Estimation of lateral-directional parameters using neural networks based modified delta method

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ABSTRACT

The aim of the study described herein was to develop and verify an efficient neural network based method for extracting aircraft stability and control derivatives from real flight data using feed-forward neural networks. The proposed method (Modified Delta method) draws its inspiration from feed forward neural network based the Delta method for estimating stability and control derivatives. The neural network is trained using differential variation of aircraft motion/control variables and coefficients as the network inputs and outputs respectively. For the purpose of parameter estimation, the trained neural network is presented with a suitably modified input file and the corresponding predicted output file of aerodynamic coefficients is obtained. An appropriate interpretation and manipulation of such input-output files yields the estimates of the parameter. The method is validated first on the simulated flight data using various combinations and types of real-flight control inputs and then on real flight data. A new technique is also proposed for validating the estimated parameters using feed-forward neural networks.

NOMENCLATURE

a_{ym}	measured acceleration along y body axis
C_l, C_n	coefficient of rolling and yawing moment
$C_{l(.)}$, $C_{n(.)}$, $C_{y(.)}$	nondimensional derivatives
C_y	coefficient of lateral force
g	acceleration due to gravity
I_x, I_y, I_z	moments of inertia about x, y, and z axis
I_{xz}	cross product of inertia
m	mass of aircraft
p, q, r	roll, pitch, and yaw rates
$\dot{p}$, $\dot{q}$, $\dot{r}$	roll, pitch, and yaw accelerations
$\bar{q}$	dynamic pressure
s	half the wing span
S	reference wing area
u,v,w	velocity component along x, y, z body axes
V	airspeed
α, β	angle-of-attack and angle of side-slip
δ_a, δ_r	aileron and rudder deflections
ϕ, θ	bank and pitch angles
ρ	air density

Superscript

$(\dot{})$	derivative with respect to time

1.0 INTRODUCTION

A new thrust area is emerging in the area of aircraft aerodynamic modeling and parameter estimation: development of techniques using artificial neural networks (ANN) for flight vehicle identification. Recently ANN modeling has been attempted for aircraft dynamics where aircraft motion variables and control inputs are mapped to

Paper No. 3150. Manuscript received 15 November 2006, revised 23 May 2007, accepted 22 August 2007.

https://doi.org/10.1017/S0001924000004838 Published online by Cambridge University Press

predict the total aerodynamic coefficients[1-4]. In the past, the most widely used parameter estimation methods have been equation error methods, output error methods and filter error methods. Applications of these methods require *a priori* postulations of an aircraft model. On the other hand, a class of neural networks called the feed forward neural networks (FFNNs) work as a general function approximators, and are capable of approximating any continuous function to any desired accuracy by an appropriate network structure[5]. This ability of FFNNs has been utilized to model aircraft dynamics. However, the FFNNs lead to a black-box type of modelling wherein no physical significance can be attached to either the network structure or the network weights[2].

The recent interest in, and fascinating with the evolving applications of ANNs to diverse fields such as signal processing, pattern recognition, system identification and control have led many researchers to explore their capabilities for aircraft aerodynamic modeling and estimation of aerodynamic coefficients (stability and control derivatives). Significant contributions have been made in this direction by Hess[1], Linse and Stengel[3], Youseff and Juang[4], and Raol and Jategaonkar[6]. In all these papers, the emphasis has been on aerodynamic modeling and estimation of aerodynamic coefficients using FFNNs, without any attempt to estimate aircraft parameters as conventionally defined in terms of stability and control derivatives in the equations of motion of an aircraft. Raol and Jategaonkar[6] have used the recurrent neural network (RNN) to model aircraft aerodynamics in a way that allows aircraft parameters to be estimated from flight data. However, as the authors[6] pointed out, RNNs have only a limited scope for aircraft identification applications and it is the FFNNs which may prove to be more flexible, and thereby to have a higher potential for future applications for aircraft identification and parameter estimation.

Only recently, Raisinghani, Ghosh and Kalra[7,8] proposed two new methods for explicitly estimating aircraft parameters from the flight data using FFNNs. The results obtained for simulated flight data and real flight data have shown the success and the potential of the proposed methods. It was further shown that the number of estimated values for each of the parameters was equal to the number of data points used for training the network[7,8]. For real flight data, in addition to training being less than perfect, the parameters may not be strictly constant, i.e., the parameters may vary slightly with other motion and control variables. Furthermore, all of the corrections and axes transformations done on the data would introduce their own uncertainties. All these factors, contribute toward different estimates at different time points[7,8]. However, a near normal distribution of the estimated values may be observed for most of the parameters[7,8]. For calculating standard deviation of the estimates, the estimated parameters were first arranged in descending/ascending order then 25% of the estimates were removed from both the ends of the order set before calculating the mean and sample standard deviations[7,8]. One of the reasons responsible for getting different estimates at different time point through the Delta method is attributed to training being less than perfect[7,8]. One of the area of interest to improve training includes approaches to modify the optimisation method. There are several possible techniques, including the more advanced Marquardt-Lavenberg algorithm[9-11]. The Marquardt-Lavenberg algorithm provides a numerical solution to the mathematical problem of minimising a function, generally non-linear, over a space of parameters of the function. The performance of the standard back- propagation (BP) algorithm is determined by the step size (learning rate) μ. A very small value generally leads to extremely slow convergence. On the other hand, larger values can lead to parasitic oscillations, particularly when the cost function has sharp peaks and valleys[11]. Modified Back-Propagation (BP) algorithm proposed by Scalero and Tepedelenlioglu[12] overcomes these difficulties. Modified BP algorithm results from minimisation of the mean squared error with respect to the summing junction outputs. This is in contrast to the standard BP procedure that minimises the mean square error with respect to weights. There exist many types of feed forward neural networks in the literature, for example multilayer perception (MLP), radial basis function (RBF) networks[13, 14] etc. Among them is the RBF network which is considered a good candidate for approximation problem because of faster learning capability compare to other feed forward networks[13]. Continuing research in the direction of improving training by modifying the optimisation method, a sequential learning algorithm for realising a minimal radial basis function neural networks was proposed in Refs 15 and 16. This algorithm augments the growth criterion of the resource-allocation network via Extended Kalman Filter (RANEKF) and combines with it a scheme to resume these hidden units that make insignificant contribution to the output of the network. In modeling complex non linear dynamic, the use of the state dependent autoregressive (AR) model with functional coefficient is recommended in Ref. 17. Radial basis function — autoregressive (RBF-AR) model[18] has the advantage of both the state-dependent AR model for nonlinear dynamics and of RBF networks in function approximation[17]. An extension of RBF-AR was proposed in Ref. 17, namely RBF-ARX models which used far fewer RBF centres when compared with a single RBF network model. It may be appreciated that the main advantage and strength of FFNN modeling is in its ability to capture highly nonlinear complex phenomena in a global sense, for which we may not be in a position to postulate model with physical understanding. In such cases only will the advantages of FFNN be fully exploited. The methods described through Refs 9 to 18, are expected to be more effective in handling typical nonlinear aerodynamic models. In the present work, the flight data did not have classical nonlinear components. Further, the Modified Delta method is expected to locally linearise a not so highly nonlinear aerodynamics while estimating the parameters. The use of methods[9-18] is expected to improve the effectiveness of both the Delta method and the Modified Delta method. In the present work, the relative advantage of Modified Delta method over the Delta method is explored. No attempts were made to introduce modified learning schemes[9-18] in the present study.

In order to obtain estimates with lower standard deviation (higher confidence) from flight data, improved Delta method for estimating aircraft parameters from flight data using FFNNs is proposed. A careful look into the Delta method proposed in Ref. 7 revels that it does not suggest any procedure for validating the estimates by comparing estimated response (with the help of estimated parameters) with the flight generated response (real flight data) for a known control input, other than used for generating real flight data for parameter estimation purpose. In this paper in addition to improving the Delta method, a procedure based on FFNNs is also proposed to validate the method using measured flight variables. The proposed method is first validated on simulated lateral-directional flight data. The final validation is done on real flight data of ATTAS aircraft supplied by DLR Germany. The results show that the proposed improved Delta method (Modified Delta method) has good potential to improve the utility of the Delta method for parameter estimation. Further, the proposed procedure of validating the Delta method using FFNN will increase its acceptability for practicing engineers for field applications. The results show that the proposed method has good potential as alternative tools for parameter estimation from flight data. Many conventional methods (e.g. the output error, the maximum likelihood, the filter error etc.) need a reasonable guess of parameter values to be used as starting values by such algorithm[19]. In contrast, the proposed Modified Delta method when compared to the Delta method yields estimates with lower standard deviation (higher confidence). Further and more importantly, the proposed procedure of validating the Modified Delta method using FFNN make it in true sense, a method which does not at all require solving of equations of motion for parameter estimation and validation using flight data.

2.0 MODIFIED DELTA METHOD

The Delta method[7,8,20] is based on the understanding of what a stability/control derivatives stands for; the stability/control derivatives represent the variation in the aerodynamic force or moment coefficients caused by a small variation in one of the motion/control

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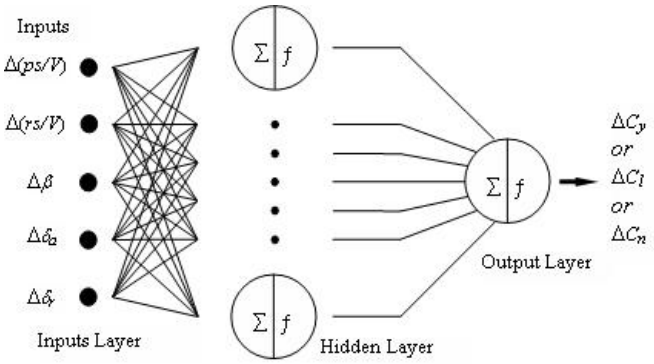


Figure 1. Schematic of feed forward neural network for proposed aerodynamic modelling.

variables about the nominal value, whereas all of the other variables are held constant. For example, C_{y_β} represents a variation in C_y with respect to β, whereas all other variables (ps/V, rs/V, δ_a and δ_r) are held constant. Let us consider an estimation of C_{y_β} via the Delta method. For this purpose, the neural network is first trained such that the network input variables (ps/V, rs/V, β, δ_a and δ_r) are mapped to C_y. Next, a modified network input file is prepared wherein β values at each time point are perturbed by ±Δβ while all of the other variables retain their original values. This modified file is now presented to the trained network and the corresponding predicted values of the perturbed C_y (C_y^+ for β + Δβ and C_y^- for β − Δβ) are obtained at the output node. Now, the stability derivative C_{y_β} is given by $C_{y_\beta} = (C_y^+ - C_y^-)/2\Delta\beta$. Similarly perturbing only, say δ, in the network input file will yield the control derivative C_{y_δ}. In application of the Delta method, it was observed that the estimated parameters showed large spread in their numerical values. It was conjectured that a less than perfect match between the actual and the predicted values of aerodynamic coefficients is primarily responsible for observed spread in the estimated values. The present work makes an attempt to evolve a scheme to estimate aerodynamic parameters with less scatter in the numerical values by modifying the Delta method proposed in Refs 7 and 8. The utility and advantage of the modified Delta method is presented in Ref. 21. In order to reduce the scatter in the estimates, the Delta method was modified (Modified Delta method) by establishing a neural map between differential variations of input variables (ΔX_1, ΔX_2, and ΔX_3) and the differential variations of output variables (ΔO_1 and ΔO_2).

The proposed Modified Delta method is based on interpreting the stability and control derivatives as follows: If we could obtain variation in the value of an aerodynamic coefficient due to variation in only one of the motion/control variables while the variation in other motion/control variables are identically zero, then the ratio of the variation of the aerodynamic coefficient to variation of the non-zero motion/control variable will yield the corresponding stability/control derivative. Let us say that the FFNN is trained to map differential variations in input variables, ($\Delta(ps/V)$, $\Delta(rs/V)$, Δβ, $\Delta\delta_a$ and $\Delta\delta_r$) to the network output variable (variation), ΔC_y. Now one input (say Δβ) at a time is chosen to be at its original value while the rest of the network inputs ($\Delta(ps/V)$, $\Delta(rs/V)$, $\Delta\delta_a$ and $\Delta\delta_r$) are set to zero. The predicted value of the aerodynamic coefficient ΔC_y corresponding to such a modified file is divided by the non-zero variation in motion variable (Δβ) to yield the corresponding stability/control derivatives, C_{y_β}. Similarly, all the parameters can be estimated by suitably modifying the input file. Figure 1 schematically represents the training strategy for application of the Modified Delta method using FFNN.

A detail study was carried out for a few sets of simulated data to understand the influence of various network parameters on training and prediction capability. A matrix of tuning parameters such as the number of hidden layers, the number of nodes in each of the hidden layer(s), the learning rate, the momentum rate, the logistic gain factor of the sigmoidal function, the initial network weights, and the scaling of input-output data was generated, wherein each parameters were varied with in a prescribed range[1-3], and the network was trained to arrive at the best possible set that led to minimum MSE for the given flight data. The final set of tuning parameters is chosen as follows: number of hidden layers = 1, number of neurons in the hidden layers = 5, learning rate = 0·3, momentum rate = 0·5 logistic gain = 0·85 and number of iterations = 1,200. After the training, the same input data are passed to check the prediction capability of the network. The predicted aerodynamic coefficients are deemed acceptable only if the MSE is less than the specified value. Once the network is trained satisfactorily, to map network input variables ($\Delta(ps/V)$, $\Delta(rs/V)$, Δβ, $\Delta\delta_a$ and $\Delta\delta_r$) to each of the network output variables (ΔC_y, ΔC_l, and ΔC_n), it is then used for estimation of lateral-directional stability and control derivatives by using the Modified Delta method discussed earlier.

3.0 SCHEME TO VALIDATE DELTA METHOD USING MEASURED FLIGHT VARIABLES

The standard procedure to validate aircraft parameter estimation method is to compare the estimated response (generated with estimated parameters) with the flight measured response generated with control input other than used for estimation purpose. Only way to validate by comparing motion variables, generated using new control input, would require solving of equations of motion. In this paper a scheme using FFNN to validate the proposed Modified Delta method by comparing flight measured variables generated using different control inputs (not used for estimation) is presented. This proposed scheme does not require solving of equations of motion for validation. As the first step, the lateral-directional parameters (C_{y_p}, C_{y_r}, C_{y_β}, $C_{y_{\delta a}}$, $C_{y_{\delta r}}$, C_{l_p}, C_{l_r}, C_{l_β}, $C_{l_{\delta a}}$, $C_{l_{\delta r}}$, C_{n_p}, C_{n_r}, C_{n_β}, $C_{n_{\delta a}}$ and $C_{n_{\delta r}}$) are estimated by applying Modified Delta method on flight data generated by a known control inputs (say δ_{a_1}, δ_{r_1}). For training, a neural mapping between input vector containing time histories of $(p_1 s/V)_t$, $(r_1 s/V)_t$, $(\beta_1)_t$, $(\delta_{a1})_t$, $(\delta_{r1})_t$, $(C_{y1})_t$, $(C_{l1})_t$, $(C_{n1})_t$ and the output vector containing $(p_1 s/V)_{t+1}$, $(r_1 s/V)_{t+1}$, $(\beta_1)_{t+1}$ is established using back propagation algorithm (BPA) as shown in Fig. 2(a).

The numerical value of $(C_{y1})_t$, $(C_{l1})_t$, and $(C_{n1})_t$ can be computed by plugging flight measured values of motion variables and inertia characteristics of aeroplanes[22] in the following equations:

$$C_{y_1} = (m/\bar{q}S)\left[a_{ym} - (p_1 q_1 + \dot{r}_1)X_a + (r_1^2 + p_1^2)Y_a - (r_1 q_1 - \dot{p}_1)Z_a\right] \quad \ldots (1)$$

$$C_{l_1} = (1/\bar{q}Ss)\left[\dot{p}_1 I_x - \dot{r}_1 I_{xz} - p_1 q_1 I_{xz} + p_1 r_1 (I_z - I_y)\right] \quad \ldots (2)$$

$$C_{n_1} = (1/\bar{q}Ss)\left[\dot{r}_1 I_z - \dot{p}_1 I_{xz} + q_1 r_1 I_{xz} - p_1 q_1 (I_x - I_y)\right] \quad \ldots (3)$$

where X_a, Y_a and Z_a denote accelerometer offset distances from the centre of gravity of the aircraft.

Once the training has been established by satisfying the MSE criteria, a new set of flight data is generated for validation using a different control input(s), say δ_{a_2} and δ_{r_2}, other than used for estimation purposes. The weights estimates during the training is kept fixed for prediction using measured data obtained through control inputs δ_{a_2} and δ_{r_2}. The motion variables $p_2 s/V$, $r_2 s/V$, β_2 and control inputs δ_{a_2} and δ_{r_2} are recorded. However, the estimated numerical value of C'_{y_2}, C'_{l_2}, C'_{n_2} are computed using estimated values of parameters through the following equations:

$$C'_{y_2} = C_{y_p}(p_2 s/V) + C_{y_r}(r_2 s/V) + C_{y_\beta}\beta_2 + C_{y_{\delta a}}\delta_{a_2} + C_{y_{\delta r}}\delta_{r_2} \quad \ldots (4)$$

$$C'_{l_2} = C_{l_p}(p_2 s/V) + C_{l_r}(r_2 s/V) + C_{l_\beta}\beta_2 + C_{l_{\delta a}}\delta_{a_2} + C_{l_{\delta r}}\delta_{r_2} \quad \ldots (5)$$

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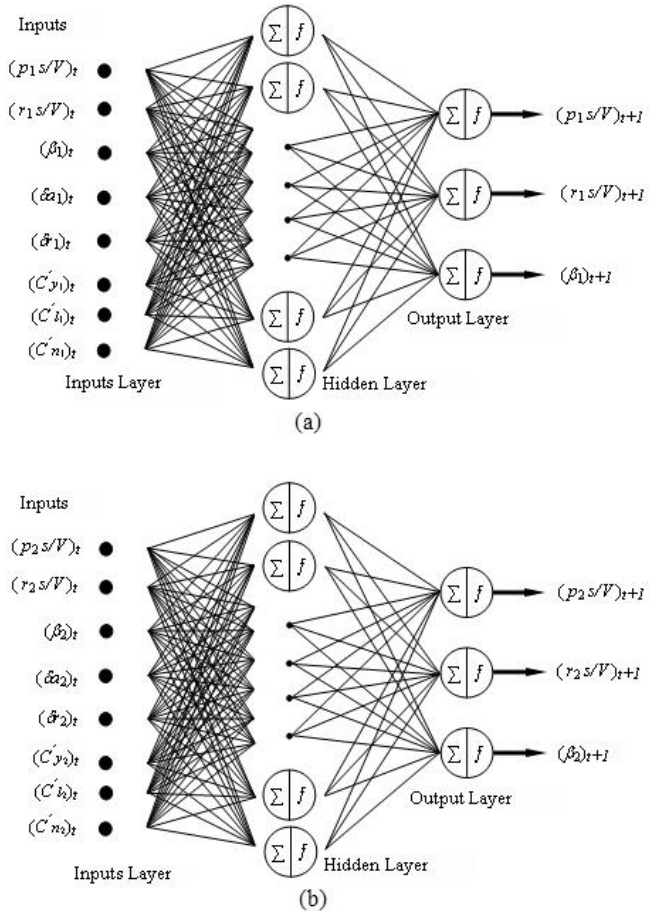


Figure 2. Scheme for validation of proposed method using FFNN; (a) training, (b) validation.

$$\dot{\beta} = -r + (g/V)\mathrm{Sin}\phi + (\bar{q}S/mV)C_y \quad \ldots (6)$$

The already FFNN trained neural model is used to predict motion variables $(p_2 s/V)_{t+1}$, $(r_2 s/V)_{t+1}$, and $(\beta_2)_{t+1}$ corresponding to new control input vector containing time histories of $(p_2 s/V)_t$, $(r_2 s/V)_t$, $(\beta_2)_t$, $(\delta_{a_2})_t$, $(\delta_{r_2})_t$, $(C'_{y2})_t$, $(C'_{l2})_t$, and $(C'_{n2})_t$ as shown in Fig. 2(b). The estimated responses of $(p_2 s/V)_{t+1}$, $(r_2 s/V)_{t+1}$, $(\beta_2)_{t+1}$ are then compared with the measured responses of $(p_2 s/V)_{t+1}$, $(r_2 s/V)_{t+1}$, $(\beta_2)_{t+1}$ generated using control inputs δ_{a_2} and δ_{r_2}.

4.0 GENERATION OF SIMULATED FLIGHT DATA

Because real-flight data was made available for the DLR research aircraft, advanced technology testing aircraft system (ATTAS)[22], it is found expedient to generate simulated data using flight control input for the same aircraft. Detail of the aircraft mass, moment of inertia, geometric characteristics, etc., are given in Ref. 22. The six-degree-of-freedom equations of motion[22] in a body-fixed axes system are first reduced to three-degree-of-freedom equations of motion pertaining to the lateral-directional dynamics, and then solved using the fourth-order Runga-Kutta method to generate simulated flight data for various types of aileron and/or rudder control inputs. The following decoupled lateral-directional equations of motion have been used:

$$\dot{p} = \bar{q}Ss\left(I_z C_l + I_{xz} C_n\right) \Big/ \left(I_x I_z - I_{xz}^2\right) \quad \ldots (7)$$

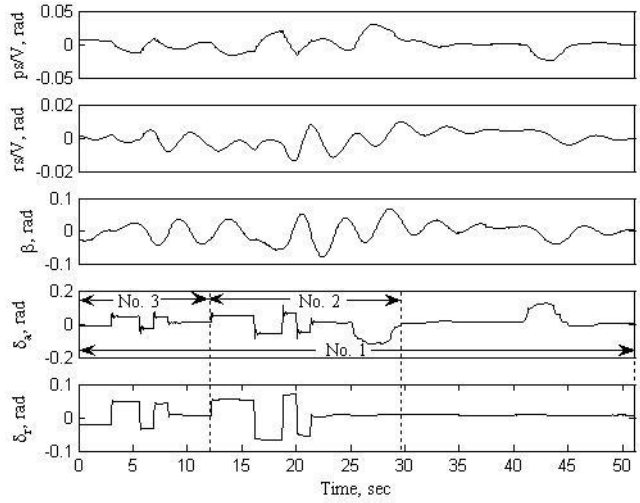


Figure 3. Real flight data supplied by DLR for V_{IAS} = 160 knots.

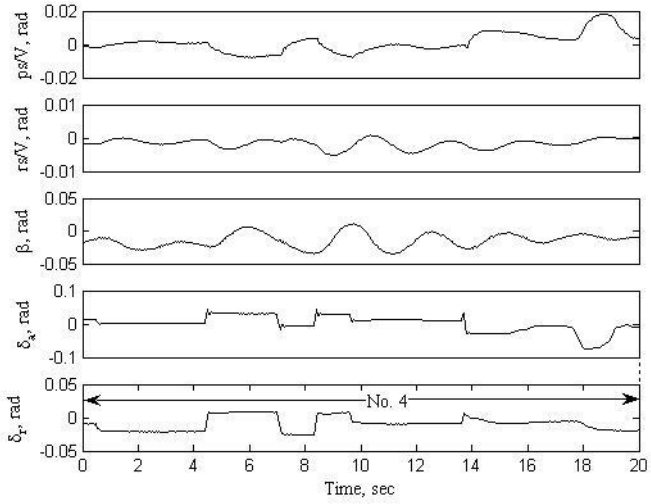


Figure 4. Real flight data supplied by DLR for V_1 = 250 knots.

$$\dot{r} = \bar{q}Ss\left(I_x C_n + I_{xz} C_l\right) \Big/ \left(I_x I_z - I_{xz}^2\right) \quad \ldots (8)$$

$$\dot{\phi} = p \quad \ldots (9)$$

$$C_y = C_{y_p}(ps/V) + C_{y_r}(rs/V) + C_{y_\beta}\beta + C_{y_{\delta a}}\delta a + C_{y_{\delta r}}\delta r \quad \ldots (10)$$

where $\bar{q} = \rho V^2/2$ and

$$C_y = C_{y_p}(ps/V) + C_{y_r}(rs/V) + C_{y_\beta}\beta + C_{y_{\delta a}}\delta a + C_{y_{\delta r}}\delta r \quad \ldots (11)$$

$$C_l = C_{l_p}(ps/V) + C_{l_r}(rs/V) + C_{l_\beta}\beta + C_{l_{\delta a}}\delta a + C_{l_{\delta r}}\delta r \quad \ldots (12)$$

$$C_n = C_{n_p}(ps/V) + C_{n_r}(rs/V) + C_{n_\beta}\beta + C_{n_{\delta a}}\delta a + C_{n_{\delta r}}\delta r \quad \ldots (13)$$

The flight condition defined by a landing flap deflection δ_f = SP (1deg), and indicated airspeed V_{IAS} = 160kt and V_{IAS} = 250kt was chosen for generating simulated flight data because the real flight data for the same flight condition were also available for analysis[22]. The estimated values of parameters reported in Ref. 22 were used as the true values of the parameters for solving the equations of motion and subsequently preparing the network input file ($\Delta(ps/V)$, $\Delta(rs/V)$,

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Table 1
Parameter estimates from simulated flight data using real flight control input

Parameter	V_{IAS} = 160kt					V_{IAS} = 250kt		
	Ref. 22	Case 1		Case 2		Ref. 22	Case 3	
	True value	DM	MDM	DM	MDM	True value	DM	MDM
$-C_{l_p}$	0·978	0·9779 ($2·3e^{-04}$)+	0·9780 ($7·0e^{-05}$)+	0·9779 ($6·1e^{-04}$)	0·9779 ($4·5e^{-04}$)	1·014	1·0139 ($5·2e^{-04}$)	1·0140 ($2·6e^{-05}$)
C_{l_r}	0·418	0·4180 ($3·9e^{-05}$)	0·4180 ($7·7e^{-05}$)	0·4180 ($3·6e^{-04}$)	0·4179 ($2·2e^{-04}$)	0·319	0·3190 ($4·7e^{-04}$)	0·3190 ($6·4e^{-05}$)
$-C_{l_\beta}$	0·126	0·1260 ($3·0e^{-04}$)	0·1260 ($1·6e^{-05}$)	0·1260 ($1·3e^{-04}$)	0·1260 ($1·1e^{-05}$)	0·116	0·1160 ($6·6e^{-05}$)	0·1159 ($1·9e^{-04}$)
$C_{l_{\delta a}}$	0·247	0·2469 ($56e^{-06}$)	0·2470 ($3·4e^{-06}$)	0·2469 ($1·7e^{-04}$)	0·2470 ($6·3e^{-05}$)	0·256	0·2559 ($1·3e^{-04}$)	0·2562 ($1·7e^{-03}$)
$C_{l_{\delta r}}$	0·046	0·0460 ($2·6e^{-05}$)	0·0459 ($7·5e^{-06}$)	0·0460 ($2·0e^{-04}$)	0·0460 ($2·6e^{-05}$)	0·043	0·0430 ($7·3e^{-04}$)	0·0431 ($4·8e^{-05}$)
$-C_{n_p}$	0·115	0·1150 ($6·6e^{-04}$)	0·1150 ($1·9e^{-05}$)	0·1150 ($1·5e^{-04}$)	0·1151 ($1·0e^{-04}$)	0·049	0·0492 ($3·3e^{-03}$)	0·0490 ($1·1e^{-04}$)
$-C_{n_r}$	0·495	0·4949 ($3·9e^{-04}$)	0·4950 ($1·9e^{-05}$)	0·4949 ($1·1e^{-03}$)	0·4950 ($5·2e^{-04}$)	0·599	0·5988 ($4·6e^{-03}$)	0·5989 ($3·7e^{-04}$)
C_{n_β}	0·281	0·2810 ($1·1e^{-05}$)	0·2810 ($4·0e^{-06}$)	0·2811 ($2·4e^{-04}$)	0·2810 ($2·3e^{-05}$)	0·284	0·2839 ($1·4e^{-03}$)	0·2839 ($1·1e^{-03}$)
$C_{n_{\delta a}}$	0·0	$-4·8e^{-06}$ ($1·1e^{-06}$)	$5·8e^{-06}$ ($1·8e^{-06}$)	$-1·0e^{-06}$ ($8·7e^{-06}$)	$2·1e^{-05}$ ($1·7e^{-04}$)	0·0	$6·5e^{-06}$ ($3·8e^{-04}$)	$1·0e^{-04}$ ($1·0e^{-03}$)
$-C_{n_{\delta r}}$	0·166	0·1660 ($6·7e^{-06}$)	0·1660 ($1·8e^{-06}$)	0·1660 ($2·0e^{-05}$)	0·1660 ($9·5e^{-04}$)	0·169	0·1690 ($1·1e^{-03}$)	0·1690 ($4·1e^{-05}$)
C_{y_p}	0·303	0·3031 ($2·7e^{-04}$)	0·3030 ($3·8e^{-04}$)	0·3031 ($8·0e^{-03}$)	0·3030 ($2·4e^{-04}$)	0·207	0·2071 ($9·3e^{-04}$)	0·2072 ($3·3e^{-04}$)
C_{y_r}	0·727	0·7267 ($4·4e^{-04}$)	0·7270 ($4·1e^{-04}$)	0·7267 ($1·0e^{-02}$)	0·7267 ($3·0e^{-04}$)	0·110	0·1099 ($8·5e^{-04}$)	0·1101 ($4·6e^{-04}$)
$-C_{y_\beta}$	1·333	1·3333 ($1·4e^{-04}$)	1·3330 ($2·8e^{-05}$)	1·3320 ($3·5e^{-03}$)	1·3330 ($9·1e^{-05}$)	1·156	1·156 ($7·7e^{-04}$)	1·156 ($1·4e^{-04}$)
$C_{y_{\delta a}}$	0·029	0·0290 ($4·4e^{-05}$)	0·0290 ($1·1e^{-05}$)	0·0289 ($9·3e^{-04}$)	0·0289 ($2·5e^{-03}$)	0·0037	0·0036 ($1·0e^{-04}$)	0·0037 ($3·8e^{-05}$)
$C_{y_{\delta r}}$	0·191	0·1910 ($4·2e^{-05}$)	0·1910 ($1·4e^{-05}$)	0·1910 ($1·2e^{-03}$)	0·1909 ($1·0e^{-04}$)	0·222	0·2220 ($3·7e^{-04}$)	0·222 ($4·6e^{-05}$)

+ *Values in parentheses indicate sample standard deviation.*

$\Delta\beta$, $\Delta\delta_a$, $\Delta\delta_r$) and the output file (ΔC_y, ΔC_l, ΔC_n). Such sets of network input-output files for several types of control inputs were separately used to train the FFNN and the parameters estimated via the Delta method and the Modified Delta method. The main findings are illustrated by presenting results for the following cases:

Case 1: Inputs; marked as No. 1 in Fig. 3, taken from real flight data consisted of two multistep 3-2-1-1 type δ_a and δ_r input sequences of increasing amplitudes followed by two aileron step inputs in opposite direction for V_{IAS} = 160kt.

Case 2: Inputs; marked as No. 2 in Fig. 3, taken from real flight data consisted of two multistep 3-2-1-1 type δ_a and δ_r input sequences of increasing amplitudes followed by aileron step inputs for V_{IAS} =160kt.

Case 3: Inputs; marked as No. 4 in Fig. 4, taken from real flight data consisted of two multistep 3-2-1-1 type δ_a and δ_r input sequences of increasing amplitudes followed by aileron step inputs for V_{IAS} = 250kt.

5.0 PARAMETER ESTIMATION FROM SIMULATED FLIGHT DATA

For Cases 1, 2 and 3 parameters were estimated using the proposed modified Delta method. The numerical values of the lateral-directional estimated parameters are listed in Table 1. Table 1 also lists the numerical values of estimated parameter along with standard deviation obtained by applying the Delta method on same flight data. It may be noted that while calculating standard deviation, the estimates (obtained through the Delta method) were arranged in ascending/descending order and 25% data from both the ends of this set were deleted before calculating standard deviation[7]. Since the Modified Delta method, used the variations in motion and control variables as input to FFNN, it was expected to result in better FFNN training to be used for parameter estimation. The flight data corresponding to Case 1, was processed with both the Delta and the

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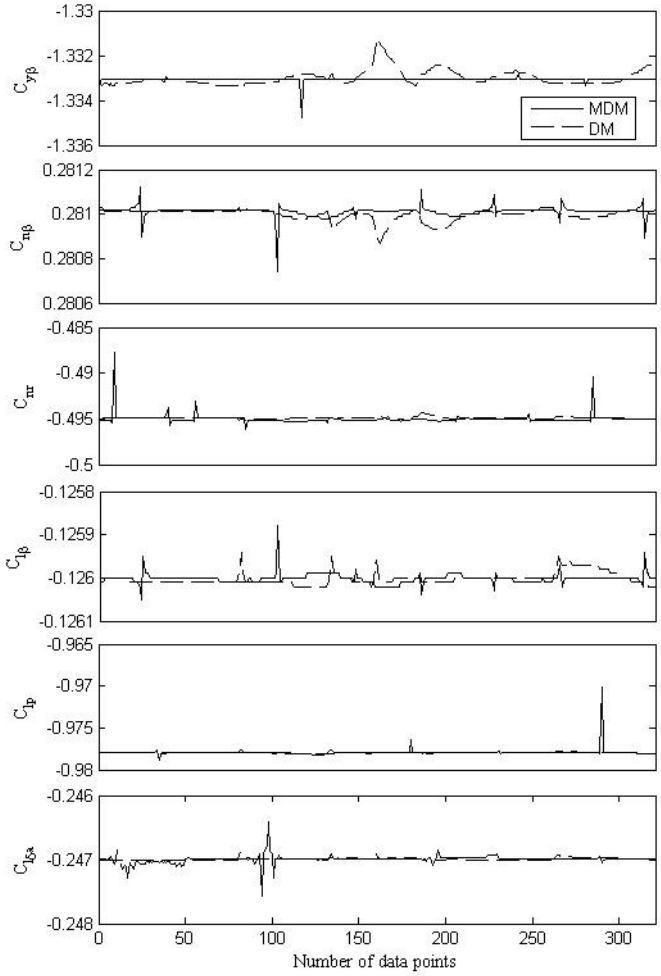


Figure 5. Comparison of estimated derivatives obtained from Modified Delta method and Delta method for Case 2.

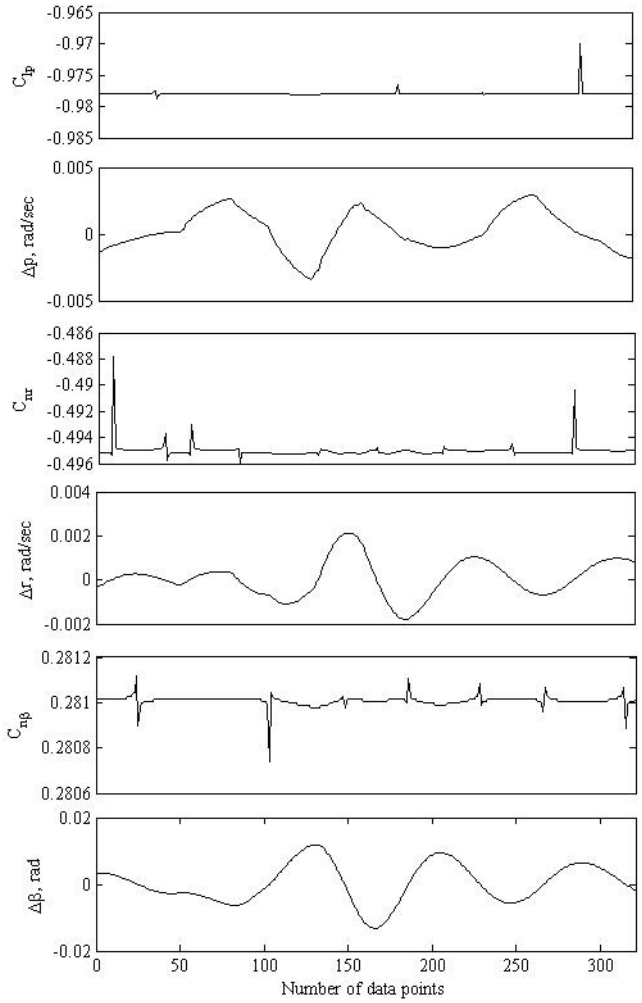


Figure 6. Variation of Case 2 estimated derivatives obtained from Modified Delta method corresponding to differential variation of motion variables respectively.

Modified Delta method to estimate aerodynamic parameters. The number of estimated values for each of the parameters was equal to the number of data points used for training the network.

Figure 5 presents the numerical values of estimated parameters namely C_{y_β}, C_{n_β}, C_{n_r}, C_{l_β}, C_{l_p} and $C_{l_{\delta a}}$ at a particular data point. Consistently, it could be seen that the numerical values of the estimated parameters obtained using the Modified Delta method showed negligible scatter in their magnitude. However, estimates obtained using the Delta method showed appreciable variations in their magnitudes.

Referring to Fig. 5, it could be observed that although the estimated numerical values of the parameters almost remain constant, when estimated using Modified Delta method, however, at some time points, some large 'spikes' showing large numerical values of the estimates could be seen on the same figure. If we observe, the variation of C_{y_β} with data points, we could observe that at around 120th, or 280th data points, there had been sudden jump in the numerical values (spikes) of the estimates. To understand this behaviour, it was decided to plot numerical values of the estimates versus the numerical values of the differential variable at a particular data point. Figure 6 presents graphically the variation of C_{l_p}, C_{n_r} and C_{n_β} corresponding to Δp, Δr, and $\Delta\beta$ respectively at a particular data point. Referring this Fig. 6, it could easily be seen that wherever the spikes occurred, the corresponding values for Δp, Δr, and $\Delta\beta$ were almost zero. Few such points where the differential variations in the motion/control variable were zero could easily be removed from the input file required for prediction purposes. The observation through Fig. 6, indeed confirms the advantage of using Modified Delta method over the Delta method proposed in Ref. 7.

6.0 PARAMETER ESTIMATION FROM REAL FLIGHT DATA

The flight records supplied by DLR for the ATTAS aircraft had raw data for V, α, β, p, q, r, $\dot{p}$, $\dot{q}$, $\dot{r}$, a_{xm}, a_{ym}, a_{zm}, δ_a and δ_r: the information about 1) the fuel consumption (to help to calculate the mass, cg, and the moment of inertias of the aircraft at any desired time point), 2) the location of measuring instruments, and 3) the time delays in the measured quantities. The parameter estimates (via the maximum likelihood method) from the same fight data are given in Ref. 22; the estimates are with respect to an experimental axes system with its origin at a chosen reference point[22]. To facilitate direct comparison, raw data were processed to account for 1) the offset of the recording instruments and the reference point and 2) the axes transformation. Additional corrections for the time delays and fuel consumption were done as per information supplied by DLR[22]. The aerodynamic coefficients were calculated using the Equations (1) to (3) obtained from the six-degree-of-freedom equations of motion in body-fixed axes with their origin at the cg[22].

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Table 2
Parameter estimates from real flight data

Parameter	V_{IAS} = 160kt					V_{IAS} = 250kt		
		Case 4		Case 5			Case 6	
	(Ref. 22) ML	(Ref. 20) DM	MDM	(Ref. 20) DM	(Ref. 22) MDM	(Ref. 20) ML	DM	MDM
$-C_{l_p}$	0·978 (0·020)*	0·866 (0·013)+	0·992 (0·011)+	0·954 (0·043)	0·891 (0·012)	1·014 (0·022)	0·958 (0·098)	1·007 (0·032)
C_{l_r}	0·418 (0·430)	0·594 (0·029)	0·566 (0·023)	0·596 (0·008)	0·4326 (0·042)	0·319 (0·048)	0·951 (0·099)	0·538 (0·014)
$-C_{l_\beta}$	0·126 (0·390)	0·110 (0·003)	0·132 (0·010)	0·114 (0·008)	0·135 (0·021)	0·116 (0·910)	0·108 (0·014)	0·141 (0·019)
$C_{l_{\delta a}}$	0·247 (0·200)	0·209 (0·004)	0·215 (0·046)	0·231 (0·017)	0·214 (0·015)	0·256 (0·020)	0·265 (0·020)	0·268 (0·065)
$C_{l_{\delta r}}$	0·046 (0·120)	–0·027 (0·007)	0·057 (0·021)	–0·003 (0·003)	0·052 (0·011)	0·043 (2·160)	0·033 (0·025)	0·050 (0·038)
$-C_{n_p}$	0·115 (0·730)	0·068 (0·003)	0·324 (0·030)	0·096 (0·034)	0·255 (0·037)	0·049 (1·200)	0·097 (0·017)	0·058 (0·035)
$-C_{n_r}$	0·495 (0·560)	0·864 (0·026)	0·334 (0·041)	0·242 (0·080)	0·463 (0·039)	0·599 (0·940)	0·793 (0·065)	0·369 (0·094)
C_{n_β}	0·281 (0·070)	0·264 (0·005)	0·248 (0·011)	0·216 (0·072)	0·227 (0·038)	0·284 (1·540)	0·233 (0·016)	0·280 (0·030)
$C_{n_{\delta a}}$	0·0	0·011 (0·006)	–0·023 (0·013)	–0·016 (0·008)	–0·002 (0·022)	0·0	0·006 (0·001)	–0·001 (0·019)
$-C_{n_{\delta r}}$	0·166 (0·120)	0·169 (0·004)	0·158 (0·007)	0·156 (0·068)	0·171 (0·035)	0·169 (0·360)	0·168 (0·009)	0·167 (0·017)
C_{y_p}	0·303 (5·190)	0·112 (0·025)	0·285 (0·150)	0·319 (0·044)	0·353 (0·049)	0·207 (8·120)	0·205 (0·028)	0·215 (0·062)
C_{y_r}	0·727 (2·320)	1·146 (0·603)	1·074 (0·014)	2·088 (0·108)	1·552 (0·145)	0·110 (6·960)	2·530 (0·158)	2·172 (0·132)
$-C_{y_\beta}$	1·333 (0·330)	1·083 (0·049)3	1·00 (0·079)	1·051 (0·045)	1·076 (0·036)	1·156 (0·690)	0·923 (0·032)	0·962 (0·061)
$C_{y_{\delta a}}$	0·029 (13·5)	0·109 (0·011)	0·0627 (0·057)	0·191 (0·010)	0·076 (0·018)	0·0037 (108·0)	0·035 (0·003)	0·031 (0·01)
$C_{y_{\delta r}}$	0·191 (2·020)	0·095 (3·790)	0·177 (0·075)	0·027 (0·004)	0·169 (0·031)	0·222 (3·790)	0·235 (0·001)	0·231 (0·051)

* *Values in parentheses indicate standard deviation in %*
\+ *Values in parentheses indicate sample standard deviation*

After applying the necessary corrections and transformations, the network input file with motion and control variables $\Delta(ps/V)$, $\Delta(rs/V)$, $\Delta\beta$, $\Delta\delta_a$ and $\Delta\delta_r$, and the output file having ΔC_y, ΔC_l and ΔC_n were prepared. For illustration, flight data for the flight conditions defined by a landing flap deflection δ_f = SP(1deg), and perturbations about steady-state flights at indicated speeds V_{IAS} = 160kt (Cases 4 and 5) and V_{IAS} = 250kt (Case 6) are chosen[22]. Case 4 and 5 analysed data for the control inputs marked as No. 1, and No. 2 respectively in Fig. 3. Case 6 analysed data for the control input marked No. 4 as shown in Fig. 4. Control input (No. 1) consisted of two multi-step 3-2-1-1 type δ_a and δ_r input sequence of increasing amplitudes, followed by two aileron step inputs in opposite directions. From Fig. 3, Case 4 used whole segment of data corresponding to the simultaneous application of 3-2-1-1 type δ_a and δ_r inputs in the same interval of 0·0-51·2 s. Table 2 lists parameter estimates obtained via the Modified Delta method for Cases 4 to 6, along with the parameter estimates as reported in Ref. 20 and Ref. 22 for ready comparison. It may be noted that the estimated values of the parameters obtained via the Delta method were arranged in descending order as that 25% estimates from both the ends of the ordered set were removed before calculating the mean and sample standard deviations. However, for the application of the Modified Delta method, such procedure was not required.

For Case 4 and 5, most of the parameters obtained via Modified delta method are well estimated with less standard deviation as compared with Delta method. The presence of large roll maneuver data (generated by the two aileron pulse inputs) has helped in the estimation of C_{n_β} and also interrupted, to a large extent, the correlation between the control derivatives ($C_{l_{\delta a}}$ and $C_{l_{\delta r}}$), ($C_{n_{\delta a}}$ and $C_{n_{\delta r}}$), and ($C_{y_{\delta a}}$ and $C_{y_{\delta r}}$). However, estimates of relatively weak control derivatives, $C_{y_{\delta a}}$ and $C_{y_{\delta r}}$ obtained via Delta method show correlation. This, we believe, is a result of the first part of the control inputs (up to about the first 22·5s, Fig. 3) having similar-looking δ_a and δ_r inputs. This conjecture is further supported by reasonable estimates of these control derivatives for Case 6, wherein δ_a and δ_r that were used have dissimilar forms. On the other hand, control derivatives obtained via Modified Delta method do not show any correlation because differential variations in input and output

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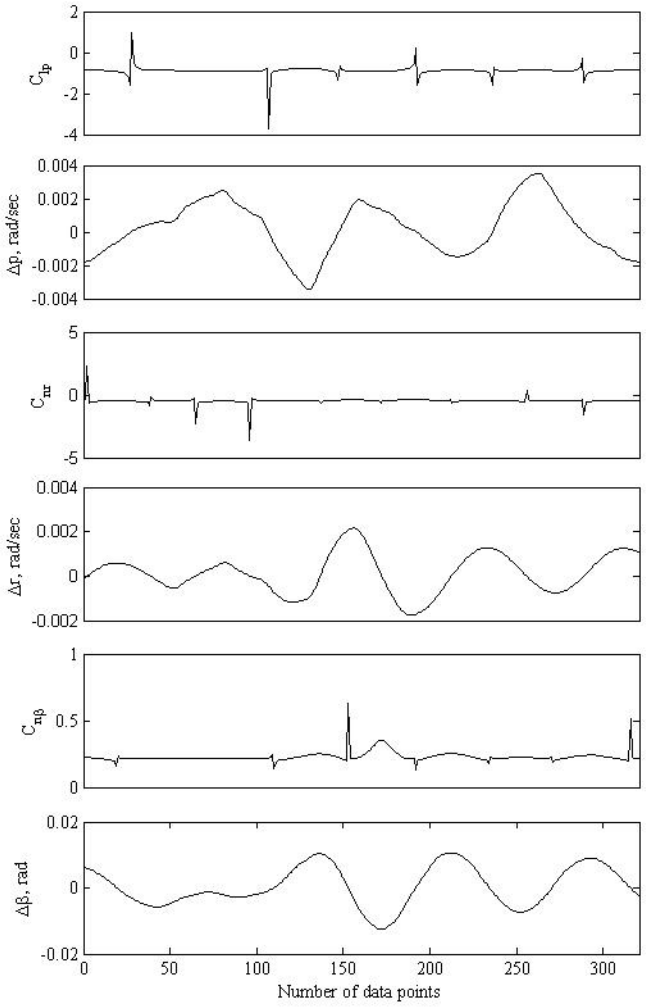


Figure 7. Variation of Case 5 estimated derivatives obtained from Modified Delta method corresponding to differential variation of motion variables respectively.

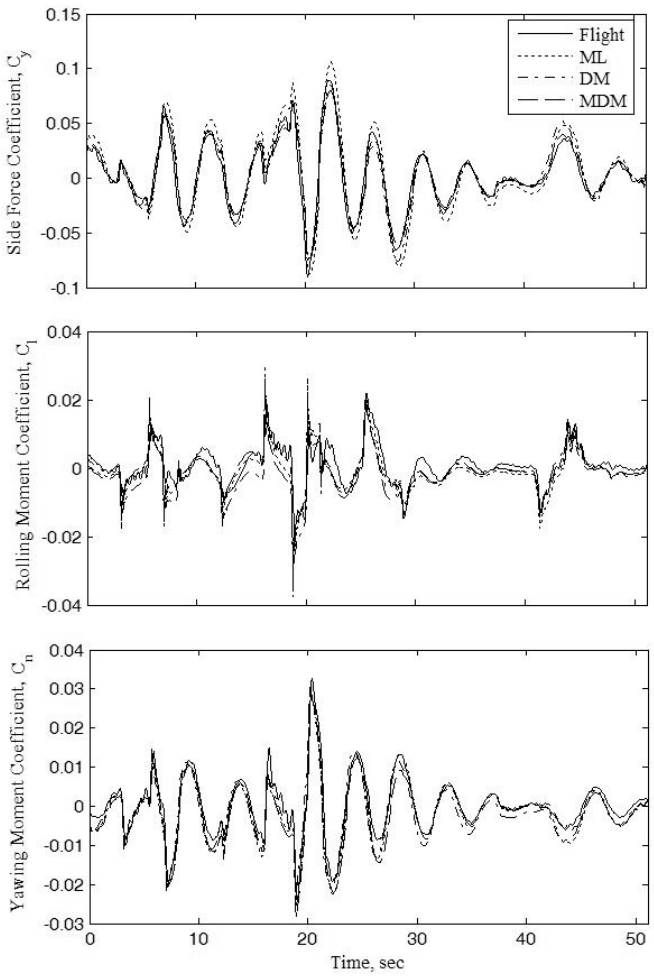


Figure 8. Comparison of actual and estimated total aerodynamic coefficient.

variables are used to train the FFNN. It may be mentioned here that while computing standard deviation of the estimates obtained using Modified Delta method, few data points showing large values (spikes) of estimates were removed from the set. As seen for simulated flight data case, these spikes corresponded to data points where differential variations of motion/control variables were almost zero. Figure 7 graphically shows such spikes for real flight data (Case 5) corresponding to Δp, Δr and $\Delta\beta$ numerically equal to zero.

For Case 6, it may be noted from Fig. 4 that the 3-2-1-1 type of δ_a and δ_r inputs for this case are appended by dissimilar looking δ_a and δ_r inputs and, therefore, we expect better estimates as compared with Cases 4 and 5. Results for Case 6 confirm this expectation, and most of the parameters are fairly well estimated. Some of the weak derivatives, such as C_{l_r}, C_{n_p} and C_{y_r} however, have values larger than those reported in Ref. 22. Also, the estimated value of C_{n_β} via Modified Delta method using flight data corresponding to Case 6 is in excellent agreement with the value reported in Ref. 22. It is of interest to compare the total coefficients C_l, C_n and C_y obtained from 1) Equations (1), (2), and (3) using the flight data; 2) Equations (11), (12), and (13) using estimated parameters via maximum likelihood (ML) method[22]. 3) Equations (11), (12), and (13) using estimated parameters via the Delta method[20]; and 4) Equations (11), (12), and (13) using estimated parameters via Modified delta method. Figure 8 illustrates such a comparison for Case 4 estimates; based on these results, it is difficult to claim that the estimates from either of the methods, i.e., the maximum likelihood method[22] or the Delta method[20] or the Modified Delta method, are definitely superior when compared with the other.

The standard procedure to validate aircraft parameter estimation method is to compare estimated response with the flight measured response generated with control input other than used for estimation purpose. Therefore, for validation of the Modified Delta method, as a first step, lateral-directional parameters were estimated by applying the Modified Delta method on the flight data generated using control input marked No. 2 in Fig. 3. In the next step, a neural mapping between input vector containing time histories of $(p_1 s/V)_t$, $(r_1 s/V)_t$, $(\beta_1)_t$, (δ_{a1}), (δ_{r1}), $(C_{y_1})_t$, $(C_{l_1})_t$, $(C_{n_1})_t$ and the output vector containing $(p_1 s/V)_{t+1}$, $(r_1 s/V)_{t+1}$, $(\beta_1)_{t+1}$ generated using control input No. 2 was established using the scheme as described in Fig. 2(a). The numerical value of $(C_{y_1})_t$, $(C_{l_1})_t$, and $(C_{n_1})_t$ were computed using Equations (1) to (3). Once the training had been established by satisfying the MSE criteria, to validate the proposed method, a new set of flight data was generated using control input marked No. 3 in Fig. 3. However, the numerical values of lateral-directional coefficients, C'_{y_2}, C'_{l_2} and C'_{n_2} were computed using the estimated parameters obtained from flight data corresponding to control input No. 2 in the aerodynamic model as described by Equations (4) to (6). The already trained FFNN neural model for flight data generated with control input No. 2 was used to predict motion variables $(p_2 s/V)_{t+1}$, $(r_2 s/V)_{t+1}$ and $(\beta_2)_{t+1}$ corresponding to new control input vector (No. 3)

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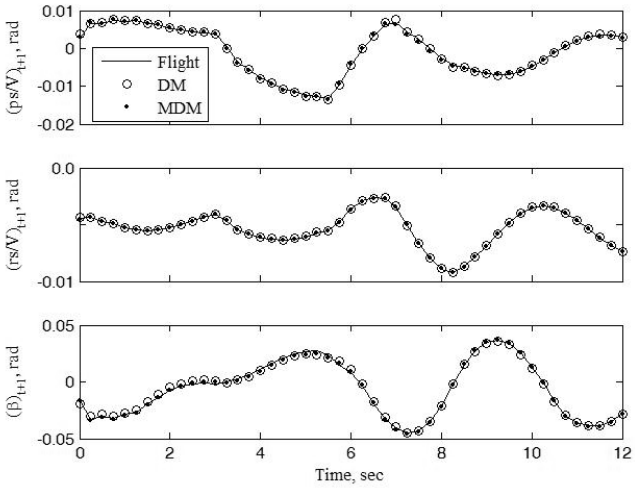


Figure 9. Validation of Case 5 estimates using real flight data control input No. 3.

containing time histories of $(p_2s/V)_t$, $(r_2s/V)_t$, $(\beta_2)_t$, $(\delta_{a2})_t$, $(\delta_{r2})_t$, $(C'_{y2})_t$, $(C'_{l2})_t$ and $(C'_{n2})_t$ as shown in Fig. 2(b). The estimated responses of $(p_2s/V)_{t+1}$, $(r_2s/V)_{t+1}$, $(\beta_2)_{t+1}$ was then compared with the measured responses of $(p_2s/V)_{t+1}$, $(r_2s/V)_{t+1}$, $(\beta_2)_{t+1}$ generated using control input No. 3. A comparison among estimated and measured motion variables is presented in Fig. 9. Excellent matching among the estimated and measured variables was observed. Based on this result, it can be concluded that the Modified Delta method can advantageous be apply on real flight data for estimation of aerodynamic parameters.

7.0 CONCLUSION

An improved Delta method, the Modified Delta method (by improving the existing Delta method), has been proposed for estimating the aircraft parameters from flight data using the feed forward neural networks. The results obtained for simulated flight data and real flight data have shown the success and potential of the proposed methods. As compared to the Delta method, the proposed Modified Delta method yields estimates with lesser standard deviation. The proposed Modified Delta method is a straightforward method to apply; the FFNN is trained on the given flight data and the parameters estimated in one try. It is worth emphasising that, unlike many of the popular estimation algorithms, e.g., the maximum likelihood method, the filter error method, etc., that need initial values of parameters to begin the algorithm, the Modified Delta method does not even require order of magnitude information about the parameters to be estimated. Further, in addition to improve the Delta method, a procedure based on FFNNs is also proposed to validate the method using measured flight variables. Thus, the method may be viewed as alternative and complimentary to the existing methods of parameter estimation. It may also be used for generating initial values of parameters that can be used as starting values for the methods such as the maximum likelihood method that can subsequently further fine tunes the estimates.

ACKNOWLEDGEMENT

The authors are grateful to P.G. Hamel and R.V. Jategaonkar of DLR, German Aerospace Center, Institute of Flight Mechanics, Germany, for supplying and granting permission to use the flight data of ATTAS aircraft. We are grateful to Jategaonkar for his help in interpreting and answering our questions about the flight data.

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