Research Stay: Predictive Maintenance of Industrial Equipment

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Agenda

Introduction

Maintenance scheduled by data analytics on historical data

- Enhance operational efficiency
- Sustainability and cost reduction
- Competitive advantage
- **Safety at the forefront**

Figure: Turbine failure mid-flight [1]

Problem Statement

Predictive maintenance faces 2 main challenges:

Implementation

Need a model to estimate the RUL of a set of machinery, in an efficient and reliable manner

Interpretability

Need to *understand* why a model produces a given RUL estimate, becomes more important in critical environments

Objectives

This research project aims to develop:

- PdM framework to predict RUL for a designated fleet of machinery
- Model which ensures reproducibility, stability, robustness and confidence Modelo estable, robusto, reproducible y confiable
- Tools to interpret and visualize the model's predictions

Scope

The previous objectives are to be accomplished subject to the following constraints and assumptions:

- RUL prediction of an uniform fleet of machines
- Availability of a labeled dataset with run to failure sequences of each machine

Hypothesis

Throughout this research stay it is postulated:

Hypothesis

Using a set of sensor readings from a uniform fleet of machines in conjunction with environmental descriptors, it is possible to train an integrated predictive model for the Remaining Useful Life of an equipment, which is stable, robust, reproducible and reliable

Flight conditions and readings from a fleet of turbofan engines, derived from NASA's CMAPSS model, including real flight conditions and relates the degradation process to the operating history of the machine. [2]

- Used in the PHMAP 2021 Data Challenge [3]
- State of the art prognosis dataset (akin to MNIST and CIFAR for CV)

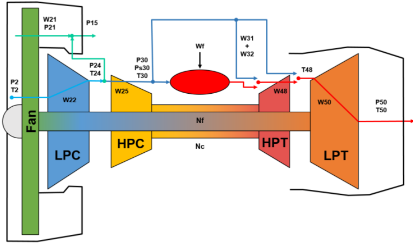

Figure: CMAPSS turbofan engine schematic

- Split into 10 h5 files
- Sampling frequency of 1 second
- Contains sensor readings, environmental descriptors, auxiliary variables, virtual sensor readings and RUL values
- Corrupted file in the dataset

Symbol	Description	Units
alt	Altitude	ft
Mach	Flight Mach number	-
TRA	Throttle-resolver angle	%
T2	Total temperature at fan inlet	°R
Wf	Fuel flow	pps
Nf	Physical fan speed	rpm
Nc	Physical core speed	rpm
T24	Total temperature at LPC outlet	°R
T30	Total temperature at HPC outlet	°R
T48	Total temperature at HPT outlet	°R
T50	Total temperature at LPT outlet	°R
P15	Total pressure in bypass-duct	psia
P2	Total pressure at fan inlet	psia
P21	Total pressure at fan outlet	psia
P24	Total pressure at LPC outlet	psia
Ps30	Static pressure at HPC outlet	psia
P40	Total pressure at burner outlet	psia
P50	Total pressure at LPT outlet	psia
RUL	Remaining Useful Life	cycles
unit	Unit number	-
cycle	Flight cycle number	-
Fc	Flight class	-
hs	Health state	-

Table: General description of dataset variables [3]

Exploratory Data Analysis

Flight Class Distribution

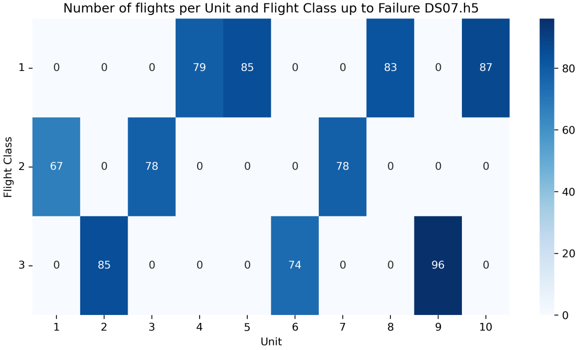

Figure: Flights recorded for each class per unit

Flight classes encode flight duration[1], and there are no inter-class units

[1] FC1 ranges between 1 and 3 hours, FC2 between 3 and 5, and FC3 is greater than 5

Exploratory Data Analysis

Sample Operating Conditions

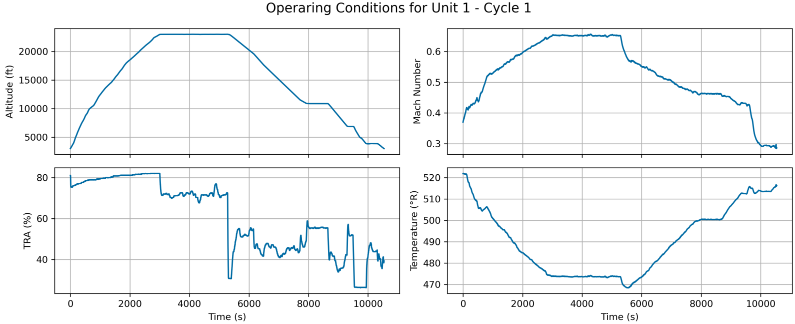

Figure: Operating conditions for the first flight of Unit 1

Exploratory Data Analysis

Sample Operating Conditions

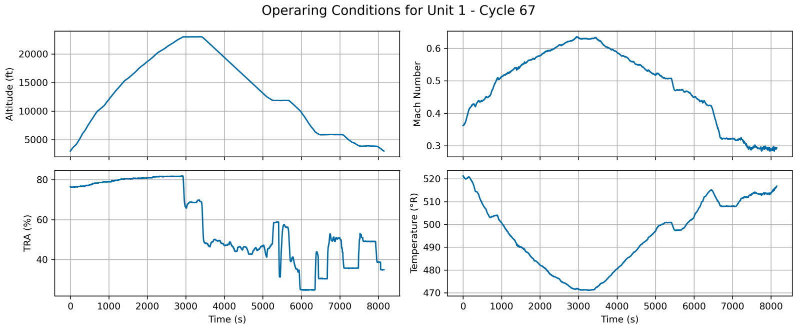

Figure: Operating conditions for the last flight of Unit 1 (EOL)

Exploratory Data Analysis

Operating Conditions per Flight Class

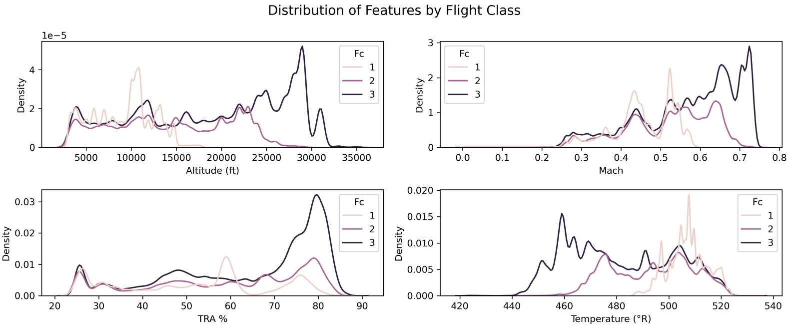

Figure: Distribution of operating conditions per Flight Class

Distinctive operating conditions per FC where FC2 can be seen as a mixture of FC1 and FC3

Exploratory Data Analysis
Altitude and Mach Number

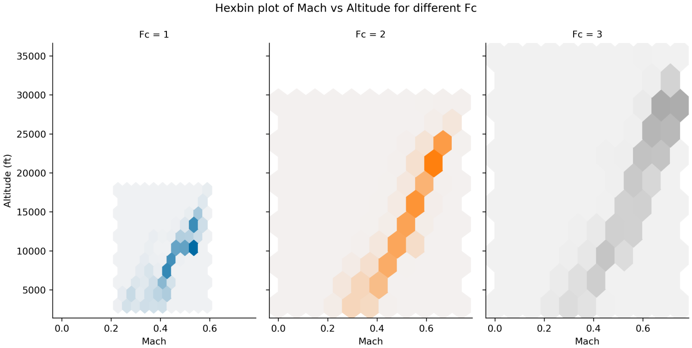

Figure: General relationship between Altitude and Mach Number

General alignment in FC2 and FC3, but FC1 has a higher dispersion [1]

[1] Potentially caused by the shorter flight duration

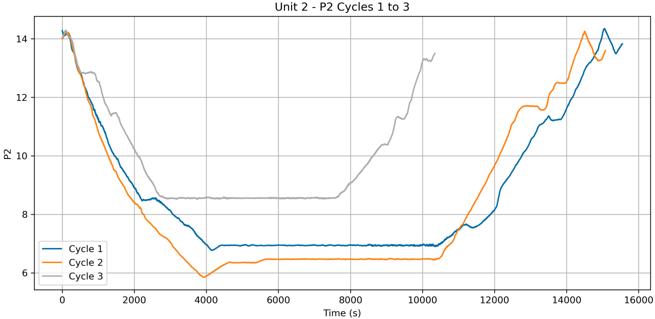

Figure: Total Pressure at fan inlet (P2) for the first 3 cycles of unit 2

Mostly smooth readings with predictable abrupt changes

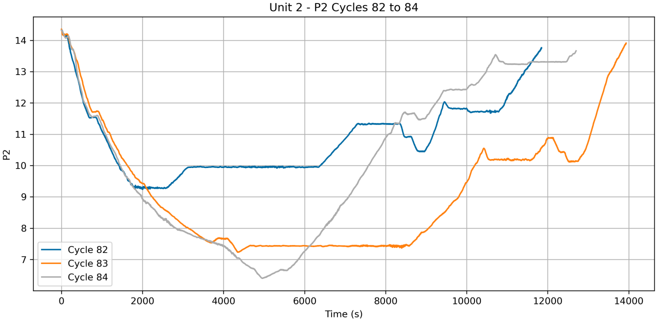

Figure: Total Pressure at fan inlet (P2) for the last 3 cycles of unit 2

Smoothness degradation with a presence of new plateaus near the end of the flight

In general the framework can be broken down to:

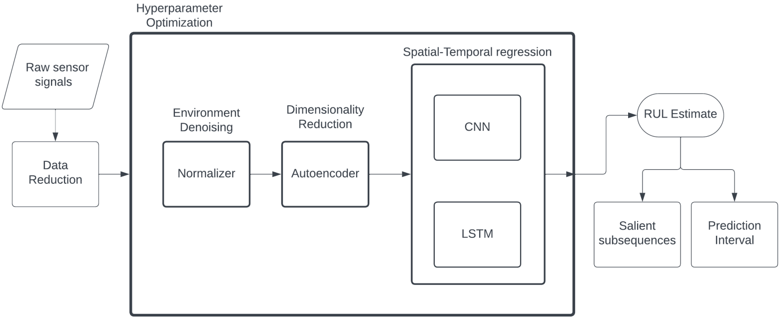

Figure: Proposed Methodology

Normalizer

RUL prediction is usually based on sensor readings of each operating cycle, but:

- Sensor readings encoding degradation can be obfuscated by environmental conditions.
- No easy way to analyze a machine's degradation without a detailed analysis

Proposition

Design a normalizer function to model a machine's degradation based upon environmental descriptors and analyzed in sensor readings

Degradation Model Proposition

Given a vector E_t of m environmental descriptors and a vector S_t of n sensor reading variables for each timestamp t, a function f is proposed as follows:

$$f : \mathbb{R}^m \to \mathbb{R}^n \tag{1}$$

The function f is then an internal model of how S_t **should** look like if the machine were healthy.
The normalized measures for each timestamp will be:

$$\hat{S}_t = S_t - f(E_t) \tag{2}$$

Degradation Model Learning

Prepare a subset of data where the machine is known to operate in optimal conditions and use a neural network to learn the mapping f, the baseline architecture is then a DNN:

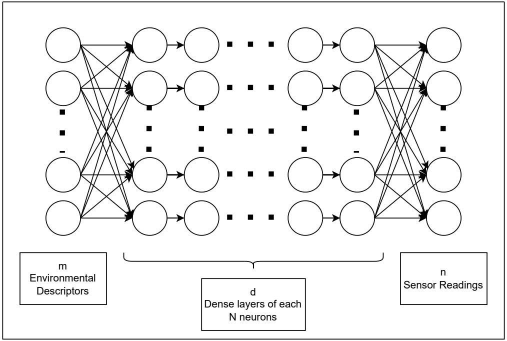

Figure: Baseline sequential model for the degradation function

Normalizer

Model Parameters

- Test Dataset: NCMAPSS DS01, all FC, only failures in Low Pressure Turbine
- Input: Environmental descriptors, operating cycle, flight class, and time (scaled between 0 and 1)
- Output: Sensor readings
- 5 dense layers of 32 neurons each with a L2 kernel regularizer ($\lambda = 0.005$)
- Adamax for faster and more stable convergence rates
- Training for maximum number epochs of a 100 epochs with early stopping of 5% of the maximum epochs if there's no improvement in validation loss

Normalizer

Training Overview

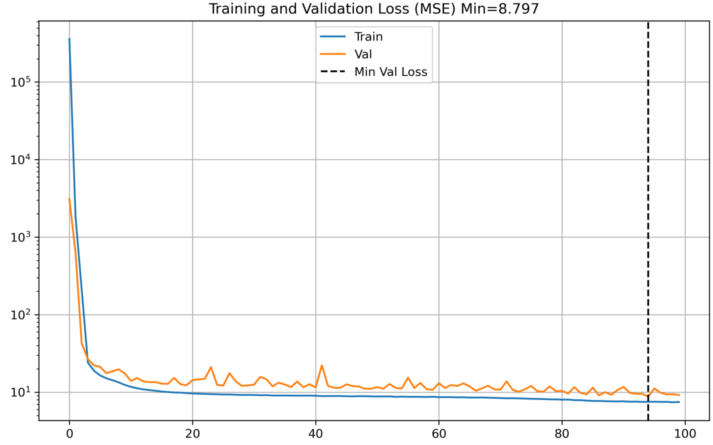

Figure: Training and Validation Loss for proposed model

Normalizer

Sample Predictions

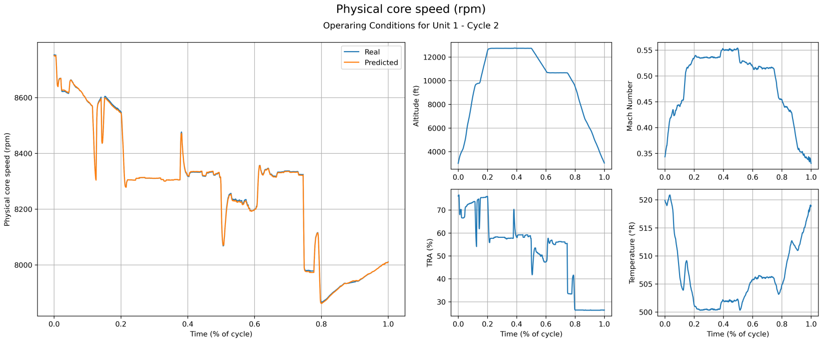

Figure: Comparison of Physical Core Speed predictions and real values

Normalizer

Sample Predictions

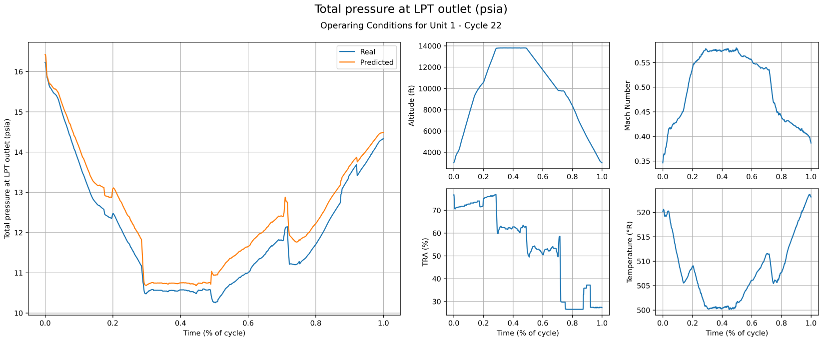

Figure: Comparison of Total Pressure at Low Pressure Turbine outlet predictions and real values

References

BBC News, "Boeing 777: Dozens grounded after denver engine failure,", Feb. 22, 2021. [Online]. Available: https://www.bbc.com/news/world-us-canada-56149894.

M. Arias Chao, C. Kulkarni, K. Goebel, and O. Fink, "Aircraft engine run-to-failure dataset under real flight conditions for prognostics and diagnostics," *Data*, vol. 6, no. 1, p. 5, 2021.

PHM Society. (Oct. 21, 2021), 2021 phm conference data challenge - phm society data repository, [Online]. Available: https://data.phmsociety.org/2021-phm-conference-data-challenge/.