EVALUATION OF AIRCRAFT PERFORMANCE VARIATION DURING DAILY FLIGHT OPERATIONS

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Abstract

A novel energy-based methodology to predict the flight performance within an entire aircraft fleet based on flight data records is presented. It combines knowledge about the aircraft's flight mechanics with statistical methods and estimation techniques to solve the big data problem. Therefore, this method provides a new smart way to analyze the flight data of modern aircraft during daily flight operations (normal airline operation) to monitor the change of individual aircraft characteristics. The methodology is described in detail first, validated with simulated flight data afterwards and finally applied to flight data of more than 75 000 flights with a Boeing B737 fleet. The corresponding very promising results show that this distinct knowledge-based methodology allows to reliably predict the aircraft flight performance variation and can easily overcome several shortcomings such as poor data resolution or limited quality.

NOMENCLATURE

Symbols

$\overline{(\cdot)}$	mean value	
$C_{(\cdot)}$	aerodynamic coefficient	
C_{D0}	zero-lift drag coefficient	
$\Delta C_{\widetilde{D}}$	equivalent drag coefficient	
D	drag force	N
$\Delta\widetilde{D}$	predicted drag variation	
Δf	additional model function to describe the thrust influence on power imbalance	
δ_{throttle}	engine power lever angle	rad
E	energy	J
$\dot{E}$	energy change in time respectively power, aircraft power imbalance	W
EGT	exhaust gas temperature	K
EPR	engine pressure ratio	
F	force	N
g	acceleration due to gravity	m/s^2
γ	flight path angle	rad
H	altitude	m
k	variable	
L	lift force	N
m_{AC}	aircraft mass	kg
$\dot{m}_{\text{fuel}}$	fuel flow	kg/s
N	number of data points	
N_1	engine fan speed	
N_2	engine shaft rotational speed	%
V	velocity,	m/s
P	model parameter	
$\mathcal{P}$	percentile/ quantile	
p_{stat}	static pressure	N/m^2
$\overline{q}$	dynamic pressure	Pa
R^2	coefficient of determination	
σ	residual	
S_{W}	wing surface area	m^2
t	time	s
T_{stat}	static air temperature	K
z	measured value	

Subscripts

IAS	indicated airspeed
LH	left hand
max	maximum
min	minimum
opt	optimal
ref	reference
sim	simulation
TAS	true airspeed
tot	total

Abbreviations

ATRA	Advanced Technology Research Aircraft
QAR	Quick Access Recorder

1 INTRODUCTION

For today's cost-efficient daily flight operations airlines have to reduce the direct operating costs of their fleet. Beside several other impact factors, the amount of fuel required for typical flight scenarios is one main driver of overall costs. The fuel consumption of a particular aircraft is directly linked to its flight performance which normally drives the airline's decision to buy aircraft of specific type. But even within a fleet of a single aircraft type the flight performance characteristics of each individual aircraft slightly differs. Some of the factors causing the flight performance variations across airplanes from the same type are: production tolerances, aircraft skin repairs, aircraft skin contamination (e.g. dirt), engine aging causing reduced efficiency, or engine contamination (e.g. dirt). For example, an aircraft is normally expected to show at least a drag increase up to 2% in five years [1]. But depending on e.g. the factors given above this increase can be significantly higher. Airbus provides in Ref. 1 some further drag-increasing influences and corresponding scales for different aircraft types in its portfolio. Therefore it is expectable that for a given large flight data set the resulting performance variation becomes visible. This knowledge about the detailed deterioration of individual aircraft performance further allows to e. g. plan necessary actions of aircraft maintenance.

Figure 1 illustrates this expectable flight performance with respect to the aircraft drag curve in the lift-drag-coefficient plane as an area of varying drag coefficient in the vicinity of the typical normal operation's lift-to-drag ratio. In cruise flight, its optimal value $(L/D)_{\text{opt}}$ is around 0.866 of the maximum lift-to-drag ratio[1] resulting in a minimal fuel consumption [2]. The fight data analysis of an entire aircraft fleet presented in this paper reveals very comparable results in terms of the location of the expected variation.

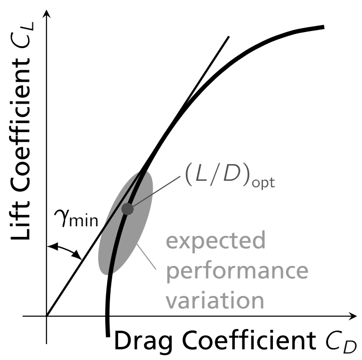

Figure 1: Expected flight performance variation within an aircraft fleet illustrated as change of drag coefficient

There has been several noticeable previous works related to the extraction of flight performance from flight data recorder data sets, e.g. Ref. 3, or to estimate in real-time, aboard the aircraft, the impact of aerodynamics deterioration on the flight safety and on the safe flight envelope [4–6]. However, these approaches are not well suited for the considered case. For instance, the proper estimation of dynamic derivatives (for example roll and yaw damping coefficient) requires some amount of excitation of the aircraft, which is usually not present in data recorded on-board with the flight data recorder (FDR) and even if some relatively aggressive maneuvers would have been flown, the sampling rate of FDR data is usually too low to permits this kind of modeling. Note that even for on-board real-time performance monitoring (for which the sampling rate is sufficient), the need for dynamic excitation is a strong disadvantage for the application to civil airliners in regular operations. Furthermore, there had been some work on the prediction and evaluation of aircraft fuel consumption based on flight data records [7–9], which is directly linked to the flight performance.

This paper presents a novel energy-based methodology to determine the typical and abnormal flight performance variation encountered during regular airline operations (due to a real performance variation or sensor errors) based on flight recorder data sets. Fortunately, the performance monitoring technique presented in this paper does not require dynamic excitations but relies on the information already contained in the achieved steady state conditions. The goal and the approach of Ref. 3 is very similar to the FDR data analysis shown in this paper, but the analysis that is presented herein focuses more on pure performance (no dynamic

[1] which corresponds to the best glide at γ_{min}

derivatives) and is more general, for example a 1 g flight is not assumed whereas it is implicitly assumed in [3]. Ref. 10 deals with a comparable problem of detection of flight performance variation, but mainly focuses on the detection simulated faults instead of flight performance variation itself.

In the presented case, the available flight data records are obtained from the aircraft's quick access recorder (QAR), which records the same information as the well known flight data recorder (FDR) for accident investigation but can be accessed post-flight by the airline to analyze the flight and monitor the aircraft characteristics. As this data have only limited quality (e.g. concerning sample rate) typical and common system identification methods (see [11] for further information on these techniques) to evaluate the aircraft aerodynamic characteristics cannot be applied for this analysis. In general, the determination of an aircraft flight performance variation based on numerous flight data records is a big data problem, which is nowadays often faced by the application of machine learning or statistical methods. For example, such problem based on flight data records was addressed in [12] to e.g. monitor the aircraft speeds during approach. But in the presented case, the big data problem should be solved by utilizing as much general knowledge about flight mechanics as possible. Therefore, the big data is transferred into smart data[2], which eases the subsequent analysis. Note that no distinct knowledge about the individual system but only the physics of flight is required.

In section 2 of this paper, the energy-based methodology used to evaluate the flight data set resulting from normal airline operations is described. Section 3 presents a first feasibility study which was done with the presented methodology on simulated flight data similar to the real aircraft data sets. Finally, the evaluation results of data[3] recorded by the German airline TUIfly during their regular operations are given in section 4.

2 METHODOLOGY

The aircraft flight performance can be seen as follows

$$\textbf{A/C Flight Performance} = \begin{array}{l} \text{Nominal A/C Flight Performance} \\ + \text{Nominal Engine Influence} \\ + \textit{Variation} \end{array}$$

whereby the

- "Nominal A/C Flight Performance" represents the aircraft's expected performance[4] at the given flight condition (e.g. steady horizontal flight),
- "Nominal Engine Influence" is the additional influence of thrust due to a different engine parameter setting than the nominal one required for the given flight condition,
- "*Variation*" part gathers the effects mentioned previously and is here the part that need to be analyzed.

By having a deep knowledge about the aircraft to be investigated, the analysis of flight performance is an easy task: if all the influencing factors – for example aircraft aerodynamics, engine thrust, atmospheric conditions – are perfectly known, the variation can be directly calculated by solving a corresponding set of equations, which describe the individual aircraft's forces and moments equilibrium, for the searched "*Variation*" as e.g. an additional part of the total drag force. But without such detailed individual system knowledge assumptions and simplifications have to be made to allow a combined evaluation of the big data collected with an entire fleet of specific aircraft type. As the determination of one individual aircraft's distinct aerodynamic characteristics and engine status[5] late after the actual flight is not possible by only analyzing flight data recorded with the QAR during normal operations, another reliable approach to reliably calculate the searched "*Variation*" must be found.

The methodology proposed in this paper to allow combined evaluation of the flight data from a fleet of same aircraft type is based on the variation of the aircraft's total energy during quasi-steady flight. It connects knowledge about the fundamental flight mechanics with statistical methods. A detailed description of this analysis is given in section 2.1 hereafter including an approach to determine the "Nominal Engine Influence" by introducing a linear thrust-related power imbalance model. A feasibility study on this modeling approach to find a suitable representation for the unknown thrust influences is presented in section 2.2.

2.1 ANALYSIS OF AIRCRAFT POWER IMBALANCE

The methodology used to derive the aircraft performance from the recorded data is based on the total energy of the airplane or rather its time-derivative. As the flight performance of an aircraft is driven by its characteristics to move through the surrounding air, the influence of large scale atmospheric disturbances such as horizontal and vertical wind must be considered within this energy-based approach. The methodology to account for such wind influences is depended on the choice of the reference system which is used to make

[2] subset of data extracted from big data with certain algorithms containing only the information desired for a distinct analysis

[3] these flight data records were completely anonymized and did only contain flight parameters without any information on the distinct aircraft or crew.

[4] for a representative aircraft of given type

[5] related to the engine's ability to produce a certain amount thrust with a given system state at a certain flight point

up the balance of the total energy[6]. Within the presented approach the aerodynamic system is chosen to calculate the total energy removing the need of a complex wind correction in the equation and giving directly an information about the aircraft flight performance itself. The total energy of the aircraft with respect to the surrounding air is

$$E_{\text{tot}} = \frac{1}{2} \cdot m_{\text{AC}} \cdot V_{\text{TAS}}^2 + m_{\text{AC}} \cdot g \cdot H \tag{1}$$

and the time-derivative of the energy $\dot{E}_{\text{tot}}$ describes the aircraft's real power imbalance, e.g. whether the total energy level is increasing due to an excess of engine thrust for the current flight situation. The power imbalance further describes the actual deviation of the aircraft performance from its nominal expected performance, containing both of the previously given influences on flight performance ("Nominal Engine Influence" and the "*Variation*") in one value. The difficult task is to discriminate these influences from each other, especially when no distinct engine model is available.

But such engine model can be derived out of all the data by searching the model structure and parameter values that minimizes the error between the model-based computed power imbalance $\dot{E}_{\text{tot,model}(P)}$ (with P being the parameters of the engine model) and the actual power imbalance $\dot{E}_{\text{tot}}$. Basically, the problem can be formulated as:

$$P_{\text{opt}} = \text{argmin}_P \left(\sum_{\text{data}} \left(\dot{E}_{\text{tot,model}(P)} - \dot{E}_{\text{tot}} \right)^2 \right) \tag{2}$$

Later, the vector of optimal parameter values P_{opt} is estimated and the corresponding power imbalance ($\dot{E}_{\text{tot,model}(P_{\text{opt}})}$) will be compared to the actual power imbalance $\dot{E}_{\text{tot}}$ to obtain the searched variation.

In practice, before being able to find P_{opt} by solving the problem of equation (2) the flight data need to be preprocessed. This preprocessing includes the detection and cleanup of erroneous data (which can for instance happen at times when some of the onboard computers are being reset) as well as bringing the individual channels to the same constant sampling rate and time base. Then, the data are searched for steady engine and quasi-steady flight conditions for which several engine and flight parameters only slightly vary within predefined boundaries. According to these conditions the flight data are segmented resulting in time slices of steady conditions with an individual length between 60 s and 120 s. Note that such duration is required to guarantee that local small scale effects (e.g. short gusts) do not falsify the resulting flight performance variation. For each time slice mean values of altitude, speed or Mach number, temperature, gross weight, engine fan speed, fuel flow and energy change are calculated and used for further evaluation. Using only mean values over data segments with steady flight conditions allows to reduce the data significantly although all necessary information is still available. Furthermore, the resulting segments are presorted in categories of similar operating points (e.g. altitude, speed, gross weight and engine status). Eventually, $\dot{E}_{\text{tot,model}(P_{\text{opt}})}$ (the reference power imbalance corrected from some of the unknowns affecting the engine thrust) can be written as

$$\begin{aligned} \dot{E}_{\text{tot,model}(P_{\text{opt}})} = \dot{E}_{\text{tot,nominal}} \\ + \Delta f \big(N_1, N_2, \text{EGT}, \text{EPR}, \dot{m}_{\text{fuel}}, \\ T_{\text{stat}}, V_{\text{TAS}}, \text{Ma}, \ldots \big) , \end{aligned} \tag{3}$$

with Δf being the optimal affine adjustment of the engine thrust model on the considered category. A more detailed description about the modeling approach used to define the thrust influence Δf is given in section 2.2. The remaining deviations between the expected power imbalance $\dot{E}_{\text{tot,model}(P_{\text{opt}})}$ and the actual power imbalance $\dot{E}_{\text{tot}}$ (rate of change of the aircraft total energy) are the variations of the flight performance within the considered aircraft fleet.

While the chosen energy-based approach encompasses all aspects of the flight performance and especially the couplings between the involved physical parameters, the scaling of the power imbalance $\dot{E}_{\text{tot,model}(P_{\text{opt}})} - \dot{E}_{\text{tot}}$ into a nondimensional equivalent drag coefficient variation $\Delta C_{\widetilde{D}}$ eases the physical interpretation (same order of magnitude for different speeds, current lift, or even aircraft type). This scaling is realized as follows:

$$\Delta C_{\widetilde{D}} = \frac{\dot{E}_{\text{tot,model}(P_{\text{opt}})} - \dot{E}_{\text{tot}}}{V_{\text{TAS}} \cdot \overline{q} \cdot S_{\text{W}}} \tag{4}$$

The equivalent drag coefficient $\Delta C_{\widetilde{D}}$ computed using equation (4) describes the aircraft flight performance variation inside the fleet, mostly but not only resulting from variation of the aircraft aerodynamic performance (e.g. due to dirt, structural deformation and repairs, or ice accretion). Other possible causes for this variation are sensor errors, unaccounted wind influences (e.g. downdrafts), and variations in the actual engine performance.

2.2 LINEAR ENGINE THRUST MODEL

The thrust of modern jet engines is dependent on several internal states and external influences. Basically, calculating thrust is a difficult task even with complete system knowledge and detailed actual state information and almost impossible without both of them.

[6] conventionally a body-fixed inertial system would be used to balance the total energy which would require a determination and consideration of the current 3D wind vector

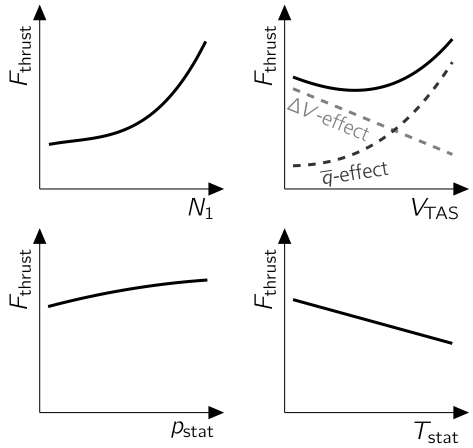

Figure 2: Relative influence of different internal and external parameters on engine thrust (adapted from [13, 14])

Hence, any approach to model the searched engine influence in $\dot{E}_{\text{tot,model}(P_{\text{opt}})}$ (see equation (3)) based on the limited information available in QAR data is only an approximation of the actual thrust conditions. Using a linear engine model for the herein presented analysis of flight performance variation is the best trade-off between model accuracy, simplicity and available information. In general, the thrust F_{thrust} is a thermodynamical process inside the engine depending e.g. the airspeed and the current atmospheric conditions. Figure 2 gives and overview on the several internal and external parameters affecting engine thrust and the corresponding change of thrust with their variation.

Due to the different nonlinear effects of several parameters on thrust, local linear models at certain operating points are the best approach to reliably cover the engine thrust influence on the flight performance. Nevertheless, the linear regressors must be well chosen to prevent overfitting but ensure good data coverage at the same time. For example, as the power imbalance is directly dependent on the airspeed, V_{TAS} could not be a regressor of the linear thrust model in that case: the true airspeed is able to mathematically explain the power imbalance – as it is part of equation (1) and consequently directly related to the resulting $\dot{E}_{\text{tot}}$ – and therefore the flight performance variation and consequently mask the actual thrust effects. Hence, the Mach number will be used because it physically contains a similar information about the aircraft's speed but is not part of power imbalance calculation in equation (1).

To define a suitable set of regressors describing the internal engine parameters, a first study was made based on an existing engine model used for real time aircraft simulation. An arbitrary data set of varying internal engine parameters was defined and the corresponding time history of engine thrust was generated (see Fig. 3). These data were fitted with the linear regression model

$$F_{\text{thrust},model} = \Delta f\left(N_1, N_2, \text{EGT}, \text{EPR}, \dot{m}_{\text{fuel}}\right), \qquad (5)$$

and provide a more realistic scenario for the evaluation. Measurement errors were added to the input data in form of white noise with corresponding maximum amplitudes as given in table 1.

$\|\Delta\text{EPR}\|$	0.001
$\|\Delta\dot{m}_{\text{fuel}}\|$	0.0005 kg/s
$\|\Delta\text{EGT}\|$	5 K
$\|\Delta N_1\|$	0.1 %
$\|\Delta N_2\|$	0.1 %

Table 1: Amplitudes for signal noise

All possible combinations of regressors were used to fit the given thrust data with the corresponding linear model. The results were then evaluated concerning their goodness of fit respectively the linear model's capability to accurately reproduce the thrust data. Therefore, the coefficient of determination R^2 was calculated in each case. It allows to define the goodness of fit in one single value between 0 (no correlation between used the regression model outputs y and given measurements z) and 1 (perfect fit with completely linear correlation). It is defined as

$$R^2 = 1 - \frac{\sum_k \sigma_k^2}{\sum_k \left(z_k - \overline{z}\right)^2}, \qquad (6)$$

where $\overline{z}$ denotes the mean value of given k measurements, z_k the k-th measurement and σ_k the residual of k-th simulation and measurement.

As an example, Fig. 4 contains the resulting coefficients of determination for 5 different regression models containing a different number of regressors. The example shows that even with two well chosen regressors ($\dot{m}_{\text{fuel}}, N_1$) a good fit is possible. Taking additional regressors into account and therefore adding more information to the regression problem results in a slightly better fit for the given example. But this increases also the risk of overfitting when using real flight data later on because the simple linear model structure is only a rough approximation of the real engine/aircraft behavior and more regressors do not necessarily enhance the accuracy in that case. This shows that a trade-off between the accuracy of the model (data fitting) and the model complexity is necessary. The analysis of all other combinations revealed that the most of the regressor combinations did not result in a satisfactory fit of the measured data. Direct correlation between fan speed or engine pressure ratio and thrust – as it is commonly known – is clearly noticeable in the subset of combinations which contains the highest values of R^2. As the fan speed and fuel flow are able to describe the

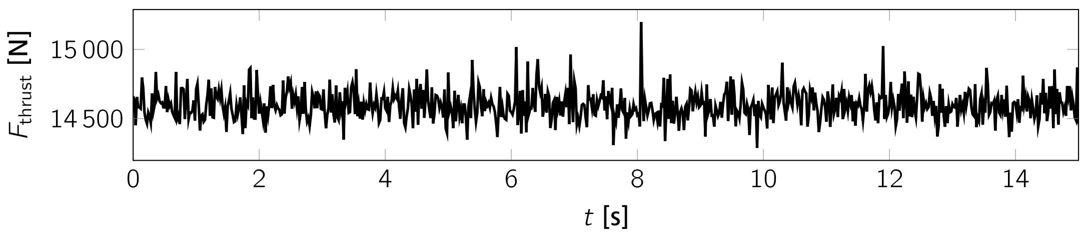

Figure 3: Time history plots of engine thrust simulation: example case for determination of suitable regressor combinations

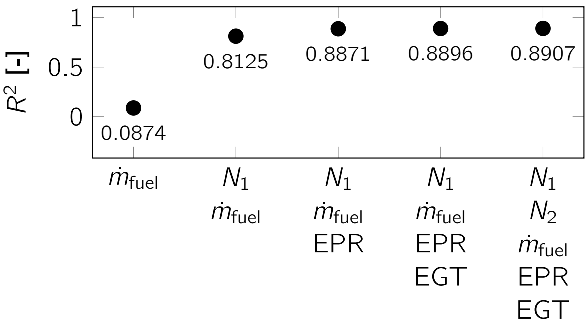

Figure 4: Results of engine thrust regression: coefficient of determination R^2 for regression models with different combinations of regressors

parameter	step size	maximum change
altitude (H)	50 ft	±100 ft
velocity (V_{IAS})	1 kt	±6 kt
flight path angle (γ)	0.25°	±0.75°

Table 2: Variation of trim points around one example operating point to generate a wide range of simulated flight data for method validation: ranges and step sizes of altitude, airspeed and flight path angle variation

thrust variation in general, N_1, $\dot{m}_{\text{fuel}}$ and Ma seem to be a good choice for regressors of the linear model in Equation (3).

3 METHODOLOGY VERIFICATION

The herein presented approach for the determination of the flight performance variation within an aircraft fleet is independent of the aircraft type analyzed. Hence, simulated flight data of any arbitrary large transport aircraft can be used to verify the methodology prior to the final flight data analysis. Therefore, simulated flight data with a known variation was generated with a simulation model of DLR's research aircraft Airbus A 320 ATRA ("Advanced Technology Research Aircraft"). The operation point for the following example was chosen as steady horizontal flight at an altitude of 15000 ft and 320 kt indicated airspeed. Based on this condition, several small variations of altitude, airspeed and flight path angle (see table 2) were introduced to obtained a data base similar to the flight data records at the chosen aircraft operating point in the aircraft flight envelope. All data sets contain time histories of aircraft inputs and outputs necessary for the previously presented approach of flight performance evaluation. With a minimum simulation time of 90 s it is possible to extract time slices of steady conditions with a length of at least 60 s as described in section 2.1. For all these simulations no flight control system of the A 320 was activated.

Beside the slight variation of the aircraft trim conditions, a change of engine state was introduced to further create a subset of simulated flight data with a distinct power imbalance. Therefore, the engine throttle δ_{throttle} was varied 3 % around the value obtained for the trimmed horizontal flight conditions:

$$(\delta_{\text{throttle}})_{\text{sim}} = (\delta_{\text{throttle}})_{trim} \cdot k \quad \text{with } k \in [0.97, 1, 1.03]$$

With the additional thrust variation most of the sources of an aircraft power imbalance during normal operation should be covered. But the presented methodology is developed to determine an aircraft's flight performance within a fleet and consequently an additional data set with changed aircraft flight performance characteristics is needed to validate this approach. This change of characteristics was done with a distinct variation of aircraft drag coefficient during the first 20 s of the aircraft flight simulation by constantly fading in an additional drag coefficient ΔC_D (from zero to its maximum predefined value). Eight different cases of drag variation were used, defined by

$$\Delta C_D = \pm k \cdot C_{D0} \quad \text{with} \quad k \in [0.05, 0.1, 0.15, 0.2].$$

Consequently, the goal of the presented validation attempt to reliably predict this change of aircraft drag with the proposed methodology.

As an example, the results of several of these different aircraft simulations (at given speed and altitude) are presented in Fig. 5 as time history plots of flight path angle, altitude, speed, engine fan speed and power imbalance. The direct comparison of the different cases shows the individual influence of each case (change of flight path angle, throttle command and additional drag coefficient) on the resulting power imbalance as

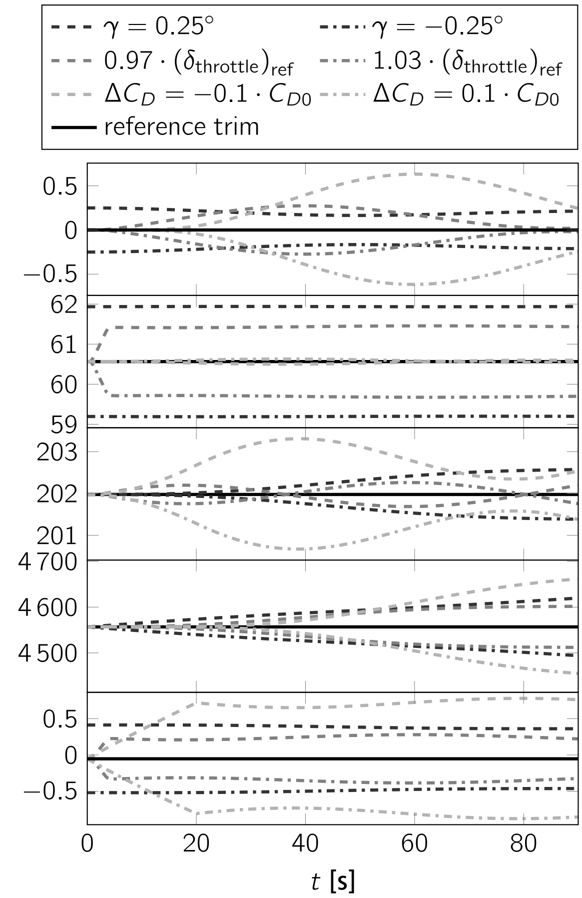

Figure 5: Example of (simulated) flight data from different cases: baseline simulation (reference trim point), change of flight path angle, engine thrust variation (throttle change) and change of aircraft drag coefficient; time history plots of flight path angle, left hand engine fan speed, true airspeed, altitude and total power imbalance for different dynamic aircraft simulations starting from a reference trim point

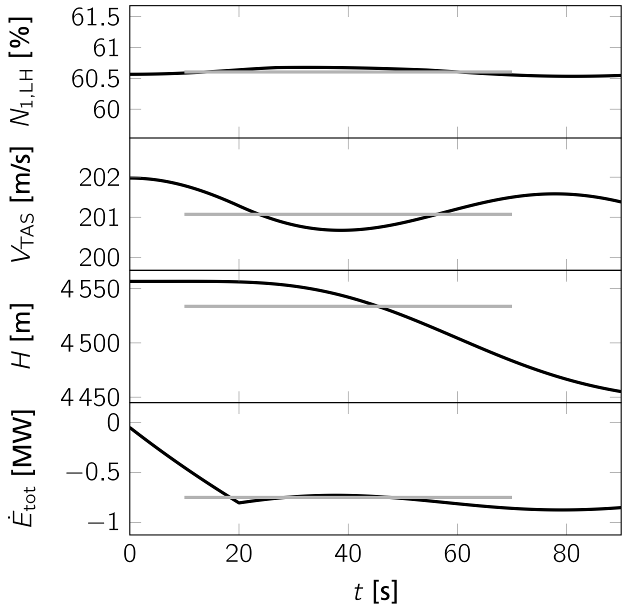

Figure 6: Example of selected (simulated) flight data segment with steady flight conditions: time history plots of left engine fan speed, true airspeed altitude and total power imbalance for a simulation with variation of drag coefficient ($\Delta C_D = 0.1 \cdot C_{D0}$); illustration of mean values as horizontal lines for the selected data segment

well as comparable magnitude of the power imbalance in all cases. Within this example it gets clear that completely different sources have similar effects on $\dot{E}_{\text{tot}}$ and the challenge of the analysis is to reliably split the influences.

The results of the 1950 different simulations were pre-processed for the flight performance evaluation: data segments with (nearly) steady conditions were extracted and corresponding mean values of observation calculated. Figure 6 shows the time histories of several simulation outputs for one example (additional drag influence) in Fig. 5 and in addition the extracted data indicated through horizontal lines of mean values in the time histories.

Application of the method described in section 2 with the regression model of nominal thrust influence defined in section 2.2 allows to split the total measured power imbalance $\dot{E}_{\text{tot}}$ into the thrust related influence $\dot{E}_{\text{Engine}}$ and the remaining variation $\dot{E}_{\Delta\tilde{D}}$. The latter contains the applied drag variation as well as a combination of all errors introduced through the simplifications and approximations with the proposed methodology. For example, the assumption of a linear thrust model is a good approximation but does not fully cover the complexity of the engine model used during simulation on the one hand, and the regressors used for the prediction of $\dot{E}_{\text{Engine}}$ cannot complete describe the thrust behavior on the other. Also the approach of using the mean values of the observed aircraft parameters does further introduce some errors in the analysis.

Figure 7 shows the split of the power imbalance of all 1950 analyzed segments and the energy change is plotted against the combined engine fan speed[7]. The left plot shows that for $\dot{E}_{\text{tot}}$ a linear dependency of some data is clearly visible, but also contains some data without any visible correlation (which results from the drag change). This dependency is fully covered by the predicted thrust related power imbalance $\dot{E}_{\text{Engine}}$ in the center plot. The remaining (not predictable) variation $\dot{E}_{\Delta\tilde{D}}$ in the right plot is related to the drag change which was introduced to several of the aircraft flight simula-

[7]mean value of both engine within one segment; due to the symmetric thrust and similar engine states of left and right engines, this combination of information does not affect the results, but simplifies the data evaluation

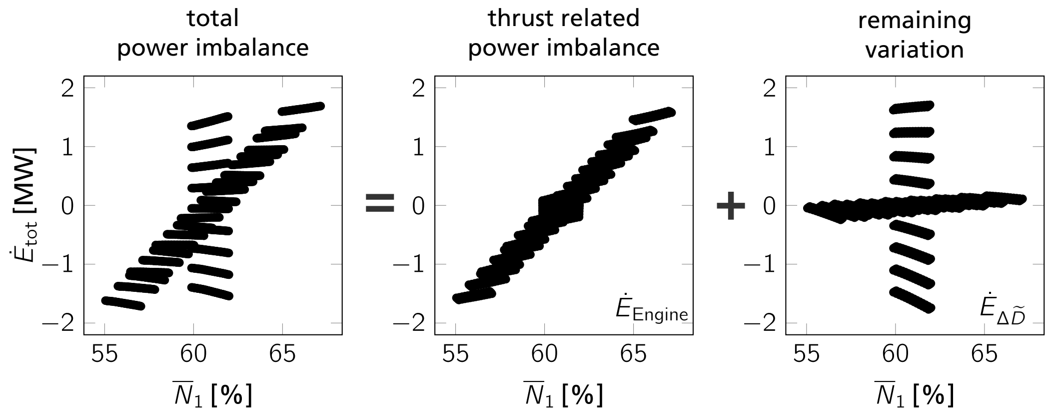

Figure 7: Power imbalance variation for simulated flight data segments: fan speed $\overline{N}_1$ versus total power imbalance $\dot{E}_{\text{tot}}$ as well as separation into estimated thrust-related power imbalance $\dot{E}_{\text{Engine}}$ and the remaining not-assignable variation (in this particular example related to the introduced drag change ΔC_D)

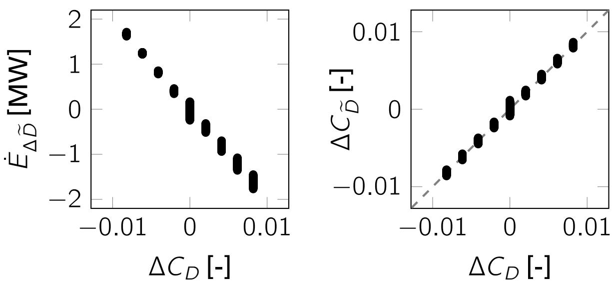

Figure 8: Comparison of predicted drag-change related aircraft power imbalance $\dot{E}_{\Delta\tilde{D}}$ and drag coefficient $\Delta C_{\tilde{D}}$ with actual drag change (ΔC_D) in simulation: measure for flight performance variation around a certain example trim point

tions and also contains the above described additional effects and errors. Similar plots result for the remaining two regressors ($\dot{m}_{\text{fuel}}$ and Ma) used in the linear model for $\dot{E}_{\text{Engine}}$.

The illustration of the drag change ΔC_D versus the remaining variation $\dot{E}_{\Delta\tilde{D}}$ in the left plot of Fig. 8 shows the searched dependency with the drag change. The right plot in Fig. 8 further compares the predicted equivalent drag coefficient $\Delta C_{\tilde{D}}$ with the actual drag change in the simulation. The direct correlation validates the proposed methodology to determine the flight performance variation within a large flight data set with only some small remaining variation caused by the used approximations and simplifications.

4 FLIGHT DATA EVALUATION

In order to determine the real typical flight performance variation encountered during daily flight operations, data of 75,689 flights with Boeing B 737-700 and

Figure 9: TUIfly Boeing 737-800 during final approach[8]

B 737-800 aircraft operated by TUIfly (see Fig. 9[8]) are analyzed. The data of each flight was recorded with the quick access recorder (QAR), which receives the same signals as the flight data recorder, and downloaded by the airline after the flight. The data time resolution of the individual signals ranges from 8 Hz (e.g. accelerations) to 1/64 Hz (e.g. gross weight).

No direct information about the aircraft thrust was recorded in the data and no engine simulation model permitting the calculation of these values out of measured engine parameters was available. This would normally posed some difficulties for the intended flight performance analysis due to the major role played by the engines. But this problem could be overcome acceptably well thanks to the proposed methodology with estimation of engine influence from fight data and the huge quantity of data available itself.

Unfortunately the data used for this analysis were anonymized such that the correspondence between a particular airplane and a recorded flight data was not available. As a consequence, all available information of each fleet (B 737-700 and the B 737-800 separately) is used together to estimate a global engine influence and predict the flight performance variation. Note that

[8] ©TUIfly, with permission for publication; https://www.tuifly.com/downloads/Boeing_737_-_800_bereit_zur_Landung_gr.JPG (download: October 11th, 2016)

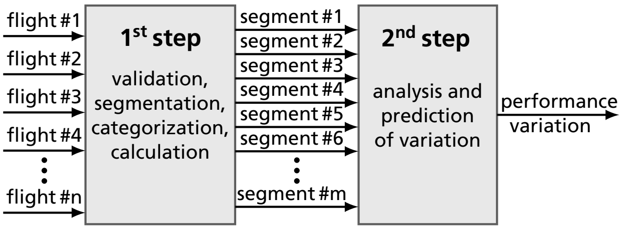

Figure 10: Flight data analysis: two step approach to predict the flight performance variation within a fleet

for this analysis it is crucial to consider the data from all the aircraft of the same type since the aim is to compensate the missing engine data / information but not to adjust the performance for each individual aircraft. The unavailability of the correspondence information prevented the detection of outliers in the data, which for instance happens if one of the airplanes has a significantly better or worse performance than the others. Eventually, this process enabled to obtain an acceptable estimate of the missing information on the engines, but a real engine model would probably have been significantly more precise.

The herein presented flight data evaluation contains of two different steps: first the a-priori data analysis and segmentation and second the prediction of the aircraft flight performance variation. As illustrated in Fig. 10, the data was first checked and validated to remove erroneous data sets from the subsequent analysis containing unreliable sensor measurements, unexplainable data jumps or missing time segments. The data was automatically segmented in relatively short time-slices during which the aircraft was flying in a quasi-steady state (see section 2): stabilized flight path (cruise, but also climb or descend) and possibly steady turns. One key requirement for each segment was a well comparable engine state, which is required by the evaluation method applied afterwards. Data segments with very dynamical maneuvers (e.g. high roll rate or rapid variation of load factor) were ignored in this first analysis but could be considered in future evaluations as well. Later on, the segments were categorized according to their average speed, altitude, fan speed, gross weight and outside air temperature. Each category describes an engine operating point allowing the estimation of the linear model describing the engine influence on the flight performance similar to the validation example in section 3. Calculation of the necessary values for each segments completed the first evaluation step. In a second step, the data segments of each evaluated category were analyzed and the flight performance variation represented by the equivalent drag coefficient $\Delta C_{\widetilde{D}}$ was predicted. This procedure is very similar to the methodology validation presented in section 3.

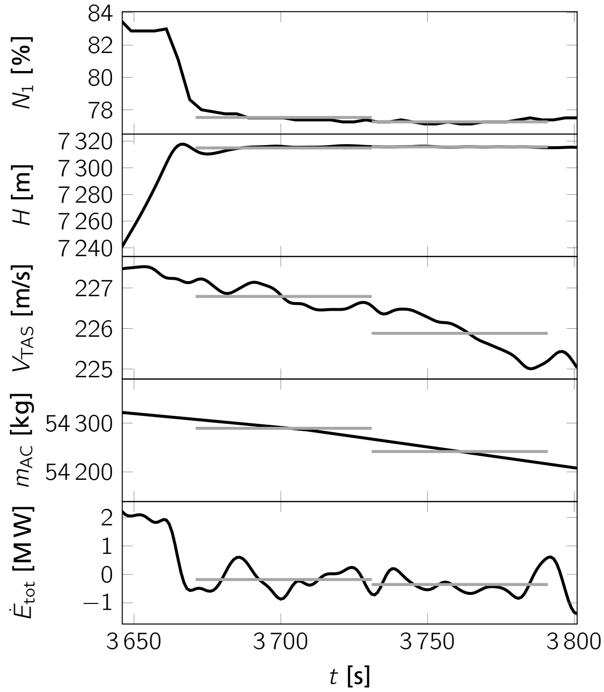

Figure 11: Example of automatically selected flight data segments with nearly steady flight condition

An example of such extracted flight data segments is given in the time histories of several aircraft observation variables in Fig. 11. In the case shown in this figure, segments during cruise flight right after the aircraft climbed to 24 000 ft (7 315 m) are selected. With stabilized engine conditions the aircraft speed only contains small variations and the quasi-steady flight assumption is valid. This applies also to the resulting power imbalance, which shows only small oscillations around zero, indicating no significant change of the flight condition.

With this method 202 797 segments were extracted from the B 737-700 data set and 5 161 814 segments from the B 737-800 data set. These segments contain mainly parts of the en-route flight but climb to and descend from the cruise flight levels are also represented within the extracted data sets. The estimation of the local engine influence on the recorded aircraft flight performance in each category of the above mentioned five-dimensional domain (V,H,T_{stat},N_1,m_{AC}) is performed using a regression technique on a subset of the data. It is possible to reliably estimate the engine model parameter values within a category only if each evaluated category contains enough segments. In the B 737-700 data set the 340 categories with the highest number of segments were selected, which resulted in the above given number of extracted segments. Similarly, in the B 737-800 data set the 750 categories with the highest number of segments were selected. The lowest number of segments in these categories were respectively

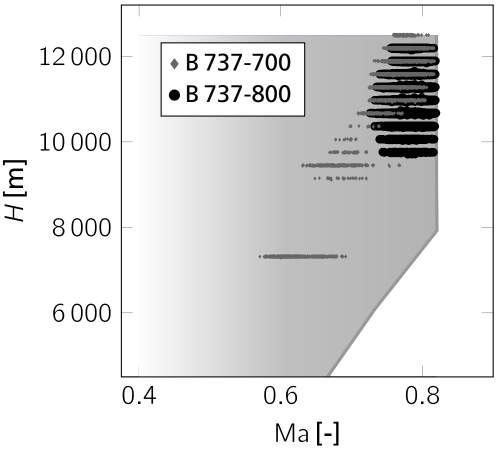

Figure 12: Quasi-steady flight points of evaluated flight data segments in altitude-Mach diagram within the limits of the B 737 flight envelope

271 in the the B 737-700 case and 572 in the B 737-800 case. In both cases, an affine adjustment of the performance based on only three engine parameters (the fan speed N_1, the fuel flow $\dot{m}_{\text{fuel}}$, and the Mach number Ma) was found sufficient for the presented case, but must be eventually extended in future applications e.g. considering data of different points of the flight envelope. Note that when an affine adjustment with only 3 linear terms (one per parameter) on data sets containing several hundreds of data points is applied, there is no real risk of overfit.

In Fig. 12, all quasi-steady flight points of the extracted data segments are plotted together with the limits of the B 737 flight envelope in the altitude-Mach diagram. Most of selected data is related to cruise flight points which is logical as the en-route flight phase mainly contains quasi-steady flight conditions with the required duration of more than 60 s. Note that due to the large number of flights available for the B 737-800 the corresponding segments are all located in the upper right corner of the flight envelope after limitation to 750 categories as the presented analysis was not entitled to cover all data available or the complete flight envelope.

The second step of the evaluation was the segment data analysis and prediction of the flight performance variation within the fleet of same aircraft type. The estimation of engine influence and calculation of remaining power imbalance was conducted similar to the example in section 3 and Fig. 13 contains the combined engine fan speed versus the power imbalance for one example category (B 737-700). Comparison of the left and right plot reveals that considering the thrust related power imbalance allows to explain several outliers and a general linear trend and can reduce some of the variation. It gets visible again that without the estimation and removal of the engine thrust influence the resulting predicted flight performance variation would be deficient. The removal of engine thrust influence turns the scattered distribution of power imbalance points (comparison of left and right plot) which reduces the predicted variation except for the fact that some outliers cannot be explained with this method at all. The remaining power imbalance $\dot{E}_{\Delta\tilde{D}}$ was then used to calculate the equivalent drag coefficient $\Delta C_{\tilde{D}}$ per category as defined in Equation (4).

In order to represent the complete data (millions of data points) in an intelligible way, convex hulls (in the (C_D,C_L)-plane, nominal drag polar extracted from "Base of Aircraft Data" Family 3 [15]) corresponding to several quantiles of the data were computed and represented graphically in Fig. 14 for the B 737-700 (left) and B 737-800 (right). On these individual figures

- the black line represents the nominal drag polar of the aircraft,
- the dot-dashed gray lines are defined as by shifting the nominal drag polar by steps of 25 % C_{D0} and serve as grid in this figure,
- the gray area represents schematically the accuracy that the author expects to be able to reach with better resolution of flight data and more detailed knowledge about the individual aircraft, which could be used to track a single aircraft's performance degradation in operational service,
- the areas defined by the dashed dark, dot-dashed dark, dotted gray and solid light gray polygon lines are the convex hulls of the selected data quantiles (95 %, 99 %, 99.9 % and 100 %).

Most of the variation is found around the optimal cruise flight point $(L/D)_{\text{opt}}$, where most of the data is available. The distribution of the different convex hulls show that less than 0.1 % of data contains the majority of predicted variation. The $\mathcal{P}_{99}$-line indicates that 99 % of the flight performance variation lies below 10 % of zero lift drag. Moreover, the predicted $\mathcal{P}_{95}$-variation of $\Delta C_{\tilde{D}}$ is even lower and similar to the values of normal drag increase for in-service airplanes given in [1].

There are several sources of errors affecting this analysis and presumably causing the large predicted variation of the small subset of data: a limited knowledge on the engine power characteristics of these two aircraft types, a low resolution (sampling-time and quantization) of the recorded data, a missing vertical wind information (which can hardly be recovered from the data available). In addition, the B 737-800 data include aircraft equipped with different types of winglets. Moreover, the results are further affected by missing information about e.g. large scale atmospheric effects, sensor miscalibration, engine deficiencies or aircraft icing. After considering the knowledge gained from the data

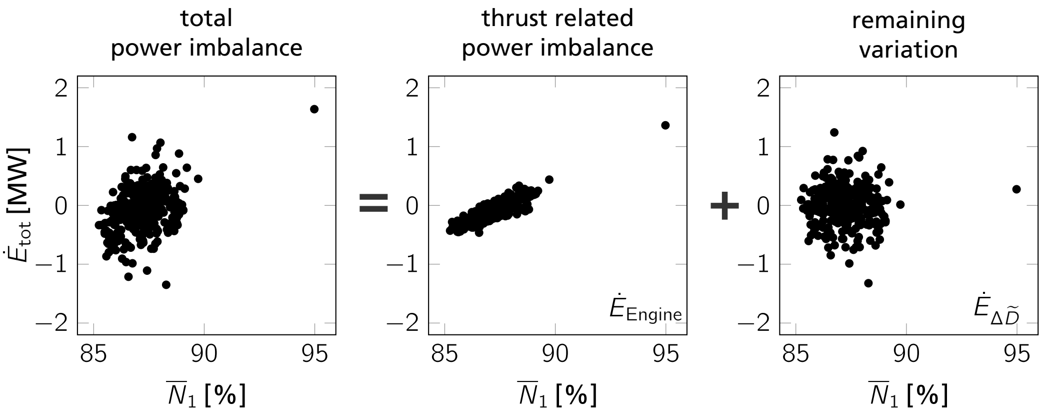

Figure 13: Power imbalance variation for different analyzed data segments in one example category (B 737-700): fan speed $\overline{N}_1$ versus total power imbalance $\dot{E}_{\mathrm{tot}}$ as well as separation into estimated thrust-related power imbalance $\dot{E}_{\mathrm{Engine}}$ and the remaining not-assignable variation

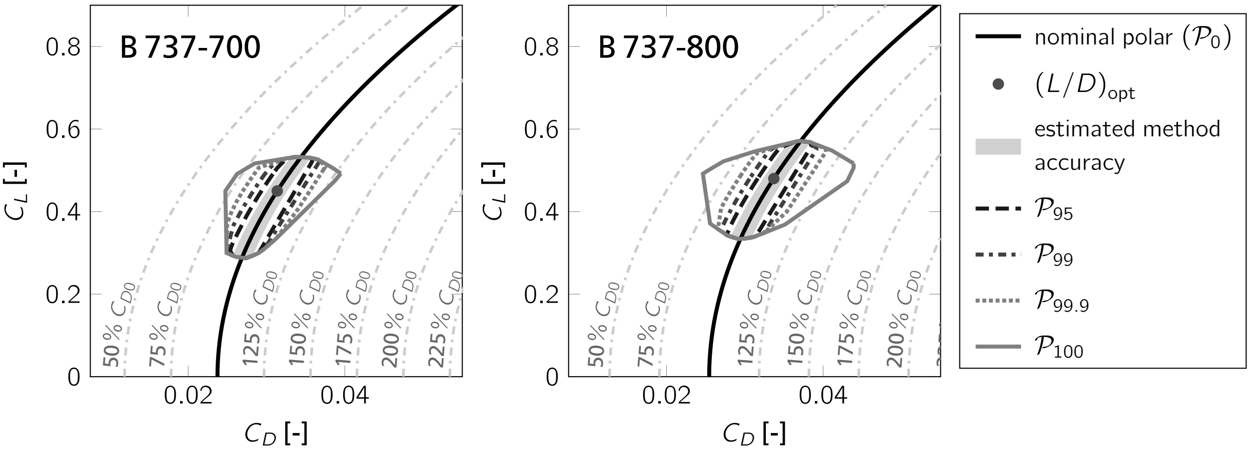

Figure 14: Obtained equivalent drag coefficient (convex hulls of $\mathcal{P}_{95}$, $\mathcal{P}_{99}$, $\mathcal{P}_{99.9}$ & $\mathcal{P}_{100}$) within the two different fleets of B 737-700 and B 737-800 aircraft; resulting flight performance variation during normal airline operations with respect to nominal aircraft drag polar ($\mathcal{P}_0$) and optimal cruise flight point for minimal fuel consumption $(L/D)_{\mathrm{opt}}$; estimated methodology accuracy for better data resolution and without anonymization

and the sensitivity of the results to the different sources of errors, an educated guess was made for the performance estimation uncertainty that can be reached in practice by using the methodology and the standard aircraft instrumentation (air data and inertial reference systems) but with higher sampling rate and more detailed knowledge about the individual aircraft history. This estimate on the achievable precision is represented by the gray areas in Fig. 14.

The results of this QAR data analysis support the initial guess that it is possible to monitor the aircraft performance of all aircraft from a complete fleet using the regular sensors and with a level of precision that permits to detect a flight performance variation and consequently degradation. The way the QAR data was processed in the analysis presented in this section was strongly tailored to a long term big data analysis, but a slightly adapted version of the methodology might be used for post-flight or even on-board flight performance monitoring.

5 CONCLUSION

A novel methodology to determine and monitor the aircraft flight performance during regular airline operations within a fleet of same aircraft type was presented. The validity and applicability of the approach is supported by two separated analysis. First, the methodology was tested and validated with simulated flight data of DLR's Airbus A 320 research aircraft ATRA. It was proven that an artificially introduced flight performance variation could be reliably and accurately predicted by the evaluation of the large flight data set. Second, the analysis of a very large real flight data set indicated that the searched flight performance variation could be predicted with the presented methodology and that it is feasible to extract the flight performance information with very limited system knowledge. The overall results are very promising and in the methodology will be further developed in future projects to consider more data within all flight phases and aircraft configurations or also track the individual flight performance change of a single aircraft within the fleet.

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