Defence Science Journal, Vol. 67, No. 1, January 2017, pp. 3-11, DOI : 10.14429/dsj.67.9995

Parameter Estimation from Near Stall Flight Data using Conventional and Neural-based Methods

S. Saderla*, R. Dhayalan!, and A.K. Ghosh#

*Department of Aerospace and Software Engineering, Gyeongsang National University, South Korea
!Department of Aerospace Engineering, Indian Institute of Space Science and Technology, Thiruvananthapuram - 695 547, India
#Department of Aerospace Engineering, Indian Institute of Technology Kanpur - 208 016, India
*E-mail: subrahmanyam.saderla@gmail.com

ABSTRACT

The current research paper is an endeavour to estimate the parameters from near stall flight data of manned and unmanned research flight vehicles using conventional and neural based methods. For an aircraft undergoing stall, the aerodynamic model at these high angles of attack becomes non linear due to the influence of unsteady, transient and flow separation phenomena. In order to address these issues the Kirchhoff's flow separation theory was used to incorporate the nonlinearity in the aerodynamic model in terms of flow separation point and stall characteristic parameters. The classical Maximum Likelihood (MLE) method and Neural Gauss-Newton (NGN) method have been employed to estimate the nonlinear parameters of two manned and one unmanned research aircrafts. The estimated static stall parameter and the break point, for the flight vehicles under consideration, were observed to be consistent from both the methods. Moreover the efficacy of the methods is also evident from the consistent estimates of post stall hysteresis time constant. It can also be inferred that the considered quasi steady model is able to adequately capture the drag and pitching moment coefficients in the post stall regime. The confidence in these estimates have been significantly enhanced with the observed lower values of Cramer-Rao bounds. Further the estimated nonlinear parameters were validated by performing a proof of match exercise for the considered flight vehicles. Interestingly the NGN method, which doesn't involve solving equations of motion, was able to perform on a par with the MLE method.

Keywords: Parameter estimation; Unmanned aerial vehicle; High angle of attack; Flight data; Conventional maximum likelihood

NOMENCLATURE

a_x, a_y, a_z	Accelerations along x, y and z body axes, m/s^2
C_D, C_L	Coefficients of drag and lift force, respectively
C_{D_0}, C_{L_0}	Coefficients of drag and lift force at zero angle of attack
C_m	Coefficients of pitching moment
$\bar{c}$	Mean aerodynamic chord, m
g	Acceleration due to gravity, m/s^2
I_y	Moment of inertia about y axis, kg-m^2
J	Cost function
k	Induced drag correction factor
m	Aircraft mass, kg
q	Pitch rate, rad/s
s	Wing plan form area, m^2
u,v, w	Airspeed components along x, y and z axis of aircraft, m/s
V	Airspeed, m/s
α, β	Angle of attack and Angle of slide slip, deg
$\delta_a, \delta_e, \delta_r$	Aileron, elevator and rudder deflection angles, deg
ϕ, θ, ψ	Angles of roll, pitch and yaw, deg
ρ	Density, kg/m^3
Θ	Vectors of unknown parameters
$a_1, \alpha^*, \tau_2, C_{D_X}, C_{m_X}$	Stall characteristic parameters

Received : 25 April 2016, Revised : 27 June 2016
Accepted : 19 August 2016, Online published : 22 December 2016

1. INTRODUCTION

Parameter estimation from flight data constitutes a major subroutine of system identification process. The estimation process quantifies the unknown model parameters in a pre-decided model structure of the system. This process requires the input of observed variables that depicts the actual state of the system at a particular instant. Indeed in a deterministic system these measured variables are assumed to be noisy/random and the unknown parametric vector is constant. The parameters in the assumed mathematical model are estimated by minimising the error between computed response and measured variables. Although various numerical estimators are available, identifying the appropriate methods which can efficiently handle the measurement noise is crucial in accurate estimation of the parameters.

For more than three decades, the maximum likelihood (MLE) parameter estimators have been successfully applied to the flight data for estimation of aircraft stability and control derivatives. The application of MLE estimators to flight data with either the measurement noise or the process noise has been accepted as a standard approach for parameter estimation. However, in the presence of both (measurement and process noise) the MLE estimator might lead to convergence problems and other practical difficulties. In recent times, the applicability of the output error method has also been extended to the general non-linear systems[1]. The main advantage of the MLE method is that the estimates are asymptotically unbiased, consistent and efficient. The method also provides a measure of accuracy in terms of the Cramer-Rao bound[1,2]. The newly emerging Neural-Gauss-Newton (NNG) method was also stood promising in handling the flight data with measurement noise[3–6]. The NGN method uses feed forward neural networks (FFNN) to establish a neural model that could be used to predict subsequent time histories, given the suitable measured initial conditions. Although analytical methods, computational techniques and wind tunnel measurements provides reasonable estimates, parameter estimation from flight data will overcome the limitations of the above mentioned conventional techniques and also enhances the confidence in the estimates.

Introduction of highly manoeuverable, unstable, high performance aircraft has motivated researchers to work in the field of aerodynamic model extraction using flight data pertaining to high angles of attack. This class of aircraft often operates at high angles of attack (near stall) and hence encounters highly complex unsteady aerodynamics. Due to the limited available non-linear aerodynamic models, researchers face serious difficulties in handling such flight data for the purpose of parameter estimation. Research on high angle of attack flight has been mainly focused on the aerodynamic modelling of manned fighter aircrafts. Many scholars carried out detail research on the non-linear modelling of conventional fixed wings, delta wings and swept wings from various perspectives. Goman and Khrabrov[7] have developed a state space representation of aerodynamic characteristics of an aircraft at high angles of attack. Fischenberg and Jategaonkar[8] have presented the quasi steady stall modelling to perform the stall modelling of C-160 military transport aircraft and also discussed about the parameter estimation of the aerodynamic coefficients of the proposed steady stall model. Nelson and Pelletier[9] have used the non-linear indicial response (NIR) method to represent the aerodynamic functions in the non-linear regime of F-18 and X-31 aircraft. Leishman and Nguyen[10] modelled the unsteady aerodynamic behaviour of the airfoil using state space representation. Ghoreyshi and Cummings[11] have applied time depended surrogate method to model the unsteady aerodynamics for various aircraft manoeuvers. Chowdhary and Jategaonkar[12] have carried out parameter estimation from flight data using unscented Kalman filter. Kumar[13], *et al.* have performed the non-linear aerodynamic modelling of cascade fins near stall angles of attack for various g/c conditions, using steady state stall model. It is generally observed from the contemporary research that the main focus is on non-linear aerodynamic modelling of fighter aircrafts and the flight vehicles related to military applications. The research on the high angle of attack modelling of the unmanned aerial systems is currently taking higher attention.

The static attached flow aerodynamics can be sufficiently modelled by using the time-invariant parameters and linear aerodynamic models[1]. But at high angles of attack, apart from data acquisition, the postulation of exact aerodynamic model is another challenging task. The present research work uses the Kirchhoff's flow separation model to perform the non-linear aerodynamic modelling from high angles of attack flight data[1]. The present research work also highlights the application of the MLE and the NGN methods for parameter estimation at high angles of attack. For this purpose three sets of high angle of attack flight data has been used, one each from two manned and one unmanned aircrafts. The estimated response of the state variables, using MLE and NGN method, pertaining to the flight data at high angles of attack have been presented. The obtained stall characteristic parameters along with the respective Cramer-Rao bounds from three sets of compatible flight data have been tabulated. Further, the comparison of the measured and estimated stall hysteresis of manned and unmanned flight vehicles, using MLE and NGN methods, is also presented.

2. GENERATION OF FLIGHT DATA

As mentioned earlier, three sets of high angles of attack flight data have been used to estimate stall characteristic parameters. Primarily, the first set of high angle of attack flight data, pertaining to longitudinal dynamics, was generated in-house using Hansa-3 aircraft available at Indian Institute of Technology Kanpur (IITK). The second set of flight data was obtained from Ref. 1. This set off light data was generated using ATTAS aircraft at DLR Germany[1]. Finally the third set is obtained from an unmanned configuration which was designed, fabricated and instrumented in-house at flight laboratory of IITK[14]. The detailed geometric and inertial characteristics of the manned aircrafts, namely ATTAS, and Hansa-3 are presented in Ref. 6 and Ref. 1, respectively.

The designed unmanned configuration has cropped delta plan form with a reflex airfoil cross section (NACA 23110) as shown in Fig. 1. For the rest of this paper the designed unmanned configuration is termed as CDRW. From Fig. 1, it can also be noticed that CDRW is a wing alone blended wing configuration with no separate horizontal tail. A high aspect ratio all moving vertical tail serves the purpose of rudder as well as vertical stabiliser for CDRW. The cross section of this vertical tail is NACA 0012, a symmetric airfoil. The longitudinal and lateral control is achieved with the help of the elevons located at the trailing edge of the designed configuration and is also presented in Fig. 1(a). These elevons acts as elevator when deployed together and serves as elevons when applied asymmetric deflections. The geometric characteristics of the current unmanned configuration along with Hansa-3 aircraft have been presented in Table 1.

To perform the parameter estimation from the flight data, various motion variables have to be recorded during the flight tests. Hence the CDRW configuration has been instrumented to record linear accelerations (a_x, a_y, a_z), angular rates (p, q, r), Euler angles (ϕ, θ, ψ), velocity (V_∞), flow angularity (α, β) and control surface deflections $(\delta_a, \delta_e, \delta_r)$ etc. during the flight tests. Figure 2 present the photograph of the instrumented (ready for flight) CDRW configuration.

The data acquisition system is equipped with a 9 DOF

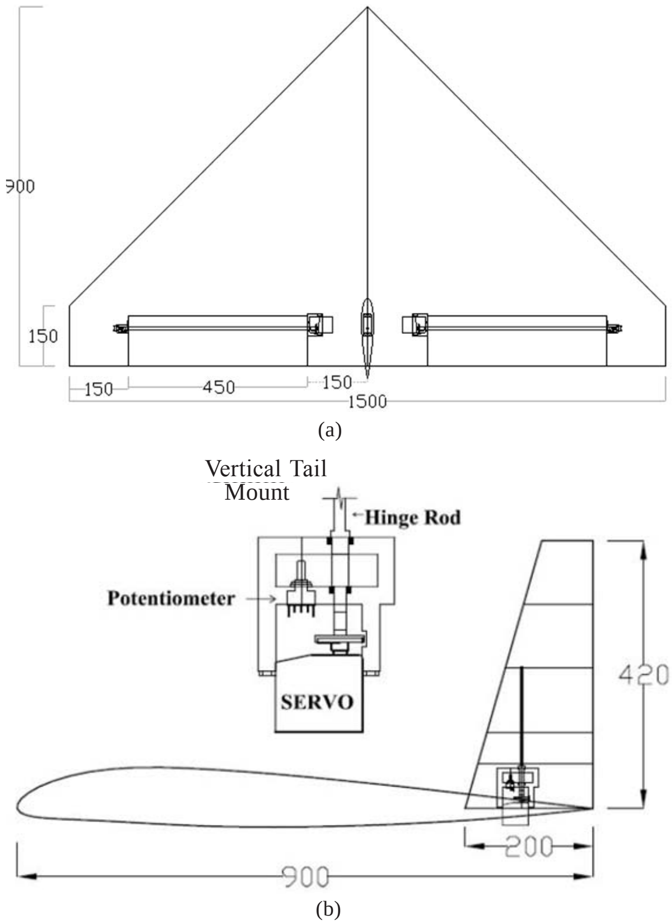

Figure 1. (a) CAD model representing the Planform view CDRW[14] and (b) CAD model representing the side view of CDRW configuration[14].

Table 1. Geometric and design parameters of Hansa-3 and CDRW configuration

Parameters	Hansa-3	CDRW
Wing span (b)	10.47 m	1.50 m
Planform area (S)	12.47 m^2	0.787 m^2
Aspect ratio (AR)	8.79	2.93
Root chord (c_r)	1.30 m	0.90 m
Tapper ratio (λ)	0.62	0.17
Mean aerodynamic chord (MAC) ($\bar{c}$)	1.21 m	0.61 m
Weight (W)	7357.50 N	35.81 N

Figure 2. Photograph representing instrumented prototype of CDRW configuration[14].

Inertial measurement unit (IMU to record $a_x, a_y, a_z, p, q, r, \phi, \theta, \psi$), differential pressure sensor (to measure V_∞), GPS unit etc. The acquisition system can simultaneously record five analog inputs, five digital inputs and six PWM signals. The system is capable of both onboard logging and telemetry to ground station. The velocity of the flight has been obtained with the help of a differential pressure sensor attached to the in-house fabricated mini Pitot and static tubes. A prior calibration of this pressure sensor has been performed to convert the obtained voltage signal to corresponding velocity of flight. The angle of attack and sideslip angles (α, β) were obtained from an in-house manufactured vane type flow angularity sensors mounted at the tip chord of the unmanned configurations, presented in Fig. 2. The data acquisition system is embedded with a two quad core ARM (Advanced RISC Machines) processors capable of performing onboard logging at 20 Hz and telemetry at 11 Hz[15,16]. A dedicated graphical user interface (GUI) has been developed using lab-view platform to perform data logging at the ground station. Flight data for aerodynamic characterisation studies of CDRW has been generated by performing various flight test manoeuvers at flight laboratory in IITK, India.

Initially the pilot of these remotely controlled unmanned flight vehicle has trimmed the aircraft at a comfortable altitude (usually 50 m to 70 m) from the ground station. From this trim condition pre-decided control inputs were applied in an attempt to excite various modes of flight. These flight tests were performed during the days with moderately calm weather. Further it is assumed that there is no significant effect of wind on the acquired flight data. The generated high angle of attack flight data is designated as HNS_STL1 for Hansa-3, ATS_STL1 for ATTAS and URW_STL1 for CDRW configuration, respectively. The acquired flight data is susceptible to corruption by systematic errors like scale factors, zero shift biases and time shifts. Since these errors may introduce data incompatibility; for example, the measured incidence angles not being in agreement with those reconstructed from the accelerometer and rate gyro measurements, it is imperative to perform data compatibility check before proceeding for parameter estimation. In other words, the data compatibility check, which is called as flight path reconstruction (FPR), is an integral part of aircraft parameter estimation[1]. The main aim of a data compatibility check is to ensure that the measurements used for subsequent aerodynamic model identification are consistent and error free. The following set of unknown parameters, presented in Eqn. (1), were considered adequate for reconstructing the longitudinal dynamics of the Hansa-3 and CDRW configuration for data compatibility check.

$$\Theta = \left[\Delta a_x \; \Delta a_y \; \Delta a_z \; \Delta p \; \Delta q \; \Delta r \; K_\alpha \; \Delta\alpha\right]^T \tag{1}$$

Data compatibility check has been performed on HNS_STL1 and URW_STL1, using MLE method. Whereas ATS_STL1 flight data set, which has been taken from Jategaonkar[1], is already compatible and can be readily used for parameter estimation. The estimated biases and scale factors obtained during the data compatibility check of near stall flight data of Hansa-3 and CDRW are presented in Table 2.

It can be observed from Table 2 that, even for high angles of attack flight data the biases are almost negligible and the scale factors (K_α) appeared to be close to the expected value (unity) for both Hansa-3 and CDRW aircrafts. Further the lower values of values of Cramer-Rao bounds, for the estimated compatibility parameters, has established higher level of confidence in the generated flight data sets. The following Fig. 3 presents the compatible flight data (ATS_STL1) that has been used to estimate the stall characteristic parameters of ATTAS aircraft[1].

The measured and computed response of motion variables obtained during the data compatibility check of Hansa-3 and CDFP aircrafts are presented in Figs. 4(a) and 4(b), respectively.

3. QUASI STEADY STALL MODEL

The aerodynamic model during stationary attached flow conditions can be sufficiently described with a set of time-invariant parameters and linear models[1]. But for an aircraft performing high angle of attack manoeuvers, the associated aerodynamics becomes highly non-linear. This may be attributed to the flow separation phenomenon as well as unsteady aerodynamic effects[1]. The lift generated by the aircraft during these manoeuvers is highly influenced by the unsteady effects. Further these effects are dominant in the post stall region due

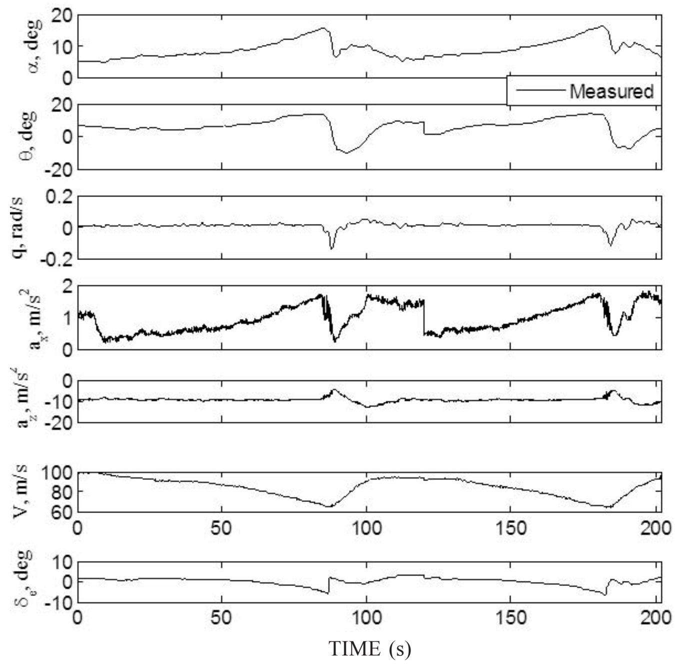

Figure 3. Compatible flight data of ATTAS aircraft: ATS_STL1[1].

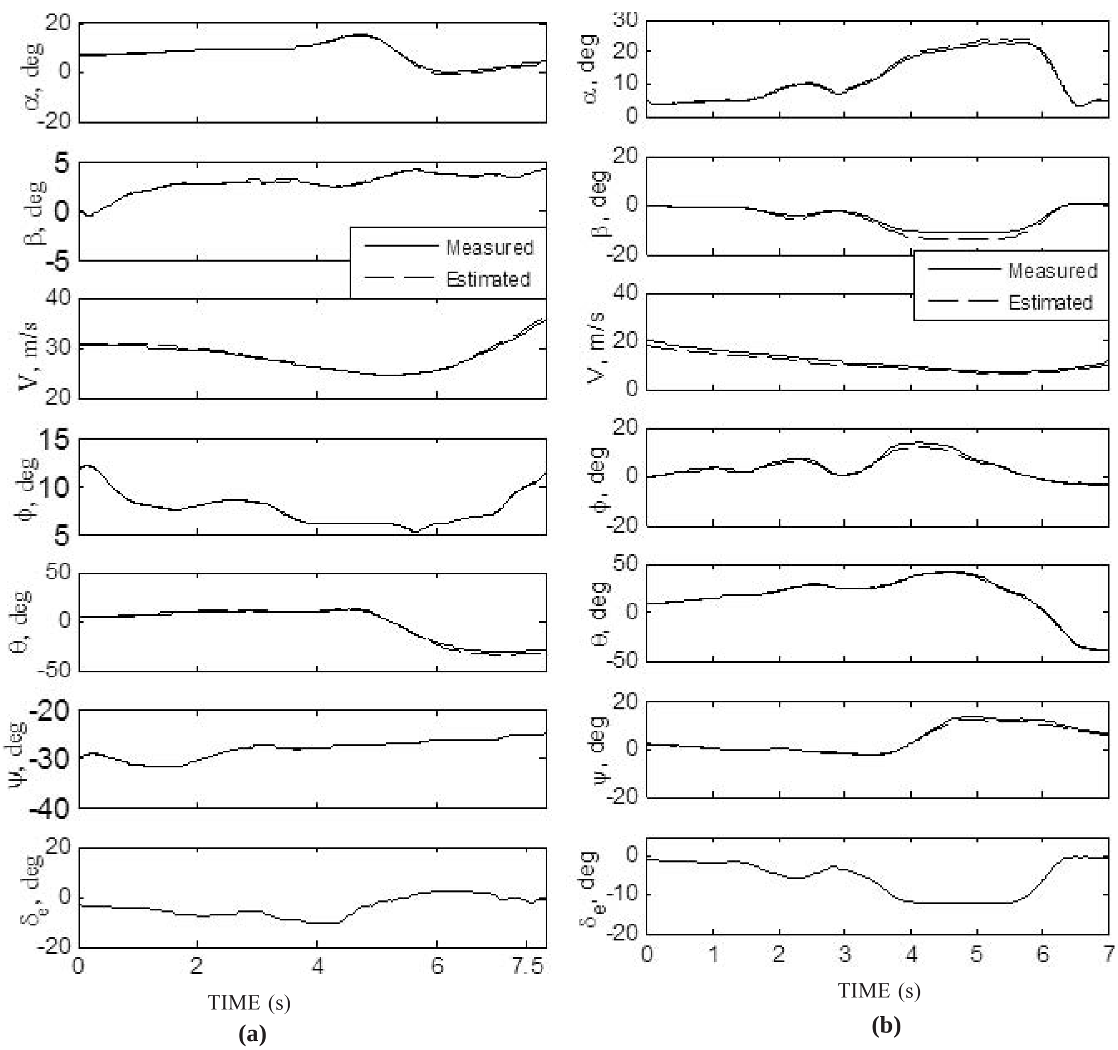

Figure 4. Data compatibility check: HNS_STL1, URW_STL1[6,14]: (a) HNS_STL1 and (b) URW_STL1.

Table 2. Data Compatibility check: HNS_STL1, URW_STL1

	Δa_x (m/s²)	Δa_y (m/s²)	Δa_z (m/s²)	Δp (rad/s)	Δq (rad/s)	Δr (rad/s)	K_α (-)	$\Delta\alpha$ (rad)
HNS_STL1	0.035 (0.0016)	0.042 (0.0015)	-0.008 (0.0022)	0.004 (0.0015)	0.003 (0.0011)	0.006 (0.0018)	0.895 (0.012)	0.018 (0.0011)
URW_STL1	-0.171 (0.0194)	-0.667 (0.0041)	0.513 (0.0061)	0.057 (0.0020)	-0.003 (0.0011)	-0.045 (0.0041)	1.129 (0.0020)	0.027 (0.0023)

( ) Cramer-Rao Bound

the flow separation. The type of flow separation differs from one configuration to other. In order to analytically postulate this complex flow phenomena, researchers have followed an approach based on Kirchhoff's theory of flow separation[1]. This theory describes analytically the flow separation point including the hysteresis as a function of internal state variables. With the help of Kirchhoff's theory the non-linearity has been incorporated by postulating the aerodynamic model as a function of flow separation point and stall characteristic parameters. Based on this theory, for a asymmetrical profile the total lift acting on the wing can be modelled as a function of angle of attack (α) and the flow separation point (X)[1].

$$C_L(\alpha, X) = C_{L_0} + C_{L_\alpha}\left\{\frac{1+\sqrt{x}}{2}\right\}^2 \alpha \qquad (2)$$

where C_{L_α} is the lift curve slope.

The position of the flow separation point in Eqn. (2) is described by using the following single ordinary differential equation[1].

$$\tau_1 \frac{dX}{dt} + X = \frac{1}{2}\left\{1 - \tanh[\mathrm{a}_1(\alpha - \tau_2\dot{\alpha} - \alpha^*)]\right\} \qquad (3)$$

where τ_1 and τ_2 are transient and hysteresis time constants, respectively. The terms a_1 and α^* corresponds to static stall characteristic of airfoil and break point respectively. The non dimensional term $X(0 \le X \le 1)$ represent the instantaneous location of idealissed flow separation point on the upper surface of the wing.

Equation (3) is a generalised mathematical model used to estimate the flow separation point including the hysteresis and unsteady effects. To estimate the parameters a_1, α^*, τ_1 and τ_2 the flight manoeuvers should contain a dynamic stall, which is in general a difficult task to perform. As an alternative, it is considered that the execution of quasi-steady stall manoeuver is relatively less difficult and risky compared to the dynamic stall manoeuver. Therefore, a simplified approach accounting for quasi-steady stall characteristics (a_1, α^* and τ_2) has been used for the estimation from flight data[1]. Accordingly, the transient effects were neglected by setting τ_1 to zero in Eqn (3). Therefore, the following mathematical model is sufficient to adequately model the stall hysteresis[1].

$$X = \frac{1}{2}\left\{1 - \tanh[\mathrm{a}_1(\alpha - \tau_2\dot{\alpha} - \alpha^*)]\right\} \qquad (4)$$

With this backdrop, the Kirchhoff's quasi steady stall model have been used to incorporate the non-linearity in the aerodynamic model of CDRW configuration.

4. HIGH ANGLE OF ATTACK PARAMETER ESTIMATION

The near stall longitudinal aerodynamic modelling from high angles of attack flight data has been performed by using MLE and NGN methods for Hansa-3 and CDRW configurations and by using NGN method for ATTAS aircraft. The Eqns. 5(a)-5(c) were used to postulate the lift coefficient of Hansa-3, ATTAS and CDRW configurations, respectively, in terms of flow separation point[1].

$$C_L(\alpha, X)_{HNS} = C_{L_0} + C_{L_\alpha}\left\{\frac{1+\sqrt{x}}{2}\right\}^2 \alpha \qquad (5a)$$

$$C_L(\alpha, X, M)_{ATS} = C_{L_0} + C_{L_\alpha}\left\{\frac{1+\sqrt{x}}{2}\right\}^2 \alpha + C_{L_M} M \qquad (5b)$$

$$C_L(\alpha, X, q, \delta_e)_{URW} = C_{L_0} + C_{L_\alpha}\left\{\frac{1+\sqrt{x}}{2}\right\}^2 \alpha + C_{L_q}\frac{q\bar{c}}{2V} + C_{L_{\delta_e}}\delta_e \qquad (5c)$$

The drag and pitching moment coefficients for the configurations of interest have been modelled by using Eqns (6) and (7), respectively.

$$C_D = C_{D_0} + kC_L^2 + \frac{\partial C_D}{\partial X}(1 - X) \qquad (6)$$

$$C_m = C_{m_0} + C_{m_\alpha}\alpha + C_{m_q}\frac{q\bar{c}}{2V} + C_{m_{\delta_e}}\delta_e + \frac{\partial C_m}{\partial X}(1 - X) \qquad (7)$$

The flow separation point in the Eqns (6) and (7) are estimated by using Eqn. (4). The three parameters a_1 (airfoil static stall characteristics), τ_2 (time constant) and α^* (break point) are adequate to model the stall hysteresis[1]. These parameters have been estimated by using MLE and NGN methods by minimising the error between the measured and estimated aerodynamic coefficients. Since it is not possible to measure the aerodynamic force and moment coefficients (C_L, C_D, C_m) during the flight tests, these coefficients have been reconstructed from the measured accelerations and flow angles. For the rest of this paper the reconstructed C_L, C_D, C_m from flight data are considered as measured aerodynamic force and moment coefficients. The following vectors $(\Theta_{HNS}, \Theta_{ATS}\, and\, \Theta_{URW})$ represents the parameters that are to be estimated from the flight data pertaining to high angles of attack of Hansa-3, ATTAS and CDRW aircrafts, respectively.

$$\Theta_{HNS} = \left[C_{L_0}\; C_{L_\alpha}\; e\; C_{D_0}\; C_{m_0}\; C_{m_\alpha}\; C_{m_q}\; C_{m_{\delta_e}}\; a_1\, \alpha^*\, \tau_2\; C_{D_X}\; C_{m_x}\right]^T \qquad (8)$$

$$\Theta_{ATS} = \left[C_{L_0}\; C_{L_\alpha}\; C_{L_M}\; e\; C_{D_0}\; C_{m_0}\; C_{m_\alpha}\; C_{m_q}\; C_{m_{\delta_e}}\; a_1\, \alpha^*\, \tau_2\; C_{D_X}\; C_{m_x}\right]^T \qquad (9)$$

$$\Theta_{URW} = \left[C_{L_0}\; C_{L_\alpha}\; C_{L_q}\; C_{L_{\delta_e}}\; C_{D_0}\; C_{m_0}\; C_{m_\alpha} C_{m_q}\; C_{m_{\delta_e}}\; a_1\, \alpha^*\, \tau_2\; C_{D_X}\; C_{m_x}\right]^T \qquad (10)$$

Figures. (5) - (7) presents the measured and estimated aerodynamic coefficients from near stall flight data of Hansa-3, ATTAS and CDRW configurations respectively using MLE and NGN methods.

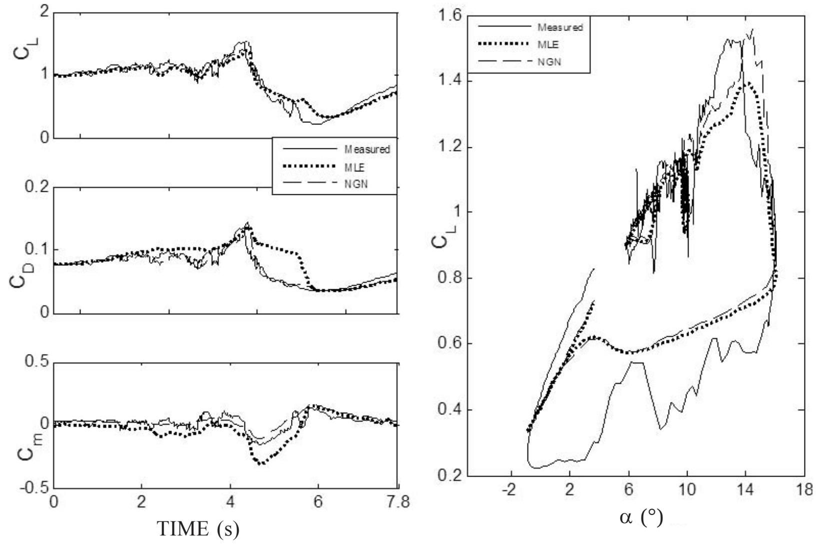

Figure 5. Parameter estimation using MLE and NGN methods: HNS_STL1[6].

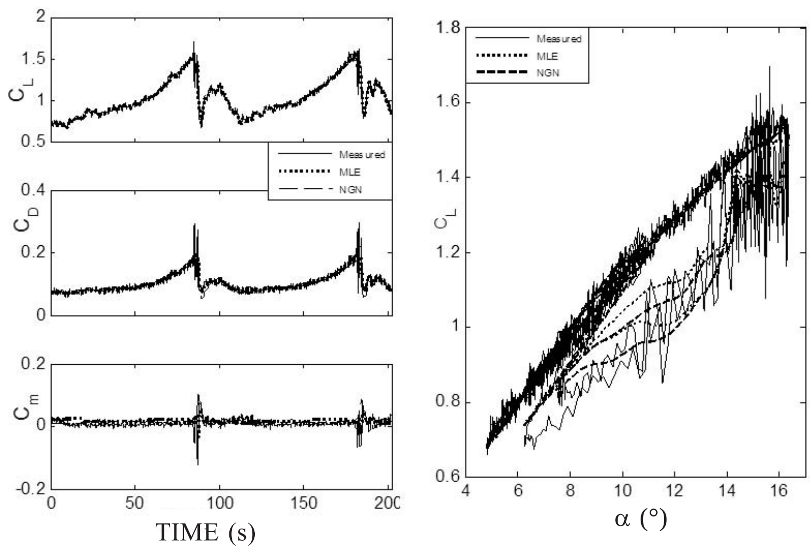

Figure 6. Parameter estimation using NGN method :ATS_STL1[1].

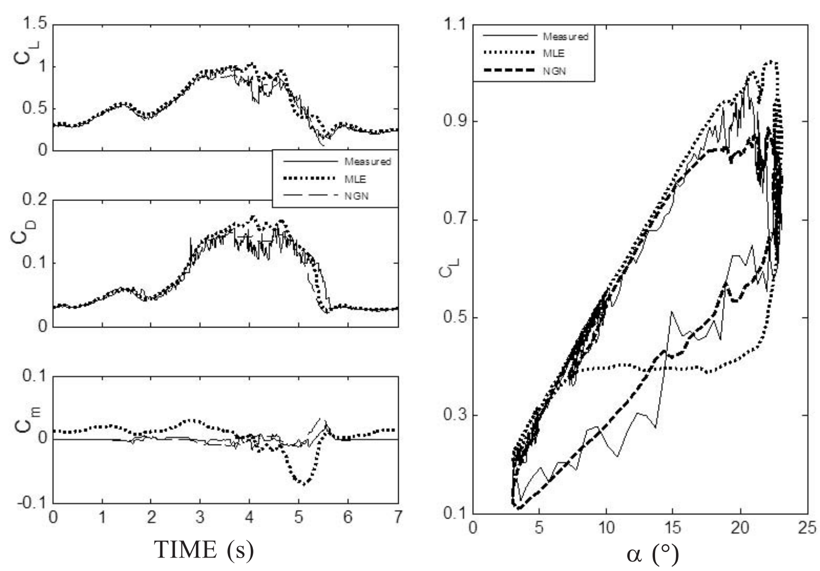

Figure 7. Parameter estimation using MLE and NGN methods: URW_STL1[14]

Table 3 presents the MLE and NGN estimates and their corresponding Cramer Rao bounds of Hansa-3, ATTAS and CDRW configurations, respectively.

Referring Fig. 5, it is observed that the maximum lift coefficient measured during the single high angle of attack manoeuver of Hansa-3 aircraft is 1.52 at around an angle of attack of 13.6°.The stall for Hansa-3 aircraft during wind tunnel tests, with similar reynold's number, occurs at. $\alpha \approx 12°$. Hence the generated flight data can be considered as sufficiently high angle of attack flight data which can be used to estimate the non-linear parameters. Whereas the high angle of attack flight data considered to estimate the stall characteristic parameters of ATTAS aircraft have two back to back quasi steady stall manoeuvers, as shown in Fig. 6. It is observed that the first instant of stall occurred at 85 s and the second at 180 s, respectively. In case of CDRW, as presented in Fig. 7, the high angle of attack manoeuver has been performed by smoothly varying the elevator deflection from -3° to -12° over 1.05 s and held constant for 1.66 s then trimmed back to -0.5° approximately. During this excitation the unmanned vehicle has reached a maximum angle of attack close to 23°. It can be inferred from Figs. 5-7 that the estimated response of longitudinal aerodynamic force and moment coefficients, using MLE and NGN methods, are in close match with the measured flight data. However there is a small but noticeable deviation in the estimation of C_m for both Hansa-3 and CDRW using MLE method. The competency of quasi steady stall model for manned and unmanned aircrafts is evident from the estimated hysteresis lift coefficient, presented in Figs. 5-7. It is also noticed that both MLE and NGN methods were able to reproduce the hysteresis quite satisfactorily using the Kirchhoff's quasi-steady stall model. Referring Table 3, for most of the parameters the estimates from MLE method are in close agreement with NGN estimates. For the sake of comparing the NGN estimates, the MLE estimates presented for ATTATS aircraft have been referred from Jategaonkar[1]. Further the lower values of Cramer Rao bounds have increased the confidence in the estimated parameters using MLE and NGN method. It can be inferred that the estimates of stall characteristic parameters such as α^*, τ_2 and C_{D_X} are in close agreement from both the methods where as the estimates of a_1 and C_{m_X} from MLE method differs from that of NGN estimates.

The predictive capability of the identified model is determined by comparing the flight measured response with those predicted by the model for the same ('identical') control inputs[1]. In flight vehicle applications terminology, this process is often called 'proof-of-match'[1].During this proof-of-match exercise, the identified aerodynamic model is kept fixed. In order to gain more confidence in the estimated parameters, the proof-of-match exercise

Table 3. Parameter estimation: HNS_STL1, ATS_STL1, URW_STL1

Parameter	HNS_STL1		ATS_STL1		URW_STL1	
	MLE	NGN	MLE	NGN	MLE	NGN
C_{D_0}	0.034 (3.42E-04)	0.029 (2.55E-04)	0.044	0.037 (4.12E-04)	0.024 (9.80E-03)	0.013 (1.64E-03)
e	0.836 (6.74E-03)	0.759 (4.08E-03)	0.84	0.843 (1.22E-02)	-	-
C_{L_0}	0.402 (7.43E-03)	0.401 (4.39E-03)	0.158	0.159 (2.24E-03)	0.077 (1.10E-03)	0.052 (4.79E-03)
C_{L_α}	5.030 (7.94E-02)	5.259 (5.57E-02)	3.298	3.253 (3.37E-02)	3.340 (2.59E-01)	3.114 (1.21E-01)
C_{L_M}	-	-	9.07	9.416 (1.50E-01)	-	-
C_{L_q}	-	-	-	-	5.105 (4.39E-01)	3.296 (3.26E-01)
$C_{L_{\delta_e}}$	-	-	-	-	0.677 (3.00E-01)	0.623 (1.58E-01)
C_{m_0}	0.025 (2.26E-03)	0.083 (9.09E-03)	0.051	0.049 (2.14E-03)	0.022 (3.20E-03)	0.008 (7.89E-04)
C_{m_α}	-0.811 (2.78E-02)	-0.765 (1.00E-01)	-0.176	-0.450 (1.98E-02)	-0.182 (9.20E-03)	-0.153 (1.92E-02)
C_{m_q}	-14.309 (2.91E-01)	-9.335 (1.39E+00)	-6.146	-2.095 (2.75E-01)	-0.669 (2.40E-03)	-0.488 (5.10E-02)
$C_{m_{\delta_e}}$	-1.132 (2.38E-02)	-0.719 (8.51E-02)	-0.391	-0.129 (1.45E-02)	-0.299 (1.34E-02)	-0.224 (2.59E-02)
a_1	25.152 (1.51E-01)	19.427 (6.43E-01)	23.716	17.503 (1.41E-01)	9.401 (1.51E-01)	3.681 (2.99E-01)
$\alpha^*(rad)$	0.183 (1.51E-03)	0.183 (1.27E-03)	0.309	0.380 (2.75E-03)	0.469 (5.33E-02)	0.429 (1.26E-02)
τ_2	22.748 (4.49E-01)	22.339 (4.22E-01)	23.99	22.910 (4.22E-01)	14.187 (8.95E-01)	11.990 (6.74E-01)
C_{D_X}	0.004 (4.07E-04)	0.002 (4.37E-04)	0.079	0.166 (1.04E-02)	0.09 (1.48E-02)	0.097 (5.61E-03)
C_{m_X}	-0.125 (5.50E-03)	-0.075 (2.36E-02)	-0.126	-0.273 (3.05E-02)	-0.055 (4.70E-03)	-0.015 (5.61E-03)

() Cramer Rao Bound

was performed using three sets of flight data, one for each configuration, and the obtained results were presented in Figs. 8-10, respectively.

Referring Figs. 8-10, it could be appreciated that the estimated/simulated response computed using the MLE and NGN methods have a decent match with the measured flight data for all the three aircrafts. It is also observed from the proof of match exercise that the estimated stall characteristic parameters and subsequently the quasi steady aerodynamic model is able to reproduce the measured hysteresis corresponding to a different stall manoeuver. Further to enhance the confidence in the estimated stall characteristic parameters and also to check their consistency, using both methods, a higher number of stall manoeuvers for each configuration have to be considered.

5. CONCLUSION

The endeavour to perform non-linear aerodynamic modelling at high angles of attack (near stall) for manned and unmanned aircrafts has been accomplished using MLE and NGN methods. The non-linear aerodynamic modelling was achieved using Kirchhoff's quasi steady stall model. The stall characteristic parameters have been estimated for Hansa-3, ATTAS and unmanned CDRW configuration using one set of near stall flight from each aircraft. The lower values of estimated systematic errors and their corresponding Cramer Rao bounds, using data compatibility check, have enhanced the confidence in the generated flight data Hansa-3 and CDRW configurations. The estimates of most of the stall characteristic parameters from flight data using both MLE and NGN methods were in close

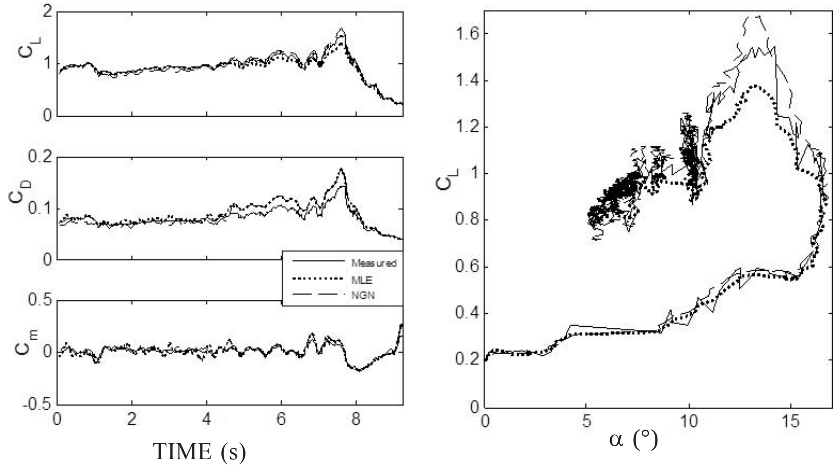

Figure 8. Proof of match exercise for Hansa-3 aircraft.

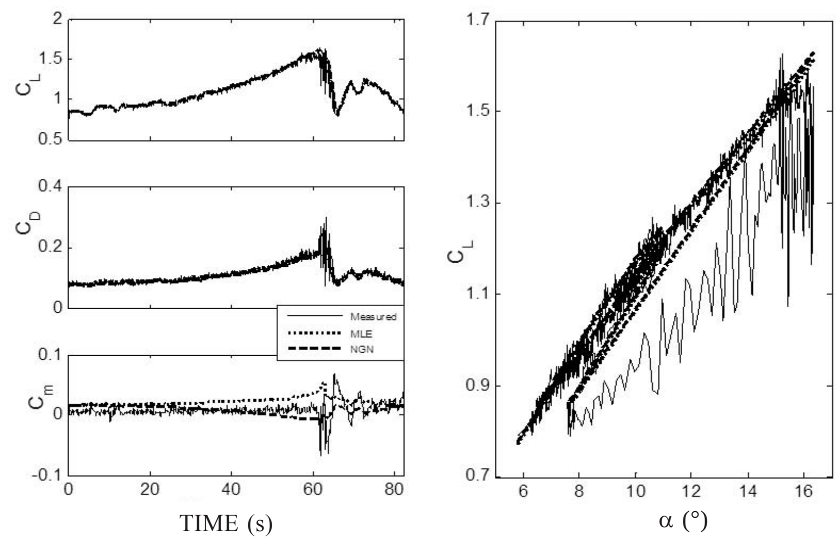

Figure 9. Proof of match exercise for ATTAS aircraft.

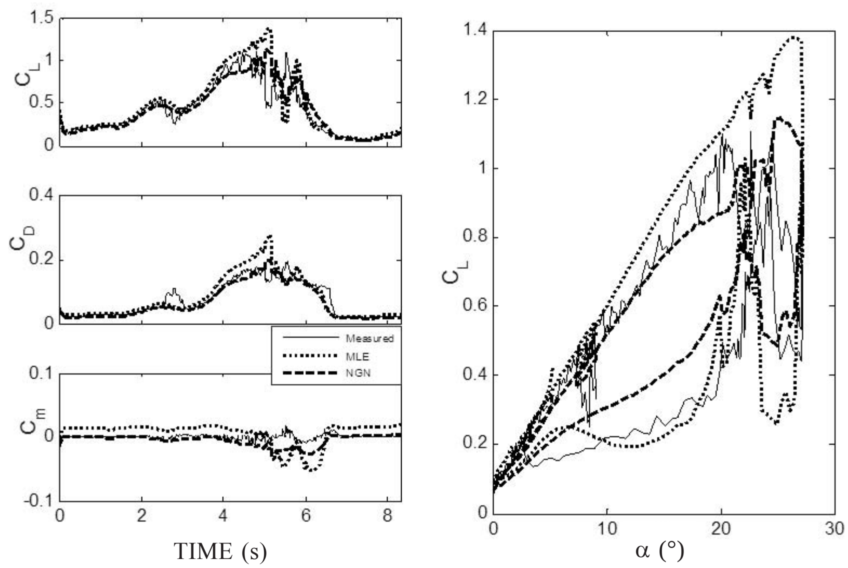

Figure 10. Proof of match exercise for CDRW configuration.

agreement with lower values of corresponding Cramer Rao bound. Further the Kirchhoff's quasi steady stall model is able to estimate the hysteresis quite satisfactorily (closer to measured data)using both MLE and NGN methods. It is also evident from the proof of match exercises that the NGN method, which utilise a trained neural network and thus bypassing the need to solve equations of motion, was able to perform on a par with the classical MLE method. However the consistency in the estimates of stall characteristic parameters using both MLE and NGN method have to be verified with the higher number of high angle of attack flight data sets.

ACKNOWLEDGMENTS

The authors would like to take this opportunity to thank government of India for allowing us to perform flight tests at Flight Laboratory of Indian Institute of Technology Kanpur (IITK). I would also like to extend my sincere thanks to 'BK21 Plus programme (Brain Korea 21 Program for Leading Universities and Students)' for funding my post-doctoral fellowship.

REFERENCES

1. Jategaonkar, R.V. Flight vehicle system identification - A Time Domain Methodology. *In* AIAA Progress in Aeronautics and Astronautics. Reston, VA, 2006, **216**.
   doi: 10.2514/4.866852
2. Balakrishnan, A.V. Stochastic system identification techniques. Stoch Optim Control, John Wiley {&} Sons, London. 1968.
3. Peyada, N. & Ghosh, A. Aircraft parameter estimation using neural network based algorithm. *In* AIAA Atmospheric Flight Mechanics Conference. Chicago, Illinois; 2009, 1-13.
   doi: 10.2514/6.2009-5941.
4. Peyada, N.K. & Ghosh, A.K. Aircraft parameter estimation using new filtering technique based on neural network and gauss-newton method. *Aeronaut. J. UK*, 2009, **113**(1142), 243-252.
   doi: 10.1017/S0001924000002918.
5. Kumar, R. & Ghosh, A.K. Non-linear aerodynamic modelling of Hansa-3 aircraft using neural gauss-newton method. *J. Aerosp. Sci. Technol. AeSI*, **63**(3), 194-204.
6. Dhayalan, R. Parameter estimation of flight vehicles using conventional and neural based methods. 2015. http://172.28.64.70:8080/jspui/handle/123456789/15498.
7. Goman, M.G. & Khrabrov, A.N. State-space representation of aerodynamic characteristics of an aircraft at high angles of attack. *J.*

Aircraft, 1994, **31**(5), 1109-1115. doi: 10.2514/3.46618.

8. Fischenberg, D.; Jategaonkar, R.V.; Fischenberg, D. & Jategaonkar, R.V. Identification of aircraft stall behavior from flight test data. *In* RTO SCI Symposium on System Identification for Integrated Aircraft Development and Flight Testing. 1998, **17-1** - 17-18. http://www.dtic.mil/cgi-bin/GetTRDoc?AD=ADA361699{#}page=228.
9. Nelson, R.C. & Pelletier, A. The unsteady aerodynamics of slender wings and aircraft undergoing large amplitude manoeuvers. *Prog. Aerosp. Sci*. 2003, **39**(2-3), 185-248. doi: 10.1016/S0376-0421(02)00088-X.
10. Leishman, J.G. & Nguyen, K.Q. State-space representation of unsteady airfoil behavior. *AIAA J.*, 1990, **28**(5), 836-844. doi: 10.2514/3.25127
11. Ghoreyshi, M. & Cummings, R.M. Unsteady aerodynamics modelling for aircraft manoeuvers: A new approach using time-dependent surrogate modelling. *Aerosp. Sci. Technol*., 2014, **39**, 222-242. doi:10.1016/j.ast.2014.09.009.
12. Chowdhary, G. & Jategaonkar, R. Aerodynamic parameter estimation from flight data applying extended and unscented kalman filter. *Aerosp. Sci. Technol*., 2010, **14**(2), 106-117. doi: 10.1016/j.ast.2009.10.003.
13. Kumar, Rakesh & Ghosh, A.K. Non-linear modelling of cascade fin aerodynamics using kirchhoff's steady-stall model. *J. Aircraft, AIAA, USA*, 2012, **49**(1), 315-319. doi: 10.2514/1.C031254
14. Saderla, S. Parameter estimation using flight data of unmanned flight vehicles at low and moderately high angles of attack using conventional methods. Ph.D thesis, Dept. Aerospace Engineering, IIT Kanpur, 2015. http://172.28.64.70:8080/jspui/handle/123456789/15499.
15. Saderla, S.R.D. & Ghosh, A.K. Longitudinal parameter estimation from real flight data of unmanned cropped delta flat plate configuration. *Int. J. Intell. Unmanned Syst*. 2016, **4**(1), 2-22. doi: 10.1108/IJIUS-07-2015-0008.
16. Saderla, S.; Rajaram, D. & Ghosh, A. Parameter estimation of unmanned flight vehicle using wind tunnel testing and real flight data. *J. Aerosp. Eng.*, 2016, 04016078. doi: 10.1061/(ASCE)AS.1943-5525.0000679

CONTRIBUTORS

Dr Subrahmanyam Saderla obtained his BTech (Aeronautical Engineering) from JNTU, Hyderabad in 2008, MTech and PhD (Aerospace Engineering) from IIT Kanpur, in 2010 and 2015, respectively. Presently, he is working as a postdoctoral fellow in the department of aerospace and software engineering at Gyeongsang National University, South Korea. He is mainly working in the areas of Design, flight tests and parameter estimation of unmanned aerial vehicles. His research interests also include real time system identification, high angle of attack aerodynamic modelling and dynamic wind tunnel testing as well as experimental flight dynamics.
In the current study, he has contributed in the design, flight tests, instrumentation and parameter estimation of the unmanned vehicle using ML method.

Dr Dhayalan R. has obtained his BTech (Aeronautical Engineering) from Anna University, in 2005. He has obtained his MTech and PhD (Aerospace Engineering) from IIT Kanpur, in 2007 and 2015, respectively. Presently, he is working as a visiting faculty in the Department of Aerospace Engineering at Indian Institute of Space Science and Technology, India. His areas of interest mainly include: Flight Vehicle system identification, flight dynamics, neural modelling and parameter estimation from flight tests of manned and unmanned aircrafts.
In the current study, he includes the parameter estimation using neural based methods.

Prof. A.K. Ghosh has obtained his BTech, MTech and PhD in Aerospace Engineering from IIT Kanpur. Presently he is a Professor in the Department of Aerospace Engineering at IIT Kanpur. His research interest includes: Flight mechanics, parameter estimation from flight images, neural modelling, design of air borne stores, aircraft bombs, artillery shells and rockets design of control law of guided missiles as well as design and analysis of lighter than air flight systems. His team is also working in the design and development of autonomous unmanned vehicles for tactical surveillance.
In the current study, he has contributed in the analysis of the obtained flight data and its post processing for parameter estimation.