Cost -Oriented Predictive Maintenance using Exponential Degradation Modelling: Application on Manufacturing Industries

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Abstract—In the era of Industry 4.0, characterized by the seamless integration of Internet of Things (IoT) and advanced analytics, Predictive Maintenance (PdM) emerges as a transformative strategy, addressing the limitations of reactive maintenance approaches. PdM is a condition-based maintenance strategy that relies on monitoring equipment in real-time, with the aim of executing maintenance actions precisely when required avoiding unnecessary preventive measures or unforeseen failures. This study intends to develop a comprehensive PdM methodology that integrates Remaining Useful Life (RUL) estimation and economic performance assessment within a novel framework. An evolutionary algorithm is proposed to model and optimize the maintenance schedule for industrial equipment based on exponential degradation patterns and a RUL-based decision support tool to determine the optimal timing for maintenance activities. This methodological approach not only extends the intervals between maintenance operations, but also evaluates and compares the cost-effectives of the suggested PdM strategy with the current manufacturing industries practices, in order to improve operation efficiency and minimize costly downtime. A key feature of this research work lies in its real-world applicability, as the effectiveness of the proposed framework is assessed within an actual manufacturing system. The findings of this study can provide valuable insights on the importance of intelligent, economic-oriented PdM strategies to improve the industrial environment in terms of costs, control and quality of production.

Index Terms–Predictive maintenance, exponential degradation, remaining useful life, cost analysis.

I. INTRODUCTION

Maintenance plays a fundamental role in ensuring the efficient operation and extended lifespan of equipment in manufacturing industrial sectors. This importance arises from production systems being significantly affected by degradations and failures that can be caused by operational and environmental conditions. The implementation of effective maintenance strategies is, therefore essential, for minimizing downtime, maximizing productivity, and reducing overall operational costs.

The evolution of maintenance strategies in industrial sectors has progressed through distinct generations. The first generation, also referred to as Corrective Maintenance (CM), addressed equipment failures after they occurred. Industries during this period primarily relied on CM because the equipment was simple in design, and preventing potential failures was not a high priority. The second generation experienced increased machinery complexity and rapid production growth thus, leading to high maintenance costs. To overcome these challenges the planned Preventive Maintenance (PvM) was adopted. PvM is a proactive approach that involves scheduled inspections, servicing, and parts replacements to prevent failures. However, PvM faced criticism as overly cautious maintenance practices could disrupt normal operations and, thus, lead to malfunctions due to missed procedures [1].

The necessity of turning the manufacturing industries into predictive manufacturing industries to address the limitations of CM and PvM strategies, has motivated the present research effort. Predictive Maintenance (PdM) which overlaps with the scope of PvM in terms of scheduling maintenance activities in advance to avoid machine failures, has arose significant interest as a key component of the third generation of industrial maintenance [2]. The exponential growth of Internet of Things (IoT) devices and the massive amounts of data they generate have enabled the monitoring of equipment performance in real-time in order to predict trends, behavior patterns and correlations, with the aim of anticipating failures in advance to avoid equipment downtime. The joint application of IoT technologies and Artificial Intelligence (AI) methods in an industrial environment adds value to PdM process from the viewpoint of effectively monitoring and analyzing assets and equipment performance data in real-time. The development of intelligent industries is directly related to the precise prediction of maintenance requirements and the detection of failures, in order to optimize maintenance schedules and enhance operational efficiency [3].

In general, PdM processes are carried out in two main steps: (i) Remaining Useful Life (RUL) prediction and (ii) maintenance decision-making. The predictive capability allows for proactive maintenance scheduling based on anticipated component or system failures. The selection of the proper RUL prediction method strongly depends on the

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availability of data and the specific application requirements. For instance, in cases that there are no available historical data on component failures, degradation modeling can be applied for RUL prediction. This approach proves particularly effective when a distinct correlation exists between the degradation of a component condition indicator and the impending failure of the component. Degradation models often involve linear or exponential trends, which are applied to the historical degradation trajectory of the condition indicator. These models then calculate the remaining time until the indicator reaches a predefined threshold, providing valuable insights into the potential failure of the component [4], [5].

In recent years, studies have proposed data-driven and model-driven approaches for PdM, with specific focus on predicting equipment RUL using historical sensor data. The fundamental distinction between these PdM approaches lies in their underlying methodologies. Specifically, data-driven models employ advanced analytics techniques to identify patterns and correlations, while model-driven methods rely on physics-based principles or system knowledge to simulate the equipment behavior [6]. Si et al. (2013) [7] introduced a novel model-driven approach that combines Bayesian updating with the expectation maximization (EM) algorithm in order to continuously update the model parameters and the corresponding RUL distribution calculations. The proposed approach lies in precise probability distribution formulations in both linear and exponential degradation scenarios, thus resulting in more accurate predictions compared to previous approximated methods. Anis (2018) [8] proposed a model-driven approach that utilizes the exponential degradation model to predict the RUL of a rotating shaft, also considering noise variation. A similar study was carried out by Bejaoui et al. (2020) [9], who used the exponential degradation model to predict the degradation pattern and estimate the RUL of a faulty rotor. Their findings outlined the effectiveness in estimating the system's RUL once degradation is detected.

Although numerous published works have been dedicated to the prediction of the RUL of industrial equipment/assets, there are rather limited studies that identify the relationship between operational efficiency and cost parameters. Gilabert et al. (2017) [10] employed Monte Carlo simulation to explore the effect of selecting the optimal maintenance strategy (CM, PvM or PdM) on cost-effectiveness. Florian et al. (2021) [11] provided more concise information on the cost-effectiveness of ML-based PdM compared to existing maintenance strategies. A comprehensive cost model was developed and integrated into a Decision Support System (DSS) to streamline the PdM implementation. The models were applied in a real-world critical process industry scenario. It was found that the optimized maintenance strategy could result in significant cost savings; 54% and 36%, in particular, compared to corrective preventive maintenance, respectively. This study intends to provide a robust data-driven PdM methodological framework that leverages the exponential degradation model. The main contribution of this study is that it builds a historical data-dependent RUL model, that optimizes the maintenance scheduling with minimum cost, while also integrating real-time data for accurate and timely predictions. To this end, the economic viability of the suggested PdM processes is investigated and compared with the corresponding one of the current maintenance strategies applied in manufacturing industry. A dedicated decision support tool is also established that incorporates cost parameters and RUL prediction estimations, to account for the positive ideal (or negative) scenarios. An additional contribution of this study is that it is applied and validated on an existing equipment, namely, CO_2 evaporator, in a brewery facility located in Greece. It is envisaged that the proposed holistic cost-oriented, degradation-based PdM framework could be adapted in different industries for optimizing equipment health in a cost-competitive manner.

II. REMAINING USEFUL LIFE ESTIMATION

The estimation of Remaining Useful Lifetime (RUL) plays a significant role in ensuring the proper functioning and maintenance of a system. RUL refers to the duration of time an asset or component is anticipated to continue functioning within acceptable performance limits before it becomes unreliable or unusable [12]. The main challenge of RUL prediction lies in the fact that RUL labels are often absent in the training dataset, rendering supervised ML algorithms unusable. To tackle this challenge, a health index should be precisely defined and interpolated to establish the correlation between features and RUL. Following this interpolation, a data-driven or model-based approach can be employed to predict the health index by effectively learning from the interpolated data.

A. Exponential Degradation Model

The exponential degradation model is a widely applied data-driven method for predicting equipment failure. It assumes that the equipment degradation rate is proportional to the remaining life of the equipment. In other words, the more degraded the equipment is, the faster it will continue to degrade. According to the degradation modeling approaches proposed by Lu and Meeker (1993) [13] and Wang (2000) [14], the errors in the degradation signal are considered to be independent and identically distributed (iid). An example of an exponential degradation signal with iid errors is illustrated in Figure 1. This assumption has been widely validated in previous studies [15], [16] highlighting the effectiveness of the exponential model in predicting equipment failure. Consistent with this assumption, the current study also considers exponential degradation signals with iid errors to effectively model and analyze equipment degradation.

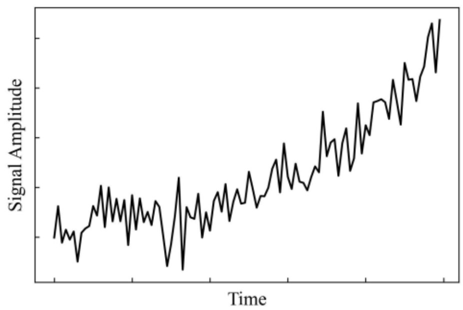

Figure 1: Typical Degradation Signal with iid Errors

B. Exponential Degradation Signal Model

The degradation signal, denoted by $S(t)$, represents the critical indicators of a system, and it can be considered as a continuous stochastic process with respect to time t. The degradation signal is observed at discrete points in time, $t1, t2, \dots, tn$ depending on the frequency of the monitoring process. The mathematical model for degradation-based signals, as proposed by Gebraeel et al. [5], reads:

$$S(t) = \varphi + \theta(t) \cdot exp\left(\beta(t) \cdot t + \varepsilon(t) - \frac{\sigma^2}{2}\right) \qquad (1)$$

Where φ is a known constant denoted as the model's intercept, θ is a random variable modeled as a lognormal distribution, β is a Gaussian random variable and ε is a random error term that follows a normal distribution with zero mean and σ^2 variance.

C. Data Acquisition and Preprocessing

In data-driven PdM models, the acquisition and preprocessing of sensor data are required to ensure accurate and reliable RUL estimations. By leveraging the opportunities provided by the growth of IoT devices, the data collection process involves continuous monitoring of parameters that contribute to potential system failures. Upon collecting the necessary parameters, these data are subjected to preprocessing and analysis to extract valuable insights that inform maintenance decision-making and assess the RUL of the systems. Without proper preprocessing, noisy and irrelevant data can skew the results and lead to incorrect estimations of the RUL.

The initial step in data acquisition focuses on feature selection, which aims to identify those parameters that are directly associated with equipment degradation. The identification of the most relevant features intends to reduce the dimensionality of the problem, by concentrating exclusively on the key factors that significantly affect the system's performance [17]. Various methods have been reported in the relevant literature for feature selection, including: (i) statistical techniques, such as correlation analysis, (ii) ML algorithms, such as recursive feature elimination and (iii) domain knowledge-driven approaches [17]. In this study, feature selection is conducted based on the experience and expertise of maintenance personnel who have a deep understanding of the equipment and its degradation patterns. By incorporating their insights, the study prioritizes and selects critical indicators that serve as robust indicators of the equipment's degradation. This personalized approach ensures alignment with real-world observations and practical knowledge.

Once the relevant features are identified, the next step focuses on maintaining a consistent scale across these features. In this study, the Standard Scaler normalization technique is utilized, scaling the data to have zero mean and unit variance. This widely adopted technique ensures that subsequent analyses are not influenced by differences in the magnitude of the features, and it is applied as follows:

$$x_{normalized} = \frac{x - mean}{standard\ deviation} \qquad (2)$$

Where $x_{normalized}$ is the standardized value, x is the original value of the critical indicator, while $mean$ and $standard\ deviation$ are the mean and standard deviation of the entire dataset, respectively.

In cases that a system's degradation is strongly affected by multiple parameters/indicators, their combination into a single parameter, is suggested to simplify the high-dimensional dataset. The main objective of this approach, also referred to as dimensionality reduction, is to decrease data complexity. Principal Component Analysis (PCA) is a popular linear dimensionality reduction technique, that involves the transformation of the original high-dimensional sensor data into a lower-dimensional space without losing important information. The PCA aims to find a set of orthogonal linear combinations of the initial monitoring parameters, referred to as principal components (PCs), which capture the maximum amount of variation in the data. The implementation of PCA involves the computation of the eigenvalues and eigenvectors of the covariance matrix. The eigenvectors are then used to transform the data into the lower-dimensional space of principal components. The first PC captures the most significant variation in the data, and it is referred as the primary health indicator (HI), while each subsequent PCs capture the next most significant variation in descending order [18]. In general, a sufficient number of PCs should be retained to account for at least 70-80% of the total variation in data [19]. The transformed data can then be analyzed using conventional statistical techniques to identify patterns and relationships that were not apparent in the original high-dimensional dataset.

D. Least Squares Regression

After identifying the first PC as the primary HI of the system, the least squares regression approach is applied to estimate the parameters of the exponential degradation model. Least squares regression involves the minimization of the sum of squared residuals between the actual (Y_{actual}) and predicted ($Y_{predicted}$) values of the critical indicators to find the best-fit parameters of the signal. By iteratively adjusting the model parameters, the least squares regression method finds the best-fit parameters that minimizes the prediction errors and provide the closest approximation to the observed data [equation (3)].

$$minimize \sum \left(Y_{actual} - Y_{predicted}\right)^2 \qquad (3)$$

Once the parameters of the exponential degradation model are estimated, a trendline that represents the degradation of the system can be generated. In Figure 2, the blue line depicts the trendline obtained from the exponential degradation model. This trendline visually represents the expected deterioration pattern of the equipment over time based on the estimated model parameters. The trendline serves as a valuable tool for monitoring the health of the system, and it is continuously updated as new observations of the critical monitoring parameters become available. This approach ensures consistency and accuracy in capturing the evolving degradation patterns.

E. Remaining Useful Life Estimation

After identifying the degradation parameters, the exponential degradation model is applied to estimate the RUL. A significant advantage of this specific model is that it eliminates the need for extensive data required for RUL prediction. Specifically, RUL prediction exploits historical data of equipment operation instead of relying on data from current equipment operation until failure occurrence. This approach allows for RUL predictions by extrapolating the degradation trend and comparing it with a predefined failure threshold.

The prediction of the RUL of a system relies on mathematical expressions derived from the degradation signal, as defined in equation (1). Equations (4) and (5) are employed to determine the failure time interval, which involves the assessment of the total lifespan of the equipment, or the time required for the degradation signal to reach the failure threshold. Through logarithmic functions, the equipment's total life can be accurately estimated. To obtain the RUL of the system, equation (6) is utilized. It involves subtracting the current state, represented by the observed time, from the total life determined through equation (5). The resulting value represents the remaining lifespan of the equipment at a given point in time.

$$threshold = \varphi + \theta \cdot exp\left(\beta \cdot t + \varepsilon - \frac{\sigma^2}{2}\right) \quad (4)$$

$$t = total\ life = \left(ln\frac{threshold\ - \varphi}{\theta} - \varepsilon + \frac{\sigma^2}{2}\right)/\beta \quad (5)$$

$$RUL = total\ life - current\ state\ (time) \quad (6)$$

Figure 2 illustrates the process of estimating the RUL of a component using the exponential degradation model. It demonstrates the extrapolated degradation trend, the predefined failure threshold and the RUL calculation based on the estimated total life and the current observed cycle.

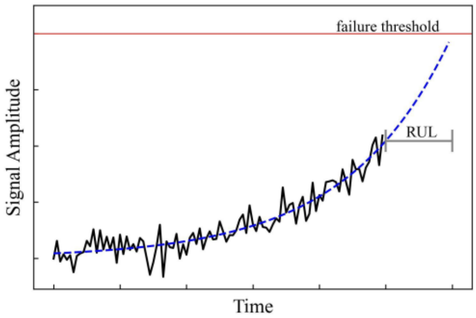

Figure 2: Exponential Degradation Fit and RUL Prediction

III. COST ANALYSIS

This study aims to assess the cost-effectiveness of the proposed PdM approach by conducting a comparative analysis against prevalent maintenance strategies in industrial sectors. A hybrid maintenance strategy that incorporates corrective & preventive measures is commonly applied in manufacturing industries, including the one considered in the present research work. The cost function for the proposed hybrid strategy is expressed as follows:

$$C_{CURRENT} = C_{CM} + C_{PvM} \quad (7)$$

Where, C_{CM} and C_{PvM} represent the total cost (€) of corrective and preventive maintenance, respectively.

A. Corrective Maintenance

Corrective maintenance (CM) involves repairing or replacing faulty equipment post-failure and comprises either planned or unplanned maintenance. Planned CM is a scheduled activity that is performed after the identification of the system's failure, in order to allow deferred repairs without immediate harm to operations. On the other hand, unplanned CM is a reactive activity that addresses unexpected failures urgently, potentially causing downtime and lost productivity. The cost function of CM reads:

$$C_{CM} = UEC_{CM_{UP}}N_{CM_{UP}} + UEC_{CM_P}N_{CM_P} + C_{INSP_{CM}} \quad (8)$$

Where $UEC_{CM_{UP}}$ is the cost (€/year) of an unplanned CM, $N_{CM_{UP}}$ is the annual number of unplanned maintenance failures, UEC_{CM_P} is the cost (€/year) of a planned CM, N_{CM_P} is the annual number of planned CM instances and $C_{INSP_{CM}}$ is the annual inspection cost (€/year) associated with CM. The cost per failure for unplanned and planned maintenance is determined as:

$$C_{CM_{UP,P}} = C_{L_{CM_{UP,P}}}t_{L_{CM_{UP,P}}} + C_{SP_{CM_{UP,P}}} + C_{PL_{CM_{UP,P}}}t_{L_{CM_{UP,P}}} \quad (9)$$

Where $C_{L_{CM_{UP,P}}}$ is the labor cost (€/h) associated with each CM, $C_{SP_{CM_{UP,P}}}$ is the cost of the spare parts (€/year), $C_{PL_{CM_{UP,P}}}$ is the cost of production losses (€/h) and $t_{L_{CM_{UP,P}}}$ is the duration (h) of the maintenance action, usually referred to as mean time to repair (MTTR). Index P refers to planned CM costs, while index UP refers to unplanned CM expenses.

B. Preventive Maintenance

Preventive maintenance (PvM) is a proactive approach for maintaining equipment and systems, designed to prevent potential failures and reduce the likelihood of downtime. It involves regularly inspecting, cleaning, and servicing equipment to keep it in optimal working condition. The specific maintenance approach includes lubricating moving parts and replacing worn components. The cost function of PvM is expressed as:

$$UEC_{PvM} = C_{PvM} \cdot N_{PvM} + C_{INSP_{PvM}} \quad (10)$$

$$C_{PvM} = C_{L_{PvM}} \cdot t_{L_{PvM}} + C_{SP_{PvM}} + C_{PL_{PvM}} \cdot t_{L_{PvM}} \quad (11)$$

Where UEC_{PvM} is the annual PvM cost (€/year), C_{PvM} is the PvM cost (€) per failure, N_{PvM} is the annual number of PvM instances, $C_{INSP_{PvM}}$ is the inspection cost (€/year) related to PvM, $C_{L_{PvM}}$ is the labor cost (€/h), $C_{SP_{PvM}}$ is the cost (€/year) associated with the materials, $C_{PL_{PvM}}$ is the cost (€/h) due to production losses and $t_{L_{PvM}}$ is the average duration (h) of a PvM action.

C. Predictive Maintenance

PdM, as a strategy that relies on optimization techniques, incurs additional costs compared to traditional maintenance approaches. The PdM implementation requires the installation and development of an Information Technology (IT) infrastructure to support the exponential degradation model. Therefore, the data-driven PdM strategy includes both an investment cost for the IT technology and operating costs associated with maintenance actions, which are closely linked to the performance of the model. The investment cost for the IT infrastructure may include hardware, software, and personnel costs. In addition, the ongoing operating costs for PdM are driven by data acquisition and processing, model updating, and maintenance action implementation. Although PdM may require additional investment, it can provide significant benefits, such as reduced downtime, improved equipment reliability and increased operational efficiency. It is evident that the decision to adopt a PdM strategy should be based on a careful evaluation of the potential costs and benefits associated with this approach. The cost of the PdM strategy is defined as:

$$UEC_{PdM} = C_{INV} + C_{PvM} \cdot N_{PdM} + C_{FA} \tag{12}$$

Where UEC_{PdM} is the total unitary cost (€/year) for the implementation of the PdM, C_{INV} is the annual investment cost (€/year), N_{PdM} refers to the annual number of PdM instances and C_{FA} is the false alarm cost (€/year) associated with the performance of the model.

D. False Alarm

The integration of ML or statistical models into a maintenance strategy can enhance equipment efficiency and minimize downtime. However, inaccurate predictions of optimal maintenance times can lead to false alarms. In statistics, false alarms are classified into four categories: (i) true positive, (ii) true negative, (iii) false positive, and (iv) false negative. The positive and negative category represent the actual state of the system, while the true and the false ones refer to the performance of the PdM model. More specifically, true negatives occur when the model correctly predicts that maintenance is required when the component is not functioning efficiently. On the contrary, a false negative occurs when the model fails to predict the maintenance requirement when it is necessary. A true positive occurs when the component is working efficiently, and the model correctly predicts this state. A false positive arises when the component is functioning efficiently, but the model predicts that maintenance is required, leading to unnecessary maintenance [20].

The cost of a false alarm in the proposed PdM strategy is influenced by the Estimated Lifetime (ELT) of a component and the timing of PvM implementation. Specifically, if the ELT is shorter than the time interval between two PvM actions, the cost of the false alarm considers that additional maintenance actions will be carried out throughout the year, resulting in higher maintenance expenses. Conversely, if the ELT of the component is longer than the time interval between two scheduled PvM, this cost is linked to the likelihood of equipment breakdown, considering the potential consequences. It is evident that the cost of a false alarm depends on different factors, including the PvM timing, the ELT, and potential breakdown consequences, and it is expressed as follows:

$$C_{FA} = C_{CM_{UP}} \cdot N_{PdM} \cdot n \tag{13}$$

Where n is a binary variable dependent on the connection between the estimated lifespan of the component under investigation and the time interval between two scheduled PvM and it is defined as follows:

$$n = \begin{cases} 0 \; if \; ELT < T_{PvM} \\ 1 \; if \; ELT > T_{PvM} \end{cases} \tag{14}$$

E. Predictive Maintenance Optimization

The exponential degradation model presented in this study serves as the basis for investigating both the optimal conditions and the cost-effectiveness of the application of the proposed PdM approach. The algorithm developed compares the overall costs of the proposed PdM approach with those of the existing maintenance strategies, namely preventive and corrective maintenance. The PdM optimization process unfolds in the following sequence, as illustrated in Figure 3:

Step 1: Gather sensor data associated with critical system parameters for the development of the exponential degradation model.
Step 2: Estimate the system's ELT by leveraging historical data and continuous monitoring.
Step 3: Compare the estimated ELT with the time interval between consecutive PvM interventions (T_{PvM}).
Step 4: Based on the comparison results, determine the type of maintenance intervention.
Step 5: Evaluate the cost associated with the selected maintenance intervention.
Case a: If ELT exceeds PvM time interval, the cost of a false alarm pertains to potential CM expenses due to inaccurate ELT prediction.
Case b: If the ELT falls short of the PvM time interval, the cost of the false alarm encompasses extra maintenance expenses arising from unnecessary interventions.
Step 6: Compare the PdM cost calculated in Step 5 with the cost associated with the current maintenance strategy to determine whether PdM presents a more cost-effective approach.

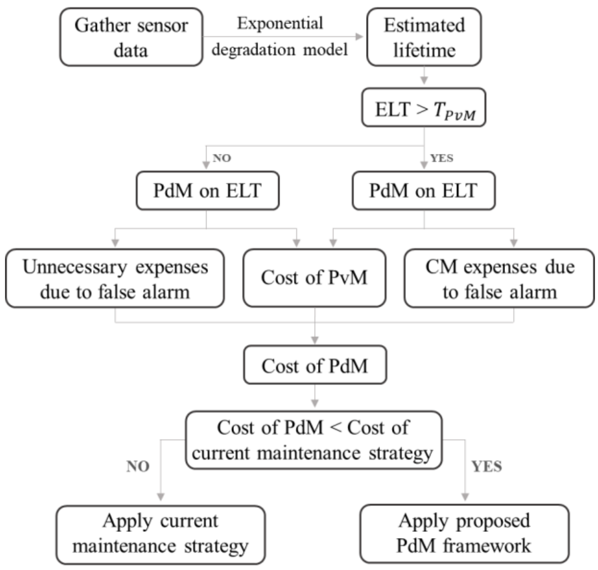

Figure 3: Comparative Cost Analysis Flowchart

IV. CASE STUDY

The proposed PdM optimization process undergoes validation retrieving historical data from a brewing facility in Greece. The CO_2 evaporator was selected for adapting the PdM process, as it is a critical component in beverage production due to its high capital investment and the potential for significant production disruptions if malfunctions occur. In collaboration with the industry's maintenance engineers, three critical parameters are selected for the monitoring process: (i) the outlet temperature of heated oil, (ii) the outlet temperature of gasified CO_2, and (iii) the outlet pressure of gasified CO_2. These parameters exhibit a degradation trend; the relevant stablished threshold values determined by the demo site are - 90ºC, 60ºC and 18bar, respectively. Figure 4 displays the historical data for these parameters over a one-year period.

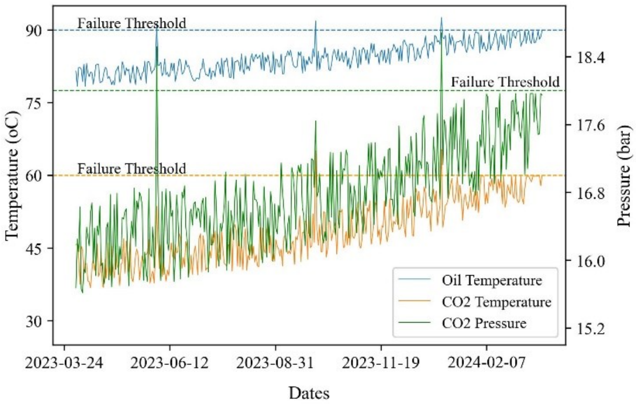

Figure 4: Critical Parameters: One-Year Overview

After identifying the three critical parameters for characterizing the system degradation, the PCA method is employed to derive the primary health indicator (HI) and simplify further analysis. The primary HI efficiently captures 81% of the relevant information from these three parameters. This primary HI is then incorporated into the exponential degradation model, yielding an 83% R-squared value through the least square optimization. Figure 5 depicts the primary HI of the CO_2 evaporator, alongside the corresponding extracted degradation signal. The estimated degradation parameters are utilized in equations (5) and (6) to estimate the RUL of the CO_2 evaporator. Based on the most recent observations, the system's RUL is anticipated to be 16 days.

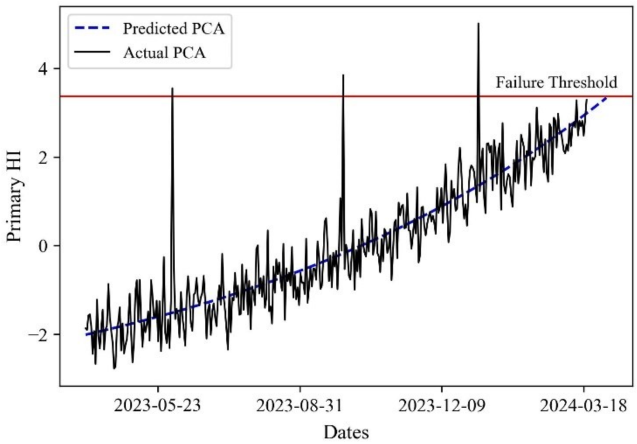

Figure 5: Primary HI and Degradation Signal

To evaluate potential cost savings, a comparison is conducted between the cost of the current maintenance strategy and that of the proposed PdM framework. Technical and economic parameters related to the current maintenance of the CO_2 evaporator are summarized in Table I. The technical parameters involve maintenance-related metrics, such as MTTR and the annual number of failures associated with the maintenance strategies currently employed. Economic parameters include labor costs, spare parts costs, and production losses associated with the different maintenance strategies. Notably, the two maintenance activities carried out for the CO_2 evaporator are unplanned CM or breakdown and PvM. The application of the cost equations indicate that the annual maintenance cost of the CO_2 evaporator reaches 108,695 €.

To implement the proposed PdM framework, the CO_2 evaporator was equipped with metering sensors for the monitoring of the critical parameters. Thus, the investment cost related to the IT infrastructure entails exclusively the installation of a platform to serve as the local/edge data platform, and it is estimated at 1,500 €. It should be noted that this platform enables the interconnection between the facility's monitoring infrastructure, the Supervisory Control and Data Acquisition (SCADA) system, and a distributed event streaming platform. Computational results show that the application of the suggested PdM framework could result in notable cost savings (approximately 11%).

TABLE I. Technical and Economic Maintenance Parameters

Strategy	Parameter	Value
CM	MTTR (hrs/failure)	*8*
	Number of failures/year	*3*
	Labor cost (€/year)	*95*
	Spare parts cost (€/year)	*840*
	Production losses cost (€/year)	*52,800*
PvM	MTTR (hrs/failure)	*64*
	Number of failures/year	*1*
	Labor cost (€/year)	*160*
	Spare parts cost (€/year)	*160*
	Production losses cost (€/year)	*54,740*

V. CONCLUSIONS

This study presents an effective PdM algorithm that utilizes exponential degradation patterns to estimate the RUL of industrial equipment through the monitoring of critical health indicators. The key advantage of the proposed model is that it improves the RUL's predictive reliability and applicability across diverse manufacturing systems, by providing more statistical information based on historical data up to the present. An additional contribution of this study is the introduction of a cost-oriented decision support tool that compares the economic viability of the PdM strategy against current maintenance techniques. The efficacy of the proposed model is assessed by applying it to a real-world industrial equipment. Computational results suggest that implementing the proposed PdM approach could lead to notable cost savings and, at the same time, improve operational efficiency and the availability of production systems.

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REFERENCES

[1] N. S. Arunraj and J. Maiti, "Risk-based maintenance-Techniques and applications," *J. Hazard. Mater.*, vol. 142, no. 3, pp. 653–661,

2007, doi: 10.1016/j.jhazmat.2006.06.069.

[2] L. Pintelon and A. Parodi-Herz, "Maintenance: An Evolutionary Perspective," *Springer Ser. Reliab. Eng.*, vol. 8, pp. 21–48, 2008, doi: 10.1007/978-1-84800-011-7_2.

[3] T. Zonta, C. A. da Costa, R. da Rosa Righi, M. J. de Lima, E. S. da Trindade, and G. P. Li, "Predictive maintenance in the Industry 4.0: A systematic literature review," *Comput. Ind. Eng.*, vol. 150, no. August, p. 106889, 2020, doi: 10.1016/j.cie.2020.106889.

[4] N. Gebraeel, "Sensory-updated residual life distributions for components with exponential degradation patterns," *IEEE Trans. Autom. Sci. Eng.*, vol. 3, no. 4, pp. 382–393, 2006, doi: 10.1109/TASE.2006.876609.

[5] N. Z. Gebraeel, M. A. Lawley, R. Li, and J. K. Ryan, "Residual-life distributions from component degradation signals: A Bayesian approach," *IIE Trans. (Institute Ind. Eng.*, vol. 37, no. 6, pp. 543–557, 2005, doi: 10.1080/07408170590929018.

[6] M. Bennett, E. J. Kleczyk, K. Hayes, and R. Mehta, "Evaluating Similarities and Differences between Machine Learning and Traditional Statistical Modeling in Healthcare Analytics," pp. 1–15, 2022, doi: 10.5772/intechopen.105116.

[7] X. S. Si, W. Wang, M. Y. Chen, C. H. Hu, and D. H. Zhou, "A degradation path-dependent approach for remaining useful life estimation with an exact and closed-form solution," *Eur. J. Oper. Res.*, vol. 226, no. 1, pp. 53–66, 2013, doi: 10.1016/j.ejor.2012.10.030.

[8] M. D. Anis, "Towards remaining useful life prediction in rotating machine fault prognosis: An exponential degradation model," in *2018 Condition Monitoring and Diagnosis (CMD)*, 2018. doi: 10.1109/cmd.2018.8535765.

[9] I. Bejaoui, D. Bruneo, and M. G. Xibilia, "A Data-Driven Prognostics Technique and RUL Prediction of Rotating Machines Using an Exponential Degradation Model," *7th Int. Conf. Control. Decis. Inf. Technol. CoDIT 2020*, pp. 703–708, 2020, doi: 10.1109/CoDIT49905.2020.9263930.

[10] E. Gilabert, S. Fernandez, A. Arnaiz, and E. Konde, "Simulation of predictive maintenance strategies for cost-effectiveness analysis," *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.*, vol. 231, no. 13, pp. 2242–2250, 2017, doi: 10.1177/0954405415578594.

[11] I. Florian, Eleonora; Sgarbossa, Fabio; Zennaro, "Machine learning-based predictive maintenance: A cost-oriented model for implementation," *Int. J. Prod. Econ.*, vol. 236, no. 108114, 2021, doi: 10.1016/j.ijpe.2021.108114.

[12] C. Okoh, R. Roy, J. Mehnen, and L. Redding, "Overview of Remaining Useful Life prediction techniques in Through-life Engineering Services," *Procedia CIRP*, vol. 16, pp. 158–163, 2014, doi: 10.1016/j.procir.2014.02.006.

[13] C. J. Lu and W. O. Meeker, "Using degradation measures to estimate a time-to-failure distribution," *Technometrics*, vol. 35, no. 2, pp. 161–174, 1993, doi: 10.1080/00401706.1993.10485038.

[14] W. Wang, "A model to determine the optimal critical level and the monitoring intervals in condition-based maintenance," *Int. J. Prod. Res.*, vol. 38, no. 6, pp. 1425–1436, 2000, doi: 10.1080/002075400188933.

[15] Y. Shao and K. Nezu, "Prognosis of remaining bearing life using neural networks," *Proc. Inst. Mech. Eng. Part I, J. Syst. Control Eng.*, vol. 214, no. 3, pp. 217–230, 2000, doi: 10.1243/0959651001540582.

[16] Y. Zhang and A. Wang, "Remaining Useful Life Prediction of Rolling Bearings Using Electrostatic Monitoring Based on Two-Stage Information Fusion Stochastic Filtering," *Math. Probl. Eng.*, vol. 2020, no. 6, pp. 1–12, Mar. 2020, doi: 10.1155/2020/2153235.

[17] I. Guyon, S. Gunn, M. Nikravesh, and L. Zadeh, *Feature Extraction*, vol. 207. in Studies in Fuzziness and Soft Computing, vol. 207. Berlin, Heidelberg: Springer Berlin Heidelberg, 2006. doi: 10.1007/978-3-540-35488-8.

[18] J. Jolliffe, Ian T; Cadima, "Principal component analysis: a review and recent developments," *Philos. Trans. A. Math. Phys. Eng. Sci.*, vol. 374, no. 2065, 2016, doi: 10.1098/rsta.2015.0202.

[19] I. T. Jolliffe, *Principal Component Analysis*. in Springer Series in Statistics. New York, NY: Springer New York, 1986. doi: 10.1007/978-1-4757-1904-8.

[20] S. Spiegel, F. Mueller, D. Weismann, and J. Bird, "Cost-Sensitive Learning for Predictive Maintenance," pp. 1–18, 2018.