International Journal of Progressive Sciences and Technologies (IJPSAT)
ISSN: 2509-0119.

Vol. 43 No. 2 March 2024, pp. 01-11

Longitudinal And Lateral UAV Fixed-Wing Robust Controller With Optimal Estimation-Kalman Filter

Rakotoarimanana Johary Anodith[1], Ratsimba Mamy Nirina[2], Ramafiarisona Hajasoa Malalatiana[3]

[1]Ecole Supérieure Polytechnique d'Antananarivo Madagascar
*johary.rakoto@gmail.com

[2]Ecole Supérieure Polytechnique d'Antananarivo Madagascar

[3]Ecole Supérieure Polytechnique d'Antananarivo Madagascar
* mhramafiarisona@yahoo.fr

Abstract – This paper aim is to present a comparative study between Linear Quadratic Regulator (LQR), Linear Quadratic Gaussian (LQG) and nonlinear controllers for pitch control of an Aircraft. Due to a good stability margin and strong robustness LQR has been selected. LQG was chosen because is able to overcome external disturbances. Kalman Filter controller was also introduced to the Aircraft flight control. Further, we designed an autopilot that controls the pitch angle of the Aicraft. In the end, the control laws are simulated in Matlab/Simulink. The results obtained are compared to see which method is faster, more reliable and more robust.

Keywords – Longitudinal And Lateral UAV, Fixed-Wing Robust, Controller, Optimal Estimation-Kalman Filter.

I. INTRODUCTION

Fixed-wing drones are complex systems with many parameters of their dynamics. Standard controls such as PID controllers fail to control a variety of functions. This does not take into account the details and procedures resounding on the plane. Second, add the additional indicator and the development of the actuator improves the improvement of the function of all systems. The control system must therefore be able to control many sensors and actuators simultaneously. Linear Quadratic Gaussian (LQG) controllers are a modern approach to this problem.

LQG is based on a linear quadratic regulator (LQR) and a linear quadratic estimator (LQE) or Kalman filter [2]. This is further explained in [3], [4] and [5]. This allows LQR to regulate power while receiving relatively noise-free complete state measurements from the Kalman filter. Both LQR and LQE can be designed independently, allowing for design simplicity. The design of the Kalman filter requires the calculation of noise covariances, which are accurate only in an experimental design. Therefore, the controller must be robust enough to adapt to noise model errors.

II. METHODOLOGY

2.1. LQG Controller

The linear quadratic Gaussian (LQG) controller is one of the most popular optimal controllers. It can be used to control a linear system with additive white Gaussian noise by reducing the state space error to a quadratic cost function that can then be minimized. The solution to this minimization is unique and easy to compute. The LQG controller is one of the most popular controllers for optimally controlling nonlinear systems after they are linearized around the equilibrium point. Previously used for motion prediction [8]

The LQG control allows the regulation of the trade-off between power and control power while taking into account the noise of the system and its dimensions. LQG is just an extended version of the linear quadratic controller (LQR). However, since the controller considers that not all states may be available and the measurements may be noisy, it requires a Kalman estimator for full state feedback.

State space equations for the regulator can be given as:

$$\frac{d}{dt}\hat{x} = [A - LC - (B - LD)K]\hat{x} + Ly_v \quad (1)$$

$$u = -Kx \quad (2)$$

Regulating the output y to near 0 is the goal. The plant has disturbances incorporated which are given by $y_v = y + v$. These disturbances are accounted for by the controller while generating the control signals. The state equations can be given by the following:

$$\dot{x} = Ax + Bu + Gw \quad (3)$$

$$y_v = Cx + Du + Hw + v \quad (4)$$

Here, v and w are modeled as white noise. As mentioned above, the LQG consists of both optimal state feedback and a Kalman filter. For the purposes of the LQG, the Kalman filter and the Optimal state feedback can be designed independently.

2.1.1. Optimal State feedback gain

LQG reduces the state error to a quadratic function that can be minimized. This quadratic performance criterion can be given by:

$$J(u) = \int_0^{\infty} [x^T Qx + 2x^T Nx + u^T Ru] \quad (5)$$

The limits to the integration are from 0 to ∞. The function J(u) is to be minimized by the regulator and regulated to near 0. The matrices Q,N and R are user defined, and are used to specify the trade o˙ between control e˙ort and regulation performance. This optimal feedback gain is called the LQ optimal gain. This is basically the optimal full state feedback gain K which minimized the error function. It is multiplied with the feedback and subtracted from the reference signal.

2.1.2. Kalman State Estimator

The control scheme u = −kx is not possible to implement without full state feedback x. The states may not always be directly measurable. Hence, we derive the states from the output of the system and the state transition matrix of the system, while taking into account the noise from the process and the measurements. This is the basic function of the Kalman filter or the Linear Quadratic Estimator (LQE). The Kalman filter generates the state estimate xˆ which remains optimal for the output-feedback problem. The state equation is given by:

$$\frac{d}{dt}\hat{x} = A\hat{x} + Bu + L(y_v - C\hat{x} - Du) \quad (6)$$

Where L is the observer gain. For the controller and estimator, there are two separate sets of Riccati equations to be solved. This allows their design to be independent of each other. For the control signal u, and the measurement y_v, noise covariance data is as follows:

$$E(ww^T) = Q_n \quad (7)$$

$$E(vv^T) = R_n \quad (8)$$

$$E(wv^T) = N_n \quad (9)$$

These covariances are calculated as follows:

E(x) = Expected value of x

E(y) = Expected value of y

E(x, y) = E[x − E(x)][y − E(y)] = E[x] − E[x]E[y]

The Kalman gain L can be determined through the algebraic Riccati equation. Kalman filters are the optimal estimators when dealing with white Gaussian noise. The minimization of estimation error is given by:

$$\lim_{x\to\infty} E\big((x-\hat{x})(x-\hat{x})^T\big) \tag{10}$$

For the regulation of the plant to near zero, the input disturbance at low frequency with Power Spectral Density(PSD) below 10rad/sec. was chosen.

2.2. Linear Quadratic Regulator

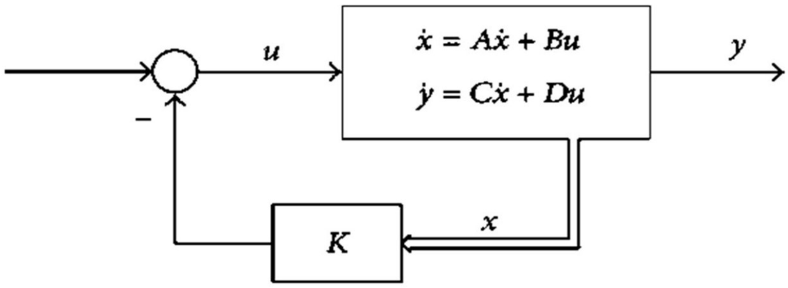

Figure 1 - Architecture of LQR control system.

The LQR assumes an absence of disturbance in the system. It requires the state space approach to analyze a system. This makes it easy to work with multi-output system. The LQR relies on full state feedback. Thus if the pair (A, Bk) is stabilizable, then we look for a feedback gain k which minimizes the following quadratic cost function [9]:

$$J\left(k,\vec{x}(0) = \int_0^\infty \vec{x}(1)^T Q\vec{x}(t) + \vec{u}_k(t)^T R\vec{u}_k(t)dt\right) \tag{11}$$

Here, Q and R are positive definite. The optimal solution is given by the following controller

$$k = -\,R^{-1}{B_k}^T P \tag{12}$$

Here, P is a positive symmetric solution of the following stationary Riccati equation:

$$A^T P + PA - PBR^{-1}B^T P = -Q \tag{13}$$

Now ; the cost function $J = (k,\vec{x}(0))$ can be expressed as :

$$J(k,\vec{x}(0) = \int_0^\infty \vec{x}(1)^T Q\vec{x}(t) + [x^T(t)k^T]R[kx(t)]dt \tag{14}$$

$$u = kx \tag{15}$$

$$J(k,\vec{x}(0) = \int_0^\infty x^T(Q +\ k^T Rk)xdt \tag{16}$$

Substituting value of u in the state space equations:

$$\dot{x} = Ax + B_k u = Ax + B_k kx = (A + B_k)x \tag{17}$$

$$x(t) = e^{(A+B_kK)t}x(0) \tag{18}$$

$$J\big(k,\vec{x}(0)\big) = x(0)\int_0^\infty e^{(A+B_kK)^T t}(Q + k^T Rk)e^{(A+B_kK)t}dtx(0) \tag{19}$$

$$= x^T(0)Px(0) \tag{20}$$

Where P is the symmetric positive definite solution to:

$$(A + B_k k)^T P + P(A + B_k k) = -(Q + k^T R k) \tag{21}$$

Using completion of squares, we can rewrite the equation as:

$$A^T P + PA = -k^T R k - k^T B_k P - Q + P B_k R^{-1} {B_k}^T P \tag{22}$$

$$A^T P + PA - P B_k R^{-1} {B_k}^T P = -Q \tag{23}$$

This is the Riccati equation.

2.3. Kalman Filtering

For the purpose of designing the Kalman filter, we can assume the discrete plant to be represented as:

$$x(n+1) = Ax(n) + B\big(u(n) + w(n)\big) \tag{24}$$

$$y(n) = Cx(n) \tag{25}$$

w(n) is the additive noise to the input. The Kalman filter should be able to estimate y(n), given

u(n) despite v(n) added to the output measurements.

$$y_v(n) = Cx(n) + v(n) \tag{26}$$

v(n) is modeled as Gaussian white noise.

2.3.1. Discrete Kalman Filter

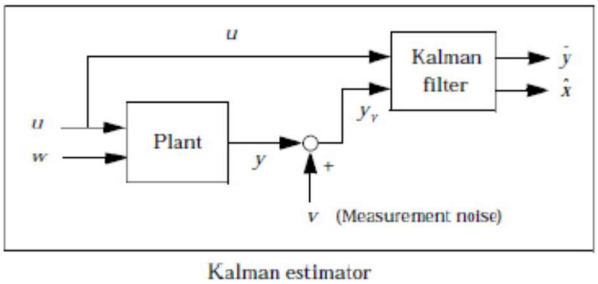

Figure 2 - Block representation of the Kalman estimator.

The discrete Kalman filter has two modes i.e. Time update and Measurement update. The time update mode is responsible for the calculation of the projected value of the state based on the previous values of the state.

The measurement update is responsible for the update to the time update, so it can recalculate the projected values based on the current measurement.

The equations for the discrete steady state Kalman filter are as follows:

Measurement update:

$$\hat{x}\left({}^{n}/_{n}\right) = \hat{x}\left({}^{n}/_{n-1}\right) + M\left(y_v(n) - C\hat{x}\left({}^{n}/_{n-1}\right)\right) \tag{27}$$

Time update :

$$\hat{x}\left({}^{n+1}/_{n}\right) = A\hat{x}(n) + Bu(n) \tag{28}$$

Here,

$\hat{x}\left({}^{n+1}/_{n}\right)$ is the estimate of x(n) given past measurements up to $y_v(n-1)$

$\hat{x}\left({}^{n}/_{n}\right)$ is the updated measurement given the last estimate $y_v(n)$

III. Results

3.1. UAV fixed-wing longitudinal dynamics

There are three primary ways for an aircraft to change its orientation relative to the passing air. Pitch (movement of the nose up or down), Roll (rotation around the longitudinal axis, that is, the axis which runs along the length of the aircraft) and Yaw (movement of the nose to left or right.) Turning the aircraft (change of heading) requires the aircraft firstly to roll to achieve an angle of bank; when the desired change of heading has been accomplished the aircraft must again be rolled in the opposite direction to reduce the angle of bank to zero. [5]

3.1.1. Equations of motion

The general equations of the movement are governed by the equations of mechanics

$$m\frac{\overrightarrow{du}}{dt} = \sum \overrightarrow{F_e} \tag{29}$$

$$\frac{\overrightarrow{dC}}{dt} = \sum \overrightarrow{M_e}$$

3.1.2. Equation of longitudinal motion

$$\beta = p = r = \Phi = 0 \tag{30}$$

Longitudinal equations can be rewritten as:

$$\begin{aligned} \dot{u} &= \frac{X_u}{m}u + \frac{X_w}{m}w - \frac{g\cos\Theta_0}{m}\theta + \Delta X^C \\ \dot{w} &= \frac{Z_u}{m - Z_{\dot{w}}}u + \frac{Z_w}{m - Z_{\dot{w}}}w + \frac{Z_q + mU_0}{m - Z_{\dot{w}}}q - \frac{mg\sin\Theta_0}{m - Z_{\dot{w}}} + \Delta Z^C \\ \dot{q} &= \frac{[M_u + Z_u\Gamma]}{I_{yy}}u + \frac{[M_u + Z_u\Gamma]}{I_{yy}}w + \frac{[M_q + (Z_q + mU_0)\Gamma]}{I_{yy}} - \frac{mg\sin\Theta_0\Gamma}{I_{yy}}\theta + \Delta M^C \\ \dot{\theta} &= q \end{aligned} \tag{31}$$

With :

$$\begin{aligned} \Delta X^c &= \frac{X_{\delta_e}}{m}\delta_e + \frac{X_p}{m}\delta_p \\ \Delta Z^c &= \frac{Z_{\delta_e}}{m - Z_w}\delta_e + \frac{Z_{\delta_P}}{m - Z_{\dot{w}}}\delta_p \\ \Delta M^c &= \frac{M_{\delta_e} + Z_{\delta_e\Gamma}}{l_{yy}}\delta_e + \frac{M_{\delta_p} + Z_{\delta_p\Gamma}}{l_{yy}}\delta_p \end{aligned} \tag{32}$$

Rewrite in state space form as:

-Since $u \approx 0$ in this mode, then $\dot{u} \approx 0$ and can eliminate the X force equation:

$$\begin{bmatrix} \dot{w} \\ \dot{q} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \dfrac{Z_w}{m - Z_{\dot{w}}} & \dfrac{Z_q + mU_0}{m - Z_{\dot{w}}} & \dfrac{-mg\sin\Theta_0}{m - Z_{\dot{w}}} \\ \dfrac{[M_u + Z_u\Gamma]}{I_{yy}} & \dfrac{[M_q + (Z_q + mU_0)\Gamma]}{I_{yy}} & \dfrac{mg\sin\Theta_0\Gamma}{I_{yy}} \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} w \\ q \\ \theta \end{bmatrix} + \begin{bmatrix} \Delta Z^C \\ \Delta M^C \\ 0 \end{bmatrix} \tag{32}$$

$$\begin{bmatrix} \dot{w} \\ \dot{q} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \dfrac{Z_w}{m} & U_0 & -g\sin\Theta_0 \\ \dfrac{[M_u + Z_u\Gamma]}{I_{yy}} & \dfrac{[M_q + (Z_q + mU_0)\Gamma]}{I_{yy}} & \dfrac{mg\sin\Theta_0\Gamma}{I_{yy}} \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} w \\ q \\ \theta \end{bmatrix} + \begin{bmatrix} \Delta Z^C \\ \Delta M^C \\ 0 \end{bmatrix} \tag{33}$$

The transfer function can be represented in state-space form and output equation as state by equation

$$\begin{bmatrix} \dot{w} \\ \dot{q} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} -0.3149 & 235.8928 & 0 \\ -0.0034 & -0.4282 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} w \\ q \\ \theta \end{bmatrix} + \begin{bmatrix} -5.5079 \\ 0.0021 \\ 0 \end{bmatrix} \delta_e \tag{34}$$

$$y = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} w \\ q \\ \theta \end{bmatrix} + [0] \tag{35}$$

The current variable of interest is the pitch angle and it is reflected in the values of the C matrix.

3.1.3. Stability and controlability

The Eigen values for the longitudinal dynamic equations are as follows:

$$0.0000 + 0.0000i\,, -0.3715 + 0.8938i\,, -0.3715 + 0.8938i$$

Thus, based on the Eigen values, it can be concluded that the system is marginally stable. The controllability of the system can be deduced by the rank of the controllability matrix

$$[B \quad AB \quad \ldots \quad A^{n-1}B] \tag{36}$$

The controllability matrix for the longitudinal dynamics is as follows:

$$\begin{bmatrix} -5.5079 & 2.2298 & 3.5032 \\ 0.0021 & 0.0178 & -0.0152 \\ 0 & 0.0021 & 0.0178 \end{bmatrix}$$

Which has rank 3, i.e. full rank. Thus it can be concluded that the longitudinal dynamics of the aircraft are controllable. A similar test can be run for observability, to verify if full state feedback is possible. The observability matrix is as follows:

$$\begin{bmatrix} 0 & 0 & -0.0034 \\ 0 & 1.0000 & -0.4282 \\ 1.0000 & 0 & 0 \end{bmatrix}$$

The rank for this matrix is 3, i.e. full rank. Thus full state feedback is possible for the longitudinal dynamic states. The input to the system is the elevator deflection impulse of 0.2rad or 11 deg.

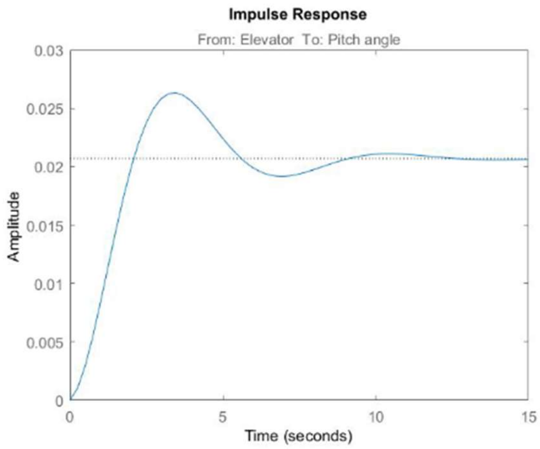

Figure 3 - Open loop impulse response (Pitch Angle θ).

3.2. UAV Fixed-wing Lateral dynamics

Using a similar method to the longitudinal dynamic equations, the state equations for the aircraft's lateral dynamics can be deduced. The state variables are chosen as Sideslip Angle(β), Roll rate(p), Yaw rate (r) and Roll angle(∅). The inputs to the system are aileron and rudder (δ_a and δ_r) deflection. These can be represented as a state space model, as follows :

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + Du \end{cases}$$

$$\begin{bmatrix} \dot{\beta} \\ \dot{p} \\ \dot{r} \\ \dot{\emptyset} \end{bmatrix} = \begin{bmatrix} \frac{Y_\beta}{U_0} & \frac{Y_p}{U_0} & \frac{Y_r}{U_0} & \frac{g\cos\vartheta}{U_0} \\ L_\beta & L_p & L_r & 0 \\ N_\beta & N_p & N_r & 0 \\ 0 & 1 & \tan\theta & 0 \end{bmatrix} \begin{bmatrix} \beta \\ p \\ r \\ \emptyset \end{bmatrix} + \begin{bmatrix} \frac{Y_{\delta_r}}{U_0} & \frac{Y_{\delta_a}}{U_0} \\ L_{\delta_r} & L_{\delta_a} \\ N_{\delta_r} & N_{\delta_a} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \delta_a \\ \delta_r \end{bmatrix} \tag{37}$$

This is a nonlinear state space equation. The author of the paper as linearized it about a non- specific equilibrium point. The author also hasn’t mentioned the values of the various constants used in the state space models used to achieve the following result:

$$\begin{bmatrix} \dot{\beta} \\ \dot{p} \\ \dot{r} \\ \dot{\emptyset} \end{bmatrix} = \begin{bmatrix} -0.0558 & -0.9968 & 0.0802 & 0.0415 \\ 0.5980 & -0.1140 & -0.0318 & 0 \\ -3.0500 & 0.3880 & -0.4650 & 0 \\ 0 & 0.0805 & 1.0000 & 0 \end{bmatrix} \begin{bmatrix} \beta \\ p \\ r \\ \emptyset \end{bmatrix} + \begin{bmatrix} 0.0729 & 0 \\ -4.7500 & 0.0077 \\ 0.1530 & 0.1430 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \delta_a \\ \delta_r \end{bmatrix} \tag{38}$$

$$y = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \beta \\ p \\ r \\ \emptyset \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \delta_a \\ \delta_r \end{bmatrix} \tag{39}$$

It can be seen that the outputs of concern are the Sideslip angle β, and the Roll angle $\emptyset$.

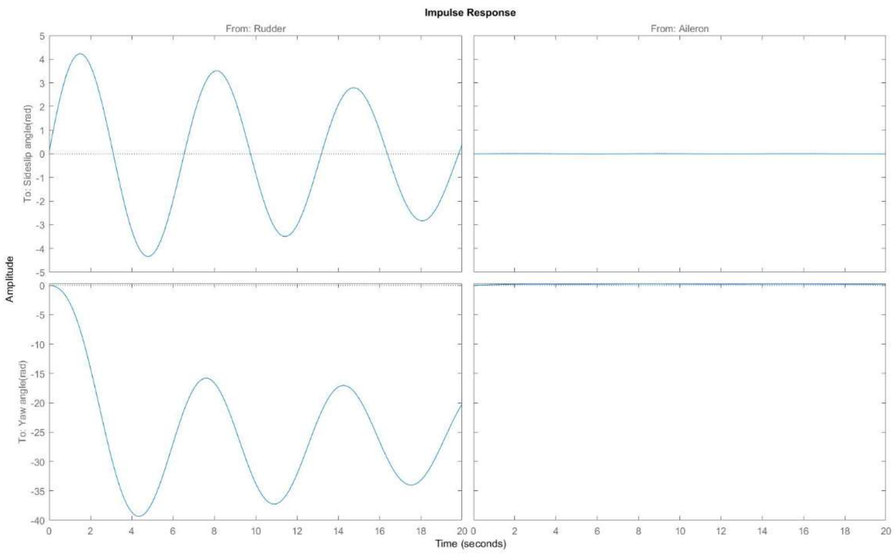

Figure 4 - Open loop impulse response (Sideslip Angle and Roll Angle)

3.2.1. Stability and controllability

The Eigen values for the lateral dynamic equations are as follows:

$$-0.0329 + 0.9467i - 0.0329 - 0.9467i - 0.5627 + 0.0000i - 0.0073 + 0.0000i.$$

Thus, since all the real parts of the EIgen values are negative, the system is stable. The controllability of the system can be deduced by the rank of the controllability matrix :

The controllability matrix for the lateral dynamics is as follows:

$$\begin{bmatrix} 0.0729 & 0 & 4.7430 & 0.0038 & -1.0286 & 0.0061 & -3.9195 & -0.0066 \\ -4.7500 & 0.0077 & 0.5850 & -0.0054 & 2.8370 & 0.0049 & -0.5202 & 0.0026 \\ 0.1530 & 0.1430 & -2.1365 & -0.0635 & -13.2457 & 0.0159 & 10.3973 & -0.0240 \\ 0 & 0 & -0.2294 & 0.1436 & -2.0894 & -0.0639 & -13.0173 & 0.0162 \end{bmatrix}$$

The rank for this matrix is 4, i.e. the matrix is half rank. This means that not all poles can be controlled. However, the matrix is stabilizable due to its inherent stability. Here, the impulse response for the roll angle is different from the output the author observed in the paper. The paper has an output which rises up to a value of 0.18rad, before showing an under-damped oscillation. The simulations run during the review of the paper show that the roll angle drops below zero to a value of −40rad followed by under-damped oscillations similar to those seen in the paper. The reason for this discrepancy has not been fully explored yet, but preliminary examining reveals no differences in the state space or the input to the state space from the paper.

3.3. Linear Quadratic Regulator simulation

The **lqr** function in MATLAB can be used to design the optimal feedback gains for any system. This paper attempts to design the feedback using the same. This is done by inputting the state matrices (A, B), and the weight matrices Q and R. The Q matrix can be calculated as $Q = C^T * C$. The paper assumes the following values for the matrices in the longitudinal dynamic model:

$$R_{long} = 1, Q_{long} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (40)$$

The matrices for the lateral model have not been mentioned in the paper, but they can be calculated as follows:

$$R_{lat} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, Q_{lat} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (41)$$

However, the response achieved using the values from the paper result in a different rise time for the response in each case. Different values of scalar multipliers for the R matrix were tried and the values for which the response matched the response in the paper are:

$$R_{long} = 5 * 10^{-4}, R_{lat} = 0.02 \quad (42)$$

The k matrices for both the models are as follows:

$$K_{long} = [-0.1391 \quad 31.5864 \quad 44.7213], K_{lat} = \begin{bmatrix} 7.9929 & -2.0883 & -4.6226 & -6.5483 \\ -0.4177 & 0.1924 & 1.7464 & 2.6065 \end{bmatrix} \quad (43)$$

The response for these gains is give in figure 6.

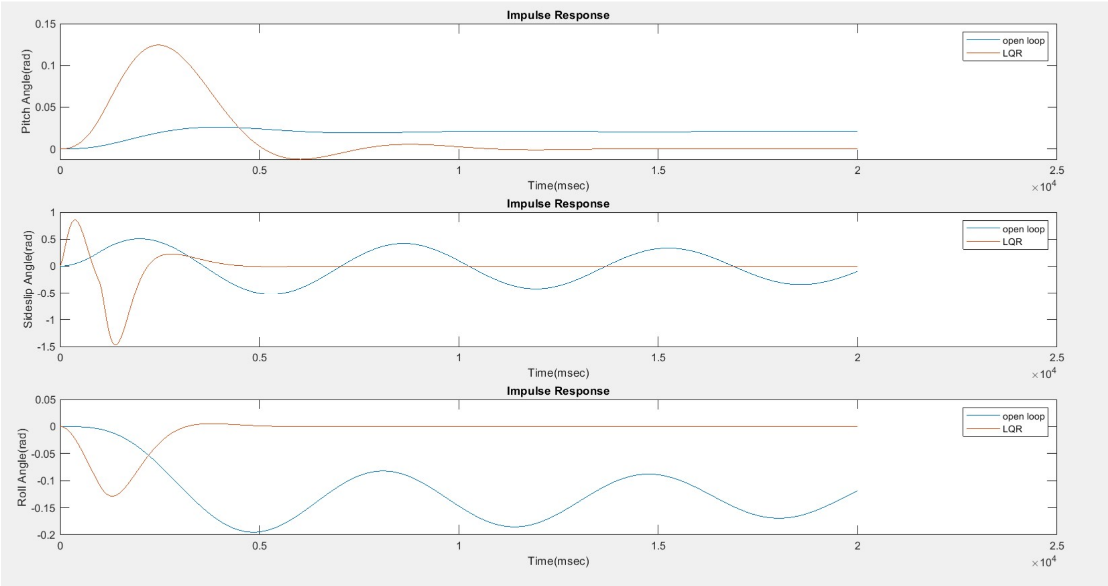

Figure 5 - Comparison of Open-loop and Closed-Loop Impulse Response

3.4. Kalman filtering results

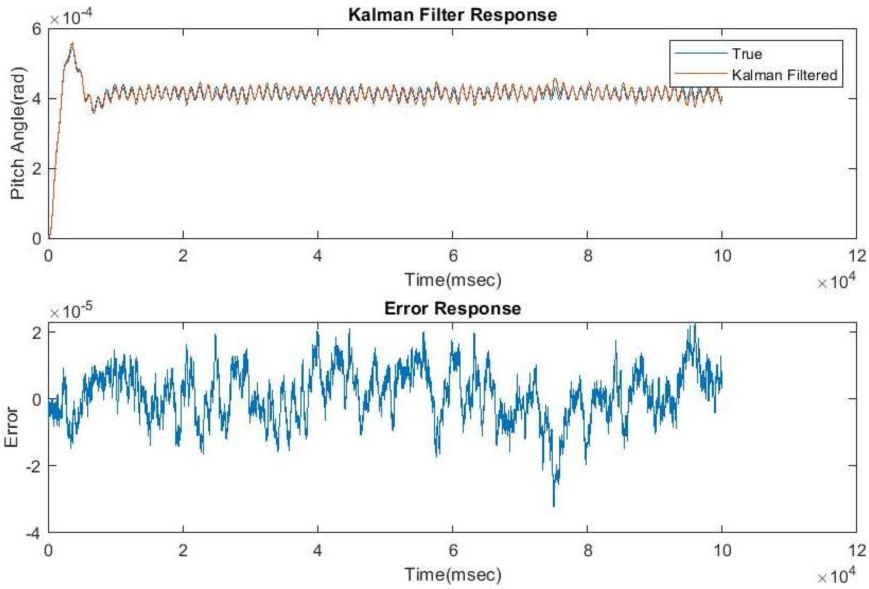

Figure 6 - Kalman filter response for pitch angle θ.

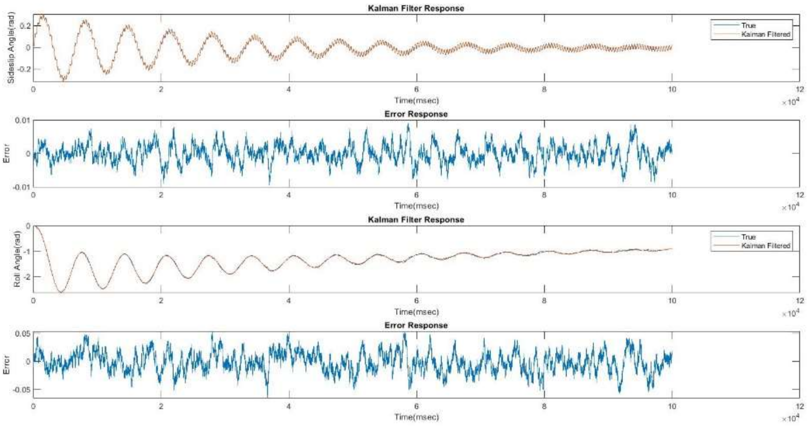

Figure 7 - Kalman Filter Response for the sideslip angle, β (b) Kalman Filter Response forthe roll angle ∅.

Given the current estimate $\hat{x}(n/n)$, the time update predicts the state value at the next sample $n+1$ (one-step-ahead predictor). The measurement update then adjusts this prediction based on the new measurement $y_v(n-1)$. The correction term is a function of the innovation, that is, the discrepancy between the measured and predicted values of $y(n+1)$.

$$y_v(n-1) - C\hat{x}(n/_{n-1}) = C\left(x(n+1) - \hat{x}(n+1/_{n})\right) \tag{44}$$

The innovation gain M is chosen to minimize the steady-state covariance of the estimation error given the noise covariances.

$$E(w(n)w(n)^T) = Q \tag{45}$$

$$E(v(n)v(n)^T) = R \tag{46}$$

Thus the time and update equations can be bundled into one state space model, i.e. the Kalman filter:

$$\hat{x}(n+1/_{n}) = A(I - MC)\hat{x}(n/_{n-1}) + [B \quad AM]\begin{bmatrix} u(n) \\ y_v(n) \end{bmatrix} \tag{47}$$

$$\hat{y}(n/_{n}) = C(I_M C)\hat{x}(n/_{n-1}) + CMy_v(n) \tag{48}$$

This generates the optimal estimate $\hat{y}(n/_{n})$ of $y(n)$

State of the filter is $\hat{x}(n/_{n-1})$. For the design of the Kalman filter block in Simulink, the gain matrices Q, N and R had to be chosen. The matrices for the lateral and longitudinal model are as follows:

$$\hat{R}_{long} = [1], \hat{Q}_{long} = [1], \hat{N}_{long} = 0 \tag{49}$$

$$\hat{R}_{lat} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \hat{Q}_{lat} = [1], \hat{N}_{lat} = 0 \tag{50}$$

These values or the method to obtain them is not discussed in the paper. The simulation results for the Kalman filter output for a sine wave input for each of the models has been described in the figures 7 and 8.

IV. DISCUSSION

The control scheme developed by the end of the paper should serve as a robust controller for the regulation of the Pitch angle, Sideslip angle and the Roll angle. Compared to a more primitive controller such as the PID, the LQR and the LQG are more optimal. This controller takes into account the various process disturbances by implementing the Kalman filter for a an accurate state measurement.

Instead of tuning gains to match performance parameters, the optimal gains can be calculated by solving the Riccati equations for the system. This is a more powerful control scheme, as the system specific features in the response are accounted for instead of manually tuning the gains.

REFERENCES

[1] Yash Manian, A Paper Review on Aircraft Control using LQR and LQG Controllers with Optimal Estimation-Kalman Filter Design, November 2016

[2] Robert C. Nelson.1998. Flight Stability and Automatic Control. University of Notre Dame.

[3] Ranjan Vepa, Flight Dynamics, Simulation, and Control of Aircraft: For Rigid and Flexible Aircraft.CRC Press, 2023

[4] Wong, K.C, 2006, UAV Design Activities in a University Environment.. University of Sydney.

[5] Da-Wei Gu Petko H. Petkov Mihail M. Konstantinov.2013. Robust Control Design with MATLAB

[6] Andrew J. Keane, Andras Sobester, James P. Scanlan, Small Unmanned Fixed-Wing Aircraft Design. A Practical Approach - Wiley.2017

[7] Reed Siefert Christiansen (2004). Design of an Autopilot for Small Unmanned Aerial Vehicle Brigham Young University.

[8] R.Vepa, Nonlinear Control of Robots and Unmanned Aerial Vehicles,CRC Press, 2017.

[9] R. M. Murray Control and Dynamical Systems. California Institute of Technology, 11 January 2006