Estimation of Remaining Useful Life of Equipment and its Role in the Optimization of Predictive Maintenance

Bouchra Abouelanouar[1*], *and Abdeslam Lachhab*[1]

[1]Modeling, Materials and Systems Control Research Team, ESTM, University of Moulay Ismail. Meknes, Morocco

Abstract. In predictive maintenance, estimating the remaining useful life (RUL) of equipment and machines is essential to plan maintenance, optimize efficiency and avoid unplanned downtime. RUL refers to the estimated duration an asset can continue to operate effectively before it requires repair or replacement. It serves as a key indicator for optimizing maintenance schedules, improving asset utilization, and sustaining overall plant efficiency. In the manufacturing industry, where even minor disruptions can result significant production losses, reliable RUL estimation is crucial for maintaining workflow continuity and product quality. This study highlights the crucial importance of estimating RUL in manufacturing systems, reviews recent advances in prognostic methodologies and addresses the limitations of purely data-based or physics-based approaches by proposing a hybrid RUL estimation framework. The proposed method integrates statistical reliability measures to allow more accurate and robust predictions in dynamic industrial environments. The results obtained validate the proposed methodology and demonstrate its effectiveness in improving the accuracy and robustness of the RUL estimation.

1 Introduction

Maintenance is one of the most critical factors for any manufacturing process due to the fact of keeping the execution time high with optimal operational efficiency. By preventing unexpected equipment failures, maintenance minimizes production downtime, maintains consistent product quality, and extends the lifespan of machinery. The planning of the various maintenance operations, whether preventive, corrective or conditional and reactive, consists in establishing a provisional schedule of maintenance work, determining the tasks to be performed, the necessary resources, deadlines and priorities [1]. However, with the advent of sensors and algorithms, as well as AI techniques, many organizations are adopting predictive maintenance (PdM) to identify maintenance needs in advance and estimate the operational life of the machine in advance.

* Corresponding author:b.abouelanouar@umi.ac.ma

In fact, PdM is a proactive maintenance strategy that uses real-time data and analytics to predict when equipment failure might occur, allowing maintenance to be performed just before a problem arises. Remaining Useful Life (RUL) is a key metric used within this approach, representing the estimated time or usage left before a component fails. In practical terms, the RUL plays a crucial role in guiding PdM decisions. By continuously tracking equipment condition through sensors, data, or machine learning models, RUL estimates pinpoint the optimal timing for maintenance activities. This approach prevents unnecessary preventive maintenance and reduces the risk of unexpected failures that cause unplanned downtime. Fundamentally, RUL offers a data-driven foundation that enables PdM to be timely, cost-efficient, and risk-conscious [2].

Moreover, the RUL is commonly used in PdM to program the maintenance activities that must be performed on the equipment to extend its service life and guarantee its reliability. By its definition, represents the estimated time that an asset has until it becomes unusable or requires replacement. To calculate it, various data needs to be analysed, including equipment history, environmental factors, maintenance records and sensor readings. The RUL represents the expected service life, or the time of use of the equipment or machine defined according to the quantity used to measure the service life of the system. this quantity is expressed in different measurable units such as operating hours, cycles performed, or distance travelled. The estimation of RUL encompasses several methodologies, including similarity models, survival models, and degradation models. The choice of method for estimating RUL largely depends on the type of data available and the specific operational context of the machinery in question.

In response to these challenges, our objective is to establish generalizable guidelines for the effective estimation and prognosis of RUL, With the primary objective of enhancing operational reliability and minimizing downtime in industrial equipment. These guidelines are intended to support the development of robust and scalable PdM frameworks that can adapt to varying operational conditions and asset types. Through a comprehensive review of existing approaches and identification of key success factors, this work seeks to contribute to the advancement of data-driven and hybrid RUL prediction techniques. The rest of the paper is organized as follows: In Section 2, the theoretical background. Section 3 provides the proposed method for the RUL estimation. In the subsequent section, the results of the evaluations assessing the effectiveness of the proposed methods are presented. Section concludes the study and discusses possible future works.

2 Theoretical backgrounds

2.1 Diagnosis and Prognosis

The diagnosis and prognosis are among the basic procedures for the implementation of PdM which allow to determine the state of health and to evaluate the residual service life of the components of the system. Let us note that the diagnosis and the prognosis are strongly correlated: the diagnosis determines the faulty components by explaining the observed malfunctions (causes and effects), the prognosis determines the future state of the components based on aging/degradation models of the monitored system (see fig.1).

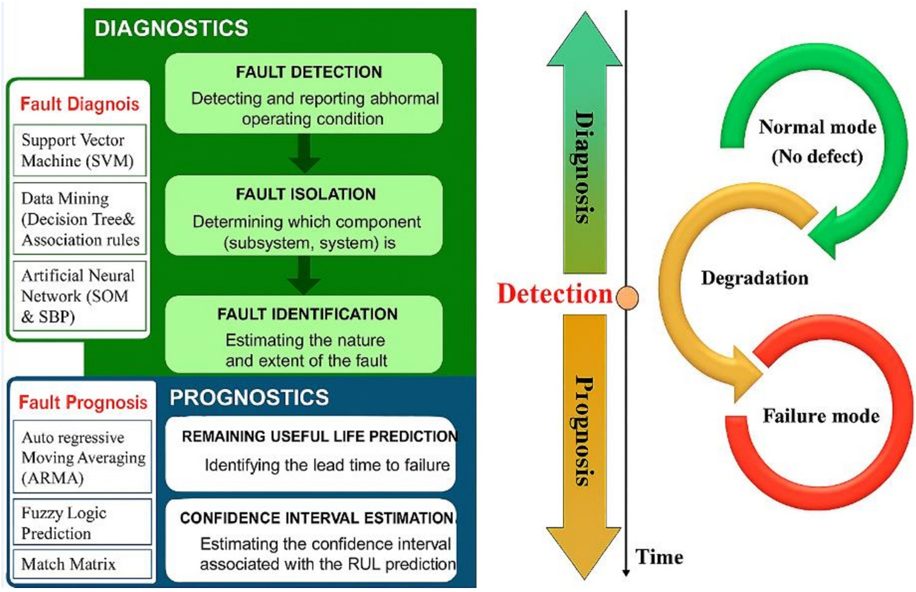

Fig. 1. PdM implementation based on diagnosis and prognosis procedures.

With reference to [2], the authors have discussed and will define the relationship between prognosis and diagnosis by presenting certain factors to be considered when implementing prognostic modelling in industrial applications. So, these approaches are challenging and require effective and efficient predictive models that are given under two different categories, physical-based and data-driven models [3]. The physical-based models require a thorough understanding of the sophisticated degradation mechanisms. While data-based models deploy condition monitoring data to analyse and predict current and future health conditions [4]. Due to the promising applications of AI and the appropriate choice of sensors, data-based models are becoming attractive in recent years.

2.2RUL calculation approaches

The calculation of RUL leverages a range of methodologies, which vary based on asset complexity, data availability, and industry-specific practices (see table 1). Common approaches include data-driven models, such as machine learning and deep learning techniques, physics-based models grounded in the underlying failure mechanisms, and hybrid frameworks that combine both paradigms [4]. Model-based approaches offer physically interpretable predictions but depend heavily on accurate system modelling. Data-driven techniques, on the other hand, excel in handling complex datasets and learning from historical trends, though they may suffer from limited interpretability and data dependency. Hybrid approaches seek to leverage the strengths of both paradigms, offering enhanced accuracy and adaptability across varying operational conditions [2]. The choice of method is typically influenced by the nature and volume of sensor data, the interpretability requirements, and the operational context in which the system functions. Ultimately, the integration of diverse RUL estimation methodologies tends to produce the most robust and actionable predictions, supporting informed maintenance planning, and effectively reducing the risk of unplanned downtime.

Table 1. An overview of the main methodologies of RUL estimation.

Approach	Data Required	Key Features	Typical Applications
Lifetime Data-Based	Historical failure times	Statistical survival and hazard models	Assets with extensive failure records
Run-to-Failure Data	Complete degradation histories	Pattern recognition from sensor data	Complex assets with sensor monitoring
Threshold-Based	Condition indicators and thresholds	Failure threshold projection	Systems with clear degradation signals
Model-Based	Physical degradation models	Physics-based simulation and filtering	Systems with known failure mechanisms
Data-Driven / Machine Learning	Large sensor and operational data	Nonlinear, adaptive models, AI-based	Complex, non-linear degradation processes
Hybrid	Combination of above	Combines physics and data-driven advantages	High-reliability, complex systems
Mathematical Formulas	Reliability metrics (MTBF, MTTF)	Simple calculations based on failure statistics	Well-understood, less complex systems

3 Proposed approach

Data-driven models such as neural networks, regression techniques, and physics-informed learning have shown strong predictive capabilities in RUL estimation. However, they face several limitations, including a high dependency on large and well-labelled datasets, limited generalization to unseen conditions, sensitivity to noise or sensor faults, and a lack of physical interpretability [3]. Moreover, most models do not naturally provide uncertainty estimates, which can compromise reliability in critical maintenance decisions. These challenges highlight the need for hybrid approaches that combine data-driven insights with physical knowledge to enhance robustness and trustworthiness.

To overcome the limitations of data-driven models, we propose a reliability-oriented methodology to predict the RUL, taking advantage of historical degradation data and classic reliability measures namely the Mean Time to Failure (MTTF) and Mean Time between failures (MTBF). In fact, these reliability measures play a crucial role in the accuracy of the RUL estimation. They impact predictions directly by providing statistical reference bases and indirectly by improving the interpretability and robustness of the predictive models.

3.1 Historical Reliability Data Analysis

The methodology presented in this paper is based on the collection of historical data for a set of components or systems operating under similar conditions. Accurate prediction of RUL and meaningful estimation of reliability metrics require a well-structured dataset capturing the operational history and failure events of components under observation. The first step in the proposed approach involves systematically collecting and processing historical failure data to compute essential reliability indicators: MTTF and MTBF.

Each instance is characterized by its total operational time or usage until failure, denoted by Ti, which may correspond to elapsed time, load cycles, distance, or another usage measure. From this, the MTTF is computed as:

$$MTTF = \frac{1}{N}\sum_{i=1}^{N} Ti \qquad (1)$$

Where N is the number of observed failure events. If components are repaired and returned to service, the MTBF is used instead:

$$MTBF = MTTF + MTTR \qquad (2)$$

With MTTR (Mean Time To Repair) representing the average time spent on restoration.

3.2Baseline RUL Estimation from Historical Data

The Baseline RUL is defined as the expected time remaining before failure under nominal conditions, computed as:

$$R\hat{U}L_{baseline}\,(t) = MTTF - t \qquad (3)$$

Where t is the elapsed operating time for the component of interest. This estimate assumes a uniform degradation rate and no influence from external or context-specific factors. While simplistic, this approach is highly interpretable and requires minimal data, making it particularly useful as a reference model or early-stage prediction tool.

An enhanced version of the baseline estimator is also supported using survival analysis, where the conditional expectation of remaining life given survival up to time tis computed from a fitted failure distribution:

$$R\hat{U}L(t) = \frac{\int_t^{\infty} R(u)du}{R(t)} \qquad (4)$$

This formulation captures the non-linear nature of wear-out and enables a probabilistic interpretation of the remaining life.

3.3A Hybrid Fusion Framework for RUL Estimation

The combined RÛL is given by:

$$R\hat{U}L_{hybrid} = \alpha .\, R\hat{U}L_{model} + (1-\alpha).\ R\hat{U}L_{baseline} \qquad (5)$$

Where $\alpha \in [0,1]$ is a tunable weighting factor that reflects the confidence or reliability of the model-based estimate relative to the statistical baseline. This fusion approach is particularly effective in reducing overfitting, handling sensor uncertainty, and enabling graceful degradation when sensor data becomes sparse or unavailable.

4 Discussion

To evaluate the effectiveness of the proposed hybrid fusion framework, we conducted experiments on the C-MAPSS dataset [5], a widely used reference for estimating the remaining useful life (RUL) of turbofan engines. The dataset contains several time series of

sensor readings ranging from execution to failure under various operating conditions and failure modes.
Three models were evaluated:

- **R̂UL$_{model}$**: A data-driven prediction model based on a Long Short-Term Memory (LSTM) neural network.
- **R̂UL$_{baseline}$**: A statistical reliability-based estimation computed using historical MTTF and MTBF values.
- **R̂UL$_{hybrid}$**: The proposed fusion model

The models were evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) as performance metrics.

Table 2. Calculation of RMSE and MAE for the proposed model.

	RMSE (cycles)	MAE (cycles)
R̂ULbaseline	37.8	28.4
R̂UL model	23.2	17.9
R̂UL hybrid (α = 0.7)	19.5	14.6

The results show that the hybrid fusion model outperforms both the data-driven and reliability-only models. By blending statistical reliability information with learned patterns from sensor data, the hybrid model achieves lower error rates and exhibits greater robustness across different operating conditions.

To provide a clearer understanding, the graph below depicts the evolution of RUL predictions over time for the baseline model, the data-driven LSTM model, and the proposed hybrid fusion model, in comparison to the actual RUL values. The hybrid approach successfully combines the advantages of both constituent models, resulting in predictions that are not only smoother but also more accurate than those generated by either method alone (see Fig. 2).

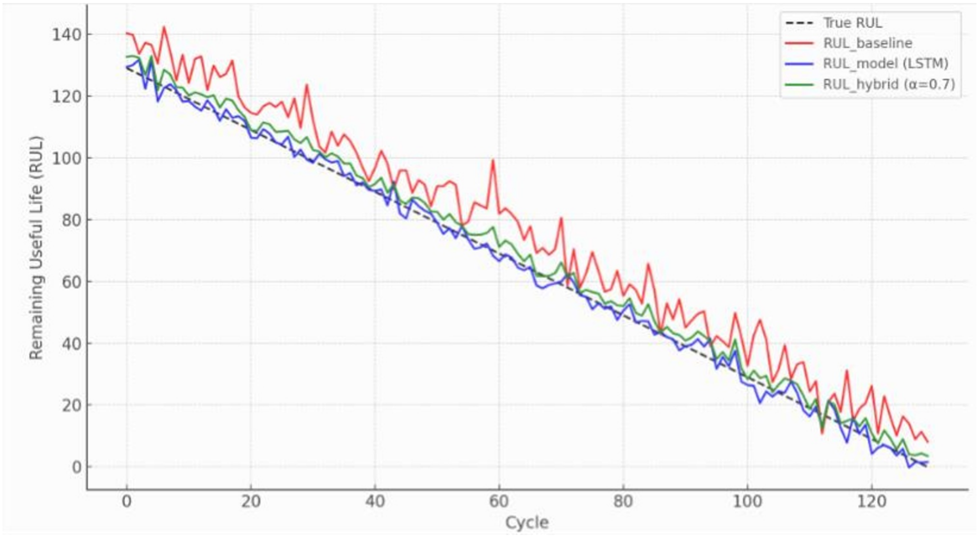

Fig. 2. Comparison of RUL Estimations: Hybrid, Model, and Baseline.

5 Conclusion and future works

In summary, this reliability-oriented RUL estimation framework complements existing data-driven techniques by embedding statistical rigor, operational insight, and interpretability, thereby enhancing the overall robustness and usability of predictive maintenance systems. In this study, we have proposed a methodology based on the use of MTTF and MTBF for the calculation of the RUL. This is especially useful in environments where sensor data is not available or insufficient to train reliable data-based models. Even in hybrid environments, this approach can provide a benchmark against which predictions based on real-time degradation can be calibrated or validated.

Looking ahead, we aim to adapt and validate this methodology in the context of wheel wear prediction, a critical aspect of railway asset management. Predicting wheel degradation presents unique challenges due to the interplay between mechanical wear, dynamic loading, environmental conditions, and operational variability. After collecting the data on the condition of the wheels, future research will focus on the design of task-specific degradation indicators and the dynamic adjustment of the hybrid weighting factor α according to contextual indices. In addition, the incorporation of real-time monitoring data can improve the responsiveness of the model and allow proactive maintenance planning. Ultimately, the objective is to establish a generalized, interpretable and scalable RUL estimation framework applicable to different components and operational domains within predictive maintenance systems.

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