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RISK-BASED APPROACH TO ASSESS TECHNO-ECONOMIC FEASIBILITY OF GAS TURBINE COMPONENT LIFE EXTENSION

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ABSTRACT

Growing demand for flexibility and high maintenance costs make gas turbine systems increasingly expensive. Reliability and availability are both key factors and have a direct impact on the economics of these systems. The plants operators require fast and reliable methods to assess the remaining lifetime of the gas turbine components. Nowadays, inspection and replacement intervals for gas turbine components are typically determined by model-based assessment of equivalent operating hours (EOH). However, this method requires a lengthy and expensive process, which needs to be repeated in case of components upgrades.

The innovative method proposed in this work collects a considerable number of operational data on different types of machines (ranging from small engines to heavy duty), through which it is possible to build a curve representing the probability of failure. The curve can be updated at each inspection by assessing the presence of damage mechanisms from time to time (implementing data-driven procedures for monitoring, diagnosis, and advanced prognosis). The result will be an updated risk curve that provides operators with information about the health status of the components and the potential risk associated to late replacement.

Integrating the model developed with the costs associated to maintenance, a comparative cost analysis is carried out to support the decision-making process and evaluate the possible benefits. It is clear that a risk-based approach (based on statistical data analysis) is easier to use, less costly than a modelling approach and can result in significant economic benefits.

Keywords: Gas turbines, Risk-based approach, Decision-making procedure, Statistical method, Cost-benefits analysis.

1. INTRODUCTION

Due to the increasing demand for the integration of renewable energies, thermal power plants are required to be more and more flexible to fill the gaps left by intermittent green energy sources. However, traditional energy sources were originally designed for constant load operation, and the sudden changes in load demanded by the energy market produce thermal and mechanical stresses that cause much greater degradation than originally expected.

At present time, the useful life of components is generally estimated by OEMs (Original Equipment Manufacturers) through the calculation of equivalent operating hours (EOH). This methodology gives the equipment an initial useful life which is "consumed" at a rate dependent on the operations done by the equipment (e.g., starts/stops, hours in full load, hours in partial load, trips, etc.). Examples of how various OEMs calculate EOH are provided by Aminov and Kozhevnikov (2013) [1]. In their work they explain how EOHs are counted by considering different OEMs using different calculation models. These calculations proved to be quite efficient for systems operating mainly at full load. In the last 20 years, however, increased demand for flexibility has introduced cyclic operation. For this reason, the accuracy of the EOH calculation has decreased and some degradations are occurring before planned outages based on the EOH models.

To obtain more accurate estimates, various methods of estimating RUL (Remaining Useful Life) have been proposed over the years: FEM stress analysis, data-based models, and hybrid physical-statistical models. Great results have been achieved by Scheibel et al. (2014) [2] who, through geometric NDE analyses combined with the knowledge of material properties and operating conditions, have built ANSYS finite element models of some components to obtain good estimates of the health condition and remaining useful life. A problem related to this type of approach may be the complexity of modelling the components and especially the uselessness of the models in case of plant upgrades as they are very specific. Kundu et al. (2015) [3] proposed an approach instead based on failure risk estimation. This estimation is initially based on a General Log Linear Lognormal model. Then, through a Bayesian approach, the parameters of the initial model are updated based on inspection data (e.g., crack length) providing updated and more accurate estimates than the initial ones. Since this estimate is based on the inspection results, criticalities may arise in the intermediate times of the inspections that cannot be quickly considered by the risk calculation algorithm (there is therefore a discrete risk update and not a continuous one).

This paper evaluates the benefits of a purely data-driven approach to this topic by continuously monitoring information from sensors to provide estimates of RUL.

In this way, additional information on the health of the system can be obtained without the need to build complex models (which in some cases may require plant downtime) on a continuously and non-discretely updated basis and, with this information, mitigation actions can be taken as efficiently as possible.

2. GAS TURBINE DEGRADATION ANALYSIS

Gas turbine systems are subject to different types of degradation depending on different mechanisms. By studying the specific mechanisms, however, it is possible to try to establish a link between the damage mechanism and observable variations in the sensors available to the systems under investigation.

2.1 GAS TURBINE KEY DAMAGES

Understanding the below phenomena is the starting point and lays the foundations for subsequent analyses. The main failure mechanisms are the following: Wearing, Foreign Object Damage (FOD), Creep, Fouling, Corrosion, Erosion, Fatigue. Depending on the components belonging to these systems, the failures mechanisms vary as the operating conditions change. About that, a general overview is provided by Hua-dong Yang and Xu Hong (2011) [4] summarized in **Table 1**.

Foreign Object Damage (FOD): Gas turbine systems suck in large quantities of air. Together with the air, other elements that cause damage, especially in the early stages of compression, can also be sucked in. This problem mainly concerns air transport applications. The elements that are sucked in can be of various kinds: metal objects, birds, bolts, seals, sand, ice, etc. The resulting damage therefore depends on the nature and the dimension of the ingested element. For stationary applications, the filtration system generally protects against FOD, but there may be DOD (Domestic Objects Damage) which corresponds to material liberation in the stream (generally a piece of blade or vane).

Creep: The Creep mechanism is the tendency of a material to deform when subjected to prolonged thermal and mechanical stress. For this reason, creep, for turbine blades, is very often the life-limiting process because blades tend to stretch during operation. This elongation can result either in cracking on the blade, or in the blade tip rub on the non-rotating shroud.

Fouling: The fouling mechanism is caused by the adhesion of substances and particles on the surface of the compressor and turbine components. This causes a change in geometry and an increase in surface roughness. This results in worse aerodynamic properties and a reduction in mass flow and components efficiency, which leads to not inconsiderable power output reductions.

Corrosion: Corrosion is a degradation mechanism generated by the ingestion of pollutants by the system. Corrosion during operation generally does not affect the compressor as it works in dry conditions even if Cold Corrosion phenomena cannot be excluded, especially for units operated in coastal areas and with non-coated compressor blades and vanes. However, when the system is switched off, humidity can settle (condensing) and react with pollutants (e.g., hydrochloric acid and sulphur trioxide) creating corrosive substances. On the turbine, on the other hand, acts the hot corrosion mechanism. Hot Corrosion is a form of accelerated oxidation that is produced by the reaction between the component and the material deposited on it. The aggressiveness of this mechanism is dependent on the temperature.

Erosion: The air entering gas turbine systems, even if there are filters, carries a significant number of solid particles that may consist of ash, sand, dust, iron oxides, etc. These particles colliding at high speeds against the surfaces of the components, remove part of the material and cause significant damage. This damage is manifested by pitting and cutting of the blade leading and trailing edges and an increase in the blade surface roughness.

Fatigue: This mechanism can begin when a component is cyclically loaded. This mechanism is divided into two types according to the deformation induced in the material: Low Cycle Fatigue (LCF) and High Cycle Fatigue (HCF). LCF occurs when a series of plastic deformations are induced in the material while HCF occurs when the material undergoes elastic deformations. Hence the name, because in the case of LCF the number of cycles to failure is lower while for HCF it needs a higher number to reach the failure.

The temperature differentials developed during turbine start-up and shutdown produces thermal stress. The cycling of these thermal stresses is thermal fatigue.

Component	***Element***	***Failure modes***	***Loading source***
Compressor	Rotor Blades	Fatigue, Erosion, FOD, Fouling, Rubbing	Vibration, Particles
	Rotor (disk)	Fatigue, Creep	Centrifugal, Thermal
Combustion	Liner	Fatigue, Creep, Oxidation	Temperature Gradients
	Casing	Fatigue	Pressure Cycles
Turbine	Rotor Blades	Creep, Fatigue, Rubbing	Centrifugal, Vibrations
		Corrosion, Erosion, Fouling, Oxidation	Exhaust products, Thermal Environments
	Rotor (disk)	Creep, Fatigue, Oxidation	Centrifugal, Thermal
	Stators	Corrosion, Erosion, Fatigue, Creep, Oxidation	Exhaust products, Thermal Environments, Pressure

Table 1: Failures modes of a gas turbine

2.2 IMPACT OF OPERATING HISTORY

Operating regimes play a decisive role in the generation of faults. Depending on the operating history of the loads there may be one fault instead of another. Table I makes a distinction between the most common faults in systems that perform continuous operations and systems that perform cyclical operations. As can be seen from the **Table 2** elements highlighted in bold, for peaking machines, thermal-mechanical fatigue is the main life limiting failure mode. For continuous duty machines, creep, oxidation, and corrosion are the main life limiters.

An example of the influence of operating regimes on component degradation is reported in the work of D. Bosak et al. (2016) [6] within which the effects of a power adjustment made through variation of the Variable Inlet Guide Vane (VIGV) angle and through a variation in fuel quantities are analysed. The former leads to more gradual adjustments which induce lower thermal stresses than the latter, which results in rapid adjustment and high thermal stresses. From this it can be understood that introducing abrupt load adjustment operations increases component degradation by the same amount as the number and size of these operations.

3. CORRELATION BETWEEN DATA AND FAILURE

In the literature there is a vast amount of case studies that create a link between the occurrence of a failure and information from sensors. This correlation is very evident in some cases while it is more difficult to determine in others.

3.1 PERFORMANCE INDICATORS

Using the information from the sensors, several indicators are described in the literature, which are used to obtain more information on the health and operating efficiency of gas turbine engines. Among the indicators that provide general information on the health of the system are Power Output, Thermal Efficiency, Heat Rate and Exhaust Gas Temperature (EGT). The latter is very often used in performance monitoring. An increase in EGT often results in performance degradation as well as damage and/or reduced life of parts of the system. EGT is often used as the difference between its threshold value and its peak values, which are usually reached during the start-up phase (EGT Margin) [7]:

$$EGT_{Margin} = EGT_{threshold} - EGT_{peaks} \tag{1}$$

However, for constant load applications, this indicator is more difficult to apply as the gas turbine is not operated under the conditions to generate the peak EGT (necessary for the calculation of EGT Margin). Furthermore, when the turbine is operated under varying load and environmental conditions, EGT values can vary independently from performance degradation. It is also for this reason that H. Hanachi et al. (2014) [8] introduced the Excess Heat Ratio

Continuous Duty	Cyclic Duty
Creep **Oxidation** **Corrosion** Erosion FOD Rupture Rubbing/Wear High-Cycle Fatigue Combined failure mechanism (creep/fatigue, corrosion/fatigue, oxidation/erosion and so on)	**Thermal-Mechanical Fatigue** High-Cycle Fatigue Rubbing/Wear FOD Combined failure mechanism (creep/fatigue, corrosion/fatigue, oxidation/erosion and so on)

Table 2: Typical failure modes for hot gas components inside a gas turbine

(EH) as a performance indicator that is more suitable to provide estimates of system health under varying operating conditions:

$$EH = \frac{H_T - H_{T_M}}{P_D} = m\, c_p \frac{EGT - EGT_M}{P_d} \quad (2)$$

Where H_T and H_{T_M} are the measured and modelled turbine outlet enthalpy flow, respectively. P_D is the power design point, c_p is the specific heat capacity of the exhaust gas and m is the mass flow.

3.2 DEGRADATION INDICATORS

Some of the most used performance indicators were described in the previous section. In the monitoring of a gas turbine system, however, measurements are also carried out with the exclusive objective of monitoring the presence of damage to the components. For this purpose, vibrations, acoustic emissions, oil conditions, etc. are monitored.

An interesting report by S. Chatterton et al. (2019) [9] investigates the link between the presence of a transverse annular crack on the rotor and vibratory trends. This work describes the presence of abnormal harmonic components in the frequency spectrum of shaft vibrations. This vibration behaviour is influenced by crack depth and crack shape. The importance of oil monitoring is emphasised by Shell [10]. For example, the presence of copper, iron and lead in the oil can indicate the degradation of one or more components of the gas turbine engine.

3.3 FAULT IDENTIFICATION

The identification of a specific failure from the analysis of sensor information requires the availability of information about the plant, its operating history, and a large sampling of data. Some examples are available in the literature.

The work of Y.S.H. Najjar et al. (2020) [11] correlates the phenomena of compressor fouling, compressor erosion, compressor corrosion, turbine fouling and turbine corrosion with exhaust mass flow rate reduction and exhaust flow temperature increase. In addition, this work shows very clear degradation trends in compressor and turbine polytropic efficiency, in GT efficiency at partial and full load and in GT power output at partial and full load. In addition, Nurlan Batayev (2019) [12] defined an algorithm to evaluate the degradation due to fouling and defined a methodology that based on measurements of inlet and outlet pressure, inlet and outlet temperature, mass flow, fuel flow, exhaust gas temperature and compressor discharge pressure evaluates the need for compressor washing. Another interesting insight is provided by S. Chatterton et al. (2019) [9], already mentioned before, who point out a correlation between the opening and closing of cracks, caused by gravity during a complete rotor revolution, and vibratory phenomena (particularly for cracks on the shaft).

Very often, therefore, in the presence of damage to one of the components of gas turbine systems, there is the presence of one or more indicators that can provide information. Sometimes, however, it can happen that the symptoms are too general to trace back to a specific fault based on the observation of a trend in the data coming from the plant. In fact, if variations in EGT, Power Output or even efficiency are observed, it is quite difficult to pinpoint the failure to a specific component. In this case, additional analysis and observations are required.

A method that can be used in the Fault Identification phase is the use of the Signature Matrix. By analysing all the information coming from the sensors it is evaluated which measurements are in a faulty state (defined as symptoms) and collected within a vector. Specific vectors (called symptom vectors) are associated with specific faults [13].

	STATE OF HEALTH				
	S_1	S_2	S_3	…	S_N
Fault 1	0	1	1	…	1
…	…	…	…	…	…
Fault *n*	1	0	1		1

Table 3: Fault signature matrix

4. RUL AND MITIGATION ACTIONS

The next steps following the identification of specific faults concern the choice of the best fault mitigation action. To do this, however, it is necessary to establish how much time is available to carry out the mitigation, so an intermediate step is necessary: the calculation of the RUL.

4.1 RUL

Once a specific fault has been identified, based on the information available in the literature, using regression techniques and, if necessary, data-fusion procedures [14], it is possible to estimate the RUL for that specific fault. However, these RUL estimates, based on on-line monitoring, are constantly updated. In fact, taking as input only a certain number of last observations, the calculated RUL value is continuously updated.

In the toy-example shown in **Figure 1** varying the length of the data set taken as input for the regression analysis results in different RUL values. Therefore, the prediction based on the latest data is more effective as data that are too far away are often not representative of the current state of the system and negatively affect the prediction.

Data fusion techniques, on the other hand, are used to provide an overview of the system. In fact, by constructing a fused health indicator, it is possible to observe the performance of several sensors at the same time and have an estimate of the overall RUL of the system.

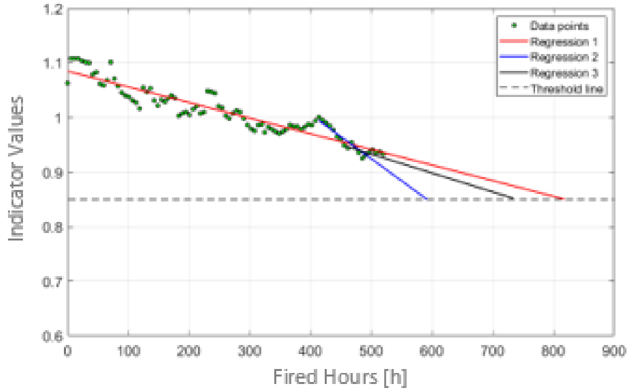

Figure 1. Prediction of the RUL with different input data lengths

4.2 MITIGATION ACTIONS

The choice of the most appropriate mitigation action is based on the estimated RUL times. In fact, four different scenarios can be configured in relation to the type of fault and the time available for fault mitigation as shown in **Figure 2**.

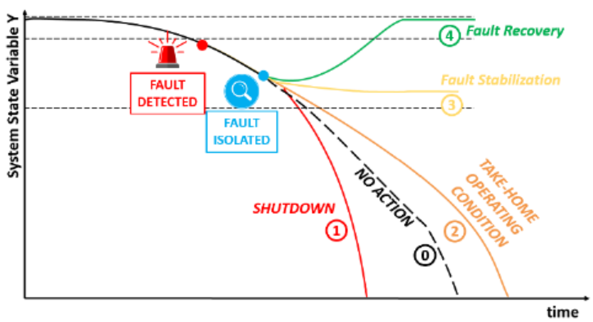

Figure 2. Fault mitigation approach

Fault Recovery allows the system to be restored to its initial conditions.. If this is not possible, *Fault Stabilisation* can be implemented, modifying the operating parameters, and limiting the failure. If it is not possible to stabilize the fault, *Take-Home Operating Conditions* are used to obtain time to prepare for maintenance. Finally, in the most critical cases, a system *Shutdown* is performed to avoid catastrophic events and excessive costs [13].

5. COST AND RISK ANALYSIS

As the curve representing the RUL approaches its threshold value, the probability of failure increases. In fact, the prediction is often associated with a probability distribution based on the distribution of the data from which the regression was obtained. The choice to carry out a maintenance action must therefore follow two decision logics: the probability of failure and the costs. The decision tree shown in **Figure 3** represents the decision process to be followed to consider costs the risks related to a maintenance action.

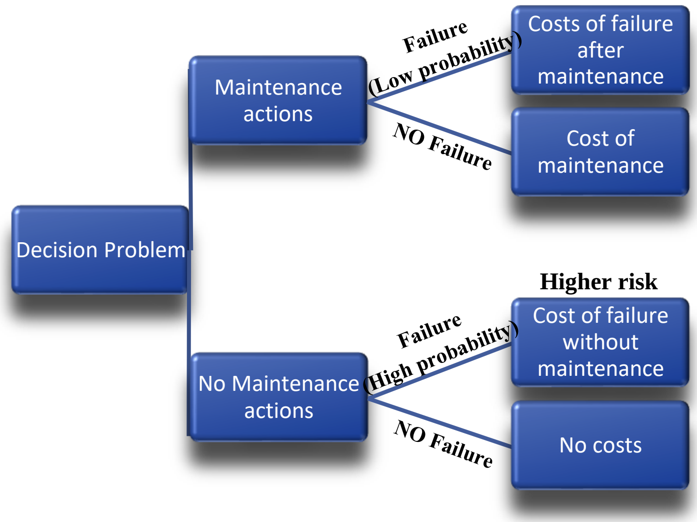

Figure 3. Maintenance decision tree

This analysis considers the probability of failure both if the maintenance action is carried out and if it is not carried out. Multiplying the probability of a certain event by the cost associated to that specific event, it is possible to obtain a cost indicator useful to support the decision-making process. In fact, it is recommendable to make the choices that present the lowest risks.

Not carrying out maintenance leads to lower maintenance costs but exposes to higher risks (and thus failure costs) that increase with operating hours. Conversely, investing a certain amount of capital for a maintenance action entails a cost that generates a lower risk. By comparing the two scenarios, it is possible to define a point at which it is more convenient to carry out maintenance, defining in this way the precise timing of intervention as shown in **Figure 4**.

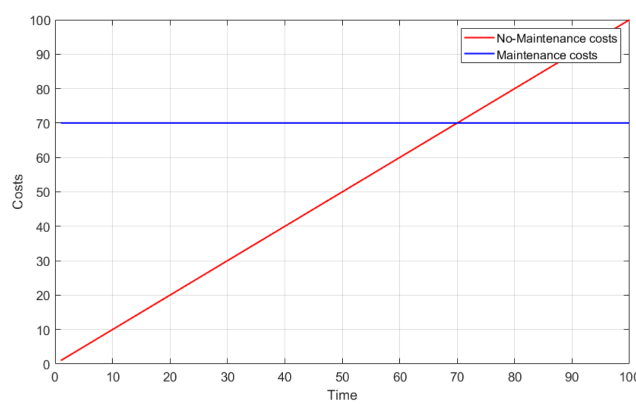

Figure 4. Comparison of the costs of the different scenarios (toy example)

6. CASE STUDY

The data used in this case study are available from NASA [15]. The data were generated from a simulation using C-MAPSS. The data refer to 21 sensors of 100 units and are divided into "train" data and "test" data. The former collect measurements until failure while the latter stop at a number of cycles before failure.

In applying this method, train data were used up to 20 cycles before failure and then the ability to predict RUL was assessed.

6.1 SENSOR SELECTION

Permutation Entropy (PE) has been treated extensively by C. Brandt and B. Pompe (2002) [16]. This parameter provides a measure of the complexity of data sets by comparing them with a matrix of permutations. Due to its nature, this parameter can be used to assess the presence of trends within data sets. Considering a generic time series $\{x_t\}_{t=1,\ldots,T}$ all permutations π of order n will be evaluated. The relative frequency for each type of permutation is calculated as:

$$p(\pi) = \frac{\#\{t|0 \le t \le T-n, (x_{t+1}, \ldots, x_{t+n}) \text{ has type } \pi\}}{T-n+1} \tag{3}$$

The PE of order n≥2 is then calculated using the following formula:

$$H(n) = -\sum p(\pi) * log_2 p(\pi) \tag{4}$$

From 192 data available on unit 1, the last 92 measurements were considered. Calculating the permutation entropy on the first 73 data the following results are obtained (**Fig.5**):

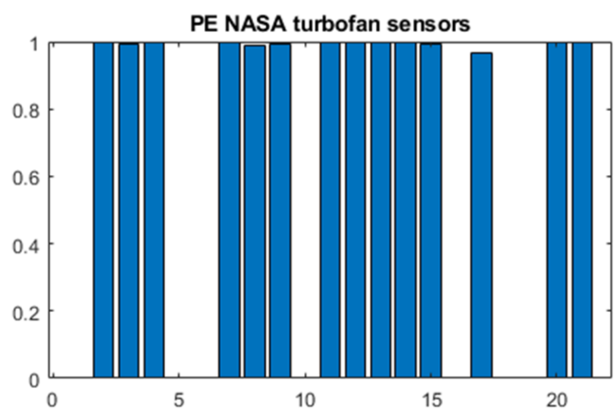

Fig.5. PE of the 21 sensors

Sensors #1, #5, #6, #10, #16, #18 and #19 were immediately eliminated from the study as they had a PE of zero. This is due to the fact that these sensors have constant trends and are therefore of limited use for degradation analysis. The sensors with the lowest non-zero values were #3, #8, #9 and #17. Due to their higher information content they were selected for the data-fusion technique.

6.2 DATA FUSION

The data fusion technique consists of constructing a new degradation indicator from a matrix containing some initial indicators and multiplying them by a vector of weights.

$$\begin{bmatrix} x_{1,1} & \cdots & x_{1,n} \\ \vdots & & \vdots \\ \vdots & \ddots & \vdots \\ \vdots & & \vdots \\ x_{t,1} & \cdots & x_{t,n} \end{bmatrix} * \begin{bmatrix} w_1 \\ \vdots \\ \vdots \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} v_1 \\ \vdots \\ \vdots \\ \vdots \\ v_t \end{bmatrix} \tag{5}$$

The objectives of this optimization were to minimize the variance and PE (4) in order to find a vector of weights that, when multiplied by the matrix of measurements, results in a vector (fused indicator) that has a more monotonic trend than the initial sensors and therefore allows a better prediction to be made [14].

At the end of the optimisation, the weights corresponding to the lowest PE were selected.

6.3 RUL CALCULATION

Once the weights have been obtained the fused indicator is calculated as in equation (5). A grade 2 regression was applied to this indicator for trend extrapolation purposes. The threshold line was also calculated in a similar way to equation (5). Having in fact the data corresponding to the moment in which the failure occurs, it was possible to derive the threshold value as a multiplication of the data of the sensors selected at the time of the failure and the vector of weights. The result is shown in **Fig. 6**.

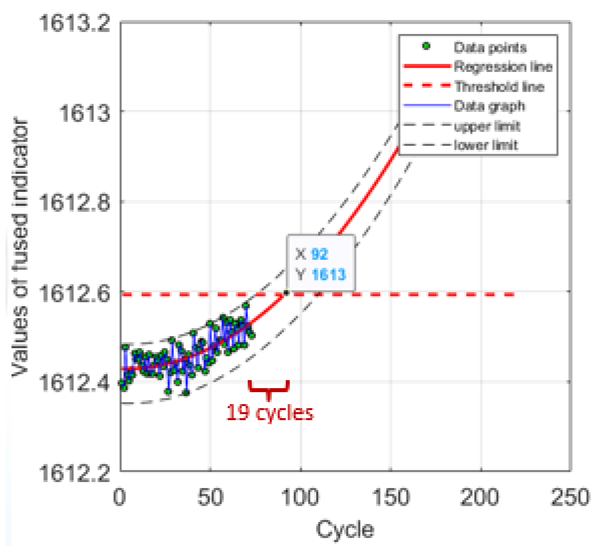

Fig.6. RUL estimation

A RUL of 19 cycles is obtained, perfectly compatible with the real RUL generated by the simulation system (failure occurs at 92, just as calculated by the regression).
The use of a limited number of last observations ensures that the provided estimate is continuously updated. By observing only the latest measurements, the sensor selection algorithm changes the selected sensors based on the latest observed trends.

6.4 COST AND RISK ANALYSIS

The analysis of costs and risks is closely dependent on the specific failure affecting the system. In the case study used, an RUL was calculated with a fused indicator that provides a general view of the system and not a specific one. In order to arrive at a more specific risk analysis, it is sufficient to evaluate which sensors have been selected by the sensor selection algorithm that will be the main responsible for the estimate generated by the fused indicator.

7. CONCLUSIONS

In this study, the possibility of carrying out a degradation assessment of gas turbine systems through a data-driven statistical approach was evaluated. The results obtainable from this procedure have the potential to offer crucial supporting information in the decision-making process regarding maintenance. The absence of specific material analysis and geometric modelling (which also requires plant shutdowns) ensures minimal implementation costs compared to other approaches. This method therefore aims at choosing optimal maintenance times which are given by the optimum between the probability of failure and the costs associated with such an event.
Continuing in this direction, advanced data-driven techniques are under development to obtain more precise estimates of RUL through in-depth analysis of sensor data. In addition, if several measurements are available for each sensor, it is also possible to add Trendability, Prognosability and Monotonicity analyses to assess the repeatability of trends, the dispersion of values at failures and quantify the monotonic trend. The goal is to provide a tool that gives reliable on-line indications of the state of health of the system in addition to the result of inspections and the judgement of plant experts, enabling users to make more accurate maintenance choices.

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REFERENCES

[1] R.Z. Aminov, A.I. Kozhevnikov (2014), “Estimating the influence of intermittent operation on the change of life of a gas turbine”, Electric Power Systems Research, Volume 107, Pages 153-157, ISSN 0378-7796, https://doi.org/10.1016/j.epsr.2013.10.003.

[2] John Scheibel/Electric Power Research Institute, V. P. ‘Swami’ Swaminathan/TurboMet International, Gil J Dean/ AccTTech, LLC (2014), “Integrated approach to gas turbine rotor condition assessment and life management”, 7th International Gas Turbine Conference.

[3] Kundu, Pradeep & Chopra, Seema & Lad, Bhupesh (2015). “Development of a Risk Based Maintenance Strategy to Optimize Forecast of a Gas Turbine Failures”. International Journal of Performability Engineering. 11. 403-412.

[4] H. Yang and H. Xu (2011), "Reliability Analysis of Gas Turbine Based on the Failure Mode and Effect Analysis" Asia-Pacific Power and Energy Engineering Conference, 2011, pp. 1-4, doi: 10.1109/APPEEC.2011.5749000.

[5] Mevissen, F.; Meo, M. (2019) “A Review of NDT/Structural Health Monitoring Techniques for Hot Gas Components in Gas Turbines”. Sensors, 19, 711. https://doi.org/10.3390/s19030711.

[6] Bosak, David & Dabbashi, Siddig & Thank-God, Isaiah & Pilidis, Pericles & Di-Lorenzo, Giuseppina. (2016). “Gas Turbine Flexibility and Life Assessment Method”.

[7] S. Ackert (2010),“Engine Maintenance Concepts for Financiers” Macquarie AirFinance, Mar.

[8] Hanachi, Houman & liu, jie & Banerjee, Avisekh & Chen, Ying & Koul, Ashok. (2014), “A Physics-Based Performance Indicator for Gas Turbine Engines Under Variable Operating Conditions”. Proceedings of the ASME Turbo Expo. 6. 10.1115/GT2014-26367.

[9] S. Chatterton, P. Pennacchi, A. Vania, P. Rubio (2019), “Analysis of the periodic breathing of a transverse annular crack propagated in a real rotating machine”, Engineering Failure Analysis, Volume 99, Pages 126-140, ISSN 1350-6307, https://doi.org/10.1016/j.engfailanal.2019.02.029.

[10] https://www.shell.com/business-customers/lubricants-for-business/sector-expertise/power-industry/turbines/three-reasons-why-turbine-oil-degrades.html.

[11] Najjar, Y. S. H., Alalul, O. F. A. & Abu-Shamleh, A. (2020), “Degradation analysis of a heavy-duty gas turbine engine under full and part load conditions”. Int. J. Energy Res. 44, 4529–4542.

[12] Batayev, Nurlan. (2019), “Axial compressor fouling detection for gas turbine driven gas compression unit”. Indonesian Journal of Electrical Engineering and Computer Science. 15. 1257. 10.11591/ijeecs.v15.i3.pp1257-1263.

[13] Marco Gallo, Carmine Costabile, Marco Sorrentino, Pierpaolo Polverino, Cesare Pianese, (2020), “Development and application of a comprehensive model-based methodology for fault mitigation of fuel cell powered systems”, Applied Energy, vol. 279, Article number 115698.

[14] H. Zhang, J. Jiang, Z. Mo and Q. Miao, (2019) "A Remaining Useful Life Prediction Framework for Multi-sensor System," 2019 IEEE 19th International Conference on Software Quality, Reliability and Security Companion (QRS-C), pp. 255-259, doi: 10.1109/QRS-C.2019.00056.

[15]https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/

[16] C. Bandt and B. Pompe, (2002), “Permutation Entropy: A Natural Complexity Measure for Time Series”, Phys. Rev. Lett. 88 174102.