A Preliminary Study of Parameter Estimation for Fixed Wing Aircraft and High Endurability Parafoil Aerial Vehicle

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Abstract: *High Endurability Aerial vehicle includes Airship, Powered parafoil aerial vehicle (PPAV). These flying aerial vehicles have excellent endurance and durability. Nowadays, research in lighter than air technology is pacing up fast. In the past years, the design and development of high endurable flying vehicle has grown due to their application in monitoring of floods/ drought, aerial photography, transportation, surveillance in terrain prone areas, reconnaissance missions etc. System Identification is a mathematical tool applied to develop mathematical model of any physical system based on measured data. Research on System Identification of these types of vehicles is on latest trends. Dynamic modelling of these types of vehicles is more complex than fixed wing aircraft. A detail Literature review in system Identification of PPAV and fixed wing aircraft is presented aiming to provide a source of information for researchers to make vehicle fully autonomous from manual controls. Various system Identification Techniques to estimate parameters of flying aerial vehicles are discussed. Longitudinal stability derivatives of fixed wing Hansa-3 aircraft and PPAV are compared. The methodology used in this study to estimate the longitudinal stability derivatives is ML Method. The results obtained in form of stability derivatives of Hansa-3 aircraft and Powered parafoil aerial vehicle are presented in tabular form. This study will give insight of identification techniques used to estimate parameters.*

Key Words: *Continuous time-model, Data compatibility check, Maximum Likelihood Method, Parameter Estimation*

1. INTRODUCTION

Parameter identification is the most illustrated example of identifying the system used to define the characteristics of the dynamic system. Aerodynamic modelling of aerial vehicle is introduced by Bryan which defines the relationship of forces & moment equation [1]. Aircraft system identification is a tool with wide application to engineering system like aerial flying vehicles. This technique helps researchers to generate the mathematical model of dynamic systems [2, 3] Advancement in technology allows to use state estimation optimization

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techniques to determine parameters. In recent years, system identification has expanded its growth due to its application in designing controllers, health monitoring, analysis of dynamic systems, making system fully autonomous, fault-tolerant etc.

Some assumptions are followed to get accurate results such as neglecting process noise. FEM (Filter Error Method) has capability to handle process noise as well as measured noise [13, 16].

This filtering technique is used in linear and non-linear systems. In this paper, we use the statistical output error method (ML) algorithm for estimation of longitudinal stability parameters of Hansa-3 aircraft and parafoil aerial vehicle.

Flight testing at low and moderate angle is performed of Hansa-3 aircraft by deflecting the elevator using various control inputs like Multi-step (3-2-1-1), doublet and pulse inputs to gather real flight data.

2. LITERATURE REVIEW

Parameter estimation is categorized into three types, namely: (i) equation error method (EEM), (ii) output error method (OEM), (iii) filter error method (FEM) [8]. Equation error method defines a class as least square method which defines the cost function. Output Error Method minimizes the error occurring between the system output variable and the system predicted variable. This method is widely applicable in Time-domain analysis to estimate the derivatives using flight data of vehicle. Maximum Likelihood is a widely used statistical technique to minimize the error and make the system dynamically stable. ML is the best tool to define the output error method. This methodology is highly efficient when the sample size is large but inefficient in handling the process noise. This statistical technique is not used for non-linear dynamic systems and noisy environmental interruptions [4].

Klein explained various topics related to aircraft parameter estimation such as linear and stepwise regression, properties and applicability of statistical method like Maximum likelihood, data compatibility [9]. Jann, T [10] used an ALEX system which includes GPS, Receiver, Magnetometers, Rate gyros, Accelerometers, Air data probes, Video Camera for data acquisition for estimation of the derivatives using system identification techniques such as the output error method.

G. Hur and J. Valasek [11] used the Buckeye system which includes Inertial Measurement Unit (IMU), Flow Sensors, accelerometers for gathering flight data and used FEM (Filter error method) approach such as Kalman filter.

Umenberger, Jack, and A. H. Göktoğan [12] used six degree of freedom to develop Small-Scale paramotor which includes three axis accelerometer, three axis rate gyro, three axis magnetometer, 32 bit micro-controller to fetch flight data using system Identification technique such as Recursive weighted least squares approach with linear Kalman filter.

a. Hansa-3aircraft

Hansa-3 is research cum trainer, two seater type aircraft manufactured by NAL, India and useful for research purpose.

In order to fetch the flight data, multi-variant sensors are instrumented in the aircraft for flight data acquisition.

The aircraft structure is fully composite having low wing configuration with tricycle landing gear arrangement. It consists of a Rotax-914 F3 engine coupled with a Hoffmann propeller as shown in figure [7].

Fig. 1 Hansa-3 aircraft [4]

3. PARAMETER ESTIMATION

Steps involved in parameter estimation include file processing of generated flight data, Data Compatibility and Estimation of parameters using ML Methodology. This paper will give insight of parameter estimation of fixed wing aircraft and high endurability aerial vehicle.

3.1 Fixed Wing Aircraft

3.1.1 File processing of Generated Flight data

The flight test of Hansa-3, trainer cum research aircraft is conducted and data in form of attitude, altitude, velocity (V, α, β, p, q, r θ, ψ, δ_e, δ_a, δ_r, φ, a_x, a_y, a_z) were generated using a data acquisition system to estimate the longitudinal stability derivatives.

The flight test was conducted in flight laboratory at altitudes ranging from 4000, 6000 and 8000ft [7]. As this study is restricted to longitudinal stability parameters, the aircraft is controlled longitudinally using elevator deflection and thrust. The flight test was performed at thrust input of 1200N. The generation of accurate real flight data requires the ability to process it. The flight data are processed in form of angular rates, deflection angles, linear, lateral accelerations, linear rates, dynamic pressure & Temperature T is measured by using OAT Gauge, etc. This model also contains various parameters including derivatives of acceleration, rates, and elastic derivatives which make the model complex [15]. The gyroscope will provide rates, the accelerometer measures the acceleration along the body axis of the system, the control surface deflection is calibrated using a potentiometer. The scale factors and the bias factor are considered to avoid the measurement errors produced by sensors. These effects are considered in data compatibility check. The flight data in terms of multi-step, doublet and pulse is obtained to study the longitudinal motion of the vehicle. These data depict the respective motion of the control variables.

Figures 2(a-g) present the elevator control (3-2-1-1); input, doublet and pulse input will generates five data sets to study the longitudinal motion at low/moderate angles of attack. The abbreviations used for type of elevator input such as Multi-step, doublet and pulse are HLM1, HLD1, HLP1 where H stands for Hansa-3 aircraft, L stands for longitudinal motion of an aircraft. M, D, P refers to the type of the elevator input such as Multi-step, doublet and pulse and digits signifies the number of data sets used to study the longitudinal motion of an aircraft.

MULTI- STEP INPUTS

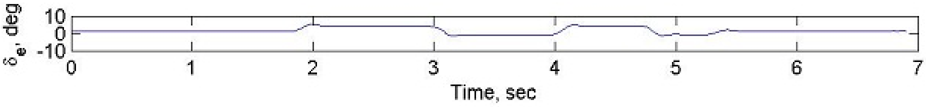


Fig. 2 (a): Elevator Input, HLM1

DOUBLET INPUTS

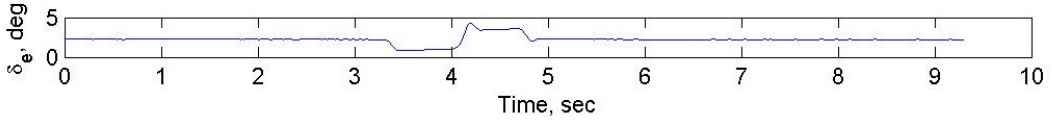


Fig. 2(b): Elevator Input, HLD1

PULSE-INPUTS

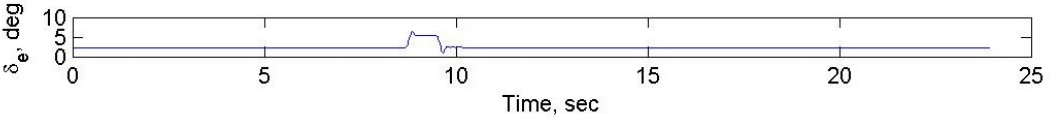


Fig. 2(c): Elevator Input, HLP1

The elevator deflection angle is varied from (±2 to ±6 degrees).
The values of linear acceleration along *x*-axis (a_x) and *z*-axis (a_z) at the trim condition are about $1ms^{-2}$ and $-10ms^{-2}$. The trim angle of attack varies from 2 to 10 degrees (approximately) and the perturbation speed is 56m/s [9].

The Figure below explains the set of processed longitudinal flight data explaining the variations of the variables such as: angle of attack (α), pitch angle (θ), pitch rate (q), velocity (v), and linear acceleration along X axis and Z axis.

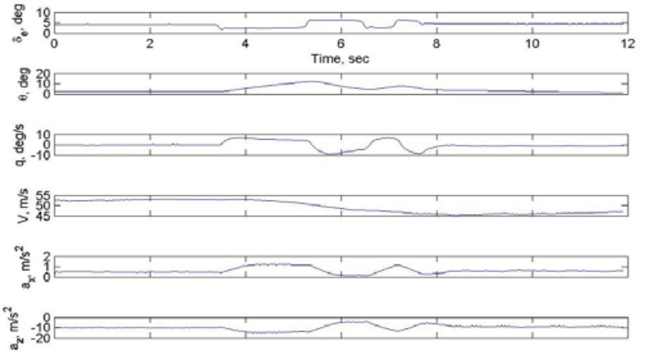


Fig. 3 (a): Longitudinal Flight Data, HLM1

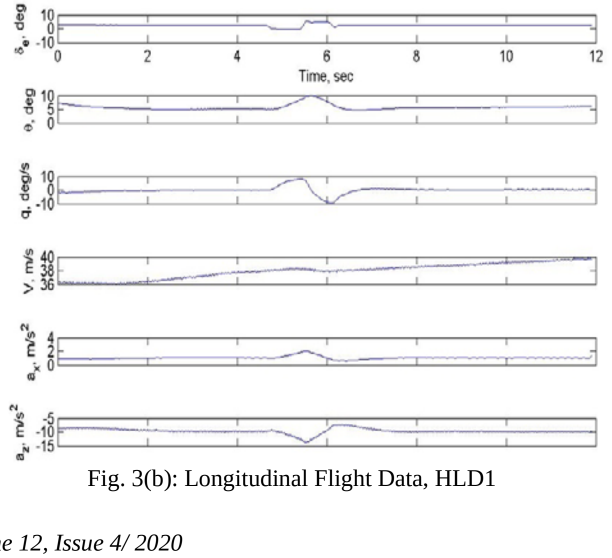


Fig. 3(b): Longitudinal Flight Data, HLD1

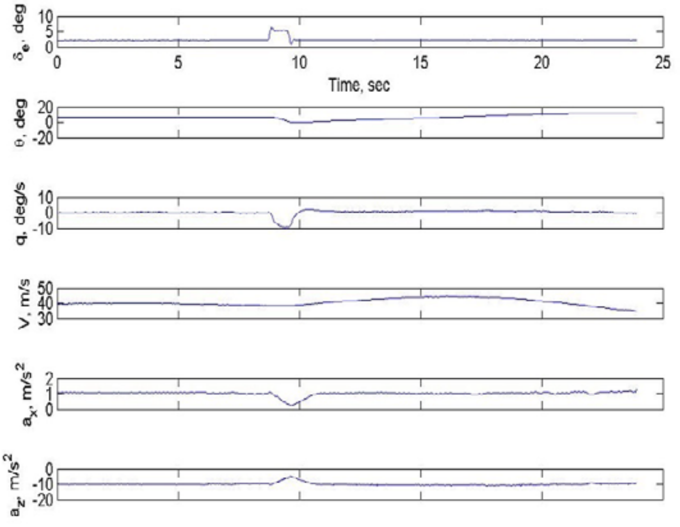


Fig. 3(c): Longitudinal Flight Data, HLP1

3.1.2 Data Compatibility

Recorded data include errors produced due to systematic errors like Scale factors, bias factor, time-delay. These errors made data incompatible, so to avoid measurement errors produced by sensors it is required to check the data compatibility. It will ensure the accuracy of the data fetched from data acquisition system.

After processing the flight data compatibility check, we need to ensure whether the data set is ready for modelling or not.

Flight path reconstruction (FPR) is another name of the data compatibility check. It is a step followed while parameter estimation.

It makes the system while modelling consistent and error free. The steps used for the data compatibility check are:

(i) Determine the systematic instrument errors such as scale factors, zero shifts and time. Delay in the measurements of flight variables [8].

Mathematical Model of aircraft

Modelling of an aircraft includes translational, rotational and navigation equations to check data compatibility of the system.

Translational Kinematics

$$\dot{u} = -q w + r v - g \sin\theta + a_x \tag{1}$$

$$\dot{v} = -ru + pw + g \cos\theta \sin\phi + a_y \tag{2}$$

$$\dot{w} = -pv + qu + g \cos\theta \cos\phi + a_z \tag{3}$$

Rotational Kinematics

$$\dot{\phi} = p + q \sin\phi \tan\theta + r \cos\phi \tan\theta \tag{4}$$

$$\dot{\theta} = q \cos\phi - r \sin\phi \tag{5}$$

$$\dot{\psi} = q \sin\phi \sec\theta + r \cos\phi \sec\theta \tag{6}$$

Navigation Kinematics

$$\dot{x}_E = u \cos\psi\cos\theta + v\,(\cos\psi \sin\theta \sin\phi - \sin\psi \cos\phi) + w(\cos\psi \sin\theta \cos\phi + \sin\psi \sin\phi) \tag{7}$$

$$\dot{y}_E = u \sin\psi \cos\theta + v\,(\sin\psi \sin\theta \sin\phi + \cos\psi \cos\phi) + w\,(\sin\psi \sin\theta \cos\phi - \cos\psi \sin\phi) \tag{8}$$

$$\dot{h} = u \sin\theta - v \cos\theta \sin\phi - w \cos\theta \cos\phi \tag{9}$$

The equations used to evaluate the scale factor, the bias and time delay for a simple model, can be expressed as [9]:

$$y_m(t) = k_y\, y(t - \zeta) + \Delta y \tag{10}$$

where k_y, Δy and ζ are the calibration (scale) factor, the unknown instrument bias and the time delay, respectively [8].

The value of k_y is nearly equals to one for the Ideal case. The linear accelerations (a_{xCG}, a_{yCG}, a_{zCG}) measured at COG (a_{xm}, a_{ym}, a_{zm}) measured by the accelerometer and X, Y, Z represent the position of the accelerometer with respect to the Centre of gravity. Δa_x, Δa_y and Δa_z represent biases in measurement [10].

$$a_{xCG} = a_{xm} + (q^2 + r^2)\ X + (pq-r)\, Y - (pr + q) Z - \Delta a_x \tag{11}$$

$$a_{yCG} = a_{ym} - (pq + r)\, X + (p^2 + r^2)\, Y - (qr - p)\, Z - \Delta a_y \tag{12}$$

$$a_{zCG} = a_{zm} - (pr-q)\, X - (qr-p)\, Y + (p^2+q^2)\, Z - \Delta a_z \tag{13}$$

The angle of attack and the sideslip angle in term of scale factor and bias factor is represented as [8]:

$$\alpha_{NB,m} = K_\alpha \tan^{-1} (w_{NB}/u_{NB}) + \Delta\alpha_{NB} \tag{14}$$

$$\beta_{NB,m} = K_\beta \sin^{-1} \left(\frac{\mathrm{VNB}}{\sqrt{(u2+v2+w2)}} \right) + \Delta\beta_{NB} \tag{15}$$

The equation used to estimate the factors using the Maximum Likelihood method is presented below by unknown parameter vector [8]

$$\Theta = [\Delta p \Delta q\ \Delta r \Delta ax \Delta ay\ \Delta a\ z \Delta\alpha\Delta\ k\alpha]^T \tag{16}$$

Table 1: Indicating scale and biases are presented for five data sets at low and moderate angle of attack

S. No	**Data Sets**	Δa_x	Δa_y	Δa_z	**Δp**	**Δq**	**Δr**	**K_α**	**Δα**
1	**HLM1**	0.41	-0.21	-0.59	0.0019	-0.0007	-0.0059	0.93	0.045
2	**HLM2**	0.23	-0.23	-0.297	0.0015	-0.0015	-0.0058	0.85	0.045
3	**HLM3**	0.13	-0.11	-0.286	-0.0001	-0.0015	-0.0021	0.91	0.143
4	**HLD1**	0.81	0.11	-0.45	0.000005	0.00001	-0.0035	0.89	0.194
5	**HLP1**	1.01	0.15	-0.09	0.000003	0.00002	0.00001	0.87	0.073

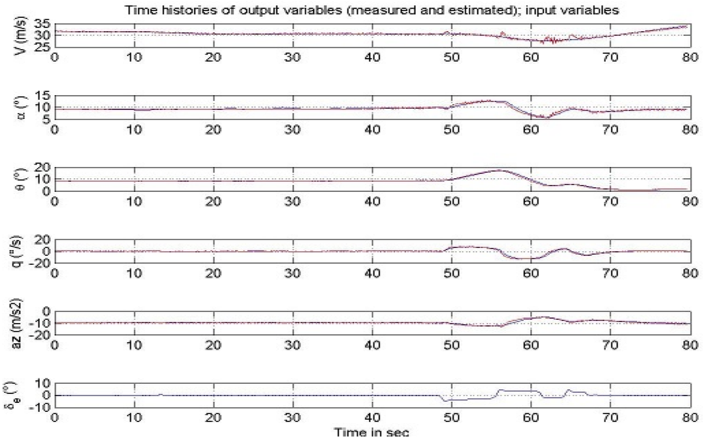


Fig. 4 (a): Data Compatibility Check, HLM1

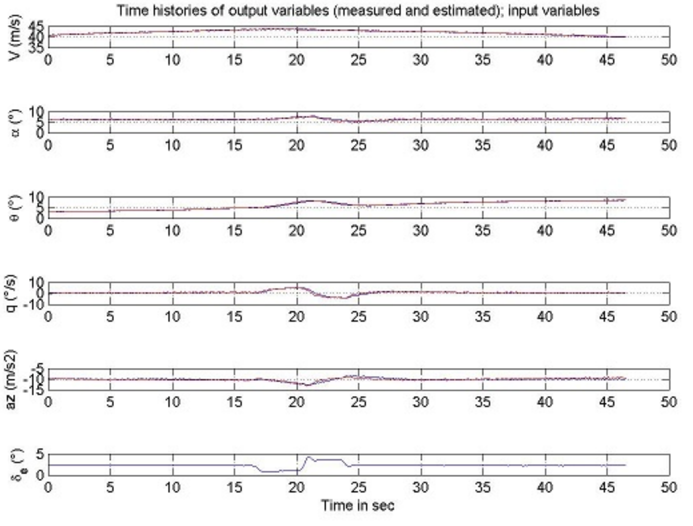


Fig. 4 (b): Data Compatibility Check, HLD1

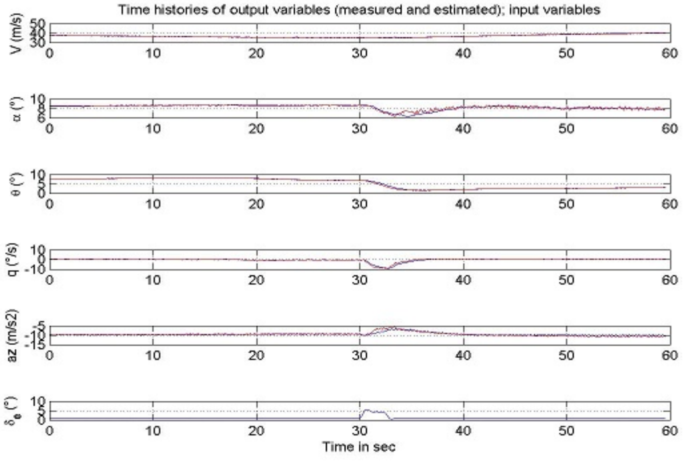


Fig. 4(c): Data Compatibility Check, HLP1

Fig 4(a-c) shows that the computed response of motion variables matches well with the measured response.

3.1.3 Methodology for Estimation of Stability derivatives

Maximum Likelihood Method

The Maximum Likelihood is applicable for longitudinal parameter estimation of the dynamic model using real flight data. This statistical technique is applied in time domain to estimate derivatives. It is applied for no state noise and co-variance matrix. The cost function is minimized by using the ML Method. Cost function is the difference between measured and estimated responses [8]. It is denoted by ‘J’

$$J(\Theta,R) = L(z|\Theta,R) = \tfrac{1}{2}\sum_{k=1}^{N}[z(tk)-y(tk)]^{R-1}[z(tk)-y(tk)] + N/2\ \ln[\det(R)] + Nn_y/2\ \ln(2\prod) \quad (16')$$

Mathematical Model for Parameter Estimation

The following set of state equations, the observation equations are used to estimate longitudinal parameters.

Equations of motion [14]

$$C_L = C_{L0} + C_{L\alpha}\,\alpha + C_{Lq}\,(q\bar{c}/2v) + C_{L\delta e}.\delta_e \quad (17)$$

$$C_D = C_{D0} + C_{D\alpha}.\,\alpha + C_{D\delta e}.\delta_e \quad (18)$$

$$C_M = C_{m0} + C_{m\alpha}\,\alpha + C_{mq}\,(q\bar{c}/2v) + C_{m\delta e}.\delta_e \quad (19)$$

The Maximum Likelihood method is used to determine the unknown parameter vector Θ from longitudinal flight data using equation

$$\Theta = [C_{L0}\,C_{L\alpha}\,C_{Lq}\,C_{L\delta e}\,C_{D0}\,C_{D\alpha}\,C_{D\delta e}\,C_{m0}\,C_{m\alpha}\,C_{mq}\,C_{m\delta e}]^T \quad (20)$$

State Equations

$$\dot{u} = -\frac{\dot{\rho}VS_w}{2m}C_D \quad (21)$$

$$\dot{\alpha} = q - \frac{\dot{\rho}\dot{V}S_w}{2m}C_L \quad (22)$$

$$\dot{\theta} = q \quad (23)$$

$$\dot{q} = -\frac{\rho\dot{V}^2S_w\bar{c}}{2I_y}C_m \quad (24)$$

Observation Equations

$$V_m = \sqrt{u^2 + v^2 + w^2} \quad (25)$$

$$\alpha_{NB,m} = K_\alpha \tan^{-1}(w_{NB}/u_{NB}) + \Delta\alpha_{NB} \quad (26)$$

$$\theta_m = \theta \quad (27)$$

$$q_m = q \quad (28)$$

From the above equations, "m" subscripts denotes the measured variable, V denotes the true airspeed, q signifies the pitch rate, α is the angle of attack, θ denotes the pitch attitude, k_α is the scale factor, δ_e is the elevator deflection, and $\Delta\,\alpha_{NB}$ is the bias factor for angle of attack at nose boom. The parameter vector (Θ) can be determined by using the ML Technique in terms of non- dimensional longitudinal derivatives [7]

$$\Theta = [C_{L_0}\ C_{L_\alpha} C_{L_q} C_{L_{\delta e}} C_{D_0}\ \ C_{D_\alpha} C_{D_{\delta e}} C_{m_0} C_{m_\alpha} C_{m_q} C_{m_{\delta e}}]^T$$

Fig 5 (a-c) showing the convergence of HLM1 Multi-step Input in terms of stability Derivatives using ML ($C_{L_q}, C_{L_\alpha}, C_{L_0}, C_{D_0}, C_{D_\alpha}, C_{D_{\delta e}}, C_{m_q}, C_{m_0}, C_{m_\alpha}, C_{m_{\delta e}}$)

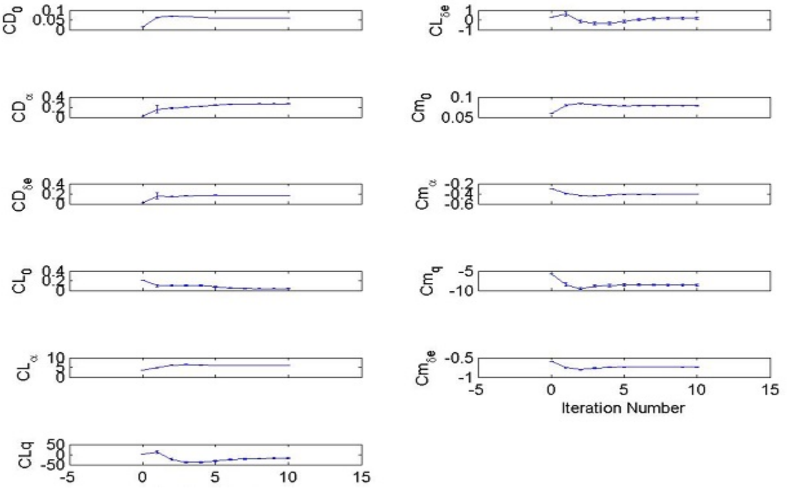


Fig. 5(a): showing responses of HLM1 Multi-step Input

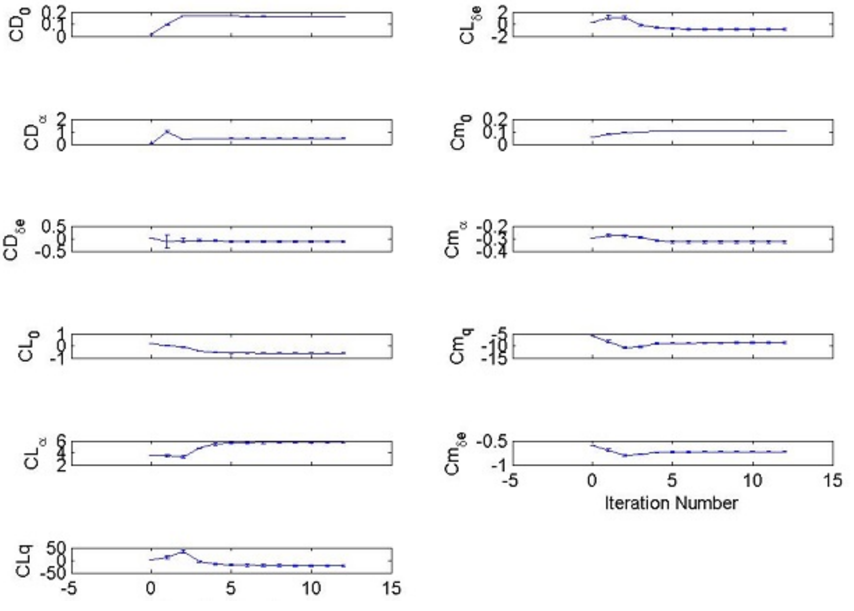


Fig. 5(b): showing responses of HLD1 Doublet Input

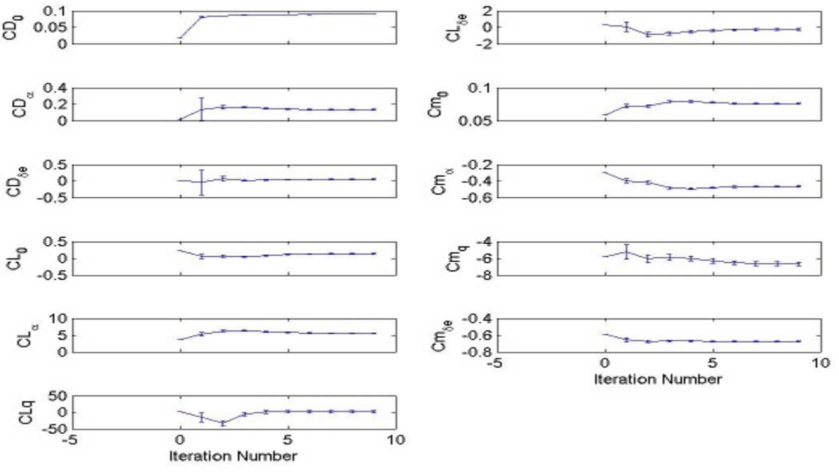


Fig. 5(c): showing responses of HLP1 Pulse Input

Table 2: presents the values of the parameters estimated using the ML method from the longitudinal flight data pertaining to Multi-step, doublet and pulse inputs

Data Sets	C_{D0}	$C_{D\alpha}$	$C_{d\delta e}$	C_{L0}	$C_{L\alpha}$	$C_{l\delta e}$	C_{M0}	$C_{M\alpha}$	$C_{m\delta e}$	C_{mq}
W.T Values	0.035	0.086	0.026	0.354	4.97	0.26	0.052	-0.4596	-1.008	
HLM1	0.059	0.263	0.165	0.037	5.964	0.194	0.078	-0.407	-0.734	-8.57
HLM2	0.053	0.216	0.136	0.0842	5.69	0.184	0.076	-0.429	-0.711	-8.11
HLM3	0.145	0.408	0.202	0.1141	6.16	0.27	0.0918	-0.6437	-0.909	-6.77
HLD1	0.2178	0.344	-0.577	-0.44	3.75	-2.027	0.183	-6.67	-0.51	-0.642
HLP1	0.164	0.463	-0.128	-0.606	5.78	-0.818	0.103	-8.67	-0.33	-0.728

3.2 High Endurability Aerial Vehicle

Fig. 6 Parafoil Aerial Vehicle [5]

The generic term aircraft is used for lighter than aerial vehicles as well as for heavier than aerial vehicles. The parafoil is a non-rigid wing that falls into the lighter than aerial vehicle category and can be propelled through the air once inflated. It produces lift in the air due to the buoyant force acting on it. The parafoil behaves like a balloon and depends on the wind for manoeuvrability, so it is necessary to provide power to this vehicle. This non-rigid wing is connected to a fly-bar that is connected to the payload [5]. This powered vehicle is now controlled by the pilot and provides stability to the system.

Specifications of powered aerial vehicle

The navigation and guidance systems used in this vehicle are the GPS, the 3-axis accelerometer, and the 3-axis gyroscope [5]. These systems are used to acquire information of attitude, altitude and rates. The flight data include V, α, β, p, q, r θ, ψ, δ_e, δ_a, δ_r, φ, a_x, a_y, a_z . The navigation and guidance system also include a Servo motor to provide the directional motion to the vehicle such as Brushless DC motor.

3.2.1 File processing of Generated Flight data

The flight test of the aerial vehicle is conducted and data related to attitude, altitude, velocity (β, p, q, r, δ_r, a_x) were generated using the data acquisition system to estimate lateral/directional stability derivatives. The abbreviations used for the type of input such as PAV1 where PAV represents the parafoil aerial vehicle and “1” stands for data set one.

Figure 7(a) below explains set of processed flight data showing the variations of variables such as the angle of side slip (β), the roll rate (p), the Yaw rate (r), the pitch rate (q), the rigging angle (δs), and the linear acceleration along the X axis

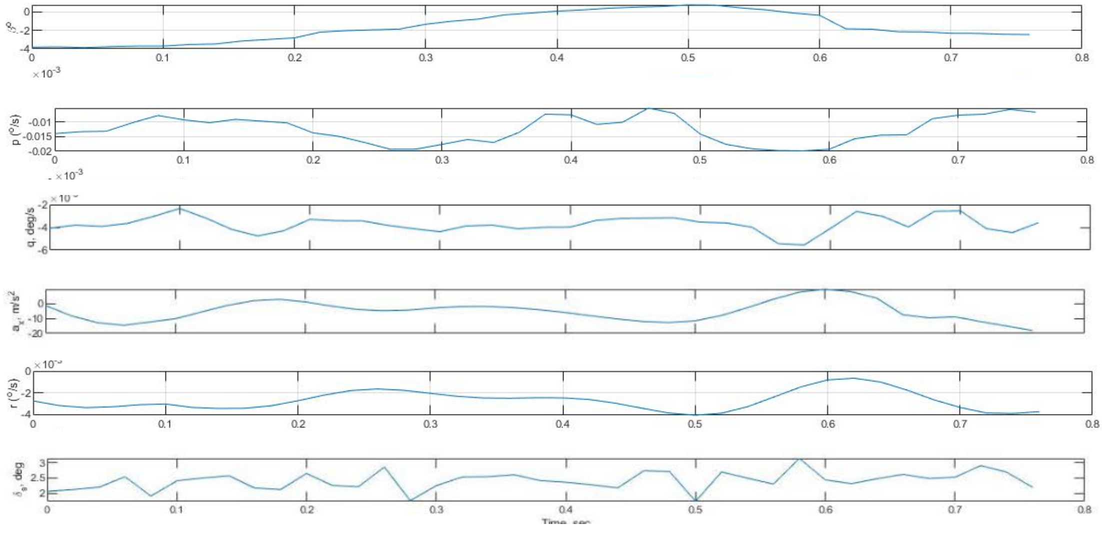
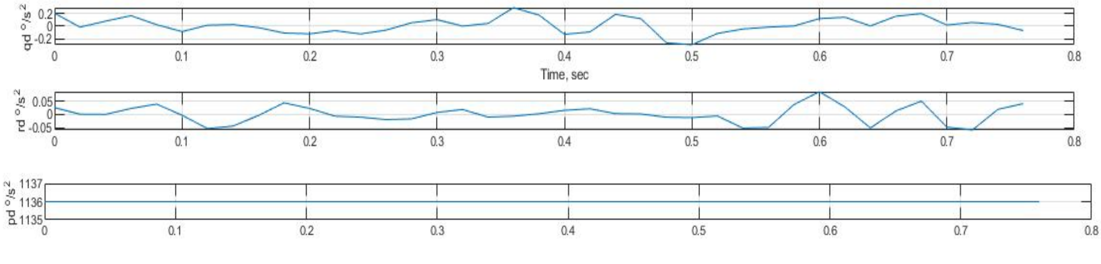


Fig. 7 (a): Flight Data, PAV1



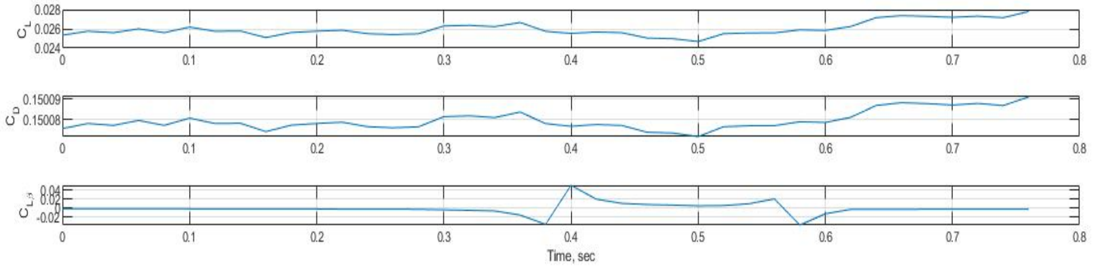


Fig. 7 (b): Flight Data, PAV1

Fig. 7 (b) above explains the set of processed flight data showing the variations of variables such as $\mathbf{C_{L\beta}}$, C_L, C_D, pdot, qdot and rdot

3.2.2 Mathematical Model of PAV

The modelling of an aircraft includes (translational, rotational and navigation) equations used to check the data compatibility of the system.

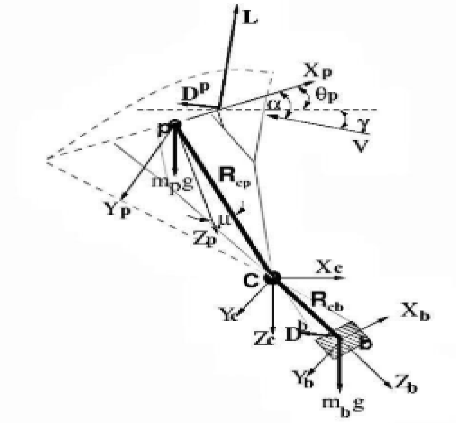


Fig. 8 Nine degree freedom Model [6]

Equation 29 presents 12 equations which consist of the equation of motion and the joint force equation. Equation (30-37) is the combination of kinematic, rotational, and navigational components that make a parafoil payload system.

$$\begin{bmatrix} -M_b R_{cb} & 0 & -M_b T_b & T_b \\ 0 & (-M_p+M_F)R_{cp} & (-M_p+M_F)T_p & -T_b \\ I_b & 0 & 0 & -R_{cb}T_b \\ 0 & I_P+I_m & 0 & R_{cp}T_p \end{bmatrix} \begin{bmatrix} \dot{\omega_b} \\ \dot{\omega_p} \\ V_C \\ F_C \end{bmatrix} = \begin{bmatrix} B_1 \\ B_2 \\ B_3 \\ B_4 \end{bmatrix} \tag{29}$$

$$\begin{gathered} B_1 = F_b^A + F_b^G + F_b^T - \omega_b \times M_b \omega_b \times R_{cb} \\ B_2 = F_p^A + F_p^G - \omega \times (M_p+M_F)\,\omega_p \times R_{cp} + M_F\, \omega_p \times T_P V_C - \omega_p \times M_F T_p V_C \\ B_3 = -\,\omega_b \times I_b \omega_b - M_C \\ B_4 = M_p^A - \omega_p \times (I_p+I_m)\,\omega_p + M_C \end{gathered} \tag{30}$$

$$M_C = \begin{bmatrix} 0 \\ 0 \\ K_C(\Psi_p - \Psi_b) + C_C(\Psi_P^* - \Psi_b^*) \end{bmatrix} \tag{31}$$

$$\Psi_p = \tan^{-1}\frac{(\mathrm{Sin}\phi_p \mathrm{Sin}\,\Theta_p\,\mathrm{Cos}\Psi_p + \mathrm{Cos}\phi_p\,\mathrm{Sin}\Psi_p)}{\mathrm{Cos}\Theta_p \mathrm{Cos}\Psi_p}$$
$$\Psi_b = \tan^{-1}\frac{(\mathrm{Sin}\phi_b \mathrm{Sin}\,\Theta_b\,\mathrm{Cos}\Psi_b + \mathrm{Cos}\phi_b\,\mathrm{Sin}\Psi_b)}{\mathrm{Cos}\Theta_b \mathrm{Cos}\Psi_b} \tag{32}$$

$$\Psi^*_P = -\,\mathrm{Cos}\Psi_p \tan\Theta_p p_b + \mathrm{Sin}\Psi_p\,\tan\Theta_p q_p + r_p \tag{33}$$

$$\Psi^*_b = -\,\mathrm{Cos}\Psi_b \tan\Theta_b p_b + \mathrm{Sin}\Psi_b\,\tan\Theta_b q_b + r_b \tag{34}$$

$$\tan\Theta_p = \frac{\mathrm{Cos}\phi_p\,\mathrm{Sin}\Theta_p\,\mathrm{Cos}\Psi p\ -\mathrm{Sin}\,\phi_p\,\mathrm{Sin}\Psi p}{\mathrm{Cos}\Theta_p \mathrm{Cos}\Psi_p}\mathrm{Cos}\Psi^*_P \tag{35}$$

$$\tan\Theta_b = \frac{\mathrm{Cos}\phi_b\,\mathrm{Sin}\Theta_b\,\mathrm{Cos}\Psi b\ -\mathrm{Sin}\,\phi_b\,\mathrm{Sin}\Psi b}{\mathrm{Cos}\Theta_b \mathrm{Cos}\Psi_b}\mathrm{Cos}\,\Psi^*_b \tag{36}$$

Equation 37 presents (*u*, *v* and *w*) velocity components, Euler rates (ϕ, Θ, Ψ) in term of angular rates (*p, q, r*) in the body axis system.

$$\begin{bmatrix} x_c^{\&} \\ y_c^{\&} \\ z_c^{\&} \end{bmatrix} = \begin{bmatrix} u_c \\ v_c \\ w_c \end{bmatrix}$$
$$\begin{bmatrix} \phi_b^{\&} \\ \Theta_b^{\&} \\ \Psi_b^{\&} \end{bmatrix} = \begin{bmatrix} 1 & S\phi_b t\Theta_b & C\phi_b t\Theta_b \\ 0 & c\phi_b & -s\phi_b \\ 0 & \frac{S\phi_b}{C\Theta_b} & \frac{C\phi_b}{C\Theta_b} \end{bmatrix} \begin{bmatrix} p_b \\ q_b \\ r_b \end{bmatrix} \tag{37}$$
$$\begin{bmatrix} \phi_p^{\&} \\ \Theta_p^{\&} \\ \Psi_p^{\&} \end{bmatrix} = \begin{bmatrix} 1 & S\phi_p t\Theta_p & C\phi_p t\Theta_p \\ 0 & c\phi_P & -s\phi_P \\ 0 & \frac{S\phi_P}{C\theta_p} & \frac{C\phi_P}{C\theta_p} \end{bmatrix} \begin{bmatrix} p_p \\ q_p \\ r_p \end{bmatrix}$$

3.2.3 Methodology for Estimation of Stability derivatives

The Maximum Likelihood Methodology is applied while estimating the stability derivatives of the parafoil aerial vehicle. This statistical technique is suitable to be used in time domain. Details about Maximum Likelihood Technique are discussed in section IV.

The parafoil canopy coefficients can be expressed as

$$C_X = (-C_D^p u_p + C_L w_p)/V_p \tag{38}$$

$$C_Y = C_Y \tag{39}$$

$$C_z = (-C_D^p w_p + C_L u_p)/V_p \tag{40}$$

$$C_l = C_{l_\beta}\boldsymbol{\beta} + C_{l_p} p_p\ \frac{b}{2V_p} + C_{l_r} r_p\ \frac{b}{2V_p} \tag{41}$$

$$C_n = C_{n_\beta}\boldsymbol{\beta} + C_{n_p} p_p\ \frac{b}{2V_p} + C_{n_r} r_p\ \frac{b}{2V_p} \tag{42}$$

$$C_m = \{\ C_{m_{\frac{c}{4}}}(\alpha_P, \delta_S) + x_{p_\alpha} C_z\} + C_{mq} q_p\ \frac{C}{2V_p} \tag{43}$$

The Maximum Likelihood method is used to determine the unknown parameter vector Θ from the flight data, using the equation below:

$$\Theta = [C_{Y_Y} C_{Y_\beta} C_{L0} C_D\ C_{l_\beta} C_{l_p} C_{l_r} C_{n_\beta} C_{n_p} C_{n_r} C_{m\alpha}\ C_{mq}]^{\mathrm{T}} \tag{44}$$

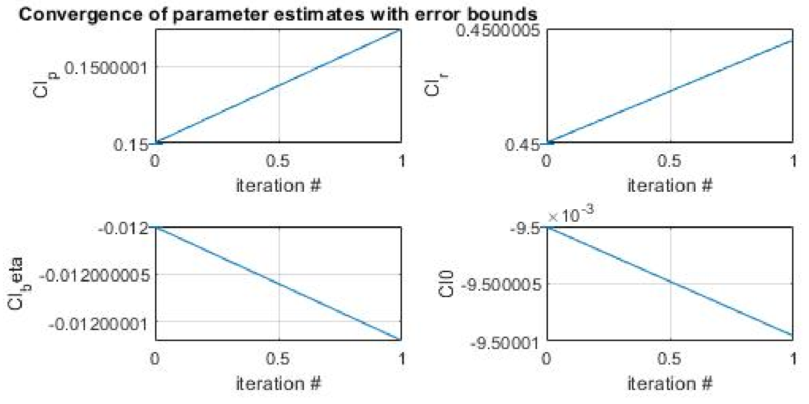


Fig. 9 showing convergence of data set PAV1 in terms of stability Derivatives using ML (C_{L0} $C_{l_\beta} C_{l_p} C_{l_r}$)

4. RESULTS AND CONCLUSIONS

The objective of this study is to estimate the aerodynamic derivatives taking into account the flying vehicle system identification, using statistical ML Technique. This methodology was used to model and estimate the parameters of the parafoil aerial vehicle and trainer cum research aircraft. This study gives accurate information that calibration is the key step in providing a good quality data set and the ML method provides a good estimation of the parameters if the recorded flight data are free from biases.

Table 3: Values of the parameters estimated using the ML method from the [2] flight data set PAV1

S.No.	Stability Derivatives	Values
1.	C_{l_p}	1.50000e-01
2.	C_{l_r}	4.50000e-01
3.	C_{l_β}	-1.20000e-02
4.	C_{L0}	-9.50001e-03
5.	C_{n_p}	-1.40000e-03
6.	C_{n_r}	5.00000e-04
7.	C_{n_β}	-1.08640e+01
8.	C_L	4.50000e-01
9.	C_{DP}	1.50000e-01
10.	C_m	-1.00000e-02
11.	C_{Y_β}	-9.50001e-03
12.	C_{Y_γ}	-6.00000e-02

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