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

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Introduction

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The aim of this work is to propose a purely **data-driven approach** to maintenance.

This need arises for **two main reasons**:

- The preventive maintenance intervals set by OEMs sometimes prove to be **inaccurate**, leading to considerable increases in **maintenance costs**.
- The physical modelling proposed in many works, even if it can provide accurate answers, is very **complex** and **specific** and often requires **costly analysis** and plant **downtime**.

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Gas Turbine degradation

When a gas turbine system is put into operation, an expected "**natural**" **degradation** is attributed to it. On the basis of the **operating history**, the initially expected value is updated.

It is clear that if a failure occurs, the **useful life** of the system undergoes a **faster reduction** than the "natural" expected.

It is therefore necessary to identify a failure as soon as possible in order to take **mitigation actions** as efficiently as possible

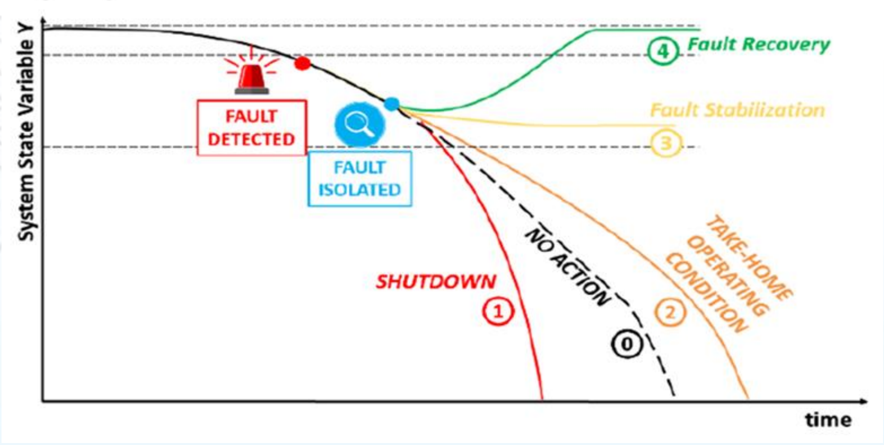


Figure 1: Fault mitigation approach [1]

Literature analysis

Literature analysis

- Study of the main **damage mechanisms**, maintenance policies and the **state of the art**.

Definition of the methodology

- Data-driven **methodology** that provides alternative solutions.

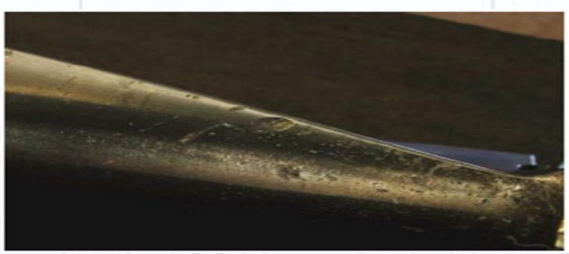
Testing & validation

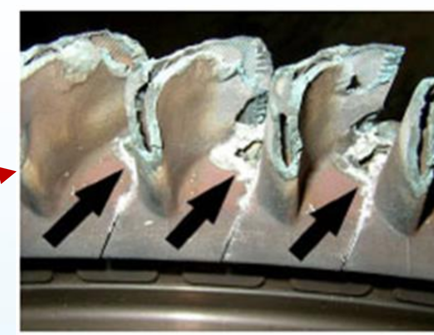
- **Application** of methodology on a dataset.

Key Damages

The main damage mechanisms involved in gas turbine systems are:

- FOD
- CREEP
- FOULING
- EROSION
- CORROSION
- FATIGUE





State of art

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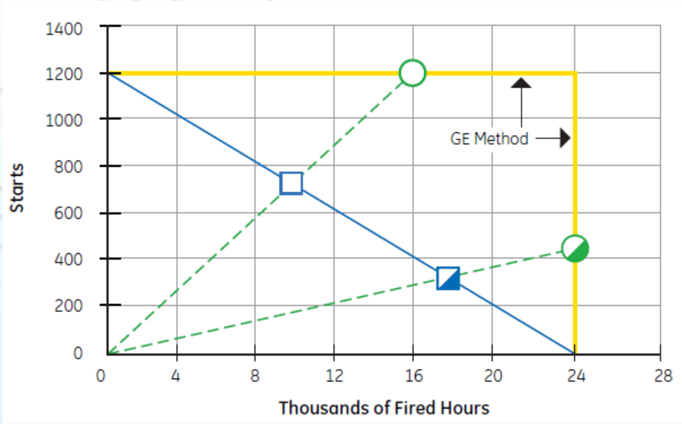
The most widely used approach by the OEMs to define the life reduction of a component is to establish **equivalent operating hours (EOH)**.
The most general **formula** to calculate the EOH is as follow [2]:

$$EOH = a_1 * n_1 + a_2 * n_2 + \sum_{i=1}^{n} t_i + f * w * (b_1 * t_1 + b_2 * t_2)$$

- $\boldsymbol{a_1}$ and $\boldsymbol{n_1}$ are the coefficient and number of starts, respectively.
- $\boldsymbol{a_2}$ and $\boldsymbol{n_2}$ are the coefficient and number of emergency starts, respectively.
- $\boldsymbol{b_1}$ and $\boldsymbol{t_1}$ are coefficient and operating time in basic load, respectively.
- $\boldsymbol{b_2}$ and $\boldsymbol{t_2}$ are coefficient and operating time of the peak load, respectively.

GE bases gas turbine maintenance requirements on independent counts of starts and hours.



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Impact of operating history

The following table makes a distinction between the most common faults in systems that perform **continuous operations** and systems that perform **cyclical operations**.

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 II: Typical failure modes for hot gas components inside a gas turbine [3]

Definition of the methodology

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Methodology

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Data collection

↓

Sensor selection
(Permutation Entropy)

$H(D) = -\sum p(\pi) * log_2 p(\pi)$

↓

Data fusion
(Multi-objective optimization)

$Obj = \min\{PE(D), \sigma^2\}$

↓

Remaining useful life estimation

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Permutation Entropy

PE is a measure of complexity of a dynamic system based on comparison of neighbouring values [9].

Probability of each permutation:

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

Permutation Entropy calculation:

$$H(n) = -\sum p(\pi) * log_2 p(\pi)$$

Divide all by $log_2 n!$ **to normalise** $\Rightarrow$ $0 \leq H(n) \leq log_2 n!$

How it works 1/3

To give an idea of how PE is calculated [10], an **example** of calculation on the following vector x is provided:

$$x = [\,4 \;\; 7 \;\; 9 \;\; 10 \;\; 6 \;\; 11 \;\; 3\,]$$

+1

3

Embedding time delay $\tau = 1$

Embedding dimension $n = 3$

$$\begin{bmatrix} 4 & 7 & 9 & 10 & 9 \\ 7 & 9 & 10 & 6 & 11 \\ 9 & 10 & 6 & 11 & 3 \end{bmatrix}$$

All columns have 3 elements (since *n = 3*) and all the column vectors are one step ahead of the previous one (since τ *= 1*)

How it works 2/3

The next step is to calculate 3! = 6 **permutations** and collect them into vectors.

$$\pi_1 = [\,0 \quad 1 \quad 2\,]$$
$$\pi_2 = [\,0 \quad 2 \quad 1\,]$$
$$\pi_3 = [\,1 \quad 0 \quad 2\,]$$
$$\pi_4 = [\,1 \quad 2 \quad 0\,]$$
$$\pi_5 = [\,2 \quad 0 \quad 1\,]$$
$$\pi_6 = [\,2 \quad 1 \quad 0\,]$$

$$\begin{bmatrix} 4 & 7 & 9 & 10 & 9 \\ 7 & 9 & 10 & 6 & 11 \\ 9 & 10 & 6 & 11 & 3 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 0 & 1 & 1 & 1 \\ 1 & 1 & 2 & 0 & 2 \\ 2 & 2 & 0 & 2 & 0 \end{bmatrix}$$

$\pi_1 = [\,0 \quad 1 \quad 2\,]$ because 4 < 7 < 9

How it works 3/3

Permutation	*Occurrences*	*Relative Frequency (p_i)*
π_1	2	2/5
π_2	0	0/5
π_3	1	1/5
π_4	2	2/5
π_5	0	0/5
π_6	0	0/5

$$PE = -\sum_{i=1}^{n!} p_i * log_2 p_i \approx 1{,}522$$

With n=2 $PE = 0{,}918$

Data Fusion

The sensors selected based on the sensor selection algorithms can be used in **data fusion**, which offers the following advantages:

- It allows to obtain a health indicator with more **evident trends**.
- It allows us to observe **multiple sensors** simultaneously.
- By calculating the weights on a limited number of the latest observations, it is possible to **update it** continuously.

Fused indicator calculation

The objective of data fusion is to calculate a **vector of weights** which when multiplied by the **matrix containing the chosen sensors** allows us to obtain a fused indicator.

$$\underbrace{\begin{bmatrix} \text{Selected sensor \#1} & \text{Selected sensor \#2} & \cdots & \text{Selected sensor \#n} \end{bmatrix}}_{\mathbf{m \times n}} * \underbrace{\begin{bmatrix} \text{Weights vector} \end{bmatrix}}_{\mathbf{n \times 1}} = \underbrace{\begin{bmatrix} \text{Fused indicator} \end{bmatrix}}_{\mathbf{m \times 1}}$$

The vector of weights is calculated from the matrix of selected sensors with the aim of **minimizing objective functions**.

Multi-objective optimization problem

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The objective functions to be minimized in this specific case are two: **variance** and **permutation entropy** [11].

$$Obj = min_w\{PE(D), \sigma^2\}$$

The variance is calculated according to the following formula:

$$\sigma^2 = \frac{\left(Yw - \frac{1_M Yw}{M}\right)'\left(Yw - \frac{1_M Yw}{M}\right)}{M-1}$$

Where Y is the matrix of selected sensors, but it only contains a **limited number** of the latest observations. M is the number of units.

This allows the algorithm to update itself and follow new trends in the data [1].

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RUL estimation 1/2

The following formula describes what the RUL is and how it is calculated:

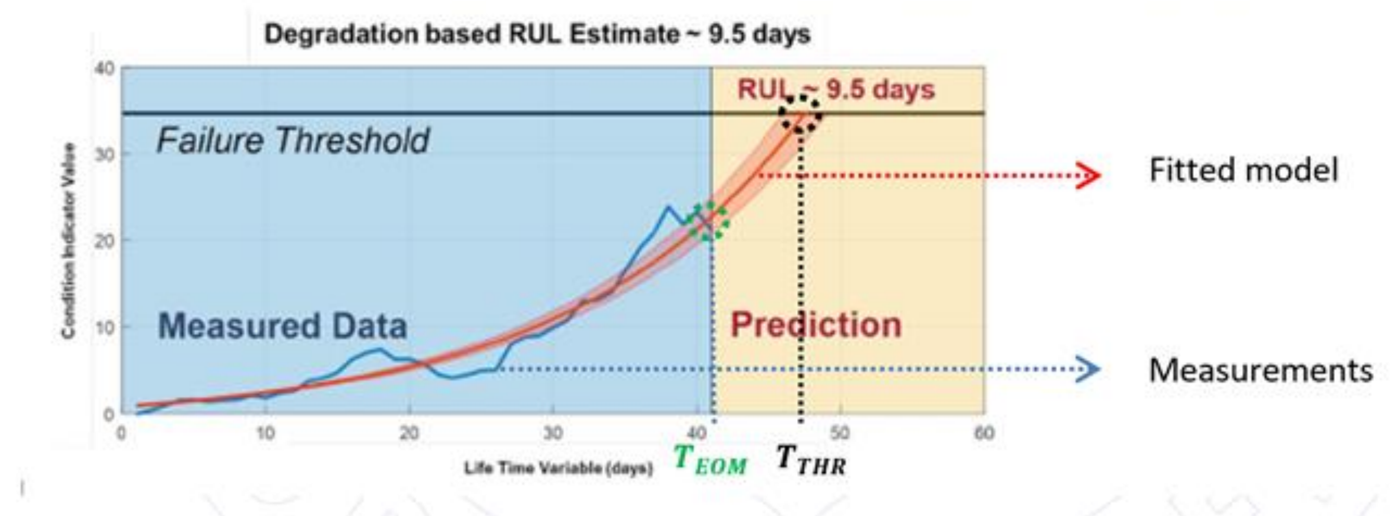
$$RUL = T_{THR} - T_{EOM}$$

where T_{EOM} (**end of measurements time**) is the time corresponding to the end of the available measurements and T_{THR} (**threshold time**) is when the predicted degradation curve meets the threshold.

The method used to calculate RUL **depends on the kind of data available**.

RUL estimation 2/2

In most cases the only data available are on **prescribed threshold values**. With this kind of information, it is possible to fit time series models to **condition indicators** extracted from **sensor data**, which rise or fall over time. These degradation models estimate RUL by predicting **when the condition indicator will cross the threshold**.



Testing & validation

Literature analysis

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Dataset description

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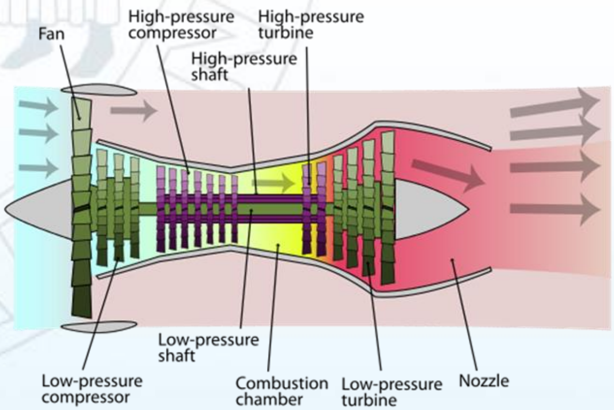
Measurements of 21 sensors from an **aircraft engine** are taken from the NASA database [12].

These data were generated with a simulation tool and are available online. Each data set is comprised of a time series of flight cycle measurement **“snapshots” at cruise conditions** [13].

Data from the **first fleet** (divided into 21 sensors) were used for this analysis.



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PE calculation - Discarded sensors

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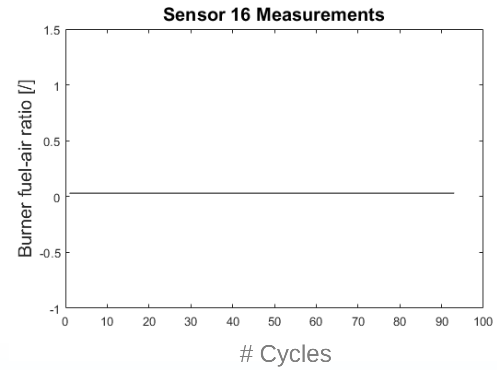
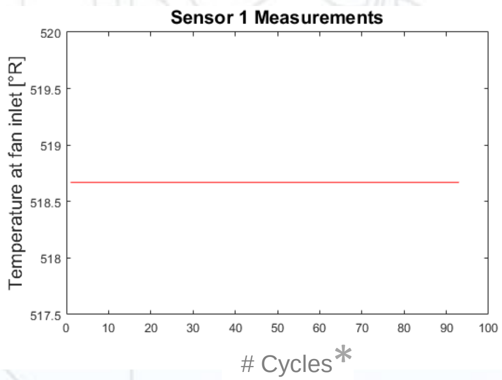
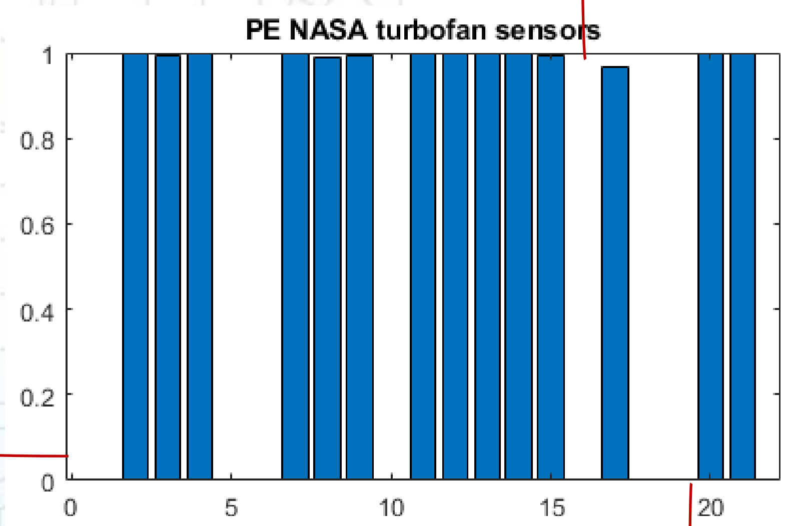
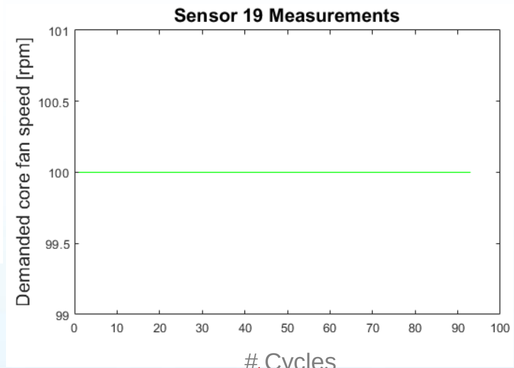
Sensors #1, #5, #6, #10, #16, #18 and #19 show a zero PE value justified by the fact that these sensors have a **constant trend**.









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PE – Selected sensors

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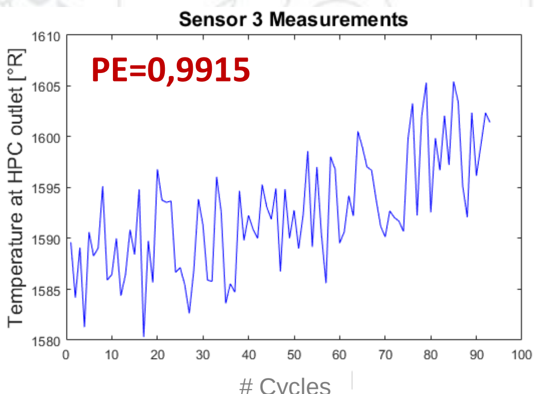
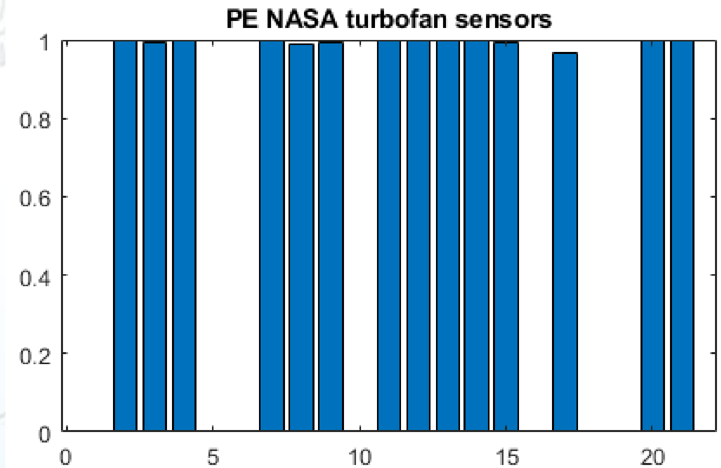
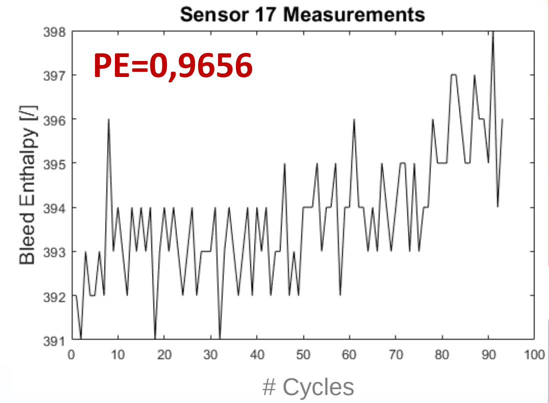
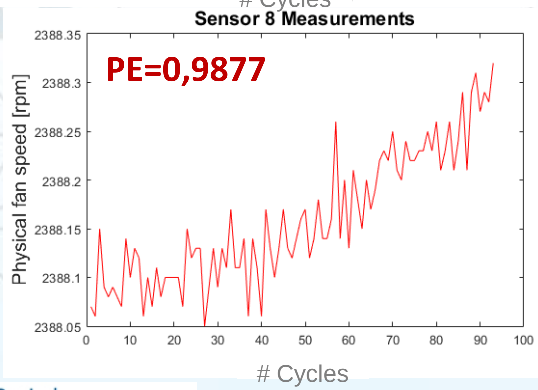
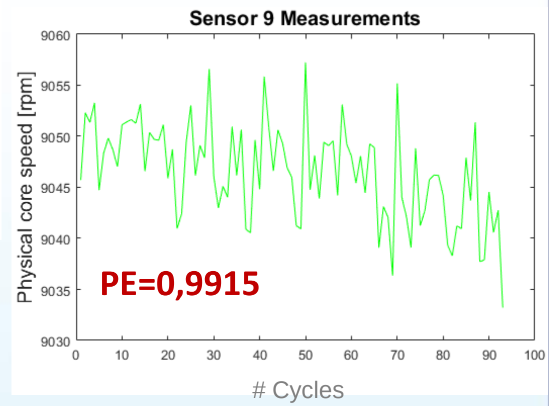
Sensors #3, #8, #9 and #17 show the lowest PE values. Therefore, they potentially represent the measurements of **highest interest** in a degradation analysis.











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Fused indicator calculation

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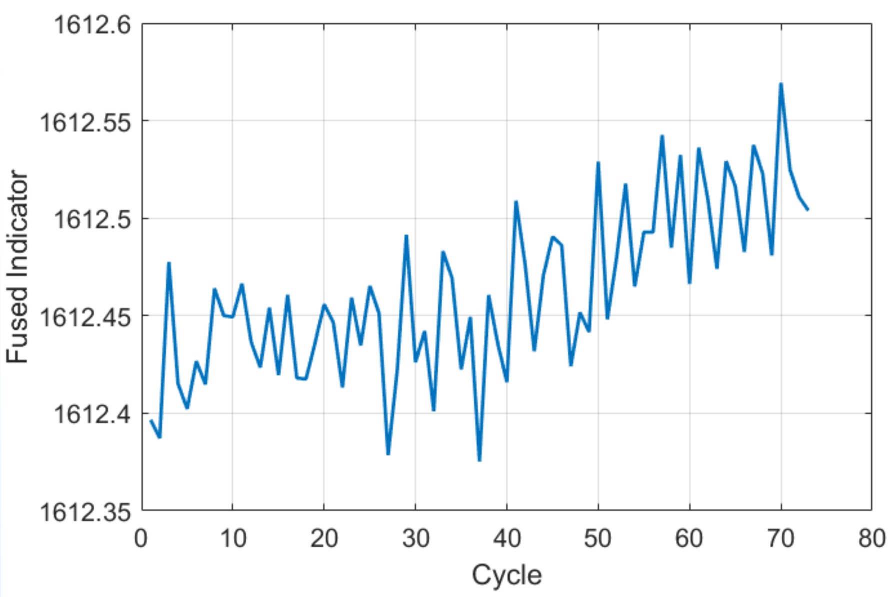
$$\underbrace{\begin{bmatrix} \text{Selected sensor \#3} & \text{Selected sensor \#8} & \text{Selected sensor \#9} & \text{Selected sensor \#17} \end{bmatrix}}_{m \times n} * \underbrace{\begin{bmatrix} \text{Weights vector} \end{bmatrix}}_{n \times 1} = \underbrace{\begin{bmatrix} \text{Fused indicator} \end{bmatrix}}_{m \times 1}$$



Selected sensors	#3	#8	#9	#17
weights	0,0022	0,6598	0,0032	0,0115

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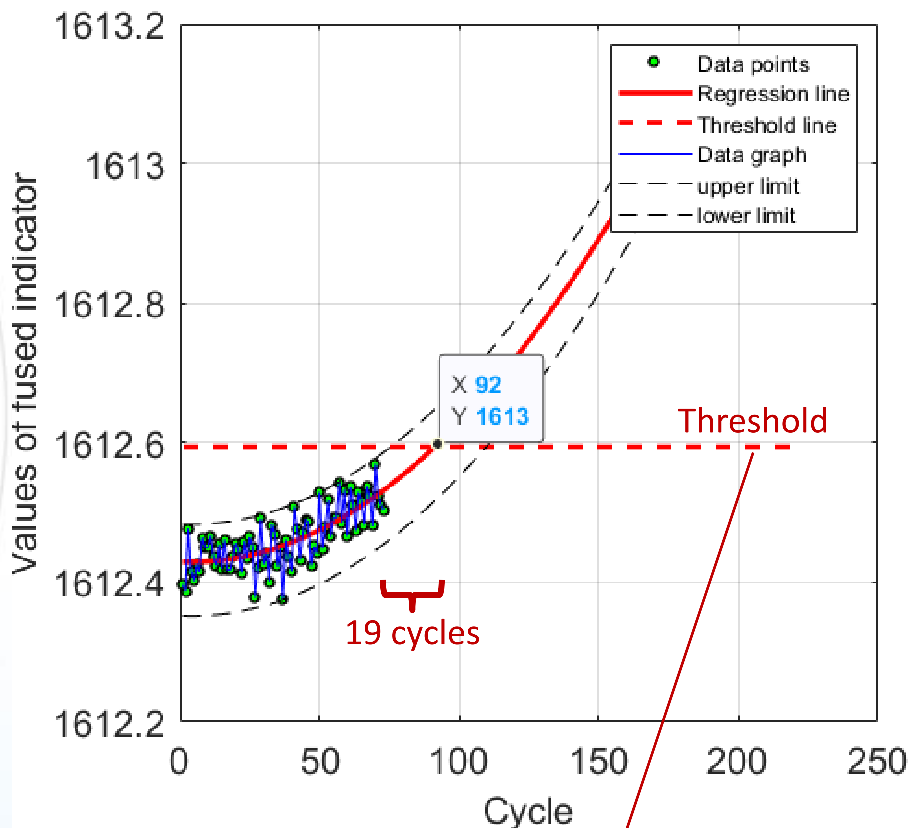
Remaining useful life

The prediction made on the fused indicator shows a remaining useful life (RUL) of **19 cycles**. Failure occurs at the 92nd cycle and the **effectiveness** of this prediction is therefore confirmed.

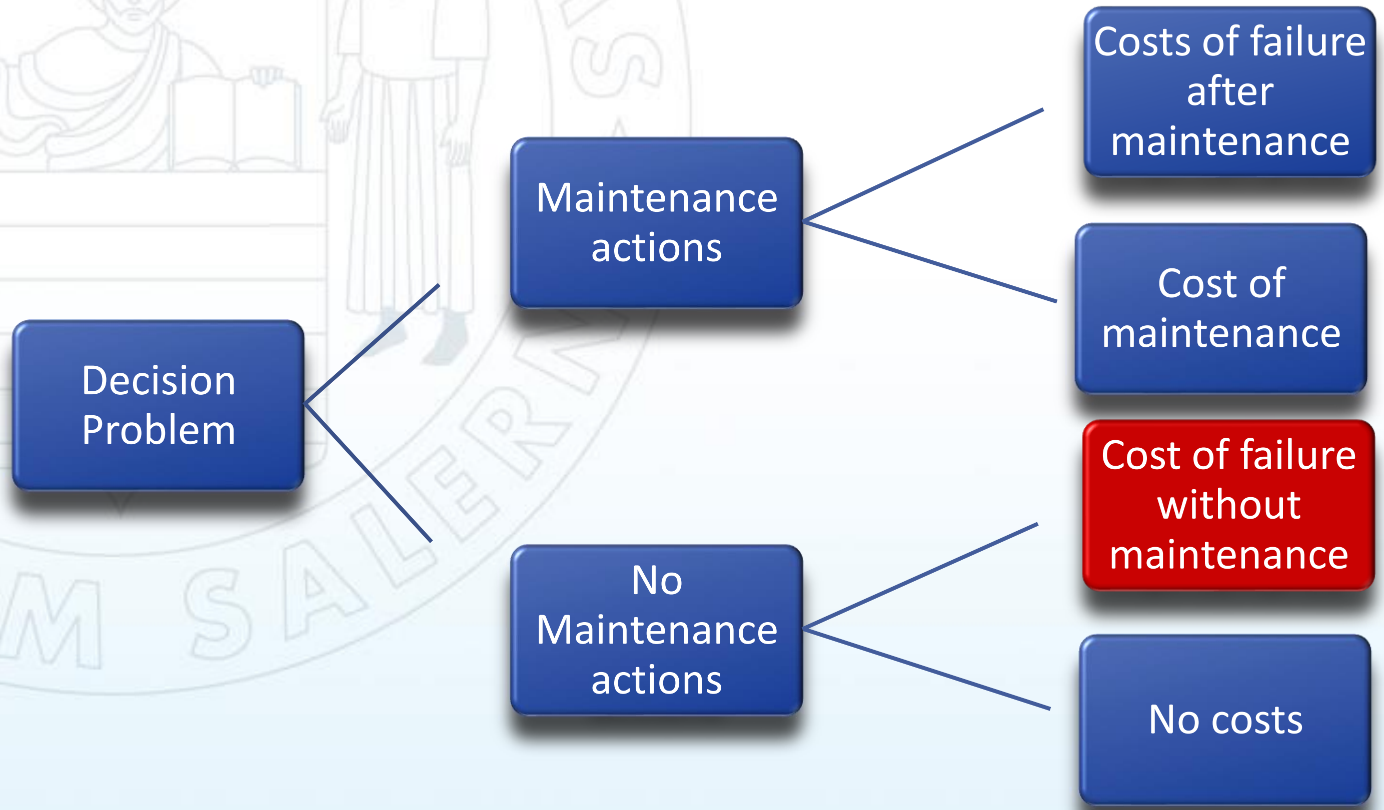


$$Threshold\ Values * Weights = \boldsymbol{Fused\ Indicator\ Threshold}$$

Costs & Risk

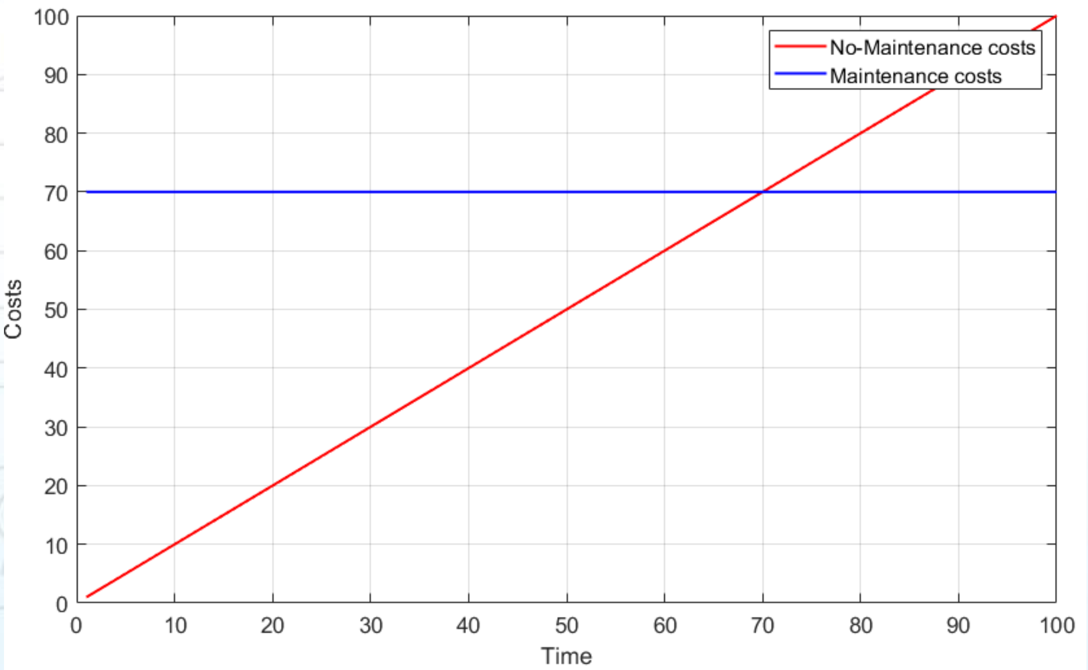
Costs & Risk 1/2

As the curve representing the RUL approaches its threshold value, the probability of failure increases. The choice to carry out a maintenance action must therefore follow two decision logics: the **probability of failure** and the **costs**.



Costs & Risk 2/2

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**.



Conclusions

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 following results are observed:

- The **sensor selection** activity based only on PE led to the selection of the most significant sensors.
- **Multi-objective optimization** achieved satisfactory levels of PE and variance.
- The fused indicator proved capable of predicting **RUL** effectively.

The absence of specific material analysis and geometric modelling (which also requires plant shutdowns) ensures **minimal implementation costs** compared to other approaches.

Thanks for your attention

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