Aircraft Engine Fuel Consumption

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Abstract

This work aims to mathematically model the fuel consumption of an aircraft engine. The objective is to compare engines and assess missions and flight phases to gain insights into fuel consumption patterns.

Keywords: Aircraft Engine, Mathematical Modeling, Simulation, Fuel Consumption, Engine Performance, Flight Data, Comparative Analysis.

1 Motivation

In response to the imperative of mitigating climate change, the aviation industry has mobilized under the banner of the Air Transport Action Group ATAG to achieve the ambitious goal of zero-carbon operations by the year 2050.
A primary contributor to carbon emissions in aviation is the combustion of traditional fossil fuels, the transition towards sustainability involves exploring alternatives such as hydrogen and sustainable aviation fuels SAF. Concurrently, advancements in technology have enabled engine manufacturers to significantly reduce fuel consumption. Other innovations include the incorporation of ceramic components CMC for hot parts, additive manufacturing

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of intricate components, and the integration of carbon fibers to enhance the efficiency of blades and carter.
Illustrating this progress, Safran's latest turbojet engine, the LEAP, demonstrates a 15% reduction in fuel consumption compared to its predecessor, the CFM56, which powers widely-used Boeing 737 and Airbus A320 series.
Despite these advancements, optimizing fuel efficiency extends beyond engine design to encompass operational aspects. Engineers are actively engaged in developing physical and numerical models to identify critical flight phases, recommend optimal piloting practices, and suggest more fuel-efficient routes. This paper does not present a specific model but proposes a foundational numerical baseline as a precursor to more intricate solutions. Once established, this baseline will serve as a reference for understanding the standard behavior of an aircraft. Observing deviations from this standard will facilitate the identification of missions with either excessive or below-normal fuel consumption, thereby contributing to the broader objective of sustainable aviation practices.

2 Methodology

In this study, we aim to construct a predictive model for global consumption by leveraging rigorous methodologies to assess its robustness through a cross-validation process. Following the precision evaluation of the model, we will proceed to scrutinize flights displaying atypical consumption patterns.

The study employs a dataset containing 3 datasets with around 1000 flights each, that describe the dynamic behavior of aircraft engines. It includes factors accounting for typical engine wear and records various engine wear parameters such as position, pressure, temperature, and other critical operational variables. Our primary objective is to mathematically model engine fuel consumption, systematically comparing engines, missions, and flight phases.

2.1 Data Evaluation

The aviation process is split into distinct phases, encompassing five primary stages: an initial and final *taxi* phase [1], a *climb* phase, a *cruise* phase, and a *descent* phase. Within the purview of this particular investigation, our focus is specifically directed towards the essential phases of the flight, namely the climb, cruise, and descent periods, since the *taxi* phase depends on the airport.
The aircraft records flight-data during each journey, capturing measurements from both engines and various sections within each engine. To distinguish these measurements, suffixes $_1$ and $_2$ are used for the left and right engines respectively [2].
The measurements of particular interest to us for this work are described in the table below.

Variable [u]	**Description**
ALT [ft]	Altitude
TAT [deg C]	Total Air Temperature (measured by the aircraft)
M [Mach]	Mach [3]
EGT_# [C]	Exhaust Gas Temperature for r.e [4]
FMV_# [mm]	Fuel Metering Valve position for r.e
HPTACC_#[%]	High Pressure Turbine Automatic Clear Control for r.e
NAIV_# [bl]	Anti Ice Valve for r.e
Q_# [lb/h]	Fuel flow for r.e
TLA_# [deg]	Level Angle for r.e
T_OIL_# [C]	Oil temperature for r.e

Table 1: Description of variables in the dataset

As introduced other measurements are taken at various locations on each engine, referred to as Stations, with the index "i" indicating the position of the measurement accoording to Figure 1.

[1] period during ground operations when the aircraft moves on the runway under its own power, either prior to takeoff or after landing, to and from the runway and parking areas
[2] notated as $_\#$ below

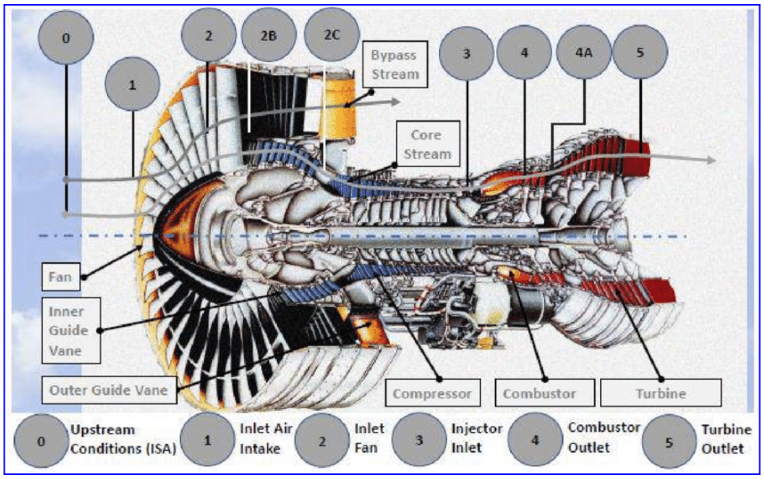

Figure 1: Engine parts

Some variables that include this notation are Temperature (T), Pressure (P) and Speed (N):

Variable [u]	Description
P0_# [psia]	Pressure at the inlet for r.e [5]
T1_# [deg C]	Temperature at the fan level for r.e
T2_# [deg C]	Temperature after the booster for r.e
T3_# [deg C]	Temperature at the compressor outlet and before the combustion chamber for r.e
T5_# [deg C]	Temperature of the air in the nozzle for r.e
N1_# [% rpm]	Speed of the secondary shaft (fan) for r.e
N2_# [% rpm]	Speed of the primary shaft (core) for r.e

Table 2: Description of variables regarding the Station

Illustrated in Figure 2 is an example of two variables in a particular flight: the red bottom line refers to Alt (altitude in feet) of the aircraft and the top blue line corresponds to a boolean variable NAIV_1 that indicates whether anti-ice is activated or not for the first engine. In particular the anti-ice system acts where the engine's power is attenuated through the implementation of hot air sampling. This particular measure assumes significance owing to its capacity to influence consumption positively. Notably, the anti-ice system is invoked during both takeoff and landing procedures.

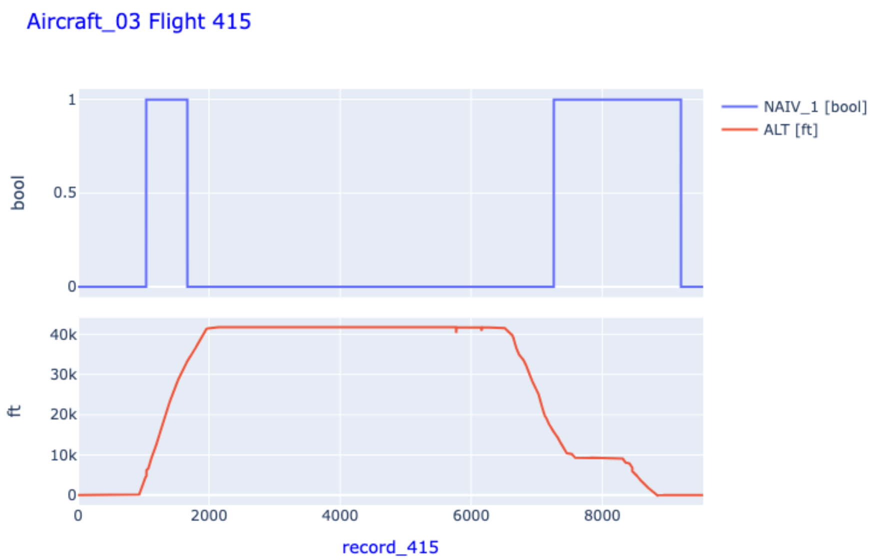

Figure 2: Example of variables altitude (Alt) and anti-ice system (NAIV)

In general the dataset provides a detailed and comprehensive view of engine behavior during different phases of flight, the data enables a thorough investigation into the mathematical modeling of aircraft engine performance, allowing for in-depth analyses and comparisons across various flights and engine conditions.

2.2 Data Treatment with Python

The primary focus of our investigation is to predicting the overall fuel consumption and observing its evolution across multiple flights.
In this study, our methodology involves a systematic approach to handling and analyzing the dataset of engine aircraft data.

Initially, we access and display the raw data, laying the foundation for subsequent analyses. A key step involves the construction of a comprehensive summary table, incorporating relevant indicators for each flight, providing an overview of critical parameters [6].
Subsequently, data cleaning and normalization procedures are implemented to ensure the quality and consistency of the dataset. To enhance our understanding, we explore influential indicators, working towards minimizing uncertainties in the dataset.

2.3 First approach

An initial proposition involves examining fuel consumption with respect to the duration of the flight, constituting a preliminary logical approximation. We use a function that undertakes the determination of the flight duration through a systematic consideration of various phases and it uses Q_i the total fuel flow used for each engine is computed as follows [7]:

$$C_i = \frac{Q_i \times 0.453592}{0.73}$$

The following illustration, presented in Figure 3, shows the outcome derived from a linear predictive model. In particular it represents of the overall consumption of the three planes over the duration of each flight, where each plane is represented by a color and the two engines are distinguished by circles and diamonds respectively.

[6] in particular we consider the engine, flight, total time of flight, Alt_max, Mach_max and Mach

[7] where 0.453592 represents the number of kilograms (kg) equivalent to one pound (lb) and 0,73 refers to the density in kilograms per liter (kg/l) of the fuel.

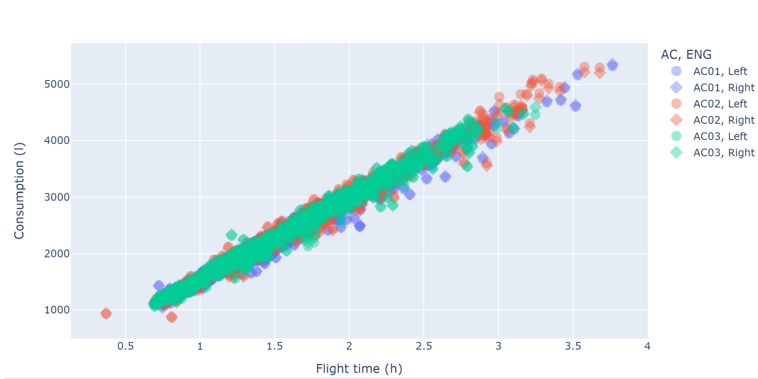

Figure 3: Fuel consumption in relation to flight duration

This display is interactive; when zooming in on a specific time duration, one realizes a significant variance as we can check in Figure 4.

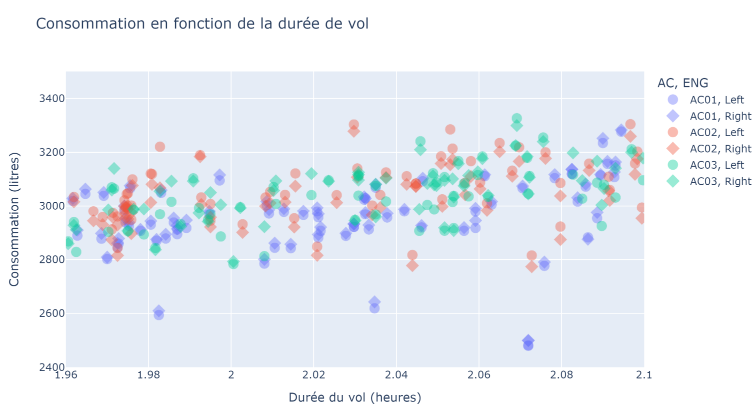

Figure 4: Fuel consumption in relation to flight duration

The first approach to check the validity of the model involves taking the standard deviation of the estimation error divided by the mean consumption to begin the analysis. The Ordinary Least Squares regression results unveil a highly effective model, demonstrating a fit with an R-squared of 0.982, indicative of 98.2 % explanatory power for the dependent variable Consumption. The model's coefficients reveal a significant intercept at 126.0679 [8] and a substantial slope for the 'Leg' variable at 1419.4782 [9], underscoring their substantial contributions to explaining the dependent variable's variance. Nevertheless, diagnostic tests suggest potential issues, including non-normality in residuals, possible autocorrelation, and skewness and kurtosis in residuals according to the Jarque-Bera test.

We proceed by computing the relative accuracy, and we conclude that the predicted values from the model could deviate by approximately 16% from the actual observed values.

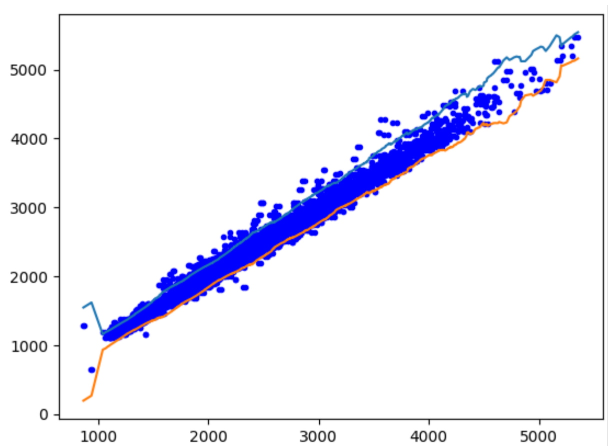

Figure 5: Observed values vs Predicted

In Figure 5 we can see the observed values against the predicted values along with upper and lower bounds based on a specified precision of 100 liters level and confidence interval of 95%.

A further analysis reveals notable imprecision in the predictions, with a maximum deviation of 1078 liters, representing 44% variability, observed in a consumption scenario of 2429 liters. Furthermore, the maximum relative imprecision is calculated at 698 liters, constituting an 80% variation, within a consumption context of 869 liters. On average, the model exhibits a moderate imprecision of 700 liters, equivalent to 29% variability, when considering a mean consumption of 2412 liters.

[8] t-value: 30.104, p-value: 0.000

[9] t-value: 574.876, p-value: 0.000

2.4 Study of each phase

This second approach enables the retrieval of each flight phase independently for a better understanding. In particular we propose a model that explains the consumption from the duration duration, Alt_max and Mach_max :
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In order to test the model we conducted a ordinary least squares regression model to asses the relationship between the consumption and the selected variables: duration, Alt_max, and Mach_max . We obtained a remarkably high R-squared value of 0.967 [10]. The substantial F-statistic of 1.965e+04, coupled with a p-value of 0.00, attests to the overall statistical significance of the model, offering a comprehensive understanding of the factors influencing Consumption.

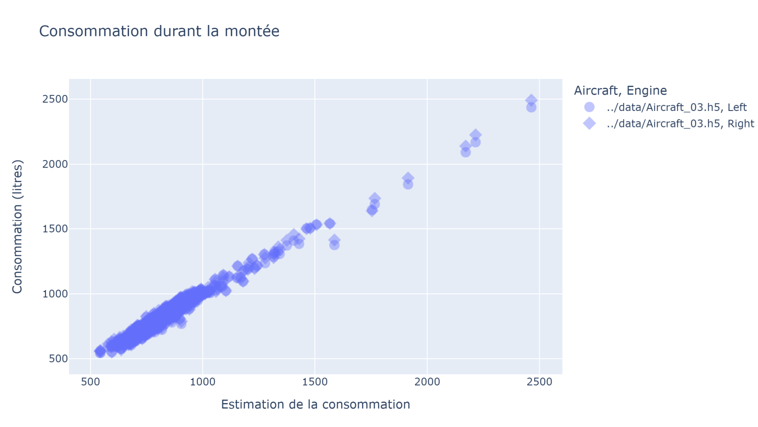

Figure 6: Consumption

[10] approximately 96.7% of the variability in the consumption can be explained by the selected independent variables

3 Results

Presentation of findings, tables, and graphs

4 Discussion

Interpretation of results, comparison with literature, limitations, and implications

5 Conclusion

Summary of main findings and their significance:

This study contributes to the understanding of aircraft engine performance through a meticulous analysis of a simulated dataset. The mathematical models developed offer valuable insights into the intricate relationships between different engine parameters.

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Further research can leverage this foundation to enhance fuel efficiency, optimize maintenance schedules, and contribute to the overall sustainability of aviation.

6 Acknowledgments

Acknowledgments: individuals, organizations and data sources Tabata?

7 References

List of references