

Physics-Based In-Flight Take-Off Weight Estimation from ADS-B and Weather Reanalysis

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Abstract

The take-off weight of a commercial aircraft is generally not shared with air navigation service providers. Consequently, air traffic management trajectory predictors commonly assume a fixed reference weight, introducing a systematic error. This article presents a physics-based method to estimate aircraft take-off weight in flight using openly available data. The estimation is formulated as a pointwise force-balance problem along the observed climb. ADS-B trajectories from the OpenSky Network and weather reanalysis are used to recover the true airspeed and atmospheric state, while a performance model provides the thrust and drag required to solve the specific-energy equation for the aircraft mass. A thrust factor, calibrated per aircraft type using flights with known take-off weights, is used to correct the systematic per-type bias between the modelled thrust and the effective thrust in the observed climb. Accuracy is further improved by independently estimating the mass from the flown distance and combining both estimates through inverse-variance weighting, without requiring additional data. The method is validated using the EUROCONTROL Performance Review Commission Data Challenge 2024 dataset and compared with a gradient-boosting baseline trained on the full labelled dataset. The proposed method achieves an RMSE of 5.8%, compared with 4.7% for the baseline, while requiring no large labelled training set—only a small per-type calibration dataset—and remaining physically interpretable. Furthermore, for aircraft types operated close to a constant weight, both methods yield comparable results. Accurate take-off weight estimates improve trajectory prediction and, since weight is a primary driver of fuel consumption, enable better fuel-burn and emissions assessment in air traffic management.

Keywords: Take-off weight estimation; ADS-B; Physics-based estimation; Total energy model

1. Introduction

Estimating the weight of a commercial aircraft from its observed motion is a well-studied problem, since take-off weight is one of the most important and least accessible inputs for the trajectory predictors used in the modernisation of the air traffic management (ATM) system [1, 2]. Because it is treated as commercially sensitive, the take-off weight is not shared with air navigation service providers, and predictors commonly assume a fixed reference mass, at the cost of a systematic error that is particularly significant during the climb.

Two main families of methods have been used to estimate aircraft mass from observable quantities. Physics-based methods use the equations of motion along the observed trajectory together with an aircraft performance model. In [3], mass and thrust are estimated by fitting the modelled specific power to the observed energy rate from ground radar tracks. The mass is estimated online from the available points of the current trajectory, whereas the thrust law is learned offline from historical trajectories. Other physics-based approaches use Bayesian inference or particle filtering. In [2], the initial mass is estimated from surveillance data using Bayesian inference, while mass and thrust setting are jointly estimated using a particle filter in [4]. These studies show that observation noise limits the extent to which mass and thrust can be estimated separately. Data-driven methods instead

learn the mass from a set of example flights with known mass. In [1], aircraft mass is treated as the response variable of a machine-learning model trained on example trajectories, while [5] uses statistical models based on flight data. The EUROCONTROL Performance Review Commission (PRC) Data Challenge 2024 [6] produced several models of this type, with the best-performing approaches combining trajectory-derived features, such as flown distance and estimated fuel consumption, with gradient-boosted trees [7].

This work builds on the physics-based approach and extends it through three main contributions. The force-balance estimator based on the specific-energy equation, the use of an aircraft performance model, and the per-flight unidentifiability of the thrust setting are established results. The first contribution is a correction of the systematic per-type discrepancy of the physical estimate using a single empirical factor calibrated against known weights. The second contribution is the combination of the physical estimate with an independent, distance-based estimate of mass through inverse-variance weighting. This second estimate introduces neither additional free parameters nor labelled data. The third contribution is a validation against the actual take-off weights in the PRC Data Challenge 2024 dataset using a protocol with strictly disjoint calibration and evaluation sets, together with a comparison with a data-driven baseline to identify the conditions under which each approach is preferable. The complete pipeline uses open surveillance and weather data.

2. Methodology

2.1 Specific-energy formulation

The estimation is formulated as a pointwise force-balance problem along the observed climb. For a climbing aircraft, the specific-energy (total-energy) equation relates the rate of climb to the excess thrust:

$$\dot{h} = \frac{(T - D)V}{mg} f_{\text{ESF}}, \quad (1)$$

where T denotes thrust, D drag, V true airspeed, m aircraft mass, g gravitational acceleration, and f_{ESF} the energy-share factor. The aircraft kinematics are obtained from Automatic Dependent Surveillance–Broadcast (ADS-B) trajectories provided by the OpenSky Network, while the ERA5 reanalysis provides the wind and temperature fields needed to reconstruct V and the atmospheric state. An aircraft performance model is used to obtain T and D . The mass is estimated at each clean-configuration point of the climb by rearranging Equation (1). The proposed method uses BADA 3.16 [8] as the performance model, but is not tied to a particular source of T and D and alternative performance models can be used instead.

2.2 Calibration and correction of the mass estimates

The proposed approach uses flights with known take-off weight to correct the systematic bias of the physics-based estimate and to construct a complementary distance-based estimate, with both estimates subsequently combined through inverse-variance weighting.

Using the modelled maximum climb thrust in (1) leads to a systematic bias in the mass estimate. This bias is corrected by introducing a single multiplicative factor η on the modelled thrust, so that the corrected physical estimate becomes

$$\hat{m}_{\text{phys}} = \frac{(\eta T - D)V}{g \dot{h}} f_{\text{ESF}}, \quad (2)$$

with η calibrated separately for each aircraft type so that the median mass error over the calibration flights is zero. The per-flight estimate is obtained by aggregating the pointwise values of $\hat{m}_{\text{phys}}$ over the clean-configuration points of the climb.

The factor η represents the net systematic discrepancy between the modelled and observed specific-energy rates in (1). It therefore captures the combined effects of differences between the actual and modelled thrust, including possible thrust derating, errors in the thrust and drag models, the fixed energy-share-factor approximation, and residual biases in the ADS-B kinematics and atmospheric reconstruction. The assumption is that their combined effect is sufficiently stable within an aircraft type to be represented by a single calibrated factor. Consistent with [4], η cannot be identified independently for each flight together with the aircraft mass, and is therefore estimated at the aircraft-type level.

Pooling η by aircraft type leaves a residual error, particularly for types with a wide range of take-off weights. To reduce this error, a second mass estimate is obtained from the flown distance d , which is related to the fuel carried and, consequently, to the take-off weight. For each aircraft type, a polynomial regression of the known take-off weight on distance is fitted using the calibration flights: a linear model is used when fewer than 40 flights are available and a quadratic model otherwise. This provides the distance-based estimate $\hat{m}_{\text{dist}}(d)$. The physical and distance-based estimates, $\hat{m}_{\text{phys}}$ and $\hat{m}_{\text{dist}}$, are then combined by inverse-variance weighting:

$$\hat{m} = w \hat{m}_{\text{phys}} + (1 - w) \hat{m}_{\text{dist}}, \quad w = \frac{\sigma_{\text{dist}}^2}{\sigma_{\text{phys}}^2 + \sigma_{\text{dist}}^2}, \quad (3)$$

where σ_{phys}^2 and σ_{dist}^2 are the residual variances of the two estimates, computed separately for each aircraft type from the calibration flights.

3. Results

The method is validated against the actual take-off weights in the PRC Data Challenge 2024 dataset. Flights are stratified by aircraft type and divided into a calibration set, used exclusively to fit η and the distance regression, and a disjoint test set, used only for evaluation. Aircraft types with fewer than 30 calibration flights are excluded from the analysis, leaving 21 types with between 61 and 117 calibration flights each. The calibration–test split is repeated for ten random draws, and the reported metrics are averaged across the resulting test sets. Thus, no flight is used for both calibration and evaluation in any split.

ADS-B barometric altitude is reported in quantised steps, which introduces noise in the rate of climb and consequently in the pointwise mass estimate. To mitigate this effect, only the clean climb phase is retained, above 10,000 ft and positive rate of climb, and the pointwise mass estimates are aggregated over the flight to reduce the effect of quantisation noise.

The results are reported in Table 1 and Figure 1. Across all aircraft types, the proposed method achieves a mean absolute error (MAE) of 4.0% and a root-mean-square error (RMSE) of 5.8%. Its performance is mainly determined by the dispersion of take-off weights within each type, measured by the coefficient of variation (CV), rather than by aircraft size. Types are therefore divided into low ($\text{CV} < 0.09$) and high ($\text{CV} \geq 0.09$) variability groups, with the threshold corresponding to a natural gap in the data. A gradient-boosting baseline [9], trained on the full labelled dataset and evaluated on the same test flights, is included for reference. For low-variability types, the proposed method achieves an RMSE of 4.6%, compared with 4.9% for the baseline, despite requiring only a small number of labelled flights for calibration. For high-variability types, the baseline performs better.

The difference between the two approaches is further illustrated in Figure 1, which shows the baseline RMSE as a function of the number of labelled training flights. The physical estimate captures flight-to-flight weight variations from each aircraft's climb, whereas the data-driven baseline learns

Table 1. Take-off weight estimation error. MAE and RMSE in per cent of the actual take-off weight. The last column is the number of labelled flights the baseline needs to reach the RMSE of the proposed method.

Weight variability	Types	Flights	MAE / RMSE [%]		Labels to match RMSE
			Proposed	Baseline	
Low ($CV < 0.09$)	15	602	3.3 / 4.6	3.3 / 4.9	> 300,000
High ($CV \geq 0.09$)	6	240	5.8 / 8.0	2.9 / 4.2	~3,000
All	21	842	4.0 / 5.8	3.1 / 4.7	~5,000

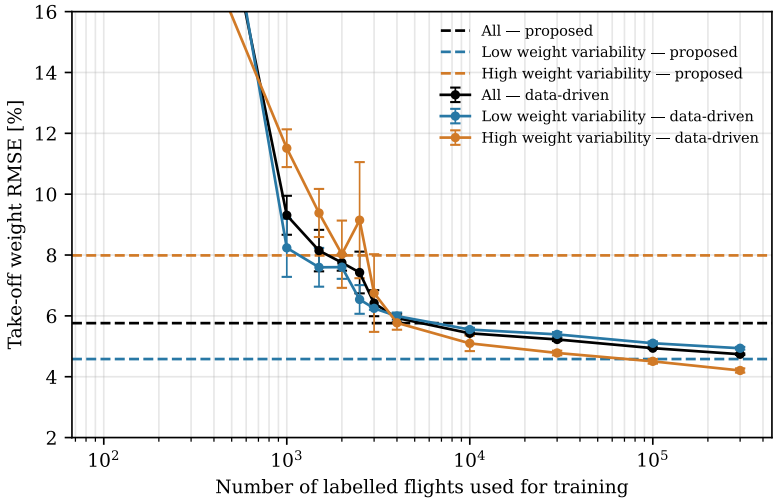


Figure 1. Take-off weight RMSE of the data-driven baseline against the number of labelled flights used for training, compared with the proposed method.

typical loading patterns from the training data. Consequently, the baseline quickly approaches the performance of the proposed method for high-variability types and improves further with additional labelled data, while it does not surpass the proposed method for low-variability types even when trained on more than 300000 flights. The proposed method therefore provides a competitive label-free alternative, particularly when within-type weight variability is limited.

4. Conclusion

A physics-based method has been presented for estimating the take-off weight of a commercial aircraft in flight from ADS-B and weather data, correcting the systematic per-type discrepancy with a single calibrated factor and combining the resulting estimate with a distance-based estimate. On the PRC Data Challenge 2024 dataset, the method achieves an MAE of 4.0% and provides a competitive label-free alternative to a data-driven baseline, particularly for aircraft types with limited weight variability. The surveillance and weather inputs are fully open, while the BADA 3.16 performance model is licensed by EUROCONTROL. The method is nevertheless independent of the specific performance model and can use open alternatives such as OpenAP [10] or the Poll-Schumann model [11]. Future work will assess the effect of replacing BADA with an open model and refine the treatment of the energy-share factor and thrust uncertainty.

Author Contributions

Conceptualization (all); Methodology (A.B.); Software (A.B.); Validation (all); Formal Analysis (all); Investigation (all); Data Curation (A.B.); Writing – Original Draft (A.B.); Writing – Review & Editing (all); Visualization (A.B.); Project Administration (A.B.); Funding Acquisition (all).

Open Data Statement

The data used in this work are publicly available. The EUROCONTROL PRC Data Challenge 2024 dataset is accessible at <https://ansperformance.eu/study/data-challenge/dc2024/>, and the ERA5 reanalysis data at <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels>.

Reproducibility Statement

The code supporting the results reported in this work is available upon request.

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