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Predictive Modeling for Health Condition and RUL Estimation in Critical Equipment of Nuclear Power Plants

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Spanish nuclear power plants are surpassing 40 years of operation, requiring the highest standards of safety and reliability to be maintained across all systems. In this context, the development of tools capable of accurately assessing equipment health and predicting Remaining Useful Life (RUL) is highly valuable. By leveraging data from online condition monitoring, equipment degradation can be detected early and failures prevented, ensuring the safe and efficient operation of nuclear facilities.
This work introduces a methodology for RUL prediction, structured in three main steps. First, the variables most closely associated with equipment degradation are identified and processed to extract meaningful information, resulting in a degradation indicator. Second, various probability distributions are fitted to construct a reliability model, enabling the estimation of failure probability over time. Third, the evolution of the degradation indicator across operating cycles is modelled. This, combined with the reliability model, allows for future failure probability projection and RUL estimation.
Results from a case study demonstrate the model's predictive capability, providing a robust framework for proactive maintenance management of nuclear assets, contributing to the continued safety and sustainability of Spain's nuclear fleet.

Keywords: Condition monitoring, Remaining Useful Life (RUL), nuclear safety, proactive maintenance.

1. Introduction

Nuclear power plants (NPPs) have been operating worldwide for several decades, contributing to the generation of low-carbon energy. However, this technology requires high safety standards that continuously evolve to take advantage of new tools and knowledge and to address emerging problems. In this context, ageing management is an issue of concern for the safety community, as stated by the International Atomic Energy Agency (IAEA) in its Nuclear Safety Review (IAEA, 2024). According to this document, 67% of the 412 operating power reactors have been in operation for 30 years or more and 33% exceed 40 years, which was their expected operational life when designed. This means that, approximately, a third of the nuclear reactor fleet has been licensed to extend its design life, entering a phase known as Long-Term Operation (LTO).

In the case of Spain, although the National Integrated Plan of Energy and Climate (PNIEC) establishes the gradual shutdown of NPPs by 2035 (Ministry for the Ecological Transition and the Demographic Challenge, 2020), all NPPs in Spain will be required to request authorization to enter the LTO and operate beyond 40 years.

During this phase, certain safety-critical reactor elements may have experienced significant degradation, making it even more important to accurately predict their reliability and associated risks. Given this scenario, it is essential to integrate research and development efforts to ensure the safe and optimal operation of NPPs.

In line with this perspective, the United States Nuclear Regulatory Commission (US NRC) recognized the importance of artificial intelligence (AI) and machine learning (ML) in enhancing risk-informed applications in its 2023-2027 Strategic Plan (U.S.NRC, 2023).

For condition-based maintenance equipment, AI techniques enable improved recognition of degradation patterns, leading to more accurate diagnosis and prognosis of equipment health and projected failure rates. Moreover, the application of heuristics optimization methods, such as Genetic Algorithms (GAs), together with the flexibility of RAM (Reliability, Availability and Maintainability) models for both condition-based and time-based maintenance, enables the integrated assessment of maintenance and surveillance policies.

In this context, this paper presents a set of techniques currently being developed by the MEDASEGI research group to improve the surveillance and maintenance management of the NPPs in the LTO. Specifically, the project aims to develop tools to predict the effect of maintenance and surveillance activities, as well as to optimize them for safety-critical equipment, thereby supporting an integrated approach to NPP management.

2. Study Framework

The project is structured around three main tasks, which are briefly described in this section.

- *Task 1. Development of advanced RAM models.*
- *Task 2. Development of condition-based models.*
- *Task 3. Apply heuristics optimization.*

2.1. *Development of advanced RAM models*

For time-based maintenance equipment, the primary objective is to quantify the plant's total risk while explicitly accounting for the effects of surveillance and maintenance activities. To achieve this, historical data on reliability parameters, failure rates, system structure and maintenance policy are employed to develop a metamodel.

To evaluate the feasibility of this approach, an initial model was developed to predict the Core Damage Frequency (CDF) based on reliability parameters, basic events and a set of test intervals (TIs) combinations. The model obtained showed high accuracy, shifting the risk profile by changing TI values the way it was expected attending to commercial software. The results are reported in (Navarro et al. 2025).

2.2. *Development of condition-based models*

The second task focuses on the development of condition-based models that exploit monitored signals to assess equipment health and support the prediction of degradation evolution. These models aim to transform raw condition monitoring data into meaningful health indicators that can be linked to reliability metrics and maintenance decision criteria.

By detecting degradation trends, this task provides the foundation for prognostic analysis and for the integration of condition-based information into maintenance strategies.

2.3. *Apply heuristics optimization*

Once the condition-based models are developed and integrated into the advanced RAM models, heuristics methods can be applied to optimize the surveillance and maintenance strategies.

Given the potentially large number of parameters involved, such as preventive maintenance criteria, frequency of time-based maintenance or TIs for standby equipment, the optimization process intends to find a good solution, close to the optimal in terms of performance while maintaining reasonable computational effort.

The solutions proposed by the heuristic methods must be compatible with legal requirements and operational specifications, but these types of constraints can be modelled and addressed by the heuristic. A preliminary approach to this problem is presented in (Navarro et al. 2025).

While the three tasks are related, this paper primarily focuses on the development of condition-based models. The methodology adopted to implement this task is described in detail in the following section.

3. Methodology

This section presents a simplified version of the workflow applied to develop the condition-based maintenance model.

3.1. *Data*

The dataset selected for this study is the C-MAPSS (Commercial Modular Aero-Propulsion System Simulation), which simulates the degradation process of aircraft turbine engines until failure. This dataset was developed by the NASA (National Aeronautics and Space Administration) and is publicly available (NASA Prognostics Data Repository, 2008). Although C-MAPSS is an aeronautical dataset, it is widely used as a benchmark for developing and validating prognostics methodologies, which can later be transferred to other fields.

The C-MAPSS dataset presents four sub-datasets with different number of operating and fault conditions and each of the subsets is further divided into training and test data. However, this study addresses the simplest scenario, where only one operational condition and one fault type are considered (subset FD001). Each subset's row is a snapshot of data taken during a single operating time (cycle), recording 26 variables (columns): 1st column represents the engine's ID, 2nd column refers to the current operational cycle, three to five columns correspond to the three operational settings, and the rest of the columns represent the 21 monitored sensors. More information related to the sensors can be found in (Ramasso and Saxena 2014).

3.2. *Signal preprocessing*

Before the construction of health indicators, the raw monitored signals must be processed to reduce noise and enhance the underlying degradation trends. Signal preprocessing is therefore a necessary step to improve the robustness and interpretability of the subsequent analysis. In this work, smoothing and dimensionality reduction techniques are applied to obtain compact and informative representations of system behaviour.

3.2.1. *Exponential moving average*

The Exponential moving average (EMA) is a method used to smooth time series data that gives more importance to recent data, making the effect of past data to decrease exponentially. It is defined recursively as:

$$s_t = \alpha x_t + (1-\alpha) s_{t-1}, \quad (1)$$

Where x_t is the observed value at time t, s_t denotes the smoothed series, and $\alpha \in (0,1)$ is the smoothing parameter that controls the trade-off between responsiveness to recent changes and overall stability. This formulation allows the EMA to react more quickly to new information than traditional moving averages while retaining information of past observations.

3.2.2. *Principal components analysis*

PCA is an unsupervised dimensionality reduction technique used to transform a set of potentially correlated variables into a reduced number of orthogonal components that successively maximize variance (Bro and Smilde 2014). Each PC is defined as a linear combination of the original variables, with loadings indicating their relative contribution.

$$\boldsymbol{z}_k = \boldsymbol{X}\boldsymbol{w}_k \quad (2)$$

Where:

$\boldsymbol{w}_k$ is the loading vector of the k-th principal component.

$\boldsymbol{z}_k$ contains the component scores for all observations.

The loading vector is chosen to maximize the variance of the projected data by solving the following optimization problem:

$$\boldsymbol{w}_k = arg\,max\,Var(\boldsymbol{Xw}) \quad s.t. \quad \|\boldsymbol{w}\| = 1 \quad (3)$$

In this work, PCA is employed to extract compact representations of system behaviour while preserving the dominant sources of variability relevant to degradation dynamics.

3.3. *Reliability model*

Once a representative health indicator has been obtained from the monitored signals, a reliability model is constructed to relate its evolution to the probability of failure, providing a quantitative measure of system reliability.

The reliability model is developed using the values of the selected health indicator at the time of failure. Based on this information, probabilistic models are fitted to derive a reliability function expressed in terms of the health indicator. This formulation allows the definition of reliability thresholds that can be subsequently used to trigger maintenance actions.

While the reliability model establishes a quantitative relationship between the health indicator and the probability of failure, it does not provide information about the future evolution of the indicator. Consequently, an additional prognostic model is required to forecast its temporal behavior and estimate the time at which the predefined reliability threshold will be reached.

3.4. *Regression model*

The quadratic mixed-effects model extends the linear mixed-effects framework by incorporating second-order polynomial terms to capture nonlinear relationships. Fixed-effects describe the population-level trend, while random effects account for unit-specific deviations. This formulation allows the model to represent heterogeneous trajectories while maintaining statistical efficiency and robustness (Jiang 2022). For unit i observed at time t_{ij} the model prediction is defined as:

$$\hat{y}_{ij} = \beta_o + \beta_1 t_{ij} + \beta_2 t_{ij}^2 + b_{0i} + b_{1i} t_{ij} \quad (4)$$

Where β_o, β_1, β_2 are fixed effects, and b_{0i}, b_{1i} are the unit-specific random effects assumed to follow a multivariate normal distribution.

4. Application Case: Condition-based Maintenance

This section presents an application case aimed at illustrating the proposed methodology for condition-based maintenance. The different modelling steps described in the previous section are applied to the C-MAPSS FD001 dataset to derive a health indicator, construct a reliability model, and perform prognostic analysis to support maintenance decision-making.

4.1. *Signal preprocessing*

Considering that the phenomenon of interest is the degradation's evolution, the most promising signals to model it should be monotonical, given that it is the expected behaviour of the degradation without maintenance intervention.

An EMA with $\alpha = 0.05$ is applied to smooth the signals and reduce noise. Then, the constant signals are discarded due to the fact they are not adding any useful information.

Once the constant signals are discarded, the Pearson correlation between the signals and the number of cycles each engine has been operating (which increases constantly) is obtained. However, most of the sensors present high correlation values and it is difficult to discern which one will better model the degradation. To exploit the information contained in all available sensors, PCA is performed across all cycles and engines of the dataset.

Attending to the results obtained, the first principal component (PC1) represents the 66% of the variance present in the 17 sensors included in the PCA. Figure 1 illustrates the evolution of the first component.

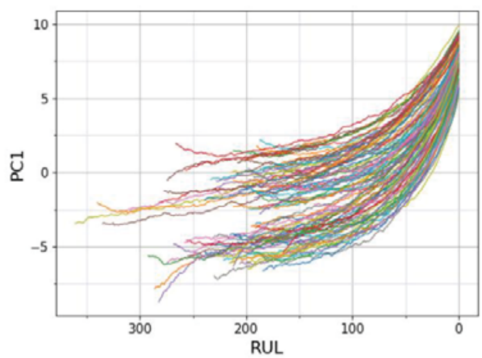

Figure 1. PC1 trajectories for all the engines.

All the engines present similar signal behaviour, corresponding to a unique failure mode, where the degradation trend becomes more pronounced from the last 100 cycles onwards.

4.2. *Reliability model*

Once the preprocessed data is available, the next step consists of linking reliability to the signal-based health indicator (PC1). To do this, several distributions are fitted to the histogram of PC1 values at failure and the distribution with the highest likelihood is selected. Table 1 presents the log-likelihood and Figure 2 compares the fit of the four distributions.

Table 1. Log-likelihood of the fitted distributions.

Exponential	Normal	Lognormal	Weibull
-184.40	-144.06	-144.06	-143.12

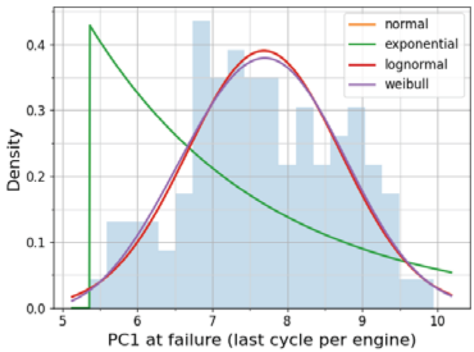

Figure 2. Histogram of CP1 values at failure and fitted distributions.

As reported in Table 1, the Weibull distribution presents the highest likelihood, followed by the normal and lognormal distributions, which have the same value and overlap in the plot shown in Figure 3. Once reliability is expressed as a function of the first principal component, it becomes feasible to define a reliability threshold as a criterion for maintenance intervention.

In this case, a reliability level of 90% (0.9) is selected, corresponding to a PC1 value of 6.37. As can be inferred from Figure 2, this value implies that some engines will fail before reaching the threshold, so from now on they will not be further considered in the analysis. Figure 3 highlights the trajectories corresponding to the 12 failed units.

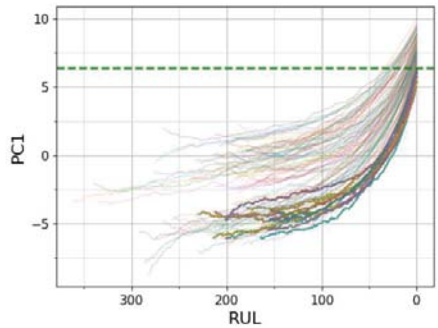

Figure 3. PC1 trajectories and reliability threshold (0.9).

4.3. *Regression model*

Having established the relationship between PC1 and reliability, the next step involves forecasting the future behavior of PC1. A quadratic mixed-effects model is applied to forecast the future evolution of PC1. The model uses the last 40 available operational cycles for fitting and then extrapolates until the predefined maintenance threshold (PC1 = 6.37) is reached. Figure 4 shows the evolution of PC1 for one of the units and the time at which the fitted model predicts the threshold to be exceeded. The model is fitted using data from 70 and 135 cycles before threshold; therefore, the predictions correspond to 30 and 95 cycles before the threshold crossing.

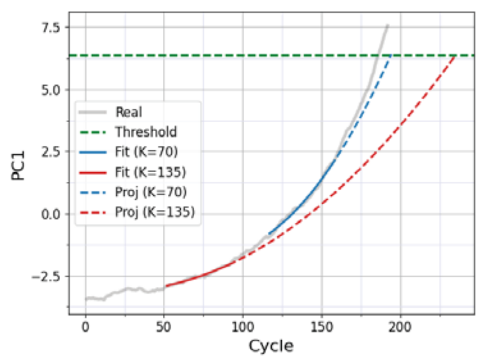

Figure 4. Cycle to reach threshold predicted by the quadratic mixed-effect model 30 and 95 cycles before threshold.

The comparison between both suggests that accuracy increases as data closer to the crossing point is used to fit the model. To quantify the accuracy evolution as threshold is approached, the root mean squared error (RMSE), and the mean absolute error (MAE) are computed from 80 cycles before the crossing onwards for the remaining 88 engines. Figure 5 illustrates the evolution of both metrics.

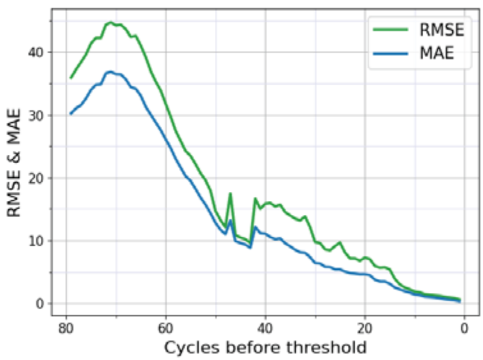

Figure 5. RMSE and MAE evolution as threshold is approached.

Considering the behaviour shown in the figure, the error associated with the earliest predictions is unacceptable. However, from cycle 50 onwards, and especially from cycle 30, the prediction accuracy improves significantly. Considering that each cycle can be interpreted as a full flight or, at least, as an engine start-up and shutdown (Saxena and Goebel 2008), it seems reasonable to assume that the obtained results could help predicting the appropriate maintenance time with sufficient advance.

The proposed approach is intentionally kept simple, which facilitates its implementation by users of different profiles, and offers a certain degree of flexibility, such as the election of the reliability threshold for maintenance actions or the number of cycles used to fit the model before extrapolation. Nevertheless, in terms of precision and predictive capability, the approach is still far from other more sophisticated architectures.

5. Conclusions

The results obtained so far support the validity of the proposed approach for enhancing maintenance plans and lifetime management of NPPs within the framework of LTO. However, the accuracy achieved by the developed models remains insufficient for them to be regarded as a fully operational tool for resource management and optimization.

Nevertheless, the integration of more complex models, together with the application of machine learning and AI techniques, is expected to improve the accuracy and robustness of the predictions, thereby enabling further progress towards the project objectives and reinforcing the practical applicability of the proposed framework.

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