crack initiation on the bearings, thus proving the relevance of the data set acquired. It is due to the data set being a complete run-to-failure data set, which encompasses both vibration and temperature data, that it is suitable for the analysis that is conducted in this research.

2.2 *Proposed Methodology*

The proposed methodology is expected to deal with the fault detection and degradation assessment of the ball bearings operating in a run-to-failure mode based on vibration and temperature signals. A description of the methodology will be given below based on Fig. 1. The methodology adopts a sequence of algorithms, including preprocessing of the input signal, extraction of the feature vectors, development of the index of degradation, identification of the healthy baseline, threshold value estimation of the statistical model of the machine's degradation, and fault identification.

First, the publicly available "run-to-failure" dataset is preprocessed for the purpose of ensuring a reliable extraction of features. This is achieved by segmenting the raw signal values for both the vibration and temperature into one-second segments. To remove the effects of the startup conditions, the first three hours of the extracted features are disregarded. Missing values in the extracted features are dealt with to ensure continuity. From these preprocessed signals, the RMS features are extracted from vibration data in the x and y directions and from the temperature signal. The choice of these features is based on its ability to represent signal energy. In this case, vibration and temperature features that provide details on vibration and thermal changes associated with bearings are extracted.

To achieve a combined view of vibration-based degradation, the RMS values for both vibration directions are combined to derive a combined degradation index (DI). This allows a concise view of the bearing condition to be obtained by aggregating information from different directions of sensing. The normal operating range is determined by postulating that the first 30% of bearing life is in a normal operating mode based on the observed vibration characteristics of the initial period of the run-to-failure traces. The statistical properties of the degradation index in the normal operating region are utilized to set up a threshold for fault identification. The statistical threshold is determined to draw the line between normal and abnormal activities.

The first 30% of the bearing life was selected as the healthy baseline based on both the dataset and signal behavior analysis. The dataset publication reports that structural damage, including spalling and crack formation verified through microscopic and X-ray analysis, occurred only near the end of the 128-hour run-to-failure test. No physical damage was reported during the early operational stage. Additionally, RMS vibration and temperature features during the initial period exhibited stable mean and variance without monotonic drift, indicating consistent behaviour before degradation progression. The baseline selection reflects both the physical validation provided in the dataset study and the statistical stability of early vibration characteristics.

The fault detection uses a persistence-based thresholding method. A fault is reported only if the degradation index exceeds a preset threshold for at least one minute, showing persistence. This persistence factor helps eliminate transient responses from excursions. The development of the faulty condition at the component level is identified by examining the pattern of vibration and temperature feature degradation. The point of failure is also established at this stage. Overall, this new method provides a clear and understandable way to detect bearing faults and analyze degradation using straightforward but informative features. The proposed method does not rely on black-box techniques.

2.3 *Implementation*

Using the run-to-failure bearing dataset, this section tells the practical implementation of the feature-based fault detection and degradation analysis framework. It mainly focuses on extracting RMS features from vibration and temperature signals, constructing degradation indexes, estimating statistical thresholds and application of persistence-based fault detection. The methodology described in Section 2.2 was followed in the sequential processing of the temperature and vibration data. MATLAB was used for all signal processing and analysis. The raw time-domain signals are segmented into non-overlapping windows of one-second duration. This results in a uniform temporal resolution for feature extraction across the whole bearing life. This window length is selected to balance sensitivity to transient behavior and robustness against noise.

The vibration signals measured along the X and Y directions for a one-second window are used to extract RMS features. These features show the effective vibration energy within each window and provide an understanding of the bearing's dynamic response. In parallel, the RMS temperature values from the temperature measurements were used to record the bearing's thermal evolution over time. To eliminate any initial transient effects associated with system warm-up, the first three hours of RMS feature data were excluded from additional analysis.

A vibration-based degradation index is made by RMS vibration features which are collected from orthogonal directions. This index is a single health indicator that tells the overall vibration of the bearing and reduces the directional bias due to individual vibration components. Fault detection and degradation trend analysis are done based on the resulting degradation index. 30% of the bearing life after warm-up removal is designated as the healthy operating region which is taken as a reference point for bearing behaviour. The fault detection threshold is measured with the help of statistical features of the degradation index. The degradation index is then continuously compared with the statistical threshold, which represents the upper limit of healthy operation.

A persistence-based approach is used for fault detection to improve robustness. Fault is seen when the degradation index exceeds the threshold for at least one minute. In order to exceed false alarms caused due to noise-induced threshold crossings, this condition is implemented. The remaining vibration and temperature data are examined after the identification of fault onset to track the progress of degradation and to identify the failure point.

Temperature features are examined with vibration-based indicators to check the progress of bearing degradation. In order to provide an interpretation of the degradation process, the temporal relationship between temperature rise and vibration-based fault detection was studied. The suggested framework maintains physical interpretability while enabling dependable fault detection and degradation analysis. This relies on interpretable RMS features and statistical thresholding instead of predictive models.

3 Results and Discussion

The findings of fault detection and degradation analysis using RMS vibration and temperature features are shown in this section. Table 1 presents a representative portion of the processed dataset obtained after feature extraction using a one-second non-overlapping window. The table includes time in seconds, RMS vibration features along the x and y-directions, the corresponding RMS-based degradation index (DI), RMS temperature, and the remaining useful life (RUL) in hours. The RMS vibration features capture the instantaneous vibration energy in each direction, while the degradation index provides a compact representation of overall vibration severity by combining directional information. The RMS temperature reflects the thermal condition of the bearing and complements the vibration features. The RUL column indicates the remaining operational time until failure, decreasing monotonically as the bearing progresses toward the end of its life.

3.1 *Vibration-Based Fault Detection and Degradation Analysis*

RMS features extracted from acceleration signals measured along two orthogonal directions were used to analyse the bearing's vibration response. RMS vibration is sensitive to variations in bearing dynamics brought by surface wear, spalling, and contact irregularities. It is frequently used as a signal energy indicator in bearing condition monitoring studies [17,18]. To describe healthy behaviour, degradation progression, and fault onset under run-to-failure conditions, the evolution of RMS vibration features was analysed.

Figure 2 illustrates the RMS vibration measured along the x- and y-directions during the first 40 hours of operation. Both RMS components show comparatively stable behaviour in this early stage, with only minor random fluctuations and no long-term upward trend. Such stable RMS behaviour during the healthy phase is also reported in run-to-failure studies, where energy-based indicators remain bounded before crack propagation accelerates degradation [19]. Due to variations in load transmission routes, sensor orientation, and structural stiffness, the RMS vibration in the y-direction exhibits a higher baseline amplitude and more variability than the x-direction. However, healthy bearing operation during this time is indicated by the lack of impulsive growth or monotonic increase in both directions. The premise that the early part of the experiment reflects typical operating conditions and can be utilised to create baseline statistics is supported by this observation.

Table 1: Extracted RMS features with one second window.

Time (Seconds)	RMS_x Vibration	RMS_y Vibration	DI	RMS Temperature	RUL (hours)
0	0.428681	0.642532	0.772409	41.61491	128
1	0.277909	0.432536	0.514121	41.61491	127.9997
2	0.45745	0.75889	0.886101	41.61491	127.9994
3	0.328285	0.562878	0.651615	41.61491	127.9992
4	0.31288	0.457171	0.553985	41.61491	127.9989
5	0.484744	0.680096	0.835169	41.61491	127.9986
6	0.374159	0.607904	0.713823	41.61491	127.9983
7	0.328844	0.4473	0.555171	41.60936	127.9981
8	0.363003	0.595401	0.697333	41.60335	127.9978
9	0.359747	0.571757	0.675517	41.60335	127.9975
10	0.329925	0.516724	0.61307	41.60335	127.9972
11	0.411425	0.707904	0.818779	41.60335	127.9969
12	0.302761	0.501766	0.586032	41.60335	127.9967
13	0.389039	0.72759	0.825069	41.60335	127.9964
14	0.385306	0.582298	0.698235	41.60335	127.9961
15	0.289143	0.535044	0.608175	41.60335	127.9958
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464382	1.561833	1.533214	2.188622	100.4165	-0.995
464383	1.227757	1.506297	1.943275	100.4165	-0.99528
464384	1.543091	1.358171	2.055665	100.4165	-0.99556
464385	1.560634	1.456882	2.134967	100.4165	-0.99583
464386	1.524607	1.508605	2.144834	100.4165	-0.99611
464387	1.669976	1.485514	2.235078	100.4158	-0.99639
464388	1.410642	1.453093	2.025189	100.4136	-0.99667
464389	1.226166	1.556569	1.981512	100.4136	-0.99694
464390	2.328908	1.995499	3.066892	100.4136	-0.99722
464391	1.687804	1.84074	2.4974	100.4136	-0.9975
464392	1.122772	1.205356	1.647271	100.4136	-0.99778
464393	1.179945	1.435903	1.858518	100.4136	-0.99806
464394	1.622817	1.499185	2.209319	100.4136	-0.99833
464395	1.111236	1.194225	1.631263	100.4136	-0.99861
464396	1.684342	1.540585	2.282632	100.4136	-0.99889

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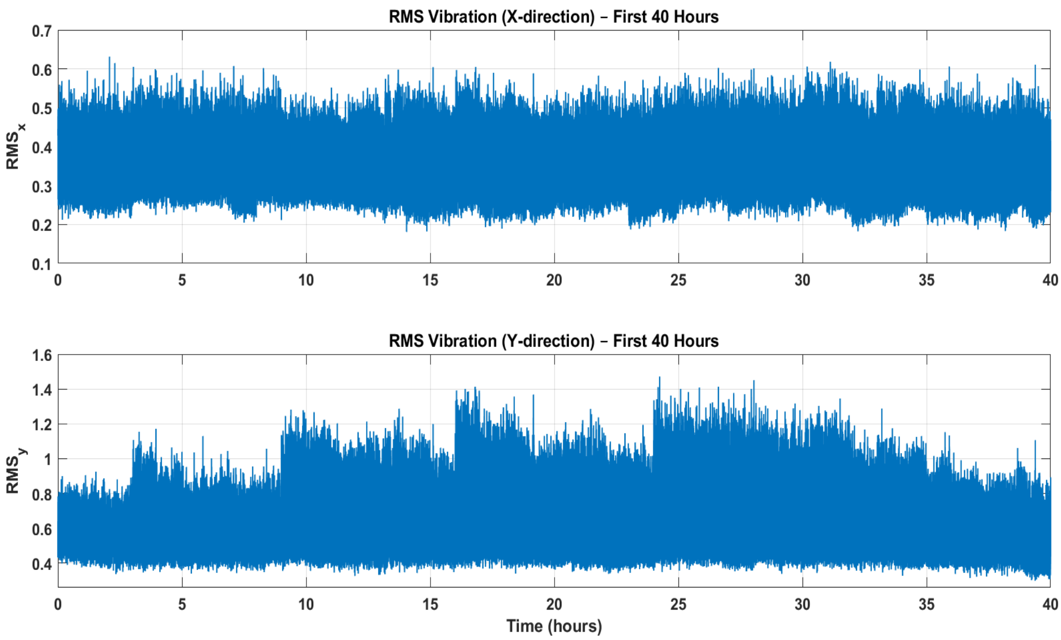

Figure 2: RMS vibration response during the initial healthy operating period.

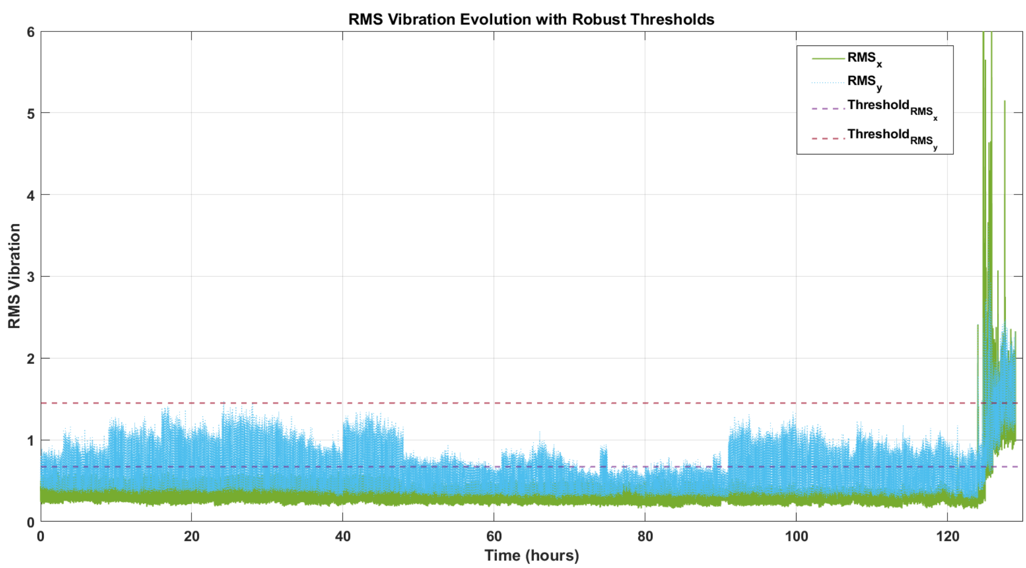

Figure 3 : Evolution of RMS vibration over the complete bearing life.

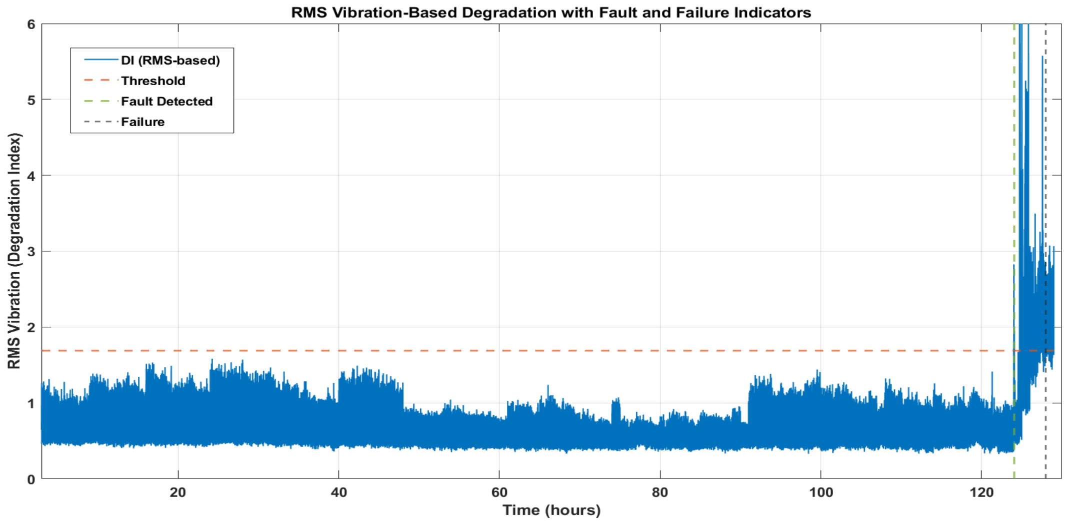

Figure 4: RMS-based degradation index with statistical threshold, fault, and failure.

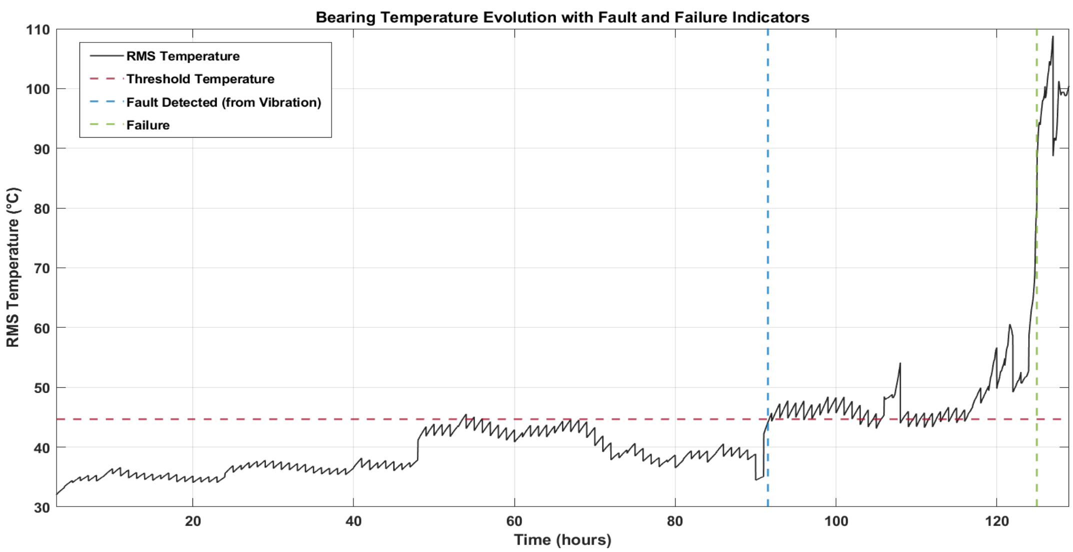

Figure 5: Evolution of RMS bearing temperature with fault and failure indicators.

Figure 3 displays the long-term evolution of RMS vibration along both directions over the full bearing life along with reference thresholds that were statistically determined. The first 30% of the bearing life was designated as the healthy operating region in order to determine these thresholds. Statistical techniques were used to lessen the impact of skewed distributions and outliers. The median absolute deviation was employed as a reliable indicator of dispersion, and the median value of the RMS vibration in the healthy region served as the central tendency. The median plus three times the MAD was then used to calculate the threshold for each vibration component. Thresholding techniques such as MAD and sigma-based limits are widely adopted in vibration-based anomaly detection to reduce sensitivity to outliers and skewed distributions [20]. Figure 3 illustrates that for the majority of the bearing, both RMS_x and RMS_Y stay below their corresponding thresholds.

Although axis-wise RMS features offer valuable information about directional vibration behaviour, fault detection may become unclear due to their individual variability. By combining the vibration data from both directions, a combined RMS-based degradation index (DI) was created to provide a more accurate depiction of bearing health. The temporal evolution of this degradation index, the failure point, and the fault detection threshold are all displayed in Figure 4. The construction of composite health indicators from multi-directional vibration features has improved monotonicity and prognostic relevance compared to single-axis features [9,19]. Using a three-sigma (3σ) criterion, the mean and standard deviation of the DI within the healthy region were used to calculate the threshold for the degradation index. The upper bound of typical vibration behaviour under healthy circumstances is represented by this statistical limit.

A persistence-based fault detection criterion was used to prevent false alarms brought on by minor fluctuations. Only when the degradation index consistently exceeded the threshold for a minimum of one minute was a fault identified. Only continuous and physically significant increases in vibration are considered as faults due to this persistence requirement. Figure 4 illustrates how the degradation index shows a sharp increase in the late stage of operation after remaining largely stable during the healthy and early degradation phases. The fault detection point, which happens just before the ultimate failure time, keeps robustness against noise-induced threshold crossings while offering an early warning of abnormal bearing behaviour.

Since the detection mechanism relies on sustained statistical deviation from baseline behaviour, moderate variation in baseline window selection (e.g., 20% or 40%) is not expected to alter the detected fault onset time, as degradation is characterized by persistent threshold crossing in the later stage of operation.

The vibration-based results show that RMS features effectively record the bearing's breakdown process under run-to-failure conditions. While the combined degradation index provides a more accurate and transparent indication of fault onset, directional RMS analysis shows variations in vibration response along orthogonal axes. The suitability of RMS vibration analysis for bearing condition monitoring is confirmed by the use of effective thresholding and persistence-based detection, which allow for early and stable fault identification before catastrophic failure.

3.2 *Temperature-Based Degradation Analysis*

In addition to the vibration-based degradation assessment, the bearing's thermal behaviour was examined using the RMS temperature feature. Figure 5 shows the final failure point, the vibration-based fault detection time, and the bearing temperature evolution over the whole run-to-failure period. The first three hours of temperature data were not included in the analysis in order to remove any initial transient effects related to system warm-up.

In Figure 5, under steady-state conditions, the bearing temperature only slightly fluctuates over the course of the operating life. There are slight variations that can be explained by typical changes in lubrication conditions, load distribution, and friction. A dashed line in the figure represents a temperature reference level that was calculated using robust statistical measures from the healthy operating region. Despite increasing mechanical wear detected by vibration analysis, the temperature stays below the reference level during the healthy and early degradation phases. This indicates normal thermal behaviour.

The vertical dashed line in Figure 5 represents the vibration-based fault detection point, which is followed by a noticeable shift in thermal behaviour. After that, the temperature starts to gradually increase due to increased friction and loss of energy created on by surface damage, splitting, and decreasing lubrication conditions. As the bearing gets closer to the end of its useful life, the temperature rises noticeably, reaching a peak just before failure. Severe contact damage and loss of load-carrying capacity are consistent with quick temperature increase.

It is observed that temperature reacts more slowly and mostly reflects later-stage damage, whereas vibration features are dependent on early mechanical degradation and allow for prompt fault detection. As a result, temperature is a useful supplementary indicator that confirms the course and degree of bearing degradation found through vibration analysis. This delayed thermal response relative to vibration-based indicators is consistent with previous studies, where temperature rise was associated primarily with advanced lubrication breakdown and severe surface damage [13,21]. Temperature is not appropriate for early fault detection on its own.

4 Conclusions

This study presented a feature-based framework for fault detection and degradation analysis of ball bearings operating under run-to-failure conditions. A combined RMS-based degradation index was constructed to provide a transparent representation of bearing health. Statistical thresholds are derived from the healthy operating region. These thresholds, together with a persistence-based detection criterion enabled reliable identification of fault onset avoiding false alarms due to transients. The results showed that RMS vibration features responded at an early stage to mechanical degradation whereas temperature showed a delayed response with a pronounced rise only in the final stage of bearing life, thereby serving as a complementary indicator that confirms the severity of degradation identified through vibration analysis. As a future extension, this work can be advanced toward remaining useful life prediction by implementing machine learning and deep learning models capable of learning complex and nonlinear degradation patterns, with particular emphasis on developing approaches using raw vibration signals or alternative feature representations for improved prognostic accuracy and generalization.

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Author Contributions

E.G.: investigation, methodology, data analysis; P.G.: methodology, data analysis; S.R.: conceptualization, methodology, writing-original draft, M.P.: formal analysis, supervision, reviewing and editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors have not utilised any generative AI tool for any assistance in the writing process.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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