Sound & Vibration 2026, 60(5), 4490.
doi: https://doi.org/10.59400/sv4490

Article

Condition-based maintenance threshold determination for gearbox fault progression using vibration envelope features and accelerated life testing

Asokan Vasudevan[1], Suleiman Mohammad[2,3,*], Mohammad Ahmmad Hunitie[4], Gui Jie[5], Jonathan Lee[1], Mbiatke Andrew[1]

[1] Faculty of Business and Communications, INTI International University, Nilai 71800, Malaysia
[2] Department of Business Administration, Business School, Al al-Bayt University, Mafraq 25113, Jordan
[3] Research Fellow, INTI International University, Nilai 71800, Malaysia
[4] Department of Public Administration, School of Business, University of Jordan, Amman 11942, Jordan
[5] Faculty of Psychology, Shinawatra University, Pathum Thani 12160, Thailand
* **Corresponding author:** Suleiman Mohammad, dr_sliman@yahoo.com

CITATION

Vasudevan A, Mohammad S, Hunitie MA, et al. Condition-based maintenance threshold determination for gearbox fault progression using vibration envelope features and accelerated life testing. Sound & Vibration. 2026; 60(5): 4490. https://doi.org/10.59400/sv4490

ARTICLE INFO

Received: 8 June 2026
Revised: 30 June 2026
Accepted: 10 July 2026
Available online: 27 July 2026

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Abstract: Gearbox failures represent a critical problem faced by industrial machines, considering the impacts of such failures on machine reliability, efficiency, and maintenance cost. Despite the well-established use of vibration-based condition monitoring techniques for diagnosing the presence of faults, few attempts have been made in transforming information about fault progression into thresholds that could be used in making condition-based maintenance (CBM) decisions. In this work, a CBM system for analysing gearbox fault progression based on vibration envelope features is presented, alongside accelerated life testing. An experimental approach has been adopted, whereby accelerated life testing was performed to induce gearbox degradation progressively. Then, vibration data were analysed through the envelope technique, out of which six vibration envelope features, namely RMS Envelope, Kurtosis, Crest Factor, Peak Amplitude, Envelope Energy, and Sideband Energy Ratio, were derived and analysed based on their sensitivity through correlation, monotonicity, trendability, and separability tests. Thereafter, a composite health index based on the most sensitive features was formulated, and a multilevel maintenance threshold system consisting of Alert, Warning, and Critical levels was created. The findings show that Envelope Energy, Sideband Energy Ratio, and Kurtosis have the highest sensitivity to degradation and can accurately represent the evolution of gearbox faults. The composite health index shows a strong correlation with the extent of degradation ($R^2 = 0.962$) and successfully discriminates between different health states of the gearbox. The developed framework for determining maintenance thresholds achieves an accuracy of 94.9%, which allows accurate identification of maintenance intervention phases.

Keywords: gearbox fault progression; vibration envelope analysis; condition-based maintenance; health index; maintenance thresholds; accelerated life testing

1. Introduction

Gearboxes constitute a critical mechanical sub-system in current industrial machines that facilitate power transmission, speed adjustment, and torque transformation. They are utilized in many different applications, including manufacturing plants, wind farms, mines, ships, automobiles, and heavy machinery, among others. The proper functionality of these systems is dependent largely on the condition of gearboxes, and thus gearbox monitoring constitutes an important aspect of research and industrial operations [1–3]. With the need to increase productivity and maximize equipment utilization in the face of increased competition, there has been an increased need for efficient gearbox condition monitoring techniques. The development of Industry 4.0 and the adoption of smart maintenance systems have further facilitated this trend from routine maintenance and planned maintenance to condition-based maintenance. Unlike corrective maintenance that focuses on repairing breakdowns after their occurrence and planned maintenance which operates on a pre-defined schedule, condition-based maintenance uses real-time information regarding the status of machines in order to identify the best course of maintenance [4, 5]. There has thus been much attention given to techniques that detect deterioration in machinery and facilitate informed maintenance decisions. Among several methods of monitoring conditions, vibration analysis stands out as an excellent approach that has shown great promise for detecting gearbox failures due to the wealth of information that vibration signals offer on gearbox dynamics, gear tooth interactions, and the degradation process. Several studies have found that gear tooth wear, pitting, cracks, spalling, and poor lubrication lead to specific vibration characteristics that can be detected and analysed even before a catastrophic failure occurs [6, 7]. As a result, vibration analysis plays a central role in preventive maintenance of machinery.

Despite the popularity of vibration analysis, its application to gearbox condition monitoring has several limitations. The most commonly used vibration features, such as RMS, Peak Amplitude, Crest Factor, and frequency amplitude measurements, have been found quite useful in predicting abnormal operating conditions; however, the diagnostic power of these techniques tends to decrease during the initial stages of faults when fault-related vibration signals are not distinguishable from operating noise [8, 9]. Hence, there is a need for more sophisticated signal processing techniques in extracting fault-related information from vibrations.

Among the mentioned methods, the envelope technique has gained significant interest due to its capability in extracting the modulation characteristics of the vibration signals caused by faulty equipment. Enveloping is known for its ability to detect localized gear and bearing faults by accentuating repeated impact signatures caused by deterioration within the machines [10, 11]. The effectiveness of using envelope-based features such as envelope RMS, Kurtosis, Envelope Energy, and sideband energy features has been well demonstrated in many studies related to fault detection and machinery diagnostics. However, most of the existing literature focused mainly on developing methods for diagnosing and classifying faults without emphasizing on analysing fault progressions and formulating maintenance strategies based on the obtained diagnosis information. As such, this research aims to address the problems arising between fault diagnosis of the gearboxes and their maintenance planning. While there are a vast number of successful studies that have utilized various vibration analysis techniques in detecting gearbox faults, the development of maintenance strategies that could make use of the degradation information is far less explored [12, 13]. Maintenance decision-making still depends largely on preset alarm limits, personal judgments, and past experience rather than actual degradation conditions and trends. As a result, maintenance technicians face difficulty in deciding when an inspection should be carried out or when a repair is needed. The core problem addressed in this research is the absence of a usable decision support model that would systematically convert information about vibration conditions into the criteria for the necessary maintenance activities. The diagnostic techniques developed to date are quite effective in identifying faults in gearboxes but do not provide any useful information about when the maintenance should be performed, how serious the fault is, and what decisions should be made in this regard. The lack of such information often results in premature or late maintenance decisions.

In addition to the gap in the literature concerning scholarly work in this area, the current study is inspired by the problem that arises from an industrial context in practice. Even though vibration monitoring systems that are available today are able to detect when there is unusual behaviour of the gearbox, the problem that is commonly faced by maintenance engineers is the lack of clear information about the appropriate moment for carrying out maintenance activities. Alarm signals or unusual conditions generated by existing vibration monitoring systems do not always provide enough information about whether the maintenance action should be taken immediately or the fault should just be monitored. This means that maintenance is done based on alarm levels, experience of engineers, or their personal judgments. This might result in unnecessary maintenance activity, extra downtime caused by false alarms, or even delay in maintenance causing problems to develop into catastrophes.

The importance of the study is based on its ability to connect condition monitoring processes and maintenance activities implementation. It will contribute to further elaboration of condition-based maintenance through defining a relationship between vibration envelope features and gearbox degradation process and using this information for developing practical maintenance criteria. As a result, the outcomes of the study will allow the maintenance engineer to detect degradation levels, monitor fault evolution, and implement preventive maintenance procedures before a critical failure occurs. In some industries, such as mining or heavy industrial facilities, gearbox failure is associated with high economic expenses. The innovation of the study includes integrating the processes of analysing vibration envelope features, measuring the sensitivity of the selected indicators, developing the composite health index, and determining appropriate maintenance thresholds. Despite the fact that previous studies dealt separately with vibration envelope feature diagnostics, Health Index models building, or fault classification, few researchers considered their combination as the basis for building a condition-based maintenance strategy. Additionally, the authors use an accelerated life testing method that allows analysing the entire life cycle of gearbox faults, including degradation phases. The proposed methodology is based on vibration diagnostics, which makes it possible to define the severity of a fault and set up three types of maintenance thresholds (Alert, Warning, and Critical).

This research does not introduce a new fault diagnosis technique; instead, it solves a maintenance decision-making problem using vibration envelope analysis, health index generation for degradation-sensitive features, and determination of maintenance thresholds through an engineering decision support system approach. While the novelty of the present study is not based on the creation of a novel vibration analysis approach, the novelty stems from the comprehensive incorporation of different approaches into an integrated condition-based maintenance framework. Previously existing studies have primarily been limited to a particular element of gearboxes' condition monitoring, including the diagnosis of faults, feature extraction, development of a Health Index, or maintenance threshold determination. All of the above-mentioned elements, however, are rarely incorporated into an approach that transforms vibration information into actual maintenance recommendations. In contrast, the present framework involves all three components: degradation-dependent analysis of envelope features, development of a composite health index, and multi-level threshold determination for maintenance planning purposes.

2. Literature review

2.1. Gearbox faults and vibration-based condition monitoring

One of the key components found in any rotating machinery system is the gearbox, which plays an important role in the transmission of power and speeds between different mechanical components for industrial systems such as manufacturing systems, wind turbines, mining equipment, marine propulsion systems, automotive transmissions, and others. Due to the impact of dynamic loading, oil breakdown, temperature variation, and operational fatigue, gearboxes can undergo deterioration over time. The modes of failure may include tooth wear, pitting, spalling, crack formation, and tooth fracture. These failures affect the dynamics of the gearbox, resulting in changes in the vibration characteristics of the gear system [7, 14]. Prevention of gearbox failure and unnecessary downtime requires employing condition monitoring techniques. In this regard, vibration analysis is one of the methods that allows monitoring the current state of equipment, because vibration signals are directly related to the interactions of moving components inside the gearbox [1, 9]. Changes in vibration amplitude, signal frequency, and impulsiveness can serve as warning signs for defect formation even in cases where visible changes are still not observable. Conventional approaches to vibration monitoring involve calculating RMS, peak values, Crest Factor, and conducting spectral analysis to analyse the current state of the gearbox [9,15]. Despite high efficiency in detecting serious gearbox failures, these algorithms do not show satisfactory sensitivity while detecting the earliest signs of damage due to the low amplitude of signals generated during the process. Therefore, modern research is aimed at exploring advanced signal processing techniques.

2.2. Envelope analysis for gearbox fault diagnosis

Envelope analysis has recently emerged as an effective tool for gearbox failure detection based on its ability to emphasize the effects of periodic impacts caused by local defects. Gear tooth damage often results in periodic impacts modulating high-frequency components of vibration. This causes unique changes in vibration amplitudes, which are difficult to detect using traditional vibration spectrum analysis methods. Envelope analysis captures such modulation patterns and thus helps to reveal information about failures better [16, 17]. The approach has been successfully used in gearbox and bearing failure diagnostics due to its potential to isolate the features of impact-induced vibrations from a complicated vibration environment. Research suggests that envelope spectrum analysis allows detecting sideband structures around frequencies of gear teeth interactions. It is well known that such a phenomenon is one of the typical symptoms of gear tooth wear [18, 19]. Furthermore, the increase in the sidebands' amplitude shows progression of faults and is therefore considered a useful instrument for assessing the condition of machinery. Several studies have analysed various envelope-based parameters for their suitability for diagnosing equipment conditions, including envelope RMS, Kurtosis, Crest Factor, Envelope Energy, and sidebands' amplitude [20,21]. Particularly, Kurtosis has drawn significant attention due to its ability to respond strongly to impulses created by localized defects. Simultaneously, Envelope Energy was found to be effective in reflecting the extent of vibration impact degradation. Still, most research in the field has mainly focused on fault detection and classification tasks while overlooking long-term monitoring requirements.

2.3. Condition-based maintenance and prognostic approaches

condition-based maintenance (CBM) has become a possible maintenance strategy that schedules maintenance procedures depending on the status of the equipment, rather than doing periodic maintenance. It makes the maintenance process more efficient since the maintenance procedure will not be redundant, but at the same time will decrease the risk of unexpected breakdowns [5, 22]. However, the success of condition-based maintenance (CBM) largely depends on the ability to evaluate the rate of degradation and find the moment when intervention should be made before the machine fails. As a result, there have been extensive research works devoted to developing methods of prognosis and health management using condition-monitoring data in order to evaluate the condition of equipment and predict future performance degradation [23, 24]. In other words, these approaches combine monitoring data and degradation models. In relation to gearboxes, many CBM systems based on vibration analysis have shown their great promise in the field of fault detection and degradation evaluation [25,26]. At the same time, most current approaches are still targeted at diagnosis accuracy, rather than maintenance planning. Although it is necessary to detect a fault, the aim of maintenance planning is to make decisions about the maintenance.

2.4. Health index development for machinery health assessment

The methodologies of health index (HI) are gaining popularity as an advanced way to evaluate machine condition by combining various condition indicators into a single parameter of equipment healthiness. In comparison with conventional monitoring features, the health index provides a more complex image of the fault process and reduces uncertainty involved in interpreting individual indicators [27, 28]. Multiple approaches for HI calculation have been introduced, including the use of statistical weighting techniques, principal components analysis, fuzzy inference systems, machine learning algorithms, and data fusion techniques [29,30]. Regardless of the methodology applied, the key factor of success in calculating the Health Index is the choice of appropriate degradation indicators that can reliably reflect the fault process. Research shows that composite indicators generally demonstrate better performance compared to single vibration parameters as they provide additional dimensions of degradation. The combination of time-domain and frequency-domain parameters has been proven effective in improving degradation detection. At the same time, most research on health indexes has focused on applications related to fault classification, prognosis of faults, or estimation of remaining useful life.

2.5. Maintenance threshold determination in condition-based maintenance systems

Thresholds form an integral part of the maintenance strategy due to their ability to separate routine operations from maintenance interventions. Well-chosen thresholds help ensure that companies manage equipment reliability and availability and minimize cost and chances of failures during operations [31,32]. In the past, maintenance thresholds have been determined through fixed alarm limits, experience-based judgments, manufacturers' recommendations, or through operational experience [9, 15]. Despite continued use, such strategies often do not take into consideration the machine-specific behaviour of equipment. The consequence is that fixed thresholds either lead to unnecessary maintenance or insufficient warnings concerning degradation. Modern research efforts have looked into maintenance threshold determinations based on degradation modelling, reliability assessment, machine learning techniques, and prognostics [33, 34]. However, despite increased emphasis on data-driven solutions, most of the research efforts focus more on the effectiveness of fault detection and identification. Very few studies have focused on the development of multi-level maintenance threshold frameworks based on vibration envelope features for differentiation between degradation and advanced stages of deterioration and fault occurrence.

2.6. Research gap and study contribution

First, the literature highlights notable progress in gearbox fault diagnosis, vibration signal processing, condition monitoring, Health Index design, and the application of condition-based maintenance. Previous studies have confirmed the efficiency of vibration analysis for gear box fault identification [6, 35], and envelope analysis proved effective in extracting fault-related features and revealing modulation caused by gear degradation [17, 35]. At the same time, Health Index approaches revealed their potential for machinery condition evaluation and prognosis [36, 37]. However, some limitations can be identified. First, existing envelope analysis studies mostly focus on fault detection and classification without paying sufficient attention to the continuous monitoring of the degradation process. Thus, there is insufficient evidence on the differential degradation sensitivity of various features extracted by envelope analysis throughout the entire life cycle of the gearbox. Second, despite many vibration-based indicators used for condition monitoring, there is a lack of studies investigating the efficiency of such indicators based on correlation, monotonicity, trendability, and separability before Health Index creation. Third, existing Health Index studies concentrate on the diagnostic and prognostic aspects but pay little attention to maintenance thresholds. Finally, current studies in gearbox monitoring do not translate vibration-based degradation information into maintenance criteria required for condition-based maintenance.

The present contribution goes further than applying the vibration analysis approach individually. Even though the methods such as envelope analysis, statistical features evaluation, and Health Index approaches have been used separately in previous work, relatively little effort has been done in combining these approaches together in order to form a maintenance focused approach. The presented method describes the logical flow of the vibration feature extraction, vibration feature sensitivity evaluation, composite health index development, and finally the maintenance threshold calculation. The combination of these methods allows gearbox condition data to be utilized for maintenance purposes. While there have been many ways devised to determine the threshold from the use of fixed threshold alarms to statistical methods and machine learning-based techniques for deriving thresholds from data, not many attempts have been made to incorporate all of feature selection sensitive to degradation, the development of a physically meaningful Health Index, and threshold determination that facilitates maintenance activities within one methodology.

2.7. Conceptual model of the study

The conceptual model proposed for the study focuses on understanding the interaction between gearbox fault progression, characteristics of the vibration envelope, health condition assessment, and maintenance threshold determination. According to the model, gearbox fault progression results in changes in the behaviour of gearbox vibrations, which can be observed using the vibration envelope and used as indicators of faults and maintenance needs. As a result of the wear of components, pitting, cracks formation, and the general deterioration of gearbox surfaces, vibrations generated during interactions between gear teeth grow increasingly powerful and impulsive. This effect is particularly noticeable in the vibration envelope because it enhances the modulation components and thus becomes more sensitive to the presence of any abnormalities. Hence, vibrations envelope features such as Root Mean Square (RMS), Kurtosis, Crest Factor, Peak Amplitude, Envelope Energy, and Sideband Energy Ratio become the indicators of fault progression.

All of the features in **Figure 1** are associated with specific states of the gearbox throughout its operational life cycle. The progression of these parameters corresponds to the transition from normal conditions to early fault development, followed by moderate and severe faults, and finally—to failure. Based on that assumption, the model suggests that certain trajectories of gearbox degradation can be identified and used as guidelines for assessing the current state of health. In order to improve the accuracy of fault progression assessment, the identified envelope vibration features are used to develop the composite health index, which reflects the state of health of the gearbox as a whole. The health index eliminates uncertainties arising from analysing individual vibration features. The health condition indicator is expected to change as fault progression occurs, making it possible to identify transitions in the system's operational state. Finally, one of the key stages in the conceptual model consists in identifying the maintenance thresholds. Based on the Health Index, it is possible to determine three hierarchically related thresholds—Alert, Warning, and Critical. The Alert threshold signals the onset of abnormal degradation, the Warning zone represents the condition when maintenance activities are required, and the Critical zone signals imminent failure. Therefore, according to the conceptual model, gearbox fault progression results in changes in the vibration envelope characteristics, which have a direct effect on the health condition index, and the latter helps define maintenance-intervention thresholds. Accelerated life testing is used as a means of validating the proposed approach since it provides data on degradation throughout the entire lifecycle of the system.

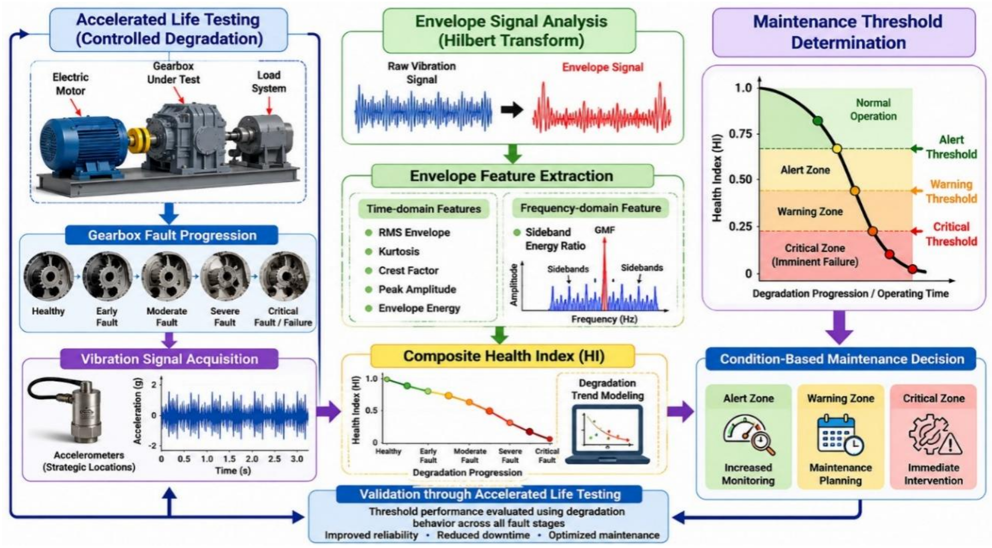

Figure 1. Conceptual workflow of the study.

3. Methodology

The research employs an experimental and quantitative research design in the determination of condition-based maintenance thresholds for fault development in a gearbox using vibration envelope features obtained from accelerated life testing. Replication of the fault development characteristics of a gearbox in a controlled laboratory environment where vibration responses are measured as faults develop becomes the key approach in the study. The main objective of the research design involves the identification of maintenance thresholds that can distinguish between health, degradation, developing faults, and catastrophic failure. Accelerated life testing, vibration measurement, envelope analysis, feature extraction, degradation model, and threshold determination constitute the core components of the experiment. In accelerating the fault development time frame, the test gearbox is put through accelerated life testing by operating it under controlled conditions. Through vibration signals from the accelerated life testing, envelope analysis is performed to extract fault information such as local defects and gear mesh interaction effects. In the process of accelerated life test, the operating conditions have been set under control throughout the experiment, in order to achieve a constant degradation process. The operational speed, loading state, lubrication state, and inspection period were predetermined before the experiment was conducted. The controlled experimental conditions facilitated the objective assessment of the degradation phases independent of the vibration characteristics. In this study, an accelerated degradation test procedure was used whereby mechanical loading was intentionally increased to accelerate the degradation of the gearboxes in a relatively realistic testing time frame. The purpose of using this procedure was to accelerate the degradation process but at the same time retain a controlled operating environment that is fit for vibration monitoring. Unlike in Classical Accelerated Life Testing, where life stress acceleration functions are developed to predict lifetimes, the current study focused more on degradation paths.

For vibration monitoring and condition monitoring purposes, a laboratory-scale gearbox accelerated life test setup was used to collect vibration signals associated with progressive gearbox faults. It consisted of an electric drive motor, reduction gearbox, loading assembly, coupling setup, and vibration data acquisition hardware. Acceleration sensors with high sensitivities based on piezoelectric technologies were mounted on specific locations of the gearbox case to monitor gear interaction vibrations. These sensors were arranged according to known guidelines in machinery condition monitoring techniques to achieve maximum sensitivity to faults in the gearbox. During the entire testing process, the gearbox was operated within a set range of rotational speed and loading conditions. To make fault development more rapid and to mimic long-time operations, the system was subjected to increased stress loads while operating within a defined parameter regime. Vibration monitoring started from the healthy condition and continued until the occurrence of critical faults. Gearbox acceleration signals were recorded continuously during its progression to a critical fault. In order to provide an accurate picture of gear mesh frequency, sideband frequency, and other transient vibration effects due to gearbox faults, high-frequency data acquisition was conducted. The gathered vibration data reflected degradation of gearbox condition at several stages. The entire population included all vibrations caused by gearbox systems under progressive fault conditions, reflecting all possible health levels of a gearbox from normal operation to severe gearbox degradation, up to failure conditions. Since the goal of this study was to understand fault progression behaviour, the population encompassed vibrations related to fault progression at all possible stages of operation. The sample included all vibration data obtained during accelerated life testing procedures. It should be noted that each observation represented a vibration measurement of a certain time period. This period corresponded to one particular point in the gearbox degradation process. Samples were selected continuously during the testing period in order to get sufficient representations of all possible fault stages. The degradation process of the gearbox was divided into various health states to enable the examination of the progress of the fault process and maintenance threshold setting. These categories were informed by the progressive degradation witnessed in the life acceleration tests. The health of the gearbox was characterized based on the controlled degradation methodology used in accelerated life testing and not on vibration characteristics alone. Every degradation state is associated with a predetermined period of operation under consistent experimental conditions and was additionally confirmed through regular visual inspections of gear teeth for wear, pitting, cracking, and surface deterioration. The process of labeling also took into consideration the set operating conditions throughout the experiment, which include rotational speed, loading condition, and operating period. Envelope vibration features were not used in health-state labels. Rather, vibration data were processed after the health-state identification and were used as independent variables for the calculation of Health Index and maintenance threshold values.

Table 1 shows the health states of the gearbox considered through the experimentation process. It is clear from **Table 1** that the progression in health state goes from normal operational status up until total failure, and each stage holds great importance from an operational perspective.

Table 1. Classification of gearbox health states.

Health state	Description	Operational interpretation
Healthy	No observable fault signatures	Normal operation
Early Fault	Initial defect development	Increased monitoring recommended
Moderate Fault	Detectable degradation progression	Maintenance planning required
Severe Fault	Significant deterioration present	Maintenance intervention recommended
Critical Fault	Imminent failure condition	Immediate corrective action required
Failure	Functional breakdown of gearbox	System shutdown

From **Table 1**, it is evident that the gearbox degradation process does not occur suddenly but progressively. In this research work, several envelope vibration metrics were employed to measure the condition of the gearbox and assess the progress of gearbox faults. This group of variables was chosen due to their proven sensitivity to specific conditions like gear faults, impacts, and changes in vibration patterns. **Table 2** represents important variables used in the process. These variables are indicative of differences in the amplitude of vibration signals, impulsiveness, energy levels, and vibration frequencies typical of faults.

Table 2. Summary of main variables.

Variable	Category	Unit	Description
RMS Envelope	Time-domain	g	Overall vibration energy
Kurtosis	Statistical	Dimensionless	Measure of signal impulsiveness
Crest Factor	Statistical	Dimensionless	Ratio of Peak Amplitude to RMS
Peak Amplitude	Time-domain	g	Maximum envelope magnitude
Envelope Energy	Time-domain	g^2	Total signal energy
Sideband Energy Ratio	Frequency domain	Dimensionless	Fault-sensitive modulation indicator
Health Index	Composite	Dimensionless	Integrated degradation indicator
Maintenance Threshold	Outcome Variable	Dimensionless	Decision boundary for maintenance action

From **Table 2** above, it can be seen that both time and frequency domain variables were used to represent specific aspects of gearbox degradation.

The state of the gearbox was diagnosed based on the vibration features of the envelope analysis performed on the collected signals. The envelope analysis was used since it improves the clarity of repetitive impact processes caused by the emergence of gear faults and is more sensitive to local damage than traditional vibration diagnostics methods. For measuring the energy content of the envelope vibration process, the

Root Mean Square (RMS) statistic was used. Kurtosis was used to measure the impulsiveness of the signal and the transitory impacts caused by defect emergence and development. For calculating the degree to which the vibration peaks dominate over the vibration levels, the Crest Factor was computed. For identifying the magnitude of the maximal vibration value detected in each data collection interval, Peak Amplitude was utilized. To estimate the total vibration energy, the feature of Envelope Energy was applied. Apart from these time-domain measures, the Sideband Energy Ratio feature was derived from the envelope frequency spectrum to identify modulations in the vicinity of gear mesh frequencies. Such sidebands usually indicate gear tooth damage and their further development. In order to present an integral image of the gearbox condition, all the individual measures have been combined into one complex Health Index that characterizes the overall deterioration state of the gearbox.

The analysis technique used attempted to establish operational thresholds based on measured vibrations. All signal processing and analysis activities were conducted using MATLAB and Python environments, which have capabilities to analyse vibrations and perform statistical computations. Initial signal pre-processing involved removal of any noise and unnecessary frequencies. Next, the envelope was generated based on the Hilbert transform method in order to extract useful vibration information from modulations related to the existence of faults in the gears. Once the envelope was generated, both time and frequency domain features of the vibration signal were extracted for each window of data. Extraction of the feature set involved normalization to account for any differences in the level of fault development at different points in time. Trend analysis was conducted to understand the pattern of each individual feature as a function of degradation. Only those features that exhibited monotonically decreasing behaviour and good sensitivity to fault development were considered for threshold establishment. The Health Index is a single scalar value calculated through the use of the most sensitive envelope features. It provides continuous monitoring of the deterioration process and facilitates identification of state transitions during the progression of the fault development process. Based on the distribution and behaviour of individual features as well as health state transitions during accelerated aging, it is possible to establish appropriate maintenance thresholds. It is planned to introduce three different zones to enable condition-based maintenance implementation. Thresholds establishing boundaries between normal, Alert, Warning, and critical states will be used to define the Alert, Warning, and Critical Zones. The thresholds will be selected based on trends, sensitivity to degradation and fault progression, and the ability to distinguish health states.

4. Results

4.1. Accelerated life test and characteristics of failure progression

An accelerated life test scheme was developed for simulating failure progressions of the gearbox during operation in an accelerated mode. During ALT, the test rig worked in continuous cycles with additional load and rotating stresses to stimulate typical wear phenomena experienced by industrial gear transmission systems.

Vibration signals were collected periodically as the gearbox shifted from its initial operational regime to its regime of failure during the ALT process. The degradation progress of the gearbox was assessed through visual inspection and vibration analysis. Visual examination revealed the growth of wear tracks, increasing roughness, and pitting, as well as the onset of tooth degradation over time. Simultaneously, the intensification of vibrations and impulses indicated the appearance and progression of the failure regime in the gearbox. The classification of health statuses of the gearbox was performed by dividing the degradation process into five stages of gearbox health. This division was based on the results of visual inspection and the properties of the obtained vibration signals. Classification allowed analysing the failure progression in the gearbox and creating maintenance thresholds. **Table 3** provides the operational features of the investigated gearbox during each degradation stage.

Table 3. Operating characteristics across gearbox fault progression stages.

Health state	Operating duration (h)	Observed condition	Vibration severity
Healthy	0–50	No visible defects	Low
Early Fault	51–120	Initial surface wear	Low–Moderate
Moderate Fault	121–200	Noticeable pitting and wear marks	Moderate
Severe Fault	201–280	Advanced tooth deterioration	High
Critical Fault	>280	Extensive damage and imminent failure	Very High

As shown in **Table 3**, fault progression took place progressively over the course of the accelerated life test. When it came to the healthy stage, the operational state was relatively consistent with little vibration activity. With increased stages, the degree of degradation became higher progressively with more severe vibration activity. Specifically, the highest level of degradation happened in the critical fault stage with many gear tooth damages causing much dynamic excitation and instability. As indicated in **Figure 2**, there is an illustrated progression of gearbox fault condition during accelerated life testing process from normal operation up to a critical failure point.

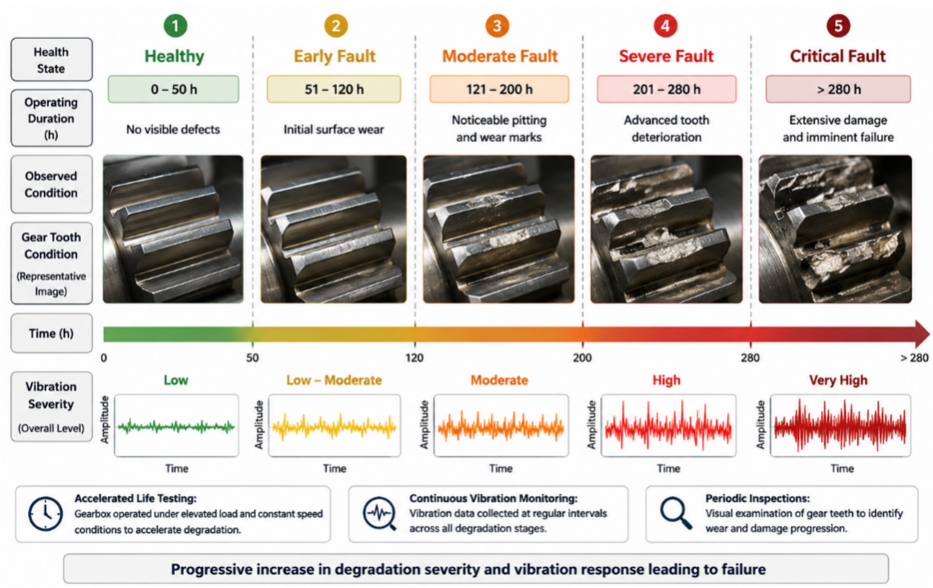

Figure 2. Degradation progression of the gearbox during accelerated life testing, from healthy operation up to a critical failure condition.

Consequently, the above results clearly confirmed that the accelerated life test method successfully induced many levels of degradation states that are needed in condition-based maintenance analysis. The degradation process resulted in a complete degradation database including healthy and faulty states, forming the foundation for further analysis of the envelope signal, feature selection, health index design, and threshold setting. Additionally, it can be noted that the progressive fault process led to detectable changes in vibration behaviour prior to failure. This finding particularly applies to the application of a condition-based maintenance strategy, showing that there would exist some warning periods before critical failures take place.

4.2. Envelope signal characteristics during fault progression

After completion of accelerated life tests, the vibration signals recorded were subjected to envelope analysis to ensure the enhanced detection of any fault-induced modulating effects on the signals. It was evident that although the original vibration signal carried useful machine condition information, the localized defect of gears caused repeated impacts that were partly hidden due to structural and operational frequencies of the gearbox. Thus, envelope analysis was used to detect any amplitude-modulating effects and to highlight the fault-related signatures. The vibration envelope was obtained using the Hilbert Transform, which is used to convert a real-valued vibration signal to the corresponding analytic one. The envelope vibration was calculated using the equation below:

$$E(t) = \sqrt{x(t)^2 + \widehat{x}(t)^2},$$

$E(t)$—envelope signal;

$x(t)$ —original vibration signal;

$\widehat{x}(t)$ —Hilbert transform of the original signal.

Analysis of the envelope vibration signal showed substantial differences in the signal properties during different stages of degradation. In the case of healthy gear, the envelope was rather stable with only slight amplitude variations showing proper gear meshing processes and no excessive impact activities. During the initial stage of fault formation, small amplitude changes were detected. In the case of moderate faults, the number of transients increased; in severe conditions, impulsive events occurred periodically. During the critical fault, repetitive impacts occurred with high amplitudes; there was an obvious increase in instability of the signal. **Figure 3** shows envelope signals obtained during various stages of gearbox degradation in terms of accelerated life testing.

From the observation of the envelope signals presented in **Figure 3**, it becomes evident that both the impulsive nature of the vibration and the amplitude increased progressively along with the deterioration of the gears. There is a visible amplification of fault-induced impulses from the healthy state of the gearbox to its critical state. Therefore, it may be concluded that envelope analysis is capable of detecting degradation-sensitive information. An increase in the number of high-amplitude peaks found in the severe and critical stages implies that early indications of gear fault could be obtained using envelope analysis. In order to investigate the frequency characteristics of the obtained fault-related information, envelope spectra were computed for each of the studied degradation levels. Envelope spectrum analysis helps identify sidebands related to gear defects and allows detecting their location relative to the gear mesh frequency. The appearance of these sidebands is considered to be a good indicator of progressive degradation. **Figure 4** shows the envelope spectrum for each stage of gearbox degradation.

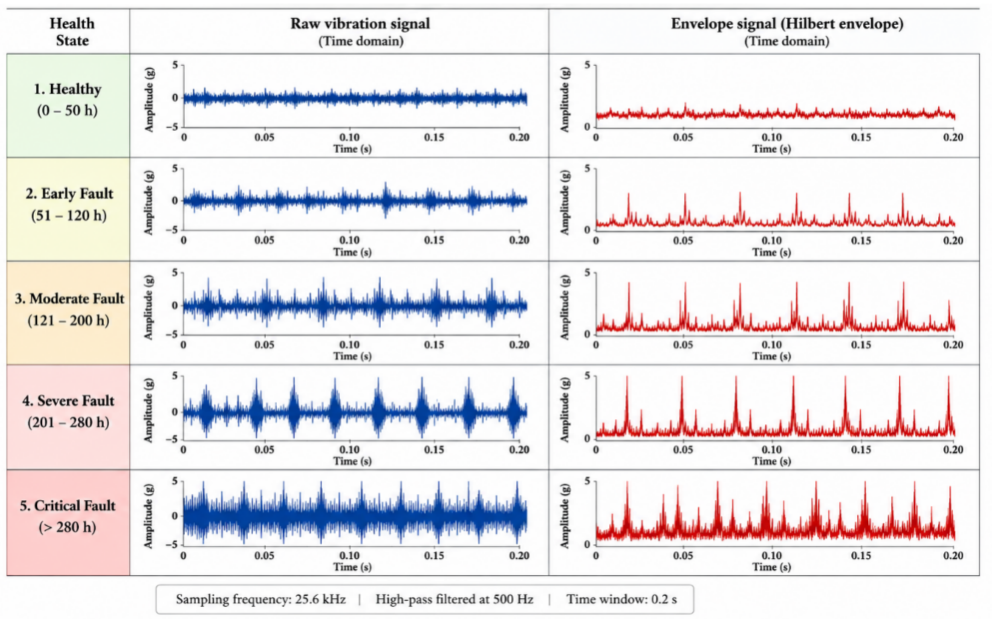

Figure 3. Envelope signals for healthy, early fault, moderate fault, severe fault, and critical fault gearboxes.

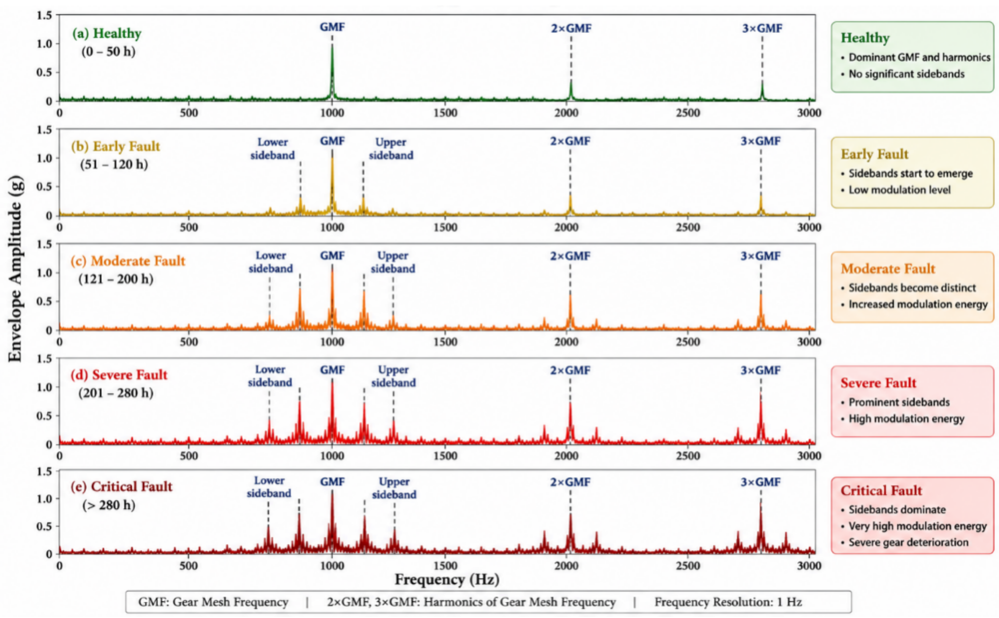

Figure 4. Envelope spectra illustrating the appearance of sidebands around the gear mesh frequency in different stages of gearbox degradation.

Envelope spectra clearly show substantial changes of frequency domain characteristics during the degradation process. A healthy gearbox spectrum shows mainly gear mesh frequency and its harmonics with minor sideband effects. Early faults indicate the presence of low-amplitude sidebands around the gear mesh frequency, which indicates the modulation process. With further degradation, up to moderate and severe, the sidebands become more pronounced and concentrated. During the critical gearbox state, the largest sideband amplitudes and energy spectrum are observed. In order to conduct a qualitative evaluation of the obtained envelope features, vibration responses were classified according to their amplitude behaviour and impulsiveness. Characteristics of the obtained envelopes during different gearbox degradation states are summarized in **Table 4**.

Table 4. Envelope signal characteristics across gearbox degradation stages.

Health state	Envelope amplitude	Impulsive activity	Sideband development	Signal stability
Healthy	Very Low	Minimal	Absent	Highly Stable
Early Fault	Low	Slight	Emerging	Stable
Moderate Fault	Moderate	Noticeable	Distinct	Moderately Stable
Severe Fault	High	Significant	Prominent	Unstable
Critical Fault	Very High	Extreme	Dominant	Highly Unstable

The trend is clearly shown in **Table 4,** where the vibration patterns show a systematic change based on increasing gearbox deterioration level. Enveloped signals show increasing amplitudes with decreasing stability as they move from normal to critical fault levels. On the other hand, impulsive features and sidebands become more and more evident as faults escalate. This proves once again that envelope analysis can be used effectively to detect time- and frequency-domain indicators of gearbox damage. From the results, we can see that the use of envelope analysis makes it easier to observe gearbox faults. This is evident from the systematic increase in terms of amplitude modulation, impulsive features, and sidebands as gearbox deterioration escalates. These results provide an excellent foundation for using the feature extraction techniques explained in the following sections. More importantly, the differences between degradation levels point out clearly that there is great potential in using envelope signals in tracking fault progression and setting up maintenance limits.

4.3. Statistical analysis of envelope features

Having successfully extracted envelope signals, the next step involved conducting a thorough statistical analysis aimed at evaluating the dynamics of vibration behaviour in the process of gearbox deterioration. For the purposes of statistical analysis, envelope features were chosen due to their increased sensitivity to impact phenomena, modulations, and local gear damage during the wear process. The objective of such an analysis consisted in finding out whether there are any distinctive changes in the selected envelope features over different gearbox health stages and determining their applicability for assessing gearbox faults' progression. In particular, a series of analyses was performed using the following envelope features: Root Mean Square (RMS) Envelope, Kurtosis, Crest Factor, Peak Amplitude, Envelope Energy, and Sideband Energy Ratio. For each vibration acquisition window, all of these features were calculated and later aggregated for the five degradation stages observed during accelerated life testing. This procedure resulted in the construction of feature distributions representing the process of gearbox health deterioration from its initial state to failure. RMS Envelope was used as a measure of the energy contained in the envelope signal and was calculated as follows:

$$\text{RMS} = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N} x_i^2},$$

where x_i is the envelope signal value, N is the total number of samples in the acquisition window. Kurtosis was used as an indicator of vibration impulsiveness and was calculated based on the following formula:

$$K = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4}{\left(\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2\right)^2},$$

where $\bar{x}$ is the mean signal value. Crest Factor (CF) was calculated as an indicator of vibration peak magnitude and was defined as:

$$\text{CF} = \frac{X_{peak}}{\text{RMS}},$$

where X_{peak} is the Peak Amplitude value. The mean values of extracted envelope features for different gearbox health levels are provided in **Table 5** below.

Table 5. Statistical characteristics of envelope features across fault progression stages.

Feature	Healthy	Early fault	Moderate fault	Severe fault	Critical fault
RMS Envelope (g)	0.32	0.51	0.87	1.42	2.11
Kurtosis	3.12	4.68	7.95	11.74	16.82
Crest Factor	2.84	3.47	4.92	6.71	8.53
Peak Amplitude (g)	1.15	1.76	3.24	5.87	8.94
Envelope Energy (g^2)	0.11	0.26	0.76	2.02	4.45
Sideband Energy Ratio	0.04	0.11	0.28	0.57	0.83

As can be seen from **Table 5**, a consistent growth is observed in all the envelope features related to the process of gearbox deterioration. Thus, the RMS envelope grows from 0.32 g in the healthy state to 2.11 g in the critical fault state due to the increasing vibration energy in the gearbox. The pattern indicates that fault development entails increased dynamic excitation of the system. As for Kurtosis, it shows one of the highest levels of growth observed in all considered features. Namely, Kurtosis is increased from 3.12 in the healthy state to 16.82 in the critical fault state, indicating increasing impulse activity associated with pitting, cracks, and local tooth destruction. Accordingly, Kurtosis turns out to be very sensitive to fault development. Like Kurtosis, the Crest Factor increases consistently in all health states of the gearbox, thus evidencing the growing shock excitation caused by fault development. Besides, Peak Amplitude and Envelope Energy grow quite significantly, thus corroborating the general picture of increased vibration severity due to fault development.

When considering the characteristics of frequencies, one can say that the Sideband Energy Ratio shows one of the clearest patterns of variation. Namely, the Sideband Energy Ratio changes from 0.04 in the healthy state to 0.83 in the critical fault state, which indicates the development of modulation phenomena around gear mesh frequency. This result is consistent with the analysis of envelope spectra shown in **Figure 4**. In order to illustrate the degradation trajectories of the extracted features, evolution curves were constructed for the selected envelope features. These curves are shown in **Figure 5**.

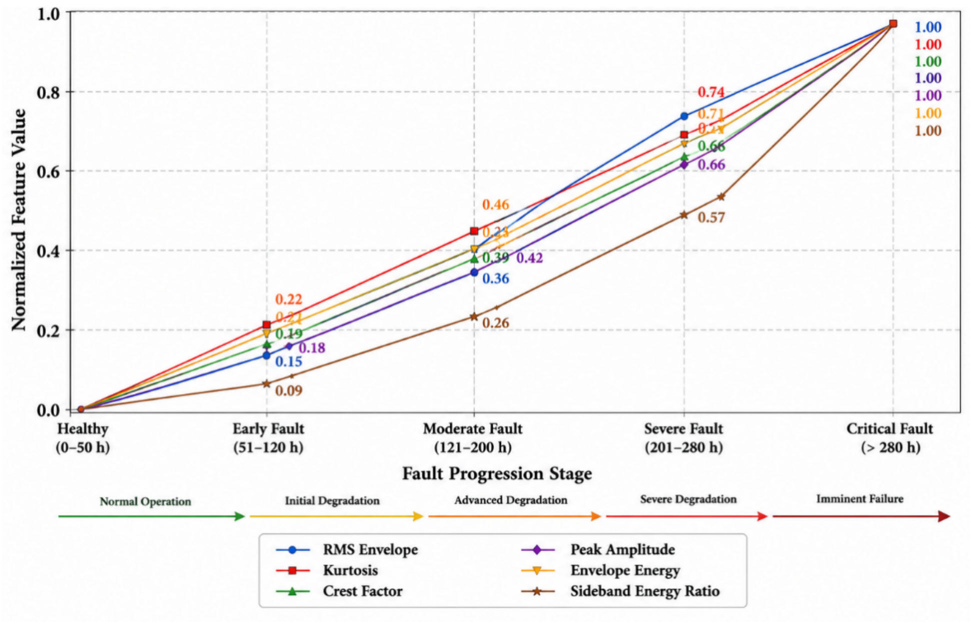

Figure 5. Evolution of normalized envelope features during gearbox fault progression.

From the plot above, it can be seen that all features show growing values with increasing fault severity. Nevertheless, the dynamics differ between various indicators: while RMS Envelope and Envelope Energy grow relatively smoothly and therefore show high sensitivity to degradation severity, Kurtosis and Crest Factor start growing faster at later stages, which indicates their sensitivity to severe localized damage and impulses. In order to statistically verify the significance of variations between the health states for different features, the one-way analysis of variance (ANOVA) was conducted for all extracted features. The obtained ANOVA statistics prove the existence of statistically significant differences in all analysed features ($p < 0.001$). **Table 6** below presents the ANOVA results for envelope features.

Table 6. ANOVA results for envelope feature variations across health states.

Feature	F-value	*p*-value	Significance
RMS Envelope	42.37	<0.001	Significant
Kurtosis	56.84	<0.001	Significant
Crest Factor	48.12	<0.001	Significant
Peak Amplitude	51.66	<0.001	Significant
Envelope Energy	59.23	<0.001	Significant
Sideband Energy Ratio	63.45	<0.001	Significant

According to **Table 6**, it can be concluded that the value of F for all envelope features is different depending on the specific stage of damage. The highest values of F have been obtained for the Sideband Energy Ratio and Envelope Energy, which means their great ability to distinguish gearbox condition states. Thus, the presented data prove the possibility of using the considered envelope parameters to determine the changes that occur while faults develop. Moreover, the obtained values of F confirm the effectiveness of the chosen envelope features to reveal gearbox degradation behaviour during the experimental process. The increasing value of vibration energy, impulse, shock, and sidebands proves a close connection between the damage state development and envelope features change.

4.4. Feature sensitivity and degradation assessment

Although changes were detected for all features under consideration, not all envelope features can be equally effective indicators of the progress of the fault in gearboxes. While some of them showed linear and steady changes from the beginning to the end of the degradation process, others reacted to gearbox faults only in the advanced fault stages. Therefore, an assessment of feature sensitivity was carried out to select the best parameters for monitoring gearbox faults and determining maintenance thresholds. The usefulness of a degradation indicator is determined by its ability of this parameter to monitor the fault progression process steadily and monotonically in different operating conditions. In the context of condition-based maintenance, such a feature must show a high correlation with the degradation process, demonstrate the monotonicity of changes, and ensure the separation of adjacent health levels. Features that have these properties are considered more adequate for building a health index. First of all, the sensitivity of features to fault progression was calculated based on their correlation with the fault progression level. To do so, the correlation coefficient r was calculated using the formula:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}},$$

where x_i is the feature value, y_i is the degradation stage value, and n is the number of pairs of values. The analysis showed that there was a high positive correlation between each envelope feature and gearbox degradation severity; however, the degree of dependence was different among all indicators tested. Correlation coefficients of each envelope feature are provided in **Table 7**.

Table 7. Correlation between envelope features and gearbox fault progression.

Envelope feature	Correlation coefficient (r)	Relationship strength
RMS Envelope	0.924	Strong
Kurtosis	0.958	Very Strong
Crest Factor	0.936	Strong
Peak Amplitude	0.911	Strong
Envelope Energy	0.972	Very Strong
Sideband Energy Ratio	0.964	Very Strong

It can be seen from **Table 7** that each of the evaluated features is positively correlated with gearbox degradation. Specifically, the highest value of the correlation coefficient was provided by the Envelope Energy (r = 0.972), the Sideband Energy Ratio (r = 0.964), and the Kurtosis (r = 0.958). It means that these features are capable of tracing the development of faults much better and, therefore, may provide more accurate estimates of the current health condition of the transmission system.

However, it should be stressed that correlation analysis does not completely illustrate the consistency of the studied parameter changes. For this reason, monotonicity analysis of all the features was performed. Monotonic feature implies constant development without numerous variations, and therefore, it is more appropriate for degradation modelling. The monotonicity index M was calculated as follows:

$$M = \frac{N_{positive} - N_{negative}}{N_{positive} + N_{negative}}.$$

Here, $N_{positive}$ and $N_{negative}$ stand for the numbers of upward and downward transitions in the feature evolution sequence, correspondingly. The results of the analysis of monotonicity and trendability are provided in **Table 8**.

Table 8. Monotonicity and trendability assessment of envelope features.

Envelope feature	Monotonicity	Trendability	Overall rank
RMS Envelope	0.901	0.887	4
Kurtosis	0.931	0.918	3
Crest Factor	0.914	0.892	5
Peak Amplitude	0.882	0.871	6
Envelope Energy	0.948	0.936	1
Sideband Energy Ratio	0.939	0.925	2

As seen from **Table 8**, Envelope Energy emerges as the indicator with the best monotonicity and trendability scores out of all the analysed parameters. The parameter displays a steady growth pattern during the entire process of degradation, thus becoming very useful for conducting monitoring of equipment performance throughout the life cycle. Similarly, both Sideband Energy Ratio and Kurtosis display good monotonicity characteristics and degradation trends, which is another sign of their suitability for fault progression representation. In order to determine interstage separability between adjacent states of degradation, additional analysis must be conducted. The feature should not only correlate well with the level of damage but also show its capacity to differentiate between different conditions. A higher value for separability means that the transition between adjacent stages is easier to detect.

As can be seen from **Table 9**, Envelope Energy obtains the highest mean separability (0.94), followed by Sideband Energy Ratio (0.89) and Kurtosis (0.85). It should be noted that the results above convincingly prove the capability of these features to reliably distinguish between consecutive fault states. In addition, the fact that a high separability was achieved for the fault transitions from severe to critical state is especially noteworthy because the maintenance action is usually performed in the late stages of degradation when the risks of failure become elevated. Combining the findings obtained during the investigation of correlations, monotonicity, trendability, and inter-stage separability, it can be concluded that Envelope Energy, Sideband Energy Ratio, and Kurtosis have been identified as the most informative vibration envelope features indicating the occurrence of gearbox faults. The proposed features demonstrate significant correlation with the progression of faults while maintaining a stable trend and distinct separability between health states. Overall, the findings reported above prove Hypothesis H1 on the substantial impact of fault progression on variation of vibration envelope features. At the same time, it is necessary to note that the results provide a rationale for selecting indicators for developing the Health Index.

Table 9. Inter-stage separability analysis of envelope features.

Feature	Healthy–early	Early–moderate	Moderate–severe	Severe–critical	Average separability
RMS Envelope	0.52	0.68	0.77	0.84	0.70
Kurtosis	0.61	0.79	0.92	1.06	0.85
Crest Factor	0.58	0.73	0.86	0.97	0.79
Peak Amplitude	0.49	0.65	0.82	0.91	0.72
Envelope Energy	0.67	0.88	1.03	1.18	0.94
Sideband Energy Ratio	0.63	0.84	0.98	1.11	0.89

4.5. Composite health index development

According to the findings presented above in the feature sensitivity analysis, the Envelope Energy (EE), Sideband Energy Ratio (SER), and Kurtosis (K) were more effective at indicating the gearbox's condition deterioration than the rest of the envelope-related indicators. The reason for their higher effectiveness lay in the fact that they yielded higher correlation coefficients, monotonicity measures, trendability values, and inter-stage separability metrics. However, while each of these features could individually provide valuable insights into fault progression, basing the estimation only on one of them could be questionable because of the presence of measurement variations and process irregularities. Thus, it became necessary to design a composite health index (HI). The main purpose of developing the Health Index was the need for a single measure able to represent the current state of gearbox health status over all the accelerated life tests performed. In addition, the implementation of such an aggregate indicator would also help to set up maintenance thresholds as condition transition criteria, which would be based on a single continuous indicator rather than several separate features. To begin with, prior to constructing the Health Index, it was necessary to normalize the selected features in order to eliminate any potential scale differences between them. This was accomplished via feature normalization based on the min-max formula:

$$X_{norm} = \frac{X_i - X_{min}}{X_{max} - X_{min}},$$

where X_i was the corresponding feature value, while X_{min} and X_{max} were the minimal and maximal values, respectively. Afterwards, the weights for each normalized feature were assigned according to its ranking in terms of degradation sensitivity. The greater the sensitivity to changes in the health state, the higher the weight was assigned. Eventually, the following formula was used to calculate the composite index:

$$\mathrm{HI} = w_1(\mathrm{EE}) + w_2(\mathrm{SER}) + w_3(\mathrm{K}),$$

where:

HI = composite health index;
EE = Normalized Envelope Energy;
SER = Normalized Sideband Energy Ratio;
K = Normalized Kurtosis;

w_1, w_2, w_3 = Feature weighting coefficients.

The coefficients w_1, w_2, w_3 were determined on the basis of normalized sensitivity rankings derived from previous correlation, monotonicity, and trendability analysis results. **Table 10** shows the coefficients applied to build the Health Index.

Table 10. Feature weight allocation for composite health index development.

Feature	Correlation score	Monotonicity score	Trendability score	Composite sensitivity score	Weight
Envelope Energy	0.972	0.948	0.936	0.952	0.36
Sideband Energy Ratio	0.964	0.939	0.925	0.943	0.34
Kurtosis	0.958	0.931	0.918	0.936	0.30

According to **Table 10**, Envelope Energy (EE) achieved the highest weighting coefficient due to its higher performance in degradation-tracking ability. In order to test how robust the selected weighting approach is, a further study on weight sensitivity was conducted by comparing the suggested sensitivity-weighting method with equal weighting, PCA weighting, and entropy weighting. The objective of such comparisons is to find out whether there is any other data-based weighting method that can improve the robustness and separability of the composite health index. Equal weighting gives equal contributions for each of the three features used: Envelope Energy, Sideband Energy Ratio, and Kurtosis, while PCA weighting calculates the contributions of each feature in terms of the direction of greatest variance in the normalized feature space.

It is worth mentioning that the weighting factors were established based on the overall degradation monitoring ability of the features rather than their sensitivity to changes in a certain stage of degradation. Even though Kurtosis showed a comparatively greater sensitivity at the transition point between the Healthy and Early Fault stages, Envelope Energy performed better in terms of the three criteria mentioned above, i.e., correlation, monotonicity, and trend ability over the whole degradation period. Thus, the maximum weighting factor was allotted to Envelope Energy since it offered a more reliable assessment of the health condition of the gearbox throughout the process of degradation. Though a stage-based weighting approach can increase the sensitivity of the indicator in different operating stages, the current degradation state needs to be identified prior to assigning the weighting factors. Such dependency leads to higher computational cost and limits the practical application of this approach to continuous condition monitoring of the equipment.

While Sideband Energy Ratio (SER) and Kurtosis (K) were awarded slightly lower weighting coefficients, they still made substantial contributions to the final Health Index (HI). This implies that all three selected parameters exhibited high levels of performance. Using the proposed weighting model in **Table 10**, the equation used to calculate the Health Index is:

$$\mathrm{HI} = 0.36(\mathrm{EE}) + 0.34(\mathrm{SER}) + 0.30(\mathrm{K}).$$

Health indices were derived from vibration data acquired from all records under accelerated life testing. Subsequent analysis was carried out on these HI results to examine whether they can be used to capture changes in gearbox health status. **Table 11** presents the Health Index mean value corresponding to each gearbox degradation stage.

Table 11. Health index values across gearbox degradation stages.

Health state	Mean health index	Standard deviation
Healthy	0.08	0.02
Early Fault	0.24	0.04
Moderate Fault	0.47	0.05
Severe Fault	0.73	0.06
Critical Fault	0.94	0.04

The data presented in **Table 11** demonstrate a definite progressive growth of the Health Index as the severity of gearbox faults increases. The average Health Index grows from 0.08 for healthy gearboxes to 0.94 when the critical fault state occurs. As it could be seen, there is little or no overlap between consecutive health states. Such an outcome testifies to the high discriminatory capability of the index under consideration and implies its successful use in condition-based maintenance strategy implementation. **Figure 6** presents the change in the composite health index through the course of the degradation process.

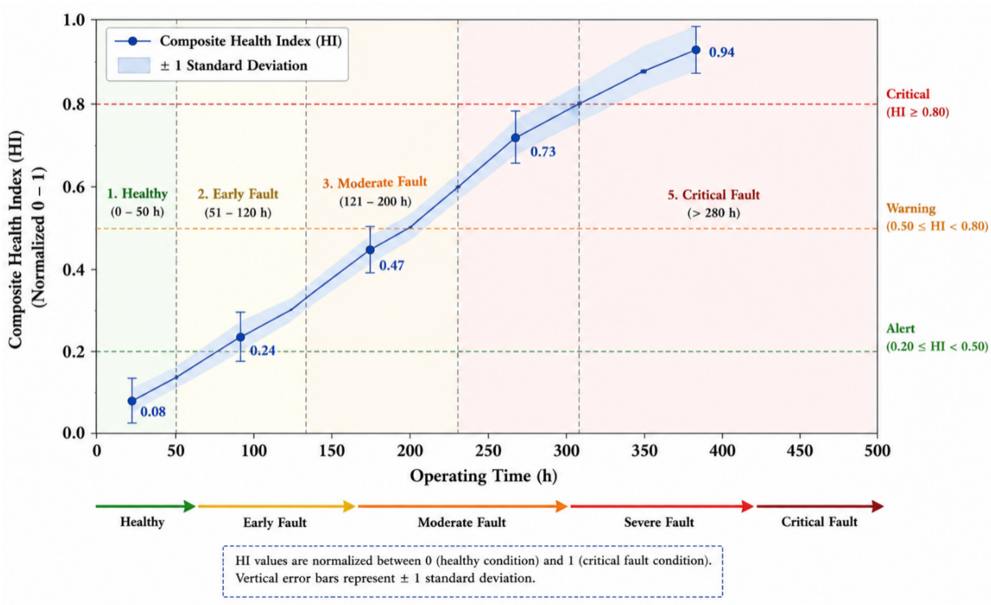

Figure 6. Changes in the composite health index during gearbox degradation.

As it could be observed, the trend line shows a very reliable and predictable degradation pattern with progressive growth from the healthy state up to the critical fault state occurrence. In opposition to numerous indicators demonstrating local fluctuations, the composite health index presents relatively stable performance along the entire range of degradation severity states. To investigate the existence of a dependency between the Health Index and degradation severity, regression analysis was applied. The results of the investigation demonstrate the existence of a significant positive correlation between Health Index values and gearbox degradation severity ($R^2 = 0.962$).

The correlation analysis carried out in **Table 12** confirms the high predictability ability of the composite health index. The strong correlation coefficient, together with its statistical significance, demonstrates that the proposed indicator successfully captures the state of the gearbox at all degradation stages. The experimental evidence provided in this study provides sufficient grounds to accept Hypothesis H2, which suggests that degradation-sensitive envelope features significantly impact the formation of the composite health index. The chosen features were quite successful at forming the Health Index and, altogether, helped to establish a consistent and very representative index of the current condition of the system. The strong trend exhibited by the Health Index serves as a very sound basis for estimating maintenance thresholds, which will be further discussed in the following section. The construction of the composite health index allowed combining several degradation-sensitive envelope features in one condition indicator for effective monitoring of gearbox fault progression.

Table 12. Regression analysis between the health index and fault progression.

Parameter	Value
Correlation Coefficient (r)	0.981
Coefficient of Determination (R^2)	0.962
Adjusted (R^2)	0.957
p-value	<0.001

4.6. Maintenance threshold determination

The main goal of the research project was to construct a model for setting maintenance thresholds by considering the evolution process of gearbox fault signalling and the features of vibration envelopes. Although the composite health index, introduced in the previous chapter, can serve as an appropriate tool to describe the current status of the gearbox, the key issue was the ability to convert health information to real maintenance decisions. For this reason, a multi-stage maintenance-threshold model was constructed. First, the process of Health Index evolution was considered. **Figure 6** demonstrates that the Health Index shows a stable monotonic evolution trend, from the beginning to the moment when the critical level is reached. It means that there exist natural decision boundaries in the Health Index evolution process that should be taken into account when implementing condition-based maintenance procedures. Maintenance thresholds are based on the statistical properties of Health Index distributions for each gearbox health state. The idea is to find such threshold levels that provide a good separation between adjacent degradation states while preserving sensitivity. The framework described above leads to the partitioning of gearbox condition into four operational zones—Normal Operation, Alert, Warning, and Critical Maintenance. Alert threshold (T_A) is considered as the point when the Health Index exceeds the normal behaviour boundary and reaches the degradation level. The Warning threshold (T_W) indicates the transition from moderate to accelerated degradation. The Critical threshold (T_C) represents the situation when a critical level of fault progression is reached, and immediate maintenance action is needed.

Maintenance thresholds were calculated using the following formula:

$$T_i = \mu_i + k\sigma_i,$$

where:

T_i = maintenance threshold value;

μ_i = mean Health Index of the corresponding degradation stage;

σ_i = standard deviation of the health index;

k = threshold scaling factor.

The value of the threshold scaling factor (k) was determined through the optimization of the entire classification results within the developed maintenance paradigm. During the optimization stage, all classification results were considered to be equally important as part of an effort to establish a general methodology of threshold determination that would be application-independent. The use of an equal-weighting optimization procedure prevents the introduction of any maintenance cost or equipment criticality assumptions specific to the application. While engineering maintenance decisions are typically based on asymmetric costs of misclassification, the structure of such costs shows wide variability from industry to industry and is, thus, not considered in the current study. To find the optimal value for the threshold scaling parameter, classification performance criterion was maximized. Optimal parameters for the maintenance thresholds are presented in **Table 13**.

Table 13. Proposed maintenance thresholds for condition-based maintenance decision-making.

Threshold zone	Health index range	Operational interpretation	Recommended action
Normal Operation	HI < 0.20	Healthy condition	Continue normal operation
Alert Zone	0.20 ≤ HI < 0.50	Early degradation detected	Increase monitoring frequency
Warning Zone	0.50 ≤ HI < 0.80	Significant fault progression	Schedule maintenance intervention
Critical Zone	HI ≥ 0.80	Imminent failure risk	Immediate maintenance required

As shown in **Table 13**, the new maintenance threshold framework provides a step-by-step maintenance decision tool to detect gearbox condition. In the Alert Zone, the abnormal degradation is at the early stage, giving enough time to monitor and enhance the inspection of gearbox faults. In the Warning Zone, the gearbox is under rapid wear; this stage is considered ideal for maintenance planning because any corrective action could be taken before serious damage occurs. The Critical Zone is a high-risk operation condition related to gearbox failure; immediate actions must be undertaken in order to prevent failure of the machine. In evaluating the efficiency of the new maintenance threshold scheme, an analysis was performed regarding the Health Index distribution through different gearbox degradation stages. The key point is that the maintenance zones that are being recommended serve as decision thresholds based on condition and not fixed periods of time as the gearbox degrades. This method does not assume a constant rate of degradation of the gearbox nor that the gearboxes go through each one of the maintenance zones within the same periods of time. On the contrary, the Health Index serves to show the status of degradation of the gearbox. This means that a gearbox can stay in the same zone of maintenance for a long period of time when the conditions are stable or go through several maintenance zones very quickly. **Figure 7** illustrates the relationship between Health Index values and proposed maintenance threshold levels.

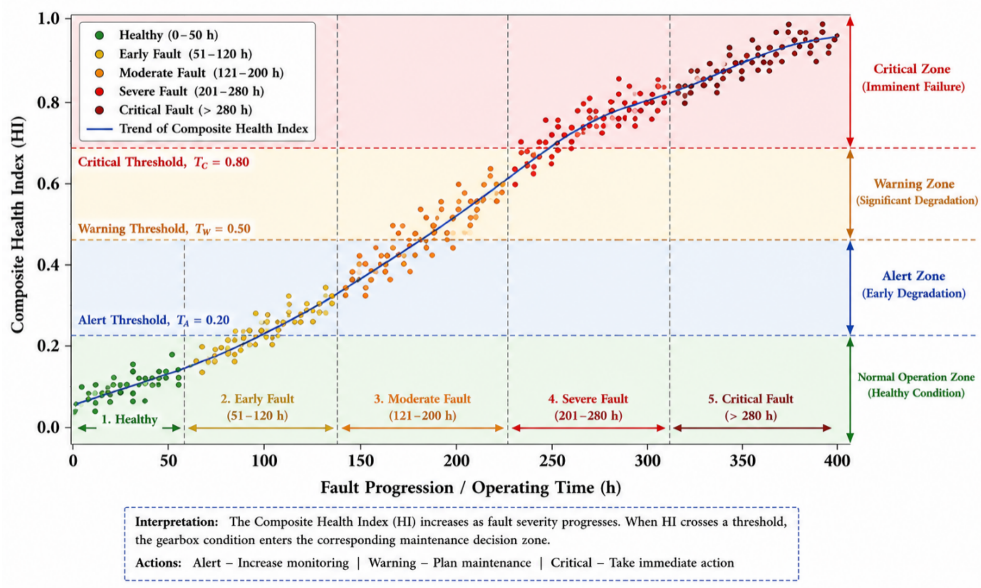

Figure 7. Maintenance threshold levels framework for different health conditions with respect to composite health index values.

From **Figure 7**, it could be seen that the proposed threshold levels are in good agreement with the actual degradation stages of a gearbox. The healthy gearboxes are distributed within the Normal Operation Zone, and early fault condition gears mainly lie within the Alert Zone. Moderate gearbox fault degradation conditions are mostly found within the Warning Zone, whereas severe and critical faults are detected within the Critical Zone. Despite the saturation trend observed in Kurtosis at the transformation stage from Severe Fault to Critical Fault, the monotonicity of the composite health index was not affected by the nonlinear behaviour. The fact is that Kurtosis mainly depends on the impulsiveness of the vibrations and is thus very sensitive in the initial stage of local defect development. With time and further deterioration of the component, the occurrence of repetitive impacts becomes more frequent, and thus there is a gradual decrease in the growth rate of Kurtosis. In order to offset the effect of the nonlinear trend, the composite health index considers Kurtosis along with Envelope Energy and Sideband Energy Ratio, the latter two exhibiting a monotonically increasing trend up to the last degradation stage.

As it could be seen from **Figure 8**, there is no significant overlap among the proposed maintenance threshold levels. The second evaluation of the maintenance threshold levels was done to determine the maintenance risk within the proposed levels. **Table 14** presents the average Health Index value and maintenance priority at each degradation stage.

Table 14. Health index progression and maintenance priority assessment.

Health state	Mean health index	Threshold zone	Maintenance priority
Healthy	0.08	Normal Operation	Low
Early Fault	0.24	Alert	Moderate
Moderate Fault	0.47	Alert–Warning Transition	High
Severe Fault	0.73	Warning	Very High
Critical Fault	0.94	Critical	Immediate

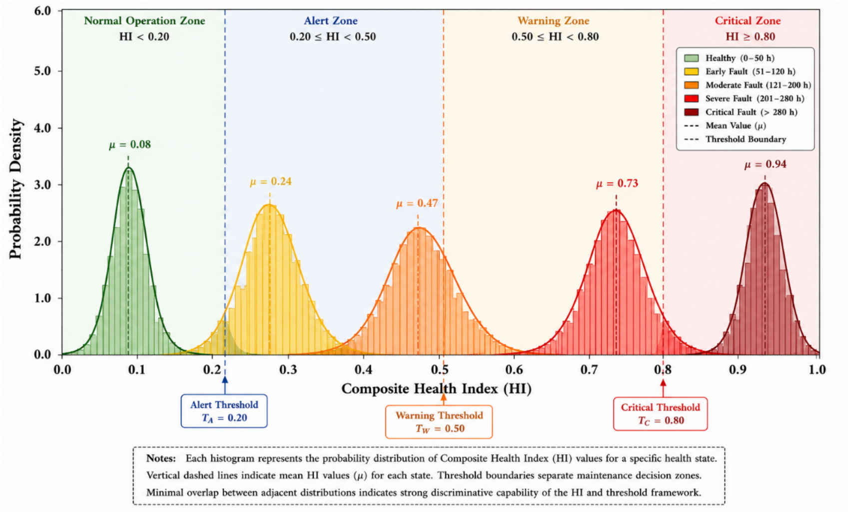

Figure 8. Probability distribution of composite health index values illustrating maintenance threshold separation and decision boundaries.

According to **Table 14**, it can be noted that the severity level of gearbox degradation leads to an increased priority of maintenance operations. The transition from the Alert Zone to the Warning Zone occurs at the stage of moderate fault development. Thus, it can be assumed that maintenance should be planned in advance when the gearbox condition is still far from severe. From an industrial perspective, this finding implies that the proposed threshold boundaries will help achieve a balance between maintenance expenses and the risk of system failure. The proposed threshold boundaries were assessed using the confidence interval method to determine whether the distributions of Health Index values have sufficient degree of separation between adjacent zones. The obtained distributions revealed low degrees of overlap between the zones, which supports the robustness of the proposed threshold boundaries. Moreover, the Alert Threshold was found to provide the most accurate response to early stages of fault development, while the Critical Threshold offers reliable results regarding imminent failure state identification. The distributions of Health Index values across the proposed maintenance zones are presented in **Figure 9**.

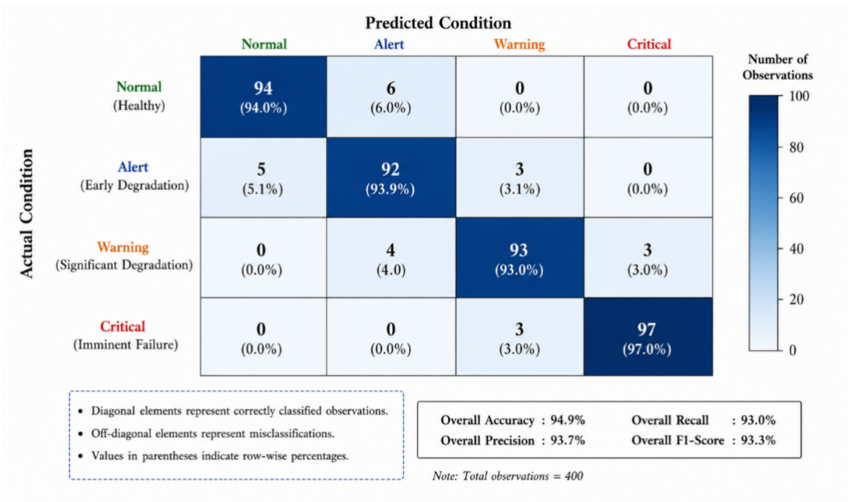

Figure 9. Confusion matrix demonstrating the classification accuracy of the proposed maintenance threshold framework.

As shown in **Figure 8**, the distributions of the Health Index show obvious distinctions among the suggested maintenance thresholds, with only partial overlapping taking place along the edge areas of neighbouring thresholds. The numerical values of overlap coefficients provided in **Table 15** show that the overlapped regions are still below 0.10, indicating satisfactory robustness of the thresholds. Uncertainty was highest on the threshold between Alert and Warning because this is a transitional area from early fault to advanced fault. Hence, it can be concluded that the threshold framework allows maintaining sufficient sensitivity and reliability throughout the gearbox degradation process. Finally, the results of threshold determination allow confirming the main aim pursued in this research. Instead of focusing on pure fault detection, the proposed threshold framework converts the information about gearbox condition into decisions to plan maintenance in advance. The inclusion of envelope parameters, representing gearbox degradation stages in a Health Index, along with the process of threshold determination provides a reliable tool for decision-making. Moreover, the results suggest preliminary support for Hypothesis H3 concerning the significant impact of the composite health index on maintenance threshold determination. In addition, it has been confirmed that Health Index progression can be used to trigger transitions between threshold levels and make corresponding maintenance decisions. The measure used to calculate the degree of uncertainty associated with the overlap in Health Index distributions is called the overlap coefficient. It measures the common probability mass between two Health Index distributions that are next to each other and represents threshold uncertainty. The formula for calculating the overlap coefficient is as follows:

$$OVL_{ij} = \int_{-\infty}^{\infty} \min\left[f_i(\mathrm{HI}), f_j(\mathrm{HI})\right] d(\mathrm{HI}).$$

Where OVL_{ij} represents the overlap coefficient between adjacent health states i and j, and $f_i(\mathrm{HI})$ and $f_j(\mathrm{HI})$ are the probability density functions of the Health Index distribution.

Table 15. Overlap coefficient analysis for adjacent maintenance zones.

Adjacent maintenance zones	Overlap coefficient	Boundary uncertainty level	Interpretation
Normal–Alert	0.061	Low	Clear early degradation separation
Alert–Warning	0.084	Moderate-Low	Highest transition uncertainty
Warning–Critical	0.047	Low	Strong severe-fault separation

According to **Table 15**, the overlapping area among the probability distribution curves of the Health Index was insignificant for all boundaries of the maintenance. The overlapping rate between the Alert and Warning stages reached its maximum value at 0.084, implying that the largest uncertainty existed within this boundary since the process of degradation was rather gradual. At any rate, the degree of overlap did not exceed 0.10 for any of the neighbouring maintenance zones, meaning that the proposed boundaries possessed the sufficient level of robustness.

Despite the outstanding results demonstrated by the proposed maintenance thresholds under the conditions of Accelerated Life Testing, their direct application to the analysis of real-world gearbox systems should be preceded by proper calibration. Indeed, the objective of Accelerated Life Testing was to create conditions under which the complete process of degradation could be simulated during a period of time acceptable for experiments, without changing the basic principles underlying the development of gearbox faults. In an industrial setting, deviations from optimal conditions in terms of operating speed, loading, lubrication conditions, temperature, installation, and specific machine dynamics may lead to a change in absolute values of the vibration envelope parameters and, thus, shift the optimal positions of maintenance thresholds. Hence, the proposed Alert, Warning, and Critical threshold values should be seen as indicative rather than strict boundaries of the maintenance decisions to be made.

4.7. Validation of maintenance threshold performance

In order to validate the proposed thresholds within the multi-level maintenance threshold scheme, an analysis of their performance was undertaken. Validation was designed to prove that proposed Alert, Warning, and Critical thresholds are capable of accurately classifying gearbox health states at different fault progression stages without generating unnecessary alerts or missing important signals regarding the gearbox's condition. During the validation process, CHI values measured during the accelerated life test were allocated to appropriate maintenance threshold zones based on their threshold limits specified in Subsection 4.6. The classification results were later compared with the actual gearbox health state defined by experimental measurements and degradation stage labelling. The validation process thus allowed determining the performance of the multi-level maintenance threshold scheme in real-life conditions. In order to analyse the quality of classification, the most common measures of classification effectiveness were calculated. These included Accuracy, Precision, Recall, and F1-Score measures, described as follows:

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}},$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}},$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}},$$

$$\text{F1-Score} = \frac{2(\mathrm{Precision})(\mathrm{Recall})}{\mathrm{Precision} + \mathrm{Recall}},$$

where:

TP = True Positives;

TN = True Negatives;

FP = False Positives;

FN = False Negatives.

Classification performance for each maintenance zone has been evaluated using the four mentioned measures and summarized in **Table 16**.

Table 16. Classification performance of the proposed maintenance threshold framework.

Maintenance zone	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Alert Zone	92.8	91.4	90.7	91.0
Warning Zone	94.6	93.1	92.5	92.8
Critical Zone	97.3	96.5	95.9	96.2
Overall Framework	94.9	93.7	93.0	93.3

Table 16 shows a good classification performance among all the maintenance zones. The entire system achieved an accuracy of 94.9%, which suggests that the majority of gearboxes were classified into the correct maintenance state. The best performance is shown by the Critical Zone, with an accuracy rate of 97.3% and an F1 score of 96.2%. Such a high rate of classification performance in the Critical Zone is especially important since a false classification of the severe damage of the gearboxes could lead to a complete breakdown of the gearbox, causing significant financial losses. The accuracy in the Alert Zone was somewhat lower than in the Warning Zone and the Critical Zone. The findings from the validity test clearly confirm that the local saturation of Kurtosis encountered during the advanced stage of deterioration did not have an impact on the efficiency of the composite health index. If the effect of local saturation had impacted the health index, a reduction in the classification performance would be expected in the critical region of maintenance. However, the Critical Zone demonstrated the highest level of classification performance (97.3%) with the lowest false alarms in all zones of maintenance, which shows that further development of the Envelope Energy and sideband energy ratio compensated for the nonlinearity of the Kurtosis.

It is evident from **Table 17** that the developed framework consistently retained its ability to classify across all the validation subsets. The average accuracy across all the validation folds was 94.6% with a standard deviation of 0.45%. This shows that the Health Index as well as the boundaries did not rely heavily on any specific subset of the data set. However, it is expected since the process of switching from normal condition to degraded one usually occurs without any abrupt changes in vibration features, making it difficult to distinguish between normal and abnormal vibrations. Regardless of such difficulty, the Alert Threshold was able to achieve an accuracy rate above 92%. In order to investigate the classification performance, the Confusion Matrix was performed. The Confusion Matrix displays a visualization of classification results by depicting the distribution of observations classified either correctly or incorrectly.

Table 17. Cross-validation performance of the proposed threshold framework.

Validation fold	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Fold 1	94.1	92.9	92.4	92.6
Fold 2	95.2	94	93.6	93.8
Fold 3	94.6	93.4	92.8	93.1
Fold 4	95	93.8	93.3	93.5
Fold 5	94.3	93.1	92.6	92.8
Mean	94.6	93.4	92.9	93.2
Standard Deviation	0.45	0.47	0.45	0.48

As shown in **Table 18**, the most common classifications occur between adjacent maintenance zones, such as some of the Alert observations being misclassified into the Normal maintenance zone, as well as some of the Warning observations being misclassified into the Alert maintenance zone. Such misclassifications seem to be quite obvious, considering that transition conditions between states can have overlapping features. Importantly, none of the critical observations were misclassified into the Normal and Alert maintenance zones. **Figure 9** depicts the corresponding confusion matrix plot of the proposed framework.

Table 18. Confusion matrix for maintenance threshold classification.

Actual condition	Normal	Alert	Warning	Critical
Normal	94	6	0	0
Alert	5	92	3	0
Warning	0	4	93	3
Critical	0	0	3	97

Accordingly, the provided confusion matrix shows that as the degradation level rises, classification performance becomes better. Thus, it seems that the discriminant power of the CHI increases with the increase in degradation levels of the examined equipment. In turn, this means that the proposed framework is able to operate most effectively when maintenance decision-making is at its peak importance. Furthermore, the robustness of the framework was evaluated using its false alarm rate and missed detection rate analyses. While the former involves unnecessary maintenance decision-making, which occurs due to incorrect classification of healthy equipment into a degraded state, the latter means incorrect classification of degraded equipment into a healthy state, resulting in an unanticipated failure. The results of the evaluation are presented in **Table 19**.

Table 19. False alarm and missed detection analysis.

Threshold zone	False alarm rate (%)	Missed detection rate (%)
Alert Threshold	4.6	5.1
Warning Threshold	3.4	4.2
Critical Threshold	1.8	2.3

According to **Table 19**, the false alarm and miss rates stayed fairly low regardless of the chosen level of maintenance threshold. The Critical Threshold provided the most reliable prediction of imminently occurring failures due to the lowest percentage of errors. This property is especially valuable when used in industrial condition-based maintenance systems, since it prevents potential breakdowns without overexerting maintenance activities. In order to evaluate the classification efficiency of different maintenance threshold levels, an analysis of Receiver Operating Characteristics (ROC) was done. The Area Under the Curve (AUC) indicators for the Alert, Warning, and Critical thresholds amounted to 0.931, 0.954, and 0.981, respectively. Thus, the discrimination efficiency of the proposed framework proved to be rather high as demonstrated by the high classification ability of the CHI. ROC curves for the three different threshold types are presented in **Figure 10**.

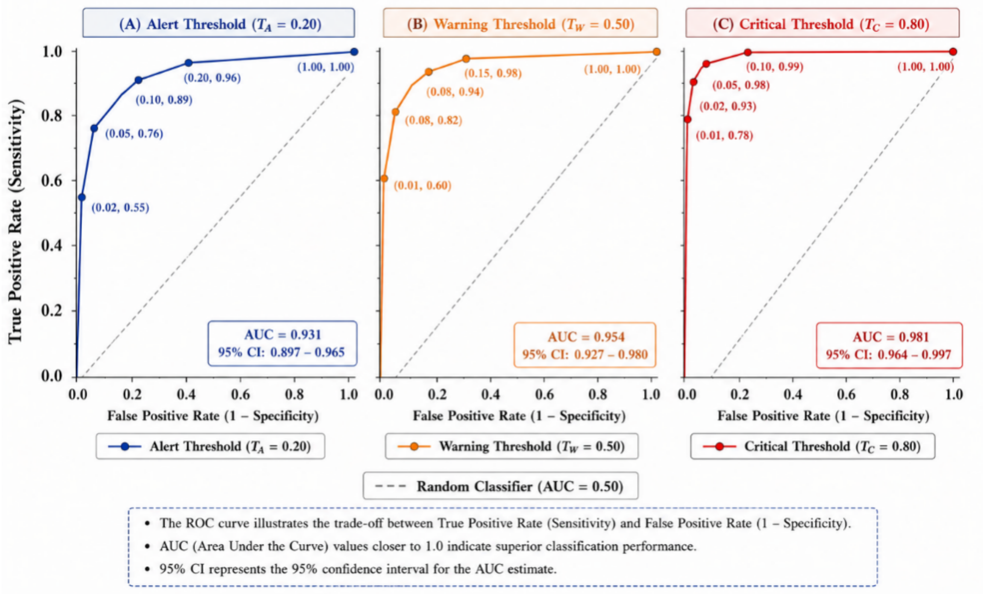

Figure 10. Receiver operating characteristic (ROC) curves for Alert, Warning, and Critical maintenance thresholds.

As one can see from the results of the ROC analysis, the proposed approach proved to be highly effective in classifying the state of the studied machine. Specifically, the Critical Threshold reached the highest score in terms of AUC and thus provided the highest possibility of correct prediction of critical operating states. Meanwhile, the Alert and Warning thresholds demonstrated high classification performance as well. Thus, it is possible to argue that Hypothesis H3 is confirmed, according to which the composite health index has a significant influence on determining maintenance thresholds required for making CBM decisions. Overall, the high classification efficiency, low error rate, strong results in the confusion matrix test, and high quality of the ROC analysis show that the proposed method of setting the maintenance threshold is highly applicable.

5. Discussion

5.1. Interpretation of envelope feature behaviour

It is clear that all studied envelope features display an increasing tendency from healthy to degraded gearboxes. These results are consistent with our expectations, as wear on gear tooth surfaces leads to impacts, irregular meshing, and greater dynamic loading of the transmission system, resulting in larger vibration amplitudes and increased impulsiveness, and, hence, changes in RMS Envelope, Kurtosis, Crest Factor, Peak Amplitude, Envelope Energy, and Sideband Energy Ratio values. Envelope Energy was found to be the most sensitive degradation tracking metric among all those used in the analysis. It can be interpreted that energy information contained in the envelope signal proves to be a good degradation metric as well. Compared to the Peak Amplitude feature, which is likely to experience significant variability due to possible single impulsive events, Envelope Energy better tracks the overall process of gearbox wear. The superior sensitivity of energy-based indicators to progressive degradation was demonstrated in previous vibration monitoring studies [38,39]. Kurtosis increases during the advanced degradation stage and can be explained by an increased number of impulsive events, namely impacts related to pitting, cracking, and surface defects of teeth. As is known, Kurtosis serves as a reliable measure of repetitive impacts in rotating machinery vibration monitoring because any mechanical faults lead to a higher number of transient impacts in the vibration response [40]. These findings confirm that Kurtosis indeed proved its ability to identify gearbox faults at an advanced level of degradation. Similarly, the Sideband Energy Ratio displayed strong progressive behaviour throughout the life tests. The emergence and enhancement of sidebands near the gear meshing frequency were usually attributed to modulation processes occurring due to damaged teeth. The greater extent of degradation resulted in greater sideband energy levels. The findings agree well with the theory of gearbox fault diagnosis, where growth of sidebands serves as a major fault identification feature [19,41].

5.2. Significance of feature sensitivity analysis

One key contribution of the current study is the analysis of feature sensitivity based on four different criteria: correlation, monotonicity, trendability, and separability. Despite the abundance of vibration monitoring works that use several features simultaneously, only a small number of studies conduct quantitative analysis of the comparative capability of each of them to track degradation before the construction of the health index. The research results show that Envelope Energy, Sideband Energy Ratio, and Kurtosis are the most efficient in terms of all the mentioned criteria, being strongly correlated with degradation, showing monotonous growth in the progression trajectory, and demonstrating satisfactory separability between adjacent states. These attributes are critical for applications in condition-based maintenance, since maintenance decision-making requires reliable indicators. Another important aspect of this paper lies in the dominance of the Envelope Energy indicator. Even though the RMS and Peak Amplitude remain among the most popular vibration parameters used in practice, the indicators related to energy are often more suitable because of their higher stability regarding transients. As a result, in this paper, Envelope Energy can be considered an alternative to amplitude-based monitoring. In addition, it should be noted that the Sideband Energy Ratio performs well in this study. This fact is explained by its frequency-domain nature, allowing the assessment of fault progression in the domain where changes directly correlate with modulation.

5.3. Performance of the composite health index

The introduction of the composite health index marked a key point in terms of translating vibration data into maintenance information. As demonstrated by the results, the incorporation of several degradation-sensitive condition indicators leads to a more steady and reliable degradation curve as compared to any particular individual feature. In terms of the relationship with the fault progression rate, the Health Index exhibited a strong correlation and reached $R^2 = 0.962$. This result reveals the fact that the integrated condition indicator is able to capture the bulk of the variation associated with the degradation of gearboxes through the test run. The high explanatory power of the Health Index implies that the combination of several indicators helps to minimize the effects of randomness in individual measurements while retaining sensitivity to degradation. As previously reported by a number of researchers who investigated the problem of machine condition diagnosis and prognosis, the use of composite indicators was crucial in order to reliably assess the status of machinery [42,43]. The current study confirmed this hypothesis by revealing that the weighted combination of three indicators provided an excellent approximation of the gearbox health. Another interesting finding in the current study is the lack of substantial overlap between the distributions of the Health Index in different degradation stages. Such high separability greatly simplified condition classification and contributed to determining maintenance threshold values. It is worth mentioning that this property may prove particularly beneficial in industrial applications when maintenance decisions have to be made based on unambiguous diagnostics. Even though there might be improvements in sensitivity to local deterioration thresholds in using adaptive or stage-based weighting systems, the fixed system of weighting used in the current study provided a consistent deterioration profile for the entire lifecycle of the gearbox. In future studies, there can be an investigation of adaptive weighting systems in order to detect early deterioration [44,45].

Alternative methods such as Principal Component Analysis (PCA) and deep learning approaches have been employed in machinery health evaluation. The method of PCA provides a very efficient way to reduce feature dimensionality; nonetheless, the produced principal components represent a transformation that is often not physically meaningful. This way, the task of defining maintenance limits according to principal component values can become rather challenging for maintenance personnel at industrial facilities. While deep learning approaches can autonomously create sophisticated representations of features, they usually require much larger data sets and more computing power than that of the proposed sensitivity-based Health Index. In addition, the model becomes more complex and not easily interpretable. The key advantage of the suggested methodology lies in its capability of utilizing a combination of various parameters sensitive to degradation, and not in relying on one vibration parameter. The individual envelope parameters tend to show stage-dependent dynamics. As an example, Kurtosis shows a strong dependency at an initial stage of degradation but saturates at the advanced stage, while Envelope Energy and Sideband Energy Ratio show a continuous increase during the entire process of degradation. Thus, utilizing only one parameter can fail to fully describe the degradation dynamics. The composite health index addresses this drawback by utilizing a combination of different parameters with complementary dynamic properties.

5.4. Implications of the maintenance threshold framework

It is essential to note that the maintenance threshold framework is the most critical contribution of the paper. Unlike the fault detection framework, the new model allows converting the information related to the machine's degradation into the maintenance zones (Alert, Warning, and Critical). The first level, or Alert Threshold, serves as an early indicator of the malfunctioning of the gearbox and provides a chance to increase the monitoring rate before any significant damage occurs. Early detection is one of the primary goals of the CBM strategy since it helps maintenance workers track changes in the condition without stopping activities. Therefore, defining such a zone gives additional operational freedom and reduces the risk of unforeseen breakdowns. In turn, Warning Thresholds are considered optimal for the development of maintenance strategies. It turns out that these thresholds are located where the degradation accelerates rapidly. As a result, interventions made when the gearbox is in Warning Zones help prevent more critical problems and save unnecessary expenditures. Thus, this discovery supports the basic principles of condition-based maintenance [12]. As for the Critical Threshold, the results obtained showed that it was the most accurate across all the thresholds. This result deserves attention because failure to identify this condition could mean the destruction of the gearbox and significant financial losses. From an industrial point of view, the suggested maintenance thresholds could be seen as initial decision boundaries that can be fine-tuned according to the risk appetite for operations and maintenance policies. For example, critical systems might purposefully set their Critical Threshold lower to avoid potential problems of missing fault detection, while maintenance cost minimization systems would use more conservative threshold settings to avoid false alarms. Therefore, the suggested approach provides the possibility for flexible customization of risk attitudes within application domains without changing the basic idea of the Health Index approach. From an industrial perspective, the framework for maintenance needs to be considered condition driven and not time driven. The maintenance decisions will be based on the calculated Health Index instead of making any considerations about how long a particular stage of deterioration takes place or the order in which these stages occur. This feature allows the maintenance framework to incorporate the variability that is usually present in industrial equipment deterioration processes. However, there might be some failure modes where the deterioration happens very quickly, thus reducing the time spent in the intermediate maintenance areas.

5.5. Industrial implications

The results have several important implications for industrial condition monitoring and maintenance management. Today's industrial organizations are using predictive and condition-based maintenance approaches in their operations with the goal of improving equipment reliability and minimizing expenses. Still, many condition monitoring systems remain based on standalone vibration indicators and individual criteria for carrying out maintenance tasks. The developed algorithm fills this gap by providing a comprehensive approach to deriving maintenance tasks from vibration data. Through implementing feature extraction, health index derivation, and setting of thresholds, it becomes possible to systematically track the course of degradation and make timely maintenance decisions. The framework is intended to be applied to gearbox operation systems that operate in manufacturing, mining, wind energy generation, maritime propulsion, and industrial machinery applications. In these environments, failure of gearboxes usually leads to high costs of downtime and production losses.

5.6. Contributions, limitations, and future research directions

The study makes several significant contributions to advancing the field of vibration-based condition monitoring. Firstly, it proves that Envelope Energy, Sideband Energy Ratio, and Kurtosis are the three most sensitive to degradation features among the selected envelope characteristics. Secondly, it establishes a methodology for constructing a composite health index that is able to effectively model degradation progression and provide reliable estimates. Finally, the study suggests a reasonable framework for determining multi-level maintenance thresholds based on condition monitoring results. At the same time, certain limitations should be mentioned. The current investigation is carried out under the conditions of accelerated life tests. Therefore, it is likely that some factors like loading conditions, environmental impacts, lubrication characteristics, etc., might affect the process of degradation and location of thresholds in real-life conditions. Thus, the latter can vary significantly and need to be calibrated before practical application. Further research should focus on validating the suggested methodology through the use of long-term field data for operational systems. In addition, adaptive threshold strategies should be explored in order to make it possible for maintenance decision-making systems to account for different types of operating conditions and machines' configurations. Another promising direction of future work is the combination of machine learning approaches with health index modelling. As one can see, the current study provides a good basis for implementing a condition-based maintenance strategy for gearboxes by means of vibration envelope analysis. The results of the investigation suggest that vibration analysis can be successfully employed in such cases, along with health index modelling and threshold determination.

A number of limitations need to be considered when evaluating the results obtained in the current study. To begin with, the suggested methodology was verified through conducting one controlled accelerated degradation test aimed at verifying the concept of the Health Index and maintenance threshold evaluation. While conducting degradation tests under controlled conditions allowed achieving a stable degradation process, it is necessary to conduct more degradation tests on several gearboxes to determine the statistical repeatability and to find out how much variability can be expected between different specimens. Second, the degradation tests involved the use of elevated loads to speed up the process of degradation and did not involve applying classical acceleration models for reliability assessment. Thus, the current study focuses on degradation monitoring rather than life prediction. Finally, the suggested numerical values for maintenance thresholds are machine specific and were based on the properties of the experimental gearbox. Before the application of the current method in industry, it needs to be adjusted for the specific machine. However, there are some limitations that should be noted in spite of the value added by this work. The experimental study was carried out within the framework of accelerated life tests to simulate the process of the gradual destruction of the gearbox. While this technique successfully reflected the physical parameters of fault evolution, real-world gearboxes have to operate at changing speeds, loads, lubrication regimes, and environmental factors that can affect the actual values of the vibration envelope features. Therefore, the proposed thresholds have to be adapted to the operational data before their application to a particular situation in industry.

Despite this limitation, the methodology for evaluation of vibration envelope features, composite health index creation, and setting up the maintenance thresholds is easily applicable to various gearbox units and can serve as a basis for further condition-based maintenance implementation. While the health state labeling was done based on the controlled degradation procedure and verified through regular physical observation, this experiment was carried out in a lab setting using defined operating conditions. The next step for future research will be to verify the framework using actual field data from varying operating speeds, torque variations, and different loading conditions. Adding more operating data to the definition of health states would increase the independence of the labels and improve the proposed framework.

6. Conclusion

The current paper formulates a condition-based maintenance approach that uses the vibration envelope features in addition to the accelerated life testing of a gearbox to evaluate its condition deterioration. According to the findings, the proposed envelope-based features show highly significant differences in their values as the fault level of the investigated gearbox increases from health state to critical fault state. Among those features that have been tested in the paper, Envelope Energy, Sideband Energy Ratio, and Kurtosis can be regarded as the most appropriate features to evaluate the gearbox condition due to their high levels of correlation, monotonicity, trendability, and stage separability.

Subsequently, a composite health index was constructed in order to aggregate the above-mentioned features. As a result of constructing such an index, a condition indicator capable of presenting a gearbox condition in a stable and precise way was achieved. In particular, a strong connection between the obtained index and the level of fault can be seen. In addition, the Health Index enables one to distinguish different stages of the studied system degradation. Based on the Health Index, three zones were defined for making decisions regarding maintenance activities: Alert, Warning, and Critical. The obtained maintenance threshold model was validated to test the accuracy of classification and determine the false alarm rate in each zone. According to the results, a high level of accuracy was observed, and false alarms were rarely identified in all zones.

Author contributions: Conceptualization, MAH and AV; methodology, GJ; software, JL; validation, SM, MAH, and MA; formal analysis, AV; investigation, MA; resources, SM; data curation, JL; writing—original draft preparation, MAH; writing—review and editing, AV; visualization, GJ; supervision, SM; project administration, MA; funding acquisition, JL. All authors have read and agreed to the published version of the manuscript.

Funding: This work received no external funding.

Institutional review board statement: Not applicable.

Informed consent statement: Not applicable.

Data availability statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Conflict of interest: The authors declare no conflict of interest.

AI use statement: The authors declare that no artificial intelligence (AI) tools were used in the preparation of this manuscript.

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