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Evolution of Flight Vehicle System Identification

Peter G. Hamel and Ravindra V. Jategaonkar
DLR, German Aerospace Research Establishment, 38022 Brunswick, Germany

Introduction

SYSTEM identification, as it is termed today, is a scientific discipline that provides answers to the age-old inverse problem of obtaining a description in some suitable form for a system, given its behavior as a set of observations. The inverse problem and, hence, system identification has been fundamental to the evolution of the human being, who is characterized by his inquisitive nature, not only to know more about the principle underlying (i.e., model formulation of) the process he is observing, but also in adequate details (i.e., analysis and parameter estimation).

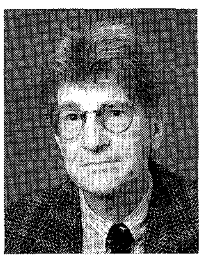
In a very broad sense, several of the physical laws are the outcome of system identification methodology. For example, the inference of the acceleration due to gravity by Newton was an outcome of his exploring an answer to the observation he had made, namely that of a free-falling apple. Although this example may appear less justifying, the roots of modern system identification can definitely be traced back to the 18th century. In the year 1795, Gauss[1] invented the least-squares method to compute the orbit of a planet from astronomical observations. Gauss applied Bayes rule and the method of maximum likelihood, as it is called today, to derive the least-squares principle.

Although Gauss used the maximum likelihood principle, the earliest reference to this principle is found in a paper "The most probable choice between several discrepant observations and the formation therefrom of the most likely induction," by Bernoulli[2] in the year 1777. The terms likelihood function and maximum likelihood were not explicitly introduced; also no rigorous proof, a hallmark of today's approach, was provided, but clearly these concepts, together with the solution obtained by differentiating the likelihood function, were introduced; providing the foundation for the evolution of system identification methodology.

Even though the ideas of likelihood function were introduced by Bernoulli and Gauss during the 18th century, the method of maximum likelihood was first introduced as a general statistical parameter estimation method by Fisher[3] in the year 1912. Until the early forties, much of the work on parameter estimation was deterministic in nature. With the work of Wiener[4] in 1942 and that of Kolmogorov[5] in 1941, however, the focus essentially changed from deterministic to stochastic estimation. Following the pioneering work of Wiener, it was in the year 1960 that Kalman[6] provided a recursive solution to a filtering problem. The recursive solution being directly amenable to digital computations, the Kalman filter quickly became popular and is today the most widely used approach to stochastic estimation.

It was in the year 1965 that Åström and Bohlin[7] first implemented the maximum likelihood method on a digital computer and applied it to estimate parameters of an industrial plant based on the difference equation representation. This marked the beginning of the modern era of system identification methodology for which Zadeh had already provided a classical definition in 1962[8]: "Identification is the determination, on the basis of observation of input and output, of a system within a specified class of systems to which the system under test is equivalent."

Today, the fascinating field of system identification covers applications in the areas of biology, chemical processes, economics, geology, materials, mechanical systems, and flight ve-



Peter G. Hamel has been the Director of the Institute of Flight Mechanics of the German Aerospace Research Establishment (DLR) since 1971. He received his Dipl.-Ing. and Dr.-Ing. degrees in Aerospace Engineering from the Technical University of Braunschweig in 1963 and 1968, and his SM degree from M.I.T. in 1965. During 1970–71 he was Section Head of Aeronautical Systems at Messerschmitt-Bölkow-Blohm in Hamburg. He is also the Manager for the DLR's Rotorcraft Technology Research Program and the German Coordinator for the AGARD Flight Vehicle Integration (FVP) Panel. He is the recipient of the AGARD 1993 Scientific Achievement Award and since 1995 an Honorary Professor at the Technical University of Braunschweig. He is an Associate Fellow of AIAA, a Member of AHS, and of the DGLR Senate.

Ravindra Jategaonkar is a Senior Scientist at the German Aerospace Research Establishment (DLR), Institute of Flight Mechanics in Braunschweig, Germany. He received his Bachelor's and Master's degrees in Engineering from the Calicut University, India in 1972 and 1975, and his Ph.D. degree from the Indian Institute of Science in Bangalore, India in 1986. He has been extensively involved in the applications of system identification methods to flight vehicle modeling. Before joining the DLR in 1986, Dr. Jategaonkar was a Scientist at the National Aerospace Laboratories, Bangalore, India. He is a Member of AIAA.

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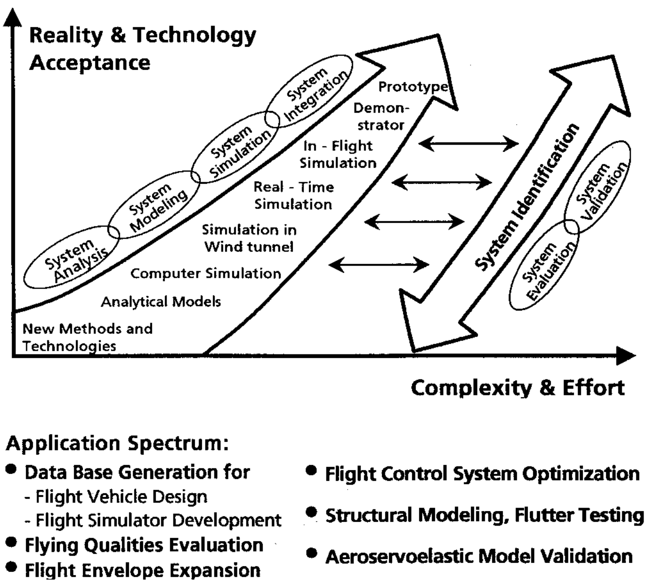

Fig. 1 Key role of system identification.

hicles, etc. A cursory glance at the published literature makes it evident that the aircraft parameter estimation is the most outstanding and illustrated example of system identification methodology.

The highly successful application of system identification to flight vehicle is possible partly because of the advances in measurement techniques and data processing capabilities provided by digital computers, partly due to the ingenuity of the engineers in advantageously using the developments in other fields like estimation and control theory, and partly due to the fairly well-understood basic physical principles underlying flight vehicles enabling adequate modeling and the possibility of carrying out the proper flight tests.[9–11] Today, these tools have reached such a level of maturity that they are an integral part of any aircraft development and assessment program (Fig. 1).

Parameter Estimation in Flight Mechanics

Flight mechanics is the branch of engineering that deals with motion of a flight vehicle. The central issue in flight mechanics is to predict and evaluate the performance and dynamical characteristics of a flight vehicle, whether it is a conventional transport aircraft, a highly augmented unstable aircraft flying at high angles of attack, a rotorcraft or a missile. Representation of motion of a flight vehicle, which is in general free to move in any direction, involves coupled equations of motion. The basic equations of motion are derived from the Newtonian mechanics, usually considering the flight vehicle as a rigid body. These equations, defining the characteristic motion, involve the fundamental assumption that the forces and moments acting on the flight vehicle can be synthesized. Validity and utility of the mathematical models depend to a large degree on the adequacy and accuracy with which these external forces and moments acting on the flight vehicle can be modeled.

The various forces and moments acting on a flight vehicle can be broadly classified as 1) aerodynamic, 2) inertial, 3) gravitational, and 4) propulsive forces. Determination of aerodynamic forces, a problem already recognized in the early 20th century, even today constitutes the most difficult problem in flight mechanics, in spite of the significant advances made in the field of modeling. The present challenge to flight vehicle system identification is the determination of an aerodynamic model of a high-performance, highly augmented vehicle from rapid, large-amplitude maneuvers. Such a model is, in general, of unknown structure, highly nonlinear and affected by elastic modes, unsteady aerodynamics, and erroneous air data measurements.

The aerodynamic modeling, which provides a means to obtain relationships between the three forces X, Y, and Z along the three Cartesian coordinates and the moments L, M, and N about these axes as functions of linear translational motion variables u, v, and w and rotational rates p, q, and r, was introduced by Bryan[12] in the early 20th century. This marks the beginning of the evolution of flight vehicle system identification. The developments over the last nine decades have led to three different, but complementary, techniques of determining aerodynamic coefficients: 1) analytical methods, 2) wind-tunnel methods, and 3) flight test methods.

The first two techniques are employed to generate basic information about the flight mechanical parameters. The analytical estimations, however, have doubtful validity and also have the disadvantage of being based on inadequate theory. Nevertheless, computational fluid dynamics has in recent years positively influenced the analytical scenario by providing numerical solutions of complete configurations via sophisticated and advanced Euler and Navier–Stokes flow solvers.[13,14] Experimental methods are essential to corroborate the analytical predictions. Wind-tunnel techniques, which are relatively inexpensive, have in the past provided a huge amount of data on innumerable flight vehicle configurations and are, as a rule, a basis for any new flight vehicle design. These techniques are, however, often associated with certain limitations of validity arising out of, for example, model scaling, Reynold's number, dynamic derivatives, cross coupling, and aeroservoelasticity effects. Moreover, these measurements could also be affected by tunnel unsteadiness or model support vibrations and interferences. Determination of aerodynamic derivatives from flight measurements is, therefore, important and necessary to reduce limitations and uncertainties of the aforementioned two methods.[15] It is for this reason that this paper focuses on aircraft parameter estimation from flight data, although the other two techniques have contributed in ample measure to the objective of flight vehicle modeling.

Estimation Techniques of the Past

The importance of obtaining flight-derived aircraft parameters was recognized early. A few years after the introduction of the classical stability approach by Bryan, Glauert's[16] work in 1919 on the analysis of phugoid motion and that of Norton[17,18] during 1919–1923 on estimating a number of derivatives such as L_p, Y_v, L_v, N_v, and M_w, marks the beginning of the experimental investigation of dynamic stability in actual flight. The interest in the dynamic behavior of aircraft grew steadily over the period. During the late forties and early fifties several techniques were introduced, such as steady-state oscillatory excitations by Milliken,[19,20] pulse-input methods incorporating Fourier analysis by Seamans et al.,[21] and weighted least-squares by Shinbrot.[22] Although Shinbrot had introduced the response curve-fitting method in the early fifties,[23] which is equivalent to the today's output error method, it was found to be impracticable due to the lack of adequate (digital) computational means. The time–vector method, which also became popular during this period of time,[24–28] was first applied to analyze the aircraft dynamic stability problem by Doetsch[27] through his familiarity with electrical engineering. The analog-matching techniques were also applied towards the end of this era.[29,30] An excellent account of dynamic stability and control research during this early period is found in Ref. 20 and a survey of methods for determining stability and control derivatives from dynamic flight measurements is found in Ref. 31. The techniques of the forties to early sixties were frequency response methods and were either limited to estimation of incomplete sets of coefficients, to simple motions, or restricted because of other reasons.[32]

The aforementioned sketch of the historical background is by no means exhaustive. Nevertheless, in view of the authors, they represent the important milestones in the history of aircraft parameter estimation prior to the advent of digital computers. Nostalgically, a brief account of some of these early methods, which have practically become techniques of the past, is provided here. Brief discussions of these methods in comparison with the modern methods of system identification may also be found in Refs. 33 and 34.

First Dynamic Flight Test

During the investigation of dynamic stability in flight,[17,18] which had started during 1919–1923, flight tests were carried out applying specific control inputs, either generated by the pilot or by some additional device mounted on the aircraft. For example, Norton used a step function generated by dropping sand boxes from the wingtips. In yet another application, applied known moments were generated by parachutes at the wingtips. It is interesting to point out that the ideas behind applying specific inputs to excite the characteristic aircraft motion for parameter estimation were well appreciated even in those early days. As will be discussed later, the aspect of optimal control inputs is one of four important aspects for successful application of modern system identification techniques. The test aircraft JN4 (Fig. 2) on which this pioneering work on dynamic flight testing was carried out at NACA is of equal historical importance as the estimates of the damping-in-roll obtained from JN4h flight data.

Longitudinal Oscillation Method

This test technique was first used during the late forties to determine full-scale aerodynamic stability and control data from flight tests.[19,20] The test procedure consisted of stabilizing the aircraft at a given flight condition and establishing steady-state pitching oscillations of small amplitude at a chosen frequency by applying continuous sinusoidal input to the elevator. The procedure was repeated for several frequencies at the same flight condition and also at other flight conditions.

The recorded data enabled one to check between the measured response and the conventional theory in terms of frequency response characteristics. Further analysis or fairing of the experimental response data with the so-called "circle diagram" led to determination of the effective damping and spring constants. However, more significantly, the analysis method also provided a means to obtain directly the aerodynamic derivatives, which could then be inserted into the classical equations.

Pulse Method of Dynamic Response Testing

As an alternative to the time-consuming and in some cases undesirable sinusoidal response testing, the transient response method was introduced during the early fifties.[21] The technique was based on the evaluation of performance function, which is the ratio of the Fourier transform of the aircraft response to that of the input. Approximation of a continuous function by a series of delayed triangular functions provided a convenient means to obtain the necessary information from the oscillograph records. Although an electromechanical Fourier synthesizer was developed at MIT, the method was well suited for paper and pencil computation.

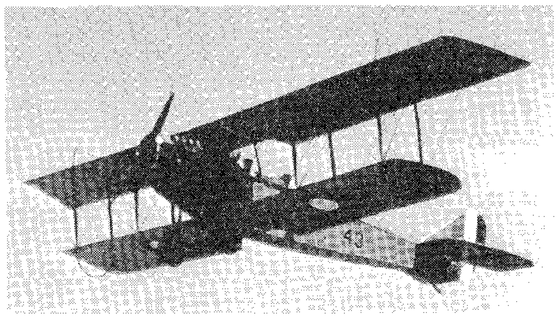

Fig. 2 Test aircraft JN4 (photograph courtesy NASA Ames Research Center).

Time–Vector Method

During the fifties and sixties, the time–vector method was one of the commonly applied graphical procedures of determining aerodynamic derivatives.[25–28] The test procedure consisted of stabilizing the aircraft at a given flight condition and initiating a free oscillation by an abrupt pulse. With the controls held fixed, the resulting free-oscillation was allowed to damp out. The time–vector decomposition, carried out separately for each moment or force equation, required substituting the amplitude and phase relationships, which were obtained from the locations of the peaks of the oscillatory motion.

The method provided an insight into the comparative contributions of the various terms to the particular mode. It was, however, associated with certain disadvantages: 1) the method allowed estimation of only two of the three derivatives in the lateral moment equation; 2) as is the case with any graphical procedure, the method was time consuming in generating a consistent set of results; and 3) it was difficult to apply it to a heavily damped aircraft.

Analog Matching

Prior to the advent of digital computers, in the early sixties analog matching was a popular technique of updating and validating wind-tunnel predictions of stability derivatives based on flight tests.[29,30] It provided a means of determining stability derivatives that was simple and straightforward, providing the operator an insight into vehicle response characteristics.

Briefly stated, the mathematical model, in several instances the decoupled equations of aircraft motion, was programmed on an analog computer, incorporating theoretical or wind-tunnel predictions of the stability derivatives as first approximations. The flight-recorded control inputs, duplicated through function generators incorporating diodes and amplifiers, etc., were fed into the simulation. Comparing qualitatively the simulated response with the actual aircraft response, the stability parameters were manually tuned to reduce the differences.

The analog matching technique, although appealing, had several shortcomings, namely 1) the success or failure depended on the ingenuity of the operator in adjusting the proper parameter, 2) it was time consuming, 3) it was restricted by the quality of the flight data, 4) it involved qualitative judgment of the operator, and 5) it was limited to a few primary derivatives.

Modern Methods of Aircraft Parameter Estimation

The automatic data processing capability provided by digital computers dramatically changed the focus of flight data analysis from frequency domain methods to time domain methods. It became possible to obtain a significantly larger number of stability and control derivatives from a single flight test. A coordinated approach based on the flight test techniques, flight test instrumentation, and methods of data analysis gradually evolved for flight vehicle system identification. Research activities at several organizations, like the NASA Ames–Dryden Flight Research Facility, NASA Langley Research Center, the U.S. Army Aeroflightdynamics Directorate at NASA Ames; DLR, the German Aerospace Research Establishment, Germany; DUT, the Delft University of Technology, NLR, the National Aerospace Laboratory, The Netherlands; DRA, the Defence Research Agency, England, United Kingdom; and NRC, the National Research Council, Canada, etc., have culminated into the present state of maturity.

The coordinated approach to flight vehicle system identification can be divided into three major parts[35]:

1) *Instrumentation and filters*, which cover the entire flight data acquisition process including adequate instrumentation and airborne or ground-based digital recording equipment. Effects of all kinds of data quality have to be accounted for.

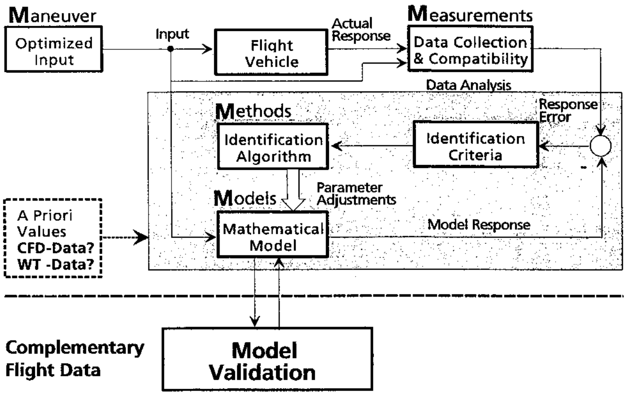

Fig. 3 Quad-M basics of flight vehicle system identification.

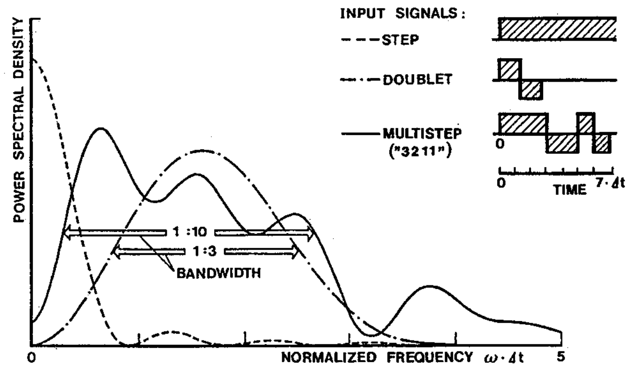

Fig. 4 Frequency domain comparison of input signals.

2) *Flight test techniques*, which are related to the selected flight vehicle maneuvering procedures. The input signals have to be optimized in their spectral composition to excite all response modes from which parameters are to be estimated.

3) *Analysis of flight data*, which includes the mathematical model of the flight vehicle and an estimation criterion that devises a suitable computational algorithm to adjust starting values or a priori estimates of the unknown parameters until a set of best parameter estimates is obtained that minimizes the response error.

Corresponding to these strongly interdependent topics, four important aspects of the art and science of system identification have to be carefully treated (Fig. 3): 1) design of the control input shape to excite all modes of the vehicle dynamic motion, 2) selection of instrumentation and filters for high accuracy measurements, 3) type of flight vehicle under investigation to define the structure of a possible mathematical model, and 4) the quality of data analysis by selecting the most suitable time or frequency domain identification method.

These "quad-M" requirements must be carefully investigated for each flight vehicle from a physical standpoint and are the key to the successful flight vehicle system identification. These requirements fall within the framework of the contemporarily and widely accepted definition provided by Zadeh.[8] A systematic treatment of these key issues has been provided by Maine and Iliff,[10] Klein,[11] Hamel,[9] and Mulder et al.[36] A survey of contributions to flight vehicle system identification up to 1980 has been provided by Iliff.[33]

Optimal Input Design

The accuracy and reliability of parameter estimates, obtained applying either the recent modern methods like the maximum likelihood or the methods of the past such as forcing function, depend heavily on the amount of information available in the vehicle response. This fact was recognized early during the evolution stages as evident from the Milliken's statement in 1951[20]: "It would appear that the optimum input in a given case is that which best excites the frequency range of interest, and hence the harmonic content of the input should be examined before the test to ensure that it is suitable." Throughout the history of flight vehicle system identification this has been, in essence, the guiding principle in designing a proper flight test maneuver for extracting aerodynamic parameters.

The early developments in the mid-forties and early fifties led to the design of input signals such as the continuous sinusoidal input, the step input, or the pulse input. These designs were mainly governed by the method of analysis applied to extract stability and control derivatives from flight data. In the general field of system identification, the theoretical developments on input design were started during the sixties.[37–39] Around the same time, optimal input design for flight vehicle system identification started with the work of Gerlach.[40,41] In the seventies there were significant contributions to the optimal input design.[42–46] Considering the aircraft as a linear multivariable system, the inputs were optimized with respect to the information or covariance of the parameters, the design carried out either in the time or the frequency domain. The work on optimal input signals for aircraft parameter estimation continued in the following decade as well.[47–50]

References 48 and 49 provide a thorough comparison of five input signals, namely 1) doublet, 2) multistep 3211, 3) Mehra, 4) Schulz, and 5) DUT signal. With regard to the accuracy of parameter estimates, it was conclusively established that the 3211, Mehra, and DUT signals were equally efficient. The more recent Langley input design also compares favorably with these inputs.[50] Figure 4 shows the 3211 input and its spectrum in comparison to the other two commonly applied input signals. The multistep input signal developed by Koehler at DLR is, however, easily realizable and relatively easy to fly manually by pilots. In addition, the frequency contents could be readily adapted to match the changing flight conditions.

Although sporadic developments on optimal input design have been reported since then [e.g., as recently as 1992 (Ref. 51)], the 3211 signal remains as the one most accepted worldwide and utilized by the international flight test community, mainly because of its two aforementioned advantages. An overview on optimal input and maneuver design is also provided by Mulder et al.[52]

The frequency sweep test techniques, although rarely used for fixed-wing aircraft, has found renaissance in the field of rotorcraft system identification during the recent past through the work of Tischler et al.[53] These techniques are useful and necessary, not only for the next generation specification requirements,[54] but are also an integral part of the interdisciplinary modeling aspects discussed later in this Paper. Critical flight incidences have, however, occurred while sweep testing due to, for example, exceeding the aeroservoelastic range or the flight permissible maximum loads.[55] Proper coordination is, hence, necessary through careful preparation, buildup, realtime monitoring, and analysis to prevent possible structural damage and to avoid any increase in the risk factor.

Flight Test Instrumentation

The accuracy of the parameter estimates is directly dependent on the quality of the flight measured data, and hence, high accuracy measurements of the control inputs and of the motion variables are a prerequisite for successful application of the modern methods of flight vehicle system identification. Classical information on flight test instrumentation for parameter identification is provided by Wolowicz[30] and also found in, for example, Ref. 56. Furthermore, the vertical/short takeoff and landing (V/STOL) flight test instrumentation requirements have been described by Hill et al.[57] During the seventies the various aspects of flight test instrumentation have been investigated in detail.[58] The pioneering work carried out at DUT and NLR has resulted into a sophisticated level of flight instrumentation. The measurements are further refined through a data preprocessing, generating at the same time any unmeasured flow variables. Based on the high-quality data, the subsequent aerodynamic modeling carried out in those institutions is mostly based on the regression analysis, which is the simplest of various parameter estimation methods discussed next. Although, more recently, flight instrumentation systems based on commercially available sensors and standard signal processors have been developed, the flight instrumentation is still a laborious and time-consuming job. In addition, particularly when full-fledged data gathering for the purpose of high-fidelity flight simulators is desired, more often than not, flight certification of the installed hardware by the proper authorities is necessary.

Methods of Data Analysis

The various parameter estimation methods can be broadly classified into three categories: 1) equation error, 2) output error, and 3) filter error methods. Choice of a particular method is generally dictated by the model formulation and assumptions made regarding the measurement and process noise, both of which are unavoidable in practical cases. The previous three methods belong to a class called the direct approach. The other approach to aircraft parameter estimation is called the indirect approach in which a nonlinear filter provides estimates of the unknown parameters that are artificially defined as additional state variables. The equation error methods represent a linear estimation problem, whereas the remaining methods belong to a class of nonlinear estimation problems. The equation error and the output error methods are deterministic methods, whereas the other two are statistical. More recently the neural network approach to aircraft parameter estimation has also been investigated.

Equation Error Method

Synthesis of aerodynamic forces and moments acting on a flight vehicle through Taylor series expansion invariably leads to a model that is linear in parameters. To this class of problems, the classical regression techniques can be conveniently applied.[11,36,59] Application of the regression technique requires measurements of the dependent variables, for flight vehicles these are the aerodynamic forces and moments. Though these variables are not directly measurable, they can be computed with relative ease from measurements of linear and angular accelerations.

At any instant of the time t_k, the dependent variables, in this case the aerodynamic forces and moments $y(t)$ can be expressed in terms of the independent variables $x(t)$, for example, the angular rates and flow variables, etc., as

$$y_i(k) = \theta_{i1}x_1(k) + \cdots + \theta_{ir}X_r(k) + e_i(k) \tag{1}$$

where e_i denotes the stochastic equation-error, and hence, the synonymously used name equation error method. From N discrete measurements of the dependent and independent variables, for $N > r$ the unknown parameters can be estimated applying the least-squares method

$$\hat{\theta} = (X^TX)^{-1}X^TY \tag{2}$$

where θ is the r dimensional vector of parameters, Y is the N dimensional vector of measured values of y_i, and X is the Nxr matrix of independent variables. Considering one dependent variable at a time, the parameters of the three aerodynamic forces and three aerodynamic moments acting on the aircraft are estimated separately.

The main advantage of the regression technique is its simplicity. For a given model structure, the least-squares estimates are obtained with minimal computation in one shot. One of the regression techniques is the stepwise regression. This method, including statistical evaluation of the residuals, is particularly helpful in efficiently arriving at an unknown aerodynamic model structure through successive augmentation of the postulated model.[60] Several aspects of model structure determination have been discussed by Refs. 60–62. Furthermore, since the method does not rely on the temporal relation between the data points, several separate maneuvers can easily be concatenated to estimate a single set of derivatives common to all of the time segments.[63] Based on this property, the data partitioning approach can be applied to analyze large amplitude maneuvers by dividing the maneuver into several smaller portions to which a simplified model can be fitted.[11,64,65]

The main disadvantage of the regression method, however, is that due to the presence of measurement errors in the independent variables, the least-squares estimates are asymptotically biased, inconsistent, and inefficient.[59] Nevertheless this method has found several applications to aircraft parameter estimation, providing acceptable results compared to the more complex methods. It is mainly because of two reasons. First, the high-quality sensors and instrumentation system minimize these errors. Secondly, prior to applying the regression method, more reliable signals can be generated through a data preprocessing step. The well-defined kinematic equations of aircraft motion provide a sound basis for this step, which is often called the flight-path reconstruction or aircraft state estimation.[66–68] The separation of the state estimation and aerodynamic modeling is called in literature as the two-step method[52] or estimation before modeling (EBM).[69,70]

Output Error Method

The output error method is a nonlinear optimization method that has been most widely used for aircraft parameter estimation ever since its introduction around the seventies. The modified Newton–Raphson method introduced by Taylor and Iliff[71] is equivalent to the quasilinearization method applied by Larson and Fleck.[72] Figure 5 provides a schematic of the output error method that accounts for measurement noise only.

The equations of aircraft motion are formulated in state space as

$$\dot{\boldsymbol{x}}(t) = A(\beta)\boldsymbol{x}(t) + B(\beta)\boldsymbol{u}(t) + \boldsymbol{b}_x \tag{3a}$$

$$\boldsymbol{y}(t) = C(\beta)\boldsymbol{x}(t) + D(\beta)\boldsymbol{u}(t) + \boldsymbol{b}_y \tag{3b}$$

$$\boldsymbol{z}(k) = \boldsymbol{y}(k) + \boldsymbol{\nu}(k) \tag{3c}$$

where $\boldsymbol{x}$ is the state vector, $\boldsymbol{y}$ the observation vector, and $\boldsymbol{u}$ the control input vector. The matrices A, B, C, and D contain the unknown parameters β representing the stability and control parameters, and $\boldsymbol{b}_x$ and $\boldsymbol{b}_y$ are the bias terms accounting for the

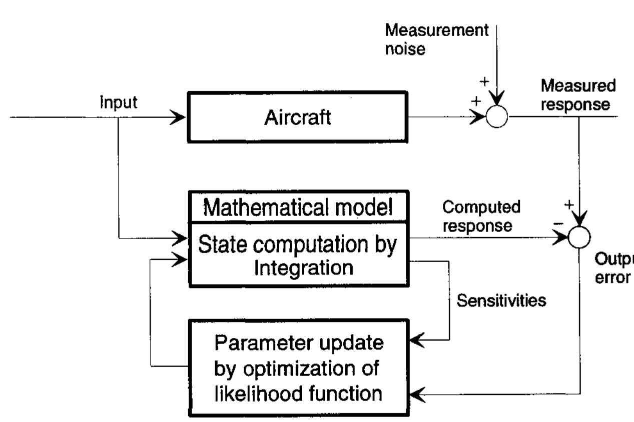

Fig. 5 Schematic of output error method.

nonzero initial conditions and possible systematic errors in the measurements of output and control variables.[73–75]

The estimates of parameter vector $\Theta^T = [\beta^T, b_x^T, b_y^T]$ are obtained by minimizing the cost function[73]:

$$J = \frac{1}{2}\sum_{k=1}^{N} [z(k) - y(k)]^T R^{-1}[z(k) - y(k)] + \frac{N}{2}\ell n|R| \quad (4)$$

where R is the measurement noise covariance matrix. Equation (4) is the negative logarithm of the likelihood function (probability density of the measurement vector), which, for a given R, reduces to the output error cost function. Starting from suitably specified initial values of the parameter vector the new updated estimates are obtained applying the Gauss–Newton method[73]:

$$\Theta_{i+1} = \Theta_i + \Delta\Theta \quad (5a)$$

$$\Delta\Theta = \left\{\sum_k \left[\frac{\partial y}{\partial \Theta}(k)\right]^T R^{-1} \frac{\partial y}{\partial \Theta}(k)\right\}^{-1} \times \left\{\sum_k \left[\frac{\partial y}{\partial \Theta}(k)\right]^T R^{-1}[z(k) - y(k)]\right\} \quad (5b)$$

where the subscript i indicates the ith iteration. The first term in braces on the right-hand side of Eq. (5b) is an approximation of the second gradient $\partial^2 J/\partial\Theta^2$ suggested by Balakrishnan.[76] This approximation helps to reduce the computational costs without significantly affecting the convergence.[77]

The maximum likelihood estimation being asymptotically bias free and efficient, the Fisher information matrix, which is the first term on the right side of Eq. (5), provides a good approximation to the parameter error covariance matrix P. The diagonal elements of P, which are the variances of the estimates, are indicators of the accuracies of the estimates and are called the Cramer–Rao bounds. In addition, the correlation coefficients, which are a measure of statistical dependence between the parameters, can also be obtained from the off-diagonal elements of P.[11,73]

Implementation of the output error method requires computation of the state variables x, of the response variables y and of the response gradients $\partial y/\partial\Theta$ based on the postulated model of Eq. (3). The computational aspects of the maximum likelihood function and of the sensitivities are discussed by Gupta and Mehra[78] and by Maine and Iliff.[73] The state-space approach and the matrix representation readily enable computation of the states using the state transition matrix. Computation of the response variables is then a simple matter of plugging the right quantities into Eq. (3b). Computation of the response gradient is a little more complex requiring the sensitivity equations $\partial x/\partial\Theta$ and $\partial y/\partial\Theta$ obtained by partial differentiation of the system equations with respect to the unknown parameters. Linear representation facilitates the solution of $\partial x/\partial\Theta$ using the same state transition matrix already computed for state variable computations.

Extension of Output Error Method to General Nonlinear Systems

During the seventies the output error method developed for linear systems became very popular due to its simplicity. A number of estimation software packages were developed worldwide.[74,75,77,79–82] and applied to a multitude of cases.[83] During this period the need for estimation of nonlinear aerodynamics was also developing. Logically, it was attempted to extend the then well-established output error method for linear systems to nonlinear systems as well. The two most commonly adapted approaches were 1) to consider the nonlinear terms in aerodynamic coefficients such as w^2, α^2, . . . , $\alpha\delta_e$ as pseudocontrol inputs, computing these prior to estimation and thereby retaining basically the linear system representation[84–87] and 2) augmentation of the state vector with nonlinear terms α^2, $\alpha\delta_e$ using the computed variables, which principally retains the nonlinear equations of motion.[88] The second approach, although more justified, was limited in the scope of application since it often involved modifications in the estimation program for different nonlinear terms considered. In the presence of measurement errors, the first approach of pseudocontrol inputs yielded biased estimates. Thus, a more complete approach to aircraft parameter estimation based on the use of nonlinear equations of motion and/or aerodynamic model postulates with nonlinear terms was still necessary.

The difficulty of applying the output error method to nonlinear systems was one of practice. Any time the structure of the postulated nonlinear model was changed, it entailed tedious and laborious algebraic derivation and software implementation of the sensitivity equations. The sensitivity coefficients are essential in the optimization of the cost function. A numerical approach investigated based on the Levenberg–Marquardt method by Trankle et al.[89] and on the modified Newton–Raphson method by Jategaonkar and Plaetschke[90] provided the much needed solution to this general problem during the early eighties.

In the general case, a dynamic system is represented as

$$\dot{x}(t) = f[x(t), u(t), \Theta] \qquad x(t_0) = x_0 \quad (6a)$$

$$y(t) = g[x(t), u(t), \Theta] \quad (6b)$$

where f and g are general nonlinear real valued vector functions. Numerical integration methods, for example, a fourth-order Runge–Kutta, are required to compute the state variables. The response gradients are approximated by finite differences. The procedure is fairly straightforward. Perturbing one parameter at a time, and each time solving the perturbed state equations by numerical integration, the perturbed response variables $y_p(\theta_j)$ are computed. The response gradient for this parameter can be approximated as[90]

$$\left[\frac{\partial y}{\partial \Theta}(k)\right]_{ij} \approx \frac{y_{pi}(k) - y_i(k)}{\delta\Theta_j} \quad (7)$$

Concatenation of these response gradients yields the sensitivity matrix. Several estimation packages catering to general nonlinear systems have been developed since then, based on the previously discussed approach of numerical approximation of the sensitivities.[91–93] An alternative approach based on surface fitting is also possible to approximate the sensitivities.[94,95] The modified Newton–Raphson method with numerical approximation of the sensitivities is found to be far more efficient than the derivative free, so-called, direct search methods.[96,97]

Filter Error Method

The filter error method is the most general stochastic approach to aircraft parameter estimation, which accounts for

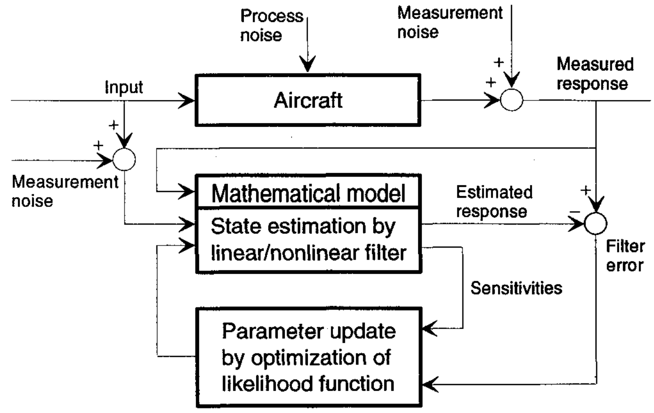

Fig. 6 Schematic of filter error method.

both process and measurement noise and was proposed by Balakrishnan.[98] With the pioneering work of Mehra[99–101] and Iliff[102] during the early seventies, these techniques provided capabilities to estimate aircraft parameters from flight data in a turbulent atmosphere (Fig. 6). Several applications have since been reported.[103–106]

The dynamic system is assumed to be described by the following stochastic equations:

$$\dot{x}(t) = A(\beta)x(t) + B(\beta)u(t) + Fw(t) + b_x \tag{8a}$$

$$y(t) = C(\beta)x(t) + D(\beta)u(t) + b_y \tag{8b}$$

$$z(k) = y(k) + Gv(k) \tag{8c}$$

where w and v represent the process and measurement noise, respectively, and F and G are the corresponding distribution matrices.

In such a case, the cost function of Eq. (4) gets modified to

$$J = \frac{1}{2}\sum_{k=1}^{N} [z(k) - \tilde{y}(k)]^T\tilde{R}^{-1}[z(k) - \tilde{y}(k)] + \frac{N}{2}\ell n|\tilde{R}| \tag{9}$$

where $\tilde{y}$ is the filter-predicted observation vector and $\tilde{R}$ is the covariance matrix of the innovations. Computation of $\tilde{y}$ requires the predicted state vector $\tilde{x}$. The Kalman filter, which is an optimal state estimator for linear systems, provides predicted state variables:

$$\tilde{x}(k + 1) = \Phi\hat{x}(k) + \Psi Bu(k) + \Psi b_x \tag{10a}$$

$$\tilde{y}(k) = C\tilde{x}(k) + Du(k) + b_y \tag{10b}$$

$$\hat{x}(k) = \tilde{x}(k) + K[z(k) - \tilde{y}(k)] \tag{10c}$$

where $\tilde{x}$ and $\hat{x}$ denote the predicted and corrected state vectors, respectively, K denotes the Kalman filter gain matrix, $[z(k) - y(k)]$ is the residual (innovation), and Φ and Ψ are the state transition matrix and its integral, respectively. In many applications, particularly for the time-invariant systems, it is often adequate to use a steady-state filter for state estimation.[73] This simplification results in significant reduction of computational burden. Even under this assumption, computation of the gain matrix K is the most complex part of the filter error method.

Partial differentiation of Eq. (8) yields the sensitivity equations in this case, which can be solved using the same state transition matrix Φ and its integral Ψ. This computation requires computation of the gradient of covariance matrix, which requires solving the Lyapunov equations. In the case of linear systems, the Riccati equation and the Lyapunov equations can be solved efficiently, although with some computational complexity. The algorithmic details are found in Ref. 105.

Extension of Filter Error Methods to General Nonlinear Systems

Difficulties of extending the aforesaid filter error method to nonlinear systems are twofold: 1) efficiently implementing the computations that provide flexibility to handle conveniently different model structures without software modifications and 2) to derive a suitable filter for nonlinear state estimation. The numerical approach of finite difference approximation, which was already found to be working efficiently in the case of the output error method, can be extended to the filter error method to compute the response gradients. Since optimal filters for nonlinear systems are practically unrealizable, an extended Kalman filter based on a first-order approximation of the state and measurement equations can be used for nonlinear filtering; flexibility for different nonlinear model postulates without requiring software programming changes being implicit in the implementation.

Without going into any further detail, it can be stated that the algorithmic development is on similar lines as that of linear systems. The algorithm in this case requires a numerical integration of perturbed state equations and the computation of the perturbed gain matrices for each unknown parameter. These extensions proposed and validated by Jategaonkar and Plaetschke[107,108] are found to work well for the practical purposes of estimating stability and control derivatives from flight data in the presence of process and measurement noise.

Estimation in Frequency Domain

Although during the last three decades the time domain methods have dominated the field of aircraft parameter estimation, there are a few cases (e.g., rotorcraft identification), in which the frequency domain approach as demonstrated by Klein may be preferable.[109]

Applying the Fourier transformation, the system equations get transformed into

$$j\omega x(\omega) = A(\beta)x(\omega) + B(\beta)u(\omega) \tag{11a}$$

$$y(\omega) = C(\beta)x(\omega) + D(\beta)u(\omega) \tag{11b}$$

$$z(\omega_l) = y(\omega_l) + v(\omega_l) \tag{11c}$$

The cost function to be minimized is then given by

$$J_{\mathrm{FR}} = \sum_{l=1}^{M} [z(\omega_l) - y(\omega_l)]^* S_{vv}^{-1}[z(\omega_l) - y(\omega_l)] + \log|S_{vv}| \tag{12}$$

where $\omega_l = 2\pi l/T$ is the lth discrete frequency, M is the number of frequencies to be evaluated, and S_{vv} is the spectral density matrix of the measurement noise. Minimization of Eq. (12) by the Gauss–Newton method yields the maximum likelihood estimates of the parameters. The scope of the frequency domain method has been extended to include nonperiodic signals and to enable multirun evaluations.[110,111]

The transformation of system equations to the frequency domain leads to a set of algebraic equations, i.e., no integration is involved in the frequency domain. This makes the method suitable for unstable systems for which numerical integration in the time-domain can lead to numerical divergence problems. Furthermore, without affecting the estimation results, the zero-frequency can be neglected in the evaluation, which can be advantageous not only in eliminating the need to account for a large number of bias parameters and thereby drastically reducing the total number of parameters to be estimated, but also to overcome the problems of correlation between the bias parameters and the aerodynamic bias terms. For multirun evaluations, bias parameters often far exceed the number of aerodynamic derivatives. The aforementioned advantages of the frequency domain method are, however, associated with a substantial disadvantage of the method being applicable to only linear systems.

More recently, Tischler and Cauffmann have demonstrated yet another frequency domain approach to state-space model identification.[112] In this approach based on transfer functions, a cost function in terms of frequency response error, rather than in terms of the output error of Eq. (12), is minimized:

$$J_{\mathrm{FR}}(\Theta) = \sum_{l=1}^{M} \varepsilon^T(\omega_l, \Theta)W\varepsilon(\omega_l, \Theta) \tag{13}$$

where W is the weighting matrix based on the values of coherence at each frequency point and ε is the error between the frequency response T extracted from the flight data and the model responses T_m:

$$T_m(j\omega) = \{C[j\omega I - A]^{-1}B + D\}e^{-j\omega\tau} \tag{14}$$

where the subscript m refers to the postulated state-space model and τ is the matrix of time delays.

The frequency-response error formulation may have some advantages over the output-error formulation such as, eliminating the effects of uncorrelated process and measurement noise, emphasizing the most accurate data through multiple coherence functions, and selectively accounting for the frequency ranges of good coherence. However, as in the other case, the approach requires preprocessing of data and is restricted to linear models.

Although this Paper focuses on the state-space model identification, it is worth mentioning here that other techniques in terms of frequency analysis based on the spectral, coherence, and frequency response functions catering to multi-input/multi-output (MIMO) systems are also possible.[113,114]

Parameter Estimation by Filtering Approach

In this indirect approach the parameter estimation problem is transformed into a state estimation problem by artificially defining the unknown parameters as additional state variables. Considering the constant system parameter vector Θ as the output of an auxiliary dynamic system:

$$\dot{\Theta} = 0 \tag{15}$$

and by defining an augmented state vector $x_a^T = [x^T, \Theta^T]$, the extended system can be represented as

$$\dot{x}_a(t) = \left\{\frac{f[x_a(t), u(t)]}{0}\right\} + \left[\frac{F|0}{0|0}\right]\left[\frac{w(t)}{0}\right] \tag{16a}$$

$$y(t) = g[x_a(t), u(t)] \tag{16b}$$

$$z(k) = y(k) + v(k) \tag{16c}$$

The extended Kalman filter yields the solution to this combined state and parameter estimation problem.[115] As in the case of filter error methods for nonlinear systems, a numerical approach to compute the first-order system matrices leads to flexible software that can be easily applied to general nonlinear systems.[108]

The filtering approach identification of aerodynamic derivatives was introduced at Calspan,[84,116] but is seldom used, mainly because the performance strongly depends upon the statistics of the measurement and process noise, i.e., on the covariance matrices, which are, in general, unknown. The approach is, however, well suited for on-line application[117] and applicable to unstable systems as well. It has recently found some application with renewed interest.[118,119]

Neural Network-Based Methods

Artificial neural network (ANN), sometimes called perceptron, is an information-processing system that can be made to learn through examples, and can be adopted thereafter for other purposes such as prediction. Through a flexible set of basic functions (also called hidden units, nodes, or neurons), having certain properties, the ANNs provide a means of nonlinear mapping the given input/output (I/O) subspace and provide an overall characterization of a system. There are two types of networks that have found some application in aircraft identification. They are 1) feedforward neural network and 2) recurrent neural network.[120–122]

The feedforward neural network, as implied by the name, is characterized by the unidirectional flow of the signals. Typically, it contains a number of hidden layers between the input and output layers. The input and output layers define the given data subspace that is to be modeled (Fig. 7). In the context of estimation of aerodynamic coefficients, the input variables are typically the variables pertaining to the aircraft motion such as angle of attack, angle of sideslip, angular rates, and the control inputs exciting the aircraft motion. The output variables are the aerodynamic force and moment coefficients. The size of the neural network is determined by the number of hidden layers and by the number of nodes in each layer, the nodes in the input and output layers being fixed through the data subspace being modeled. The weights or parameters of the network, defining the forward and cross connectivities, are estimated by the back-propagation method.[123,124] In contrast to the conventional approach of aircraft parameter estimation based on the well-understood basic principles underlying the aircraft dynamics and aerodynamic forces and moments, the neural network approach leads to a black-box model to which no physical significance can be attributed, either to the structure or weights.[124–127]

In contrast to the feedforward neural network in which the nodes represent some neural variables, in the recurrent neural network the outputs of the nodes represent the unknown parameters of the dynamic system. The outputs of the nodes are some nonlinear function of the internal states of the network, which are evolved in time through differential equations describing the dynamics of the network. The recurrent neural network has a fixed number of mutually connected nodes equal to the number of unknown parameters of the postulated state-space model.[122] Conceptually, the recurrent neural network can be compared with the extended Kalman filter in which the unknown system parameters are propagated in time by defining them as additional states (see the previously mentioned text).

Although the recurrent neural network is amenable to state-space models, its performance is found to critically depend upon tuning of the sigmoid nonlinearity that can, at best, be carried out on a heuristic basis. It is partly due to this reason and partly due to the fixed structure that the applicability of the recurrent neural networks to practical cases of aircraft identification is very limited in scope.[122] From this viewpoint, the

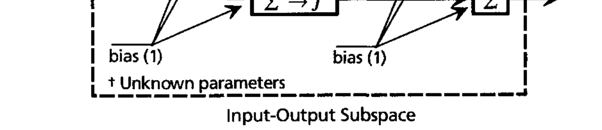

Fig. 7 Feedforward neural network with one hidden layer.

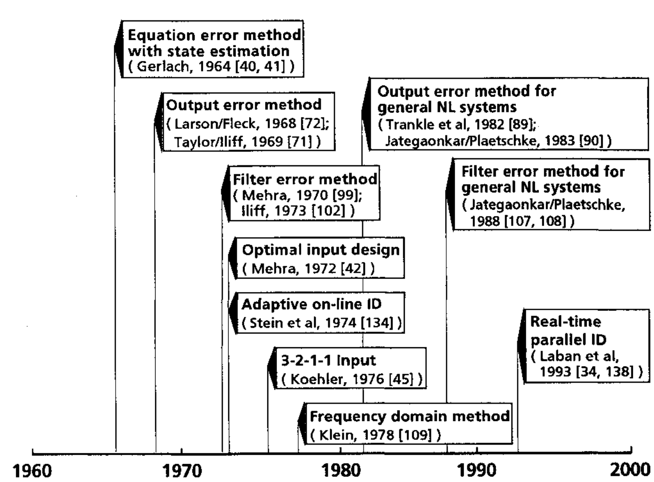

Fig. 8 Milestone of advances to flight vehicle parameter estimation methods, a retrospective.

feedforward neural networks, although leading to a black-box model structure without physical interpretation of the estimated weights, may prove to be more flexible and may have a somewhat wider application than the recurrent neural networks.

To summarize the progress in the advancements of the flight vehicle parameter estimation methods, in view of the authors, Fig. 8 provides a retrospective of the important milestones during the last three decades.

Model Validation

As depicted in Fig. 3 the parameter estimation and the model validation are an integral part of system identification. The parameter estimation methods provide an answer to the question: "Given the system responses, what is the model?," whereas model validation tries to provide an answer to the related question: "How do you know that you got the right answer?."

Several criteria, to be used in conjunction with each other, help to validate the model: 1) standard deviations of the estimates (i.e., estimation uncertainties in terms of Cramer–Rao bounds); 2) goodness of fit (i.e., value of the cost function being minimized, e.g., the determinant of the covariance matrix of the residuals); 3) correlation coefficients among the estimates; 4) plausibility of the estimates from physical understanding of the system under investigation or by comparison with other predictions such as wind-tunnel or analytical methods; and 5) model predictive capability.

The predictive capability of the identified model is determined by comparing the flight measured aircraft responses with those predicted by the model for the same control inputs. In this proof-of-match process, the aerodynamic model is kept fixed. The initial conditions have to be suitably adjusted to match the flight conditions being tested. The flight maneuvers used for model validation are, as a general rule, not used in estimating the aerodynamic model. The complementary flight data, often called validation test data, for which the model predictive capability has to be demonstrated, is an important part of flight simulator certification and acceptance.

To eliminate subjective evaluation, the Federal Aviation Administration (FAA) has specified guidelines in terms of tolerances for each variable, depending upon the nature of the validation test.[128] For example, in the case of short period dynamics, the tolerances are ± 2 deg/s for the pitch rate, ± 1.5 deg for the pitch attitude, and ± 0.1 g for the vertical acceleration. For the roll response the tolerances are ± 2 deg/s for roll rate and ± 2 deg for bank angle. The flight measurements with these tolerances define a band within which the model predicted response must lie to meet the specified accuracy requirements. Although the majority of the validation tests are verified in time domain either through time histories or in terms of period and damping ratios of the oscillatory modes such as phugoid or dutch roll, it is also possible to extend the verification to the frequency domain, which may bring out more clearly the range of applicability of the identified model. This is particularly important for high authority flight control systems or in cases where aeroservoelastic effects may be dominant.

Practical Utility of Filter Error Methods

For flight data gathered in turbulence, the filter error methods are inevitable, since the output error method is known to yield biased estimates in the presence of atmospheric turbulence.[11,73] Even in the case of flight maneuvers in smooth air, the filter error method could lead to better estimation results, since some of the unavoidable modeling errors are then treated as process noise characterized by low-frequency contents rather than as measurement noise.[105] Moreover, although it is generally argued that the flight tests for aircraft parameter estimation could be carried out in calm air, in any practical exercise one has no control over the prevailing atmospheric conditions, or due to very tight time schedules and due to cost factors involved in a time-bound project, very little choice of waiting for steady atmospheric conditions.

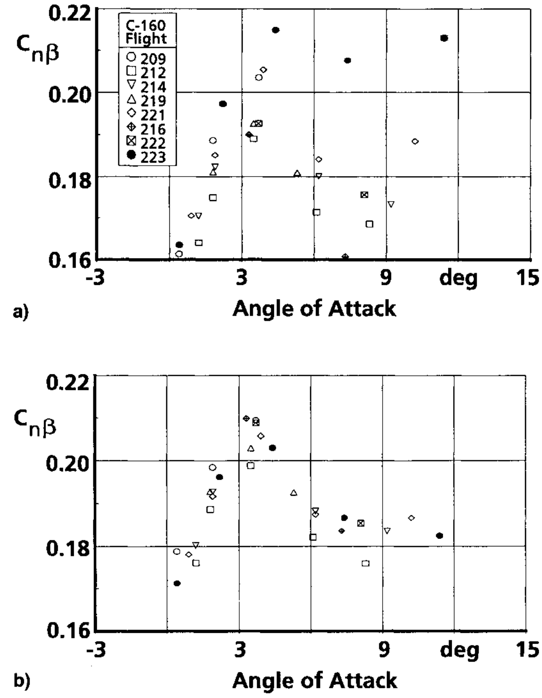

Fig. 9 Flight estimates of weathercock stability: a) output error and b) filter error methods.

As a typical example, the estimates of the weathercock stability, derivative $C_{n\beta}$, obtained by applying the output error and the filter error method to the same set of flight data, are provided in Fig. 9.[129] The C-160 data analyzed here were gathered from eight flights carried out during a span of less than two weeks, seven of them being in a seemingly steady atmosphere, whereas one encountered a moderate amount of turbulence. It is clearly visible that the estimates provided by the output error method, particularly those for flight 223 during which moderate turbulence was encountered, differ from those of other flights at the same nominal flight conditions. A fair amount of scatter is observed in the estimates from other flights in a seemingly steady atmosphere, making a final conclusion regarding the nature of the nonlinearity or fairing of data difficult. On the other hand, the filter error method yields clearly grouped estimates with much less scatter and the estimates from the flight 223 match well with the other estimates. The nonlinear dependency of the weathercock stability on the angle of attack is now to be observed much better.

Another example for which the estimation methods accounting for process noise are essential pertains to X-31A identification. At high angles of attack, the forebody vortices, which are shed stochastically from the aircraft nose, act as process noise exciting randomly the lateral-directional motion. The results presented later in this Paper demonstrate that the filter error method was well suited for this application, whereas the output error method provided estimation results that could not be completely resolved.

The filter error method, due to its formulation, contains a feedback proportional to the fit error. This feedback stabilizes numerically the filter error algorithm and also helps to improve the convergence properties. The stabilizing property of the filter error algorithm, as will be discussed in this Paper, makes it suitable for open-loop identification of unstable aircraft.

These few selected typical examples provide an answer to the question often raised regarding the practical utility of the filter error method. It can be pragmatically concluded that these methods can yield better estimates, are not limited to linear systems, and are indispensable for many future applications such as identification at high angles of attack or of unstable aircraft. These advantages outweigh the disadvantage of higher computational overheads. Even in such a case it needs to be reminded that in any exercise on parameter estimation the actual CPU time is only a minor part of the total time, the major part being consumed by mundane tasks such as the checking of flight data, collecting and analyzing the results, and generating plots, etc.

Unstable Aircraft Identification

The demands of high-performance characteristics have led to aerodynamically unstable aircraft configurations. Although unstable aircraft can be flown only with the aid of a flight controller, i.e., in closed loop, the determination of aerodynamic characteristics of the basic unstable aircraft, i.e., of the open-loop plant, is of primary interest in several instances.

The simplest approach to identification of unstable aircraft is to use linear regression in the time domain or as already mentioned, the maximum-likelihood method in the frequency domain. Application of the other time-domain methods to such cases, however, needs some consideration. The most widely used output error method in this case encounters numerical difficulties of diverging solution. Some special techniques and modifications are, hence, necessary to prevent the growth of errors introduced by poor initial values, roundoff or discretization, and propagated by inherent instabilities of the system equations. Several solutions such as 1) S-plane transformation,[130] 2) output error method with artificial stabilization,[131,132] 3) equation decoupling,[133] and 4) a relatively new approach called multiple-shooting based on efficient techniques for the solution of two-point boundary value problems are possible.[134] These approaches, although providing solutions in particular cases, were either found to involve engineering judgment or required considerable effort, so that the results could not be completely resolved.[134] The filter error method and the regression method appear to be more readily applicable to unstable aircraft. The filter error method may have some advantages, particularly in the presence of considerable measurement noise in which case the regression analysis yields biased estimates. In any case, a method that accounts for process noise is preferable, since the controller feeds back the measured variables containing measurement noise, and thereby introduces a component of stochastic input.

Apart from the choice of a suitable method, yet another serious difficulty encountered in the unstable aircraft identification is that of parameter identifiability. The controller tends to suppress the oscillatory and transient motion. This is what the controller is designed for. It is, however, detrimental to the identifiability and accuracy of the parameter estimates, since the information in the data is drastically reduced. Furthermore, the feedback results in correlated inputs and also correlated motion variables. The combined solution to both of these problems is to introduce controlled inputs directly deflecting the control surfaces. This is often called in literature as separate surface excitation.

As a typical example, Fig. 10 shows the estimates of the canard control effectiveness obtained from the X-31A flight test data for two cases, namely the pilot input maneuvers and the separate surface excitation.[65] As is evident from Fig. 10a, the pilot input maneuvers yield estimates with a large standard deviation and, moreover, the scatter is large. This is definitely attributed to the aforementioned difficulties of insufficient information content and correlated variables. On the other hand, the separate surface excitation maneuvers yield well-identifiable estimates (Fig. 10b).

As demonstrated, the separate surface excitation eliminates the problems due to the correlated inputs and correlated motion variables. The separate surface excitation is, however, a complex procedure requiring hardware modifications, and often, flight certification. Otherwise, the alternative approach would be to attempt parameter estimation based on data collinearity and mixed estimation.[11,135] In such cases, however, it may be possible to obtain unbiased estimates of only a subset of parameters. Moreover, the basic problem of insufficient excitation still persists.

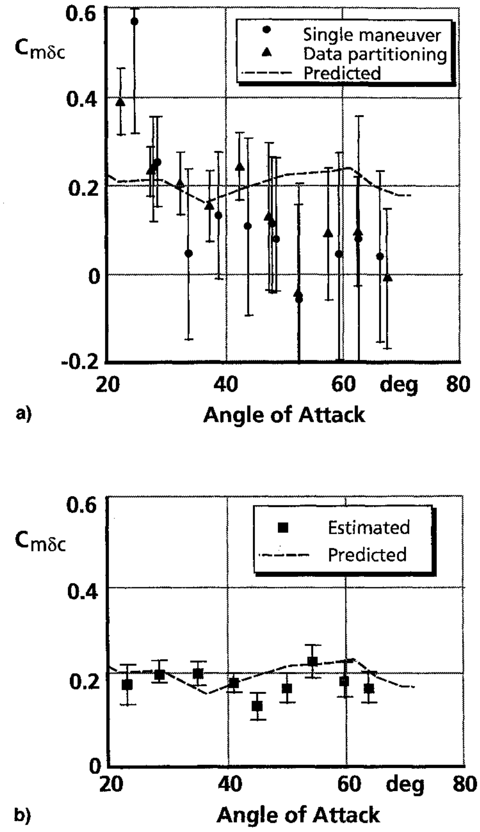

Fig. 10 Estimates of canard control effectiveness from X-31A flight data: a) pilot input and b) separate surface excitation maneuvers.

Although the aspects of parameter identifiability and data collinearity have been discussed in the context of unstable aircraft, these issues are equally applicable to stable aircraft as well.

Identification of open-loop unstable aircraft via closed-loop identification, although feasible, is rather impractical. From such an attempt, to obtain the open-loop parameters of the basic aircraft, it would require incorporating the models for the controller and actuator dynamics in the estimation procedure. The overall system being stable, any standard parameter estimation method can be applied without encountering any serious difficulty. With the current state of the art, even the increased model size should not be a serious problem. The primary difficulty is to obtain the exact models for the complex control laws containing discrete nonlinearities and that the actuator performance and controller gains may be flight dependent. Moreover, this approach may result in open-loop parameter estimates with low accuracy.

On-Line Aircraft Identification

The primary motivation for on-line identification is adaptive control, although other minor benefits can also be derived from the immediate knowledge of the aircraft model. The adaptive control investigations in flight on the X-15 aircraft date back to 1971,[136] which were based on the concepts of analogue computation. The modern methods of parameter estimation were investigated by Stein et al.[137] and others during the year 1977 for adaptive control of F-8 DFBW aircraft. The scope of identification was then restricted mainly to a subset of aircraft parameters from decoupled and simplified equations of aircraft motion. Recently, based on parallel processing, Laban and Mulder have successfully extended the on-line identification capabilities to a complete set of aerodynamic derivatives during the flight.[34,138] In other investigations the near real-time approach has been adopted to check the simulation accuracy and for flight test planning purposes.[139,140]

Selected Examples

Few selected applications presented in this Paper pertain to the determination of aerodynamic databases for high-fidelity simulators, verification of stability and control characteristics of a commercial transport aircraft, identification of a highly augmented unstable flight vehicle, and high bandwidth rotorcraft modeling.

Aerodynamic Databases for High-Fidelity Flight Simulators

Prior to the advent of digital computers, the accuracy of aircraft simulation was marginal due to the inherent limitations of analog computers. The development of digital computers opened up new horizons, not only in the field of aircraft parameter estimation, but also in the field of flight simulators.[141] With the evolution of high-performance modern aircraft and with the spiraling developmental and experimental costs, the importance of ground-based flight simulators and that of in-flight simulators has increased significantly. Simulators are increasingly used not only for pilot training, but also for other applications such as flight planning, envelope expansion, design and analysis of control laws, handling qualities investigations, and pilot-in-the-loop studies. Many of these applications demand a high-fidelity flight simulator. The fidelity of a simulation depends to a large extent on the accuracy of the mathematical model and of the aerodynamic database representing the flight vehicle.

Although validation and update of aerodynamic databases derived from analytical predictions and wind-tunnel measurements through flight tests is a viable approach,[142] such updates are possible only through repetitive procedures involving considerable engineering judgments. Moreover, incremental modifications of aerodynamic predictions may not lead to a homogeneous database. On the other hand, system-identification methodology provides an alternative and efficient approach to derive flight-validated database covering the entire operational flight envelope.[143–146]

Estimation of a comprehensive aerodynamic model suitable for a flight simulator is an iterative process, which starts with point identification at all of the points flight tested. Point-identification results in a model related to specific trim conditions. Based on this bulk of estimation results, the aerodynamic model postulates can be extended to include angle-of-attack or Mach number dependencies, coupling derivatives, and nonlinearities. Through multipoint identification, several flight conditions can be analyzed simultaneously to arrive at a comprehensive model. This general approach was followed in the generation of an aerodynamic database for the ATTAS in-flight simulator,[147,148] and in the example presented next.

C-160 Data Gathering

The C-160 Transall is a military transport aircraft capable of carrying troops, casualties, freight, supplies, and vehicles, and serves the needs of the German as well as the French Air Force. To meet the current demands of improved pilot training at reduced cost and increased safety, as well as the optimal deployment of existing fleets of aircraft, a modern high-performance flight simulator was required by the German Air Force. Although the wind-tunnel measurements of the Transall, made in the sixties, are still available, this wind-tunnel-generated database was found to be unsuitable for a flight simulator that has to meet the level D quality standards specified by the FAA.

The complete data gathering program, carried out with the instrumented aircraft (Fig. 11), consisted of flight tests for 1) the calibration of an air data system; 2) the estimation of an aerodynamic database; 3) ground tests (taxiing, ground acceleration/deceleration, stopping distances); 4) validation tests for simulator certification and approval according to FAA guidelines; 5) sound data; 6) C-160 specific operational characteristics (load drop, landing, and takeoff on unprepared terrain and short field, single-engine flights); and 7) stall dynamics. Altogether 28 flights were carried out, totaling a flight test time of 79 h. A total of 350 trim conditions and 964 system-identification maneuvers, including 22 stall maneuvers, were investigated covering altitudes up to 26,000 ft and Mach numbers up to 0.52. Test points were judiciously chosen to span the entire operational envelope and possible configurations: 1) clean configuration ($\eta_K = 0$ deg, nominal c.g. of 28% MAC); 2) landing flaps ($\eta_K = 20$, 30, 40, and 60 deg); 3) c.g. locations (forward 23%, nominal 28%, and aft 33% MAC); 4) landing gear; 5) ramp door; and 6) one engine out.

Detailed descriptions of aerodynamic modeling and of all other pertaining issues are found in Refs. 145 and 149–152. For illustration purposes, the estimates of the dihedral effect, derivative $C_{l\beta}$, obtained by point identification are shown for four landing flap positions in Fig. 12. The estimates are clearly a function of angle of attack and also of landing flap position. The same figure shows the multipoint identification results for each flap position, obtained by analyzing several flight maneuvers simultaneously.[145]

From the quasisteady and dynamic stall maneuvers an unsteady aerodynamic model for high lift including flow separation and stall was identified. Based on the Kirchhoff's theory

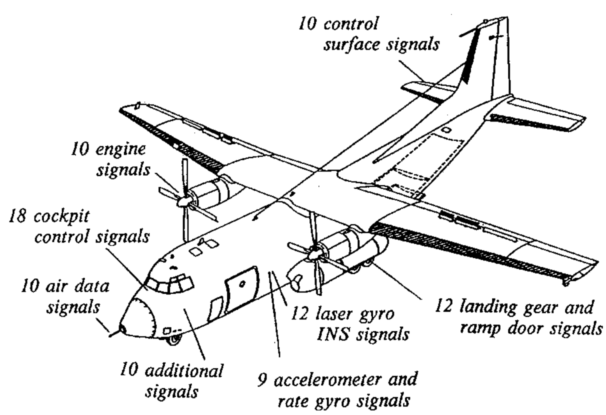

Fig. 11 Instrumented C-160 Transall.

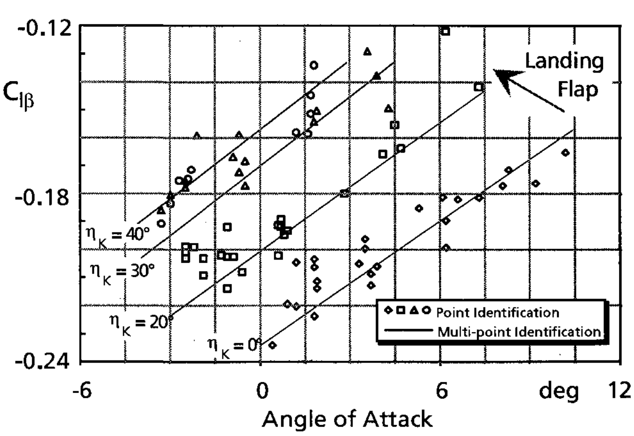

Fig. 12 Flight estimates of dihedral effect.

of flow separation, the wing lift can be modeled as a function of angle of attack and flow separation point X[153,154]:

$$C_L(\alpha, X) = C_{L\alpha}\{(1 + \sqrt{X})/2\}^2\alpha \tag{17}$$

Based on an approximation of the Wagner or Theodorson function,[155] the time-dependent flow separation point can be expressed as[156]

$$\tau_1 \frac{dX}{dt} + X = X_0(\alpha - \tau_2\dot{\alpha}) \tag{18}$$

The steady flow separation point X_0 may be determined from static wind-tunnel tests or can also be identified from the flight tests using the approximation:

$$X_0 = \tfrac{1}{2}\{1 - \tanh[a_1(\alpha - \alpha^*)]\} \tag{19}$$

The model in terms of the two parameters (a_1, α^*) appearing in Eq. (19) and the two time constants appearing in Eq. (18) yield the identified lift coefficient and the separation point shown in Fig. 13.[154]

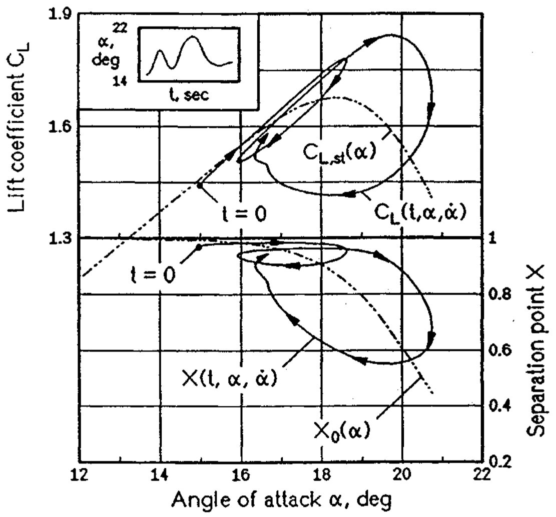

Fig. 13 Estimated lift coefficient and flow separation point.

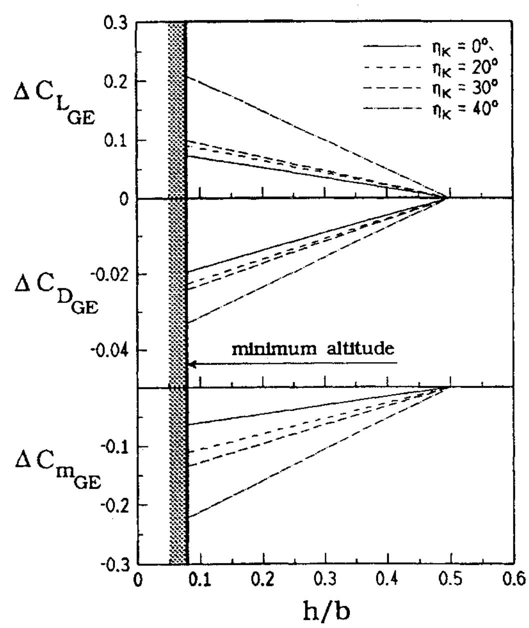

Fig. 14 Estimated ground effect (GE).

The parameter estimation techniques were also applied to identify the ground effects, which have a dominant influence on the landing and takeoff performance. In general, it is known that three main effects of the ground effect are 1) a reduced downwash angle at the tail, 2) an increase in the wing-body lift curve slope, and 3) an increase in the tail lift curve slope. Figure 14 shows the identified ground-effect parameters as a function of ratio of aircraft altitude to wing span (h/b) and landing flap deflection η_K. A linear model was found adequate to model the flight performance, since the altitudes for which the ground effect changes nonlinearly ($h < \bar{c}$), are not reached for the top-wing configuration.[152]

The accuracy of the flight-derived aerodynamic database is verified through predictive capability of the identified model. Typical results are presented in Fig. 15 for the short period dynamics. The model-predicted responses shown by solid lines are well within the specified band obtained from the flight measurement plus/minus the tolerances defined by the FAA for the highest fidelity training simulations (Level D). For the same maneuver the validation in frequency domain is shown in Fig. 16. The boundaries of the so called unnoticeable dynamics, shown in terms of magnitude and phase angle in this figure, can be interpreted as equivalent to the FAA Level D

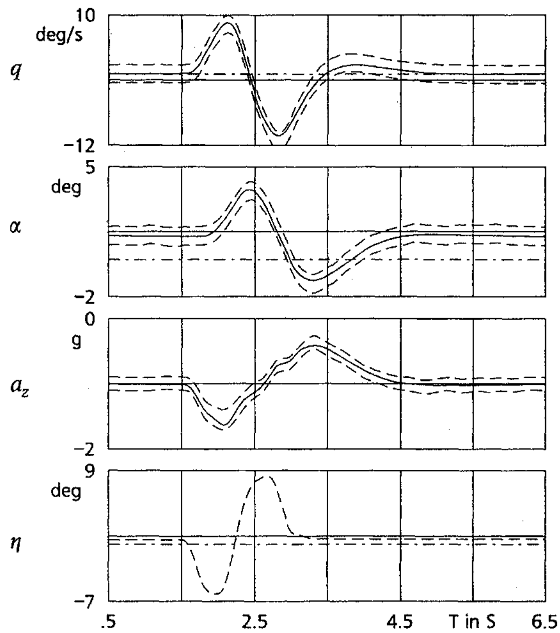

Fig. 15 Proof-of-match for short period dynamics (--- measured ± tolerance; —— estimated).

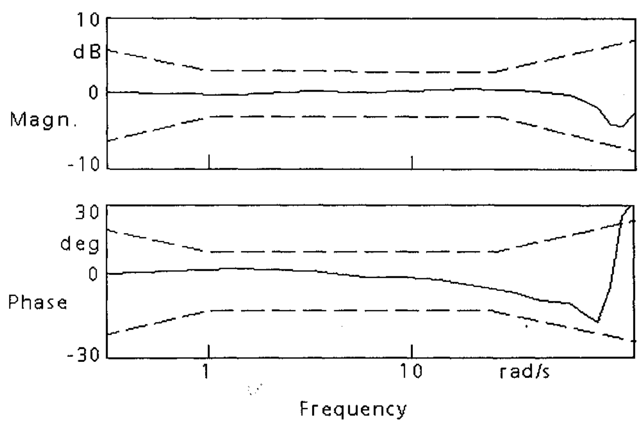

Fig. 16 Proof-of-match in the frequency domain for pitch rate (short period dynamics) (--- tolerance band of unnoticeable dynamic effects; —— $q_{estimated}/q_{measured}$).

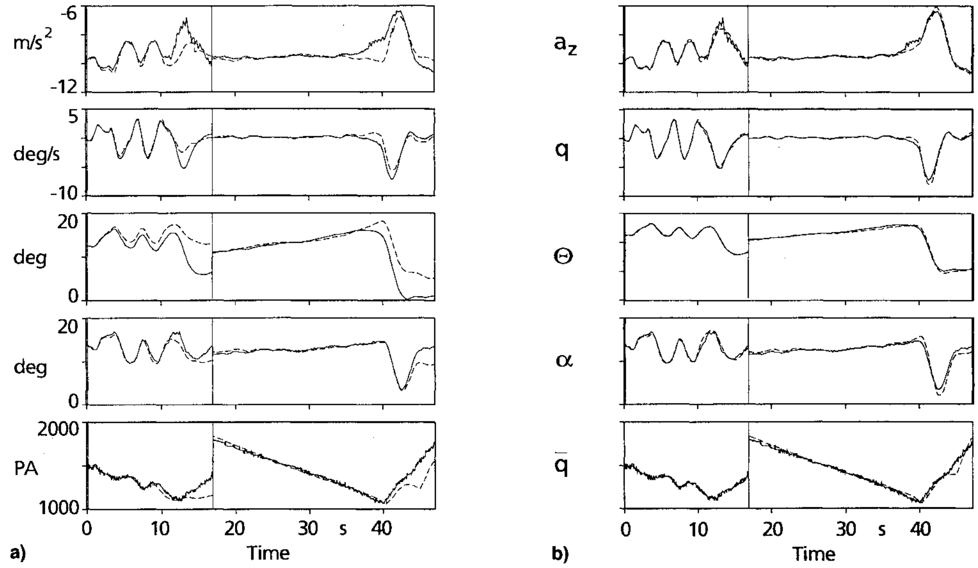

Fig. 17 Validation of C-160 stall dynamics (—— flight measured; --- estimated): a) neglecting and b) accounting for unsteady effects.

fidelity. In these limits the pilot will not notice simulation deficiencies.[157]

Matching of the long period phugoid dynamics, which has to complete three full cycles of oscillation, is one of the more difficult tasks.[158] Even this objective was achieved within the margins specified for frequency and damping terms. As evident from Fig. 17 pertaining to the validation tests for stall maneuvers, the identified model yields an acceptable match. For the same maneuver, neglecting the unsteady aerodynamic effects leads to discernible deviations in the response match (see Fig. 17a). The model predictive capability in terms of plots such as Fig. 15 is often referred to in the flight simulator context as the proof-of-match data. It demonstrates the suitability of the identified database for a flight simulator that has to meet the standards specified by the regulatory authorities, in the present case level D.

Starting from the specification of a flight instrumentation system, calibration and certification of the installed hardware, proposing and carrying out the flight test program, analyzing the huge amount of flight data, generating the aerodynamic characteristics valid over the entire operational envelope, and providing the simulator manufacturer with appropriate documentation, the complete data gathering project was carried out within a span of about 13 months. The broad spectrum of C-160 system identification results demonstrate that the system identification methods have reached a maturity level, that enables them to generate homogeneous databases suitable for high-quality flight simulators. Such applications, under the severe constraints of time put by the industry, however, demand dedicated efforts from a group of engineers and may be possible only through team work.

X-31A System Identification

The U.S./German experimental aircraft X-31A (Fig. 18) is a highly controlled augmented fighter with enhanced maneuverability. Poststall maneuvering is enabled by applying advanced technologies such as high angle-of-attack aerodynamics and flight control system integrated thrust vectoring.[159] System identification methods were employed to predict aerodynamic behavior at new flight conditions and to validate and update the predicted aerodynamic database.[160] The X-31A posed several challenges in aircraft system identification mainly because the aircraft is inherently unstable, because the integrated flight control laws lead to correlated deflections of the control surfaces and of the thrust vector vanes, and because the flight tests were not optimized for system identification purposes.

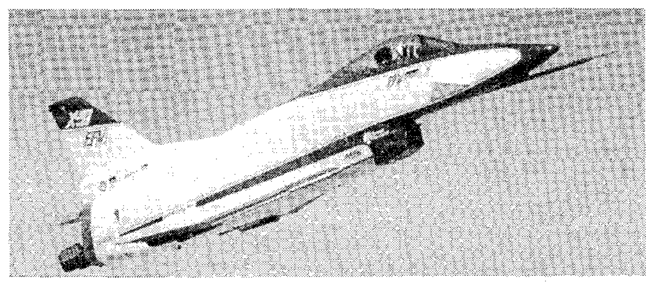

Fig. 18 X-31A aircraft (photograph courtesy NASA Ames—Dryden Research Center).

The thrust vector (TV) system consists of three vanes that can be moved into the aircraft's jet engine exhaust, deflecting the thrust vector and thereby providing additional control in pitch and yaw. Two pitch doublet maneuvers flown with TV engaged are analyzed. To this data, with TV engaged, applying the aerodynamic model obtained at the same flight condition without engaging TV yields the response match shown in Fig. 19a (TE: trailing-edge deflection, CAN: canard deflection, and σ: thrust deflection angle in pitch). A discernible mismatch is visible in pitch acceleration $\dot{q}$, pitch rate q, and pitch attitude θ, which is attributed to the thrust deflection in pitch. On the other hand, modeling of the thrust vector influence on pitching motion yields the response match shown in Fig. 19b. From this figure, the effect of thrust-vector modeling on the system identification quality is apparent.[161]

The thrust vector control effectiveness in pitch and yaw were identified from flight data. It was found that the TV effectiveness in pitch $C_{m\sigma}$, in general, follows the prediction. On the other hand, the TV effectiveness in yaw $C_{n\sigma}$ is somewhat lower than predicted (see Fig. 20). Once again, as in the case of Fig. 10, the pilot input maneuvers yield estimates that are scattered having large uncertainty levels due to the problems of correlation and insufficient excitation, whereas the separate surface excitation maneuvers provide more accurate results.

Although the output error method with artificial stabilization was successfully applied to the TV modeling and to the longitudinal case, the approach was tedious due to the iterations required to eliminate diligently the effect of stabilization on the estimates. Application of this method to the lateral–directional mode was, however, feasible only on part of a bank-to-bank maneuver. Moreover, the estimation results could not be completely resolved. A necessity for application of other methods was indicated. The filter error method and regression anal-

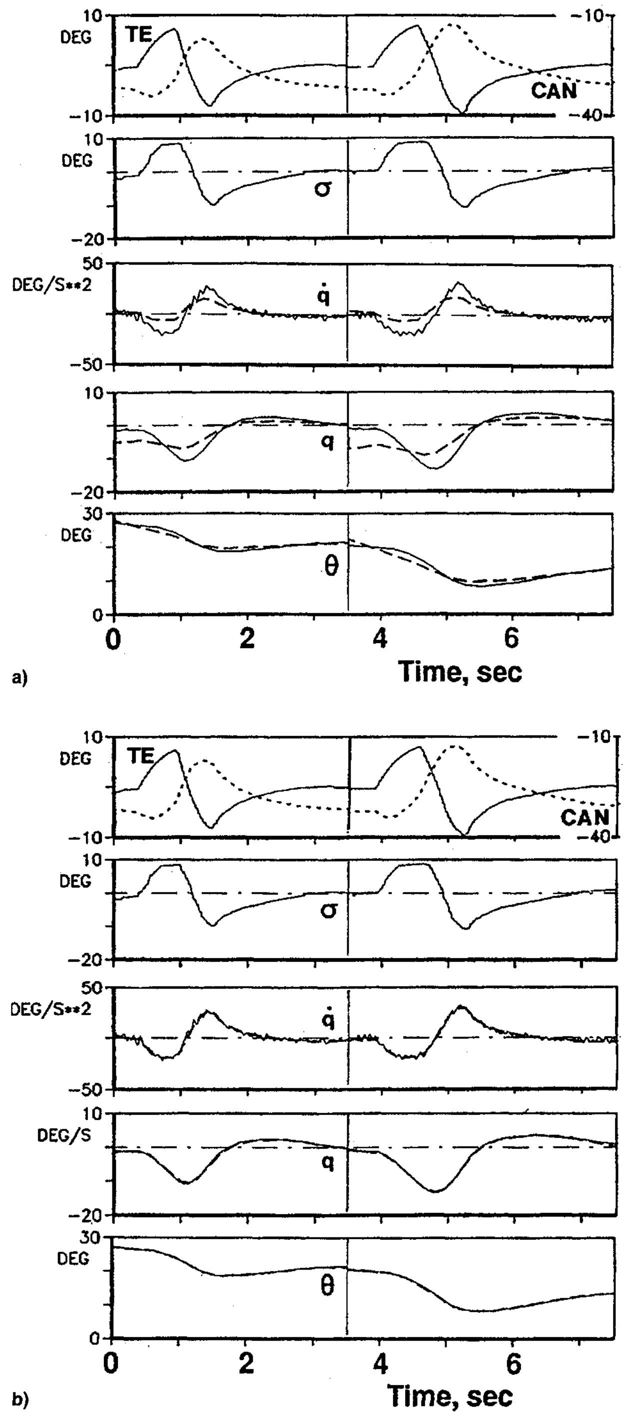

Fig. 19 Identification of thrust vector effectiveness (—— measured; --- estimated): a) neglecting and b) accounting for TV-effects.

ysis were applied. It is interesting to note that the simpler approach of regression and the more complex filter error method yield approximately the same results, except that the uncertainty levels are somewhat larger for regression.[162] The frequency domain method also provided viable approach to unstable aircraft identification.[163]

The results of X-31A system identification have been used to validate and in several cases update the wind-tunnel-predicted database. Two typical examples have been provided in Fig. 21.[65] As evident from Fig. 21a, the flight estimates did not confirm the wind-tunnel-predicted large value of the dihedral effect between 30–45 deg of angle of attack (SSE: separate surface excitation). Similarly, considerable discrepancies

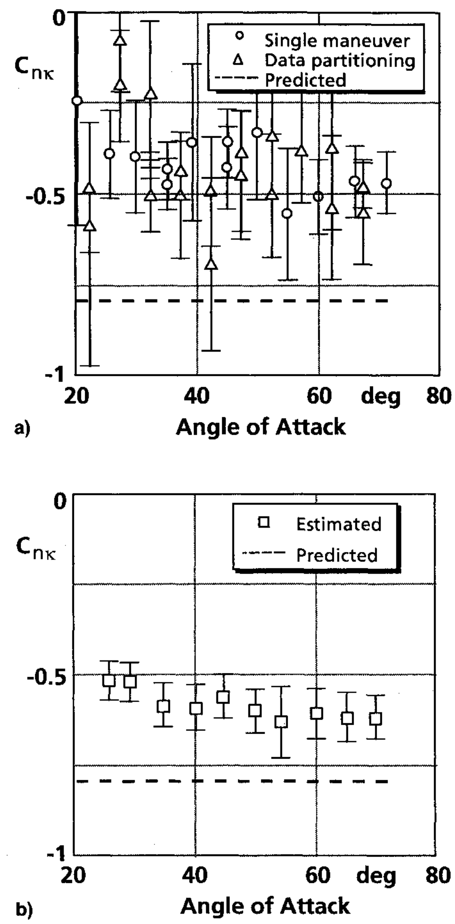

Fig. 20 Thrust vector effectiveness in yaw: a) pilot input maneuvers and b) separate surface excitation.

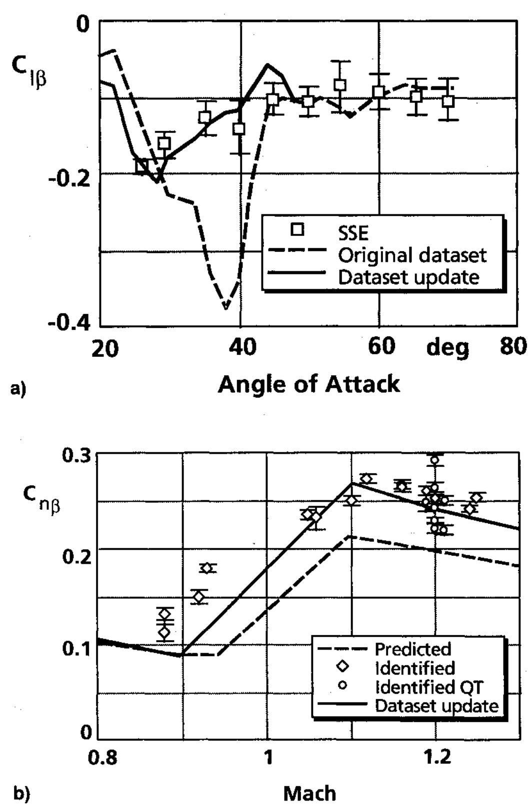

Fig. 21 Examples of X-31A database updates: a) dihedral effect and b) directional stability.

were also observed in the estimates of the directional stability (Fig. 21b) (QT: quasi tailless configuration).

In conclusion, diligent modeling and a wide variety of estimation techniques provided flight validated aerodynamic characteristics, including poststall regime and thrust vector control.[164] Furthermore, the crux of the problem pertaining to highly augmented aircraft was the data correlation and insufficient excitation, and an efficient solution to this problem was provided by separate surface excitation.

System identification provided improved results for flight test planning, flight envelope expansion, and a database for simulation and control law modifications and validation, and catered to actual needs of the aircraft industry.

System Identification Applied to Related Topics

Having briefly traced the evolution of flight vehicle system identification and also having provided some typical examples in the area of flight mechanics, it is now attempted in this Paper to illustrate a few applications in some related areas. This attempt neither traces the history in these areas nor is it claimed to be exhaustive in nature. These examples serve the sole purpose of indicating some possibilities of applying system identification methods, and it is hoped that these methods will also become in these, and other related fields, as popular, successful, and indispensable as they have become in flight mechanics.

Aircraft Accident Analysis via Wind Estimation

The well-defined kinematic equations of aircraft motion can be effectively used not only for the classical purpose of estimating unmeasured or poorly measured variables like angle of attack and for checking instrument accuracies, but also for more difficult applications such as estimating winds along a flight trajectory.

Although dedicated flight test instrumentation, a basis for many investigations on estimation of stability and control derivatives, is often not available with commercial aircraft, a combination of digital flight data recorder (DFDR) and air-traffic control (ATC) data provides sufficient amounts of the required information. These advanced applications of state estimation methodology, as reported by Bach and Wingrove,[165,166] have proved to be useful in assisting the analysis of aircraft accident.

In-Flight Estimation of Airload Parameters

Determination of airload parameters from flight tests of a prototype aircraft is required not only for flight certification of that particular aircraft by the regulatory bodies, but also for prediction of loadings on a new airplane of similar design. The system identification methods have been employed in the past to obtain airload parameters in conjunction with identification of aerodynamic parameters from the same set of flight test data. This combined approach leads to a significant reduction in the total flight test time required for certification. A typical example of estimating the aerodynamic parameters pertaining to the lateral-directional motion and the airload parameters is found in Ref. 167. For such applications, however, in addition to the rigid-body motion variables, the measurements of horizontal tail rolling moment, the vertical tail side force, and pilot rudder pedal force are necessary.

Flutter Testing

The main aim of flutter testing is to identify the frequency and damping of the structural modes either from flight test on a prototype or from wind-tunnel tests on a scaled model. In several instances the wind-tunnel flutter model testing has become an integral part of the aircraft development.[168,169] In the early days, classical methods of analysis like power spectral density, peak-hold spectrum method, or randomdec method were applied to measure the frequency and damping from model response, assuming that the response can be approximated by that of a single-degree-of-freedom system. During the last decade or two, however, the advanced system identification methods have also been applied to flutter test data analysis. For example, Perangelo and Waisanen[168] applied the maximum-likelihood method to the randomly excited fin response of F-14A aircraft, identifying a 13th-order model to characterize the power spectral density up to about 70 Hz.

Compared to the least-squares flutter analysis, the maximum likelihood method yields more accurate estimates and can be successfully applied to flutter test data in the presence of atmospheric turbulence. The more accurate estimates of the modal characteristics enable better extrapolation of flutter margins.

Aeroservoelastic Modeling

In contrast to the purely flight mechanical models characterized adequately by low-order dynamics or purely structural models by higher-order dynamics, the aeroservoelastic (ASE) models cover both the low- as well as high-frequency range.

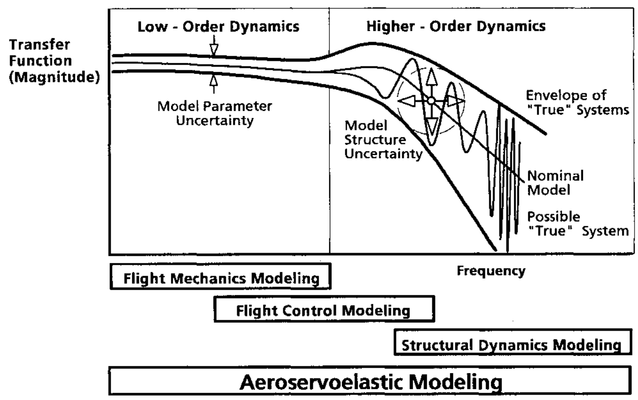

Fig. 22 Interdisciplinary flight vehicle modeling.

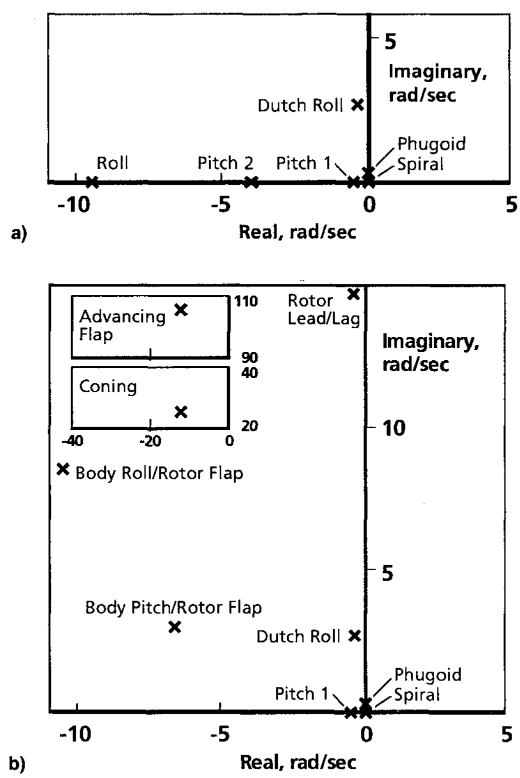

Fig. 23 Eigenvalues of different model structures (BO-105 data): a) rigid-body dynamics and b) rigid-body and rotor dynamics.

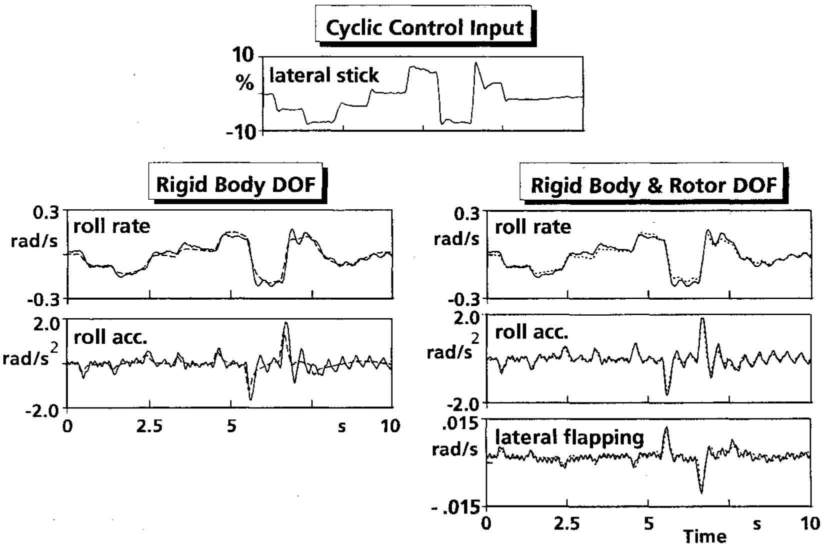

Fig. 24 Comparison of BO-105 helicopter flight test data with six-degree-of-freedom rigid body and nine-degrees-of-freedom extended model responses. ——, measured; ---, rigid body degree of freedom; and - - -, rigid body and rotor degree of freedom.

An interdisciplinary flight vehicle modeling approach shown in Fig. 22 is necessary to arrive at appropriate models for the aeroservoelastic applications. The ASE dynamics include coupling due to structural, control, sensor, aero, and actuator dynamics. Since accurate models can be obtained for structural dynamics through ground vibration tests, for the control dynamics through the design knowledge, and for the sensor dynamics through air-data calibration, the ASE modeling uncertainties are predominantly dictated by the actuator and aerodynamic models.[170]

The aerodynamic models must include both the rigid body modes as well as the unsteady dynamics. The typical examples presented in this Paper clearly demonstrate that the modern methods of system identification provide adequate tools to obtain high-fidelity flight-mechanics models. Hence, it would be desirable to include such flight derived models in terms of aerodynamic derivatives instead of those based on the generalized aerodynamic forces.

Determination of actuator models from flight data is mostly restricted to equivalent models. Such flight-derived models are usually low-order models, typically second to fourth order, and are obtained either in frequency domain by fitting a transfer function to measured data or in time-domain through state-space representation.[147] However, for some applications it may be necessary to incorporate higher order actuator models based on the physical properties of the system (main ram, servovalve, ram feedback, etc.) and its compliance with the structure.[170]

The structural modes, particularly in the case of an aeroelastic airplane, can influence the accuracy of the flight mechanics models, i.e., of the stability and control derivatives. Rynaski et al.[171] report such investigations during the late seventies, and others more recently.[172,173] Techniques based on removal of structural effects through filtering of data, pseudostatic structural modeling, and dynamic structural modeling have been discussed by Iliff.[174]

Although the control inputs such as impulse, doublet, and 3211 are sometimes used for aeroservoelastic applications and for flight flutter investigations,[175] it is more common to adopt the frequency sweep testing in these cases. In general though the frequency sweeps may not be time optimal, they have a broader bandwidth. The frequency sweep testing has been applied, for example, to X-29 aircraft by Clarke et al.[176] and to EAP aircraft by Caldwell.[177] Acree and Tischler[178] report successful identification of several structural modes from frequency sweep flight data of an XV-15 Tilt-Rotor aircraft.[178]

Rotorcraft System Identification

Another application that demands extended mathematical models pertains to a helicopter in-flight simulator incorporating modern concepts of active control technology. The philosophy of model-following control based on feedforward regulation provides safer and more accurate mode control; the performance, however, depends strongly on the validated mathematical model of the host flight vehicle. The high bandwidth requirements of the rotorcraft flight control system demand augmentation of rigid-body model through higher-order rotor dynamics.[114,179,180] The flight test and system identification results of Figs. 23 and 24 obtained with the BO-105 ATTHeS in-flight simulator clearly indicate the effect of unmodeled rotor modes on the identification quality.[181,182]

Figure 23 illustrates that the low-frequency rotorcraft eigenvalues (phugoid, spiral, dutch roll, and pitch) are the same for both the models, whereas the higher frequency behavior is characterized by the more refined description of the nine-degree-of-freedom model. Figure 24 compares the roll axis time history responses for both the models to the measured data. It can be observed that only the nine-degree-of-freedom model can match the amplitude peaks and the high-frequency lead-lag rotor dynamics of the roll acceleration data. The model differences become even more obvious when the results (not shown here) are compared in frequency domain.[182]

An excellent repertoire of various aspects of rotorcraft identification is provided by the Working Group 18 of the Flight Vehicle Integration Panel (FVP) of AGARD.[181,182] By ingeniously extending the system identification methods to this complex problem this group has significantly enlarged the application domain of these methods.

In all of the examples presented in this Paper, and for any exercise on flight vehicle system identification, it is obvious that the inverse principle is applied to arrive at the model description. To this inverse principle the following remarks by Iliff are most appropriate[183]: "Given the answer, what are the questions?," which in his words is nothing but "We look at the results and try to figure out what situation caused those results." Compared to the classical definition based on the technical aspects by Zadeh,[8] the previous remarks provide the philosophical definition to system identification.

Concluding Remarks

From the nostalgic remembrance of the first dynamic flight test this Paper traces several milestones in the history of flight vehicle system identification. A brief overview is provided of the Quad-M key issues and of the various modern methods of parameter estimation. This Paper demonstrates successful application of system identification methodology to a broad spectrum of flight vehicle modeling problems. The selected examples focus on 1) development and update of databases from flight test data including nonlinear and unsteady aerodynamics for high-fidelity flight or in-flight simulators, for flight control law optimization, or for other applications; 2) identification of a highly augmented unstable aircraft incorporating modern concepts of thrust vectoring and high-angle-of-attack aerodynamics; and 3) interdisciplinary modeling aspects of rigid-body and rotor dynamics for high bandwidth requirements. From the high quality of the results presented in this Paper, and that of the several other applications reported during the recent past, it can be concluded that many of the application areas that were considered as emerging areas a decade ago have now been, more or less, well established; and that the system identification methods have reached a high level of maturity, making them a sophisticated and powerful tool not only for research purposes, but also to support the needs of the aircraft industry. Since the quest for better understanding of aerodynamic phenomena will continue in the future, it can be said that today the scope of flight vehicle modeling will mainly be limited by the imagination and innovative approach of the analyst and little by the methods of parameter estimation.

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