AIRCRAFT ENGINES

Mathematical approaches in artificial intelligence for the digital clone of an aircraft engine

Jérôme Lacaille

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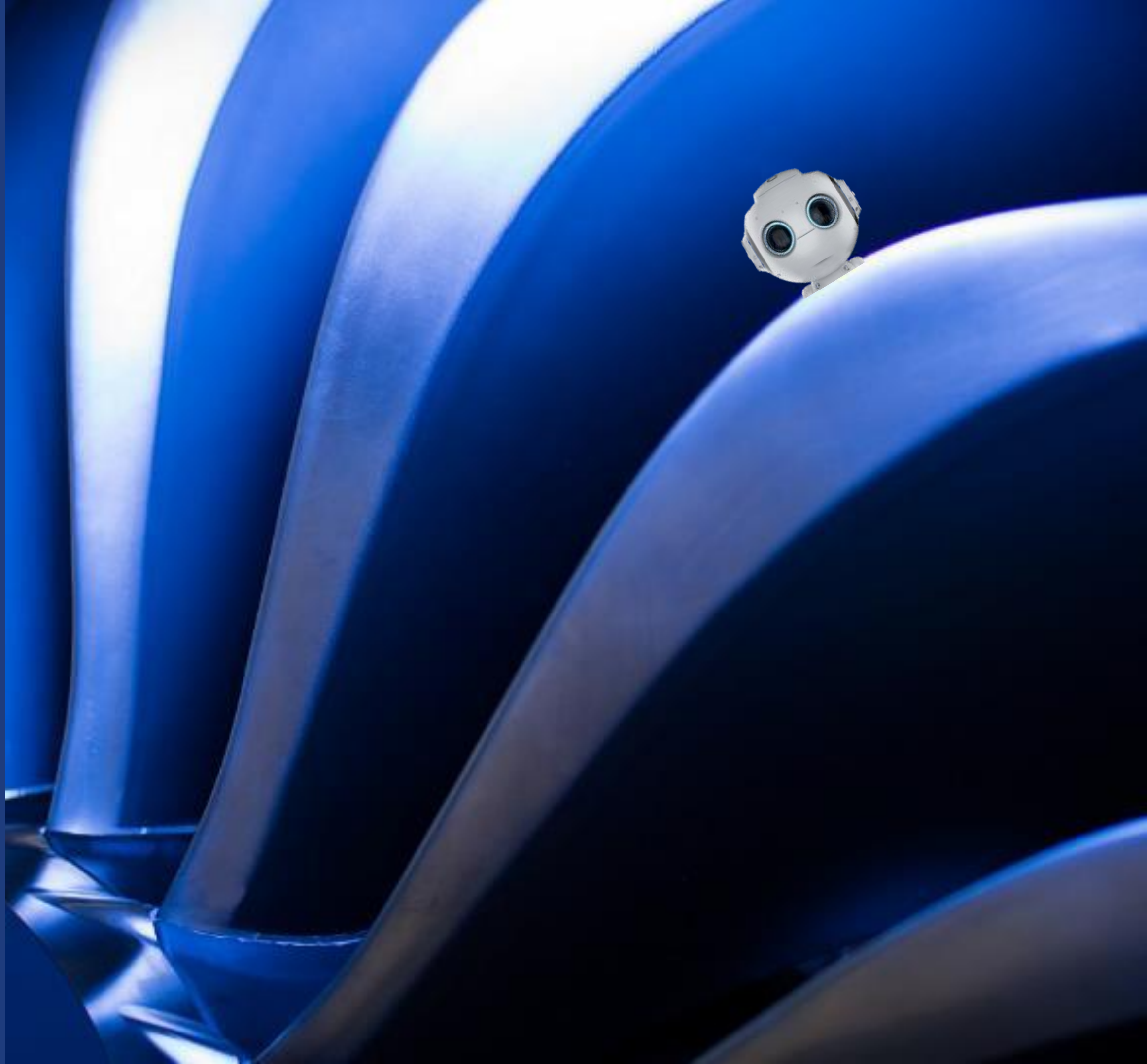
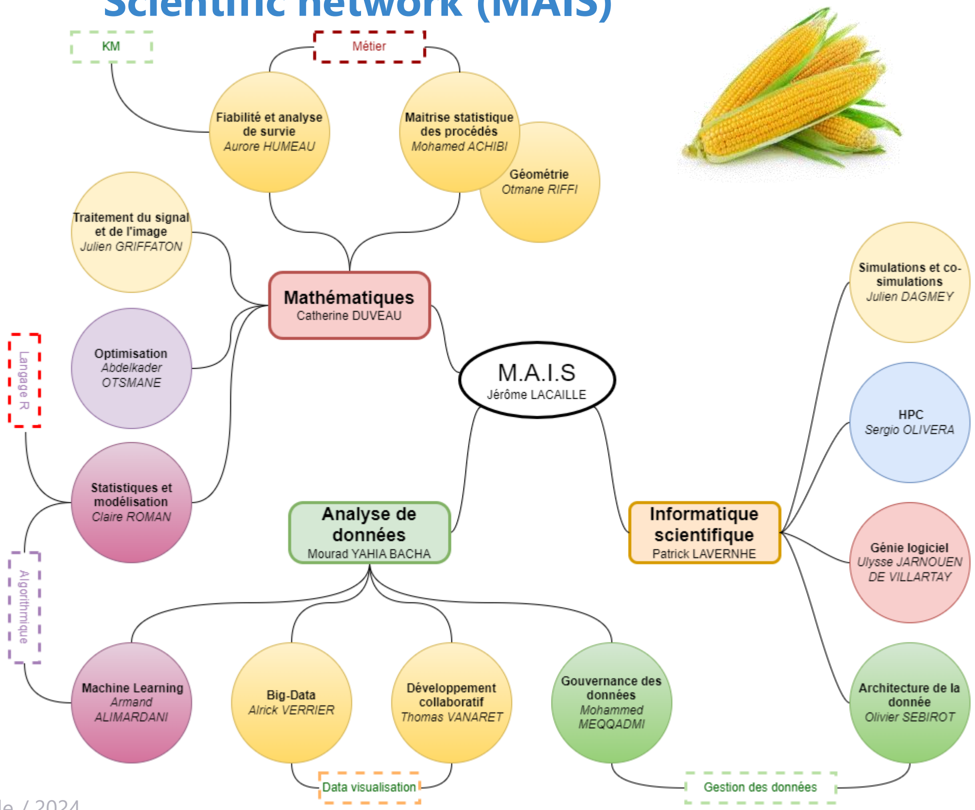


Expertise in Safran Aircraft Engines

- **Jérôme Lacaille**
  - Safran Emeritus Expert
    - Research team manager
    - Head of M.A.IS network
      - 50 experts, 300+ members.
    - Founder of the DataLab
      - 20 members to help solve data analysis based problems and build algorithmic tools.
      - Data analysis training for company engineers.
    - Algorithm platform development for the PHM (Prognostic and Health Monitoring) business unit.
  - Associate professor
    - University Sorbonne Paris Nord
    - Ecole Normale Supérieure of Saclay
  - Associate Member of the SAMM laboratory
    - University Panthéon Sorbonne

- **Mathematic, Algorithms, Informatics Scientific network (MAIS)**



SAFRAN AIRCRAFT ENGINES AT A GLANCE

€9.1bn

REVENUES **IN 2022**

16,400 PEOPLE

INCLUDING **13,000 IN FRANCE**

at Dec. 31, 2022

Over 30 sites

INCLUDING 14 IN FRANCE

A global footprint

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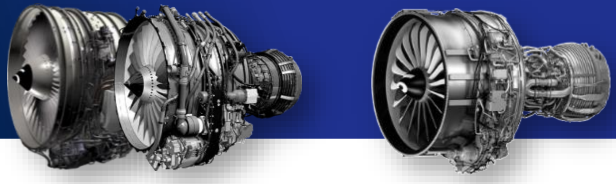
OUR RANGE OF ENGINES FOR COMMERCIAL AVIATION

CFM56

LEAP



- CFM56: B737, A320
- LEAP: B737 MAX, A320NEO, C919

GE90/GE9X/CF6/GP7200

- B777, B777X
- B747, A310/330
- A380

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CFM®: A UNIQUE PARTNERSHIP IN AVIATION HISTORY

SAFRAN AIRCRAFT ENGINES
AND GE AEROSPACE

45+ years

OF SUCCESS

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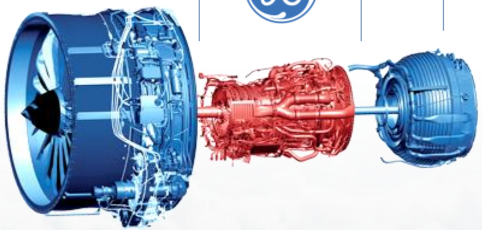

A **50**/50 **company**

DESIGN, DEVELOPMENT, PRODUCTION, SALES AND SUPPORT OF CFM56 AND LEAP ENGINES

No. 1

GLOBAL SUPPLIER OF ENGINES

for mainline commercial aircraft (over 100 seats)

Over 680

CUSTOMERS WORLDWIDE

AGREEMENT NOW EXTENDED TO

2050

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LEAP®: A NEW-GENERATION ENGINE – **QUIETER** AND **MORE ENERGY EFFICIENT**

AIRBUS A320neo

LEAP-1A
Service entry: ***August 2016***

BOEING 737 MAX

LEAP-1B
Service entry: ***May 2017***

COMAC C919

LEAP-1C
Service entry: ***May 2023***

PROVEN ENVIRONMENTAL BENEFITS IN OPERATION

-15% to 20% C02 EMISSIONS AND FUEL CONSUMPTION

SIGNIFICANT NOISE REDUCTION

ON SPEC *Compared to previous-generation engines*

ORDER BOOK
OVER **10,000** ENGINES

OVER **30m** FLIGHT HOURS

OVER **160** OPERATORS worldwide

70% SINGLE-AISLE COMMERCIAL JETS POWERED BY LEAP

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DECARBONIZATION OF AVIATION

ULTRA-EFFICIENT ENGINE ARCHITECTURE

SUSTAINABLE AVIATION FUELS

HYBRID AND ELECTRIC PROPULSION

FUTURE ULTRA-EFFICIENT SINGLE-AISLE JET

SMARTER ENGINES **AND SERVICES**

- ✔ In-flight data capture and analysis
- ✔ Predictive maintenance
- ✔ Reduced consumption
- ✔ Improved reliability

LOWER CO_2 EMISSIONS WITH EACH NEW GENERATION

ONGOING **CONTRIBUTION** TO THE **CLIMATE CHALLENGE**

CFM56

1982

-25%

LEAP

2016

-15% to 20%

RISE

2035

-20%

40% REDUCTION SINCE 1982

For a total of **60% reduction in CO_2 emissions**

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Agenda

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Chapter 1

Safran Aircraft Engines PHM

(Prognostic & Health Monitoring)

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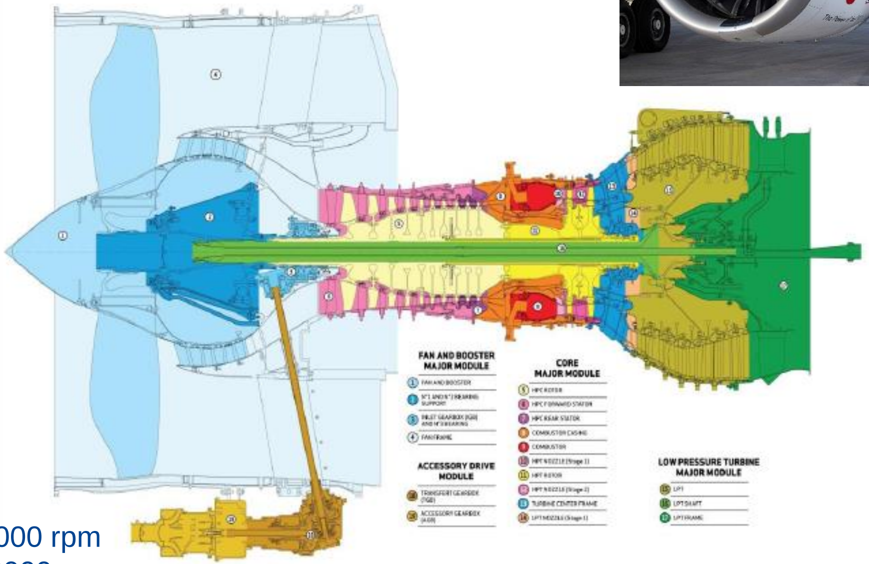
The LEAP aircraft engine



Birotor
LP Rotor supported by 3 bearings 4000 rpm
HP rotor supported by 2 bearings 20000 rpm
Diameter : 2m, lenght: 3,3m
Thrust : 110 kN
16000 parts, 2400 references, …30 sensors

For more information :
http://www.safran-aircraft-engines.com/tab_app/howengineswork/index-en.html

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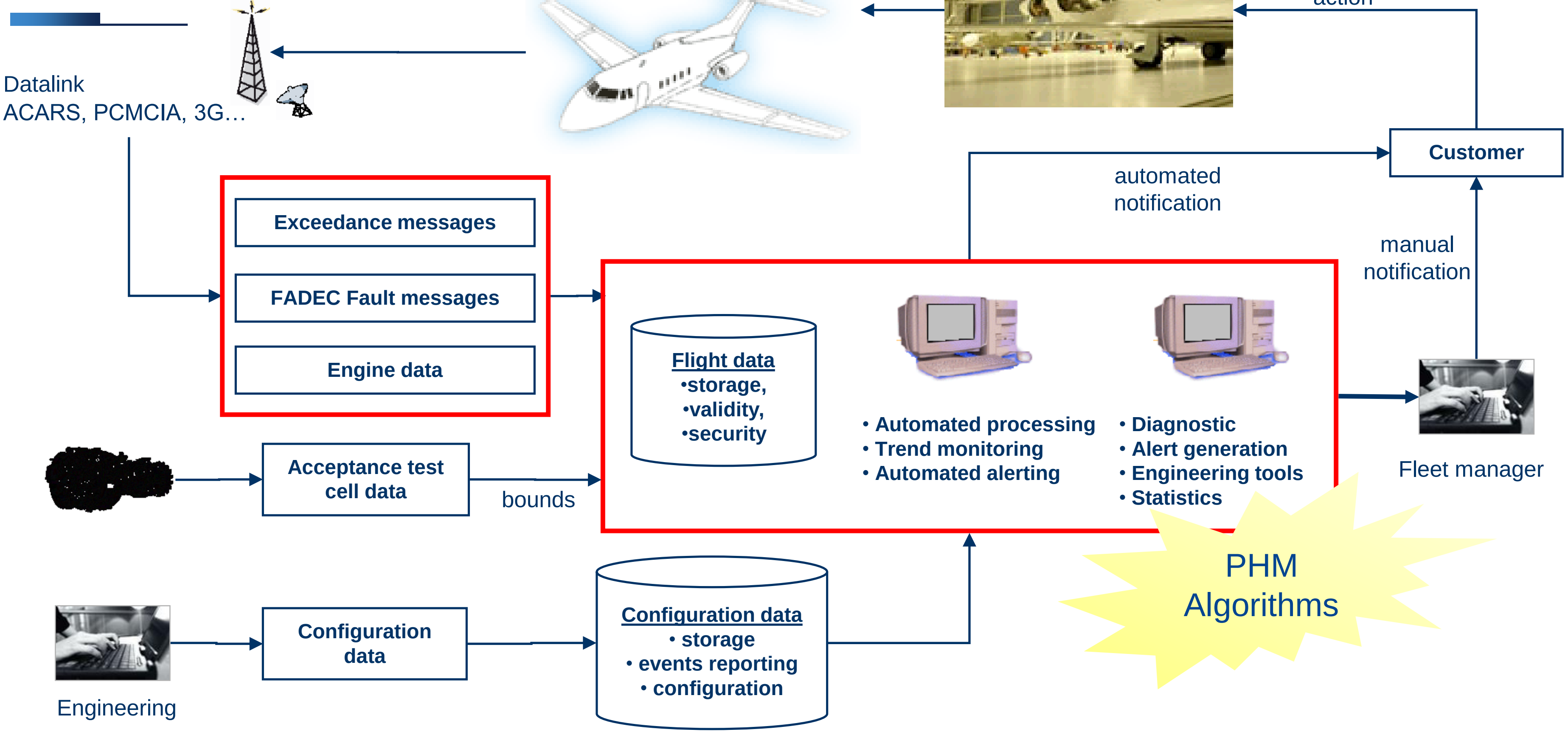
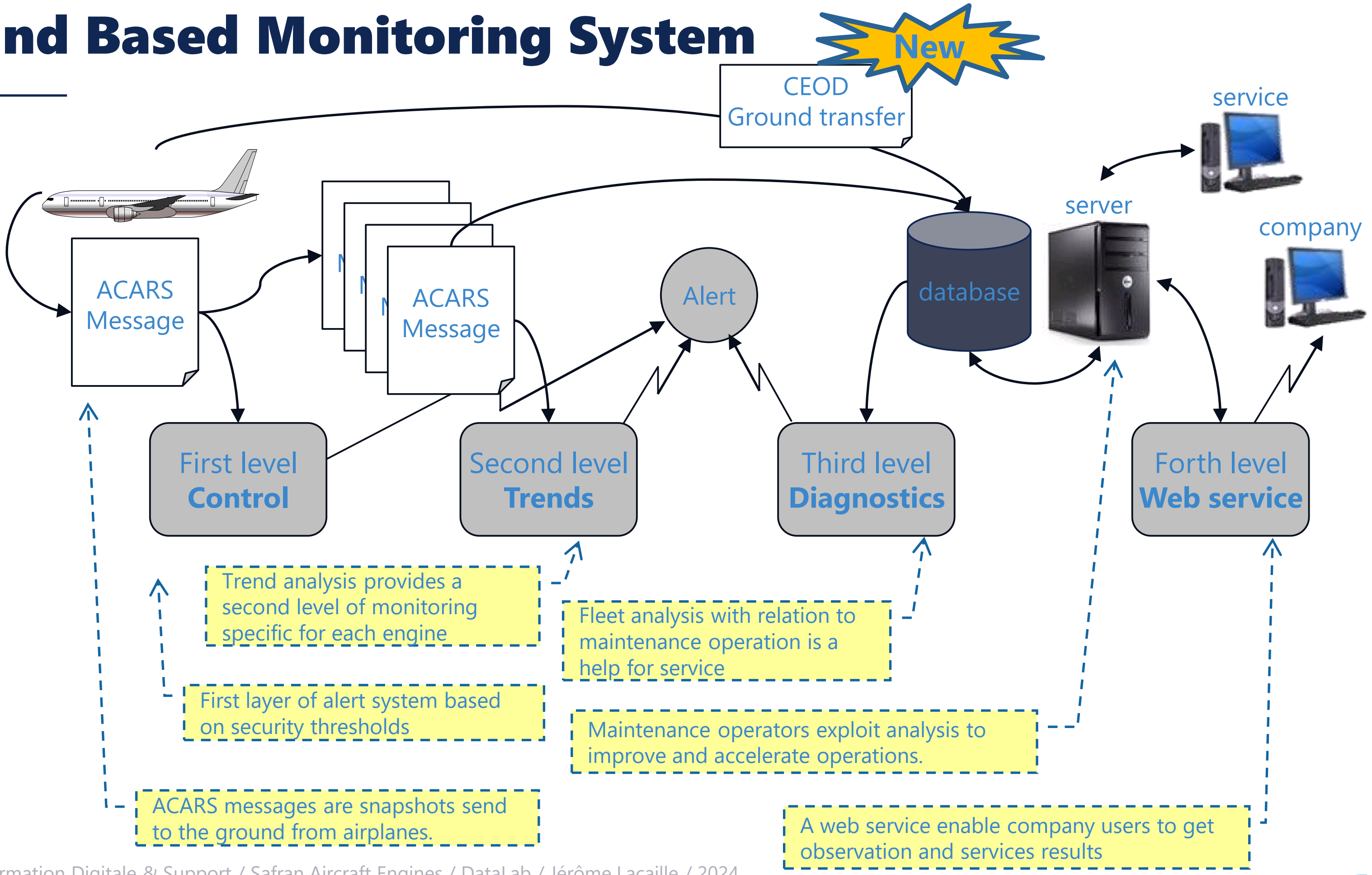
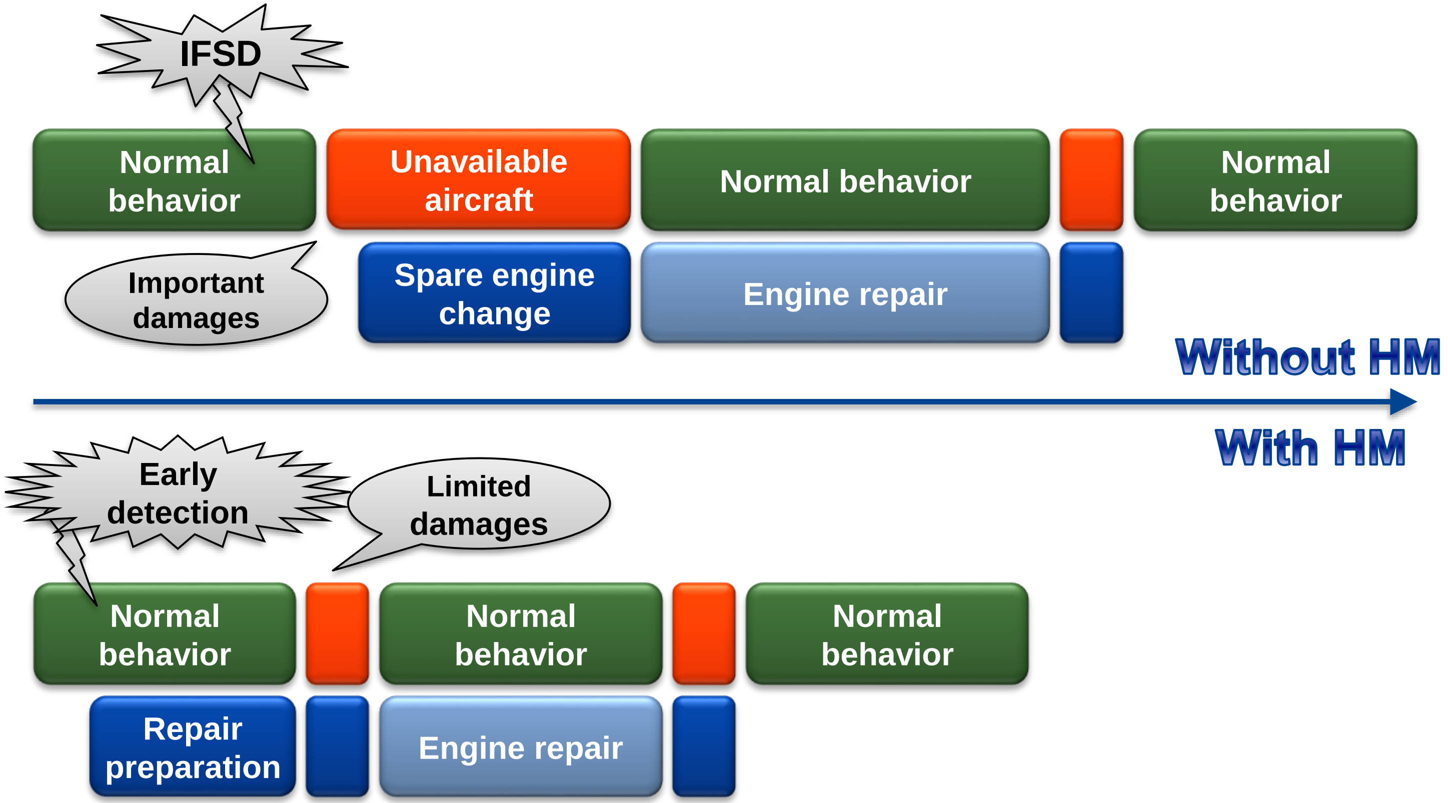
Engines maintenance



Ground Based Monitoring System

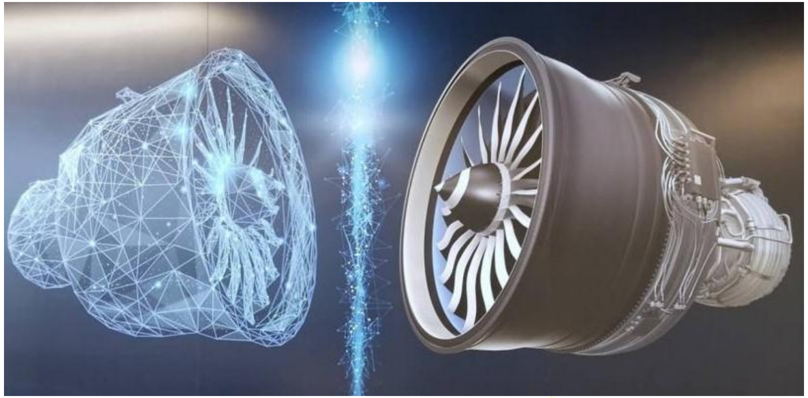


PHM Story Board



Digital twin

An application integrate all documents related to each engine SN, from design to operations and repair.



And we want to boost this digital twin with state-based mathematical models!

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Chapter 2

Deep Survival

(Cumulative damage models)

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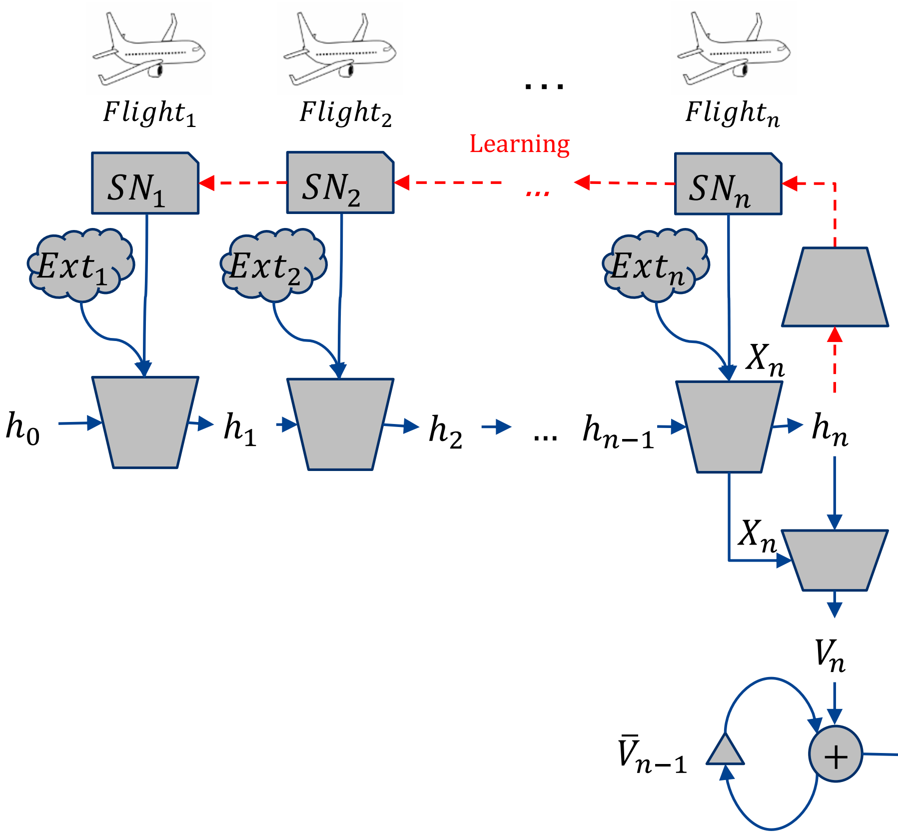
Deep survival

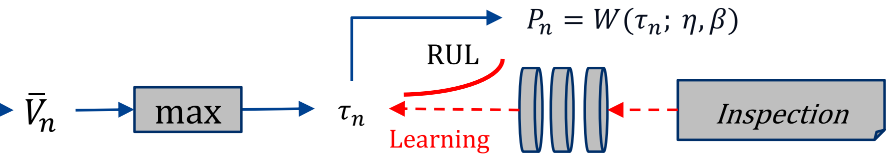


Evaluation of the engine current state

- Using flight categorization and flights sequences encoding.
- Then state categorization (again).

Continuous Damage Models

- Deep survival algorithms based on intrinsic state.



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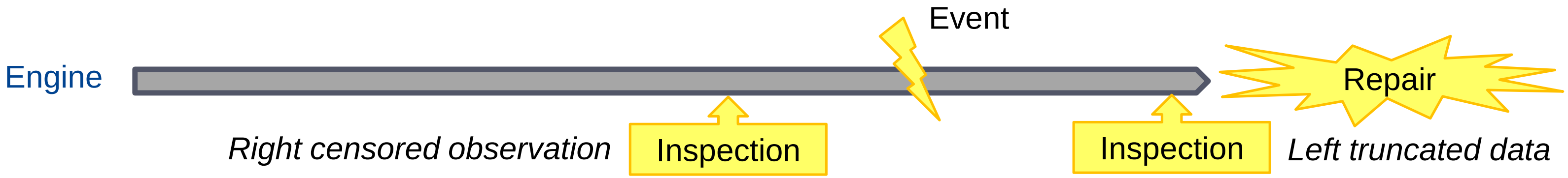
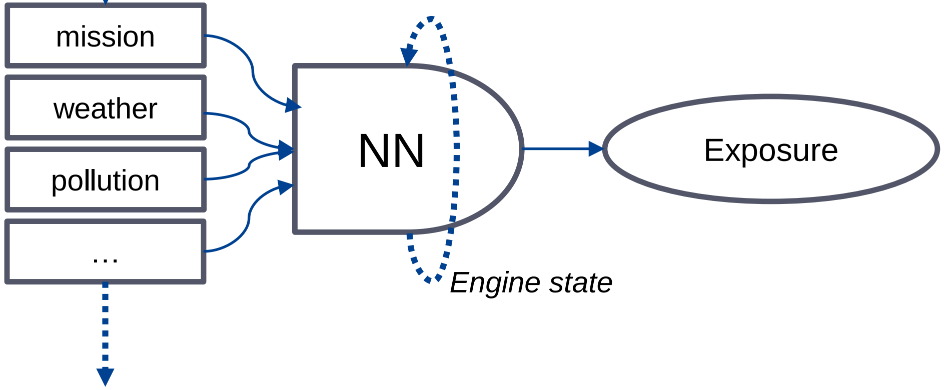
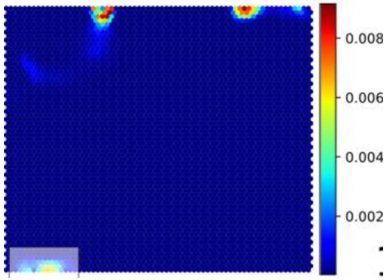
Example 1 : hot corrosion on turbine blades



Construction of a neural exposure rate to wearing conditions.

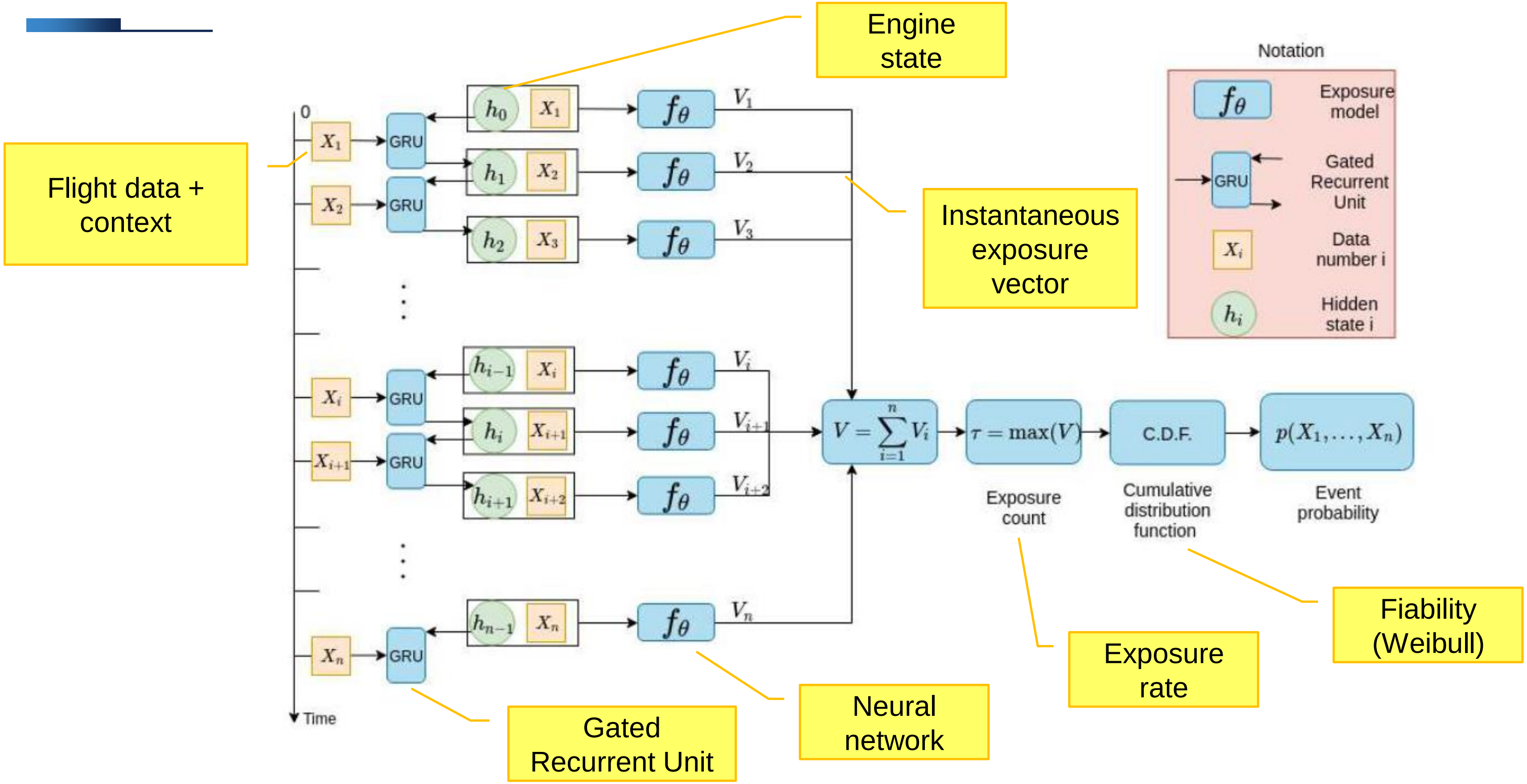




pitting

dripping

Detail of the recurrent neural network



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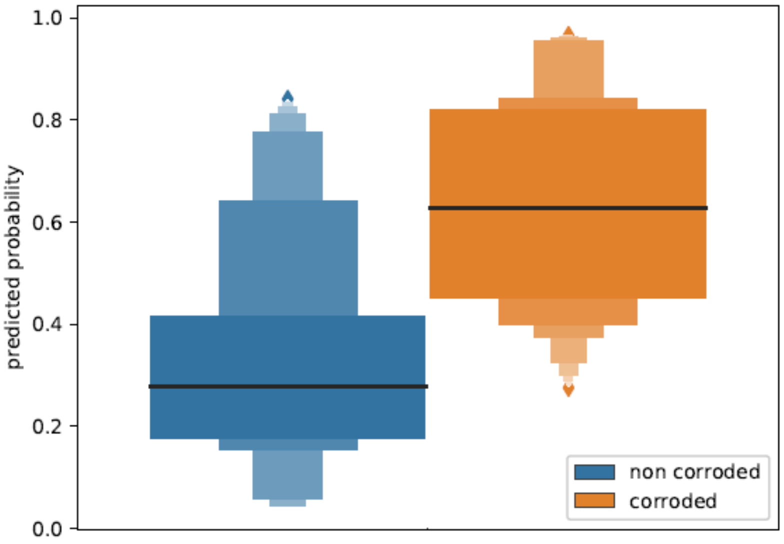
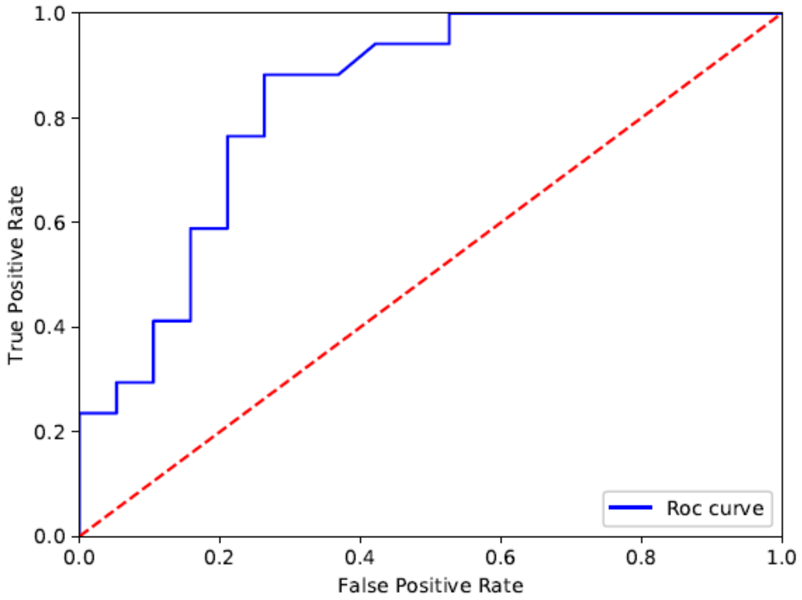
Results on hot corrosion



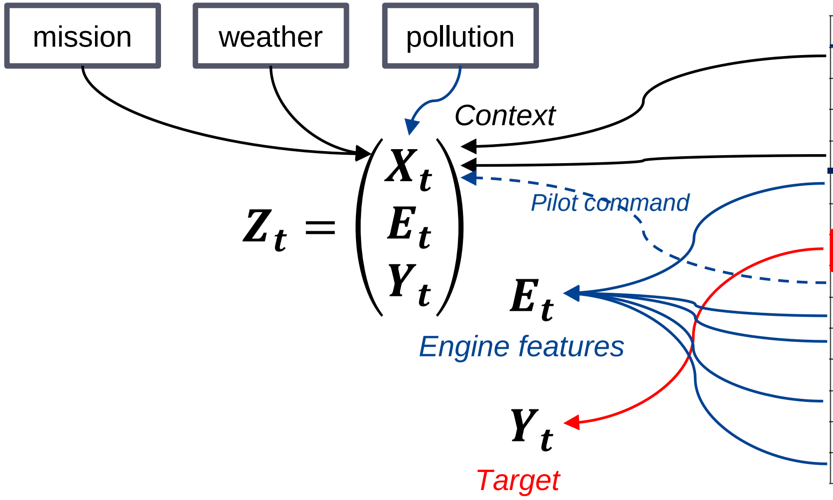


Example 2: monitoring of the general wear of an engine

We have a lots of input data capitalized in a big vector Z_t for each flight t.

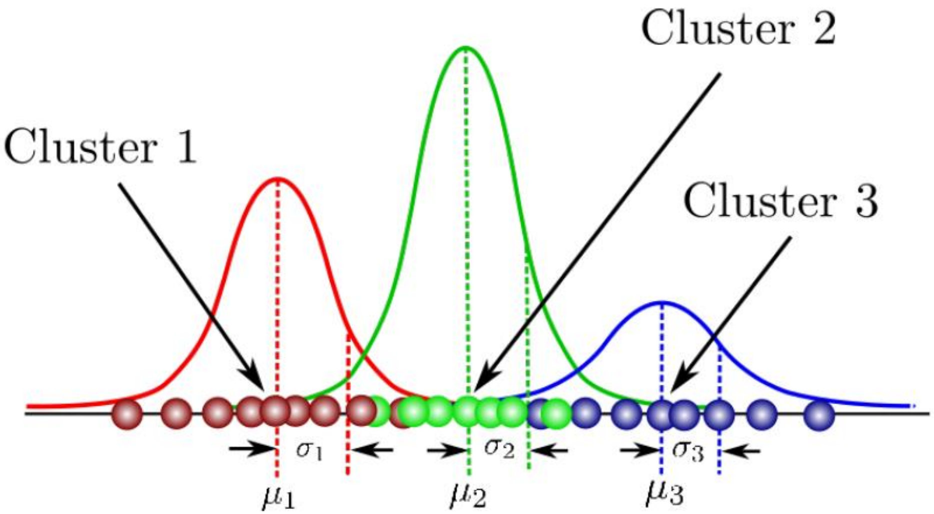
> Data coming from any phase of each flight,

- There is two kind of data: context and engine measurements. From the vector Z_t we extract a part X_t to suppress all engine measurements, except pilot command which is clearly part of the context.



Parameter	Description
TAT	External temperature
Altitude	Altitude
Mach number	Instant speed
Ground Speed	speed with respect to the ground
N2	Core speed
T25	Compressor Inlet Temperature
EGT	Exhaust Gas Temperature
N1	Fan Speed
PS3	Compressor Discharge Pressure
T3	Compressor Discharge Temperature
T12	Inlet temperature
PT2	Inlet Total Pressure
Fuel Flow	Fuel flow
VBV Position	Variable Bleed Valve Position

Stochastic output that manage different modes



Number m of clusters

Engine i

$$p_t^i(x) = \sum_{j=1}^{m} \pi_t^{i,j} \mathcal{N}(\mu_t^{i,j}, \sigma_t^{i,j})$$

Flight t

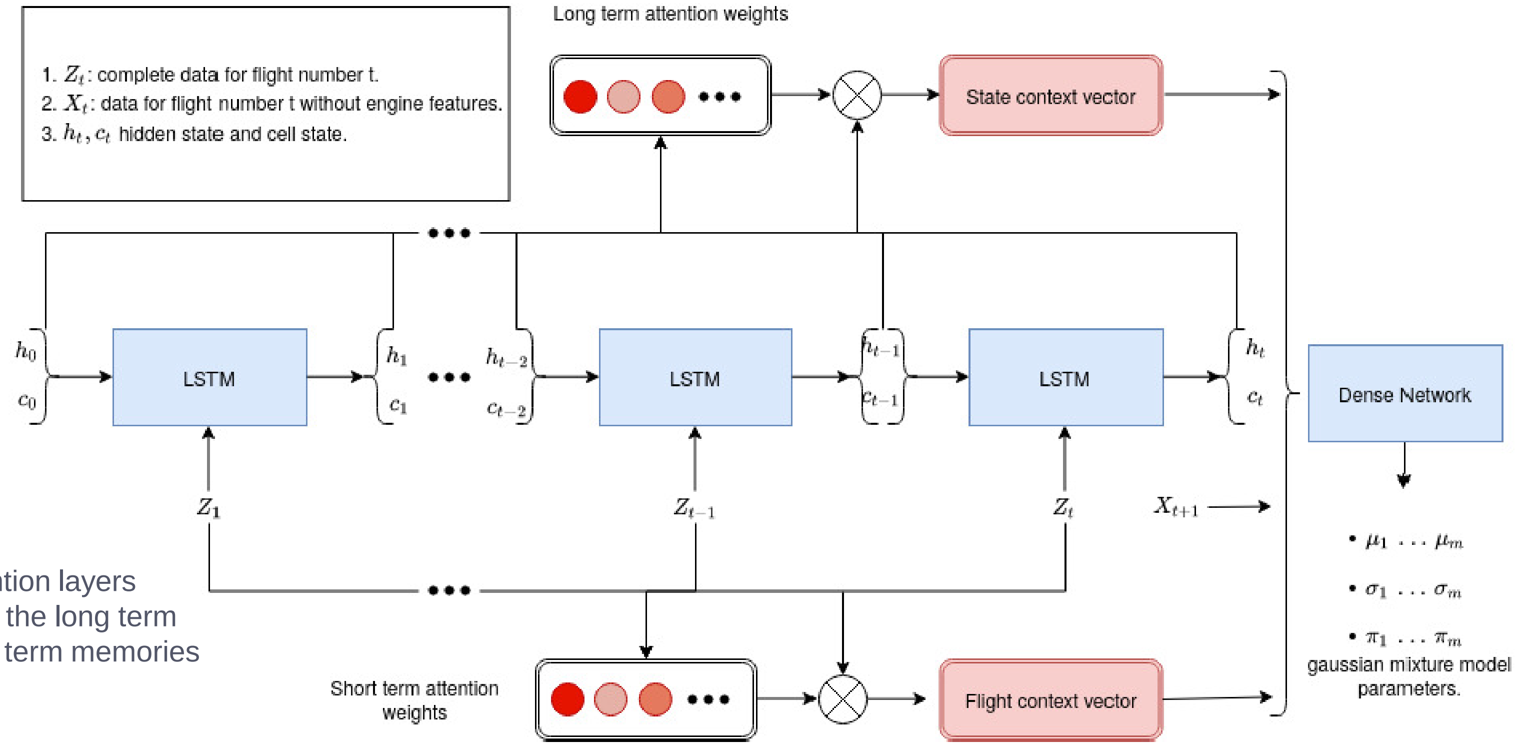
Probability of cluster j for engine i at flight t

Different actions can explain the behaviour observed:

- progressive wear due to the last mission
- but also interventions on the engine which can cause sudden changes in the measurements.

Therefore, we are looking for a stochastic output that will sum up all these possibilities.

A model that uses two attention layers



Two attention layers moderate the long term and short term memories

A short reminder of the attention mechanism

Gradient descent

- ADAM optimizer
- Based on negative log-likelihood minimization
- With dropout
- Implemented in Pytorch

Attention mechanism

- Short-term memory calibrated by a neural network

$$a_{s,t} = (W_2)'\sigma\left(W_1[X_s, X_t] + w_0\right)$$

$$\alpha_{s,t} = \frac{\exp(a_{s,t})}{\sum_{r=t_a}^{t-1} \exp(a_{r,t})}.$$

$$\mathcal{C}_f(t) = \sum_{s=t_a}^{t-1} \alpha_{s,t} Z_s$$

- Long-term memory by similarity

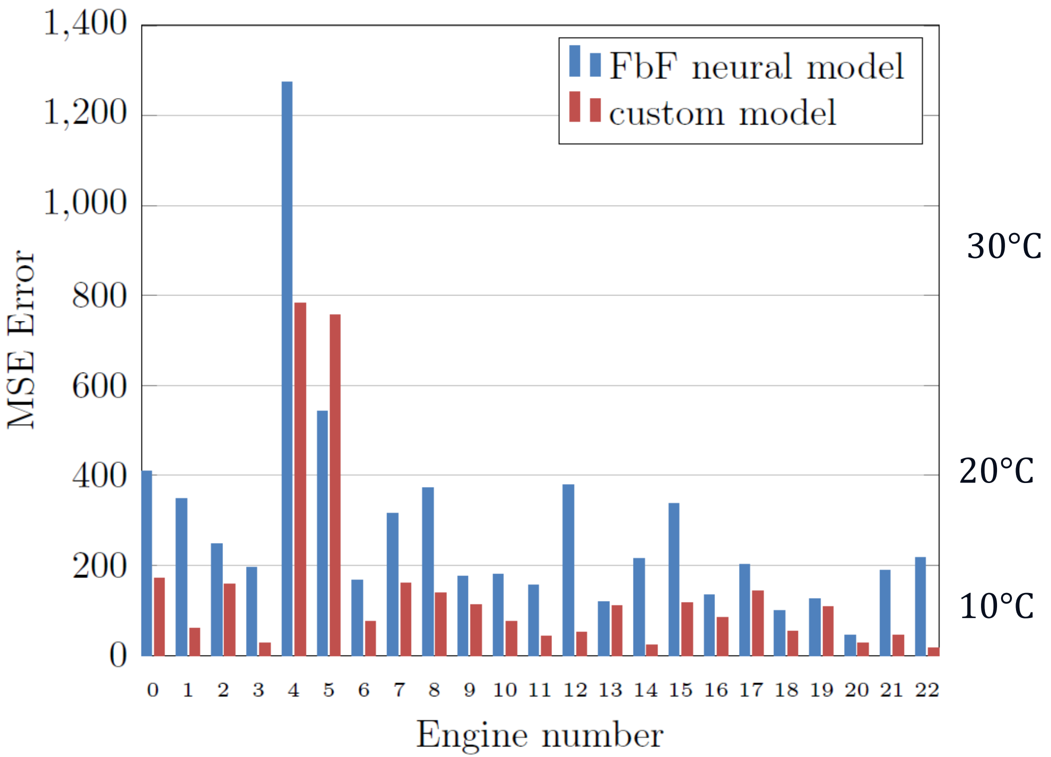
$$b_{s,t} = sim\left(h_s, h_{t-1}\right).$$

$$\beta_{s,t} = \frac{\exp(b_{s,t})}{\sum_{r=t_b}^{t-1} \exp(b_{r,t})}$$

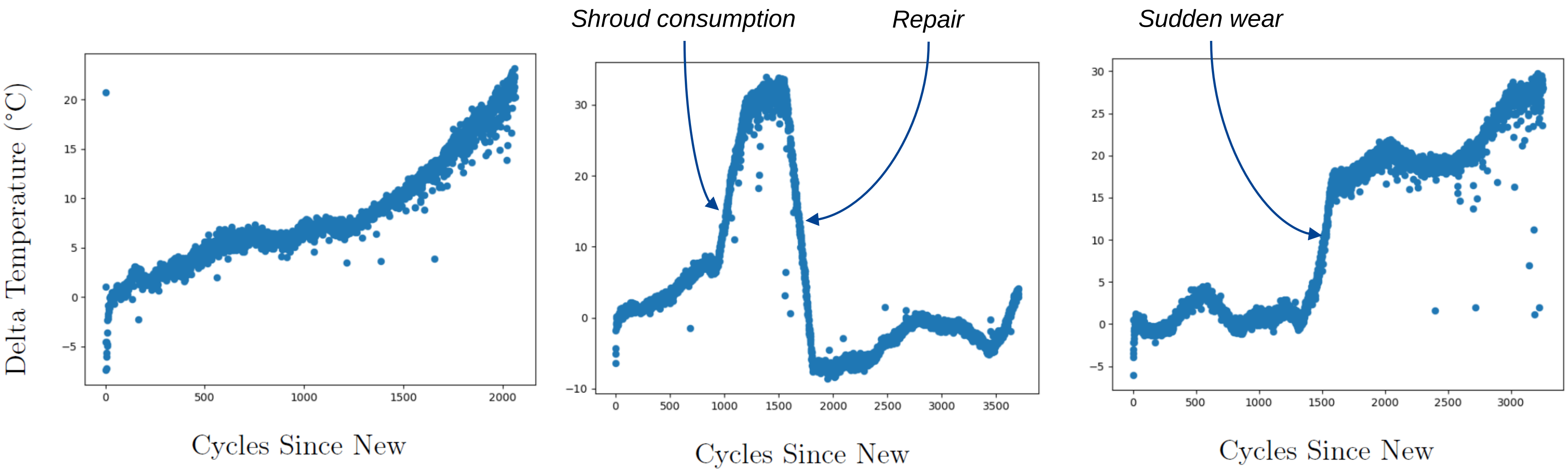
$$\mathcal{C}_s(t) = \sum_{s=t_b}^{t-1} \beta_{s,t} h_s$$

Net gain compare to classical model without memory

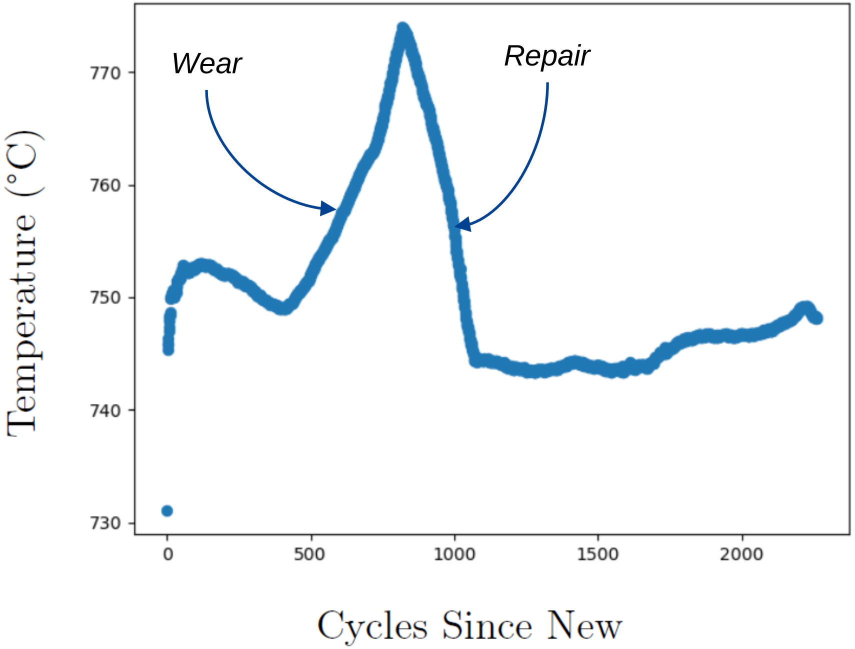
The goal of this comparison is to measure the effect of memory

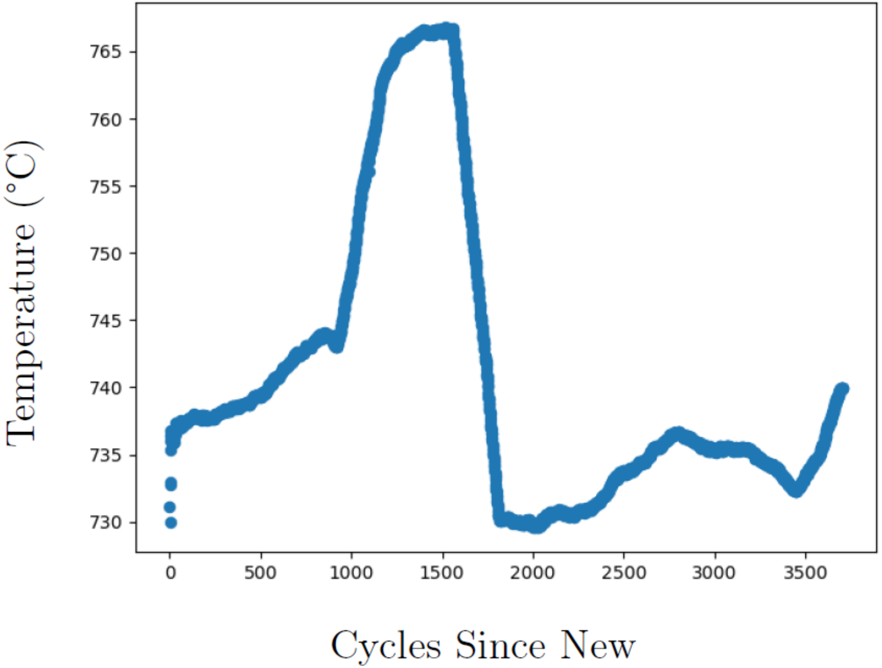


EGT of each engine compared to is state new

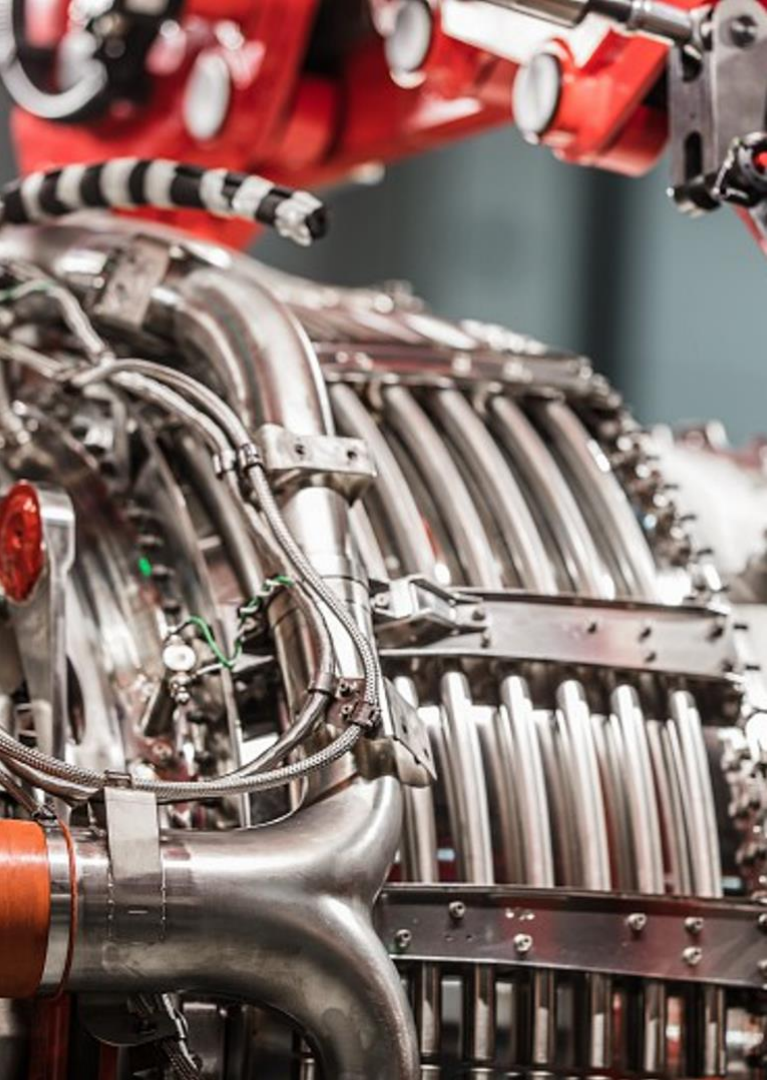


Mean of 10000 flight simulations





We use the model to simulate engine measurements from 10000 different flights contexts.



Chapter 3

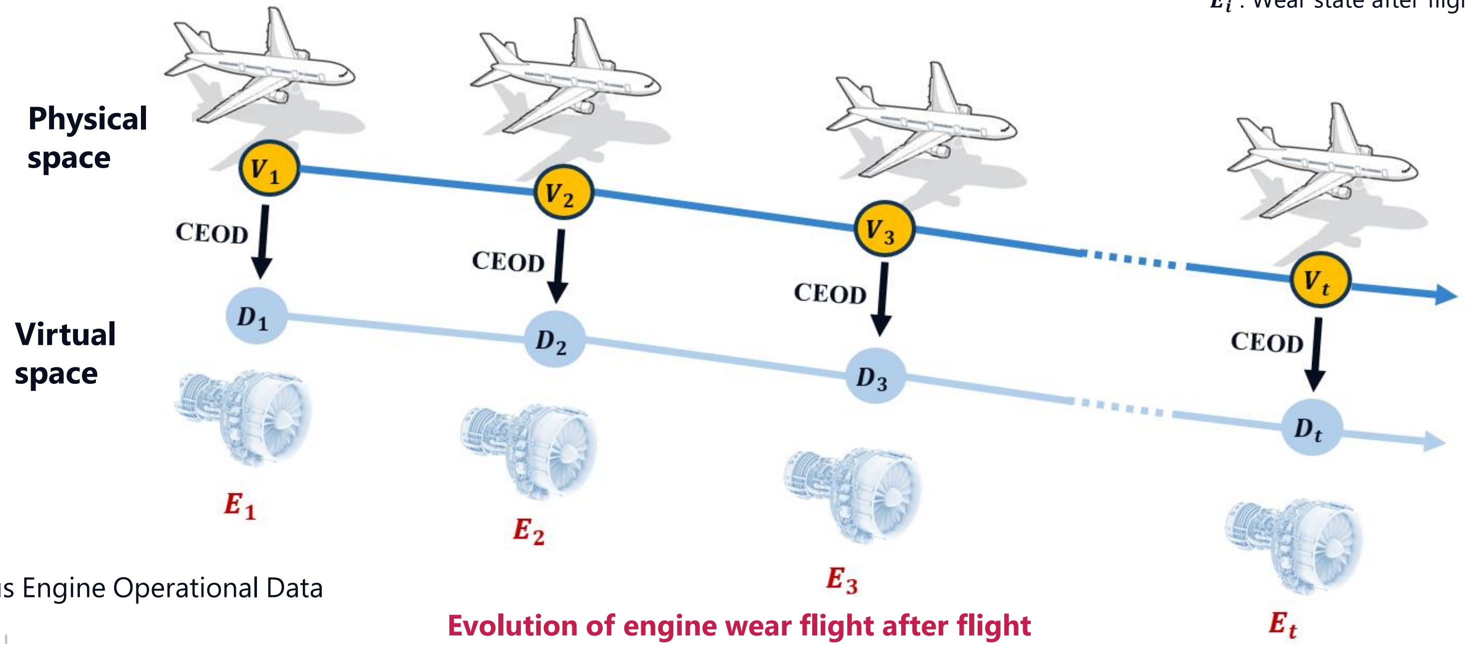
Wear categorization

(Flight data generation)

Motivation

Over the course of the aircraft's missions, the model of the digital twin is refined and increases in precision.

V_i : Flight i
D_i : Digital twin after flight i
E_i : Wear state after flight i

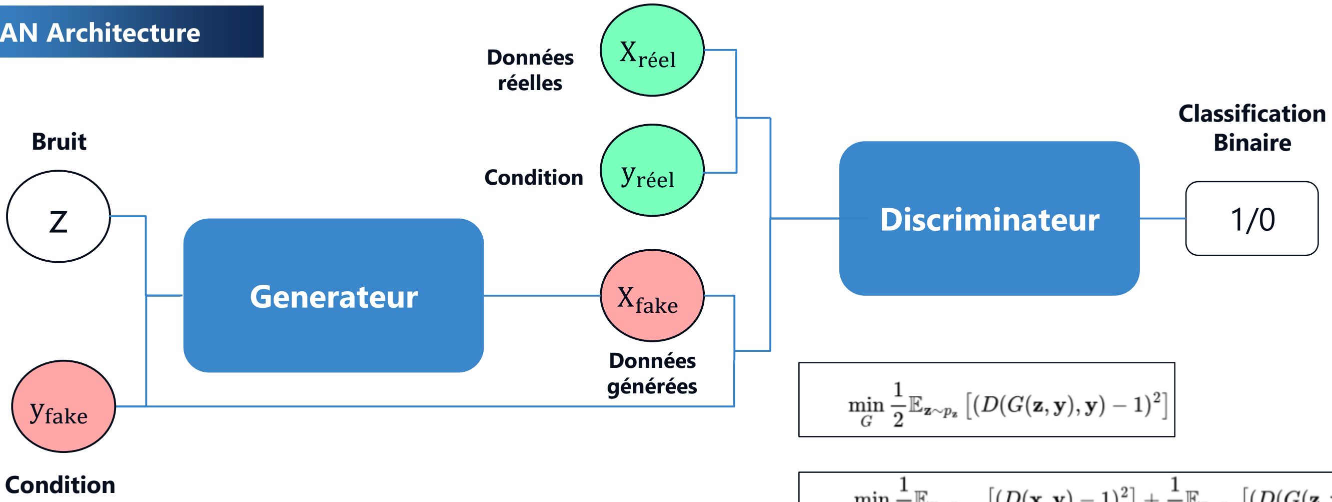


CEOD:
Continuous Engine Operational Data

Evolution of engine wear flight after flight

Conditional Generative Adversarial Network (CGAN)

CGAN Architecture



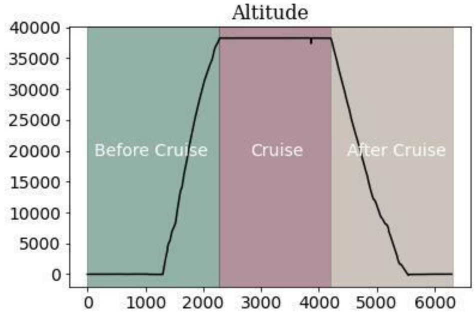
$$\min_G \frac{1}{2}\mathbb{E}_{\mathbf{z}\sim p_\mathbf{z}}\left[(D(G(\mathbf{z},\mathbf{y}),\mathbf{y})-1)^2\right]$$

$$\min_D \frac{1}{2}\mathbb{E}_{\mathbf{x}\sim p_{\text{data}}}\left[(D(\mathbf{x},\mathbf{y})-1)^2\right]+\frac{1}{2}\mathbb{E}_{\mathbf{z}\sim p_\mathbf{z}}\left[(D(G(\mathbf{z},\mathbf{y}),\mathbf{y}))^2\right]$$

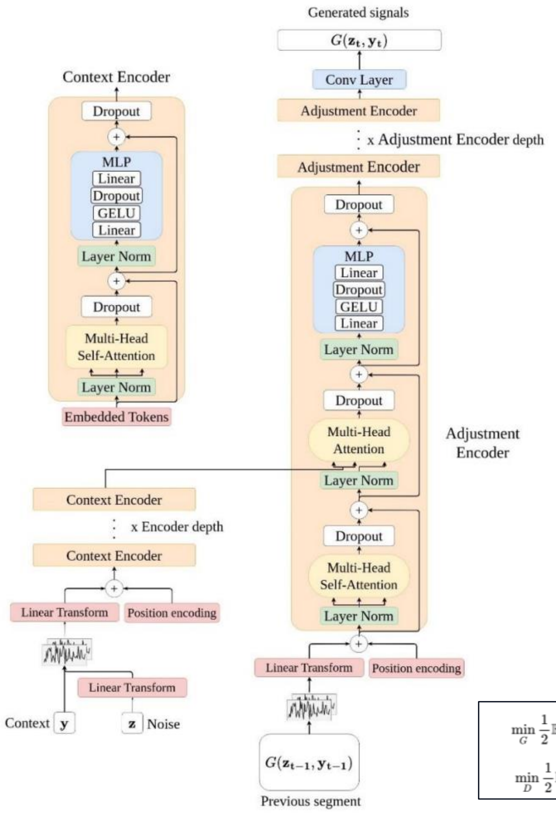
MIRZA, Mehdi et OSINDERO, Simon. Conditional generative adversarial nets. arXiv preprint arXiv:1411.1784, 2014.

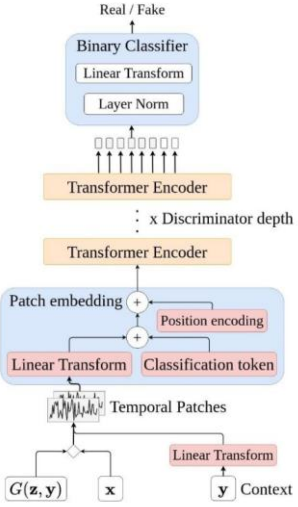
Transformer-based Generator and Discriminator

- Segmentation of flight data into three phases: before, during and after cruise.
- Division of the sequences into discrete windows of 300 time steps (5min).
- Carry out the generation process sequentially for each window: the generation of a window takes into account the previously generated window.



Splitting the time series into three phases according to altitude

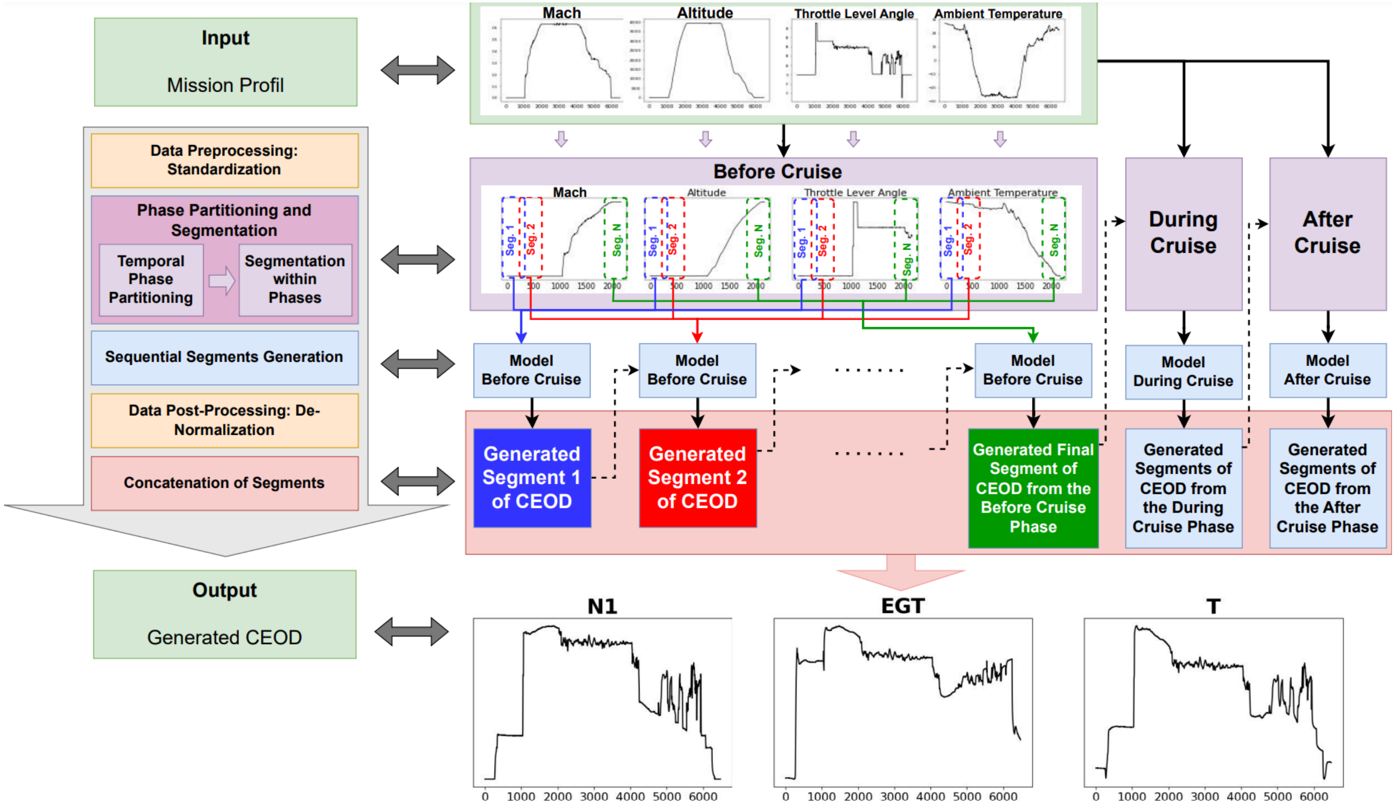




$$\min_G \frac{1}{2}\mathbb{E}_{\mathbf{z}\sim p_\mathbf{z}}\left[(D(G(\mathbf{z},\mathbf{y}),\mathbf{y})-1)^2\right] + \|G_{1:20}(z_t, y_t) - G_{end-19:end}(z_{t-1}, y_{t-1})\|_2$$

$$\min_D \frac{1}{2}\mathbb{E}_{\mathbf{x}\sim p_{data}}\left[(D(\mathbf{x},\mathbf{y})-1)^2\right] + \frac{1}{2}\mathbb{E}_{\mathbf{z}\sim p_\mathbf{z}}\left[(D(G(\mathbf{z},\mathbf{y}),\mathbf{y}))^2\right]$$

Aeronautic Engine Continuous Data Simulator



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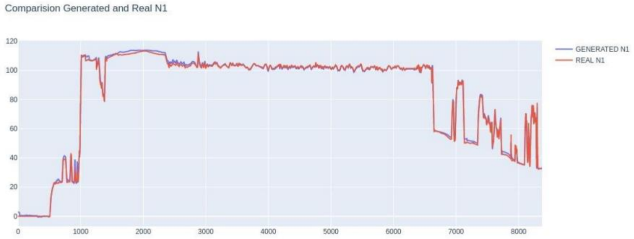
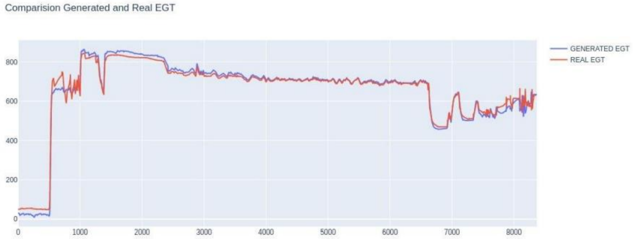
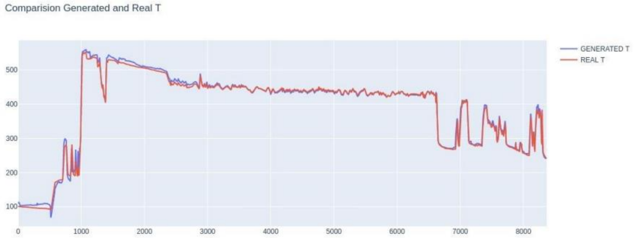
Demonstrator : Input & Output Data Example

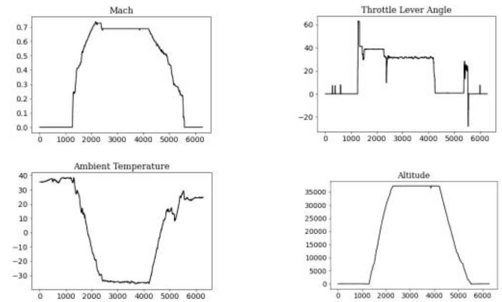
- QAR (Quick Access Record) for SAM146 engines
- Context variables used: ALT, TLA, M, TAT, EOF
- Engine variables generated: N1, EGT, T3







Inputs: mission profil



Outputs:

engine measurements

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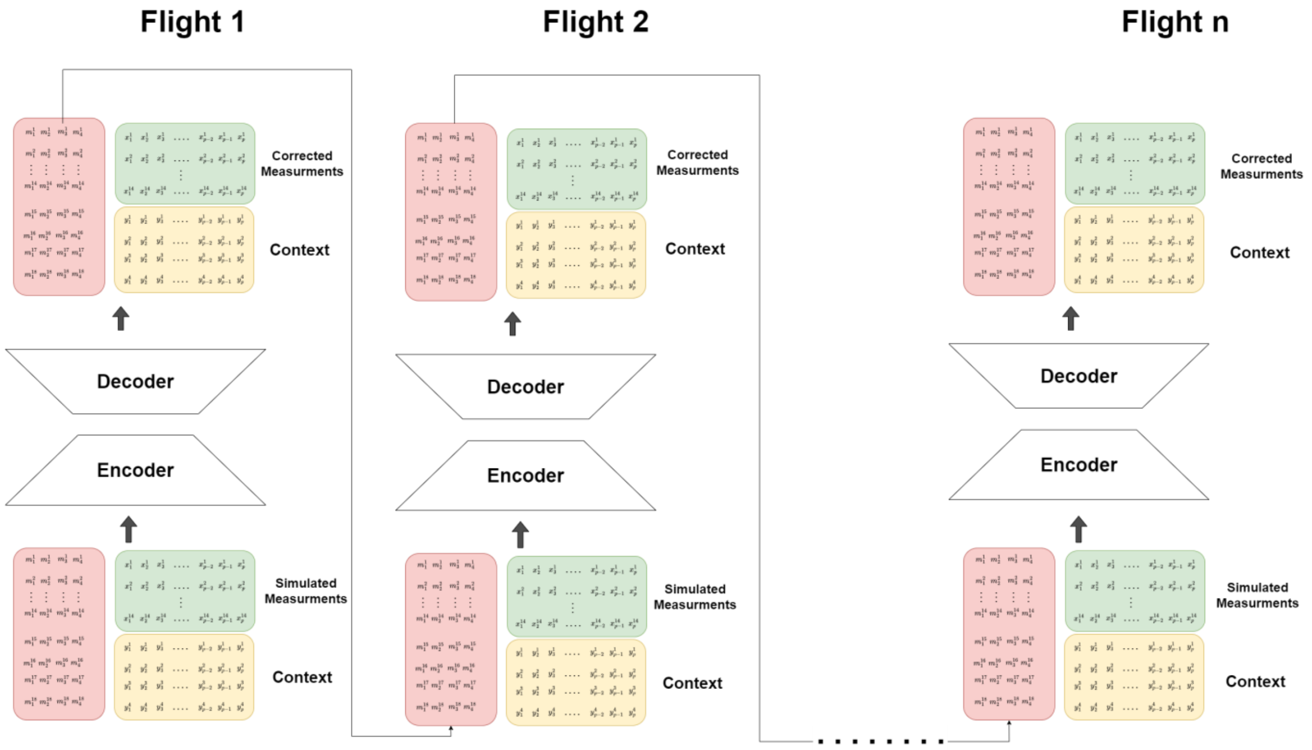
Serial Engine State Corrector Model

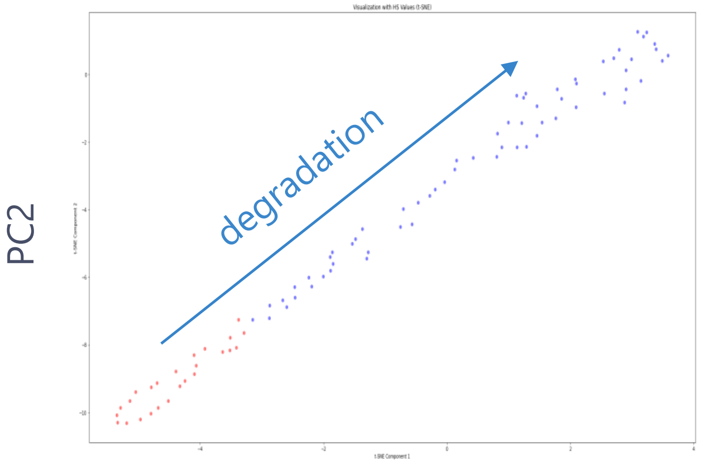
- **Input**
  - Flight context
  - Result of engine data simulation
  - State Memory

- **Output**
  - Flight context
  - Real observed data
  - New state memory



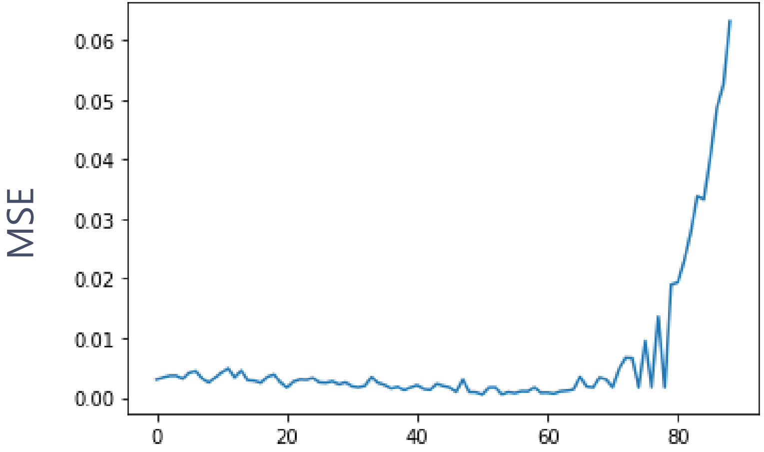
Result obtained dysfunctional data simulation

PCA projection of memory state



PC1

MSE between simulated and real observations



Flight

We use a rough dysfunctional simulator to produce known degradations.
Next step: expertise on real known dysfonctionnal data from MRO.

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QUESTIONS ?

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