Two-Stage Kalman Filter Based Estimation of Boeing 747 Actuator/Control Surface Stuck Faults

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Abstract: - This research aims to construct a two-stage Kalman filter (TSKF) that is available to estimate the control effectiveness of the actuator on behalf of an actuator stuck fault incident occurring on Boeing-747 commercial airplane. The actuator faults can be diagnosed via TSKF that maintains the states and stuck positions or control loss by two section encapsulated estimation algorithms. The performance of the TSKF algorithm is tested. The source of accidents can be as a result from a control surface stuck such an aileron, rudder, elevator; also, it can be present and appear as bird strike that could tear some part of the control surfaces located on the wings or tail of the airplane. In this study, there is a stuck fault on the rudder control surface and the proposed algorithm introduces the value of the stuck of the broken control surface and it is achieved that utilizing TSKF performs satisfying estimation values which are verified as well on lateral dynamics of the airplane.

Key-Words: - Actuator, Control Surface, Fault Tolerant Control, Estimator, Two-Stage Kalman Filter

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1 Introduction

During the design phase of any mechanism, the most critical point is to assemble a system that guarantees safety for its customers. Control systems of aircrafts shall be based on solid foundations providing the ability of handling possible risky situations. The primary purpose here is to minimize the effects arising from those faults, and if possible, completely avoiding those effects would be the best case. Fault Tolerant Control (FTC) is an essential method for aircrafts to maintain a safe flight in the events of unknown disturbances, uncertainties or unplanned system compound, and also actuator or sensor failures.

The Boeing 747 is an ideal test bed and an excellent example for any of the commercial aircrafts currently flying, by having a wide lineup of characteristics (spoilers, control surface variations, four turbofan engines...) [1].

The fault-tolerant control plays an essential role in aerospace applications and is studied by several researchers as to deal with difficulties. A fault tolerant control is described as having the ability to keep utilizing its purpose even afterwards the fault. The solutions to fault can be categorized into two sections which are passive and active controls. Former solution, passive control consists of managing the system process with the wrecked controller; the capability of the remnant system effectualness is linked to the main default control law. The passive control laws are commonly based on robust control laws that are proper for apparent structural faults. Those types of failures are remarked as uncertainties on peripheral radius of the original model. Yet, a lot of faults cannot be overcome by defining them as uncertainties. For this reason, solid definitions must be made first hand by constructing control structure.

On the active control side, the control infrastructure is reestablished instantly post fault accrue or switch to a predefined control law [2].

An active fault-tolerant control form that is tolerant to various levels of actuator faults is applied in this study.

The active fault-tolerant systems include two essential nodes:

1. Fault detection and isolation (FDI) or system identification and
2. Control restructure

FDI notation is followed by detection and identification of faults just as time goes on instantly. The measurements taken by the FDI action has to meet the requirements of qualified active fault-tolerant control stem. Several model-based FDI approaches are present to detect and locate the faulty sensor or actuator by analytical redundancy algorithms, state-estimation and system identification methods [2].

The actuators are healthy in proceeding the control commands if they perform the track as required from input signals they are %100 running by the controller structure within normal activity. As treating a faulty case as such a small fraction loss of control surface, wrecked hydraulics, stuck at valve, shortage at electrical servos, seen on actuators, they are not eligible to accomplish the tasks from inputs entirely. The problems pointed out would mean actuator control effectiveness loss. The proceedings in fault-tolerant control accepted the actuator fault parameter as the control effectiveness factor which is calculated by the Kalman filter [2]. It is also remarked that the faulty actuator' s control effectiveness factor is suggested to be the same in the entities of the related control distribution vector.

Another notion is problems seen on control surfaces by having partial loss or harmed/broken parts even if the actuator is in a healthy condition. When encountered with such an incident, the corresponding loss of effectiveness of the actuator/control surface, formerly mentioned solution, is not capable of detection. Technically it can be accepted as a measurement for determined surface faults like a control surface part loss, icing of control surface in winter conditions, those accounted as altering control effectiveness factors on the actuator [3].

Research on the FTC system builds a struct that is able to cope with faults on sensors and actuators that are observed at the same time. The proposed FTC system includes a sensor FDD system and a controller that can be reconfigured. The detection and estimation of the sensor faults are gained by an adaptive three-step unscented Kalman filter that is capable of estimating the values of state and fault with unbiasedness. The unbiased state estimation data is sent to a reconfigurable controller when there is a sensor fault. In presence of an actuator fault, an incremental backstepping approach is added to adjust the controller, by help of this process sensor and actuator fault detection and control is available at the same time [4].

The two-stage Kalman filter (TSKF) produces the estimation values of the system state values and faulty control surface or actuator's related control distribution matrix terms [2-4]. This method is applicable for actuator/surface faults that lead to altered control effectiveness factors.

TSKFs are used in aerospace widely for estimation of system states and model parameters [2-10, 13]. In [5], an estimation algorithm based on TSKF was developed for wind speed and Unmanned Aerial Vehicle (UAV) motion parameters. In [6-8] the vector measurement-based algorithms are used with the Kalman filter to form complete two-stage attitude filters.

The connection between the control commands created by the controller and the physical actions in the systems are expressed by actuators [9]. Ailerons and rudders will be used as the actuators in this study and Kalman filter technique will be applied to detect and minimize the effects of those actuator faults observed in Boeing 747. The fault / faults are going to be estimated with the help of the residuals, and they will be analyzed with respect to the selected confident level thresholds by making the algorithm available to detect errors simultaneously with a fast-working observer. Two stage Kalman filter will be used for estimating the faulty states even if there are malfunctions on the system and this method sustains a value (residual) to take remedial action which is going to be configured by the controller in order to cover flight safety. Some cumulative studies led the filter to become an adaptive two-stage Kalman filter [10]. The TSKF introduced in [11] is implemented for a linear aircraft model and also covariance-based forgetting factors [12] are presented in order to estimate the state and control influence simultaneously.

In this study, the non-linear Simulink model of Boeing 747 is linearized as a first step, then, the lateral state-space model is obtained and transferred into a code in the MATLAB environment. The actuator fault detection and isolation processes are again implemented in MATLAB and this procedure is applied step by step, focusing on an actuator fault. It is shown that TSKF algorithm has detected the fault and made fault isolation possible that brought out the faulty actuator and estimated both faulty parameters and states firmly.

2 Mathematical Model of Boeing 747

A proper model of the system dynamics is necessary during the implementation of Kalman filtering technique [6]. For this reason, model information for Boeing 747 is also included. Since the studies will be carried out on the linearized model in order not to be affected by the nonlinear dynamics, some conditions are defined for the linearization process. Being in a trim point, the values 920 km/h as true air speed and 30000 ft as altitude have been chosen and linearization is done within those conditions.

Further information can be seen at Table 1 in Appendix 1.

2.1 Non-Linear Mathematical Model of Boeing 747 in Simulink

Equations of motion were obtained by making the assumptions that the earth is standing still and flat, the airplane is rigid and not damaged, the mass of the aircraft does not change within time, and the moments of inertia I_{xy}, I_{yz} are equal to zero. The equations obtained based on [8] are as follows:

External forces:

$$F_x = \frac{1}{2}\rho V_t^2(-c_D \cos\alpha + c_L sin\alpha) + F_{T_x} - mgsin\theta \quad (1)$$

$$F_y = \frac{1}{2}\rho V_t^2 S c_Y + F_{T_y} - mgcos\theta sin\emptyset \quad (2)$$

$$F_z = \frac{1}{2}\rho V_t^2 S(-c_D \sin\alpha - c_L cos\alpha) + F_{T_z} - mgcos\theta cos\emptyset \quad (3)$$

Outer moments:

$$M_x = \frac{1}{2}\rho V_t^2 Sbc_{lb} + M_{engx} \quad (4)$$

$$M_y = \frac{1}{2}\rho V_t^2 Sb\bar{c}c_{mb} + M_{engy} \quad (5)$$

$$M_z = \frac{1}{2}\rho V_t^2 Sbc_{nb} + M_{engz} \quad (6)$$

The forces and moments calculated as in above are required for mathematical modeling.

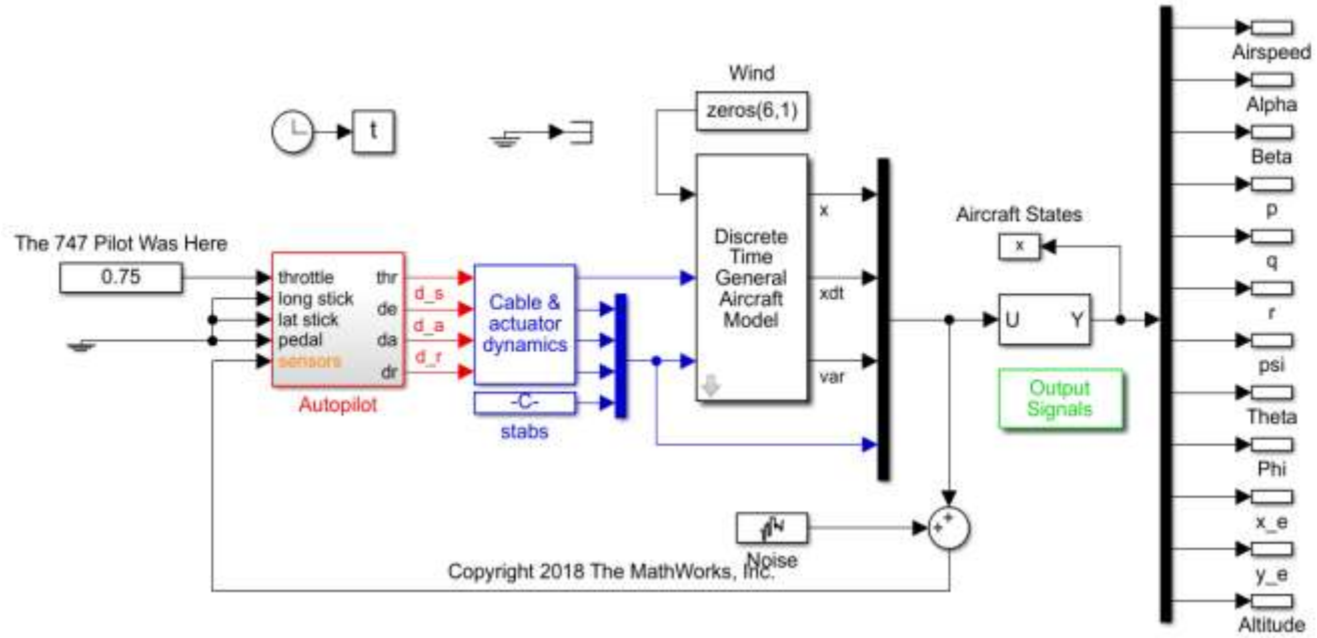

Fig. 1 Non-Linear Mathematical Model of Boeing 747 in Simulink [18]

The Simulink model for Boeing 747 is obtained with the help of the open-source library Airlib, created by MATLAB developers. By using the models in this library, possible behavior of a system in case of any fault can be observed, thus, various improvements can be made to eliminate the effects of those faults. Details of the model of Boeing 747 can be examined from Figure 1.

The main purpose of using the Simulink model of Boeing 747 provided by Airlib is to apply a linearization process based on previously defined trim and steady-state flight conditions by obtaining nonlinear system dynamics. In addition, the model is also used to examine how the system behaves in case of any fault. The faulty conditions here are analyzed by creating residuals while considering the difference between faulty and fault-free conditions, and a threshold value is defined for the faulty states.

2.2 Linearized State-Space Model of Boeing 747 in MATLAB

In this work, obtaining a proper lateral orientation in case of a fault will be the main field of study. The linearization process is done in MATLAB, with the help of a linear analysis tool. The model is linearized through the non-linear Boeing 747 model in flight conditions at 0.8 Mach $\approx$ 910 km/h and 30000 ft $\approx$ 10.5 km altitude and steady-state flight. The lateral dynamics of the aircraft as follows:

The system transition matrix:

$$A = \begin{bmatrix} -0.08895 & 0.06282 & -0.9795 & 0.04362 \\ -2.419 & -0.602 & 0.3438 & 0.01244 \\ 1.491 & -0.2827 & -1.19 & -0.2719 \\ 0 & 1 & 0.05824 & 0 \end{bmatrix} \quad (7)$$

Control distribution matrix:

$$B = \begin{bmatrix} 0 & 0.01024 \\ -0.1967 & 0.009127 \\ -0.0138 & -0.5503 \\ 0 & 0 \end{bmatrix} \quad (8)$$

Measurement matrix:

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (9)$$

Feedforward matrix:

$$D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \quad (10)$$

The latera states and control inputs are:

$$x = [\beta, r, p, \emptyset]^T$$

$$u = [\delta a, \delta r]^T$$

2.3 Controllability, Observability and Stability Properties of Boeing 747

For *controllability check* → from MATLAB, rank (ctrb(A, B)) = 4. Therefore, Boeing-747 commercial airplane is controllable which is equal to the number of states which is 4 lateral states, sideslip angle, yaw rate, roll rate and roll angle.

For *observability check* → from MATLAB, rank(obsv(A,B)) = 4 Therefore, Boeing-747 is observable which is equal to the number of states which is 4 lateral states, sideslip angle, yaw rate, roll rate and roll angle.

For *stability check* → The eigenvalues are gathered from MATLAB eig(A):

Dutch roll mode

$$\begin{cases} -0.2897 + 1.0765\mathrm{i} \\ -0.2897 - 1.0765\mathrm{i} \end{cases}$$

Spiral mode

$$\begin{cases} -0.6507 + 0.4102\mathrm{i} \\ -0.6507 - 0.4102\mathrm{i} \end{cases}$$

The eigenvalues are on the left-hand plane so our aircraft is laterally stable.

3 Estimation of Actuator/Control Surface Stuck Faults

Detection of the grade at which the control surface is stuck and the size at which control effectiveness vanishes is the main objective of fault parameterization in a linear estimator design [13]. Rudders and ailerons are the control surfaces at the trailing edges of the tail and wings respectively. Rudder, which will be one of the main objects of our study is the component controlling the rotation of an aircraft, referred to as yaw angle. In aviation history, serious financial loss and personal casualties resulted from a degeneration of the control system performance which may be caused by the faults of an aileron actuator, including motor / sensor coil break, cylinder leakage, and amplifier gain reduction [14]. Thus, in order to avoid such risks, a rudder stuck fault will be implemented on the aircraft and the roll and yaw movement will be affected by the faulty actuator, then, isolation and reconfiguration process will be applied. The other actuator faults to be investigated are the faults observed in the ailerons that are used to turn the aircraft right or left by running asymmetrically by the pilot input from pedals.

The Kalman-filter is established in case of achieving a residual between the actual value and estimated values of states to accomplish fault detection via exceeding the threshold value. A two-stage Kalman filter algorithm is performed in case of control surface/actuator faults.

If there is a process noise the Kalman filter relies on measurements for future state estimates. However, if there is measurement noise in the system, this time Kalman filter relies more on state estimations to produce state predictions accurately. The Q and R matrices are process and noise covariance matrices respectively and they are selected as random Gaussian noise with zero mean and they have no coupling between to not have an effect on state estimations.

The Two stage Kalman filter has two stages considered as from the name, first it estimates the actuator control loss and stuck degree and later on it estimates the states [15].

3.1 Problem Formulation

Considering the open-loop aircraft model that has been linearized around a trim operating point and a parametrization of two different category of actuator faults, the following model is achieved as in discrete time as the execution of adaptive TSKF:

$$x_{k+1} = A_k x_k + B_k u_k + E_k \gamma_k + B_k \beta_k + w_k^x \quad (11)$$

$$\zeta_{k+1} = \zeta_k + w_k^\zeta, \quad \zeta_k = \left[\gamma_k^T \; \beta_k^T\right]^T \quad (12)$$

$$y_{k+1} = C_{k+1} x_{k+1} + v_{k+1} \quad (13)$$

Here $x_k \in R^n, u_k \in R^l$, and $y_{k+1} \in R^s$ = state, control input and output variables, respectively; and γ_k and β_k = bias vectors of dimension l, representing the faults are entered actuators. Suggested noise w^x, w^ζ, and v are white Gaussian noise sequences, zero-mean uncorrelated.

$$M_z = \left\{ \begin{bmatrix} w_k^x \\ w_k^\zeta \\ v_k \end{bmatrix} \begin{bmatrix} w_j^x & w_j^\zeta & v_j \end{bmatrix} \right\} = \begin{bmatrix} Q^x & 0 & 0 \\ 0 & Q^\zeta & 0 \\ 0 & 0 & R \end{bmatrix} \delta_{kj} \quad (14)$$

Here $Q^x > 0$, $Q^\zeta > 0$ and $R > 0$, and δ_{kj} =Kronecker delta. The initial states $x(0)$ and $\zeta(0)$ are suggested as uncorrelated with the white noise processes w_k^x, w_k^ζ and v and have covariances $\tilde{P}_0^x$ and $\tilde{P}_0^\zeta$ respectively.

The components

$$-1 \le \gamma_k^i \le 0, \quad j = 1,2 \dots, l \quad (15)$$

of γ_k describe the percentage reduction in the control effectiveness when the terms $B_k u_k + E_k \gamma_k$ are considered together, where

$$E_k = B_k U_k \quad and \quad U_k = diag\left(u_k^1, \dots, u_k^l\right) \quad (16)$$

Estimator design model Eq. (11-13) is inherited from Eq. (15), with a set of new bias components [10]

$$\beta_k^i, \quad i = 1,2 \dots, l \quad (17)$$

added to note the degrees at which control surfaces are stuck. A combination consists of three terms forms stuck fault model from Eq. (11-13):

$$B_k u_k + E_k \gamma_k + B_k \beta_k \quad (18)$$

We point out the conditions formed by the value of fault parameters. The nominal case is represented by

$$\gamma_k^i = 0 \quad and \quad \beta_k^i = 0, \quad i = 1,2 \dots, l \quad (19)$$

Loss of control effectiveness as percentage $100\gamma_k^i\%$ in the i^{th} actuator is represented by

$$-1 \le \gamma_k^i \le 0 \quad and \quad \beta_k^i = 0 \quad (20)$$

and a control surface stuck fault of magnitude β_k^i degrees is shown by

$$\gamma_k^i = -1 \quad and \quad \beta_k^i \ne 0 \quad (21)$$

The linear adaptive TSKF [10] can be used for estimation both for γ_k and β_k by a general form of $E_k \gamma_k$ to

$$E_k \gamma_k + B_k \beta_k = [E_k \quad B_k][\gamma_k^T \quad B_k^T]^T = [E_k \quad B_k]\zeta_k \quad (22)$$

Where $\zeta_k = [\gamma_k^T \quad B_k^T]^T$ which already models stuck fault at the same time. Since $E_k = B_k U_k$

$$E_k \gamma_k + B_k \beta_k = B_k U_k \gamma_k + B_k \beta_k = B_k (U_k \gamma_k + \beta_k) \quad (23)$$

By this method, it is crystal clear that the inputs of $U_k = diag(u_k^1, \ldots, u_k^l)$ must alter and develop in time independently which is named as "persistently excited" to make possible the estimator to figure out among and also γ_k and β_k their components [8].

3.2 Two-stage Kalman Filter Algorithm

The TSKF algorithm in [10] can be found as below: The algorithm estimates both actuator fault parameters and system states as well, is as follows:

Bias free state estimator:

$$\tilde{x}_{k/k+1} = A\tilde{x}_{k/k} + B_k u_k + [W_k - V_{k+1/k}]\hat{\zeta}_k \quad (24)$$

$$\tilde{P}^x{}_{k+1/k} = A_k \tilde{P}^x{}_{k/k} A_k^T + Q_k^x + W_k P_{k/k}^{\zeta} W_k^T - V_{k+1/\mathrm{k}} P_{k+1/\mathrm{k}}^{\zeta} V_{k+1/\mathrm{k}+1} \quad (25)$$

where W_k, $V_{k+1/k}$ and $V_{k+1/k+1}$ are calculated is in equations (36), (37), (39), and $P_{k+1/k}^{\zeta}$ as in (35):

$$\tilde{x}_{k+1/k+1} = \tilde{x}_{k+1/k} + \tilde{K}_{k+1}^x [y_{k+1} - C_{k+1}\tilde{x}_{k+1/\mathrm{k}}] \quad (26)$$

$$\tilde{K}_{k+1}^x = \tilde{P}_{k+1/\mathrm{k}}^x C_{k+1}^T [C_{k+1}\tilde{P}_{k+1/k}^x C_{k+1}^T + R_{k+1}]^{-1} \quad (27)$$

$$\tilde{P}_{k+1/k+1}^x = [I - \tilde{K}_{k+1}^x C_{k+1}]\tilde{P}_{k+1/k}^x \quad (28)$$

The covariance of the filter and its residual vector of the filter are obtained as below:

$$\tilde{r}_{k+1} = y_{k+1} - C_{k+1}\tilde{x}_{k+\frac{1}{\mathrm{k}}} \quad (29)$$

$$\tilde{S}_{k+1} = C_{k+1}\tilde{P}_{k+1/\mathrm{k}}^x C_{k+1}^T + R_{k+1} \quad (30)$$

Bias estimator:

$$\tilde{\zeta}_{k+1/\mathrm{k}} = \tilde{\zeta}_{k/k} \quad (31)$$

$$\tilde{P}^{\zeta}{}_{k+1/k} = \tilde{P}^{\zeta}{}_{k/k} + Q_k^{\zeta} \quad (32)$$

$$\tilde{\zeta}_{k+1/k+1} = \tilde{\zeta}_{k+1/k} + K_{k+1}^{\zeta}[\tilde{r}_{k+1} - H_{k+1/\mathrm{k}}\tilde{\zeta}_{k/k}] \quad (33)$$

$$K_{k+1}^{\zeta} = P_{k+1/k}^{\zeta} H_{k+1/k}^T [H_{k+1/k} P_{k+1/k}^{\zeta} H_{k+1/k}^T + \tilde{S}_{k+1}]^{-1} \quad (34)$$

$$P_{k+1/k+1}^{\zeta} = [I - \tilde{K}_{k+1}^x H_{k+1/\mathrm{k}}] P_{k+1/\mathrm{k}}^{\zeta} \quad (35)$$

where $H_{k+1/k}$ is calculated as in Eq. (38).

Coupling equations:

$$W_k = A_k V_{k/k} + E_k \quad (36)$$

$$V_{k+1/k} = W_k P_{k/k}^{\zeta} \left[P_{k+1/k}^{\zeta}\right]^{-1} \quad (37)$$

$$H_{k+1/\mathrm{k}} = C_{k+1} V_{k+1/\mathrm{k}} \quad (38)$$

$$V_{k+1/k+1} = V_{k+1/k} - \tilde{K}_{k+1}^x H_{k+1/k} \quad (39)$$

Error and state covariance estimates, compensated:

$$\hat{x}_{k+1/k+1} = \tilde{x}_{k+1/k+1} + V_{k+1/k+1}\tilde{\zeta}_{k+1/k+1} \quad (40)$$

$$\hat{P}_{k+1/k+1} = \tilde{P}_{k+1/k+1}^x + V_{k+1/k+1} P_{k+1/k+1}^{\zeta} V_{k+1/k+1}^T \quad (41)$$

3.2 The Forgetting Factor

The Kalman filter is a recursive technique and measures the value of the current variables by analyzing previous steps, so the forgetting factor technique can be used in this algorithm. The forgetting factor reduces the weight of the previous data when a new data is obtained, thus, it accelerates the convergence to the actual value. [16]

4 Simulation Results

Rudder control loss of %100 and stuck fault at 2 degrees are introduced. Our first case consists of a stuck fault at a time interval between 200 – 600 seconds at rudder. The fault detection stuck fault case relates to the control surface which cannot move and respond to pilot or flight control inputs.

From Figure 2, the control surface rudder is stuck at 2 degrees so the control loss at the actuator is 100% as can be shown between the implemented time interval. Stuck actuator fault with magnitude 2 (deg) has occurred in the rudder because $\hat{\zeta}_1 = \hat{\gamma}_1 = -1$ and $\hat{\zeta}_2 = \hat{\beta}_2 = 2$. When $\hat{\gamma} = -1$ we can obtain the estimated stuck magnitude in the corresponding control channel. The estimation error $\zeta - \hat{\zeta}$ seems very oscillating, but yet it is relatively small and close to zero approximately.

The fault detection and isolation are done by TSKF and the estimated surface stuck faults are converged to actual surface stuck faults, which confirms that the presented algorithm works reliably and well.

Actual and estimated state variables in case of rudder stuck fault are given in Figures 3 - 6.

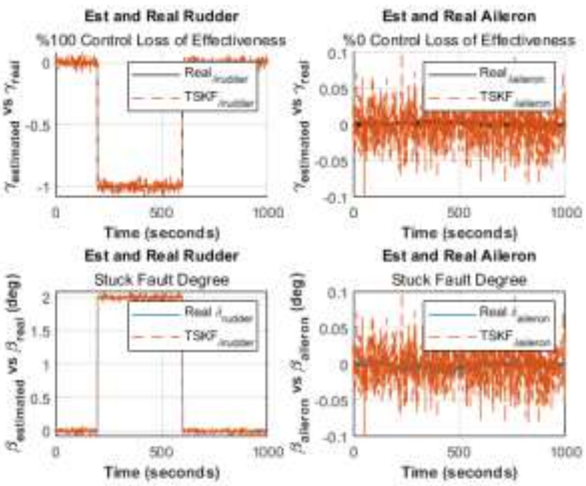

Fig. 2 Actual inputs and estimations when a stuck actuator fault in rudder occurred at 200 seconds till 600seconds

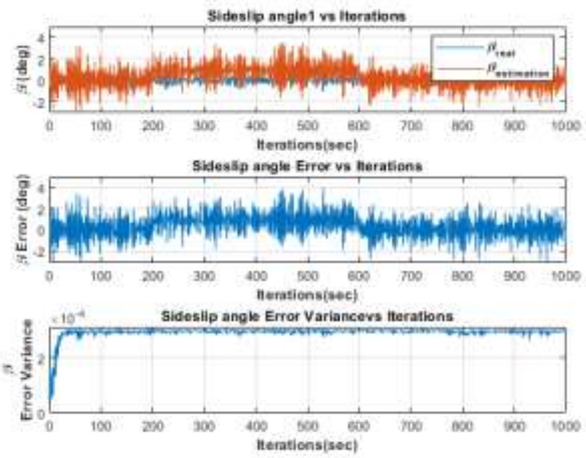

Fig. 3 Actual and estimated sideslip angle

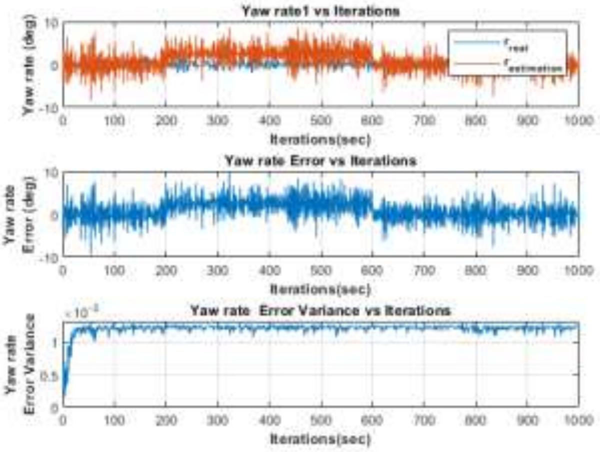

Fig. 4 Actual and estimated yaw rate

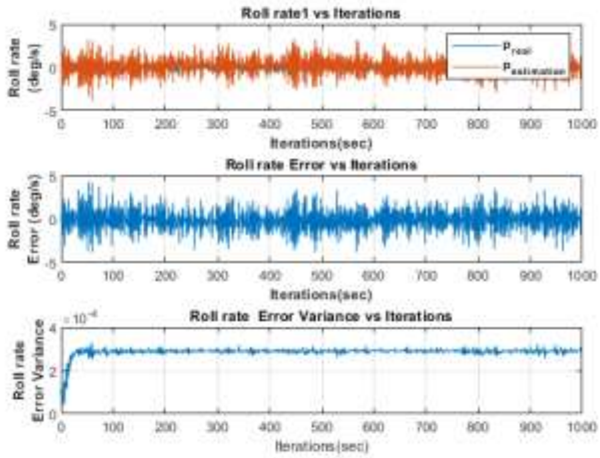

Fig. 5 Actual and estimated roll rate

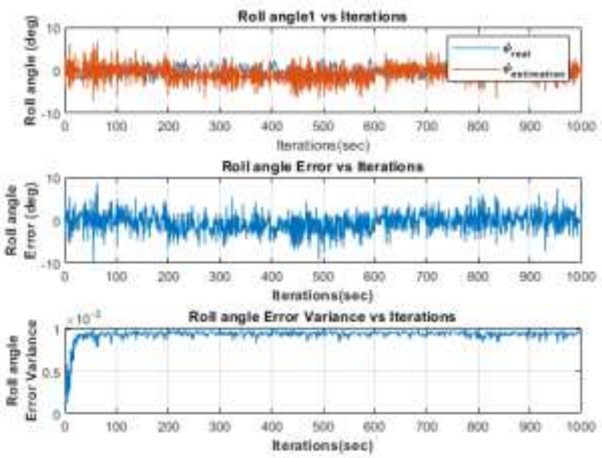

Fig. 6 Actual and estimated roll(bank) angle

We can imply from Figures 3 – 6 that all the states are broken due to the fault in the rudder actuator and all are affected because of rudder stuck fault, thus, estimations are also broken between the time period from 200 to 600 seconds. Since there is no fault in sensors, measurements are satisfactory, but Kalman filter estimations are affected by rudder stuck fault. It can be clearly seen from Figure 2 that the actuator faults are detected and isolated well using TSKF.

4 Conclusion

The two-stage Kalman filter is used to estimate the control effectiveness of the actuator on behalf of an actuator stuck fault incident occurring on Boeing-747 commercial airplane. The actuator faults can be diagnosed via TSKF that maintains the states and stuck positions or control loss by two sections that include encapsulated estimation algorithm

The simulation results show that the TSKF algorithm performed well and estimated both the faulty parameters and states as desired.

For the following study, a remedial control action which is going to be taken by flight computer for reconfiguration purposes of the flight control is planned to be established. By estimating the grade of the control loss of effectiveness and stuck degree of faulty actuator, the required control action can be taken place by remaining control accommodation. This control enhancement is going to be ready for maintaining flight safety whether there is a fault occurring during flight envelope and reconfigurable control actions can be structed by the information of the Kalman filter sustains.

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Appendix

Table 1: Aerodynamic coefficients and trim conditions for Boeing-747 [17]

Initial Flight Condition of Boeing 747	**Cruise(low)**
State and Control	**Value**
V_T	826.772 ft/s
α	0.0582 rad
β	0 rad
φ	0 rad
$\emptyset$	0 rad
p	0 rad/s
q	0 rad/s
r	0 rad/s
θ	0.0436 rad
x_e	0 ft
y_e	0 ft
h_e	35,000 ft
δ_{th}	0.49 rad
δ_a	0 rad
δ_e	0 rad
δ_r	0 rad
Geometry and Inertias	**Value**
S	$5500\ ft^2$
b	$196\ ft$
m	$636{,}636\ lbs$
I_{xx}	$18.2\ x\ 10^6\ slug - ft^2$
I_{zz}	$43.1\ x\ 10^6\ slug - ft^2$
I_{xz}	$0.97\ x\ 10^6\ slug - ft^2$
Lateral Directional aerodynamic stability coefficients	**Value**
c_{l_β} : roll moment caused from sideslip angle derivative	-0.160
c_{l_p} : roll moment caused from roll rate derivative	-0.340
c_{l_r} : roll moment caused from yaw rate derivative	0.130
$c_{l\delta_a}$: roll moment caused from aileron deflection	-0.013
$c_{l\delta_r}$: rol moment caused from rudder deflection	0.008
c_{n_β}: yaw moment caused from sideslip angle derivative	0.160
c_{n_p} : yaw moment caused from roll rate derivative	-0.026
c_{n_r} : yaw moment caused from yaw rate derivative	-0.280
$c_{n\delta_a}$: yaw moment caused from aileron deflection	-0.001
$c_{n\delta_r}$: yaw moment caused from rudder deflection	-0.100
c_{y_β} : side force caused from the side slip derivative	-0.900
c_{y_p} : side force caused from roll rate derivative	0
c_{y_r} : side force caused from yaw rate derivate	0
$c_{y_{\delta_a}}$: side force caused from aileron deflection	0
$c_{y_{\delta_r}}$: side force caused from rudder deflection	0.12

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