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F-15B Quiet Spike™ Aeroservoelastic Flight-Test Data Analysis

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ABSTRACT

System identification is utilised in the aerospace community for development of simulation models for robust control law design. These models are often described as linear, time-invariant processes and assumed to be uniform throughout the flight envelope. Nevertheless, it is well known that the underlying process is inherently nonlinear. Over the past several decades the controls and biomedical communities have made great advances in developing tools for the identification of nonlinear systems.

In this report, we show the application of one such nonlinear system identification technique, structure detection, for the analysis of Quiet Spike™ (Gulfstream Aerospace Corporation, Savannah, Georgia) aeroservoelastic flight-test data. Structure detection is concerned with the selection of a subset of candidate terms that best describe the observed output. Structure computation as a tool for black-box modeling may be of critical importance for the development of robust, parsimonious models for the flight-test community.

The objectives of this study are to demonstrate via analysis of Quiet Spike™ aeroservoelastic flight-test data for several flight conditions that: linear models are inefficient for modelling aeroservoelastic data, nonlinear identification provides a parsimonious model description whilst providing a high percent fit for cross-validated data and the model structure and parameters vary as the flight condition is altered.

NOMENCLATURE

AIC	Akaike's information criterion
LTI	linear time-invariant
MDL	minimum description length
NARMAX	Nonlinear AutoRegressive, Moving Average eXogenous
NL	nonlinear

INTRODUCTION

System identification, or black-box modeling, is a critical step in aircraft development, analysis and validation for flightworthiness. The development and testing of aircraft typically takes many years and requires considerable expenditure of limited resources. One reason for lengthy development time and cost is assuming the underlying system is linear and invariant throughout the flight envelope. This assumption is related to having an inadequate knowledge of an appropriate model type or structure to use for parameter estimation. Selection of an insufficient model structure may lead to difficulties in parameter estimation, giving estimates with significant biases and/or large variances (ref. 1). This often complicates control synthesis or renders it infeasible. The power of using structure detection techniques as a tool for model development (i.e., black-box modeling) is that it can provide a parsimonious system description which can describe complex aeroelastic

behaviour over a large operating range. Consequently, this provides models that can be more robust and, therefore, reduce development time.

Moreover, when studying aeroelastic systems it may not be practical to assume that the exact model structure is well known a priori. In aerospace systems analysis one of the main objectives is not only to estimate system parameters but also to gain insight into the structure of the underlying system. Therefore, structure computation is of significant relevance and importance to modelling and design of aircraft and aerospace vehicles. Structure computation may indicate deficiencies in an analytical model and could lead to improved modelling strategies and also provide a parsimonious, black-box, system description for control synthesis (ref. 2).

For linear systems modelling a commonly used approach for determining model structure is the minimum description length (MDL) proposed by Rissanen (ref. 3). The MDL was specifically developed to overcome some of the inconsistencies of the Akaike's information criterion (AIC) (ref. 4), i.e., its variance does not tend to zero for larger sample sizes, N.

Recently, the bootstrap method has been shown to be a useful tool for structure detection of nonlinear models (refs. 5–7). The bootstrap is a numerical method for estimating parameter statistics which requires few assumptions (ref. 8). The conditions needed to apply bootstrap to least-squares estimation are quite mild; namely, that the errors be independent, identically distributed, and have zero-mean.

Identification of flight dynamics is not well understood in the subsonic, transonic and supersonic regimes. Therefore, in this report, we investigate whether (1) a linear or nonlinear model best represents the observed data and (2) the system is invariant during envelope expansion (varying Mach number). The data analysed in this study is from the F-15B (McDonnell Douglas, now the Boeing Company, Chicago, Illinois) Quiet Spike™ (Gulfstream Aerospace Corporation, Savannah, Georgia) flight-test program which was a collaborative effort between Gulfstream Aerospace Corporation and the NASA Dryden Flight Research Center (refs. 9–11). The results show that (1) linear models are inefficient for modelling aeroservoelastic data, (2) nonlinear identification provides a parsimonious model description whilst providing a high percent fit for cross-validated data and (3) the model structure and parameters vary as the flight condition is altered.

NARMAX MODEL FORM

The dynamic behavior of many nonlinear systems can be represented as a discrete polynomial which expands the present output value in terms of present and past values of the input signal and past values of the output signal (refs.12–14). A system modelled in this form is popularly known as a NARMAX (Nonlinear AutoRegressive, Moving Average eXogenous) model and is linear-in-the-parameters.

Recently, Kukreja et al. (ref. 15) showed that NARMAX identification is well suited to describing aeroelastic phenomena. The NARMAX structure is a general parametric form for

modelling nonlinear systems (ref. 12). This structure describes both the stochastic and deterministic components of nonlinear systems. Many nonlinear systems are a special case of the general NARMAX structure (ref. 16). In this report, we focus on a special class of NARMAX models: nonlinear polynomial models. The polynomial NARMAX structure models the input-output relationship as a nonlinear difference equation of the form shown in eq. (1):

$$z(n) = f^{l}\left[z(n-1),\ldots,z\left(n-n_y\right),u(n),\ldots,u\left(n-n_u\right),e(n-1),\ldots,e\left(n-n_e\right)\right]+e(n). \tag{1}$$

f denotes a nonlinear mapping, l is the order of the nonlinearity, u is the controlled or exogenous input, z is the measured output, and e is the uncontrolled input or innovation. This nonlinear mapping may include a variety of nonlinear terms, such as terms raised to an integer power, products of present and past inputs, past outputs, or cross-terms. In general, the nonlinear mapping, f, can be described by a wide variety of nonlinear functions such as sigmoids or splines (refs. 17, 16). This system description encompasses many forms of linear and nonlinear difference equations that are linear-in-the-parameters.

Identifying a NARMAX model requires two things: (1) structure detection and (2) parameter estimation. Structure detection can be divided into: (1a) model order selection and (1b) selecting which parameters to include in the model. We consider model order selection as part of structure detection since, theoretically, there are an infinite number of candidate terms that could be considered initially. Establishing the model order, then, limits the choice of terms to be considered. For the NARMAX model, the system order is defined to be an ordered tuple as shown in eq. (2):

$$O \doteq \left[n_u n_z n_e l\right] \tag{2}$$

where n_u is the maximum lag on the input, n_z the maximum lag on the output, n_e the maximum lag on the error and l is the maximum nonlinearity order. Note that for non-polynomial NARMAX models, l may be simply replaced by a nonlinear mapping of some specified class. In this report, we assume that the system order is known.

STRUCTURE DETECTION

The structure detection problem is that of selecting the subset of candidate terms that best describes the output. Therefore, the parametrisation of a system is still further reduced by determining which of the components are required. The maximum number of terms in a NARMAX model with n_z , n_u and n_e dynamic terms and lth order nonlinearity is shown in eq. (3):

$$p = \sum_{i=1}^{l} p_i + 1; p_i = \frac{p_i - 1\left(n_u + n_z + n_e + i\right)}{i}; p_0 = 1. \tag{3}$$

As a result, the number of candidate terms becomes very large for even moderately complex models making structure detection difficult. We define the maximum number of terms, p, as the number of candidate terms to be initially considered for identification. Due to the excessive parameterisation (the curse of dimensionality), the structure detection problem often leads to computationally intractable combinatorial optimisation problems.

TIME SERIES

The data considered in this report is time series since the input signal, $u(n)$, is assumed to be zero or constant. Time series analysis is used when inputs are not available to the experimenter, or where it is unclear which signals are inputs and which are outputs (ref. 18). Models arising from time series data can have many forms (ref. 1). However, in our treatment of the data the ARMA and NARMA model class are of practical significance.

This special case of the general NARMAX model [eq. (1)] can be written as shown in eq. (4):

$$z(n) = f^{l}\left[z(n-1),\ldots,z(n-n_z)\ldots,e(n-n_e)\right] + e(n) \tag{4}$$

where we redefine the model order for this model set as shown in eq. (5):

$$O = \left[n_z n_e l\right]. \tag{5}$$

The maximum number of candidate terms in a model [eq. (4)] with n_z and n_e dynamic terms and lth order nonlinearity is shown in eq. (6):

$$p = \left\lceil \prod_{i=1}^{l} \frac{n_z + n_e + i}{i} \right\rceil \tag{6}$$

Note that ARMA models can be estimated using the Yule-Walker equations or the instrumental variable (IV) estimator to avoid estimating the MA part (ref. 1). This is the approach taken in this report. For a NARMA model the NMA part must be modelled. For nonlinear systems, output additive noise can produce multiplicative terms between input, output and itself. To compute unbiased parameter estimates a noise model (i.e. NMA) needs to be estimated (ref. 19).

STRUCTURE DETECTION METHODS

With the model types defined for the flight-test data available for analysis, we describe two approaches applicable to these model classes. The first is appropriate for AR models whilst the second is appropriate for NARMA models.

Minimum Description Length

A commonly used technique in linear system identification to determine model structure is MDL (ref. 3). The MDL was specifically developed to overcome some of the inconsistencies of the Akaike's information criterion (AIC) (ref. 4), i.e. its variance does not tend to zero for larger sample sizes, N.

The number of parameters necessary to reproduce an observed sequence $\{ z_1 , \ldots , z_N \}$ of a time series depends on the model and parameters assumed to have generated the data (ref. 3). The MDL technique finds the model which minimises the description length and thereby computes an estimate of model order (ref. 3).

Binary prefix codes are used to encode data strings. These data strings can be made up of symbols, parameters, numbers, etc. It is known that the average length of a code word is bounded by Shannon's theorem (ref. 3). Therefore, it is possible to write eq. (7) (ref. 3):

$$\sum_x p(x) L(x) \geq -\sum_x p(x) \log p(x) \tag{7}$$

where $L(x)$ is the length of the code word (i.e. length of parameter vector θ) and $p(x)$ is the probability of x. It is also possible to write eq. (8):

$$L(z|x,\theta) = -\log p(z|x,\theta) \tag{8}$$

where $L(z|x,\theta)$ is known as the log-likelihood function (to be maximised). Let $\hat{\theta}$ denote the value of the parameter which maximises the likelihood and thus minimises the parameter vector length (i.e. code word length) $L(z|x,\theta)$. Since $\hat{\theta}$ can only be encoded up to a certain precision, the code word length, $L(z|x,\theta)$, becomes longer than the desired minimum $L(z|x,\hat{\theta})$, given noise considerations. Let the precision be $\delta = 2^{-q}$ where q is the number of bits used for encoding the parameter. It is possible to save on the code word length if q is small. However, the result is a loss in precision. The optimal precision depends on the size of the observed data via $-\log \delta = 0.5 \log N$, and hence the total code word length for k parameters is given by the MDL, eq. (9):

$$\mathrm{MDL}(k) = -\log[\text{maximised likelihood}] + \frac{1}{2} k \log N \tag{9}$$

which, for an AR(n_z) model gives eq. (10):

$$\mathrm{MDL}(n_z) = \log[\text{maximised likelihood}] + \frac{n_z}{N} \log N. \tag{10}$$

Bootstrap

Recently, the bootstrap has been shown to be a useful tool for structure detection of nonlinear models (ref. 6). The bootstrap is a numerical method for estimating parameter statistics which requires few assumptions (ref. 8). The conditions needed to apply bootstrap to least-squares estimation are quite mild; namely, that the errors be independent, identically distributed, and have zero-mean.

The bootstrap is a technique to randomly reassign observations which enables re-estimates of parameters to be computed. This randomisation and computation of parameters is done numerous times and treated as repeated experiments. In essence, the bootstrap simulates a Monte Carlo analysis. For structure computation, the bootstrap method is used to detect spurious parameters, those parameters whose estimated values cannot be distinguished from zero.

Application of an appropriate ℓ_2 estimator to measured data gives the model response $\hat{Z}$, residuals $\hat{\varepsilon}$ and parameter estimate $\hat{\theta}$. The bootstrap assumes that these residuals, $\hat{\varepsilon} = [\hat{\varepsilon}_1, \hat{\varepsilon}_2, \ldots, \hat{\varepsilon}_N]$, arise from an unknown distribution, *D*. By randomly resampling these residuals, with replacement, it is possible to generate a resampled version of the prediction errors, $\hat{\varepsilon}^* = \left[\hat{\varepsilon}_1^*, \hat{\varepsilon}_2^*, \ldots \hat{\varepsilon}_N^*\right]$, whose distribution estimates *D*. The resampling procedure for each $\hat{\varepsilon}_i^*$ involves randomly selecting from $\hat{\varepsilon}$ with an equal probability associated with each of the *N* elements. For example, a possible resampled version of the errors for $N = 5$ is $\hat{\varepsilon}^* = [\hat{\varepsilon}_4, \hat{\varepsilon}_1, \hat{\varepsilon}_4, \hat{\varepsilon}_2, \hat{\varepsilon}_3]$. The star notation indicates that $\hat{\varepsilon}^*$ is not the calculated error $\hat{\varepsilon}$ but rather a resampled version of it. These resampled errors are added to the model response to generate a bootstrap replication of the original data, shown in eq. (11):

$$\hat{\mathbf{Z}}^* = \Psi_{z\varepsilon}\hat{\theta} + \hat{\varepsilon}^*. \tag{11}$$

A new bootstrapped parameter estimate $\hat{\theta}^*$ is obtained from this bootstrapped data Z^*. This procedure is repeated *B* times to provide a set of parameter estimates from the *B* bootstrap replications, as shown in eq. (12):

$$\hat{\Theta}^* = \left[\hat{\theta}_1^*, \ldots, \hat{\theta}_B^*\right]. \tag{12}$$

Parameter statistics can then be easily computed from $\hat{\Theta}^*$ by forming percentile intervals at a chosen level of significance, α .

Structure detection can provide useful process insights that can be used in subsequent development or refinement of physical models. Therefore, in the sequel, we investigate the applicability of MDL and the bootstrap to experimental aircraft data. Specifically, MDL and bootstrap methods are used as structure detection tools to assess whether the (1) underlying data

is best described by a linear time-invariant (LTI) or nonlinear model and (2) model structure is invariant during envelope expansion.

EXPERIMENTAL F-15B QUIET SPIKE™ DATA

The MDL and bootstrap technique were applied to experimental flight-test data from the F-15B Quiet Spike™ project by Gulfstream Aerospace Corporation and the NASA Dryden Flight Research Center (refs. 9–11). The data analysed for this study used structural accelerometer response output of the Quiet Spike™ boom tip when fully extended.

Procedures

Flight data was gathered during subsonic, transonic and supersonic flutter clearance of the F-15B Quiet Spike™ (fig. 1). This report considers accelerometer data measured during pilot induced pitch-raps at Mach 0.85, 0.95 and 1.40 at an altitude of 12,192 m (40,000 ft). The output was taken as the response of an accelerometer mounted near the Quiet Spike™ boom tip (fig. 2). Data was sampled at 400 Hz. For analysis, the recorded flight-test data was decimated by a factor of 2, resulting in a final sampling rate of 200 Hz.

ED06-0184-33

Figure 1. Flight test article in extended configuration.

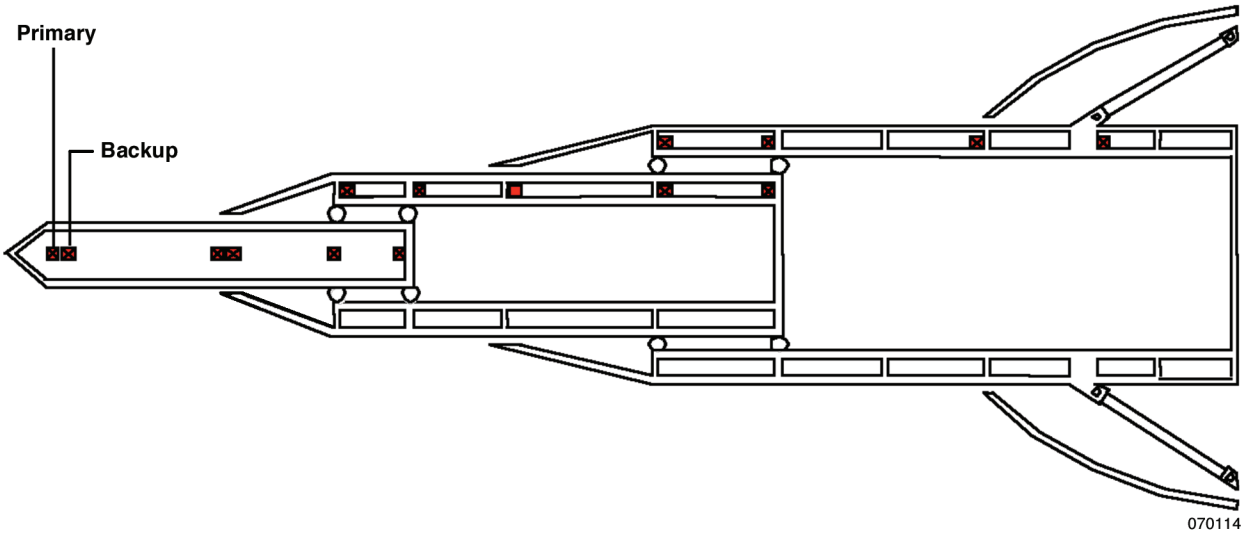


Figure 2. Quiet Spike™ sensor location.

For identification of a linear model an arbitrarily large AR model of fiftieth order ($n_z = 50$) was posed for estimation and the MDL technique used to determine the optimal linear model. For identification of a nonlinear model a model order with fourth-order output and error dynamics and second-order nonlinearity, $O = [4, 4, 2]$, was used. A model with fourth-order dynamics was selected because it has been observed that aeroservoelastic structures are well defined by a fourth-order LTI system (ref. 20). The nonlinearity order was chosen as second-order because empirical results showed models of higher nonlinear order were not efficient to describe the data sets available for analysis. This gave a full model description with 45 candidate terms. The nonlinear model was identified applying the bootstrap approach. For the bootstrap method, $B = 100$ bootstrap replications were generated to assess the distribution of each parameter. For all three techniques, each parameter was tested for significance at the 95 percent confidence level.

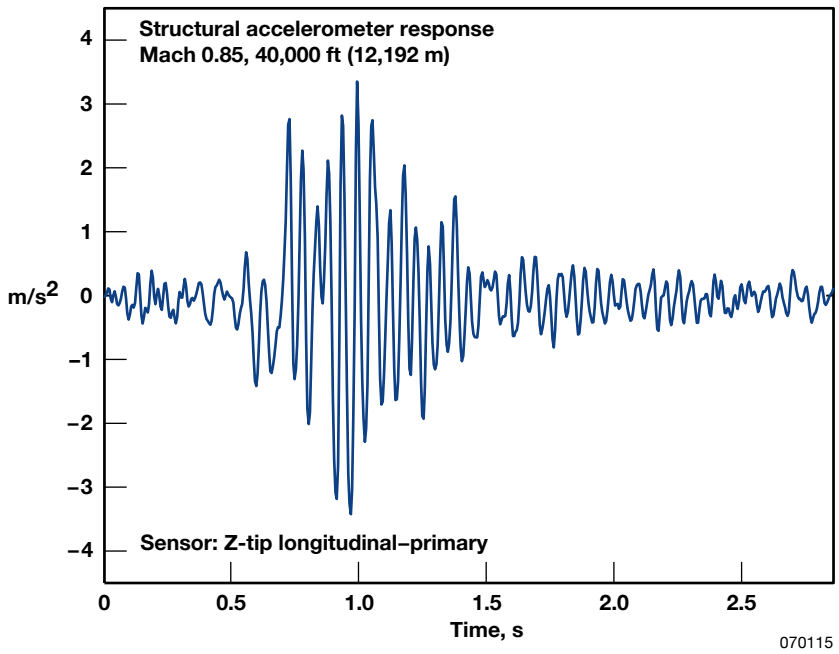
For both linear and nonlinear identification, table 1 shows the number of data points available for each flight condition. The estimation data sets were from accelerometer response measurements of the primary sensor on the boom tip and the cross-validation data sets were of the backup sensor at the same location.

Table 1. Data points available at each flight condition.

Altitude 12,192 m (40,000 ft)			
Mach number	0.85	0.95	1.40
Estimation data	572	400	504
Validation data	572	400	504

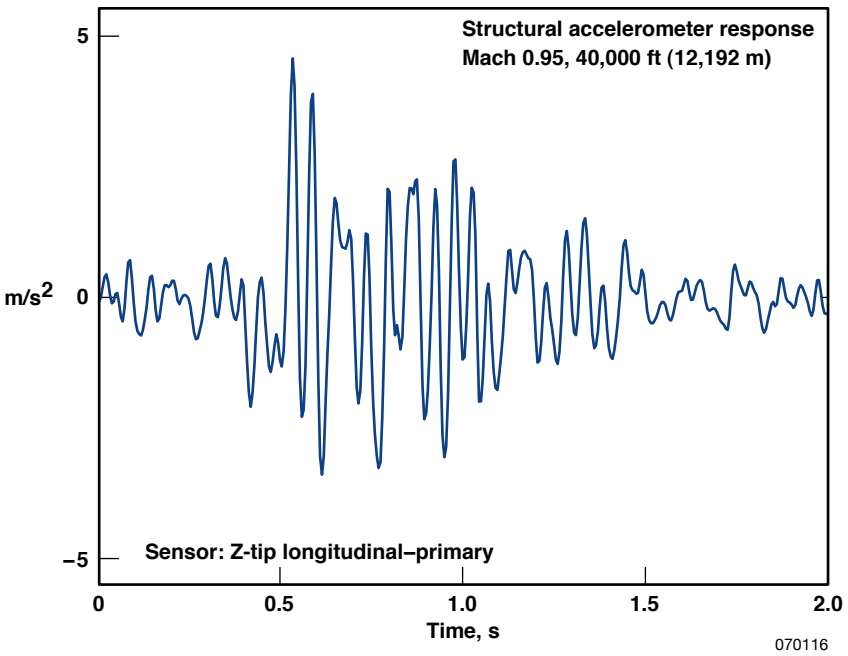
Results

The results of identifying the F-15B Quiet Spike™ data are presented. Figures 3(a)–3(c) show the output data sets used for this analysis. The data represents structural accelerometer response (primary sensor boom tip) used to compute the system structure.

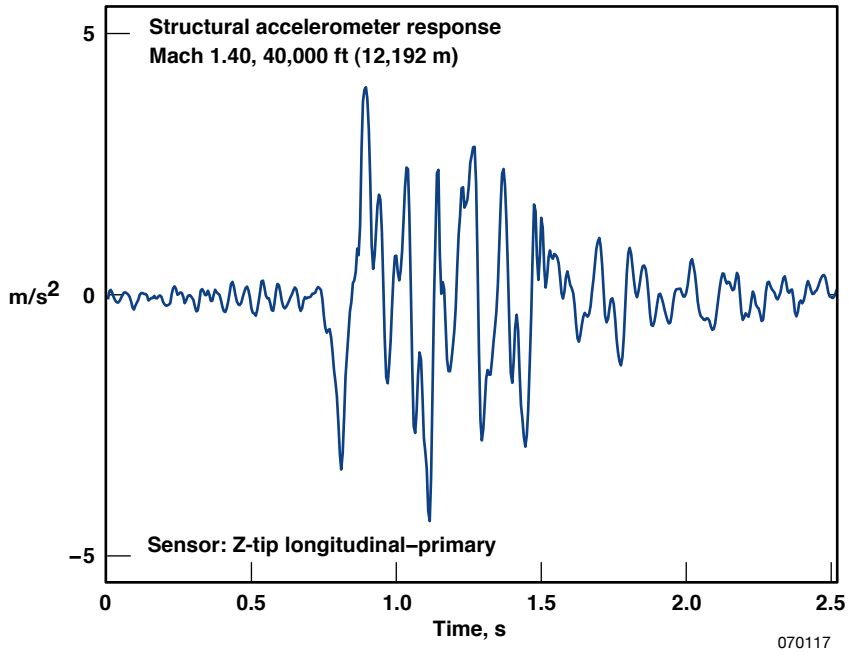


(a) Mach 0.85.

Figure 3. Estimation data: recorded structural accelerometer response to stick-raps.



(b) Mach 0.95.



(c) Mach 1.40.

Figure 3. Concluded.

Equations (13)–(15) depict the model structure computed by the bootstrap method.

Mach 0.85, altitude 40,000 ft (12,192 m)

$$\begin{aligned} z(n) = {} & \hat{\theta}_1 z(n-1) + \hat{\theta}_2 z(n-2) + \hat{\theta}_3 z(n-3) + \hat{\theta}_4 z^2(n-4) + \hat{\theta}_5 \varepsilon(n-1) \\ & + \hat{\theta}_6 \varepsilon(n-2) + \hat{\theta}_7 \varepsilon(n-3) + \hat{\theta}_8 z(n-4)\varepsilon(n-4) + \hat{\theta}_9 \varepsilon^2(n-4) + \varepsilon(n) \end{aligned} \tag{13}$$

Mach 0.95, altitude 40,000 ft (12,192 m)

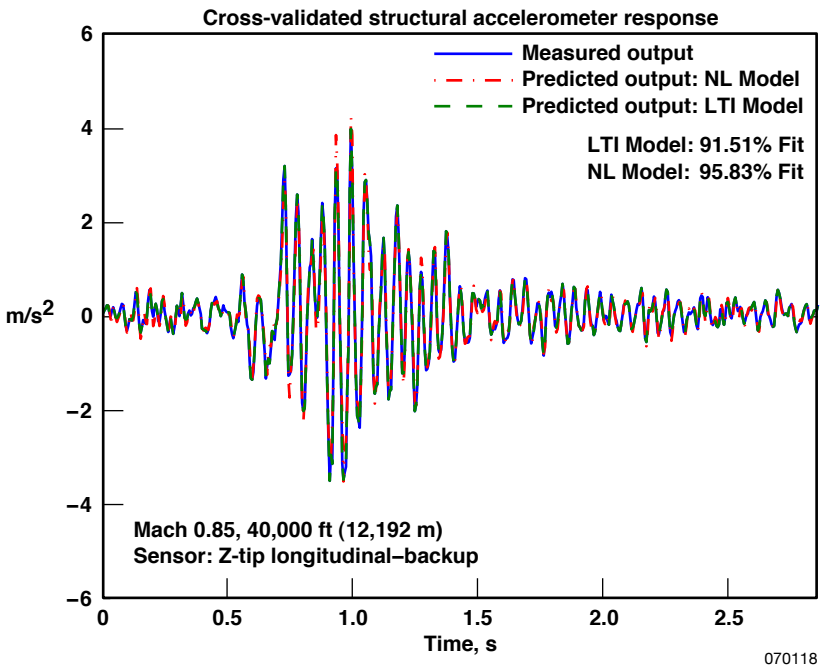
$$\begin{aligned} z(n) = {} & \hat{\gamma}_1 z(n-1) + \hat{\gamma}_2 z(n-2) + \hat{\gamma}_3 z(n-3) + \hat{\gamma}_4 z(n-3) z(n-4) \\ & + \hat{\gamma}_5 z^2(n-4) + \hat{\gamma}_6 \varepsilon(n-1) + \hat{\gamma}_7 \varepsilon(n-2) + \hat{\gamma}_8 \varepsilon(n-3) \\ & + \hat{\gamma}_9 z(n-3)\varepsilon(n-4) + \hat{\gamma}_{10} z(n-4)\varepsilon(n-3) + \hat{\gamma}_{11} \varepsilon(n-3)\varepsilon(n-4) \\ & + \hat{\gamma}_{12} z(n-4)\varepsilon(n-4) + \hat{\gamma}_{13} \varepsilon^2(n-4) + \varepsilon(n) \end{aligned} \tag{14}$$

Mach 1.40, altitude 40,000 ft (12,192 m)

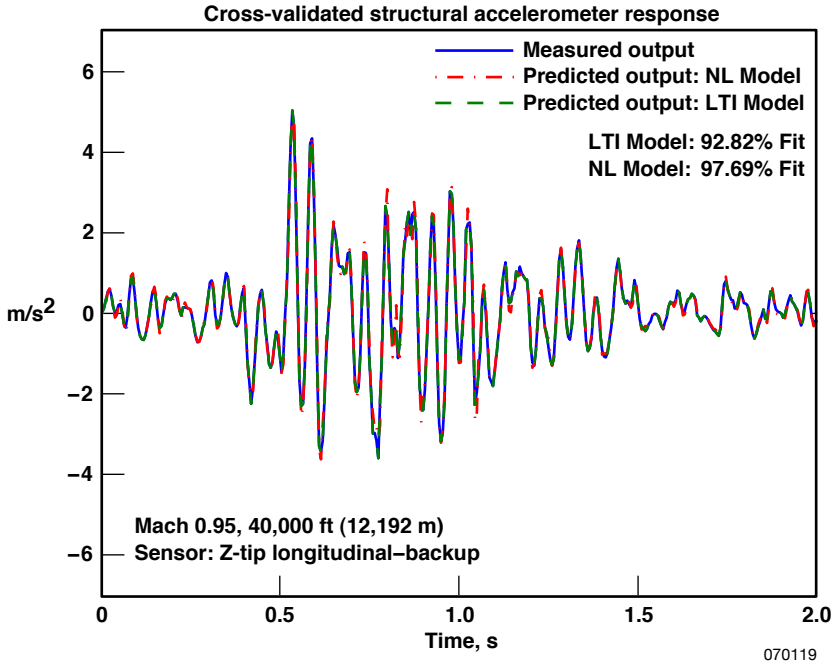
$$\begin{aligned} z(n) = {} & \hat{\beta}_1 z(n-1) + \hat{\beta}_2 z(n-2) + \hat{\beta}_3 z(n-3) + \hat{\beta}_4 z(n-1) z(n-4) \\ & + \hat{\beta}_5 \varepsilon(n-1) + \hat{\beta}_6 \varepsilon(n-2) + \hat{\beta}_7 \varepsilon(n-3) + \hat{\beta}_8 z(n-1)\varepsilon(n-4) \\ & + \hat{\beta}_9 z(n-4)\varepsilon(n-1) + \hat{\beta}_{10} \varepsilon(n-1)\varepsilon(n-4) + \varepsilon(n). \end{aligned} \tag{15}$$

Equations 13 through 15 represent the computed model structure for flight conditions Mach 0.85, 0.95 and 1.40, respectively. The computed model structures are represented by a combination of linear and nonlinear, lagged input-output terms and contain 9, 13 and 10 terms for Mach 0.85, 0.95 and 1.40, respectively. Hence, the bootstrap technique successfully produced a parsimonious model description from the full set of 45 candidate terms.

For AR (linear) model identification using MDL to compute structure, the estimated models were of order $n_z = 42$, 44, and 46 for Mach 0.85, 0.95 and 1.40, respectively. These models are not shown since they are simply a dynamic expansion of the output up to the order stated. However, for cross-validation data, we show the model fit of these linear models compared to the cross-validation fit obtained with the NARMA models [see figs. 4(a)–4(c)].

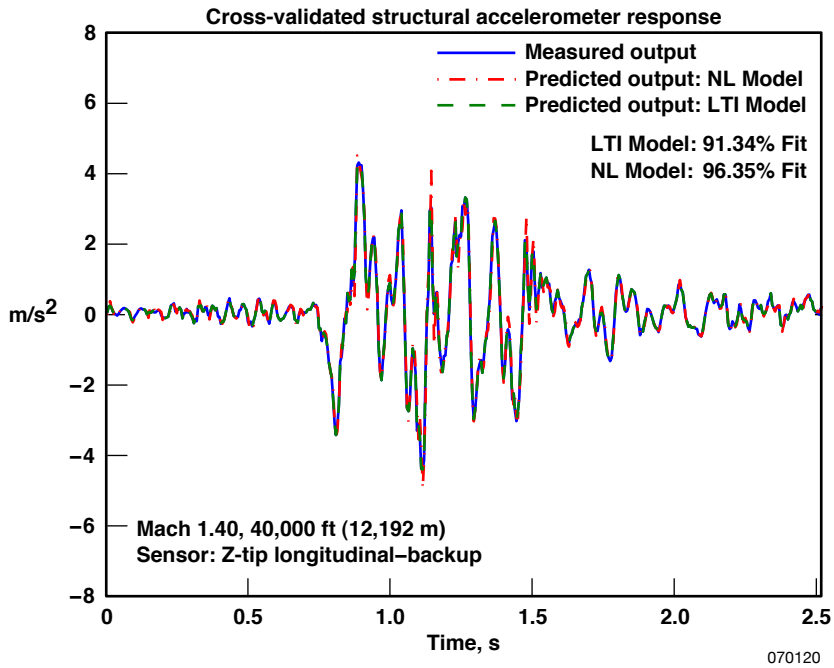


(a) Mach 0.85.



(b) Mach 0.95.

Figure 4. Cross-validation data: predicted linear and nonlinear model accelerometer response of z-tip longitudinal sensor superimposed on measured accelerometer output.



(c) Mach 1.40.

Figure 4. Concluded.

Figures 4(a)–4(c) show the predicted output for the cross-validation data sets for the identified structures [(a): eq. (13) and AR(n_z = 42); (b): eq. (14) and AR(n_z = 44); and (c): eq. (15) and AR(n_z = 46)]. Each panel displays the full time history of the predicted output of the linear and nonlinear models superimposed on top of the measured output. For Mach 0.85 [fig. 4(a)] the predicted output of the linear and nonlinear models account for over 91 percent and 95 percent of the measured outputs variance, respectively. For Mach 0.95 [fig. 4(b)] the predicted output of the linear and nonlinear models account for over 92 percent and 97 percent of the measured outputs variance, respectively. For Mach 1.40 [fig. 4(c)] the predicted output of the linear and nonlinear models account for over 91 percent and 96 percent of the measured outputs variance, respectively.

The results demonstrate that although the AR models contain many more terms to explain the underlying process they still offer a lower percent fit compared to the nonlinear model at the cost of model complexity (higher order) which often leads to more complex control synthesis. The nonlinear models contain only a few terms and were capable of explaining a larger percent of the output variance. For these data sets the results show linear models are inefficient for accurate modelling of aeroservoelastic data. These results show a nonlinear identification approach offers a parsimonious system description whilst providing a high percent fit for cross-validated data. Moreover, the results illustrate the need to vary model structure for different flight conditions.

DISCUSSION

Experimental results demonstrate that structure computation as a tool for black-box modeling may be useful for the analysis of dynamic aircraft data. The bootstrap successfully reduced the number of regressors posed to aircraft aeroelastic data yielding a parsimonious model structure for each data set. Additionally, these parsimonious structures were capable of predicting a large portion of the cross-validation data, collected on a backup sensor at a similar location. However, for linear analysis, the MDL approach was not able to reduce the model order (structure) as well and yielded a more complex system description. Whilst these linear models have higher complexity (degrees of freedom), they provided a model predictive capability that explained a smaller percent of the observed output variance. This find indicates a linear model may not be appropriate to describe aeroservoelastic data. A higher percent fit offered by the parsimonious nonlinear models suggests that the identified structures and parameters explain the data well. Using percent fit alone as an indicator of model goodness could lead to incorrect interpretations of model validity. Nevertheless, in many cases for nonlinear models this may be the only indicator that is readily available.

In this work, the results show that whilst the linear dynamics remained invariant for all flight conditions available for analysis, the nonlinear dynamics changed as Mach number increased. For Mach 0.85 the model [eq. (13)] displayed a mildly nonlinear process which physically makes sense since the airflow is mainly subsonic. When the Mach number was increased to 0.95 the model [eq. (14)] demonstrated a richer nonlinear dynamic description which is likely due to embedded shock formations in the transonic regime. For Mach 1.40 the model [eq. (15)] displayed a mildly nonlinear process again which physically makes sense since in this regime the shocks become fixed. It is difficult to make definitive comments on the underlying physics responsible for this behaviour without extensive analysis of different flight conditions. The important points to note are, this study suggests (1) nonlinear models are appropriate to describe the dynamics behaviour of advanced aircraft and (2) models describing aircraft dynamics vary with flight condition. This suggests nonlinear modelling may afford a robust and parsimonious system description over a larger operating regime and models used for prediction (e.g. control) should not be invariant for all flight conditions. This may hold significant implications for aircraft development.

For this study, only a polynomial mapping with fourth-order output and error lag was used as a basis function to explain the nonlinear behaviour of the F-15B Quiet Spike™ data. Clearly, different basis functions and a higher dynamic order (lag-order) should be investigated to determine if another basis can produce accurate model predictions with reduced complexity. Moreover, further studies are necessary to evaluate whether the model structure is invariant under different operating conditions, such as altitude, and model parameterisations.

This study illustrates the usefulness of structure detection as an approach to compute a parsimonious model of a highly complex nonlinear process, as demonstrated with experimental data of aircraft aeroelastic dynamics. Moreover, analysis of flight-test data can provide useful process insights that can be used in subsequent development or refinement of physical models.

In particular, morphological models are based on assumptions (e.g. these effects are important and those are negligible) which may be incorrect (refs. 21 and 22). A structure computation approach to model identification may help uncover such surprises.

CONCLUSIONS

Results show that linear models are inefficient for modelling aeroservoelastic data and nonlinear identification provides a parsimonious model description whilst providing a high percent fit for cross-validated data. Moreover, the results demonstrate that model structure and parameters vary as the flight condition varies. These results may have practical significance in the analysis of aircraft dynamics during envelope expansion and could lead to more efficient control strategies. In addition, this technique could allow greater insight into the functionality of various systems dynamics, by providing a quantitative model which is easily interpretable.

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14. ABSTRACT

System identification is utilised in the aerospace community for development of simulation models for robust control law design. These models are often described as linear, time-invariant processes and assumed to be uniform throughout the flight envelope. Nevertheless, it is well known that the underlying process is inherently nonlinear. Over the past several decades the controls and biomedical communities have made great advances in developing tools for the identification of nonlinear systems. In this report, we show the application of one such nonlinear system identification technique, structure detection, for the analysis of Quiet Spike™ (Gulfstream Aerospace Corporation, Savannah, Georgia) aeroservoelastic flight-test data. Structure detection is concerned with the selection of a subset of candidate terms that best describe the observed output. Structure computation as a tool for black-box modeling may be of critical importance for the development of robust, parsimonious models for the flight-test community. The objectives of this study are to demonstrate via analysis of Quiet Spike™ aeroservoelastic flight-test data for several flight conditions that: linear models are inefficient for modelling aeroservoelastic data, nonlinear identification provides a parsimonious model description whilst providing a high percent fit for cross-validated data and the model structure and parameters vary as the flight condition is altered.

15. SUBJECT TERMS
Aeroservoelasticity, Linear system identification, Nonlinear system identification, Quiet Spike™, Structure detection

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