

Review of Aerodynamic Parameter Estimation Techniques

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Abstract: Estimating the aerodynamic derivatives accurately has been the subject matter of research in last several decades. Several methods of parameter estimation are discussed in the literature such as output error, filter error, equation error and artificial neural network based methods. OEM has been most widely used method for linear and non-linear solutions for stable aircraft. FEM has been used for less stable aircraft, turbulent environment and for high angle of attack. Neural network architectures have parallel processing ability that have been used for real time parameter estimation. The technique has been used even when noise levels have been high. Apart from these techniques maximum likelihood (ML), delta and modified delta methods have also been successfully employed. All these techniques with appropriate modifications are found to give useful results within acceptable errors. Attempt is made to critically review the research work of different authors, summarize and compare their results.

Keywords: Parameter estimation, aerodynamic derivatives, maximum likelihood method, output error method, neural network

I. INTRODUCTION

Aerodynamic parameter estimation or estimation of aerodynamic derivatives is the exercise of finding the most suitable partial derivatives of the aerodynamic coefficients with respect to motion variables as well as flight control variables. Partial derivatives of aerodynamic model can be used to represent a system. These parameters are important for the design and development of flight vehicles. They are used to develop flight dynamic model which can be used in flight simulator and control law design, to validate wind tunnel and analytical prediction, to validate design parameters, prediction of full design of the aircraft, deeper understanding of aerodynamic phenomena, verification of system performance and expansion of flight test envelop. In the literature, it is found that there are three ways of determining aerodynamics derivatives of the flight vehicle: theoretical methods, wind tunnel testing and flight testing [1].

In the preliminary stage of design of any system, parameters are estimated theoretically [2-4] with limited accuracy. The accuracy of the estimated parameters can be improved by determining the values of these parameters using wind tunnel testing. Wind tunnel testing is very expensive and time consuming way of determining the values of aerodynamic

derivatives. Accurate simulation of flight vehicle control inputs and power effects of flight conditions is very difficult during the wind tunnel testing. The flight model, which is placed in the wind tunnel for testing, is not similar mostly with actual flight vehicle due to the last minute changes in the configuration. Interference effects due to support system and wall of wind tunnel test section and difference in Reynold number are other reasons of mismatch between the results of wind tunnel and actual flight. It is therefore advantageous to validate parameters which are estimated using the wind tunnel by comparing the results obtained from real flight data.

The most usually used methods for parameter estimation are: Equation error, Output error, Filtering approach, Filter-error and Neural Network based methods. Dynamics of the flight vehicles (system) can be modelled by the state equations, which are known as six degree of freedom equations of motion, as shown Fig. 1.

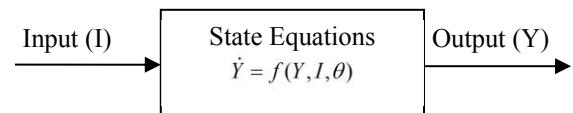


Fig. 1. Dynamic model (system) of a flight vehicle

Three types of the problems are encountered in the dynamics of flight vehicles. (i) Classical problem where unknown output (Y) is determined for a given input (I) and known dynamic model parameters (θ). (ii) Control Problem where control input (I) is determined for the known output (Y) and dynamic model parameters (θ). (iii) System identification problem where unknown parameters (θ) are determined for a given input (I) and output (Y). Unknown parameters are estimated by minimizing the difference between computed and measured output using various parameter estimation methods. There are many approaches for solving system identification problem. All these approaches are strongly depend on the type and amount of a priori knowledge available about the dynamic system. Aerodynamic parameter estimation techniques are the approached of system identification. The concept of parameter estimation for a real flight data is shown in Fig.2.

CFD methods are good techniques for theoretical aerodynamics estimation models which include rigid body modes, flexible body modes and unsteady aerodynamics. Identification of dynamic system supplies sufficient tools to

obtain most reliable dynamic models which are derived from flight data and corroborated in terms of aerodynamic derivatives. CFD methods for predicting and corroborating unsteady aerodynamic and non-linear responses taking into account the aircraft time histories are postulated in [5]. CFD analysis has influenced the scenario largely and positively giving numerical solutions through 'Advanced Euler and Navier Stokes Flow Solver [6-7].

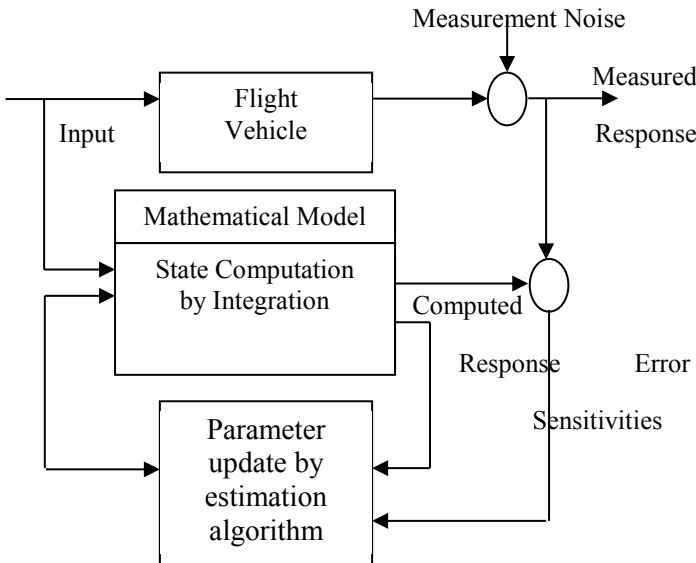


Fig. 2. Concept of parameter Estimation.

Wind tunnel testing is less expensive and has provided huge data for innumerable flight vehicles design. Wind tunnel testing predictions are based on model scaling i.e. geometric similarity and dynamic similarity i.e. Mach no and Reynolds no. Wind tunnel testing has inaccuracies caused due to wall effects, measurement errors and model unsteadiness etc. Errors caused by these methods are eliminated through flight testing, which is expensive but can be undertaken for different flight conditions. Before 1960, the time vector method was utilized for determining aerodynamic parameters using small perturbation method [8-10].

Ref [11] introduced curve fitting method in April 1951. Many researchers at that time used analog matching which had inherent drawback of adjusting the parameters. Digital computer provided capability of self-executing of data processing. This changed the focus of determining aerodynamic derivative using the flight testing data from frequency to time domain methods. As a result, it was practically feasible to estimate all the longitudinal as well as lateral-directional aerodynamic derivatives from the flight of single flight. Ref [12] work is remarkable as it demonstrated that flight recording systems can be used for estimating stability and control parameters.

Flight testing is most significant part of validating the parameters estimated through wind tunnel and analytical

methods. Designing optimum input, proper instrumentation, selecting time or frequency domain help in investigation of mathematical modeling. This process was termed as Quard- M requirement i.e. maneuver measurement, methods and models by [13] in 1962

II. CLASSIFICATION OF DIFFERENT APPROACHES RESEARCH WORK OF LAST THREE DECADES

Ref. [14] and Ref. [15] researched the subject of optimal input design for parameter estimation before 1980. Their designs were based on 'priori' models. Better 'priori' models' resulted in better estimation and vice versa. From their experience it became clear that it is better to design general procedure for different type of flight vehicles and also design a suitable data acquisition system. Ref. [16] designed a digital data acquisition system and tested it on Schweitzer 2-32 sailplane. It had on board computer and sensor system to take measurements of flight variables and to process them in real time.

Ref. [17] used maximum likelihood method for non-linear systems. The method represented normal formulation for a dynamic system. The process is investigated at regular intervals of time. Subsequent observations are recorded at predecided time intervals and [Ref 17] are used to estimate the aircraft parameters from real flight data. In this method, cost function is minimized by reducing difference between measured response and computed response. Validation of estimates is also presented with their Cramer-Rao bound values. Ref. [18] used line search algorithm in Gauss -Newton method for obtaining maximum reduction in cost function and Ref. [19] used filter error method and extended Kalman filter for estimation of aerodynamic parameters for unstable aircraft under turbulent conditions because of their excellent filtering ability.

Ref [20] and Ref. [21] Output error method (OEM) is widely used algorithm for estimation of aircraft parameters. They brought out that considering only the measurement noise simplifies the algorithm. In earlier times, OEM was used only for linear systems. And it was a normal method for determining parameters of dynamic models of aircraft during post-flight analysis. This became possible due to its characteristics of favourable asymptotic properties, realistic assumptions relevant with real flight test conditions as well as a practical approach which had been tested and improved upon using various alternative methods. Ref. [22] presented their work for stability and control of dynamic systems using neural network. They demonstrated that neural network can be applied on non-linear static and dynamic systems for parameter estimation. Models are multilayer and recurrent neural networked in different configurations. Simulation results show identification and adaptive controlled schemes are feasible.

Ref. [23] applied wind tunnel simulation technique for estimating aerodynamic derivatives of longitudinal motion as well as lateral motion using delta wing model. Wind tunnel tests are conducted for all three rotational degrees of freedom about the body axes of model. Tests input are applied to excite the model in these three modes of pitch, roll and yaw. Characteristic motion of the model was analysed for extracting derivative data. Results showed good comparison with conventional methods of wind tunnel tests of free oscillation rig and forced oscillation rig. Ref. [24] developed global non-linear parametric modelling using multi-variate orthogonal function. A minimum squared-error criterion was used to determine which orthogonal function should be retained. Each orthogonal function was decomposed in ordinary polynomial for independent variable so that final model could be selectively retained from the power series. The model is tested on F-18 aircraft at high angle of attack. The model showed good predictive capability, global validity and deeper insight in non-linearity functions.

Ref. [25] applied the global non-linear parametric modeling technique for F-16 aerodynamics. Multi variate function was used for generating modeling polynomial, for testing non dimensional aerodynamics, force and moment components for F-16 aircraft at high angle of attack. The results showed 10 % difference between wind tunnel and predicted values. Ref. [26] used neural networks for aerodynamic modeling and parameter estimation for aero-elastic aircraft. Neural model developed was able to predict generalized coefficients (force and moment) from measured flight variables. Furthermore, it is shown that such a neural model can be used for estimating aerodynamic parameters of a flexible aircraft. Results of aircraft with different levels of flexibility are presented.

Ref. [27] presented a review report of research work of a decade at DLR, German Aerospace Center which described different methods of parameter estimation and their procedures in recording flight data. Authors brought out the necessity of high fidelity global aerospace database for training simulators, models for real time on board simulators and developing models for stall hysteresis. Ref. [28] brought out in their survey report several examples of research work done at Dryden Flight Research Centre using output error method, listing statistical properties and computational steps. Their work established that OEM is natural 'estimator' of error function for estimating aerodynamic parameters for stable aircraft.

Ref. [29] presented survey report of research activities on system identification for aircraft undertaken at Langley Research Center (LaRC) in the recent past and outline of ongoing as well as future work. Authors identified the necessity of parameter estimation in real time, flying qualities, design features and modelling needs.

Ref. [30] estimated aerodynamic parameters from flight data for X-43A hypersonic research vehicle. This flight vehicle is also called Hyper-X. These flight tests included maneuvers using orthogonal optimized sweep inputs. They also used simultaneous control surface perturbations at Mach numbers varying from 3 to 8 during the vehicle maneuvers. Longitudinal, lateral stability and controls were estimated from data so measured during the flight at different Mach numbers. Different inputs were given at same flight condition to estimate prediction capability of these identified models. Prediction errors were found to be comparable with modelling errors. Results obtained from wind tunnel testing and computational fluid dynamics were utilized for final estimation of aerodynamic parameters. These results were compared with pre-flight aerodynamic database which showed good agreement between flight estimated and computed values. Ref. [31] describes the problem of Flight Path Reconstruction (FPR) using output-error and the Levenberg-Marquardt optimization algorithm. FPR is important step towards the aircraft design and evaluation process. This technique was used to obtain aerodynamic parameters of a jet aircraft from flight data which contained noise as well as bias. Results of flight tests are reported. Real time estimation reduces analysis time and costs for identifying dynamic models from flight test records. Real time modeling feedback can help in diagnosing problems in shortest time while the aircraft is still in flight. Ref. [32] proposed neural network based modified delta method for estimation of aerodynamic parameters from real flight data of missile and aircraft. Feed Forward Neural Network (FFNN) based methods are being used very often for estimation of aerodynamic parameters. Authors have presented Modified Delta method which draws its strength from FFNN based Delta method for estimating the parameters. The differential aerodynamics, i.e. coefficient of force and moments are used for training the neural network as outputs and the flight variables of aircraft as inputs. The modified input file is presented to the trained neural network for processing the output. A proper understanding and use of such network input-output files provides the values of aerodynamic derivatives. The Modified Delta method shows better estimates than those obtained using delta method.

Ref. [33] estimated aircraft parameters using equation error method. EEM does not require integration process, so it is suitable for stable and unstable aircraft. The technique of linear regression of the unknown parameter is employed. Experimental results using flight data for lateral directional maneuver are presented and discussed. For removing the instrument biases data has been preprocessed. Initial state conditions are established using output error and Levenburg-Marquardt method.

They are able to reduce the mismatch between the measured and predicted outputs within acceptable limits. Ref. [34] presented parameter estimation of aircraft and short range missiles using flight data. The linear aerodynamic models are

inadequate for short distance and dynamic missiles. The presence of noise has increased complexity and computational time. The authors estimated aerodynamic derivatives of a short range missile from simulated and wind tunnel data. Wind tunnel data was generated to estimate the priori fix of model including force and moment coefficients. Identification techniques were used to capture the normal form of the aerodynamic model. The estimation algorithm assumes that aerodynamic model identified by the wind tunnel testing is exact while applying the ML method. Whereas, Delta method used measured flight data as input to the FFNN and aerodynamic coefficient (force or moment) as output for training FFNN, it resulted in large scatter estimates. Thereupon this method was modified to change the training strategy. This gave good estimates with less errors and was called Modified Delta Method. The estimations were further improved using flight data having measurement noise.

Ref. [35] used extended Kalman Filter method, which is a mostly used algorithm for recursive parameter identification for aerospace systems because of its superior filtering qualities and is based on a first order approximation. For nonlinear filtering, Unscented Kalman Filter (UKF) is used as an alternative method to the EKF method. The UKF and the augmented version of the UKF employed have given fastest convergence. Rotary wing UAV (ARTIS) and fixed wing aircraft (HFB-320) is considered for the estimation of parameters. The results as estimated by the three algorithms are comparable. Ref. [36] estimated aerodynamic derivatives at high angle of attack and used flight data of the aircraft. Quasi-steady stall model (QSSM) is developed and applied to flight data of HANSA-3 aircraft for longitudinal dynamics at near stall condition. Due to high correlation existing between the aerodynamic derivatives, the wind tunnel results were used as priori fix to compute longitudinal derivatives through QSSM model at near stall condition. The aerodynamic derivatives estimated through QSSM model are very close to the derivatives estimated from measured data. Some deviations are shown to occur due to the distorted orientation of the sensors.

Ref. [37] used ML method to estimates derivatives instead of OEM and EEM in the frequency domain from the flight data. ML is an unbiased estimation method which is based on maximum probability of initial guess value of estimates. The procedure for flight test is discussed and many flights tests results are analysed, discussed and presented. It was shown that the OEM and equation-error method in frequency domain are in statistical agreement. Ref. [38] applied OEM parameter estimation technique to the problems, which are associated with the real time modelling of the dynamic system. Errors of these algorithms were investigated with the goal of making the method appropriate for the operation in real-time. Results showed that accurate value of estimates and uncertainties for the dynamics model of short period were updated every 2 second for the time domain data, or every 3 second for

frequency domain data. The importance and results of data compatibility check, which is used to remove error in the flight data, is also discussed and presented.

Ref. [39] brought out a new formulation of the filter error method for estimation of parameter in turbulent aerodynamic flows. They developed and demonstrated the non-linear aircraft dynamic model during turbulence. Approach used estimation of measurement noise covariance to identify the model parameter, their uncertainties and process noise covariance. Priori fix was used and post estimation correction was applied to the coloured residuals, the method was used in simulation on NASA generic transport aircraft. It was also tested on T-2 jet engine aircraft to demonstrate the efficacy of the method. Ref. [40] proposed modified delta (MD) method base on neural network for parameter estimation of the aeroelastic aircraft from the measured data. The network is trained using variation (differential) in flight variable (motion and control) as the network input and outputs respectively. Lavenberg-Marquardt Back Propagation is used to train the network. A corrected input file is given to the network to train it and to obtain the computed output file of coefficients (force and moment). A proper understanding and necessary manipulation of such input-output files provides estimated value of arodynamic derivatives. The method is applied on the simulated flight data of two configurations of an aero-elastic aircraft for the parameter estimation. The same technique is applied to validate the estimated aerodynamic derivatives. The results show Feed Forward Neural Network based Modified Delta method can easily be applied for estimation of parameters of aero-elastic aircraft.

III. CONCLUSIONS

The process of representing a flying vehicle with a dynamic model for estimating the aerodynamic parameters has been studied and reviewed for 40 research papers. The researchers have employed various methods, such as frequency and time domain approaches and estimated parameters for different flying vehicles. OEM has been employed for stable aircraft and steady state conditions. EEM do not require solution of partial differential equations, so these have been used for stable and unstable aircraft. EKF and UKF have given good results for high angle of attack, unsteady and turbulent conditions because of their excellent filtering abilities. OEM has been used for Flight Path Reconstruction (FPR) using Levenberg Marquardt optimization algorithm. Stall characteristics have been established by developing QSSM models. Parameters have been estimated in subsonic, supersonic and hypersonic flight conditions using multi step perturbations. Various other methods used are dynamic wind tunnel testing, maximum likelihood, delta and modified delta. The neural network methods have shown great advantage that these methods do not require solution of partial differential equations. These methods are faster in convergence due to their ability for parallel processing and are useful for real time analysis. The future challenge lies in estimating parameters in

real time for subscale flying vehicles, models, multi-copter of less rigid configurations where structural deformations cause non linearity beyond acceptable level of errors.

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