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Aircraft initial mass estimation using Bayesian inference method

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ABSTRACT

Aircraft mass is a crucial piece of information for studies on aircraft performance, trajectory prediction, and many other topics of aircraft traffic management. However, It is a common challenge for researchers, as well as air traffic control, to access this proprietary information. Previously, several studies have proposed methods to estimate aircraft weight based on specific parts of the flight. Due to inaccurate input data or biased assumptions, this often leads to less confident or inaccurate estimations. In this paper, combined with a fuel-flow model, different aircraft initial masses are computed independently using the total energy model and reference model at first. It then adopts a Bayesian approach that uses a prior probability of aircraft mass based on empirical knowledge and computed aircraft initial masses to produce the maximum a posteriori estimation. Variation in results caused by dependent factors such as prior, thrust and wind are also studied. The method is validated using 50 test flights of a Cessna Citation II aircraft, for which measurements of the true mass were available. The validation results show a mean absolute error of 4.3% of the actual aircraft mass.

1. Introduction

Aircraft mass is a fundamental parameter for studies on aircraft performance and trajectory prediction. However, data concerning the mass of almost all modern commercial flights are treated as confidential information by airliners, which poses a challenge for the research community. Studies from Jackson et al. (1999) and Coppenbarger (1999) have shown that having inaccurate aircraft mass estimations introduces a significant source of error, which affects ground based trajectory predictions. The study of Thipphavong et al. (2012) implemented an adaptive aircraft weight algorithm to improve the accuracy of climbing predictions. Fricke et al. (2015) illustrated the significant influence of aircraft mass on fuel burn during continuous descent operations.

Within the air traffic management research community, several methods have been developed to estimate aircraft mass based on flight data, either from radar data or more recently from ADS-B data. In two separate studies, Alligier et al. (2013, 2015) developed a least-squares method and a machine-learning method, which focused on the climb phase of aircraft. In a similar approach considering climbing aircraft, Schultz et al. (2012) implemented an adaptive estimation method for mass and thrust approximation. More recently, Sun et al. (2016) used ADS-B data from takeoff to estimate the initial mass of an aircraft with two different analytical methods. On the operational side, a different approach has been proposed by Lee and Chatterji (2010), which tries to calculate the weight of an aircraft based on an approximation of each individual weight component, i.e. aircraft empty weight, fuel weight, and payload weight.

For most of these studies, the focus was on a specific part of the flight (takeoff or climb). It is often not possible to produce a reasonable estimate for individual flights. One can only infer the possible distribution of aircraft mass based on a great number of flights. This is not only due to the variance in the data, but also due to uncertainties in aircraft configuration, something that is suggested in all of these studies. To develop a method that can estimate the mass of any flight becomes the focus of this paper.

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Nomenclature

m	aircraft mass (kg)	μ	runway friction coefficient (–)
η	thrust coefficient (–)	a	aircraft acceleration (m/s^2)
T	total dynamic thrust (N)	V	true airspeed (m/s)
T_∞	maximum static thrust (N)	V_z	vertical speed (m/s)
D	total drag force (N)	C_D	drag coefficient (–)
L	aircraft lift force (N)	C_L	lift coefficient (–)
		C_{d0}	zero lift drag coefficient (–)
		C_{di}	induced drag coefficient (–)

In a preliminary study presented earlier by Sun et al. (2017a), the use of multiple mass estimations was identified as a potential improvement for mass estimation, studying not just one specific flight phase, but a combination of all phases. This allows more insight into aircraft mass to be inferred. In this paper, the mass estimation problem is considered as a single parameter Bayesian inference problem (Gelman et al., 2014, p. 29), considering masses computed along the entire flight as 'observations'. In addition to multiple observations, prior knowledge on weight can be used to improve the estimation. For instance, aircraft will never operate above their maximum takeoff weight or below their minimum operational weight. In practice, given an approximation of the number of passengers, one can even further constrain the weight estimation range by making an estimate of the aircraft payload. These kinds of prior knowledge can be very valuable for estimation of actual aircraft mass when applying Bayesian inference.

The remainder of this paper is structured as follows: first, this paper presents several existing methods to calculate aircraft mass independently in each flight phase. Then, in Section three, a Bayesian inference approach is established to use these calculations as independent measurements, combining a priori knowledge of initial aircraft mass probability distribution to produce a maximum a posteriori estimation. The advantage of the Bayesian approach is that it takes into account prior probability distribution and physical limitations of possible aircraft mass. It has the potential to produce an estimate for any given flight based on flight data with the knowledge of aircraft type. Fig. 1 gives an illustration of this method.

Section four discusses the results for several aircraft types and parameter sensitivities. Section five uses a real flight dataset to validate the Bayesian inference method. Finally, discussion and conclusions are presented in sections six and seven.

2. Individual aircraft mass estimates

This section describes five methods that can be used independently to compute aircraft mass at different flight phases. The total energy model (TEM), shown in Eq. (1), is used in most of the methods. In addition, BADA3 aerodynamic coefficients are used to calculate the thrust and drag in some of the phases when applicable (Nuic, 2014).

$$\begin{aligned}
&(T-D)\cdot V = m\cdot a\cdot V + m\cdot g\cdot V_z\\
&D = C_D\cdot\tfrac{1}{2}\rho V^2 S\\
&L = C_L\cdot\tfrac{1}{2}\rho V^2 S\\
&C_D = C_{d0} + C_{di} C_L^2
\end{aligned}\tag{1}$$

Here, T and D are the thrust and drag of the aircraft, V,a, and V_z are the airspeed, acceleration, and vertical rate respectively. C_D,C_L,C_{d0}, and C_{di} are coefficients for drag, lift, zero lift drag, and lift-induced drag. ρ and S are the air density and the aircraft reference wing surface. In addition, the forces acting on an airborne aircraft are also illustrated in Fig. 2.

With the complete flight trajectory based on the total energy model, mass can be computed at different phases as illustrated in Fig. 3, where the subscripts *TO, LOF, CL, DE,* and *APP* represent takeoff, liftoff moment, climb, descent, and final approach,

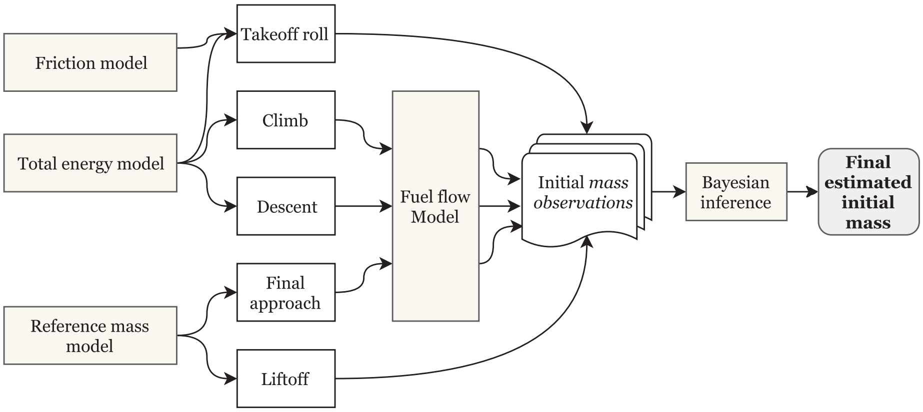

Fig. 1. Flow chart of the estimation structure.