Rapid Automated Aircraft Simulation Model Updating From Flight Data

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Abstract

Techniques to identify aircraft aerodynamic characteristics from flight measurements and compute corrections to an existing simulation model of a research aircraft were investigated. The purpose of the research was to develop a process enabling rapid automated updating of aircraft simulation models using flight data and apply this capability to all flight regimes, including flight envelope extremes. The process presented has the potential to improve the efficiency of envelope expansion flight testing, revision of control system properties, and the development of high-fidelity simulators for pilot training.

Keywords: Aerodynamics, Parameter Estimation, Aircraft Modelling and Simulation

Introduction

The National Aeronautics and Space Administration Langley Research Center (NASA LaRC) is participating in a broad research initiative looking into aviation safety for civilian transport aircraft operations. Investigating safety issues when operating near or at the extremes of the flight envelope is an element of this research, with a special interest in those conditions leading to departure from controlled flight.

Examining the flight characteristics of transport aircraft near the extremes of the flight envelope is challenging due to the logistics, cost, and risk associated with flight testing full-scale transport aircraft. Accurate aerodynamic data are required to predict and simulate the flight behaviour for pilot training and flight control system design while operating in this regime. Wind tunnel testing using scaled models can provide representative aerodynamic data. Computational Fluid Dynamics (CFD) methods may also be used to estimate aerodynamic data. However, the behaviour of the aircraft predicted using these data may not represent that in flight due to experimental and computational limitations. These data are typically used to form the basis of a mathematical representation of the aircraft that is improved using flight test measurements.

NASA LaRC has constructed a dynamically-scaled model of a generic transport aircraft to collect flight data supporting research investigating full-scale transport aircraft behaviour [1,2]. Research has also been conducted investigating techniques to rapidly analyse flight measured data for updating aircraft simulation models [3,4,5,6,7]. Rapid parametric model estimation techniques are particularly valuable when investigating flight envelope extremes as they offer the potential to minimise dangerous flight testing while improving models derived from wind tunnel and CFD data sources. Additionally, NASA is contributing to the development of an aircraft simulation model data exchange standard [8] that provides a framework to simplify the exchange of aircraft models within the simulation user community. Combining the rapid parametric model estimation research with the data exchange standard offers the potential to significantly improve the timeliness and efficiency of updating aircraft simulation models using flight data.

This paper presents research on applying rapid simulation model adjustment techniques to the scale-model generic transport aircraft operated by NASA LaRC. Techniques to identify aircraft aerodynamic characteristics from flight measurements and efficiently apply corrections to an existing aircraft simulation model are included.

The Generic Transport Model

Overview

NASA LaRC has constructed a number of scale-model aircraft representing commercial transport aircraft to support research investigating the behaviour of these aircraft operating at extreme flight conditions. The current research vehicle is known as the Generic Transport Model (GTM) T2, and is shown in Figure 1.

Figure 1: NASA LaRC T2 scale-model Generic Transport Model

The T2 aircraft has been scaled to represent the geometric proportions of a full-sized transport aircraft, as well as its mass properties, including the mass centre and moments of inertia. Consequently, the dynamics and response to controls for the scaled aircraft are representative of the full-sized vehicle when subjected to equivalent control stimuli. The T2 aircraft has 16 control surfaces, all of which may be independently articulated.

In flight test configuration, the T2 aircraft has a takeoff weight of 57 pounds. It is powered by two turbojet engines, and is fitted with an extensive flight test instrumentation suite. A detailed description of the aircraft and its construction is presented in [1,2,9].

Testing

Wind tunnel test programmes of the T2 aircraft were carried out in both the NASA LaRC 14 ft x 22 ft subsonic wind tunnel and the NASA LaRC 20-Foot Vertical Spin Tunnel facilities to gather aerodynamic data from which an initial simulation model was developed [10]. The simulation model was used for the design of flight system control laws and preparation of the flight test programme.

The flight test programme of the T2 aircraft was designed to evaluate the vehicle behaviour in normal operational flight conditions, and in regions of the flight envelope traditionally considered outside normal operating conditions, together with researching adaptive control strategies for protecting against loss of control [11]. In particular, testing was conducted at angles of attack near and beyond normal stall flight conditions, and at high side-slip angles.

Data were gathered for estimating vehicle aerodynamics at these flight conditions. The aerodynamic data from flight test supplemented those from wind tunnel testing, and were used to improve the representation of the T2 aircraft simulation model, as well as providing insight into the propensity for the vehicle to depart from controlled flight.

Pre-programmed control excitations were injected and summed with pilot control commands to exercise the vehicle motion in a desired manner, and the gathered data were analysed using parametric model estimation techniques to estimate aerodynamic characteristics. The control excitations took the form of optimized multi-axis orthogonal multi-sine sweeps [5,12]. These excitations permitted both the longitudinal and lateral aerodynamics to be estimated from the data gathered during a single manoeuvre. References [5] and [12] discuss the design of optimized multi-axis orthogonal multi-sine control excitations for aerodynamic parameter estimation, together with remarks on data correlation.

Improvements in the efficiency of the data gathering and aerodynamic estimation activities were possible as a result of using optimized orthogonal multi-axis excitations. Furthermore, the coupling of these excitation techniques with the rapid flight data analysis techniques described in [3,5,6,7] provided a framework onto which rapid aircraft simulation model updating could be attached.

The Flight Dynamics Model Exchange Standard

The Modeling and Simulation Technical Committee (MSTC) of the American Institute of Astronautics and Aeronautics (AIAA) is developing a series of standards to facilitate the exchange of aircraft dynamics simulation models between aircraft simulation agencies and research establishments. One standard is for the exchange of aircraft characteristic data – BSR/AIAA S-119-2010 Flight Dynamics Model Exchange Standard [8], to which NASA and the Australian Defence Science and Technology Organisation (DSTO) are contributing. The standard defines procedures and formats for exchanging aircraft characteristics such as aerodynamic, propulsion, and mass property data.

The objectification of this standard is the Dynamic Aerospace Vehicle Exchange Markup Language (DAVE-ML), which defines a syntactical language for encoding model data [13]. DAVE-ML employs a text-based format built upon the eXtensible Markup Language (XML) Version 1.1 [14], and Mathematical Markup Language (MathML) Version 2.0 open standards developed by the World Wide Web Consortium (W3C) [15]. It defines additional grammar to provide a domain-specific language for aerospace flight dynamics modelling, verification, and documentation.

Data for the scale-model T2 aircraft were encoded using the DAVE-ML syntactical language and the Flight Dynamics Model Exchange Standard. Coupled with flight modelling software [12], a simulation capability was developed for predicting and verifying vehicle behaviour subsequent to changes to the existing simulation model using data derived from flight experiments. The DAVE-ML syntactical language was chosen for this task as it provided a framework simplifying the process of the updating the original characteristic data with increments utilising a mix of tabular data and equations. In addition, data uncertainty measures could be recorded in conjunction with the respective data, which were then available for subsequent use in simulation studies.

Simulation Model Updating

Simulation models of aircraft are used for a variety of applications including flight behaviour prediction, performance analysis, flight control system design, and pilot training. They combine data defining vehicle characteristics such as the mass, aerodynamics, propulsion, and control systems properties. Accurate data for each of these is required to authentically represent vehicle dynamics and response to control stimuli. A change to aircraft configuration, and/or the availability of improved data for the various sub-systems necessitates updating of the simulation model to ensure its authenticity persists. In the context of this paper, simulation model updating refers to updating the aerodynamic representation of the aircraft using data gathered from flight testing.

Aerodynamic Parameter Estimation

Parametric estimation techniques have been developed for computing estimates of vehicle aerodynamics from flight data [3,4,12,16]. These are often a process of estimating a mathematical representation of the aerodynamic characteristics related to a flight condition. Analysis techniques are available for applying parameter estimation techniques in both the time and frequency domains. The efficiency of these techniques depends on the nature of the manoeuvres flown, the degree to which the natural modes of the vehicle motion are excited, and the accuracy of measured data.

Parameter estimation techniques were chosen and applied to the task of developing a capability for rapidly updating simulation models with revised estimates of aerodynamic characteristics derived from flight data. Time and frequency domain equation-error parameter estimation techniques were chosen for estimating the aerodynamic properties of the T2 aircraft. The aerodynamic estimation process adopted aligned closely with that proposed by Morelli and Ward in [6].

Parameter estimation relies on prior knowledge or assumption of the form of a suitable mathematical representation, with the unknown model parameters then determined from measured data. For flight conditions associated with departure from controlled flight, the form of the mathematical expression of the aerodynamics may be non-linear and multi-dimensional. The form of the expression was not known prior to analysing T2 aircraft flight data. Thus, aerodynamic data gathered from scale-model wind tunnel experimentation, represented as tables, were used to estimate the form of the expression, thereby providing both a structure and *a priori* estimates for its parameters. A multivariate orthogonal function model, covering the flight envelope mapped out by the aircraft during a flight test manoeuvre, was derived from the wind tunnel data. Reference [12] describes of the construction of such models for aeronautical applications. Equation 1 represents an example of a model for the body-axis normal force coefficient C_Z derived using this process for the manoeuvre illustrated in Figure 2. The model is only valid over the ranges of variation of the aircraft states and controls associated with the manoeuvre. In this equation α is the angle of attack in degrees, δ_e the elevator deflection in degrees, and $\hat{q}$ the normalised pitch rate, while $K_0 ... K_3$ are the respective parameters of the model with K_0 representing a bias parameter. The aircraft states and controls were absolute quantities, as opposed to changes around a trim condition.

$$C_Z = K_0 + K_1\alpha + K_2\delta_e + K_3\hat{q} \tag{1}$$

Parameter	Estimate	95% Confidence Interval
K_0	-3.312E-02	[-3.300E-02, -2.900E-02]
K_1	-8.446E-02	[-8.446E-02, -8.446E-02]
K_2	-8.277E-03	[-8.277E-03, -8.277E-03]
K_3	-29.186	[-29.186, -29.186]

The resulting model, together with its parameters acting as *a priori* estimates, was refined using flight data by firstly applying real-time frequency domain equation-error parameter estimation to estimate the model parameters [3,4,12], and then time domain equation-error parameter estimation to estimate the bias term. With reference to the normal force coefficient example, the model parameter estimates for the refined model were:

Parameter	Estimate	95% Confidence Interval
K_0	-1.755E-01	[-1.790E-01, -1.720E-01]
K_1	-6.394E-02	[-6.394E-02, -6.394E-02]
K_2	-6.329E-03	[-8.0E-3, -5.0E-3]
K_3	-18.152	[-18.233, -18.071]

Figure 2 presents the results obtained from applying this process for estimating the normal force coefficient C_Z from a flight test manoeuvre. Figure 2a presents the elevator control input for the manoeuvre together with the measured angle of attack. Figure 2b presents the normal force coefficient computed from accelerations measured during the manoeuvre as well as the corresponding coefficient extracted from wind tunnel data using flight data for the aircraft states and controls. Figure 2c presents the flight-derived normal force coefficient overlayed with the coefficient values computed from the identified model showing an improved match compared to the wind tunnel data.

Figure 3 presents the data with respect to the flight envelope region mapped out during the manoeuvre. Figure 3a presents the normal force coefficient computed from flight measurements together with the relevant wind tunnel data. The wind tunnel data exhibit a trend that differs from the flight data. Figure 3b presents the flight data and identified model with the trend of the identified model aligning closer to the flight data.

The parameter estimation process produced mathematical expressions for the aerodynamic quantities closely matching the characteristics exhibited by the flight data. Furthermore, the process could be automated, including implementation in DAVE-ML, making it ideal for rapidly updating aircraft simulation models.

Aerodynamic Model Framework

Updating an aircraft simulation model by merging flight-derived aerodynamic data with other data sources can be time consuming and reliant on engineering judgement. A goal of this activity is to ensure that the final data, whilst representing the vehicle characteristics, form a continuum between neighbouring data spaces. Discontinuities in the data cause the simulated behaviour of the vehicle to respond in an unnatural fashion to control excitations, and produce unrealistic motions and cues to pilots and/or auto-pilot systems.

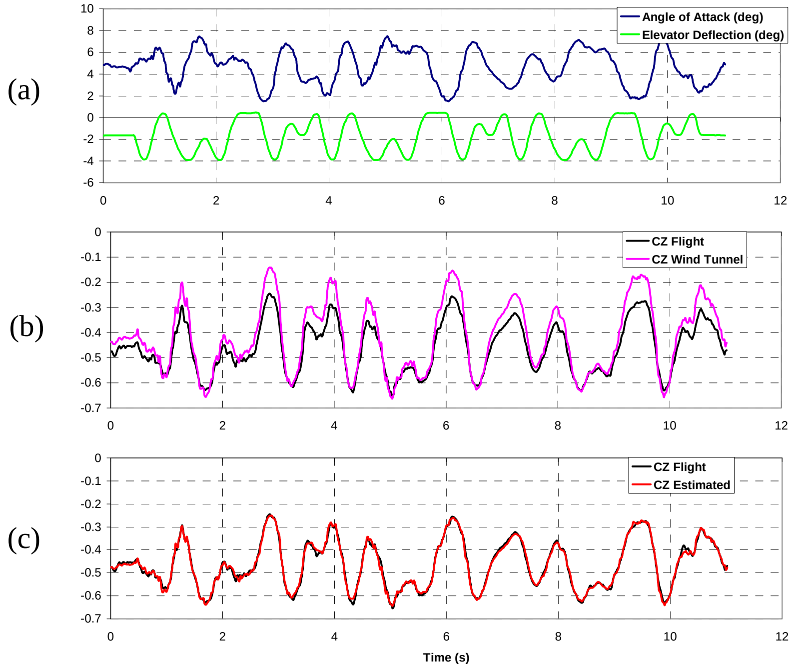
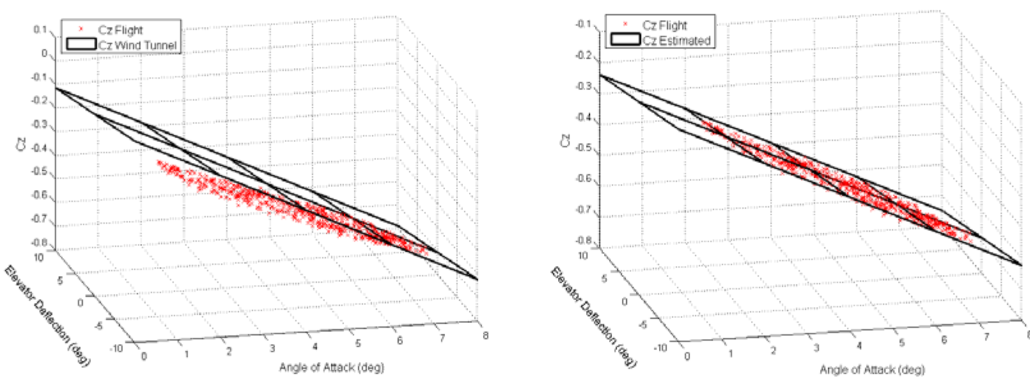


Figure 2: Estimation of the normal force coefficient C_Z.



(a) (b)

Figure 3: Normal force coefficient C_Z wind tunnel and estimated representations.

A cause for these discontinuities results from the use of local mathematical models of the vehicle aerodynamics describing a data-space about an operating point (cf. Equation 1), and assuming the model is applicable over a wide region about that operating point. This assumption may be acceptable for aircraft operating at low incident angles, indicative of cruise flight conditions and linear aerodynamic dependencies. However, as incident angles increase, such as approaching stall, the aerodynamic characteristics exhibit non-linear trends. A linear model rapidly becomes unrepresentative as the flight condition deviates from the nominal operating point. It is therefore necessary to constrain the size of each data-space to minimise the discontinuities.

One solution is to define a fine grid of operating points and associated linear models where non-linear trends exist; however, this requires more flight data in order to represent the non-linear trend to an acceptable degree of accuracy. An alternative solution is to apply higher order mathematical representations. This requires more complex flight test manoeuvres to be flown so sufficiently rich data may be gathered permitting the identification of the contributions from higher order terms. The blending of data from sparser neighbouring data-spaces offers a potentially simpler solution, and if applied appropriately results in data that, in effect, corresponds to a higher order mathematical representation.

A technique for automating the process of incorporating new data was required for data blending to be applied to the task of rapidly updating aircraft simulation models. The approach described herein reformulated the aircraft model in terms of a baseline model, such as one derived from wind tunnel experiments, and a correction to the baseline model derived from aerodynamic parameter estimation of flight data; for example, the normal force aerodynamic coefficient C_Z had the form:

$$C_Z = C_{Z\ baseline} + \Delta C_Z \tag{2}$$

This form conveniently avoided structural differences in the underlying models for the baseline and the correction. In addition, the data uncertainty for the baseline remained unchanged, while that for the correction resulted from parameter estimation.

The correction was computed by identifying a model of the difference between the coefficient computed from the flight-data derived model, CZ Estimated - Figure 2c, and the coefficient computed from wind tunnel data using flight data for aircraft states and controls, CZ Wind Tunnel - Figure 2b. The model structure identified previously from wind tunnel data was used in conjunction with equation-error parameter estimation to estimate the parameters of the correction model. *A priori* information was computed by differencing the parameter estimates of the flight-data model and wind tunnel based orthogonal function model. The following represents the correction computed for the case presented in Figure 2:

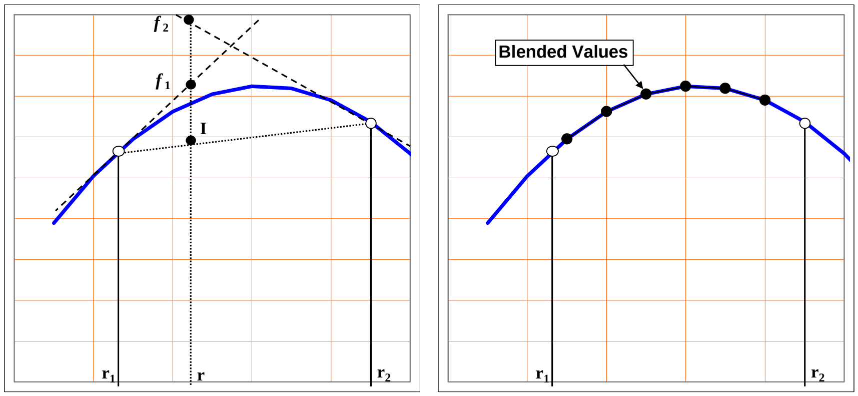
$$\Delta C_Z = K_0' + K_1'\alpha + K_2'\delta_e + K_3'\hat{q} \tag{3}$$

Parameter	Estimate	95% Confidence Interval
K_0'	-1.346E-01	[-1.380E-01, -1.310E-01]
K_1'	2.049E-02	[2.049E-02, 2.049E-02]
K_2'	1.440E-03	[0.0, 2.880E-3]
K_3'	8.399	[8.316, 8.482]

This process was able to be automated and applied to the task of rapid simulation model updating. DAVE-ML, with its ability to mix tabular data and equations, provided an ideal framework for applying aircraft model changes using the form defined by Equations 2 and 3. The corrections computed for the T2 aircraft were recorded using the MathML equation syntax. Blending was applied to the correction component for adjacent data-spaces ensuring data continuity.

Data Blending

The algorithm developed for blending the correction components of the aerodynamic data was based on the principle that neighbouring data-spaces overlapped, and therefore, multiple estimates of the aerodynamic quantity were available. The blended value was computed from a weighted sum of estimates derived for each data-space, as described with the assistance of the example shown in Figure 4.



(a) (b)

Figure 4: Blending data from overlapping data spaces

Figure 4a presents an example non-linear aerodynamic coefficient, shown as a solid blue line. Linear models, shown as dashed lines, were identified for the coefficient about the operating points $\boldsymbol{r_1}$ and $\boldsymbol{r_2}$ respectively. Each operating point was a function of all its dependencies, including the aircraft states and control deflections. For flight data, these operating points represented the trim point associated with a manoeuvre. As illustrated, neither model correctly predicted the coefficient trend away from their respective operating points.

An operating point $\boldsymbol{r}$, for which the aerodynamic coefficient was to be evaluated, was located between the respective reference operating points. For this example three estimates of the coefficient were computed at $\boldsymbol{r}$, being: $\boldsymbol{I}$ a linear interpolation computed from the operating point values; $\boldsymbol{f_1}$ a value computed from the first linear model, and $\boldsymbol{f_2}$ a value computed from the second linear model. Averaging $\boldsymbol{I}$ with $\boldsymbol{f_1}$ and $\boldsymbol{f_2}$ respectively gave two new estimates of the coefficient:

$$avg_1 = \frac{I + f_1}{2} \; ; \; avg_2 = \frac{I + f_2}{2} \qquad (4)$$

The blended coefficient value was a weighted sum of these averages, as shown in Equation 5. The weightings were defined so as to maximise the influence of the averaged value from each model near their respective operating points and wash out the influence of the alternative model. They were computed as a linear proportion of the region described by the operating points $\boldsymbol{r}$, $\boldsymbol{r_1}$ and $\boldsymbol{r_2}$:

$$\text{blended value at } r = \left(w_1 avg_1 + w_2 avg_2\right) = \frac{I + \left(w_1 f_1 + w_2 f_2\right)}{2}$$
$$\text{where } \; w_1 = 1 - w_2 , \quad w_2 = \frac{r - r_1}{r_2 - r_1} \qquad (5)$$

Figure 4b illustrates the result of applying this algorithm for blending data from two overlapping linear models of a coefficient represented by a polynomial function, with the blended data shown as black dots. The blended data compares well with the expected trend.

However, the ability of the blending algorithm to estimate the coefficient trend degrades when the trend exhibits an inflection between the respective model operating points. Further study is required examine the behaviour of the algorithm where such trends exist, and to explore the effect of model operating point grid sizing. The blending algorithm may be used to blend data from non-linear local mathematical models. Furthermore, it may be extended to high numbers of overlapping regions.

Since the operating points were defined as functions of all their dependencies concurrently it was unnecessary to blend data for each dependency separately. For example, it was unnecessary to blend data for the normal force coefficient as a function of angle of attack, and separately blend data for its variation with elevator control deflection. Another advantage was that it could be applied either when constructing aerodynamic datasets for a simulation model or while executing the simulation model as the flight condition changed and aerodynamic data were sourced from datasets. This later approach was applied to the task of rapidly updating the simulation model of the T2 aircraft.

Conclusions

A procedure for the rapid updating of aircraft simulation models based on flight data has been presented in this paper. The application of optimized multi-axis orthogonal multi-sine control sweeps and rapid aerodynamic parameter estimation techniques offers the potential to improve the efficiency of analysing flight data for computing corrections to existing aircraft simulation models. The blending of data for neighbouring data-spaces should ensure the aircraft aerodynamic characteristics are continuous even when local linearised models are employed to represent the trends. The Flight Dynamics Model Exchange Standard, and the Dynamic Aerospace Vehicle Exchange Markup Language, provides a framework for encoding changes to the simulation model, and applying these changes during execution of the simulation. Automating these processes offers a means to increase the efficiency of aircraft simulation model updating. Improving the timeliness and efficiency of envelope expansion flight testing, revision of control system properties, and the development of high-fidelity simulators used to train pilots whilst flying at unusual flight conditions, may also be possible through the application of this capability.

Further analysis of data from the Generic Transport Model flight test programme, together with data from other aircraft flight tests, will permit refinement of the techniques presented, the maturing of the application performing these tasks, as well as quantifying the potential improvements for updating aircraft simulation models.

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