Maintenance Strategy Selection and Its Impact on the Optimization of Life Cycle Costs in Industrial Systems

Zineb Znaidi
Enset Mohammedia, University Hassan II, Morocco
zineb.znaidi@gmail.com (corresponding author)

Moulay El Houssine Ech-Chhibat
Enset Mohammedia, University Hassan II, Morocco
echchhibate@gmail.com

Azeddine Khiat
Enset Mohammedia, University Hassan II, Morocco
Khiat@enset-media.ac.ma

Mounir El Khiate
Enset Mohammedia, University Hassan II, Morocco
mounir.elkhiate@gmail.com

Hassan Samri
Enset Mohammedia, University Hassan II, Morocco
samri@enset-media.ac.ma

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ABSTRACT

This paper proposes to examine the impact of corrective, preventive, and predictive maintenance strategies on the Life Cycle Cost (LCC) of industrial equipment. A baseline assessment of current Reliability, Availability, and Maintainability (RAM) and LCC was performed using real maintenance and failure data, supported by a cost-based model covering acquisition, operation, downtime, and repair costs. To enhance decision-making, a Random Forest model was applied as a machine learning tool to identify the most appropriate maintenance strategy for each subsystem or critical spare part. By combining RAM indicators with cost data, the model enabled the optimal assignment of maintenance types, linking technical performance to economic outcomes. Results show that transitioning from corrective to preventive maintenance improves Mean Time Between Failures (MTBF) by 15% and reduces Mean Time to Repair (MTTR) by 10%, lowering LCC by 8–10%, whereas moving further to predictive maintenance enhances MTBF by 20% and decreases MTTR by 15%, achieving up to an 18% additional LCC reduction. Although preventive and predictive strategies require higher initial investments, they significantly reduce downtime and unplanned failures compared with corrective approaches. Overall, this work highlights the value of integrating RAM–LCC analysis with machine learning to guide maintenance strategy selection and demonstrates a practical path toward improving reliability, cost efficiency, and sustainability in Industry 4.0.

Keywords-maintenance strategy; reliability; availability; maintainability; Life Cycle Cost (LCC); random forest

I. INTRODUCTION

The analysis of the impact of industrial maintenance types on the Life Cycle Cost (LCC) is a major strategic challenge for the management of machinery fleets. Reliability, Availability, and Maintainability (RAM) of equipment are key factors in optimizing these costs [1]. Reliability, by ensuring the stable operation of machines, directly influences the frequency of failures and, consequently, the frequency of maintenance interventions. Availability measures the ability of machines to be used efficiently, whereas maintainability assesses the costs and time required for repairs or adjustments. LCC, which encompasses acquisition, operating, maintenance, and disposal costs, is deeply impacted by these three factors [2]. The strategic choice of maintenance type—whether preventive, corrective, or predictive—must be based on a thorough analysis of these elements to minimize long-term costs while ensuring optimal machine fleet performance. This approach thus enables a balance between economic profitability and operational efficiency [3].

In recent years, several studies have addressed maintenance optimization and cost reduction, but few have analyzed the direct relationship between maintenance type and its overall impact on LCC [4-7]. Most existing works treat RAM and LCC separately, which limits the understanding of how maintenance choices influence long-term performance and costs. This study aims to fill this gap by proposing an integrated, cost-based framework linking RAM indicators, maintenance strategies, and LCC, to support data-driven maintenance decisions.

In the same context, the present study was conducted on a fleet of industrial production machines. The aim was to define a maintenance strategy to be adopted based on data derived from the analysis of the RAM of these machines, as well as their LCC. This maintenance strategy will enable:

- Optimizing maintenance costs by selecting the most appropriate interventions based on the actual needs of the machines, thereby reducing unnecessary costs.
- Improving equipment reliability by enabling better planning of preventive and predictive actions, which reduces the frequency of unforeseen failures and increases machine availability [8].

This paper first examines the importance of LCC analysis for reducing maintenance costs and then discusses the role of RAM analysis in the selection of maintenance type. Subsequently, the parameters used to analyze the impact of maintenance type on LCC are introduced, followed by the presentation of the applied methodology for LCC analysis and the related results.

Although the concepts addressed in this work are well established in the literature, the novelty of this work lies in the integration of these frameworks into a single decision-support model. By linking RAM analysis with LCC evaluation, this study provides a unified approach to assess the economic impact of maintenance strategies, offering a practical tool for optimizing maintenance decisions based on both reliability metrics and cost considerations.

II. THE IMPORTANCE OF LIFE CYCLE COST ANALYSIS FOR REDUCING MAINTENANCE COSTS

LCC analysis plays a crucial role in industrial maintenance, particularly in reducing costs related to the upkeep, repair, and replacement of equipment. This comprehensive approach enables the integration of all expenses associated with a product or system throughout its entire life cycle, from design to decommissioning, including operational and maintenance phases [9]. In an industrial environment where maintenance costs represent a significant portion of operational expenditures, LCC analysis serves as a strategic tool that enables:

- A comprehensive cost evaluation: by extending beyond the traditional analysis of acquisition and repair costs, through the integration of production interruptions and productivity losses. This enables managers to plan targeted interventions, thus reducing future costs and enhancing preventive equipment maintenance management [10, 11].
- Optimization of maintenance strategies: by identifying the most cost-effective strategy through the comparison of different approaches, such as preventive, corrective, condition-based, and predictive [12].
- Compliance with environmental standards: by considering the costs related to waste management, energy consumption, and the ecological impact of equipment throughout its life cycle. This approach allows for the reduction of both maintenance costs and ecological footprint, while assisting companies in meeting regulatory standards.

III. THE IMPORTANCE OF RELIABILITY, AVAILABILITY, AND MAINTAINABILITY ANALYSIS FOR SELECTING THE MAINTENANCE TYPE

RAM analysis is important in selecting the maintenance strategy to be implemented. These three parameters are crucial for assessing the performance of equipment throughout its life cycle, and their study allows for the identification of the most suitable maintenance strategy based on the specific characteristics and requirements of industrial systems.

A. Reliability Analysis

A thorough reliability analysis enables the assessment of equipment failure probabilities and the identification of associated failure modes. Equipment with high reliability may justify the adoption of corrective maintenance, whereas less reliable equipment requires more frequent preventive maintenance interventions to reduce the risk of failures [13, 14].

B. Availability Analysis

Availability is intrinsically linked to the reliability and maintainability of equipment. High availability indicates that the equipment is rarely out of service [15], which influences the choice of maintenance strategy. In environments where availability is critical, such as in high-demand production industries, a condition-based or predictive maintenance strategy, focused on real-time monitoring of operating parameters, may be preferred to prevent unplanned interruptions.

C. Maintainability Analysis

Maintainability analysis enables the assessment of the speed and costs associated with the interventions required to restore equipment to an operational condition [16]. High maintainability implies that repairs are carried out quickly and at a lower cost, making corrective maintenance economically viable. In contrast, equipment that is difficult to maintain may justify the adoption of preventive or condition-based maintenance strategies, aimed at reducing production interruptions and optimizing the long-term performance of the equipment.

In summary, this analysis not only helps to reduce costs associated with failures and unplanned outages but also optimizes the management of maintenance resources [17], thereby ensuring effective and cost-efficient production continuity.

IV. PARAMETERS FOR ANALYZING THE IMPACT OF MAINTENANCE TYPE ON LIFE CYCLE COST

A. Reliability

Reliability calculation relies on statistical models that incorporate various parameters related to component wear and failures. The reliability function $R(t)$ represents this probability and is often determined using probability distributions, particularly the Weibull, exponential, or normal distributions [18].

1) Reliability with an Exponential Distribution

The exponential distribution is commonly used when it is assumed that failures occur at a constant rate [19]. The reliability function $R(t)$ is then given by (1):

$$R(t) = e^{-\lambda t} \tag{1}$$

where:

- λ is the constant failure rate;
- t is the elapsed time.

2) Reliability with a Normal Distribution

If it is assumed that the lifespan of a system follows a normal distribution, typically due to wear-out or aging effects, the reliability function is expressed as follows:

$$R(t) = \frac{1}{2}\left[1 + erf\left(\frac{t-\mu}{\sigma\sqrt{2}}\right)\right] \tag{2}$$

where:

- μ is the mean failure time;
- σ is the standard deviation of failure times;
- erf is the error function.

3) Reliability with a Weibull Distribution

The Weibull distribution is used to model the lifespan of a system due to its ability to describe various failure behaviors (constant, increasing, or decreasing) [20]. The reliability function is expressed as follows:

$$R(t) = e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}} \tag{3}$$

where:

- η is the scale parameter; it serves as a time-scaling factor that determines how quickly or slowly failures occur.
- β is the shape parameter ($\beta > 0$); it defines how the failure rate changes over time—$\beta > 1$ indicates an increasing rate, $\beta = 1$ a constant rate, and $\beta < 1$ a decreasing rate.
- γ is the location parameter ($-\infty < \gamma < +\infty$); it shifts the origin of the time scale, indicating the point where failures are expected to begin.

B. Availability

It is a key performance indicator of systems, combining both their reliability and their ability to be maintained in an operational state. The basic formula for calculating availability is as follows:

$$\text{Availability} = \frac{\text{Operating Time}}{\text{Total Time}} \tag{4}$$

where:

- Operating Time is the period during which the system is operational and performs its functions without failure;
- Total Time includes both the operating time and the downtime.

Availability can also be expressed in terms of Mean Time Between Failures (MTBF) and Mean Time to Repair (MTTR). These two parameters are crucial for evaluating a system's performance in terms of availability [21]. The formula for availability in terms of MTBF and MTTR is as follows:

$$\text{Availability} = \frac{\text{MTBF}}{\text{MTBF+MTTR}} \tag{5}$$

C. Maintainability

The calculation of maintainability relies on the evaluation of the MTTR, which represents the average time required to diagnose, repair, and return a system to service after a failure [22]. The MTTR is generally calculated as:

$$\text{MTTR} = \frac{\text{Total Repair Time}}{\text{Number of Failures}} \tag{6}$$

D. Kolmogorov-Smirnov Test

The Kolmogorov-Smirnov (K–S) test determines whether a sample follows a specific distribution [23]. It can be employed either to compare a sample with a known probability distribution (one-sample test) or to compare two distinct samples (two-sample test). This test is based on the maximum absolute difference between the Empirical Distribution Function (EDF) of the sample and the Cumulative Distribution Function (CDF) of the reference distribution.

The Kolmogorov-Smirnov statistic (D) is calculated as follows:

$$D = \sup_x |F_n(x) - F(x)| \tag{7}$$

E. Life Cycle Cost

LCC is a cost evaluation method that considers all expenses associated with a product, system, or project from its design phase to its disposal or end-of-life [24]. The formula for calculating the LCC encompasses all costs related to a product or system throughout its life cycle. The general formula for LCC is as follows:

$$LCC = C_{acquisition} + C_{operation} + C_{maintenance} + C_{end\ of\ life} \tag{8}$$

where:

- $C_{acquisition}$: Initial cost of acquiring or purchasing the product or system.
- $C_{operation}$: Costs related to the operation or use of the system (e.g., energy costs, consumables).
- $C_{maintenance}$: Maintenance and repair costs over the product's lifespan (including labor, spare parts, etc.).
- $C_{end\ of\ life}$: Costs associated with the product's end of life.

V. APPLIED METHODOLOGY FOR LIFE CYCLE COST ANALYSIS AND RELATED RESULTS

The adopted methodology compares the impact of corrective, preventive, and predictive maintenance strategies on the LCC of industrial equipment. It aims to identify the optimal strategy that minimizes costs while maintaining high equipment RAM. The analysis focuses on a fleet of industrial machines over a one-year time horizon, incorporating all relevant costs, including maintenance and downtime. The analysis parameters include RAM and LCC are evaluated in the initial state and after simulating different strategies. Technical and financial data were collected from maintenance reports and interviews with relevant operational and maintenance personnel. Figure 1 presents the methodology flow.

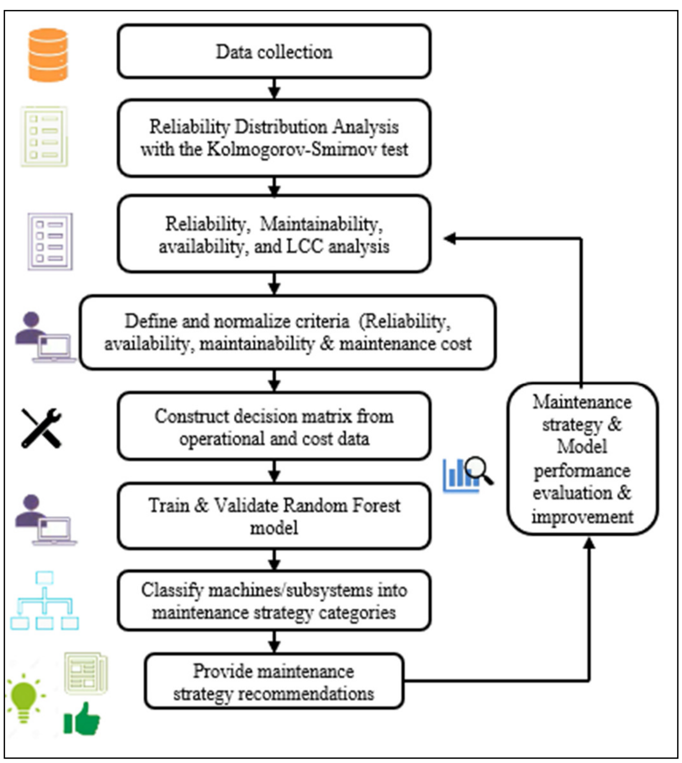


Fig. 1. The adopted methodology flow.

A. *Data Collection*

Historical failure data over one year were collected and systematically preprocessed to ensure accuracy and consistency. A total of 1,174 data points were collected over the full historical period considered in this study. Owing to the homogeneity of the 13 industrial automotive machines examined, the analysis focuses on spare parts referred to as "subsystems" and "units" that correspond to the most frequently replaced components. Nine common units were identified and selected as the basis for the comparative assessment.

B. *Reliability Distribution Analysis with the Kolmogorov-Smirnov Test*

To identify the most suitable reliability law, we examined the failure data using three commonly used statistical models in reliability engineering: exponential, Weibull, and normal. These models were selected due to their widespread use, with the Exponential and Weibull covering constant and variable failure rates, respectively, and the Normal serving as a baseline reference.

The K–S test was utilized to determine the most suitable reliability model by comparing the empirical failure data distribution with various theoretical distributions. Table I and Figure 2 present the K–S test results for the studied data.

TABLE I. RESULTS OF THE K–S TEST FOR THE STUDIED DATA

Distribution	K–S statistic	p-value
Normal	0.0807	0.0000
Exponential	0.1237	0.0000
Weibull	0.0377	0.0696

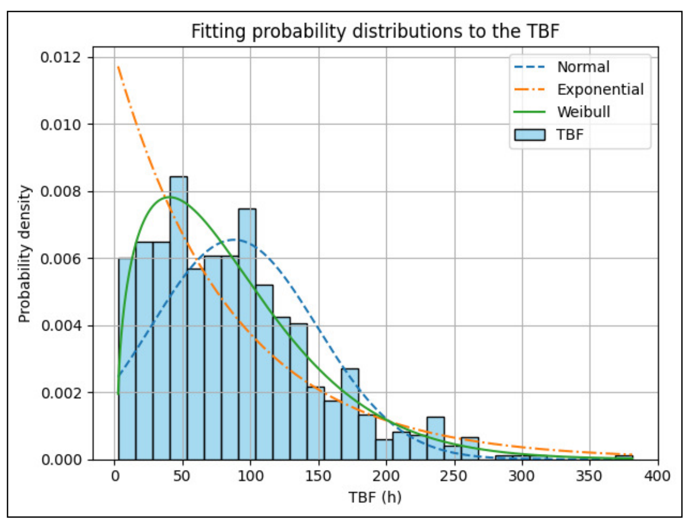


Fig. 2. Results of the K–S test for the studied data.

The K–S test was applied to assess the goodness-of-fit of three candidate distributions: Normal, Exponential, and Weibull. Results indicate that both the Normal and Exponential distributions are significantly rejected, as their p-values fall below the 0.05 threshold. In contrast, the Weibull distribution yields a K–S statistic of 0.0377 with a p-value of 0.0696, exceeding the significance level. This suggests no significant difference between the observed data and the Weibull distribution, making it the most appropriate fit among the distributions tested.

C. Reliability, Availability, and Maintainability and Life Cycle Cost analysis

1) Actual System Reliability

Building upon the reliability framework introduced previously, this section focuses on modeling the system's reliability using the Weibull distribution, which is widely recognized for its flexibility in representing various failure behaviors over time. The Weibull model is particularly suitable for industrial systems, as it can effectively characterize both early-life failures and wear-out periods depending on its shape parameter. This study conducts a reliability analysis for the nine important spare parts ("units"). The key parameters of the Weibull distribution (the shape (β), scale (η), and location (γ)) are estimated using the Maximum Likelihood Estimation (MLE) method, which ensures statistically robust parameter fitting based on the observed failure times. The likelihood function for a set of independent failure times $x_1, x_2,..., x_n$ following a three-parameter Weibull distribution [25] is given by:

$$L(\beta,\eta,\gamma) = \prod_{i=1}^{n} \frac{\beta}{\eta}\left(\frac{x_i-\gamma}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{x_i-\gamma}{\eta}\right)^{\beta}\right], \text{ for } x_i > \gamma \quad (9)$$

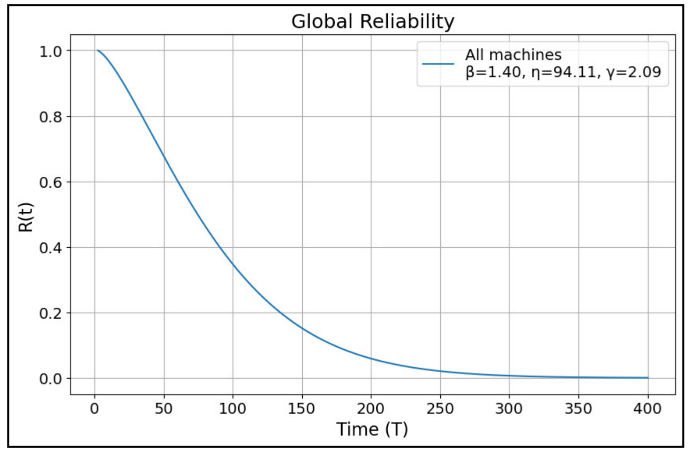
Taking the natural logarithm of the likelihood function yields the log-likelihood, which simplifies the optimization process:

$$\ln L(\beta,\eta,\gamma) = n\ln(\beta) - n\ln(\eta) + (\beta-1)\sum_{i=1}^{n} \ln(x_i-\gamma) - \sum_{i=1}^{n}\left(\frac{x_i-\gamma}{\eta}\right)^{\beta} \quad (10)$$

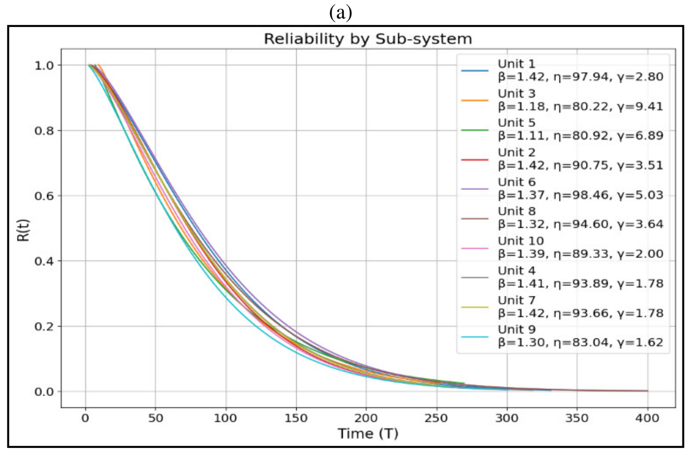
The estimation of the location parameter γ is particularly critical, as it determines the minimum failure-free period before the system or component begins to experience degradation. Once the parameters are estimated, the reliability function for each machine or subsystem can be derived using:

$$R(t) = e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}}, \text{ for } t > \gamma \quad (11)$$

Figures 3(a) and 3(b) present the current reliability. The reliability analysis results for the overall system, as well as for each machine and subsystem individually, were generated using Time-Between-Failures (TBF) data, providing a visual overview of how each element behaves over time. Machines and subsystems are classified based on the values of the three Weibull parameters: shape (β), scale (η), and location (γ). This approach reflects the actual reliability characteristics of the system more accurately than relying on a single parameter. By considering all three parameters, this classification offers a complete and realistic picture of the system's condition and supports better decision-making for maintenance planning, as illustrated in Figure 4.



(a)



(b)

Fig. 3. Global and by-unit current reliability: (a) global machine reliability, (b) reliability by subsystem (unit).

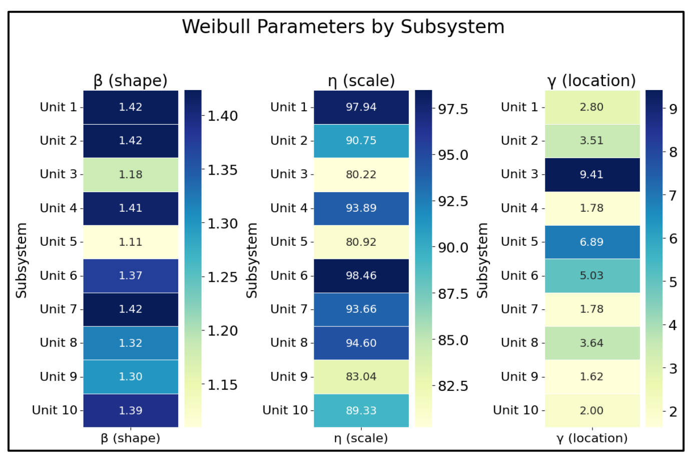
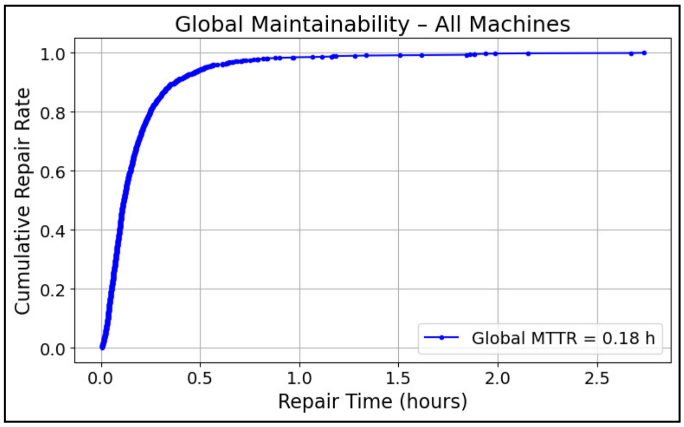


Fig. 4. Matrix of the three Weibull parameters by unit.

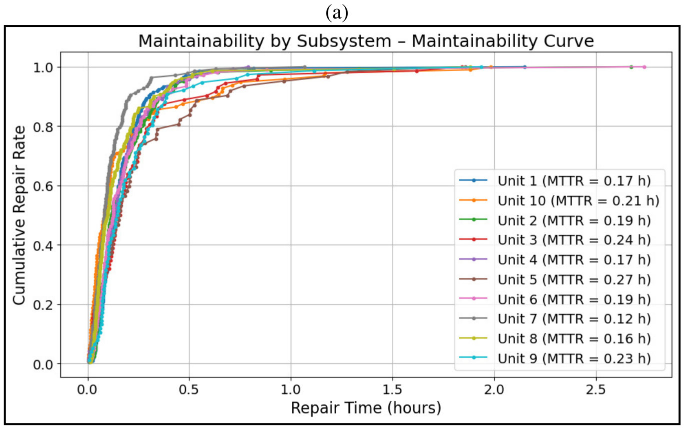
Most subsystems exhibit β (shape) values greater than 1, indicating an increasing failure rate and wear-out behavior over time. The η (scale) parameter, which represents the characteristic life, shows variability across subsystems, reflecting differences in their expected operating durations before significant failure probabilities arise. Regarding the γ (location) parameter, subsystems display a wide dispersion, suggesting heterogeneous minimum time thresholds before failures may occur. Overall, these findings highlight diverse reliability patterns among subsystems, emphasizing the need for tailored maintenance strategies adapted to each component.

2) Actual Maintainability

Figures 5(a) and 5(b) present the current system maintainability. The MTTR analysis shows that most subsystems have repair times between 0.16 h and 0.27 h. The global MTTR is 0.18 h. Unit 5 has the highest MTTR (0.27 h), suggesting slower repair processes. Unit 7 shows the lowest MTTRs, reflecting better maintainability. These results help identify areas needing maintenance improvement.



(a)



(b)

Fig. 5. Global and by-unit current maintainability: (a) global machine maintainability, (b) maintainability by subsystem (unit).

3) Actual Availability

Figure 6 presents the current system availability. The average availability varies between 81.06% and 89.07%, with a mean value of 84.83%. These metrics indicate a stable system performance, with room for targeted maintenance efforts to improve availability where it is lowest.

4) Actual Life Cycle Cost

This study aims to evaluate the average LCC of the studied machines over a ten-year operational period, considering the primary cost components associated with their acquisition and use. The analysis begins with the initial investment cost, estimated at €100,000 per machine. Installation costs typically range from 10% to 30% of the purchase price [26]; in this study, the lower bound of 10% is adopted, corresponding to the current actual installation cost for this type of machine.

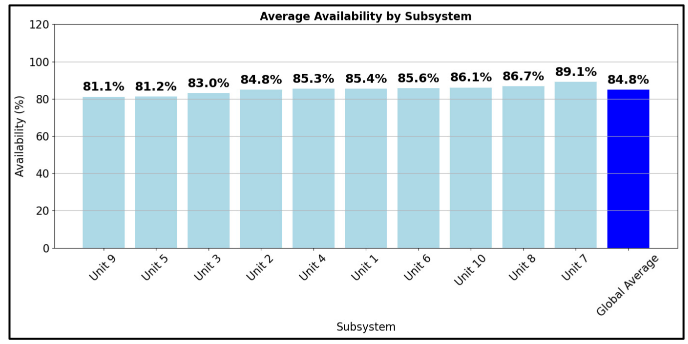


Fig. 6. Current availability by subsystem (unit).

The annual operating costs considered in the LCC model include only two components that have a direct and significant impact on the machine's total LCC: repair costs and downtime-related costs. Other cost elements, such as energy consumption, are excluded from the analysis because they are considered stable and non-significant in the context of the case study.

Based on this framework, the actual average LCC curve is generated with an uncertainty of €5,821, based on a Monte Carlo approach for the machines (Figure 7), derived from data collected in the industrial environment under study.

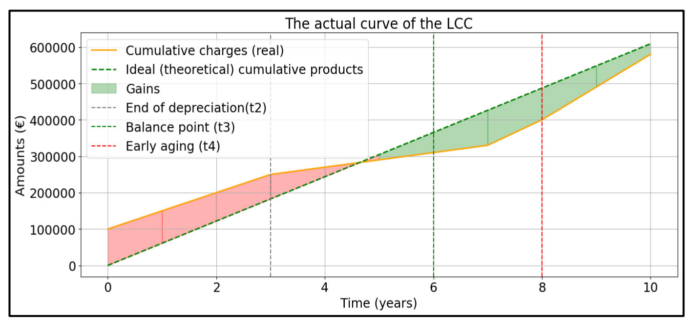


Fig. 7. Actual curve of the LCC.

D. Matrix for Maintenance Strategy Application

The approach is based on constructing a decision matrix that integrates key performance criteria—availability, reliability, maintainability—and the associated maintenance costs. This matrix serves as the foundation for structuring the decision problem and quantifying trade-offs between operational performance and economic considerations. A Random Forest classifier is then applied to the matrix data to identify patterns [27] and classify equipment into suitable maintenance strategy categories. The Random Forest classifier was chosen for its ability to handle complex, nonlinear data while maintaining high accuracy [28].

The dataset used in this study consists of historical maintenance intervention records capturing information such as failure types and intervention durations. The model's hyperparameters, including the number of trees, maximum depth, and minimum samples per leaf, were optimized using grid search. An 80%–20% train-test split was applied, and five-fold cross-validation was performed on the training set to ensure robustness. By combining structured decision modeling with a robust machine learning algorithm, the proposed method aims to enhance objectivity, accuracy, and consistency in the selection of maintenance strategies. In Figure 8, a comparison is shown between the current maintenance per subsystem and the proposed maintenance strategy by our machine learning model.

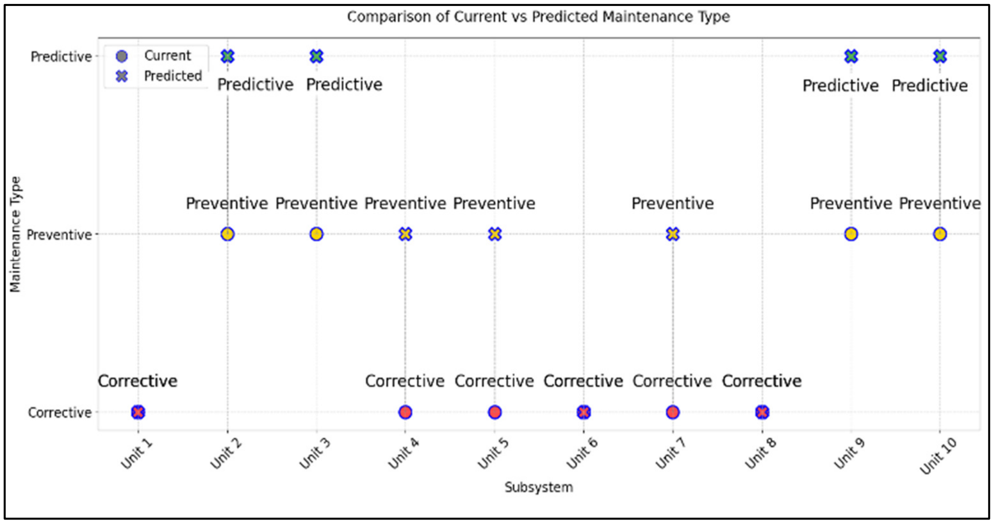


Fig. 8. Current maintenance per subsystem vs proposed maintenance strategy from the Random Forest model.

Based on the RAM analysis and total cost, the Random Forest model suggests a more targeted maintenance strategy. Units with high reliability and availability (Units 1, 6, 8) remain under corrective maintenance, indicating stability. Units with moderate risk (Units 4, 5, 7) shift from corrective to preventive to reduce unplanned downtime. Critical units with lower reliability and high costs (Units 2, 3, 9, 10) are recommended for predictive maintenance to optimize interventions. Overall, this approach enhances equipment availability, reduces costs, and prioritizes resources efficiently. It also provides a data-driven basis for decision-making, ensuring maintenance actions are aligned with the actual condition of each subsystem. By integrating this strategy with LCC analysis, the company can minimize total ownership costs while maximizing system reliability and performance.

E. Life Cycle Cost Simulation after Maintenance Type Assignment

To assess the economic implications of the revised maintenance strategies, a second LCC evaluation was conducted. This analysis was designed to quantify the effect of transitioning from corrective or preventive maintenance toward preventive, predictive, and optimized strategies on the total cost of ownership, including repair costs, downtime losses, and operational expenditures. By contrasting LCC values under the baseline and improved scenarios, the financial benefits associated with data-driven maintenance decisions were established. The purpose of this assessment is to demonstrate that targeted maintenance interventions not only enhance system RAM but also improve cost efficiency over the entire life cycle of the equipment. This approach provides a systematic framework for evaluating the return on investment derived from the adoption of appropriate maintenance strategies. A follow-up evaluation was performed six months after implementation to capture the measurable impact of the newly applied practices. The observed and estimated improvements are summarized in Table II.

TABLE II. OBSERVED AND ESTIMATED MTBF AND MTTR IMPROVEMENTS

Transition	MTBF improvement (%)	MTTR reduction (%)
Corrective → Preventive	+15	–10
Preventive → Predictive*	+20 (estimated)	–15 (estimated)

*Results currently under validation.

The results indicate that the transition from corrective to preventive maintenance yielded a 15% increase in MTBF and a 10% reduction in MTTR. Although the transition from preventive to predictive maintenance remains under validation, preliminary estimates suggest potential gains of 20% in MTBF and 15% in MTTR. As availability is mathematically dependent on MTBF and MTTR, these improvements imply a corresponding increase in operational availability. Figure 9 presents the recalculated global LCC with an uncertainty of €5,732, based on a Monte Carlo approach, highlighting the economic impact of the revised maintenance strategies.

F. Results and Discussion

The comparison between the old and new LCC shows a clear financial benefit from the improved maintenance strategy. Across the life cycle, the optimized approach generates cumulative savings of €49,000, with phase-by-phase reductions ranging from 1.2% to 2.6%, particularly during the operational phase (years 4–6), where annual savings reach €7,000. These gains result mainly from improved preventive actions and spare parts planning, which reduce downtime and corrective interventions. Although some phases show slightly higher short-term costs, these correspond to planned investments that prevent more expensive failures later in the life cycle. Overall, the numerical and graphical results confirm that the new strategy reduces total cost while improving cost stability, provided that operating conditions remain consistent.

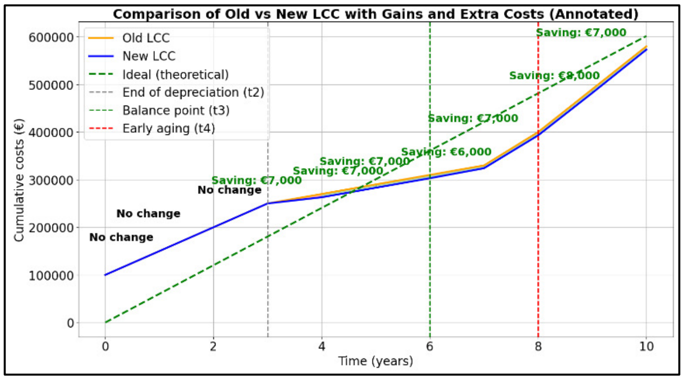


Fig. 9. Recalculated global LCC.

VI. CONCLUSION

This study provides quantitative evidence that the selection of maintenance strategy has a decisive impact on the Life Cycle Cost (LCC) of industrial assets. Results indicate that shifting from corrective to preventive maintenance reduces LCC by approximately 8–10%, driven by a 15% increase in Mean Time Between Failures (MTBF) and a 10% decrease in Mean Time to Repair (MTTR). Transitioning further to predictive maintenance yields an additional 12–18% reduction, with gains of about 20% in MTBF and 15% in MTTR. These findings, based on real operational data, reveal a clear downward trend in LCC as maintenance becomes more proactive.

However, strategy selection must align with asset criticality, complexity, and cost. Non-critical components may remain under corrective or preventive regimes, whereas critical systems benefit significantly from predictive approaches. Although predictive maintenance requires upfront investment in sensors, Internet of Things (IoT) infrastructure, and Artificial Intelligence (AI) analytics, it delivers substantial long-term value through higher reliability, minimized downtime, and improved decision-making.

To sustain these benefits, periodic reassessment of LCC using updated operational data is recommended. Future work should examine phased implementation strategies that prioritize the most critical assets and apply advanced reliability models, such as Weibull, Markov, or Monte Carlo methods, to enhance prediction accuracy. Ultimately, predictive maintenance should be regarded not merely as a technical solution but as a strategic enabler of Industry 4.0 transformation.

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