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 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

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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 the dataset in [1] 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 1 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

[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] denoted as $_\#$ below

to as Stations, with the index $i = \{0, 1, 2, 3, 4, 5\}$ indicating the position of the measurement according to Figure 1 from [3].

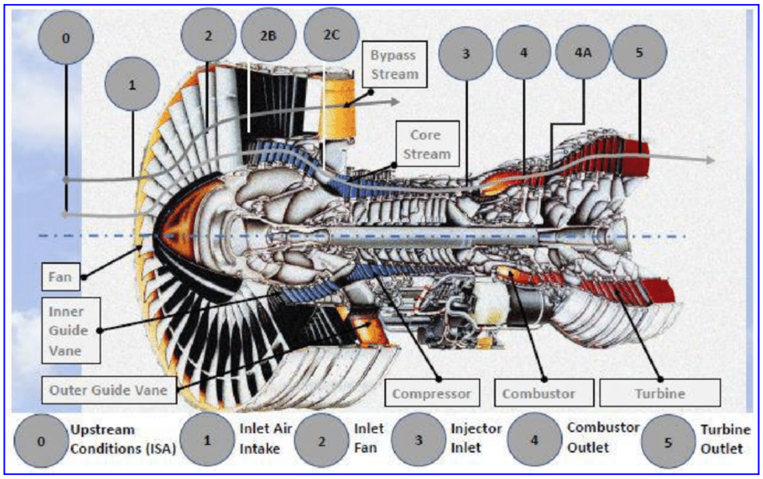

Figure 1: Stations numbering and flow paths inside a jet engine

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.

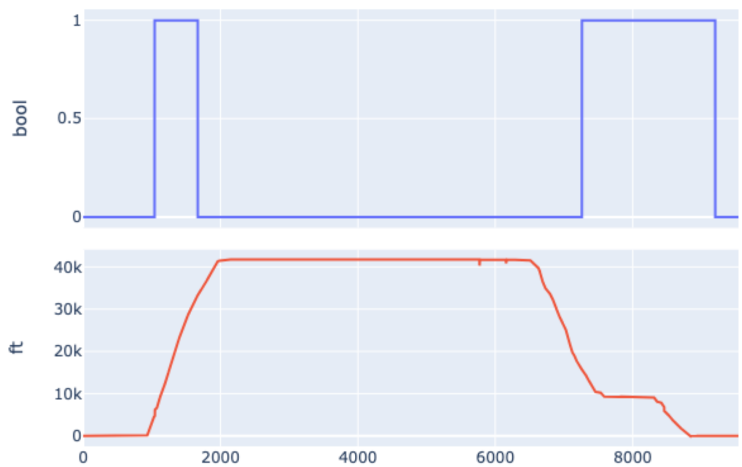

Figure 2: Example of variables altitude (Alt) and anti-ice system (NAIV)

In general the dataset found 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.
The research will be conducted using Python and GitHub. We will leverage essential libraries alongside *Tabata* in [2] a dedicated package designed to streamline the manipulation of time series of numerical signals. Functioning as a toolbox, *Tabata* is developed to illustrate statistical concepts, encompassing elements of machine learning and graphical visualization with a primary emphasis on interactivity within Python notebooks. Within the realm of data processing, particularly with our flight datasets, the *Opset* object facilitates the efficient organization of signals stored in pandas DataFrames into a single HDF5 file and provides functionalities for iteration and visualization.
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

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

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:

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

where $w_1 = 0.453592$ represents the number of kilograms (kg) equivalent to one pound (lb) and $w_2 = 0,73$ refers to the density in kilograms per liter (kg/l) of the fuel.
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.

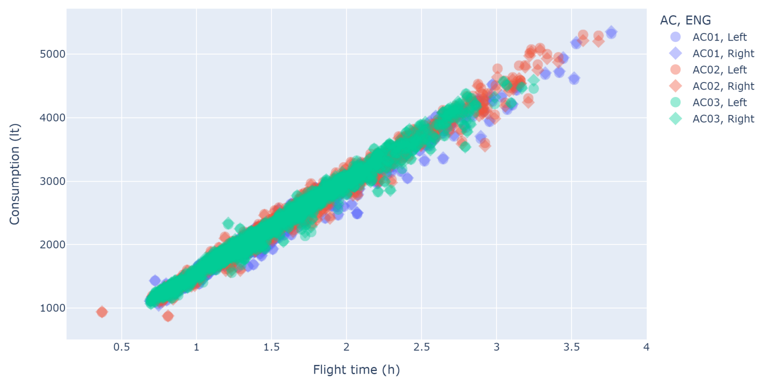

Figure 3: Fuel consumption in relation to flight duration

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

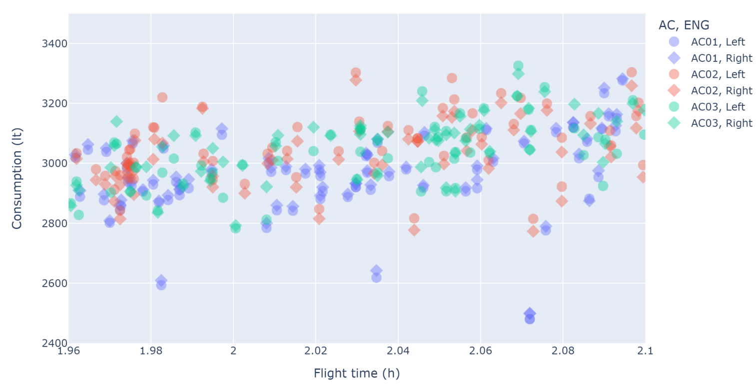

Figure 4: Fuel consumption focused on a specific duration

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 [7] and a substantial slope for the 'Leg' [8] 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, the precision assessment centers around the computation of relative errors between the predicted and actual values. Specifically, the relative percentage error is computed by dividing the disparity between predicted and actual values by the actual values. We conclude that the predicted values from the model could deviate by approximately 17% from the actual observed values.

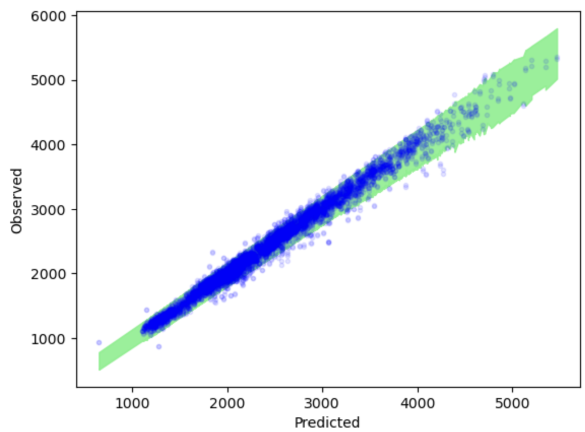

Figure 5: Relative envelope with 95% confidence and local proximity of 20%

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 as we can see in Table 3:

Description	**liters**	**(%)**
Maximum Imprecision on a consumption of 4676 liters	838	18%
Maximum Relative Imprecision on a consumption of 869 liters	697	80%
Average Imprecision on an average consumption of 2412 liters	382	16%
Average Relative Imprecision on an average consumption of 2412 liters	394	16%

Table 3: Calculations with a precision of 100 liters.

As the global model approach yields significant unpredictability, we opt to further refine our analysis by segmenting the data into distinct phases based on altitude. Subsequently, we endeavor to model the consumption levels separately for each identified phase.

[7] t-value: 30.104, p-value: 0.000
[8] flight time (h)
[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. We employ a *detect-phase* function to identify different phases of the flight based on altitude changes, and the resulting breakpoints are stored in the breaks variable. Finally, a color plot is generated, illustrating altitude changes during different phases of the flight on different colors as we can see in Figure 6.

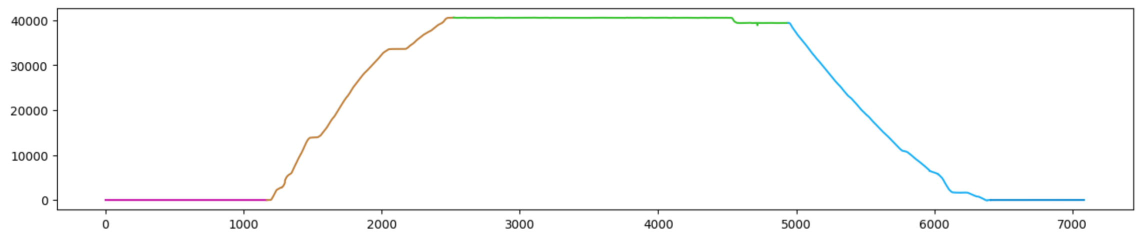

Figure 6: Time indices on x-axis, altitud values on y-axis

We start by proposing a regression model on the climbing phase that explains the consumption from the duration, the highest altitude and mach archived [10]. We plot the estimated value in Figure 7.

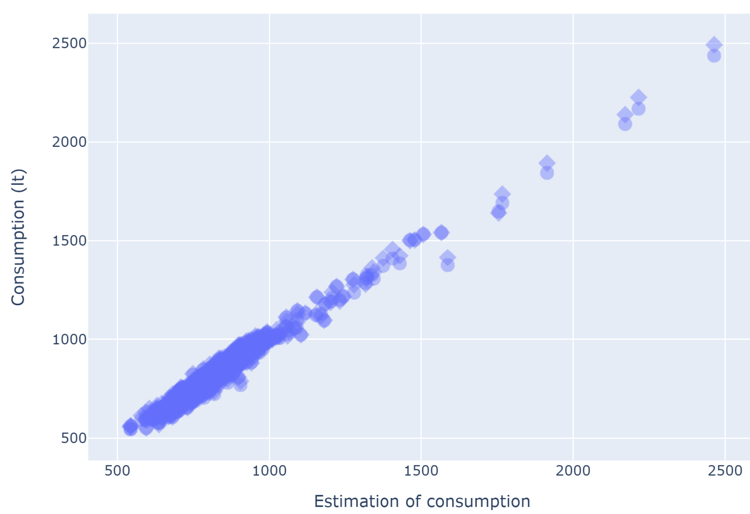

Figure 7: Estimated consumption values during climb phase

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 [11]. 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.

[10]'Leg', 'Alt_max' and 'Mach_max'

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

3 Variations on fuel consumption

In light of the insights gleaned from Figure 5, a pivotal question emerges: given the presence of flights exhibiting both overconsumption and underconsumption of fuel, can we categorize these instances into distinct groups and discern patterns to elucidate the underlying similarities and peculiarities contributing to such anomalies? In particular Figure 8 shows how some flights are above and under the regular conditions of consumption.

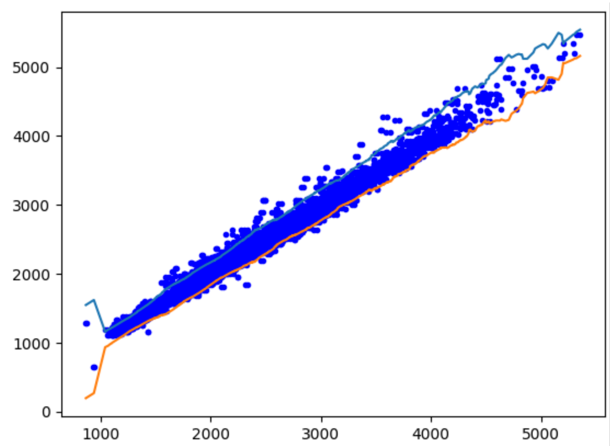

Figure 8: Observed values on x-axis, estimated values on y-axis

This prompts an exploration to identify relationships between flights characterized by over-consumption and those characterized by under-consumption, with the objective of uncovering potential factors influencing these divergent fuel consumption behaviors.

4 Results

Presentation of findings, tables, and graphs

5 Conclusion

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

References

[1] *A simulated dataset capturing engine aircraft data during flights accounting for typical engine wear,* Public, dfdr1000

[2] Jerome Lacaille, *Package for the manipulation of series and numerical signals,* tabata

[3] Paul Palies, Ragini Acharya, and Andreas Hoffie, *Design and Challenges of Lean Fully Premixed Injectors for Gas Turbine Engines*. In *Proceedings of the Conference*, 2019, August. DOI: 10.2514/6.2019-4257.