Defence Science Journal, Vol 48, No 1, January 1998, pp. 69-86

Identification of Helicopter Rigid Body Dynamics from Flight Data

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ABSTRACT

This paper discusses helicopter modelling and identification related aspects. By applying the system identification methodology, longitudinal and lateral-directional rigid body helicopter dynamics are identified from flight data. Aerodynamic parameters from single input excitation as well as multimanoeuver evaluation are estimated utilising output-error approach. The formulated mathematical models yield adequate fit to measured time histories. Results obtained from the proof-of-match for model validation indicate that the identified derivatives can satisfactorily predict longitudinal dynamics to a given arbitrary input. It is further demonstrated for the present study that lateral body dynamics can be adequately predicted by including cross-coupling terms in the estimation model.

NOMENCLATURE

a_x	Linear acceleration along longitudinal body axis
a_y	Linear acceleration along lateral body axis
a_z	Linear acceleration along normal body axis
$b_{( )}$	Biases in model equations for parameter estimation
g	Acceleration due to gravity
h	Altitude
p	Roll rate
q	Pitch rate
r	Yaw rate
u	Component of air velocity along the longitudinal body axis
v	Component of air velocity along the lateral body axis
w	Component of air velocity along the normal body axis
V	Total air speed
β	Angle of sideslip
δ	Control deflection
Δ	Biases in kinematic equations for consistency analysis
θ	Pitch angle
φ	Roll angle
$X_{( )},Y_{( )},Z_{( )}$	Specific force derivatives
$L_{( )},M_{( )},N_{( )}$	Specific moment derivatives.

Superscripts & Subscripts

col	Collective
lat	Lateral
lon	Longitudinal
m	Measured
p	Specific derivative w.r.t. p
ped	Pedal
q	Specific derivative w.r.t. q
r	Specific derivative w.r.t. r
u	Specific derivative w.r.t. u
v	Specific derivative w.r.t. v
w	Specific derivative w.r.t. w

Received 04 April 1997, revised 13 September 1997

Quantities fixed during estimation.
Derivative w.r.t. time

1. INTRODUCTION

Over the last two decades, the methodology of system identification has been successfully applied to aerospace systems[1]. The objective lies in not merely obtaining a quantitative minimisation of the fit-error between the flight data and the model predictions, but rather in obtaining a reliable set of parameter estimates for general applicability. Evaluation of flight test data has, hitherto, been effectively used to validate wind tunnel results, improve confidence in mathematical models, and reduce uncertainty levels of important stability and control derivatives. Other important benefits of aerospace system identification are related to potential to reduce the amount of costly and time-consuming flight testing, improve assessment and evaluation of flying qualities, assist in flight control system design and provide accurate mathematical models for ground-based system simulators[1-3]. Although the approach of determining stability and control derivatives for the fixed wing aircraft is used with confidence, the application of same techniques to helicopters is not so advanced[4]. This is mainly due to the complexity in helicopter dynamics which requires more degrees-of-freedom (DOFs) and higher order models with large number of unknown parameters to adequately replicate the vehicle motion. Besides, higher noise levels, inherent instabilities and high intensity mode coupling adversely affect successful estimation of aerodynamic parameters. The development of an adequate model structure and its identification from rotorcraft data is, therefore, still a major research task.

Successful identification of helicopter aerodynamic derivatives requires three fundamental steps: (i) depending upon the intended purpose of results, modelling requirements and important DOFs must be defined; (ii) an accurate identification technique for extraction of model parameters must be available; (iii) formulated models must be applied to flight test data and the accuracy of estimated derivatives be evaluated.

Based on the experience gained on fixed wing aircraft at the National Aerospace Laboratories (NAL), Bangalore, it was decided to investigate the helicopter modelling and identification related aspects. To this end, flight data gathered from flight manoeuvers conducted with the test helicopter were used to estimate stability and control derivatives. Output-error parameter estimation algorithm, modified to adjust to the requirements of helicopter identification, was used to extract linear rotorcraft models from flight test data. A preliminary study on estimation from flight data of helicopter stability and control derivatives was conducted by Girja & Raol[5].

This paper considers the issues related to helicopter modelling. Model equations required to identify longitudinal and lateral-directional rigid body dynamics from flight data are described. Following this, flight testing and data consistency analysis are briefly described. The bias terms obtained from compatibility check of the selected data runs are provided in Table 1. Finally, applying output-error method to the formulated equations, stability and control derivatives for the test helicopter are identified from the reconstructed flight path trajectories. Identification results are presented in the form of estimated values of derivatives shown in Tables 2 and 3, and as time history comparisons of flight measurements and model predictions depicted in Figs 1-4.

2. HELICOPTER MODELLING

Helicopter modelling is a major problem area because of large number of DOFs and complexity in aerodynamics. Besides, helicopter identification studies may require inplane lag, torsion and air mass dynamics, particularly if the investigation concerns rotor instability problems. Figure 5 shows various DOFs that may contribute to helicopter motion[6]. Prediction of helicopter dynamics therefore demands complex models, wherein large number of unknown parameters have to be estimated. This, coupled with noisy data due to high vibration level and inherent instabilities, makes it

Table 1. Kinematic consistency results

Parameters	Run 1	Run 2	Run 3	Run 4	Run 5
Δp	0.0716	0.0725	0.0718	0.0726	0.0706
Δq	0.0074	0.0077	0.0049	0.0053	0.0077
$\Delta\phi$	−0.2075	−0.1992	-0.1916	−0.1992	0.0297
$\Delta\beta$	0.1695	0.5196	—	—	—
$\Delta\theta$	—	—	0.0604	0.0850	0.0721
u_0	30.8542	24.9534	36.6913	36.4512	47.4834
v_0	−7.4464	−16.3969	−2.4155	−0.7931	−1.7322
w_0	0.06110	−0.8795	−1.7479	−2.5330	−2.1946
ϕ_0	−0.01184	−0.08872	−0.05035	−0.05586	−0.02869
θ_0	0.0193	0.01108	−0.04291	−0.06111	−0.06742
h_0	1524.859	1549.652	1529.806	1524.859	1514.951

difficult to achieve success in the application of parameter identification techniques.

Complexity of the desired model, in general, depends upon the intended use of results. Unlike for conventional fixed wing aircraft, where 3-DOFs decoupled longitudinal and lateral-directional models are often utilised, a 6-DOFs (eighth-order) model is generally required for helicopter identification in the low frequency range. For high frequency transient predictions, the 6-DOFs model is likely to prove inadequate and a 9-DOFs (fourteenth-order) rotor and fuselage model (Fig. 6) may be required to give better simulation of short period time histories[7]. Flight test experience has revealed that hingeless rotor stability is significantly influenced by elastic and inertial coupling terms[8]. This is particularly true at high speeds and would necessitate appropriate representation of rotor dynamics in helicopter mathematical model. If engineering simulation validation and flight control system design is the objective, then a 12-DOFs helicopter simulation model structure is the minimum requirement.

In principle, the model to be formulated for identification studies should represent the helicopter dynamics as realistically as possible and, at the same time, should be sufficiently simple and mathematically tractable. Furthermore, in view of the limited number of flight runs available for the current investigations, it stands to reason to determine minimal order model that would best fit the flight test data. Consequently, it was decided to work with 3-DOFs (fourth-order) decoupled longitudinal and lateral-directional rigid body equations of motion to identify aerodynamic derivatives from helicopter flight data.

2.1 Longitudinal Derivative Model

A 3-DOFs (fourth-order) linearised longitudinal derivative model for the purpose of flight data analysis can be expressed as follows:

(a) State equations

$$\dot{u} = X_u u + X_w w + (X_q - w_0)q + X_{\delta lon}\delta_{lon} + X_{\delta col}\delta_{col} - g\sin\theta_0 - \theta\cos\theta_0 + v_0 r + b_{\dot{u}}\,; \qquad u(0) = u_0$$

$$\dot{w} = Z_u u + Z_w w + (Z_q + u_0)q + Z_{\delta lon}\delta_{lon} + Z_{\delta col}\delta_{col} + g\cos\theta_0 - g\theta\sin\theta_0 - v_0 p + b_{\dot{w}}\,;\ w(0) = w_0$$

$$\dot{q} = M_u u + M_w w + M_q q + M_{\delta lon}\delta lon + M_{\delta col}\delta_{col} + b_{\dot{q}}\,;\ q(0) = q_0$$

$$\dot{\theta} = q\cos\varphi - r\sin\varphi + b_\theta \qquad ;\ \theta(0) = \theta_0 \tag{1a}$$

To complete the model equations necessary for extraction of aerodynamic derivatives from flight test data, the relationship between the observed variables and state variables needs to be specified.

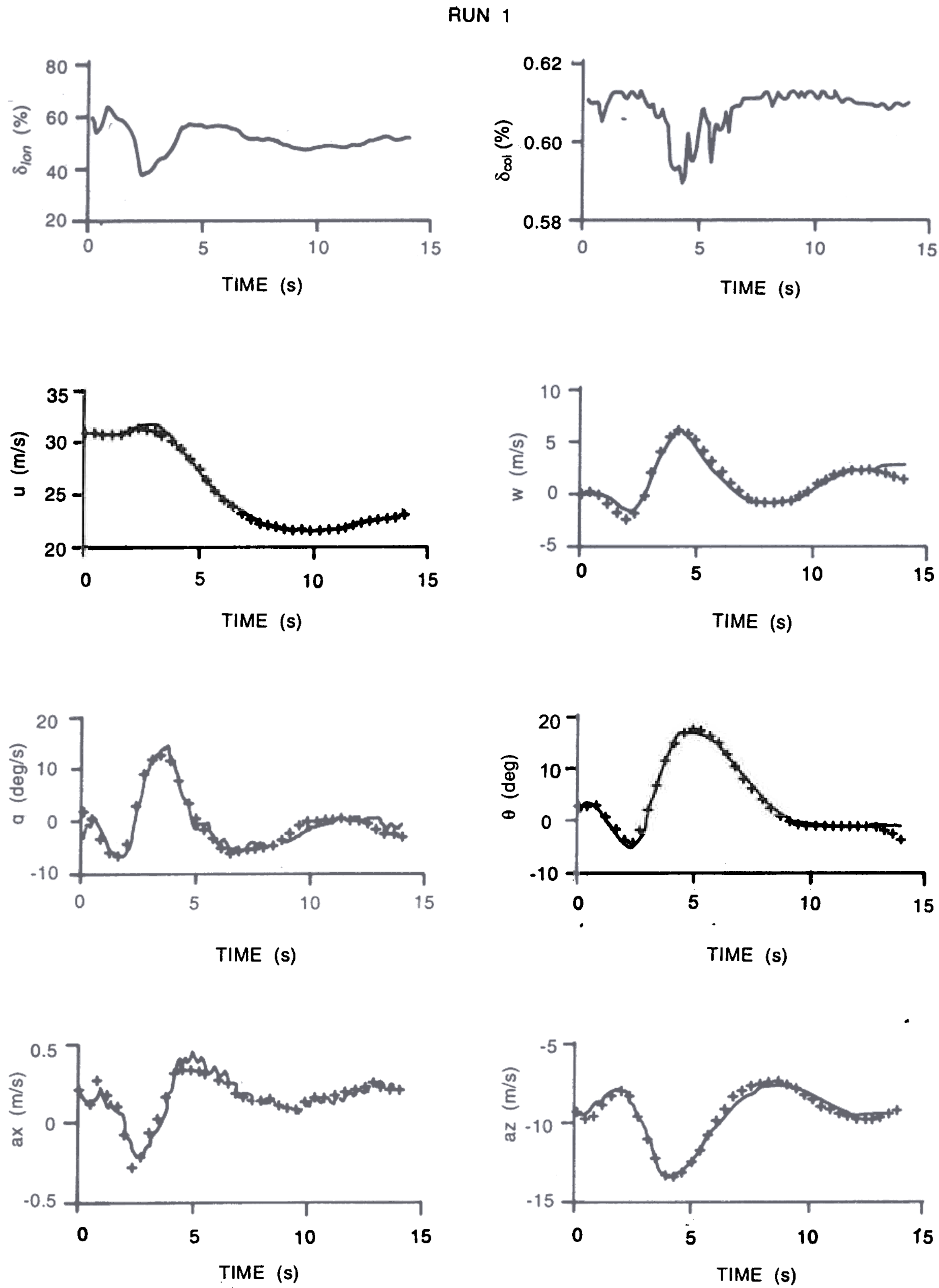


Figure 1(a). Comparison of measured rigid body data with model response — body longitudinal dynamics identified using fourth-order (3-DOF) derivative model (— flight, ++++ model).

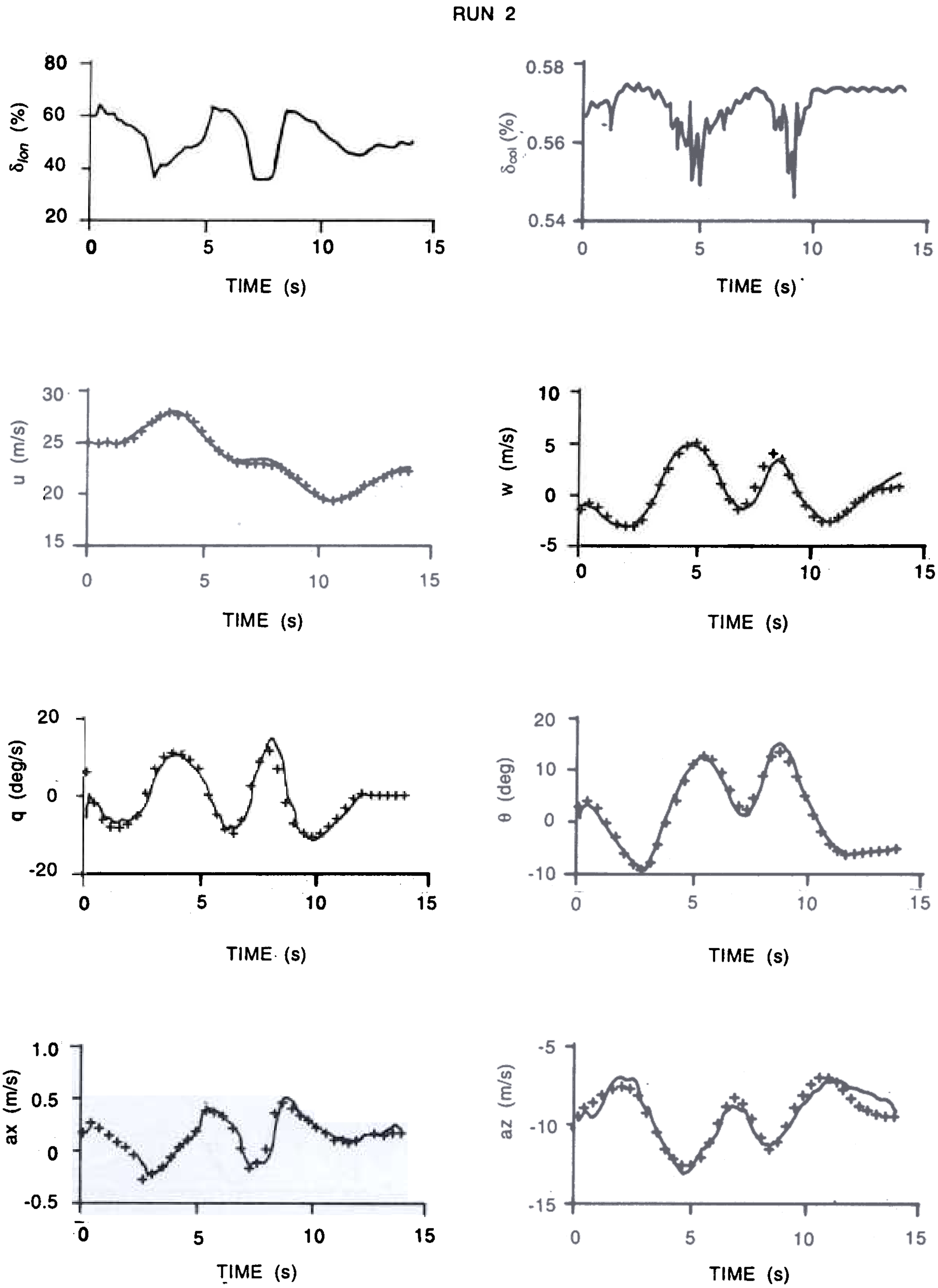


Figure 1(b). Comparison of measured rigid body data with model response — body longitudinal dynamics identified using fourth-order (3-DOF) derivative model (— flight, ++++ model).

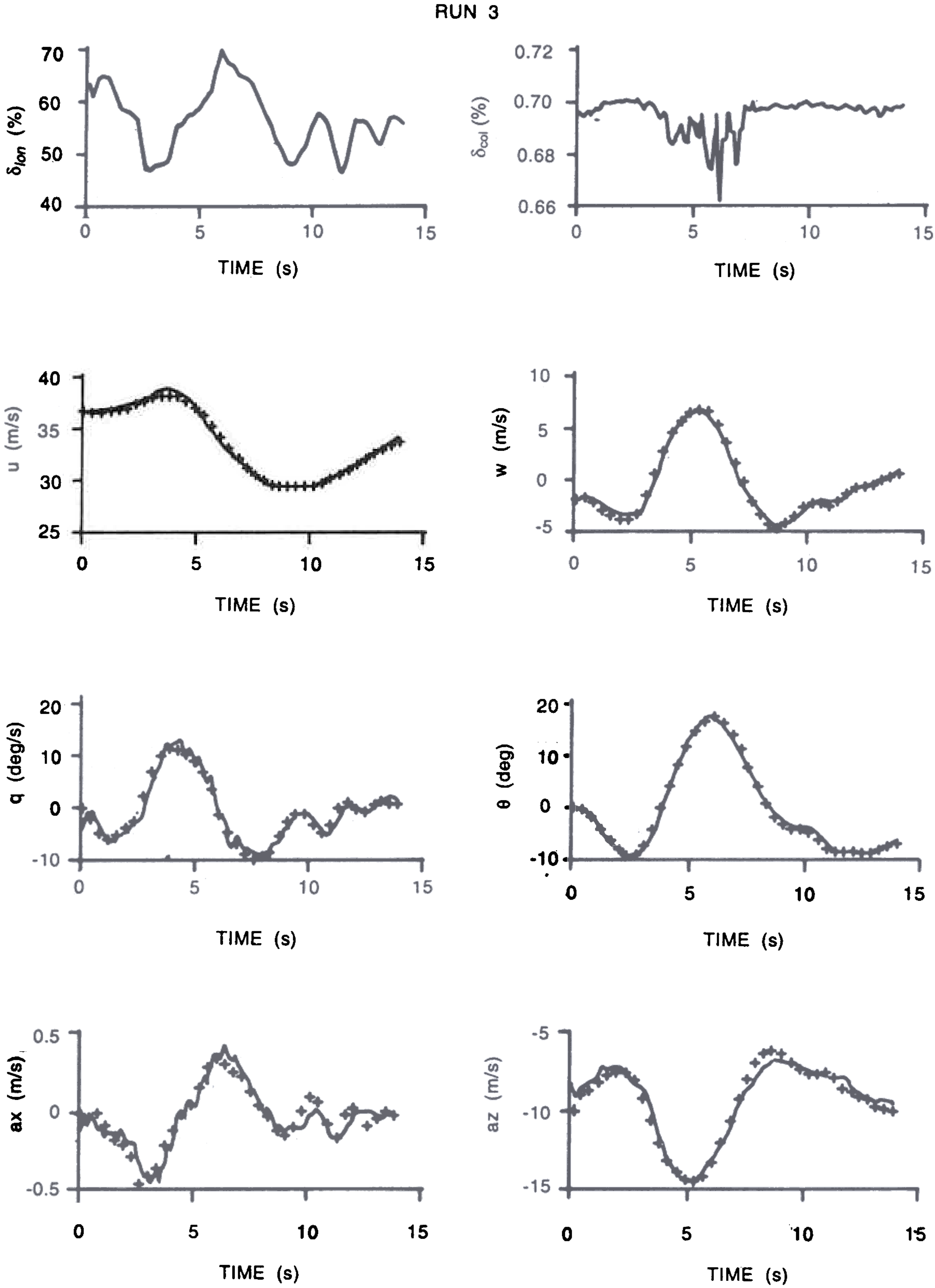


Figure 1(c). Comparison of measured rigid body data with model response — body longitudinal dynamics identified using fourth-order (3-DOF) derivative model (— flight, ++++ model).

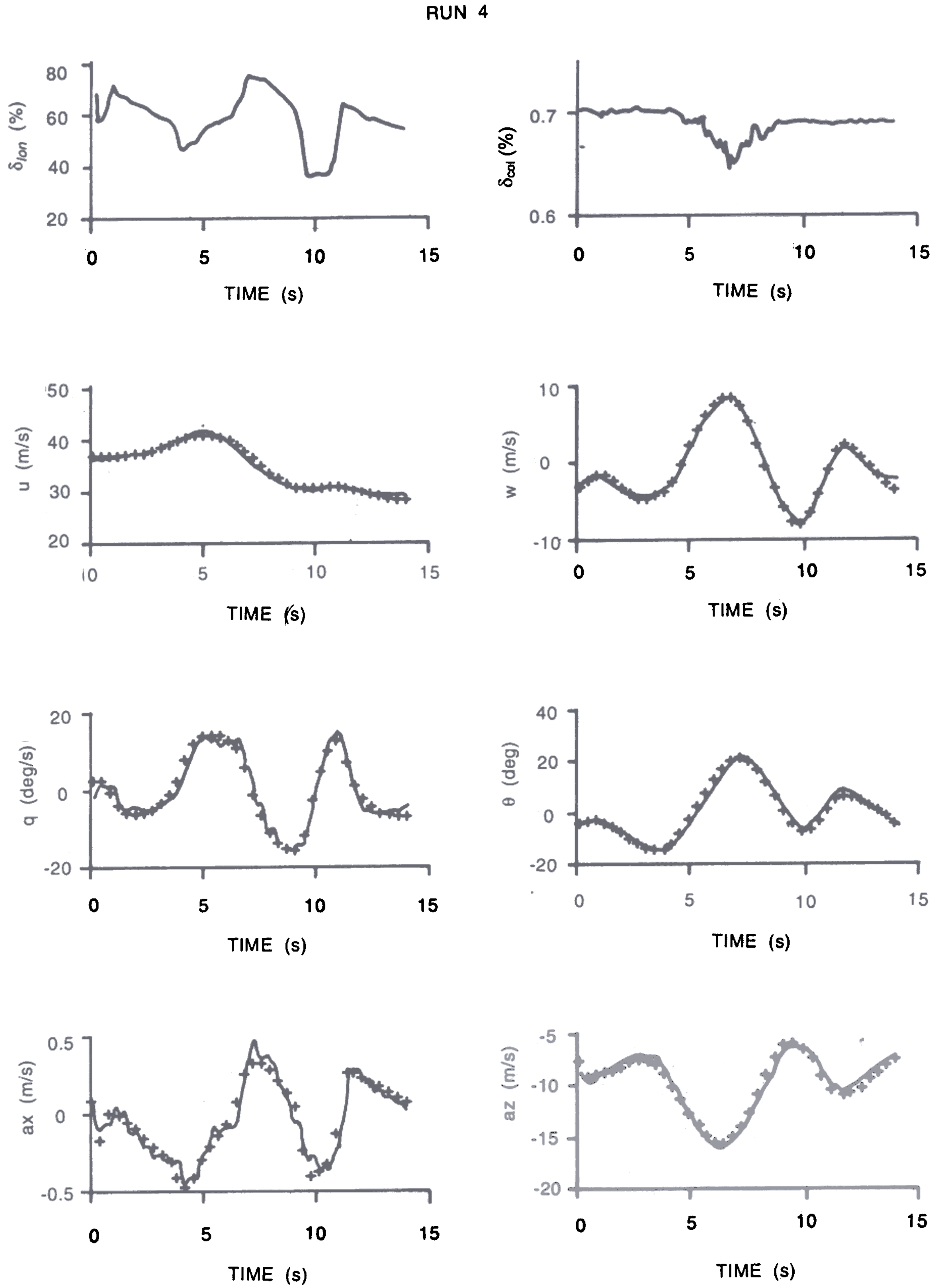


Figure 1(d). Comparison of measured rigid body data with model response — body longitudinal dynamics identified using fourth-order (3-DOF) derivative model (— flight, ++++ model).

Table 2. Estimated values of longitudinal derivates

Stability & control derivatives	Values obtained from analysis of separate runs				Values obtained from multiple run evaluation
	Run 1	Run 2	Run 3	Run 4	
X_u	-0.0165 (0.00108)	-0.0341 (0.00204)	-0.0386 (0.00186)	-0.0404 (0.0014)	-0.0336 (0.00108)
X_w	0.0256 (0.00199)	0.0263 (0.00221)	0.0242 (0.00193)	0.0236 (0.00145)	0.0246 (0.00109)
X_q	0.0*	0.0*	0.0*	0.0*	0.0*
$X_{\delta lon}$	1.9705 (0.01603)	1.705 (0.06310)	2.1342 (0.01823)	1.6021 (0.01534)	1.7093 (0.03754)
Z_u	-0.1830 (0.00512)	-0.1514 (0.00138)	-0.1237 (0.00818)	-0.0996 (0.0081)	-0.1037 (0.00848)
Z_w	-0.6866 (0.01488)	-0.6095 (0.01796)	-0.6600 (0.00976)	-0.6400 (0.01026)	-0.6447 (0.00865)
Z_q	0.0*	0.0*	0.0*	0.0*	0.0*
$Z_{\delta lon}$	-0.2341 (0.03209)	-0.0013 (0.00053)	-0.0001 (0.00001)	7.3301 (0.4252)	2.3974 (0.30047)
M_u	0.0143 (0.00018)	0.0224 (0.00085)	0.0221 (0.00036)	0.0244 (0.00035)	0.0245 (0.00052)
M_w	0.0079 (0.00047)	0.0058 (0.00145)	0.0162 (0.0003)	0.0045 (0.00037)	0.0127 (0.00074)
M_q	-1.0086 (0.01643)	-1.2546 (0.05971)	-1.0959 (0.01429)	-0.8206 (0.0138)	-1.1150 (0.02710)
$M_{\delta lon}$	-2.7838 (0.00121)	-2.9130 (0.07745)	-2.6756 (0.00265)	-2.2631 (0.02074)	-2.6123 (0.04057)

Parameter kept fixed during estimation

) Terms in parenthesis indicate lower Cramer Rao bounds

(b) Observation equations

$$u_m = u + b_u$$

$$w_m = w + b_w$$

$$q_m = q + b_q$$

$$\theta_m = \theta + b_\theta$$

$$a_{x_m} = X_u u + X_w w + X_q q + X_{\delta lon}\,\delta_{lon} + X_{\delta col}\,\delta_{col} + b_{a_x}$$

$$a_{z_m} = Z_u u + Z_w w + Z_q q + Z_{\delta lon}\,\delta_{lon} + Z_{\delta col}\,\delta_{col} + b_{a_z} \qquad \text{(1b)}$$

2.2 Lateral Derivative Model

Likewise, the usual equations of motion can be reduced to obtain a linearised 3-DOFs (fourth-order) decoupled lateral derivative model of the following form:

(a) State equations

$$\dot{v} = Y_v v + (Y_p + w_0)p + (Y_r - u_0)r + Y_{\delta lat}\,\delta_{lat} + Y_{\delta ped}\,\delta_{ped} + g\,\varphi\cos\theta_0 + b_{\dot{v}} \qquad ;v(0) = v_0$$

$$\dot{p} = L_u u + L_v v + L_w w + L_p p + L_q q + L_r r + L_{\delta lat}\,\delta_{lat} + L_{\delta ped}\,\delta_{ped} + b_{\dot{p}} \qquad ;p(0) = p_0$$

$$\dot{r} = N_u u + N_v v + N_w w + N_p p + N_q q + N_r r + N_{\delta lat}\,\delta_{lat} + N_{\delta ped}\,\delta_{ped} + b_{\dot{r}} \qquad ;r(0) = r_0$$

$$\dot{\varphi} = p + (\varphi q + r)\tan\theta_0 + b_{\dot{\varphi}} \qquad ;\varphi(0) = \varphi_0$$

(b) Observation equations

$$v_m = v + b_v$$

$$p_m = p + b_p$$

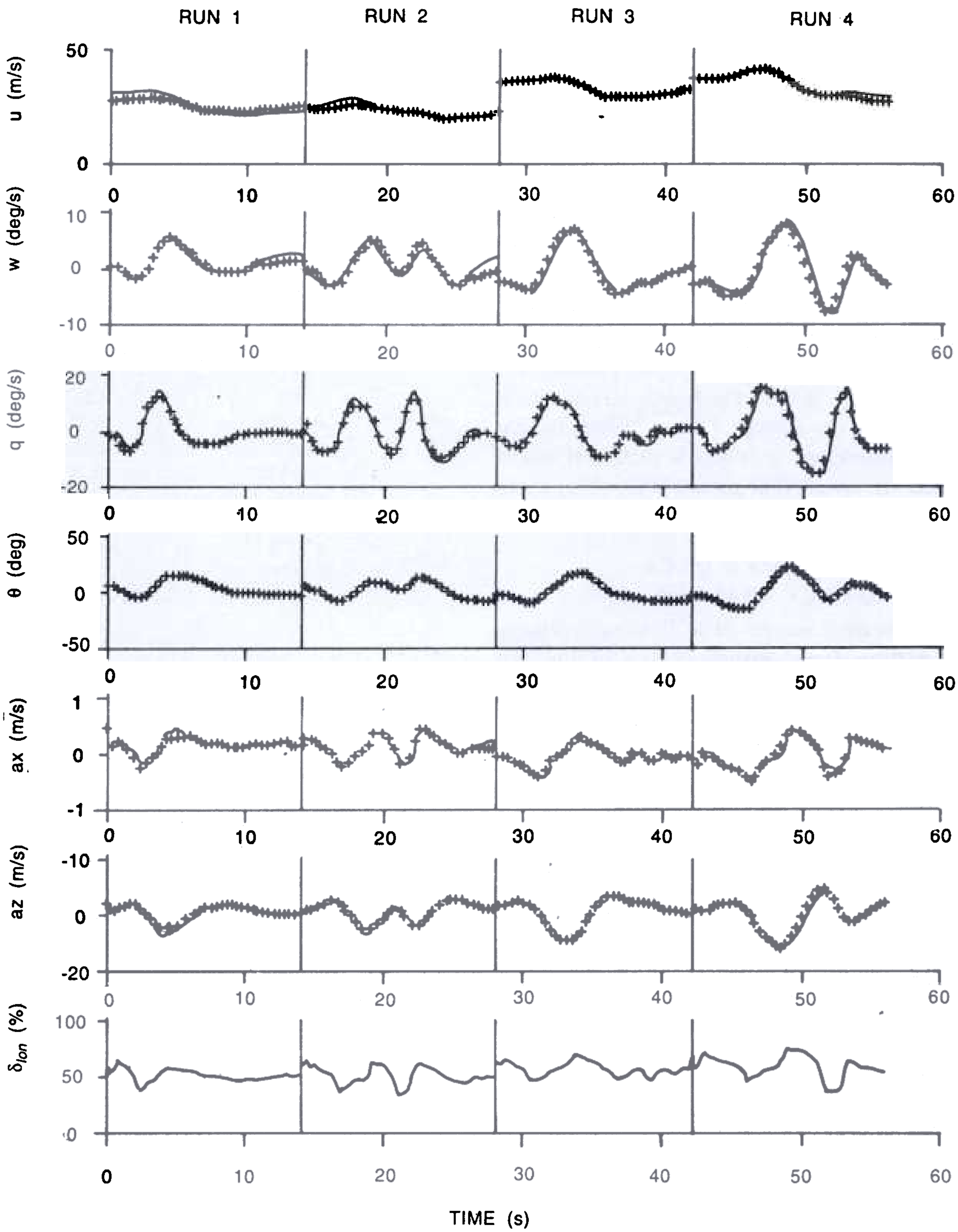


Figure 2. Quality of fit obtained from multi-manoeuver evaluation body longitudinal dynamics alone (flight, ++++ model)

$$r_m = r + b_r$$

$$\varphi_m = \varphi + b_\varphi$$

$$a_{y_m} = Y_v v + Y_p p + Y_r r + Y_{\delta lat}\,\delta_{lat} + Y_{\delta ped}\,\delta_{ped} + b_{a_y}$$

The mathematical models defined in Eqns (1) and (2) contain linearised forms of gravity and rotation related terms, and the derivatives used are specific derivatives. The models also assume that angular rates, p, q and r are small and the variations in attitude angles φ and θ and the speed components are within small perturbation assumption. Terms with suffix '0' represent the initial (trim) values of the flight variables and the parameters $b_{\dot{u}}, b_{\dot{v}}, \ldots\ldots\ldots, b_{a_y}$ denote the biases. Using flight measured data, variables p, r and φ in longitudinal model equations and q, u and w in lateral model equations are included as pseudo-control inputs to account for cross-coupling effects.

3. FLIGHT TESTING & DATA CONSISTENCY ANALYSIS

A flight database for identification studies is gathered from flight manoeuvers with the test helicopter. Test points are generally flown at high enough altitude to establish calm and steady conditions. Typically, starting from trim flight condition, the pilot applies control input in an attempt to excite dynamic modes and DOFs of interest. The magnitude of input is limited to keep the deviations in helicopter response from trim within the linear range. The gathered flight data is then processed and checked for kinematic consistency before being applied to extract linear models through output-error parameter estimation.

3.1 Manoeuvers

The flight test data consists of 14 data runs recorded at a uniform sampling rate of 8 samples/s. Out of the 14 sets, only 5 data runs are observed to be amenable to analysis. Longitudinal DOFs are excited by applying a doublet and a near 3-2-1-1 longitudinal cyclic control input. The selected flight data sets have no collective pitch excitation. Furthermore, data run 5 depicting a lateral doublet manoeuver appears to be the only data set that can possibly yield some meaningful lateral-directional derivatives. The data runs are of short duration, each lasting for about 15 s. Flight measurements are

Table 3. Estimated values of lateral derivatives

Stability & control derivatives	Values obtained from the analysis of Run 5: Cross-coupled derivatives not estimated	Cross-coupled derivatives estimated
Y_v	0.0948	0.0843
	(0.0071)	(0.0042)
Y_p	-0.6463	-0.5066
	(0.1139)	(0.0800)
Y_r	-0.1834	-0.2138
	(0.2395)	(0.1642)
$Y_{\delta lat}$	0.9477	1.4615
	(0.3643)	(0.2621)
$Y_{\delta ped}$	0.0027	-0.1859
	(0.0039)	(0.2226)
L_v	-0.0515	-0.0467
	(0.0023)	(0.0039)
L_p	0.3049	0.2907
	(0.0485)	(0.2181)
L_r	-0.1677	0.5321
	(0.0862)	(0.2069)
$L_{\delta lat}$	3.6827	2.3323
	(0.2543)	(0.2246)
$L_{\delta ped}$	-0.5371	0.0*
	(0.0681)	
L_u		0.0008
		(0.00074)
L_w		-0.0179
		(0.00265)
L_q		0.2694
		(0.13885)
N	0.0407	0.0331
	(0.0018)	(0.00065)
N	0.1953	0.3889
	(0.0269)	(0.02842)
N	-0.9953	-0.1142
	(0.0559)	(0.03568)
$N_{\delta lat}$	-2.5362	-2.1073
	(0.1162)	(0.06895)
$N_{\delta ped}$	0.6397	1.7560
	(0.0868)	(0.09447)
N		-0.0104
		(0.00077)
N		-0.0038
		(0.00068)
N		0.0079
		(0.01231)

* Parameters kept fixed during estimation

( ) Terms in the parenthesis indicate lower Cramer Rao bounds

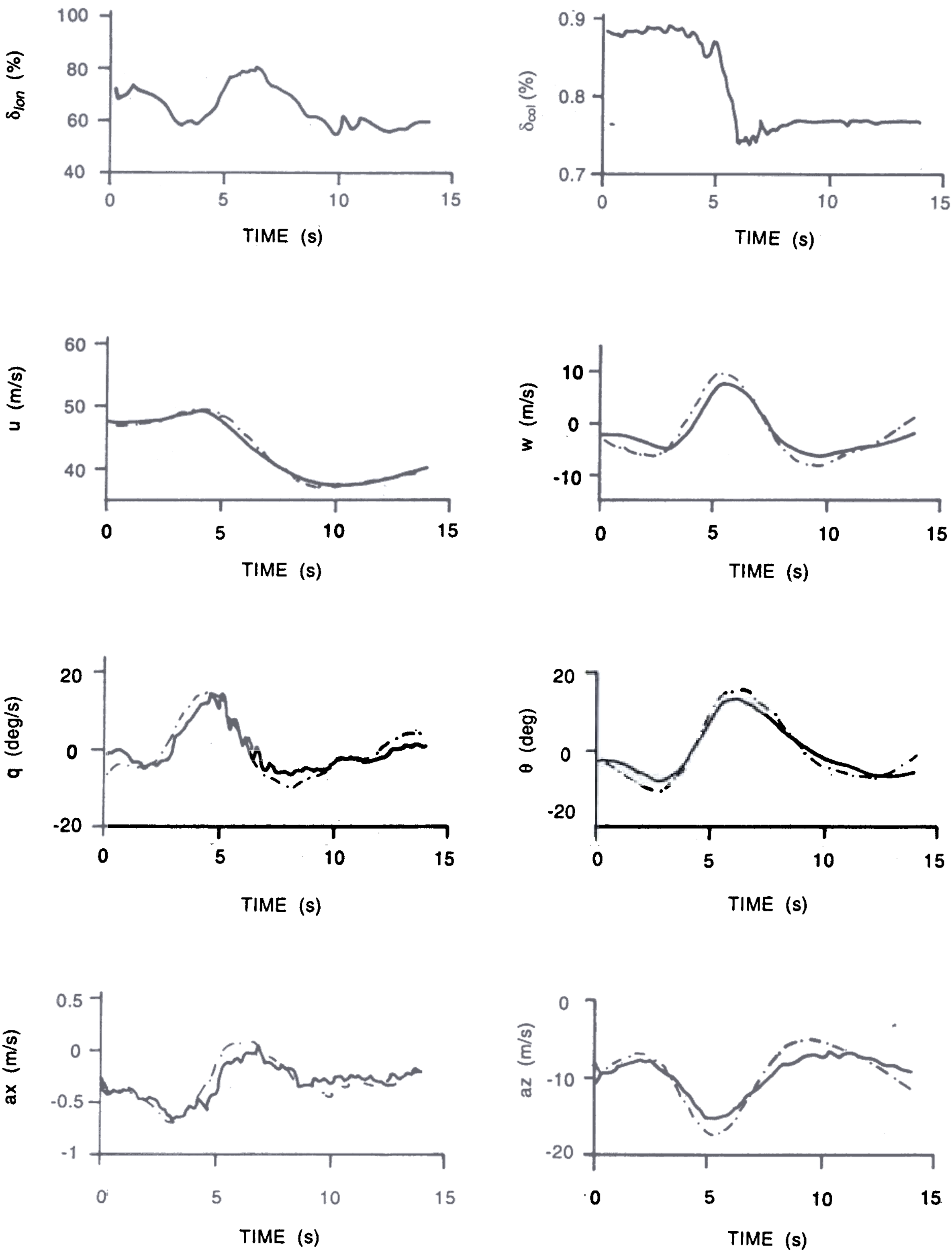
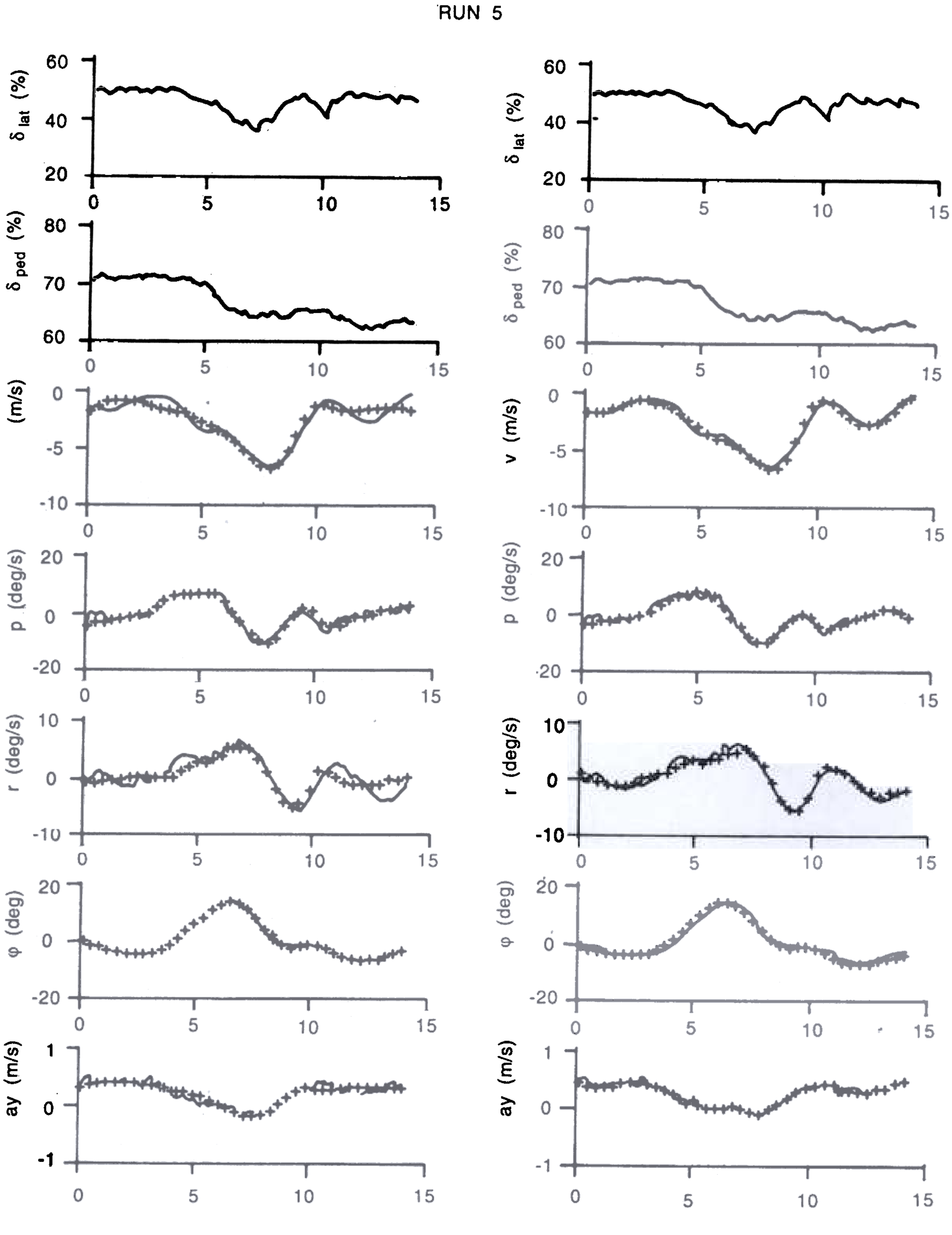


Figure 3. Model predictions *vs* flight test data not used in identification (Run 5, — flight, --- model predicted)



(a) Match with cross-coupling derivatives omitted in model

(b) Match with cross-coupling derivatives omitted in model

Figure 4. Comparison of measured rigid body data with model response — body lateral dynamics using fourth-order (3-DOF) derivative model (run 5; — flight. ++++ model).

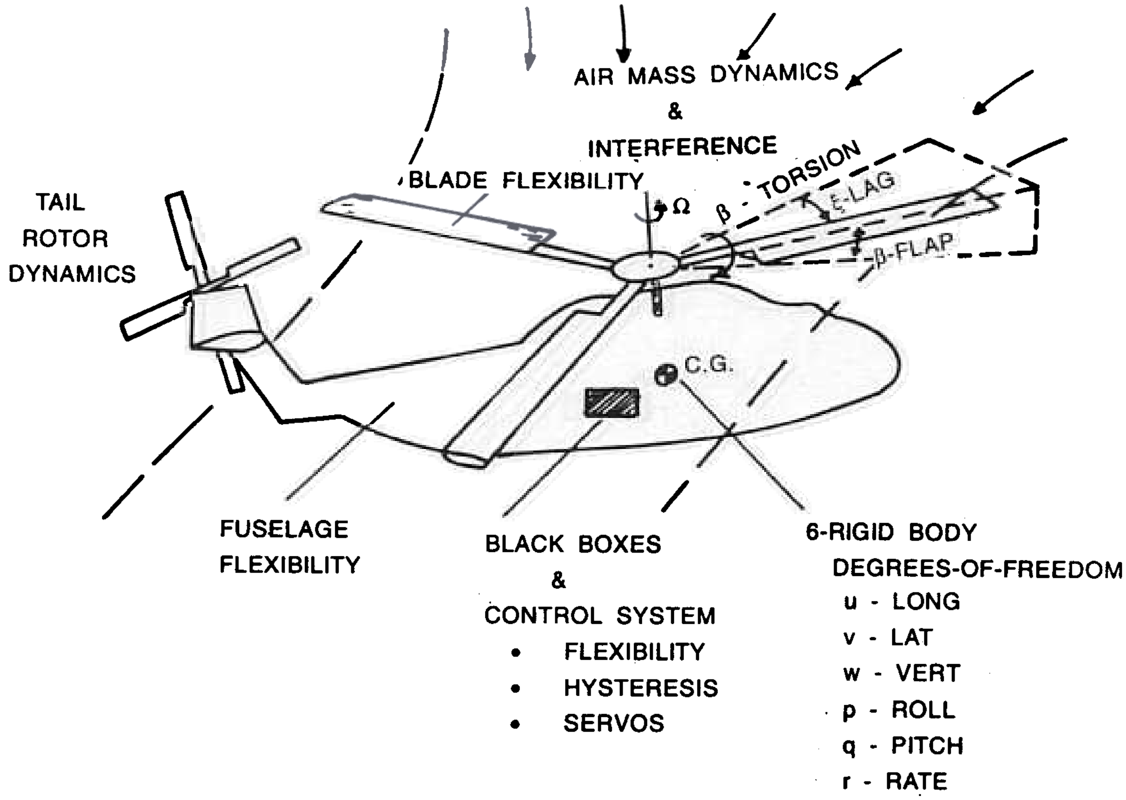


Figure 5. Helicopter degrees-of-freedom describing total vehicle motion

available for control positions δ_{lon}, δ_{col}, δ_{lat} and δ_{ped}, linear accelerations a_x, a_y and a_z angular rates p, q and r sideslip angle β, altitude h, and attitude angles φ and θ.

3.2 Kinematic Consistency Analysis

A detailed data compatibility check is necessary before initiating parameter estimation procedure. The following nonlinear state and observation equations are used to perform consistency checks on the selected data runs:

(a) State equations

$$\dot{u} = (a_x - \Delta a_x) + (r - \Delta r)\, v - (q - \Delta q)\, w - g \sin\theta$$

$$\dot{v} = (a_y - \Delta a_y) + (p - \Delta p)\, w - (r - \Delta r)\, u - g \cos\theta \sin\phi$$

$$\dot{w} = (a_z - \Delta a_z) + (q - \Delta q) u - (p - \Delta p) v + g \cos\theta \cos\varphi$$

$$\dot{\varphi} = (p - \Delta p) + (q - \Delta q) \sin\phi \tan\theta + (r - \Delta r) \cos\varphi \tan\theta$$

$$\dot{\theta} = (q - \Delta q) \cos\varphi - (r - \Delta r) \sin\varphi$$

$$\dot{h} = u \sin\theta - v \cos\theta \sin\varphi - w \cos\theta \cos\varphi$$

(b) Observation equations

$$V_m = \sqrt{(u^2 + v^2 + w^2)}$$

$$\beta_m = \sin^{-1}(v \quad V_m) + \Delta\beta$$

$$\varphi_m = \varphi + \Delta\varphi$$

$$\theta_m = \theta + \Delta\theta$$

$$h_m = h$$

Output-error program is applied for state estimation during data processing. The nonlinear kinematic equations are integrated with measured rates and linear acceleration included as inputs. Speed components u, v and w attitude angles ϕ and θ and altitude h are treated as states and calculated from Eqn (3a). Measurements provided in the flight data base for linear accelerations, flight velocity V and sideslip angle β are defined for C.G. location and as such, no further correction of speed components w.r.t C.G. is required. To correct the data for instrumentation errors, the derived time histories from Eqn (3b) are compared with flight measured data and the biases (treated as unknown model parameters) estimated. It is observed that linear accelerations are of good quality while angular rates p and r have small biases. Adequate agreement for the attitude angles is obtained after the measurements are corrected for biases. The sideslip measurement, in general, is not satisfactory. For all selected data runs, reconstructed trajectories for speed components, roll rate, yaw rate and attitude angles are used in parameter identification. Table 1 summarises the estimated values of biases obtained from consistency check on all the data runs. Comparison between the measurements and the reconstructed data for some of the flight variables pertaining to data run 1 and data run 2 are illustrated in Fig. 7. The agreement, in general, is satisfactory.

4. RESULTS & DISCUSSION

To predict the helicopter rigid body dynamics, linear models defined in Eqns (1) and (2) are extracted from flight test data using output-error method. The estimation algorithm is equipped with the option to conduct multiple run evaluation. During parameter estimation, it was observed that convergence of the estimation algorithm is highly dependent on the accuracy of the initial estimates with which the iteration had begun. Unfortunately, no estimates of aerodynamic parameters are available from wind tunnel tests or theoretical predictions. Although, the sensitivity of the analysis to initial values is reduced by adopting equation error approach, the choice of the start-up values still remains critical.

4.1 Longitudinal Parameter Estimates

Estimated values of parameters obtained from identification of fouth-order linear longitudinal derivative model for data run 1 to data run 4 are listed in Table 2. Physically realistic values and low standard deviations of the parameter estimates indicate successful identification of longitudinal dynamics. As shown in Figs 1(a)-(d), the identified parameter values yield satisfactory fit to measured time histories for all the flight variables u, w, q, θ, a_x and a_z. The quality of fit improves when a_x and a_z are included in the observation equations.

As expected, fairly close values are obtained from separate data runs for majority of parameters listed in Table 2. However, variation among a few parameters is discernible, particularly in the control derivatives $Z_{\delta lon}$ and $X_{\delta lon}$. A likely cause for such variations could be the peculiarities in response arising from particular characteristics of the control inputs, which are different for each of the data runs analysed. Considering the short duration of data runs and the need to obtain parameter estimates with reduced uncertainty, multiple run evaluation is mandatory. In this approach, different data runs are concatenated to increase the information content for the identification algorithm and a common set of parameters is extracted. Multiple run evaluation has shown its effectiveness for helicopter identification applications and is now being used on routine basis by the flight analysts. Applying this approach in the present study, the longitudinal derivatives are identified from the combined analysis of data run 1 to data run 4 and listed in Table 2. A small increase in the value of cost function is obtained by multiple run evaluation approach. However, this is of little consequence when one considers the increased confidence with which the identified derivatives can be used for general applicability. Comparison of the flight and the model time histories for multiple run evaluation are illustrated in Fig. 2.

4.2 Verification of Identified Longitudinal Model

The verification of the identified model is a key step in the identification process to assess the predictive capabilities of the extracted model. One approach is to compare the flight determined parameter estimates against the values obtained from wind tunnel tests or analytical predictions.

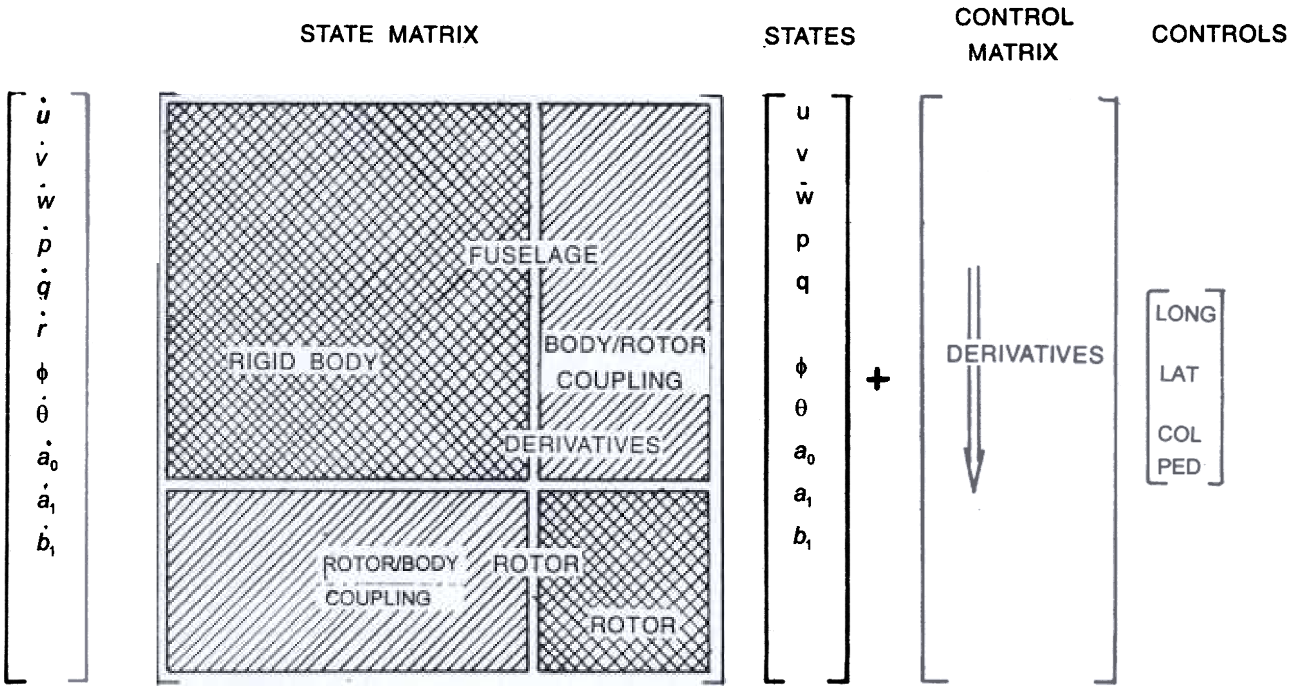


Figure 6. Principal approach for extension of 6-DOF model by rotor degrees-of-freedom

Unfortunately, no such reference values of the dynamic derivatives are available for the helicopter considered in the present study. The other approach is known as the proof of match. It is a widely used approach based on the comparison of model predictions with flight measurements. To this end, flight data omitted from the identification studies is selected to ensure that the model is not tuned to specific data record or input form. In the present study, the proof of match validation of the longitudinal derivative model, identified from the multiple run evaluation (Table 2), is illustrated in Fig. 3 through comparison of the flight measurements with model predictions for data run 5 (not included in the multiple run analysis). Although, some small discrepancies in the time history fits of flight variables are discernible, the overall model is satisfactory. Further improvement in model prediction can only be reached when the model order is extended by additional DOFs.

4.3 Lateral Parameter Estimates

Using state space model defined in Eqn 2, output-error algorithm is applied to flight data from data run 5 to extract the lateral parameter estimates. As a first step, the cross-coupling derivatives are obtained from the estimation model and only the lateral stability and control derivatives (Table 3) are estimated. A comparison of the model response with flight measurements for this case is illustrated in Fig. 4(a). Noticeable discrepancies are observed in the response match for flight variables v and r. Next, cross-coupled roll moment derivatives L_u, L_w, L_q and yaw moment derivatives N_u, N_w, N_q are included in the model to be used for lateral parameter estimation. The estimated derivatives are shown in Table 3 and the time history comparison depicted in Fig. 4(b). It is observed that inclusion of cross-coupled derivatives improves the quality of time history fit and the previously observed discrepancies in response match for flight variables v and r no longer exist. There is a noticeable change in values of the parameters (Table 3). The variation in derivatives L_r and N_r, in specific, is observed to be significant. The standard deviations (Cramer Rao bounds indicated in the parenthesis) for some of the extracted parameters are unusually high. This is apparently due to insufficient control input excitation and strong coupling between the lateral stick and pedal control inputs. The high quality

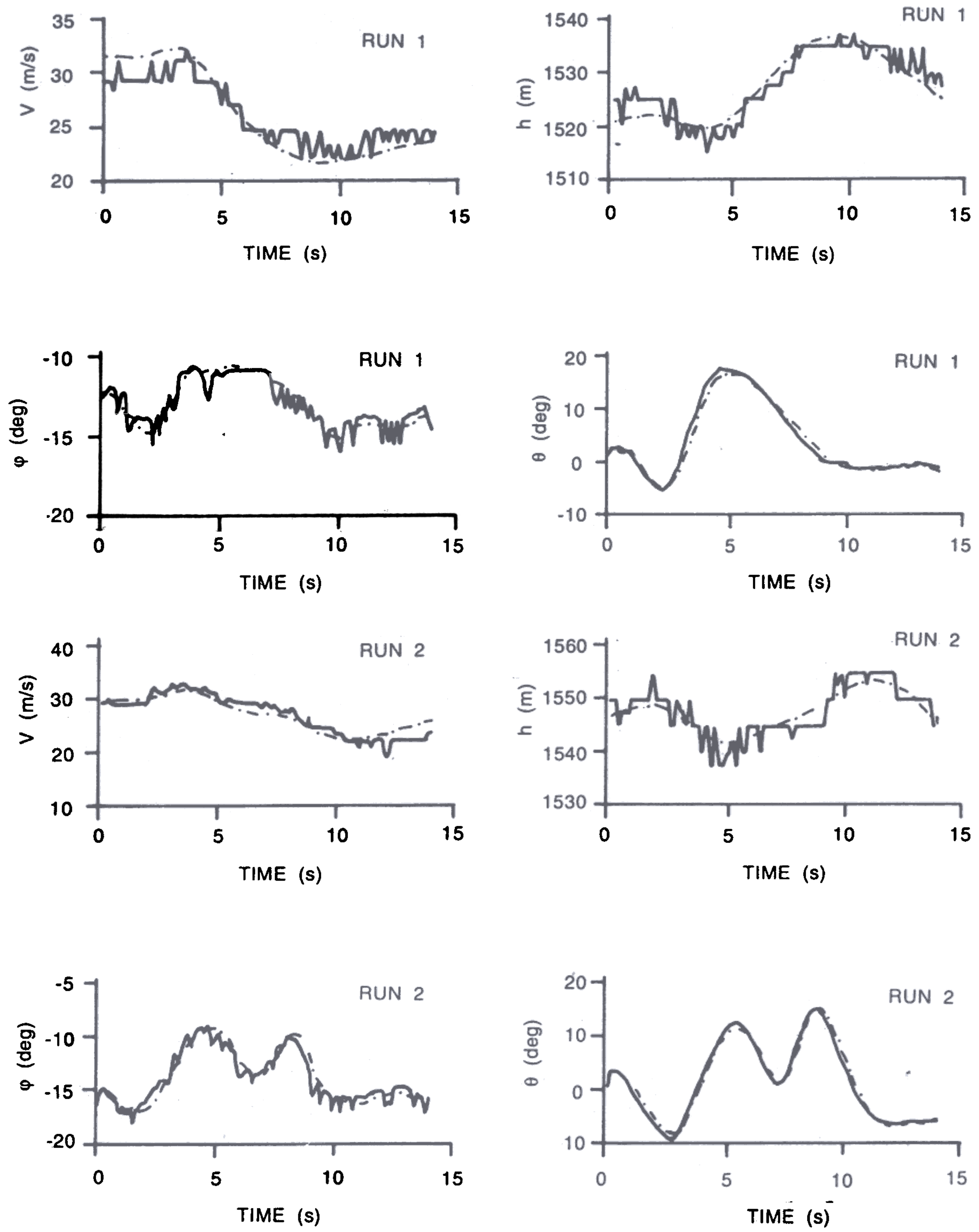


Figure 7. Data compatibility of measurement obtained using standard kinematic equation (— measured, --- calculated)

response match observed in Fig. 4(b), in itself, is not a sufficient proof of reliability of the estimated lateral derivatives. In fact, correlation among some of the estimated parameters and high relative standard deviations observed during model identification indicate the possibility of arriving at an equally good match with different parameter values. To reduce uncertainties in the parameter estimates, it is essential to compare the identified derivatives with results from other sources. In this paper, however, multimanoeuver analysis and proof-of-match validation for lateral derivative model are not investigated due to lack of sufficient lateral flight data.

Attempts to identify rigid body dynamics from data run 5 (which includes both longitudinal and lateral control input excitation) utilising a fully coupled 6-DOFs model did not yield a convergent solution. It is, therefore, concluded that a multimanoeuver analysis is imperative to successfully identify 6-DOFs or higher order models. Similar observations made by Kaletka are also reported[9].

5. CONCLUSION

Utilising 3-DOFs (fourth-order) linear decoupled longitudinal and lateral-directional derivative models, output-error method is applied to identify rigid body dynamics from helicopter flight data. Measured time histories, suitably reconstructed from kinematic consistency analysis, are used in the investigations. Identification results obtained from single input excitation and multimanoeuver evaluation show that the formulated models yield satisfactory fit to the measured time histories. Cross-coupling terms are observed to have significant impact on the directional motion and are, therefore, included in the lateral derivative model. Results of longitudinal model validation prove that, within the defined frequency range, the identified derivatives can predict the helicopter longitudinal dynamics to any arbitrary control input. It is further argued that the prediction capabilities of the identified model can be improved by extending it with additional DOFs. The choice of start-up values and multiple manoeuver analysis to identify 6-DOFs or higher order models need to be further investigated.

7. ACKNOWLEDGEMENTS

Authors express their thanks to Sqn. Ldr. K. Mati, ASTE, Bangalore, for his invaluable help in conducting the helicopter flight test experiments and in data acquisition. The authors also thank their colleagues Dr. J.R. Raol and Mr. V. Parameswaran for their useful suggestions and views on this manuscript. The constant encouragement from Dr. S Srinathkumar, Head, Flight Mechanics & Control Division, NAL, during the course of this work is deeply appreciated.

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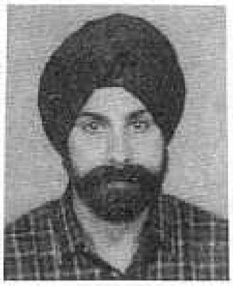

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