Aircraft neural modeling and parameter estimation using neural partial differentiation

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Abstract

Purpose – The purpose of this paper is to build a neural model of an aircraft from flight data and online estimation of the aerodynamic derivatives from established neural model.

Design/methodology/approach – A neural model capable of predicting generalized force and moment coefficients of an aircraft using measured motion and control variable is used to extract aerodynamic derivatives. The use of neural partial differentiation (NPD) method to the multi-input-multi-output (MIMO) aircraft system for the online estimation of aerodynamic parameters from flight data is extended.

Findings – The estimation of aerodynamic derivatives of rigid and flexible aircrafts is treated separately. In the case of rigid aircraft, longitudinal and lateral-directional derivatives are estimated from flight data. Whereas simulated data are used for a flexible aircraft in the absence of its flight data. The unknown frequencies of structural modes of flexible aircraft are also identified as part of estimation problem in addition to the stability and control derivatives. The estimated results are compared with the parameter estimates obtained from output error method. The validity of estimates has been checked by the model validation method, wherein the estimated model response is matched with the flight data that are not used for estimating the derivatives.

Research limitations/implications – Compared to the Delta and Zero methods of neural networks for parameter estimation, the NPD method has an additional advantage of providing the direct theoretical insight into the statistical information (standard deviation and relative standard deviation) of estimates from noisy data. The NPD method does not require the initial value of estimates, but it requires *a priori* information about the model structure of aircraft dynamics to extract the flight stability and control parameters. In the case of aircraft with a high degree of flexibility, aircraft dynamics may contain many parameters that are required to be estimated. Thus, NPD seems to be a more appropriate method for the flexible aircraft parameter estimation, as it has potential to estimate most of the parameters without having the issue of convergence.

Originality/value – This paper highlights the application of NPD for MIMO aircraft system; previously it was used only for multi-input and single-output system for extraction of parameters. The neural modeling and application of NPD approach to the MIMO aircraft system facilitate to the design of neural network-based adaptive flight control system. Some interesting results of parameter estimation of flexible aircraft are also presented from established neural model using simulated data as a novelty. This gives more value addition to analyzing the flight data of flexible aircraft as it is a challenging problem in parameter estimation of flexible aircraft.

Keywords Aircraft parameter estimation, Neural modeling, Neural partial differentiation, System modeling and identification

Paper type Research paper

Nomenclature

α	= angle of attack;
q	= pitch rate;
N_z	= normal acceleration;
δ_e	= elevator input;
η_1, η_2	= elastic states of the flexible aircraft;
$(C_{z_{(\cdot)}}, C_{m_{(\cdot)}}, C_{(\cdot)}^{\eta_1}, C_{(\cdot)}^{\eta_2})$	= on-dimensional derivatives;
Δa_{mk}	= differential accelerometer measurements at kth position; and
Φ_k	= bending mode displacement coefficient at kth position.

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Introduction

In a fairly complex system like aircraft, modeling and parameter estimation play a crucial role in determining its stability and control characteristics. Applications of the parameter estimation method to estimate such parameters from flight data in the linear flight regime have been highly successful in the past (Maine and Iliff, 1986b; Bucharles *et al.*, 2012). The neural modeling represents an appealing alternative for aircraft system modeling and control mainly because the neural network can learn nonlinear input/output mappings from flight data. A neural network brings important benefits of suppressing theoretical difficulties that appear when applying classical techniques on aircraft systems including nonlinearities in their structure. As a result, the neural network can describe or

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control aircraft nonlinear systems accurately with few *a priori* theoretical knowledge, and it is able to find many successful applications of the neural network in the aerospace industry. Neural network-based adaptive flight controller for uncertain, nonlinear dynamical systems eliminates the need for offline gain tuning and scheduling methods (Chowdhary and Johnson, 2007; Khosravani, 2012; Pashilkar *et al.*, 2006). A fault-tolerance, neural network-based algorithm was also successfully applied for flush data sensing system (Rohlloff *et al.*, 1999). Many researchers have shown that aircraft neural model has potential to accommodate changes in aircraft dynamics due to system uncertainties (Trani *et al.*, 2004; Raisinghani *et al.*, 1998a, 1998b).

Parameter estimation from flight data, as applied to aircraft in the linear flight regime, is currently being used on a routine basis with the assumption that the rigid body model is valid (Maine and Iliff, 1986b; Bucharles *et al.*, 2012). Elastic degrees of freedom are, therefore, absent from the aircraft derivative model used in the estimation algorithm. The aircraft with a high degree of flexibility may yield to system dynamics containing too many parameters, which are required to be estimated. The estimation of a rigid body and elastic body derivatives was also demonstrated by Majeed *et al.* (2012); Majeed (2017) Majeed and Jatinder (2013) and Bruno (2011) for a valid model of flexible aircraft in a wide range of frequency. However, the recently introduced neural partial differential method is able to give theoretical insight into statistical information of relative standard deviation (RSTD) of estimates from noisy data (Das *et al.*, 2010). In the presence of a change in process noise, an adaptive unscented Kalman filter is used to estimate aerodynamic parameters accurately from flight data (Majeed and Kar, 2013), but this algorithm requires high computational power and initial values of the estimates.

As the aircraft is a complex, highly coupled and nonlinear system, it needs a higher-order modeling method to completely describe the system. The commonly used methods to estimate aircraft parameters are output error method (OEM) and filtering methods. They need *a priori* knowledge of dynamic model and initial values of aerodynamic parameters to estimate aircraft stability and control parameters (Maine and Iliff, 1986a; Klein and Moreli, 2006). The initial values of parameters for rigid body aircraft are mostly available from the wind tunnel database. But, a lot of aeroelastic derivatives are involved in the flexible aircraft model and initial values of certain derivatives are not known. Conversely, the use of scaled version of aircraft in the wind tunnel may introduce the errors in the prediction of aerodynamic derivatives. These predicted values will be using the initial value of parameters for estimation algorithm. This requires the application of an alternative method that can provide accurate estimates of aircraft parameters without their initial values (Kutluay and Mahmutyazicioglu, 2009; Theodore *et al.*, 2008).

The equation error method (EEM) is an alternative method but can only be used for the deterministic system as opposed to the stochastic approach of filtering method. This is considered as the simplest method for the aircraft parameter estimation, which was successfully applied to flight data of F-18 High alpha research vehicle (Morelli, 2000), and to a gliding flight vehicle (Kutluay and Mahmutyazicioglu, 2009). EEM needs only the model structure of the aircraft dynamics and does not require initial values of parameters. However, in the presence of noise, the least squares estimates of EEM are asymptotically biased, inconsistent and inefficient. Therefore, neural networks have become a preferred alternative for aerodynamic parameter estimation, as they do not require *a priori* information about the model structure and the parameters of aircraft system dynamics (Raisinghani *et al.*, 1998a, 1998b; Pedro and Kantue, 2011; Pesonen *et al.*, 2004; Raisinghani and Ghosh, 2000; Singh and Ghosh, 2007). A class of neural network called the feed-forward neural networks (FNNs) has been used to model the aircraft dynamics wherein aircraft motion variables and control inputs are mapped to predict the total aerodynamic coefficients (Hess, 1993; Linse and Stengel, 1993). The capability of FNN for aerodynamic modeling of a flexible aircraft and the applicability of the delta method and the lambda gamma learning rule for extracting parameters from a neural model are demonstrated (Raisinghani and Ghosh, 2000; Samal *et al.*, 2009).

The mathematical model of the dynamical system either has linear or nonlinear structure. Delta and Zero Method of neural networks can be used to extract aircraft aerodynamic derivatives from flight data irrespective of model structure (Raisinghani *et al.*, 1998a, 1998b). These methods provide the estimate of aircraft parameters, but the statistics of estimates are not inferred directly. Whereas, neural partial differential (NPD) method (Sinha *et al.*, 2013) is used to estimate flight stability and control parameters with their RSTD. This method has been originated from the fact that the solution of ordinary differential equation and the partial differential equation can be obtained by neural networks (Lagaris *et al.*, 1998). Moreover, the NPD method can also extract parameters of dynamical systems, which are appearing as nonlinear to the states of the system. This paper extends the use of the NPD method for multi-input and multi-output (MIMO) aircraft system; previously it was used only for multi-input single-output system (MISO) (Sinha *et al.*, 2013). Thus, the presented results from MIMO neural model for online aircraft parameter estimation enhance the application of neural network-based flight controller for the uncertain system dynamics. The main contributions of this paper are the following:

- A neural model of rigid aircraft from flight data is established, and its longitudinal and lateral-directional derivatives using neural partial differentiation (NPD) method are extracted. The extracted aerodynamic derivatives are compared with the estimates obtained from OEM.
- The estimated neural model of rigid aircraft is validated by a complementary set of flight data. The results are encouraging and this method is applied to the flexible aircraft containing more number of unknown parameters.
- Besides the estimations of aerodynamic derivatives of flexible aircraft, unknown frequencies of structural modes of flexibility are also identified from its simulated data of frequency sweep input. The identified flexible aircraft model has validated with a complimentary set of data that has generated with the use of 3-2-1-1 input signal of an elevator.

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Aircraft neural modeling and parameter estimation method

Primarily neural model of aircraft system dynamics is needed to be established to estimate the aircraft aerodynamic parameters. The accuracy of the estimates will depend on the validity of the aircraft neural model, which is described below.

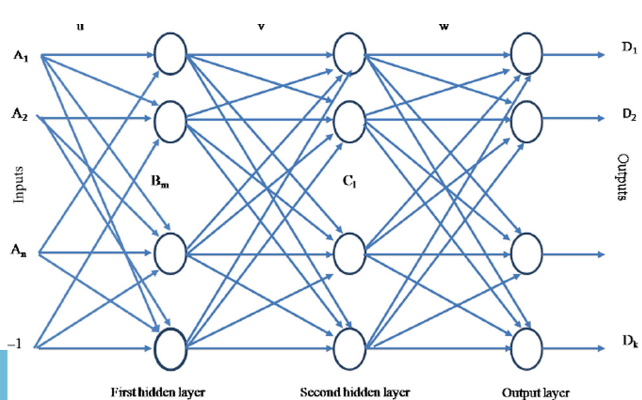
Aircraft neural modeling

The neural networks are made up of two main components namely neuron or nodes and the connectors. The connectors have own weights between two nodes. The neural network uses the data set of input and output, to map the function on to the network in the form of weights between the internal nodes, as shown in the Figure 1. The schematic structure of a three-layered FNN is consisting of two hidden layers with activation function and one output layer with summation function exempted from activation function. The weights indirectly represent the function of a given system for which the neural network is trained. The output of each node is the sum of the product of the total input to the particular node and their respective weights, applied to an activation function. Back-propagation approach is used for training the neural network. The neural networks learn through an input–output pair of the system and give an approximate function in the form of weights. The complexity of the network can be changed with a number of neurons and/or the number of hidden layers; this decision is purely based on trial and error method. The input and output vectors of neural network are defined as $A \in \Re^{n+1}$ and $D \in \Re^{k}$, respectively. Similarly, $B \in \Re^{m+1}$ and $C \in \Re^{l+1}$ represent the first and second hidden layer of neural network, respectively. Except for the output layer, all the layers contain a bias term. Thus, the output of neural network is given by:

$$D = W^T C \tag{1}$$

where W is the set of weights between the second hidden layer and output layer containing the bias terms:

Figure 1 Schematic of neural network



$$W = \begin{bmatrix} b_{w1} & \cdots & b_{wk} \\ w_{11} & \cdots & w_{1k} \\ \vdots & \ddots & \vdots \\ w_{l1} & \cdots & w_{lk} \end{bmatrix} \tag{2}$$

Similarly, we define:

$$\begin{cases} C = f(V^T B) \\ B = g(U^T A) \end{cases} \tag{3}$$

where f and g are the activation function vectors and are defined as $f = \left[-1 \quad f(x_1) \ \cdots \ f(x_k)\right]^T$ where $f(x)$ is expressed as:

$$f(x) = \frac{1 - e^{-\lambda x}}{1 + e^{-\lambda x}} \tag{4}$$

And the weight matrix is represented as:

$$V = \begin{bmatrix} b_{v1} & \cdots & b_{vm} \\ v_{11} & \cdots & v_{1l} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{ml} \end{bmatrix} \tag{5}$$

$$U = \begin{bmatrix} b_{u1} & \cdots & b_{um} \\ u_{11} & \cdots & u_{1m} \\ \vdots & \ddots & \vdots \\ u_{n1} & \cdots & u_{nm} \end{bmatrix} \tag{6}$$

Input is defined by the vector $A = \left[a_0 \quad a_1 \cdots a_n\right]$, where a_0 defines bias input to the neural network. The input and output are scaled for neural network using the following equation:

$$D_{i,norm} = D_{i,norm_{\min}} + \left(D_{i,norm_{\max}} - D_{i,norm_{\min}}\right) \times \left(\frac{D_i - D_{i,\min}}{D_{i,\max} - D_{i,\min}}\right) \tag{7}$$

where $D_{i,norm_{\max}}$ and $D_{i,norm_{\min}}$ denote the higher and lower limits of scaling range of D_i respectively. They are set to 0.9 and -0.9, respectively. $D_{i,max}$ and $D_{i,min}$ denote the higher and lower values of D_i.

Using the above notations, output of neural network can be written as:

$$D = \left\{W^T f\left[V^T g\left(U^T A\right)\right]\right\} \tag{8}$$

Neural partial differentiation method

In this method, the neural network is trained with input and output data so as to map the nonlinear function in the form of weights. The activation function holds the key for the neural partial difference method. This method does not need extra post-processing as the Zero and Delta method demands. Moreover, it has the facility to determine the higher-order partial derivatives of a nonlinear system. The partial differentiation of a system can be computed from the end of a training session of the neural network, and provide

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aerodynamic derivatives directly as follows (Dongare and Mohamed, 2015).

The input and output of function are mapped after the training session of the neural network. Subsequently, the output variables can be differentiated with respect to input variables. Differentiating equations (1) and (3), we will have the form of:

$$\frac{\partial D}{\partial C} = W^T \tag{9}$$

$$\frac{\partial C}{\partial B} = f'(V^T) \tag{10}$$

$$\frac{\partial B}{\partial A} = g'(U^T) \tag{11}$$

Multiplication of equations (9), (10) and (11) gives:

$$\begin{cases} \frac{\partial D}{\partial C} \cdot \frac{\partial C}{\partial B} \cdot \frac{\partial B}{\partial A} = W^T \cdot f' V^T \cdot g' U^T \\ \frac{\partial D}{\partial A} = W^T \cdot f' V^T \cdot g' U^T \end{cases} \tag{12}$$

where $f' = diag\left[0 \quad f'_1 \quad \cdots \quad f'_l\right]$ and $g' = diag\left[0\, g'_1 \cdots g'_m\right]$. If the input and output of neural network are normalized, then:

$$\frac{\partial D}{\partial A} = \frac{\partial D}{\partial D_{norm}} \times \frac{\partial D_{norm}}{\partial A_{norm}} \times \frac{\partial A_{norm}}{\partial A} \tag{13}$$

The normalized output of neural network can be de-normalized by equation (13). Where:

$$\frac{\partial D}{\partial D_{norm}} = \begin{bmatrix} \frac{\partial D_1}{\partial D_{1,norm}} & 0 & \cdots & 0 \\ 0 & \frac{\partial D_2}{\partial D_{2,norm}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{\partial D_k}{\partial D_{k,norm}} \end{bmatrix} \tag{14}$$

$$\frac{\partial A}{\partial A_{norm}} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & \frac{\partial A_{1,norm}}{\partial A_1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{\partial A_{n,norm}}{\partial A_n} \end{bmatrix} \tag{15}$$

Equations (14) and (15) can be computed from equation (7). The trained network of aircraft neural model allows given as:

Table I Estimated aerodynamic derivatives from flight data

Parameter	Wind tunnel	NPD	OEM
C_{L_α}	5.5338	4.7813 (0.05)*	4.5346 (0.13)
$C_{L_{\delta e}}$	0.4318	0.6272 (0.16)	0.5923 (0.12)
C_{m_α}	−1.1768	−0.9455 (0.09)	−1.2586 (0.02)
C_{m_q}	−23.0223	−25.34 (0.025)	−22.7156 (1.84)
$C_{m_{\delta e}}$	−1.4168	−1.2418 (0.04)	−1.3553 (0.03)

Note: *The values in parenthesis denote relative standard deviation values in percentage

Figure 3 Variation in parameters with respect to data points

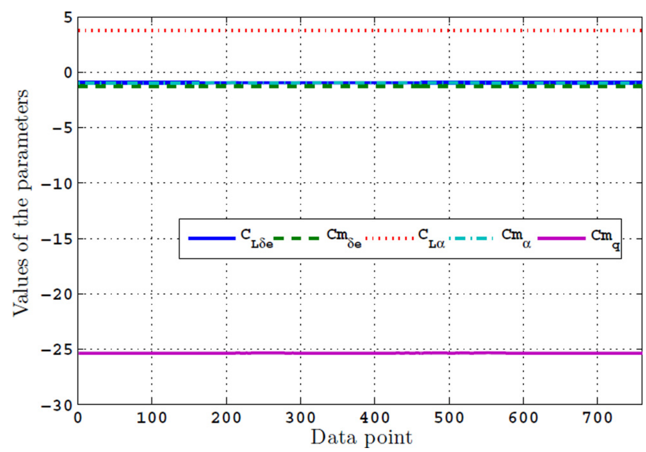


Figure 2 Time history response of flight data and neural model

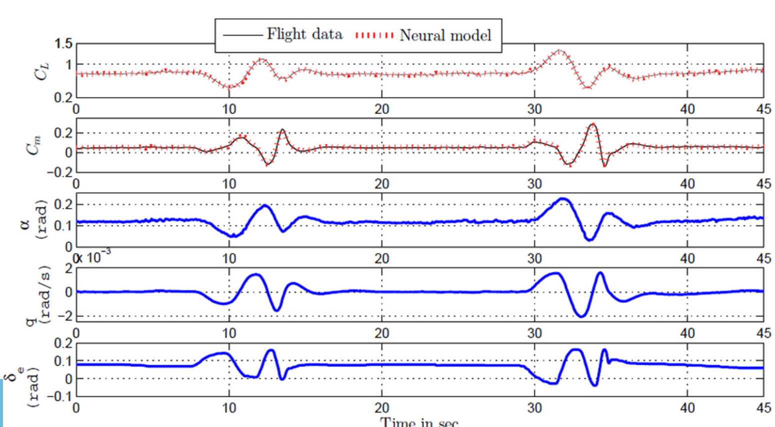
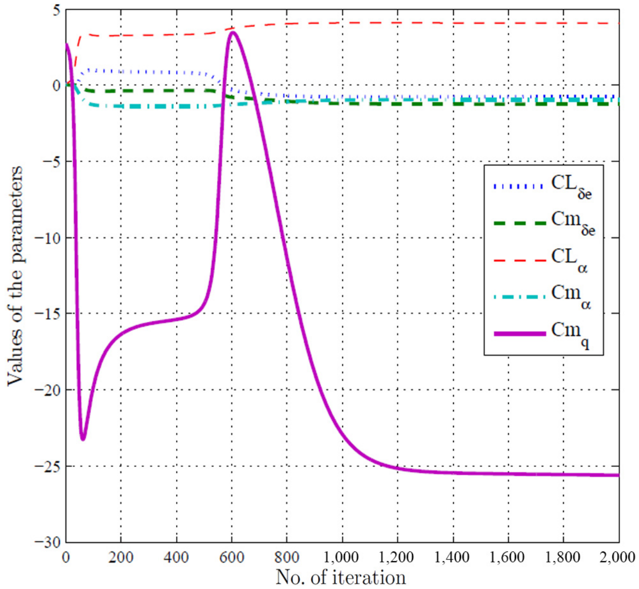


Figure 4 Variation in parameters w.r.t. number of iterations during the training



$$\frac{\partial D}{\partial A}=\begin{bmatrix}\frac{\partial D_1}{\partial A_0} & \cdots & \frac{\partial D_1}{\partial A_n}\\ \vdots & \ddots & \vdots\\ \frac{\partial D_k}{\partial A_0} & \cdots & \frac{\partial D_k}{\partial A_n}\end{bmatrix} \tag{16}$$

The standard deviation of estimated parameters in equation (16) is computed by:

$$STD=\sqrt{\frac{\sum_{p=1}^{P}\left[\sum_{m=1}^{M}\left(\sum_{l=1}^{L}C'_{l_p}v_{lm}w_{kl}D'_{k_p}\right)B'_{m_p}u_{mi}-AVG\right]^2}{P}} \tag{17}$$

where:

$$AVG=\frac{\sum_{p=1}^{P}\sum_{m=1}^{M}\left(\sum_{l=1}^{L}C'_{l_p}v_{lm}w_{kl}D'_{k_p}\right)B'_{m_p}u_{mi}}{P} \tag{18}$$

Figure 5 Comparison of $\dot{q}$ from flight data and reconstructed from neural model

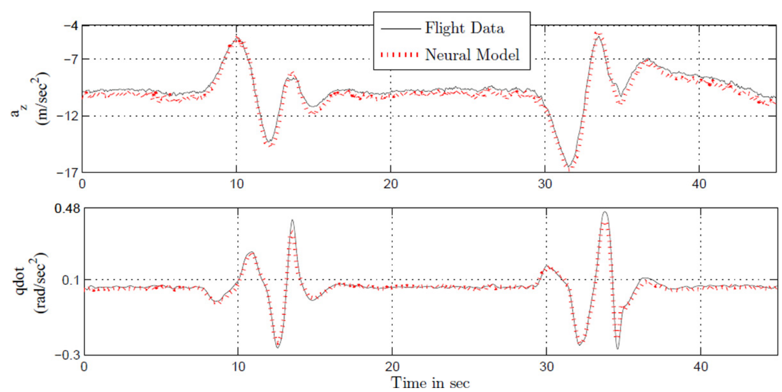
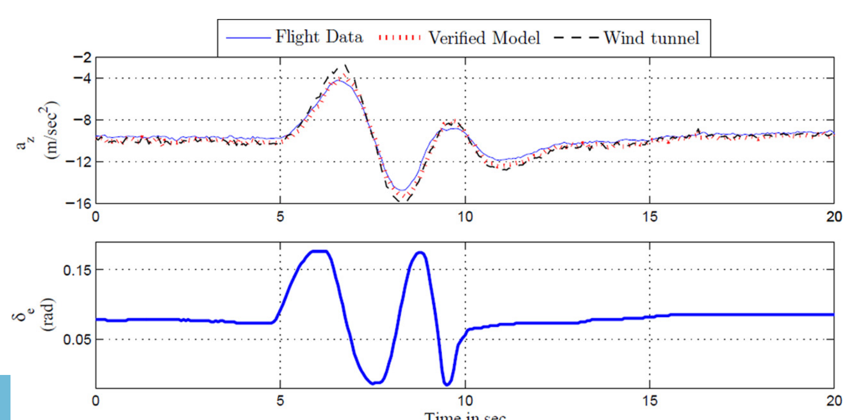


Figure 6 Time history verification of identified neural model



where, STD and AVG are standard deviation and average of data points, respectively. The RSTD of estimates is given by:

$$RSTD = \frac{STD}{AVG} \times 100\% \tag{19}$$

Parameter estimation for an aircraft

Parameter estimation was carried out with flight test data of small transport aircraft. The following sub-sections illustrate the identification of aerodynamic derivatives separately for the longitudinal and lateral-directional motion of the aircraft dynamics.

Identification of aircraft longitudinal derivatives

This section describes aircraft longitudinal parameter estimation from flight data. For this, the flight data of small transport aircraft are gathered by conducting a flight test with multiple 3-2-1-1 elevator input(δ_e) signal with time duration of 45 s. Aircraft has trimmed at an angle of attack 3.588 degree at Mach 0.25. The postulated model structure of aircraft longitudinal dynamics is given by:

$$\begin{aligned} C_L &= C_{L0} + C_{L\alpha}\alpha + C_{Lq}\frac{q\,\bar{C}}{2U_0} + C_{L\delta e}\delta_e \\ C_m &= C_{m0} + C_{m\alpha}\alpha + C_{mq}\frac{q\,\bar{C}}{2U_0} + C_{m\delta e}\delta_e \end{aligned} \tag{20}$$

where $C_{L_{(\cdot)}}$ and $C_{m_{(\cdot)}}$ are non-dimensional parameters which need to be computed from the measurements of a_z and $\dot{q}$, respectively, and U_0 is velocity at which aircraft is trimming. The derivative of $C_{L\alpha}$ represents the lift curve slope and $C_{m\alpha}$ shows the static stability of an aircraft. C_{Lq} and C_{mq} are damping derivatives. $C_{L\delta_e}$ and $C_{m\delta_e}$ are representing the control effectiveness of an aircraft elevator deflection. The measurements of acceleration for the z-axis a_z and pitch $\dot{q}$ are used to compute C_m and C_L using the following equations:

$$\begin{aligned} a_z &= -\frac{\bar{q}s}{m}C_L\cos\alpha - \frac{F_e}{m}\sin\sigma_t \\ \dot{q} &= \frac{\bar{q}s\bar{c}}{I_y}C_m + \frac{pr}{I_y}(I_z - I_x) + \left(r^2 - p^2\right)\frac{I_{xy}}{I_y} + \frac{F_e}{I_y}(l_{tx}\sin\sigma_t + l_{tz}\cos\sigma_t) \end{aligned} \tag{21}$$

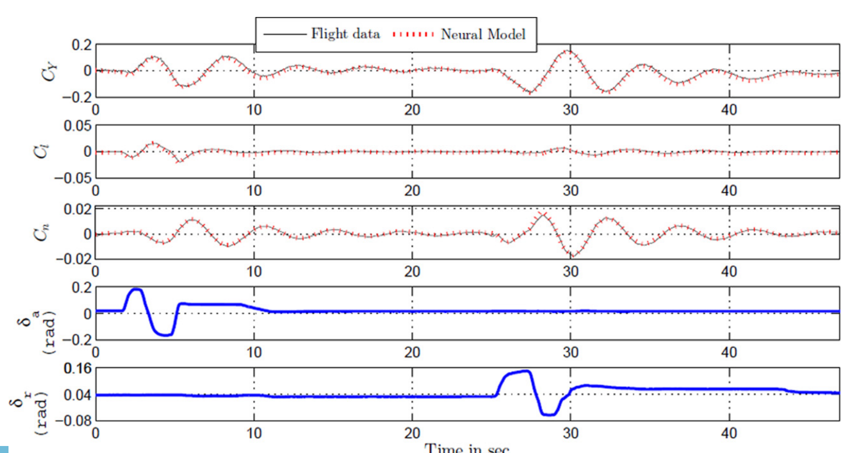
where m is mass, $\bar{q}$ is dynamic pressure, s is platform area of wing, $\bar{c}$ is mean chord length, α is angle of attack (AoA), σ_t is engine inclination angle, F_e is total thrust force, p roll rate, r is yaw rate, $I_{(\cdot)}$ is moment of inertia about an axis and $l_{(\cdot)}$ is the location of engine from the C.G.Considering the input vector of α, q, δ_e and output vector of C_m and C_L to the neural network, it is able to establish the longitudinal dynamics of an aircraft neural model. The time histories of these signals are given in Figure 2 and it shows that estimated neural model is close agreement with flight data. The NPD method discussed in the previous section is applied to the established neural model for the online estimation of aircraft aerodynamic derivatives. The estimated parameters are procured at the end

Table II Estimated lateral-directional derivatives from flight data

Parameters	Wind tunnel values	NPD	OEM
Cy_b	−1.432	−1.648 (0.53)*	−1.423 (0.49)
Cl_b	−0.109	−0.0895 (1.43)	−0.113 (1.02)
Cn_b	0.103	0.120 (0.56)	0.114 (0.38)
Cy_p	−0.102	−0.366 (0.28)	−0.190 (19.56)
Cl_p	−0.599	−0.462 (0.14)	−0.597 (19.56)
Cn_p	−0.175	−0.047 (3.25)	−0.124 (2.04)
Cy_r	0.454	1.405 (0.63)	1.975 (2.36)
Cl_r	0.221	0.02 (1.29)	0.365 (1.57)
Cn_r	−0.141	−0.371 (0.22)	−0.236 (1.13)
$Cy_\delta a$	−0.002	−0.037 (0.34)	−0.076 (8.76)
$Cl_\delta a$	−0.119	−0.111 (0.19)	−0.124 (0.85)
$Cn_\delta a$	−0.011	−0.002 (0.83)	−0.005 (8.95)
$Cy_\delta r$	0.328	0.365 (0.25)	0.248 (2.53)
$Cl_\delta r$	0.051	0.029 (9.26)	0.033 (2.02)
$Cn_\delta r$	−0.110	−0.079 (0.21)	−0.077 (0.45)

Note: *The values in parenthesis denote relative standard deviation values in percentage

Figure 7 Lateral-directional response of flight data and neural model



of training of the neural network. Standard deviation and RSTD of these parameters are calculated independently from equations (17) to (19) after the training process. Estimated aerodynamic derivatives from flight data are tabulated in Table I. Figure 3 shows the estimated values of the aerodynamic derivatives with respect to the data points. Whereas, the variation of parameters with change in a number of iteration is plotted in Figure 4. As the number of iteration increases, the parameters attain a stable value of their estimates.

Figure 5 compares flight measured $\dot{q}$ and a_z with those derived from the neural model and shows a satisfactory match between them. The estimated aircraft neural model is needed to be verified with complimentary flight data. For this, the neural network is trained with certain data set and new data set is passed through the trained network. The output of networks is used to compute a_z for a given input of a complementary flight data and compared with a_z derived from lift force coefficient obtain from the wind tunnel value. The comparison plot of a_z signals is given in Figure 6. The time history of estimated response a_z shows mismatch with a_z derived from the wind tunnel, whereas it matches well with flight data. This reconfirms that estimates of aerodynamic derivatives are not very closer to wind tunnel values as shown in Table I and the estimated neural model is valid.

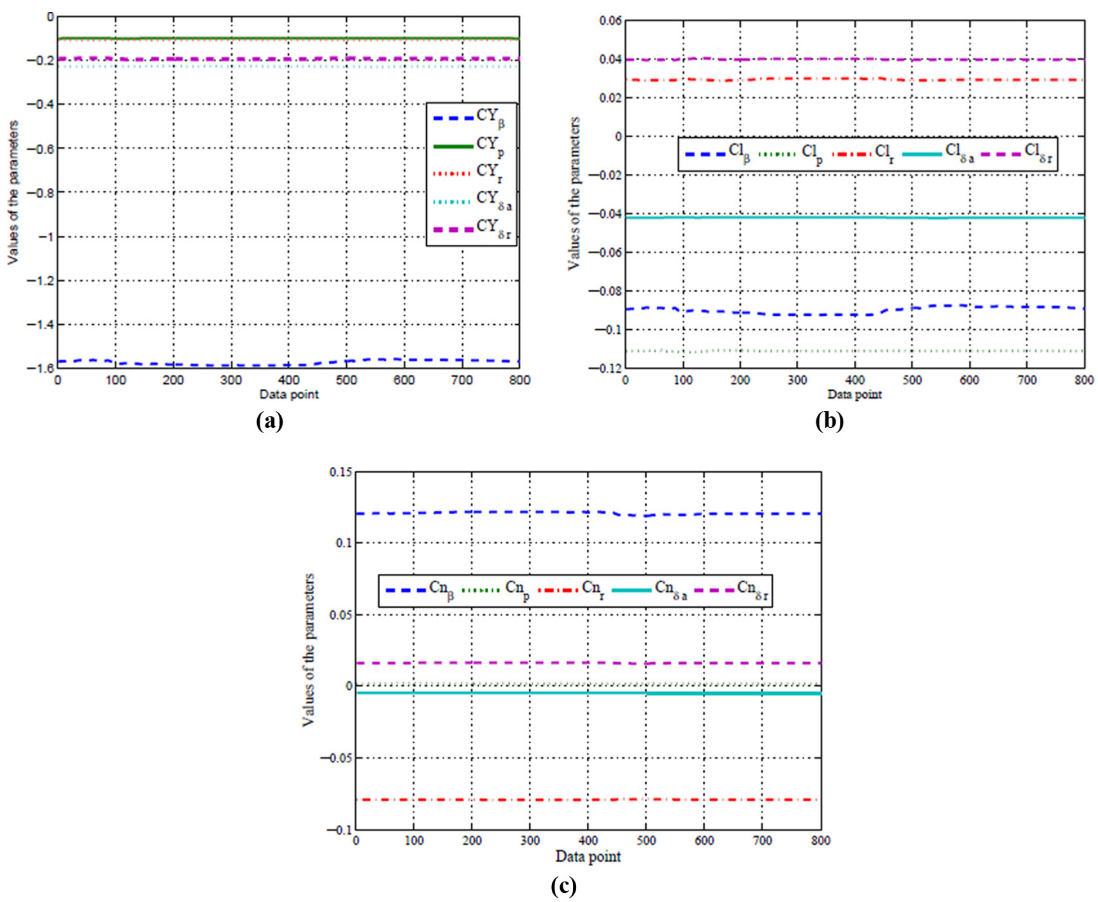
Identification of aircraft lateral-directional derivatives

The flight test data of small transport aircraft are used to estimate aerodynamic derivatives appearing in the expression of side force, yawing and rolling moment coefficients. During the flight test, the aircraft has trimmed at flight condition of 6.28-degree angle of attack, Mach 0.22 at an altitude of 2,652 m. The postulated model for the lateral-directional aircraft dynamics is given by:

$$\begin{aligned} C_y &= C_{y_0} + C_{y_\beta}\beta + C_{y_p}\frac{pb}{2U_0} + C_{y_r}\frac{rb}{2U_0} + C_{y_{\delta a}}\delta a + C_{y_{\delta r}}\delta r \\ C_l &= C_{l_0} + C_{l_\beta}\beta + C_{l_p}\frac{pb}{2U_0} + C_{l_r}\frac{rb}{2U_0} + C_{l_{\delta a}}\delta a + C_{l_{\delta r}}\delta r \\ C_n &= C_{n_0} + C_{n_\beta}\beta + C_{n_p}\frac{pb}{2U_0} + C_{n_r}\frac{rb}{2U_0} + C_{n_{\delta a}}\delta a + C_{n_{\delta r}}\delta r \end{aligned} \quad (22)$$

where $C_{y(\cdot)}$, $C_{l(\cdot)}$ and $C_{n(\cdot)}$ are non-dimensional parameters which need to be extracted, and U_0 is velocity at which aircraft is trimming.

Figure 8 Variation in parameters w.r.t data points



Notes: (a) Side force derivative in C_y; (b) lateral stability and control derivative in Cl; (c) directional stability and control derivative in C_n

The static directional (Weathercock) stability of aircraft can be ensured by the positive value of C_{n_β}. C_{l_β} is one of the most important parameters for lateral-directional stability and handling qualities. A negative value of C_{l_β} ensures the roll stability of aircraft. The positive roll rate makes restoring moment and hence the damping in roll derivative C_{l_p} has a negative value. The side force coefficient C_{y_p} is contributed by the vertical tailplane and considered to be negative for a negative horizontal force toward positive roll rate. The yawing moment induced by roll rate has contributions from both the vertical tail and the wing, and it is represented by C_{n_p} derivative. As C_{n_p} is cross derivative, it has an influence on the Dutch roll mode frequency. C_{n_r} is the most important yaw rate stability derivative and it is contributed by the vertical tailplane. As yawing motion causes a horizontal force on the vertical tailplane that damps the yawing motion, C_{n_r} has a negative value. The positive aileron deflection δa causes a negative rolling, and hence $C_{l_{\delta a}}$ becomes negative. The rudder effectiveness of an aircraft is indicated by desirable derivative $C_{n_{\delta r}}$.

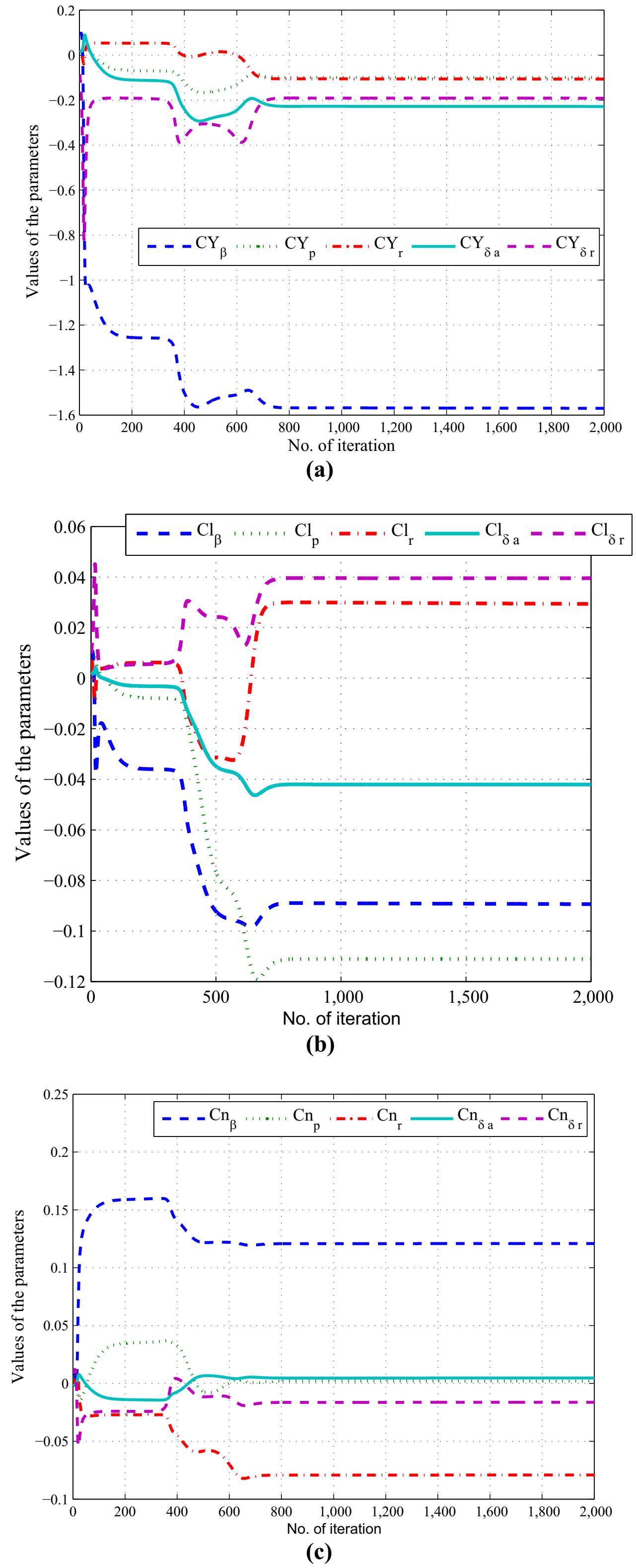
Accelerometer measurements a_y, p and r, are used for the purpose of computational of force and moment coefficients in the lateral-directional derivative estimation and they are given as:

$$
\begin{aligned}
a_y &= \frac{1}{g}\left[\frac{\bar{q}s}{m}C_y + (pq+\dot{r})X_{ay} - \left(r^2-p^2\right)Y_{ay} + (rq-\dot{p})Z_{ay}\right] \\
\dot{p} &= \frac{qsb}{I_xI_z - I_{xz}^2}\left[I_zC_l + I_{xz}C_n\right] - qr\frac{I_{xz}^2 - I_yI_z + I_z^2}{I_xI_z - I_{xz}^2} + pq\frac{I_{xz}(I_x - I_y + I_z)}{I_xI_z - I_{xz}^2} \\
\dot{r} &= \frac{qsb}{I_xI_z - I_{xz}^2}\left[I_xC_n + I_{xz}C_l\right] + pq\frac{I_{xz}^2 - I_yI_z + I_z^2}{I_xI_z - I_{xz}^2} - qr\frac{I_{xz}(I_x - I_y + I_z)}{I_xI_z - I_{xz}^2}
\end{aligned} \tag{23}
$$

where m is mass, $\bar{q}$ is dynamic pressure, s is platform area of wing, b is the wing span, p roll rate, q is pitch rate, r is yaw rate, $I_{(\cdot)}$ is moment of inertia about an axis and $l_{(\cdot)}$ is the location of engine from the C.G.

The lateral-directional response of flight data and estimated responses are given in Figure 7, and it is found that they are in close agreement with other. This ensures that the dynamics of aircraft model have been accurately identified. Estimated lateral-directional derivatives from flight data are tabulated in Table II. The variation of parameters associated with side force, lateral stability, directional stability and control with respect to data points is shown in Figure 8. The variation of these parameters with number of iterations is also given in Figure 9. The close agreement of flight data with reconstructed lateral-directional responses from the neural model is shown in Figure 10 and therefore, estimated neural model of aircraft system is accurate. To verify the estimated aircraft neural model, complimentary flight data set is passed through the trained network and computed a_y using the outputs of the network for the given input complementary flight data. The a_y can also be computed by using the side force coefficient obtained from the wind tunnel and estimates of OEM. These computed a_y is compared with measured a_y for the same input, and comparison plot for the accelerations a_y is given in Figure 11. A good match

Figure 9 Variation in parameters w.r.t number of iterations during training



Notes: (a) Side force derivative in C_y; (b) lateral stability and control derivative in C_l; (c) directional stability and control derivative in C_n

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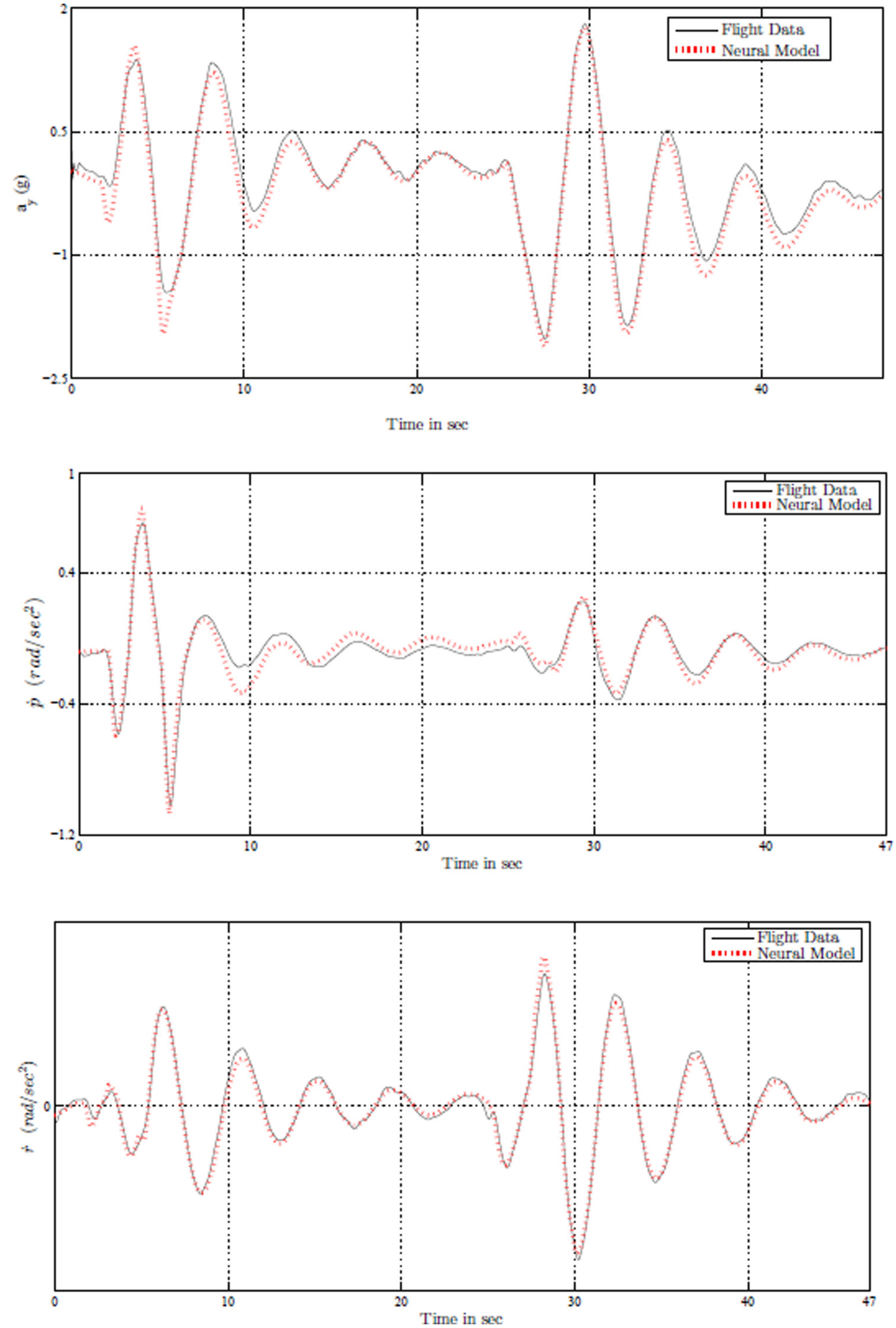
Figure 10 Comparison of a_y, $\dot{p}$, $\dot{r}$ measured and reconstructed from neural networks



between these flight measured and predicted response is witnessed.

Parameter estimation for a flexible aircraft

In the absence of flight data, simulated data of flexible aircraft are generated by using the postulated model of a large transport aircraft. The following subsection describes the details of structural modes excited with a rigid body mode of the aircraft.

Flight simulation of a flexible aircraft

The simulated data of flexible aircraft containing the two elastic modes get excited in the longitudinal axis. The included two structural modes in flight simulation characterize fuselage

Figure 11 Time history verification of identified neural model

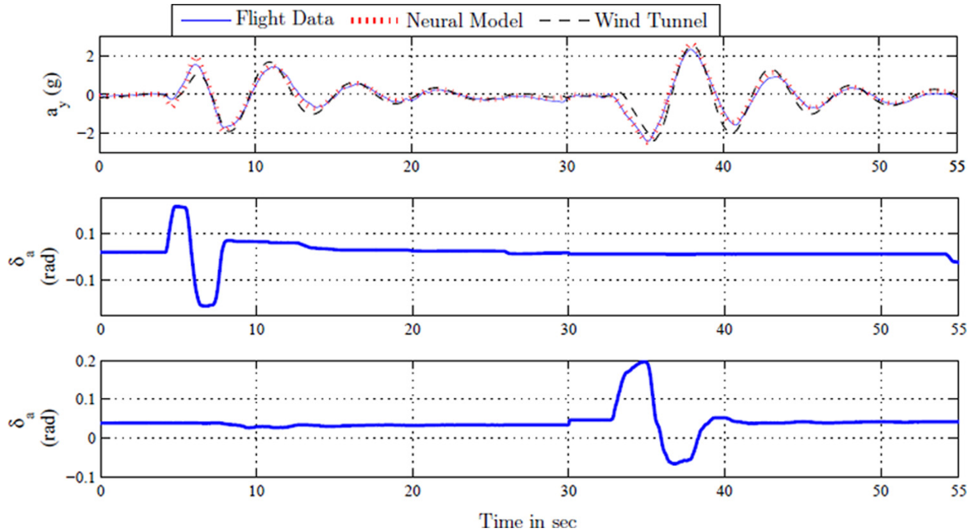
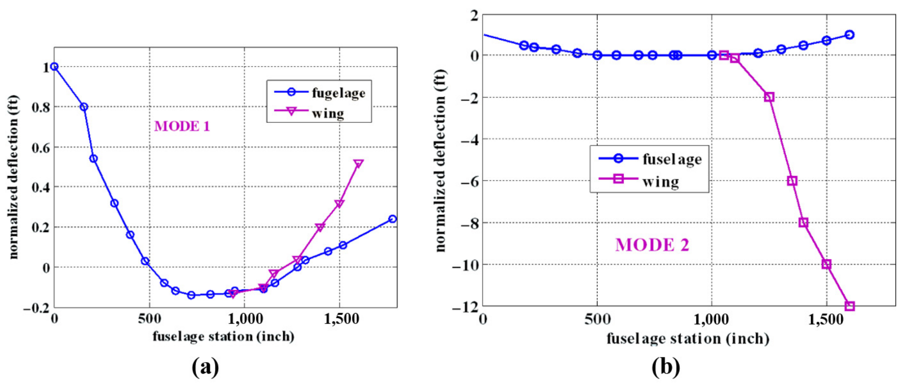


Figure 12 Mode shapes of flexible aircraft



Notes: (a) Symmetric and (b) anti-symmetric

Figure 13 Comparison of aircraft responses

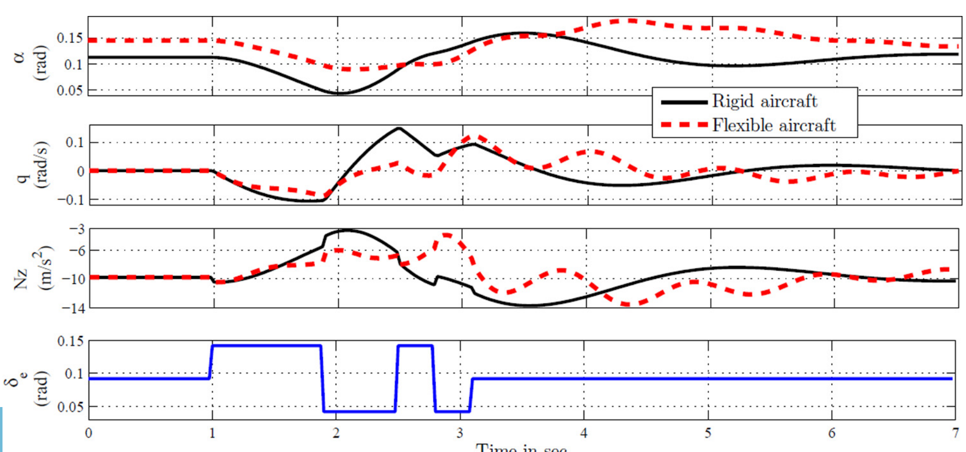


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Figure 14 Frequency response for pitch rate to elevator input $(\frac{q}{\delta_e})$

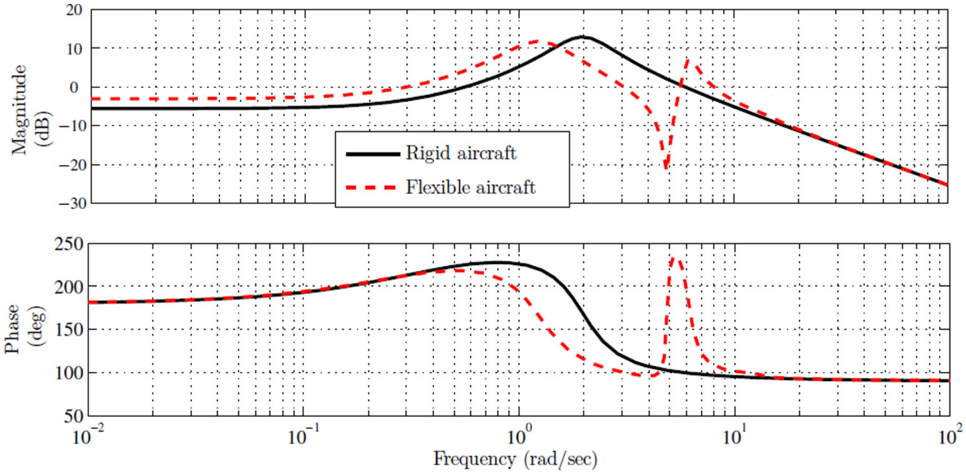

Table III Estimated aerodynamic derivatives of flexible aircraft

Parameter	True value	NPD	OEM
$Cz_{\delta e}$	−0.435	−0.429 (6.34)*	−0439 (2.23)
Cz_{α}	−2.922	−2.744 (0.09)	−2.963 (0.29)
Cz_q	14.765	15.545 (1.69)	14.56 (4.19)
$Cz_{\dot\eta_1}$	−0.0848	−0.052 (1.67)	–
$Cz_{\dot\eta_2}$	1.03	1.087 (1.95)	–
Cz_{η_1}	−0.0288	−0.029 (0.17)	−0.0291 (0.54)
Cz_{η_2}	0.306	0.31 (0.51)	–
Cm_{δ_e}	−2.578	−2.293 (0.28)	−2.546 (0.31)
Cm_{α}	−1.66	−1.566(0.17)	−1.639 (0.56)
Cm_q	−34.75	−32.476 (1.47)	−34.57 (0.30)
$Cm_{\dot\eta_1}$	−0.159	−0.112 (0.92)	0.157(1.37)
$Cm_{\dot\eta_2}$	1.23	0.628 (3.22)	–
Cm_{η_1}	−0.0321	−0.034 (0.13)	−0.031 (0.96)
Cm_{η_2}	−0.025	0.027 (2.11)	–
$C_{\delta}e^{\eta_1}$	−0.0128	−0.013 (1.04)	−0.0127 (0.07)
$C_{\alpha}^{\eta_1}$	−0.0149	−0.016 (0.24)	−0.015 (0.12)
$C_q^{\eta_1}$	−0.095	−0.084 (5.78)	–
ω_1	6.29	6.254 (2.47)	–
ω_2	7.21	7.18 (3.47)	–
$C_{\dot\eta_2}^{\eta_1}$	−2e−04	−2.2e−4 (6.14)	–
$C_{\eta_1}^{\eta_1}$	6e−05	6e−05 (0.13)	5.7e−05 (0.6)
$C_{\eta_2}^{\eta_1}$	−9e−05	−7e−05 (1.86)	–
$C_{\delta_e}^{\eta_2}$	−0.064	−0.065 (1.66)	−0.0634 (0.19)
$C_{\alpha}^{\eta_2}$	0.026	0.026 (0.75)	–
$C_q^{\eta_2}$	0.012	0.012 (4.57)	–
$C_{\dot\eta_1}^{\eta_2}$	0.009	0.009 (1.46)	–
$C_{\dot\eta_2}^{\eta_2}$	−0.298	−0.290 (0.54)	–
$C_{\eta_1}^{\eta_2}$	0.004	0.004 (0.09)	–

Note: *The values in parenthesis denote relative standard deviation values in percentage

bending with wing participating in phase and wing bending and fuselage participating out of phase. The mode shapes of these two modes of aircraft are given in Figures 12(a) and (b). Postulated model of a flexible aircraft for pitching motion can be approximated by neglecting variations in velocity, which are given as (Ghosh and Raisinghani, 1994):

$$\dot\alpha = q + \frac{\rho u S}{2m} C_Z$$
$$\dot q = \frac{\rho u^2 S\bar c}{2I_y} C_m \tag{24}$$

where C_Z and C_m represent the aerodynamic coefficients that consist of the aircraft stability and control derivatives (Waszak and Schmidt, 1988). Air density ρ, total inertial velocity u, wing area S, wing chord $\bar c$, aircraft mass m and the moment inertia I_y about y-axis are the other quantities used in the above equations. The aerodynamic coefficients C_Z and C_m used in aerodynamic models of flexible aircraft can be written as:

$$C_Z = C_{Z_0} + C_{Z_\alpha}\alpha + C_{Z_q}\frac{q\bar c}{2u} + C_{Z_{\delta_e}}\delta_e + C_{Z_{\eta 1}}\eta_1 + C_{Z_{\eta 2}}\eta_2$$
$$+ \frac{\bar c}{2u}C_{Z_{\eta 1}}\dot\eta_1 + \frac{\bar c}{2u}C_{Z_{\eta 2}}\dot\eta_2 C_m = C_{m_0} + C_{m_\alpha}\alpha$$
$$+ C_{m_q}\frac{q\bar c}{2u} + C_{m_{\delta_e}}\delta_e + C_{m_{\eta 1}}\eta_1 + C_{m_{\eta 2}}\eta_2$$
$$+ \frac{\bar c}{2u}C_{m_{\eta_1}}\dot\eta_1 + \frac{\bar c}{2u}C_{m_{\eta 2}}\dot\eta_2 \tag{25}$$

Next, we have to consider the elastic states of the flexible aircraft to augment with rigid body dynamic model represented in terms of elastic states (η_1, η_2) and $(\dot\eta_1,\ \dot\eta_2)$.

For this, the generalized coordinates satisfying equation (25) was introduced by Waszak and Schmidt (1988):

$$\ddot\eta_1 + 2\xi_1\omega_1\dot\eta_1 + \omega_1^2\eta_1 = \frac{\rho u^2 S\bar c}{2M_1}\left[C_\alpha^{\eta_1}\alpha + C_q^{\eta_1}\frac{q\bar c}{2u} + C_{\delta_e}^{\eta_1}\delta_e\right.$$
$$\left. + \left(C_{\eta 1}^{\eta_1}\eta_1 + C_{\eta 2}^{\eta_1}\eta_2 + C_{\eta 1}^{\eta_1}\frac{\dot\eta_1\bar c}{2u} + C_{\eta 2}^{\eta_1}\frac{\dot\eta_2\bar c}{2u}\right)\right]\ddot\eta_2$$
$$+ 2\xi_2\omega_2\dot\eta_2 + \omega_2^2\eta_2 = \frac{\rho u^2 S\bar c}{2M_2}\left[C_\alpha^{\eta_2}\alpha + C_q^{\eta_2}\frac{q\bar c}{2u} + C_{\delta_e}^{\eta_2}\delta_e\right.$$
$$\left. + \left(C_{\eta 1}^{\eta_2}\eta_1 + C_{\eta 2}^{\eta_2}\eta_2 + C_{\eta 1}^{\eta_2}\frac{\dot\eta_2\bar c}{2u} + C_{\eta 2}^{\eta_2}\frac{\dot\eta_2\bar c}{2u}\right)\right] \tag{26}$$

The simulated data for α, q, N_z (normal acceleration) and the elastic states are generated. The aeroelastic effects would affect

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the aircraft response for given control input. Simulated data are plotted for rigid body and flexible aircraft, as shown in Figure 13. As seen, α and q responses for flexible data not only differ quantitatively but also qualitatively from the rigid body response. The frequency response of the rigid model and the aeroelastic models are given in Figure 14. Review of this result reveals that the two elastic modes are excited at frequencies of 6.29 rad/s and 7.21 rad/s with damping factor $\xi_1 = \xi_1 = 0.02$. Thus, the application of a rigid body model in the estimation algorithm would lead to erroneous and unacceptable results for a flexible aircraft.

Parameter estimation results and discussion for flexible aircraft

The neural model of a flexible aircraft has been established by training the neural network with input vector $[\delta e,\ \alpha,\ q,\ .\eta_1,\ \eta_2^{\cdot},\ \eta_1,\ \eta_2]$ and output vector $[Cz,\ Cm,\ \eta_1^{\cdot\cdot},\ \eta_2^{\cdot\cdot}]$. The NPD method is applied to simulated data of flexible aircraft with *a prior* information of model structure presented in equation (25). The frequency of the structural modes, rigid body and elastic body derivatives of flexible aircraft are estimated and tabulated in Table III with their standard deviations and RSTDs of estimates in parenthesis. Figure 15 shows time histories of the output signals $(Cz, Cm,\ \eta_1^{\cdot\cdot},\ \eta_2^{\cdot\cdot})$ to the neural network and Figure 16 shows input signals $(\delta e,\ \alpha,\ q,\ \eta_1^{\cdot},\ \eta_1^{\cdot},\ \eta_2,\ \eta_2)$. The flight simulation is carried out by input frequency sweep signals of elevator for time duration of 90 s.

In the case of flight data, elastic information of flexible aircraft is not available in the flight test instrumentation. But, the elastic information of $\ddot{\eta}_1$ and $\ddot{\eta}_2$ are indirectly measurable using differential accelerometers and their measurement models are given by:

$$\Delta a_{mk} = \phi_k \ddot{\eta}_k,\ k = 1,2 \tag{27}$$

where Δa_{mk} is measured through the installation of accelerometers at different positions along the aircraft structure, and ϕ_k defines the structural modes contributed

Figure 15 Time history response of flexible aircraft and neural model (output signal)

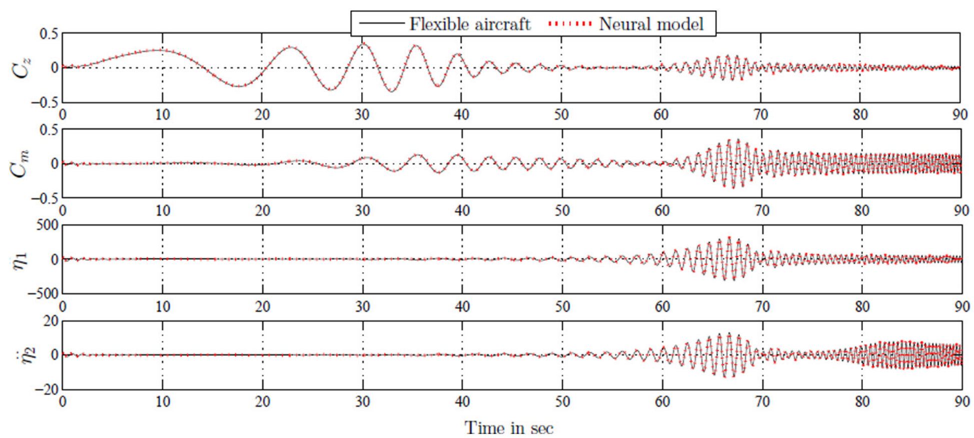


Figure 16 Time history response of input signal to neural network

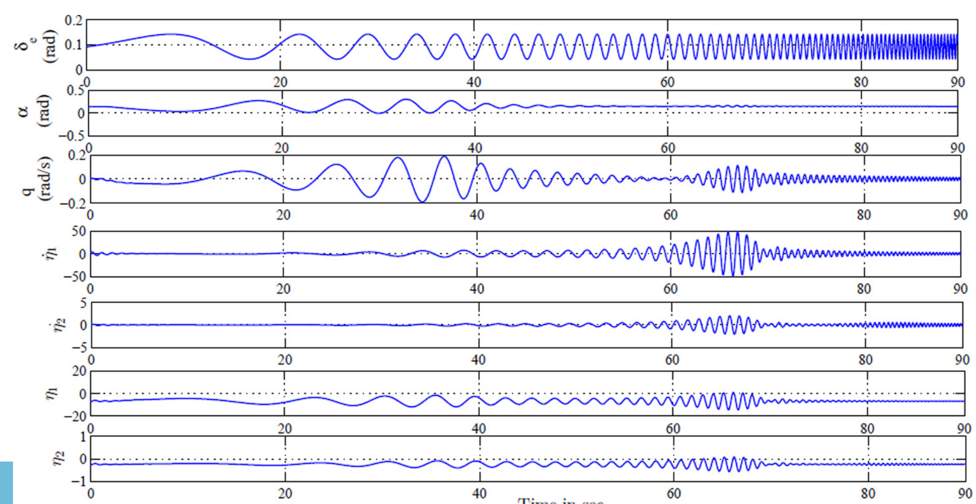


Figure 17 Variation in parameters w.r.t. data points of flexible aircraft

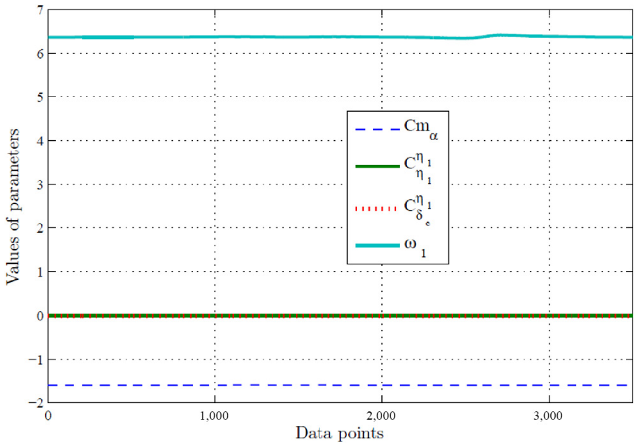
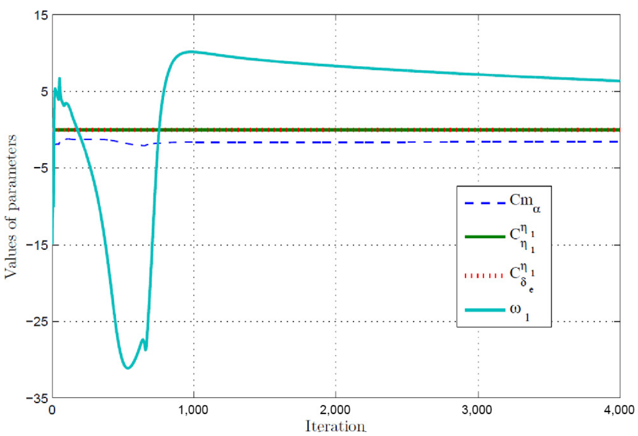


Figure 18 Variation in parameters w.r.t. number of iterations during training of flexible aircraft



to each of measurements. Subsequently, elastic information of $\eta_1, \eta_2, \dot{\eta}_1, \dot{\eta}_2,$ is computed from these measurements. Figure 17 shows the estimation of parameter Cm_α, $C_{\eta_1}^{\eta_1}$, $C_{\delta e}^{\eta_1}$, ω_1 using the NPD method for simulated data with respect to data points. It shows there is a marginal variation in $C_{\delta e}^{\eta_1}$ with respect to the different data points. The variation of parameter Cm_α, $C_{\eta_1}^{\eta_1}$, $C_{\delta e}^{\eta_1}$, ω_1 with respect to the number of iteration is shown in Figure 18. As the number of iteration increases, the parameters attain stable value of its estimates. The time history response of simulated data and estimated responses are given in Figure 15, and it is found that they are in good agreement. This ensures that the dynamics of flexible aircraft model have been accurately identified. Figure 19 shows comparison between N_z from simulated data and reconstructed from neural networks. Predictable neural model of flexible aircraft is required to be verified with a complementary set of simulated data. For this, the neural network is trained with data set given by an elevator input signal of the frequency sweep, then a new data set is generated with an elevator input signal of 3-2-1-1 and passed through the trained network. The output is used to compute N_z for the given input of complementary data. Comparison plot for the normal accelerations N_z is given in Figure 20 and the responses are matched for simulated and predicted neural network signal.

Conclusions

The NPD method is applied to flight data for the purpose of online estimation of aircraft parameters. For this, initially a neural model representing the MIMO aircraft system is established. Moreover, a separate consideration for the rigid and flexible aircraft dynamic is made to simplify the model considerably in terms of structure and the number of parameters. Aircraft longitudinal and lateral-directional derivatives are estimated from flight data using the NPD method, and it is found that the estimates are close to wind tunnel values and comparable with estimates obtained from the OEM. The complimentary flight data are used to validate the identified neural model of aircraft. This shows that the NPD method has become preferred approach to estimate parameters as it does not require the initial value of estimates. As the initial values of parameters are not available in a practical situation as well as OEM requires these initial parameters, application of the NPD approach

Figure 19 Comparison of N_z of flexible aircraft

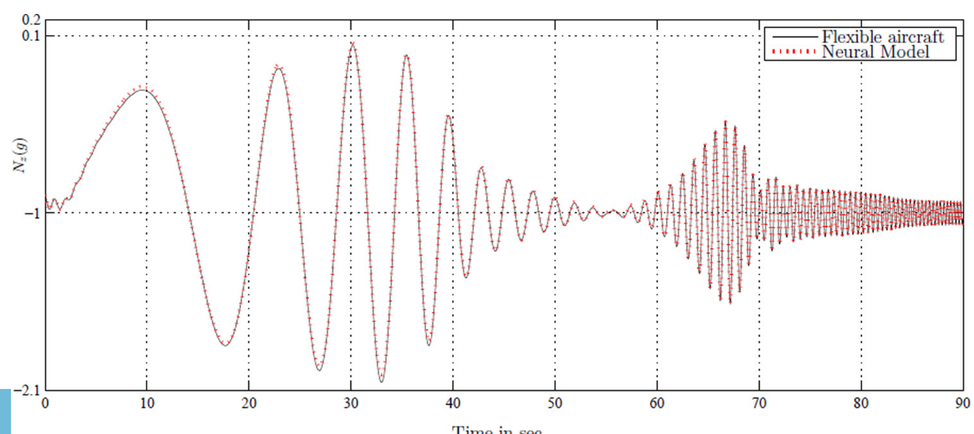
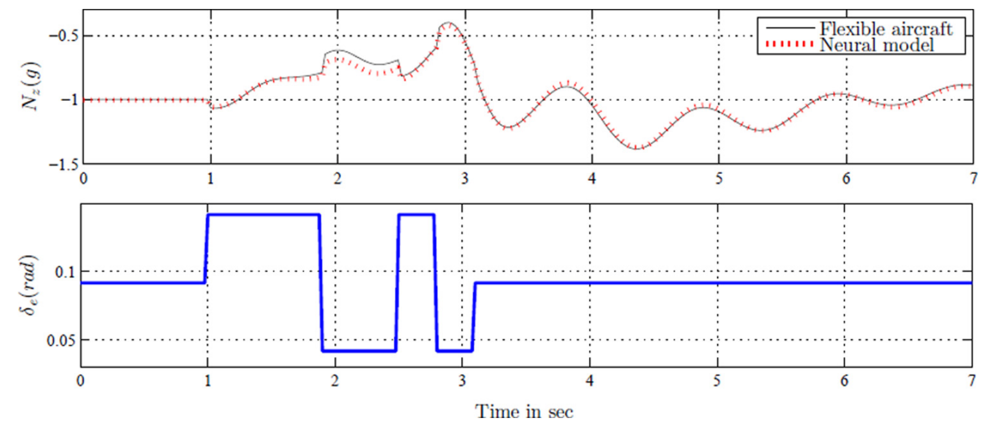


Figure 20 Time history verification of identified neural model



gives an advantage over OEM to estimate aerodynamic parameters from flight data.

Furthermore, we extended the use of the NPD method to a flexible aircraft and estimated rigid body and elastic body derivatives from simulated data. The flight simulation of flexible aircraft is carried out for an elevator input of frequency sweep. Moreover, symmetric and antisymmetric structural modes are included in the flight simulation to represent the flexibility of aircraft. As a result, a mathematical model of flexible aircraft contains too many parameters. Proposed neural network approach of NPD works well for the parameter estimation with their noise statistics, as this approach does not have convergence issue in estimates from established neural model.

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