

Predictive analysis of industrial safety based on noise, vibrations and machinery reliability

Henry Nelson Aguilera Vidal* , Ruth Isabel Torres Torres , Irene Teresa Bustillos Molina , Eudes Martínez Porro 

Faculty of Industrial and Production Sciences, Quevedo State Technical University, Quevedo EC120550, Ecuador

* Corresponding author: Henry Nelson Aguilera Vidal, haguilera@uteq.edu.ec

CITATION

Aguilera Vidal HN, Torres Torres RI, Bustillos Molina IT, et al. Predictive analysis of industrial safety based on noise, vibrations and machinery reliability. *Sound & Vibration*. 2026; 60(2): 3995.
<https://doi.org/10.59400/sv3995>

ARTICLE INFO

Received: 4 February 2026
Revised: 19 March 2026
Accepted: 24 March 2026
Available online: 2 April 2026

COPYRIGHT



Copyright © 2026 Author(s).
Sound & Vibration is published by Academic Publishing Pte. Ltd. This work is licensed under the Creative Commons Attribution (CC BY) license. <https://creativecommons.org/licenses/by/4.0/>

Abstract: This study develops a predictive approach for assessing industrial safety risk through the integrated analysis of physical indicators associated with machinery operation, specifically noise, vibration, and mechanical reliability. The research was conducted in industrial environments characterized by the continuous operation of rotating equipment, including motors, pumps, compressors, and transmission systems. A dataset of approximately 18,000 operational records collected over a 12-month period was analyzed, incorporating acoustic measurements, vibration parameters, machinery condition, and records of potentially unsafe operating states. Equivalent sound pressure level (Leq), Root Mean Square (RMS) acceleration, and crest factor were calculated as the main dynamic indicators, and these variables were normalized and integrated into an Industrial Risk Index (IRI) designed to represent the operational safety state of the equipment. Subsequently, a logistic regression model was developed to classify operating conditions into safe or risk states. The results showed that the combined use of acoustic and vibration indicators improves the identification of hazardous conditions compared with isolated metrics. The predictive model achieved strong classification performance, with an accuracy of 0.88, sensitivity of 0.86, specificity of 0.84, and an AUC-ROC of 0.90, demonstrating a high capacity to distinguish safe operation from risk scenarios. Sustained increases in noise and vibration, particularly when associated with signs of mechanical degradation, were found to precede unsafe states. The findings confirm that integrating dynamic condition monitoring with predictive analytics strengthens failure anticipation and supports preventive decision-making, providing a technically interpretable basis for more proactive industrial safety management systems.

Keywords: industrial safety; noise exposure; vibration analysis; machinery reliability; predictive modeling; risk assessment; condition monitoring; logistic regression

1. Introduction

Industrial safety in modern production environments is closely linked to the dynamic behavior of the mechanical systems that make up production processes. In industries characterized by the continuous operation of machinery, the generation of noise and vibrations is an inherent phenomenon associated with dynamic forces, structural contacts, component rotation, and variations in loading conditions. These physical manifestations constitute a central focus of study in sound and vibration engineering. Traditionally addressed from the perspectives of acoustics and structural dynamics, they have acquired increasing relevance due to their effects on occupational

health and their direct relationship with machinery reliability and the occurrence of workplace accidents [1–3].

Several studies have shown that industrial noise, commonly assessed using indicators such as the equivalent sound pressure level (Leq), affects long-term hearing and influences cognitive performance, risk perception, and the responsiveness of workers during the operation of industrial equipment. Continuous exposure to high noise levels can lead to mental fatigue, decreased attention, and operational errors, factors that increase the likelihood of accidents in critical tasks [4,5]. In this sense, noise ceases to be merely a matter of comfort or health and becomes an indirect indicator of risk in the context of industrial safety.

Furthermore, mechanical vibration is one of the main indicators of the dynamic condition of machinery. Parameters such as RMS acceleration, peak value, crest factor, and frequency spectral analysis are widely used to identify imbalances, misalignments, bearing defects, and structural fatigue processes. The specialized literature has shown that anomalous variations in these indicators often precede mechanical failures, which can lead to unscheduled downtime, loss of equipment control, and hazardous situations for operators [6–8]. From this perspective, vibration reflects the condition of the machinery and, in turn, acts as an early warning signal of potentially unsafe scenarios.

Machinery reliability thus emerges as a central element in the relationship between noise, vibration, and industrial safety. Modern reliability approaches consider that the progressive degradation of mechanical systems can be monitored using dynamic signals, allowing for the anticipation of failures before they reach critical states. In this context, condition monitoring based on vibrations and acoustic signals has become established as a key tool for operational risk management and the prevention of accidents associated with mechanical failures [9, 10]. Integrating these approaches allows us to overcome fragmented views that analyze safety solely from the perspective of organizational or human factors.

However, traditional industrial safety management systems still rely, in many cases, on reactive approaches based on post-incident analysis, periodic inspections, and regulatory compliance. While these strategies have helped reduce the frequency of accidents, they have significant limitations in capturing the dynamic and nonlinear nature of the risks associated with machinery operation. In particular, the interaction between noise, vibration, operating load, and mechanical wear generates complex patterns that are difficult to interpret using conventional statistical methods [11, 12].

Advances in data acquisition systems, dynamic sensors, and industrial monitoring platforms have led to the availability of large volumes of information related to the vibrational and acoustic behavior of machinery. This technological evolution has opened the door to predictive analytics approaches capable of transforming physical signals into useful information for decision-making in industrial safety. In this context, data-driven predictive models make it possible to identify trends, critical thresholds, and hidden relationships between physical variables and operating conditions, facilitating the anticipation of risk scenarios before accidents occur [13, 14].

However, one of the fundamental challenges in applying predictive models in industrial settings is ensuring their interpretability and practical applicability. In

disciplines such as mechanical engineering and industrial safety, plant managers need to understand the relationship between model results and the underlying physical phenomena. Therefore, approaches that combine physical noise and vibration metrics with analytical and numerical methods are particularly relevant for journals specializing in sound and vibration, where physical soundness and practical utility are central editorial criteria [6, 15].

In this context, the present study focuses on the predictive analysis of industrial safety using noise, vibration, and machinery reliability indicators. The objective is to develop a quantitative approach that allows for the evaluation of the risk associated with the operation of dynamic mechanical systems, integrating measurable physical signals with predictive analysis techniques applicable to real-world industrial environments. Unlike studies focused exclusively on organizational variables or abstract models, this work highlights the role of dynamic indicators as key tools for preventing workplace accidents.

The main contribution of this research lies in articulating an engineering approach that links sound and vibration analysis with industrial safety from a predictive perspective. By integrating concepts of machine reliability, condition monitoring, and dynamic analysis, it seeks to provide a solid technical foundation for the development of more proactive industrial safety systems, aligned with current engineering demands.

2. Theoretical framework

2.1. Industrial noise as a dynamic indicator of risk

Industrial noise is a physical manifestation inherent to the operation of machinery and dynamic processes, originating from phenomena such as mechanical impacts, friction, turbulence, and structural vibrations. From an acoustic engineering perspective, noise is commonly assessed using indicators such as sound pressure level (SPL) and continuous equivalent sound level (Leq), which characterize the acoustic energy emitted over a specific time interval. In industrial environments, these indicators not only reflect comfort conditions or regulatory compliance but also provide relevant information about equipment operational status [15, 16].

Recent studies have shown that anomalous increases in noise levels can be associated with incipient mechanical defects, such as gear wear, cavitation, structural looseness, or failures in rotating systems. These acoustic changes often precede more serious failures, making noise an early indicator of machinery degradation and, therefore, a potential risk to industrial safety [17, 18]. Consequently, noise analysis transcends the scope of occupational hygiene and is integrated into the diagnosis of the dynamic behavior of production systems.

From an industrial safety perspective, exposure to high noise levels also affects human performance. Ergonomics and human factors research have shown that excessive noise impairs concentration, auditory perception of warning signals, and reaction time, increasing the likelihood of operational errors during human-machine interaction [4, 5]. This indirect relationship between noise and accidents reinforces the need to consider acoustic metrics as an integral part of industrial risk assessment

models.

2.2. Mechanical vibrations and monitoring of the condition of machinery

Mechanical vibration is one of the main parameters used to evaluate the dynamic state of industrial systems. From an engineering perspective, vibration is defined as the oscillatory motion of a system around an equilibrium position, generated by internal or external dynamic forces. Its analysis is based on indicators such as RMS acceleration, peak value, crest factor, and spectral content in the frequency domain, which allow the identification of anomalies associated with mechanical failures [6, 19].

In recent years, vibration monitoring has become a fundamental tool in predictive maintenance and reliability programs for machinery. Recent research indicates that defects such as imbalance, misalignment, bearing wear, and structural cracks generate characteristic vibration patterns that can be detected before reaching critical states [20,21]. Early identification of these patterns reduces the likelihood of catastrophic failures and minimizes hazardous situations for workers.

From an industrial safety perspective, vibration not only represents an occupational health problem but also constitutes an operational risk factor. Excessive vibrations can lead to equipment instability, loosening of components, sudden failures, and the uncontrolled release of mechanical energy—situations that increase the likelihood of workplace accidents [22]. Therefore, vibration assessment should be considered a key element in comprehensive industrial risk management.

2.3. Machinery reliability and industrial safety

Machinery reliability is defined as the probability that a system will perform its intended function under specified conditions for a given period. In an industrial context, reliability is closely linked to safety, since unexpected equipment failures can lead to serious accidents, operational disruptions, and loss of life and property. In this sense, reliability acts as a conceptual link between the dynamic behavior of machinery and the prevention of workplace accidents [9,23].

Modern reliability approaches incorporate condition monitoring techniques based on physical signals, such as noise and vibration, to assess the degradation state of systems. These approaches allow a shift from corrective or preventive maintenance strategies to predictive schemes, where decisions are based on the actual evolution of dynamic indicators [24]. From this perspective, machinery reliability becomes an active component of industrial safety, enabling the anticipation of unsafe scenarios before failures occur.

Recent literature highlights that industrial accidents are rarely the result of a single cause, but rather arise from the interaction between technical failures, adverse operating conditions, and human factors. Therefore, integrating machinery reliability into industrial safety models is fundamental to addressing the systemic nature of risk in complex industrial environments [11,12].

2.4. Predictive approaches in industrial safety based on physical indicators

Advances in detection and data acquisition systems have driven the development of predictive approaches that integrate physical indicators for industrial risk assessment. Unlike traditional models based on historical accident statistics, predictive approaches allow the identification of dynamic patterns and nonlinear relationships between operational, environmental, and mechanical variables [13,25].

In particular, the combination of noise and vibration metrics with analytical and numerical models has proven effective in anticipating machinery failures and assessing their potential impact on industrial safety. Recent studies highlight that the use of physical indicators as input variables improves the ability of models to represent the actual behavior of industrial systems and facilitates the interpretation of results from an engineering perspective [17,20].

In this context, predictive approaches based on noise, vibration, and machinery reliability offer a solid foundation for developing more proactive industrial safety systems. By integrating dynamic signals with quantitative models, early identification of risk scenarios and the implementation of preventive measures aimed at reducing workplace accidents in industrial environments becomes possible.

3. Methodology

3.1. Study design and methodological approach

The study was developed using a quantitative, analytical, and predictive approach, aimed at evaluating industrial safety through the integrated analysis of physical indicators of noise, vibration, and machinery reliability. The methodological design is based on the combination of normalized dynamic metrics, statistical analysis, and predictive modeling, with the objective of identifying patterns associated with unsafe operating conditions and anticipating risk scenarios before workplace accidents occur [11,12].

From an engineering perspective, the methodology is structured in four main stages: acquisition and preprocessing of acoustic and vibratory signals; calculation of normalized dynamic indicators; construction of a quantitative industrial risk index; and application of predictive models for the assessment of the risk and reliability of machinery.

3.2. Study area, population and data source

The research was conducted in industrial environments characterized by the continuous operation of rotating machinery and dynamic mechanical equipment, typical of manufacturing and industrial production processes. In the national context, Ecuador has a large and diverse industrial sector, with a high concentration of production facilities in provinces such as Pichincha and Guayas, where the intensive use of industrial machinery predominates.

The study focused on a representative set of five industrial plants, selected based on the presence of critical mechanical equipment that generates significant noise and vibration. A total of 25 pieces of industrial equipment were analyzed, including electric

motors, pumps, compressors, and mechanical transmission systems, operating under continuous or semi-continuous load conditions.

The study population consisted of approximately 18,000 operational records, corresponding to measurement intervals obtained during a 12-month operating period. Each record included information on noise levels, vibration parameters, machinery operating status, and events associated with unsafe conditions or operational incidents, allowing for analysis of the temporal evolution of dynamic indicators and their relationship with industrial safety.

Data were collected using noise sensors and accelerometers installed at strategic points on the selected equipment, following standard condition monitoring practices. Historical operating and maintenance records were also incorporated to complement the dynamic information with records of failures, technical interventions, and operating conditions of the machinery. This type of data source has been widely used in machinery reliability studies and condition monitoring due to its ability to capture the actual behavior of mechanical systems under operating conditions [20].

The final dataset used for the analysis was structured from the operational records collected during the observation period, generating a base of approximately 18,000 observations corresponding to measurement intervals of the dynamic behavior of the industrial equipment. Each record simultaneously integrated acoustic, vibrational, and mechanical condition variables of the machinery. The structure of the dataset allowed for the analysis of the temporal evolution of the dynamic indicators and their relationship to potentially unsafe operating states, which is consistent with condition monitoring approaches used in maintenance and reliability engineering for machinery.

3.3. Instrumentation and signal acquisition

Noise and vibration measurements were taken using acoustic sensors and accelerometers installed at representative points on the analyzed mechanical equipment, following the general principles of rotating machinery condition monitoring. For vibration measurements, piezoelectric accelerometers were used, mounted on bearing housings and at structural points near the main sources of dynamic excitation, as these locations allow for adequate capture of the transmission of vibrational energy generated by imbalances, misalignments, or mechanical defects.

Dynamic signals were recorded in analysis time windows using digital data acquisition systems. Sampling frequencies suitable for the analysis of industrial rotating machinery were used to process the vibration signals, allowing the capture of dynamic behavior within a frequency range characteristic of this type of equipment. The signals were subsequently processed using standard vibration analysis procedures, including the calculation of global time-domain indicators such as RMS acceleration and crest factor, widely used in predictive maintenance and condition monitoring programs.

3.4. Variables analyzed

The variables considered in the study are grouped into four main categories: acoustic indicators (instantaneous sound pressure level and equivalent sound pressure

level), vibration indicators (RMS acceleration, peak acceleration value, and crest factor), machinery reliability indicators (equipment operating status, failure and maintenance history, and cumulative operating time), and the dependent variable, defined as the industrial safety condition (safe state or risk state), established from potentially hazardous operating conditions identified using dynamic noise and vibration indicators. This set of variables reflects the multifactorial nature of industrial risk and allows for the integration of physical signals with reliability criteria, in accordance with the recommendations of recent studies in safety and predictive maintenance.

The dependent variable of the study was defined as the state of operational risk, classified into two categories: safe condition and risk condition. In the context of this research, the state of risk does not refer directly to the occurrence of confirmed workplace accidents, but rather to potentially hazardous operating conditions associated with the dynamic deterioration of machinery, which can act as precursors to technical failures or unsafe situations.

The classification of the recordings was based on a combination of anomalous physical operating indicators, including simultaneous increases in equivalent sound pressure levels (L_{eq}), RMS vibration acceleration, and crest factor, along with information on the mechanical condition of the equipment. Recordings in which the indicators remained within normal operating ranges were labeled as safe, while recordings characterized by significant deviations in the dynamic indicators were classified as hazardous.

The operating thresholds used for classification were defined considering typical operating ranges reported in rotating machinery condition monitoring and vibration diagnostics studies. Specifically, simultaneous increases in equivalent sound pressure level, RMS acceleration, and crest factor were considered indicative of anomalous dynamic conditions in the mechanical system. This criterion allows for the identification of incipient mechanical degradation states that may precede equipment failures or unsafe operating conditions.

From a reliability engineering perspective, this approach allows for the identification of mechanical degradation states and anomalous dynamic behaviors that can precede equipment failures or unsafe operating situations. Therefore, the predictive model developed in this study should be interpreted as a technical model for the early detection of hazardous operating conditions, based on physical indicators of noise and vibration, with relevance to the preventive management of industrial safety.

3.5. Calculation of noise indicators

Industrial noise was quantified using the equivalent sound pressure level (L_{eq}), calculated from the acoustic pressure signal recorded during defined time intervals, according to the expression:

$$L_{eq} = 10 \log_{10} \left((1/N) \sum (p_i^2 / p_0^2) \right)$$

where p_i represents the sound pressure measured at each instant, p_0 corresponds to the reference pressure (20 μ Pa) and N is the number of samples. This indicator allows

characterization of the average acoustic energy generated by machinery during its operation and is widely used in industrial acoustic analysis [15].

3.6. Calculation of vibration indicators

Mechanical vibration was evaluated by calculating the RMS acceleration, used as an indicator of the vibrational energy transmitted by the machinery. This parameter was defined as:

$$a_{\text{RMS}} = \sqrt{\left(\frac{1}{N}\right) \cdot \sum a_i^2}$$

where a_i represents the acceleration measured at each instant and N the total number of samples considered in the analysis window.

In addition, the crest factor (CF) was calculated, which is used for the detection of shocks and transients associated with mechanical defects and anomalous dynamic conditions. The crest factor was defined as the ratio between the peak acceleration and the RMS acceleration:

$$\text{CF} = \text{peak}/a_{\text{RMS}}.$$

These indicators are widely used in condition monitoring and fault diagnosis in rotating machinery, due to their high sensitivity to changes in the dynamic behavior of the system [6, 19].

Considerations on spectral analysis

While frequency-domain spectral analysis is a fundamental tool for the detailed diagnosis of specific faults in rotating machinery, the objective of this study was not the precise identification of individual defects in mechanical components, but rather the evaluation of the overall dynamic behavior associated with potentially unsafe operating conditions. For this reason, the analysis focused on global time-domain indicators, such as RMS acceleration and crest factor, which allow for the detection of general increases in the system's vibrational energy. This approach is consistent with condition monitoring applications aimed at the early detection of anomalies, where changes in overall vibration levels can indicate the onset of mechanical degradation processes before specific faults identifiable through spectral analysis become apparent.

3.7. Construction of the quantitative industrial risk index

In order to integrate acoustic, vibration, and reliability indicators into a single measure representative of industrial risk, an Industrial Risk Index (IRI) was defined as a weighted combination of the main dynamic indicators associated with machinery operation. This index allows for the synthesis of information from multiple physical variables into a single quantitative parameter capable of reflecting the operational state of the mechanical system.

The index was initially defined as:

$$\text{IRI} = w_1 \cdot \text{Leq} + w_2 \cdot a_{\text{RMS}} + w_3 \cdot \text{CF} + w_4 \cdot \text{Cm}$$

where:

- Leq represents the equivalent sound pressure level associated with the operation of the equipment,
- aRMS stands for root mean square vibrational acceleration, used as an indicator of the vibrational energy of the system,
- CF is the crest factor of the vibration signal, related to the presence of shocks or dynamic transients,
- Cm corresponds to an indicator of the state of the machinery linked to its operational condition and mechanical reliability,
- w_1 , w_2 , w_3 and w_4 represent the weighting coefficients associated with each indicator.

The index was constructed based on the principle that industrial risk in mechanical systems does not depend on a single physical parameter, but rather on the simultaneous interaction of dynamic variables that reflect the operational behavior of the machinery. For this reason, the IRI integrates acoustic, vibration, and mechanical condition information into a composite metric aimed at the early identification of potentially hazardous operating conditions.

Normalization of variables and determination of weights

Since the indicators used in the index have different physical units, decibels in the case of sound pressure level, m/s^2 for vibration acceleration and dimensionless values for crest factor and machine condition, a variable normalization process was previously applied in order to allow their integration into a single quantitative metric.

Normalization was performed using a linear min-max transformation, which scales each indicator to the interval [1], according to the following expression:

$$X_{\text{norm}} = (X - X_{\text{min}}) / (X_{\text{max}} - X_{\text{min}})$$

where X represents the original value of the indicator and X_{min} and X_{max} correspond to the minimum and maximum values observed in the data set.

This procedure allows for the comparison of variables originally expressed in different physical scales and is widely used in the construction of composite indices and synthetic metrics in multivariate analysis and risk assessment studies.

Normalization ensures that variables originally expressed in different physical units can be coherently integrated within the Industrial Risk Index (IRI), allowing the consistent combination of acoustic, vibratory, and mechanical condition indicators into a single quantitative metric representative of the system's operating state.

Once the indicators were normalized, the index was calculated as a weighted sum of the normalized variables, according to the following general expression.

$$IRI = w_1 \cdot Leq_{\text{norm}} + w_2 \cdot aRMS_{\text{norm}} + w_3 \cdot CF_{\text{norm}} + w_4 \cdot Cm_{\text{norm}}$$

The weighting coefficients w_1 , w_2 , w_3 , and w_4 were determined through an analysis of the relative variability of the indicators, evaluating each variable's ability to differentiate between normal operating conditions and anomalous dynamic scenarios within the dataset. This procedure allows for assigning greater weight to those

indicators that exhibit greater sensitivity in detecting relevant changes in the dynamic behavior of the machinery.

The final aggregation of the index through a weighted sum allows for obtaining a synthetic measure of the dynamic state of the mechanical system. This approach is consistent with the methodological principles used in constructing composite risk indicators, where multiple physical variables must be integrated into a single metric representative of the phenomenon being analyzed.

From a reliability engineering and condition monitoring perspective, the Industrial Risk Index (IRI) allows the transformation of complex dynamic signals into an interpretable quantitative indicator that facilitates the early identification of unfavorable operating conditions, supporting decision-making related to technical inspection, predictive maintenance, and preventive management of industrial safety.

3.8. Predictive risk modeling

Once the dynamic indicators and the Industrial Risk Index (IRI) were calculated, a predictive model was developed to classify the operating conditions of the machinery into two states: safe condition and risk condition. The model's objective was to identify patterns in the physical indicators that would allow for anticipating potentially hazardous scenarios associated with the dynamic behavior of industrial equipment.

A logistic regression algorithm was used to develop the model. This algorithm is widely employed in binary classification problems due to its ability to model the probability of an event occurring based on continuous explanatory variables. The model's input variables included normalized acoustic and vibration indicators ($L_{eq_{norm}}$, $aRMS_{norm}$, CF_{norm}), as well as the equipment's mechanical condition indicator (Cm_{norm}).

In order to evaluate the predictive performance of the model and avoid overfitting, the dataset was divided into two subsets: 70% of the records were used for the 30% is used for model training and the remaining 30% for validation. This strategy allows us to estimate the model's ability to generalize to data not used during the training process.

Before training the model, all explanatory variables were normalized using min-max transformation, which ensures that the indicators have comparable scales and prevents variables with greater numerical magnitude from dominating the learning process.

Furthermore, the class balance between observations labeled as safe and hazardous conditions was verified. This is especially relevant in industrial safety applications, as a highly unbalanced distribution could bias the model toward the majority class. In cases of moderate differences between classes, class weight adjustment techniques were applied during model training to maintain classification stability.

To avoid information leaks, associated with the temporal dependence of the records or the repetition of measurements by the same equipment, the division between training and validation was carried out considering the structure of the operational records, ensuring that the data used to evaluate the model were not previously used during training.

The model's performance was evaluated using standard classification metrics employed in predictive analytics studies in engineering and industrial safety, including

accuracy, sensitivity, specificity, and the area under the ROC curve. These metrics allow for the assessment of the model's ability to correctly identify risk scenarios while simultaneously minimizing the occurrence of false negatives, a critical aspect in accident prevention applications.

Additionally, a cross-validation procedure was applied during model training to assess the stability of predictive performance across different partitions of the dataset. This approach reduces the model's dependence on a single training-validation split and provides a more robust estimate of its generalizability.

3.9. Performance Evaluation

The performance of the predictive models was evaluated using standard classification metrics, such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve (AUC). These metrics allow for the assessment of the model's ability to correctly identify risk scenarios and minimize false negatives, a crucial aspect in industrial safety applications. Furthermore, false positive and false negative rates were analyzed using the model's confusion matrix to evaluate its performance in identifying risk conditions.

3.10. Ethical considerations

The study was conducted using technical and operational data from the machinery, without including personally identifiable information from the workers. Therefore, individual informed consent was not required, and the confidentiality of the records was guaranteed at all times, with the information being used exclusively for research purposes and to improve industrial safety.

4. Results

4.1. Characterization of noise and vibration levels in industrial operation

Analysis of the collected data allowed for the characterization of the dynamic behavior of noise and vibration levels associated with the continuous operation of industrial machinery. From 18,000 operational records, distinct patterns were identified between stable operating conditions and scenarios of greater mechanical stress.

In the case of industrial noise, the equivalent sound pressure levels (L_{eq}) showed a wide distribution, with values concentrated in ranges characteristic of normal operation and peaks associated with start-ups, changes in operating conditions, and transient events. These results reflect the dynamic nature of industrial processes and the direct influence of mechanical behavior on acoustic emissions. **Figure 1** presents the distribution of the equivalent sound pressure levels (L_{eq}) obtained from the analyzed dataset.

The L_{eq} values were calculated by applying the equivalent sound pressure level expression:

$$L_{eq} = 10 \log_{10} \left(\frac{1}{N} \sum (p_i^2 / p_0^2) \right)$$

where p_i represents the sound pressure measured at each instant, p_0 the reference

pressure (20 μPa) and N the number of samples considered in the analysis window.

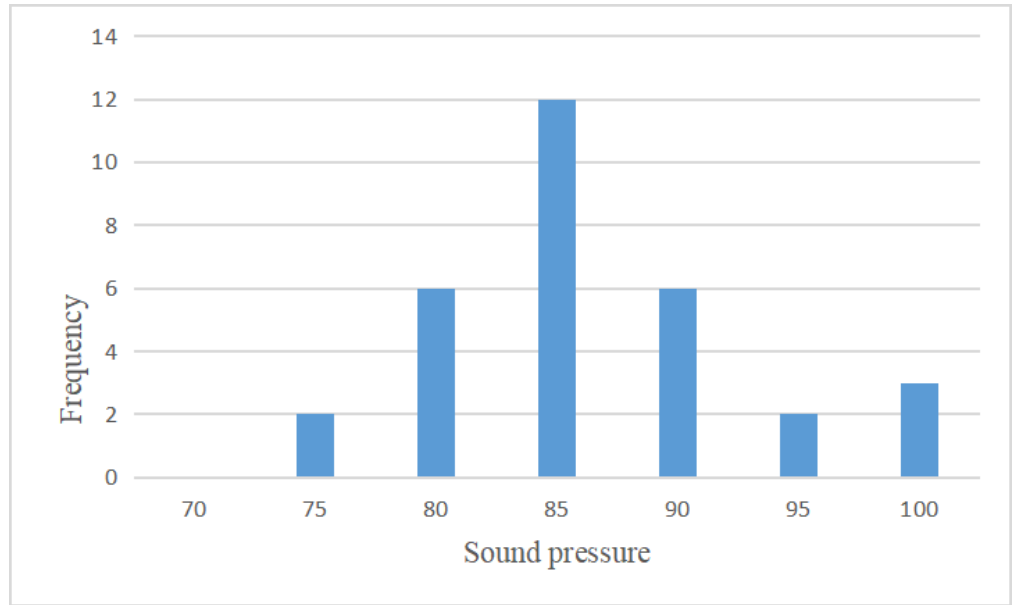


Figure 1. Distribution of equivalent sound pressure levels (L_{eq}) recorded during the operation of industrial machinery.

Note: The histogram represents the distribution of the equivalent sound pressure level L_{eq} (dB) recorded during the operation of industrial machinery. Class intervals were established at 5 dB ranges, based on acoustic recordings obtained under representative operating conditions. The horizontal axis corresponds to the equivalent sound pressure level L_{eq} (dB), while the vertical axis indicates the frequency of observed recordings.

Source: Author’s own elaboration.

4.2. Vibration indicator analysis

Regarding mechanical vibration, the analysis of acceleration records allowed for the characterization of the dynamic behavior of critical equipment during the study period, differentiating between stable operating conditions and scenarios of greater mechanical stress. Under nominal conditions and with a stable load, the equipment exhibited relatively constant vibration levels; however, progressive increases and transient episodes were identified associated with speed changes, load variations, starts and stops, as well as with conditions of mechanical deterioration such as dynamic imbalances, misalignments, looseness, and wear of transmission components. These patterns are consistent with the principles of condition monitoring in rotating machinery, where vibration increases in response to changes in the system’s dynamic energy or the appearance of incipient defects that alter its structural response.

Vibration severity was quantified using root mean square (RMS) acceleration, selected for its ability to robustly represent the vibration energy transmitted by the machinery within a defined time interval. RMS acceleration was calculated from the time-domain acceleration signal recorded by the accelerometers, using the continuous expression that describes its physical basis.

$$\frac{a_{RMS}}{T} = \sqrt{\frac{1}{T} \int_0^T a(t)^2 dt}$$

For discrete data processing (which is what the software actually does), the same

magnitude was obtained using the equivalent sample-based format:

$$\frac{a_{RMS}}{N} = \sqrt{\frac{1}{N} \sum_{i=1}^N a_i^2}$$

where T represents the duration of the analysis window, N the number of samples, and a, i the acceleration measured at each instant. This indicator allowed for the evaluation of the equipment's operational stability and the detection of relevant variations in its dynamic behavior, both in the form of sustained trends and abrupt, short-duration peaks.

From an industrial safety perspective, the interpretation of RMS acceleration focuses on two main behaviors: (i) progressive increases in vibration level, associated with the gradual degradation of the mechanical condition, and (ii) transient events, linked to impacts, momentary resonances, or abrupt changes in operating conditions. Progressive trends are particularly relevant, as they anticipate scenarios of reduced machinery reliability and a higher probability of operational failures, unplanned downtime, and unsafe conditions during operation or maintenance. Transients, on the other hand, become especially important when they are repetitive or coincide with high load levels, due to their potential to generate immediate risks to personnel and equipment.

Time-series analysis of RMS acceleration revealed distinct behaviors among the evaluated equipment. While some maintained relatively stable values within a characteristic range, others showed stepped increases or recurring peaks throughout the analysis period. This behavior suggests that vibration depends not only on the type of machine but also on its condition, operating and maintenance history, and the work regime to which it is subjected. In particular, sustained increases in RMS were more frequent in equipment subjected to continuous operation and higher load demands, reinforcing the importance of incorporating vibration indicators as key variables in the quantitative assessment of industrial risk. This behavior is clearly illustrated in **Figure 2**, which presents the temporal evolution of RMS acceleration in the analyzed equipment.

A key finding is that, while isolated vibration analysis can identify changes in mechanical condition, its greatest value for industrial safety is achieved when interpreted in conjunction with other physical indicators. In this regard, combined noise and vibration analysis revealed that simultaneous increases in both parameters tend to coincide with unfavorable operating conditions, such as overload, increased friction, imbalance, or incipient failures. This simultaneity strengthens the reliability of the diagnosis by reducing the likelihood that the observed changes are solely due to instrumental variability or measurement noise and improves the system's ability to distinguish between normal and hazardous states.

In operational terms, the scenarios of greatest interest for prevention were those characterized by: (a) progressive increases in RMS acceleration over time, indicative of mechanical degradation; (b) recurring peaks above the equipment's normal behavior, associated with repeated transients; and (c) the coincidence of vibration increases with an elevation in the equivalent noise level (Leq), suggesting mechanical conditions that

simultaneously increase the system’s vibrational and acoustic energy. These patterns constitute useful early warning signals for prioritizing inspections, adjusting operating procedures, scheduling predictive maintenance, and reducing personnel exposure to unsafe conditions.

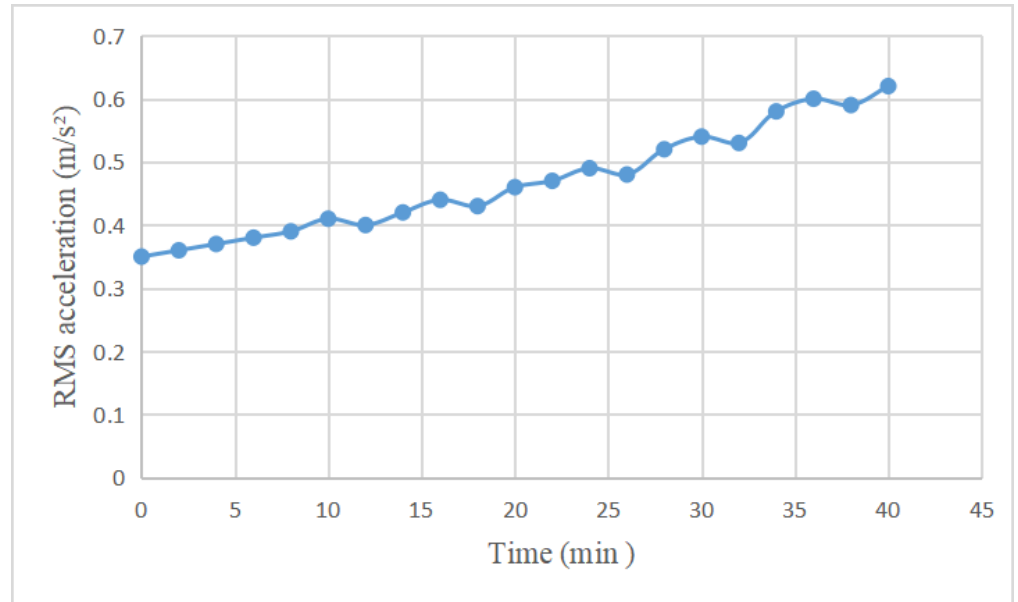


Figure 2. Time evolution of RMS acceleration in critical mechanical equipment during the analysis period.

Note: The figure shows the temporal evolution of the RMS aRMS acceleration (m/s²) calculated from analysis windows during the operation of critical mechanical equipment. The horizontal axis represents the analyzed operating time intervals or records, while the vertical axis corresponds to the RMS aRMS acceleration (m/s²). Sustained increases and transient peaks represent relevant changes in the equipment’s dynamics.

Source: Author’s own elaboration.

In summary, vibration analysis based on RMS acceleration provides a quantitative, physically sound, and operationally interpretable measure of the dynamic behavior of critical equipment. Its ability to detect both progressive degradation processes and transient events, along with its integration with acoustic indicators, reinforces its usefulness as an essential variable for assessing industrial risks and developing preventive strategies based on machinery reliability.

4.3. Evaluation of the industrial risk index

Based on the dynamic indicators obtained, the Industrial Risk Index (IRI) was calculated, designed to integrate acoustic, vibration, and machinery reliability information into a single parameter representative of the operational safety status. The index was defined as a weighted combination of the main physical indicators:

$$IRI = w_1 \cdot Leq + w_2 \cdot aRMS + w_3 \cdot CF + w_4 \cdot Cm$$

where CF represents the vibration crest factor and Cm corresponds to an indicator associated with the mechanical condition of the equipment.

The temporal evolution of the IRI allowed for the clear identification of periods of safe operation and scenarios of increasing risk. In most of the records associated with stable operation, the index remained in low ranges; however, sustained increases

in the IRI were observed in intervals characterized by high levels of noise and vibration, especially when these coincided with signs of mechanical degradation. This behavior is illustrated in **Figure 3**, which shows the temporal evolution of the Industrial Risk Index (IRI) during the analyzed period.

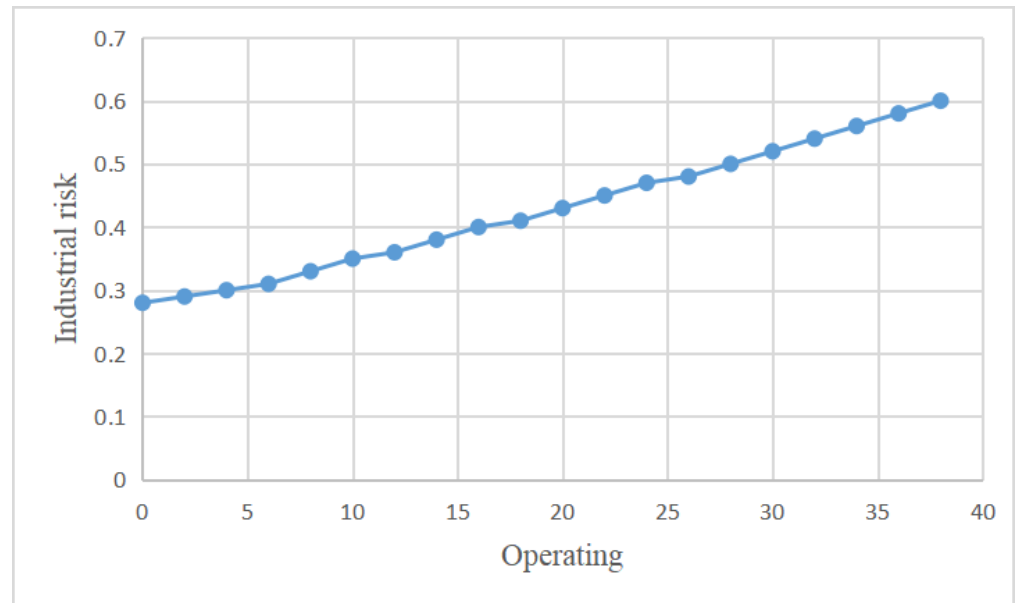


Figure 3. Temporal evolution of the industrial risk index (IRI) during the analyzed operating period.

Note: The figure shows the evolution over time of the Industrial Risk Index (IRI) calculated from the integration of acoustic, vibration, and mechanical condition indicators of the machinery. The horizontal axis represents the analyzed time intervals or operational records, while the vertical axis corresponds to the IRI value (dimensionless). Sustained increases in the index reflect a progressive accumulation of operational risk associated with changes in the dynamic behavior of the system.

Source: Author's own elaboration.

Furthermore, the behavior of the IRI demonstrated that industrial risk does not manifest abruptly, but rather is usually preceded by cumulative trends detectable through continuous monitoring of dynamic signals. This characteristic reinforces the index's usefulness as a preventative tool, allowing for the anticipation of risk scenarios and supporting decision-making aimed at early intervention, adjustment of operating procedures, and maintenance planning from a comprehensive industrial safety perspective.

4.4. Results of the predictive risk model

The predictive model trained with physical indicators demonstrated adequate ability to classify operating conditions into safe and hazardous states. The results indicated that the simultaneous incorporation of acoustic and vibration variables improves the discrimination between these two states, compared to approaches based on isolated indicators.

Analysis of the model's performance showed a favorable balance between sensitivity and specificity, a particularly relevant aspect in industrial safety applications where early detection of risk scenarios is crucial. The model enabled the identification of critical combinations of high noise, intense vibrations, and mechanical degradation associated with potentially hazardous operating conditions.

The performance of the predictive model was evaluated using standard

classification metrics employed in predictive analytics and industrial safety studies. The results are presented in **Table 1**.

Additionally, the classifier's behavior was examined using the confusion matrix and the analysis of false positives and false negatives, in order to assess its usefulness in the early detection of risk conditions.

Table 1. Performance metrics of the industrial risk predictive model.

Metrics	Result
Accuracy	0.88
Sensitivity	0.86
Specificity	0.84
AUC-ROC	0.90

Source: Own elaboration.

The results indicate a robust predictive model performance, with an overall accuracy of 88% and an area under the ROC curve of 0.90, demonstrating a high discriminatory capacity between safe operating conditions and risk scenarios. The sensitivity achieved (0.86) is particularly relevant from an industrial safety perspective, as it prioritizes the early detection of potentially hazardous situations associated with high levels of noise, vibration, and mechanical deterioration.

4.5. Integration of noise, vibration and industrial risk states

The combined analysis of acoustic and vibration indicators allowed for the identification of consistent patterns associated with situations of greater industrial risk. In particular, the bivariate analysis between equivalent sound pressure levels (Leq) and RMS acceleration demonstrated that the most critical scenarios do not necessarily correspond to extreme values of a single indicator, but rather to specific combinations of high noise and intense vibration that reflect unfavorable dynamic conditions of the machinery.

From an engineering perspective, these results confirm that industrial risk arises as a multifactorial phenomenon, in which the simultaneous interaction of different physical quantities increases the probability of anomalous mechanical behavior and, therefore, unsafe operating conditions. The simultaneous increase in noise and vibration is often associated with processes such as increased friction, misalignment, dynamic imbalances, or the progressive degradation of rotating components, all of which generate higher noise emissions and more intense vibrations.

Integrating these indicators into the Industrial Risk Index (IRI) allowed this interaction to be synthesized into a single quantitative measure, facilitating the identification of periods of increasing risk and their differentiation from stable operating conditions. This approach overcomes the limitations of assessments based on isolated parameters and strengthens the reliability of the diagnosis by reducing the likelihood of false alarms resulting from temporary fluctuations or measurement noise.

From an operational standpoint, the results demonstrate that simultaneous noise and vibration monitoring is an effective tool for anticipating risk scenarios, prioritizing predictive maintenance interventions, and supporting decision-making in industrial

safety management systems. The ability to transform complex dynamic signals into useful information helps reduce personnel exposure to unsafe conditions and improve the overall reliability of machinery.

In this sense, the proposed approach reinforces the link between sound and vibration engineering and industrial safety, fully aligning with the practical applications of condition monitoring, machinery reliability, and risk prevention in industrial environments characterized by continuous operation and high mechanical demands.

Rather than relying on complex predictive architectures, the value of the proposed approach lies in the technically interpretable integration of acoustic, vibratory, and mechanical condition indicators for the early detection of unsafe operating states.

5. Discussion

The results of this study support the premise outlined in the introduction: in production environments dominated by dynamic machinery, noise and vibration should not be understood solely as occupational exposures or comfort variables, but as physical manifestations of dynamic behavior and mechanical condition, with direct implications for machinery reliability and, by extension, for industrial safety. This integrative view is consistent with contemporary approaches that recognize the multifactorial and nonlinear nature of occupational risk, especially when the technical condition of the equipment, the operational load, and regime changes generate complex patterns that are difficult to capture with conventional statistical methods [11, 13].

Regarding industrial noise, characterization based on the equivalent sound pressure level (L_{eq}) showed a wide distribution, with values concentrated in typical operating ranges and peaks associated with start-ups, changes in operating conditions, and transient events. This behavior is expected: when dynamic forces, structural contacts, friction, or impacts increase, the acoustic energy radiated by the system also increases. However, the main contribution lies in its interpretation from an industrial safety perspective: previous evidence suggests that high noise levels are linked to both auditory and non-auditory effects and can impair human performance (attention, mental workload, and reaction times), increasing the likelihood of errors in critical tasks [4,5]. Furthermore, recent epidemiological studies suggest an association between occupational noise exposure and higher rates of fatal and non-fatal injuries, reinforcing the importance of treating noise as a variable relevant to safety, and not just to occupational hygiene.

Furthermore, the analysis of vibration indicators confirmed that RMS acceleration (a_{RMS}) allows differentiation between stable operating conditions and scenarios with greater mechanical stress and/or progressive degradation. The presence of sustained increases and transient peaks is consistent with the logic of condition monitoring: defects such as imbalance, misalignment, play, and bearing degradation alter the equipment's dynamic response before causing critical failures [18, 20]. The incorporation of metrics such as the crest factor (CF) reinforces this interpretation because it increases sensitivity to shocks and transients associated with incipient defects. In terms of reliability, vibration provides operational evidence of loss of condition, and in terms of industrial safety, it anticipates scenarios where the probability of sudden

failure, unplanned downtime, and exposure of personnel to unsafe situations increases, especially during operation or maintenance [20,21].

A key finding is that the preventive value is enhanced when noise and vibration are interpreted in an integrated manner, rather than analyzed separately. The results showed that simultaneous increases in Leq and aRMS tend to coincide with unfavorable operating conditions. This is important because it strengthens the robustness of the diagnosis: if both indicators increase at the same time, the probability increases that the change corresponds to a real physical phenomenon of the system (greater dynamic excitation, friction, impacts, or degradation), and not to instrumental variability or minor fluctuations. This integrated reading aligns with recent risk assessment approaches that recommend combining physical and operational variables to represent the actual behavior of the industrial environment and improve the explanatory and predictive capacity of models [13].

The construction of the Industrial Risk Index (IRI) represented a valuable methodological contribution to synthesizing dynamic information into a quantitative variable interpretable at the plant scale. By combining Leq, aRMS, CF, and a mechanical condition indicator (Cm), the IRI revealed that risk does not emerge abruptly, but rather as cumulative trends associated with degradation and the coexistence of adverse conditions. This behavior is particularly relevant for decision-making in industrial safety, as it allows a transition from reactive (post-incident) approaches to proactive schemes focused on early detection and prioritization of intervention. In this regard, the literature on incident prevention through advanced analytics highlights that the ability to identify risk trajectories increases the effectiveness of preventive actions and improves operational risk management [25].

Regarding the predictive component, the results suggest that the simultaneous incorporation of acoustic and vibration variables improves the discrimination between safe and hazardous states. This aligns with recent work where data-driven models capture nonlinear relationships and interactions between technical and operational variables that are difficult to model using traditional methods [12,13]. In practical terms, this allows the development of monitoring systems that reduce false negatives (failure to detect hazardous conditions), a critical aspect of industrial safety. Furthermore, the current trend in safety, especially in industries with intensive use of machinery, is to integrate prediction with interpretable tools, so that the model results are translated into technical actions (load adjustment, inspection, predictive maintenance, exposure reduction) rather than remaining as an abstract “score” [25].

5.1. Operational application of the industrial risk index

From an applied occupational safety and health perspective, the Industrial Risk Index (IRI) can be integrated into condition monitoring and predictive maintenance systems used in industrial environments with dynamic machinery. In these systems, sensors installed on the equipment continuously record physical variables such as vibration or noise, which are analyzed to identify deviations from the normal behavior of the machinery. When these indicators exceed certain operating thresholds,

preventive actions can be activated to avoid failures or unsafe situations [9,25].

In this context, the IRI can be used as an early warning indicator to establish different levels of operational response. For example, moderate values of the index may trigger technical inspection procedures or verification of the machinery's condition, while sustained increases in the IRI may trigger predictive maintenance interventions or adjustments to the equipment's operating conditions. When the index exceeds critical thresholds, actions may include preventive equipment shutdown, temporary restriction of certain tasks, or immediate notification of operators and supervisors responsible for the system.

This phased approach aligns with the principles of condition monitoring and data-driven maintenance, where physical indicators enable the early detection of anomalies and the activation of preventive measures before critical failures or unsafe conditions for workers occur. Thus, the proposed model can be interpreted both as an analytical tool and as a potential component of industrial safety management systems focused on prevention and decision-making based on technical information.

5.2. Scope of the model from the perspective of industrial safety

It is important to note that the approach proposed in this study should be interpreted primarily as a predictive technical model based on physical indicators of machinery, and not as a comprehensive framework for assessing occupational safety and health. While industrial safety arises from the interaction of multiple dimensions, including technical, organizational, and human factors, this work focused specifically on dynamic variables associated with the operational behavior of industrial equipment and its mechanical reliability. In this sense, the developed model allows for the identification of potentially hazardous operating conditions associated with the dynamic deterioration of machinery, relevant for prevention and technical risk management, but without attempting to exhaustively represent all dimensions of occupational risk. This delimitation is consistent with recent data-driven safety approaches, which recognize that predictive models can provide value even when focused on specific subsets of the risk system, provided their scope is clearly defined [12,25].

However, it is important to recognize that variables such as the type of task performed, the worker's proximity to the equipment, shift conditions, procedural deviations, training, fatigue, or the use of personal protective equipment were not explicitly incorporated into the model. Therefore, the results should be interpreted as a specific contribution to the technical analysis of industrial risk, where noise, vibration, and mechanical condition act as early warning signs of potential unsafe states. Future research could expand this approach by integrating human and organizational factors, in order to move toward more comprehensive occupational safety assessment models [11,12].

The value of this study lies in its connection of dynamic engineering metrics (noise and vibration) with a highly relevant practical application: the prevention of unsafe scenarios and support for reliability/maintenance decisions that impact safety. The technical narrative is coherent: noise and vibration indicators reflect the dynamic state of systems; reliability translates that state into a probability of degradation/failure;

and the Intermediate Reliability Index (IRI), together with the predictive model, converts physical signals into useful information for risk management. This articulation aligns with recent research applying analytics and machine learning to improve accident prevention and severity/cost assessment, demonstrating the advantages of using variables that better represent operational reality [13,19].

Finally, it is important to acknowledge the limitations that also guide future work. First, while the study uses representative operating logs and physical signals, the results may vary depending on the industry, equipment age, sensor mounting architecture, and operating regimes; therefore, generalization should be made with caution. Second, the IRI index relies on weights (w_1 – w_4) that, although empirically calibrated, require transparency and external validation to facilitate replicability and comparability across plants. Third, predictive performance can be improved by incorporating validation and feature optimization strategies recommended in intelligent safety monitoring, ensuring that the model is robust to regime changes, seasonality, and non-stationary conditions inherent in mechanical systems. Even with these limitations, the evidence presented supports the integration of noise, vibration, and machine reliability data, providing a solid and relevant technical basis for advancing predictive and condition-based industrial safety, in line with research and practice interests in sound and vibration engineering.

6. Conclusions

This study demonstrates that noise and vibration, traditionally addressed from the perspectives of occupational hygiene and structural dynamics, are important physical indicators of the operational condition and reliability of machinery, with direct implications for industrial safety. The results confirm that these variables reflect exposure conditions and also allow for the identification of dynamic changes associated with mechanical degradation and potential risk scenarios before workplace accidents occur.

Characterization of equivalent sound pressure levels (L_{eq}) revealed that acoustic increases are associated with operational events such as start-ups, changes in operating conditions, and situations of increased mechanical stress. From a safety perspective, these increases should not be interpreted solely as regulatory deviations, but rather as indirect signals of dynamic alterations that can affect both equipment reliability and human performance during operation, increasing the likelihood of errors and unsafe events.

Analysis of vibration indicators, particularly RMS acceleration and crest factor, identified consistent patterns of progressive degradation and transient events associated with mechanical anomalies. The temporal evolution of these indicators confirmed their usefulness in detecting anomalous states before critical failures occur, thus reinforcing the role of vibration monitoring as a fundamental tool for preventing industrial risks arising from machinery deterioration.

One of the study's main contributions was the integration of acoustic, vibration, and reliability indicators through the construction of the Industrial Risk Index (IRI). This index allowed for the synthesis of large volumes of dynamic information into an

interpretable quantitative measure, demonstrating that industrial risk tends to manifest as cumulative trends rather than abrupt events. This characteristic is especially valuable for preventive management, as it enables the early identification of risk scenarios and the prioritization of corrective and predictive actions.

The results of the predictive model demonstrated that the simultaneous incorporation of noise and vibration improves the ability to differentiate between safe and hazardous states, compared to approaches based on isolated indicators. This finding supports the idea that industrial safety in dynamic machinery environments depends on the nonlinear interaction of multiple physical variables, and that data-driven predictive approaches offer significant advantages over traditional reactive analysis methods.

From an applied perspective, the proposed approach offers a solid technical foundation for developing condition-based industrial safety management and monitoring systems, aligned with the principles of machine reliability and predictive maintenance. Integrating sound and vibration metrics into quantitative models facilitates informed decision-making, aiming to reduce personnel exposure to unsafe conditions, optimize maintenance plans, and decrease the likelihood of workplace accidents associated with mechanical failures.

This study contributes to strengthening the link between sound and vibration engineering and industrial safety, demonstrating that dynamic signals constitute a strategic source of information for risk prevention. Future research can expand this approach by incorporating spectral analysis, real-time data, and advanced modeling strategies to consolidate increasingly proactive, predictive, and physically evidence-based industrial safety systems, in accordance with current engineering and industrial practice demands.

Author contributions: Conceptualization, methodology, writing—original draft: HNAV; Validation: RITT and EMP; Investigation: HNAV and RITT; Data curation: RITT and ITBM; Writing—review & editing: RITT, ITBM, and EMP; Supervision: HNAV and EMP; Formal analysis: HNAV and ITBM; Visualization, software: ITBM; Project administration, resources: EMP. All authors have read and agreed to the published version of the manuscript.

Funding: The research did not receive funding from any institution; it was financed by the authors.

Institutional review board statement: This study was exempted from ethical review and approval because it was not required according to the policies of the Quevedo State Technical University.

Informed consent statement: Not applicable. This study did not involve human participants or personal data.

Data availability statement: The datasets supporting the findings of this study are available in an Excel file and can be accessed upon request or through the corresponding author.

Conflict of interest: The authors declare that there is no conflict of interest between them.

References

1. Hämäläinen P, Takala J, Saarela KL. Global estimates of occupational accidents. *Safety Science*. 2006; 44(2): 137–156.
2. Griffin MJ. *Handbook of Human Vibration*. Academic Press; 2012. pp. 1–1005.
3. Singh I, Nigam SP, Saran VH. Modal analysis of human body vibration model for Indian subjects under sitting posture. 2015; 58(7): 1117–1132. doi: 10.1080/00140139.2014.961567
4. Themann CL, Masterson EA. Occupational noise exposure: A review of its effects, epidemiology, and impact with recommendations for reducing its burden. *The Journal of the Acoustical Society of America*. 2019; 146(5): 3879–3905.
5. Basner M, Babisch W, Davis A, et al. Auditory and Non-Auditory Effects of Noise on Health. *The Lancet*. 2014; 383(9925): 1325–1332. doi: 10.1016/S0140-6736(13)61613-X
6. Randall A. *Risk and Precaution*. Cambridge University Press; 2011.
7. Luque-Mohedano R. *Dynamic Modeling and Analysis of the Olive Tree Subjected to Mechanical Vibration [PhD thesis]*. University of Córdoba; 2024. Available online: <https://produccioncientifica.ugr.es/documentos/68505d194e31682f4064766c> (in Spanish)
8. Contreras IT. *Diagnosis of Mechanical Failures in Rotating Machines Considering Nonlinear Dynamic Behavior Using Recurrence Diagrams [PhD thesis]*. Universidad Autónoma de Querétaro; 2023.
9. Mobley RK. *An Introduction to Predictive Maintenance*. Elsevier; 2002. pp. 1–451.
10. Jia F, Lei Y, Lu N, et al. Deep normalized convolutional neural network for imbalanced fault classification of machinery and its understanding via visualization. *Mechanical Systems and Signal Processing*. 2018; 110: 349–367.
11. Ordysiński S. Prediction of the Injury Severity of Accidents at Work: A New Approach to Analysis of Already Existing Statistical Data. *Applied Sciences*. 2025; 15(19): 10666. doi: 10.3390/app151910666
12. Obasi IC, Cheng P, Varianou-Mikellidou C, et al. Machine learning for occupational accident analysis: Applications, challenges, and future directions. *Journal of Safety Science and Resilience*. 2026; 7(1): 100–250.
13. Xia X, Xiang P, Khanmohammadi S, et al. Predicting Safety Accident Costs in Construction Projects Using Ensemble Data-Driven Models. *Journal of Construction Engineering and Management*. 2024; 150(7). doi: 10.1061/JCEMD4.COENG-14397
14. Xu X, Qiao Z, Lei Y. Repetitive transient extraction for machinery fault diagnosis using multiscale fractional order entropy infogram. *Mechanical Systems and Signal Processing*. 2018; 103: 312–326.
15. Harris CM, Piersol AG. *Shock and Vibration Handbook*, 5th ed. McGraw-Hill; 2002. pp. 1–1050.
16. Jacobs N, Roberts B, Reamer H, et al. Noise exposures in different community settings measured by traditional dosimeter and smartphone app. *Applied Acoustics*. 2020; 167: 107408. doi: 10.1016/j.apacoust.2020.107408
17. Jiang W, Zhou R, Jia H. Research on Mechanical Equipment Fault Diagnosis and Prediction Technology Based on Vibration Signal Analysis. In: *Proceedings of the 2024 International Conference on Power, Electrical Engineering, Electronics and Control (PEEEEC)*; 14–16 August 2024; Athens, Greece. pp. 494–498.
18. Li Z, Zhao Y, Zhang Y, et al. A novel transformer-enhanced and acoustic-based approach for wind turbine blade fault detection with integrated system implementation. *Journal of Engineering Design*. 2025; 36(5–6): 642–671. doi: 10.1080/09544828.2024.2332122
19. Lee J, Lee U, Oh J. Development of Algorithm for Vibration Analysis Automation of Rotating Equipments Based on ISO 20816. *Journal of the Korean Institute of Gas*. 2024; 28(2): 93–104.
20. Cerrada M, Macancela JC, Cabrera D, et al. Reciprocating Compressor Multi-Fault Classification Using Symbolic Dynamics and Complex Correlation Measure. *Applied Sciences*. 2020; 10(7): 2512. doi: 10.3390/app10072512
21. Macias ÁAT, González EDPT. *Vibration Analysis in Rotating Machinery: Fault Diagnosis and Predictive Maintenance Strategies*. *Revista Sociedad Fronteriza*. 2024; 4(4): e44365–e44365. (in Spanish)
22. Ali M, Lee YS, Chowdhury M, et al. Analysis of Driving Stability and Vibration of a 20-kW Self-Propelled 1-Row Chinese Cabbage Harvester. *Journal of Biosystems Engineering*. 2021; 46(1): 48–59. doi: 10.1007/s42853-021-00087-w
23. Solé AC. *Reliability and Safety of Industrial Processes (Vol. 49)*. Marcombo; 1991. Available online: <https://www.>

- amazon.com/-/es/Fiabilidad-Seguridad-Procesos-Industriales-Prod%C3%BActica/dp/8426708153 (in Spanish)
24. Bakdash RS, Younis MN, Chanbasha B, et al. Analytical detection methods for measuring residual corrosion inhibitors in oil and gas and other industrial facilities. *Results in Engineering*. 2026; 29: 108547. doi: 10.1016/j.rineng.2025.108547
 25. Pandey S, Singh AK, Parhi S, et al. Transforming workplace safety through leveraging predictive analytics and explainable AI in steel industries. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*. 2025; 239(6): 1332–1345. doi: 10.1177/1748006X251331681