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Frequency-Domain Estimation of Parameters from Flight Data Using Neural Networks

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A recently proposed method (the delta method) of estimating aircraft parameters from flight data using feed forward neural networks is applied for the extraction of lateral-directional parameters from simulated as well as real-flight data in the frequency domain. To apply the delta method in the frequency domain, the time-domain flight data are frequency transformed using a base-two fast Fourier transform algorithm. The frequency-transformed motion and control variables and the force and moment coefficients are split into the real and imaginary parts. The network is trained using the training input–output pairs of either the real part or the imaginary part of all of the variables involved. The delta method for the frequency-domain application is first validated on simulated flight data (with and without measurement noise) for the lateral-directional dynamics and then applied to real-flight data. Implementation details of the method in the frequency domain and the results obtained thereby are presented. Relative advantages and potential applications of the frequency-domain approach for the delta method are also pointed out.

Nomenclature

a_{ym}	=	measured acceleration along y body axis, m/s^2
C_l, C_n	=	coefficient of rolling and yawing moment
$C_{l(\cdot)}$, $C_{n(\cdot)}$, $C_{y(\cdot)}$	=	nondimensional derivatives
Im[ ]	=	imaginary part of a complex number
I_x, I_y, I_z	=	moment of inertia about x, y, and z axes, kg m^2
I_{xz}	=	cross product of inertia, kg m^2
m	=	mass of aircraft, kg
p, r	=	roll and yaw rates, rad/s
$\bar{q}$	=	dynamic pressure, N/m^2
Re[ ]	=	real part of a complex number
S	=	reference wing area, m^2
s	=	half the wing span, m
V	=	flight velocity, m/s
β	=	angle of side slip, rad
δa, δr	=	aileron and rudder deflections, rad
ρ	=	air density, kg/m^3
ϕ	=	bank angle, rad
ω	=	angular frequency, rad/s

Superscript

$\sim$	=	frequency transform

Introduction

IN recent times, the most widely used parameter estimation method has been the output error method and its variants, like the maximum likelihood method, the filter error method, and so on. Application of these methods requires an a priori postulation of aircraft model. More recently, a class of neural networks called feed forward neural networks (FFNNs) has been used to model aircraft dynamics wherein aircraft motion variables and control inputs are mapped to predict the total aerodynamic coefficients.[1,2] It has been shown that FFNNs can work as general function approximators and, thereby, are capable of approximating any continous function to any desired accuracy, provided the appropriate number of hidden layers and neurons per layer exist and that the activation function is continuous.[3]

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It is because of this ability of FFNNs to act as general function approximators that FFNNs present themselves as an alternative tool for modeling aircraft aerodynamics. The FFNNs also possess a generalization property, which enables the interpolation or extrapolation using a finite set of measurements. Raisinghani et al.,[4] exploiting the generalization property of FFNNs, proposed two methods, namely the delta method and the zero method, for explicitly estimating aircraft stability and control derivatives from flight data.

Historically, many of the early approaches for estimating parameters from flight data used the measured frequency-response curves rather than the time-domain signals. With the rapid progress in the computing powers of modern digital computers, the frequency-domain approach was gradually discarded in favor of analyzing the measured data in the time domain. However, attention has been brought back to the frequency domain and its advantages, highlighted by the researchers attempting to identify an aeroelastic aircraft,[5] aircraft with unsteady aerodynamics,[6] aircraft flying in turbulence,[7] unstable aircraft,[8] and rotorcraft.[9] This provided the motivation for exploring the possibility of implementing the proposed delta and zero methods in the frequency domain. The present paper investigates the frequency-domain modeling of lateral-directional aerodynamics of an aircraft using an FFNN and the applicability of the delta method for extracting parameters from such a neural model. The frequency-domain application of the delta method is first tested on simulated-flight data and then on real-flight data. Relative advantages of the frequency-domain over the time-domain approach for estimating parameters via the delta method are pointed out.

FFNNs

FFNNs consist of groups of neurons arranged in a layered structure. Each neuron receives a signal from the neurons in the layer preceding itself and passes a signal on to the neuron in the following layer. The relationship between the summed inputs to a neuron and its output is governed by an activation function. A few of the commonly employed activation functions are a tangent hyperbolic function, a logistic (sigmoidal) function, and so on. The neurons within a network are arranged in an input layer, one or more hidden layers, and an output layer (Fig. 1). The connections between neurons are assigned their individual weights. The weights are adjusted by the so-called back-propagation algorithm (BPA) and, to a large extent, the model of the system to be approximated is encoded in the connection weights. Note, however, that the weights do not represent a specific parameter of the model; instead, it is the cumulative effect of the weights and the structure of the network that allows the network to have the adequate prediction capability and, thereby, to yield a black-box type model.

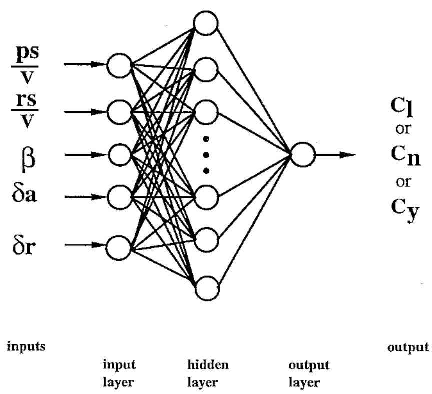

Fig. 1 Schematic of FFNN for lateral-directional aerodynamic modeling.

Frequency Transform of Flight Data and FFNN Modeling

Because real-flight data were made available for the DLR research aircraft advanced technology testing aircraft system (ATTAS),[10] it was found expedient to generate simulated data for the same aircraft and for the flight condition corresponding to real-flight data.[10] For the purpose of generating simulated data for the lateral-directional dynamics, Eqs. (1) and (2) of Ref. 11 were integrated for multistep 3-2-1-1 types of aileron and rudder inputs, an aileron input followed in one s by a rudder input (these simulated data correspond to case 5 data of Ref. 11). The maximum likelihood estimates from the real-flight data, reported in Ref. 10, were used as the true values of the parameters for generating simulated data.

For the frequency-domain application of the delta method, the motion and control variables as well as the total force and moment coefficients are frequency transformed. In the time domain, let $Y_i(pT)$, $p = 0, 1, \ldots, N - 1$ be the given sequence of N discrete simulated or measured data points obtained at equal interval of T seconds. These data are transformed by using the following discrete Fourier transform[12]:

$$Y_i(f_n) = \sum_{p=0}^{N-1} Y_i(pT)\exp\left(\frac{-2j\pi pn}{N}\right), \qquad j = \sqrt{-1} \tag{1}$$

where $f_n = n/NT$, $n = 0, 1, \ldots, N/2$.

The transformation of the time-domain signals into the frequency-domain was done through a base-two fast Fourier transform (FFT) algorithm.[12] For this purpose, if the given number of data points N do not satisfy the relationship $N = 2^p$ (p is an integer value), then a requisite number of trailing zeros are added to satisfy this relationship, for example, if $N = 230$, then 26 trailing zeros are added to make $N = 2^8$.

The transformed data are obtained as a function of the angular frequency, $\omega_n = 2\pi f_n$. The force and the moment coefficients in the frequency domain are evaluated by the following expressions:

$$\tilde{C}_l(j\omega) = j\omega(I_x\tilde{p} - I_{xz}\tilde{r})/\bar{q}Ss \tag{2a}$$

$$\tilde{C}_n(j\omega) = j\omega(I_z\tilde{r} - I_{xz}\tilde{p})/\bar{q}Ss \tag{2b}$$

$$\tilde{C}_y(j\omega) = (2m/\rho V^2 S)\tilde{a}_y \tag{2c}$$

Note that for the real-flight data, computation of moment coefficients in the time domain would require $\dot{p}$ and $\dot{r}$, obtained either from directly measured signals of angular accelerometers, or, more commonly, via the numerical differentiation of the measured angular rates p and r. Whereas the measured $\dot{p}$ and $\dot{r}$ signals are generally noisy and of poor quality, the option of numerical differentiation may introduce its own errors in $\dot{p}$ and $\dot{r}$. However, the frequency-domain neural modeling has the advantage in that the computation of frequency-transformed moment coefficients [Eqs. (2a) and (2b)] require only frequency-transformed p and r signals, unlike the time-domain neural modeling that requires the $\dot{p}$ and $\dot{r}$ signals.[11]

The network can be trained by using training pairs of either the real or the imaginary parts of the frequency transformed inputs ($\tilde{ps}/V, \tilde{rs}/V, \tilde{\beta}, \tilde{\delta a}$, and $\tilde{\delta r}$) and output ($\tilde{C}_l$, or $\tilde{C}_n$, or $\tilde{C}_y$). The training was carried out using both options for a few selected flight data, and it was concluded that both options led to almost similar training. For the sake of brevity, results are presented where the real parts of the frequency transform of the motion and control variables Re[$\tilde{ps}/V, \tilde{rs}/V, \tilde{\beta}, \tilde{\delta a}, \tilde{\delta r}$] serve as the network inputs, and Re[$\tilde{C}_l$, or $\tilde{C}_n$, or $\tilde{C}_y$] serves as the output variable for supervised training of the network and, subsequently, for parameter estimation via the delta method. The training algorithm is iterative in nature: The algorithm is started with a set of randomly initialized weights, and the BPA repeated for all data points to update weights recursively.

The mean square error (MSE) for each iteration is defined by

$$\text{MSE} = \frac{1}{\text{mxn}}\sum_{i=1}^{n}\sum_{j=1}^{m}[Y_i(j) - X_i(j)]^2$$

where Y and X are, respectively, the desired (known) and the computed (predicted) output of the neural network; n is the number of data points; and m is the number of output variables. The training sessions are continued until changes in the MSE in successive iterations are less than the prescribed value or the number of iterations exceeds the specified number. Once the training (modeling) is over and the network weights are frozen, the same input data are passed again to check the prediction capability of the neural network. The predicted values are deemed acceptable only if the MSE is less than the specified value. To achieve the desired level of MSE, various interrelated neural network parameters like the number of hidden layers, the number of nodes in the hidden layer(s), the learning rate, the momentum rate, the abruptness (logistic gain) factor of the sigmoidal function, the initial neural network weights, and the scaling of input–output data are adjusted by trial and error. The final set of neural network parameters chosen are as follows: the number of hidden layers is 1; the number of neurons in the hidden layer is 6; the learning rate is 0.3; the logistic gain is 0.85; the momentum rate is 0.50; the random seed is 0.85; the number of iterations is 5000; the initial weights are from −0.5 to 0.5.

Delta Method in the Frequency Domain

The delta method proposed by Raisinghani et al.[4] and Ghosh et al.[11] is based on the following premise: A stability or a control derivative can be thought of as a change in the aerodynamic force or moment coefficient caused by a small variation in one of the motion/control variables while the rest of the variables are held constant. A detailed discussion of the delta method and its time-domain application to estimate parameters from flight data is given in Ref. 11. The frequency-domain application of the method is illustrated with the help of an example.

Let the rolling moment coefficient C_l be written as

$$C_l = C_{lp}(ps/V) + C_{lr}(rs/V) + C_{l\beta}\beta + C_{l\delta a}\delta a + C_{l\delta r}\delta r \tag{3}$$

This aerodynamic model is postulated solely for the purpose of illustrating the frequency-domain application of the delta method and is not a prerequisite for applying the delta method. The frequency transform of Eq. (3) is split into real and imaginary parts as

$$\text{Re}[\tilde{C}_l] = C_{lp}\,\text{Re}[\tilde{ps}/V] + C_{lr}\,\text{Re}[\tilde{rs}/V] + C_{l\beta}\,\text{Re}[\tilde{\beta}] + C_{l\delta a}\,\text{Re}[\tilde{\delta a}] + C_{l\delta r}\,\text{Re}[\tilde{\delta r}] \tag{4a}$$

$$\text{Im}[\tilde{C}_l] = C_{lp}\,\text{Im}[\tilde{ps}/V] + C_{lr}\,\text{Im}[\tilde{rs}/V] + C_{l\beta}\,\text{Im}[\tilde{\beta}] + C_{l\delta a}\,\text{Im}[\tilde{\delta a}] + C_{l\delta r}\,\text{Im}[\tilde{\delta r}] \tag{4b}$$

Next, for the lateral-directional modeling, either Re[$\tilde{ps}/V, \tilde{rs}/V, \tilde{\beta}, \tilde{\delta a}, \tilde{\delta r}$] could be mapped to Re[$\tilde{C}_l$, or $\tilde{C}_n$, or $\tilde{C}_y$], or Im[$\tilde{ps}/V, \tilde{rs}/V, \tilde{\beta}, \tilde{\delta a}, \tilde{\delta r}$] to Im[$\tilde{C}_l$, or $\tilde{C}_n$, or $\tilde{C}_y$]. Once the mapping is established, a modified network input file is prepared wherein only one motion/control variable at a time is perturbed by a small (delta, Δ) value. For example, to estimate $C_{l\beta}$, the $\mathrm{Re}[\tilde{\beta}]$ value at each frequency point is perturbed by $\pm\Delta(\mathrm{Re}[\tilde{\beta}])$ while the rest of the variables are held at their original values. This modified file is now presented to the neural model to predict corresponding values of perturbed $\mathrm{Re}[\tilde{C}_l]^+$ for $\mathrm{Re}[\tilde{\beta}] + \Delta\mathrm{Re}[\tilde{\beta}]$ and $\mathrm{Re}[\tilde{C}_l]^-$ for $\mathrm{Re}[\tilde{\beta}] - \Delta\mathrm{Re}[\tilde{\beta}]$. The stability derivative $C_{l\beta}$ is evaluated as $C_{l\beta} = (\mathrm{Re}[\tilde{C}_l]^+ - \mathrm{Re}[\tilde{C}_l]^- / 2\Delta\,\mathrm{Re}[\tilde{\beta}])$. Similarly, perturbing only, for example, $\mathrm{Re}[\tilde{\delta r}]$ in the network input file will yield the control derivative $C_{l\delta r}$.

Note that the delta method yields one estimated value of a parameter at each frequency, that is, one estimate for each of the training pair used. A study of the histogram of the resulting estimates showed a near normal distribution. This justifies using the mean value as the estimated value and the sample standard deviation about the mean as the measure of accuracy of the estimates.[4,11,13]

Estimation of Lateral-Directional Parameters

Simulated-Flight Data

The applicability of the delta method in the frequency domain is first tested using simulated flight data. For this purpose, the simulated flight data pertaining to lateral-directional dynamics corresponding to a 3-2-1-1 type aileron (δa) input, followed in one s by a 3-2-1-1 type rudder (δr) input (case 5 of Ref. 11) are frequency transformed using a base-two FFT algorithm[12] to yield $\tilde{p}s/V$, $\tilde{r}s/V$, $\tilde{\beta}$, $\tilde{\delta a}$, and $\tilde{\delta r}$ as a function of angular frequency ω_n. The frequency-transformed $\tilde{C}_l$, $\tilde{C}_n$, and $\tilde{C}_y$ are computed using Eq. (2). The real part of the frequency-transformed variables $\tilde{p}s/V$, $\tilde{r}s/V$, $\tilde{\beta}$, $\tilde{\delta a}$, and $\tilde{\delta r}$ are used to form the network input file, and the real part of $\tilde{C}_l$, $\tilde{C}_n$, or $\tilde{C}_y$ form the output file for training the network. The trained network was used for estimating parameters via the delta method. All of the parameters were well estimated, and the mean values of estimates were close to those reported in Ref. 11 for the same data via the time-domain application of the delta method. One noticeable difference was that the standard deviations corresponding to almost all of the parameter estimates were significantly lower in the case of the frequency domain as compared to the time domain.

Next, the same flight data were corrupted by adding varying amounts of measurement noise. Results for 10% measurement noise in motion variables, obtained via the delta method in both the time domain and frequency domain, are shown in Table 1. From Table 1, whereas a slight improvement in the accuracy of estimates is noticeable for the frequency-domain application, it is the standard deviations that show a significant reduction. Thus, the delta method in the frequency domain seems to be estimating parameters more accurately and with an increased level of confidence (lower standard deviations).

Real-Flight Data

The final test of any scheme for parameter estimation must come from its successful demonstration on real-flight data. The frequency-domain application of the delta method is next investigated using real-flight data supplied by DLR for the ATTAS aircraft.[11] The flight data for the flight condition defined by a landing-flap condition δ_f = special position (1 deg) and perturbations about steady-state flight at indicated airspeeds (IAS), $V_{\mathrm{IAS}} = 160$ kn (case 9 of Ref. 11), are chosen (Fig. 2). The raw data were preprocessed[10,11] to account for 1) variations in the mass, c.g. location, and the moment of inertias due to fuel consumption; 2) offset of measuring instruments and reference point; 3) the time delays and bias errors in the measured quantities; and 4) axes transformation to conform to the axis system used in Ref. 10 to facilitate direct comparison with parameter estimates[10] obtained via the maximum-likelihood (ML) method from the same data.

The measured motion and control variables $p(t)$, $r(t)$, $\beta(t)$, $\delta a(t)$, and $\delta r(t)$ are transformed to the frequency domain using the discrete form of the FFT method. The transformed variables $\tilde{p}(\omega_n)$, $\tilde{r}(\omega_n)$, $\tilde{\beta}(\omega_n)$, $\tilde{\delta a}(\omega_n)$, and $\tilde{\delta r}(\omega_n)$ are used to form the neural network input file consisting of $\mathrm{Re}[\tilde{p}s/V, \tilde{r}s/V, \tilde{\beta}, \tilde{\delta a}, \tilde{\delta r}]$. The transformed motion variables $\tilde{p}$, $\tilde{r}$, and $\tilde{\beta}$ are used in Eq. (2) to compute the transformed force and moment coefficients $\tilde{C}_l$, $\tilde{C}_n$, and $\tilde{C}_y$, and these are used to prepare the network output files having $\mathrm{Re}[\tilde{C}_l]$, or $\mathrm{Re}[\tilde{C}_n]$, or $\mathrm{Re}[\tilde{C}_y]$. By the use of these input–output files, the network is trained. The trained network is used for estimating parameters via the delta method. The estimated parameters are given in the sixth column of Table 1. For ready comparison, the time-domain estimates via the Delta method[11] from the same flight data are also shown in the fifth column of Table 1.

A comparison with estimates obtained in the time domain from the same flight data shows that the frequency-domain approach has generally improved the accuracy of the estimates (we treat Ref. 10 estimates as the nominal values for comparison). In particular,

Table 1 Estimated lateral-directional parameters for simulated- and real-flight data

		Estimated simulated-flight data, 10% noise		Estimated real-flight data, V_{IAS} = 160 kn	
Parameters	Ref. 10	Time domain	Frequency domain	Time domain	Frequency domain
$-C_{lp}$	0.978	0.908	1.010	0.866	0.885
	(0.020)[a]	(0.095)[b]	(0.004)	(0.13)	(0.003)
$-C_{lr}$	0.418	0.350	0.355	0.594	0.579
	(0.430)	(0.070)	(0.006)	(0.029)	(0.009)
$-C_{l\beta}$	0.126	0.102	0.130	0.110	0.116
	(0.390)	(0.012)	(0.0006)	(0.003)	(0.0002)
$-C_{l\delta a}$	0.247	0.217	0.243	0.209	0.219
	(0.200)	(0.028)	(0.0006)	(0.004)	(0.0004)
$-C_{l\delta r}$	0.046	0.038	0.042	−0.027	0.017
	(0.120)	(0.005)	(0.0003)	(0.007)	(0.0001)
$-C_{np}$	0.115	0.132	0.122	0.068	0.134
	(0.730)	(0.036)	(0.0018)	(0.003)	(0.0006)
$-C_{nr}$	0.495	0.533	0.568	0.864	0.610
	(0.56)	(0.061)	(0.003)	(0.026)	(0.001)
$-C_{n\beta}$	0.281	0.280	0.231	0.264	0.287
	(0.70)	(0.013)	(0.0013)	(0.005)	(0.0001)
$C_{n\delta a}$	0.0	0.005	0.0006	0.011	0.0058
	——	(0.014)	(0.0002)	(0.006)	(0.00003)
$-C_{n\delta r}$	0.166	0.167	0.157	0.169	0.161
	(0.120)	(0.010)	(0.0005)	(0.004)	(0.0002)
C_{yp}	0.303	0.358	0.482	0.111	0.263
	(5.180)	(0.189)	(0.0047)	(0.025)	(0.00008)
C_{yr}	0.727	0.531	0.960	1.146	2.201
	(2.320)	(0.089)	(0.012)	(0.603)	(0.001)
$-C_{y\beta}$	1.133	1.115	0.966	1.083	1.245
	(0.330)	(0.069)	(0.0025)	(0.049)	(0.0004)
$C_{y\delta a}$	0.029	0.032	0.0077	(0.129)	0.0148
	(13.90)	(0.057)	(0.0002)	(0.011)	(0.00004)
$C_{y\delta r}$	0.191	0.190	0.193	0.095	0.218
	(2.620)	(0.018)	(0.0014)	(0.008)	(0.00004)

[a]Standard deviations in %. [b]Sample standard deviations.

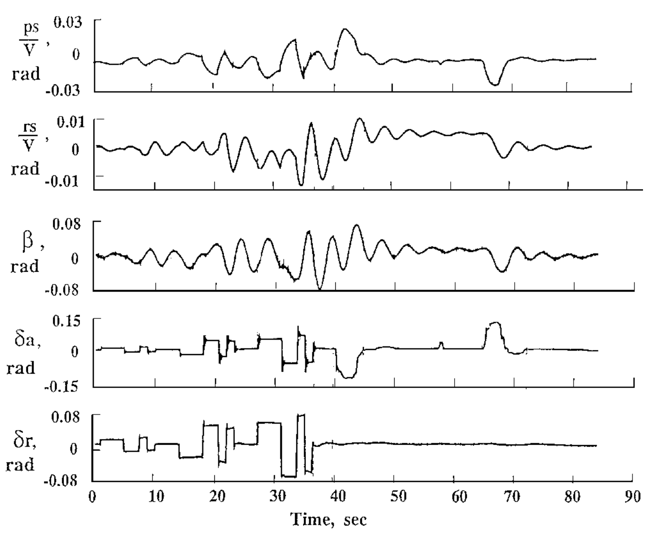

Fig. 2 Real-flight data of the ATTAS aircraft supplied by DLR.

$C_{l\delta r}$, C_{np}, $C_{n\beta}$, C_{yp}, $C_{y\delta a}$, and $C_{y\delta r}$ are better estimated in the frequency domain. Special attention is drawn to the estimated values of control derivatives $C_{l\delta r}$, $C_{y\delta a}$, and $C_{y\delta r}$ obtained from the same real-flight data at $V_{\mathrm{IAS}} = 160$ kn (case 9 of Ref. 11) in the frequency-domain vs those in the time domain.[11] In the time domain, 1) the order of magnitude of the estimated values of $C_{y\delta a}$ and $C_{y\delta r}$ (fifth column of Table 1) are opposite to those of the nominal values; 2) the sign of $C_{l\delta r}$ is opposite to that of the nominal value.[11] However, in the frequency-domain approach, 1) the estimated values of both the derivative $C_{y\delta a}$ and $C_{y\delta r}$ have the correct signs and order of magnitude (and in addition the derivative $C_{y\delta r}$ is well estimated); 2) although the magnitude of the derivative $C_{l\delta r}$ does not compare well with its nominal value, its sign does get corrected from positive to negative. In Ref. 11, it was shown that the use of identical δa and δr inputs resulted in estimated control derivatives having the same sign as well as almost equal magnitudes because the network is unable to distinguish between δa and δr inputs. It was further conjectured that for $V_{\mathrm{IAS}} = 160$ kn flight data, the control inputs δa and δr have similar form and magnitude in the first part (up to about the first 22.5 s, Fig. 2) and that this leads to poor estimates of control derivatives. In spite of the same control inputs being used here, the frequency-domain estimates of control derivatives from the same flight data show significant improvement.

The result was a bit of a puzzle initially, but a plausible explanation followed. The time-domain result was suspected to be due to the type of control inputs employed for the flight data: Similar-looking δa and δr inputs followed by the two pulses of δa were employed, and it was conjectured that the network training and subsequent parameter estimates are affected by the first segment of control inputs having similar looking 3-2-1-1 types of δa and δr. It therefore seems logical to conjecture that the frequency-domain application has undone the existing similarity between the δa and δr inputs. To verify the conjecture, the power spectral density plots of measured δa and δr inputs are compared in Fig. 3a; it is found that, indeed, the plots for δa and δr are distinct from each other. Furthermore, because the training input file uses only the real part of the transformed $\tilde{\delta a}$ and $\tilde{\delta r}$, plots of $\mathrm{Re}[\tilde{\delta a}]$ and $\mathrm{Re}[\tilde{\delta r}]$ are also compared in Fig. 3b. Figure 3b shows that the variations of $\mathrm{Re}[\tilde{\delta a}]$ and $\mathrm{Re}[\tilde{\delta r}]$ with frequency ω_n are quite dissimilar to each other. Thus, the networks using $\mathrm{Re}[\tilde{\delta a}]$ and $\mathrm{Re}[\tilde{\delta r}]$ in its input file can easily distinguish between the δa and δr inputs for the whole frequency range, unlike in the time domain where the δa and δr in the input file had almost equal values for the initial segment. A comparison of time-domain (fifth column of Table 1) and frequency-domain (sixth column of Table 1) estimates from the flight data for $V_{\mathrm{IAS}} = 160$ kn shows that most of the frequency-domain estimates compare better with the ML estimates of Ref. 10, especially the control derivatives. In addition, as observed for the simulated data, the standard deviations for the case of real-flight data also are significantly lower for estimates via the frequency-domain approach. Furthermore, it seems that the frequency-domain approach is more robust with respect to the type of control inputs employed for generating real-flight data. This is because even if similar looking δa and δr were employed by a pilot, the frequency-domain formulation using the real or imaginary part of transformed δa and δr would lead to better mapping of force/moment coefficients with network inputs, especially with δa and δr, and, thereby, to good estimates of control derivatives as compared to the time-domain approach.

With the estimated parameters, the real part of the force and moment coefficients are calculated by using the following expression:

$$\mathrm{Re}(\tilde{C}_a) = C_{ap}\,\mathrm{Re}[\tilde{p}s/V] + C_{ar}\,\mathrm{Re}[\tilde{r}s/V] + C_{a\beta}\,\mathrm{Re}[\tilde{\beta}]$$

$$+ C_{a\delta a}\,\mathrm{Re}[\tilde{\delta}_a] + C_{a\delta r}\,\mathrm{Re}[\tilde{\delta r}], \qquad a = 1, n, y \tag{5}$$

A comparison of the values so estimated [computed by Eq. (5)] of the force and moment coefficient with the corresponding actual values from the flight data [computed by Eq. (2)] is shown in Fig. 4. A good match between the actual and the estimated $\mathrm{Re}[\tilde{C}_l]$, $\mathrm{Re}[\tilde{C}_n]$, and $\mathrm{Re}[\tilde{C}_y]$ is evident from Fig. 4.

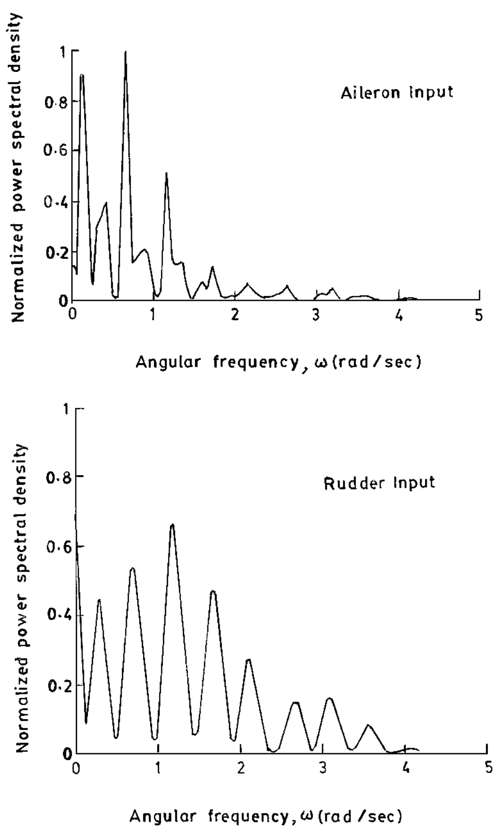

Fig. 3a Normalized power spectral density of control input used in real-flight data.

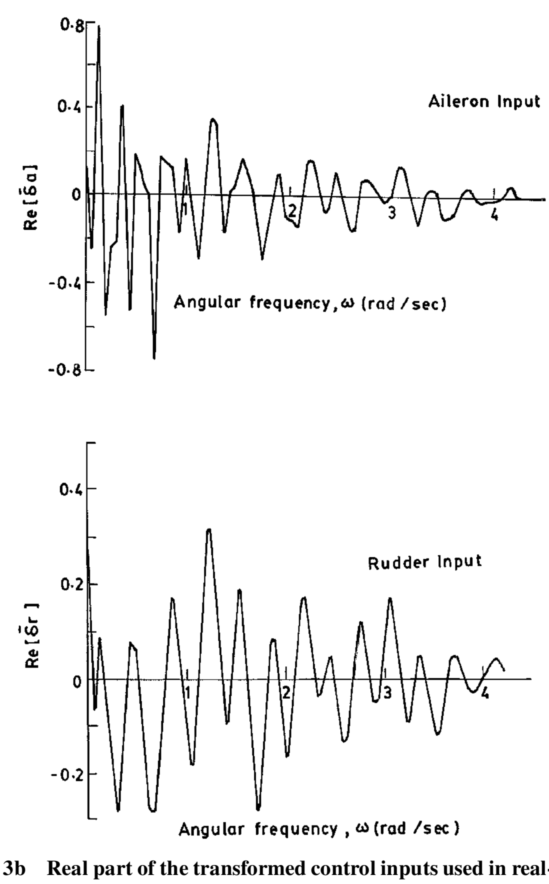

Fig. 3b Real part of the transformed control inputs used in real-flight data.

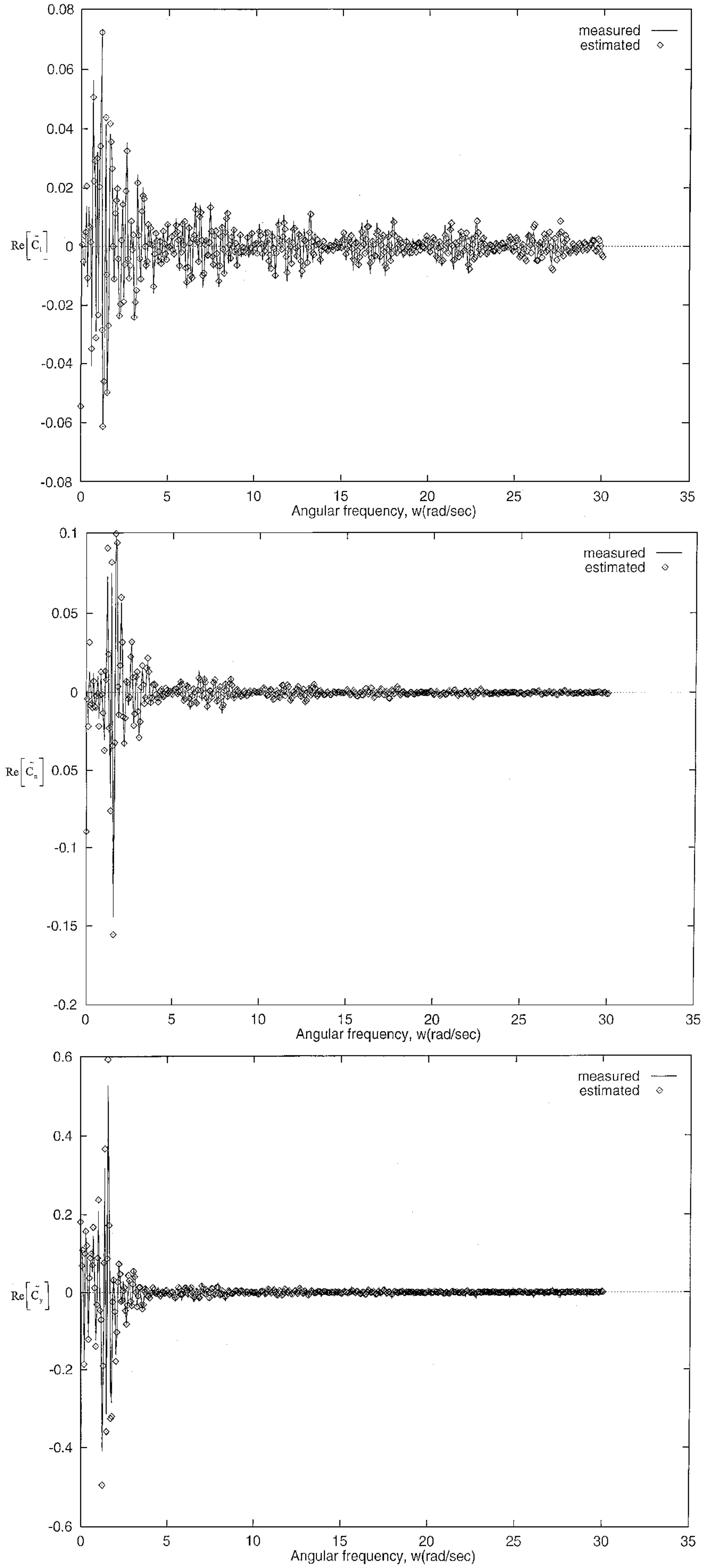

Fig. 4 Comparison of the real part of the transformed measured and estimated aerodynamic coefficients.

Conclusions

A recently proposed method, the delta method, for estimation of aircraft parameters from flight data using FFNNs has been validated on simulated- as well as real-flight data in the frequency domain. A comparison of estimates from identical flight data shows that the frequency-domain approach has generally improved the accuracy of estimates and confidence level (lower standard deviations). The frequency-domain application of the method also seems to be more robust with respect to the presence of measurement noise in the flight data. The frequency-domain applicability of the delta method provides an option of choosing a frequency range in such a way that leaving out transformed data beyond a certain cutoff frequency would act like a filter for leaving out unwanted response contents, for example, the high-frequency noise, and yet retain the signal content essentially intact in the chosen frequency range.

Such an option of selecting a frequency range from which the input–output pairs are utilized for network training could be advantageously exploited for estimating parameters of an aeroelastic aircraft, a helicopter, and so on. For example, the frequency-transformed flight data of a rotorcraft could be split into a low-frequency and a high-frequency range to correspond, respectively, to the rigid-body model and rotor dynamics. It is possible then to use the low- and high-frequency data separately to train the network and, thus, separately estimate parameters for the rigid-body model and rotor dynamics. The latter is required to augment the rigid-body model to achieve an acceptable model required for high-bandwidth rotorcraft flight control systems. Similarly, for an aeroelastic aircraft, frequency response for the rigid-body and aeroelastic modes could be used separately for training the network. Thus, the neural modeling, and, thereafter, estimation of parameters via the delta method for rigid and elastic modes, could be achieved separately. This would take care of one of the difficulties, the need to simultaneously estimate a large number of parameters involved in a model of an aeroelastic aircraft, faced by the conventional methods, namely, the ML method, the filter error method, etc. Furthermore, it must be pointed out that, unlike conventional methods of parameter estimation, the neural approach does not require solution of coupled equations of motion for the rotorcraft (rigid-body and rotor dynamics) or the aeroelastic aircraft[13] (rigid-body and elastic degrees of freedom). The recorded flight data are directly transformed to prepare input–output files for the network training and the delta method applied to estimate the parameters without a need for postulating and solving the equations of motion, or a need for a guess of reasonable sets of initial values of parameters as would be required by, for example, various variants of output-error methods.

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