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Open Loop Aircraft Take-off Mass Estimation: An Optimal Trajectory Approach

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***Abstract*—The mass of an aircraft is crucial for performance-related studies, such as predicting flight trajectories and analyzing flight emissions. In these studies, the flight trajectories are often reconstructed using a point-mass aircraft performance model combined with flight profiles from surveillance data and take-off mass information. However, airlines do not usually disclose take-off mass information, considering its sensitive nature. Thus, aircraft masses often need to be assumed or estimated.**

This paper presents a simple and computationally effective approach for estimating take-off mass using only open data and models. We explore the strong correlation between take-off mass, flight distance, cruise altitude, and partially, the airspeed during the cruise. The main idea is to generate fuel-optimal trajectories with known masses and distances, and then compare them with actual flight data. The optimal trajectories are generated using the open aircraft performance and optimization library. By assuming that actual flights follow quasi-fuel-optimal trajectories, the take-off mass of a flight can be estimated based on simple regression models trained on the optimal trajectory dataset. This open-loop take-off mass estimation approach requires no proprietary information from aircraft manufacturers or airlines. We verified the model with an anonymized dataset containing actual A320 flights with known take-off mass. Our two- and three-feature multi-linear models yield mean absolute percentage errors of 5.95% and 4.89%, respectively. This study is another step forward in open science and a contribution to the aircraft trajectory studies.

***Keywords*—Take-off mass estimation, trajectory optimization, aircraft performance**

I. Introduction

Aircraft mass is an important parameter in performance models and affects various perspectives of the flight in terms of fuel consumption, altitude, and flight performance limitations. Aircraft take-off mass (TOW) is also necessary for operations such as optimizing the flight trajectory of an aircraft when considering fuel and emissions. However, information about an aircraft's weight is often confidential and rarely available to researchers or air traffic controllers. Recently, anonymized take-off mass data started to become available with the effort from the Performance Review Commission[1], which provides objective information and independent advice to EuroControl's governing bodies with data-driven analyses.

Many studies have focused on estimating aircraft take-off mass based on flight trajectory data. In general, there are two main types of take-off mass studies: open-loop with unknown ground truth information, and closed-loop with the use of confidential weight information.

[1]https://ansperformance.eu/study/data-challenge/

The open-loop studies are mostly based on predetermining or assuming thrust settings during take-off and applying empirical methods. For example, research employing energy rate prediction assumes a common thrust profile derived from historical data and compares physics-based model profiles to real-world observations [1], [2]. A similar study used a maximum thrust setting and determined the weight at the moment of lift-off, assuming the equilibrium of the forces [3]. Some studies considered different flight stages to estimate take-off mass using the Bayesian inference method and combined the results to achieve a higher confidence level [4], [5]. These methods use a short observation period to speed up computational processes and to assume a constant weight and thrust, which simplifies estimation.

One of the drawbacks of such methods is the sensitivity of the derived model to noise in the observation data and environmental uncertainties, such as runway conditions and wind. To address these issues, a later study applied a particle filter method with four noise models [6]. It focused on estimating take-off mass from publicly available ADS-B data, taking into account noise, using changing flight dynamics and near-maximum thrust during the initial climb phase. The other limitations of the methods discussed are time-consuming model settings and the realistic performance model requirement.

The closed-loop methods have generally focused on training a statistical model. Gaussian Process Regression trained on Flight Data Recorder (FDR) data to estimate fuel flow rates [7], [8]. Those studies showed the potential of fuel flow modeling using statistical data and resulted in higher accuracy on take-off mass estimation compared to the Aircraft Noise and Performance (ANP) database.

Another study proposes a supervised machine-learning model on the take-off data of a Cessna 172 under different runway conditions [9]. The study showed how environmental uncertainties and flight conditions affect the performance of the statistical model. Similar challenges were faced in a different approach, which used fuel flow data from Quick Access Recorder (QAR) to estimate take-off mass [10]. Although statistical methods mostly proved to be more accurate in TOW prediction compared to open-loop studies discussed above, their main disadvantage is the use of not publicly available data. To summarize, the reviewed literature has indicated the following challenges:

1) For the *open-loop* approaches, where models do not use airline weight data [1]–[6], there are significant uncertainties in aircraft performance models and flight procedures

during the climb, preventing the accurate prediction of aircraft weight. In addition, the estimation process is often slow.
2) For the *closed-loop* estimation approaches, where models are built with airline weight of fuel flow data [7]–[10], the models are more accurate but cannot be shared openly. Though estimations are often fast, the lack of openness reduces the significance of the research when considering the implementation of models.

This paper proposes a new and fast open-loop approach for determining the take-off mass of an aircraft. The literature and our previous studies showed that take-off mass correlates with cruise altitude [11], [12]. This is especially relevant when generating optimal flight trajectories. In our research, we built an aircraft-type-specific dataset containing optimal trajectories across a range of take-off masses and flight distances, assuming that commercial flights are quasi-fuel-optimal.

The optimal trajectories were generated using the open performance model, *OpenAP* [13], and its associated optimization framework, *OpenAP.top* [14]. The optimal dataset is then used to train the regression models. The resulting model can estimate the take-off mass for a flight using publicly available data, such as ADS-B trajectory data and the weather ERA5 data from ECWFM database [15]. One of the advantages of this method is that the model does not heavily rely on the completeness of data, and the effect of flight data noise is insignificant. The simplest two-feature multilinear regression model showed a 5.95% mean absolute percentage error, while a more advanced model was able to achieve 4,89%. We have also tested gradient boosting models, which had mean percentage errors of 5.36% and 5.24% with two- and three-feature training.

The structure of this paper is organized as follows: Section II details the assumptions and methodology used for optimal trajectory generation and model choice. Section III presents the test outcomes and their validation against real-world data. Section IV analyzes the performance and limitations of the approach. Finally, Section V provides the conclusions and suggests directions for future research.

II. Methods

Mass estimation using the optimal trajectory approach consists of two primary stages: 1) generating a database of virtual fuel-optimal flight trajectories and 2) training the take-off mass estimator. This section details the assumptions, the methods employed for generating fuel-optimal trajectories, the scope and limitations of the optimal trajectories database, and the techniques used for constructing the regression models.

A. Assumptions

We are following an open-loop approach for the mass estimation, which means some major assumptions must be made. The general concept is based on the following two assumptions:

1) The actual flights, especially their vertical profiles, are sufficiently close to fuel-optimal trajectories due to the fuel perspective of flight operations.
2) Aircraft weight and flight distance are the main parameters significantly affecting the cruise altitude of a flight.

The second assumption ignores the flight speed, which is also related to the cost index choice. In the paper, we tested different models with and without cruise speed and compared their performance. Overall, these assumptions allow the use of an open-loop optimal trajectory approach to estimate the take-off mass of an aircraft.

B. Generation of Optimal Trajectories

To generate optimal trajectories, we employ *OpenAP.top*, an optimizer that uses the direct collocation method to solve the continuous optimal control problem of optimal trajectory generation through nonlinear programming (NLP). In this case, the optimal control problem is formulated by simplifying the aerodynamic model to a point mass model with the following state parameters:

$$\mathbf{x}_t = [x_t, y_t, h_t, m_t] \tag{1}$$

where (x, y), h, and m are the 3D position and mass of an aircraft. The control states include:

$$\mathbf{u}_t = [M_t, \mathsf{vs}_t, \psi_t] \tag{2}$$

where M, vs, and ψ are Mach number, vertical rate, and heading of the aircraft. The dependence of state variables on control variables can be expressed in the following ordinary differential equations:

$$\frac{\mathrm{d}x}{\mathrm{d}t} = v_t \sin(\psi_t)\cos(\gamma_t) \tag{3}$$
$$\frac{\mathrm{d}y}{\mathrm{d}t} = v_t \cos(\psi_t)\cos(\gamma_t) \tag{4}$$
$$\frac{\mathrm{d}h}{\mathrm{d}t} = \mathsf{vs}_t \tag{5}$$
$$\frac{\mathrm{d}m}{\mathrm{d}t} = -\mathsf{ff}_t(m, v, h) \tag{6}$$

where v is the true airspeed, which is calculated from Mach number and altitude information, using the International Standard Atmosphere model (ISA), γ is flight path angle, and ff is the fuel flow model that is dependent on the aircraft mass, speed, and altitude.

Airlines often operate flights using a cost index, weighing fuel costs against time costs. Generally, airlines prioritize fuel savings, unless a flight has strict arrival time requirements. In this research, we use minimum fuel consumption as the objective to generate fuel-optimal trajectories for our optimal dataset. The generalized form of an objective function J can be denoted as:

$$J(\mathbf{x}, \mathbf{u}, t_0, t_f) = \int_{t_0}^{t_f} \mathsf{ff}_t(\mathbf{x}, \mathbf{u}) \tag{7}$$

where t_0 and t_f are the start and end times of the flight. The cost can be dependent on control variable states and (or) flight states. In our model, the fuel flow is dependent on states including mass, altitude, speed, and vertical rate, which is calculated using the *OpenAP* fuel module.

The resulting nonlinear equations can be solved numerically. In our case, the direct collocation approach discretizes the time frames into collocation points and approximates the state variables (1) by optimizing control variables (2) using low-order polynomials over the defined intervals. The numerical solver used in the optimizer is *CasADi* [16], an open-source library and symbolic framework for numeric optimization. Input variables for *OpenAP.top* include aircraft type, start and end positions, and take-off mass, provided as a ratio of maximum take-off mass (MTOW). The information about the aircraft type allows the optimizer to obtain the aircraft-specific performance models from *OpenAP*. A comprehensive explanation of the optimization procedure is provided in [14].

C. Construction of Optimal Trajectory Dataset

For the creation of the optimal dataset (or lookup tables), we divided the range of take-off masses and flight distances into intervals. Specifically, we selected 40 intervals for take-off mass, evenly distributed between 120% of the operating empty weight (OEW) and maximum take-off mass (MTOW). Additionally, 40 intervals were chosen for flight distances, ranging from 500 km up to the maximum range for each aircraft type sourced from the *OpenAP* aircraft performance database.

Therefore, each lookup table for a specific aircraft type comprises fewer than 1,600 trajectories, accounting for physical and operational limitations preventing unrealistic trajectory generation. For instance, due to low weight, aircraft cannot undertake long-distance flights with insufficient fuel. Conversely, landing with a weight exceeding the maximum landing weight (MLW) is also undesirable

D. Estimation Using Regression Models

To estimate the take-off mass, first, we used a multi-linear regression model trained on the pre-constructed optimal flight database. The estimator requires the following input parameters: cruise altitude, flight distance, and aircraft type. The altitude and flight distance can be obtained from ADS-B data of actual flights, while aircraft type can be obtained from various databases, such as the *OpenSky* aircraft database.

In later sections of this paper, we incorporate cruise speed as an additional feature in the regression models and demonstrate its impact on estimation accuracy.

Although the multi-linear regression model is valued for its simplicity, it is often less accurate compared to decision tree-based models. We tested both multi-linear and gradient-boosting regression models, and the latter showed superior estimation accuracy in capturing the training set. However, the three-feature multi-linear regression model showed the highest accuracy when tested on real QAR data.

In order to evaluate the estimation performance and errors, we applied the trained models to two real-world flight datasets. The first dataset was obtained from the *OpenSky Network* [17] over 36 days and spread over 2022. The second dataset is an anonymized QAR dataset with known take-off masses for 637 flights.

III. Results and Analyses

A. Examples of Optimal Trajectories

As discussed in Section II-A, two assumptions are made. We hypothesize that aircraft mass and flight distance are the primary factors influencing cruise altitude. Figure 1 demonstrates the relationship between optimal flight altitude and aircraft take-off mass. It showcases optimal trajectories generated for the A320 at the same flight distance but different take-off masses. We can observe that heavier aircraft tend to have lower optimal altitudes during flight.

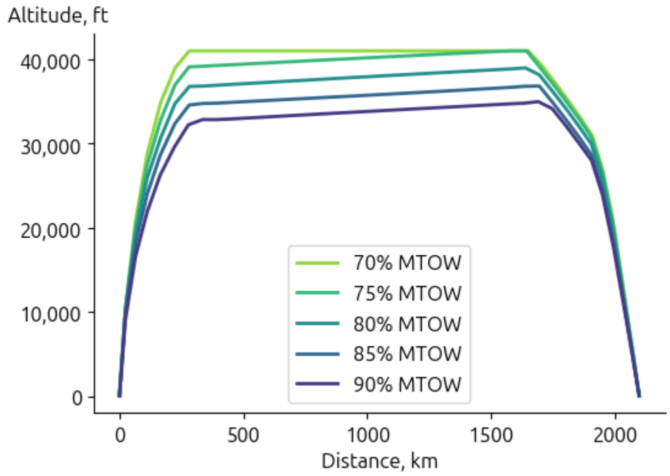


Figure 1. Generated optimal trajectories for different take-off mass and fixed flight distance of 2100 km.

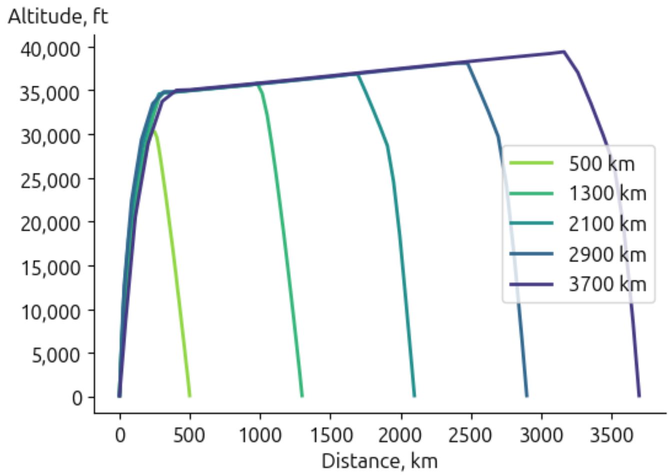


Figure 2. Generated optimal trajectories for different flight distances with the fixed take-off mass of 85% MTOW.

Figure 2 shows five optimum trajectories generated for the A320 aircraft type, all of which have the same take-off mass but vary in range. The figure demonstrates the increase in altitude during flight. This inclination occurs because the aircraft's mass decreases as it burns fuel, resulting in a higher optimum altitude. In reality, continuous climbing during the cruise phase is not typically implemented and is instead replaced by step climbing. For this reason, we consider the mean cruise altitudes when comparing the actual flights and optimal trajectories in this study.

B. The Lookup Table Dataset

Figure 3 shows the generated lookup table for the A320. In this scatter plot, each data point represents a flight trajectory, with the Y-axis indicating the mean cruise altitude during a flight and the X-axis indicating the flight distance. The dots are color-coded based on the estimated take-off mass; the darker the color corresponds to the heavier take-off mass.

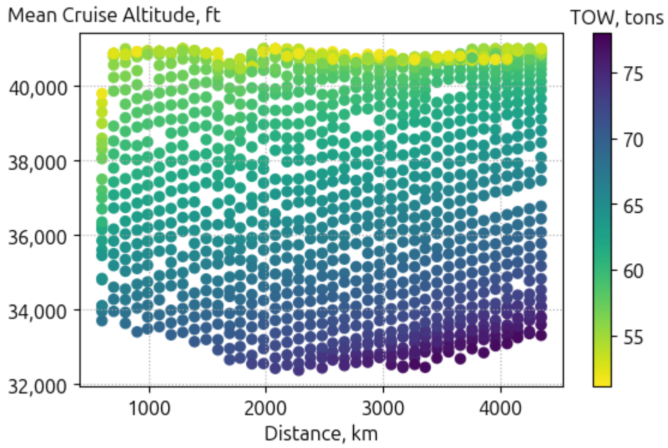


Figure 3. Generated lookup table for A320.

This figure illustrates the relationship between take-off mass, flight distance, and optimal cruising altitude (Fig. 3). The smooth color transition across the scatter plot is evident. The upper left corner, featuring lighter colors, represents lighter aircraft that travel shorter distances and have higher optimal altitudes. Conversely, the bottom right corner, with darker colors, represents trajectories for heavier aircraft that fly longer and for which higher altitudes are not optimal. Moreover, from this figure, we can visually assume that the mutual dependency of TOW, cruise altitude, and distance is linear. This means a multi-linear model trained on the lookup table must be a sufficiently accurate take-off mass estimator.

C. *Two-feature Multi-linear Regression Model*

Our two-feature multi-linear regression model was built based on the information shown in Figure 3. The model considers two features, which are flight distance and mean cruise altitude, and the prediction target is the take-off mass. The model was developed using the *scikit-learn* library [18] and is relatively simple. For example, the model for the Airbus A320 is expressed as follows:

$$m_{\text{takeoff}} = 1.8533\ d_{\text{km}} - 1.99133\ h_{\text{ft}} + 133497 \quad (\text{kg}) \tag{8}$$

where h_{ft} is the altitude in ft, and d_{km} is the total flight air distance in km.

To evaluate the variance in predictions within the lookup table dataset, we randomly split the data into training and testing sets using an 80/20 ratio. Figure 4a illustrates the test-train check results for the full optimal dataset.

During the analysis, we observed that lightweight trajectories tend to overlap at approximately 41,000 ft (Fig. 3), negatively impacting the multilinear regression model. Specifically, flights with the same flight distance at this altitude exhibit different take-off masses, introducing inconsistencies in the model predictions. To address this issue, we refined the dataset by removing the lightest flights (represented by the lightest dots in Fig. 3). As a result, the training dataset now consists of 1,307 flights instead of the original 1,324.

This refinement led to a slight improvement in model accuracy. As shown in Figure 4b, the percentage error decreased from 2.63% (full dataset) to 2.24% (cropped dataset) for the 2D multilinear model. Most data points are tightly clustered around the red reference line, indicating good predictive performance. However, greater deviations are observed for take-off masses below 58 tons and above 73 tons, with the maximum take-off mass (MTOW) for the A320 being 78 tons.

Despite the dataset adjustment, some outliers remain in the upper-left region of the test-train comparison plots (Fig. 4). This suggests that while removing the most lightweight flights has improved the performance to some extent, the overlapping has not been eliminated.

D. *Estimation of Take-off Mass Using Real-world Data*

We tested the two-feature multi-linear regression model on two real-world datasets. The open-source OpenSky flight data was used, to predict the take-off mass for over 40,000 flights. This test helped us to see how fast and efficient is the model in the prediction of the TOW by using open-source data. The second dataset is anonymized QAR data, which contains the aircraft mass and trajectory information for 637 A320 flights. This dataset was used to verify the accuracy of the estimation.

1) OpenSky ADS-B Dataset: To test the performance and computational speed of our model, we used real-world open-source data from *OpenSky*. The dataset included all A320 flights over Europe and North America during 36 days in 2022, specifically the 1st, 11th, and 21st days of each month.

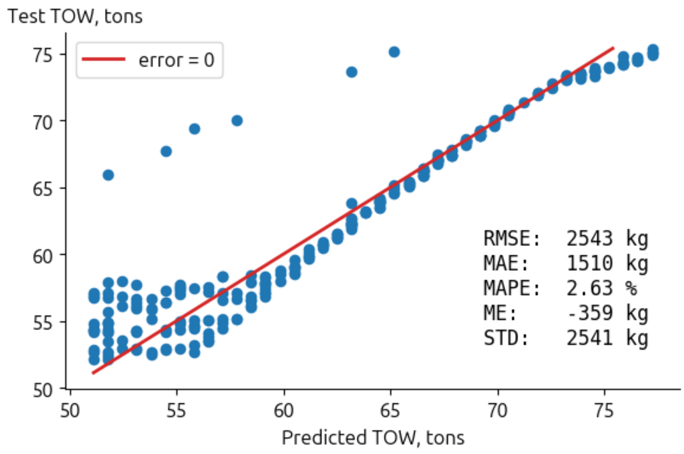
Since the model does not consider wind, we converted the flight distance to the total air distance for a more accurate estimation. The total air distance was derived from true airspeed (TAS) instead of the ground speed. To obtain the airspeed, we used the publicly available ERA 5 data [15], and the wind data is integrated with flight trajectory using the *fastmeteo* tool [19].

Moreover, we filtered out flights with a mean cruise altitude below 30,000 ft, as these flights are likely not following optimal trajectories and are restricted by air traffic controls. All data preprocessing was performed using the *traffic* library [20], with the help of which we filtered and resampled the data downloaded from the historical database of *OpenSky Network*.

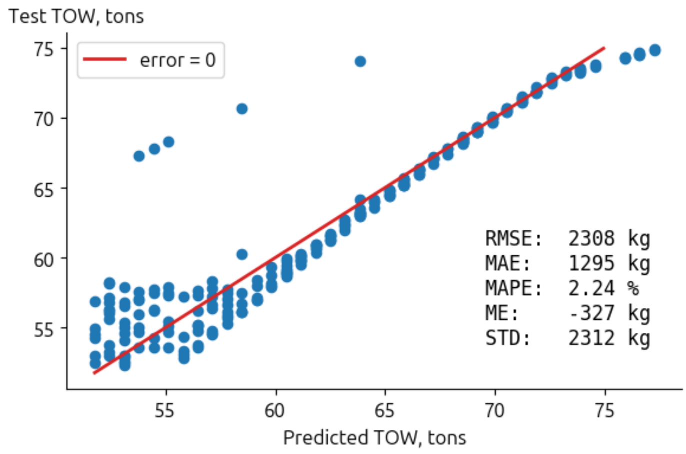
The final dataset consisted of almost 40,000 Airbus A320 flights, with mean cruise altitudes ranging from 30,000 ft to 42,000 ft and flight distances between 538 km to 4,817 km. The estimation process is relatively fast, taking less than one second for all flights, and the results are shown in Figure 5.

In this figure, we can see that the heavier mass is related to the lower altitude. Moreover, the lighter flights are correlated with the flights with shorter ranges. This aligns with the observations from the lookup table data visualized in Figure 3a and demonstrates the linearity.

2) A Flight with Known Take-off Mass: To verify the accuracy of our model, we used a QAR dataset consisting of real-world A320 flights with known mass. First, we closely



(a) Full model



(b) Cropped model

Figure 4. Model accuracy test based on a subset of the data from the lookup table dataset containing optimal trajectories of varying distance and masses. The test is conducted on (a) the full optimal flights dataset and (b) the cropped dataset with omitted lightest-weight flights.

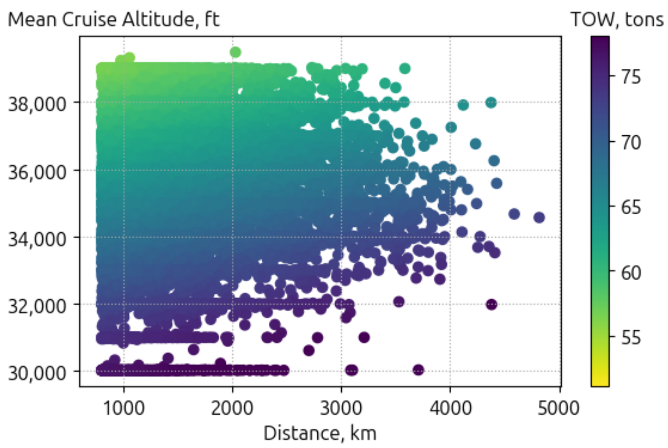


Figure 5. Estimation of take-off mass of OpenSky flights.

examined one real flight to evaluate the performance of our optimizer and regression model.

Figure 6 shows where the real trajectory with an estimated mass is located within the lookup table. The flight distance is 2053 km, and the mean cruise altitude is 35,000 ft. The estimated take-off mass is 67.19 tons, while the actual is 72.27 tons, resulting in an estimation error of 6.67%.

This figure highlights that the actual flight maintains a constant altitude (35,000 ft) during the cruise phase, most likely maintaining the field cruise altitude. In contrast, the optimal flight trajectory gradually increases the altitude from 35,000 to 36,000 ft during the cruise as the aircraft's mass decreases. Moreover, the TOW of the actual flight is higher compared to the optimal trajectory, yet they fly at almost the same flight level. This discrepancy can be because real flights are not fully optimal and often consume more fuel.

3) Verification Using QAR Flight Dataset: Next, we applied the take-off mass inference to the entire QAR dataset and compared the estimation errors. The dataset comprised 637 A320 trajectories with a maximum flight range of 3300 km. The take-off mass of these flights varied between 69.48% and 94.58% of the MTOW.

Figures 7a and 7b show the real trajectory TOW and the two-feature linear model estimation results, respectively. In those figures, each data point represents one flight trajectory. The Y-axis denotes the mean cruise altitude, while the X-axis denotes

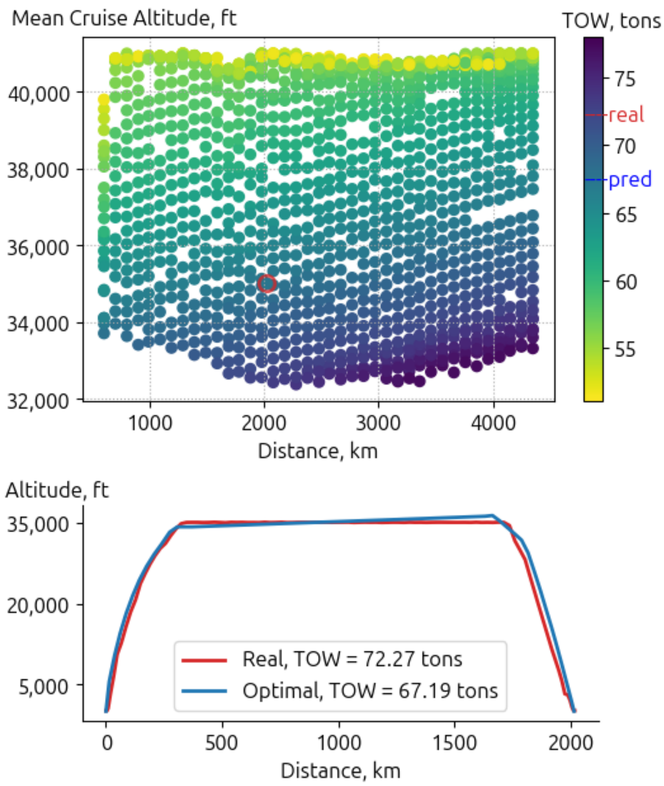


Figure 6. Location of an example trajectory in the grid of the lookup table (the red circle in the top figure) and corresponding fuel-optimal trajectory generated based on *OpenAP* (comparison in the bottom figure). The 'real' and 'pred' ticks on the colorbar represent the actual and estimated take-off mass (TOW), respectively.

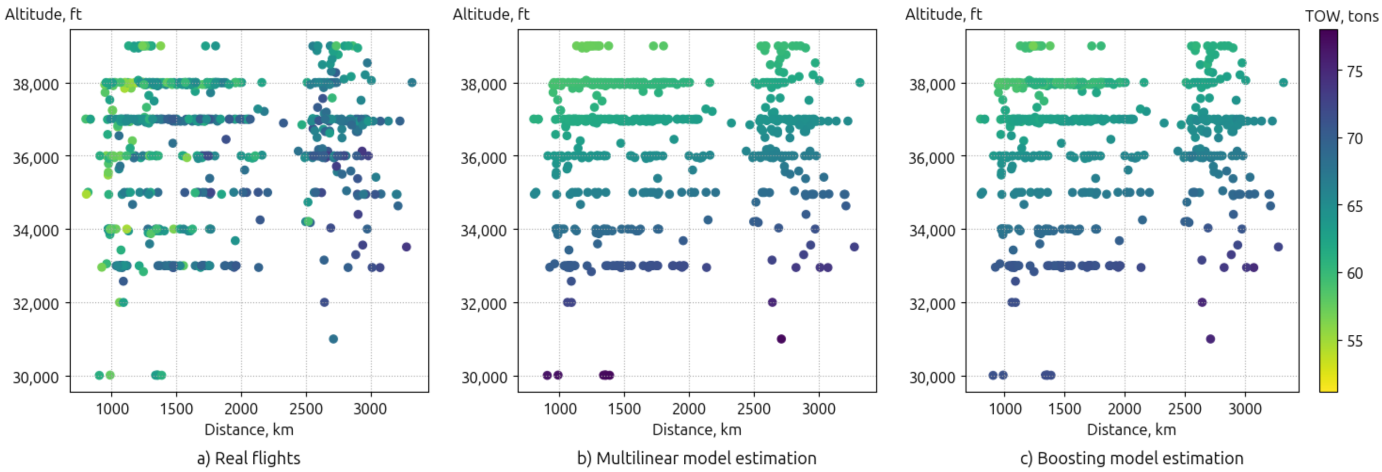


Figure 7. Estimation of take-off mass of A320 real trajectories using a lookup table and regression models.

the flight distance. The figures reveal that high-altitude flights were mostly underestimated by the linear model, while low-altitude flights were overestimated. Additionally, the plots show that the actual flight patterns are more chaotic. Heavier flights rarely exceed altitudes higher than 37,000 ft, which is not optimal. Conversely, lighter aircraft may still fly at lower and less optimal altitudes due to air traffic control.

The estimation errors for all the flights are shown in the histogram in Figure 10a, which demonstrates that the majority of flights are underestimated, with errors up to 5 tons. Although some flights have been drastically overestimated (the largest estimation error is 20,900 kg), they are few in number. Overall, the mean absolute error (MAE) is about 3,819 kg, which is 5.95% in terms of mean absolute percentage error (MAPE).

E. Considering Cruise Speed for Estimation

Our current approach is built on the strong correlation between cruise altitude, flight distance, and aircraft take-off mass. However, feature importance analysis showed that true airspeed (TAS) could also considerably impact take-off mass estimation and is another significant parameter to consider.

To further improve estimation accuracy, we developed a new regression model incorporating three features: altitude, flight distance, and TAS. By adding TAS, we aimed to assess its impact on take-off mass prediction.

Figure 8 presents the test-train check results for the three-feature multilinear model, demonstrating a significant improvement compared to the previous two-feature model (Fig. 4). In this updated model, all data points are closely aligned with the red reference line, and no distant outliers are observed. The mean percentage error has also been reduced to 1.44%, further validating the model's improved accuracy. A key benefit of incorporating TAS is that it resolves the issue of trajectory overlap at 41,000 ft. Unlike in the previous model, where flights with the same flight distance at this altitude had varying take-off masses, TAS provides an additional distinguishing factor, effectively eliminating this source of uncertainty while maintaining simplicity. For A320 the 3D multilinear model is as follows:

$$m_{\mathrm{TOW}} = 1.456\ d_{\mathrm{km}} - 2.111\ h_{\mathrm{ft}} + 187.53\ v_{\mathrm{kts}} + 55620 \quad \text{(kg)} \tag{9}$$

where v_{kts} is the mean cruise true airspeed in kts.

Figure 10c illustrates the distribution of estimation errors of the 3D multilinear model. While the median shift from zero is larger for the three-feature model ($-2{,}424$ kg) compared to the two-feature model ($-1{,}209$ kg), the overall performance is superior across multiple error metrics, namely MAPE, RMSE, MAE, and STD.

These results confirm that TAS is a crucial parameter influencing the optimal take-off mass estimation, making the three-feature model the most accurate among those tested.

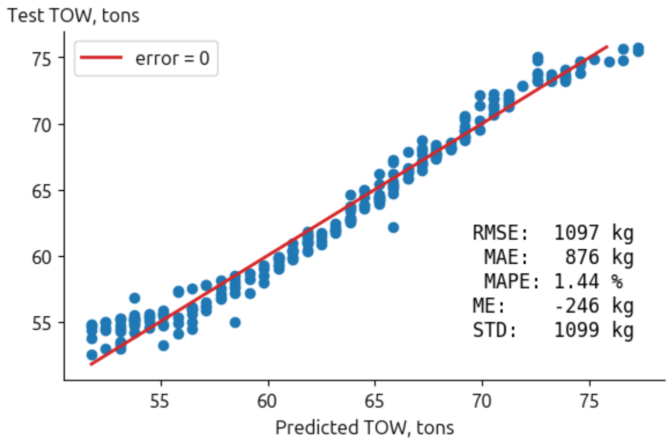


Figure 8. Train-test check for 3D multilinear model.

F. Gradient Boosting Model

The multilinear regression models have limitations when dealing with non-linear feature-target relationships, which are inherent to this problem. To address this, we tested a gradient boosting model using both 2D (distance, altitude) and 3D (distance, altitude, TAS) input features.

The resulting error distributions are shown in Fig. 10b and 10d. These histograms indicate that while the three-feature boosting model outperforms the 2D multilinear model, it still exhibits larger errors compared to the 3D multilinear regression model.

To further analyze this behavior, we evaluated the three-feature boosting model by splitting the optimal flight data into training and test sets and assessing its performance. As shown in Figure 9, the boosting model effectively captures feature dependencies and demonstrates better generalization compared to both multilinear regression models (Figures 4 and 8). This improved test-train performance is attributed to the model's ability to learn underlying non-linear patterns in the optimal dataset.

However, despite its superior adaptability, the mean absolute estimation error for the test-train check remains relatively high: 5.36% for the 2D boosting model and 5.24% for the 3D boosting model. Both values exceed the error of the 3D multilinear model (4.89%), indicating that while boost is more flexible in learning the dependencies of features, it can also introduce additional variance, potentially leading to overfitting or increased sensitivity to data variations.

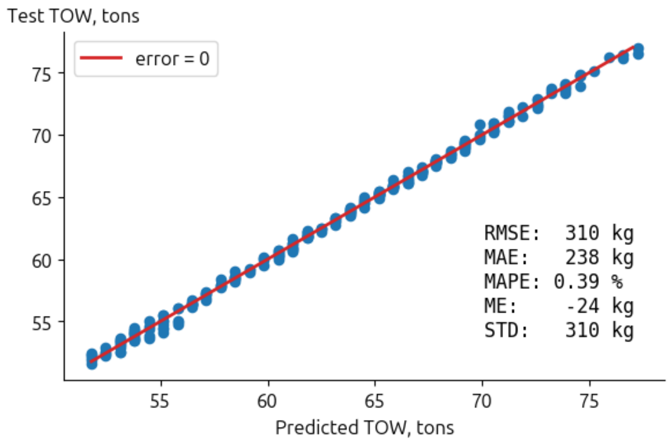


Figure 9. Three-feature boosting model accuracy test based on a subset of the data from the lookup table.

IV. Discussions

A. *Error Significance at Different Altitudes*

Upon further investigation of the error, it was discovered that considerably higher error corresponds to the lower altitude flights. Table I shows that altitudes lower than 35,000 ft are mostly overestimated, while higher altitude flights are under-estimated, resulting in a negative mean error. This is because our model assumes that flights follow optimal trajectories to minimize flight and fuel costs. Therefore, if a flight is forced to fly a non-optimal trajectory for any reason, the accuracy of the take-off mass estimate decreases.

By generating various trajectories for different take-off masses and flight distances, we demonstrated that it is rarely optimal for the A320 to fly below 32,000 ft. As a result, our two-feature multi-linear model has a greater error in estimating the take-off mass for flights with cruising altitudes below this threshold.

TABLE I. Variation of 2D multilinear model estimation error with the cruise altitude

flights	Alt. (ft)	ME (kg)	MAE (kg)	RMSE (kg)	MAPE (%)
35	39 000	-4 532	3 839	4 297	6.08%
160	38 000	-2 610	3 126	3 633	4.93%
181	37 000	-3 368	3 749	4 385	5.58%
97	36 000	-1 249	3 525	4 133	5.35%
49	35 000	-871	2 729	3 449	4.21%
48	34 000	4 879	5 413	6 403	8.88%
57	33 000	2 701	3 770	4 825	5.85%
11	32 000	14 530	13 681	14 345	22.39%

B. *Other Aircraft Types*

In this paper, we focused on the A320 aircraft due to the availability of the A320 QAR dataset for evaluation and because it is one of the most common aircraft types. However, *OpenAP* contains performance models for 34 aircraft types, 15 of which currently have accurate fuel flow models. The exact process can be applied to all other available aircraft types. In future studies, we plan to generate the mass prediction model for other common commercial aircraft types.

C. *Temperature Shift and Atmosphere Model*

In reality, the atmosphere often differs significantly from the ISA standard atmosphere model. This is addressed during flight planning by applying a temperature shift to the ISA model. For our lookup tables, we are also considering applying a temperature shift as an additional dimension to account for deviations from standard conditions.

Temperature plays a crucial role in flight dynamics, and the use of the ISA model, which assumes a fixed temperature profile, introduces inaccuracies that could affect the optimal trajectories and, consequently, the take-off mass estimation. True airspeed, which is one of the features considered in the regression model, is highly dependent on temperature. In addition, temperature impacts air density, which directly influences lift and drag forces, and variations in temperature can affect engine efficiency, as engines perform differently in warmer or colder air.

Figure 11 illustrates how actual temperatures can deviate from the ISA model. Including temperature shifts as an additional feature in our lookup tables could improve the accuracy of the take-off mass estimation. However, further investigation is required to determine whether the temperature shift should be based on the mean trajectory temperature and how it applies to flights near the poles.

V. Conclusion

In this paper, we have used the information obtained from optimal trajectories to estimate the take-off mass for real flights. This approach assumes that real flights follow fuel-optimal trajectories and compensates for the lack of real-world data by generating optimal flights with known parameters.

We have trained machine learning models on two and three features extracted from optimal trajectories: mean cruise

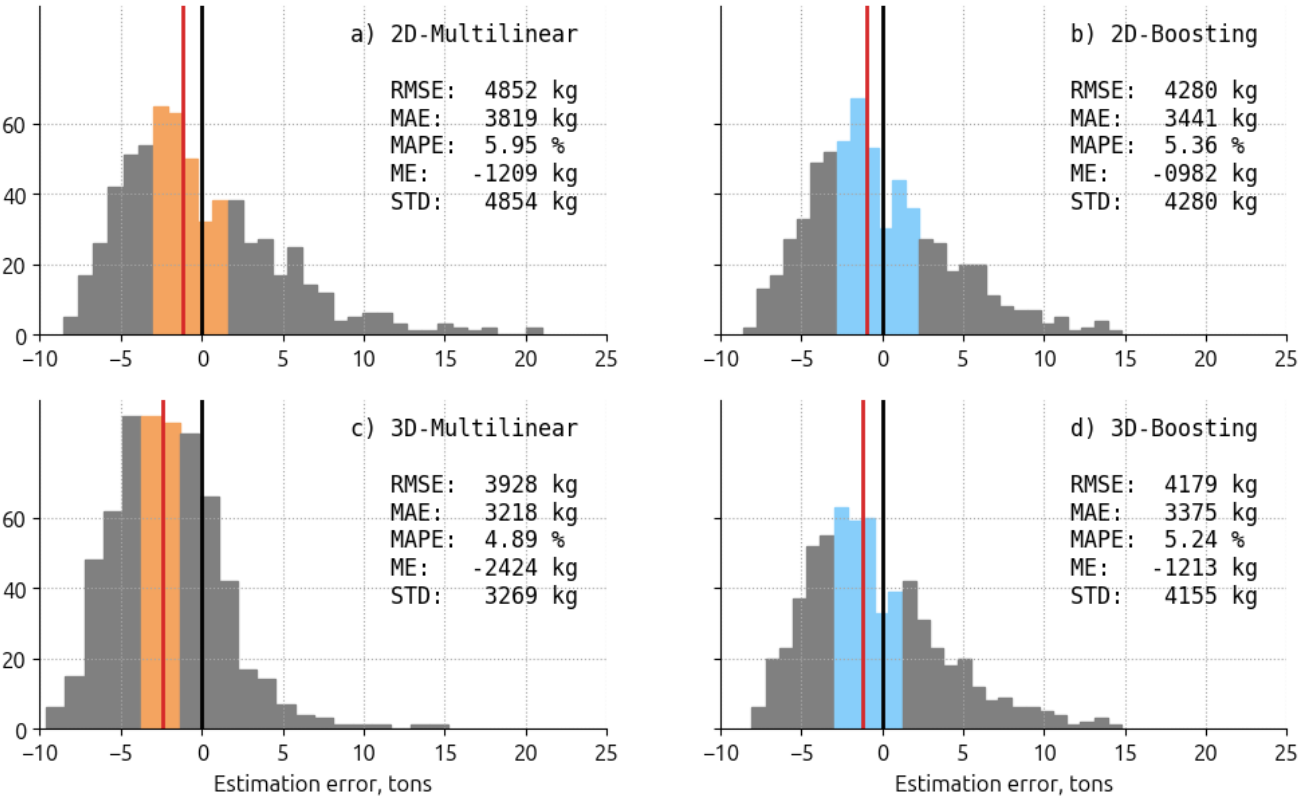


Figure 10. Estimation error histograms for multi-linear and boosting models with two (altitude and distance) and three (altitude, distance, and TAS) features considered. The metrics are as follows: root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), median (ME), and standard deviation (STD). The vertical red lines represent the median and the black lines are vertical 0 lines.

altitude, flight distance, and, partially, airspeed. The models were validated against anonymized QAR data. For the best-performing model, a three-feature multilinear model, the mean error was 4.89%, while the simplest multilinear regression model had an error of 5.95%. Gradient boosting models have also been tested in these studies, showing performance error of 5.36% with two features, and 5.24% with three features. This level of accuracy is comparable to fully statistical methods based on FDR data from prior studies [8]. Therefore, this study has shown that take-off mass can be reliably estimated by assuming a simple linear relationship with cruise altitude, flight distance, and speed, which are open-source parameters.

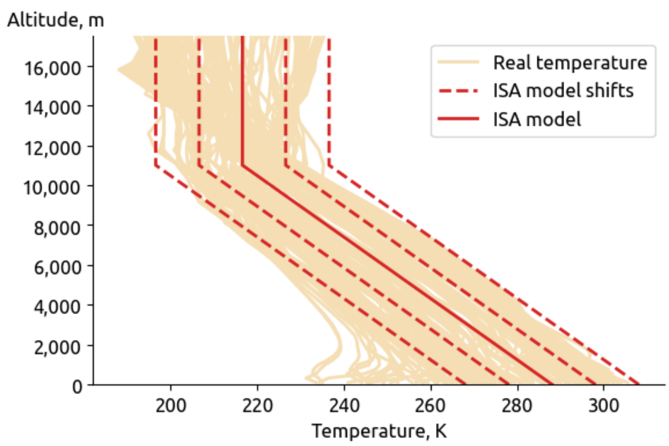


Figure 11. Real temperature approximation with the use of the International Standard Atmosphere (ISA) model and shifts.

In conclusion, the approach offers a simple and effective way to estimate take-off mass. It does not require highly accurate data, and the observation noise has little to no impact on estimation accuracy. This open-loop approach is a practical way to conduct trajectory studies in the absence of real data. It is a step forward for realistic aircraft performance modeling and flight efficiency studies.

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Reproducibility Statement

The code, data, and the model of the paper are openly shared at https://github.com/dus42/takeoff-mass

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