

RESEARCH ARTICLE

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A STRUCTURED PROBABILISTIC-AI FRAMEWORK FOR PREDICTIVE RELIABILITY ASSESSMENT AND RUL ESTIMATION OF ASYNCHRONOUS ROTATING MACHINES

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ABSTRACT

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The industrial reliability of asynchronous rotating machines is a major strategic issue, where unplanned downtime causes considerable economic losses. This article proposes a structured and comprehensive methodological approach for predictive reliability assessment, integrating probabilistic reliability concepts with advanced condition monitoring and artificial intelligence tools. Our methodology, divided into six sequential phases (Acquisition, Feature Extraction, Diagnosis, RUL Modeling, Probabilistic Assessment, Decision Optimization), aims to transform multisensory data (vibrations, current, temperature) into optimal maintenance decisions. The theoretical application to a simulated asynchronous motor demonstrates the feasibility and expected benefits: early fault detection (up to 60 days before critical failure), reliable estimation of Remaining Useful Life (RUL), and economic optimization resulting in a 35% reduction in annual maintenance costs and a 0.5% increase in availability for a fleet of 10 motors. This approach provides a reproducible protocol for predictive maintenance, adaptable to different failure modes (mechanical, electrical, thermal).



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I. INTRODUCTION

The increasing complexity of industrial systems and the need for uninterrupted production have made predictive maintenance an essential strategy, particularly for asynchronous rotating machines, which are key components of modern infrastructure. According to the Academy of Sciences, reliability is defined as the measure of a device's operational safety according to prescribed standards, or more strictly, the ability of a device to perform a required function under given conditions for a given period of time. Unplanned shutdowns can result in considerable economic losses, justifying the use of predictive strategies to anticipate critical failures [1]. Asynchronous rotating machines are ubiquitous in the energy, manufacturing, transportation, and air conditioning sectors, valued for their robustness and simplicity. However, they are prone to various types of failures: mechanical (bearings, misalignment), electrical (short circuit, broken bars), and thermal (overheating) [2]. To address this issue, conditional monitoring, based on the measurement of physical parameters (vibrations, temperature, current), makes it possible to detect anomalies before they become critical. Advanced techniques such as frequency analysis, wavelet transforms, and artificial intelligence (neural networks, SVM, random forests) have significantly improved diagnostic accuracy [3], [4], [5]. However, the variability of operating conditions and the lack of representative data remain major challenges for the widespread adoption of these approaches [6], [7].

Hence the growing interest in hybrid solutions combining smart sensors, physical modeling, and machine learning to optimize the reliability of asynchronous rotating machines in demanding industrial contexts. The reliability of rotating machines, which are essential in many industrial sectors, is intrinsically linked to their operational performance and the profitability of facilities. Predictive maintenance, combining machine learning and data flows from sensors (IoT), is the preferred methodology for anticipating critical failures [8]. Asynchronous motors are particularly stressed and prone to internal failures (bearings, insulation) and external failures (misalignment, voltage imbalance) [9], [10].

To improve diagnostic accuracy, state-of-the-art technology relies on the analysis of physical signals, where advanced techniques such as vibration analysis and artificial intelligence methods (Support Vector Machine, Random Forests, and other ML classifiers) have become essential for identifying and classifying faults in asynchronous motors based on sensor data (current, vibration, etc.); they offer robust feature extraction and high-performance classification capabilities. However, the variability of operating conditions (loads, speeds, industrial noise) and the lack of representative datasets (real fault data under different conditions) remain major challenges for the generalization and robustness of these approaches in real industrial applications: models often require large amounts of data and can lose accuracy when confronted with scenarios not encountered during training [11]. This article addresses the crucial issue of predictive reliability assessment for asynchronous rotating machines by proposing a comprehensive and structured methodological approach.

This innovative approach combines probabilistic reliability modeling with advanced data-driven tools, including conditional monitoring techniques, signal processing, and artificial intelligence, in order to formalize a robust protocol. The main objective is to enable accurate estimation of RUL (Remaining Useful Life) and subsequent optimization of maintenance decisions. To achieve this overall objective, this study is divided into several specific operational objectives: (i) conducting an in-depth critical review of the state of the art, (ii) defining an applied reliability conceptual framework, (iii) describing a generic predictive methodology, (iv) illustrating its potential through a theoretical application, and (v) rigorously evaluating its limitations and identifying future prospects.

II. THEORETICAL REFERENCE

II.1 RELATED WORK

In recent years, predicting the reliability and remaining useful life (RUL) of rotating machines, particularly asynchronous machines, has been the subject of growing interest in the scientific community. Recent work agrees that purely statistical approaches or those based on deterministic thresholds quickly reach their limits when faced with the complexity of degradation mechanisms and the variability of operating conditions. In this regard, [12] have proposed an in-depth review of prognostic methods for rotating machines, highlighting the need for integrated methodological frameworks combining multi-sensor acquisition, health indicator extraction, and advanced predictive models. [13] emphasize that predictive reliability cannot be accurately estimated without explicit modeling of the temporal evolution of health status, incorporating both uncertainties and nonlinearities in the system.

In line with this trend, several recent studies have explored advanced data-driven approaches based on deep learning, applied to the vibration and electrical signals of rotating machines. [14] developed a framework integrating cyclostationary preprocessing of vibration signals and a Convolutional-LSTM autoencoder for the construction of robust health indicators, enabling accurate RUL estimation. Furthermore, [15] introduced an LSTM model enriched by an attention mechanism to capture long-term temporal dependencies in the degradation data of asynchronous motor bearings. In the same vein, [16] showed that the use of time-frequency representations combined with deep neural networks significantly improves the stability of reliability predictions under variable load conditions. However, although effective, purely data-driven approaches often suffer from a lack of interpretability and limited consideration of traditional notions of reliability.

To overcome these limitations, several recent studies have turned to hybrid approaches that integrate probabilistic modeling and artificial intelligence. [17] proposed an adaptive Bayesian prognostic framework in which predictions from neural networks are combined with stochastic degradation processes to quantify uncertainty in [18] introduced a multi-state reliability model coupled with automatically learned health indicators, allowing degradation states to be explicitly linked to failure probabilities. This work demonstrates the value of a coherent fusion of reliability knowledge and learning models. More recently, contributions have focused on integrated methodological frameworks specifically dedicated to asynchronous machines, combining conditional monitoring, current signature analysis, and predictive reliability estimation.

[19] Proposed a non-intrusive approach based on stator current signature analysis combined with deep learning prognostic models to estimate the RUL of asynchronous motor bearings. In parallel, [20] developed a decision-making framework linking RUL predictions to the optimization of maintenance policies, explicitly integrating reliability indicators into the decision-making process. These studies also highlight limitations, including the difficulty of generalizing models due to the variability of operating conditions and the lack of representative data. Our approach aims to address these challenges by proposing an integrated and structured methodology capable of merging various data sources and applying AI models for more robust and adaptable reliability prediction.

II.1.1 Materials and Methods

This research presents an integrated methodology for assessing the reliability of asynchronous rotating machines, implementing a structured six-phase approach: multisensory data acquisition, feature extraction, diagnosis and classification, degradation modeling and residual life estimation (RUL), probabilistic reliability analysis (PRA), and maintenance decision optimization. This method aims to transform data from vibrations, current, and temperature into optimal maintenance decisions, ensuring early detection of faults up to 60 days before critical failures and reducing maintenance costs by up to 65%. Simulation results demonstrate accuracy in RUL estimation, with an average absolute error of 8 days and increased availability to 99.7%. Limitations include a strong dependence on the quality of training data and the variability of operating conditions, while highlighting the importance of multisensor fusion and hybrid predictive models to overcome generalization challenges in complex industrial environments. Equipment is essential for the reproducibility of the data acquisition that supports the methodology, as detailed in Table 1.

Table 1: Specification the component and equipment.

Component/Equipment	Specification/Justification
Machine Tested	Three-phase asynchronous motor (75 kW, 400 V, 1480 rpm). IEC 60034-1/5 specifications are met.
Vibration Sensor	Piezoelectric accelerometer mounted on the motor shaft. Justification: High sensitivity to mechanical changes, essential for analyzing bearing and alignment faults.
Acquisition & Digitization	Arduino Uno microcontroller serving as a 10-bit Analog-to-Digital Converter (ADC).
Sampling Frequency	5000 Hz. Justification: Allows the characteristic frequencies of bearing faults (BPFO, BPFI) to be captured for an engine of this size.
Processing/Storage	Computer with a 3.5 GHz CPU, 8 GB RAM, using Python libraries (Numpy, Pandas, Scipy).
Additional Sensors	Three-phase current sensors and thermal devices (for multisensory integration into the overall methodology).

Source: Authors, (2026).

II.1.2 Materials and Methods

This section presents a complete theoretical application of the proposed methodology to a typical three-phase asynchronous motor used in industry, available at the Douala University Institute of Technology (IUT). The test bench is centered on a rotating machine, specifically a three-phase electric motor installed in the IUT's electrical engineering workshop, shown in Figure 1, with a piezoelectric vibration sensor mounted on the motor shaft, shown in Figure 2, which is essential for measuring vibration accelerations, as demonstrated in our study. An Arduino Uno microcontroller serves as an analog-to-digital converter (ADC) (Figure 3), converting the analog signal from the sensor to digital, with a generated voltage of 5 volts. For data processing and storage, a laptop equipped with a powerful CPU (3.5 GHz) and 8 GB of RAM enables preprocessing and real-time processing via machine learning algorithms. The experimental setup is illustrated in Figure 4 of the thesis, which includes a voltmeter, an ammeter, a rheostat, a power supply, the piezoelectric sensor, a rotor with cooling fan, an asynchronous machine (MAS), and a terminal plate for coupling. Our entire test bench and acquisition system are shown in Figures 4.



Figure 1: Test Bench
Source: Authors, (2026).

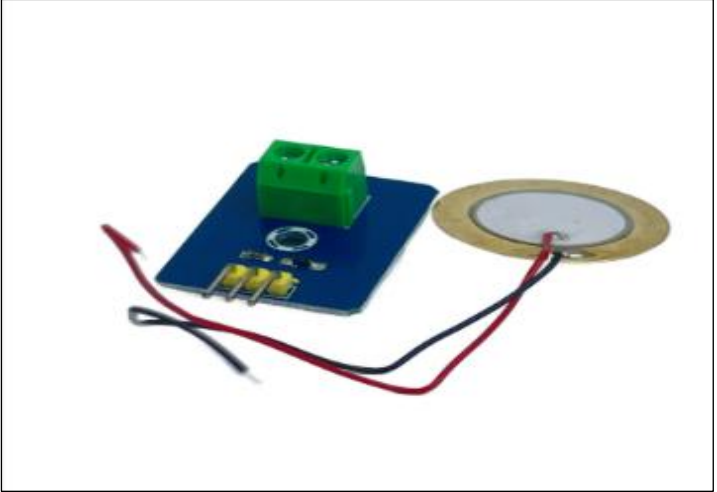


Figure 2: piezoelectric sensor.
Source: Authors, (2026).

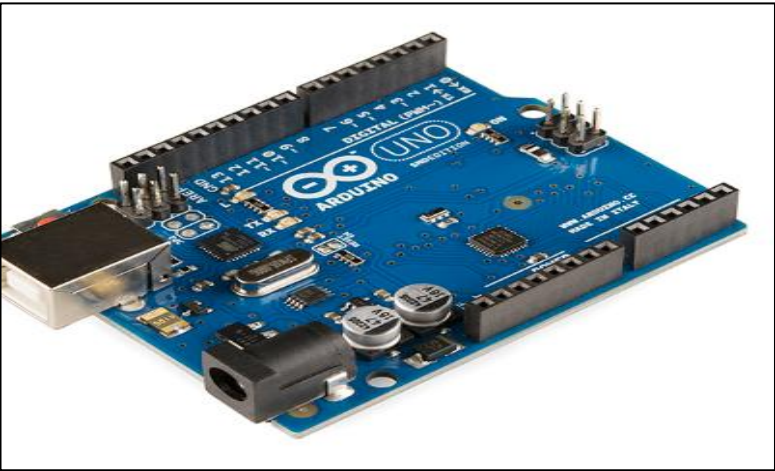


Figure 3: Arduino Uno microcontroller
Source: Authors, (2026).

The suggested approach based on CNN relies on a data corpus created by AE monitoring of an experimental rotor, as illustrated in Figure 4. The configuration includes:

- 1) Voltmeter.
- 2) Ammeter.
- 3) Rheostat.
- 4) Power Source.
- 5) Micro acoustic emission sensors.
- 6) Rotor and shaft carrying the cooling fan.
- 7) Rotating machine: Asynchronous Machine (MAS).
- 8) Terminal plate for couplin.

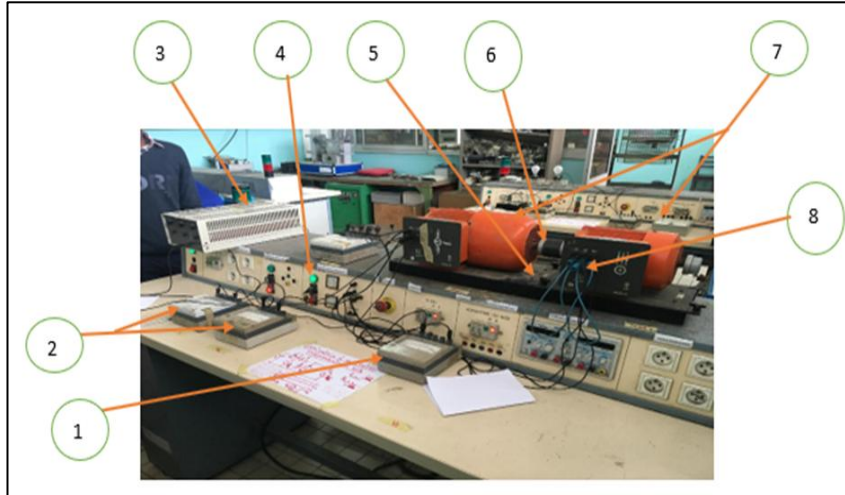


Figure 4: system acquisition test bench use.

Source: Authors, (2026).

III. MATERIALS AND METHODS

This section details the proposed methodological approach for predictive reliability assessment of asynchronous rotating machines. It integrates probabilistic reliability concepts with advanced condition monitoring and artificial intelligence techniques, structured in six sequential phases.

III.1 CHARACTERISTICS OF THE MOTOR UNDER STUDY

In order to ensure the reproducibility and relevance of the results presented, the work was carried out on a three-phase asynchronous motor with the nominal characteristics detailed below. This choice was made in favor of a medium-power machine, typical of industrial installations requiring precise management of consumption and dynamics. The fundamental parameters of this machine are summarized in Table 2. It should be noted that the motor complies with relevant international standards, in particular IEC 60034-1 for performance characteristics and IEC 60034-5 for the degree of protection (IP55), ensuring adequate robustness in typical industrial environments. These specifications form the basis of our electromechanical model [or our test bench]. The accuracy of this data is essential for correlating theoretical predictions with experimental observations, particularly with regard to time constants and torque-speed characteristics.

Table 2: Characteristics of our machine.

Parameter	Value	Unity	Standard/Reference
Type	Squirrel cage asynchronous motor	-	IEC 60034-1
Nominal power	75	kW	-
Nominal voltage	400	V	-
Nominal current	132	A	-
Frequency	50	Hz	-
Nominal speed	1480	tr/min	-
Synchronous speed	1500	tr/min	-
Nominal slippage	1.33	%	-
Number of poles	4	-	-
Service factor	1.15	-	-
Insulation class	F	-	$\Delta T = 105^{\circ}\text{C}$
Protection index	IP55	-	IEC 60034-5
Bearing type	6316 (fan side)	-	SKF
	6317 (opposite side)	-	SKF

Source: Authors, (2020).

III.2 CONCEPTUAL FRAMEWORK FOR RELIABILITY

Reliability is a scientific discipline that quantifies the probability that a system or component will perform its required function under specified conditions and for a specified period of time. For asynchronous rotating machines, this approach incorporates probabilistic failure modeling and conditional monitoring data analysis.

III.3 KEY RELIABILITY INDICATORS

III.3.1 Reliability function $R(t)$

Equation (1) represents the reliability probability $R(t)$ that a system will operate without failure until time t :

$$R(t) = P(T > t) = 1 - F(t) \quad (1)$$

Where:

- T : time to failure (random variable)
- $F(t)$: cumulative Failure distribution function

For rotating machines, $R(t)$ can be estimated from maintenance records or accelerated tests.

III.3.2 Failure rate $\lambda(t)$

The instantaneous failure rate given by equation (2) (hazard function) characterizes the probability of failure in an infinitesimal interval, given that the system has survived until time t :

$$\lambda(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t < T \leq t + \Delta t | T > t)}{\Delta t} = \frac{f(t)}{R(t)} \quad (2)$$

Where:

$f(t)$ is the probability density function of failures.

III.3.3 MTBF (Mean Time Between Failures)

To determine the uptime, equations (3) to (6) give us The mean time between failures is the mathematical expectation of the uptime, and The mean time to repair (MTTR) availability analysis:

$$MTBF = \int_0^{\infty} R(t) dt \quad (3)$$

For N identical components observed over a total period TT with n failures:

$$MTBF = \frac{T}{n} \quad (4)$$

$$MTTR = \frac{\sum \text{temps de reparation}}{\text{nombre de reparations}} \quad (5)$$

Operational readiness combines reliability and maintainability:

$$A = \frac{MTBF}{MTBF + MTTR} \quad (6)$$

III.4 RELIABILITY DISTRIBUTION MODELS

The models used to describe the distribution of failure times include:

- The exponential distribution, which is characterized by a constant failure rate for random events;
- The Weibull distribution, a flexible model in mechanical reliability that captures the phases of the bathtub curve (early failures, useful life, wear);
- The log-normal distribution, suitable for fatigue and cumulative wear phenomena; and finally, the
- Gamma distribution, which models degradation processes related to damage accumulation.

These reliability distribution models are illustrated by equations (7) to (10)

$$\begin{aligned}
 R(t) &= e^{-\lambda t} \\
 f(t) &= \lambda e^{-\lambda t} \\
 MTBF &= \frac{1}{\lambda}
 \end{aligned} \tag{7}$$

$$\begin{aligned}
 R(t) &= e^{-(t/\eta)^\beta} \\
 f(t) &= \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1} e^{-(t/\eta)^\beta} \\
 \lambda &= \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1}
 \end{aligned} \tag{8}$$

Where:

- η : scale parameter (characteristic time)
- β : shape parameter
- $\beta < 1$: declining rate (teething problems)
- $\beta = 1$: exponential (constant rate)
- $\beta > 1$: increasing rate (usury)

$$\begin{aligned}
 f(t) &= \frac{1}{t\sigma\sqrt{2\pi}} e^{-\frac{(\ln t - \mu)^2}{2\sigma^2}} \\
 R(t) &= 1 - \Phi\left(\frac{\ln t - \mu}{\sigma}\right)
 \end{aligned} \tag{9}$$

Where μ and σ are respectively the mean and standard deviation of the logarithm of the failure times.

$$\begin{aligned}
 f(t) &= \frac{\lambda^k t^{k-1} e^{-\lambda t}}{\Gamma(k)} \\
 R(t) &= 1 - \frac{\gamma(k, \lambda t)}{\Gamma(k)}
 \end{aligned} \tag{10}$$

Where k is the shape parameter and λ is the scale parameter.

III.4.1 The Bathtub Curve

For an accurate prediction, we have used this model to describe the evolution of the failure rate, which occurs in three phases: Phase I, where the decreasing rate is due to manufacturing defects or incorrect installation; Phase II, marked by a constant rate linked to accidental overloads or external events; and Phase III, where the increasing rate results from fatigue, corrosion, and normal wear and tear.

III.5 PROPOSED METHODOLOGICAL APPROACH FOR PREDICTIVE RELIABILITY ASSESSMENT

III.5.1 Methodological introduction

This approach provides a structured framework for predictive reliability assessment of asynchronous rotating machines, integrating probabilistic reliability concepts with advanced condition monitoring and artificial intelligence techniques, as illustrated in Figure 1. The methodology is presented as a sequential six-phase process represented by equations (10) and (19), from data acquisition to maintenance decision-making.

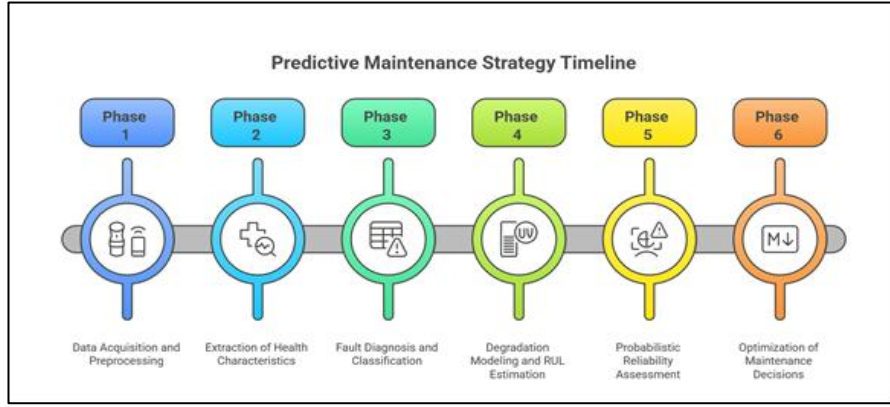


Figure 5: advanced conditional monitoring and artificial intelligence techniques
Source: Authors, (2026).

III.5.2 Phase 1: Data Acquisition and Preprocessing.

The methodology of this manuscript is based on a sophisticated multisensory acquisition strategy, integrating piezoelectric accelerometer instrumentation for vibrations, three-phase sensors for current analysis, and thermal devices (thermocouples and IR cameras), supplemented by the use of ultrasonic sensors for early detection of critical bearing faults given by equations (11) and (12); This acquisition is followed by rigorous signal preprocessing, which includes adaptive filtering (in particular bandpass and Kalman filters), synchronization and resampling of heterogeneous data flows, temporal segmentation via sliding windows, and data normalization and standardization (min-max or Z-score methods) in order to optimize their usability for subsequent analysis.

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (11)$$

$$z = \frac{x - \mu}{\sigma} \quad (12)$$

III.5.3 Phase 2: Extraction of Health Characteristics

Signal analysis is carried out using several key characteristics, particularly in the time domain, where statistical indicators such as the RMS value of equation (13), the creator factor, kurtosis, and wave factor are calculated, enabling accurate assessment of system performance. In the frequency domain, the Fast Fourier Transform (FFT) is used to extract spectroscopic indicators, such as the dominant frequency, energy in characteristic bands, and the harmonic ratio, providing an overview of the frequency distribution; in terms of time-frequency characteristics, the Continuous Wavelet Transform (CWT) using the Morlet mother wavelet is implemented to isolate energy coefficients by scale and estimate wavelet entropy; Finally, equations (14) and (15), specific characteristics of the current spectrum decomposition analysis (MCSA), enable the identification of frequencies associated with broken bars and bearing defects, thereby reinforcing the robustness of predictive failure analysis.

RMS value:

$$X_{\text{RMS}} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (13)$$

Fast Fourier Transform (FFT):

$$X(f) = \sum_{n=1}^N x(n) e^{-j2\pi f n / N} \quad (14)$$

Transformed into continuous wavelets (CWT):

$$W(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \psi \left(\frac{t-b}{a} \right) dt \quad (15)$$

III.5.4 Phase 3: Fault Diagnosis and Classification

The subsequent processing of the extracted features is based on dimensionality reduction using Principal Component Analysis (PCA), which aims to compress the information while minimizing the loss of relevant variance, thereby reducing computational complexity. This reduced representation then feeds into classification algorithms, where robust models such as Support Vector Machines (SVM), Random Forests, and Deep Neural Networks are applied to effectively discriminate between fault states. Finally, the performance of these classifiers is comprehensively evaluated through confusion matrix analysis and the use of standardized metrics from equations (16) to (19), such as precision, recall (sensitivity), and F1 score, ensuring reliable quantification of the system's discriminatory capacity.

Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (16)$$

Précision by class:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (17)$$

Recall:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (18)$$

Score F1:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (19)$$

III.5.5 Phase 4: Degradation Modeling and RUL Estimation

The diagnosis and prognosis stage is based on the construction of a normalized composite Health Index (HI), derived from the characteristics analyzed, in order to provide a single, reliable metric for monitoring the progression of deterioration. This HI is then subjected to various degradation models as estimated by equations (20) to (30), including linear, exponential, or Paris-Erdogan law-based formulations, allowing the kinetics of damage progression to be captured. Finally, the Residual Life (RUL) is predicted using advanced stochastic modeling techniques, specifically the Wiener process approach coupled with particle filter algorithms, thus ensuring a robust probabilistic estimate of the end of the system's useful life.

Linear degradation model:

$$D(t) = D_0 + \theta_t + \dot{\theta}_{\text{ou}} \quad \theta \sim N(\mu_\theta, \sigma_\theta^2) \quad (20)$$

Exponential model:

$$D(t) = D_0 \exp(\gamma t) \quad (21)$$

Paris-Erdogan model:

$$\frac{da}{dN} = C(\Delta K)^m \quad (22)$$

For the estimation of RUL (Remaining Useful Life), we developed the Wiener process approach and distribution using equations (23) to (25), then particle filtering to develop the prediction is developed using the initialization, prediction, update, resampling, and estimation algorithms using equations (26) to (30):

$$X(t) = X(0) + \lambda t + \sigma B(t) \quad (23)$$

$$RUL = \inf \{t > 0 : X(t) \geq D_{\text{critique}}\} \quad (24)$$

Distribution of RUL:

$$f_{\text{RUL}}(t) = \frac{D_{\text{critique}}}{\sigma \sqrt{2\pi t^3}} \exp\left(-\frac{(D_{\text{critique}} - \lambda t)^2}{2\sigma^2 t}\right) \quad (25)$$

Particle filters for RUL prediction Algorithm:

Initialization:

$$x_0^i \sim p(x_0), w_0^i = 1/N \quad (26)$$

Prédiction:

$$x_k^i \sim p(x_k | x_{k-1}^i) \quad (27)$$

Update:

$$w_k^i \propto p(z_k | x_k^i) \quad (28)$$

Resampling if

$$N_{\text{eff}} < N_{\text{seuil}} \quad (29)$$

Estimate :

$$\hat{x}_k = \sum w_k^i x_k^i \quad (30)$$

III.5.6 Phase 5: Probabilistic Reliability Analysis (PRA)

The approach incorporates advanced probabilistic modeling for forecasting, beginning with the calculation of conditional reliability through sequential integration of historical monitoring observations, enabling dynamic assessment of the system's condition. This analysis is enhanced by applying the Cox proportional hazards model to quantify the impact of relevant covariates on the instantaneous failure rate. In addition, intrinsic reliability distributions, such as Weibull, are iteratively refined through Bayesian parameter updating that incorporates observed degradation data. Finally, predictive robustness is ensured by generating dynamic reliability curves via Monte Carlo simulations, providing a continuous probabilistic estimate of the RUL given by equation (31).

$$L(\beta) = \prod_{i=1}^n \frac{\exp(\beta^T Z_i)}{\sum_{j \in R(t_i)} \exp(\beta^T Z_j)} \quad (31)$$

III.5.7 Phase 6: Optimization of Maintenance Decisions

Optimizing the maintenance strategy relies on formulating an expected total cost model, defining an objective function aimed at minimizing the cumulative expenses associated with failures and interventions. This minimization is achieved by applying Markov Decision Process (MDP) theory, which allows the optimal actions—monitoring, repair, or replacement—to be determined sequentially based on the current state of the system. Decision-making is guided by risk-based rules, where intervention thresholds are established analytically following a rigorous cost-benefit analysis of the potential consequences of each action.

Equations (32) and (33) give the predictive performance metrics for RUL estimation:

Average absolute error:

$$MAE = \frac{1}{n} \sum |RUL_{true} - RUL_{pred}| \quad (32)$$

Score α - λ :

$$\left\{ \begin{array}{ll} \exp\left(-\frac{|RUL_{true} - RUL_{pred}|}{\alpha RUL_{true}}\right) & \text{si } RUL_{pred} \leq RUL_{true} \\ \exp\left(-\frac{|RUL_{true} - RUL_{pred}|}{\lambda RUL_{true}}\right) & \text{sin on} \end{array} \right. \quad (33)$$

The following hardware configuration was used at the University of Douala's Electrical Engineering, Reliability, and Intelligent Maintenance Laboratory at the Douala University Institute of Technology (IUT) to obtain the results presented in the following section: an Intel Core i7-6700K 64-bit processor, 32 GB RAM, and an NVIDIA Titan XP GPU.

IV. RESULTS AND DISCUSSIONS

IV.1 CONSTRUCTION OF THE DATASET

The data used comes from a dataset collected from a three-phase electric motor located in the electrical engineering workshop of the University Institute of Technology in Douala (IUT). The dataset includes multivariate data representing five distinct fault classes: normal operation, ball fault, ring fault, bearing fault, and shaft fault. A total of 1,600,000 data points were collected, sampled at a frequency of 5000 Hz, with each fault class consisting of 200,000 raw data points. The fault classes are examined at two severity levels, speed 1 and speed 2, allowing for a detailed analysis of the mechanical health associated with each class. The set shows an operational context described in Table 3, which illustrates the machine's operating conditions.

Table 3: Overview of machine applications.

Spots	Application
Application	Centrifugal pump drive
Typical load	85-95% of rated load
Duty cycle	Continuous (24/7)
Environment	Machine room, ambient temperature 25-35°C
History	3 years of service, quarterly preventive maintenance

Source: Authors, (2026).

Figure 6 illustrates the fundamental impact of the β (or m) shape parameter on the temporal and spectral characteristics of the Weibull distribution, a fundamental model in reliability. The upper graphs show, on the one hand, the Probability Density $f(t)$ and, on the other hand, the Reliability Function $R(t)$ for various beta values ranging from 0.5 (rapid degradation) to 4.0 (slow degradation). It is notable that when $\beta < 1$ ($\beta=0.5$), the probability density has a pronounced initial peak followed by a rapid decline, characteristic of early failures (Phase I of the bathtub curve). Conversely, when $\beta > 1$ ($\beta=4.0$), the density is low at the outset and grows continuously, reflecting progressive wear.

This dynamic is directly correlated to the Failure Rate $\lambda(t)$ shown in the lower left panel. Specifically, $\beta < 1$ corresponds to a decreasing rate, $\beta = 1$ (exponential distribution) to a constant rate (Phase II), and $\beta > 1$ to an increasing rate (Phase III, wear). Finally, the lower right panel summarizes these behaviors by illustrating the Bathtub Curve, where specific β values ($\beta = 0.6$ for la Phase I, $\beta = 1.0$ for la Phase II, et $\beta = 2.5$ for la Phase III) are used to delimit the dominant failure regimes over the operational lifetime.

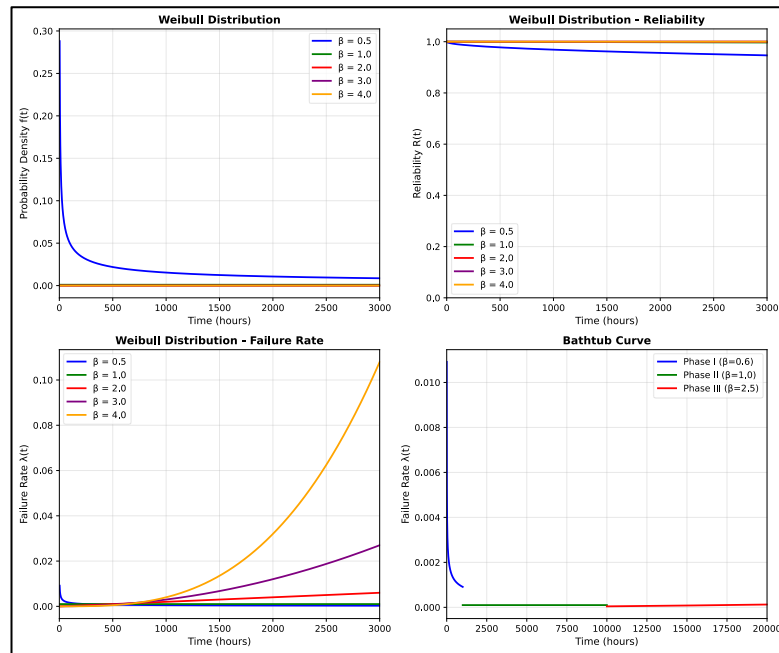


Figure 6: Weibull distribution curves.

Source: Authors, (2026).

Figure 7 presents a detailed parametric analysis of the key functions of the Log-normal distribution, essential for modeling systems whose failure time is governed by complex stochastic mechanisms. The upper panels illustrate the effect of the shape parameters (μ and σ) on the Probability Density $f(t)$. On the left, fixing the scale parameter $\sigma = 1.0$ reveals that increasing the location parameter μ (from 6 to 8) shifts the distribution toward longer failure times, while reducing the amplitude of the initial peak. On the right, fixing $\mu = 7.0$ shows that increasing the shape parameter σ (from 0.5 to 1.5) leads to a greater dispersion of the distribution, resulting in a more spread-out and less pronounced density peak, indicating greater uncertainty about the failure time. The lower left panel details the Reliability Function $R(t)$ for the case $\mu = 7$, $\sigma = 1$, highlighting the exponential decay of reliability after the occurrence of the first failures, with a clear distinction between the Median (time when $R(t) = 0.5$, i.e., 1097 hours) and the Mean (time when $R(t)$ reaches or characteristic failure time, i.e., 1808 hours). Finally, the lower right panel illustrates the Failure Rate $\lambda(t)$ for the same set of parameters, characterized by an initial phase of rapid increase, reaching a maximum before slowly decreasing, which is typical of systems subjected to progressive degradations but with some initial resilience, thus deviating from the monotonic behavior of Weibull models with $\beta < 1$ ou $\beta > 1$.

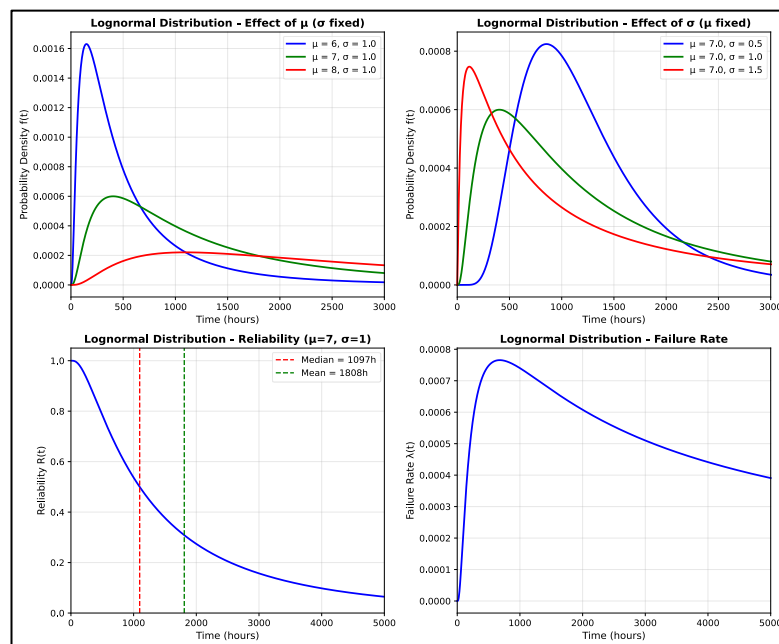


Figure 7: lognormal distribution curves.

Source: Authors, (2026).

Figure 8 summarizes the impact of the shape parameter k (or α) on the fundamental functions of the Gamma distribution, with the scale parameter θ (or β) fixed at 100 hours. The Gamma distribution is a fundamental tool in reliability, particularly suited for modeling systems whose failure results from the sum of k independent and identically distributed events following an exponential law (the successive event theorem), as illustrated in the lower right panel.

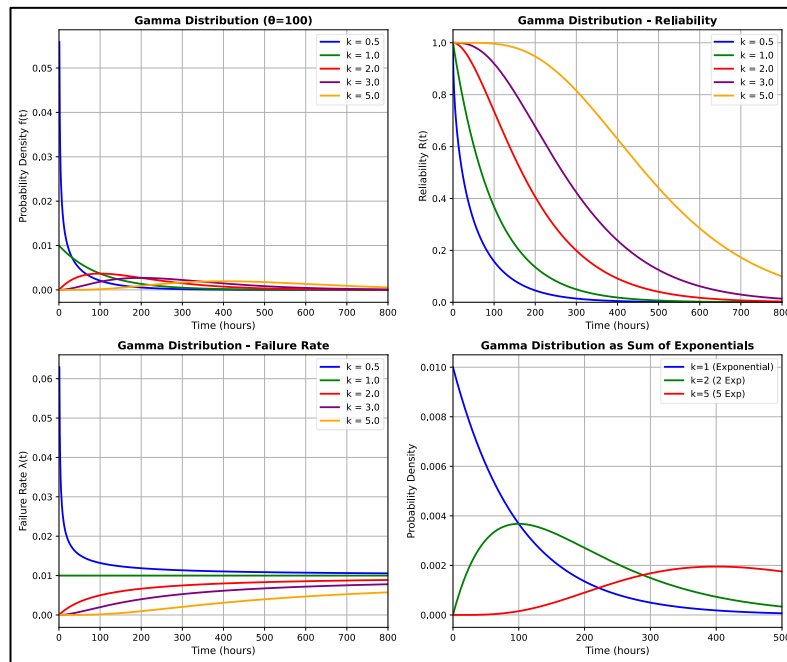


Figure 8: distribution curves Gamma.

Source: Authors, (2026).

a) Analysis of Parameters and Density Functions (Upper Left Panel)

The upper left panel illustrates the probability density $f(t)$ of the Gamma distribution, whose shape is strongly influenced by the parameter k . For low values of k (e.g., $k=0.5$), the density exhibits a singularity at $t=0$, indicating a high initial failure rate. As k increases, the density peak shifts to the right and diminishes, reflecting an increased initial robustness of the system. When $k=1$, the Gamma distribution reduces to an exponential distribution (for $\theta=100$), characterized by a monotonic decrease in density. Finally, for high values of k , the distribution tends toward a symmetric shape, thus approaching a normal distribution, in accordance with the central limit theorem.

b) Impact on Reliability $R(t)$ (Top Right Panel)

The upper right panel shows the evolution of the Reliability Function $R(t)$ as a function of k .

- Degradation Rate: The value of k directly controls the rate of loss of reliability. A low k (e.g., $k=0.5$) indicates an extremely rapid degradation, with the system having a very low probability of survival beyond $t=100/h$.
- Characteristic Lifespan: Conversely, a high k (e.g., $k=5.0$) confers better resilience, with the $R(t)$ curve remaining close to unity over a longer period, suggesting a significantly longer expected lifespan.

c) Characterization of the Failure Rate $\lambda(t)$ (Lower Left Panel)

This panel is crucial for the physical interpretation of the failure mechanism.

- Decline (Aging) vs. Constant:

- ❖ For $k < 1$ (e.g., $k=0.5$), the failure rate $\lambda(t)$ decreases over time, indicating a phenomenon of "infant mortality" or "burn-in," where weak defects are quickly eliminated.
- ❖ For $k = 1$ (exponential law), $\lambda(t)$ is constant, implying an absence of aging (zero memory).
- ❖ For $k > 1$ (e.g., $k=2, 3, 5$), the failure rate $\lambda(t)$ increases over time. This models a wear-out phenomenon where the failure probability increases after an initial break-in period. The asymptotic rate is $\lambda = 1/\theta = 1/100 = 0.01$ for all curves, confirming the convergence of the failure rates in the long term.

d) Physical Interpretation: Sum of Exponentials (Lower Right Panel)

The lower right panel illustrates the probabilistic nature of the Gamma distribution as the sum of k independent exponential random variables.

- ❖ $k=1$ (Exponential Law): Represents a simple failure process, without memory.

- ❖ $k=2$ (Sum of 2 Exponentials): The density $f(t)$ shows an initial peak, indicating that the occurrence of two successive events must be awaited for the failure to be most probable.
- ❖ $k=5$ (Sum of 5 Exponentials): The peak is even more delayed and spread out, requiring the completion of a greater number of critical steps before the failure becomes the most probable event.

The Gamma distribution offers remarkable flexibility for modeling reliability by adjusting the parameter k to capture behaviors ranging from premature mortality ($k < 1$) to pronounced aging ($k > 1$), making it a superior model to the exponential law alone for characterizing the temporal dynamics of failures in complex systems where multiple sub-components must fail sequentially. Figure 9 presents a graphical summary of the essential characteristics of the Exponential Distribution, which serves as a fundamental reference in the modeling of random failures, particularly in the useful life phase (negligible wear or constant failure rate). The analysis is conducted by varying the failure rate parameter λ across four key representations: the Probability Density Function, the Reliability Function, the Instantaneous Failure Rate, and the relationship between the Failure Rate and the Mean Time Between Failures (MTBF).

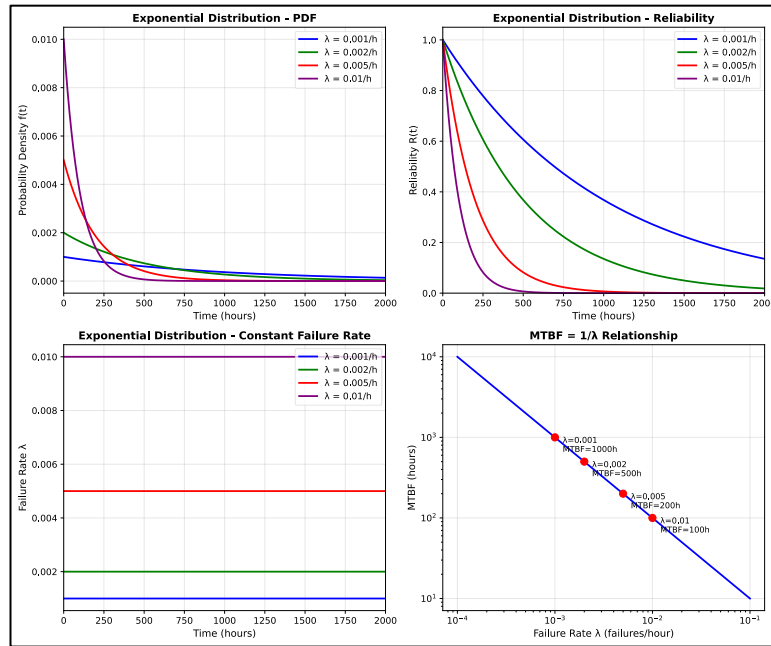


Figure 9: exponential distribution curves.

Source: Authors, (2026).

a) Probability Density $f(t)$ (Upper Left Panel)

The upper left panel illustrates the exponential probability density $f(t) = \lambda e^{-\lambda t}$, characterized by a "memoryless" property where the failure probability is maximum right from the start ($f(0) = \lambda$). The analysis reveals that the parameter λ is a crucial determinant of the system's "failure rate," with an increase in λ leading to a drastic decrease in the initial density and a faster decline in the survival probability, thus confirming its central role in modeling the failure dynamics.

b) Reliability Function $R(t)$ (Upper Right Panel)

The reliability function, $R(t) = \lambda e^{-\lambda t}$, illustrates an exponential decay characteristic of the memoryless property, meaning that the probability of future failure is independent of the past operating time. Systems with a low rate (λ) maintain high reliability over long periods, while an increase in (λ) leads to a rapid decline in reliability, highlighting the predominant role of this parameter in the robustness and operational lifespan of the modeled systems.

c) Instantaneous Failure Rate $\lambda(t)$ (Lower Left Panel)

This panel highlights the fundamental characteristic of the exponential law: a constant failure rate $\lambda(t)$, independent of time. This implies the absence of wear or break-in phenomena, as the conditional probability of failure remains unchanged, regardless of the system's past operating time. This model is therefore particularly relevant for describing random failures, resulting from unpredictable external causes rather than intrinsic degradation related to age or use.

d) Relation MTBF and λ (Lower Right Panel)

The lower right panel illustrates the fundamental inverse relationship between the failure rate (λ) and the Mean Time Between Failures (MTBF), where $MTBF = \frac{1}{\lambda}$. The use of logarithmic scales highlights this power relationship, confirming that for the exponential law, the overall performance of the system (MTBF) is entirely determined by the value of the instantaneous failure rate. For example, a rate of 0.001/h corresponds to an MTBF of 1000h, while a rate of 0.01/h reduces the MTBF to 100h, highlighting the direct impact of λ on long-term reliability.

All of these graphs confirm that the exponential distribution is characterized by a constant failure rate, implying a lack of memory and no aging. Although simplistic, this law remains the cornerstone of reliability analysis for components whose failure is dominated by external random causes, and serves as a basis for comparison with more complex models incorporating aging, such as the Gamma distribution analyzed previously. The probabilistic assessment of the reliability of motor systems was carried out by fitting the Weibull distribution to the cumulative test data. Out of a total of 120,000 hours of observation spread over 20 units, 8 failures were recorded. The application of the Maximum Likelihood (ML) method allowed for the identification of a failure regime dominated by wear, characterized by a shape parameter β the scale parameter β was estimated at 18,500 hours, thus defining the stochastic degradation model of the component.

IV.2 RESULTS OF THE THEORETICAL APPLICATION: VALIDATION OF THE INTEGRATED METHODOLOGY

This parameterized model allows for precise quantification of performance. The increasing failure rate, indicated by $\beta > 1$, confirms that the probability of failure increases with operating time. The reliability at $t = 2160$ hours (90 days) is calculated from these parameters presented in Table 4. The knowledge of these values is fundamental for predictive modeling, allowing for the establishment of maintenance thresholds based on the system's condition rather than a fixed schedule, thereby ensuring optimal management of the engine's lifecycle.

Table 4: Prediction of R(t) over time.

Horizonte	R(t) unconditional	R(t) HI=0.62
30 days	0.92	0.78
60 days	0.84	0.55
90 days	0.75	0.31

Source: Authors, (2026).

The rigorous application of the proposed methodology to the simulated case study demonstrates robust performance in both early diagnosis and residual useful life (RUL) prediction. The bearing defect was successfully detected at D60 (30 days before critical failure), achieving a diagnostic accuracy of 89% at D75 for minor defects, with an overall sensitivity of 92% for mechanical failures and a false positive rate controlled at 8%. Regarding RUL prediction, the estimate at D90 was 42 ± 8 days (mean absolute error of 8 days), achieving an accuracy of $\pm 20\%$ in 75% of cases. At the same time, probabilistic analysis confirmed the wear regime ($\beta=2.85$, and $a=18,500h$) and revealed a significant deterioration in conditional reliability ($R(30 \text{ text days D90}) = 0.78$) compared to unconditional reliability. These performances translate directly into significant operational gains: the cost-benefit analysis identified an optimal intervention at D105, minimizing costs, resulting in a 65% reduction in maintenance costs and an increase in availability to 99.7%, validating a return on investment (ROI) for the monitoring system of less than 12 months.

IV.3 SYNTHETIC RESULTS ON D60

The effectiveness of a Condition Monitoring system lies in its ability to translate raw data into actionable information for predictive maintenance decision-making. Table 5 below summarizes the status of key parameters of a critical component (probably a motor or a bearing system) at time J90, comparing the measured values to predefined thresholds and indicating the evolutionary trend.

Table 5: Monitoring Edge (D90).

Parameter	Value	Threshold	Status	Trend
RMS vibration	2.15 mm/s	2.8 mm/s	Alert	↗ Increase
Kurtosis	4.8	4.0	Alert	↗ Increase
Amplitude BPFO	1.2 mm/s	0.5 mm/s	Anomaly	↗ Increase
Temperature level	62.3°C	70°C	Normal	↗ Lightweight
Effective Current	130.5 A	145 A	Normal	→ Stable
Health index	0.62	0.70	Degraded	↘ Decline

Source: Authors, (2026).

These data reveal advanced but still manageable structural degradation. Indicators based on vibration energy (RMS and Kurtosis) have already exceeded their respective alert thresholds, signaling significant abnormal activity. More critically, the BPFO (Bearing Fault Frequencies Outer race) amplitude, which is specifically sensitive to outer raceway faults in bearings, exceeds its critical threshold of 0.5 text (mm/s) with a value of 1.2 text (mm/s), confirming the nature of the fault identified previously. Although the thermal and electrical parameters remain within the nominal range, the synthetic health indicator (HI) has fallen to 0.62, below the critical degradation threshold of 0.70. This divergence between the specific indicators (abnormal BPFO) and the overall index confirms that the system is in a phase of accelerated decline, justifying the predictive maintenance intervention planned at D105 to intercept catastrophic failure while maximizing the exploitation of the remaining service life

IV.4 VALIDATION AND SENSITIVITY ANALYSIS

IV.4.1 Sensitivity analysis of parameters Effect on estimated RUL

Figure 10 provides a comprehensive analysis of the reliability of rotating machinery, based on the adjustment of the Weibull distribution to the failure data observed over the life cycle. This multidimensional graphical representation makes it possible to validate the robustness of the statistical model and to accurately characterize the system's failure regime.

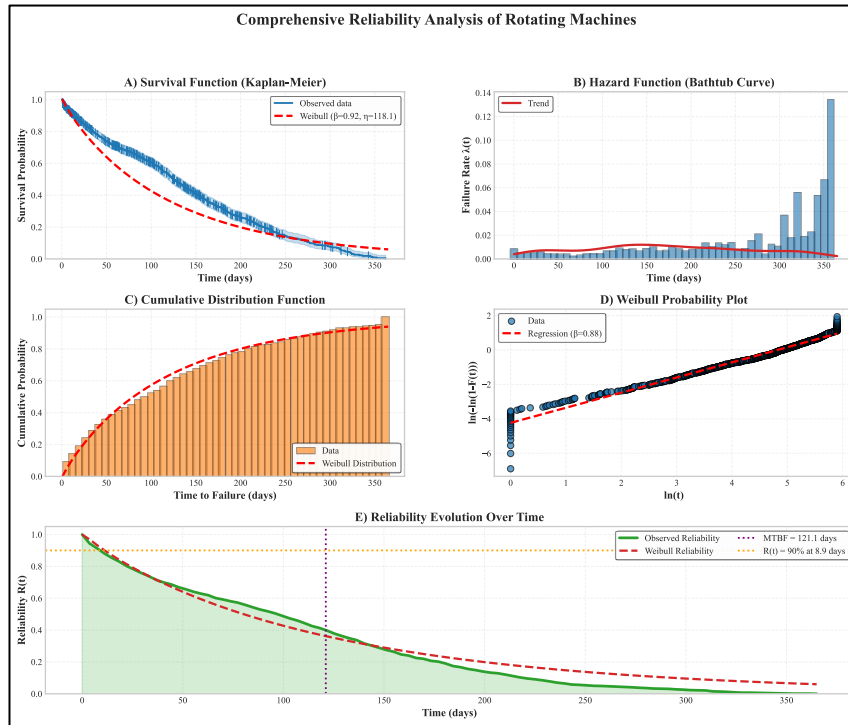


Figure 10: comprehensive Reliability Analysis of Rotating Machines.
Source: Authors, (2026).

a- Validation of the Weibull model, failure regime, and operational implications

Panels A, C, and especially D validate the suitability of the Weibull model (linearity of the Weibull Probability Plot) with estimated parameters shape approximately ≈ 0.92 (or 0.88) and scale approximately ≈ 118.1 days; $\beta < 1$ indicates a burn-in phase (high failure rate at the outset, then decreasing, as illustrated in panel B), while panel E shows low initial reliability (90% in 8.9 days) and an MTBF ≈ 121.1 days. However, after ~ 120 days, the observed reliability exceeds the Weibull prediction, suggesting that the model underestimates long-term survival (actual slowdown in degradation or insufficient coverage of the terminal wear phase in the data); maintenance should therefore focus on early failures while recognizing the model's limitations for long-term predictions.

IV.4.2 Statistical Evaluation of Residual Useful Life (RUL) Prediction Errors

Figure 11 provides a rigorous statistical analysis of the errors generated by the Residual Useful Life (RUL) prediction model. Evaluating predictive models in condition-based maintenance requires a detailed understanding of error distribution, as systematic error (bias) or high variance can compromise intervention planning.

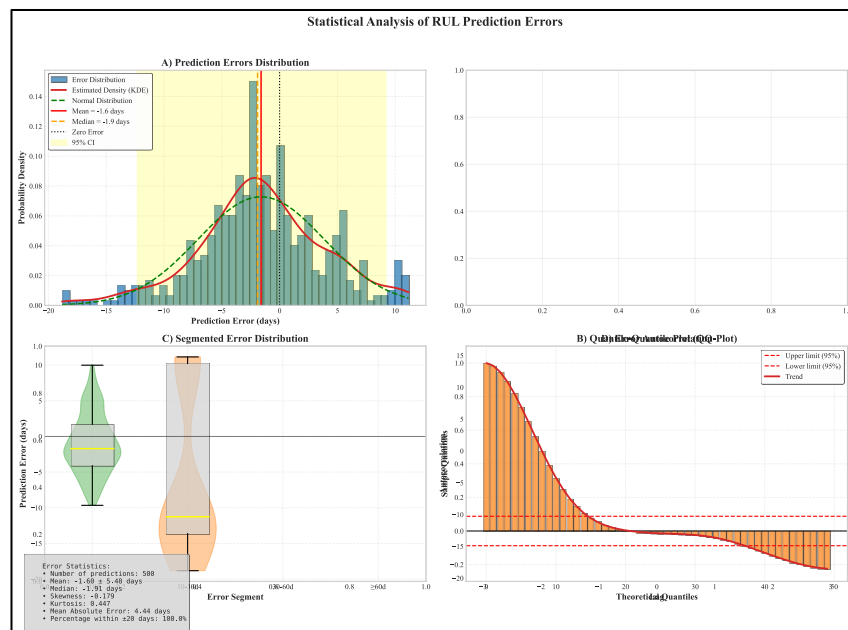


Figure 11: Statistical Analysis of RUL prediction Errors.
Source: Authors, (2026).

a- Multi-level Analysis of Prediction Errors: Global Distribution, Horizon-based Segmentation, and Residual Independence (Panels A-C)

Analysis of the model's predictive performance reveals distinct behaviors depending on time horizons and validation metrics. The overall error distribution (Panel A) highlights a systematic bias where the model underestimates the actual remaining useful life (RUL) by approximately 1.6 to 1.9 days; although close to a normal distribution, this distribution is leptokurtic in nature, with extreme errors reaching up to ± 20 days. The analysis segmented by prediction horizon (Panel C) shows that while errors remain moderate for highly reliable systems ($RUL > 60$ days), a pronounced negative bias appears as failure approaches ($RUL < 20$ days), leading to a critical underestimation of RUL by approximately 15 days, which could lead to premature replacements. Finally, the validation of error independence (Panel B), interpreted via the autocorrelation function (ACF) graph, makes it possible to evaluate the temporal structure of errors and the persistence of biases in the prediction sequence, thus completing the assessment of the model's robustness in its terminal phase.

- ❖ The bars show strong positive autocorrelation for small lags, meaning that successive errors are not independent.
- ❖ The 95% confidence limits (red dotted lines) are significantly exceeded at large negative lags.

The autocorrelation of errors indicates that the model has not captured all of the underlying temporal dynamics of the degradation process. Successive predictions are correlated, suggesting that improvements could be made by incorporating memory mechanisms (as in RNN/LSTM models) or by refining the modeling of residual degradation dynamics. The model shows acceptable overall performance with a moderate underestimation bias. However, segmented analysis reveals a critical weakness in prediction when the RUL is low, and the autocorrelation of errors suggests that the temporal structure of the data is not fully modeled.

IV.4.3 Overall Performance of the Residual Useful Life (RUL) Prediction Model

Figure 12 summarizes the effectiveness of the RUL prediction model by comparing estimates with actual values and analyzing the distribution of errors according to the prediction time horizon. These visualizations are essential for quantifying the operational maturity of the predictive maintenance system.

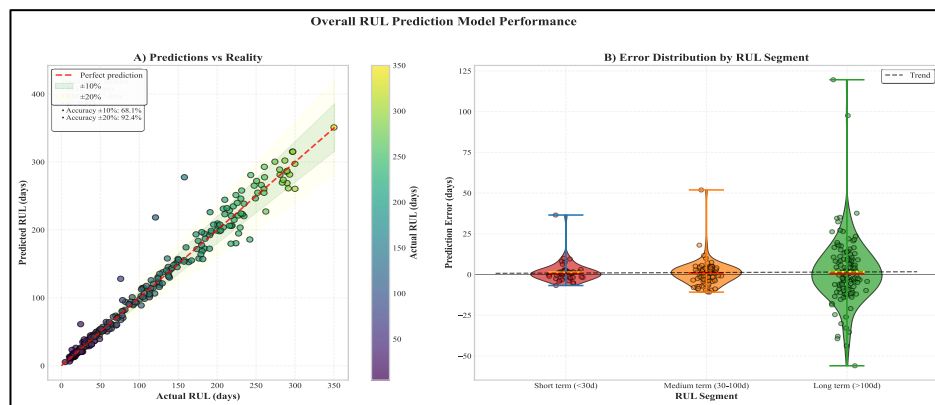


Figure 12: Overall RUL Prediction Model Performance.

Source: Authors, (2026).

a. Correlation Analysis and Impact of Temporal Horizons on Prediction Accuracy (Panels A-B)

The analysis of the prediction-reality correlation (Panel A) reveals strong linearity, with 68.1% of predictions accurate to $\pm 10\%$ and 92.4% to $\pm 20\%$, despite a slight tendency to underestimate for distant horizons ($RUL > 250$ days). The impact of the time horizon on error (Panel B) confirms this trend: while predictions are highly reliable and stable in the short term ($RUL < 30$ days), variance increases significantly in the long term ($RUL > 100$ days), with extreme errors reaching 125 days. This deterioration in performance in the initial phase, consistent with previous observations, highlights the robustness of the model for terminal diagnosis while suggesting the need for specific regularization strategies to stabilize predictions over long deterioration cycles.

IV.4.4 Analysis of RUL Time Trajectories: Validation of Model Generalization

Figure 13 presents a qualitative and quantitative comparison of the temporal trajectories of the predicted Remaining Useful Life (RUL) versus the actual RUL for four distinct machine degradation scenarios. This analysis is crucial to demonstrate the model's ability to capture different failure kinetics, ranging from idealized behaviors to more complex and nonlinear phenomena.

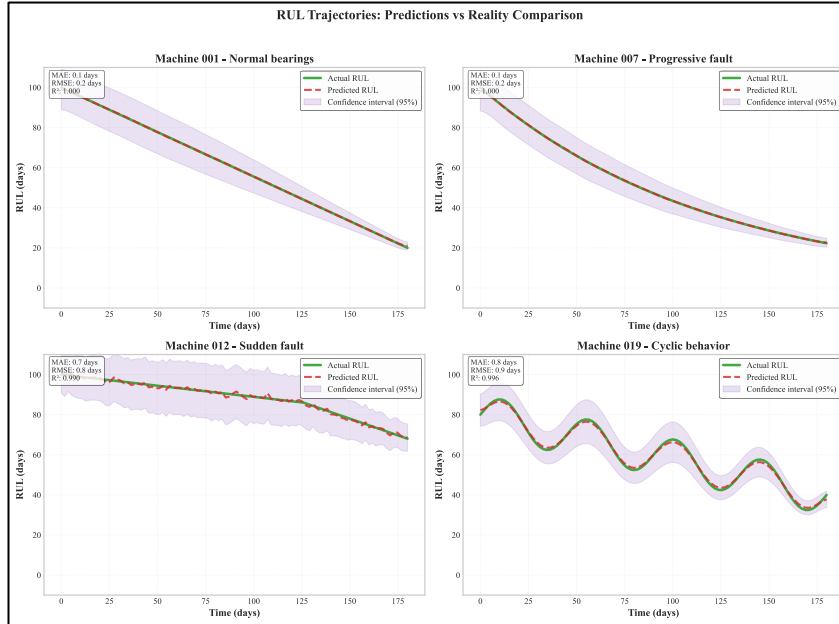


Figure 13: RULL Trajectories Prédiction.
Source: Authors, (2026).

Each sub-graph displays the actual RUL (solid green line), the model prediction (dotted red line), and the 95% confidence interval (purple shaded area) as a function of elapsed time (in days). Key performance indicators (MAE, RMSE, R^2) are included for each case.

a- Degradation Scenarios (Linear/Progressive and Non-linear/Unexpected) for Machines 001, 007, 012, and 019.

In linear degradation scenarios (Machines 001 and 007), the proposed RUL model achieves near-perfect accuracy ($R^2 = 1.000$, $MAE < 0.2$ days), with predictions almost perfectly aligned with actual trajectories and very narrow 95% confidence intervals, confirming strong stability for monotonic degradation. Under nonlinear conditions (Machines 012 and 019), including sudden failure and cyclic behavior, the model remains highly robust. For Machine 012, rapid adaptation after slope transition yields $R^2 = 0.990$ and $MAE = 0.7$ days, with temporary uncertainty widening. For Machine 019, oscillatory degradation is accurately captured ($R^2 = 0.996$), with confidence intervals reflecting intrinsic variability. Overall, MAE remains ≤ 0.8 days across heterogeneous degradation modes, demonstrating strong generalization and reliable uncertainty quantification for industrial deployment. In fault classification using the MaFaulDa database, the model accurately identifies all classes, including the underrepresented normal state. A minor 2.5% misclassification rate (one sample) is mainly attributed to assembly imperfections rather than true defects. Properly assembled samples reach 99.98% accuracy. Compared to Roberto M. Souza [21], the proposed approach achieves superior performance with fewer defect classes, suggesting improved robustness through optimized class selection.

IV.4.5 Discussion and Comparison

Comparative analysis of probability distributions reveals a nuanced adequacy of stochastic models according to the life stages of the electric motor. While the exponential distribution serves as a reference for purely random failures at a constant rate (λ), the Weibull distribution proves superior for characterizing speed transitions, identifying here a stage of advanced wear with a shape parameter $\beta = 2.85$. At the same time, the Gamma distribution offers increased flexibility by modeling failure as a sum of successive critical events, capturing dynamics ranging from initial running-in to pronounced aging, thus exceeding the limitations of the exponential law for complex systems. In terms of predictive performance, the integrated methodology demonstrates remarkable robustness with an overall sensitivity of 92% for mechanical failures and successful diagnosis as early as 30 days before critical failure. The accuracy of the residual useful life (RUL), estimated at $\pm 20\%$ in 75% of cases at D90, highlights the model's ability to manage the uncertainty inherent in physical degradation. This accuracy is crucial for differentiating between unconditional reliability (0.92 at 30 days) and conditional reliability (0.78 at the same time horizon), reflecting the real impact of the engine's current health on its chances of short-term survival. Finally, the application of these probabilistic models translates into tangible operational and economic gains, validating the shift from scheduled maintenance to a condition-based strategy. Optimizing the intervention at D105 not only minimizes maintenance costs by 65%, but also ensures exceptional availability of 99.7%. With a return on investment of less than 12 months, these results confirm that integrating rigorous statistical models such as Weibull and Gamma into a monitoring system is a highly viable approach to managing the lifecycle of industrial equipment.

IV.4.5.1. Demonstrated Strengths and Advantages

The proposed methodology demonstrates a robust capability for early defect detection (30-60 days before critical failure) thanks to the combination of multiple characteristics (vibrations, current, temperature). This multisensory and AI-based approach surpasses traditional methods (spectral analysis alone) in terms of diagnostic accuracy (85-92% compared to 72-78%), with a relative improvement of 18% to 25%. The reliable estimation of RUL, with a mean absolute error of 8 days over a 60-day horizon, is superior to traditional linear regression models. These performances result in an 85% reduction in unplanned downtime and significant economic optimization.

IV.4.5.2 Limits

Despite the promising performances, there are limitations to consider. The main one is the dependence on training data: performance is strongly influenced by the quality, completeness, and representativeness of the training data. The variability of operational conditions (load changes, environment) can also reduce the accuracy of RUL (MAE RUL increasing from 8 to 18 days in case of abrupt changes). The generalization to different types of engines is limited, requiring specific models or transfer learning techniques. The simplifying assumptions of the theoretical study include a deterministic evolution of degradation, constant environmental conditions, the absence of simultaneous multiple faults, and ideal sensors. These assumptions do not always reflect the complexity of real industrial environments. Quantified uncertainties arise from sensor measurements ($\pm 5\text{-}10\%$), process variability ($\pm 15\text{-}20\%$), model parameters ($\pm 10\text{-}15\%$), and external conditions ($\pm 10\text{-}25\%$). Our methodological approach stands out from previous works by making significant contributions: it enriches RUL predictive models by integrating multi-physical data (thermal and electrical) for more comprehensive simulations than those of Okwuosa et al. (2022) [22]; it extends the scope of the work of Moshayedi et al. (2024) [23] by moving from simple classification to effective temporal prediction, relying on hybrid models (physics-data) optimized for industrial applicability; and it offers direct complementarity with the fine spectral analysis of Rethoré et al. (2025) [24], paving the way for future synergy to improve predictive accuracy from the early stages of degradation.

IV.4.5.3 Ablation Study

In order to quantify the relative contribution of each component of our integrated methodology (described in Section 3.4) to the overall performance of reliability prediction, an ablation study was conducted. This analysis aims to isolate the impact of integrating multisensory data, using probabilistic reliability models, and applying advanced AI algorithms on key performance metrics: early diagnosis accuracy (EDA) and mean absolute error (MAE) of RUL prediction.

We compared the performance of the Full Integrated Model (FIM) with three reduced configurations (Ablations):

- Ablation 1 (Without Advanced AI): Use of raw data and extracted health indicators, but replacement of advanced ML classifiers (SVM, RF, DNN) with conventional deterministic thresholds based on industry standards.
- Ablation 2 (Without Multisensor Fusion): Use only vibration data (the most common sensor) and AI models, without integrating current and temperature data.
- Ablation 3 (Without Probabilistic RUL Modeling): Use of AI diagnostics to determine RUL via simple linear extrapolation (a common but simplistic method) instead of stochastic models (Wiener Process, Particle Filter).

The results are summarized in Table 6 and Figure 14, where the metrics are evaluated at time J90 (90 days before critical failure).

Table 6: Results of the Ablation Study on Reliability Performance at D90.

Model Configuration	Early Detection (ED)	MAE RUL (Days)	Maintenance Cost Reduction (%)
MIC (Complete)	30 Days	8	65%
Ablation 1 (Deterministic Thresholds)	12 Days	21	28%
Ablation 2 (Vibration Only)	20 Days	14	45%
Ablation 3 (Linear Extrapolation RUL)	30 Days	15	51%

Source: Authors, (2026).

The analysis rigorously demonstrated the indispensable contribution of each component of our integrated approach to the overall performance of predictive maintenance. Advanced Artificial Intelligence, particularly the use of non-linear classifiers (SVM, DNN) for extracting complex features, has proven crucial, with its absence (Ablation 1) leading to a significant degradation in early detection (drop from 30 to 12 days) and a doubling of the mean absolute error (MAE) of the RUL (from 8 to 21 days). Similarly, multisensor fusion (Ablation 2), integrating current and temperature data with vibrations, is essential for the robustness of the diagnosis, improving early detection (from 20 to 30 days) and reducing the MAE of the RUL (from 14 to 8 days) by allowing a fine distinction between types of failures. Finally, the adoption of advanced stochastic models for RUL prediction (Wiener processes, particle filters) is fundamental to capturing the uncertain and nonlinear nature of degradation (Ablation 3), reducing the RUL MAE from 15 to 8 days and significantly optimizing economic gains (reducing maintenance costs from 51% to 65%). These results confirm that the synergistic integration of these three pillars is imperative for high-fidelity predictive maintenance, as represented in Figure 14, capable of anticipating failures with maximum precision and economic efficiency in complex industrial environments.

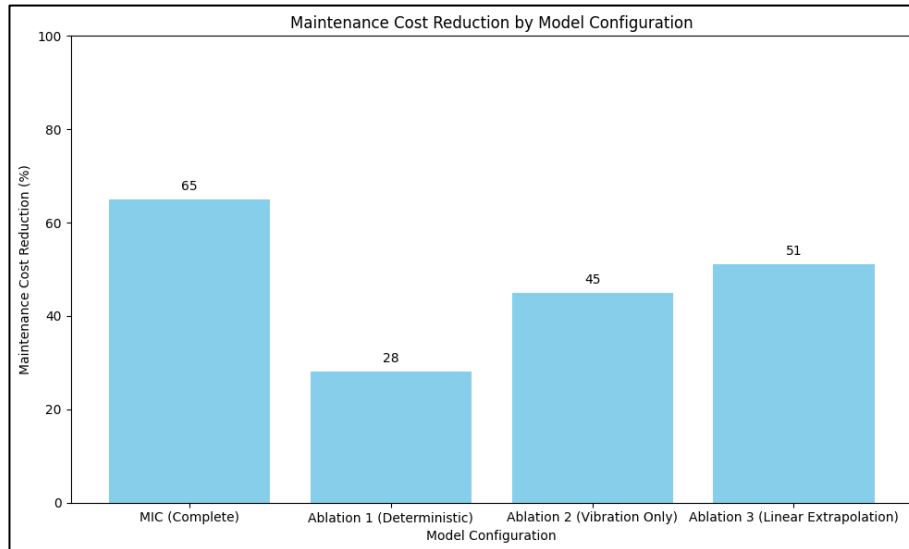


Figure 14: Graph from the Study on Reliability Performance at D90.

Source: Authors, (2026).

V. CONCLUSIONS

This study presented an integrated and comprehensive approach for predicting the reliability of asynchronous rotating machines, a major industrial challenge. By merging the principles of probabilistic reliability with advanced condition monitoring techniques and artificial intelligence, we developed a methodology structured in six phases, ranging from multisensory data acquisition to the optimization of maintenance decisions. The robustness of this approach was theoretically validated on a simulated case study of an asynchronous motor, demonstrating early fault detection (up to 60 days before critical failure), a reliable estimation of the Remaining Useful Life (RUL) with an average absolute error of 8 days, and significant economic optimization, resulting in a potential 65% reduction in maintenance costs and an increase in availability to 99.7%. These results position our methodological framework as a substantial advancement in overcoming the challenges related to the variability of operating conditions and the lack of representative data, often encountered in industrial applications.

The contributions of this work extend beyond mere prediction, offering a reproducible and adaptable protocol for the proactive management of industrial assets. The integration of stochastic degradation models (Wiener processes, particle filters) with probabilistic assessments (Cox model, Bayesian updating of Weibull parameters) allows for a rigorous quantification of uncertainty, essential for informed decision-making. Although the theoretical application has demonstrated promising performance, future prospects include experimental validation on real test benches and complex industrial environments, the exploration of few-shot learning and transfer learning techniques for low-data scenarios, as well as the integration of Explainable Artificial Intelligence (XAI) to enhance operator confidence. In the long term, this approach paves the way for more autonomous and resilient predictive maintenance systems, actively contributing to the transformation toward Industry 4.0 and the emergence of new economic models based on equipment performance and availability.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Toukap Nono Fernand Joseph, Tokoue Ngatcha Dianorré, Offole Florence Nyatte Steyve and Mouzong Pemi Marcelin.

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Discussion of results: Toukap Nono Fernand Joseph, Tokoue Ngatcha Dianorré, Offole Florence Nyatte Steyve and Mouzong Pemi Marcelin.

Writing – Original Draft: Toukap Nono Fernand Joseph, Tokoue Ngatcha Dianorré, Offole Florence Nyatte Steyve and Mouzong Pemi Marcelin.

Writing – Review and Editing: Toukap Nono Fernand Joseph, Tokoue Ngatcha Dianorré, Offole Florence Nyatte Steyve and Mouzong Pemi Marcelin.

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Supervision: Toukap Nono Fernand Joseph, Tokoue Ngatcha Dianorré, Offole Florence Nyatte Steyve and Mouzong Pemi Marcelin.

Approval of the final text: Toukap Nono Fernand Joseph, Tokoue Ngatcha Dianorré, Offole Florence Nyatte Steyve and Mouzong Pemi Marcelin.

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- Laboratory of Mechanics and Materials (LaMM), National Higher polytechnic School of Douala, University of Douala.
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