PHM Society Data Challenge 2021

Manuel Arias Chao[1,†], Chetan Kulkarni [2], Kai Goebel[3], Olga Fink[1]

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Abstract

This year's challenge addresses the problem of remaining useful lifetime (RUL) prediction in a fleet of aircraft engines under conditions of high variability in the flight envelope and multiple failure modes. The task is to develop a data-driven model to estimate RUL using the condition monitoring data as input. The challenge uses a subset of the run-to-failure degradation trajectories of the N-CMAPSS dataset [1].

1 Summary

Given here is a dataset containing full flight profile data for 100 aircraft experiencing different types of slowly developing faults that initiate at some time during the flight history. There are seven different failure modes. The task is to train a model to estimate the time to failure using the data in the development dataset. Test on data in the test dataset. Validation is done with a validation dataset that is being released for one-time assessment at the end of the data challenge. Scoring of performance (train, test, and validation) is done through a web interface at phmsociety.org (exact link to be determined)

2 System description

The system under analysis corresponds to a high-bypass, twin-spool commercial turbofan engine. The engine consists of six main components: fan, low-pressure compressor (LPC), high-pressure compressor (HPC), combustor or burner, high-pressure turbine (HPT), and low-pressure turbine (LPT). The HPC and HPT are connected through the core shaft or high-speed shaft; the fan, LPC, and LPT are all connected to the fan shaft or low-speed shaft [2]. In addition to these turbo-machinery components and the combustor, the engine has an inlet at the front, a nozzle at the rear, a bypass duct, a variable-sized inter-stage bleed valve, a set of variable-angle stator or guide vanes, and a number of cooling bleeds. Figure 1 shows a schematic representation of the engine along with the corresponding location of the sensor reading and the station numbers as defined in the CMAPSS model documentation [3].

3 Data description

The N-CMAPSS Challenge dataset provides synthetic run-to-failure degradation trajectories of a fleet of turbofan engines with unknown initial health states subject to real flight conditions. The dataset was generated with the Commercial Modular Aero-Propulsion System Simulation (CMAPSS) model [3]. Each unit of the fleet has unknown and different initial health conditions and experiences different types of slowly developing faults that initiate at some time during the flight history. Concretely, all the rotating sub-components of the engine, i.e., fan, low-pressure compressor (LPC), high-pressure compressor (HPC), low-pressure turbine (LPT), and high-pressure turbine (HPT), can be affected by degradation in flow and efficiency. The dataset contains real flight conditions as recorded on board a commercial jet (i.e., w). The units are divided into three flight classes depending on whether the unit

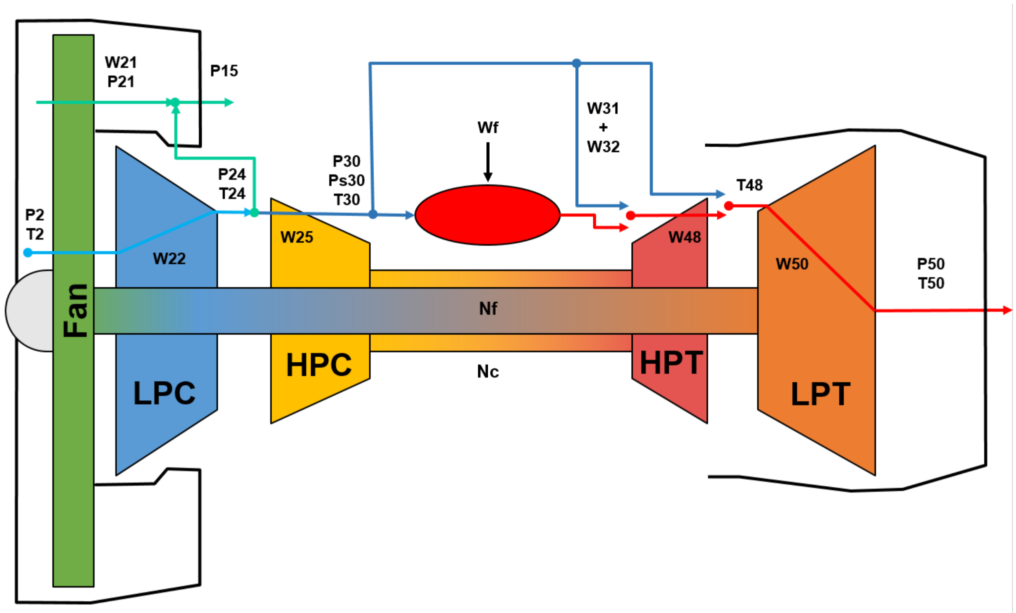

Figure 1: Schematic representation of the turbofan engine model.

is operating short-length flights (i.e., flight class 1), medium-length flights (i.e., flight class 2), or long-length flights (i.e., flight class 2) (see Table 1). A number of real flight conditions are available within each of the flight classes. Figure 2 shows a typical flight profile given by the scenario-descriptor variables w: altitude (alt), flight Mach number (XM), throttle-resolver angle (TRA), and total temperature at the fan inlet (T2). Each flight cycle contains recordings of varying lengths, covering climb, cruise, and descend flight conditions (with alt $> 10,000$ ft) corresponding to different flight routes operated by the aircraft. The remaining units of the fleet follow similar flight traces.

Flight Class	Flight Length [h]
1	1 to 3
2	3 to 5
3	> 5

Table 1: Overview of the flight classes

3.1 Data records

The N-CMAPSS Challenge dataset contains nine sets of data covering run-to-failure degradation trajectories from 100 units and seven different failure modes affecting the flow (F) and/or efficiency (E) of the rotating sub-components. Table 2 provides an overview of failure modes with each of the sets of data. Each set of data is stored in a Hierarchical Data Format version 5 (HDF5) file. The dataset is accessible publicly at the repository[1]: `https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/`. Scripts in the form of Jupyter notebooks are also available in the data repositories to demonstrate how to load the data.

Each data file provides two sets of data: the **development dataset** and the **test dataset**. Each of them contains the following types of variables: the operative conditions w, the measured signals x_s,

[1] DS02 is also included in the data repository but it is excluded from the Challenge dataset

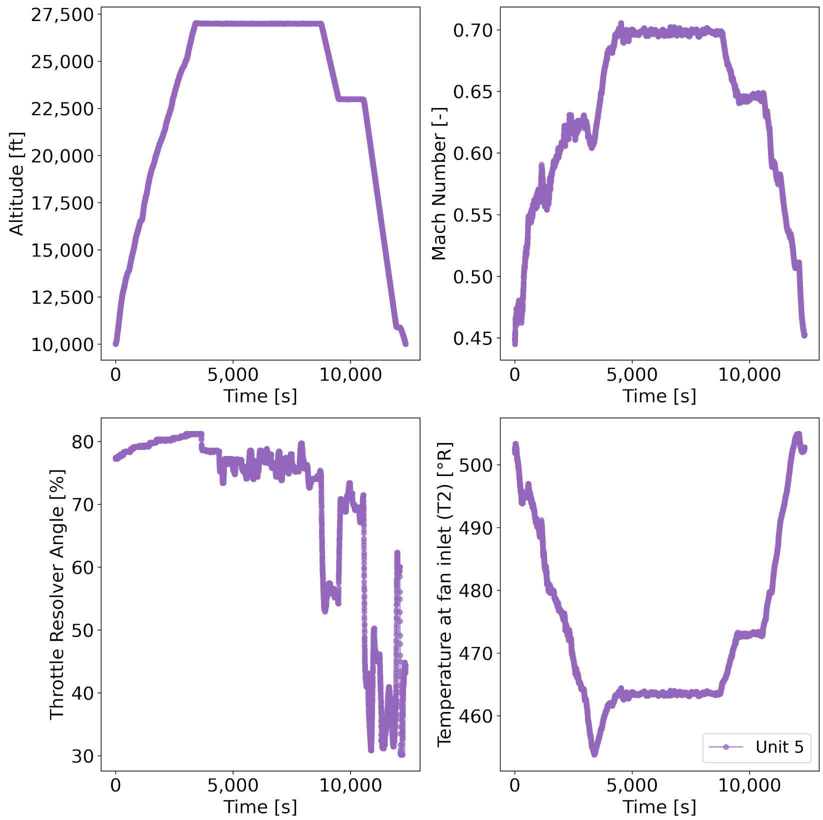

Figure 2: Example of a flight traces of altitude, flight Mach number (XM), throttle–resolver angle (TRA) and total temperature at the fan inlet (T2) covering climb, cruise and descend flight conditions

the RUL label, and the auxiliary data (i.e., the unit number u and the flight cycle number c and the flight class Fc). In addition, the name of the variables within w, x_s, and the auxiliary data is provided. Table 3 shows an overview of the variables stored in each .h5 file.

Name	# Units	Failure Modes #	Fan		LPC		HPC		HPT		LPT	
			E	F	E	F	E	F	E	F	E	F
DS01	10	1							✓			
DS03	15	2							✓		✓	✓
DS04	10	3	✓	✓								
DS05	10	4					✓	✓				
DS06	10	5			✓	✓	✓	✓				
DS07	10	6									✓	✓
DS08a	15	7	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
DS08c	10	7	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
DS08d	10	7	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 2: Overview of the datasets

Tables 4–6 provide the name, description and units of each input variable in the dataset. The variable symbol corresponds to the internal variable name in the CMAPSS model. The descriptions and units are derived from the model documentation [3]. RUL is provided in units of cycles.

Development data ($\mathcal{D}$)	
Name	Description
W_dev	Scenario descriptors - w
X_s_dev	Measurements - x_s
Y_dev	RUL [in cycles]
A_dev	Auxiliary data
Test data ($\mathcal{D}_{\mathcal{T}*}$)	
Name	Description
W_test	Scenario descriptors -w
X_s_test	Measurements - x_s
Y_test	RUL [in cycles]
A_test	Auxiliary data
Variables Name	
Name	Description
W_var	w variables
X_s_var	x_s variables
A_var	Auxiliary variables

Table 3: Variable names in .h5 files

#	Symbol	Description	Units
1	alt	Altitude	ft
2	Mach	Flight Mach number	-
3	TRA	Throttle-resolver angle	%
4	T2	Total temperature at fan inlet	°R

Table 4: Scenario descriptors (i.e., flight data) - w

#	Symbol	Description	Units
1	Wf	Fuel flow	pps
2	Nf	Physical fan speed	rpm
3	Nc	Physical core speed	rpm
4	T24	Total temperature at LPC outlet	°R
5	T30	Total temperature at HPC outlet	°R
6	T48	Total temperature at HPT outlet	°R
7	T50	Total temperature at LPT outlet	°R
8	P15	Total pressure in bypass-duct	psia
9	P2	Total pressure at fan inlet	psia
10	P21	Total pressure at fan outlet	psia
11	P24	Total pressure at LPC outlet	psia
12	Ps30	Static pressure at HPC outlet	psia
13	P40	Total pressure at burner outlet	psia
14	P50	Total pressure at LPT outlet	psia

Table 5: Measurements - x_s

#	Symbol	Description	Units
1	unit	Unit number	-
2	cycle	Flight cycle number	-
3	Fc	Flight class	-
4	h_s	Health state	-

Table 6: Auxiliary data

4 Challenge formulation

Given are multivariate time-series of sensors readings $X_{s_i} = [x_{s_i}^{(1)}, \dots, x_{s_i}^{(m_i)}]^T$ and their corresponding remaining useful life label (RUL) i.e., $Y_i = [y_i^1, \dots, y_i^{m_i}]^T$ from a fleet of $N = 60$ units ($i = 1, \dots, N$). Each observation $x_{s_i}^{(t)} \in R^p$ is a vector of p sensor readings taken at operating conditions $w_i^{(t)} \in R^s$. The length of the sensory signal for the i-th unit is given by m_i, which can, in general, differ from unit to unit. The total combined length of the available data set is $m = \sum_{i=1}^{N} m_i$. More compactly, the available dataset development dataset is denoted as $\mathcal{D} = \{W_i, X_{s_i}, Y_i\}_{i=1}^{N}$. Given this set-up, the task is to obtain a predictive model $\mathcal{G}$ that provides a reliable RUL estimate ($\hat{Y}$) on a test dataset of $M = 40$ units $\mathcal{D}_{T*} = \{W_{j*}, X_{s_j*}\}_{j=1}^{M}$, where $X_{s_j*} = [x_{s_j*}^1, \dots, x_{s_j*}^{k_j}]$ are multivariate time-series of sensors readings taken at operating conditions w_{j*}. The total combined length of the test data set is $m_* = \sum_{j=1}^{M} k_j$.

NOTE 1: The use of the full development dataset for training is not a requirement. The participants can use any subset of the development data they consider convenient from model training.

4.1 Evaluation metric

Evaluation of the model performance will be carried out using an **independent validation dataset** $\mathcal{D}_{*\mathcal{V}} = \{W_i, X_{s_i}, Y_i\}_{i=1}^{N_{V*}}$ that is being released for one-time assessment at the end of the data challenge. The metric of evaluation is an aggregation of two common evaluation metrics used to compare the prognostics results: root-mean-square error (RMSE) and NASA's scoring function [4] (s):

$$score = 0.5 \cdot RMSE + 0.5 \cdot s_c \tag{1}$$

$$RMSE = \sqrt{\frac{1}{m_{v*}} \sum_{j=1}^{m_{v*}} (\Delta^{(k)})^2} \tag{2}$$

$$s_c = \frac{1}{m_{v*}} \sum_{k=1}^{m_{v*}} exp(\alpha|\Delta^{(k)}|) - 1, \tag{3}$$

where m_{v*} denotes the total number of validation dataset, $\Delta^{(k)}$ is the difference between the estimated and the real RUL of the k sample (i.e., $y^{(k)} - \hat{y}^{(k)}$), and α is $\frac{1}{13}$ if RUL is under-estimated and $\frac{1}{10}$, otherwise. The resulting s metric is not symmetric and penalizes over-estimation more than under-estimation.

4.2 Results Submission

The RUL estimates on the validation dataset $\mathcal{D}_{\mathcal{V}*}$ need to be submitted as a csv file contating one single columm (i.e., $m_{v*} \times 1$) to `http//:...` for evaluation.

References

[1] Manuel Arias Chao, Chetan Kulkarni, Kai Goebel, and Olga Fink. Aircraft Engine Run-to-Failure Dataset under Real Flight Conditions for Prognostics and Diagnostics. *Data*, 6(1):5, 2021.

[2] Ryan May, Jeffrey Csank, Thomas Lavelle, Jonathan Litt, and Ten-Huei Guo. A high-fidelity simulation of a generic commercial aircraft engine and controller. In *46th AIAA/ASME/SAE/ASEE Joint Propulsion Conference & Exhibit*, page 6630, 2010.

[3] Dean K Frederick, Jonathan A Decastro, and Jonathan S Litt. User's Guide for the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS). Technical report, NASA, 2007.

[4] Abhinav Saxena, Kai Goebel, Don Simon, and Neil Eklund. Damage propagation modeling for aircraft engine run-to-failure simulation. In *2008 International Conference on Prognostics and Health Management*, pages 1–9. IEEE, 2008.