Journal of Open Aviation Science (2023), Vol.**1**
doi:10.59490/joas.2023.7216

JOAS

PROCEEDINGS | *The 11th OpenSky Symposium*

Generation of Parametric Climb Trajectories Considering Operational Inputs for Aircraft Engine Thrust Extraction

Maximilian Bień,* Philipp Lehmann, and Jens Friedrichs

Institute of Jet Propulsion and Turbomachinery, Technische Universität Braunschweig, Germany
*Corresponding author: m.bien@ifas.tu-braunschweig.de

(Received: 26 October 2023; Revised: 13 March 2024; Accepted: 26 April 2024; Published: 03 May 2024)
(Editor: Martin Strohmeier; Reviewers: Emy Arts and Enrico Spinielli)

Abstract
For aircraft engines costs related to maintenance, repair & overhaul make up a great proportion of the overall direct operating costs. As the aviation sector is about to face substantial technological shifts towards hybrid-electric and all-electric propulsion, tools are required to model engine operating costs and their strong interdependence to operational factors. This study presents a method for adapting the parametric climb trajectory generation of the aircraft performance model OpenAP for considering operational inputs of flight distance and ambient conditions. Flight data of Airbus A320 operated in North America are analysed for the characteristic climb parameters. The data is used to train an XGBoost machine learning model in order to link the operational inputs to the trajectory parameters. The results show that the model is able to represent global trends in the data while staying within the limits of the original model. However, the model shows some singularities, which could be addressed by parameter tuning and expanding the database. Eventually, the generated trajectories differ from the default trajectory of the original model, such that the average thrust per segment varies in the range of ±20 % to ±10 %.

Keywords: Trajectory Generation; Operation; Mission Profile; Engine Performance;

1. Introduction

Costs related to maintenance, repair and overhaul (MRO) of aircraft engines make up a great proportion of airline direct operating costs. This is due to the long service lives of aircraft engines of several decades during which multiple full overhauls are performed. Also, fuel costs are affected by the engine efficiency and thereby its maintenance status [1]. For modelling engine degradation, realistic operational data is of high relevance because the gradual progress of wear and damage depends on the specific operation of the engine. While many efforts have been made to predict on-wing time and optimising maintenance intervals for conventional aircraft engines, the behaviour of future propulsion systems is so far unknown.

For conventional aircraft engines, the influence of operational factors on MRO can be estimated by the use of so-called severity curves, see Figure 1 (left), where the operational severity is defined as a factor depending on engine take-off thrust reduction and average mission flight time. The application of thrust reductions at take-off leads to reduced peak power demands and lower peak thermal loads, thus reducing operational severity. With longer flight lengths, operational severity decreases as the frequency of take-offs decreases. The severity factor can then be applied to convert maintenance metrics from differing operating conditions. Severity curves are set up from historical databases of existing engine families and can, for rough estimation, be generalised for similar engine models [2]. However, these correlations are only valid for conventional aircraft engines. Future hybrid-electric aircraft engines, e.g. where the low-pressure spool of the gas turbine is electrically assisted, are about to significantly alter these established patterns [3]. When electric assistance is applied at high thrust settings in order to save gas turbine peak power demands, the load profile during a mission is different compared to conventional aircraft engines. Figure 1 (right) displays the relative thermal loads of a conventional (solid line) and an electrically assisted (dotted line) aircraft engine during the climb. Despite the thrust profile being identical for both engines, the peak thermal loads at take-off are lower for the hybrid-electric propulsion system. This implies an influence on engine load, degradation and eventually MRO, even if the aforementioned severity factor remains constant.

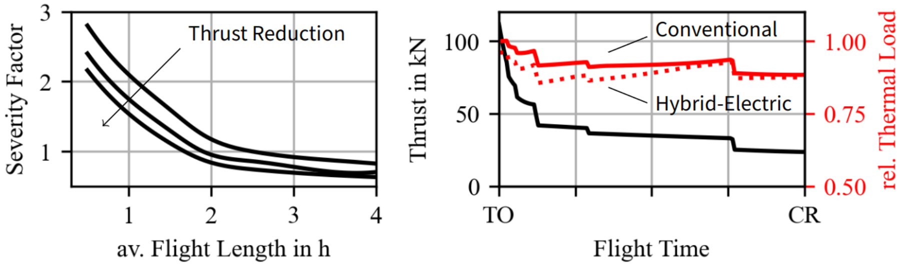

Figure 1. Severity curves for aircraft engines in short-haul operation from [2] (left), thrust profile and thermal loads for a conventional and hybrid-electric aircraft engine (right)

In order to investigate these characteristics for future aircraft engines, besides the simulation of the propulsion system itself, the modelling of operational aspects is of great significance. One main aspect is the thrust setting, which depicts the operating point of the engine and which is further influenced by the ambient conditions. While the latter can be obtained from atmospheric data sets, such as the Copernicus Atmosphere Monitoring Service (CAMS) EAC4 global reanalysis produced by the European Centre for Medium-Range Weather Forecasts [4], thrust has to be extracted from the flight trajectory by application of aircraft performance calculations. This emphasises the need for a parametric operating model, which allows for high variability and adaptability for arbitrary flight mission generation while taking into account general operational interrelations.

2. Method

A useful approach is the aircraft performance model OpenAP from TU Delft [5], where the kinematic flight trajectory is assembled based on defined parameter sets for specific flight phases. The climb phase is divided into the segments take-off (TO), initial climb (IC), PRE-CAS climb, CAS climb, MACH climb and ends in the final segment cruise (CR). Each of these segments is described by a parameter set, which defines the kinematics within the segment and the transition from one segment to another. Figure 2 shows a generated climb profile with OpenAP's default values. In addition to the default values, the statistical distributions from an extensive analysis of a large number of real flight trajectories are also given and are also displayed in Figure 2. Due to the parametric approach and the availability of the source code, the model can be easily adapted to specific requirements. These may range from operational aspects to novel aviation systems.

There are several operational aspects that influence the aircraft's trajectory. On the one hand, there are aspects directly affecting the aircraft's performance, such as take-off weight, the anticipated rate of climb and ambient conditions. Furthermore, there are indirect aspects, such as global or local flight regulations and the human factor of the pilot. Based on the assumption that the variance in

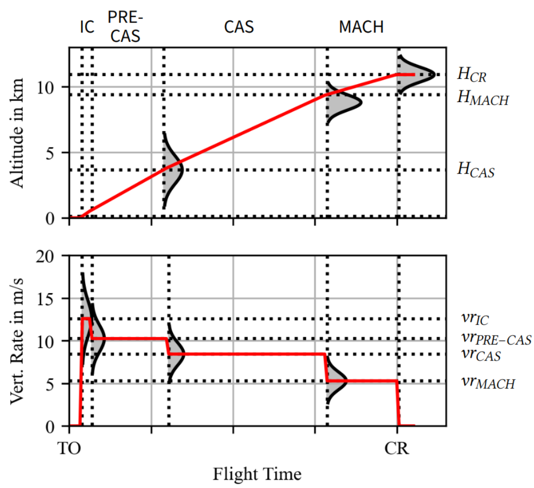

Figure 2. Climb trajectory generated with OpenAP and statistical distributions of the transition altitudes (top) and vertical rates (bottom)

climb performance mainly originates from the former aspects, it is assumed that the parameter sets can be linked to the operational factors. The latter indirect aspects are difficult to generalise but are contained in Automatic Dependent Surveillance-Broadcast (ADS-B) data and contribute to the parametrisation of real operation trajectories. In this study, a method is demonstrated to link these operational aspects to the parameter set of the OpenAP aircraft performance model. Because of the versatile interdependencies in the parameter space, this is performed by use of a machine learning algorithm. In comparison to basic statistic models, such learning algorithms are capable of finding predictive patterns in a given data set. In the case of aircraft flight trajectory parameters, which often are influenced by non-generalisable interdependencies, a predictive analysis is much more suitable than a statistic population inference. There are two main types of machine learning algorithms: Supervised learning is defined by its use of labeled data sets to train algorithms that predict outcomes precisely. Unsupervised learning algorithms, which are liable for unlabeled data and have the ability to find possible correlations by themselves. In contrast to supervised learning algorithms, these require a large amount of data. Given the nature of this study with labeled parameters and dependencies a supervised learning algorithm is pursued [6]. For regressive tasks that aim to identify certain non-linear relationships based on given variables, random forest algorithms are suitable for capturing those while demanding a relatively low amount of data. Random forests are an ensemble of multiple decision trees. Single decision trees tend to have large error rates and variances caused by many decision nodes that are run with uncertainties. Using multiple decision trees for predictive analysis results in a significantly lower variance. Furthermore, gradient boosting algorithms enhance model performance and are often utilised in similar prediction tasks. Gradient boosting algorithms automatically examine and identify predictions that show a large influence on the overall variance of the model. In an iterative process, those data sets are reevaluated until no further improvement is achieved. With this procedure gradient boosting algorithms provide an outstanding precision when it comes to supervised learning [6]. Besides that, gradient boosting is fairly easy to tune by hyperparameter optimisation and is less complex than unsupervised learning algorithms such as deep learning or neural networks.

Within the scope of an engine operation model with the ability to simulate arbitrary air traffic routes, a method is developed to generate generic flight trajectories with respect to operational influences, such as flight distance and ambient conditions. Considering those operational aspects in the flight

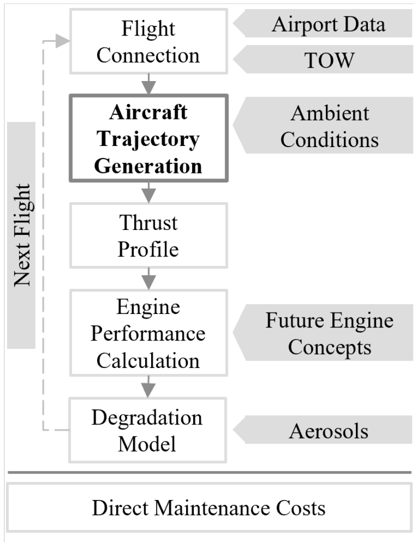

Figure 3. Overview of the global model structure

trajectory generation allows for better modeling of engine thrust and more realistic operating profiles of the propulsion system. An overview of the model is given in Figure 3. Firstly, a flight connection is defined, and airport data are read from an airport database. Between the origin and destination airport, the great circle distance is computed, and a kinematic flight trajectory is generated. Then, the thrust profile is extracted by applying aircraft performance calculations and weight estimations based on the flight distance. The thrust profile and ambient conditions along the trajectory serve as input for a stationary engine performance calculation model, where the thermodynamic cycle is solved, and operational loads are substituted. The information for the engine operation, as well as aerosols of dust, salt and chemical depositions in the ingested air, are evaluated in a degradation model. Eventually, based on the operating time and the condition of the engine, maintenance costs are predicted. This study focuses on aircraft trajectory generation.

Historical flight trajectories of A320 aircraft operated in North America in a time frame of four years are downloaded from The OpenSky Network historical database [7]. Each flight is checked for sufficient quality. First, from the coordinates of the first and the last snapshot of the trajectory distances to the nearest airport are calculated. Distances are limited to 8 km and 15 km from the origin and destination airport, respectively. Further, the geoaltitude of the beginning and the end of the trajectory is limited to 3 km, and the 10 min average vertical rate has to be greater 5 or below 2 m/s. This ensures that climb and descent trajectories are captured within the flight data and that origin and destination airports can be assigned with good accuracy. This is important for calculating the correct great circle flight distance. Then, the aircraft take-off weight is estimated by a correlation with great circle distance [8]. Based on the timestamp and coordinates of the origin airport atmospheric data is read from the CAMS global reanalysis (EAC4) model [4].

2.1 Pre-processing of the flight data

A typical A320 climb trajectory is divided into characteristic segments [9] : A climb trajectory starts with take-off, where the aircraft is accelerated until lift-off and gains altitude with a relatively higher vertical rate during initial climb (IC) until a typical altitude of 1500 ft above ground. During the PRE-CAS segment, the aircraft climbs and accelerates until reaching the CAS segment, where the calibrated airspeed (CAS) is held constant, and the Mach number increases further. In the last segment,

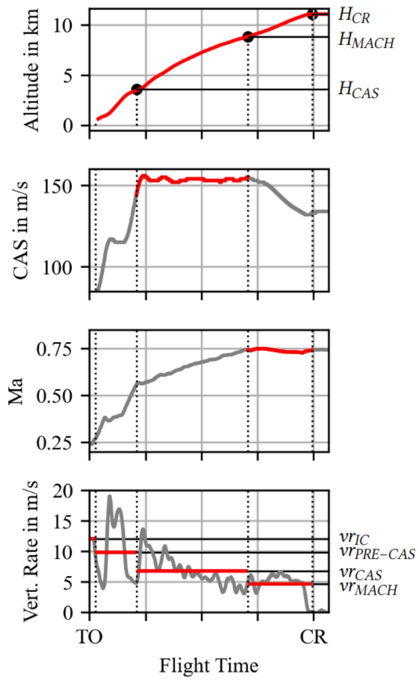

Figure 4. Illustrative example of an ADS-B climb trajectory: Altitude profile (top), calculated courses of calibrated airspeed and mach number (middle) and vertical rates (bottom) for climb segmentation and parameter extraction

the Mach number is held constant, while the calibrated airspeed decreases with a further decrease in air density. While the end of IC is defined by a rather fixed altitude, the other transition altitudes vary for each flight and have to be extracted from the ADS-B data. The ADS-B data contains recordings of coordinates, altitude, ground speed, heading and vertical speed. In order to detect the transition altitudes between the climb segments, the characteristic courses of calibrated airspeed and Mach number have to be calculated. Here, the functions of the OpenAP model are used, which have been adapted for real ambient data from take-off ground level (index gr). Temperature and pressure at altitude can be calculated from equations 1 and 2. T_{gr} and p_{gr} are read from the atmospheric data set at surface and h_{gr} is the airport elevation. The constants β, g_0 and R are stratospheric temperature lapse rate, earth's gravitational acceleration and gas constant of air, respectively.

In order to improve the quality of the velocity profiles of each flight the data is corrected for wind. Multi-level wind data from the CAMS global reanalysis (EAC4) model [4] at pressure levels ranging from 10 hPa to 1000 hPa are integrated and interpolated between. True airspeed (TAS) is calculated by equation 3 from ground speed (GS), wind velocity and angle θ between aircraft heading and wind direction [10]. Finally, velocity profiles of Mach number and CAS are calculated according to equation 4 and 5, with γ being the heat capacity ratio and reference values T_0 and p_0 at sea level standard atmosphere.

$$T = T_{gr} + \beta * (h - h_{gr}) \tag{1}$$

$$p = p_{gr} \cdot \left[1 + \frac{\beta}{T_{gr}} \cdot (h - h_{gr})\right]^{\frac{-g_0}{R \cdot \beta}} \tag{2}$$

$$v_{TAS} = v_{GS} - v_{wind} \cos\theta \tag{3}$$

$$Ma = \frac{v_{tas}}{\sqrt{\gamma RT}} \tag{4}$$

$$v_{CAS} = \sqrt{\gamma RT_0} \cdot \sqrt{5\left(\left[\frac{p}{p_0}\left(\left(1 + 0.2Ma^2\right)^{\frac{7}{2}}\right) - 1\right]^{\frac{2}{7}} - 1\right)} \tag{5}$$

2.2 Extraction of transition altitudes

A typical flight trajectory and velocity profiles are shown in Figure 4. From the velocity profiles phases with constant CAS and Mach number are identified by use of a rolling average smoothing and kink-points detection in order to split the climb trajectory into the characteristic climb segments, see vertical lines in Figure 4. The transition altitudes between climb segments are read from the altitude profile (black dots in Figure 4 (top). The vertical rates are computed as an average per segment (Figure 4 (bottom)).

2.3 Machine Learning Model

The outcome of the data acquisition and pre-processing is a data set of about 3000 flights, containing information about the flight distances and ambient conditions, as well as the target parameters of transition altitudes and vertical speeds for model prediction. The data set is used to train an XGBoost gradient boosting machine learning model [11].

The data set is split into training and validation data comprising 80 % and 20 %, respectively. Hyper-parameter optimisation is conducted by using Latin Hypercube Sampling. The model setup yielding the lowest Mean Squared Error is used for analysis. An overview of the achieved Root Mean Squared Errors can be seen in Table 1.

Table 1. Root Mean Squared Errors (RMSE) of the model validation

Parameter	H_{CAS}	H_{MACH}	H_{CR}	vr_{IC}	$vr_{PRE-CAS}$	vr_{CAS}	vr_{MACH}
MSE	812 m	539 m	620 m	2.06 m/s	1.43 m/s	1.04 m/s	1.36 m/s

3. Results

The models are used to predict the climb trajectory parameters, namely climb segment transition altitudes and vertical rates, as a function of operational factors. The results show that the transition altitudes come with a strong interdependence with the great circle flight distance, which is shown in Figure 5. The transition altitudes are modelled as a function of flight distance, while ambient conditions (temperature, pressure and air density at ground) are kept constant. Here, the median values of the analysed flight data are used. Additionally, the distribution of the database along the flight distance is shown, as well as the statistical distributions of the transition altitudes within OpenAP. While the transition altitude towards constant Mach climb is relatively constant, the transition altitudes towards constant CAS and cruise vary with flight distance. In a global trend, the former decreases with increasing flight distance. The transition altitude is higher for short flight distances where average take-off weights are lower and steeper climb rates are possible. The latter shows a steep increase for short flight distances up to 750 km and starts to decrease again with a low rate

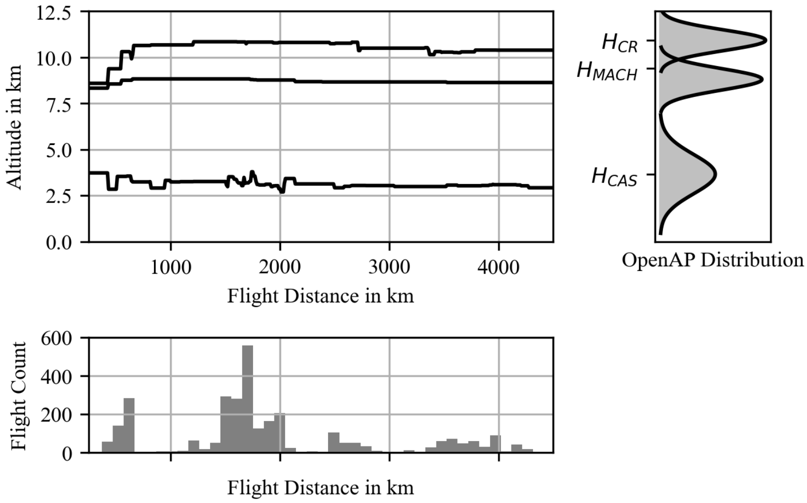

Figure 5. Predicted climb segment transition altitudes as a function of flight distance at constant ambient conditions

at a distance of 2500 km. This is due to the decreased initial cruise altitudes for heavier aircraft. For short flight distances, the climb segment is cut off at lower cruise altitudes because of fairly short cruise phases. The trend of predicted transition altitudes shows some singularities, especially where the database shows high flight counts around 750 and 1750 km. This might be an indication of overfitting and should be investigated in the hyperparameter optimisation process. Figure 6 shows the predicted climb segment vertical rates, which show the strongest interrelation to ambient temperature. The vertical rates during IC, PRE-CAS and CAS climb decrease with increasing ambient temperature, especially at low temperatures between 265 and 275K. This might be due to higher engine performance at lower temperatures allowing higher climb rates. The trend is less pronounced the higher the climb segment is.

In contrast, the vertical rate at constant Mach increases with ambient temperature. An explanation might be higher pressure altitudes at higher temperatures, requiring a longer endmost climb phase. Overall, the modelled transition altitudes and vertical rates lie within the distribution of the broad analysis of OpenAP.

Figure 7 compares the extracted thrust along generated climb trajectories in comparison to the default OpenAP parameter set. Engine thrust is calculated from the kinematic trajectory by application of take-off weight correlations [8], the OpenAP aircraft specific drag model [5] and flight mechanics [10]. Figure 7 (left) shows the thrust profiles of the analysed database. It can be seen that the profiles scatter in thrust value as well as in climb duration. In Figure 7 (right), the deviation of average thrust during the climb segments between the generated models and the default trajectory is shown. While the median values correspond with the default trajectory, the maximum deviations lie within ±20 % during the initial climb and reduce to ±15 % during the PRE-CAS climb and ±10 % during CAS and MACH climb. Hence, the influence of operational factors on thrust is highest at early climb phases and lower altitudes and decreases with onward climb. However, with the inner quartiles lying within deviations below 5 %, a great proportion of flight data shows significantly less dependence and the data is concentrated closely around the median values.

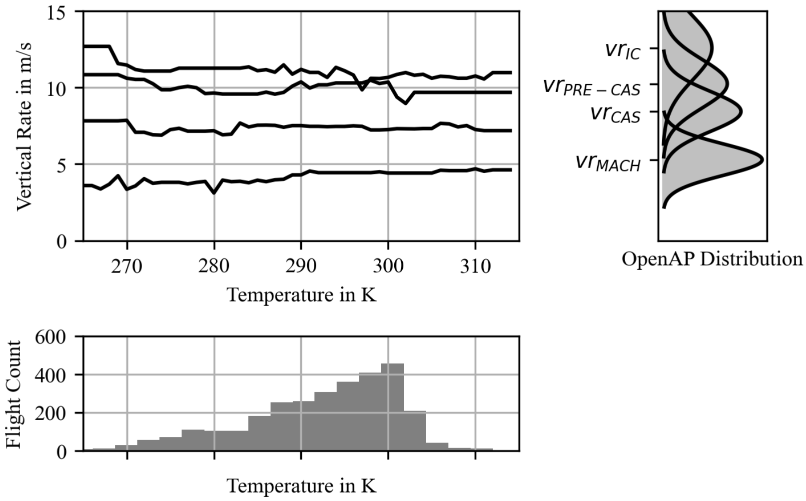

Figure 6. Predicted climb segment vertical rates as a function of ambient temperature at the ground and constant flight distance

4. Discussion

The models generated in this study model the climb trajectory parameters with respect to operational inputs of flight distance and ambient conditions. In the large parameter space with various direct and indirect influences, the predicted trends seem reasonable, and the resulting parameters are within the broad analysis of the OpenAP model. Even in regions where the underlying database is sparse and when the boundaries of the database are exceeded, see Figure 5, the predictions follow a trend and do not diverge. However, the trends show some singularities, which presumably result from sparse data or overfitting of the machine learning algorithm. Besides the benefits of random forest ensemble algorithms, the latter aspect is a typical drawback. This should be further investigated in the hyperparameter optimisation process, which is currently assessed only by minimising the Mean Squared Error. Moreover, model accuracy might be improved by expanding the database. Extrapolated predictions of machine learning algorithms should be critically investigated, as they often turn out to be of low informative value. This is why the generated model should be only applied within the flight region of the underlying data and not be used for estimations in other flight regions, especially where distinctly different environmental conditions prevail. In general, the XGBoost machine learning algorithm seems appropriate for the presented task. As can be seen in

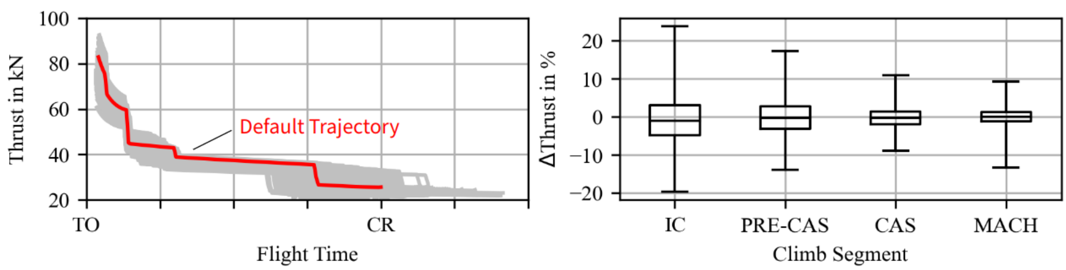

Figure 7. Thrust profiles of the generated trajectories (left) and average segment-wise comparison with the default trajectory (right)

the Root Mean Squared Error is highest in lower altitude climb segments, where individual flight maneuvers are common.

Further uncertainties arise from the following aspects: The values of the characteristic climb velocities are kept constant in this study. This is a simplification, as the absolute velocities are difficult to derive because of the high influence of exact ambient and wind conditions. Also, the resolution of the atmospheric data set, the calculation of the characteristic courses of calibrated airspeed and Mach number, and the detection of the flight segments cause further inaccuracy. This is justifiable, as the overall model is meant to represent average trends rather than individual flights. The analysis of the overall model, which eventually aims at the prediction of direct operating costs, is also conducted on an engine fleet basis, rather than individual engines. Generating flight trajectories with respect to operational factors proves to be influential on the engine thrust profile and is of high relevance for modeling operational severity.

5. Conclusion

While climb trajectories underlie various interdependencies, the presented method allows for considering operational factors in a wide parameter space, where both physical and regulatory influences result in non-linear correlations. The method seems appropriate but should be further improved by suitable hyperparameter optimisation and expansion of the database. The method allows for adapting aircraft flight trajectory generation to a specific use case in order to derive more realistic flight profiles while maintaining a generalised accuracy of average flights and keeping data handling and computational efforts at a low level. The method contributes to a general task of modelling operation and maintenance efforts of future aircraft engines. The model is set up by use of openly available data, and the methodology can be used for any specific use case or can be expanded to a global level.

6. Acknowledgement

I would like to thank the OpenSky Network for providing open access to flight trajectory data, which is of great help for research in the aviation sector. Also, I thank Junzi Sun for providing open access to the aircraft performance model OpenAP, which is a powerful tool for generalised trajectory generation and proved to be very helpful for my research tasks.

7. Author contributions

- Maximilian Bień: Conceptualization, Methodology, Formal Analysis, Writing–Original Draft
- Philipp Lehmann: Formal Analysis, Writing–Original Draft
- Jens Friedrichs: Supervision, Project Administration

8. Funding statement

This work is conducted as part of the joint research programme LuFo VI-1. It is supported by the German Federal Ministry of Economic Affairs and Climate Action under grant number 20E1913A.

9. Open data statement

The data is thankfully retrieved from:

- Historical ADS-B database:
  https://doi.org/10.1109/IPSN.2014.6846743

- CAMS Global Reanalysis Dataset of Atmospheric Composition:
  https://doi.org/10.5194/acp-19-3515-2019
- OpenAP Aircraft Performance Model:
  https://doi.org/10.3390/aerospace7080104

10. Reproducibility statement

Data for reproduction are available at https://cloud.tu-braunschweig.de/s/Y78Y46pYpHBsZS4.

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