Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

Actuation Failure Detection in Fixed-Wing Aircraft Combining a Pair of Two-Stage Kalman Filters ⋆

Rafael A. Cordeiro * **José R. Azinheira** *
Alexandra Moutinho *

* *LAETA, IDMEC, Instituto Superior Técnico, Universidade de Lisboa*
Av. Rovisco Pais, 1049-001 Lisboa, Portugal
(e-mails: rafael.a.cordeiro@tecnico.ulisboa.pt,
jose.raul.azinheira@tecnico.ulisboa.pt and
alexandra.moutinho@tecnico.ulisboa.pt).

Abstract: Actuation failure is one of the causes of loss of control in flight accidents. Aircraft usually have multiple redundant actuators to mitigate failures, and Failure Detection and Isolation Systems (FDIS) are used to diagnose failures and reconfigure software/hardware to enhance safety. However, the large number of redundant actuators interferes with the FDIS. To detect and isolate failures in fixed-wing aircraft with redundant actuators, this work proposes the combined use of two different strategies of the Two-Stage Kalman Filter. A Supervisory Loop is included using heuristics and statistics to diagnose the actuators, and a Feed-Forward Differential is implemented to improve the isolation process without interfering with the aircraft flight. The solution is evaluated in the detection of an aileron failure in a Boeing 747 simulator.

Keywords: Failure detection; Failure isolation; Two-Stage Kalman Filter; Fixed-wing aircraft

1. INTRODUCTION

The aircraft industry is constantly seeking technologies to improve flight safety. The Loss Of Control In-flight (LOCI) is one of the main causes of flight accidents for both manned and unmanned aerial vehicles (van Gils et al., 2016). In some occasions, LOCI is a consequence of failures in the aircraft actuators. Thus, it is of utmost importance that pilot and Flight Control System (FCS) be aware of actuation failure as fast as possible.

Although most aircraft have several redundancies to avoid accidents in failure scenario, the knowledge of the failure can be used to reconfigure software and hardware in order to enhance safety (Hwang et al., 2010). Therefore, Failure Detection and Isolation Systems (FDIS) applied to fixed-wing aircraft have been studied since the 1970s (Willsky, 1976).

One of the most applied FDIS technique used in aircraft consists on the Multiple Models Adaptive Estimation (MMAE) (Montgomery and Price, 1974; Menke and Maybeck, 1995; Kim et al., 2008). The main idea of this technique is to have several models of the aircraft, including one "healthy" model and additional models for each considered failure scenario. Thus, state estimations are obtained from each one of the models and a decision algorithm infers the one most likely to correspond of the actual aircraft condition (Montgomery and Price, 1974). Menke and Maybeck (1995) applied MMAE to a F-16 test aircraft where the decision making process uses a combination of all filter inputs based on the computed probability of the filters to be the one corresponding to the real scenario. In (Kim et al., 2008) a fuzzy-logic approach is proposed to combine the individual filter results.

If on the one hand the high level of redundancies in the actuation increases flight safety, on the other hand the several actuators makes the failure isolation process harder. When an abrupt change in the flight dynamics is sensed, it is necessary to identify which one of the many redundant actuators is failing. In addition, the large number of actuators increase significantly the number of models required by the MMAE technique.

This paper proposes a model-based approach for FDIS without requiring modeling the aircraft in failure scenarios. The two main contributions are:

- The combination of two strategies of the Two-Stage Kalman Filter (TSKF): 1) the standard TSKF formulation is applied to estimate biases in the control actuation (Friedland, 1969; Keller and Darouach, 1997); 2) the TSKF is used considering a multiplicative gain in the actuation, which has been successfully applied in a FDIS for detecting engine failures in a multirotor aircraft (Amoozgar et al., 2013).
- The Feed-Forward Differential (FFD) to improve the failure isolation process. This simple approach is designed to create persistent excitation in the filters without interfering with the aircraft dynamics.

⋆ This research is co-funded by the European Union in the scope of INCEPTION project, which has received funding from the EU Horizon 2020 Research and Innovation Programme under grant agreement No. 723515, and by FCT, through IDMEC, under LAETA, project UIDB/50022/2020.

The complementary information of the two filters is analyzed by a Supervisory Loop (SL) which provides the diagnosis of the aircraft actuators. The technique is implemented and tested using a Boeing 747 benchmark simulator (Smaili et al., 2010).

The sequence of the paper is presented as follows: Section 2 details the proposed FDIS; Section 3 presents the TSKF formulation and its application as bias and gain estimators; Section 4 proposes the FFD to isolate the faulty actuator; Section 5 describes the diagnosis algorithm of the SL. Section 6 shows results obtained with the FDIS applied to a Boeing 747 simulator; finally, Section 7 presents the conclusions of the authors.

2. DETECTION PROCEDURE

In this work, two TSKFs are used to detect the failure. A Supervisory Loop (SL) interprets the TSKFs output in order to isolate the failure. If the data is inconclusive to isolate the failure, the SL may demand an additional Feed-Forward Differential (FFD) to assist the detection process. Fig. 1 illustrates the proposed FDIS.

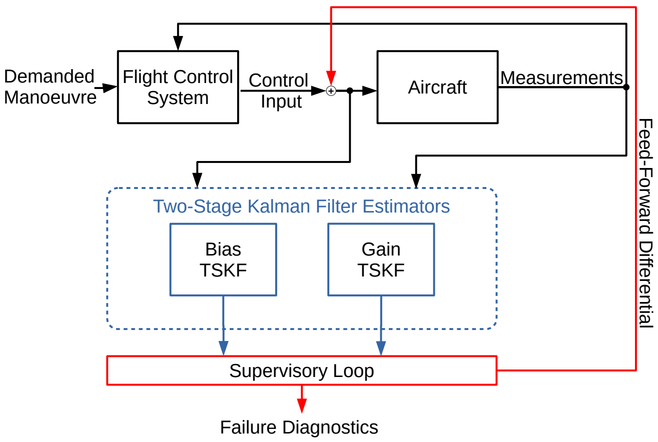


Fig. 1. Diagram of the failure diagnosis process.

When an actuator fails, the dynamics of the Degrees-Of-Freedom (DOF) corresponding to the faulty actuator will act abnormally. A standard approach to detect unexpected behaviors is using estimators to compare measurements with the expected response obtained from mathematical models. Here, the estimators are obtained using the TSKF strategy (Friedland, 1969; Keller and Darouach, 1997). Two TSKFs are used to estimate incongruities in the aircraft actuation. The first considers that the unexpected behavior is generated due to unknown bias in the input (Bias TSKF), while the other considers the error as consequence of an unknown gain in the input (Gain TSKF).

Estimators obtain better results when they are persistently excited. For aircraft, a standard approach consists on demanding extra maneuvers to create excitation in the actuation (Ignatyev et al., 2019). However, the extra maneuvers are constrained by safety and comfort requirements. Here, the FFD input injection is proposed, focusing on exciting the estimators without modifying the aircraft movement.

The results of the TSKFs provide complementary information, but may have ambiguities. Thus, a decision making system is required to interpret the data and provide diagnosis of the actuators status. A Supervisory Loop is implemented combining statistics and heuristics aiming to: a) analyze the response of the filters; b) isolate the most probable faulty actuators; c) decide if the FFD must be applied to isolate the failure; and d) provide online diagnosis of the actuators status.

3. TWO-STAGE KALMAN FILTER

The Two-Stage Kalman Filter (Friedland, 1969; Keller and Darouach, 1997) is a technique to estimate uncertain constant parameters in the system, considered as biases. When compared to the Augmented Kalman Filters, the TSKF has to invert two smaller matrices instead of an augmented one, which may provide greater robustness to numerical errors with lower computational burden.

Fig. 2 shows a TSKF diagram: a first KF estimates the states disregarding bias; then, with the bias-free predicted state, the bias is estimated by a second KF; and finally, the estimated state is corrected using the estimated bias.

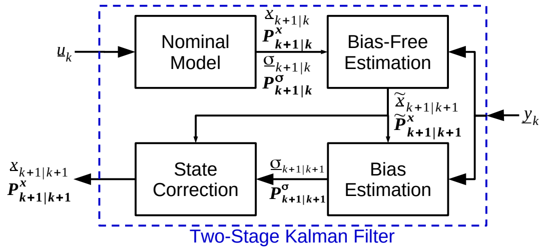


Fig. 2. Two-Stage Kalman Filter estimation diagram.

Let us consider the following discrete linear system:

$$\begin{cases} \underline{x}_{k+1} &= \mathbf{A}\underline{x}_k + \mathbf{B}\underline{u}_k + \mathbf{F}\underline{\sigma}_k + \underline{n}_k^x \\ \underline{\sigma}_{k+1} &= \underline{\sigma}_k + \underline{n}_k^\sigma \\ \underline{y}_k &= \mathbf{C}\underline{x}_k + \mathbf{D}\underline{u}_k + \mathbf{G}\underline{\sigma}_k + \underline{n}_k^y \end{cases} , \qquad (1)$$

where $\underline{x}$, $\underline{u}$, and $\underline{y}$ are state, input and output vectors; $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{F}$ are the dynamic, input and bias matrices; and $\mathbf{C}$, $\mathbf{D}$, and $\mathbf{G}$ are the output, observation input and observation bias matrices.

The state, output, and bias noises – $\underline{n}_k^x$, $\underline{n}_k^y$, and $\underline{n}_k^\sigma$ – are assumed to be uncorrelated white noises, which covariances are defined by the covariance matrices $\mathbf{Q^x}$, $\mathbf{Q^y}$ and $\mathbf{Q^\sigma}$ respectively.

Given (1), the TSKF assumes the following structure (Keller and Darouach, 1997):

a) State and bias prediction (nominal model):

$$\underline{x}_{k+1|k} = \mathbf{A}\underline{x}_{k|k} + \mathbf{B}\underline{u}_k + \mathbf{F}\underline{\sigma}_{k|k} \, ; \qquad (2)$$

$$\mathbf{P^x_{k+1|k}} = \mathbf{A}\mathbf{P^x_{k|k}}\mathbf{A}^T + \mathbf{Q^x} \, ; \qquad (3)$$

$$\underline{\sigma}_{k+1|k} = \underline{\sigma}_{k|k} \, ; \qquad (4)$$

$$\mathbf{P^\sigma_{k+1|k}} = \mathbf{P^\sigma_{k|k}} + \mathbf{Q^\sigma} \, . \qquad (5)$$

b) Bias-free state estimation:

$$\mathbf{T_k} = \mathbf{A}\mathbf{Z_{k|k}} + \mathbf{F} \, ; \qquad (6)$$

$$\mathbf{Z_{k+1|k}} = \mathbf{T_k}\mathbf{P^\sigma_{k|k}}\left(\mathbf{P^\sigma_{k+1|k}}\right)^{-1} \, ; \qquad (7)$$

$$\widetilde{\underline{x}}_{k+1|k} = \underline{x}_{k+1|k} - \mathbf{Z_{k+1|k}}\underline{\sigma}_{k+1|k} \; ; \tag{8}$$

$$\begin{aligned}\widetilde{\mathbf{P}}^{\mathbf{x}}_{\mathbf{k+1|k}} = \mathbf{A}\widetilde{\mathbf{P}}^{\mathbf{x}}_{\mathbf{k|k}}\mathbf{A}^{T} + \mathbf{Q^x} + \mathbf{T_k}\mathbf{P}^{\boldsymbol{\sigma}}_{\mathbf{k|k}}\mathbf{T}^{T}_{\mathbf{k}} \\ - \mathbf{Z_{k+1|k}}\mathbf{P}^{\boldsymbol{\sigma}}_{\mathbf{k+1|k}}\mathbf{Z}^{T}_{\mathbf{k+1|k}} \; ;\end{aligned} \tag{9}$$

$$\widetilde{\underline{\eta}}_k = \underline{y}_k - \mathbf{C}\widetilde{\underline{x}}_{k+1|k} - \mathbf{D}\underline{u}_k \; ; \tag{10}$$

$$\mathbf{K}^{\mathbf{x}}_{\mathbf{k}} = \widetilde{\mathbf{P}}^{\mathbf{x}}_{\mathbf{k|k}}\mathbf{C}^{T}\left(\mathbf{C}\widetilde{\mathbf{P}}^{\mathbf{x}}_{\mathbf{k+1|k}}\mathbf{C}^{T} + \mathbf{Q^y}\right)^{-1} \; ; \tag{11}$$

$$\widetilde{\underline{x}}_{k+1|k+1} = \widetilde{\underline{x}}_{k+1|k} + \mathbf{K}^{\mathbf{x}}_{\mathbf{k}}\widetilde{\underline{\eta}}_k \; ; \tag{12}$$

$$\widetilde{\mathbf{P}}^{\mathbf{x}}_{\mathbf{k+1|k+1}} = \left(\mathbf{I} - \mathbf{K}^{\mathbf{x}}_{\mathbf{k}}\mathbf{C}\right)\widetilde{\mathbf{P}}^{\mathbf{x}}_{\mathbf{k+1|k}} \, . \tag{13}$$

c) Bias Estimation:

$$\mathbf{H_k} = \mathbf{G} + \mathbf{C}\mathbf{Z_{k+1|k}} \; ; \tag{14}$$

$$\mathbf{Z_{k+1|k+1}} = \mathbf{Z_{k+1|k}} - \mathbf{K}^{\mathbf{x}}_{\mathbf{k}}\mathbf{H_k} \; ; \tag{15}$$

$$\underline{\zeta}_k = \underline{y}_k - \mathbf{C}\underline{x}_{k+1|k} - \mathbf{D}\underline{u}_k \; ; \tag{16}$$

$$\mathbf{K}^{\boldsymbol{\sigma}}_{\mathbf{k}} = \mathbf{P}^{\boldsymbol{\sigma}}_{\mathbf{k+1|k}}\mathbf{H}^{T}_{\mathbf{k}}\left(\mathbf{H_k}\mathbf{P}^{\boldsymbol{\sigma}}_{\mathbf{k|k}}\mathbf{H}^{T}_{\mathbf{k}} + \mathbf{C}\widetilde{\mathbf{P}}^{\mathbf{x}}_{\mathbf{k+1|k}}\mathbf{C}^{T} + \mathbf{Q^y}\right)^{-1} ; \tag{17}$$

$$\underline{\sigma}_{k+1|k+1} = \underline{\sigma}_{k+1|k} + \mathbf{K}^{\boldsymbol{\sigma}}_{\mathbf{k}}\underline{\zeta}_k \; ; \tag{18}$$

$$\mathbf{P}^{\boldsymbol{\sigma}}_{\mathbf{k+1|k+1}} = \left(\mathbf{I} - \mathbf{K}^{\boldsymbol{\sigma}}_{\mathbf{k}}\mathbf{H_k}\right)\mathbf{P}^{\boldsymbol{\sigma}}_{\mathbf{k+1|k}} \, . \tag{19}$$

d) State correction:

$$\underline{x}_{k+1|k+1} = \widetilde{\underline{x}}_{k+1|k+1} + \mathbf{Z_{k+1|k+1}}\underline{\sigma}_{k+1|k+1} \; ; \tag{20}$$

$$\mathbf{P}^{\mathbf{x}}_{\mathbf{k+1|k+1}} = \widetilde{\mathbf{P}}^{\mathbf{x}}_{\mathbf{k+1|k+1}} + \mathbf{Z_{k+1|k+1}}\mathbf{P}^{\boldsymbol{\sigma}}_{\mathbf{k+1|k+1}}\mathbf{Z}^{T}_{\mathbf{k+1|k+1}} \, . \tag{21}$$

In the algorithm equations, $\mathbf{P^x}$ and $\mathbf{P}^{\boldsymbol{\sigma}}$ are the covariance matrices of the state and bias respectively, $\mathbf{K}^{\mathbf{x}}_{\mathbf{k}}$ and $\mathbf{K}^{\boldsymbol{\sigma}}_{\mathbf{k}}$ are the Kalman gain matrices for the bias-free state estimator and the bias estimator, respectively, and $\mathbf{Z}$ is a coupling matrix between the estimators to generate an optimal estimation for random bias.

Two different strategies are proposed to estimate the error due to actuation failure: 1) Bias TSKF, for additive error; 2) Gain TSKF, for multiplicative error.

3.1 Bias TSKF

In this approach, the TSKF standard formulation is applied. Let us consider the input vector of the aircraft as:

$$\underline{u}_k = \underline{u}_{ck} + \underline{\sigma}_k \, , \tag{22}$$

where $\underline{u}$ is the actuation vector and $\underline{u}_c$ is the commanded input.

Thus, from (1) and (22) we can derive the model used for the Bias TSKF as:

$$\begin{cases} \underline{x}_{k+1} &= \mathbf{A}\underline{x}_k + \mathbf{B}\underline{u}_{ck} + \mathbf{B}\underline{\sigma}_k + \underline{n}^{x}_k \\ \underline{\sigma}_{k+1} &= \underline{\sigma}_k + \underline{n}^{\sigma}_k \\ \underline{y}_k &= \mathbf{C}\underline{x}_k + \mathbf{D}\underline{u}_{ck} + \mathbf{D}\underline{\sigma}_k + \underline{n}^{y}_k \end{cases} . \tag{23}$$

Note that to apply the TSKF algorithm, we have $\mathbf{F} = \mathbf{B}$ and $\mathbf{G} = \mathbf{D}$.

3.2 Gain TSKF

The Gain TSKF (Amoozgar et al., 2013) focuses on estimating the level of effectiveness of the actuator. With this approach, a gain $\underline{\gamma}$ is defined to diagnose the actuators, where 0 means the actuator is fully working and 1 means it is not working at all.

In this approach, the considered input vector is:

$$\underline{u}_k = \mathbf{U}_{\mathbf{c}k}\left(\underline{1} - \underline{\gamma}_k\right) = \underline{u}_{ck} - \mathbf{U}_{\mathbf{c}k}\underline{\gamma}_k \, , \tag{24}$$

where $\underline{1}$ is a vector with all elements equal to 1 and $\mathbf{U}_{\mathbf{c}k}$ is a diagonal matrix in which the main diagonal corresponds to the elements of the commanded input vector $\underline{u}_c$. Thus, the linearized discrete system is given as:

$$\begin{cases} \underline{x}_{k+1} &= \mathbf{A}\underline{x}_k + \mathbf{B}\underline{u}_{ck} - \mathbf{B}\mathbf{U}_{\mathbf{c}k}\underline{\gamma}_k + \underline{n}^{x}_k \\ \underline{\gamma}_{k+1} &= \underline{\gamma}_k + \underline{n}^{\gamma}_k \\ \underline{y}_k &= \mathbf{C}\underline{x}_k + \mathbf{D}\underline{u}_{ck} - \mathbf{D}\mathbf{U}_{\mathbf{c}k}\underline{\gamma}_k + \underline{n}^{y}_k \end{cases} . \tag{25}$$

Therefore, to use the TSKF in the gain approach, the algorithm considers $\mathbf{F}_k = -\mathbf{B}\mathbf{U}_{\mathbf{c}k}$ and $\mathbf{G}_k = -\mathbf{D}\mathbf{U}_{\mathbf{c}k}$, and replaces $\underline{\sigma}_k$ by the bias gain $\underline{\gamma}_k$.

4. FEED-FORWARD DIFFERENTIAL

The FDIS relies on the input-output relationship to diagnose the faulty actuator. However, this task is even harder when we have multiple inputs with similar effect on the output.

For example, the roll movement of the aircraft is produced by a pair of ailerons. An aileron angle δ_A produces a lift force Z_A in the left aileron and $-Z_A$ in the right aileron. Therefore, both ailerons produce the exact same angular moment L_A. If an atypical roll movement is sensed by the TSKF, the estimators cannot define which aileron is the faulty one since they produce the same effect in the roll dynamics.

To isolate the faulty actuator, the Feed-Forward Differential (FFD) is proposed. The main idea of using the FFD is to add commands with opposite signs in redundant actuators. Let us go back to the aircraft example. If the ailerons are healthy, adding a command d with opposite signs in each aileron produces no additional roll moment (see Fig. 3a). However, if there is a failure where one of the ailerons is stuck, the FFD will be executed only by the healthy actuator. Since d is small and has different signs for each aileron, the FFD will slightly decrease the roll moment if the healthy aileron is the right one (Fig. 3b), or increase it if the left one is healthy (Fig. 3c).

5. SUPERVISORY LOOP

The data provided by the Bias and Gain TSKFs have different information and both can be used to assess the failures. In some occasions, these data may have conflicting information in defining the faulty actuation and the offset level. For such, a Supervisory Loop (SL) using simple heuristics is proposed as a solution to analyze the data.

The SL receives the data from the filters and provides a diagnosis of the actuators failure within some confidence level:

- If the confidence is high, the failure is assumed as true;
- If an intermediary confidence level is achieved, the SL demands a further investigation which includes the addition of the FFD in the control signal of some actuators.
- If the confidence is low, the failure is assumed false and no further action is necessary.

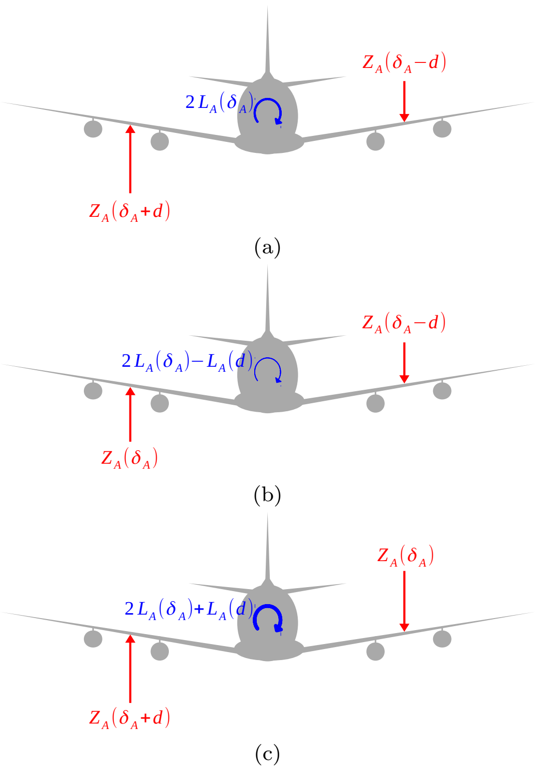


Fig. 3. FFD applied for the roll dynamics of an aircraft: (a) healthy ailerons; (b) stuck left aileron; (c) stuck right aileron.

The SL diagnosis uses metrics obtained with the data accumulated during a short time interval (time window). The considered metrics (calculated for each k-th time window) are:

- The mean value of the estimated bias/gain:

$$\underline{\mu}_{\sigma_k} = \text{mean}\left(\underline{\sigma}_k\right); \quad \underline{\mu}_{\gamma_k} = \text{mean}\left(\underline{\gamma}_k\right).$$

- A normalized mean value of the estimated bias/gain:

$$\underline{\eta}_{\sigma_k} = \frac{\left|\underline{\mu}_{\sigma_k}\right|}{\max\left(\left|\underline{\mu}_{\sigma_k}\right|\right)}; \quad \underline{\eta}_{\gamma_k} = \frac{\underline{\mu}_{\gamma_k}}{\max\left(\underline{\mu}_{\gamma_k}\right)}.$$

- The signal-noise ratio of the estimated bias/gain:

$$\underline{\nu}_{\sigma_k} = \frac{\underline{\mu}_{\sigma_k}}{\text{std}\left(\underline{\sigma}_1\right)}; \quad \underline{\nu}_{\gamma_k} = \frac{\underline{\mu}_{\gamma_k}}{\text{std}\left(\underline{\gamma}_1\right)}.$$

The metrics are used to diagnose the aircraft surfaces. The proposed algorithm runs in fixed time-windows and has four steps, described in the sequence:

STEP 1: Verify if there are possible faulty actuators.

An actuator is considered as "in possible fault" if the three following conditions are true:

- The signal-noise ratio is high;
- The mean estimated bias is high;
- The mean estimated gain is high.

STEP 2: Identify the faulty actuator

To identify the most probable faulty actuator, the actuators are sorted according to their normalized gain estimation, from higher to lower. The first of the list (which has normalized gain equal to 1) is considered the most probable faulty actuator. This result is considered questionable if the second in the list has a high normalized gain as well.

STEP 3: Apply differential injection if the identified faulty surface is questionable.

If Step 2 returns a questionable fault in two consecutive time windows, the SL adds a differential injection to the control input to aid the identification process. The differential is applied using a normal random noise. The intensity level of the differential goes from 1 to 5 (different values of covariances) and increases after each time window. The differential injection is turned off if the identification is no longer questionable for two consecutive time windows.

STEP 4: Define the position of the faulty surface.

Knowing the most probable faulty actuator, the SL estimates the actual position of the possible faulty actuator.

6. RESULTS

The proposed FDIS is used to evaluate actuation failures in a fixed-wing aircraft. Here, the strategy is applied to identify aileron failures in a Boeing 747 (B747) simulator using MATLAB/Simulink. The B747 GARTEUR RECOVER benchmark simulator, developed by TU Delft (Smaili et al., 2010), is used with modifications included by the Institute of Flight System Dynamics - *Technische Universität München* (FSD-TUM), namely, the customization of the failure simulation and the trim and linearization procedures.

The B747 is a large and heavy transportation airplane. The main actuation of the B747 consists of two pairs of ailerons; two pairs of elevators; two rudders; and four engines.

To evaluate the TSKF strategy, let us consider the linearized lateral motion of the aircraft as follows:

$$\begin{cases} \underline{x}_{k+1} &= \mathbf{A_{lat}}\underline{x}_k + \mathbf{B_{lat}}\underline{u}_k \\ \underline{x} &= [\beta\ p\ r\ \phi]^T \\ \underline{u} &= [\delta_{A11}\ \delta_{A12}\ \delta_{R1}\ \delta_{R2}\ \delta_{T21}\ \delta_{T11}\ \delta_{T12}\ \delta_{T22}]^T \end{cases}. \quad (26)$$

where β is the sideslip angle; p and r are, respectively, the roll and yaw rates; ϕ is the roll angle; δ_{Aij} are the aileron inputs; δ_{R1} and δ_{R2} are upper and lower rudders; and δ_{Tij} are the engine throttle inputs. The sub-index i corresponds to inner ($i = 1$) or outer ($i = 2$) actuators, and the sub-index j corresponds to left ($j = 1$) or right ($j = 2$). Note that the pair of outer ailerons are disregarded since the outer ailerons of the B747 are only used if flaps are required, and the flaps are turned off in the simulation.

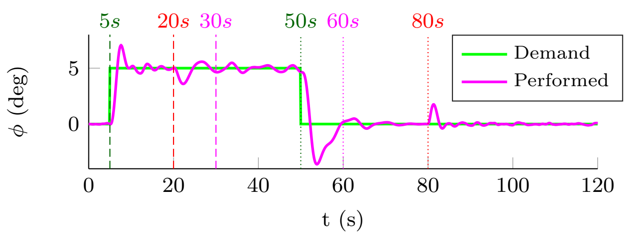
All states are assumed measured, and the dynamics and input matrices ($\mathbf{A_{lat}}$ and $\mathbf{B_{lat}}$ respectively) are obtained from the numerical linearization of the simulator at a trim condition. The trim condition corresponds to the aircraft in a straight-and-level flight with 340 knots of true airspeed and 5000 feet of altitude.

The aircraft attitude is controlled using the Incremental Backstepping strategy (Cordeiro et al., 2019). The simulation starts at the trim condition; the states are assumed measured with noise. At $t = 5s$, a bank maneuver of 5 degrees is demanded, going back to straight-and-level flight at t=50s. At $t = 20s$ the inner-left aileron detaches from its mechanism, becoming loose (floating failure), and at $t = 80s$ the failure is fixed.

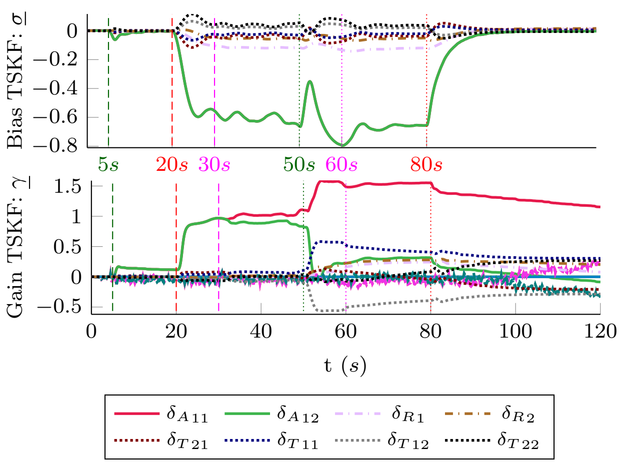
The lateral model (26) is used to synthesize both Bias and Gain TSKF, and the SL is running in a $5s$ time window. Fig. 4 presents the aircraft roll angle during the maneuver and the obtained bias and gain estimations. In the figure, vertical lines indicate the start (dashed) and finish (dotted) time of the maneuver (green), failure (red) and FFD usage (magenta). Table 1 provides the SL log entries, which include: the possible faulty actuator (number of the actuator position in vector $\underline{u}$); the estimated position of the possible faulty actuator; and the demanded FFD intensity. If the result is considered questionable, the log also indicates the actuator causing the doubt.

When the failure occurs, at $t = 20s$, both Bias and Gain TSKFs report a possible failure. However, given the redundant effect of the left and right aileron, the bias is equally distributed between both actuators, while the gain is set to one for both.

Given the filters results, the failure is detected by the SL, which indicates it in the subsequent time window ($t = 25s$), as shown in Table 1. In the next time window ($t = 30s$), the SL is still not able to define the faulty actuator and, therefore, the FFD is demanded. As consequence, the estimated gains of the redundant actuator diverge, increasing the value of the faulty one. Thus, after $t = 35s$ the SL establishes 1 (inner-left aileron) as the possible faulty actuator.



(a)



(b)

Fig. 4. Identification of the floating failure in the inner-left aileron. (a) Roll angle during the simulation. (b) Bias and Gain TSKFs output.

Table 1. SL log of the floating failure at the inner-left aileron.

Time (s)	Possible Faulty	Questionable	Faulty Real Position	Differential Intensity
0	0	0	0	0
⋮	⋮	⋮	⋮	⋮
20	0	0	0	0
25	2	1	0.18	0
30	2	1	-0.54	1
35	1	2	-0.58	2
40	1	2	-0.51	3
45	1	2	-0.63	4
50	1	0	-0.49	4
55	1	0	-0.63	0
⋮	⋮	⋮	⋮	⋮
90	1	0	-0.15	0
95	1	0	-0.02	0
100	0	0	0	0
⋮	⋮	⋮	⋮	⋮
120	0	0	0	0

Although the SL indicates the correct faulty actuator, the difference is still not conclusive to indicate the other aileron as healthy, and the SL starts to raise the differential intensity. The extra intensity increases the divergence of the gain estimation.

At $t = 50s$ the divergence created by the FFD is enough for the SL to confirm the inner-left aileron as the faulty one. In addition, at the same time, the aircraft starts to go back to straight-and-level flight. This maneuver uses the ailerons, creating extra excitation in the roll dynamics which increases even more the divergence of the estimated gains, as shown in Fig. 4b.

The failure is fixed at $t = 80s$. Note that the Gain TSKF is not able to correctly sense the end of the failure, however, the Bias TSKF senses it immediately and goes back to zero. Since the bias goes to zero, one condition of Step 1 is violated in the SL, indicating that there is no faulty surface, which is indicated in the SL log at $t = 100s$.

Therefore, we can conclude that the Gain TSKF is an important source to isolate the correct faulty actuator, while the Bias TSKF is more accurate to detect the failure, highlighting the complementary results of both filters.

The same simulation is repeated for hardover failure (the aileron suddenly goes to its maximum deflection angle) and stuck-in-position (the aileron get stuck in its last position), using either left or right ailerons. Table 2 shows the time needed to detect and correctly isolate the failure. Note that stuck-in-position is only detected when the aircraft goes back to straight-and-level flight. In fact, the stuck fault occurs during a constant bank level, where the aileron deflection is constant (near zero position). Thus,

Table 2. Required time after the fault occurs for detecting and isolating different types of failures.

Faulty Actuator	Floating		Hardover		Stuck	
	Detect	Isolate	Detect	Isolate	Detect	Isolate
δ_{A11}	5 s	30 s	5 s	35 s	35 s	45 s
δ_{A12}	5 s	35 s	5 s	35 s	35 s	–

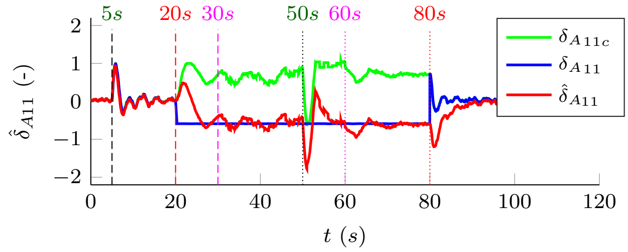


Fig. 5. Estimated normalized position of the inner-left aileron (floating failure).

the flight dynamics is not affected and no failure can be sensed. After the aircraft is in a straight flight, no aileron is needed again, and the TSKF cannot observe any abnormality in the flight. Therefore, the failure can only be sensed for a short period of time, which may not be enough to isolate the failure (right aileron case).

The Bias TSKF can also be used to estimate the real position of the faulty actuator. As indicated in (22), the real position of the actuator can be obtained as the sum of the control effort and the bias. However, given the redundancies of the actuation, the bias is equally divided by both surfaces (in Fig. 4b the bias estimation of left and right ailerons are superimposed). Thus, the SL requires to know which one is the faulty actuator in order to estimate its real position. For example, the real position of the inner-left aileron is given as:

$$\hat{\delta}_{A11} = \delta_{A11c} + \sigma_{A11} + \sigma_{A12}\,. \tag{27}$$

Figure 5 shows the estimated position of the inner-left aileron in the floating case simulation, and compares it with the real position of the surface. In the simulator the surface position is normalized by its maximum displacement, varying from -1 to 1. Note that when the failure occurs, the real position decreases, and the aircraft command increases (trying to compensate for the loss of actuation). Nonetheless, the estimated position using the bias is very similar to the real position of the surface.

Since the faulty actuator must be known, the position value shown in Table 1 is the mean value of the position calculated for the possible faulty surface.

7. CONCLUSION

A Failure Detection and Isolation System is proposed by combining the results of Bias and Gain Two-Stage Kalman Filters in order to diagnose actuators failures in a fixed-wing aircraft. The filters results are interpreted by a Supervisory Loop which provides a diagnosis of the actuators condition. The SL may also demand an additional Feed-Forward Differential to help the decision-making algorithm.

Since the FDIS is based on the estimation of the real position of the surfaces, the fault is characterized by the offset level. In addition, the approach uses only two model-based TSKFs, needing fewer models than classical MMAE solutions. Nonetheless, as a linearized model-based solution, a scheduling of the aircraft model in different points of the flight envelope may be required.

The solution is applied for detecting single failures in a Boeing 747 aircraft simulator. A case study is presented, where a floating failure is considered in one aileron. The failure is detected in a 5 seconds time-window, being required more 30 seconds to isolate the faulty actuator.

The simulations demonstrate that the FFD helps the SL to isolate the failure without interfering with the flight performance.

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