Applicability of a Framework for Estimating Performance and Associated Uncertainty for Modified Aircraft Configurations

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As improvements are made to the accuracy and reliability of modeling and simulation techniques, certification by analysis becomes a more attractive alternative compared to traditional aircraft flight testing. Certification by analysis is especially cost-effective when one considers modifications to a previously certified aircraft. However, it is important that the models and methods used are applicable and accurate throughout the intended use domain. A framework for estimating the performance and associated uncertainty was introduced in an earlier paper. The factors and limitations of this framework for estimating the performance and associated model form uncertainty are explored to determine the range of applicability of the framework, particularly with respect to model form, process and sensor noise, and quality of available flight test data. This paper focuses on the general limitations and applicability of the framework and not the applicability of the individual methods to a range of modified configurations, which requires a large number of modified configurations and is an area for future work. The effects of these factors on the performance and uncertainty results are demonstrated using NASA's Generic Transport Model aircraft.

I. Nomenclature

C_*	=	generalized aerodynamic coefficient
C_*^{base}	=	value of generalized coefficient from baseline model for the nominal configuration
u, v, w	=	body-axis velocities in the x, y, and z directions, respectively
u_0	=	aircraft trim velocity
p, q, r	=	body-axis angular rates, about the x, y, and z directions, respectively
δa	=	aileron deflection
δe	=	elevator deflection
δr	=	rudder deflection
δC_*^{tun}	=	additional correction due to tuning of modified configuration model
δC_*^{base}	=	change in baseline model due to modified configuration, difference between modified configuration and nominal configuration
$\delta C_*^{UQ}\|_{base}$	=	uncertainty bounds from model form uncertainty for modified configuration, evaluated about the baseline model

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$\delta C_*^{UQ}\|_{tun}$	=	uncertainty bounds from model form uncertainty for modified configuration, evaluated about the tuned model
ΔC_*^{tun}	=	correction due to model tuning, difference between tuned model and baseline model for nominal configuration
$\Delta C_*^{UQ}\|_{base}$	=	uncertainty bounds from model form uncertainty for nominal configuration, evaluated about the baseline model
$\Delta C_*^{UQ}\|_{tun}$	=	uncertainty bounds from model form uncertainty for nominal configuration, evaluated about the tuned model
θ	=	pitch angle
ϕ	=	roll angle

II. Introduction

The aircraft airworthiness certification process has traditionally relied on flight testing to determine whether the system meets the minimum standards of airworthiness, safety of flight, and risk [1]. Many organizations tasked with airworthiness certification, such as the Federal Aviation Administration (FAA) and Naval Air Systems Command (NAVAIR), are required to consider modified versions of a previously certified aircraft, such as those resulting from an added radome, as an entirely separate aircraft for the purposes of certification [1–3]. It is common to have a large number of modifications to a baseline aircraft over its production years. These modifications may not warrant time-intensive and cost-intensive flight testing from scratch. Instead, suitable analysis may reduce the amount of flight testing necessary for certification of the modified aircraft.

Interest in certification by analysis or the use of analysis and simulation to supplement or replace flight testing in the certification process is growing [4]. In particular, there is a desire to use analysis and simulation to model modifications to a previously certified aircraft, including the estimation of associated uncertainties [4, 5]. Modified configurations must still be accurately modeled and simulated even with limited or no flight test data in order to meet the standards of airworthiness with the required level of confidence [5]. Certification by analysis is already commonly done in the nuclear domain, due to the fundamental inability to test or high risks and costs associated with full-scale testing [6]. This paper explores the range and limits of applicability for a framework first introduced in Ref. [7] to model modified configurations.

Modified configurations of an existing aircraft can have a limited amount of data compared to the existing aircraft, including lack of data from wind tunnel tests, flight tests, and Computational Fluid Dynamics (CFD). The amount of data available depends on the development process of the proposed modification. To provide additional resources for the flight certification process, we propose a framework utilizing non-deterministic simulations of modified aircraft configurations. Since there might not always be flight test data available for model tuning, where flight test data are needed to improve the model and uncertainty quantification for these modified configurations, the framework uses knowledge of the unmodified, nominal configuration to assist in the simulation of the modified configuration. The framework consists of two methods to estimate the modified aircraft dynamics and the associated uncertainties. Both methods use aspects of the nominal system, account for changes due to the modification, and are used to perform non-deterministic simulations. This framework is designed to be independent of the source or quality of the data, as well as the model form or accuracy. The framework can also be used prior to flight testing to provide an estimate of expected performance.

The range of applicability of any model or method is important, but it is especially important when discussing certification by analysis of safety-critical systems. For aircraft it is important that the dynamics within the flight envelope be within acceptable limits, although the dynamics outside of the envelope, such as stalls and spins, are also important for performance [8, 9]. With the reduction in flight testing for certification by analysis, it is essential that the method and models used are accurate and applicable throughout the anticipated flight domain. For example, a linear model would not be expected to provide adequate results for a nonlinear system far from the linearization point. When discussing model applicability, the model is validated at a number of points within a validation domain, which may partially or fully overlap with the application domain, and must be interpolated or extrapolated to fully cover the application domain, as illustrated in Fig. 1 [10].

The AIAA Certification by Analysis community of interest believes that analysis used for certification must meet or exceed the accuracy of flight test data to be a suitable substitute [4]. However, many factors can influence the accuracy of flight test data, including steady wind, turbulence, selected sensors, and random and systemic (bias) errors in experimental measurements. The accuracy and uncertainty bounds generated by the uncertainty estimation framework

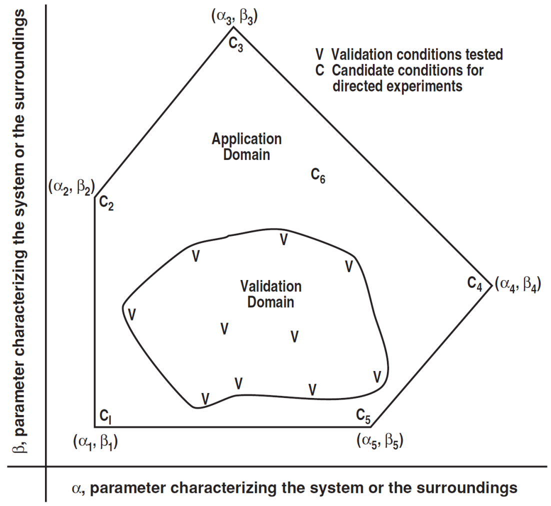

Fig. 1 Application domain and validation domain[10]. (reproduced with permission)

depend on the amount and quality of both the available higher fidelity (flight test) data and the lower fidelity (CFD or wind tunnel) data. These effects are important to capture in order to evaluate the costs associated with achieving a desired accuracy level from the framework and its methods.

This paper revisits the two methods of estimating the performance and associated uncertainty of modified aircraft configurations presented in Ref. [7] and explores the initial factors that affect the range of applicability and accuracy of this framework, focusing on the estimation and quantification of uncertainty. Specifically, this paper looks at common scenarios that negatively affect the system identification and uncertainty quantification components of the framework, resulting in poor modeling of the aircraft dynamics and associated uncertainty. Data from NASA Langley Research Center's Generic Transport Model aircraft are used to illustrate these limitations and the effect they have on the resulting non-deterministic simulation results.

III. Methods

The first step in modeling a modified configuration is modeling the nominal, unmodified configuration. The framework will be illustrated using a single model term but can be applied to all terms in the aircraft dynamics model. Using the nomenclature described in Ref. [7], C_* represents a generic aerodynamic coefficient, such as the Coefficient of Lift. The nominal configuration of this aircraft can be described using a combination of the baseline model C_*^{base}, model tuning ΔC_*^{tun}, and uncertainty ΔC_*^{UQ}. Since we can calculate uncertainty of the nominal configuration about both the baseline and tuned model, there are two related models:

$$C_*^{nom} = C_*^{base} \pm \Delta C_*^{UQ}|_{base} \tag{1}$$

and

$$C_*^{nom} = C_*^{base} + \Delta C_*^{tun} \pm \Delta C_*^{UQ}|_{tun} \tag{2}$$

Equation (1) describes the case where the uncertainty is calculated about the baseline model, $C_*^{UQ}|_{base}$, whereas Eq. (2) describes the case where the uncertainty is calculated about the tuned model, $C_*^{UQ}|_{tun}$. Eq. (2) is more accurate and should always be used, but both equations are given to aid in developing the two methods for modeling for the modified configuration.

When we describe a modified aircraft configuration using the same nomenclature, additional terms appear due to the change in configuration. After including additional model tuning to match flight test data and uncertainty quantification, the final model for the modified configuration can be written in two different ways, corresponding to Eqs. (1) and (2):

$$C_*^{mod} = C_*^{base} \pm \Delta C_*^{UQ}|_{base} + \delta C_*^{base} \pm \delta C_*^{UQ}|_{base} \tag{3}$$

$$C_*^{mod} = C_*^{base} + \Delta C_*^{tun} \pm \Delta C_*^{UQ}|_{tun} + \delta C_*^{base} + \delta C_*^{tun} \pm \delta C_*^{UQ}|_{tun} \tag{4}$$

where δ indicates the change due to modification in the configuration, δC_*^{base} is the change to the baseline model due to the modified configuration, δC_*^{tun} is the additional correction due to model tuning (if available) for the modified configuration, and δC_*^{UQ} is the additional uncertainty for the modified configuration. While δC_*^{base} can be obtained by comparing lower fidelity data of the nominal and modified configurations, such as wind tunnel or CFD data, δC_*^{tun} and δC_*^{UQ} cannot be calculated without higher fidelity data for the modified configuration, such as flight test data, which is often unavailable.

Using the prior knowledge of the nominal configuration, we propose two methods to estimate the uncertainty of the modified configuration [7]. The methods differ in the approximation of δC_*^{tun} and δC_*^{UQ} and do not require parameter tuning and uncertainty quantification for the modified configuration. The methods are intended for small and large modifications, respectively. This paper focuses on the general limitations and applicability of the framework and not the applicability of the individual methods to a range of modified configurations. To properly determine and verify the limits on acceptable modifications, flight test data are required for a large spectrum of modified configurations.

A. Uncertainty Estimation Method 1: Tuned Model Method

The first method to estimate the aerodynamic model and uncertainties of the modified configuration assumes that the total uncertainty for the modified configuration is equivalent to the uncertainty for the nominal configuration and that the model tuning for the nominal configuration also applies to the modified configuration. This is the same as assuming that no additional model tuning is needed for the modified configuration and that the uncertainty bounds of the nominal configuration are valid for the modified configuration. Using Eq. (4), this is equivalent to setting δC_*^{tun} and $\delta C_*^{UQ}|_{tun}$ equal to zero.

To generate the updated model used for non-deterministic simulations, the final model can be written as:

$$C_* = C_*^{base} + \Delta C_*^{tun} \pm \Delta C_*^{UQ}|_{tun} + \delta C_*^{base} \tag{5}$$

In other words, only the baseline model for the nominal configuration is updated using the change from the nominal configuration to the modified configuration (δC_*^{base}), as shown in Fig. 2 using example artificial data. The tuning correction from the nominal configuration (ΔC_*^{tun}) and the uncertainty bounds for the nominal configuration ($\Delta C_*^{UQ}|_{tun}$), calculated using the tuned model, are then applied to this model to obtain updated model and uncertainty bounds for the modified configuration. This process is shown in Fig. 3 for the example data.

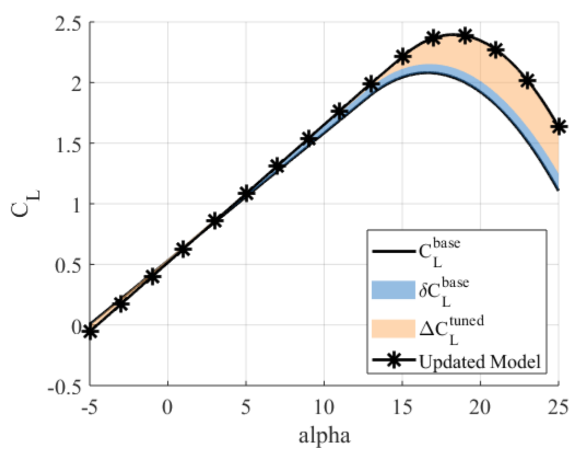

Fig. 2 Generation of updated model for the modified configuration using the tuned model method with example data. The changes due to the modification, in blue, and the tuning correction term, in orange, are added to obtain the updated model.

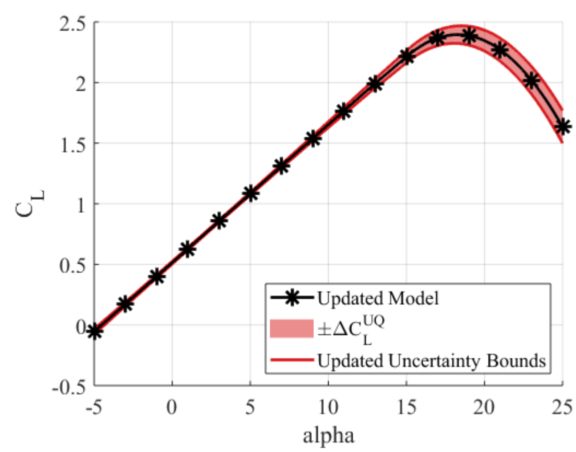

Fig. 3 Addition of the uncertainty bounds, red, from the nominal configuration to the updated model of the modified configuration using the tuned model method, showing the updated uncertainty bounds using example data.

B. Uncertainty Estimation Method 2: Baseline Model Method

The second method of estimating the uncertainties of the modified configuration assumes that the total uncertainty for the modified configuration is the uncertainty that would occur if there were no tuning for the nominal configuration. This is equivalent to assuming the model tuning correction for the nominal configuration is no longer valid and engineering judgement points toward approximating the total uncertainty for the modified configuration as the uncertainty for the nominal configuration with no tuning. Using Eq. (3), this is equivalent to stating that the model uncertainty of the modified configuration is similar to that of the nominal configuration. The updated model for the modified configuration can then be written as:

$$C_* = C_*^{base} \pm \Delta C_*^{UQ}|_{base} + \delta C_*^{base} \tag{6}$$

For this method, the baseline model for the nominal configuration has the change due to the modified configuration (δC_*^{base}) added to create the updated model, shown in Fig. 4 with the example data. Then, we use uncertainty bounds ($\Delta C_*^{UQ}|_{base}$) created using flight test data and the baseline model of the nominal configuration, as opposed to the tuned model used for the tuned model method. Using the baseline model creates much larger uncertainty bounds that include the effects of model tuning, as in Fig. 5.

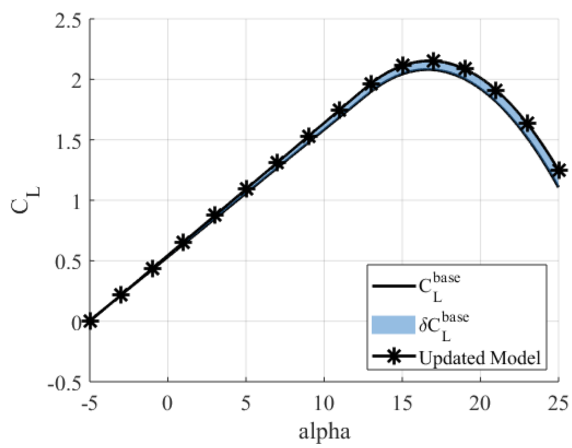

Fig. 4 Generation of updated model for the modified configuration using the baseline model method. The updated model for the modified configuration has only the changes due to the modification, in blue, added to the baseline model of the nominal configuration.

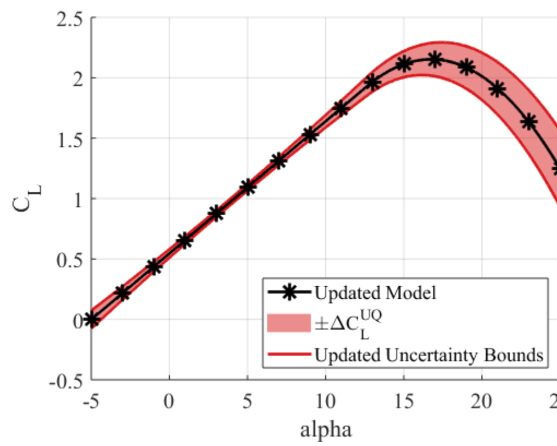

Fig. 5 Calculation of the total uncertainty for the modified configuration using baseline model method, with example data. The total uncertainty is the uncertainty from the baseline model.

C. Use of the Two Methods

The two methods of estimating the uncertainty for the modified configuration provide different levels of conservatism, depending on the characteristics of the model and configuration. The tuned model method, which assumes that the tuning is valid and leads to smaller uncertainty for the updated model, effectively tunes the model based on the nominal configuration. This leads to less conservative uncertainty bounds about the updated model. An updated model and corresponding uncertainties based on the tuned model method are accurate for modified configurations that are similar to the nominal configuration; i.e., the modifications are minor. However, the baseline model method, which assumes a larger uncertainty based on the baseline model, aims to give more conservative bounds that will account for larger differences between the nominal and modified configurations. The baseline model method does not assume that the tuning correction from the nominal configuration applies to the modified configuration but does assume that the modeling uncertainty is similar. Additional research is required to determine exactly which range of modifications are applicable for each of the two methods.

D. Example Aircraft System

NASA Langley Research Center's Generic Transport Model (GTM) aircraft, shown in Fig. 6, was chosen as the example aircraft system to demonstrate the proposed framework. The GTM has had extensive wind tunnel, CFD, and flight tests and has been used for research including loss of control prediction, spin prediction, and control development [8, 9, 11, 12]. An open-source, high-fidelity, non-linear simulation of the GTM*, created using a combination of wind tunnel, flight test, and simulation data, was used for this research.

The aircraft simulation is trimmed using a constant true airspeed, which results in the trimmed aircraft states in Table 1. Although the simulation includes many control inputs, only elevator, rudder, and aileron deflections are used for this research, with all other surfaces kept at the zero position. All simulation and uncertainty results are shown as deviations from the trimmed aircraft state and surface deflections.

The simulation includes a wind turbulence model, enabling the simulation of flight test data with process noise, as well as models of the aircraft sensors, enabling simulation of flight test data with sensor noise. We created separate simulated flight test data segments for system identification, uncertainty quantification, and uncertainty validation. Because this is simulated data, flight test data can also be created for the modified configurations.

Fig. 6 NASA Langley's GTM aircraft during a flight test [9].

Table 1 GTM Trim States and Deflections

State	Trim Value
u	164.7 ft/s
v	0 ft/s
w	8.5 ft/s
p	0 rad/s
q	0 rad/s
r	0 rad/s
ϕ	0 rad (0 deg)
θ	0.05 rad (2.86 deg)
Deflection	Trim Value
δ_e	2.45 deg
δ_r	0 deg
δ_a	-0.39 deg

E. Analysis and Uncertainty Quantification

For the GTM aircraft, both the nominal and modified configuration models come from the simulation, which is then linearized at a given trim condition. To mimic the errors that would typically exist in wind tunnel or simulation data and to account for using the same simulation for flight test data, an artificial trim offset was applied to the system when calculating the baseline models. Additionally, only the longitudinal and lateral components of the equations of motions are used to create the model, neglecting any cross terms. This model form was selected to is to simulate a lower-order aerodynamic model with specific terms neglected. The modified configurations are created by changing components in the simulation, such as mass or inertial properties.

Simulated flight test data is created using the simulation, including wind and sensor noise, using control inputs generated by the user. The tuned model is created using the output error method of system identification, using the codes associated with Ref. [13]. Although any system identification method could be selected, the output error method was chosen for its ease of use and generally good results.

A second set of simulated flight test data is used for uncertainty quantification and estimation, allowing a range of control inputs and aircraft states throughout the area of interest. The error is estimated by comparing the difference between the model and flight test derivatives and fitting a polynomial equation to the data. We then use Eq. (7) to

*Available at: https://github.com/nasa/GTM_DesignSim calculate prediction intervals for the regression fit as a function of the observed data to be used as uncertainty bounds [14, 15].

$$\hat{y}(x_o) - t_{\alpha/2,n-p}\sqrt{\hat{\sigma}^2 x_0'(X'X)^{-1}x_o} \leq \mu_{y|x0} \leq \hat{y}(x_o) + t_{\alpha/2,n-p}\sqrt{\hat{\sigma}^2 x_0'(X'X)^{-1}x_o} \tag{7}$$

Here $\hat{y}(x_0)$ is the model response about the aircraft state x_0, $t_{\alpha/2,n-p}$ is the Student's t-distribution for 100(1-α) confidence interval with $n-p$ degrees of freedom (where n is the number of samples and p is the degree of the polynomial), $\hat{\sigma}^2$ is the sample standard deviation, $\mu_{y|x0}$ is the mean error of the model response at the aircraft state, and X is the matrix of observed data.

For much of our analysis in this paper, we will be comparing the calculated uncertainty bounds from a nominal condition (low winds, low sensor noise, all states measured) to an offset condition. These bounds exist in a multi-dimensional space so they will be shown as slices about the trim for each of the aircraft states and inputs. The rate of change in upward velocity ($\Delta\dot{w}$) was selected to show the change in uncertainty, but the uncertainty bounds for each state will have a similar change.

IV. Limits on Applicability of Framework

Although we are using high-fidelity simulation data in lieu of flight test data to assess the framework, it can still be difficult to accurately predict the performance of modified configurations. Many situations, including incorrect model form, poor data quality, or limited data quantity, affect the accuracy in system identification and uncertainty quantification. Independent of any modification, these situations can result in models with high associated uncertainty, leading to results that are too conservative to be useful. The modification itself also impacts the applicability and usefulness of the framework, although this is still an area of active research.

A. Baseline Model Form

One of the most important factors that affects the accuracy of the two methods is the choice of the model form used for the baseline model. For example, a linear model could be formed using body-axis positions, velocities, angles, and angular rates creating a 12×12 system of equations, while another linear model could be formed by separating the lateral and longitudinal dynamics, creating two independent 4×4 systems of equations. Non-linear models can vary from combinations of aircraft states and inputs to combinations of states, inputs, and derivatives.

1. Missing Single Term in Model Form

If significant terms are missing from the model, such as the term relating downward velocity and pitch angle, the uncertainty will show a high correlation with the state and will have a significant non-zero value. Figure 7 shows an example of the system identification results when a model missing the single term relating downward velocity, Δw, and pitch angle, $\Delta\theta$, is fit to the data. Although the overall fit of the data is still satisfactory, Fig. 8 demonstrates how the uncertainty analysis shows a strong correlation between the uncertainty bounds for the change in downward velocity, $\Delta\dot{w}$, and pitch angle, $\Delta\theta$. Because of the close relationship between pitch angle and forward velocity, there is also strong correlation in the uncertainty bounds for change in downward velocity, $\Delta\dot{w}$, and forward velocity, Δu.If such a correlation is present in the application of the framework, the term should be added before proceeding.

2. Missing Many Terms in Model Form

If many terms are missing, the total uncertainty will be large, giving results that are too broad and ambiguous. Figure 9 shows the effect on system identification of multiple missing terms in the model, in both the lateral and longitudinal dynamics. Although other terms in the model can account somewhat for the missing terms, the uncertainty will be much larger than the nominal case, as shown in Fig. 10.

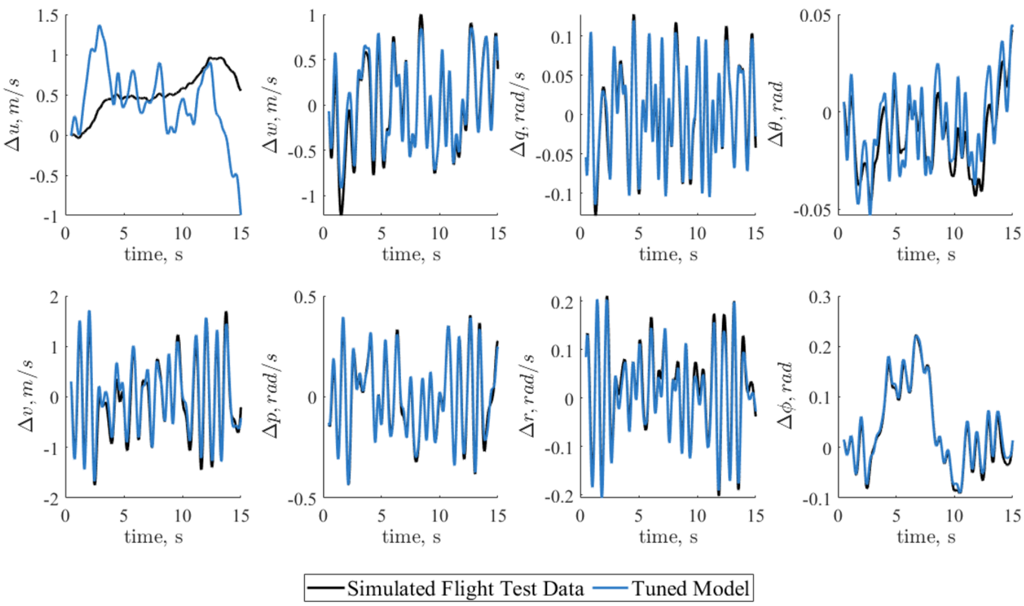

Fig. 7 Comparison of the simulated flight test data to the tuned model generated with a single missing term.

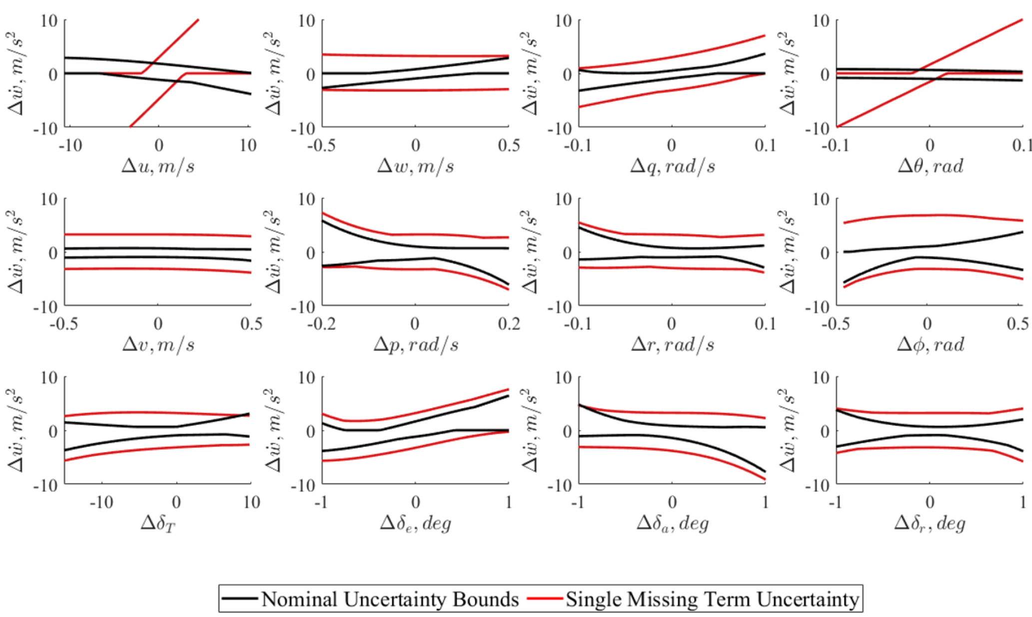

Fig. 8 Comparison of the nominal uncertainty bounds to the uncertainty bounds generated from a model with a single missing term.

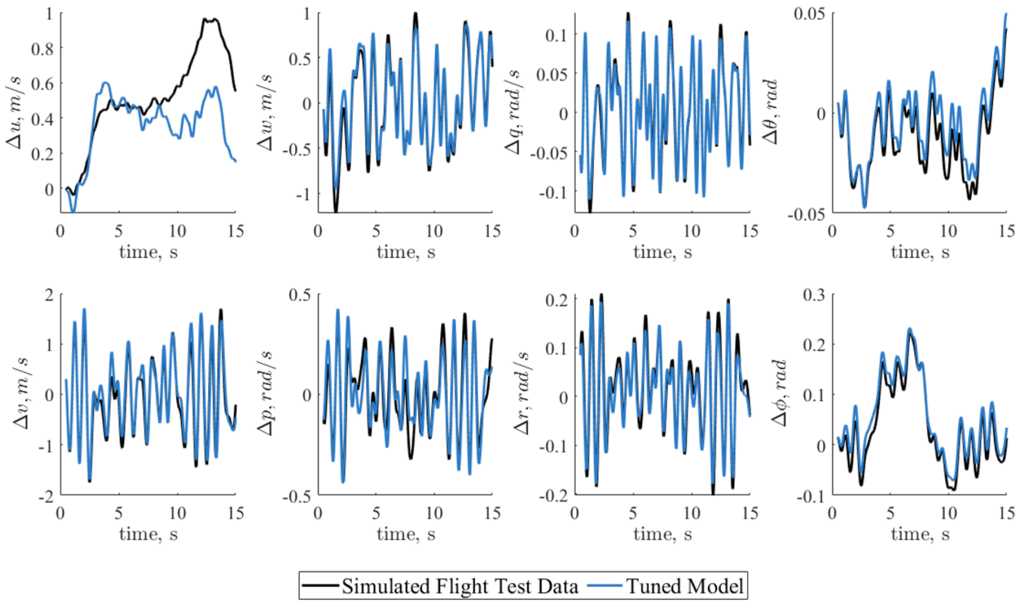

Fig. 9 Comparison of the simulated flight test data to the tuned model generated with many missing terms.

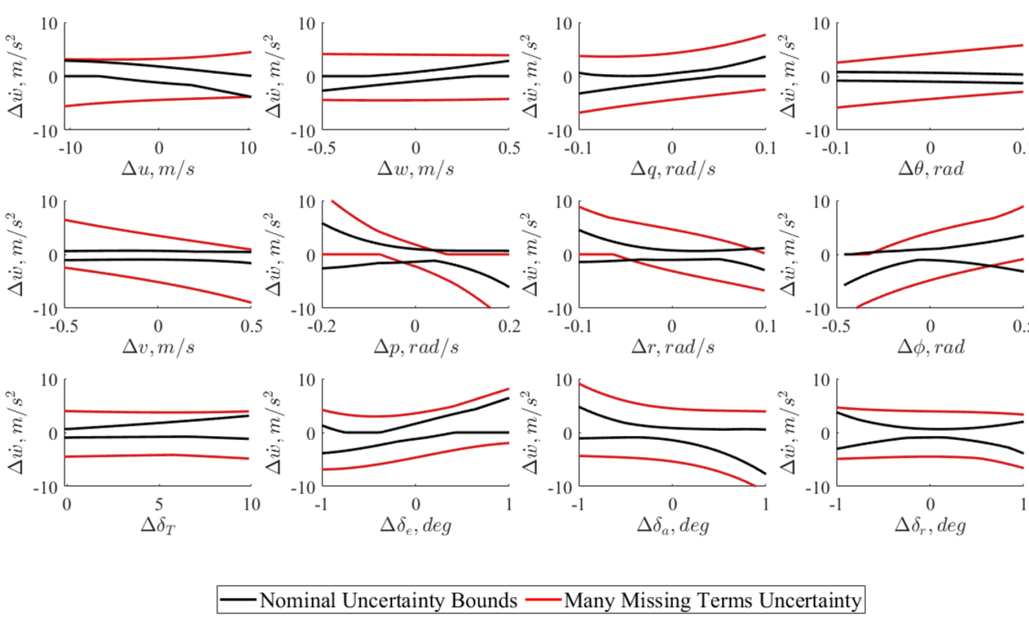

Fig. 10 Comparison of the nominal uncertainty bounds to the uncertainty bounds generated from a model with many missing terms.

B. Data Quality

Data quality is another factor that can affect the uncertainty estimation, and therefore the applicability of the methods themselves. Three of the key data quality metrics that have a large effect are process noise, sensor noise, and observed states. For the GTM aircraft simulation, a detailed wind model is included, modeling both steady-state and turbulent wind conditions at a variety of wind levels to match those seen in flight. The simulation also includes models of each of the aircraft sensors, such as the Inertial Measurement Unit (IMU) and rate gyroscopes. These sensor models have realistic noise, delay, and range limits to match the research aircraft. Because these instruments are intended for research, their quality is often very high, which serves as a good comparison to illustrate the effects of reduced quality.

1. High Process Noise

For aircraft flight testing, process noise generally arises due to wind, particularly when wind conditions are not precisely known at each timestep throughout the flight. Flight testing is typically conducted with low, constant-directional wind with a small turbulent component, but it is important to consider the impact of increased wind. Depending on the system identification method used, model tuning can still be generally accurate, as in Fig. 11. Although the model has more high frequency content than the simulated flight test data with no wind, the model still follows the trend of the data, with similar peaks and lows. However, additional process noise can increase the uncertainty, even with a good model fit. This is shown in Fig. 12, where an increase in the gust turbulence affects the uncertainty across many states. Although wind only directly affects the velocities, the effect on the uncertainty is particularly evident in roll rate, Δp.

2. High Signal Noise

Another factor which impacts the system identification and uncertainty quantification is high levels of signal noise, typically arising from variation in the sensor readings or interference. As with high process noise, different system identification methods can account for some degree of signal noise. Figure 13 shows that the model fit is still quite close to the simulated flight test data. This good fit is due in part to our selection of the output error method for system identification, which is shown to be a good estimator in the presence of sensor noise [13]. However, the uncertainty calculated from flight test data has larger bounds, as in Fig. 14. Although the tuned model is able to closely match the flight test data, the variation in the individual states muddles the calculated error, resulting in some states with smaller bounds but others with larger bounds.

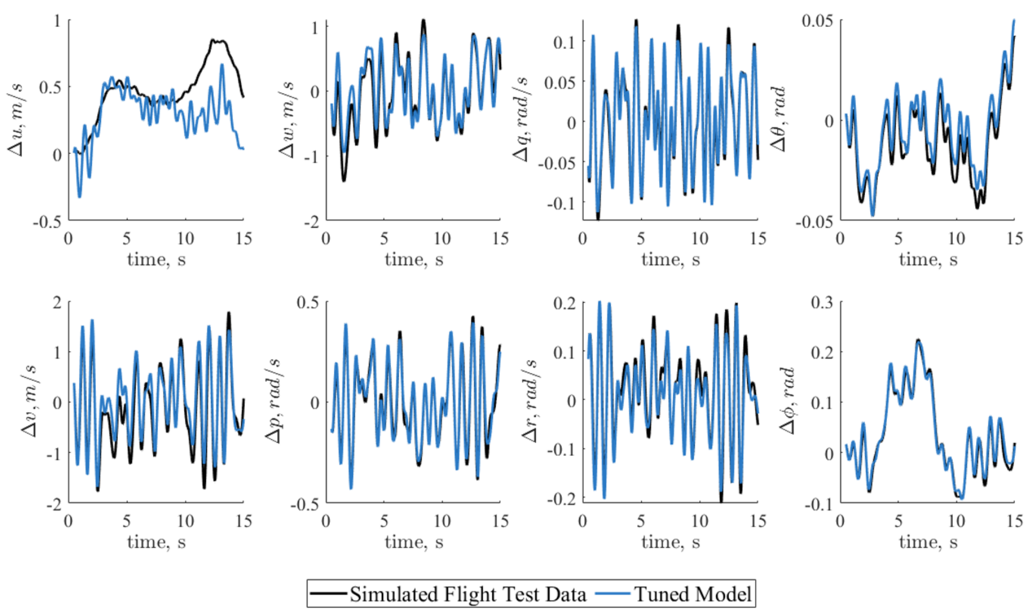

Fig. 11 Comparison of the simulated flight test data to the tuned model generated with high wind.

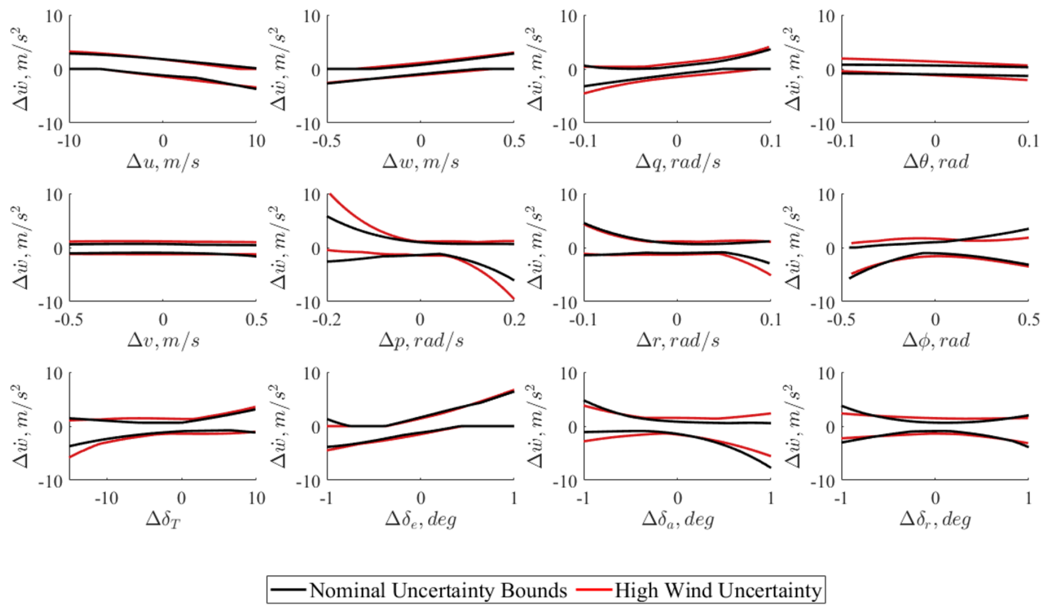

Fig. 12 Comparison of the nominal uncertainty bounds to the uncertainty bounds generated from a model with high wind.

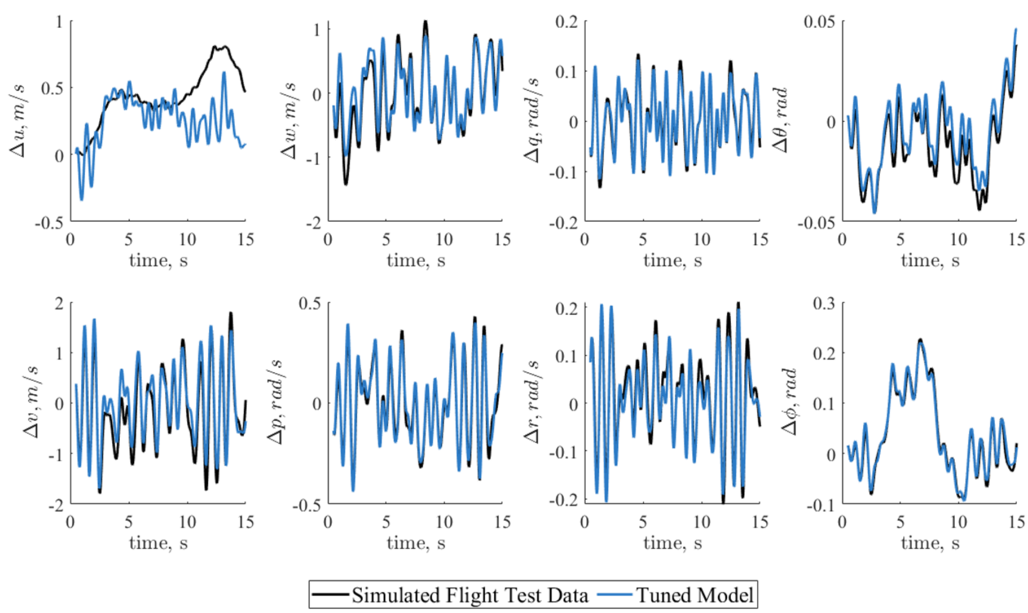

Fig. 13 Comparison of the simulated flight test data to the tuned model generated with high sensor noise.

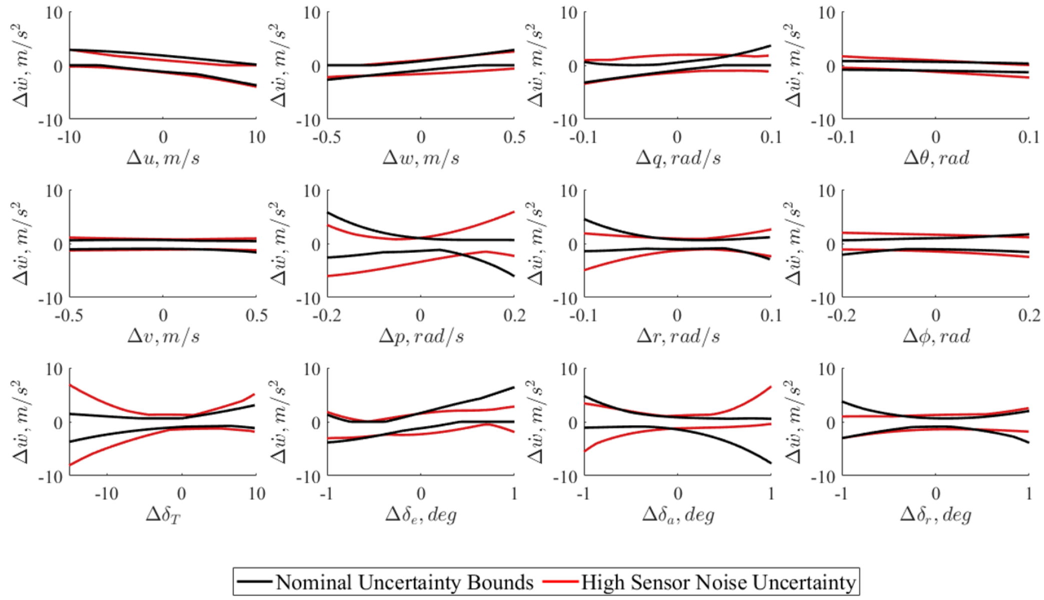

Fig. 14 Comparison of the nominal uncertainty bounds to the uncertainty bounds generated from a model with high sensor noise.

3. Quantized Signals

Quantization arises when signals are mapped to a finite set - such as when a sensor has poor sensitivity and only outputs values to the nearest unit. In addition to contributing to increased signal noise, this non-linear irreversible process can greatly impact the accuracy of the framework. Figure 15 shows an example data segment which has been quantized by rounding to the nearest m/s. For this analysis, velocities were rounded to the nearest m/s, angles were rounded to the nearest 2 deg, and angular rates were rounded to the nearest 2 deg/s. System identification of this data, in Fig. 16, shows that the higher frequency content is difficult to recover from quantized data. This is most evident in forward velocity, Δu, where the observed quantized flight test is mostly constant; the model is only able to provide a best guess of what the true velocity was. When it comes to uncertainty, Fig. 17 demonstrates that uncertainty can be quite large in these cases, particularly for the states with high quantization relative to their time histories. For example, the uncertainty bounds for pitch angle, $\Delta\theta$, are larger than the uncertainty bounds in the nominal case, but generally follow the same trend. However, the uncertainty bounds for pitch rate, Δq, have a significantly different trend and are drastically larger than the nominal case.

4. Limited Observed States

Particularly for small unmanned aircraft, not all states are measured with sensors and are therefore not discretely observed. Although some system identification methods, such as the output error method used in this research, can still identify a model with limited states, the fit is not as accurate as when all states are observed. Figure 18 shows the system identification for the GTM, where a model is fit using only velocities and angles. Larger deviations are evident in the angular rates, Δp, Δq, and Δr, where the magnitude of the model has substantial differences.The calculated uncertainty, shown in Fig. 19, shows an increase, particularly for the states that were not observed - pitch rate, roll rate, and yaw rate. Because of the choice of $\Delta\dot{w}$ to show the uncertainty, the difference is most obvious in pitch rate, since it is strongly correlated with vertical velocity.

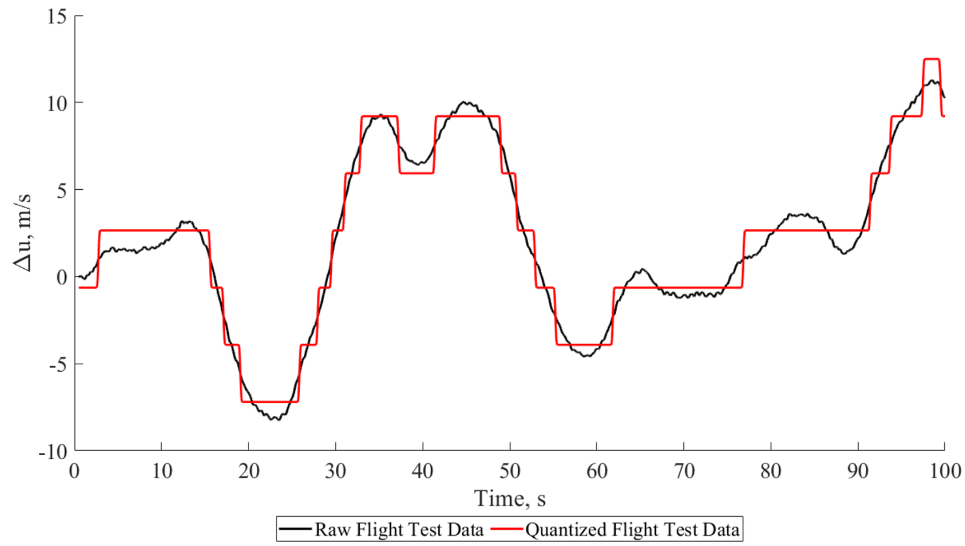

Fig. 15 Comparison of the raw simulated flight test data to the quantized flight test data, created by rounding to the nearest m/s.

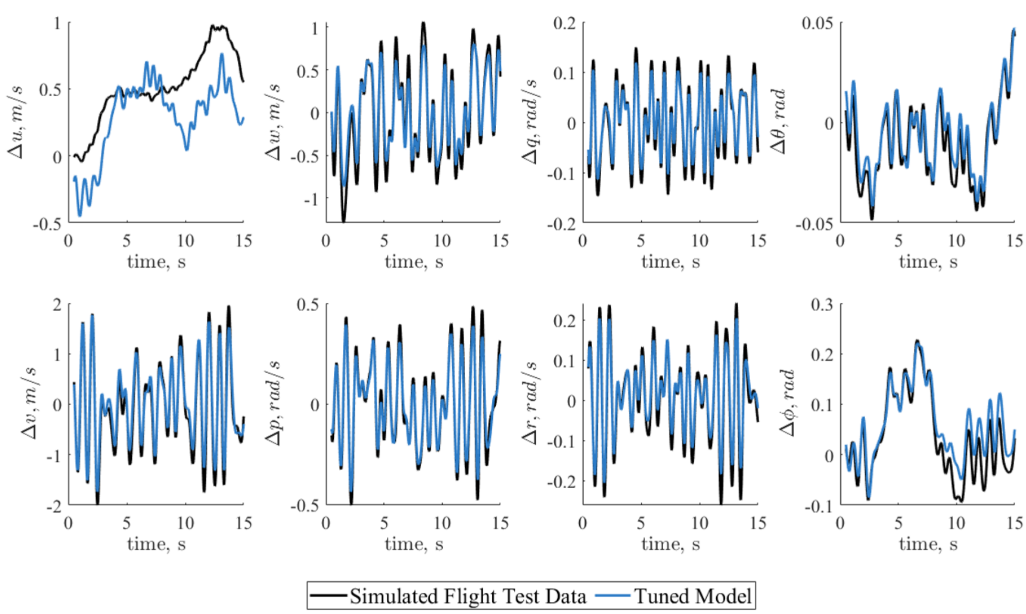

Fig. 16 Comparison of the simulated flight test data to the tuned model generated with quantized signals.

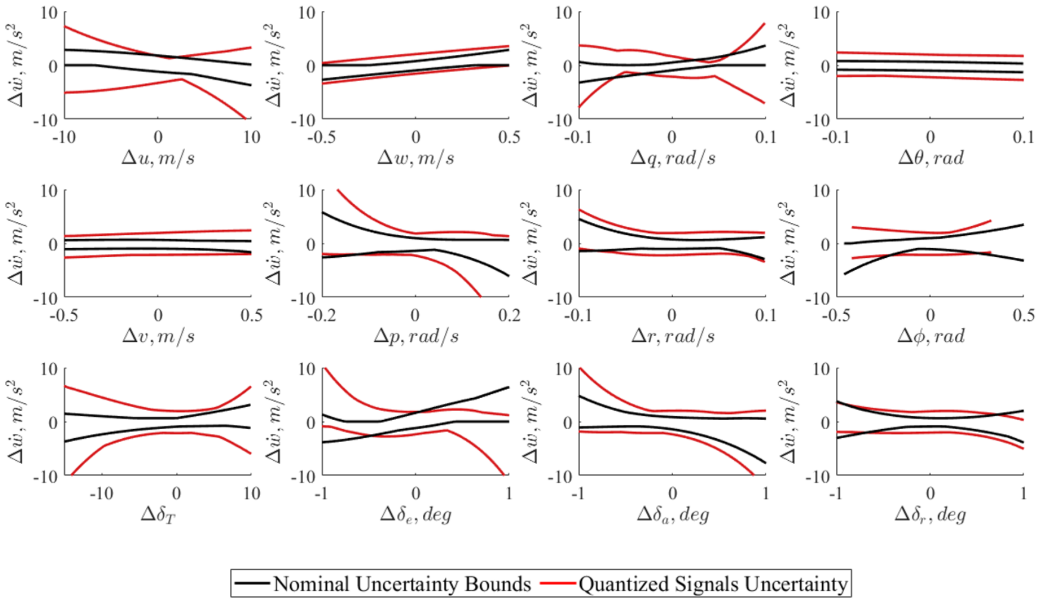

Fig. 17 Comparison of the nominal uncertainty bounds to the uncertainty bounds generated from a model with quantized data.

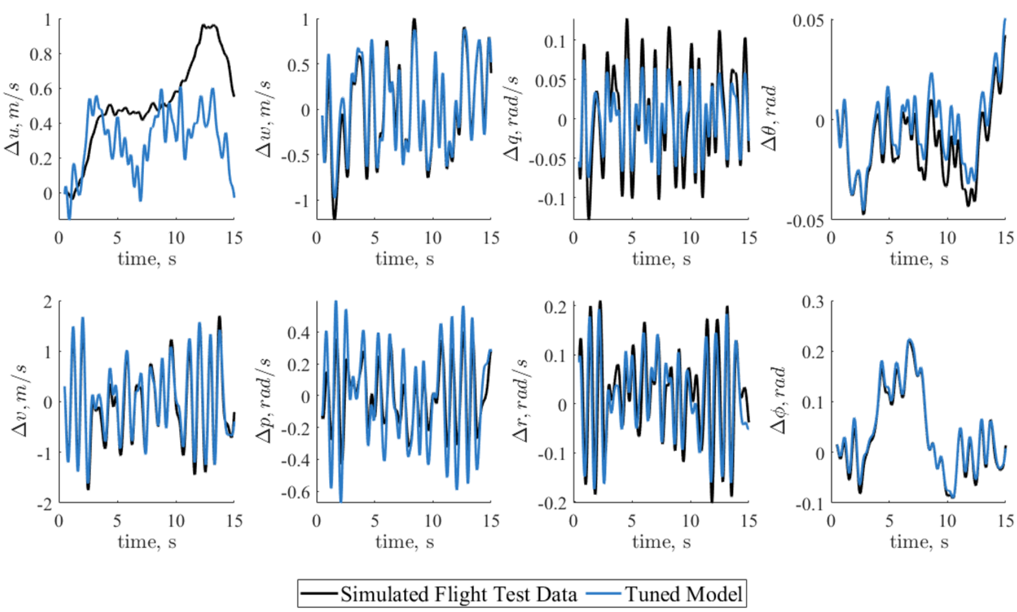

Fig. 18 Comparison of the simulated flight test data to the tuned model generated with limited observed signals.

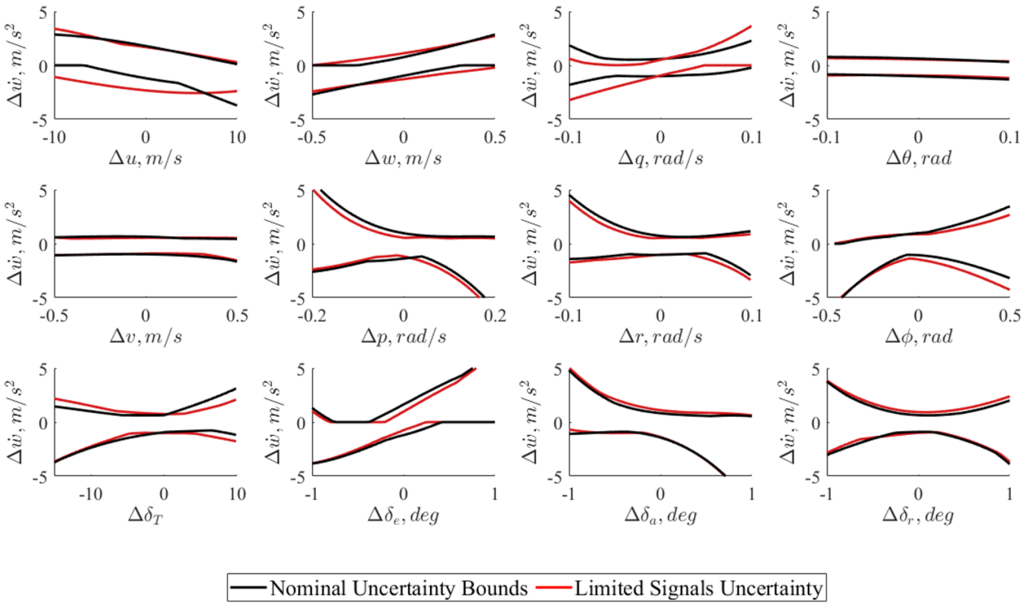

Fig. 19 Comparison of the nominal uncertainty bounds to the uncertainty bounds generated from a model with limited observed states.

C. Data Quantity

The uncertainty bounds estimation depends on the amount of data points used, with smaller bounds where there are more data and larger bounds in regions where data are sparse. The quantity of the data available, both in sheer numerical size and in relationship to the desired flight envelope, is important to ensuring the estimated uncertainty bounds are representative of the true uncertainty.

1. Limited Overall Data Availability

Although the overall volume of data is important for the system identification process, we will focus on the effects of limited data on the uncertainty quantification process, since it typically requires more data for accurate bounds. Our uncertainty bounds are dependent on the number of data points, n in Eq. (7), so fewer samples results in larger uncertainty bounds. This impact is shown in Fig. 20, where the number of samples used for uncertainty quantification was reduced by a factor of 3, creating a dramatic increase in the calculated uncertainty. The limited data affects the relationship between the states and these bounds by changing the correlation, similar to how a linear regression can be fit to sparse data from a non-linear function.

2. Limited Data in Applicability Domain

In addition to the amount of data available, the location of these data relative to the applicability range is also important. Figure 21 shows the effect of extending our existing uncertainty far from the observed data, creating exponential increases in the uncertainty. This exponential effect is seen in the uncertainty bounds for rudder deflection, δ_r, where the bounds rapidly increase away from the trimmed flight condition. The impact of the polynomial fit chosen to model the data is also present; what appeared to be a relatively constant uncertainty bound independent of state can have unexpected values outside of the observed range. This is mostly clearly shown in the bounds for elevator deflection, δ_e, where the seemingly linear relationship grows into a strong cubic relationship farther away from the observed data. When this uncertainty is used to predict performance outside of the applicability domain defined by the observed data, the 95% confidence bounds on the simulation performance are too conservative to be useful, as shown in Fig. 22. The large prediction bounds of the simulation are typical for conditions outside the observed data, since the uncertainty drives the state further from the trim condition which in turn increases the uncertainty.

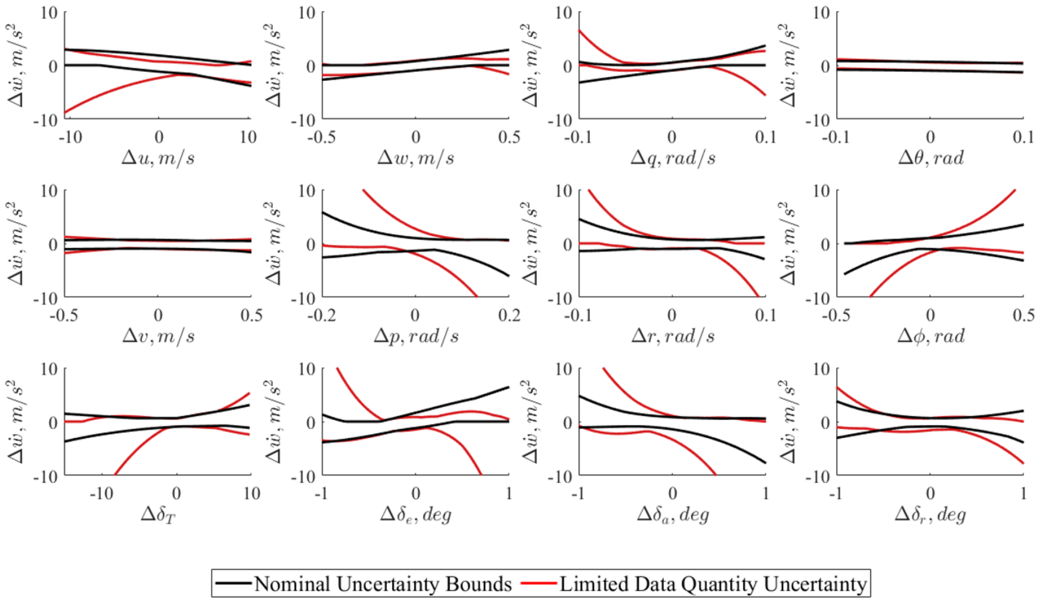

Fig. 20 Comparison of the nominal uncertainty bounds to the uncertainty bounds generated from a model with limited data.

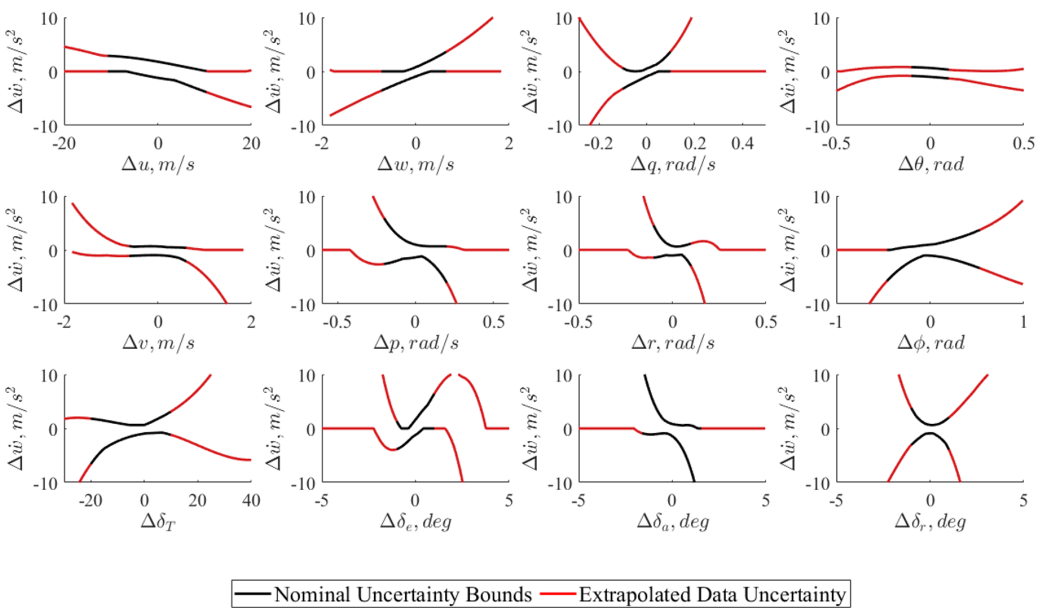

Fig. 21 Comparison of the nominal uncertainty bounds compared to the uncertainty bounds generated from extrapolating beyond the observed data.

D. Sensitivity to Model Changes

One of the key distinctions between the two uncertainty estimation methods is the ability of the baseline model to adequately represent the modified configuration. For example, if a modification resulted in only higher order changes to the aircraft dynamics, a standard linear model would be unable to model this change. An example of such a change could be using a different material for the wing structure - although the dominant dynamics may not change significantly,

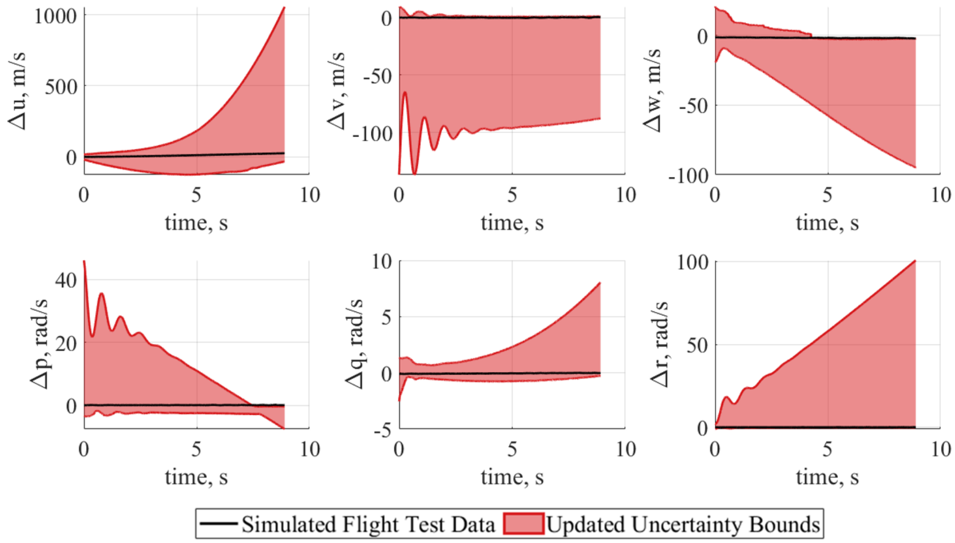

Fig. 22 Comparison of the simulated flight test data to model results generated using control inputs outside of the applicability range.

higher order effects, such as elastic deformation and load redistribution, could exist in the actual vehicle. These effects would not be shown in the framework results since they are unable to be modeled using the model form selected.

Conversely, if a modification had significant changes to the aircraft dynamics, a linear model may no longer be adequate due to a change in aircraft trim state. To demonstrate a dramatic modification, the mass of the aircraft was reduced by 50% and moments of inertia were also reduced. Figure 23 shows the predicted performance of such a large modification. Even with the more conservative uncertainty bounds calculated using the baseline model method, the framework is unable to include the actual dynamics in its prediction for the duration of the maneuver and is unable to capture the pitch rate, an important value for aircraft control, throughout maneuvers.

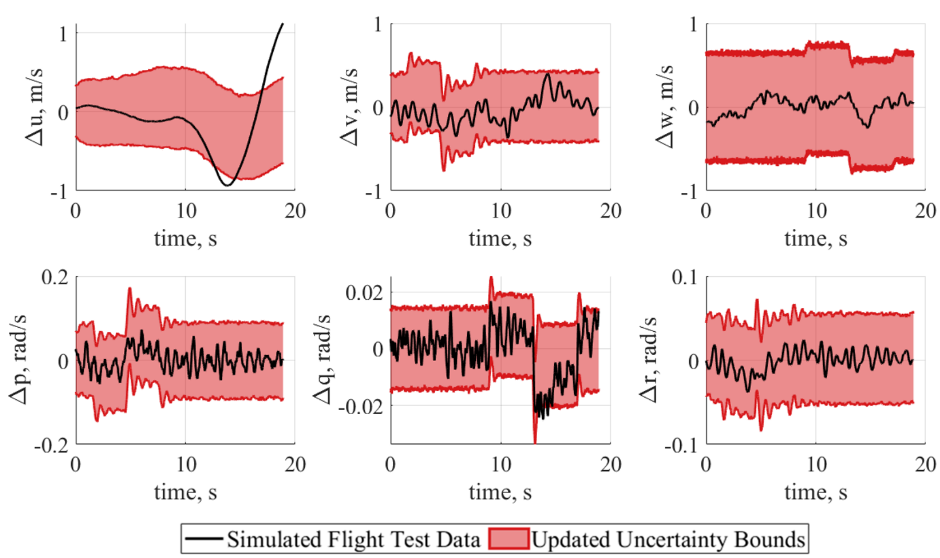

Fig. 23 Comparison of the simulated flight test data to model results generated from a large modification change.

V. Summary and Conclusions

We have evaluated a previously described framework in a number of common situations seen in flight testing and data modeling to determine the applicability and usefulness of the framework. The model form used to model the aircraft dynamics is shown to be important to correctly capturing the uncertainty and dynamics. The quality of the flight test data, including the noise levels and observed states, can also have a significant impact on the framework results. Other factors that affect the framework results include the amount of flight test data and the magnitude of the modification. Additional research into the applicability of each of the two methods, determining the range of acceptable modifications, is an area for future work and would require significant flight test data for a large spectrum of modified configurations. These results will be applied to a real aircraft system in future work, demonstrating that the framework is capable of predicting performance of modified configurations for a realistic system.

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