Machine Learning of Engine Health Monitoring Data: Development of a machine learning model for damage prediction of real flight missions

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Eidesstattliche Erklärung

Hiermit erkläre ich, Samuel Oliver Bryson (geboren am 21.12.1991 in Nottingham, Großbritannien), dass ich die vorliegende Abschlussarbeit eigenständig und ohne unerlaubte fremde Hilfe angefertigt habe sowie keine anderen als die angegebenen Quellen und Hilfsmittel verwendet habe.

Berlin, den XX.XX.XXX ______________________________

Samuel Oliver Bryson

Contents

List of Abbreviations

AI artificial intelligence

CSV comma-separated values

DL Deep learning

EASA European Union Aviation Safety Agency

EHM Engine Health Monitoring

FAA Federal Aviation Authority

FE Finite Element

FM flight mode

HP high-pressure

HPT high-pressure turbine

IP intermediate-pressure

LP low-pressure

LTFC Life To First Crack

ML machine learning

PB Petabyte

PSCL Predicted Safe Cyclic Life

TET turbine entry temperature

TRA thrust lever resolver angle

TSC time series classification

WOW weight on wheels

1 Introduction

In recent years, many industries have experienced enormous changes due to an influx of huge quantities of data, increasingly cheap data storage solutions and access to high computational power Chen et al. (2014). The aviation industry is no exception: the Airbus A350 XWB comes equipped with approximately 6 000 sensors that produce 300 GB of data every day; the next generation Airbus A380 will come with 10 000 sensors on a single wing alone (Rajaraman, 2016).

This data can only be of value if there are suitable tools for handling it. The arrival of the age of Big Data (Fan & Bifet, 2013) coincided unsurprisingly with an increase in the popularity of artificial intelligence (AI) and machine learning (ML). Today, highly optimised, specially designed programming libraries make data-orientated ML approaches more accessible and more powerful than ever.

Customers using aircraft powered by Rolls-Royce engines can return EHM data to Rolls-Royce on a voluntary basis. This data is recorded during flights and includes parameters such as temperature and pressure at various stages of the engine, flight altitude and speed, and many others.

The company uses this data for various analyses, such as determining the amount of service life consumed during the flight mission. Currently, the process involves hand-selecting individual points of interest, or features, and performing a semi-automated fatigue analysis on each of these individually, from which the consumed service life is determined. This method has been sufficient in the past due to its robustness and speed for a limited number of features, but is unfeasible for future applications that require output values for the entire surface of a component.

It is in the interest of Rolls-Royce to improve the speed, accuracy and comprehensiveness of EHM data analysis to gain an overview of the performance and remaining service life of in-service engines. This thesis, written in cooperation with Rolls-Royce Deutschland, aims to identify and evaluate a number of ML-based methods for achieving these goals.

The thesis is structured as follows: First, the theory behind the methods will be covered with a more in-depth look at subfields of deep learning that will be of interest. Then, an overview of the input data will be presented. After this, the methods identified will be implemented and evaluated in the practical section, and subsequentlty compared in the discussion. Finally, in the conclusion, suggestions will be made for further research into the topic.

2 Theoretical Background

2.1 Big Data

The term *Big Data* roughly describes the enormous datasets that have become the norm in many industries over the past two decades. A 2014 report found, for example, that Facebook produced log data of over 10 Petabyte (PB) per month. (Chen et al., 2014)

- increasingly relevant if current trends continue (Fan & Bifet, 2013)

- existentially relevant for technology companies wanting to be future-proof

2.2 Artificial Intelligence

AI, the field of research that occupies itself with giving machines the ability to think and learn, has been the focus of much research in recent years due to the increasing capabilities of hardware to tackle the challenges it involves

2.3 Machine Learning

ML is a subfield of AI in which machines extract information and patterns from data without thorough or explicit instructions, usually making use of highly contrived data from which noise (irrelevant or distracting background information) has been removed. Classifying objects based on a finite set of input values (e.g. birds based on their weight, wingspan, the colour of their back and whether they have webbed feet (Harrington, 2012)) is an ideal task for machine learning.

ML tasks are generally split into two categories: supervised and unsupervised learning (Kelleher et al., 2015). The former involves training the model to associate input data with known output data and using it on previously unseen data; in the latter, a model is given data and instructed to find patterns or groups based on input data alone (Goodfellow et al., 2016).

2.3.1 Polynomial Regression

2.4 Deep Learning

Deep learning (DL) is an application of ML that employs more complex models capable of making sense of noisier, largely unprocessed data, such as sound signals and images (Goodfellow et al., 2016). Classifying birds could in this case involve extracting necessary information from an image or diagram of the bird, requiring far less manual measurement or input.

DL has seen a huge rise in popularity in recent years, with applications including speech recognition (Deng & Li, 2013), medical diagnoses (Lee et al., 2018), stock market prediction (Krollner et al., 2010) and many others (Kelleher et al., 2015). One particular challenge among the DL research community is time series data (Yang & Wu, 2006), a sequential collection of values recorded over time. Time series data remains a great challenge due to its noisy, multidimensional nature (Kelleher et al., 2015) and the dfficulties involved in developing algorithms that can also interpret the temporal information held in the signal (Bagnall et al., 2017).

2.4.1 Multilayer Perceptron

- diagram

- weight, bias, output, optimisation (Kirk, 2017)

- The quintessential DL network: Multilayer perceptron

2.4.2 Time Series Classification

time series classification (TSC) involves reading time series data and applying one of a finite number of labels to each instance Fawaz et al. (2019).

The UCR Archive Dau et al. (2019) is a large collection of datasets released to enable research and offer a benchmark dataset to evaluate newly proposed DL approaches.

The greatest breakthroughs in TSC have only come about within the past few years since the publication of the Inception module (Szegedy et al., 2014) and its subsequent application in further DL fields Ismail Fawaz et al. (2019); Fawaz et al. (2019).

- OK for binary damage classifications, but in its original form (i.e. from (Fawaz et al., 2019)) the classes are not ordinal.

2.4.3 Time Series Regression

- Changing activation function of final TSC layer to linear and loss function to MSE as with the initial MLP, we can perform a regression on input

- Expect promising results with large datasets but to be taken with a pinch of salt: we now have infinite/continuous inputs AND outputs, therefore probably unscalable!

2.5 The Engine

The Civil Aerospace department of Rolls-Royce designs and manufactures primarily high-bypass turbofan jet engines, which offer an ideal arrangement for civil aircraft flying below the speed of sound (plc, 2015).

Engines consist of four main components (fan, compressor, combustion chamber

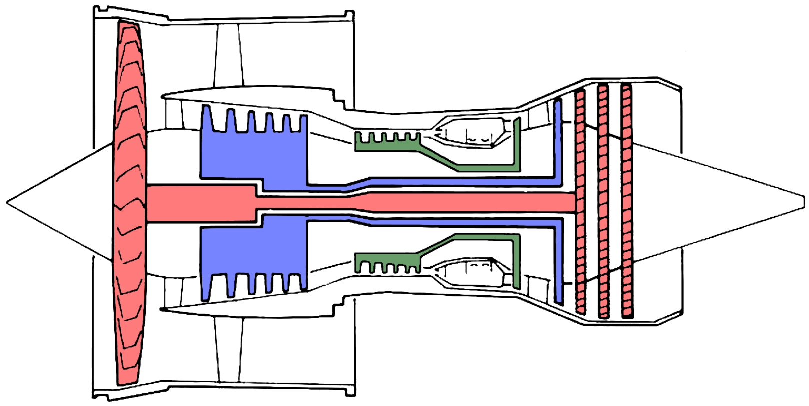

Figure 1: A schematic diagram of a triple-spool high-bypass engine with LP, IP and HP components shown in red, blue and green, respectively (based on (plc, 2015)).

and turbine) which correspond approximately to the four stages of a Brayton cycle (intake, compression, combustion, expansion). The engine draws in air, compresses it, burns fuel in the compressed air and forces this air out through the rear nozzle, while extracting some energy at the turbine stage to continue powering the fan and compressor (plc, 2015).

Many modern civil aircraft engines are equipped with two concentric shafts, split into low-pressure (LP) and high-pressure (HP), which connect respective sets of compressors and turbines (Spittle, 2003). Some, including the Rolls-Royce Trent family of engines, also have a third shaft, coupling the intermediate-pressure (IP) compressor and turbine. Figure 1 shows the configuration of such an engine.

This multi-spool arrangement allows higher temperatures, pressures and rotational speeds in the engine, and thereby enables a higher pressure ratio with lower specific fuel consumption (plc, 2015, p. 20). Despite these much improved thermal and propulsive efficiencies (plc, 2015, p. 225), the arrangement comes with the compromise of significantly increased thermal and mechanical loads within the engine, particularly as the air passes from the combustion chamber to the high-pressure turbine (HPT). The turbine entry temperature (TET) has risen to such an extent that HPT blades now operate in temperatures far above their melting point, requiring great improvements in the materials, structures and systems used, such as extracting cooler air from the compressor stage and releasing this through air holes in the blades to create an insulating barrier between the blade and hot air (Spittle, 2003).

2.6 Damage

Components used in such extreme conditions experience degradation. They therefore cannot be used indefinitely and must be removed from service after a certain amount of time to avoid potentially catastrophic failure. The amount of time for which the component is permitted for service, referred to as its Approved Life, is determined in safety analyses (EASA, 2015). Approved Life is measured in Engine Flight Cycles, to be referred to as *cycles* in the following. (These aspects will be discussed in more detail in Section 2.6.1.)

The degradation of the engine through its use is referred to as damage. The extent of damage is dependent on many parameters: Since operators use their aircraft for different purposes, flight parameters such as duration, altitude and outside temperature vary greatly and result in different levels of damage. This idea can be quantified with the aforementioned cycles.

In a Finite Element (FE) context, components are modelled digitally and separated into a finite number of individual elements, the corner points of which are called nodes. Areas of particular interest within the component (usually where stresses are expected to be highest) are referred to as features.

Within Rolls-Royce, damage from flight missions is currently calculated using one of two internal tools for flight profile analysis: SA66 and Perseus (see Sections 2.6.2 and 2.6.3, respectively). The former is ideal for processing many flights in a short amount of time, but is restricted to a low number of features due to the time involved in manually setting up the surrogate FE model for each feature. The latter can be described as a brute-force method that determines damage for all surface nodes, but is restricted by the amount of time required to process a single flight.

2.6.1 Certification

Certification of a new engine includes a thorough safety analysis as described in EASA (2015).

Of primary concern for the Rotatives department is the HPT disk due to the extreme conditions under which it operates and therefore the risk of Hazardous Engine Effects. The latter is defined to include (among others) “non-containment of high-energy debris”, “uncontrolled fire”, “complete inability to shut the engine down” according to the European Union Aviation Safety Agency (EASA) and the Federal Aviation Authority (FAA) EASA (2015); FAA (2007). A safety analysis must show that Hazardous Engine Effects are expected to occur with a probability no greater than 10^{-7} per flight hour.

Engine parts whose failure is likely to result in Hazardous Engine Effects are labelled Engine Critical Parts EASA (2015); the HPT disk also carries this label. Engine Critical Parts are assigned an Approved Life, which defines the “mandatory replacement life” EASA (2015) of the part and is measured in Engine Flight Cycles, a flight profile that defines a reference flight mission, corresponding approximately to the average flight for which the engine is expected to be used in service.

Determining a part’s Approved Life, commonly referred to as lifing, is a complex process, the majority of which involves “defining the duty the part is required to sustain” Corran & Williams (2007), i.e. the design and refinement of the Engine Flight Cycle. One lifing philosophy is that of Life To First Crack (LTFC), which involves determining the Predicted Safe Cyclic Life (PSCL) by means of statistically-determined safety factors.

2.6.2 SA66 Cycle Counter

surrogate FE model

2.6.3 Perseus

2.7 Research Question

Using the methods described in this section, the research goal of this thesis is to identify a supervised ML or DL approach that offers a sufficiently robust, verifiable, comprehensive, scalable, fast and accurate means of processing EHM data to determine the extent of damage incurred by surface nodes of a component during real flight missions.

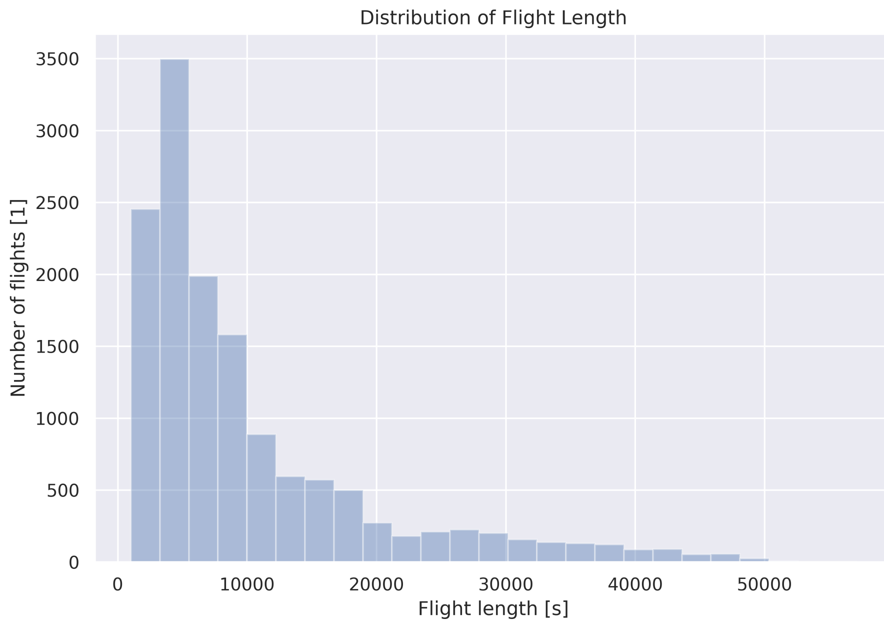

Figure 2: A histogram of the lengths of 14045 flights

3 Data

The following will include an overview and visualisation of the data acquired for the research, and how it was processed.

3.1 EHM Data

The research was carried out using EHM data. This data was recorded by sensors in 231 BR725 engines during a total of 14 045 flights, and returned on a voluntary basis to Rolls-Royce by customers for analysis. Each aircraft using the BR725 has two engines; to minimise the amount of data used, the values used in this thesis were taken from the left engine only.

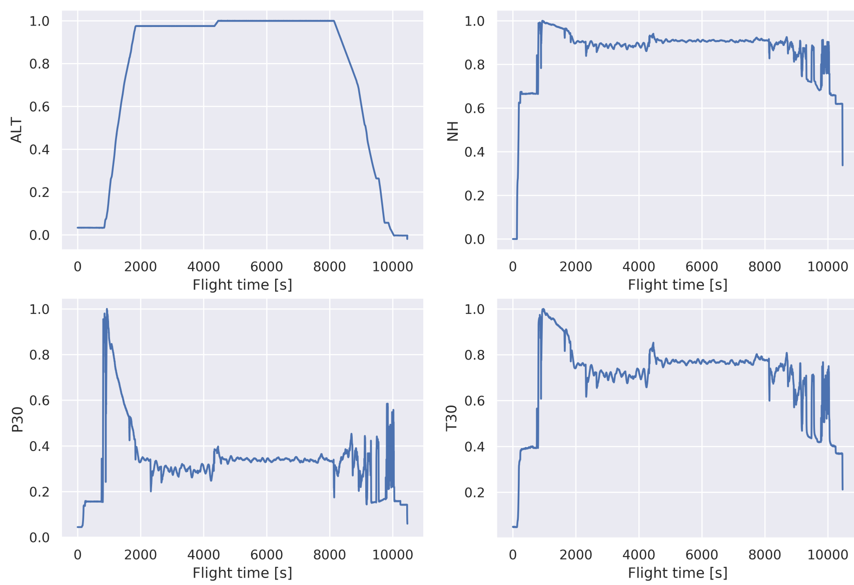

Figure 3: ALT, NH, P30 and T30 of a randomly selected flight. (All parameter values are normalised.)

3.2 Overview

The flights range in length from 1 013 to 57 062 seconds (approximately 0.28 to 15.85 hours), with a mean length of 10 182,82 seconds and a standard deviation of 9 561,03 seconds (see Figure 2).

Each flight is summarised in a comma-separated values (CSV) file with 216 columns, comprising one timestamp and 215 values per second of recording time.

The four flight parameters extracted were altitude (ALT), rotational speed of the high-pressure shaft (NH), and pressure and temperature of air exiting the compressor (P30 and T30, respectively). These are shown for one randomly selected flight in Figure 3, with dashed vertical lines representing the boundaries of flight phases (3.3).

Table 1: Summary of flight phases and conditions at which they begin (?). FM conditions in accordance with Reischl & Müller (2014).

Phase description	Conditions
Preflight	FM = 2
Taxi out	left or right engine is switched on
Take-off	FM = 4
Climb	WOW = 0
	intertial vertical speed > 500 ft/min
	altitude at least 1500 m greater than at take-off
Cruise	FM = 6
	altitude greater than 85% of maximum altitude
Descent	FM = 7 or FM = 8
	TRA < 20° for both engines
	Time to destination < 45 min
Reverse thrust	FM = 9
Taxi in	reverse thrust phase ended

The majority of flights (56.6%) reached a maximum altitude of 40 000 feet or higher.

3.3 Flight Phases

A flight can be split into several phases: preflight, taxi out, take-off, climb, cruise, descent, reverse thrust and taxi in. These phases were extracted using internal Rolls-Royce software (?) that combined the flight mode parameter from EHM data (Reischl & Müller, 2014) and custom conditions for optimisation. The conditions are summarised in table 1.

The flight mode (FM) often makes use of the parameter weight on wheels (WOW), a boolean parameter with a value of 1 if the aircraft's weight is supported by its wheels, otherwise 0. Other parameters used for determining FM include ground speed, intertial vertical speed, wing flap angle and thrust lever resolver angle (TRA).

3.4 Cycle Counter

Each flight was processed using SA66 (Section 2.6.2) to determine the damage incurred (i.e. the number of cycles consumed).

- One value per feature per flight

- Non-negligible amount of effort required to obtain this data for supervised learning. Big question: Can model scale to smaller data sets?

3.5 Visualisation

- Distribution

- Why not centred on 1 cycle if based on ”reference” cycle?

- NH-driven, thermally sensitive (F6/F7) - scatter plot F7 divided by F1

3.6 Downsampling

- Required for input layer to MLP

- Also better for scalability of models

3.6.1 (A)PLA

3.6.2 APCA

3.6.3 Data Loss

- Average percentage loss caused by downsampling.

- Will it affect model accuracy?

3.7 Optional: Case Studies

3.7.1 6014: Stress Ranges

3.7.2 6079: Long Taxi

4 Model Implementation

4.1 Polynomial Regression

4.2 MLP: Time Series Regression

4.3 Convolutional Neural Network: Time Series Classification

4.4 Convolutional Neural Network: Time Series Regression

4.5 MLP: Key Value Regression

5 Discussion

6 Conclusion

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