Table 3. Dynamic Characteristic – Longitudinal Mode

Eigenvalues	Damping	Natural Freq (rad/s)	Remarks
-10.7±6.63i	0.851	12.6	Pitch oscillation
-0.00513 ±0.266i	0.0193	0.266	Phugoid
0			Altitude var. (integrator)

Given a particular elevator deflection input, the open loop response of the UAV variables are depicted in Figures 4 and 5. It can be seen from the results that the phugoid mode of the UAV dominates the response, as indicated by the low frequency and lightly damped responses of almost all variables.

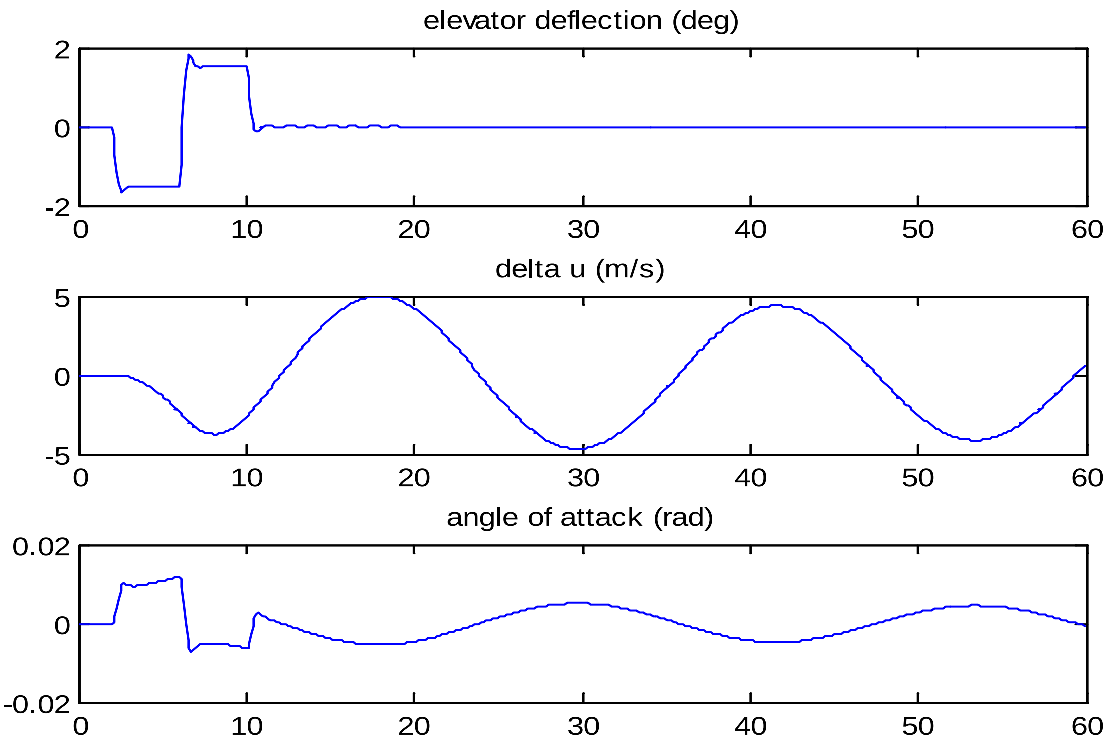

Figure 4. Linear Model Open Loop Response

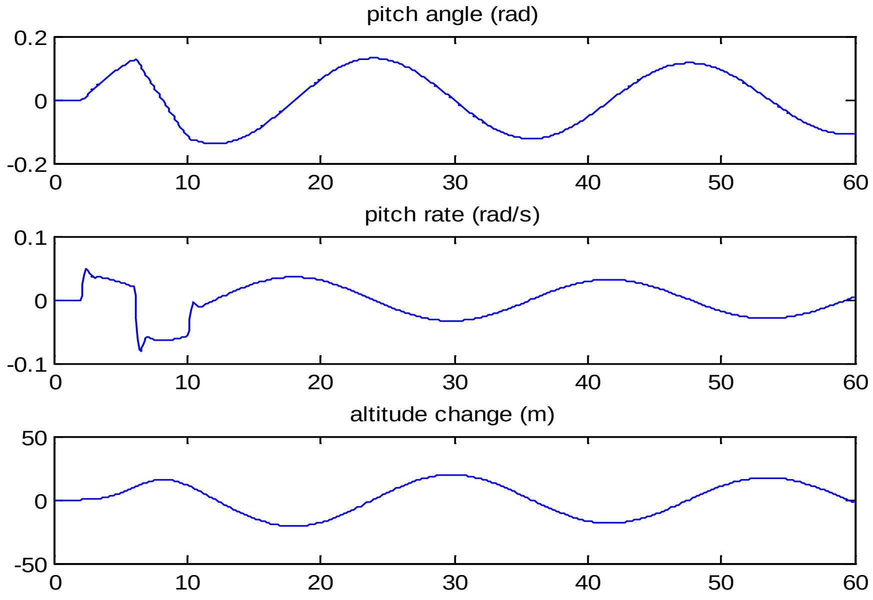

Figure 5. Linear Model Open Loop Response

Parameter Identification

The objective of parameter identification is estimatethe parameters of the flight vehicle from flight data. To estimate the parameter of the aircraft, a mathematical model of the aircraft under test must be postulated. This mathematical model can be derived from equation of motions the aircraft. Figure 6 shows the schematic diagram of parameter identification, in which the simulated output from the postulated mathematical model and sensor model is compared to the measured flight data. The difference between the measured and the simulated outputs will be minimized by adjusting the parameters in the model.

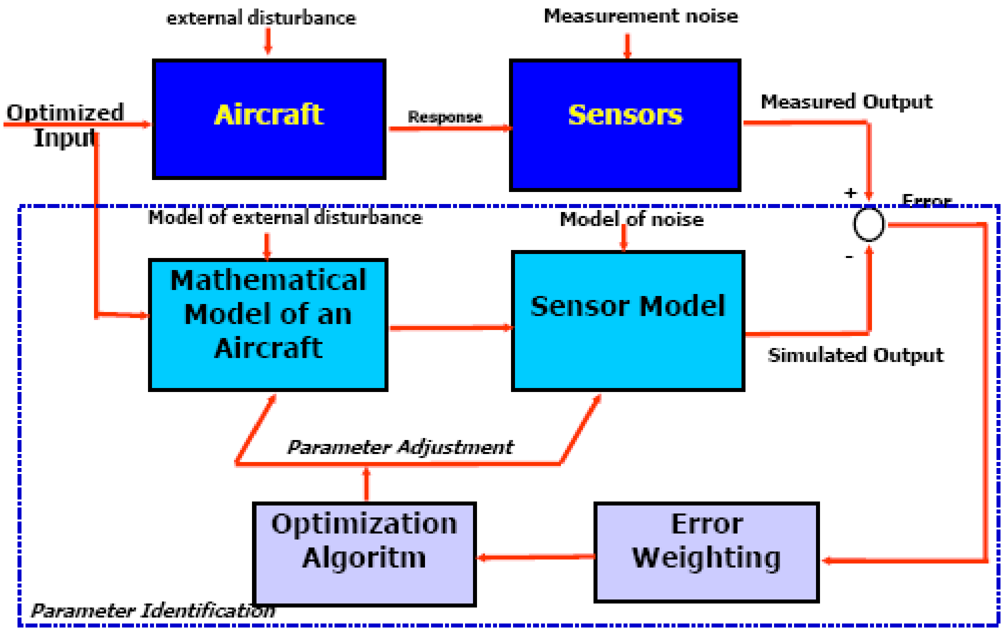

Figure 6. Schematic Diagram of Parameter Identification [9]

Mathematical Model of Aircraft

The mathematical of the aircraft can be expressed by the non-linear equations of motion of as given in Equation (2), (3), (9) and (10). The linearized forms of the equations of motion are presented in Equations (16) and (19). If only the longitudinal equation has to be considered, Equation (11) can be used. If the total force and moment are expressed as follows:

$$\begin{aligned} F_x &= \tfrac{1}{2}\rho V^2 S C_X \\ F_z &= \tfrac{1}{2}\rho V^2 S C_Z \\ M &= \tfrac{1}{2}\rho V^2 S \bar{c} C_m \end{aligned} \qquad (22)$$

Then, Equation (11) can be written as,

$$\begin{aligned} \dot{u} &= -wq - g\sin\theta + \frac{\tfrac{1}{2}\rho V^2 S C_X}{m} \\ \dot{w} &= uq + g\cos\theta + \frac{\tfrac{1}{2}\rho V^2 S C_Z}{m} \\ \dot{\theta} &= q \\ \dot{q} &= \frac{M}{I_y} = \frac{\tfrac{1}{2}\rho V^2 S c C_m}{I_y} \\ \Delta\dot{h} &= u\sin\theta - w\cos\theta \end{aligned} \qquad (23)$$

The aerodynamic forces and moment coefficients can be expressed in terms of several state and control variables of the aircraft, for example angle of attack α, pitch rate q, deflection of the elevator control surface δ_e, and the thrust coefficient T_c. The dependency of those coefficients on these variables can be expressed as follows:

$$\{C_x \quad C_z \quad C_m\}^T = f(\alpha, q, \delta_e, T_c) \qquad (24)$$

Each coefficient in Equation (24) can be expressed in a Taylor series expansion as a function of the state and control variables as well as thrust coefficient. If terms up to the first order are included, these coefficients are expressed as follows:

$$\begin{aligned} C_x &= C_{x_0} + C_{x_\alpha}\alpha + C_{x_q}\frac{q\bar{c}}{V} + C_{x_{\delta_e}}\delta_e + C_{x_{T_c}}T_c \\ C_z &= C_{z_0} + C_{z_\alpha}\alpha + C_{z_q}\frac{q\bar{c}}{V} + C_{z_{\delta_e}}\delta_e + C_{z_{T_c}}T_c \\ C_m &= C_{m_0} + C_{m_\alpha}\alpha + C_{m_q}\frac{q\bar{c}}{V} + C_{m_{\delta_e}}\delta_e + C_{m_{T_c}}T_c \end{aligned} \qquad (25)$$

In Equation (25), the pitch rate q is made dimensionless. The derivatives in Equation (25), i.e. $C_{x_\alpha}, C_{x_q}, C_{x_{\delta_e}}, C_{z_\alpha}, \ldots, C_{m_q}$, and $C_{m_{\delta_e}}$ indicate the aerodynamic parameters, also known as stability derivatives, and $C_{x_{T_c}}, C_{z_{T_c}}$, and $C_{m_{T_c}}$ are the thrust parameters expressing the effect of the thrust on the total aerodynamic forces and moment.

Finally, the longitudinal mathematical model of the aircraft can be obtained by substituting Equation (25) into (23). From numerical integration of Equation (23), the output variables such as true airspeed V, the angle of attack α, and the pressure altitude h can be predicted. Also, noise can be added to these output variables.

State and Parameter Estimation

The mathematical model of the aircraft discussed in the previous section can be written in non linear stochastic differential equations as follows :

$$\dot{x}(t) = f[x(t), u(t), \theta] + w(t); \quad x(0) = x_0 \\ y(t) = g[x(t), u(t), \theta] \tag{26}$$

and the discrete form of the observations as:

$$z(i) = y(i) + v(i); \quad i = 1,2,3,...N \tag{27}$$

where x(t), u(t), y(t) and z(i) are the state, input, observations and measurement vectors respectively, θ represents the vector of the unknown parameters, i.e. the aerodynamic parameters, x_0 is the vector of the (unknown) initial conditions of the state, w(t) and v(i) are the process and measurement noise vectors respectively, and N is the number of data points.

For a linearised mathematical model, Equation (26) can be expressed as:

$$\dot{x}(t) = A\,x(t) + B\,u(t) \\ y(t) = C\,x(t) + D\,u(t) \tag{28}$$

where matrices A and B in equation (28) are known as the **discretised state** and **input** matrices for the linearised model, C and D are known as the **discretized observation** and **input** of the linearised observation model. Note that the formulation in Equation (28) is similar to those in Equation (16) and (19).

In general, the problem of estimating the state trajectory and the aerodynamic parameters of the aircraft can be solved using the so-called **maximum likelihood method**. In this method, both the state and the parameters are estimated simultaneously by maximization of the so-called likelihood function. The likelihood function can be defined in terms of the difference between the measured and the simulated value from the sensor model.

If certain conditions concerning the accuracy and type of the variables measured in flight are met, for example the total force in X, Y and Z directions are measured using accurate accelerometers and the rotational rate **p, q, and r** are measured using rate gyro, then the maximum likelihood estimation problem can be decomposed into two separate estimation problems, i.e. a state trajectory estimation problem followed by a parameter estimation problem [14,15]. In the case of longitudinal motion, the state equation (23) can be re-written as follow:

$$\dot{u} = -wq - g\sin\theta + ax \\ \dot{w} = uq + g\cos\theta + az \\ \dot{\theta} = q \\ \Delta\dot{h} = u\sin\theta - w\cos\theta \tag{29}$$

where accelerations a_x and a_z and pitch rate **q** serve as input in state equation (29). These two separate problems are much easier to be solved than the original estimation problem.

State Estimation

The state trajectory estimation is a recursive prediction of the aircraft state and its covariance matrix from a non linear mathematical model, see Equation (11) or (23), using a state estimation technique such as the Kalman filter.

The Kalman filter equations used in the estimation of the state of the aircraft are given in three steps as follows:

Step 1 : prediction of the state $\hat{x}(i\,|\,i-1)$, observation $\hat{y}(i\,|\,i-1)$ and covariance matrix $\hat{P}(i\,|\,i-1)$ at time (i) based on the estimate of the state, observation and covariance matrix at time (i-1), where i=1,2,3 …N.

$$\begin{aligned}
&\hat{x}(i\,|\,i-1) = \hat{x}(i-1\,|\,i-1) + f[\hat{x}(i-1\,|\,i-1), u(i)]\Delta t \\
&\hat{y}(i\,|\,i-1) = g[\hat{x}(i\,|\,i-1), u(i)] \\
&\hat{P}(i\,|\,i-1) = \Phi(i\,|\,i-1)\,\hat{P}(i\,|\,i-1)\,\Phi^T(i\,|\,i-1) + \Gamma_w(i\,|\,i-1)\,V_w\,\Gamma^T(i\,|\,i-1)
\end{aligned} \tag{30}$$

with initial condition of the predicted state and covariance matrix as follows:

$\hat{x}(0\,|\,0) = x_0$ and $\hat{P}(0\,|\,0) = P_0$

Step 2: calculation of the Kalman filter gain $K_f(i)$

$$K_f(i) = \hat{P}(i\,|\,i-1)\,C^T(i-1)[C(i-1)\,\hat{P}(i\,|\,i-1)\,C^T(i-1) + V_v]^{-1} \tag{31}$$

Step 3: estimation of the state $\hat{x}(i\,|\,i)$ and the covariance matrix $\hat{P}(i\,|\,i)$ at time (i)

$$\begin{aligned}
&\hat{x}(i\,|\,i) = \hat{x}(i\,|\,i-1) + K_f(i)\{z(i) - \hat{y}(i\,|\,i-1)\} \\
&\hat{P}(i\,|\,i) = \hat{P}(i\,|\,i-1) - K_f(i)\,C(i-1)\,\hat{P}(i\,|\,i-1)
\end{aligned} \tag{32}$$

The matrices V_w and V_v are the variance of the system and measurement noises respectively. The matrices Φ and Γ_w denote the discretised system and noise matrices of the linearised mathematical model, see Equation (28). These matrices are calculated as follows:

$$\begin{aligned}
&\Phi(i\,|\,i-1) \approx I + A(i-1)\,\Delta t + \tfrac{1}{2!}A^2(i-1)\,\Delta t^2 + \ldots \\
&\Gamma_w(i\,|\,i-1) \approx B(i-1)\,\Delta t + \tfrac{1}{2!}A(i-1)\,B(i-1)\,\Delta t^2 + \ldots
\end{aligned} \tag{33}$$

The Kalman filtering solution to the state estimation problem presented in Equations (30) to (32), is recursive in the sense that the state estimate is estimated sequentially from previous measurements of Z=[z(1), z(2), …z(N)].

Figure X shows an example of time history of the estimated aircraft state trajectory using Kalman filter algorithm. The flight test data was obtained from simulated flight maneuver of the elevator doubletat altitude of 1000 m and nominal airspeed 42 m/sec, see Figures 7. The filtered estimates of the airspeed component along the longitudinal axis $\hat{u}$, the airspeed component along the vertical axis $\hat{w}$, the pitch angle $\hat{\theta}$, and the altitude variation $\Delta\hat{h}$ are presented in this figure by solidline.

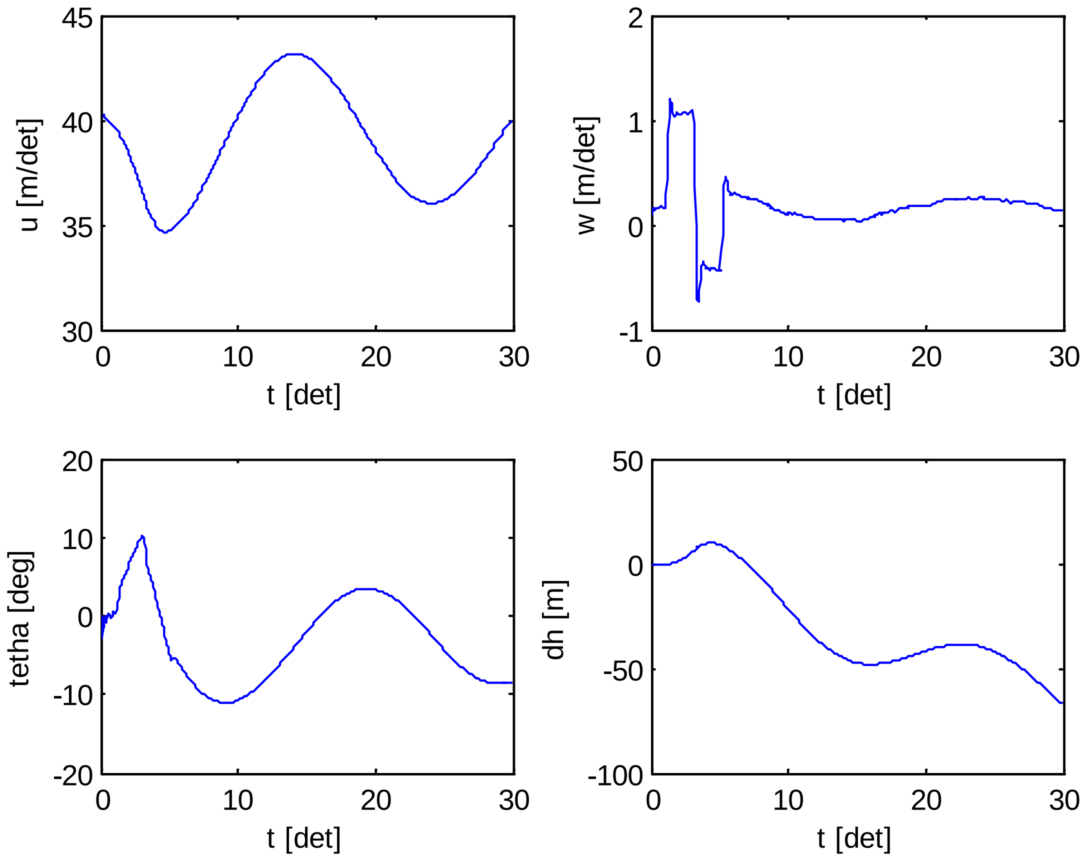

Figure 7. The estimated aircraft state trajectory from dynamic flight test maneuver

Figure 8 shows the Kalman filter estimate of true airspeed, vane-angle of attack, pitch angle, and altitude variation (dotted line). The measured true airspeed, vane-angle of attack, pitch angle and altitude variation are also given in this figure. The difference between the estimated and the measured (residual) are also presented in this figure.

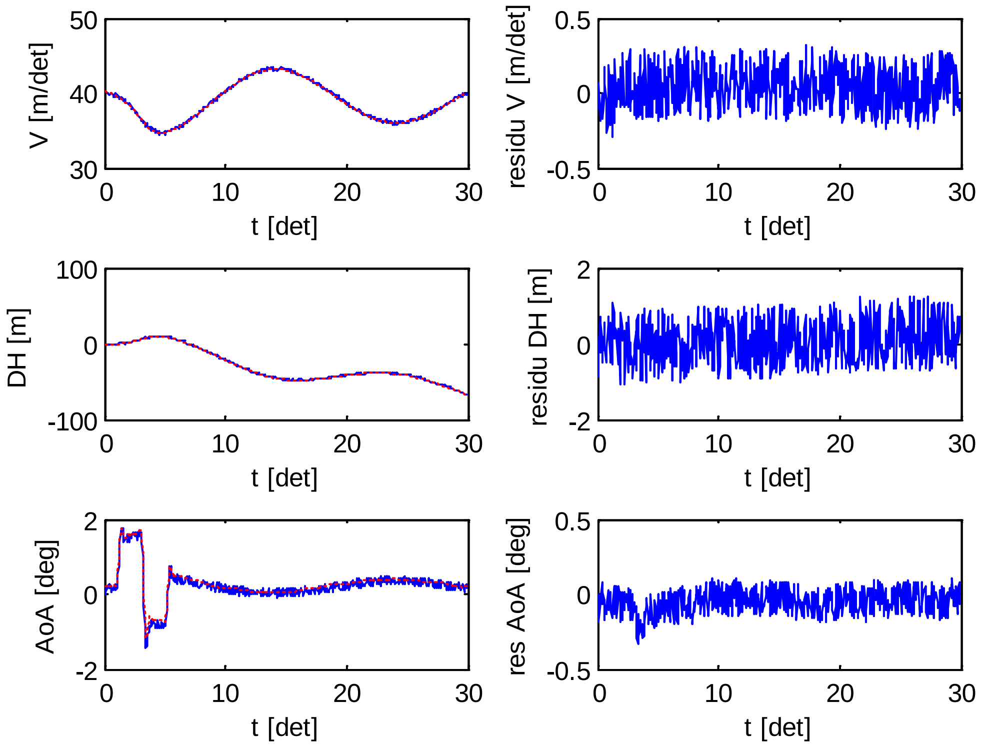

Figure 8. The estimated and measured of the true airspeed, vane-angle of attack, angle of pitch and altitude variation. Their residuals between the measured and the estimated are also given

Parameter Estimation

Assuming that the airspeed V, altitude h (consequently the air density ρ can be estimated) and the angle of attack α are estimated using Kalman filter, the coefficients of the total forces and moment in Equation (25) can be expressed as follows:

$$
\begin{aligned}
C_x &= \frac{X}{0.5\rho V^2 S} = \frac{m a_x}{0.5\rho V^2 S} = C_{x_0} + C_{x_\alpha}\alpha + C_{x_q}\frac{q\bar{c}}{V} + C_{x_{\delta_e}}\delta_e + C_{x_{T_c}}T_c + \varepsilon_x \\
C_z &= \frac{Z}{0.5\rho V^2 S} = \frac{m a_z}{0.5\rho V^2 S} = C_{z_0} + C_{z_\alpha}\alpha + C_{z_q}\frac{q\bar{c}}{V} + C_{z_{\delta_e}}\delta_e + C_{z_{T_c}}T_c + \varepsilon_z \\
C_m &= \frac{M}{0.5\rho V^2 S c} = \frac{I_y \dot{q}}{0.5\rho V^2 S c} = C_{m_0} + C_{m_\alpha}\alpha + C_{m_q}\frac{q\bar{c}}{V} + C_{m_{\delta_e}}\delta_e + C_{m_{T_c}}T_c + \varepsilon_m
\end{aligned}
\qquad (34)
$$

In Equation (34), modeling error and measurement error are included in the last term of the right hand side of that equation. In a regression equation form, Equation (34) can be expressed as

$$
y(i) = \theta_0 + \theta_1 x_1(i) + \theta_2 x_2(i) + \ldots + \theta_p x_p(i) + \varepsilon(i) \qquad (35)
$$

where y(i) is the dependent variable, i.e. the aerodynamic force and moment coefficients, $x_p(i)$ denote the independent variables, i.e. the (estimated) state and control variables, θ_p is the vector of the aerodynamic parameters, and ε(i) is the stochastic equation error, accounting for measurement error on the dependent variable.

Equation (35) can be written in the matrix form as follows:

$$\begin{Bmatrix} y_1 \\ y_2 \\ y_3 \\ . \\ y_N \end{Bmatrix} = \begin{bmatrix} 1 & x_{12} & x_{13} & \cdots & x_{1p} \\ 1 & x_{22} & x_{23} & \cdots & x_{2p} \\ 1 & x_{32} & x_{33} & \cdots & x_{3p} \\ . & . & . & \cdots & . \\ 1 & x_{N2} & x_{N3} & \cdots & x_{Np} \end{bmatrix} \begin{Bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ . \\ \theta_p \end{Bmatrix} + \begin{Bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ .. \\ \varepsilon_N \end{Bmatrix} \tag{36}$$

or, in the more compact form as:

$$Y = X\theta + \varepsilon \tag{37}$$

The matrix of independent variables X is assumed known exactly from the state estimation, i.e. using Kalman filter, or from direct measurement of state variable using instrumentation system with highest accuracy.

Using the Least Squares (LS) technique, the parameter vector θ can be estimated from:

$$\hat{\theta} = [X^T X]^{-1}[X^T Y] \tag{38}$$

Following the estimated parameter $\hat{\theta}$, the estimated dependent variable and the estimated error model can be calculated from:

$$\begin{aligned} \hat{Y} &= X\hat{\theta} \\ \hat{\varepsilon} &= Y - \hat{Y} = Y - X\hat{\theta} \end{aligned} \tag{39}$$

Finally, the goodness of fit the model can be expressed in terms of a correlation coefficient between Y and $\hat{Y}$. This coefficient is usually referred to as the multiple correlation coefficient whose square is :

$$R^2 = \frac{[\hat{Y} - \overline{Y}]^T [\hat{Y} - \overline{Y}]}{[Y - \overline{Y}]^T [Y - \overline{Y}]}; \qquad \overline{Y} = \frac{1}{N}\sum_{i=1}^{N} \hat{Y}(i) \tag{40}$$

The value of the multiple correlation coefficient R can be as high as one when the model fit is perfect, or zero when no correlation exists between the model and the measured dependent variable Y.

The estimation of the aerodynamic parameters is performed with Least Squares method after estimation of the state trajectory of the aircraft. Figure 9 shows the measured (solid line) and estimated (dotted line) values of the longitudinal force coefficient C_x, the vertical force C_z, and the pitching moment coefficient C_m. The residuals between the measured and the estimated are also presented in this figure. The values of the total correlation coefficient R of the forces and moment coefficients are 0.995, 0.997 and 0.91 respectively.

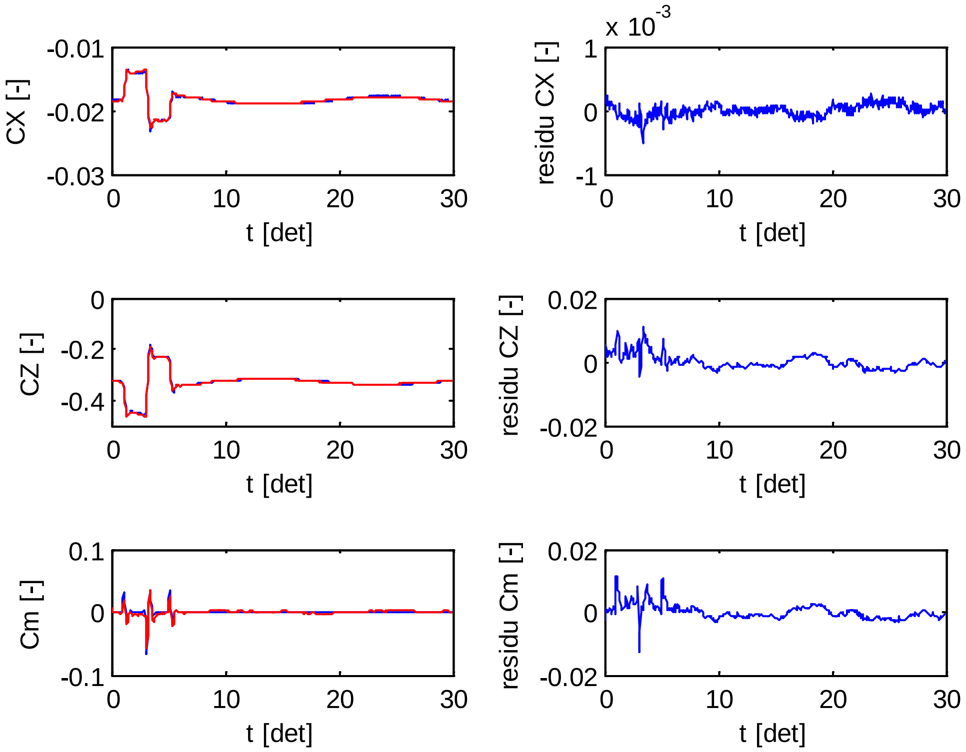

Figure 9. The estimated and measured and their residuals of the longitudinal force coefficient C_X, vertical force coefficient C_Z, and the pitching moment coefficient C_m.

Design Flight Control System

In this section, it will be demonstrated the role of aircraft dynamic model in the flight control design. As has been explained earlier, the dynamic model contains important information about the dynamics characteristic of the aircraft under consideration. Hence, it plays key role in the design process, since one of the main purposes of the flight control system is to improve and regulate the dynamics variables of the aircraft.

In this section, an altitude hold controller will be designed to improve the performance of the UAV in maintaining and regulating its flight altitude. As has been revealed by the open loop response results, it is already known that the UAV longitudinal dynamics is dominated by the low frequency and lightly damped behavior, which is not appropriate in the view of achieving good closed loop performance. Hence, in addition to achieve a good tracking behavior, the designed controller must be able to stabilize the dominant characteristics of the system so that the UAV can follow the altitude reference command. A scheme to obtain a tracking controller with good disturbance rejection property will be employed in this case.

Tracking Controller

Consider a system which is described as follows [10]:

$$\dot{\bar{x}} = A\bar{x} + B_1\bar{w} + B_2\bar{u}$$
$$\bar{z} = C\bar{x} + D_1\bar{w} + D_2\bar{u} \quad (41)$$

where $\bar{x} \in \Re^n$ is the system state, $\bar{w} \in \Re^{m1}$ is an unknownand bounded disturbance input, $\bar{u} \in \Re^{m2}$ is the control input,and $\bar{z} \in \Re^p$ is the performance output. Assuming that thestate $\bar{x}$ is available, and that the performance output $\bar{z}$ can be measured, then the problem is to design a controller which can follow a reference input $\bar{r} \in \Re^p$ from arbitrary initial condition $\bar{x}(0) = \bar{x}_0$, while keeping the system state $\bar{x}$ bounded for $t \geq 0$.

Assuming that the system is stabilizable and defining new state variable $\bar{x}_a$, performance output $\bar{z}_a$, and the disturbance input $\bar{w}_a$ as follows:

$$\bar{x}_a = \begin{bmatrix} \bar{x}^T & \bar{x}_e^T \end{bmatrix}^T$$
$$\bar{z}_a = \bar{z} - \bar{r} \quad (42)$$
$$\bar{w}_a = \begin{bmatrix} \bar{w}^T & \bar{r}^T \end{bmatrix}$$

where the state $\bar{x}_e$ is defined as the integration of the tracking error:

$$\dot{\bar{x}}_e = \bar{z} - \bar{r} \quad (43)$$

Hence we obtain the augmented plant :

$$\dot{\bar{x}}_a = \tilde{A}\bar{x}_a + \tilde{B}_1\bar{w}_a + \tilde{B}_2\bar{u} \quad (44)$$
$$\bar{z}_a = \tilde{C}\bar{x}_a + \tilde{D}_1\bar{w}_a + \tilde{D}_2\bar{u}$$

where

$$\tilde{A} = \begin{bmatrix} A & 0 \\ C & 0 \end{bmatrix} \quad \tilde{B}_1 = \begin{bmatrix} B_1 & 0 \\ D_1 & -I \end{bmatrix} \quad \tilde{B}_2 = \begin{bmatrix} B_2 \\ D_2 \end{bmatrix} \quad (45)$$
$$\tilde{C} = \begin{bmatrix} C & 0 \end{bmatrix} \quad \tilde{D}_1 = \begin{bmatrix} D_1 & -I \end{bmatrix} \quad \tilde{D}_2 = D_2$$

Having the pair $(\tilde{A}, \tilde{B}_2)$ stabilizable, we can choose a state feedback matrix K such that the closed loop $(\tilde{A} + \tilde{B}_2 K)$ is asymtotically stable. The matrix K can be partitioned as $K = \begin{bmatrix} K_P & K_I \end{bmatrix}$ where $K_P \in \Re^n$ is the first n columns of K and $K_I \in \Re^p$ is the remain p columns of K which related to variable $\bar{x}_e$ as the integration of $\bar{z} - \bar{r}$. Hence the controller for the system (41) can be obtained as:

$$\dot{\bar{x}}_e = \bar{z} - \bar{r} \quad (46)$$
$$\bar{u} = K_P\bar{x} + K_I\bar{x}_e$$

such that the controller may be expressed as a PI-like controller:

$$u = K_P\bar{x} + K_I\int(\bar{z} - \bar{r})dt \quad (47)$$

Implementing the gain feedback K, the closed loop system becomes:

$$\dot{\bar{x}}_a = \left[\tilde{A} + \tilde{B}_2 K\right]\bar{x}_a + \tilde{B}_1 \bar{w}_a$$
$$\bar{z}_a = \left[\tilde{C} + \tilde{D}_2 K\right]\bar{x}_a + \tilde{D}_1 \bar{w}_a \tag{48}$$

If a gain K can be obtained such that the closed loop (48) is asymtotically stable, and if the disturbance $\bar{w}$ is bounded, then $\bar{x}(t)$ is bounded for $\forall t \geq 0$, and $\bar{x}_e \to 0$ meaning that $\bar{z} \to \bar{r}$ ($\bar{z}$ tracks $\bar{r}$).

LQR Controller

An optimal heading hold LQR controller can be computed by taking into account the augmented system defined in Equation (44). LQR controller is computed by minimizing the following cost function [10], [11] :

$$J = \int \left(\bar{x}^T Q \bar{x} + \bar{u}^T R \bar{u}\right) dt \tag{49}$$

where Q and R are symmetric matrices for weighting the states and control variables, and the relation of the system states is as described in Equation (42). A state feedback controller then is computed, such that the control signal can be described as follows:

$$\bar{u} = -K\bar{x} \tag{50}$$

where

$$K = R^{-1} B^T P \tag{51}$$

and P is a positive definite matrix obtained by solving Riccati equation:

$$-\dot{P} = A^T P + PA - PBR^{-1}B^T P + Q \tag{52}$$

Having K computed to produce an acceptable reference tracking behaviour, then the altitude hold controller can be implemented in a structure depicted in Figure 10.

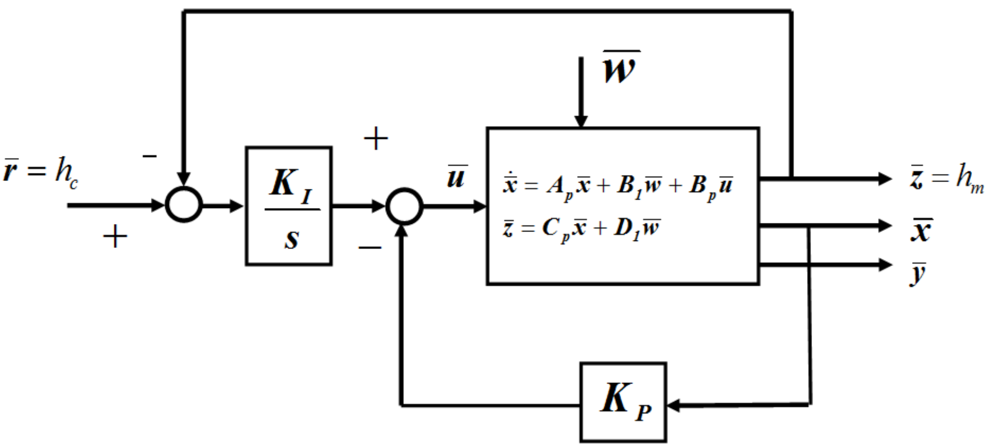

Figure 10. Tracking Controller for Altitude Hold System

Controller Design and Results

Based on the state model described in Equation (20) and (21), an altitude hold controller is designed using the approach already explained in the previous subsection. It is obvious that the variable required as the performance variable z is the measured altitude, hence it is assumed that a barometric altitude sensor is used, which is modeled as a first order system. In addition to that, a first order system is also used for modeling the elevator actuator. An augmented system then is obtained following the procedure in the previous subsection, which is modeled as in Equation (44). Using this augmented model, then an LQR controller is computed by choosing appropriate Q and R matrices. In this case, Q matrix is chosen such as it can produce more weighing on the measured altitude variable and the error variable, while R matrix is chosen to relatively limit the magnitude of the generated control signal (the elevator deflection). Solving the optimal control problem, a gain controller K is obtained, which can be partitioned into a gain feedback vector K_p and an integral gain K_i. The gain vector K_p then is used as a state feedback controller for forming an inner closed loop system, and the gain K_i will form an outer loop system, by feeding the measured altitude variable back into the controller, comparing to the reference value, and integrating the error, as illustrated in Figure 10.

The characteristics of the inner loop system which has K_p as its state feedback controller is summarized in Table 4.

Table 4. Inner Closed Loop Dynamic Characteristic – Longitudinal Mode

Eigenvalues	Damping	Natural Freq (rad/s)	Remarks
-10.7±6.63i	0.851	12.6	Pitch oscillation
-1.97± 3.09i	0.537	3.67	Phugoid
-0.304 ±1.43i	0.208	1.47	
-4.2			

The performance of the closed loop system to follow particular altitude reference command can be elaborated from some of the simulation results presented below. In Figure11, it can be seen that the controller can provide a quite good tracking performance, although further adjustment in the selection of Q and R matrices still can be carried out to obtain more improved results.

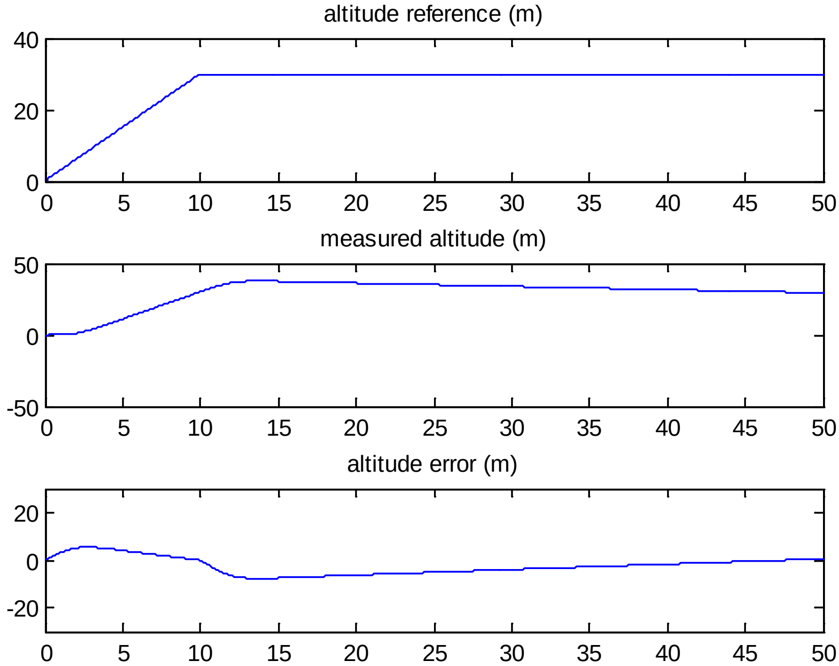

Figure11. Tracking Performance of the closed loop system

In addition to that, the simulation also shows that the developed system, while can provide an acceptable tracking behavior, may also produce realistic response of the controlled system with bounded control input, as showed in Figures 12 and 13. It can be seen that, as indicated by the elevator deflection response, the controller can manage the task with realistically bounded control action.

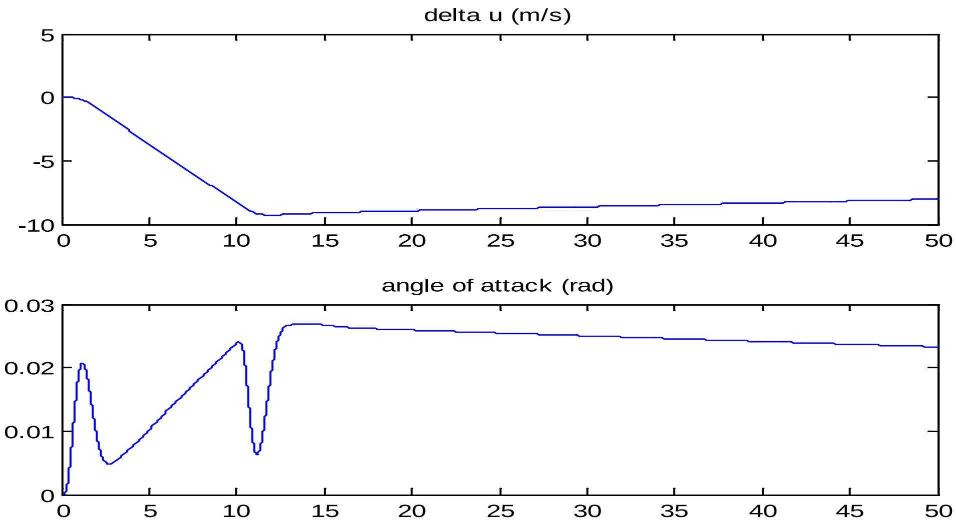

Figure12. System and control variables response (a)

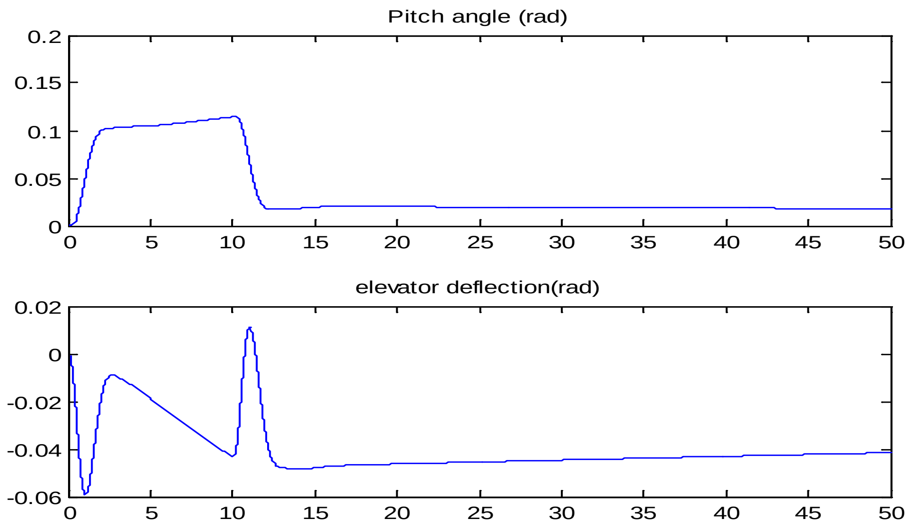

Figure13. System and control variables response (b)

Conclusions

Some aspects related to flight dynamics model of aircrafts have been discussed in this paper. Aircraft flight dynamic model can be viewed as a unifying factor, which relates most of different analysis and synthesis activities in flight mechanics fields. It has been showed how a dynamic mathematical model of aircraft motion can be derived by evaluating all forces and moments that may affect the aircraft motions. The model can be complicated by the fact that the motion of aircraft involves translational and rotational motions in 6 degree of freedom. In addition to that, any forces and moments working on aircraft body have their own characteristics, for instance they may have different mechanism that determines their magnitude and direction. These forces and moments also have their dependencies to the motions of the aircraft body, hence the amount and direction of the forces/moments will change as functions of aircraft motions. This kind of interaction is depicted mathematically in the model, and can be used for determining the characteristic and behavior of the aircraft.

It has also been described the role of aircraft dynamic model in flight control development. Flight control system is usually used for manipulating the characteristics of an aircraft so that it can generate better response. Hence, the dynamic model will play key role in the design of a control system, since it will be the basis for governing the controller equations. One point that must be noted is that the compatibility of the model with the real characteristic of the aircraft must be ensured, so that the designed control system will perform as required in the real condition.

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