Turbofan Engine Behaviour Forecasting using Flight Data and Machine Learning Methods

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SENTA A PÚA!

Dedication

I would like to dedicate this master's dissertation to a wonderful person and someone I am very fortunate to call friend, Stan, who helped me to take the first step towards achieving my master's degree.

Acknowledgements

First of all, I would like to express my gratitude to my advisor Prof. Dr. André Silva for helping me achieve my goals.

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Resumo

O moderno motor de turbina a gás amplamente utilizado para propulsão de aeronaves é um sistema integrado complexo que sofre deterioração durante a operação devido à degradação de seus componentes do percurso do gás. Esta dissertação destaca a importância da monitorização da condição do motor para um planejamento de manutenção mais eficiente. Diferentes abordagens de Machine Learning (ML) são comparadas visando a aplicação de previsão do comportamento do motor com o objetivo de encontrar o momento ideal para a remoção do motor. Os modelos selecionados foram OLS, ARIMA, NeuralProphet e Cond-LSTM.

O longo histórico de operação e manutenção de dois motores turbofan CF6-80C2 maduros foi usado para a análise, o que permitiu a identificação do impacto de diferentes fatores no desempenho do motor. Esses fatores também foram considerados no treinamento dos modelos de ML, o que resultou em modelos capazes de realizar a previsão em operação e condições de voo especificadas. Os modelos ML forneceram previsão do parâmetro Exhaust Gas Temperature (EGT) na fase de decolagem.

O Cond-LSTM demonstrou ser uma ferramenta confiável para previsão do EGT do motor com um erro absoluto médio de 7,64 °C, permitindo a deterioração gradual do desempenho sob um tipo específico de operação. Além disso, a previsão dos parâmetros de desempenho do motor tem se mostrado útil para identificar o momento ideal para realizar ações de manutenção importantes, como a limpeza do percurso do gás do motor. Esta tese mostrou que a previsão de remoção do motor pode ser mais precisa usando um monitoramento sofisticado de tendências e métodos avançados de ML.

Palavras-chave

Motor Turbofan; condition monitoring; machine learning; neural networks; forecasting; manutenção preditiva.

Abstract

The modern gas turbine engine widely used for aircraft propulsion is a complex integrated system which undergoes deterioration during operation due to the degradation of its gas path components. This dissertation outlines the importance of Engine Condition Monitoring (ECM) for a more efficient maintenance planning. Different ML approaches are compared with the application of predicting engine behaviour aiming at finding the optimal time for engine removal. The selected models were OLS, ARIMA, NeuralProphet, and Cond-LSTM.

Long operating and maintenance history of two mature CF6-80C2 turbofan engines were used for the analysis, which allowed for the identification of the impact of different factors on engine performance. These factors were also considered when training the ML models, which resulted in models capable of performing prediction under specified operation and flight conditions. The Machine Learning (ML) models provided forecasting of the Exhaust Gas Temperature (EGT) parameter at take-off phase.

Cond-LSTM is shown to be a reliable tool for forecasting engine EGT with a Mean Absolute Error (MAE) of 7.64℃, allowing for gradual performance deterioration under specific operation type. In addition, forecasting engine performance parameters has shown to be useful for identifying the optimal time for performing important maintenance action, such as engine gas path cleaning. This thesis has shown that engine removal forecast can be more precise by using sophisticated trend monitoring and advanced ML methods.

Keywords

Turbofan engine; condition monitoring; machine learning; neural networks; forecasting; predictive maintenance.

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List of Acronyms

ACARS	Airborne Communications Addressing and Reporting System
ACC	Accessories
AD	Airworthiness Directives
AGB	Accessory Gearbox
AMM	Aircraft Maintenance Manual
ANN	Artificial Neural Network
AOG	Aircraft On the Ground
APU	Auxiliary Power Unit
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
AVM	Airborne Vibration Monitor
BER	Beyond Economical Repair
BPR	Bypass Ratio
BSI	Borescope Inspections
BTB	Back-To-Birth
CRF	Compressor Rear Frame
CSLPR	Cycles Since Last Performance Restoration
CSN	Cycles Since New
CSO	Cycles Since Overhaul
CSW	Cycles Since Wash
DMC	Direct Maintenance Costs
DOC	Direct Operating Costs
ECM	Engine Condition Monitoring
EEC	Electronic Engine Controller
EGT	Exhaust Gas Temperature
EGTMax	Maximum Take-Off EGT
EICAS	Engine Indication and Crew Alerting System
ESM	Engine Shop Manual
FAA	Federal Aviation Administration
FADEC	Full Authority Digital Electronic Control
FF	Fuel Flow
FFNN	Feed-Forward Neural Network
FIM	Fault Isolation Manual
FMV	Fuel Metering Valve
FOD	Foreign Object Damage
GA	Genetic Algorithms
GCP	Google Cloud Platform
GE	General Electric
GPA	Gas Path Analysis
GPU	Graphics Processing Unit

HMU	Hydromechanical Unit
HPC	High Pressure Compressor
HPT	The High Pressure Turbine
IDG	Integrated Drive Generator
IFSD	In-Flight Shutdown
IGB	Inlet Gearbox
LLP	Life Limited Part
LPC	Low Pressure Compressor
LPT	Low Pressure Turbine
LRU	Line Replacement Unit
LSTM	Long Short-Term Memory
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCD	Magnetic Chip Detector
ML	Machine Learning
MLE	Maximum Likelihood Estimation
MPD	Maintenance Planning Document
MRO	Maintenance, Repair and Overhaul
MTBF	Mean Time Between Failure
MTBR	Mean Time Between Repair
MTOW	Maximum Take-Off Weight
NDT	Non-Destructive Tests
NGV	Nozzle Guide Vane
NIS	Non-Incident Statement
OAT	Outside Air Temperature
OATL	Oat Limit
OEM	Original Equipment Manufacturer
OLS	Ordinary Least Squares
OVH	Overhaul
PDF	Probability Distribution Function
PIMU	Propulsion Interface Monitor Unit
PN	Part Number
PR	Performance Restoration
PW	Pratt & Whitney
QEC	Quick Engine Change
RAM,	Random Access Memory
RBN	Radial Basis Network
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Networks
RPM	Rotations Per Minute
RR	Rolls-Royce
SAV	Starter Air Valve
SB	Service Bulletins
SFC	Specific Fuel Consumption

STG	Stage
SV	Shop Visit
SVM	Support Vector Machine
TAT	Turn Around Time
TGB	Transfer Gearbox
TODA	Take-Off Distance Available
TORA	Take-Off Run Available
TOW	Time On-Wing
TSFC	Thrust Specific Fuel Consumption
TSLPR	Time Since Performance Restoration
TSN	Time Since New
TSO	Time Since Last Overhaul
UER	Unscheduled Engine Removal
VSV	Variable Stator Vanes
WS	Workscope
WSPG	Workscope Planning Guide

Chapter 1 - Introduction

The modern gas turbine engine widely used for aircraft propulsion is a complex integrated system that deteriorates during operation due to the degradation of its gas path components. Gas Path Analysis (GPA) was first introduced in the late 1960s, almost as old as the engine itself. Since then, different methods of analysis and health monitoring have been explored and developed (Volponi, 2014). This dissertation outlines the importance of Engine Condition Monitoring (ECM) for a more efficient maintenance planning. Different Machine Learning (ML) approaches are evaluated aiming to develop an accurate tool for engine performance analysis, and engine behaviour prediction. The main goal of predicting the engine behaviour is to find the optimal time for removal.

Commercial aircraft engine represents a substantial fraction of any airline's Direct Operating Costs (DOC) (Bugaj et al., 2019). The life cycle costs of a gas turbine engine have driven the industry to adopt on-condition maintenance. Engine-related costs can add up to as much as a third of the total aircraft maintenance cost (Buntić et al., 2012). Several factors contribute to engine performance degradation. More demanding operation results in greater stress on the engine, which increases the wear and degradation of the components, thus a more rapid performance and mechanical deterioration. The most common degradation mechanisms are associated with the deformation in blade surfaces due to erosion, fouling, debris deposit, amongst others, which greatly affect the blade aerodynamics (Giorgi et al., 2018).

ECM is a digital service that receives in real time all the engine parameters during the flight for monitoring. Advanced instrumentation provides crucial information such as Exhaust Gas Temperature (EGT) and fuel consumption for ECM. Performance monitoring plays a major role in diagnosing problems and thus extending the engine's overall life (Meherwan P. Boyce, 2006). There are several ways to identify engines that require maintenance action proactively to prevent aircraft downtime and safety risks. Generally, airlines utilise flight data analysis tools able to automatically alert the operator when any parameter exceeds the manufacturer limits. In some cases, it allows the operator to arrange maintenance actions as soon as the aircraft lands.

Engine maintenance can be divided into maintenance on-wing and off-wing, where the former is termed as line maintenance and the latter as engine shop visit. There are three main reasons for an engine to be removed and sent to a shop for maintenance. The first concerns the restoration of the performance of the gas turbine, the second concerns the replacement of Life Limited Part (LLP); while the two first removal reasons can be planned and managed in advance by the operator, the third and last reason concerns unscheduled engine removal (Justin & Mavris, 2015), which can be very costly especially if no spare engine is available.

Therefore, engine Time On-Wing (TOW) management is a wide field that includes several factors that directly or indirectly impact the engine removal interval and shop visit costs. For this reason, in addition to improving operational safety, different approaches of ECM and diagnostics have progressed over the past decades (Volponi, 2014). Operators, as well as the engine manufacturers, recognise the benefits and challenges of establishing validated and reliable tools for predicting the engine's remaining time before removal. Currently, ECM is typically monitored using snapshots of key sensor values measured during the flight, such as temperatures, pressures, rotor vibrations, etc.

ECM systems have inefficiencies that can be overcome by integrating advanced monitoring and life prediction technologies (Suarez et al., 2003). Although the current

ECM methods provide the operator a considerable insight of the engine behaviour, it requires experienced individuals who can analyse the trended data and human misinterpretation of data may occur (Roemer, 1998). Engine fleet management has been a big challenge, especially for small airlines that have no expertise on engine diagnostics as it does not have intuitive information that could facilitate efficient decision-making regarding engine maintenance management. In addition, this can lead to premature or unexpected engine removals and consequently interrupt operation, implying Aircraft on the Ground (AOG) expenses, and in some cases, require an urgent engine leasing. Early warning of engine malfunction and loss of performance permits corrective action before extensive damage and for better engine removal planning (Roemer, 1998).

Considerable prior work regarding advanced health monitoring and prediction methods have been published, but the development of a tool to predict engine behaviour under operator specified conditions has not been equally explored and available to operators (Li, 2002)(Marinai et al., 2004)(Volponi, 2014). Our goal can be separated into two parts. First, the historical performance analysis of two different mature turbofan engines installed on different aircraft, with similar Time/Cycle Since New (TSN/CSN), and different operation profiles. This part refers to the investigation of the main factors that influence engine performance deterioration as well as its TOW. Secondly, and most importantly, the analysis of the historical flight data of a mature turbofan engine and the implementation of a forecasting model for aircraft engines.

The main contributions of this study are as follows: (i) To study the influence of measured parameters and operational conditions on the engine performance and mechanical degradation rate; (ii) To evaluate different machine learning approaches to accurately predict engine behaviour; (iii) To implement a predictive model of the engine for a more efficient engine TOW management. The ultimate objective of this study is to forecast engine behaviour while maximising engine reliability through more accurate health monitoring and life measurement capabilities.

1.1 Goals and Objectives

The main dissertation goal is to improve engine fleet management by implementing a reliable tool for engine behaviour forecasting using different machine learning approaches. The following objectives were created to achieve the main goal of this dissertation:

- Investigate the main factors that influence and impact the engine performance;
- Identify the relevance of parameters through correlation analysis using historical flight data;
- Pre-process and organise the flight data;
- Perform an exploratory flight data analysis of the most relevant parameters;
- Analyse engine maintenance history during operation life and verify its effect on engine performance;
- Compare different machine learning approaches for predicting engine behaviour;
- Simulate flights under specific conditions (independent variables).

1.2 Dissertation Outline

This dissertation is divided by chapters with the objective of presenting the project in a continuous way. To help readers to search topics of interest, this section provides a summary of the main topics from each chapter.

- Chapter 1 presents a brief introduction of the topic as well as its background, objectives, and structure.
- Chapter 2 named Literature Review is oriented for a revision of well-established methods up to the state of the art in gas turbine ECM using machine learning techniques.
- Chapter 3 presents an overview of gas turbine engine, including details of its functionality, design characteristics, and performance parameters.
- Chapter 4 provides information of types of maintenance, focusing on shop visits and detailing the primary causes of engine removal from the aircraft. This chapter also explains the main costs associated with maintenance.
- Chapter 5 presents the operation and maintenance history of two different engines to highlight the main factors that influence engine behaviour and performance. This chapter also covers the steps involved in forecasting engine behaviour, dataset explanation, as well as the statistical analysis and machine learning models considered in this dissertation.
- Chapter 6 presents the results and discussions.
- Chapter 7 concludes the findings and contributions of this project.

Chapter 2 - Literature Review

2.1 Aircraft Propulsion

Currently, the gas turbine engine is the most widespread and most effective method of aircraft propulsion. Replacing the piston engines, which, up to the 1960s, were the common power source in aviation, the gas turbine engine was developed to generate more thrust with a greater fuel efficiency in different configurations such as the turbojet, turbofan, turboprop, or turboshaft engines (Klaus Hunecke, 1997). The turbine engine development represents one of the most important technological achievements in aviation, allowing for an enormous acceleration of progress in all of its segments.

Before the end of the World War II, gas turbine engines built by Britain, Germany, and the United States were powering only combat aircraft reaching to civil aviation in the beginning of the 1950s. Within the next few decades and the technological advancements, jet engines were designed and developed with a better thrust to weight ratio, lower operating costs, and lower maintenance costs. Innovative designs for turbojet engines started to overcome the drawback that earlier engines had, such as the large quantities of fuel consumption, compressor stall, and the low thrust force generated (El-Sayed, 2008).

The turbojet was the earliest type of a turbo-propulsion engine. Although it could operate at higher speeds than the piston engine it was designed to accelerate a relatively low air mass flow. Then, Rolls-Royce introduced the “bypass” principle. The Bypass Ratio (BPR) is defined as the ratio between the mass of air that flows around the engine and the mass of air that flows through the core of the engine (Filippone, 2013). Bypass jet engines were then frequently denoted as turbofan engines. The turbofan engine was designed as a compromise between the turboprop and turbojet engines (Hill & Peterson, 1992). Like the turboprop, the turbine section is designed to absorb more energy accelerating a high air mass flow (El-Sayed, 2008). While the turboprop was designed for low-speed aircraft, the turbofan was able to reach transonic speeds of Mach 0.9 operating significantly quieter.

Civil aviation requires long-range fuel efficiency at high subsonic cruise velocities (Klaus Hunecke, 1997). Flight velocities around Mach 0.8 are too high for the turboprop but too low for the turbojet, which results in low propulsive efficiency, whereas the turbofan engines exhibit good efficiencies around Mach 0.8 as shown Figure 2.1. Hunecke et al. and El-Sayed et al. present detailed history of aircraft propulsion and gas turbine engines as well as fundamentals of theory, design and operation (El-Sayed, 2008; Klaus Hunecke, 1997).

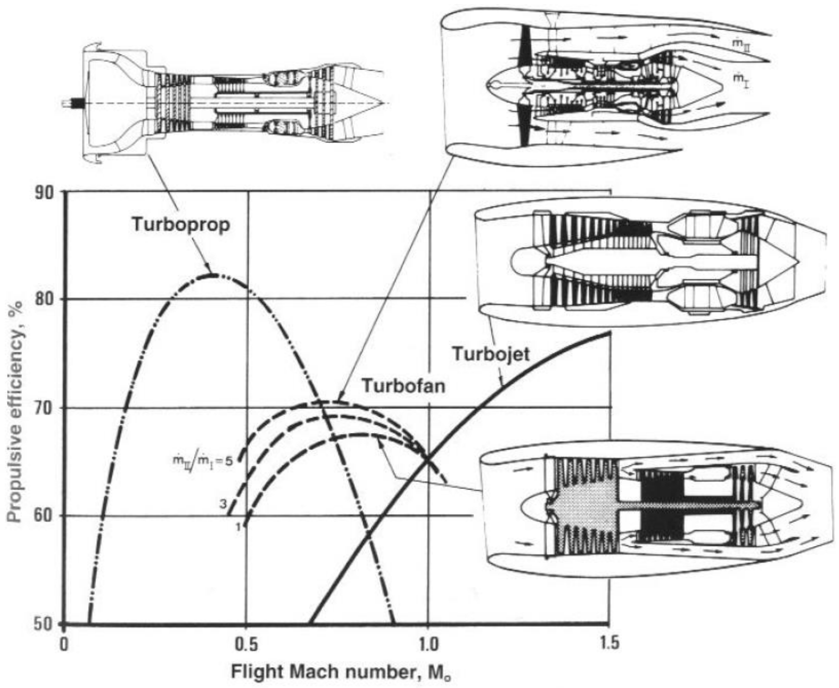

Figure 2.1 – Propulsive efficiency characteristics of turboprop, high and low bypass turbofan, and turbojet engines (Klaus Hunecke, 1997).

The turbofan engine has several advantages over both turboprop and turbojet engines. The fan is not as large as the propeller of the turboprop, so the increase of speeds along the blade is less, allowing it to reach higher speeds. Also, the aerodynamics are better controlled by enclosing the fan inside a duct or cowling, which also serve as a noise reduction buffer. The turbofan can generate more thrust than the turbojet because it intakes more air flow. Like the turboprop engine, the turbofan has low fuel consumption compared to the turbojet. Finally, the turbofan engine is the best choice for high-speed, subsonic commercial airplanes (El-Sayed, 2008).

Rolls-Royce introduced a BPR of 3 or more in 1950. General Electric led the way in 1965 with the TF39 with a BPR of 8 that was developed to power the Lockheed C-5 Galaxy. The TF39 was the first high bypass jet engine developed and was further developed into the CF6 series of engines, which have become very popular since the early 1970s and is the focus of this dissertation (Figure 2.2). Even though the CF6 engine family went through major design changes on the modules and implementation of improved material, the core characteristics of its TF39 roots persist in the subsequent variations.

With the technological advancements, the CF6 family improved its performance and design through every variant developed. During the engine's operating life, efficient maintenance is required for ensuring its safe operation, reliability, and cost-efficiency. Engine maintenance, whether scheduled or unanticipated, is very costly and represents between 35% to 40% of an airline's maintenance expenses (Ackert, 2011). Historically, engine removals for heavy maintenance were based on fixed-time intervals, also referred to as hard-time intervals, which means mandatory time or cycle limits. This maintenance strategy was soon noticed to be an unprofitable and disadvantageous process as in most cases the engines were being removed either prematurely or belatedly, the latter being more critical since prolonged exposure to damage can significantly reduce the overall engine's life and increase maintenance cost.

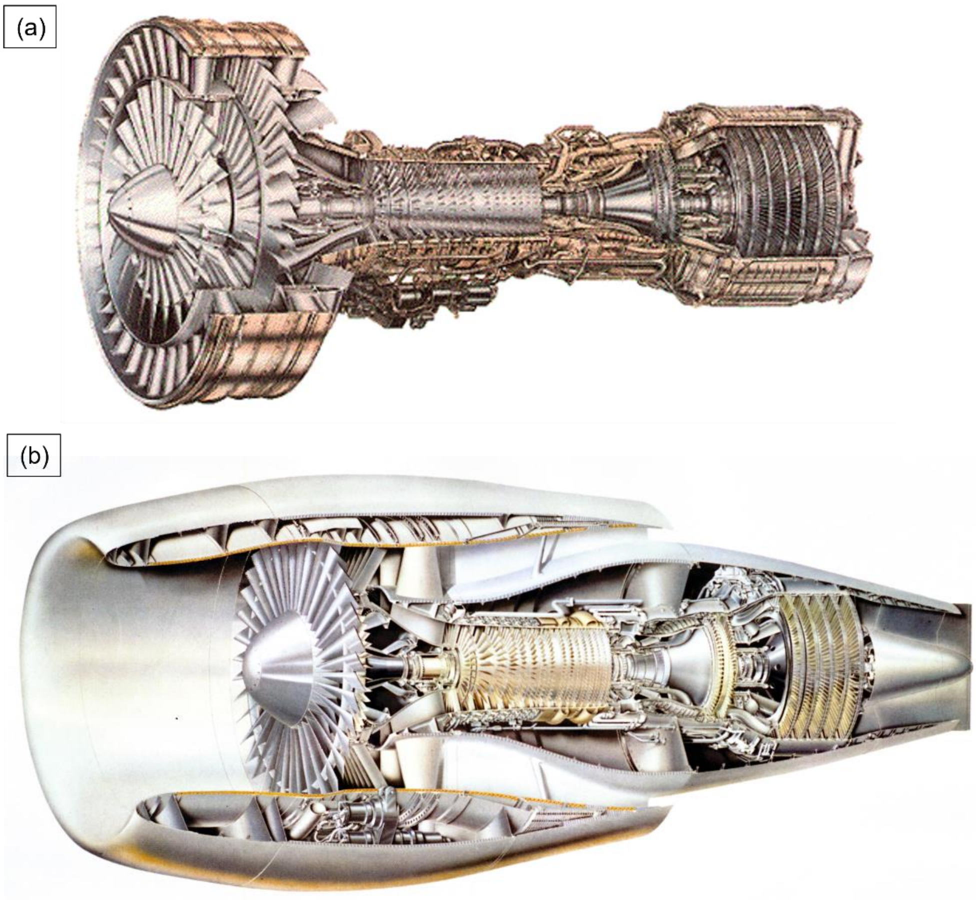

Figure 2.2 – General Electric TF39 high bypass ratio turbofan engine (a), General Electric CF6-6 high bypass ratio turbofan engine (b).

The reduction of the engine life cycle cost was a strong motivation for the monitoring practices and diagnostic developments in the recent decades. It drove the industry to abandon purely scheduled maintenance philosophy and adopt condition-based maintenance. Instruments and electronic displays that indicate engine performance became available to the operators for monitoring. These instruments cover vital information such as rotational speeds, exhaust gas temperature, fuel and oil status, and others (Klaus Hunecke, 1997). Therefore, engine condition monitoring and engine diagnosis are important assets in making more informed decisions on the usage, maintenance, overhaul or replacement of the engine or one of its components.

2.2 Engine Condition Monitoring, Diagnostics and Prognostics

The reliability and safety of modern gas turbines are high due to a combination of improved materials, advanced instrumentation for life condition monitoring, and highly conservative design and maintenance philosophies (Vittal et al., 2004). Monitoring and analysis methods have progressed over the past six decades, beginning with empirical methods focused on monitoring the mechanical integrity of the machine. Nowadays, advanced sensors allow the operator to identify parameter changes such as temperature, pressure, vibration speed, power, and more that could indicate a malfunction prior to actual failure (Volponi, 2014). The term diagnostic means both detection and identification of faults and failures, while prognostic deals with predicting the health state of the engine and its accessories.

During normal operation, all engines experience rubbing, thermal stress, mechanical stress, etc. The most common causes of degradation in the performance of a turbofan engine involve compressor fouling, wear and erosion of blades, seal damage, foreign and domestic object damage, hot end component damage, corrosion, and airborne contaminants such as dust, dirt, sand, rust, ash, and carbon particles. Information is the key element in any degradation monitoring and diagnostics. The physical causes listed above result in changes in the engine thermodynamic performance, which produce changes in the observable engine parameters (Li, 2002).

There are many approaches for condition monitoring and fault diagnostics, such as performance analysis, oil analysis, visual inspection, borescope inspection, vibration monitoring, and others. A notable performance analysis method, the GPA based on a linear method was first introduced in late 1960s by Urban (Urban, 1969). The GPA method depends on the state of individual components, which is mathematically represented by a set of independent performance parameters. The theory behind this relationship and one of its main assumptions is that the changes in the independent health parameters are small and the set of governing equations can be linearized around a given steady-state operating point.

The high costs associated with engine performance restoration, which accounts to at least a third of the airline's total maintenance costs, motivated further development of analysis methods to track performance down to the module level. In the early 1980s, the Full Authority Digital Electronic Control (FADEC) was introduced and on-board advanced instrumentation for control functions that could also provide information for diagnostic purposes was implemented in the engine's design. Investigation of the newer techniques led to the development of engine diagnostics based on optimisation techniques, and the assumption of linearity became increasingly false when deteriorations cause the engine to operate further away from the linearized equations (Marinai et al., 2004).

The development of non-linear GPA improved the accuracy of the predictions by solving the non-linear relationship between the considered health-parameters and measurements using an iterative method as described by Escher (Escher, 1995). It provided a significant advantage on the severe limitations of linear GPA models. Non-linear model-based methods combined with conventional optimisation were introduced in the 1990s by (Stamatis et al., 1990). A method of detecting faults and assessing the condition of the components was presented by employing the technique of adaptative modelling. This approach is based on the logic employed by parameter deviation estimation methods.

Deterministic solutions required a large number of measurements, therefore a statistical approach to identify degradation and malfunction of engine components using GPA and Bayesian statistical inference was developed (Consumi & d'Agostino, 1997). This method uses a Gaussian *a priori* Probability Distribution Function (PDF) to estimate unknown parameters. Maximum Likelihood Estimation (MLE) method is used on the observed data in respect to the corresponding engine nominal data by minimising a sum of squared residuals cost function. Statistical approaches were further explored and developed by implementing optimisation techniques such as Davidon-Fletcher-Power method, and Levenbery-Marquardt method (Press et al., 1986).

The disadvantages of non-linear model-based methods were overcome by using Artificial Neural Networks (ANN) such as dynamic neural networks (Tayarani-Bathaie et al., 2012), feed-forward network (Loboda et al., 2012), Radial Basis Network (RBN) (Sampath & Singh, 2006), Genetic Algorithms (GA) (Zedda & Singh, 2002), and more recently Recurrent Neural Networks (RNN) such as the Long Short-Term Memory (LSTM) networks (Triebe et al., 2019). LSTMs show great promise due to their ability to consider the temporal relationship between data and has been widely used for the development of forecasting solutions.

2.3 Engine Behaviour Prediction

Many studies in the literature focus on different methods and techniques to monitor and predict the condition of gas turbine engines used in aviation. This section describes the progress of this field of study over the years.

Suarez et al. validated a condition-based maintenance tool that consists of onboard real time component damage indicators and material property algorithms. This study developed fatigue damage indicator algorithms based on detailed military engine structural design analysis. The life algorithms were implemented onboard the engine system allowing to obtain output of the component accumulated damage assessment and to improve the effectiveness of the maintenance program (Suarez et al., 2003).

Giorgi et al. used three samples flights to training and testing two different machine learning techniques, ANN and Support Vector Machine (SVM), for performance prediction and health diagnostics. The degradation causes considered in the study were the compressor fouling and turbine erosion. Although both techniques presented good results, the model based on ANN showed to be slightly better than the SVM (Giorgi et al., 2018)

Yildirim & Kurt developed a model to predictive the EGT parameter using multiple regression analysis and ANN method where the latter presented the lowest error. With the rise of RNN, more specifically, of LSTM models, many applications of these methods have been presented in the literature regarding engine condition monitoring and prediction (Yildirim & Kurt, 2018).

Palagi et al. compared the performance of FFNN, RNN, and LSTM in predicting exhaust gas temperate from an internal combustion engine. The LSTM showed the smallest prediction error when compared to the other two models, showing the improvement of the LSTM in considering long term temporal dependencies (Palagi et al., 2019).

Hong et al. proposed a deep learning model to accurately predict the remaining useful life (RUL) of the turbofan engine. This model combines different machine learning components, such as a 1-dimensional Convolutional Neural Network (1D-CNN) layer and LSTM layer, effectively creating a Conv-LSTM model. In order to avoid overfitting due to the model’s complexity, the authors also implemented a dropout technique to improve the model’s learning ability (Hong et al., 2020). The work by Hong et al. demonstrates good efficiency and high performance but lacks the ability to include specific conditions as inputs for the model’s prediction.

Chapter 3 - Gas Turbine Engine

3.1 High Bypass Turbofan Engine

Different types of engines exist according to their tasks. The classification of the engines used in the aerospace industry (El-Sayed, 2008) is divided into two categories, the Airbreathing and the Non-Airbreathing Engines, the latter being mostly used on rockets (Figure 3.1). Airbreathing engines are further divided into Reciprocating Engines and Jet Engines. This study focuses on the Turbofan Engine, which is a gas turbine powered jet engine, first named as bypass turbojets by Rolls-Royce (Filippone, 2013).

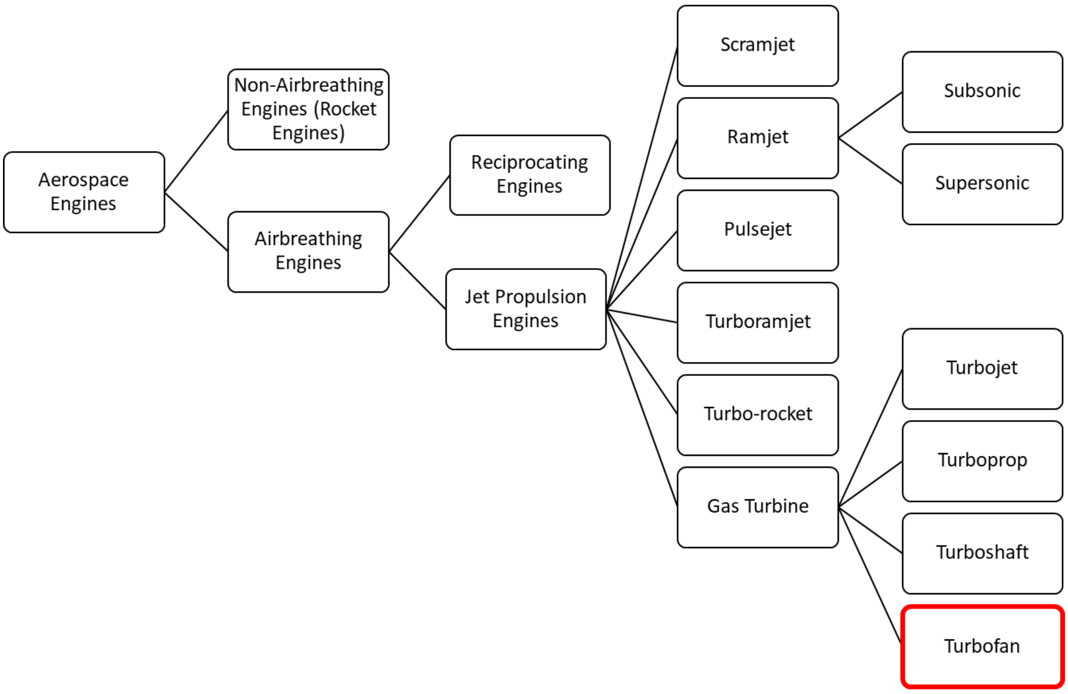

Figure 3.1 – Aerospace engines classification (El-Sayed, 2008).

Reciprocating engines, also known as piston engines, build pressure by intaking air in one stroke, which will then be converted into a rotating motion to turn the propeller and generate thrust. Piston engines were the main dominant source of power for aircraft propulsion until approximately the 1940s when jet engines were developed to be lighter, capable of higher-altitudes and higher-speed performance for the same power generated (El-Sayed, 2008).

Jet engines use combustion by creating a chemical reaction that is ignited inside a combustor chamber, discharging a fast-moving jet to generate thrust forward. Although the definition of jet engine can include rocket, water jet, and hybrid propulsion, the term usually refers to an airbreathing engine due to its typical features, such as a rotating air compressor powered by a turbine. Jet engines are further subdivided into several models that are each described in more details by El-Sayed (El-Sayed, 2008).

Gas turbine engines are also divided into different models, all of which work with the same principle. The term gas turbine is associated with the design of the engine consisting of a compressor, a combustor chamber, a power turbine – such set is known as the hot section – and an exhaust nozzle (Zohuri, 2015). Additionally, there are other parts such as the external hardware – inlet, fuel lines, fuel nozzles, sensors, collectors, and others – whose function is essential. The main types of gas turbine engines are the turbojet, the turbofan, and the turboprop (Klaus Hunecke, 1997). These three models are employed extensively in jet-powered aircraft for commercial and military operation.

The turbojet belongs to the first generation of gas turbine concept providing propulsive forces directly from the reaction forces generated by the exhaust gas. In the turbojet, all the inlet air flows through the core (Figure 3.2). The air enters the intake section and in an axial direction and streams uniformly through the compressor. As the air flows through the several stages, the compressor raises its pressure. The compressed and heated air enters the combustion chamber, where fuel is injected and burned, thus adding greater amount of energy to the airflow by chemical reaction. Then, the hot air is expanded and directed to the turbine nozzles and onto the turbine rotor, converting gas energy into mechanical work to drive the compressor as it is rigidly linked by a hollow shaft. Finally, all the hot gases are accelerated and ejected as a high speed hot jet through the nozzle providing the thrust that propels the aircraft forward (Klaus Hunecke, 1997).

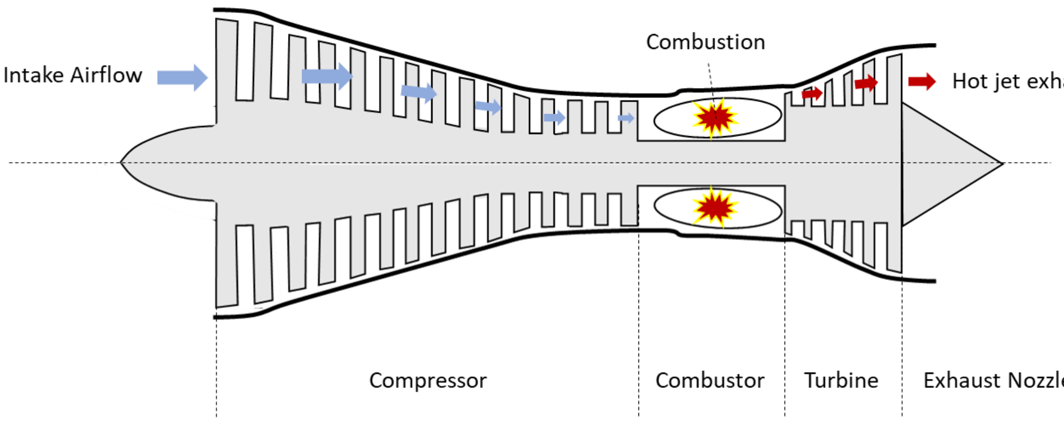

Figure 3.2 – Axial-flow turbojet powerplant diagram.

The turbofan engine is a derivative of the turbojet. Turbofan engines use part of the air that the vehicle is flying through as a source of oxidiser in the combustor chamber to mix with fuel, as well as a working fluid for generating thrust. It contains all the main elements of the turbojet, additionally the turbine section is designed to absorb more energy from the hot gas to also drive a fan. The fan is a compressor of large diameter assembled upstream of the main compressor that creates a second path for the intake airflow named as bypass duct (Figure 3.3). The advantage of this additional module is the large air mass bypassing the core, which produces high thrust level, especially at take-off. However, bypass airflow demands a relatively low fan speed. In addition, multiple-stage compressors require lower speeds at the first stages and higher speeds at the latter stages to reach high-performance and avoid surge (Klaus Hunecke, 1997). To meet these conflicting requirements, bypass turbofan has the compression process divided into two separate compressor units, each of which is driven by its own separate turbine allowing both thereby to operate at different rotational speeds. Thus, the Low Pressure Turbine (LPT) drives the fan and the Low Pressure Compressor (LPC) at low speed, and the High Pressure Turbine (HPT) drives the High Pressure Compressor (HPC) at high speed (MacIsaac & Langton, 2011).

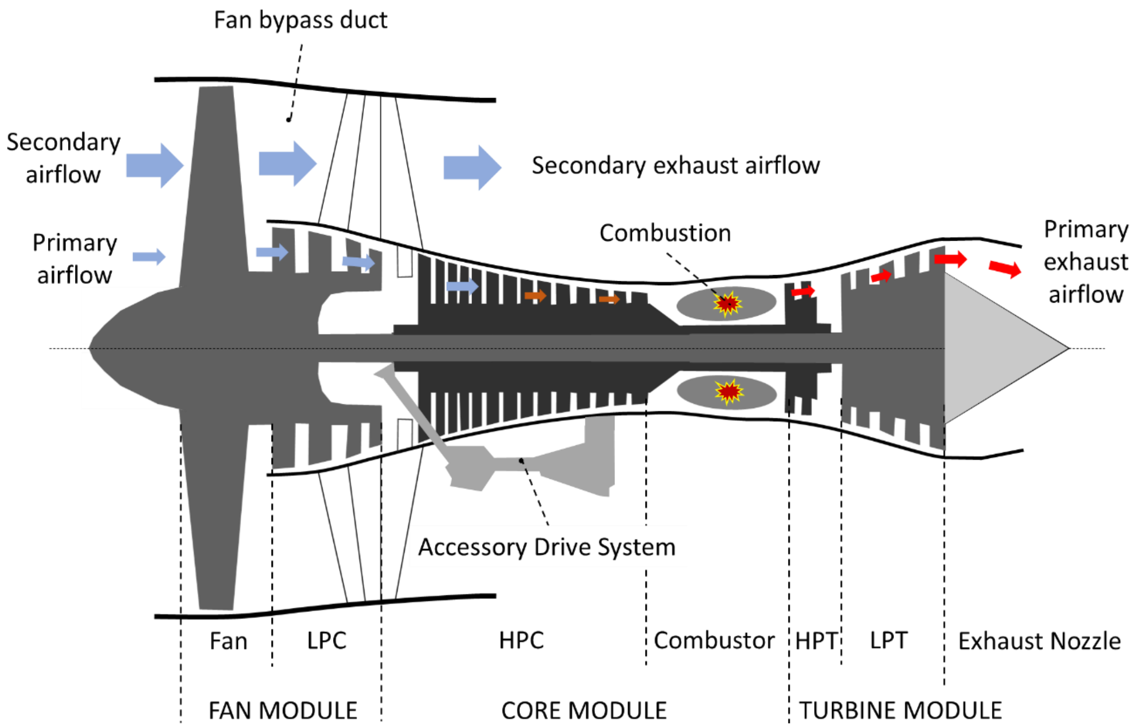

Figure 3.3 – High bypass ratio, dual-rotor, axial-flow turbofan engine diagram.

The amount of air that is bypassed in relation to the air that passes through the core engine determines the BPR, where a ratio of 5:1 and greater classify the engine as a high bypass engine. Low BPR in the range of 0.2:1 to 1:1 is widely used with modern supersonic combat aircraft. High subsonic military and commercial transport aircraft commonly use high BPR engines (Klaus Hunecke, 1997). The CF6 engine series varies its BPR between 4.3 and 5.4.

3.2 Turbofan Engine Design Characteristics

High bypass turbofan engines power the majority of today's large civil air transports as they are the most reliable engines ever developed (Luongo et al., 2009). The turbofan market has been dominated by General Electric (GE), Rolls-Royce (RR), and Pratt & Whitney (PW) since the early 1960s. A variety of engine configurations have been developed and explored by the different manufacturers. A distinction is made by the engine's design characteristics such as number of spools, principle of compression, distribution of airflow, among others (Klaus Hunecke, 1997). This work focuses on a dual-rotor, axial-flow, high BPR turbofan powerplant manufactured by GE.

The dual-rotor configuration, also called twin-spool arrangement, refers to the LPC and HPC that are shaft-driven by the LPT and HPT, consecutively. Each spool rotates at different speeds in order to maintain high efficiency in all stages of compression. The three-spool arrangement combines an intermediate pressure spool driven by its own turbine, such as in the RR engines. Although far from common, the simplest configuration is the single-spool, which has the fan and HPC driven by a single turbine on the same spool rotating at the same speed and its most reserved to Auxiliary Power Unit (APU).

Basically, there are two types of air compression, namely axial-flow, which consists of compressing the air along an axial path through the core; and centrifugal-flow, which consists of collecting and accelerating the air outwardly through centrifugal action. In other words, a centrifugal compressor discharges compressed air radially outward, at 90 degrees to the spool axis, while axial-flow compressor discharges air parallelly to the spool axis (Klaus Hunecke, 1997). Currently, the latter is used only in small engines such as shaft engines for helicopters, APUs, and turboprop engines, as it only handles low mass flow. Axial-flow configuration employs most engines due to its capability to handle large mass flow rates, consequently generating high thrust levels.

In particular, turbofan engines are classified pursuant to the amount of mass airflow that is bypassed through the fan, and are typically denominated as high BPR and low BPR engines (Klaus Hunecke, 1997). The BPR is defined as the ratio between the mass of air that flows around the engine and the mass of air that flows through the core (Filippone, 2013). This ratio has been increasing over the years as it is the key design parameter of the engine. Depending on the fan design the total thrust can be attributed about 85% to the fan, therefore, the larger the BPR, the greater the amount of energy extracted from the hot exhaust of the gas generator and consequently a lower exhaust speed, which reduces both fuel consumption (by raising core thermal efficiency) and engine noise (Luongo et al., 2009).

Turbofan engines have been designed with special attention to the disassembly/assembly of the engine. To permit for a more efficient maintenance procedure the engine can be disassembled into major modules allowing replacements and repairs of a module and its components without completely disassembling the engine (Figure 3.4). This does not affect integrity or performance of the engine as each module has its individual identity, operation history and inspections thresholds established by the Original Equipment Manufacturer (OEM). This design concept is termed as modular construction.

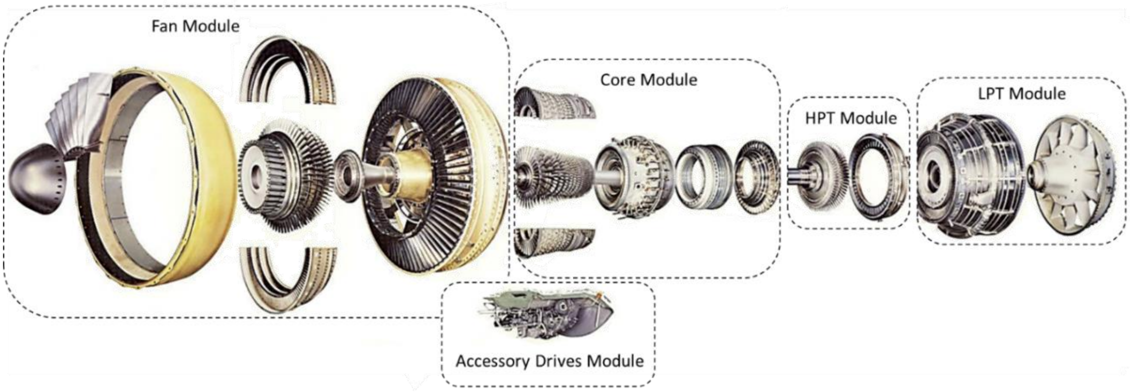

Figure 3.4 – Typical high bypass turbofan engine design. Individual modules illustrated.

The turbofan engines considered in this study are manufactured by GE Aviation model CF6-80C2. It consists of a compressor, a combustor chamber, a power turbine, and an exhaust nozzle, as depicted in Figure 3.3. The compression process is divided into two separated compressor units, each driven by its separate turbine, allowing both thereby to operate at different rotational speeds. This engine model is composed of a HPC of 14 stages driven by a 2-stage HPT, and an integrated front fan and a 4-stage booster LPC driven by a LPT of 5 stages. The annular combustor converts fuel and compressor discharge air into energy to drive the HPT and LPT. Then, the turbines convert part of the gas energy into mechanical work to drive the compressors as they are rigidly linked by shafts. The hot gases are also accelerated and ejected as a high-speed hot jet through the nozzle providing the thrust that propels the aircraft (Peach, 1973). According to the OEM technical documentation, 80% of the total engine thrust is supplied by the fan module through the secondary airflow acceleration. The fan module also increases the primary airflow that is directed to the HPC. In addition, the HPC rotor provides energy to the Accessory Drive System to power engine accessories. This system is bolted to the core module (HPC stator case) and consists of an inlet gearbox (IGB), a radial driveshaft, a transfer gearbox (TGB), a horizontal driveshaft, and an accessory gearbox (AGB).

The accessory gearbox module has two gear trains, and its function is to transmit torque from the HPC rotor system to the engine-mounted accessories and provide the core engine speed signal. The HPC forward shaft transmits power to the IGB, which then transmits power to TGB through the radial driveshaft. The TGB diverts the torque from the radial drive shaft to the horizontal drive shaft that powers the AGB. Finally, the AGB distributes torque through spur gears to drive gearbox mounted accessories such as fuel pump, starter, integrated drive generator (IDG), hydraulic oil pump, hydromechanical unit (HMU), and others.

3.2.1 *Thrust Rating*

Thrust is the most important engine operational parameter for pilots. Turbofan engines are designed and certified for two thrust ratings: maximum continuous thrust and maximum take-off thrust. The latter is the maximum rated thrust the engine will generate during normal operation, and it is based on a maximum allowable EGT at which the engine is allowed to operate for limited continuous time during the take-off phase of flight. Thus, thrust rating refers to the level of engine thrust that meets the design limitations, which are also composed of pressure and rotational speed limits in addition to EGT (Buntić et al., 2012).

Engine power management systems are designed to provide a constant level of thrust for a given altitude in order to meet aircraft performance requirements. This design feature is also known as flat-rated thrust. One of the CF6 engine models' notable features is the commonality concept between its thrust rating variants. Each variant is interchangeable between all the aircraft types it powers, and higher thrust ratings can be achieved by turning the engine at a faster rate to increase airflow. For FADEC engines, this can be easily done by changing the rating plug in the Electronic Engine Controller (EEC). Specific CF6-80C2 rating-to-rating conversions are allowed and are controlled by Service Bulletins (SB), which is an OEM document that provides modification details and instructions for compliance. In addition, mandatory hardware configuration may apply when converting lower thrust rating to higher thrust rating.

The engine rating plug and identification plug make a programmable electrical connector assembly. This assembly tells the EEC the thrust trim ratings of the engine. The rating plug supplies the interface between the EEC and the identification plug. It supplies thrust trim adjustments by the position of the switch actuation pins. The engine rating plug and identification plug together provide the desired thrust trim rating inputs to the EEC.

FADEC family models range from the CF6-80C2B1F to the CF6-80C2B8F, with flat-rated thrust varying from 51,950-61,030 lbf at flat-rated temperature varying from 30-32℃ (GE Aviation, 2011). Table 3.1 presents the thrust rating variants of the CF6-80C2 engine model, where the suffix "B" means it is applied for Boeing Aircraft. The following numbers specify thrust ratings and the suffix "F" in the end indicates that the engine is equipped with FADEC system. Because each engine model is associated with a specific airframe, sometimes there are multiple engine variants with the same thrust rating because the engines are on different aircraft.

Table 3.1 – Thrust rating model variants of CF6-80C2 engine.

Engine variant	Nameplate Thrust (lb) Take-off
CF6-80C2B1	55,980 @30℃
CF6-80C2B1F	57,160 @32℃
CF6-80C2B2	51,950 @32℃
CF6-80C2B2F	52,010 @32℃
CF6-80C2B4	57,180 @32℃
CF6-80C2B4F	57,280 @32℃
CF6-80C2B5F	60,030 @30℃
CF6-80C2B6	60,030 @30℃
CF6-80C2B6F	60,030 @30℃
CF6-80C2B7F	60,030 @30℃
CF6-80C2B8F	60,030 @30℃

Actual rates of deterioration will vary with thrust rating. The engine variant configured at higher thrust rating operates at higher EGT, which exponentially reduces the useful life of the hot section components due to high temperatures exposure. For the same level of EGT deterioration an engine operated at a lower thrust rating tends to stay on-wing longer (Figure 3.5). In addition, the engine hot section components are subject to greater deterioration when a thrust level is higher than the required for given take-off conditions (GE Aviation, 2008b).

Commonly, high thrust rating engines have high HPC and HPT airfoils scrap rate at the shop visit, which greatly affect the Direct Maintenance Costs (DMC)**.** However, the impact of engine thrust rating on DMC is not reserved to the increase in the deterioration rate of the hot section components, it also affects the LLP cost per cycle. The LLPs target life limit is stricter within the higher thrust rating configuration (Table 3.2). When comparing the cost per cycle between two CF6-80C2 variants, the B5F (low rated-thrust) and B7F (high rated-thrust), the cost per cycle of B7F is about 12% more, in addition to certain LLPs replacement being more frequent. The cost per cycle calculation was based on the OEM’s parts price catalogue from 2020.

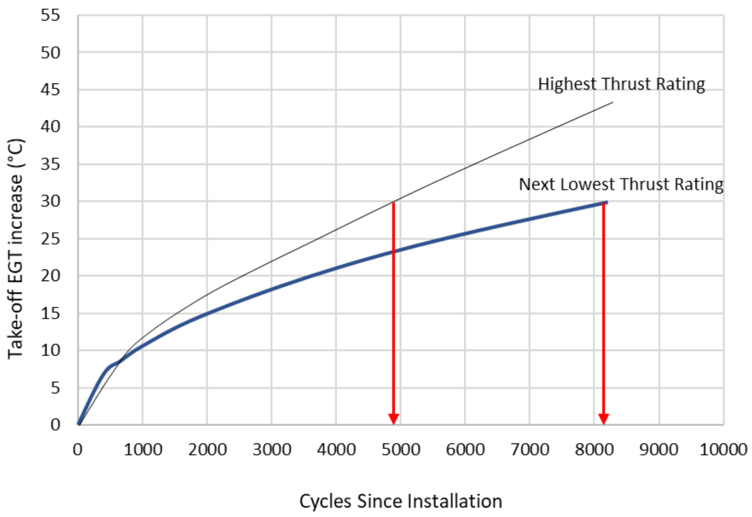

Figure 3.5 – Engine thrust rating effect on Take-off EGT over time (GE Aviation, 2008b). Red arrows indicate that an engine configured with high thrust rating will reach the same take-off EGT increase much sooner than the same engine model configured with lower thrust rating.

Aircraft engines have their thrust setting based on the design of the aircraft operation purpose. The main purpose of a long-range wide body aircraft is to carry a heavy load during a long-distance flight. Such operation profile requires engines that are capable of generating enormous thrust to lift the aircraft (Irsyadi & Nirbito, 2019). Most of the commercial aircraft are equipped with high thrust turbofan engines especially those operated by cargo companies. Usually, full flat-rated thrust is only applied if aircraft reaches its Maximum Take-Off Weight (MTOW). Otherwise, the high temperature from the excessive thrust could wear and tear the engine. In this dissertation, the analysis is particularly based on two CF6-80C2-B7F turbofan engines, denominated as Engine A and Engine B to preserve anonymity. Both engines are configured at high thrust rating since new.

3.3 Hot Section Components

The hot section of a turbofan refers to the HPC, combustor chamber, and HPT. These components operate in high stress environments with very elevated and varying temperatures and dynamic conditions. For this reason, these components' design requires highly tensile and thermo resistant materials, which results in high material cost for repair or replacement of worn parts (Seemann et al., 2011). This subchapter intends to briefly introduce the main components of the engine hot section as a further discussion regarding their degradation as well as the costs associated to their repair/replacement is presented in chapter 4.

The HPC is composed of several rows of airfoil that alternate among rotor blades and stator blades, also known as vanes (Figure 3.6). The rotor blades are connected to the rotating shaft, whereas stator blades are fixed. Without going into detailed engine design, it is important to mention that the stator vanes in the forward stages, stage 1 through 5 vanes, are variable, whereas the stages 6 through 13 are fixed. The Variable Stator Vanes (VSV) are often able to rotate open or close as necessary to balance the air load required by the aft compressor stages.

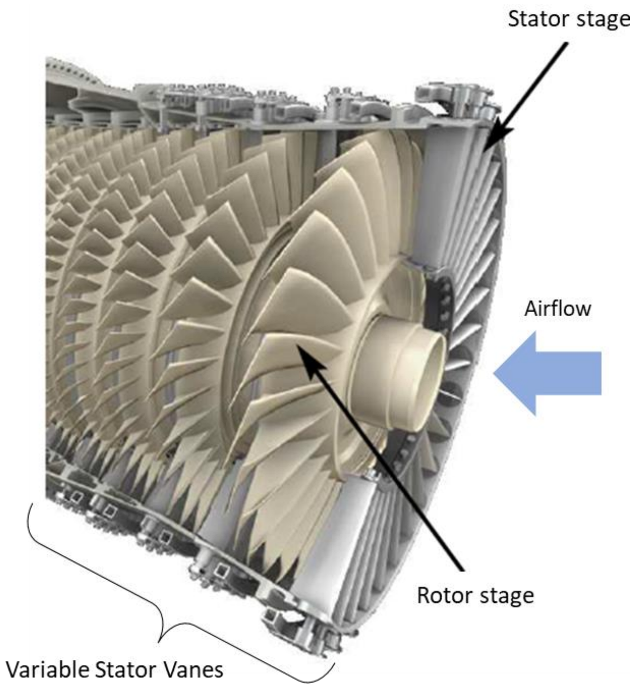

Figure 3.6 – Axial-flow compressor of a high bypass turbofan engine (GE Aviation, 2008b).

The rotor is considered the most complex component of the compressor assembly. The shape of the blades needs to be designed in a manner that the root section travels much slower than the tip section to ensure axial velocity is maintained constant across the flow path. The length of the blades decreases progressively downstream while the pressure increases (Klaus Hunecke, 1997). Like the wing, these blades, which possess an airfoil design, can experience similar aerodynamics of wing flow stall or separation due to high angle of attack. Separation of airflow results in a stall with loss of dynamic airflow progression, which consequently can cause a violent redirection of compressed air and eventually an engine shutdown.

The terms "stall" and "surge" are often interchanged. A rotating stall condition is limited to a circumferential area of the compressor and is characterised by the compressor continuing to operate but with a considerable drop in efficiency. The term surge refers to the engine's ability to absorb the stalled condition. The VSVs play a large part in the stall-free capabilities of the engine throughout its operating range. Damage to this system or to individual VSVs is a major contributor to inadequate airflow dynamics across the compressor stages. The main causes of compressor stall/surge events are HPC rotor blade airfoil damage or missing material, HPT airfoil damage, Foreign Object Damage (FOD) including runaway contamination, VSV system mechanical damage, HPC airfoil erosion, and others.

The compressor section of a gas turbine engine compresses and heats air for an optimum mix of fuel and superheated/pressurised air for combustion. In this section, mechanical energy is converted into pressure energy (Klaus Hunecke, 1997). One of the compressor performance parameters is the compressor efficiency, which denotes the amount of energy loss incurred by the conversion. Another important parameter is the compressor pressure ratio, and it relates directly to thrust, fuel consumption, and energy efficiency. The compressor pressure ratio refers to the ratio of the total pressure at compressor discharge and at compressor entry, that means, the greater the number of compressor stages the greater the pressure ratio, but in turn the engine would need to withstand higher stress levels.

The combustor chamber is where the combustion takes place and the combustor type described herein is an annular-type burner. This type of combustor has an advantage in volumetric space as it is a single concentric flame tube surrounding the shaft. The combustor is built up of inner and outer cowls, a dome, and inner and outer liners. The design of individual parts facilitates disassembly and assembly. The entire surface of the dome is swept by a film of cooling air. The liners and dome have a thermal barrier coating applied to the hot side. These components operating life is a function of their resistance to failure, which depends mostly on the operating environment and material properties.

The primary function of the combustion section is to burn the fuel/air mixture adding heat energy to the air efficiently and deliver the hot gases to the turbine section. The chamber is constructed of heat-resistant materials coated with thermal barrier materials. In addition, the annular combustion chamber uses louvers and holes to prevent the flame from contacting the walls of the combustion chamber. The flame pattern is controlled by keeping it centred in the liner, thereby preventing the burning of the liner walls.

The HPT section consists of two main elements: a set of stationary blades, named Nozzle Guide Vane (NGV) followed by a set of rotating blades. The NGVs receive very hot gases from the combustion chamber at high pressure as they are the first elements after the combustion. For this reason, the vanes must be coated to increase material resistance to corrosion and prevent damages caused by extreme temperatures. Their task is to increasing the velocity of combustion products and changing the fluid path direction in a manner such that the circumferential forces generated in the blades are maximised for the production of shaft power (Salehnasab et al., 2016).

The HPT rotor includes two stages of internally air-cooled blades. The cooling is done by air from the compressor which flows through the blades into the airfoil. (Figure 3.7). Like the first stage of NGVs, the first stage of the HPT blades is cooled by a combination of internal convection, leading edge internal impingement and external film cooling. Whereas the second stage of the HPT blades are entirely cooled by convection only. Without sufficient cooling air, HPT blades are more exposed to extremely high temperature resulting in increased blade deterioration (GE Aviation, 2007). Coatings play a critical role in protecting the hot section components operating at high metal temperatures to ensure that the full capability of the high strength superalloy is maintained and that the component life meets design expectations (Clarke et al., 2012).

The hot gas path components are manufactured with special alloys and are designed to be highly resistant to stress due to combustion gases at high temperature. The materials found in the hot section consist of superalloys and stainless steels. Nickel based superalloys are typically used for the combustor liners, buckets, blades, vanes, and shrouds because of their thermal resistance properties.

The HPT NGV assembly is subjected to the highest gas temperatures in the turbine section and such conditions frequently cause nozzle cracking and oxidation. There is a degree the nozzle distress can be tolerated; however, criteria have been established for determining when repair is required. These limits are contained in the Aircraft Maintenance Manual (AMM). Generally, first stage nozzles require repair due to findings during inspection when the module is exposed at the engine shop. Normally, turbine nozzles and combustor chamber can be repaired several times to extend life. The repair costs versus replacement costs are compared to assist the replacement decision.

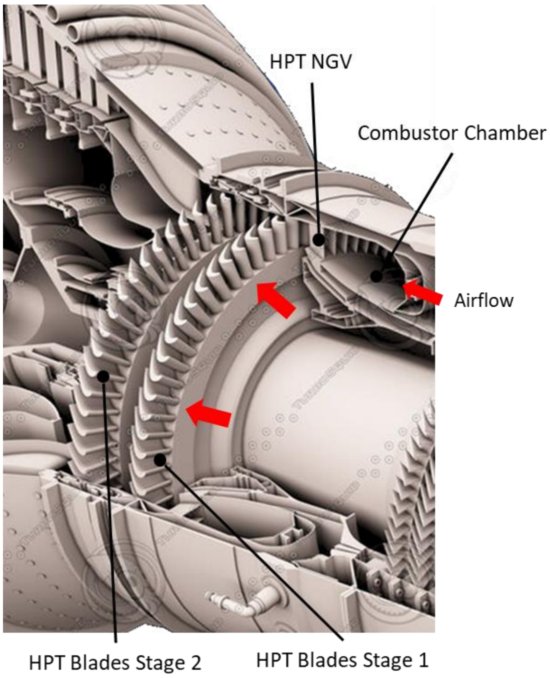

Figure 3.7 – Hot section of a high bypass turbofan engine.

Temperature has different effects on turbine components. The HPT blades must withstand the greatest thermal loads, which may eventually cause mechanical failure because of thermal fatigue, oxidation, and corrosion. Thermal fatigue is the process caused by cyclic changes of operating temperature. During engine operation, particularly at engine start, the temperature suddenly rises in the turbine section causing a temperature gradient to build up rapidly between external and internal portions of a blade. As a result, small cracks may originate from leading and trailing edges of the blade over some length of time. These small cracks expose damaged areas to metal oxidation and in some cases of extreme thermal stress the blade may be permanently deformed and become scrap or Beyond Economical Repair (BER).

3.4 Engine Life Limited Parts (LLPs)

There are certain parts within engine modules that cannot be contained in case of a mechanical failure and could potentially damage other components. These parts are considered as critical and generally consist of rotating parts such as disks, spools, and shafts, and in some engine models, stationary parts such as seals. For this reason, specific rotating components as well as stationary thrust related components have been identified by the Federal Aviation Administration (FAA) to be life limited in relation to time in service.

In aviation, limitation by "Life" is controlled by the number of cycles the component operates. A cycle consists of a take-off and landing. Although the life limit implies that over 99.9% of costly turbine rotor disks are retired before their useful life has been consumed, it is important to ensure structural integrity and safe operation. For example, a disk retires at the time when 1 in 1000 disks has initiated a short fatigue crack (Vittal et al., 2004).

The fan, HPC, HPT and LPT contain LLPs. An accurate history must be kept for the total operation of each part, with the governing factor being accumulated cycles. It is the operator's responsibility to ensure that adequate records are maintained, and cyclic life limits are not exceeded. The OEM recommends that the records should be kept in two forms: the total number of cycles operated and the number of cycles remaining.

In most cases, for high bypass engine models, the declared operating life of LLPs is between 15,000 to 30,000 cycles. The complete set of LLPs usually represents about 20% of the overall cost of an engine (Buntić et al., 2012). Thus, an engine operating in a low time-to-cycle ratio will have a relatively high cost. Additionally, Airworthiness Directives (ADs) can impose a decrease on certain LLP life to address an unsafe condition on the component due to defects that might compromise its fatigue characteristics or strength capability.

Differently from the Aircraft LLPs, which can be replaced as line maintenance, engine LLPs replacement requires the engine to be sent to an engine shop, thereby implying high shop visit costs that are primarily the result of large material expenses (Buntić et al., 2012). Therefore, the LLPs also influence the timing of engine on-wing and removals interval. Some LLP may be common to two or more series of an engine model, so depending on the engine thrust rating, certain LLPs can have differences in LLP life limits. Usually, engine variants designed for higher thrust-rated operation have smaller operating life for the same LLP compared to a lower thrust rating variant (Table 3.2).

Table 3.2 – List of LLPs for the CF6-80C2 engine model. Life limit of two different variants, low thrust rating B5F, and high thrust rating engine B7F. Highlighted in grey are LLPs that have smaller operating life for high thrust rating engines when compared to low thrust rating engines.

No.	Module	LLP Description	Life limit	
			B2F	**B7F**
1	FAN & BOOSTER	FAN STG 1 DISK	20000	20000
2		FAN FWD SHAFT	20000	20000
3		SPOOL FAN RTR	20000	15000
4		FAN MID SHAFT	20000	20000
5	HPC	HPC STG 1 DISK	20000	20000
6		HPC STG 2 DISK	20000	15000
7		STG 3-9 SPOOL	20000	20000
8		SHAFT/SPOOL	20000	20000
9		HPC CDP SEAL	20000	15000
10	HPT	HPT STG 1 DISK	15000	10720
11		HPT STG 2 DISK	15000	15000
12		IMPELLER SPCR	15000	15000
13		HPT DIF VANE	15000	9000
14	LPT	LPT STG 1 DISK	20000	20000
15		LPT STG 2 DISK	20000	19200
16		LPT STG 3 DISK	20000	20000
17		LPT STG 4 DISK	20000	20000
18		LPT STG 5 DISK	20000	20000
19		LPT SHAFT	20000	20000

The airworthiness limitations of the LLPs are usually described in a section of the Engine Shop Manual (ESM) and must have been approved by FAA. If both the cycles and the engine variant have been recorded for all the engines that the LLP operated, the total Cycles Remaining (CR) for the current engine variant must be calculated considering each variant limit, which is described in Table 3.2. For example: an HPT DIF VANE has accumulated 3000 cycles in a B5F engine variant and 5000 cycles in a B7F. The number of CR for this LLP operating at a B7F engine variant is calculated as follows:

$$CR_{B7F} = \left(1 - \left(\frac{3000}{15000} + \frac{5000}{9000}\right)\right) * 9000$$

The LLP life limit variations sometimes result in premature removals where a considerable percentage of the remaining LLP lives are not consumed due to shop visit Workscope (WS) management. When preparing the WS for an engine performance restoration, the operator must consider the replacement of LLPs that still have useful life remaining to avoid limiting the succeeding engine on-wing interval in cases where the LLP life remaining is shorter than the engine removal interval forecast.

3.5 Engine Control

Currently, the brain of modern engines is the FADEC, which consists of a hardware and a software unit. The former includes sensors to measure essential engine parameters, such as temperatures, in real time, and a digital computer called EEC, which is the main interface between the aircraft and the engine (Filippone, 2013). FADEC is a digital electronic system implemented to control the engine. The main components of the FADEC system are the thrust lever assembly, the dual channel EEC system with dedicated engine sensors for dedicated input and outputs to engine systems, the HMU, and the Propulsion Interface Monitor Unit (PIMU) which receives, and stores EEC system fault data used for engine troubleshooting.

The EEC primary function is to give full authority, closed loop control of engine thrust. It schedules fan speed and engine fuel metering as well as controls engine clearances, engine geometry, engine start/run functions, engine monitoring functions and operation of the thrust reverser doors. The EEC is also able to balance the power between the engines, that is, if there is a loss of power from one engine, the FADEC reacts quickly to increase the power of the sister engine. In addition, matched speed change rates give better thrust symmetry.

Figure 3.8 summarises the EEC schematic focusing on the relevant systems. The various parameters present along the engine's gas path not only vary with power condition but also with the ambient conditions at the engine's inlet. FADEC computes N1 thrust based on selected rating and existing flight conditions, such as air pressure, Mach number, and total air temperature. These parameters are supplied by the airframe to the EEC, but if the aircraft signal is lost the EEC uses the engine's inlet instrumentation.

In conjunction with the EEC, the HMU physically manages fuel and fuel hydraulics. It meters fuel to the combustor as commanded by the EEC throughout the Fuel Metering Valve (FMV). The EEC controls the Starter Air Valve (SAV), fuel, and ignition during starts. Moreover, the engine configuration is provided by the engine identification plug (ID Plug) while the rating plug provides the thrust rating information, both are attached to the EEC. The Airborne Vibration Monitor (AVM) system senses engine vibration levels caused by the N1 and N2 rotors by accelerometers. The AVM processes the signals and sends them to the Engine Indication and Crew Alerting System (EICAS) display. EICAS also receives several other parameter measurements from the EEC as shown in Figure 3.8. All of the signals and parameters received by EICAS are also sent to the ground-station through Airborne Communications Addressing and Reporting System (ACARS) for engine condition analysis.

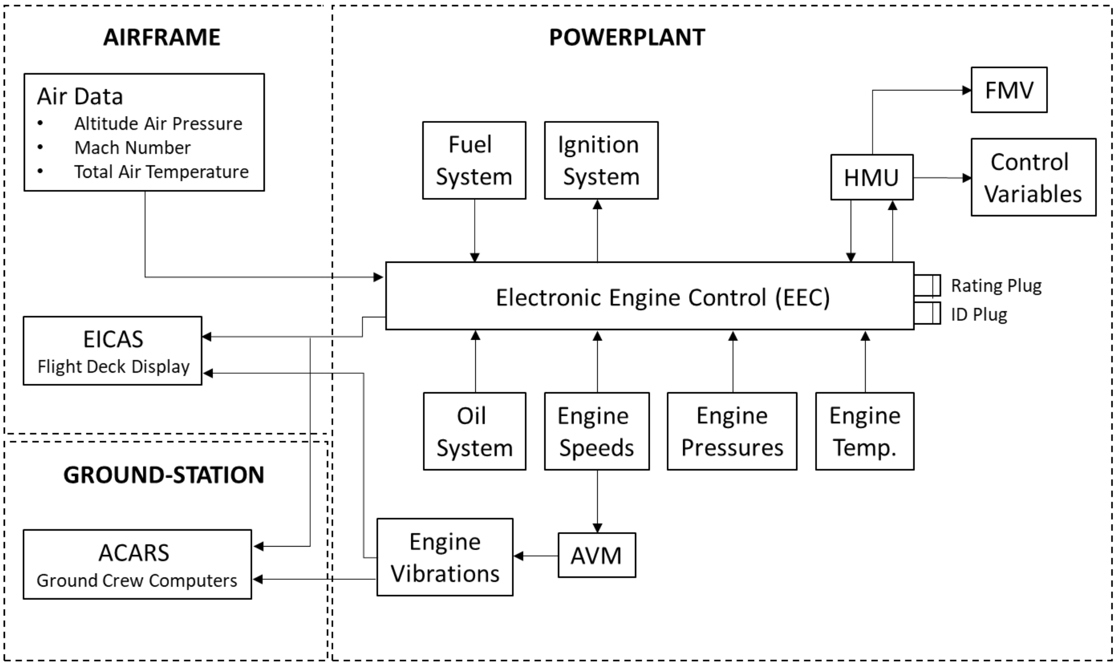

Figure 3.8 – Electronic Engine Control schematic diagram of main components.

3.6 Engine Parameters

Aircraft engines are complex machines with advanced technology systems that require advanced and expensive maintenance strategies (Kim et al., 2007). Engines must operate within specified physical limits. A considerable number of sensors and control parameters became essential for safe operation. The engine indicating system provides engine parameters status to a flight deck display. It measures selected temperatures and pressures, rotor speeds and vibrations, fuel flow, oil quantity, and others. This way if a parameter is out of the normal working range the pilots can identify the problem quickly and perform the correct troubleshooting procedures (Yildirim & Kurt, 2018). The main operating parameters for both control and monitoring are described on Table 3.3.

The engine is divided into station numbers. These stations indicate positions along the aerodynamic flow paths corresponding to changes in the flow characteristics. The station numbers are also used to identify instrumentation positions for pressure and temperature sensors. Figure 3.9 illustrates the CF6-80C2 engine model stations. Temperature and pressure sensors have a T or a P, followed by a station number which shows the location of the sensor in the airflow.

Table 3.3 – Engine instrumentation description and signal category.

	Sensor	Description
Control Signals	P0	Inlet Air Pressure
	N1	Fan Speed Sensor
	N2	Core Speed Sensor
	T12	Fan Inlet Temperature Sensors
	T25	Compressor Inlet Temperature Sensor
	P3	Compressor Discharge Pressure Sensor
	T3	Compressor Discharge Temperature Sensor
	T49	LPT Inlet Temperature Sensor (EGT)
Condition Monitoring Signals	TEO	Engine Oil Temperature Sensor
	PEO	Engine Oil Pressure Sensor
	WF	Fuel Flow Transmitter
	P14	Fan Discharge Pressure Probe
	P25	Compressor Inlet Pressure Sensor
	P49	LPT Inlet Pressure Probe
	T5	LPT Discharge Temperature Sensor
	Fan Vib	No. 1 Bearing Accelerometer
	Core Vib	CRF Accelerometer

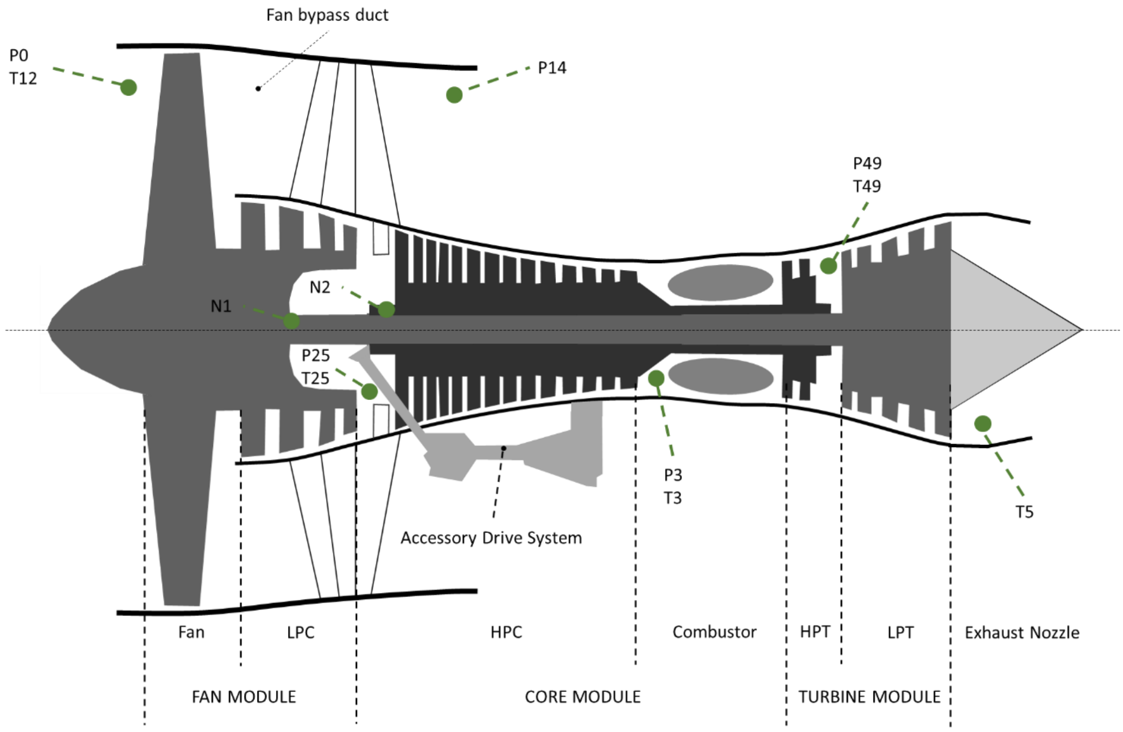

Figure 3.9 – Illustration of the engine instrumentation position.

According to the OEM's technical documentation, parameters such as engine fan speeds, vibration, oil pressure, oil temperature, exhaust gas temperature (EGT), and Fuel Flow (FF) shall be used to monitor and determine performance deterioration in gas turbine engines. The monitoring of these parameter trends is the process of which in-flight measurements are processed and then compared with a baseline model that represents the expected or "healthy" behaviour of an engine considering several other factors, such as outside air and thrust conditions. The difference between the actual measured data and the baseline model is termed as Delta, for example dFF, dEGT, and others. The main parameters used for ECM are described in greater detail in the following sections.

3.6.1 *Exhaust Gas Temperature (EGT)*

The appropriate indicator of the overall performance of the engine – compressors and turbine – is based on the core flow temperature, which is measured at the location where the gas exits the HPT section and enters the LPT section. The EGT is expressed in degrees Celsius and provides the flight compartment an indication of the engine condition during all phases of the flight. Generally, the EGT reaches its maximum during take-off or right after lift-off (Seemann et al., 2011). For this reason, pilots are instructed to monitor the EGT value especially during take-off phase.

EGT increases over time due to hardware deterioration. The higher the EGT the more wear and deterioration affect an engine, thus high EGT is an indication of degraded engine performance. In order to protect turbine hardware and guarantee safe operation, an operational limit on EGT, called "EGT redline" must be demonstrated during endurance tests by the OEM as it is a requirement for engine certification. During such tests, the engine is run for 25 blocks of 6 hours each, and for each block, the engine runs at maximum take-off power for cumulative time of up to one hour with the average EGT at redline condition (Bonnet, 2017).

An exceedance in EGT limits can lead to immediate damages and/or a life reduction of engine parts (Yildirim & Kurt, 2018). However, an engine EGT exceedance may be related to a system discrepancy such as an error in the indication system. In these cases, the AMM provides procedures for the operator to troubleshoot, identify, and perform corrective action to address the cause of the exceedance. In addition, when an EGT shift occurs, it is not used as sole criterion for engine removal. Other factors such as cruise trend analysis including correlated parameters, number of EGT over limit occurrences and the associated maintenance tasks requested by AMM must be considered prior to an engine removal decision.

Conversely, if the EGT exceedance is determined to be a basic engine deterioration, the recommended maintenance action can be engine removal for performance restoration. Depending on the duration and amplitude of the EGT above EGT redline, there are overtemperature limits and inspection requirements stablished by the OEM. Figure 3.10, is an example of how the AMM provides the limits and maintenance action requirements for each condition when the cause of the overtemperature is unknown. The tasks range from a visual inspection up to a required engine removal and overhaul:

- Area A-1
  EGT over limit of less than 15℃ and during less than 1 minute requires engine visual inspection. In addition to examination of engine exhaust for metal contamination. Metal in the exhaust after the LPT blades indicates there is damage to the engine.
- Area A-2 and Area B
  Engine visual inspection and exhaust examination for metal contamination. In addition, borescope inspection of the HPT blades must be performed within 20 flight cycles or less. If the engine has operated in these areas more than 15 times, engine must be removed prior to next flight.
- Area C
  Engine must be removed prior to next flight.

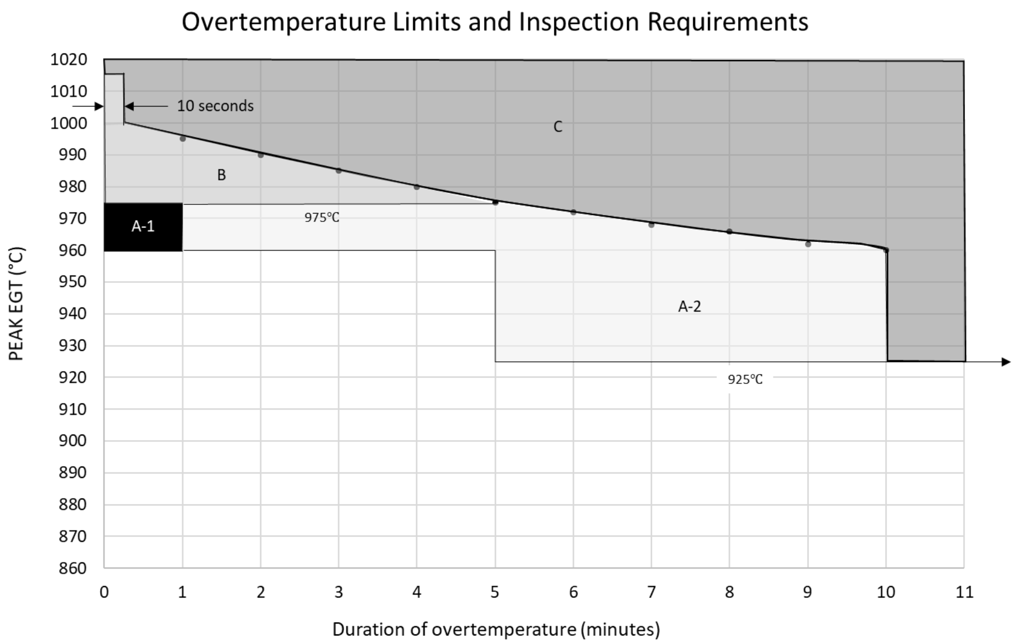

Figure 3.10 – Example of EGT Overtemperature limitations and inspections requirements according to the magnitude of EGT over limit and the duration of the event.

EGT is highly influenced by the present Outside Air Temperature (OAT). The hotter the OAT the higher the take-off EGT. The manufacturer average for GE engines at a constant take-off thrust, every 1℃ increase in OAT corresponds to an EGT increase of approximately 3℃ (Bonnet, 2017). In addition, EGT level is proportional to thrust level inputted, which means that an airplane operating at almost its maximum thrust, the EGT will be high and close to its near maximum allowable level (EGT redline).

The OAT flat rate temperature (or Corner Point, CP) is a projection of the highest ambient temperature at which an engine should be able to produce full flat-rated thrust without exceeding EGT redline, therefore once OAT reaches the flat rate temperature, EGT remains relatively constant as OAT increases. By reason of, at OATs above the flat-rated OAT temperature, engine power management reduces thrust in order to maintain EGT constant with rising OATs (Figure 3.11).

Engine power management ensures that EGT would not continue to increase at a constant rate with OAT above the CP. Therefore, another indicator of engine's health is the OAT Limit (OATL), which refers to the OAT at which EGT would reach the EGT redline. Engine deterioration causes the reduction of OATL, leading to EGT redline being reached before the CP (CP<0), as well as the reduction of EGT margin.

The difference between the certified EGT red line and the actual EGT during take-off is denoted as EGT margin (Figure 3.11). As EGT increases during the engine's operating life due to hardware deterioration, the EGT margin decreases. This parameter is routinely used to monitor the health of installed engines through the ECM tool. The greater the positive take-off EGT margin, the "healthier" the engine. A shift on EGT margin on a specific flight may indicate the need for inspections and/or maintenance, while the EGT margin trends are used to forecast an average remaining TOW until it reaches zero degrees Celsius.

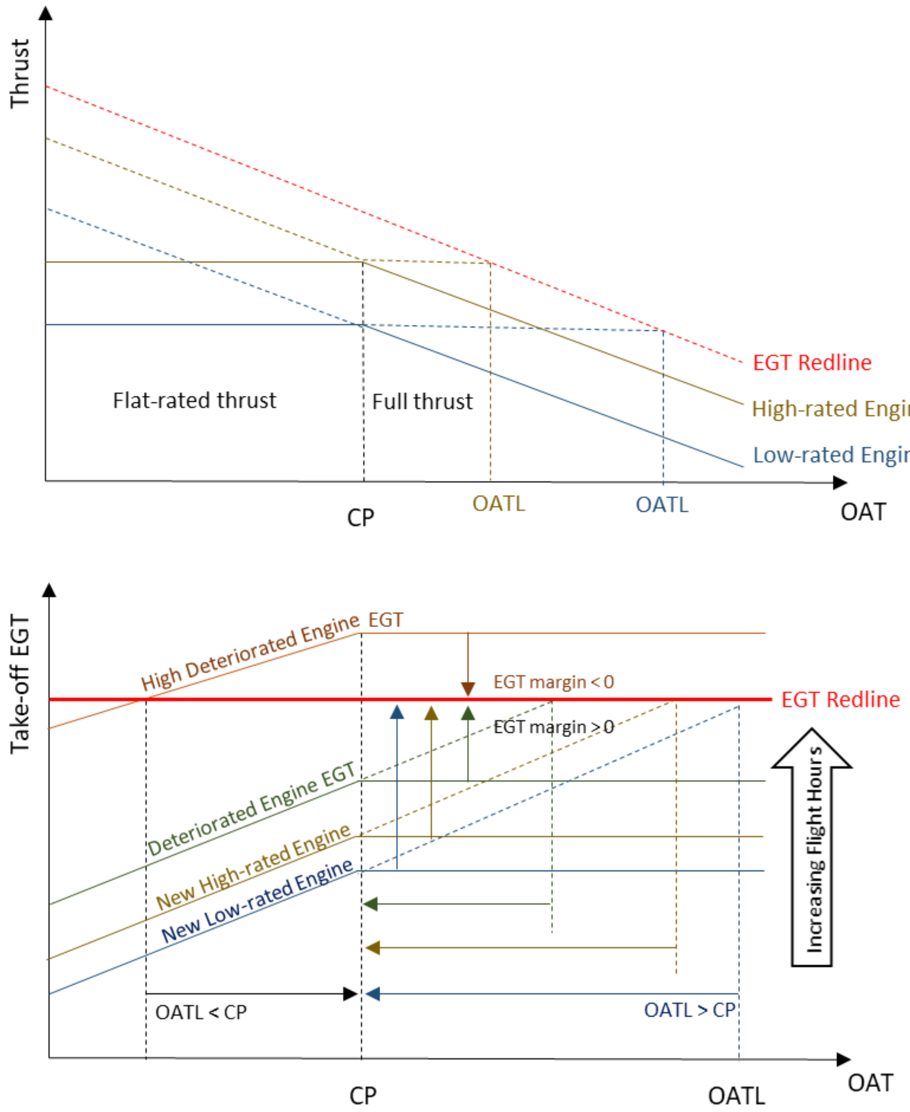

Figure 3.11 – Correlation between EGT, OAT, Thrust, and EGT margin.

In general, EGT margins are at their highest levels when the engine is either new or was recently back from a performance restoration. Nonetheless, EGT margin can be recovered by performing engine wash periodically. Washing the core removes contamination that contributes to premature wear to airfoils and can potentially increase EGT margin. This maintenance action will be further discussed in chapter 4. As the engine ages, the EGT margin decreases due to several factors, such as FOD, compressor airfoil erosion, increased air seal clearances, compressor and turbine blades tip clearances due to rubs, dirt/dust accumulation on fan and compressor airfoils. These factors increase the engine degradation and a rapid reduction in EGT margin is noted on the ECM trends. Depending on the initial EGT margin, a typical engine stays on-wing for up to 5+ years before requiring a shop visit due to take-off EGT redline exceedances. Besides engine wash, the TOW can be extended by management of thrust settings at take-off.

3.6.2 *Engine Thrust Derate*

In the cases where the thrust available is greater than the required to perform Take-Off Run Available (TORA) as well as Take-Off Distance Available (TODA) limitations, it is recommended to use either reduced take-off thrust or thrust derate. The actual method and terminology used is based upon the airframe OEM's design. Both methods refer to the take-off thrust that is below the maximum thrust level and it is defined by the crew prior to take-off. These techniques reduce the stress inside the engine during take-off phase which can prolong the engine's operating life by lowering the engine operating temperatures, pressures, rotational speeds, etc (Irsyadi & Nirbito, 2019). In addition, it can improve engine reliability, result in better EGT margin retention, extend TOW, and reduce engine DMC.

Studies result shows that the effect of reduced take-off thrust lowers temperature levels of EGT and fuel consumption (Irsyadi & Nirbito, 2019). This technique improves the performance of the engine by making it more efficient. Thus, the engine deterioration over time is retarded due to less severe engine operation. Engine thrust derate can also reduce engine related events.

The degree of engine severity can be determined by three parameters: rotor speed, internal temperature, and internal pressure. Full thrust take-off at high ambient temperatures causes the engine components to operate very near their maximum operating limits. Increased time operating at this condition can result in degradation of the thermal barrier coating of the blades, which increases blade distress and can also result in loss of turbine airfoil material. Then, a high scrap rate of turbine airfoils may occur when inspecting the turbine module.

The benefits of take-off thrust derate are listed below (GE Aviation, 2008a):

- Lower take-off EGT
- Fewer operational events due to high EGT (less stress on the engine)
- Lower fuel burn over TOW
- Lower maintenance costs (lower airfoil scrap rate)
- Better engine performance retention
- Longer TOW

Figure 3.12 presents real engine trend lines of a turbofan where each point refers to a cycle. The data clearly shows the beneficial effect of using higher thrust derate at take-offs on the EGT margin. In this dissertation, the analysis is based on two typical high bypass ratio turbofan engines. Both engines are configured at high thrust rating since new. The period of analysis herein is of six consecutive years of operation. During this period, both engines' thrust derate average was at 15%.

3.6.3 *Rotational Speeds*

Engine fan speed is the primary engine control parameter. It maintains thrust control as commanded by the throttle. One of the main engine performance parameters is the ability to provide the necessary thrust force needed in propelling an aircraft efficiently in its different flight regimes (El-Sayed, 2008). Turbofan engine speeds are measured for each rotating spool in engine Rotations Per Minute (RPM) by tachometers. Each spool turns independently at different speeds, where low-pressure and high-pressure spools are referred to N1 and N2, respectively.

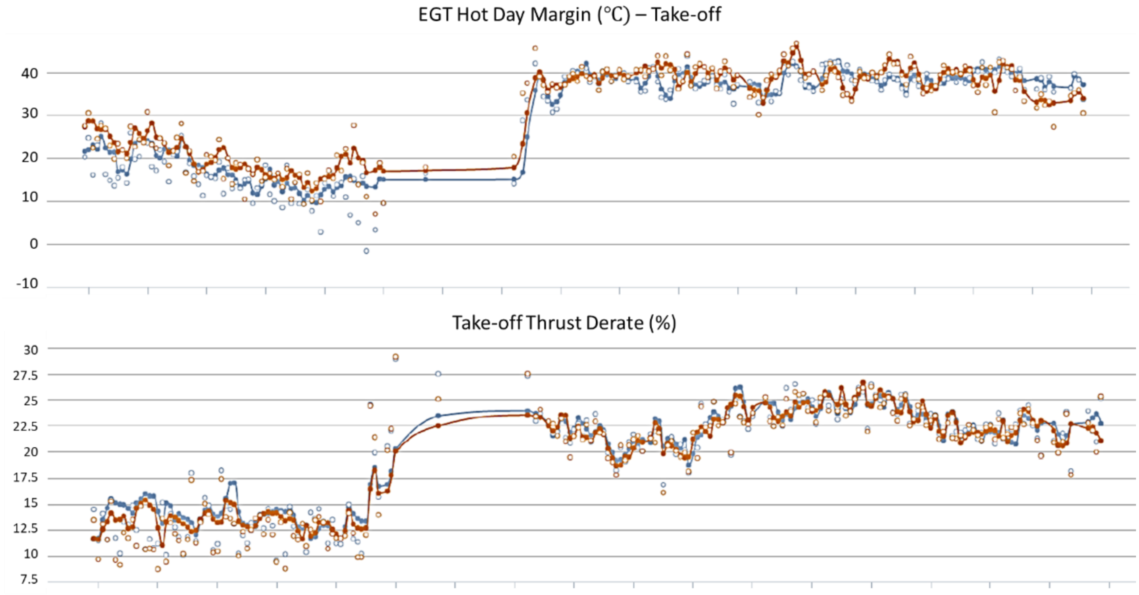

Figure 3.12 – Example of a high thrust rated turbofan engine ECM trends. It shows the effects of Thrust Derate at take-off on the take-off EGT margin. Each dot represents a snapshot of the parameter value per flight cycle.

3.6.4 *Engine Fuel Flow and Fuel Consumption*

In turbine-powered aircraft, the increase or decrease of thrust is controlled by varying the flow of fuel to the combustor chamber. The quantity of fuel supplied is adjusted automatically due to air condition changes such as ambient temperature and pressure. In addition, the mix of fuel and superheated/pressurised air for combustion must be optimal. Otherwise, if the quantity of fuel becomes excessive in relation to mass airflow through the engine, the EGT can exceed its limits or cause compressor stall. This occurs when the amount of oxygen in the air is insufficient to support combustion. The excess of fuel can also cause it to cool the mixture down below the combustion temperature. In the other hand, if fuel quantity is reduced proportionally below the air quantity the flame goes out, because the fuel-air mixture is too thin to support combustion.

The fuel system is designed to deliver fuel to the combustor in the correct quantity, pressure, and rate flow for satisfactory combustion. The fuel must be injected into the combustor chamber in a combustible condition during engine start, and that combustion must be sustained while the engine is accelerating to its normal idling speed. For that reason, the fuel distribution system receives and pressurises fuel from the airplane fuel tanks. Then, the fuel is heated by engine oil through the fuel/oil heat exchanger. Next, the fuel is filtered, heated by the IDG fuel/oil heat exchanger, and finally distributed to the engine combustor by the fuel nozzles. The fuel nozzles reduce the fuel particles prior to supply to the combustor to ensure good ignition.

Modern turbofan engines use the FADEC type of fuel control system. The fuel flow transmitter, which is controlled by the HMU, measures the fuel mass flow rate to the fuel nozzles. The HMU is controlled by the EEC through analogue electrical signals. The HMU controls thrust by managing fuel flow to the fuel nozzles. This electronic control of fuel is very accurate in scheduling fuel by sensing many of the engine parameters. The fuel flow rate is calculated by the EEC, which then sends the information to EICAS. The fuel system provides other parameters, such as fuel pressure, fuel temperature, and fuel quantity.

The fuel control can sense many different inputs, which helps it to adjust fuel flow as needed. Some of these inputs are power lever position, engine rpm (or rotational speeds) for each spool, compressor inlet pressure and temperature, burner pressure, compressor discharge pressure, and others. Fuel control has direct impact on fuel economy of an aircraft and important parameters, such as compressor pressure ratio must be monitored as it relates directly to thrust, fuel consumption, and energy efficiency. According to the OEM's technical documentation, fuel flow should be used to monitor and determine performance deterioration in gas turbine engines.

The basic parameter for describing the fuel economy of an aircraft is fuel consumption or fuel flow, which are measured in lb/h because the fuel weight is a major factor in the aerodynamics of large turbine aircraft. Fuel flow is of interest in monitoring engine performance. Additionally, the Thrust Specific Fuel Consumption (TSFC) is usually one of the requirements for an engine design as the fuel consumption is very critical to the direct operating expenses of an aircraft. TSFC is measured in lb/h divided by thrust (lb). It defines the amount of fuel used to achieve one unit of thrust. One of the objectives of this dissertation is to forecast the fuel burn rate of the engine for specific routes.

3.6.5 *Engine Shafts Vibration*

Vibration measurements are also commonly used as an indicator of the turbofan engine overall health state. The vibration indicating system uses accelerometers to measure radial acceleration and the output can be read as Acceleration (G's), Velocity (in/s), displacement (mils), or units. However, units are a generic value intended to standardize vibration limits for the flight crew. Like the performance parameters, the vibration patterns change with system dynamic changes and the actual values of the parameter can be compared with those observed at the healthy state of the system, which can be an indication of fault development. The objective of vibration monitoring is to identify possible defects at an early stage avoiding a complete component failure.

Engine vibration indication is a secondary engine instrument parameter that indicates the amount of vibration measured on the engine low- and high-pressure rotors. No. 1 bearing accelerometer measures fan (N1) vibration, also denoted as fan vibration forward, whereas the Compressor Rear Frame (CRF) accelerometer measures core (N2) vibration, and LPT vibration, which is also known as fan vibration rear. Another vibration indicator is the Broadband vibration, which is the highest level at any frequency. Vibration measurements are provided to the EICAS display for flight crew to monitor the engines, as well as to the ground crew for engineers to analyse the engine parameter trend. The magnitude of vibration will vary with engine speed tracking rotor imbalance.

Engines designed for high speeds tend to have operational problems from vibration, hence the importance of vibration analysis. All rotating equipment is assumed to have an unbalance, which produces excitation at the rotational speed, also known as the critical shaft speed. Unbalance is stimulus caused by material imperfections and tolerances, amongst other things. The mass centre of gravity is different from the geometric case, leading to a centrifugal force acting on the system.

Turbine engine rotating assemblies require balancing by the manufacturer, however only the fan blades can be balanced without disassembly of the engine. During normal operation, even minor damages can cause the fan to be unbalanced and compromise the integrity of the rotating assembly and its bearings. The balance of the set of blades is based on the radial moment weight of each individual blade. Trim balance weights can be used to reduce vibration. These weights are usually bolts fitted at right angles to the spinner securing bolts.

Fan forward vibration gradually increase over time. It can be caused by a damaged blade or worn of the dry film lubricant of the blades root. Cleaning and lubricating the fan blades periodically are tasks recommended by the OEM to avoid fan vibration exceeding operational limits. On the other hand, core vibration is more complex and may indicate a more serious problem in the compressor rotor. If core vibration exceeds its operational limits, the engine may need to be removed for repair.

Mechanical changes in the engine that may result in failure or lead to the occurrence of incidents, normally imply an abrupt shift in the corresponding parameters. There are several possible causes of high vibration indications, some of them are listed in Table 3.4. Figure 3.13 is an example of how the AMM provides the limits and maintenance action requirements for each condition, when the cause of the vibration is unknown. The tasks range from a visual inspection up to a required engine removal and repair:

Table 3.4 – Possible contributors to high vibrations.

Fan Vibration	**Core Vibration**
FOD	Residual unbalance in the HPC and HPT rotors
Loss of blade lubrication	Assembly - alignment of the HPT and HPC rotors
Dirt accumulation	No. 3 bearing at high vibration level
Ice accumulation	FOD
Fan balance	Bowed rotor during starting

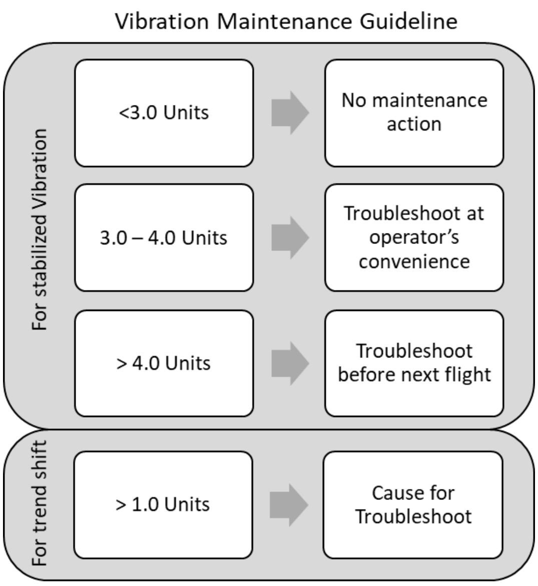

Figure 3.13 – Example of vibration measurement limitations and maintenance guideline according to the magnitude of vibration over limit.

Chapter 4 - Turbofan Engine Maintenance

Engine maintenance can be divided into maintenance on-wing and off-wing, where the former can also be termed as line maintenance and the latter as engine Shop Visit (SV). Aircraft engine is a major component, in terms of investment, operating costs as well as its complexity. Engines follow its own overhaul schedule mostly independent from the regular aircraft maintenance Check events. Differently from the landing gears, turbofan engines overhaul intervals are not due within determined calendar time basis. Modern engine maintenance is based on the so called on-condition method, where removals and overhauls only take place when the engine condition demands it (Seemann et al., 2011). Gas turbine engine maintenance procedures vary widely according to the design and construction philosophy. This chapter presents both types of maintenance and SV management. In addition, the main cost drivers of DMCs are discussed.

4.1 Line Maintenance

There are two main types of aircraft maintenance tasks, scheduled maintenance Checks and ground time maintenance. Scheduled Checks are divided into block Checks according to their periodicity and time requirements (Shaukat et al., 2020). Whereas line maintenance refers to any minor maintenance activity on the aircraft, engines, landing gears, APUs, etc., prior to the next flight to ensure airworthiness, such as defect rectification, troubleshooting, component replacement, general inspections, minor repairs and modifications, and others.

Engine maintenance on-wing is largely part of the aircraft line maintenance. Several tasks related to the engines are included in the aircraft Maintenance Planning Document (MPD), such as oil and fuel filters replacement, Magnetic Chip Detector (MCD) inspection, borescope inspection, fan blades inspection, and others. In addition to those tasks, there are specific maintenance actions, that are not in the MPD but may be required during operation to improve/maintain parameter trend in satisfactory condition and even increase TOW, such as engine wash and fan blade lubrication.

4.1.1 *Engine On-Condition Monitoring*

This section provides an overview of trend monitoring for performance and other characteristics for CF6-80C2 engines. The goal is not to operate the engine until it breaks. Engine trend monitoring is a vital element of an “on-condition maintenance” program, which engine performance and health condition are monitored on a routine and continuing basis. ECM uses data from engine performance trending, hardware condition assessed from routine and non-routine inspections, FADEC fault history, etc., to ensure that the engines are operating within certified limits and meeting performance goals. The trend monitoring is an integral part of engine maintenance and operation.

There are many approaches for gas turbine condition monitoring and fault diagnostics, such as performance analysis, oil consumption monitoring, visual inspection, borescope inspection, X-ray checks, eddy current checks, vibration monitoring, debris monitoring, noise monitoring, turbine exit spread monitoring, and so on (Zedda & Singh, 2002). Performance analysis based diagnostics is one of the most powerful tools among them, where the analysis of the gas path parameters provide information about degradation severity of gas path components (Li, 2002). The monitoring of these parameter trends is the process of which in-flight measurements are compared with a baseline model that represents the expected or "healthy" behaviour of an engine considering several other factors, such as outside air and thrust conditions. The difference between the actual measured data and the baseline model is termed as Delta, for example dFF, dEGT, and others.

The engine performance is lost over time and monitoring the evolution of the parameters and their Deltas is a way of knowing the current state of an engine allowing an estimation of the performance deterioration rate and management of when the engine will require removal. In the early days, trend monitoring would be conducted by manually calculating the parameter Deltas. The parametric information was available in the cockpit for the flight crew to monitor the aircraft and engines operation. The flight crew would record the parameter levels during cruise phase when the engines presented to be at steady-state condition. These records were then submitted to the ground crew upon landing for subsequent trending. Nowadays, advanced ECM tools automatically receive and record data in real time to provide the operator the engine behaviour status. Then, the tool generates the trend lines according to previous flight data.

Understanding the correlation between the parameters is crucial for detecting anomalies and performing the correct troubleshooting or maintenance action. Many parameters influence other parameters, for example, as the aircraft altitude increases both the air pressure and temperature decrease (Figure 4.1). The same applies for the engine parameters, for every action there is a proportional reaction. For example, as more fuel is burned, more heat is generated leading to a higher EGT, which in turn increases energy provided to the LPT. Another example is the correlation between the thrust derate and EGT, the greater the take-off thrust derate the greater the take-off EGT margin, as already seen in Figure 3.12.

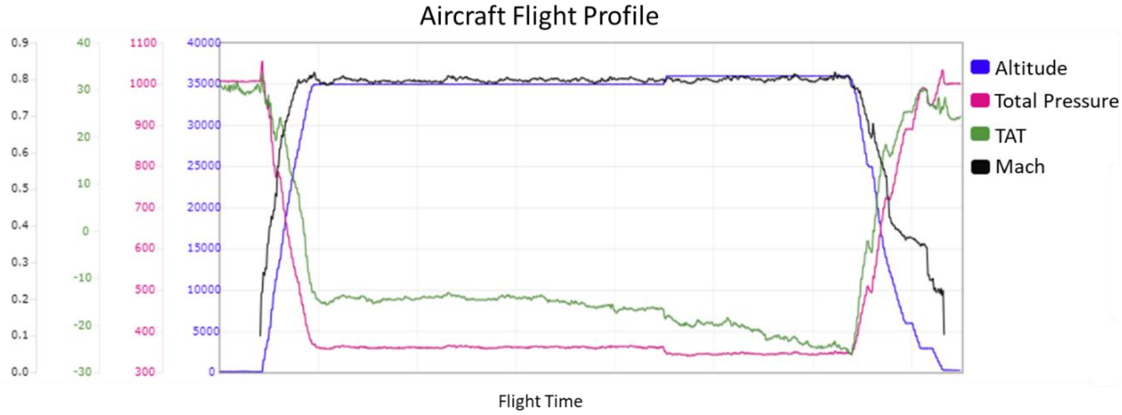

Figure 4.1 – Example of a commercial aircraft flight profile. Air data is also shown.

Some power-setting points are better for specific types of monitoring, for example EGT margin, N2 and fan vibration forward are commonly used at take-off phase. During operation, the ECM provides two important types of information that can be used for diagnostics and prognostics. With diagnostic monitoring, malfunctions or abnormal conditions are detected when a system or its subsystems are in operation and the indication is usually shown by trend shifts. With the prognostics approach, the current state of the engine and possible future failures prediction is based on the parameter's "smoothed" trends.

EGT trend shifts mean that there is a deviation from most recent average or "smoothed" trend. Figure 4.2 shows an example where an EGT shift occurred during a flight and the cause was an indicating problem. EGT up or down shifts are accompanied by a corresponding up or down shift of fuel flow and core speed (N2), therefore these parameters should be analysed together. Although all three parameters indicated a shift, in this case, both engines presented the same error simultaneously, which is an unlikely indicator of performance issues, as well as the aircraft fault message indicated a disagreement between aircraft and engine sensors. Each dot on the graph represents one snapshot, one per flight cycle, and the corresponding value of the parameter. The curves are the trends.

After analysing the parameter trends and following the instructions of the Fault Isolation Manual (FIM) an insect was found stuck inside the total air temperature probe, which caused discrepancies on aircraft and engine parameters (Figure 4.3). Errors in altitude and Mach can affect many parameters in large shifts, as seen in Figure 4.2. Once the indicating system problem is solved, engine and systems tests are usually performed to verify serviceability. Therefore, no maintenance action is done based only on the sensor measurements.

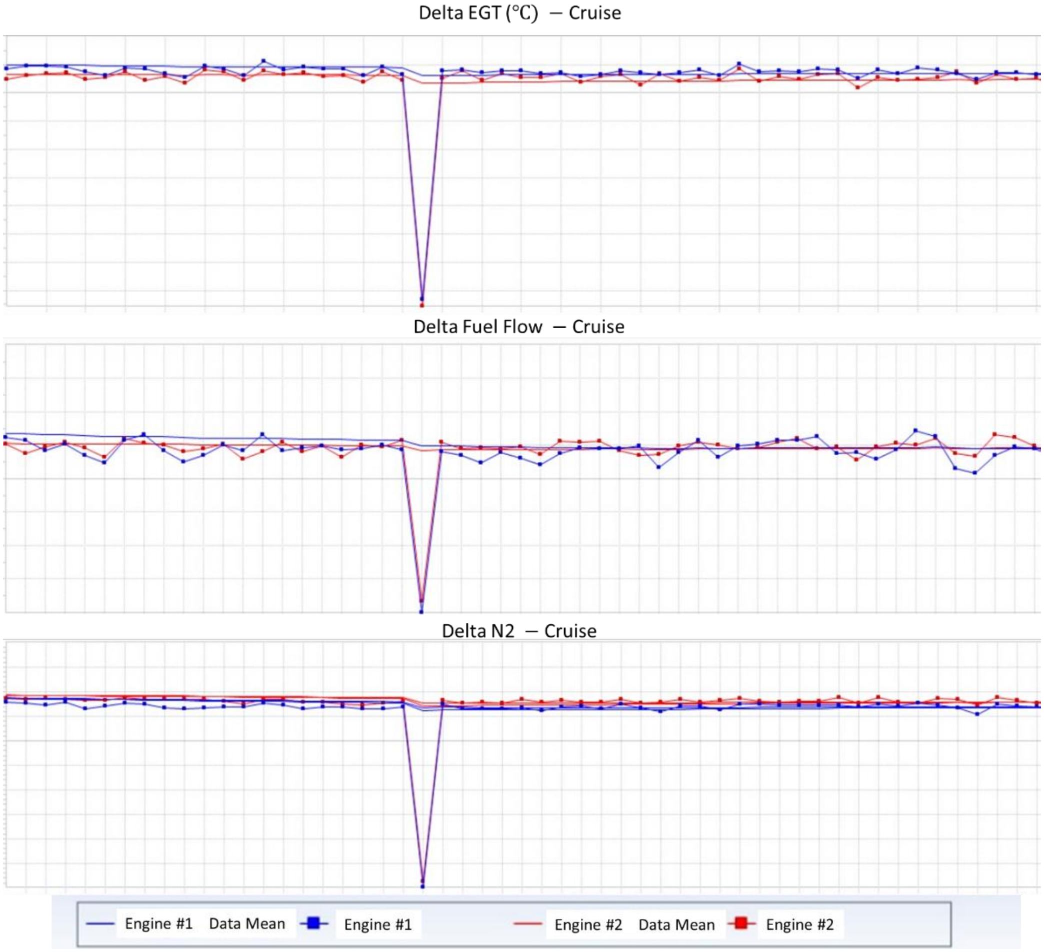

Figure 4.2 – Example of trend shifts on both aircraft engines due to aircraft total air temperature probe malfunction.

Figure 4.3 – Example of an insect stuck inside the aircraft total air temperature probe, which caused discrepancies on flight parameters.

Trend shifts where the data suffers a shift that occurs in a short period of time, for example, EGT shifts at cruise will be accompanied by a corresponding shift of FF, thus FF trend shift is useful in confirming EGT. On the other hand, if significant trend shift occurs in FF without a corresponding EGT shift, it is an FF indication error or inaccurate input data. Trend shifts are also caused by FOD events, such as bird strike, which is more likely to occur during take-off and climb or descent and landing. These events cause a trend shift in engine vibration (Figure 4.4). When the object is injected by the engine the first impact is on the fan blades, causing the fan forward and rear vibration to increase suddenly. Then, it is possible to confirm if the object entered through the primary airflow by looking at the core vibration. If no core vibration trend shift occurs it indicates that the object went through the secondary airflow only, and no borescope in the HPC would be required.

Mechanical changes in the engine that may result in failure or lead to the occurrence of incidents, normally imply an abrupt shift in the corresponding parameters. On the other hand, the effects of accumulated flight cycles can be identified by gradual increase/decrease over time of the parameter’s delta or smoothed trend. The data analysed is usually over a long period of time and at cruise phase, which is the phase where the parameters are stabilized. An effective monitoring of cruise trends helps minimizing the risks associated to unexpected engine failures and avoid excessive degradation of the engine’s performance.

Figure 4.5 shows a typical ECM plot, where each dot on the graph represents one snapshot per flight cycle and the corresponding parameter value. The blue line is the parameter trends of the snapshots. The four parameters Delta are analysed together, dEGT, dN2, dFF, and dN1. The plots show that over one year the engine had exhausted almost 35% of the EGT margin due to normal performance degradation during operation. Consequently, it is also noted an increase of approximately 1% in the FF. Unfavourable environmental effects as well as normal deterioration have increasing effects on the EGT and FF. Engine compressor wash or operational effects, such as thrust derate, can partially restore engine performance and decrease the dEGT and dFF.

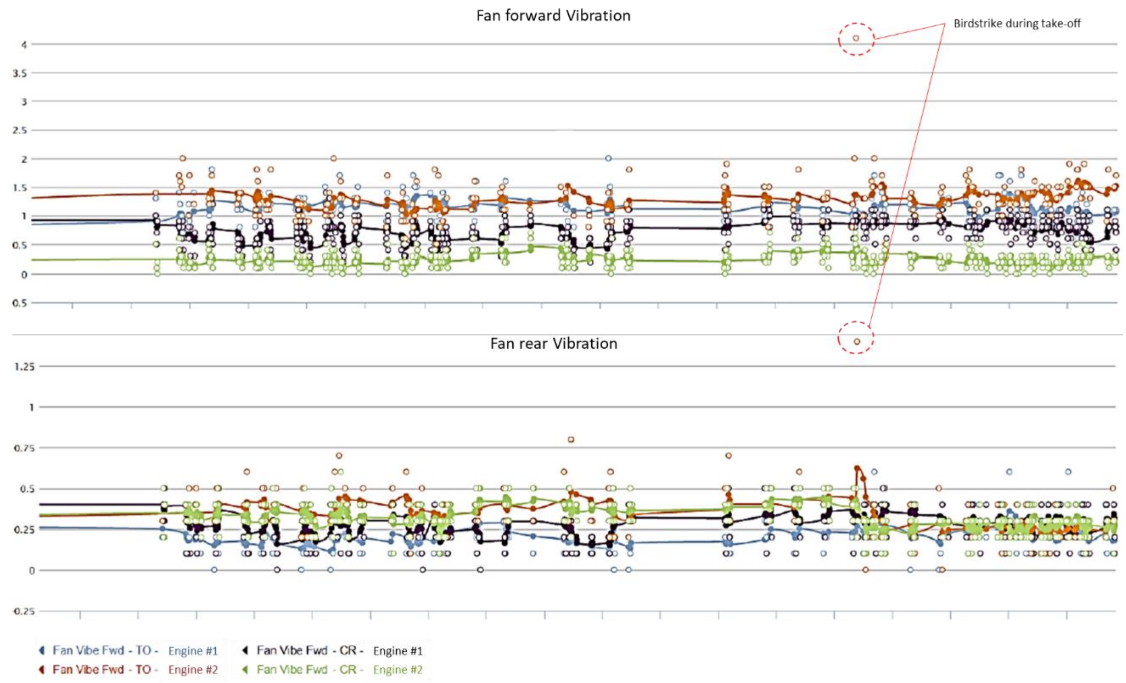

Figure 4.4 – Example of a turbofan engine ECM trends. It shows the effects of a birdstrike event during take-off on the engine fan vibration trends. Each dot represents a snapshot of the parameter value per flight cycle.

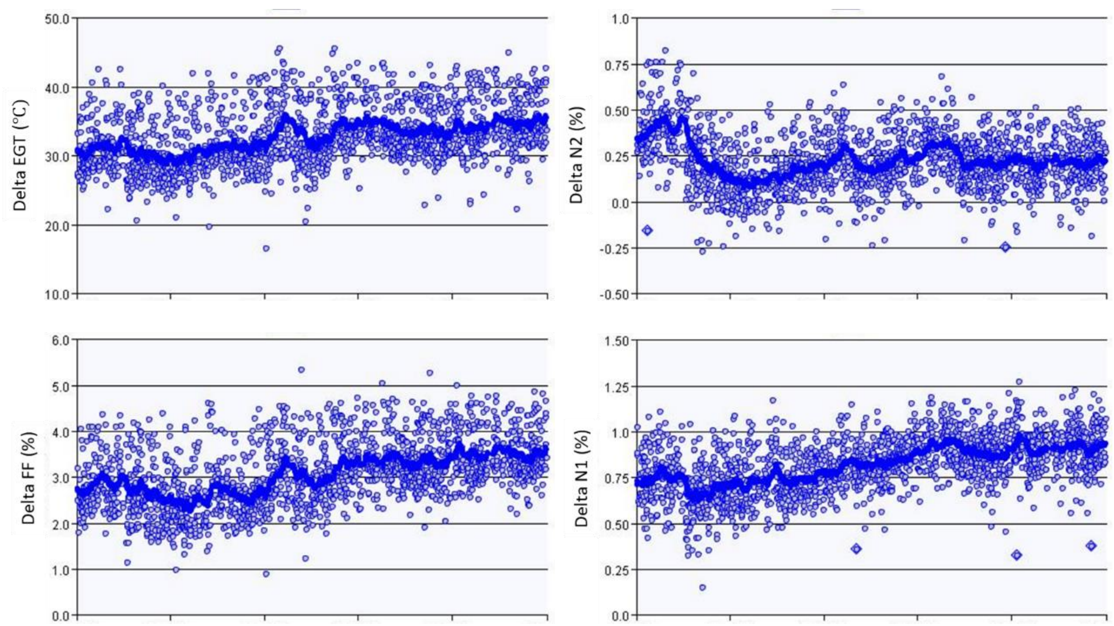

Figure 4.5 – Example of a turbofan engine ECM trends. It shows the gradual degradation over time.

According to OEM technical documents, certain changes on the parameters EGT, FF, and N2 and their correlation can provide the operator information in regard to their effects on engine module performance. For example, increase of EGT and FF and decrease of N2, can indicate low efficiency of HPT or HPC. Whereas increase of all the three parameters, EGT, FF, and N2, can indicate low efficiency of booster, LPT or fan. Low efficiency of LPT and fan will cause an increase of thrust.

Therefore, certain parameters level recorded during take-off and cruise operation are used to monitor the rate of deterioration and loss of module efficiency as indications of engine health. The EGT indicating system provides a visual indication in the flight compartment of the total exhaust temperature monitored in the LPT inlet of each engine. The procedure permits the calculation of EGT margin from an equivalent certified maximum EGT level for cruise conditions. Typical diagnostic procedure consists of four steps: data collection, observation, comparison, and diagnostic. Some examples can be found below:

1. Fan blades deteriorated do not pump air efficiently causing a reduction of the amount of air being intake into the engine core at a given fan speed, this results in less torque (work) required by the LPT, consequently fuel flow, and EGT, at the N1 baseline speed, decrease. However, to maintain the aircraft airspeed and demanded thrust, the control system increases the fan speed, which requires more energy (fuel and EGT) to the LPT. Therefore, the total fuel consumption increases. Re-profiled fan blades make more thrust, lower N1 is required to maintain required Mach. It results in lower actual EGT and total fuel consumption.

2. Detachment of a compressor airfoil may destroy the subsequent compressor stages, which is indicated by an increase on the level of core vibration. In theses situations, a borescope inspection in the HPC is performed and the damages are analysed and measured to verify the limits.

3. HPT blade distress is characterized by a decrease in EGT Margin and dN2 with a corresponding increase in dFF. The blades condition can be evaluated by performing a borescope inspection. Borescope inspections in the HPT module (blades and vanes) are mandatory within certain cycles interval, which is determined by the OEM.

4. EGT indication fault is characterized by an increase in dEGT with a decrease in EGT Margin while dN2 and dFF remain stable. Inspections and troubleshooting of the EGT indicating system can determine the root cause. The replacement of sensors can be performed in line maintenance.

5. An Oil pressure indication error is characterized by a sudden shift in oil pressure while oil temperature remains stable.

6. If HPC and\or HPT become less efficient, EGT increases. Core slows down at constant fan speed due to less mass flow needed to maintain constant flow\temperature energy ratio to LPT.

7. Abnormal increases in temperature may indicate an oil-lubricated component failure or air seal leakage.

Engine performance and health condition are monitored on a continuing basis to ensure the engine is operating within specified physical limits. The AMM includes the limits for the main engine parameters for each phase of the flight. Engine line maintenance actions can be scheduled based on ECM trends, such as engine compressor cleaning, which is highly recommended by the OEM when a decrease on EGT margin at take-off is noted.

4.1.2 *Compressor Cleaning*

Aircraft engines operate in a very wide range of condition and environments and as a result, the engine becomes contaminated during normal operations due to airborne particles, such as sand, salt, airborne dust, soot, chemicals, and unburned hydrocarbons, amongst others. These particles accumulation on the compressor blades causes surface roughness as well as airfoil’s shape distortion leading to the reduction of compressor efficiency and airflow capacity (Chen & Sun, 2018). To counteract the degradation of the airfoils, fouled engines turbine driving the compressor rotor must rotate at higher speeds, that is increasing the fuel flow to meet the required thrust during the flight. Consequently, the engine burns more fuel and runs at a higher temperature. In addition, high temperatures negatively impact the life consumption of the hot section components.

Keeping the engine “clean” is essential to lower fuel consumption and extend engine life by improving the rate of EGT. Additional benefits are obtained from an efficient core cleaning program such as TOW extension. Washing the core removes contamination that contributes to premature wear to airfoils and can potentially reduce overhaul costs at hot section. Another important benefit of an effective water wash program is the carbon emissions reduction. According to a case study of 200 CFM56 engines done by (Chen & Sun, 2018) a 3 times per year engine washing program is demonstrated to reduce fuel consumption by 5471 tons and CO_2 emission by 17,250 tons.

Engine wash is a maintenance task recommended by the OEM that improves compressor efficiency. It is accomplished by spraying water or water/detergent mix into the engine core while the engine is dry-motored. The result is a much more efficient engine which generally has higher EGT margin and better Specific Fuel Consumption (SFC) after the wash process. According to (Vince Ruppert, 2007), historical data studies found that a typical EGT recovery of 10℃ decreases SFC by approximately 0.8-1.0%. The first water wash can recover from 5°C to 20°C. Then, the amount of EGT recover varies based on engine flight hours/cycles, environmental factors, and maintenance actions. The gain also depends on the quality of the wash procedure and the interval in cycles since the last cleaning, as it relates to the length of time the contamination was allowed to contribute to wear on the airfoils (Figure 4.6).

GE Aviation recommends a core engine wash every 500 cycles or 10℃ EGT deterioration for CF6-80C2 engine model. However, the rates at which engines need cleaning vary from airline to airline and need to be based upon engine fleet history over the life of the engine service as well as the geographical region of operation. For example, operators frequently using airports near the ocean or deserts may need more frequent cleaning to remove salt deposits and sand. The operator should develop a customized engine wash plan based on their operating conditions and service experience, particularly if the engines are operated in unusual service such as high cycle-to-hour service or in detrimental environmental conditions such as undeveloped airstrips (Vince Ruppert, 2007). In this dissertation, the wash history of the engines used for this study was analysed and commented in chapter 5.

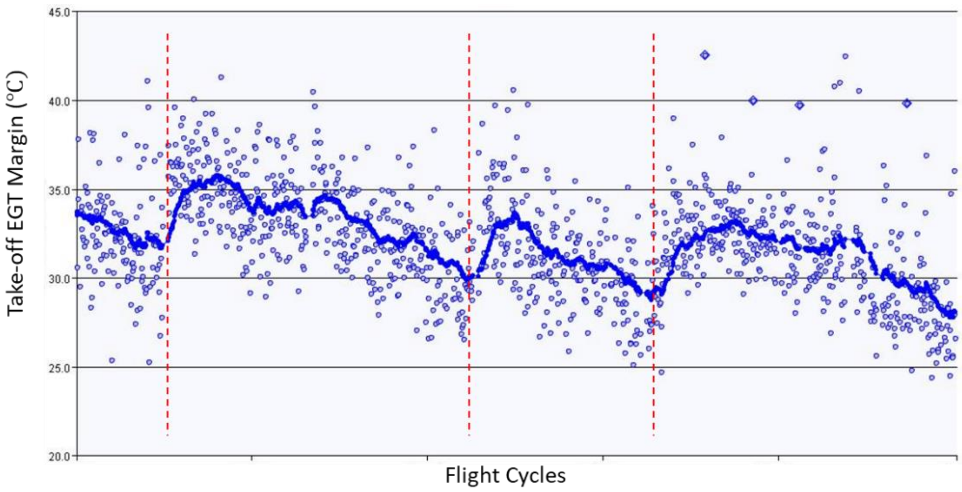

Figure 4.6 – Example of a turbofan engine ECM trends. It shows the effects of engine gas path wash (represented by the vertical red lines) on take-off EGT margin trend.

4.2 Shop Visit Maintenance

There are three main reasons for an engine to be removed and sent to a shop for maintenance. The first concerns the restoration of the performance of the gas turbine, the second concerns the replacement of LLP; while the two first removal reasons can be planned and managed in advance by the operator, the third and last reason concerns unscheduled engine removal (Justin & Mavris, 2015). Unscheduled downtime can be very costly especially if no spare engine is available.

The rate of shop visit events will depend mainly on the engine's utilization, maturity, and operational severity. Shop visit management is a wide field which includes many issues that directly or indirectly influence the shop visit intervals. Although it is difficult to consider all effects in particular, this dissertation discusses the main factors. The effective tracking of engine performance through ECM, LLPs status, SB compliance, AD status, last borescope inspection analysis, and others, will provide a clear picture of the WS likely to be required at the engine shop visit (Figure 4.7).

Figure 4.7 lists the four main elements that assist the operator to manage the engine SV. Engine on-wing history is very important information when analysing the engine current condition. It allows the operator to understand the maintenance actions already taken during operation and their effects, as well as to analyse engine faults for identifying possible engine components/systems that may need maintenance during next SV. Operation profile refers to the conditions that the engine has been operating, such as flight duration and thrust settings, which have great impact on the engine mechanical and performance degradation. In addition, environmental severity influences the performance degradation and durability of modern engines greatly (Wensky et al., 2010).

ECM provides one approach for estimation of environmental effects on the engine performance degradation. However, the confirmation of such effects can be seen during the engine SV. The geographical region of operation is one of the main factors influencing the engine SV management as well as the DMC. Dusty environments such as North Africa, Middle East, Central Asia, and others (Labban, 2016), can damage compressor and turbine airfoils. Figure 4.8 shows LPT shaft and surrounding components with dust deposits accumulated. Dust can cause clogging of airfoil's cooling holes, overtemperature, and consequently acceleration of deterioration.

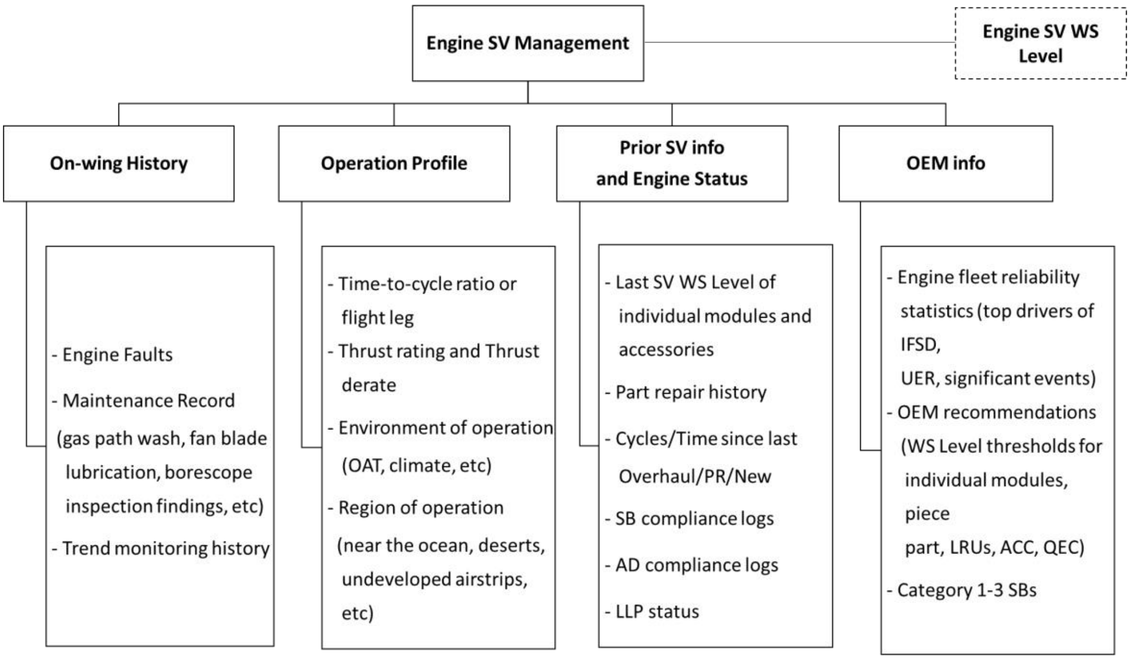

Figure 4.7 – Main elements considered during SV management.

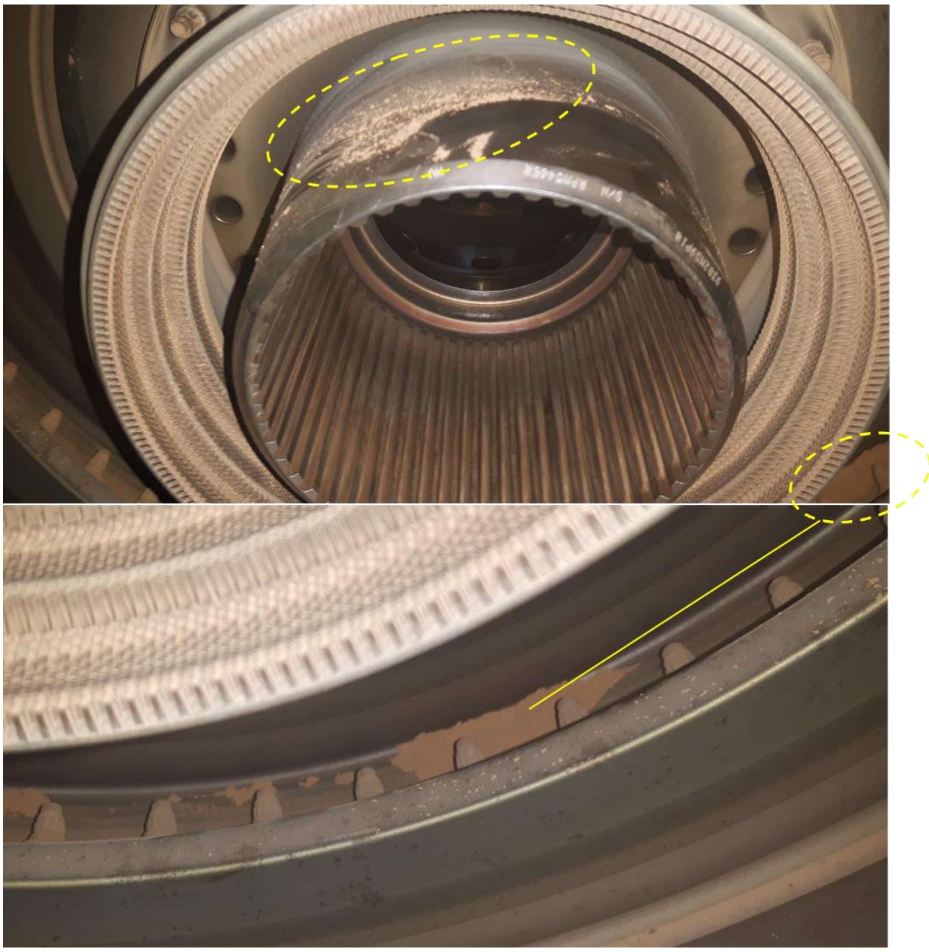

Figure 4.8 – CF6-80C2 LPT shaft with accumulation of dust deposit.

The engine SV history is mostly useful for determining the next SV WS as the OEM recommended maintenance is based on time/cycles since last maintenance was performed. Previous SV WS for each module, control and accessory should be analysed individually. Each module has its individual identity, operation history and inspections thresholds stablished by the OEM. It permits for a more efficient maintenance procedure as the engine can be disassembled into major modules allowing replacements and repairs of a module and its components without completely disassembling the engine (Figure 3.4). The engine LLP remaining cycles and open ADs must also be considered during SV management as both thresholds are considered as hard-time. Although SB is not mandatory, knowing what SBs the engine has previously complied with is useful for knowing the engine hardware Mean Time Between Failure (MTBF), which is the average time between component/system breakdowns during normal operation. SBs may improve this maintenance metric as well as the Mean Time Between Repair (MTBR).

Engine fleet reliability statistics are usually presented by the OEM annually. It demonstrates reliability scorecards, such as significant event rate, In-flight Shutdown (IFSD) rate, Unscheduled Engine Removal (UER) rate, and others. In addition, the root causes and key issues are also demonstrated, and are usually followed by the OEM control plan for corrections. This information is important for operators to be aware of possible failures their engine models can experience. Knowing the existence of the issue and what can cause it allows the operator to take the necessary actions in advance avoiding significant events, IFSD, and even UER. Following OEM recommendations is crucial for safe operation and satisfactory TOW.

Incorporation of critical SBs may affect the engine TOW considerably. SBs are technical documents provided by the OEM when a component/system modification is available. This document usually describes the reason for the modification, stablishes applicability/effectivity as well as the due time, identifies the necessary material, tools and manpower for complying with the SB, provides the accomplishment instructions, and finally determines its category and impact. Mostly, the reason for the modification is to improve the component/system performance, reliability, or/and to prevent the occurrence of a significant event. The SB category varies from 1 to 9, and it determines when the SB is recommended to be accomplished, for example, category 1 refers to SBs that should be complied with before subsequent flight or before x hours, y cycles, or a specific date. Whereas the SB impact varies from A to F, and it classifies if the SB should be considered as critical, for example, impact A refers to SBs that may affect flight safety. Several SBs have been published by the OEM in order to solve critical engine failures, increasing TOW and reducing UER. Therefore, category 1-3 SBs should be analysed and considered to be incorporated during the engine SV.

Scheduled maintenance commonly includes procedures and tasks recommended by the OEM based on design inherent features. WS level is defined as Continued Time/Assembled Engine, Minimum, Performance, or Overhaul and is determined by key factors listed in the OEM technical document named Workscope Planning Guide (WSPG). This document is a shop maintenance guide based on the powerplant Time and Cycle Since last Overhaul (TSO/CSO) and TOW expectations, diagnostic, engine trend monitoring, and on-condition findings for each module, control and Accessories (ACC), Line Replacement Unit (LRU), Quick Engine Change (QEC) components, etc. Like the engine design modular concept, the recommended maintenance is given for individual modules. Figure 4.9 describes each of the WS level based on the WSPG.

Continued time WS refers to minor repairs, or to perform urgent inspections or modifications to engines that have been removed after a short TOW and will not affect the normal interval between regular engine SVs. The WS is limited to address specific identified problems, such as replacement of the AGB, TGB, or even replacement of the combustor chamber, engine main bearings inspection, HPC blade replacement, and others. In these cases, the inspections on major modules, minor modules, areas exposed, and parts removed for access are only visually inspected for overall condition according to the AMM limits. This SV is expected to be a quick Turn Around Time (TAT) to not impact aircraft operation.

Minimum WS applies to engines/modules that demonstrate satisfactory incoming performance margin and have no apparent hardware problems when the module is removed or accessible. The engine and modules are considered continued time after a minimum WS. Minimum WS is usually used for engines that were redelivered by the operator to the owner. The modules and parts inspected are for on condition maintenance. This WS level has no specific threshold and are commonly applied for convenience maintenance.

Performance WS applies to engines that present low in-service performance prior to removal. Modules are considered zero-Timed and zero Cycles Since Performance Restoration (TSLPR/CSLPR=0) after this WS is performed. According to the OEM technical documents, the performance effect key factors include HPC and HPT modules, such as airfoil condition and grind practices, VSV bushing condition, CDP air seal condition and clearance, HPT shrouds condition and grind practices, and HPT stage 1 nozzles throat area. The engine must leave the engine shop with the EGT margin restored.

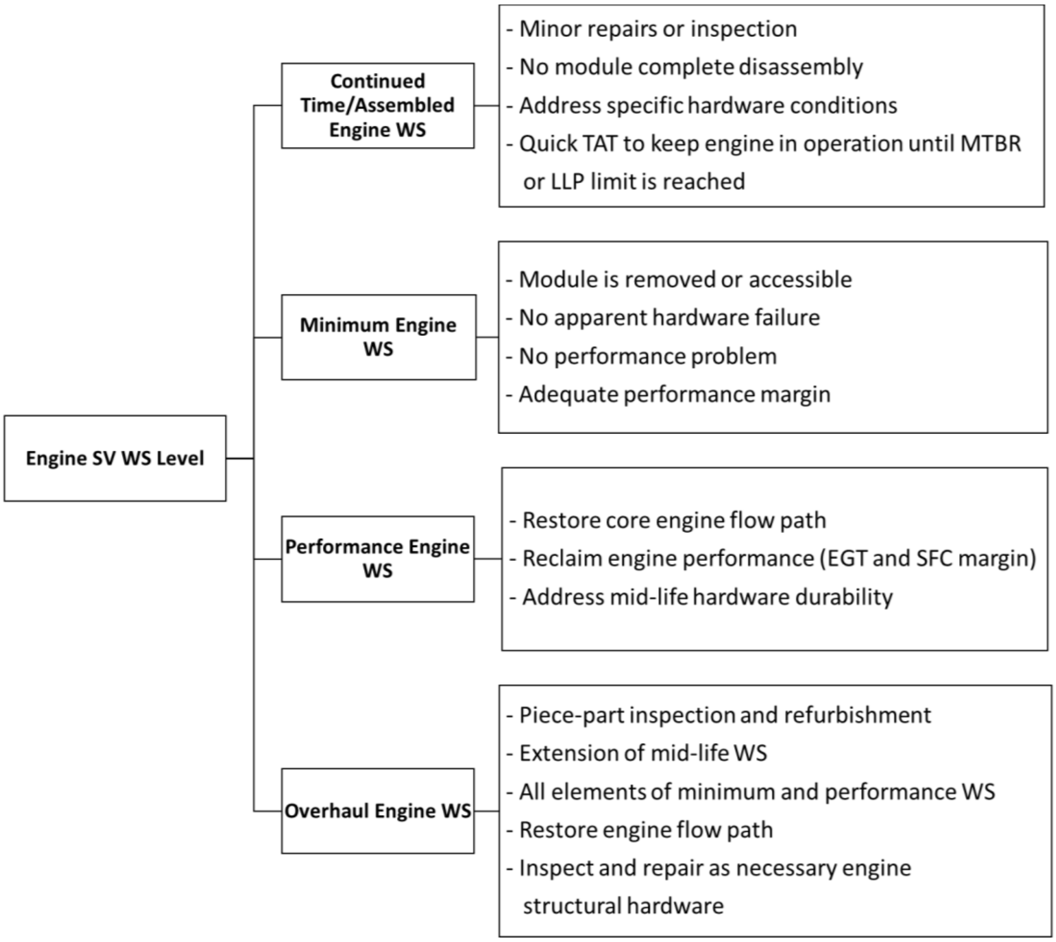

Figure 4.9 – Description of engine SV WS Levels.

The Overhaul (OVH) WS, also known as heavy maintenance, applies to modules and parts being full inspected according to the ESM, and repaired as necessary. Modules are considered zero-timed and zero cycles since overhaul (TSO/CSO=0) after full overhaul level WS. This WS requires a long TAT and commonly includes LLP replacement. The costs associated to this WS is usually the highest when compared to the others. Except for the HPT module, which has a shorter threshold, the other modules thresholds vary from 30000 hours/5000 cycles to 36000 hours/9000 cycles.

WSPG recommends soft-time thresholds of time and/or cycles since a certain maintenance task was performed. Contrary to hard-time, soft-time thresholds are not mandatory. Each operator may adjust the thresholds based on environment of operation, operation goals, and experience. In addition, other factors should be considered when defining the engine SV WS, such as engine reliability statistics, remaining LLP stub life, part repair history, anticipated severity level of operation (thrust rating and thrust derate), flight leg, and temperature, climate, sandy or dusty environments, cold or snowy environments, etc., engine operating exceedances on-wing.

Potential major problems can be detected by regularly noting the performance and condition of the gas turbine engine and its parts, which allows the operator to schedule the engine maintenance in advance. However, even the most reliable gas turbine engine will have occasional unscheduled maintenance that may result in an engine removal. Many sources in the complex functional assemblies (accessory, compressor, combustor, turbine, lubrication and ignition systems, controls, and both rotating and stationary subassemblies) can contribute to unscheduled removals.

4.2.1 *Performance Restoration (PR)*

Turbofan performance degradation is reflected through the changes of efficiencies and flow capacities of its gas path components. The main causes for a module to lose efficiency are compressor fouling, blade tip clearance increase due to wearing and erosion, seal leakage due to damage, and airfoil erosion, and others. HPC and HPT flow path condition is the most significant area of the engine for engine EGT and fuel burn. Fan blade condition have a significant influence on engine thrust and fan pumping efficiency. LPT and booster modules have limited influence on performance.

The primary objective of a PR WS is to restore flow path seals and airfoil (blades and vanes) condition to reclaim engine performance, assess structural hardware and perform maintenance on-condition, refurbish key areas of the engine for reliability (oil seals, tubes, controls and accessories, flow path hardware, etc). In addition, restore the engine mechanically to operate reliably until the next shop visit with good performance (EGT and SFC). Performance is regained by refurbishing airfoil dimensions and surface finish, as well as optimal tip and seal clearances, fan blade leading edge profile and surface condition restoration. Also, other specific non-flow path parts, will re-establish the reliability and durability of the engine until nest shop visit. Certain LRUs, gearbox and oil seals, oil tubes, among others.

Operating hours is the most significant factor for those items. However, cycles should also be considered because flight leg is an indicator of cycle severity. As the WSPG thresholds are based on an average flight leg (6 hours), some adjustments to thresholds should be considered if the flight leg is much shorter, or much longer than 6. The majority of wear out items are in HPC and HPT flow paths, oil system and controls and accessories. Types of engine performance deterioration may be classified as shown in Figure 4.10.

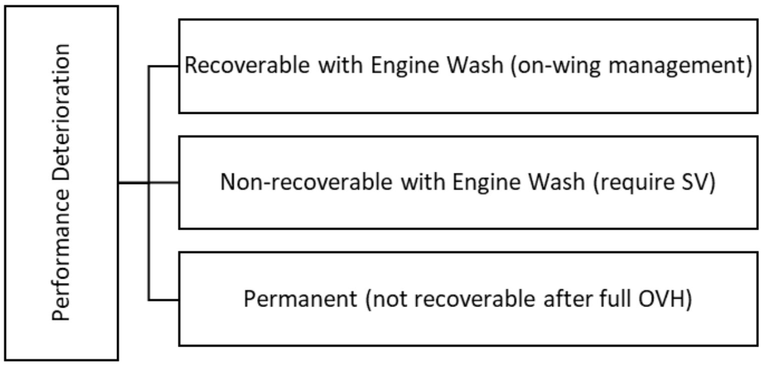

Figure 4.10 – Engine performance deterioration classification.

Compressor fouling is the most common cause of performance deterioration even with good filtration systems. Dirt, pollen, salt (offshore), saps, sand, and other particles can cause fouling by getting through the filtration system and deposit on the compressor blading, which results in reduced flow capacity and efficiency. Compressor washing helps to restore the performance of a fouled compressor. Turbine fouling is less likely and depends on the type of fuel used. Severe turbine fouling can occur if high ash content is present in fuel.

Even with regular cleaning, some surface deposits can remain, in addition any flow path damage will not be affected by cleaning the compressor. In these cases the engine must be sent to the shop for restoring the performance. During a PR SV the flow path components are thoroughly cleaned, damaged parts are replaced, tip and seal clearances are restored, any obvious leakage paths are sealed up, the airfoils thermal barrier coating restored, etc. Some of the common performance deterioration causes can be listed as below:

- Accumulation of dirt, dust, pollen, sand, ash, carbon particles;
- Blockage of the inlet filters;
- Hard particles on the compressor airfoils and gas path surfaces;
- Thick, rough, baked-on coating oil on most of the surfaces of the compressor flow paths (airfoils and shroud);
- Surface fouling (soft particles), erosion, corrosion;
- Tip and seal clearance increase, cylinder distortion;
- Icing up the filter, the inlet cylinder, the inlet guide vanes, and the front part of compressor can have a significant effect on engine performance deterioration – more severe than normal wear and tear, but icing is temporary and does not affect the rate of performance deterioration with time;
- Fuel-borne contaminants – produced as result of the combustion process.

Permanent damages examples:

- Cylinder distortion (hence eccentricity in clearances and increased leakage paths);
- Increased surface roughness of flow path components (due to erosion or rust scale deposits on compressor disks and annulus surfaces);
- Distortion in platforms causing loss of aerodynamic performance;
- Increased leakage Airfoil untwist.

These causes may result variation of degrees of performance deterioration in the different components, compressor fouling, which reduces inlet mass flow and compressor efficiency, and hot-end fouling, which reduces the overall turbine efficiency and engine firing temperature. As the engine ages, it requires performance restoration more frequently, and depending on the material conditions that are installed during engine refurbishment (new or used), only a small percentage of performance is restored, which reduces the TOW.

4.2.2 *LLP Replacement*

One of the engine removal causes is the expiry of LLP useful life. Engine's LLP replacement requires the engine to be sent to an engine shop. Therefore, the LLPs also influence the timing of engine on-wing and removals interval. In most cases, for high bypass engine models, the declared operating life of LLPs is between 15,000 to 30,000 cycles (Table 3.2). The calculation of the remaining useful life of the LLP set is an example of prognostic. There are many factors that decrease the life limit of an LLP, some of them are:

1. Low time-to-cycle ratio operation;
2. SV inspection findings;
3. Engine thrust rating;
4. Specific LLP Part Number (PN);
5. AD.

Aircraft operation on short routes tend to accumulate higher flight cycles. Engine LLPs are therefore replaced at more frequent intervals. Although, engines operating on medium to long routes will consume the LLP remaining cycles more slowly, the engines are exposed to higher levels of wear and deterioration. This leads to a higher chance of LLPs being replaced and/or repaired at the shop visit due to inspection findings. Inspections like X-ray checks, eddy current checks, ultrasonic inspection, and other Non-Destructive Tests (NDT) are mandatory when the module of the LLP is exposed at the engine shop visit.

Engine variants designed for higher thrust-rated operation have smaller operating life for the same LLP compared to a lower thrust rating variant. As shown in Table 3.2, the B7F engine has the HPT module limited to 9000 cycles, whereas the B5F HPT module can operate 15000 cycles without requiring LLP replacement. The reason is because higher thrust rating engines operate at higher EGT, which exponentially reduces the useful life of the components due to high temperatures exposures. However, the LLP life limit is not always reduced due to different thrust ratings, it may vary depending on the PN installed. Some specific PNs have less useful life than others due to either its fatigue characteristics or strength capability, or because it is affected by an AD. ADs can impose a decrease on certain LLP life to address an unsafe condition on the component due to defects that might compromise its operating life much sooner.

Engine LLP replacement is often during alternating shop visit intervals, and in extreme cases, an entire set of LLPs will require replacement once during its service life. Common shop visit practice for mature engines is to establish build-life standards such that its performance potential matches its LLP life limits. At the first and subsequent engine shop visits, careful attention is required regarding the build-life of the engines in terms of LLPs and the quality of installed hardware. There is little value in building an engine for 10,000-cycle LLP life if the core hardware installed is only capable of 7,000 cycles. Equally, it would make no sense to build an engine for 5,000-cycle LLP life whilst building a core with new hardware capable of achieving 10,000 cycles.

Some engine variants have their LLP set with different life limits between the LLPs. Maintenance costs tend to be lower if there is a uniformity in the life spans of the major LLPs. For example, all LLPs having a uniform life span of 25,000 flight cycles simplifies maintenance and fleet management for operators. Otherwise, various LLPs need to be replaced at different times — one at 10,000 cycles and another at 15,000 cycles.

LLPs are critical parts that could potentially damage other components in case of a mechanical failure. For this reason, LLPs have life limited in relation to time in service. In order to track the LLP remaining life, the operator must have the LLP ‘Back-To-Birth (BTB) traceability’, which is the birth document of an LLP up to date; and the installation and de-installation record for each time the part was removed from or installed on an engine. Additionally, in case the LLP has had different owners, an exit document is required from the last airline operator together with a removal tag signed by a licensed engineer, and a Non-Incident Statement (NIS). The latter must state that the part was not removed from any engine that was involved in any major accident or incident, including an engine over-temperature, an engine fire or an engine that has been subject to extreme stress (dropped to the ground from a height, for example). Moreover, if the LLP has been repaired, all the paperwork related to the repair of the part including the work order, the service-bulletin status, the WS and the release-to-service tag are added to the BTB. Similar to any other aircraft component, the LLP documentation is usually approved by the quality-control department of the operator. A miscalculation on the life remaining of an LLP is a serious error and must be corrected immediately.

4.2.3 *Unscheduled Repair*

Unplanned engine removal can be very costly especially if no spare engine is available. UER events cannot be anticipated by operators as most of the time the causes for failure are sudden and there are no early warning signs. Although engine periodically maintenance is performed as well as inspections and parameter monitoring, there are several factors that can drive an unscheduled removal, such as faulty engine hardware, excessive vibrations, or external factors as FOD (Figure 4.11).

Engine hardware defect can contribute to premature maintenance or unscheduled removal. Evaluating the engine’s overall performance and determining its useful life based on LLP expiry and ECM trends are important strategies, but the design and physical properties of the components are also necessary factors to consider. In addition, other factors such as operating time-to-cycle ratio, conditions, and geographical regions of operation highly contribute for unscheduled removal. Hot section components design has been improved over the years, but it is still the cause for unscheduled removals in some engines due to severe mechanisms of deterioration such as fatigue, creep, corrosion, and thermal fatigue.

Vast majority of wear-out items that effect engine reliability are in the HPC and HPT flow path, oil system and controls such as airfoils, oil seals (o-rings and carbon seals), major controls and accessories, such as HMU, pumps, actuators, valves, internal and external tubing and cabling. Engine structural items (rotors, frames) can also cause reliability issues but are not likely. Overtemperature and low power or fuel flow fluctuations can signal the need for unscheduled maintenance. Cracked, fretted, scored, fractured, worn, broken, spalled, skidded, eroded, sheared, warped, burned, or charred subassemblies can be indications of a maintenance need.

Most of the engine design affecting reliability and TOW are corrected by the OEM as the engine model reaches its mature design. It allows the OEM to have a good comprehension of the problem and perform the necessary correction by either reworking the component or designing a new one. Material improvements have reduced the UER events considerably, but improper maintenance actions have, on the other hand, been always a problem by causing dysfunctional conditions. In addition, UERs are also caused by such events as foreign object damage, which can be difficult to control.

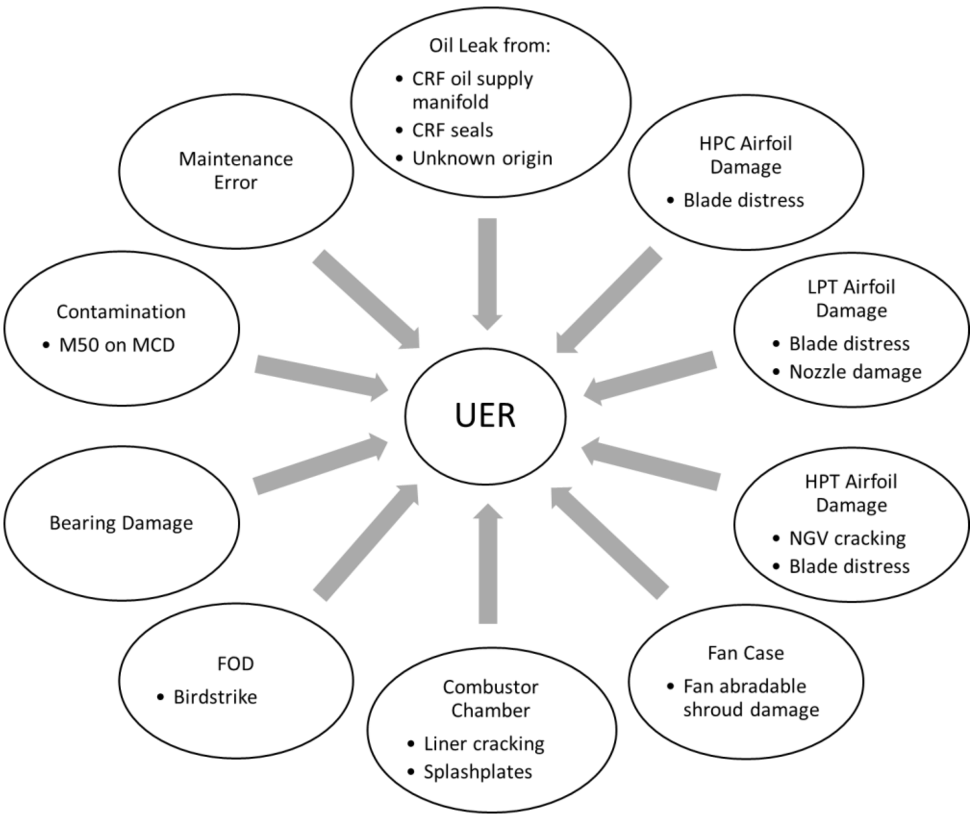

Figure 4.11 – Most common UER drivers.

Commonly, engine failures and issues that cause an UER are found during routine Borescope Inspections (BSI) due to material distress. These inspection tasks are in the aircraft MPD and their interval varies depending on the engine model and OEM. Borescope is an optical viewing device that is inserted through a small opening in the engine case to view inside the engine. If any damage is found to be out of limit, the engine may need to be removed and repaired. For example, damages on the combustor liners, HPT blades, HPT NGVs, and others. Figure 4.12 shows an example of damages found in a combustor inner liner panel. Figure 4.13is another example of BSI findings out of limit that caused UER. It shows damages found in the NGVs of the LPT. All defects found during the BSI are measured and analysed in conjunction with the AMM limits.

4.3 Direct Maintenance Costs (DMC)

Cost is a complex topic and for simplification it can be divided into two general categories: operational cost and maintenance cost. Commercial aircraft maintenance costs can be broken down into the groups line maintenance, heavy maintenance, component maintenance, and engine maintenance. The costs associated to each group depend on a large number of factors. Engine related costs can contribute to a third of the total aircraft maintenance costs (Seemann et al., 2011). Engine Maintenance, Repair and Overhaul (MRO) refers to engine SV costs.

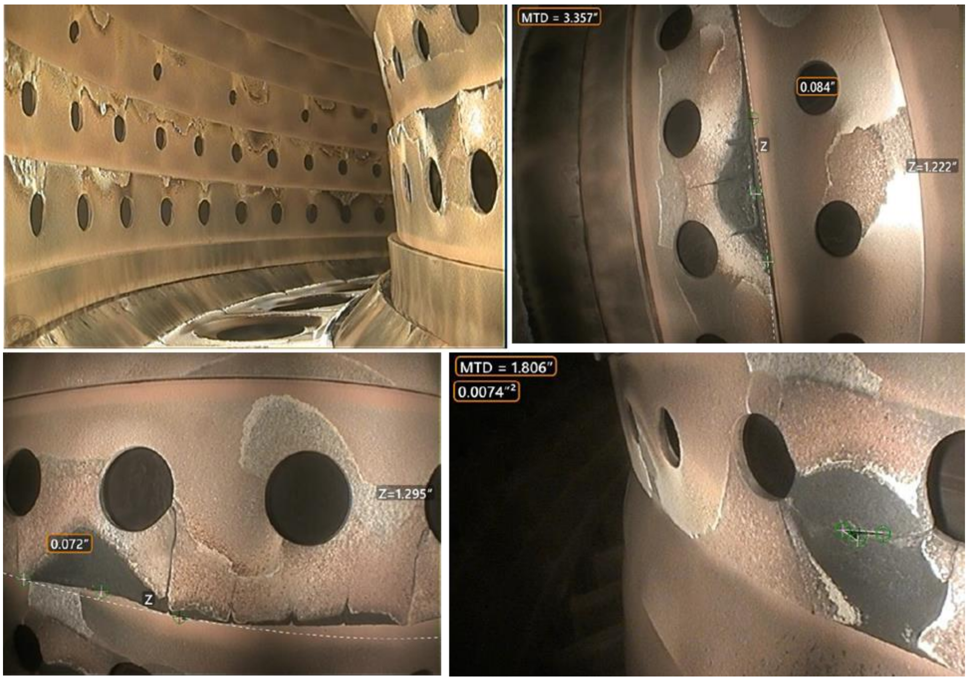

Figure 4.12 – Example of a borescope inspection of a CF6-80C2 combustor chamber. The pictures show several areas of missing material on inner liner panel one.

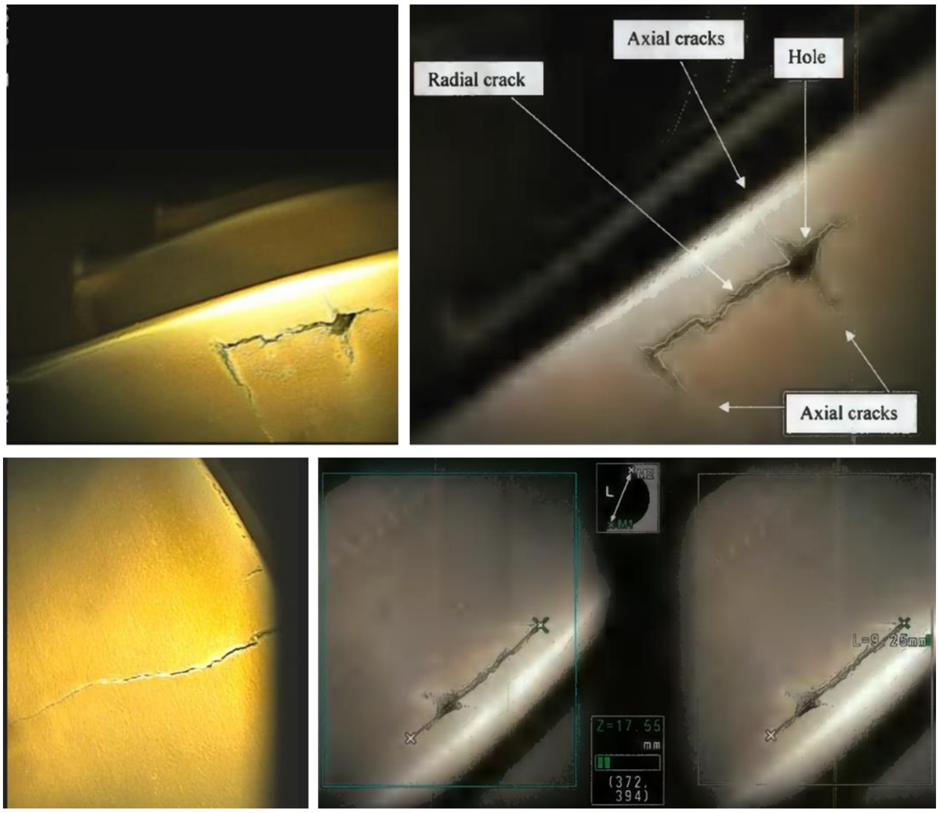

Figure 4.13 – Example of a borescope inspection of CFM56 LPT nozzle guide vanes stage one. The pictures show intersecting cracks and hole.

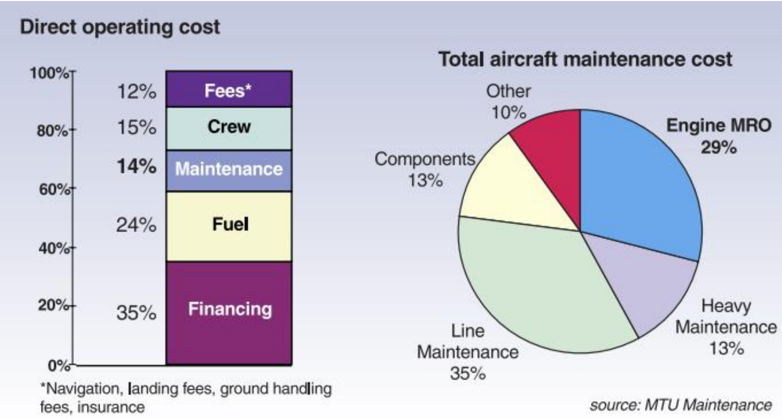

Figure 4.14 – Engine maintenance costs as part of total aircraft maintenance cost (Fendt & O'Keefe, 2005).

Engine maintenance costs are divided into on-wing – or line maintenance – and off-wing – or engine SV. Engine line maintenance costs are usually influenced by pure technical issues such as external hardware modifications and improvements that are either recommended by the OEM through a SB, or implied by the authorities through an AD. In addition, the replacement of LRUs and QECs also contribute to engine line maintenance. This dissertation focuses on the engine SV costs and the elements that most influence it, such as material, labour, and repair costs.

When an engine is removed and sent into a shop for refurbishment, the primary cost factor of the shop visit is the material cost. Approximately two thirds of the costs of an engine SV come about through the replacement of material. In cases where LLPs need to be replaced, the material cost element will increase further. Figure 4.15 presents the percentage of each SV cost elements of two different CF6 engines. Both engines were sent to the same MRO and performed similar OVH WS. The cost breakdown facilitates the understanding of the significant impact of the operation profile on the SV costs, and the impact of elements that are independent from operational conditions, such as LLP replacement costs.

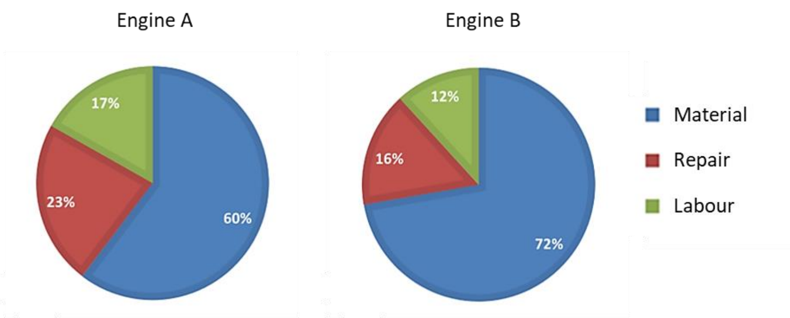

Figure 4.15 – Main elements of engine maintenance costs. Engine B included LLP replacement.

Engine operation is the main influence on how deteriorated the engine components/parts will be when the engine is disassembled. The time-to-cycle ratio, thrust derate, environment and region of operation directly impact the material scrap rate at the engine SV. Material replacement typically accounts for 60% to 70% of the engine's DMC. The engine hot section operate in high stress environments with very elevated and varying temperatures and for this reason, these components design requires highly tensile and thermo resistant materials, which results in high material cost for repair or replacement of worn parts (Seemann et al., 2011). Figure 4.16 simplifies how the main elements of an engine maintenance costs are divided.

The biggest portion of non-LLP material cost is attributable to airfoils where individual vanes can cost as much as $15,000 and blades as much as $7,000 each. Even though HPC blades airfoils are relatively cheaper when compared to the HPT airfoils, engines operating in a sandy and/or erosive environment can have HPC scrap rates close to 100%, which will increase considerably the final DMC. One option that operators find to reduce the material costs is to acquire part-run/used material instead of new material.

Used material can cost down to 40% of new materials price. However, depending on the material, installing it in used condition can impact engine TOW and DMC of the next engine SV. For example, some operators avoid re-installing hot section components, such as HPT nozzles and blades, after their third OVH maintenance to prevent UER, and higher scrap rates at the subsequent SV. As any other component, used material is more susceptible to failure than new material with high reliability.

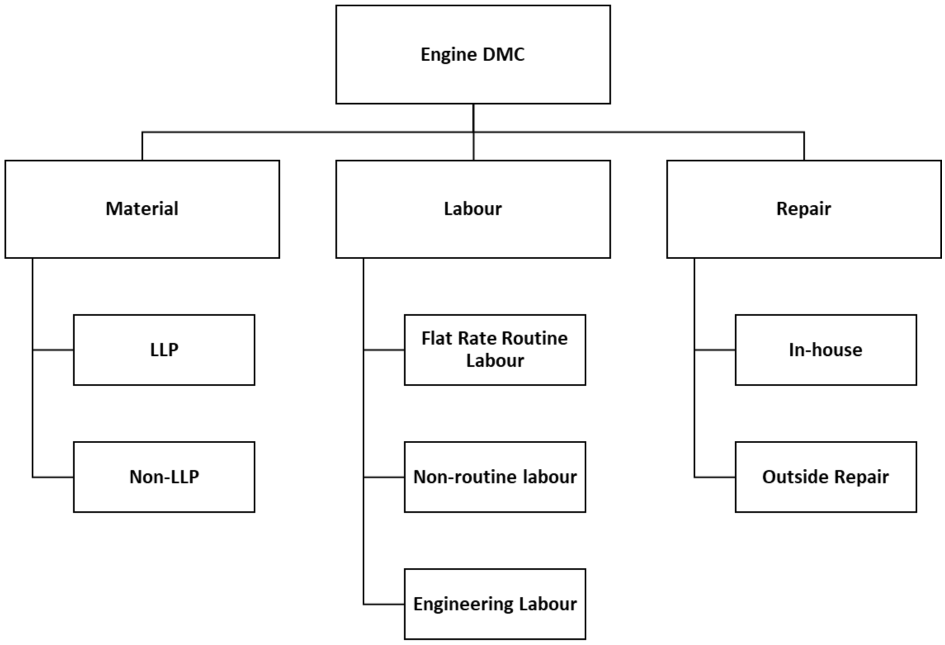

Figure 4.16 – Engine SV cost composition.

Building engine part-life requires an efficient LLP replacement management. Although LLPs are subject to hard-time intervals, most parts are removed prior to reaching their life limits, on average, varying from 5% to 15% of the cycles remaining (Ackert, 2011). Similar to the hot section components, the very high costs of LLPs lead to the conclusion that investing in new LLPs is uneconomical. Installing LLPs which have some of their life already consumed is also an attempt to reduce material costs. However, it is important to establish build standards such that its LLP life limits matches the TOW expectations.

Another important contributor for the DMC of an engine SV is related to repairs. Hence, the parts repair capabilities of an engine shop may also influence the costs. Subcontracting repair services can increase the costs significantly. There are three parameters that the operator tends to consider when selecting the MRO, which are: maintenance capability and quality, TAT, and SV cost. The latter usually has the greatest impact on the decision-making process. The WS labour rate is usually fixed and the impact on the final SV costs will depend on the MRO labour efficiency. Engine maintenance labour includes engine disassembly, cleaning, inspecting, in-house repair labour, and engine assembly according to the WS level.

Chapter 5 - Engine Behaviour Prediction

This chapter intends to present the implementation details of the ML methods used for forecasting engine behaviour. It is based on a mature CF6-80C2 turbofan engine configured as high thrust rating, which specifications are shown on Table 5.1, denominated as Engine A to preserve anonymity. The ML implementation is based on Engine A historical flight data, and this section presents the preprocessing steps necessary for preparing the data, an introduction to the different machine learning approaches used in this dissertation to accurately predict engine behaviour, the experimental setup where the models were trained and tested, and finally, a description of the metrics used to evaluate the models.

Table 5.1 – Engine model main specifications.

CF6-80C2B7F ENGINE SPECIFICATION	
Nominal Thrust Class	61,500 lbs.
Installed Take-off thrust (sea level, 92°F)	58,300 lbs.
Installed Climb Thrust (at 35,000 ft.)	12,500 lbs.
Maximum temperature (flat take off rating)	30.0°C
Exhaust gas temperature redline	960°C
Installed Cruise thrust (at 35,000 ft.)	11,600 lbs.
Bypass ratio	5.3 to 1
Compressor pressure ratio	27.4 to 1
Maximum N1 rpm	3,854 rpm (117.5%)
Maximum N2 rpm	11,055 rpm (112.5%)
Weight (bare engine)	9,295 lbs.
Nominal Engine Length	170 inches
Nominal Fan Diameter	98 inches

Traditionally engine performance deterioration monitoring is based on the observation of engine parameters trend, which is formed by snapshots taken during the flight. ECM is a useful method for monitoring the current health state of the system. It allows monitoring of both gradual and rapid deterioration. This dissertation focuses on the prediction of gradual performance deterioration. Engine behaviour prediction requires model training for each flight condition. For this reason, the prediction methods used were based on time series data. The behaviour of the sensor data contains crucial information to predict performance loss, hence engine removal decision is now converted into a data analytics problem. There are several algorithms available to address the problem of estimating gradual deteriorations (Mathew et al., 2018).

Machine learning approaches were used to predict engine behaviour considering specific conditions. The variables investigated are component performance parameters and measurements. Measurements trends and forecasts are commonly investigated at take-off and climb, which are the most critical phase of a flight as the engine's components operate at great thermal and mechanical stress. The appropriate indicator of the overall performance of the engine is based on the core flow temperature or EGT (Yildirim & Kurt, 2018).

In this section, the details of the implementation of the machine learning approaches as well as their evaluation metrics to predict EGT under specific conditions of Engine A are provided. In order to correctly train and evaluate these different approaches, it is necessary to have a workflow comprised of data preprocessing, data splitting, model selection, training the model, and evaluating the results (Figure 5.1).

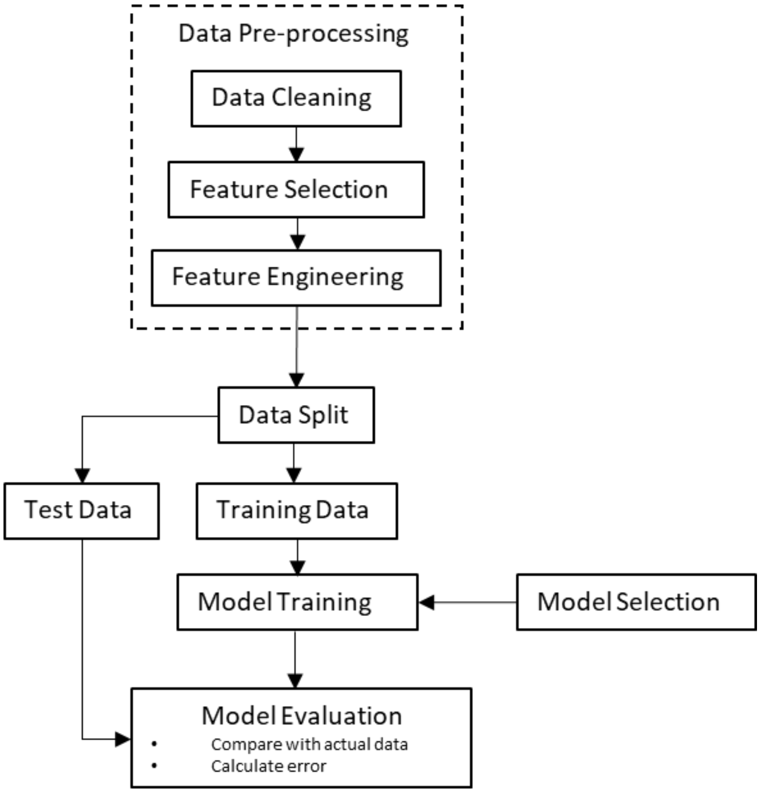

Figure 5.1 – ML implementation workflow.

5.1 Dataset

The time series flight data utilized in this work was obtained from a mature turbofan engine, namely Engine A. The flight data is composed by every second of the flight for each phase: take-off, climb, cruise, descent, and landing, for a period of six years. During the preprocessed steps, the maximum value of EGT at take-off, denominated as EGTMax, is identified for each flight. Traditionally the EGT value used for performance monitoring is a random snapshot taken during the flight. As previously mentioned, the EGT reaches its maximum during take-off phase, and its value is an indicator of turbofan engine overall health. Therefore, it is advantageous to extract the EGTMax of each flight instead of using a random snapshot of the EGT value. Each row of the dataset has 11 features, which are described on Table 5.2.

These features can be separated into two groups, the endogenous features, and the covariate features. The endogenous features are the time series data that directly represent the engine behaviors we want to forecast, such as EGTMax or Fuel Burn Rate. The covariate features represent all other features that can be related to the endogenous features and can also be known ahead of time, such as flight route and day of the year. To prevent the inaccuracies in the dataset from negatively affecting our model, and to improve overall model accuracy, data preprocessing was performed before training the model.

Table 5.2 – Dataset features.

	Features
Covariate Features	Day of the year
	CSN
	CSO
	TSN
	TSO
	CSW
	Route
	Flight Length
Endogenous Features	Maximum take-off EGT
	Maximum cruise EGT
	Fuel Burn Rate

To prepare the data for training the models, a series of preprocessing steps were taken, namely Data Cleaning, One-Hot Encoding, and Standardizing. A simple data cleaning step was taken to remove any null value or missing data from the dataset. One-Hot Encoding was performed on flight route data, which is non-numerical and considered categorical. This preprocessing step reorganizes the data from text into categorical columns, where each occurrence is represented by a numerical 1, and otherwise represented by a 0, thus the name One-Hot Encoding (Figure 5.2). Once the numerical values are assigned to each categorical column, each row is turned into a binary vector that represents our numerical values. In this case, our vector will have the length equal to the total number of flight routes in the engine's history. The One-Hot Encoded data will become part of our Covariate Conditions vector.

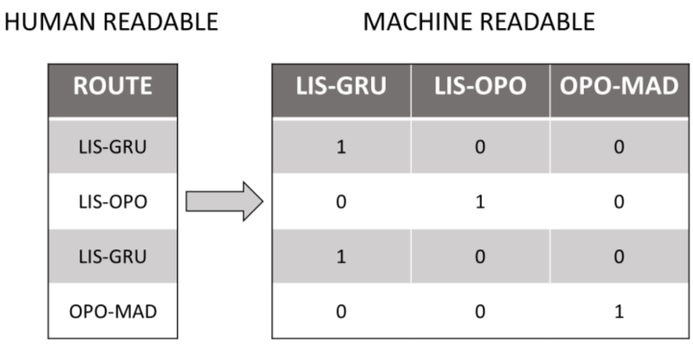

Figure 5.2 – One-Hot encoding preprocessing step for the flight route feature.

The process of Standardizing our dataset transforms the data such that the distribution of each feature will have a mean value 0 and standard deviation of 1, in other words, each column of the data is standardized independently. For each distribution of the data, each value in the dataset will have the mean value of its column subtracted, and then divided by the standard deviation of the same column. The standard score of a sample x is calculated in the following equation.

$$z_{j,i} = \frac{(x_{j,i} - \mu_i)}{s_i}$$

Where $x_{j,i}$ is the value of the j[th] row and i[th] column, μ_i is the mean value of the samples in the i[th] column, s_i is the standard deviation of the samples in the i[th] column, and $z_{j,i}$ is the standardized value of the j[th] row and i[th] column. Standardization of data is a common requirement for many machine learning solutions. If a feature has a variance that is much larger than others, it might dominate the objective function that the model is trying to learn, thus making the estimator give this specific feature more importance than other features.

The dataset was split into two distinct parts, the training dataset and testing dataset. This is done in order to provide the model enough training data, as well as reliably test the model's performance on data it has never seen before. Considering the sequential nature of the time series data, the data was split chronologically, keeping the older data as part of the training dataset and the more recent data as part of the testing dataset (Figure 5.3 a).

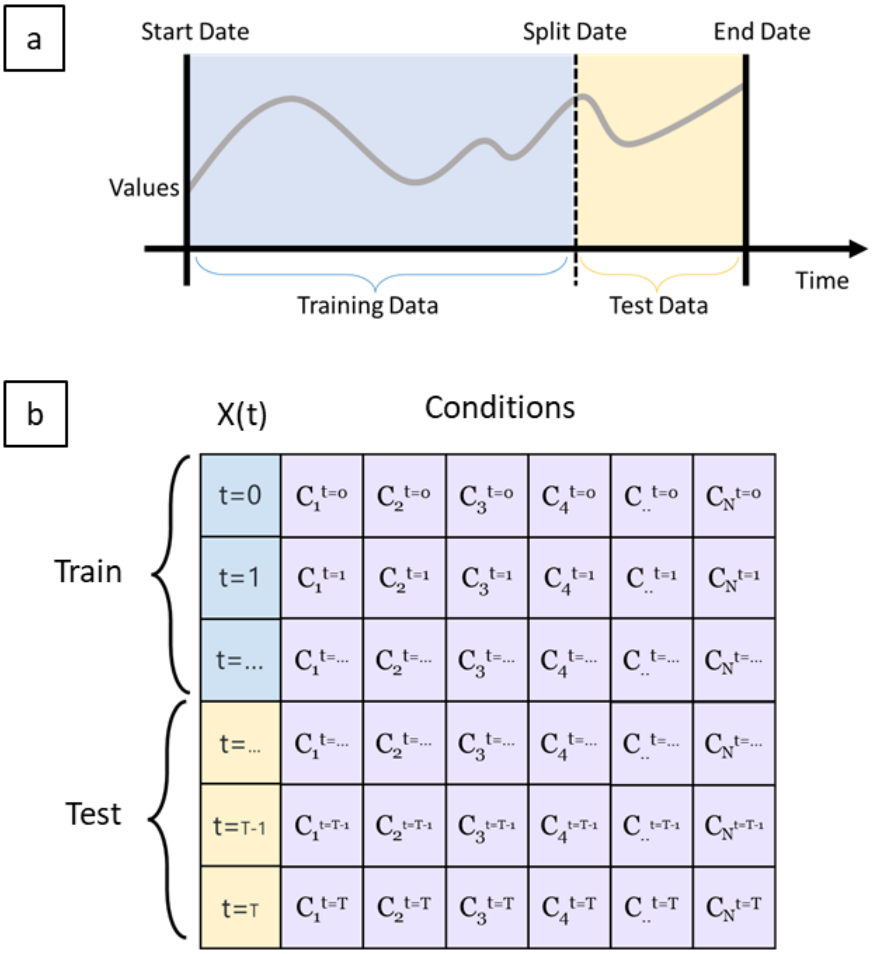

Figure 5.3 – Training and Testing data split representation.

The covariates can be item-dependent, time dependent, or both (Figure 5.3 b). Examples of time-dependent covariates include information about the day-of-the-year, CSN, CSO, TSN, TSO, and CSW encoded as increasing numerical values. Item-dependent covariates can be expected to influence the outcome, such as specific flight routes. This allows the model to learn time of the year, engine maturity, and flight route-specific behaviour. All covariate values were also standardized to have a zero mean and unit variance.

The data was reorganized before being fed into the machine learning models as three distinct vectors $\vec{C}$, $\vec{X}$, and $\vec{y}$, namely Covariate Conditions, Inputs, and Outputs, respectively. The Covariate Conditions vector contains the features of the dataset in relation to the output (i.e., the flight route and CSN at the output t). The Input vector contains 10 lagged values prior to output t. The Output vector contains the single value the model is trying to predict considering the Input and Covariate Conditions vectors (Figure 5.4).

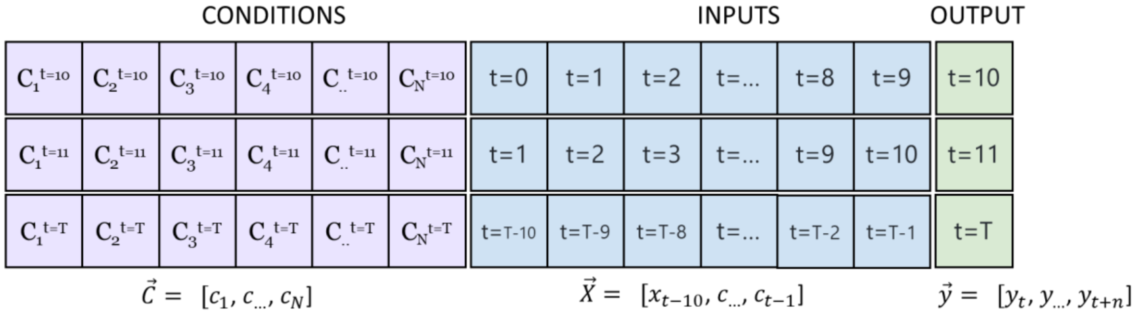

Figure 5.4 – Dataset reformatting for training the models.

5.2 Machine Learning Algorithms

Statistical regression analysis and artificial neural networks were used as the prediction models, which are described below.

5.2.1 *Ordinary Least Squares (OLS) Regression*

OLS is a regression technique in which a straight line is used to estimate the relationship between the known variables. The differences between the estimated line and the observed values of the data are defined as residuals, or errors. These errors are then squared, as to avoid positive and negative errors from cancelling each other out. OLS regression aims at minimizing the sum of the squared value of these errors in order to achieve a "best-fitting line." Generally, the best-fitting line is the one that generates the least amount of error, minimizing the distance between the fitted line and our observations. It is important to note that even though this method is widely used for many applications, it does not take into consideration any temporal relationship between time-dependent values (Banerjee, 2020) (Cavalli-Sforza & Edwards, 1967).

5.2.2 *Autoregressive Integrated Moving Average (ARIMA)*

The ARIMA model is a generalized model of Autoregressive Moving Average (ARMA) that combines Autoregressive (AR) process and Moving Average (MA) processes and builds a composite model of the time series. The ARIMA model uses the dependencies between a current observation and a number of past (lagged) observations, makes the time series stationary by measuring the differences between observations at different times, and takes into account the dependency between the current observations and the residual error of the moving average of the lagged observations (Siami-Namini et al., 2019)(Alonso & García-Martos, 2012). The advantages of ARIMA models are their flexibility due to the inclusion of both autoregressive and moving average terms (Marinai et al., 2003). The ARIMA model is a classical model for time series forecasting and, different from OLS regression, it does take into consideration the temporal relationship between the predicted value and the lagged values of the dataset.

5.2.3 *NeuralProphet*

NeuralProphet is a Neural Network based PyTorch implementation of Facebook's Prophet time series forecasting library (Taylor & Letham, 2018). NeuralProphet combines the gradient descent for optimization using PyTorch as the backend, autocorrelation modelling of time series using AR-Net (Triebe et al., 2019), and lagged regressor modelling using separate non-linear Feed-Forward Neural Network (FFNN) layers. NeuralProphet decomposes the time series into components, trend, seasonality, auto-regression, special events, future covariates, and lagged covariates.

Future covariates are Covariate Conditions which have known future values for the forecast period whereas the lagged covariates are those Covariate Conditions which have values for the observed period. Trend can be modelled either as a linear or a piece-wise linear trend by using changepoints. The AR-Net component is an Auto-Regressive FFNN for time series. Lagged covariates are also modelled using separate FFNNs (Triebe et al., 2019). Future covariates are modelled with dedicated coefficients, this helps build a forecasting model for scenarios where there are specific external factors which can influence the behaviour of the target output, such as specific flight routes.

5.2.4 *Conditional-LSTM*

The LSTM model is a unique kind of RNN built to handle temporal data and is capable of learning all the long-term dependencies in time series data. The LSTM model, like the RNN, processes the data while passing on information as it propagates forward (Siami-Namini et al., 2019)(Josh Patterson & Adam Gibson, 2017). The difference, and improvement, is the operations within the cells of the LSTM model, which allow the LSTM to keep or forget information. LSTMs enable backpropagation of the error through time and layers hence helping preserve them. The conditional aspect of the Conditional-LSTM includes item-dependent values, as Covariate Conditions, as part of the input. These conditions are fed into the model, which learns a representation of these conditions. These learned representations are then used to initialize the LSTM part of the model, thus properly incorporating these conditions as part of the forecasting process (Figure 5.5).

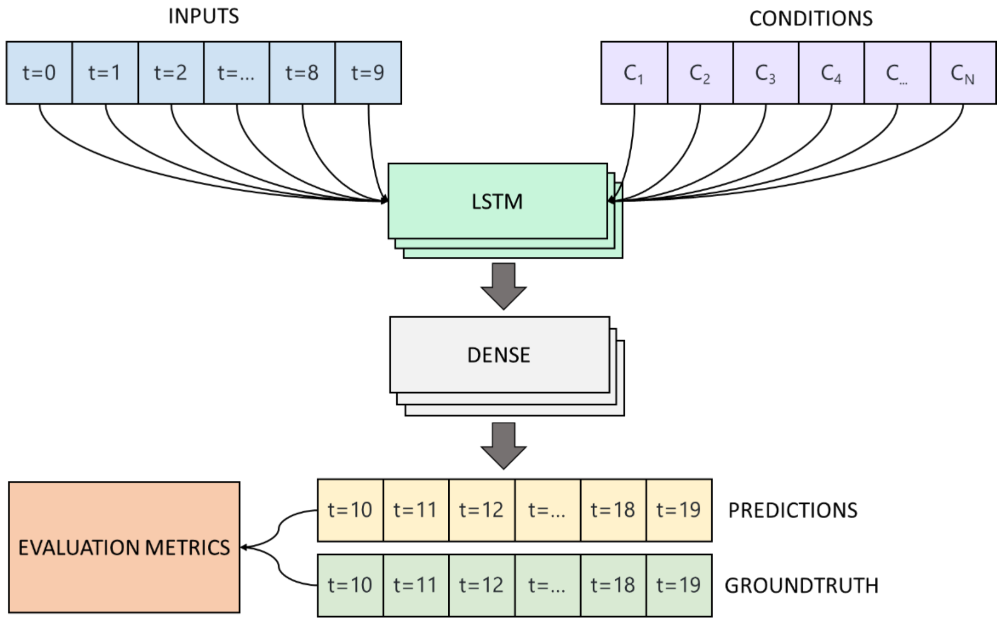

Figure 5.5 – Cond-LSTM model architecture.

5.3 Experimental Setup

The raw data files were uploaded to a Google Cloud Platform (GCP) Cloud Storage Bucket. In order to work with large amounts of data (i.e., 6 years' worth of flight data), all of the preprocessing steps model training, and evaluation metrics were executed on a GCP computing instance (64vCPUs, 240GB RAM, 1x NVIDIA Tesla T4 GPU). The computing instance was used to run a JupyterLab environment, using the open-source Python programming language to connect the instance to the Storage Bucket, perform any preprocessing steps on the data, create and train all the considered models, and finally evaluate the results (Figure 5.6).

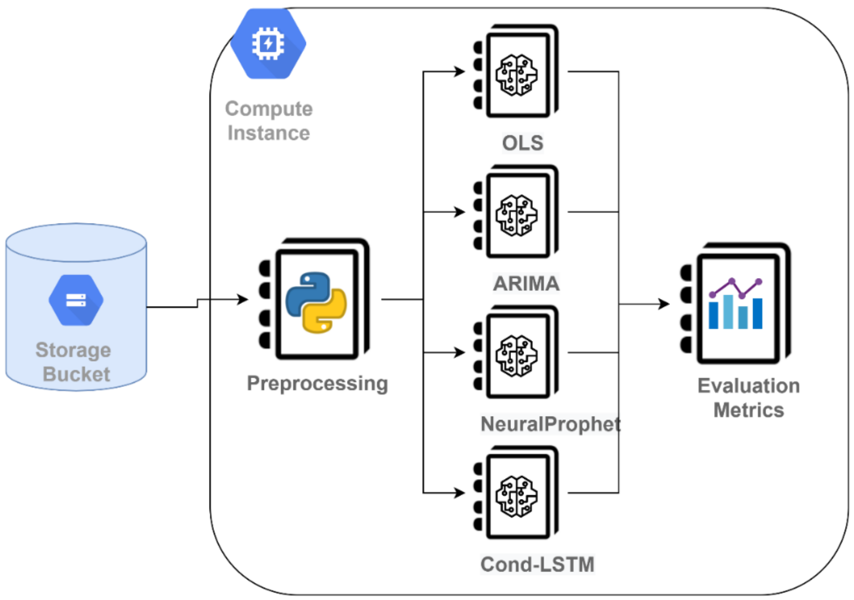

Figure 5.6 – Experimental setup.

5.4 Machine Learning Algorithms Evaluation Metrics

Forecasting models have been widely used in several sectors of the industry to prepare for conditions and situations that may occur in the future. Forecasting errors are a common aspect of any given model, and it is important to correctly identify and evaluate these errors (Kitani et al., 2012). Different forecasting applications rely on different criteria of error calculation, where the overall forecast accuracy can be calculated in several ways (Papers et al., 1995), and there is no consensus on the most appropriate metric for model errors (Willmott & Matsuura, 2005)(Willmott et al., n.d.). The evaluation metrics considered for all four models were Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

RMSE is a standard statistical metric used to measure model performance in a variety of areas. RMSE is an absolute error measure that squares the variance of the residuals to keep the positive and negative deviations from cancelling one another out. As the square root of a variance, RMSE can be interpreted as the standard deviation of the unexplained variance and maintains the same units as the response variable. Lower values of RMSE indicate better fit (Hyndman & Koehler, 2006).

MAE is another widely used metric for model evaluation. The main difference between RMSE and MAE errors is that the MAE gives the same weight to all errors, and the RMSE heavily penalizes variance as it gives more weight to errors with higher absolute values than with smaller absolute values. Therefore, when presented together, RMSE may never be smaller than MAE (Willmott & Matsuura, 2005).

MAPE uses the sum of the absolute prediction errors divided by the target value, divided by the total number of predictions, and returned as a percentage. This evaluation metric is chosen due to its intuitive interpretation of the relative error as it is important to identify relative variations in the values predicted (Armstrong & Collopy, 1992)

Chapter 6 - Results Analysis

This chapter intends to present (i) the influence of measured parameters and operational conditions on the engine performance and mechanical degradation rate as well as their impact on engine TOW and DMC, and (ii) the results of the ML methods used for forecasting engine behaviour. Section 6.1 is particularly based on two CF6-80C2-B7F turbofan engines denominated as Engine A and Engine B to preserve anonymity. Both engines are configured as high thrust rating since new and have operated on different aircraft and different routes. This section focuses on the observation of the operation profile impact on each engine performance and identification of the factors that most influence the engine behaviour before trying to predict it. Section 6.2 is based on Engine A historical flight data, which is composed of several measured parameters in addition to few aircraft sensor measurements. The flight data history, turned into a time series dataset, was used to train, and test the ML models. The selected models were OLS, ARIMA, NeuralProphet, and Cond-LSTM. The models forecasting capabilities were evaluated by different metrics.

6.1 Factors that influence engine behaviour

Except for the SV history, which is back to engine birth, all the parameters analysed were based on the last six years of operation, such as environment and region of operation, engine wash history, flight length, and flight data. During the period of analysis, both engines operated until failure and removal from the aircraft for heavy maintenance. Hence, the data can be divided into two period of times, pre-SV and post-SV. In addition to ECM trends, several other parameters and information that impact engine TOW were considered. Information from other sources were also useful for the analysis, some of which are not directly related to physical sensors, such as constraints, and domain knowledge (Volponi, 2014).

Constraints refer to the fact that with time and operational use, a gas turbine would be expected to degrade, not get healthier. This places bounds (or constraints) on the general solution and in effect reduces the number of unknowns. Domain knowledge refers to the laws of physics, which requires certain interrelationships to exist, as well as OEM technical documentation related to parameter correlation. For example, if fuel flow increases but EGT decreases, this would not be an indicative of an engine failure but would suggest a problem in engine indicating system.

Information is essential for any analysis and engine sensors provide just one avenue for potential information. Domain knowledge, constraints, analytical inferences, experience, and general methods for combining these pieces are important elements to understand engine behaviour before trying to predict it. The focus of this section is to compare Engine A with Engine B as it is important to highlight their similarities and differences in operation history and overall behaviour.

6.1.1 *Environment of Operation*

Environmental contamination, such as sand, dust, and volcanic ash, has been a major contributor to turbofan engine hardware distress, performance deterioration and, in some instances, operability problems. Although turbofan engines have significantly improved their durability due to advances in engine design and material technology, environmental contamination still impacts the engine’s TOW. Dusty environments such as North Africa, Middle East, Central Asia, and others (Labban, 2016), can damage compressor and turbine airfoils. Figure 6.1 presents the main geographical regions Engines A and B operated between the last two SVs. Note that Engine A has mostly operated in Saudi Arabia, India, and Sudan, which are very harsh environment. Engine B also operated in Saudi Arabia and India, but less frequent than Engine A. Depending on the operating time and number of take-offs in these regions, the hot section airfoils can suffer erosion by sand. In time, airborne contaminants in the environment accumulate on airfoil surfaces resulting in increased deterioration.

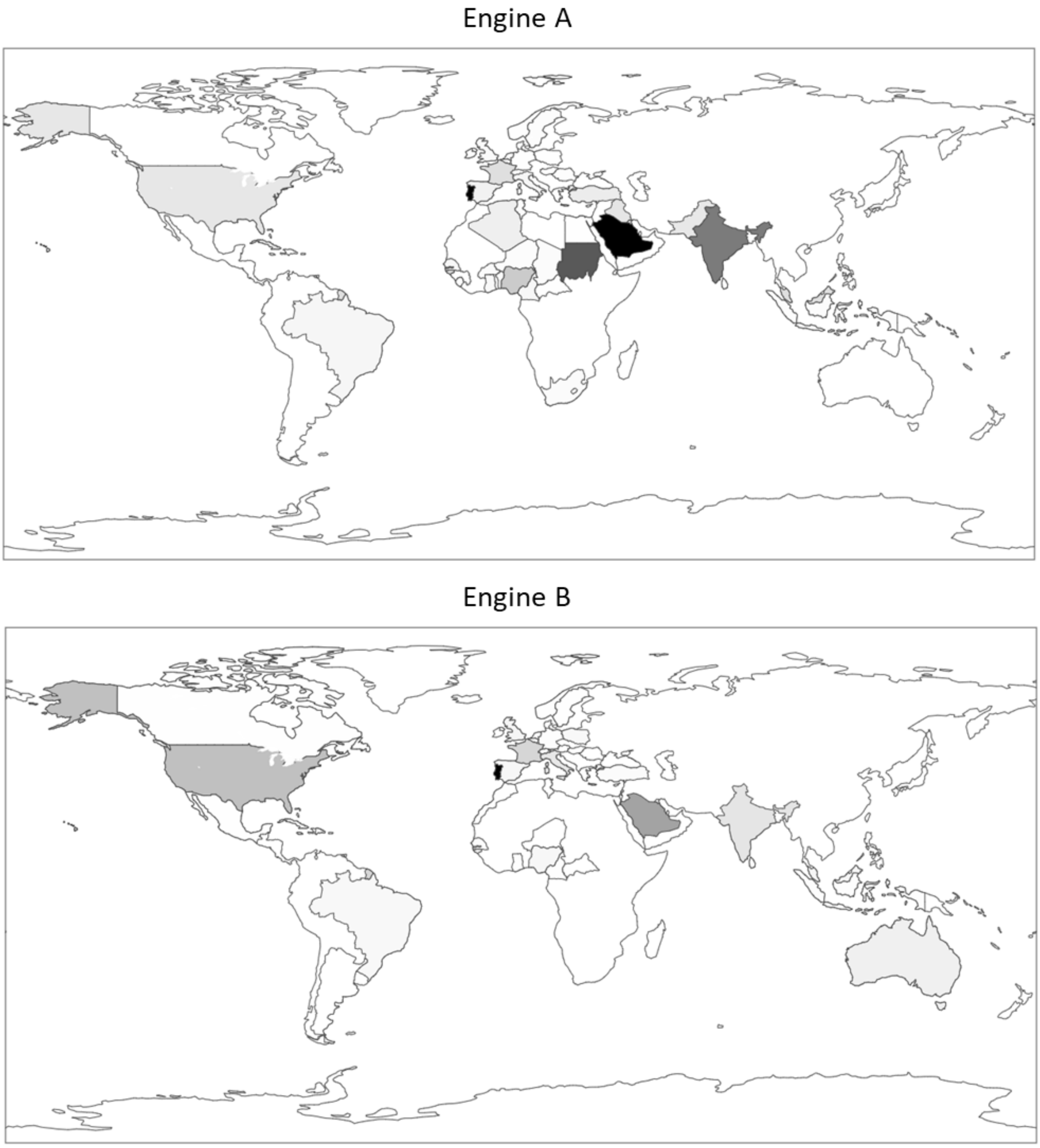

Figure 6.1 – Engines A and B locations of operation. The greyscale represents the number of flights per country, where darker tones correspond to higher number of flights.

Approximately one third of engine A's TOW was taking-off from Saudi Arabia. As a result, inspections of Engine A showed accumulations of sand and dirt inside the engine. Figure 6.2 shows the HPT components with dust deposits, which causes clogging of cooling holes, overtemperature in the turbine, and consequently acceleration of blade deterioration. Without adequate cooling air, HPT blades are more exposed to extremely high temperature. The source of the fine-grained sand appears to be from Saudi Arabia deserts. Sand particles from deserts and coastal regions are one of the major causes of blade distress. In the HPT nozzle, dust collects between the baffle insert, which is designed to distribute cooling air to the airfoils, and the inner airfoil surface. As with the HPT blades, inadequate cooling results in overheating and cracking of the nozzle airfoils.

Figure 6.2 – HPT components of Engine A during module disassembly and inspection. HPT stage 2 Blade (a), HPT Disk (b) – both components present accumulation of dust deposit, and an HPT NGV (c), which shows effects of distress due to overheating.

As previously mentioned, small dirt particles contained in the gas can block the cooling holes causing and over temperature in the turbine. If HPC becomes less efficient and/or HPT become less efficient, EGT increases. Figure 6.3 (a) compares the maximum EGT at take-off from Saudi Arabia and from Portugal for Engine A (similar trends are obtained for Engine B when operated at these location). As explained in section 3.6.1, EGT is highly influenced by the present OAT. The hotter the OAT the higher the take-off EGT. Temperature in Saudi Arabia can get close to 50℃ during summer, causing the EGT to be high and close to its near maximum allowable level (EGT redline) as shown in Figure 6.3 (b). Engines operating in this region or regions with similar climate, are highly recommended to perform compressor washing in shorter intervals than usual.

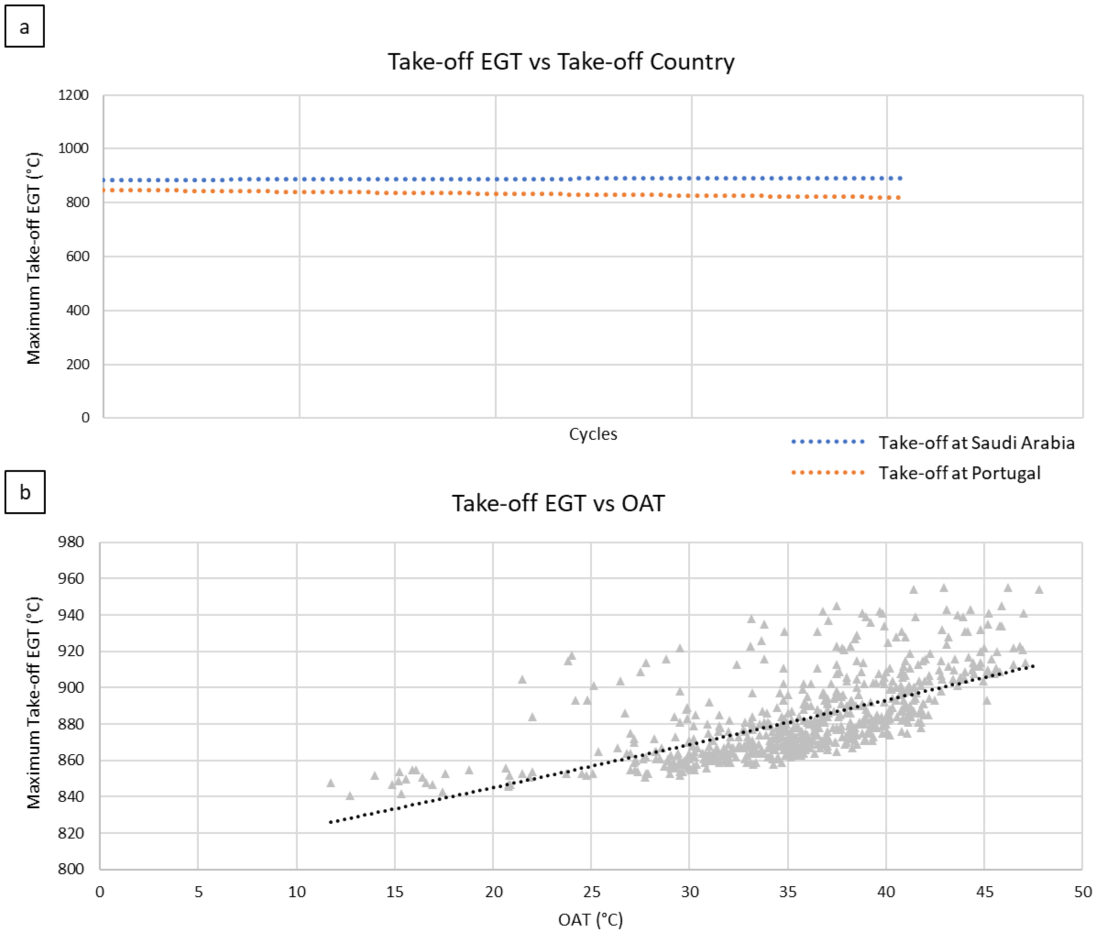

Figure 6.3 – Comparison of maximum take-off EGT at different airport locations (a), and maximum take-off EGT vs OAT during operation in Saudi Arabia (b).

Dust particles mainly damage the engine's hot section components increasing the airfoil scrap rate in the HPC and HPT due to erosion. The effect of the dust in terms of the erosive wear of components and the resulting changes in the essential performance characteristics of the engine have been shown by (Szczepankowski et al., 2017). Ingested dust particles not only cause clogging of the cooling system but also change the shape of profiles of the surrounded blades. In some cases of extreme thermal stress, the blade with no appropriate cooling may be permanently deformed and become scrap or BER condition. The effect of the region of operation, in engine A, can also be seen by analysing the scrap rate history of the OVH SV.

Figure 6.4 presents all the major SVs both engines performed since new, excluding small repairs. The interval of the last two SVs refers to the period of this analysis. Both engines present a higher scrap rate of the HPT blades on the third SV. Engine A also presents a higher HPC blades scrap rate in the last SV when comparing with the first two. There are many factors that contributed to the high scrap rates of both engines, some are: (i) engines age: both engines have been operating for 11000 to 12000 cycles since new; (ii) operation profile between the last two SVs: both engines operated in dust producing regions, which increases airfoils scrap rates; (iii) material condition installed in the previous SV: the scrapped blades of both engines in the second SV were replaced by used condition HPT blades, and used material has lower reliability and is more susceptible to failure, when compared with new material.

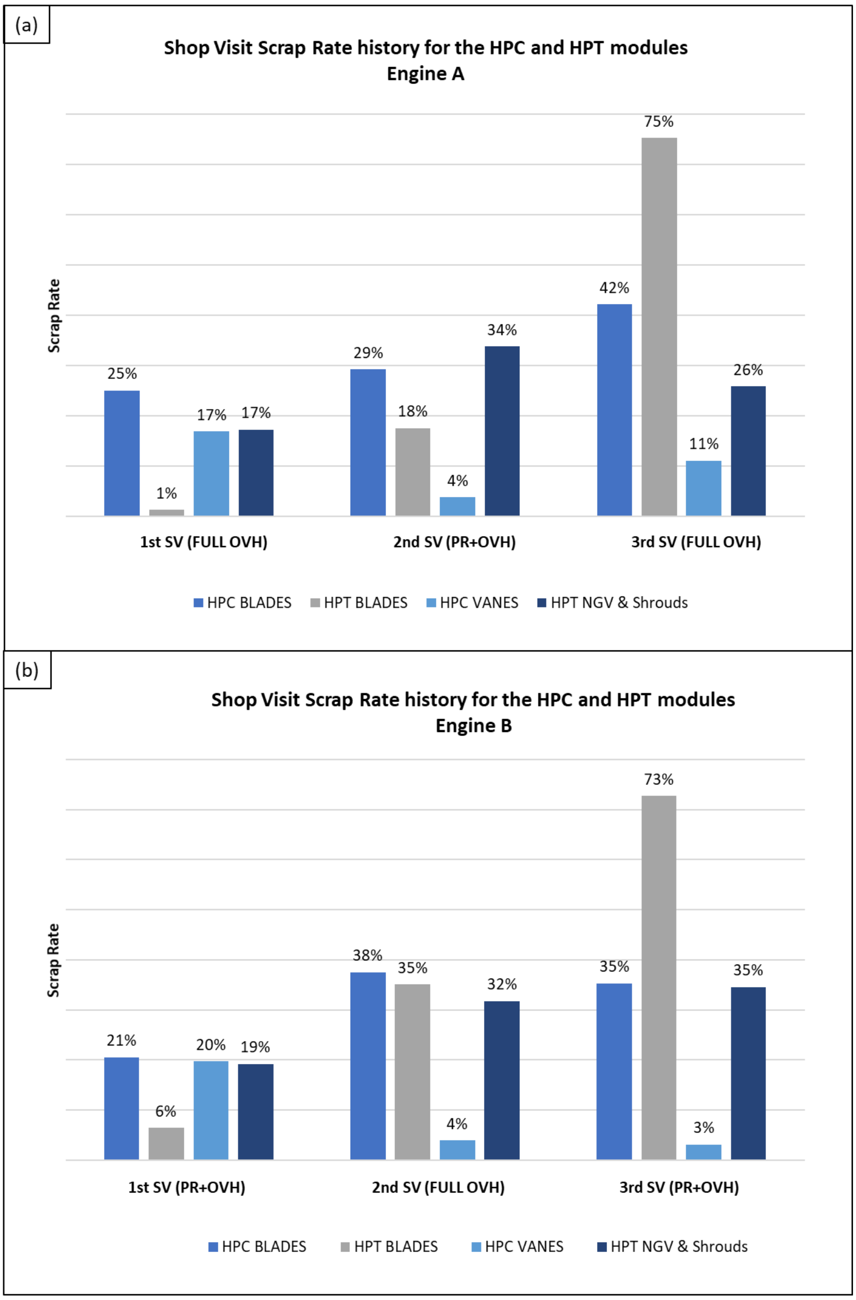

Figure 6.4 – HPC and HPT scrap rate history of Engine A and Engine B. This work analyses the period between the second and third SVs. PR+OVH indicates the WS level of HPC+HPT. Full OVH means OVH WS level for both modules.

6.1.2 *Thrust Rating and Take-Off Thrust Derate*

Actual rates of deterioration will vary with thrust rating and take-off thrust derate. For a given engine variant, EGT margin deteriorates faster when operating at higher thrust levels. Full thrust take-off at high ambient temperatures causes the engine components to operate very near their maximum operating limits. Increased time operating at this condition can result in degradation of the thermal barrier coating of the blades, which increases blade distress and can also result in loss of turbine airfoil material. Then, a high scrap rate of turbine airfoils may occur when inspecting the turbine module. Both engines are configured at high thrust rating since new. The period of analysis herein is of six consecutive years of operation. During this period, both engines' thrust derate average was between 16%-20% (Figure 6.5).

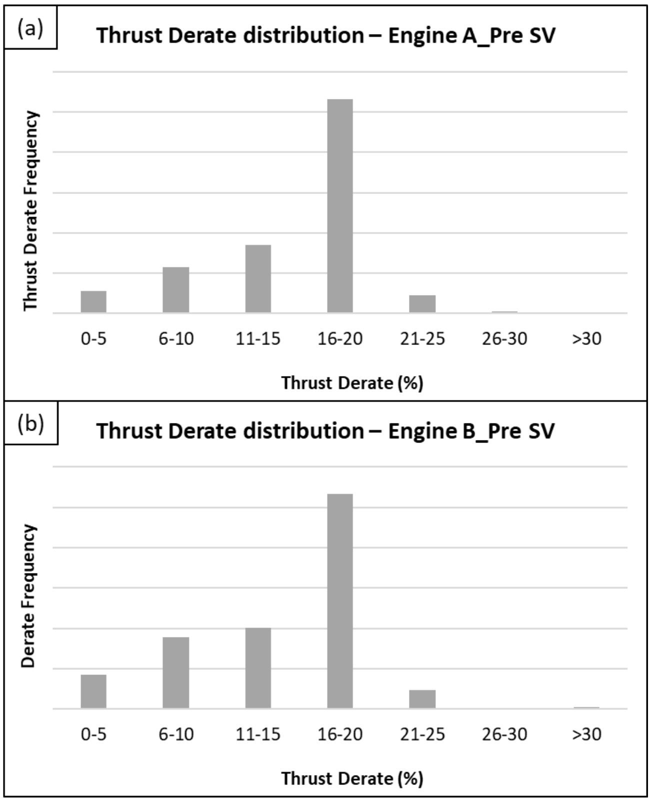

Figure 6.5 – Thrust derate frequency of Engine A and Engine B before SV.

In order to verify the impact of thrust derate on the EGT, the flight data from similar operation region were grouped according to the take-off thrust derate and plotted with the correspondent maximum take-off EGT (Figure 6.6). The differences in take-off EGT are remarkably. It is important to note that the trends are similar for thrust derate above 5%. Therefore, thrust derate below 5% has insignificant benefits for the operation, whereas operations using thrust derate above 5% not only reduces fuel consumption during take-off but also reduces engine's wear and tear caused by stress and high temperatures. The effectiveness and long-term benefits of using thrust derate aiming to reduce EGT to improve performance, prolong engine life and reduce operating costs of the operators were shown by (Irsyadi & Nirbito, 2019).

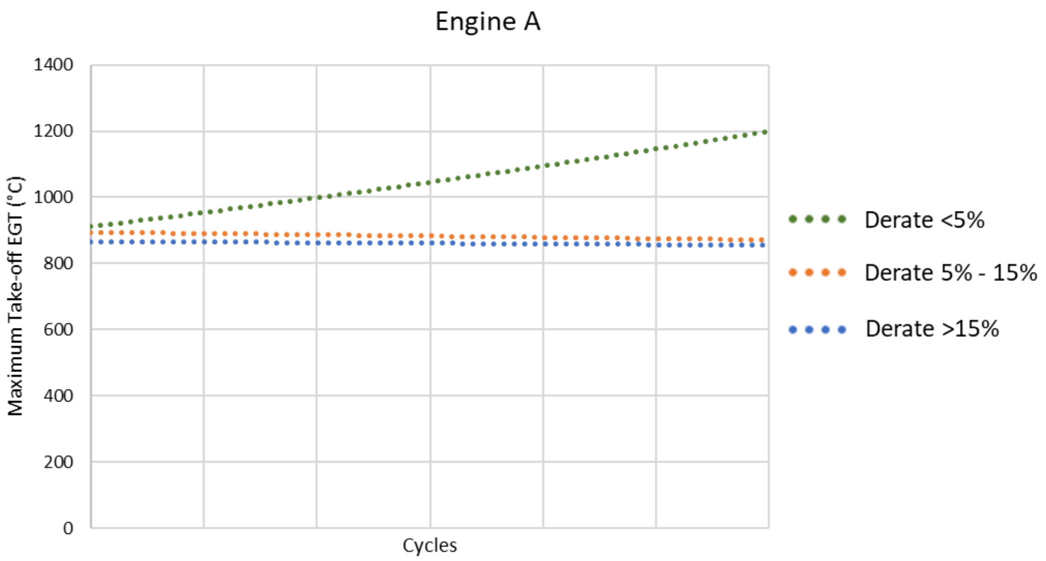

Figure 6.6 – Maximum take-off EGT according to different take-off thrust settings.

6.1.3 *Engine Age*

As the engine ages, it becomes less efficient, burns more fuel, and runs hotter to provide the same amount of thrust due to the deterioration of the components (Justin & Mavris, 2015). In terms of maintenance, an engine's life cycle can therefore be divided in first-run and mature-run phases. There is no clear definition when an engine's mature phase starts. Maturity may begin as early as after the first shop visit, depending on the engine model. In general, first-run engines will achieve considerably longer times on-wing than subsequent runs, because of the increasing rates of hardware deterioration as the engine ages.

Figure 6.7 presents the accumulated time between the life cycle phases of engines A and B. Both engines show similar TOW between the first two SVs with similar reduction between the first-run and mature-run1. However, it is noted that Engine A had a less TOW than Engine B between the second and third SVs. Many issues directly or indirectly influence the shop visit intervals. The rate of SV events depends mainly on the engine's utilization, maturity, and operational severity. The region of operation is one of the main factors influencing the engine TOW. As the focus of this section is to compare Engine A with Engine B, it is important to note that the environment of operation may have been the driver of engine removal interval and may have impacted the TOW of Engine A.

As the engine ages, the take-off EGT margin decreases and performance is lost due to several factors, such as FOD, compressor airfoil erosion, increased air seal clearances, compressor, and turbine blade tip clearances due to rubs, dust/dirt accumulation on fan and compressor airfoil, etc. This reduction in EGT margin and performance is gradual, and depending on the initial EGT margin, a typical engine can stay on-wing for up to 5+ years before requiring a performance restoration. Engine wash is a recommended procedure that extend the engine TOW. However, older engines require performance restoration more frequently, and with time only a small percentage of performance is restored, and more LLPs reach their life limit, this can increase DMC exponentially until the point where the engine becomes BER.

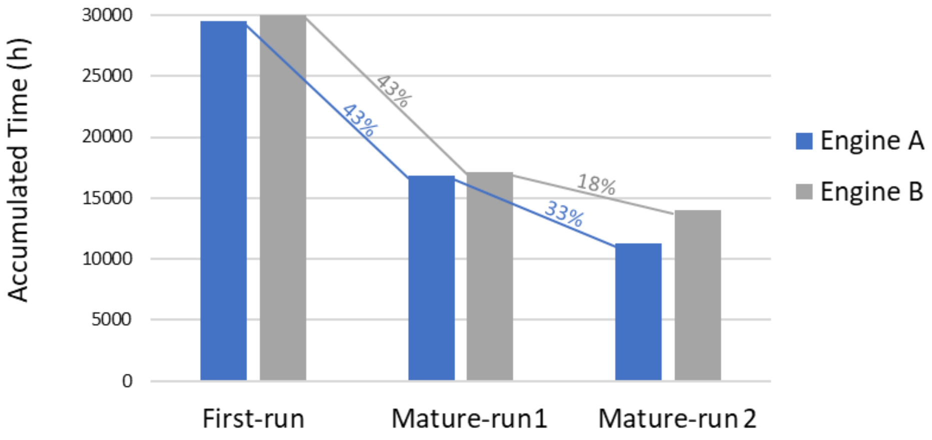

Figure 6.7 – Accumulated time between shop visits.

6.1.4 *Flight Length*

The measurements of length of time an engine remains in service, also known as TOW, is quantified in both flight hours and flight cycles. As described in section 4.2.2, engines operating in short routes tend to accumulate a greater amount of flight cycles, which implies in LLP replacement at frequent intervals since LLP lives are limited in cycles. Consequently, short routes cause higher material costs during SV. Whereas engines operating medium to long flight lengths are exposed to higher levels of wear and deterioration leading to a higher degree of parts being repaired or replaced during maintenance, which also contribute to a higher total maintenance cost.

Flight time-to-cycle ratio is another parameter that describes engine operation profile. Each thrust setting – take-off, climb, and cruise – affects the severity of engine operation, thus depending on the amount of time an engine spends at each thrust setting during its life, the engine may require more removals for maintenance than others. For example, on shorter flight lengths, a larger proportion of total flight time is during take-off and climb thrust levels, which expose the engine to higher temperatures, pressures and speeds. As a result, higher rate of performance deterioration and higher impact on the DMC.

In order to verify the impact of flight lengths on the EGT of Engines A and B, the flight data from both engines were grouped according to the total flight time and plotted with the correspondent maximum EGT during cruise (Figure 6.8). Both engines show to have lower EGT during flights between 3 and 5 hours long. Moreover, it is important to note that both engines have shown the tendency to have higher EGT at flights longer than 6 hours. Flights of 1 to 2 hours long have the most impact on these engines.

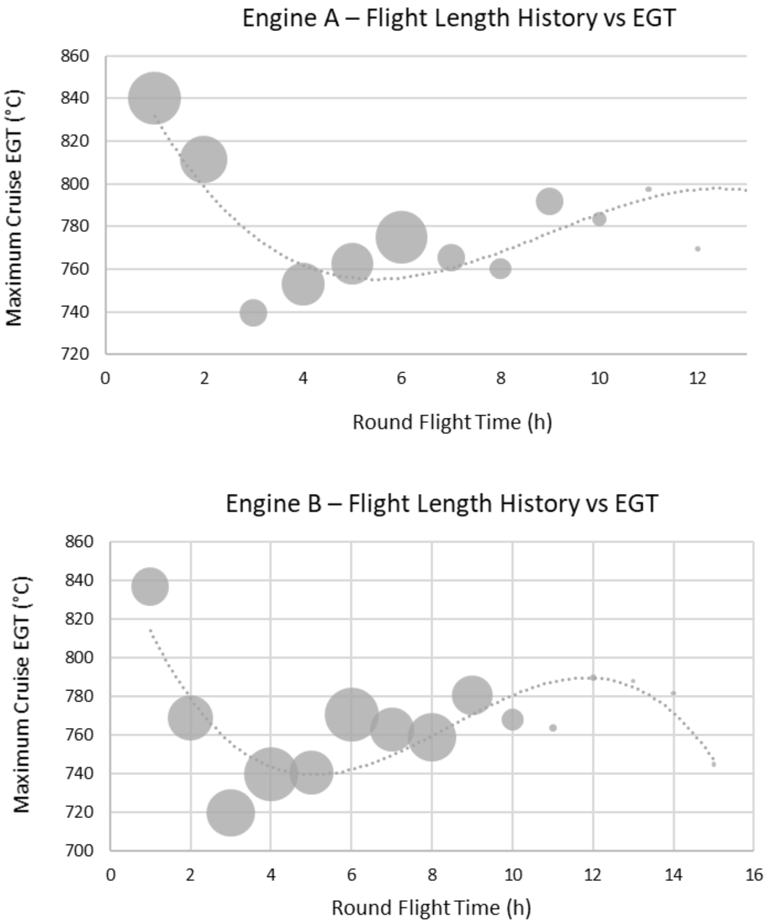

Figure 6.8 – Comparison of maximum EGT reached during cruise with total flight length.

6.1.5 *Engine Wash History*

All engines tend to lose performance during normal operation due to airfoil contamination and degradation. One of the solutions is to keep the engine core clean. This procedure is an on-wing maintenance task recommended by the OEM. As detailed in section 4.1.2, compressor cleaning has many benefits, such as lower fuel consumption and prolonged engine life by retaining the take-off EGT margin. The actual size of the benefits depends on the engine's operation profile. The climate and OAT of the region of operation, and the engine thrust setting direct impact the engine performance and efficiency. To compensate the loss of compressor efficiency, the HPC rotor must operate at higher speed level, thus more fuel is consumed to achieve the same amount of air compression in the compressor sections. The increase in fuel burn lowers overall operational efficiency, causing the hot section to operate at higher temperatures and higher speeds.

Different types of contamination on stationary as well as rotating compressor airfoils cause loss of efficiency in the HPC module. Operation at airports located in dust producing regions is usually the main cause of compressor contamination, as well as normal air pollution. The impact is very high particularly during taxing and take-off phases of flight. As shown in section 6.1.1, Engine A operated longer periods in such regions than Engine B, resulting in less TOW and higher airfoil scrap rates, in addition to a higher EGT margin deterioration rate.

Figure 6.9 shows the EGT margin trend of both engines for the operation period under analysis. The dashed vertical lines represent the time that engine wash was performed, where Engine A required cleaning more often than Engine B due to the high EGT margin loss rate caused by several factors previously mentioned. Even though Engine B started the operation with a higher margin, it is seen that the loss rate was gradual, while Engine A loss rate was more abrupt. Engine A trend shows that between the second and third wash the EGT margin recovery was less than the previous wash gains. The loss rate indicated by the red circle significantly affected the EGT margin not allowing a good recovery after wash, only margin retention. Both engines show good performance after the SV, almost reaching 50℃ in the first flights. More data would be necessary to verify the EGT margin deterioration rate post SV. However, Engine A still presents a higher loss rate.

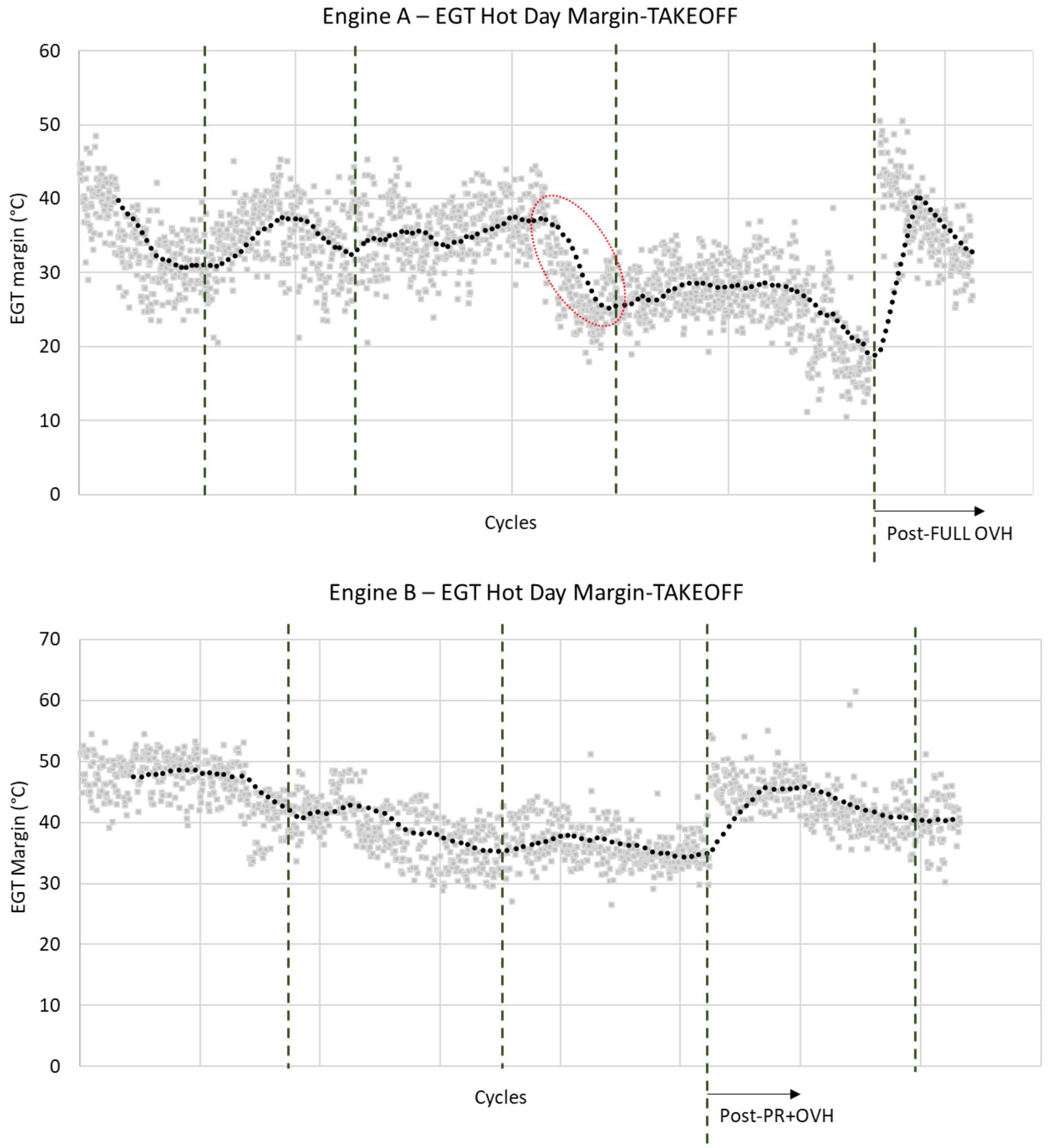

Figure 6.9 – Effect of engine compressor cleaning on take-off EGT margin of Engine A and Engine B. The vertical lines represent engine wash. PR+OVH indicates the WS level of HPC+HPT. Full OVH means OVH WS level for both modules.

6.2 Prediction of Engine behaviour

For this analysis, we collected time series data from a CF6-80C2 engine model configured as high thrust rating. The data was cleaned and pre-processed, and then used to train machine learning models to identify “healthy behaviour” for this class of engine. These machine learning models consider many factors that influence the engine behaviour, such as engine age as well as its maintenance history and region of operation. The engine historical data includes operation until failure and removal from the aircraft for heavy maintenance, and operation post heavy maintenance. The data was used to build ML models for predicting future engine behaviour.

This dissertation focused on the details of forecasting algorithms which can be applied to solve different prognostic problems in engine performance analysis, predicting the probabilities of a gradual deterioration during a period of operation in specific route conditions. The advantage of using time series analysis is to have the engine behaviour parameters for each flight condition. The engine behaviour prediction methods were implemented to provide accurate short-term forecasting of the EGT value during take-off phase allowing the operator to forecast the next engine removal more precisely.

The dataset incorporated to the ML models is composed of several measurements corresponding to (i) aircraft sensor values, such as OAT, altitude, airspeed, and distance travelled, (ii) engine sensor values, such as FF, EGT, N1, N2, etc, (iii) engine status, such as engine TSN/CSN and TSO/CSO, and (iv) operating conditions, such as take-off and landing airports. Understanding the correlation between the parameters is crucial for engine health analysis and fault diagnostics. For this, a correlation matrix was calculated as shown in Figure 6.10. The correlation coefficients vary from -1 to 1, where the former indicates inversely proportional correlation, the latter indicates proportional correlation, and coefficients close to 0 indicate weak correlation between the features. Many parameters influence other parameters, for example, as more fuel flows to the combustor, more heat is generated leading to a higher EGT, which can be noted by the correlation coefficient of 0.79. Another example is the correlation between the rotational speeds, N1 and N2, which also influence EGT.

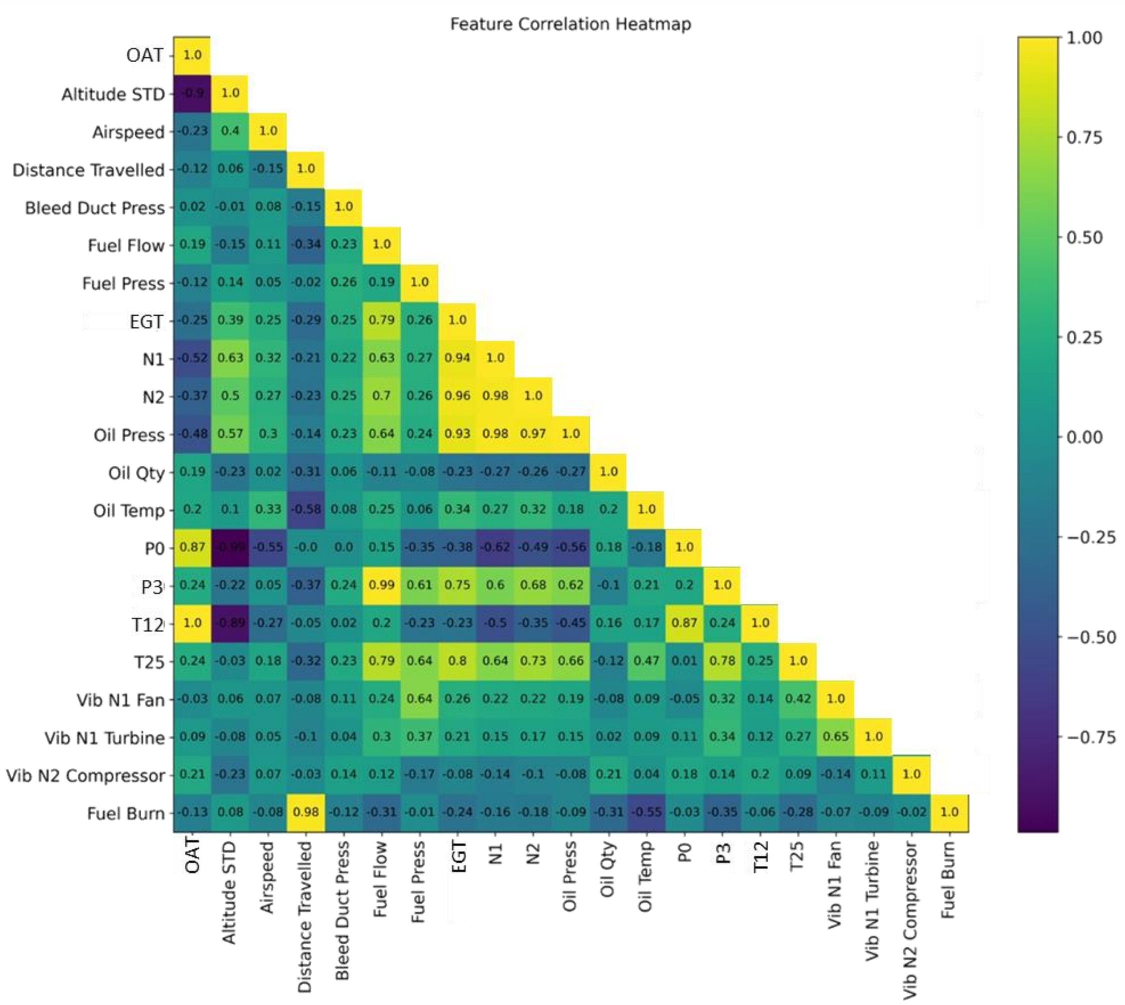

Figure 6.10 – Engine A parameters correlation matrix thermal graph.

Table 6.1 summarizes all the evaluation metrics used during the experiments for each considered model for Engine A. The results were grouped by rolling window size and separated by model. The best results for each rolling window size are highlighted. Overall results improve with higher rolling window size. This behaviour is expected as with a higher rolling window size, the data will have less residual noise, and present a "smoother" behaviour, making it easier for the model to learn. However, it is important to note that smaller rolling window sizes reflect the real data more accurately, therefore, when two distinct rolling window sizes present similar results, it is preferable to consider the smaller rolling window size as the better model. Another important aspect to note is the error threshold that should be considered. Commonly, this threshold value varies depending on the airline policy. In this case, for EGTMax at take-off phase, an error of under 10℃ is considered acceptable, thus the smallest rolling window size with MAE under 10℃ can be considered the better model.

Table 6.1 – Engine A evaluation metrics for the four considered ML models and different rolling window sizes.

Rolling Window	Model	Evaluation Metrics for Take-off EGTMax		
		RMSE	**MAPE**	**MAE**
w1	OLS	22.65	2.05	17.89
	NeuralProphet	38.62	3.82	33.72
	ARIMA	22.67	2.05	17.87
	Cond-LSTM	23.11	2.08	18.31
w2	OLS	24.41	2.29	19.72
	NeuralProphet	16.65	1.38	12.00
	ARIMA	24.46	2.29	19.76
	Cond-LSTM	15.08	1.45	12.60
w3	OLS	24.24	2.27	19.56
	NeuralProphet	15.53	1.56	13.61
	ARIMA	24.25	2.27	19.57
	Cond-LSTM	9.56	0.88	7.64
w5	OLS	24.08	2.27	19.57
	NeuralProphet	14.02	1.30	11.33
	ARIMA	24.09	2.27	19.58
	Cond-LSTM	4.32	0.40	3.48
w7	OLS	23.04	2.19	18.91
	NeuralProphet	12.81	1.20	10.50
	ARIMA	23.06	2.19	18.93
	Cond-LSTM	3.41	0.31	2.68
w10	OLS	22.49	2.11	18.24
	NeuralProphet	11.21	1.09	9.56
	ARIMA	22.54	2.12	18.29
	Cond-LSTM	3.16	0.31	2.70
w12	OLS	21.59	2.00	17.31
	NeuralProphet	9.28	0.90	7.90
	ARIMA	21.59	2.00	17.26
	Cond-LSTM	1.69	0.16	1.36
w15	OLS	21.36	2.01	17.37
	NeuralProphet	9.55	0.96	8.45
	ARIMA	21.41	2.01	17.38
	Cond-LSTM	1.28	0.12	1.05

The forecasting results for the overall best performing model, the Cond-LSTM, can be seen in (Figure 6.11). Even without any smoothing from the rolling window, the model was able to forecast the general behaviour of the engine for the specified flight routes. As previously mentioned in section 4.1.1, when performing ECM for gradual deterioration analysis, the parameters are observed through a smoothed trend in order to obtain a general behaviour of the engine, instead of considering each individual point. Therefore, this model is able to provide an output that mimics the type of analysis that is widely used in condition-based monitoring.

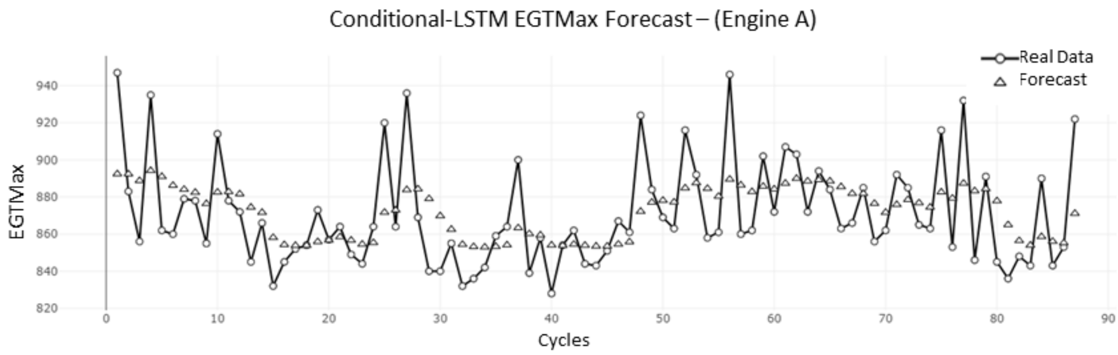

Figure 6.11 – Forecasting results for Cond-LSTM without rolling window.

The root mean squares of the errors from Table 6.1 were plotted for a better visualization of the model's comparison, and it is observed that the best results were obtained by the Cond-LSTM model (Figure 6.12). This model handles temporal data by considering 10 lagged values as well as Covariate Conditions to make its predictions. It is important to take into consideration the worst-case scenario when predicting the EGTMax in order to maintain a safe margin. This means that when using the forecast for engine health monitoring, the upper bound should be estimated using the predicted value plus the error. By considering the upper bound value of the forecast, the engine performance deterioration will be overestimated, which is preferable from a safety perspective. Even though we aim to reduce the overall error of the forecast it is ideal to consider the worst-case scenario when making decisions based on the model's results.

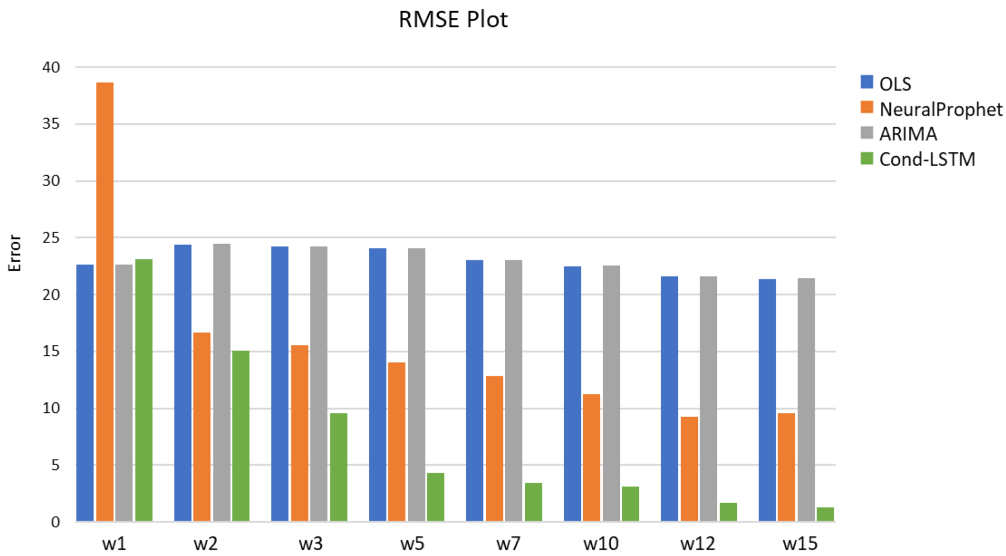

Figure 6.12 – Visualization of RMSE of EGTMax for different machine learning models with different rolling window sizes.

Figure 6.14 graphically presents the ML model Cond-LSTM EGTMax forecasting results for the different rolling window sizes for Engine A presented in Table 6.1. It is clear that even with the worst performing rolling window size (window=2), with the highest MAE of 12.6 degrees for this model type, the forecast results correctly follow the behaviour of the real data. With rolling window size of 5, the forecasting results near perfectly follow the behaviour of the real data, with a small MAE of 3.48 degrees.

Figure 6.13 shows the overall error distribution for each rolling window size using the Cond-LSTM model. All rolling window sizes present a median error very close to zero, with rolling window sizes equal to 10 or greater showing a much smaller variance in the distribution of error values. These results further solidify the assumption that higher rolling window sizes significantly improve the model's performance, with the highest rolling window size (window=15) presenting very little variance of error.

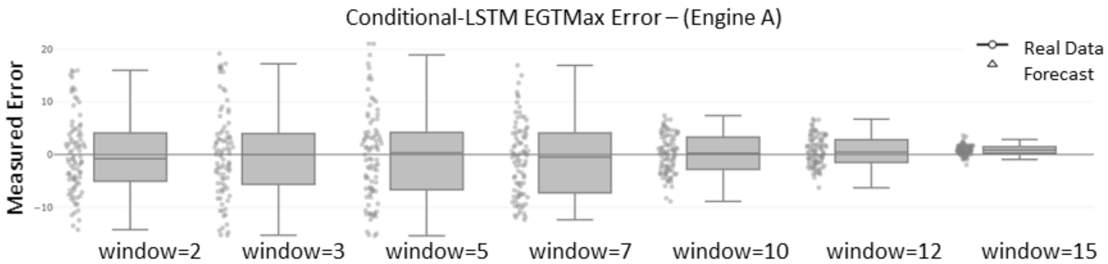

Figure 6.13 – Boxplot of distribution of errors for each rolling window size for the Cond-LSTM model.

The Cond-LSTM model also showed good results in forecasting other engine behaviours, such as Fuel Burn Rate. As shown in Figure 6.15 its clear that with a rolling window size of 5, we can confidently forecast Fuel Burn Rate values. Fuel Burn Rate, different from EGTMax, is not necessarily an indicator of engine deterioration, but it is an important aspect of condition monitoring and knowing its value for future flights can be extremely useful for airlines to estimate operating costs closer to the real scenario.

Figure 6.14 – Engine A EGTMax forecast for 85 future flights using Cond-LSTM with different rolling window sizes.

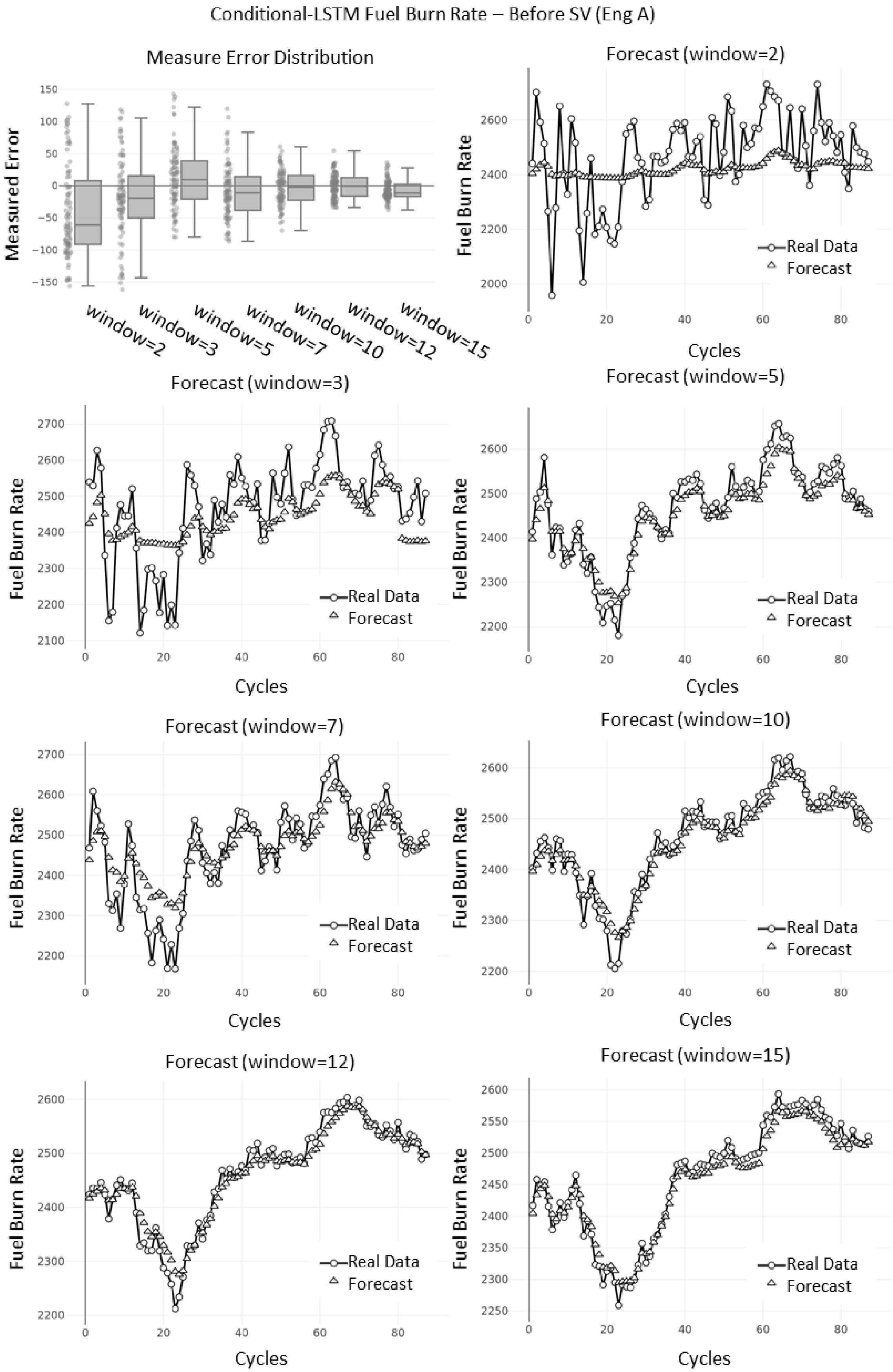

Figure 6.15 – Engine A Fuel Burn Rate boxplot of errors for all rolling window sizes and forecast for 85 future flights using Cond-LSTM with different rolling window sizes.

Chapter 7 - Conclusion

The main goal of the process was to perform accurate predictions of the take-off EGT parameter to achieve significant benefits with respect to engine TOW management. Reliable prognostics are the key to efficient condition-based maintenance and engine removal forecast for better decision-making. The potential of different machine learning approaches to predict the engine's deterioration was analysed considering both safety and economic factors. Engine TOW efficient management requires finding the optimal time for engine removal considering its performance status, and avoiding subjecting components to prolonged stress, which greatly impact engine maintenance costs. Operating and maintenance history of two mature CF6-80C2 turbofan engines were used for the analysis. Long engine operation history allowed the identification of the impact of different factors on engine performance, such as operation environment, thrust settings, flight length, engine age, compressor cleaning, and others.

The factors that most impact the engine performance as well as the engine maintenance costs were analysed and presented:

(i) Operation profile: dust producing, high temperature climate regions showed to be a greater contributor to the hot section components deterioration due to their exposure to extremely high temperatures, which results in a high airfoils scrap rates and consequently high SV material costs;

(ii) Engine thrust settings: thrust derate above 5% showed to have significant benefits such as reducing engine's wear and tear caused by stress and high temperatures;

(iii) Engine age: as the number of operating hours and cycles increase, the TOW between SVs decreases because the engine becomes less efficient, burns more fuel, and runs hotter to provide the same amount of thrust due to the deterioration of the components;

(iv) Time-to-cycle ratio: flights between 3 to 5 hours of duration showed to have less impact on engine degradation;

(v) Material condition: installing used condition HPT airfoils can increase the next engine SV scrap rate because of their low reliability, or even impact engine TOW by causing an UER;

(vi) Engine wash: this maintenance action has shown great impact on the engine's TOW as it recovers and retains engine performance, in addition, the implementation of a gas path cleaning at the beginning of EGT margin loss demonstrated to have a greater effect on recovering margin when compared to a cleaning that is implemented after a significant loss of the engine's EGT margin.

After the analysis of the factors that most impact the engine performance, advanced machine learning methods were used to predict engine parameters. The ML methods were chosen according to the kind of data analysed. Real engine flight data history, turned into a time series dataset, was used to train, test, and validate the models by different evaluation metrics. The dataset included six years of operation of a mature CF6-80C2 turbofan engine. The engine behaviour prediction methods provided immediate and short-term forecasting of the EGT parameter at take-off, which is the most critical phase of a flight as the engine's components operate at great thermal and mechanical stress. The prediction considered specific operations and flight conditions (i.e., flight route, estimated flight duration, day of the year, etc.). In addition, it has been shown that the method can be used to predict any other parameter at any flight phase, such as engine vibration, fuel flow, N2, and others.

Statistical regression analysis and artificial neural networks were used in the prediction model. The selected models were OLS, ARIMA, NeuralProphet, and Cond-LSTM. In order to compare the methods, the evaluation metrics RMSE, MAPE, and MAE were calculated, and the best model was presented on Table 6.1. Even though all four models have shown promising results, the method that presented the lowest error was the neural network method named Cond-LSTM. Rolling window of different sizes were explored in order to improve the performance of the models. These experiments showed that higher rolling window size significantly reduced the error of all models. However, it is important to maintain the training data as close as possible to the real flight data by keeping the lowest rolling window size as possible. The Cond-LSTM showed the best result with the rolling window size of 3, keeping the MAE below the considered threshold value of 10℃. Cond-LSTM as well as ARIMA and OLS models have also shown promising results without applying rolling window to the training data. The models output a smoothed trend of the forecasted variable, which is similar to what is currently done manually during ECM.

Forecasting engine parameters that indicate the engine's performance brings several advantages. The main contributions of this dissertation are listed below:

1. A predictive model that forecasts the take-off EGT allows the operator to specify flight conditions to simulate future flights. With the forecast data the operator can identify and quantify engine gradual performance deterioration rate ahead of time. This has a significant impact on TOW management:
    a. allowing a more efficient engine removal planning:
        i. with no operational impact due to engine change;
        ii. ensuring engine spare availability not implying AOG for long period of time due to missing engine;
    b. allowing more efficient maintenance planning:
        i. by detecting optimal time for performing engine wash, which permits a greater EGT margin recovery extending engine's TOW;
        ii. by managing the engine SV in advance. This allows a better negotiation with the MRO as well as a better WS level preparation, and SV costs estimation more precise.
2. With the forecast data the operator can simulate the impact of different routes on the engine performance allowing:
    a. adjustment of the severity factor to be more realistic;
    b. simulation of DOC, especially fuel consumption, in specific flights considering all the factors that impact engine degradation and consequently impact engine fuel consumption.

In conclusion, this dissertation provided detailed analysis of the main factors that impact aircraft engine performance and TOW. Moreover, the results provided different evaluation metrics to compare the prediction capabilities of four different ML methods for our time series data. This work has shown that Cond-LSTM is a reliable tool for predicting engine behaviour allowing for gradual performance deterioration prognosis under specific operation type that can be determined by the operator. In addition, forecasting engine performance parameters has shown to be useful for identifying the optimal time for performing important maintenance action, such as engine gas path cleaning. Engine removal forecast can be made easier by using sophisticated trend monitoring and advanced ML methods.

Although this dissertation explored different prediction methods for engine time series data, future work is needed for the development of a tool that can completely predict engine behaviour under any specific condition and any operation type. For this, and considering that ML models learn from experience, a larger amount of historical flight data of a higher number of engines that have had different operation types and experienced different types of failures is necessary for developing a more efficient predicting tool for aircraft engine behaviours.

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