Safe and Efficient Flight Test Execution through Digital Engineering: High-Fidelity Loads Regression Prediction Generation

Victor Luquin[1], Alyssa S. Lai[2], Alden W. Latkin[3] and Wendy N. Hashii[4],

412th Test Wing, United States Air Force Test Center, Edwards AFB, CA, 93524, USA

Analytical computer models provide initial external aircraft loads predictions at the start of a loads program, however, these predictions are typically not updated as flight test progresses, even when large deviations between measured and predicted loads are observed. External aircraft loads predictions generated with a multiple linear regression with interactions technique can provide continuously updated high-fidelity empirical predictions by using the readily available aircraft states, rates, and surface positions as predictors. Continuously updated, high-fidelity loads predictions will significantly increase both the test efficiency and safety of a loads flight test program.

I. Nomenclature

c_0	=	intercept coefficient
c_n	=	predictor coefficient
v_m, v_z	=	predictor values
g	=	32.17 ft/s^2, acceleration of gravity
M	=	Mach Number
Nz	=	normal load factor
AoS	=	Angle of Sideslip
AoA	=	Angle of Attack

II. Introduction

Flight test has an inherent risk and cost. Typically, at the start of a loads flight test program, analytical finite element model (FEM) and/or a computational fluid dynamics (CFD) model based external aircraft loads predictions are provided. However, due to cost and schedule constraints, the load models are not updated as new flight test data becomes available, even when measured loads deviate from the initial predictions.

A digital engineering approach to create a high-fidelity external aircraft loads model directly correlates to safer and more efficient flight test execution. Inaccurate predictions can result in unnecessary build-ups, repeats, and early return to base (RTB) calls that, in aggregate, can cost millions of dollars during the life of a program.

As an example, a recent six-year loads flight test program at Edwards Air Force Base (AFB) consisted of 574 flights, comprised of 2,199 loads test points with an additional 10,500 combined repeats and build-up maneuvers flown. On average, each test point was flown approximately six times (including build-ups, repeats for maneuver quality or changes in control laws). The total loads test program cost upwards of 59 million dollars. A reduction in the number of repeats and build-up maneuvers flown by only 10% equates to each test point being flown an average of

[1] Structures Engineer, 412th Test Wing, Air Force Test Center
[2] Structures Engineer, 412th Test Wing, Air Force Test Center
[3] Structures Technical Expert, 412th Test Wing, Air Force Test Center
[4] Structures Flight Chief, 412th Test Wing, Air Force Test Center

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5.5 times, resulting in a savings of approximately 4.8 million dollars over the life of the test program. This is a conservative estimate of the potential savings that could be realized with improved flight test loads predictions. A more aggressive, but still realistic, goal of no more than three repeats/build-ups per maneuver would result in an estimated savings of 18 million dollars over the life of the program.

In order to improve flight test loads predictions, multiple linear regression models with interactions were utilized to generate high-fidelity loads predictions. These regression models utilized the aircraft states, rates, and control surface positions as predictors for external aircraft load responses. Compared to other model types, multiple linear regression with interactions was chosen because of its relative simplicity and its ability to account for the relationships between predictors that influence aircraft load responses.

The loads regression prediction generator (RPG) outputs multiple regression models that predict external aircraft loads based on aircraft flight conditions, state parameters, and surface deflections. The accuracy of these predictions is a result of continuously updating the models with the latest data available through flight test. Although a robust empirical model correlated to the latest measured data does not provide a priori knowledge of airframe loads throughout the flight envelope, it does allow for a significant improvement in the accuracy of loads predictions from one test point to the next. It also provides an avenue for the loads team to gain insight into the critical parameters that drives the load for a particular airframe component.

III. Flight Test Background

Verification of external aircraft flight loads requires flight testing a structurally representative loads instrumented and calibrated test vehicle throughout the aircraft design envelope. The external aircraft loads data gathered during this flight test is utilized to validate a structural model for certification. Maneuvers are flown throughout the airspeed and maneuvering envelopes targeting specific altitudes, Mach numbers or airspeeds, and normal load factors. Each of these target parameters have an allowable variation when flown, known as test point tolerances. In addition, each maneuver type has associated control input requirements in order to match analytical predictions and enable specification verification.

Traditionally, a fairly tight adherence to maneuvering tolerances and control input requirements is required for FEM/CFD model validation purposes. The model is correlated to the external aircraft loads data gathered from each test point. Because it is impractical to re-run the model for each test point to match the “as-flown” maneuver or to correlate the model based on measured loads, flight test predictions often rely on uncorrelated analytical models that are based on a perfectly flown, “spec” maneuver leading to gross errors or inaccuracies in the flight test predictions. Due to the uncertainty inherent in flight test loads predictions, it is common to add safety build-up maneuvers to avoid inadvertently exceeding the structural limits of the test article.

Since maneuvers must be flown within tolerance and control input bounds, it is common to have to repeat maneuvers, potentially multiple times, in order to achieve the test point within the required tolerances. Fig. 1 to Fig. 3 illustrate multiple attempts at a roll targeting an elevated normal load factor, Nz, of 5.8 g, at a Mach number of 0.90, and 10,000 feet pressure altitude. With a Mach number tolerance of only ±0.02, and a sustained maximum roll stick input required throughout the duration of the roll, this example maneuver warranted two repeats.

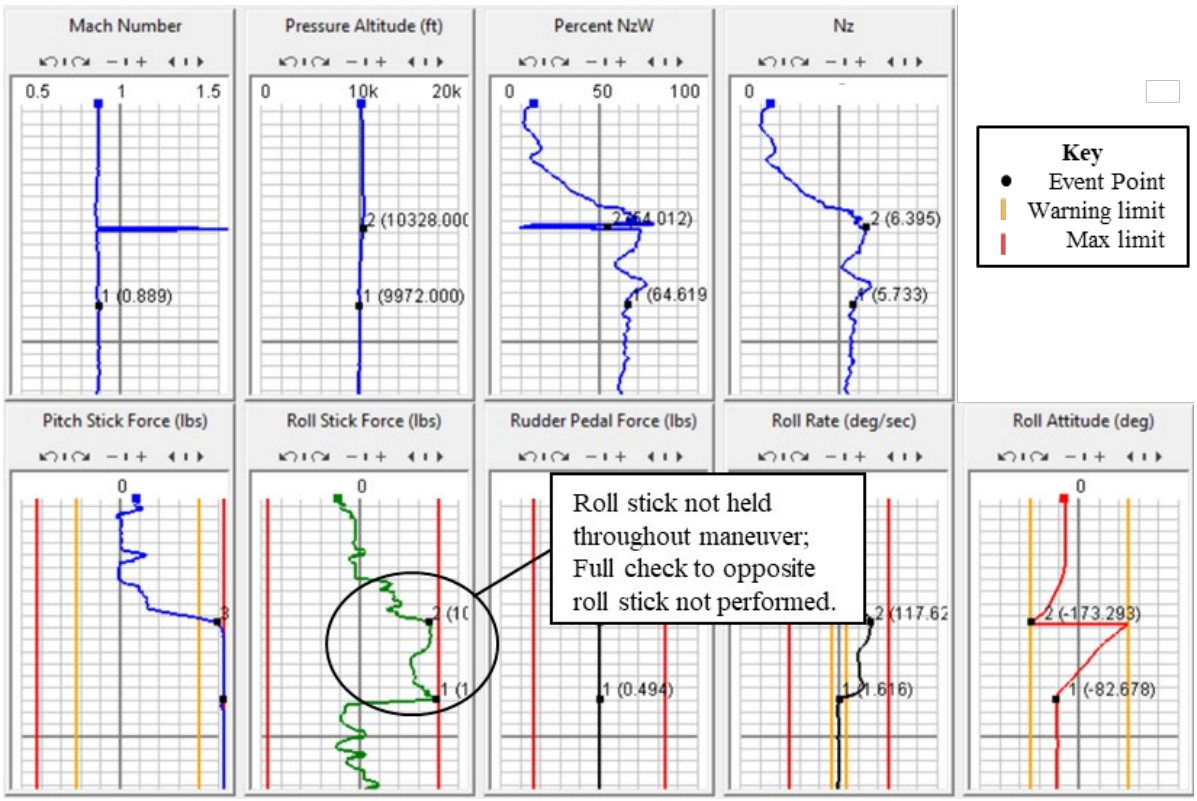

Fig. 1 1st Maneuver Attempt

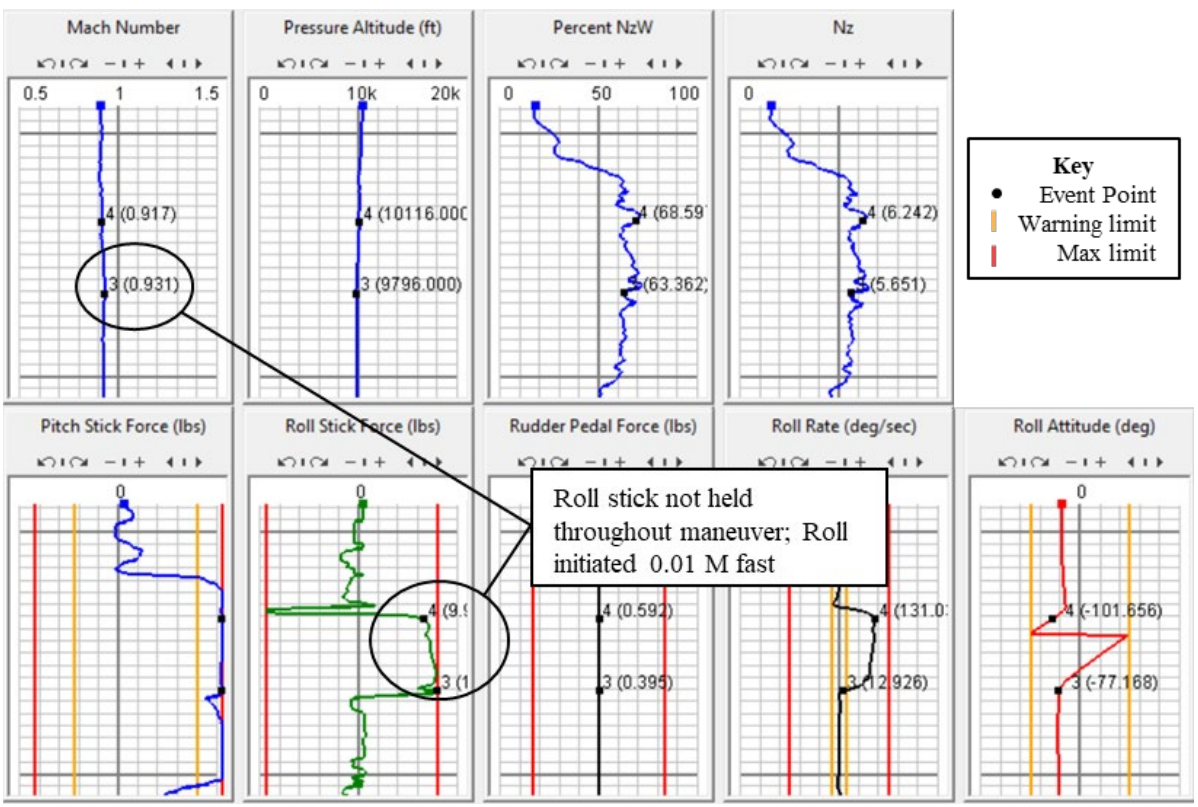

Fig. 2 2nd Maneuver Attempt

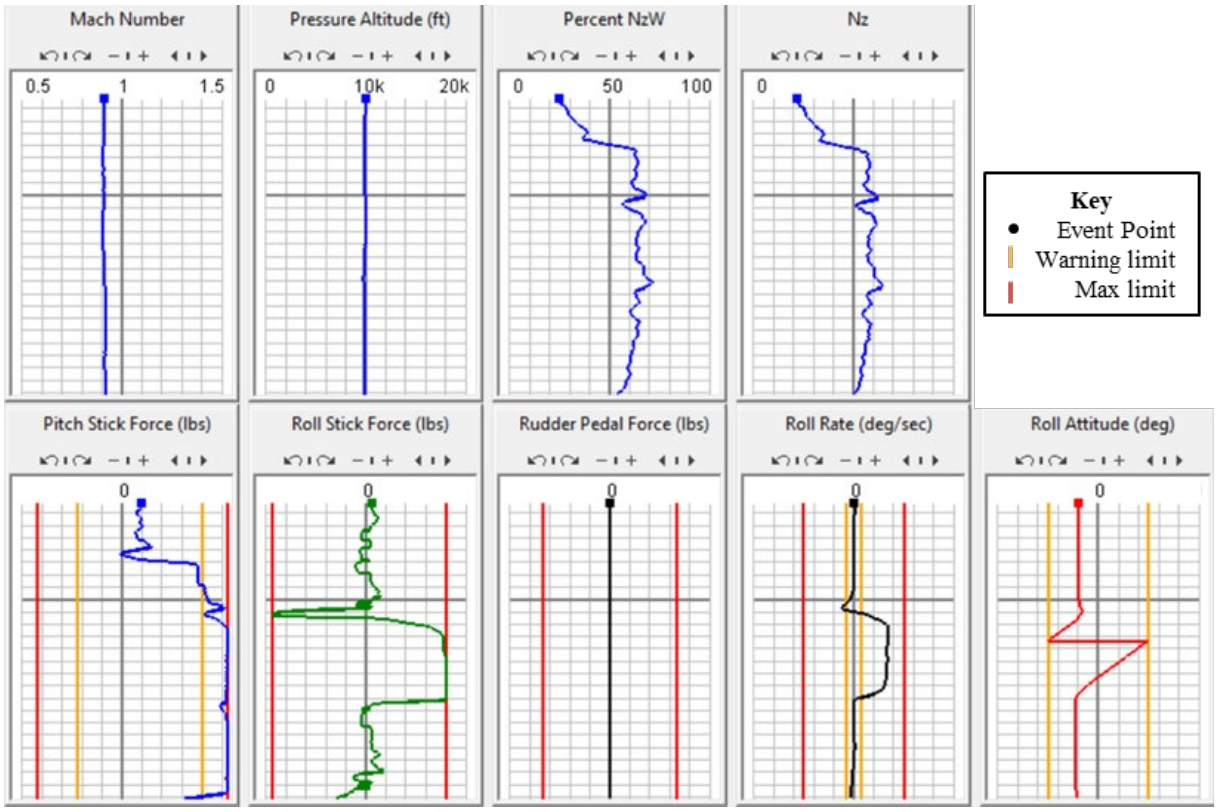

Fig. 3 3rd Maneuver Attempt (Good Maneuver)

As an envelope expansion test program progresses, it is common to make discoveries that require changes to the flight control system. In turn, these changes directly affect the external loads experienced by the airframe. As a result, when the flight control laws are updated, it is common to again re-fly those test points, with the potential to repeat each test point multiple times.

Due to a general lack of available models and time constraints, simple external aircraft load linear trends are commonly utilized to update loads predictions during a flight test program. Fig. 4 depicts a wing station bending moment versus torsion for loads flight maneuvers including maximum and minimum g symmetric maneuvers, 1g rolls and elevated-g rolls at multiple g values up to the maximum allowable rolling g at 0.80 M and 10,000 feet pressure altitude. During these maneuvers there are portions which display linear trends, but also portions where other variables are influencing the load. Since the loads are actually dependent upon multiple variables which are simultaneously changing, these methods are only useful when the change in load is temporarily dependent on a single dominant variable. These methods commonly require verification of this single variability by adding in build-up maneuvers to avoid inadvertently exceeding the structural limit. The models generated by RPG attempts to account for multiple variables simultaneously via linear regression with parameter interaction terms included.

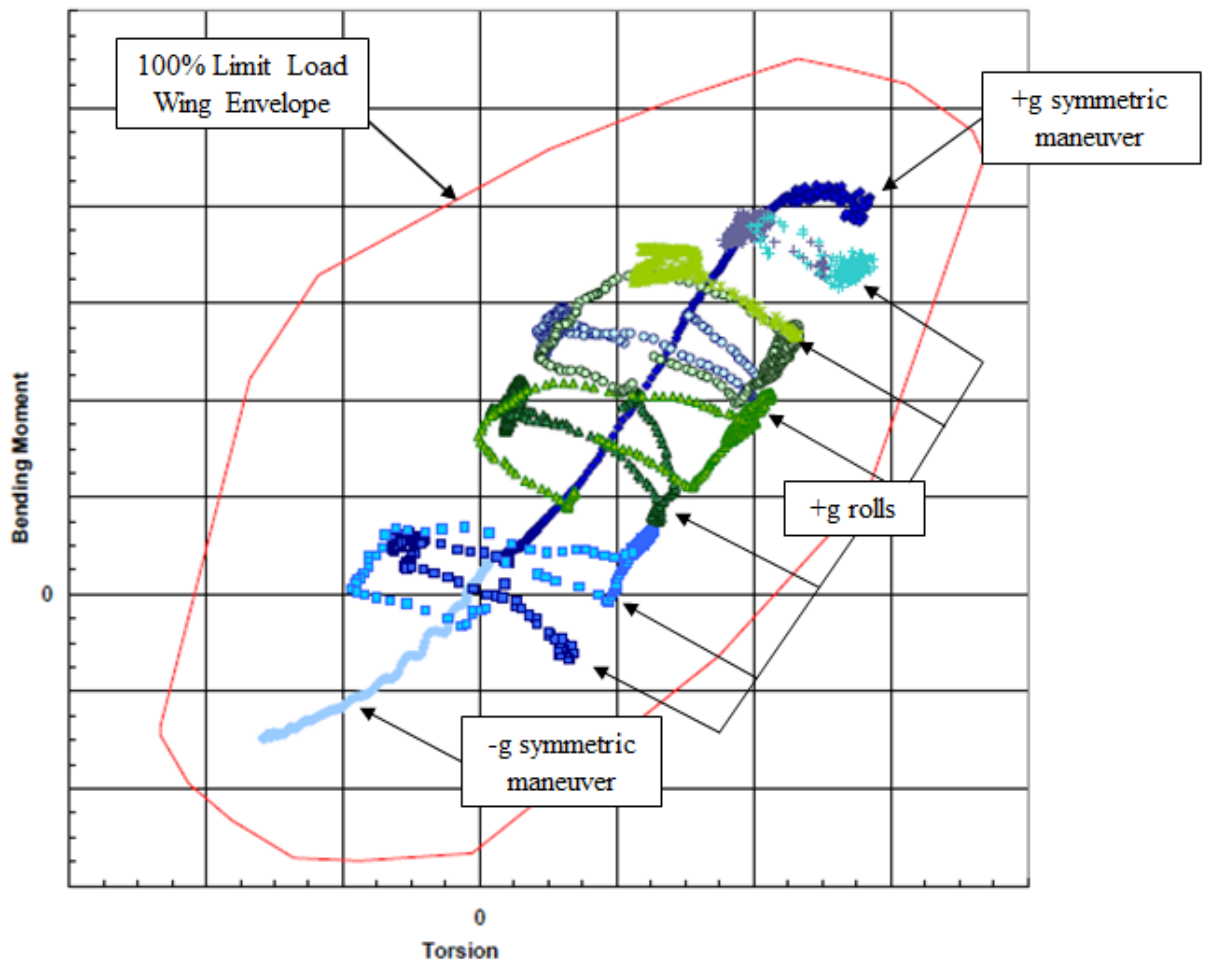

Fig. 4 Bending Moment vs Torsion Example (unique color/shape per maneuver)

IV. Development of Load Prediction Models

A. Model Methodology

The initial development of the multiple linear regression models was inspired by previous projects that were able to successfully model external aircraft loads using a similar technique. For example, Allen, Lizotte, Dibley, and Clarke used a multiple linear regression technique to model the loads on the F/A-18 Active Aeroelastic Wing airplane [1]. Hass and Imber used a stepwise multiple regression analysis to predict vibratory loads on helicopters [2].

The use of regression trees was also considered as a possible technique based on the Klein, Fournier, and Grihon case study to predict loads of a derivative aircraft [3]. An initial regression tree model indicated that the overall accuracy was better than the linear regression model. However, the regression tree model was more complex and not implemented into a real-time control room environment. Additionally, the output from the regression tree model did not look as realistic when compared to actual flight test data as the output from the linear regression (as shown in Fig. 5).

Multiple linear regression with interactions was chosen over simple linear regression in order to account for the effect that one predictor has on another. For example, as Mach number increases, the maximum allowable load factor may decrease (due to a nominal V-n cutback). The use of multiple linear regression with interactions caused a significant increase in the number of terms per equation. For example, the use of 12 primary predictors resulted in a regression equation with 79 different terms (including the intercept). However, the additional accuracy gained by the use of multiple linear regression with interactions was deemed to be worth the inefficiency caused by the additional terms in the linear regression equation.

Compared to other model types, multiple linear regression with interactions was chosen because of its relative simplicity, the ease of implementation into a real-time control room environment, and its ability to realistically simulate actual data.

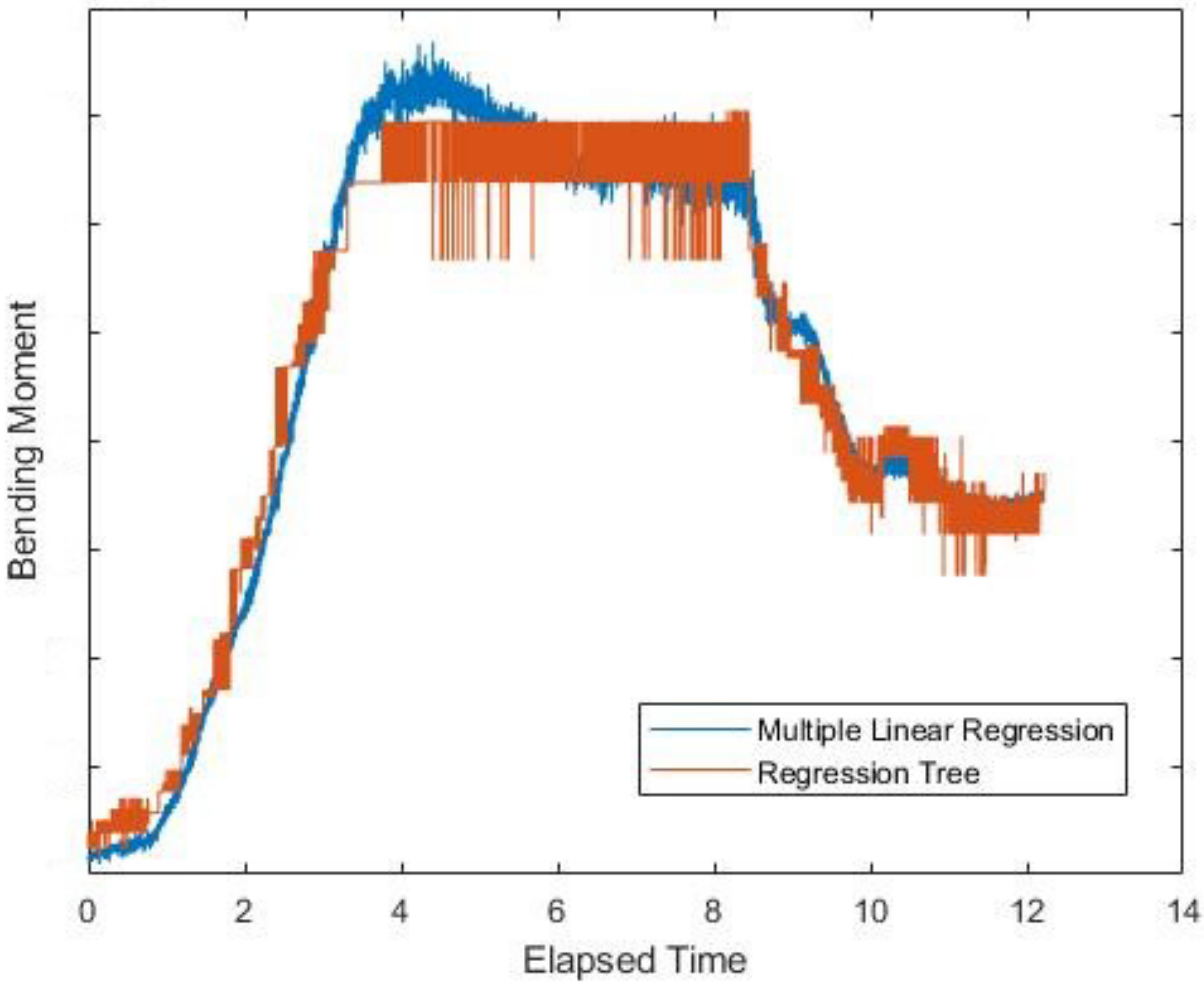

Fig. 5 Comparison of Regression Tree Versus Multiple Linear Regression for Wind Up Turn Maneuver

B. Development of Multiple Linear Regression with Interactions Models

The first step to creating the regression models was to compile a database of properly time-sliced and cleaned test maneuvers for a given configuration. Any instrumentation or telemetry dropouts were removed and data was binned by Mach number in an attempt to minimize the non-linear effects of Mach number. Separate data sets, with left versus right control surface position measurements, were used to predict loads on the left versus right side of the aircraft in order to account for potential asymmetry in the measured loads. Additionally, each load component was filtered with a low pass Butterworth filter to remove high frequency dynamic content (such as airframe structural modes and buffet responses).

Because of the different Mach number bins, multiple regression models were generated for each component load (as shown in Fig. 6). More than 100 loads regression models were developed for a single aircraft.

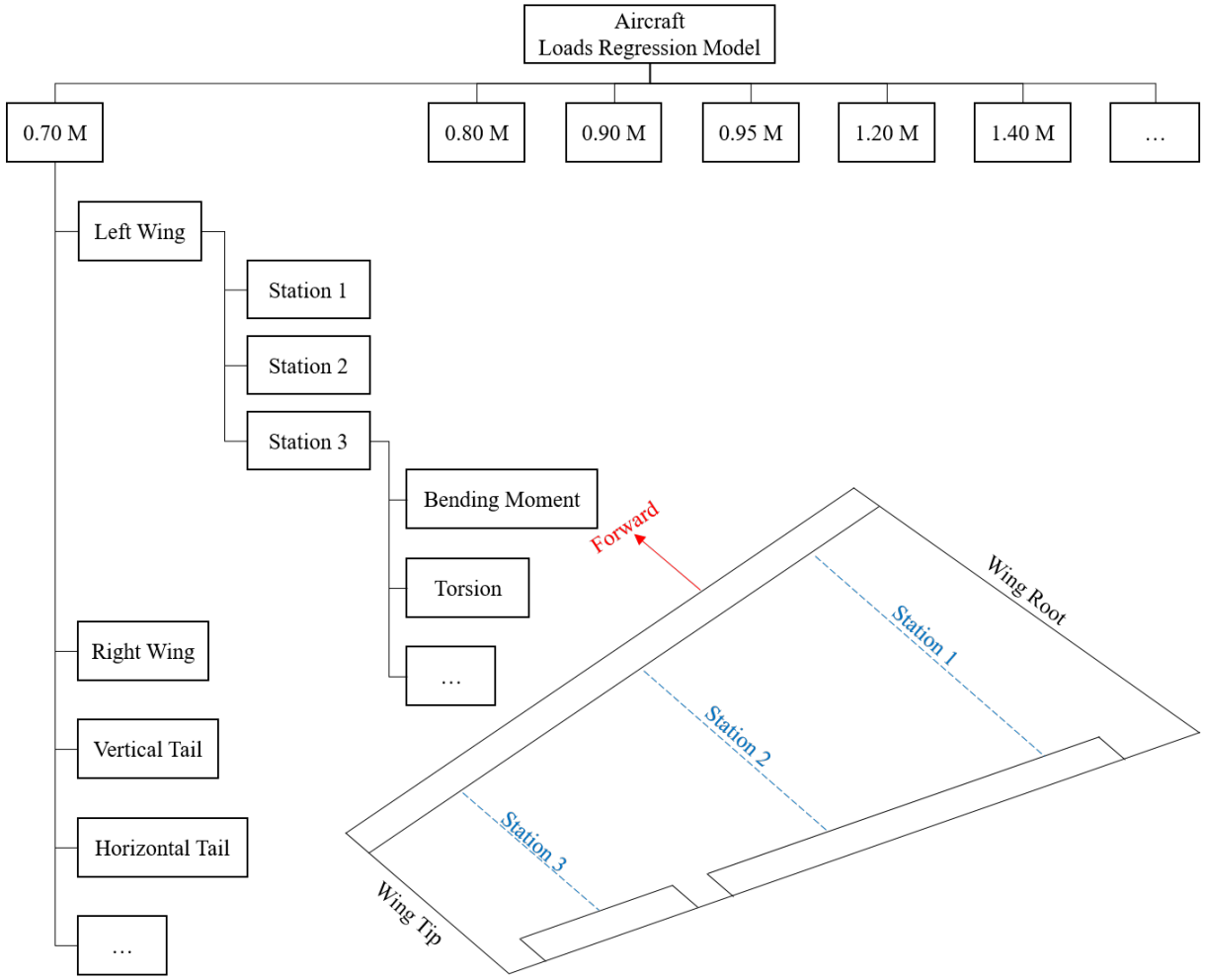

Fig. 6 Aircraft Load Regression Model Scope

The predictors selected were found to have a significant influence on external aircraft loads, based primarily on a comparison of the predicted load versus the measured loads as well as the p-value of each predictor (a p-value less than 0.05 was determined to have a significant influence on loads). The predictor selection was an iterative process that required knowledge of what parameters influenced aircraft load responses. Table 1 shows the baseline predictors that were used for each major airframe component. It should be noted that as more flight data are included in the regression, the addition or removal of predictors may be required to increase the accuracy of the model.

Table 1 Load Predictors

Predictors	Horizontal Tail	Vertical Tail	Wing
Mach Number	X	X	X
Dynamic Pressure	X	X	X
Angle of Attack	X	X	X
Angle of Sideslip	X	X	X
Roll Rate	X	X	X
Pitch Rate	X	X	X
Yaw Rate	X	X	X
Roll Acceleration	X	X	X
Pitch Acceleration	X	X	X
Yaw Acceleration	X	X	X
CG Normal Acceleration	X	X	X
CG Lateral Acceleration	X	X	
CG Longitudinal Acceleration		X	
Leading Edge Flap Positions			X
Flaperon Positions			X
Aileron Positions			X
Rudder Position	X	X	
Horizontal Tail Positions	X		
Wing Fuel Quantity			X

Based on the predictors chosen, a multiple linear regression equation with interactions was generated, taking the form of Eq. (1):

$$\text{Multiple Linear Regression Equation with Interactions} = c_0 + c_1 v_1 + c_2 v_2 + c_3 v_1 v_2 + \cdots + c_n v_m v_z \quad (1)$$

where
c_0 = intercept coefficient,
c_n = predictor coefficient
v_m, v_z = predictor values

Predictors may appear redundant, such as Mach and dynamic pressure (due to Mach binning) or Angle of Attack (AoA) and normal acceleration, but they were all found to enhance the predictive capabilities for the load regression models. Even though normal acceleration is function of AoA and dynamic pressure, when normal acceleration is removed, the regression model's accuracy decrease significantly. The same was true if AoA or dynamic pressure was removed. Angle of Sideslip (AoS) and lateral acceleration are also not independent, but still both utilized. Other dependencies were explored such as control surface positions or wing fuel quantity as they effect either aerodynamic or inertial load at the measurement location. For the wing, the total lift and lift distribution are directly affected by changes of attached control surfaces (leading edge and trailing edge) positions. Adding the rudder position to the horizontal tail loads models significantly increased its accuracy for certain maneuver types, whereas the same could not be said for the horizontal tail position and the vertical tail loads models. The addition of body-axis (pitch, roll, and yaw) rates and accelerations were also evaluated separately and accepted as predictors due to the regression model improvements across almost every load model.

C. Model Validation

Once a suitable set of predictor parameters were chosen, the accuracy of the regression model was assessed. That required the determination of relative error. The standard error calculation was problematic due to observed loads occasionally crossing or approaching zero, thus generating a large error. In order to generate an error that was relative to the structural limits of the airframe, it was decided to use the load limit of the component load to normalize the regression model error. This was expressed as the absolute value of the difference between the measured load and the regression model load divided by the design load limit (DLL). This can also be expressed as the absolute value of the

difference in percent DLL of the measured loads and the percent DLL of the regression model output. Refer to Eq. (2).

$$Difference\ in\ \%\ DLL = \left|\frac{FL-RML}{DLL}\right| * 100 \quad (2)$$

where,

FL = Flight Load
RML = Regression Model Load

For this application, the data that are most critical from an accuracy standpoint are when the external aircraft loads are relatively high and above the noise. The assessment was focused only on data where the measured external aircraft loads were equal or greater than 40% DLL. Due to the potential errors in the measured load of up to 5% DLL (due to the expected accuracy of both instrumentation and the loads calibration equations), it was concluded that an additional 5% total error due to the regression model was reasonable. Therefore, the goal of the model was to have a difference in percent DLL of the model output and measured load of no more than 10% DLL when measured loads were 40% DLL or greater. Fig. 7 depicts in-flight measured wing bending moment along with the associated regression model load prediction during a wind-up turn maneuver. The calculated difference of less than 10% DLL indicates reasonable confidence in the regression model.

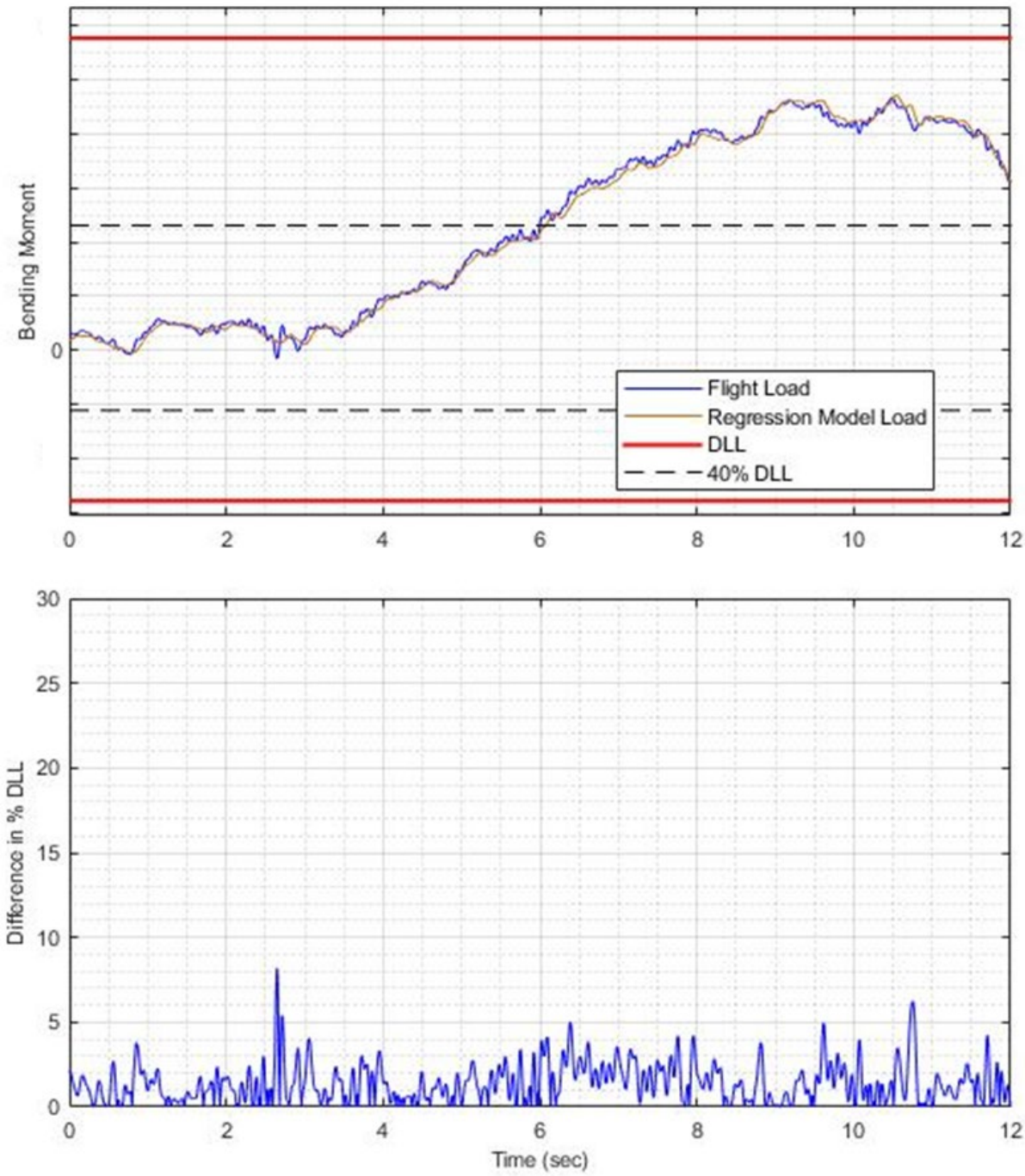

Fig. 7 Wind-Up Turn

Although regression models for loads flight test can be used for higher fidelity loads predictions, there are some limitations to this method. Outer mold line, structural, or mass property changes may impact airframe loads, so new regression models may need to be generated for different aircraft configurations. Although this methodology cannot be used to generate predictions for first flight, once initial data are available, the loads regression models will provide high-fidelity loads predictions, as long as the model is continuously updated. As any additional data are collected via flight test execution, the models are continuously re-generated, and re-evaluated.

V. Application

A. Loads Prediction Generation – Prediction Capability

With an initial validated flight loads data set, a load regression model can be generated to not only fit the loads observed but to predict the loads which will be experienced at the next condition. This is demonstrated in the examples in Fig. 8 and Fig. 9. The "0.70 M Regression" indicates the model match at the conditions that it has learned, whereas the "0.80 M Predictions" indicates the model can accurately predict the loads which would have been observed at the higher Mach condition. For this example one of the regression model predictors was Mach, but the regression was only provided with flight test maneuvers at 0.68 M to 0.72 M. The 0.80 M predictions regression is the output based upon as-flown aircraft state parameters at 0.78 M to 0.82 M. While those state parameters could not be available before execution as-flown, they could be provided via manned or unmanned simulated maneuvers with sufficient similarity to the flown maneuver to provide accurate pre-flight predictions.

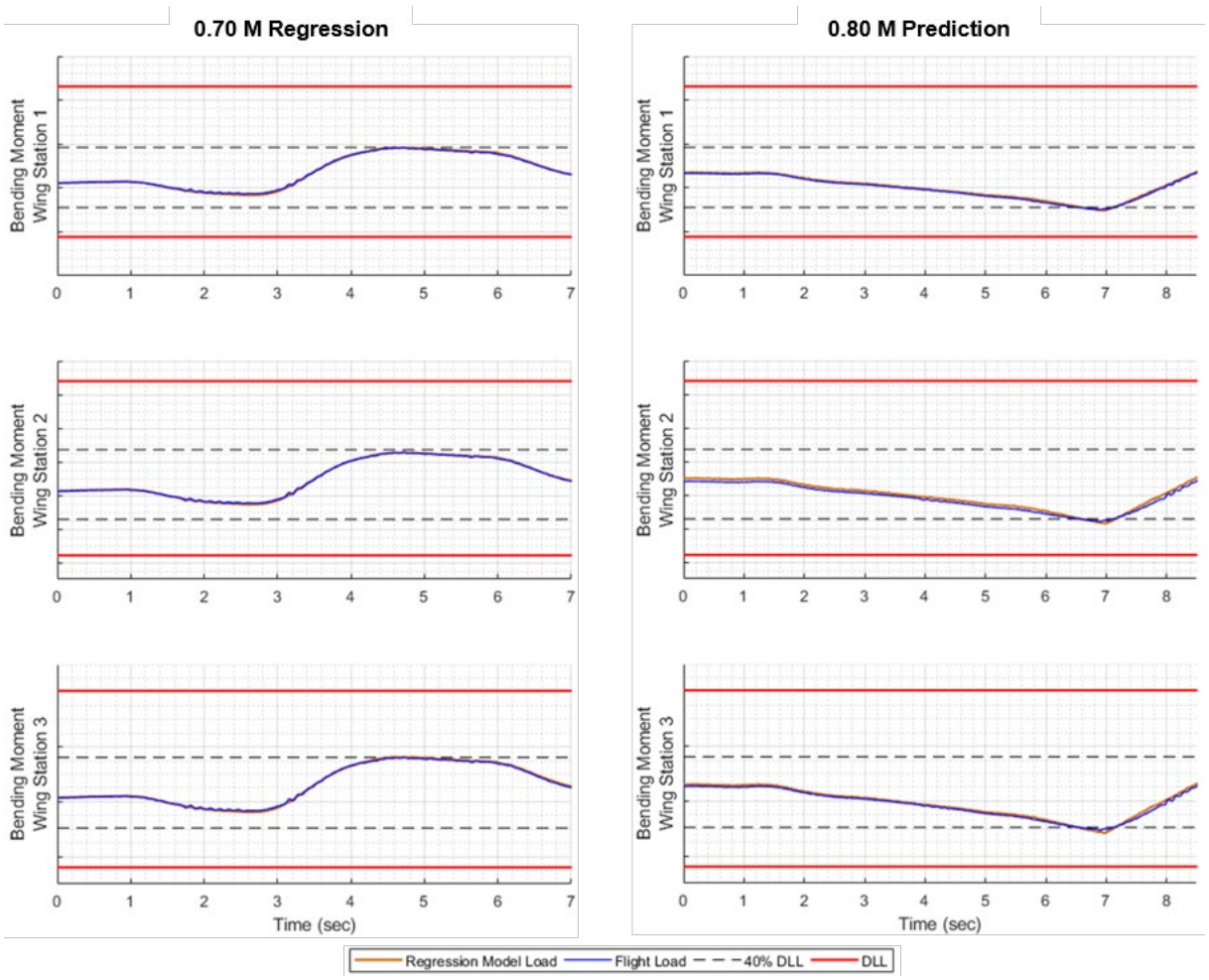

Fig. 8 Regression Output versus Flight Bending Moment for 0.70 M Learned Pushover-Pull Up Maneuver (left) and 0.80 M Predicted Pushover Maneuver (right)

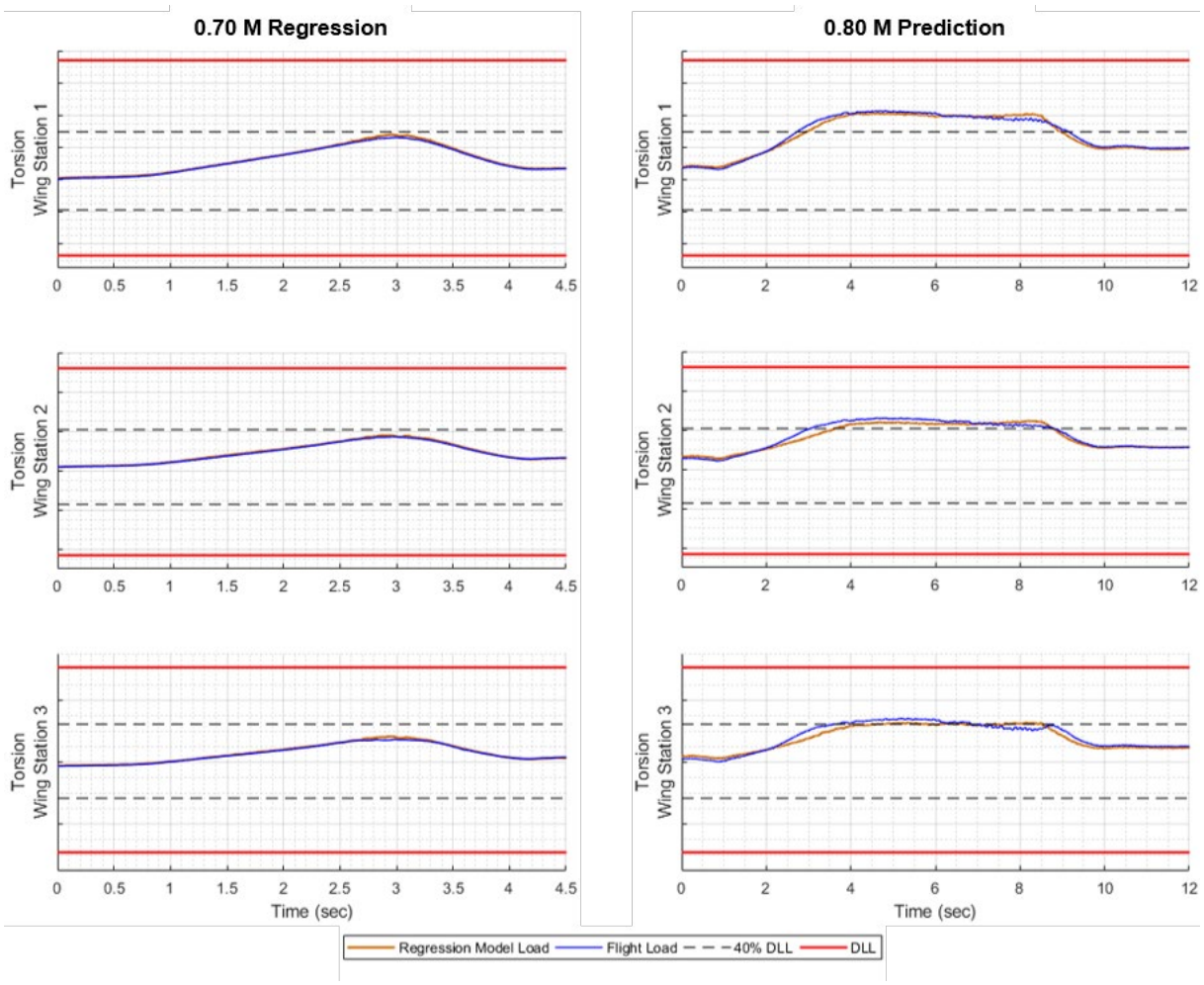

Fig. 9 Regression Output versus Flight Torsion for 0.70 M Learned Wind-up Turn Maneuver (left) and 0.80 M Predicted Wind-up Turn Maneuver (right)

B. Loads Prediction Generation – Pre-Flight Analysis

In preparation for flight test, pre-flight predictions are created to ensure that the planned maneuvers will not result in loads that surpass current aircraft load limits. FEM/CFD-based predictions are typically used to determine the initial airworthiness envelope. However, due to the cost and time required to re-run a FEM/CFD-based analysis, this type of analysis are typically only performed prior to initiation of the flight test program, and again once the flight test program is complete (for correlation with flight test results and final certification).

In contrast, a regression model can be (relatively) easily updated on a flight-to-flight basis. Additionally, a piloted simulator with integrated regression models can also be used to generate high-fidelity predictions. A flight simulator provides the aircraft states, rates, and surface deflections that can be fed into the loads prediction regression models, resulting in loads predictions for as-flown maneuvers (versus offline simulations). As a result, the regression model can account for differences in pilot inputs, and thus has the ability to capture a more accurate or realistic load prediction. For example, Fig. 10 shows that when the pilot performed the maneuver incorrectly (released roll stick during the roll), the regression model is able to capture the associated decrease in load. When the maneuver, as seen in Fig. 11, is performed correctly, the predicted load based on the regression model correctly reflects the measured load.

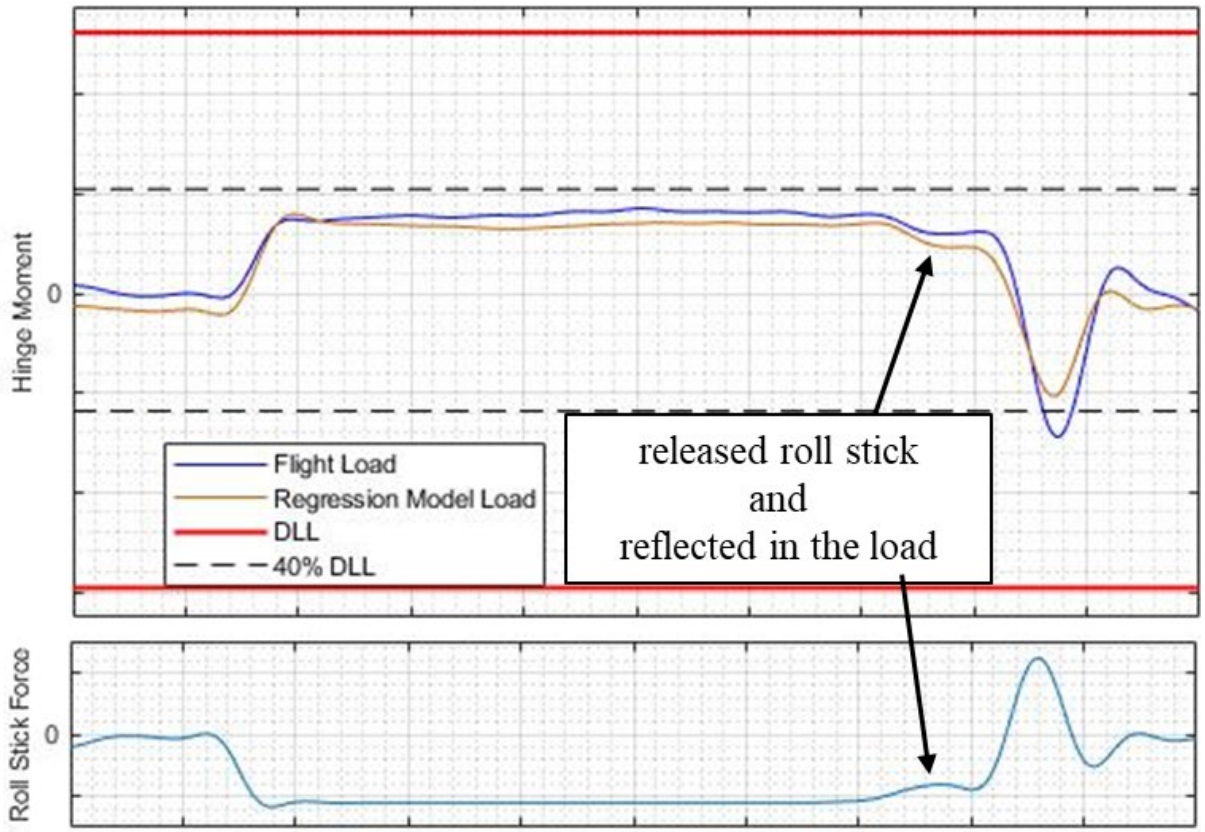

Fig. 10 Loads observed from roll stick prematurely released

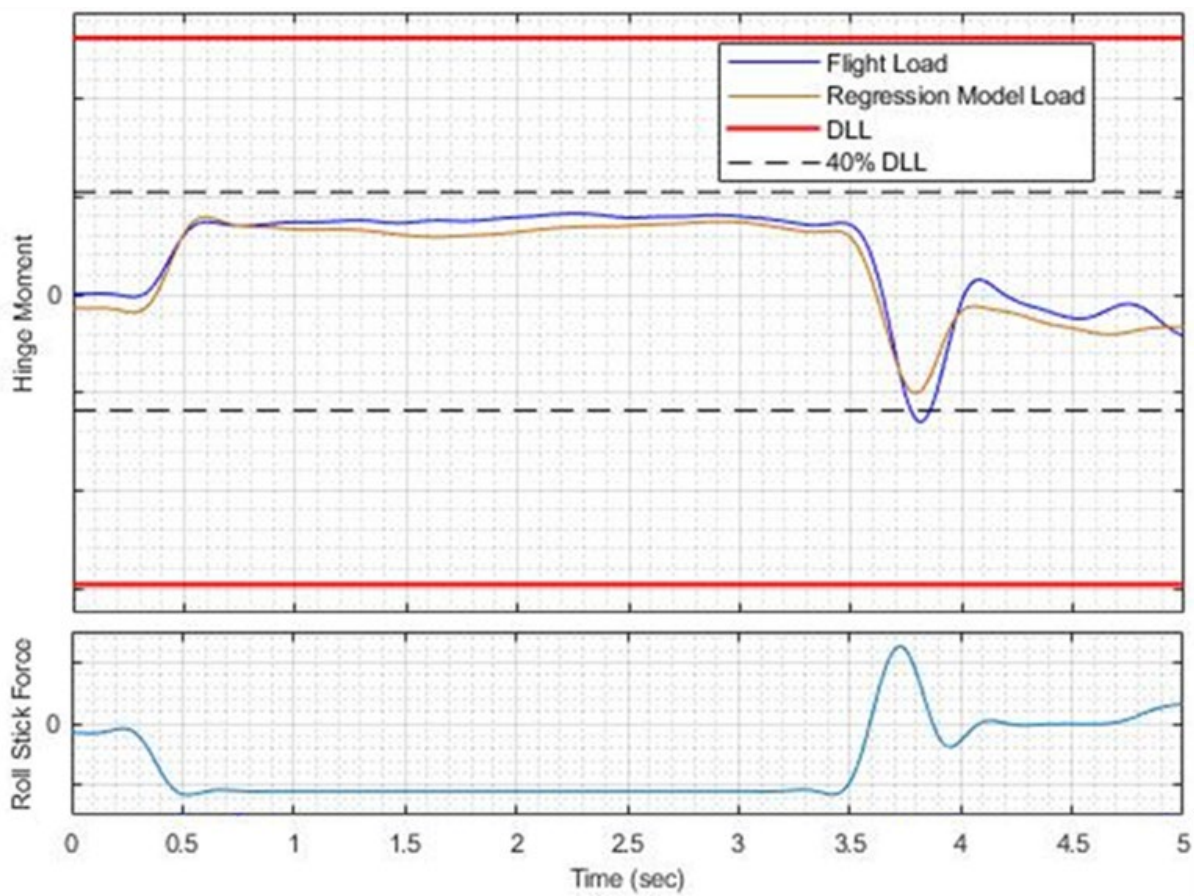

Fig. 11 Loads observed with correct roll stick inputs

Regression models can be used in mission planning to not only create accurate pre-flight predictions based on as-flown maneuvers, but also to run sensitivity studies and to determine a safe test point build-up order. Additionally, regression models can be used to determine if deviations from load predictions are the result of differences in how the maneuver was flown. Inaccurate predictions can result in an unexpected structural load limit exceedance resulting in halting certain lines of testing or ending an entire mission early – until the reason for the load deviation is addressed. The current prediction cycle, as shown in Fig. 12, allows flight test engineers to update the coefficients of the loads regression models based on maneuver conditions recorded in the mission rehearsal.

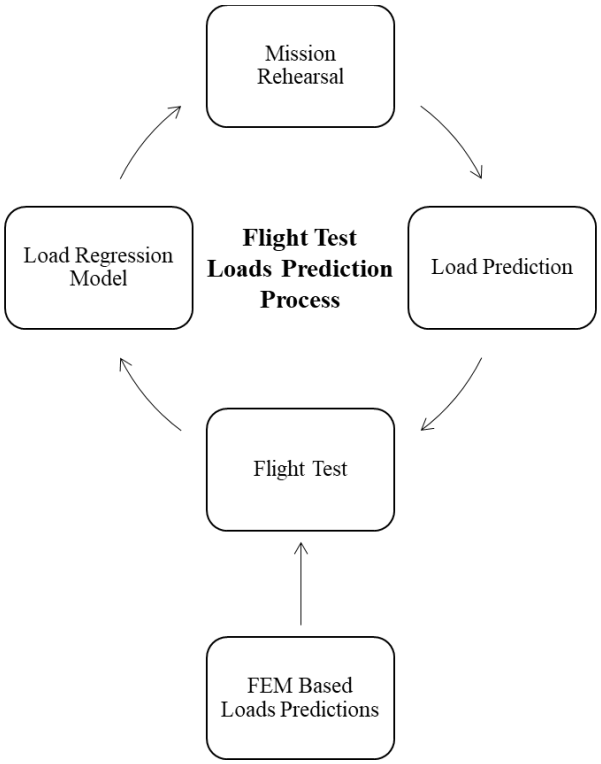

Fig. 12 Flight Test Loads Prediction Process

C. Real-Time Predictions

Integrating RPG into a control room increases test efficiency and safety as predictions are accurately updated in real-time. As previously mentioned, a piloted simulator with RPG can be used to generate pre-flight load predictions. However, differences in flight conditions and pilot technique are inherent to flight test data. Thus having the ability to compare the RPG outputs prior to a mission to those generated during a mission can provide insight to possible differences in the expected loads. This comparison will allow the flight test engineer to adjust predictions for the next test maneuver and determine if the maneuver should be skipped for that mission. As a result, a maneuver that may have resulted in an early RTB call can be avoided and another line of testing can continue, resulting in a safer and more cost effective mission.

This capability requires additional computing power, as this includes the ability to stream incoming data to a server where the regression equations can be calculated along with the measured loads. Then display the results on the engineers' screens. Currently engineers have two sets of screens. One of the set displays just the measured loads whereas the second set displays not only the measured loads, but the RLM output as well. The RPG screens, which have a unique color to help engineers not confuse them with the measured loads screens, can assist less experienced engineers in investigating unexpected loads as they can provide insight into the parameters that may have resulted in the difference between predicted to recorded load. Having the differences in regression predictions to actual flight loads can lead to engineers determining when a line of testing should be paused until the regression models are updated with the latest flight data.

A future goals is to have the ability to update the RPG RLMs near real-time, as new data becomes available. The difficulty in this is again having the hardware to run the calculation in the background and not slow down the streaming of the data into the control room.

D. Training

Historically, training a new flight test structures engineer would involve observing a flight test mission in real-time (over the shoulder of a more experienced engineer) and then actively monitoring the mission with the more experienced engineer observing the engineer in training. While this type of training can be invaluable in familiarizing new engineers with a control room environment, it is of more limited value in training a new engineer how to be an effective loads engineer in the control room. Any specific training that occurs is a target of opportunity as opposed to

more deliberate training. Furthermore, the training must, by necessity, have secondary priority behind mission execution.

In contrast, the use of the regression models capability allows a simulated training mission to be designed specifically with the goal of training engineers in mind. While simulated missions have been previously used to train control room teams, these simulated mission did not incorporate simulated loads. Rather, they only included aircraft state parameters (e.g. Mach number, altitude, airspeed, control surface positions, pitch/roll stick positions, yaw pedal position, etc.). When simulated loads training missions were established at the Air Force Test Center at Edwards AFB, the missions were specifically designed to exercise high loads on every major component of the airframe while maintaining a standard build-up procedure – building up in Mach number, down in altitude, and in maneuver type (symmetric maneuvers before rolling maneuvers, for example). Engineers were each assigned a major component of the airframe (wing, horizontal tail, vertical tail, and control surfaces) along with an assigned loads lead engineer responsible for making maneuver quality calls, coordinating the rest of the loads team, and communicating with the test conductor. While prior control room training sessions have been focused on training engineers to make maneuver quality calls or to learn test discipline in the control room environment, regression modeling allows the training to focus on training the engineer how to assess loads and how to operate in the control room environment as a loads test engineer. Fig. 13 shows one of the initial loads training classes conducted within the Integrated Facility for Avionics Systems Test (IFAST) facility at Edwards AFB.

Fig. 13 Loads Training Class at IFAST

The deliberate training conducted within the simulated missions allows the control room team to not only gain familiarization with control room screens and communication, but also to gain some experience in the decision making process. For example, how does one determine whether to proceed to the next test point? Or, if measured data begins to deviate from pre-flight predictions, how should one update their predictions for the next test point based on the data measured to-date? Simulated problems (such as telemetry dropouts at inopportune times or a loss of safety of test instrumentation) may be introduced to test the engineers' decision-making abilities.

Preliminary feedback from the initial training classes conducted to-date has been overwhelmingly positive. This training capability can be used to train a first flight control room team, train new engineers in the middle of a test program (without significant impact to flight test schedules), and retain control room currency. But, most importantly, it represents a significant improvement in how new control room engineers are trained, with an emphasis on sound external aircraft loads based decision making.

VI. Conclusion

Aircraft external loads flight test loads programs measure external loads at various critical structural locations. Upon completion of the loads flight test program, these loads are measured, recorded and correlated with FEM/CFD based models for structural certification. However, loads are also monitored real-time during flight test to verify functionality and to ensure that these critical locations do not experience structural exceedances during test. At the beginning of a flight test program, the predicted loads for a given aircraft maneuver at critical locations on the airframe are generated based on the FEM/CFD models. While the accuracy of these predictions might be sufficient for an initial flight release, it is common for these predictions to be grossly inaccurate for individual maneuvers at various flight conditions. During flight testing, these inaccurate predictions can lead to early RTBs, unnecessary build-up points and

repeat maneuvers flown, possible overstress conditions during flight test, delays in changes to flight control laws (required to keep loads within limits), and delays in final airframe certification due to unexpectedly high loads.

As a result, a digital engineering approach that can accurately model airframe loads based on expected aircraft response parameters can provide significant programmatic savings. With a limited set of flight test loads data including the reaction loads and aircraft states and rates, a multiple linear regression with interactions model can quickly and accurately predict the loads for flight test maneuvers. These regression models can be continuously updated based on the latest flight test data, and can accurately predict loads not only for maneuvers flown as prescribed, but also if flight test maneuvers are flown with less than nominal pilot control inputs. As a result, there has been a significant improvement on the accuracy of flight test load predictions. In addition to generating accurate loads predictions, these load regression models enable risk-free real-time loads training for flight test engineers, and can be integrated into a control room environment for a real-time prediction capability.

Acknowledgments

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