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Sensor Fault Detection and Isolation for Redundant Air Data Sensors

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This paper presents a Fault Detection and Isolation (FDI) method for redundant Air Data Sensors (ADS) of aircraft. In the most general case, fault detection of these sensors on modern aircraft is performed by a logic that selects one of, or combines three redundant measurements. Such a method is compliant with current airworthiness regulations. However, in the framework of the global aircraft optimization for future and upcoming aircraft, it could be required, e.g. to extend the availability of sensor measurements. So, an improvement of the state of practice could be useful. Introducing a form of analytical redundancy of these measurements can increase the fault detection performance and result in a weight saving of the aircraft because there is no necessity anymore to increase the number of sensors. Furthermore, the analytical redundancy can contribute to the structural design optimization. The analytical redundancy in this method is introduced using an adaptive form of the Extended Kalman Filter (EKF). This EKF uses the kinematic relations of the aircraft and makes a state reconstruction from the available measurements possible. From this estimated state, an estimated output is calculated and compared to the measurements. Through observing a metric derived from the innovation of the Extended Kalman Filter (EKF), the performance of each of the redundant sensors is monitored. This metric is then used to automatically isolate the failing sensors.

Nomenclature

p	Roll rate, rad/s
q	Pitch rate, rad/s
r	Yaw rate, rad/s
$\mathbf{A}$	Specific forces $[A_x\ A_y\ A_z]^\top$, m/s^2
A	Specific force, m/s^2
$\mathbf{C}$	Output matrix
$\mathbf{F}$	Jacobian of system equations
$\mathbf{f}$	Kinematic equations
$\mathbf{f}_0$	Sensor fault vector
$\mathbf{G}$	Input matrix
$\mathbf{g}$	Gravitation vector, m/s^2
$\mathbf{P}$	Covariance matrix of the state estimate
$\mathbf{Q}$	Input noise covariance matrix
$\mathbf{R}$	Output noise covariance matrix
$\mathbf{T}_{be}$	Transformation matrix from vehicle carried earth reference frame to body-fixed reference frame
t	Time, s
$\mathbf{u}$	Input vector
$\mathbf{V}$	Speed components [m/s]
$\mathbf{v}$	Output measurement noise
V_{TAS}	True airspeed, m/s
$\mathbf{w}$	Input measurement noise
$\mathbf{x}$	State vector
$\mathbf{z}$	Output vector

Subscripts

g	w.r.t. earth-fixed reference frame
k	Time instance t_k
m	Measured
x	w.r.t. body x-axis
y	w.r.t. body y-axis
z	w.r.t. body z-axis

Symbols

α	Angle-of-attack, rad
β	Side slip angle, rad
ϕ	Roll angle, rad
ψ	Yaw angle, rad
θ	Pitch angle, rad
$\boldsymbol{\omega}$	Rotational rates $[p\ q\ r]^\top$, rad/s

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I. Introduction

In this paper a newly developed architecture for redundant Air Data Sensors (ADS) monitoring is proposed. The method deals with the Fault Detection and Isolation (FDI) of measurements required for the Electronic Flight Control System (EFCS) of aircraft. The research is aimed at increasing the FDI performance of state-of-practice methods and closing the gap between the academic field of Fault Detection and Diagnosis (FDD) research and the practical application of these methods in industry.

A. Motivation

In Fig. 1 an overview is given of the typical architecture of an EFCS of an aircraft. As can be noticed, one way of how malfunctions can enter the control loop is by sensor faults, indicated as Air Data and Inertial Reference System (ADIRS) faults in the figure. Faulty measurements which are fed back to the flight control

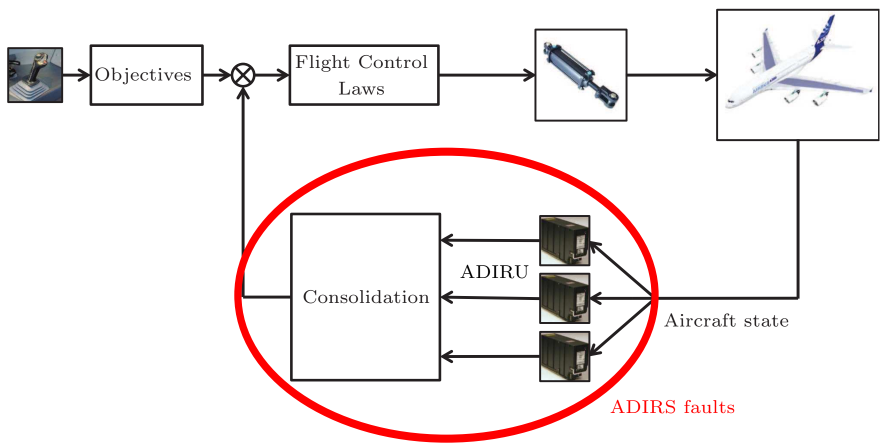


Figure 1. Flight control architecture of an aircraft

laws can create unwanted control signals, leading e.g. to higher loads on the aircraft structure. For that reason, the aircraft structures are designed to withstand these unwanted loads up to a level at which it is guaranteed that the faults can be detected and appropriate actions can be taken.

Sensor fault detection for flight parameter measurements, e.g. air data and inertial measurements in modern aircraft, is generally achieved through the use of typically three redundant measurement units (e.g. Air Data and Inertial Reference Units (ADIRUs)[1]). Through a decision logic, also called consolidation process, the correct measurement is selected and used by the EFCS.[1,2]

However, there are several motivations explaining the need for an improved FDD performance. First of all, for upcoming and future aircraft one important aspect is the structural design optimization. This can lead to a substantial decrease in the weight of the aircraft, which again leads to an increase in the aircraft's performance, including a decrease in fuel consumption, a decrease of produced noise and an increased range. Furthermore, these advantages also satisfy the newer societal imperatives toward an environmentally friendlier aircraft.[3] As explained above, an increased FDD performance will lead to smaller detectable faults. This means that the aircraft structures have to be able to cope with smaller faults and as such can be designed lighter.

A second motivation follows from the typical system availability and integrity requirements for commercial flight control electronics. These requirements specify a 10^{-9} maximum probability of critical failure per flight hour.[4] This means that fly-by-wire systems need to be able to withstand failures in both hardware components and software. In combination with the increasing complexity of EFCS architectures, these requirements indicate the need to develop advanced FDD methodologies to be able to extend the availability of sensor measurements. Instead of adding one or several new sensors, the option of adding a "virtual" sensor, i.e. analytical redundancy, gives the advantage no additional sensors, wiring, hardware is required. This results again in the same advantages as described in the previous paragraphs.

These two main reasons indicate the need to create new advanced FDD methods and to close the gap between academic research and industrial application.

B. Antecedents and main contribution

In this work a model-based FDD approach is presented for the fault detection of Air Data Sensors (ADS). As these type of sensors are directly exposed to the aircraft's operating environment, they are more likely subject to failures due to weather conditions (icing, dust) or inadequate maintenance and ground handling.

Different methods have been investigated for mitigating the effects of failing ADS, such as: signal based diagnosis,[5,6] alternative sensing methods which are fault tolerant,[7] robust fault detection approaches[8] or finding ways to operate without traditional ADS.[9] Other solutions for the problem of ADIRS monitoring dealing with oscillatory faults are presented in.[10,11]

In this paper a method is introduced based on the general kinematic relations of aircraft. By relating different available measurements in the ADIRU, it becomes possible to perform FDD of the ADS. For this purpose, an adaptive modification of the EKF is applied to the kinematic equations. The Kalman Filter (KF) and its numerous modifications have been used in the field of aerospace engineering since it was developed in the 1960s.[12] In this way, the EKF has also been used for sensor fault detection.[13]

The EKF was originally formulated for state estimation of dynamic systems when the dynamics and measurement equations are nonlinear, but linearizable[14] and has been widely used for sensor monitoring and fusion techniques.[15] The method that will be proposed here directly builds on this principle, i.e., using the redundant measurements available form the multiple ADIRUs the state of the aircraft is reconstructed by means of an adaptive version of an EKF which was first introduced by Mehra and Peschon.[16] Hajiyev *et al.*[17] proposes sensor fault detection by evaluating the innovation sequence of the filter. This information can furthermore be used to fuse the measurements in such a way that failing sensors are detected and isolated.

The advantages of the kinematic relations for the purpose of sensor FDD has not been widely exploited according to Marzat *et al.*[18] However, as these relations can be considered to be known exact, no aircraft model mismatches or unmodeled flight dynamics need to be taken into account, giving a big advantage over classical model based approaches. Furthermore, only limited knowledge about the specific aircraft is required. The main disadvantage of the proposed method is that it needs to be assumed that the FDI of the Inertial Reference Unit (IRU) measurements is already covered.

C. Structure of the paper

In the next section the fault scenarios are introduced. In Sect. III the kinematic relations are described. In Sect. IV the proposed FDD method is described and in Sect. V the simulation results are presented. The paper ends with a conclusion in Sect. VI.

II. Fault Scenario and Requirements

A. Fault Scenario

The faults investigated in this work are sensor faults related to the ADS, specifically the airspeed, the angle-of-attack and side-slip angle measurements. Different types of faults are considered, such as oscillating faults, runaway faults and increased noise faults, of which examples are shown in Fig. 2. Note that in this graph, and all other graphs in this paper, all values are normalized to the operational range of the measurements. Furthermore, also the time axis will be normalized for each simulation.

Each of the different type of faults can occur on one or simultaneously on two sensors. Whereas the fault detection of the case of only one failing sensor is a trivial task which can be performed by majority voting, the fault detection when two sensors fail at the same time is less obvious without incorporating any kind of analytical redundancy. Furthermore, simultaneous faults on different types of sensors are also considered. An overview of the different scenarios investigated and the corresponding amplitudes and fault times are shown in Table 1.

B. Requirements

An important aspect in the design of any FDD system are the requirements. The requirements follow from the main performance criteria for FDD:

- False Alarm Rate (FAR): The FAR indicates in percentages the rate of false alarms (fault declaration in a fault free situation). For safety critical systems, this requirement is often set to zero as the detection

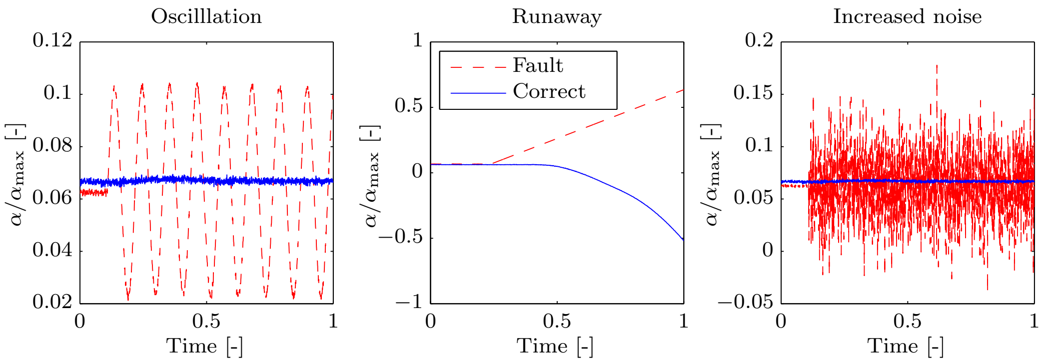


Figure 2. Examples of different types of faults applied to the measurement of e.g. the angle-of-attack α

Table 1. Scenario definitions. Note that the amplitudes are always expressed as a percentage of the maximum measurable range. The faults are initiated during simulated cruise flight.

Scenario	Sensor	Fault type	Amplitude (%)
1	α	Oscillation sensors 1 & 2	3
2	β	Runaway fast sensors 1 & 2	33
3	V_{TAS}	Extra noise sensors 1 & 2	3
4	α, V_{TAS}	Oscillation of 2 sensors each	4

of a non-existing fault could distract the operator and cause a safety-issue. If the FDD system uses a threshold based fault declaration, the threshold needs to be set to the value that corresponds to the maximum residual that can occur in a fault free situation.

- Missed Detection Rate (MDR): The MDR indicates in percentages the rate of missed detections (no fault declaration in a fault-free situation). Ideally, this value is set to zero, although in reality it depends strongly on the quality of the residual. As the FAR is often a stronger requirement and contradictory to the MDR requirement, a trade-off is necessary and a zero MDR is hard to obtain.
- Detection Time Performance (DTP): The DTP indicates the time at which a fault is declared w.r.t. the maximum detection time, i.e. $\frac{t_{\text{detect}}}{t_{\max}}$ and should always be smaller then zero. For a threshold based FDD system, a smaller threshold will result in a faster detection and a better DTP.
- Computational cost: An important factor in the design of FDD systems for online application is the computational cost of the algorithm. The available computational power on current commercial aircraft is still limited, increasing the difficulty of developing advanced FDD systems.

However, concrete guidelines for these requirements are often considered proprietary information of aircraft constructors and are not available in current literature. The lack of a general, open benchmark model with appropriate requirements for the purpose of (actuator and sensor) FDD makes good comparisons between developed methods hard. Furthermore, such an available model would also benefit a lot in the goal to close the scientific gap between academia and industry w.r.t. the development of FDD systems.

III. System Definition

One of the key elements of this method is the use of the kinematic equations that describe the aircraft's behavior, i.e., the state reconstruction is achieved using the measurements of the IRU. When the load factors and the rotational rates are used as inputs to the EKF, the state of the aircraft can be reconstructed.[19] The big advantage of this approach lies in the following points:

- The kinematic relations, and as such the method developed is valid over the whole flight envelope of the aircraft. This means that no special measures need to be taken such as gain scheduling, etc, as these relations do not change with changing flight conditions.

- Secondly, the method can be applied to any aircraft, without a big implementation cost, i.e., no aircraft specific model is needed. Only a limited amount of aircraft specific parameters are needed, e.g. the location of sensor models. So the developed method is general for aircraft.

- The kinematic relations are known exactly. This means that one does not have to take care of unmodeled dynamics or model mismatches.

- The method is insensitive to other types of faults or malfunctions, e.g. actuator faults, control surface jamming, etc. As the motion of the aircraft is sensed by the accelerometers and the rotational gyros, influences of these faults on the aircraft are sensed as well, however these do not influence the kinematic relations between the measured variables.

The only inaccuracies that need to be accounted for are related to the measurements, e.g. noise, biases and sensor dynamics.

The aircraft kinematics can be represented by the following nonlinear system:

$$\begin{aligned}\dot{\mathbf{x}}(t) &= \mathbf{f}(\mathbf{x}(t)) + \mathbf{G}(\mathbf{x}(t))\,(\mathbf{u}(t) + \mathbf{w}(t)) \\ \mathbf{z}(t) &= \mathbf{C}\mathbf{x}(t) \\ \mathbf{z}_m(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{v}(t) + \mathbf{f}_0(t)\end{aligned} \tag{1}$$

Where $\mathbf{x}$ represents the state of the system, $\mathbf{u}$ the input and $\mathbf{z}$ the measurable output of the system. $\mathbf{w}(t)$ and $\mathbf{v}(t)$ represent Gaussian white noise sequences and are the measurement noise of respectively the measured input and output of the filter. $\mathbf{f}_0$ represents the faults in the measurements, i.e., $f_{0_i} = 0$ for a fault-free sensor i, $f_{0_i} \neq 0$ for a failing sensor i. In this particular case, the state description can be reduced to a five state system, and these states are measurable:

$$\mathbf{x} = \begin{bmatrix} V_{TAS} & \alpha & \beta & \phi & \theta \end{bmatrix}^\top \tag{2}$$

$$\mathbf{u} = \begin{bmatrix} A_x & A_y & A_z & p & q & r \end{bmatrix}^\top \tag{3}$$

$$\mathbf{z} = \begin{bmatrix} V_{TAS} & \alpha & \beta & \phi & \theta \end{bmatrix}^\top \tag{4}$$

where V_{TAS} is the true airspeed, α the angle-of-attack, β the side-slip angle, ϕ the roll angle, θ the pitch angle and ψ the yaw angle.. A_x, A_y, and A_z are the accelerations at the center of gravity, p, q, and r the rotational rates. Note that a transformation may be necessary to convert the measured specific forces at the IRU to accelerations at the center of gravity. Furthermore, note that $\mathbf{C} = \mathbf{I}$. In fact, both the inputs to this system and the outputs are measured from the aircraft and can be assumed available in the EFCS for each modern aircraft. Furthermore it is assumed that influences of sensor dynamics are already accounted for and that the available measurements represent the values of the measured variables at the location of the center of gravity of the aircraft. I.e., the FDI scheme is applied to the measurements after being processed by the EFCS such that any type of software faults could also be detected.

Although the position of an aircraft can be considered as a part of the state, it is not required for the purpose of fault detection of the ADS. Having only these five states will decreases the computational load of the proposed method.

Furthermore, the lack of the position as a state variable gives the advantage that for a constant wind, the wind magnitude and direction do not need to be estimated. This is demonstrated as follows. Consider the ground speed components ($\mathbf{V}_g$) to be the sum of the air speed components ($\mathbf{V}_a$) and the wind speed components ($\mathbf{V}_w$), i.e. $\mathbf{V}_g = \mathbf{V}_a + \mathbf{V}_w$ (all components expressed in the body-fixed reference frame). As the measured specific forces are related to the inertial acceleration of the aircraft, and as such the ground speed, one can state:

$$\frac{\partial \mathbf{V}_g}{\partial t} = \dot{\mathbf{V}}_g = \mathbf{A} + \mathbf{T}_{be}\mathbf{g} - \boldsymbol{\omega} \times \mathbf{V}_g \tag{5}$$

Substituting $\mathbf{V}_g = \mathbf{V}_a + \mathbf{V}_w$ results in:

$$\left(\dot{\mathbf{V}}_a + \dot{\mathbf{V}}_w\right) = \mathbf{A} + \mathbf{T}_{be}\mathbf{g} - \boldsymbol{\omega} \times (\mathbf{V}_a + \mathbf{V}_w) \tag{6}$$

When a constant wind is assumed, the time derivative of the wind is equal to zero:

$$\frac{\mathrm{d}\mathbf{V}_w}{\mathrm{d}t} = \frac{\partial \mathbf{V}_w}{\partial t} + \boldsymbol{\omega} \times \mathbf{V}_w = 0 \tag{7}$$

By combining Eqs. (6) and (7) one gets:

$$\dot{\mathbf{V}}_a = \mathbf{A} + \mathbf{T}_{be}\mathbf{g} - \boldsymbol{\omega} \times \mathbf{V}_a \tag{8}$$

which clearly indicates that in the case of constant wind the measured specific forces can be used for the reconstruction of the air speed components. However, this derivation also shows that in the case of (abrupt) wind velocity changes, the equations are not exact anymore.

Furthermore, the value of V_{TAS}, α, and β are defined by:

$$V_{TAS} = \sqrt{u^2 + v^2 + w^2} \tag{9}$$

$$\alpha = \arctan \frac{w}{u} \tag{10}$$

$$\beta = \arcsin \frac{v}{V_{TAS}} \tag{11}$$

where $\mathbf{V}_a = [u \; v \; w]^\top$. Applying the transformation as defined by Eqs. (9) – (11) and according to Duke *et al.*,[20] the kinematic state update equations can be described by:

$$\begin{aligned}
\dot{V}_{TAS} &= g\left(-\sin\theta\cos\alpha\cos\beta + \sin\phi\cos\theta\sin\beta + \cos\phi\cos\theta\sin\alpha\cos\beta\right) \\
&\quad + A_x\cos\alpha\cos\beta + A_y\sin\beta + A_z\sin\alpha\cos\beta && (12)\\
\dot{\alpha} &= \frac{g}{V_{TAS}\cos\beta}\left(\cos\phi\cos\theta\cos\alpha + \sin\theta\sin\alpha\right) \\
&\quad + \frac{1}{V_{TAS}\cos\beta}\left(A_z\cos\alpha - A_x\sin\alpha\right) + q - \tan\beta\left(p\cos\alpha + r\sin\alpha\right) && (13)\\
\dot{\beta} &= \frac{g}{V_{TAS}}\left(\sin\theta\cos\alpha\sin\beta + \sin\phi\cos\theta\cos\beta - \cos\phi\cos\theta\sin\alpha\sin\beta\right) \\
&\quad + \frac{1}{V_{TAS}}\left(-A_x\cos\alpha\sin\beta + A_y\cos\beta - A_z\sin\alpha\sin\beta\right) + p\sin\alpha - r\cos\alpha && (14)\\
\dot{\phi} &= p + q\sin\phi\tan\theta + r\cos\phi\tan\theta && (15)\\
\dot{\theta} &= q\cos\phi - r\sin\phi && (16)
\end{aligned}$$

which defines $\mathbf{f}(\mathbf{x})$ and $\mathbf{G}(\mathbf{x})$ in Eq. (1). The advantage of this description is that the output equation reduces to the unity matrix, this in contrast to the more common description using speeds defined in the body-reference frame,[18] which are not directly measurable.

IV. FDD Approach

The general idea of the presented approach is to fuse the redundant ADS measurements based on the quality of the measurement, and using the available information for FDI of the sensors. This is achieved by filtering the available measurements using an EKF and comparing the output predictions with the redundant measurements, i.e. evaluating the innovation of the EKF. The relations between the inputs and outputs of the EKF are the kinematic relations as described in the previous section.

For this purpose, first the basic principles of the EKF are briefly explained, which is essential in understanding the methodology. Then the sensor monitoring algorithm is addressed, which is used to perform the FDD.

The standard EKF exists of two main steps. The first step can be called the prediction of the estimated mean of the state of the system, and uses the system differential equations. Also the covariance of the estimate is predicted. This step can be represented by:

$$\begin{aligned}
\hat{\mathbf{x}}_{k|k-1} &= \hat{\mathbf{x}}_{k-1|k-1} + \int_{t_{k-1}}^{t_k} \left[\mathbf{f}(\hat{\mathbf{x}}(\tau)) + \mathbf{G}(\hat{\mathbf{x}}(\tau))\mathbf{u}_m(\tau)\right] \mathrm{d}\tau && (17)\\
\mathbf{P}_{k|k-1} &= \boldsymbol{\Phi}_k \mathbf{P}_{k-1|k-1} \boldsymbol{\Phi}_k^\top + \mathbf{Q}_d && (18)
\end{aligned}$$

Where $\hat{\mathbf{x}}_{k|k-1}$ is the estimated state at time $t = t_k$, knowing the measurement at time $t = t_{k-1}$. $\mathbf{u}_m(t)$ represents the measured input to the system. The matrix $\mathbf{P}_{k-1|k-1}$ represents the covariance matrix of the estimated state at time $t = t_{k-1}$. The matrix $\mathbf{\Phi}_k$ is the discretized version of the Jacobian matrix $\mathbf{F}_k$, both defined as follows:

$$\mathbf{\Phi}_k = e^{\mathbf{F}_k \Delta t} = \sum_{n}^{\infty} \frac{\mathbf{F}_k^n (\Delta t)^n}{n!} \tag{19}$$

$$\text{with: } \mathbf{F}_k = \left. \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} \right|_{\mathbf{x}=\hat{\mathbf{x}}_{k|k}} \tag{20}$$

and from Lombaerts[21] we can approximate $\mathbf{Q}_d$ as:

$$\mathbf{Q}_d(k) = \mathbf{\Gamma}_k \mathbf{Q} \mathbf{\Gamma}_k^\top \tag{21}$$

$$\text{with: } \mathbf{\Gamma}_k = \left(\int_{k-1}^{k} \mathbf{\Phi}_k \Delta t \right) \mathbf{G}(\hat{\mathbf{x}}_{k|k}) \tag{22}$$

where $\mathbf{Q} = E\left[\mathbf{w}(t)\mathbf{w}^\top(t)\right]$ represents the input noise covariance matrix. This way, the input measurement noise is mapped as process noise.

The second step is the measurement update. It is represented by:

$$\mathbf{K}_k = \mathbf{P}_{k|k-1}\mathbf{H}^\top \left(\mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^\top + \mathbf{R} \right)^{-1} \tag{23}$$

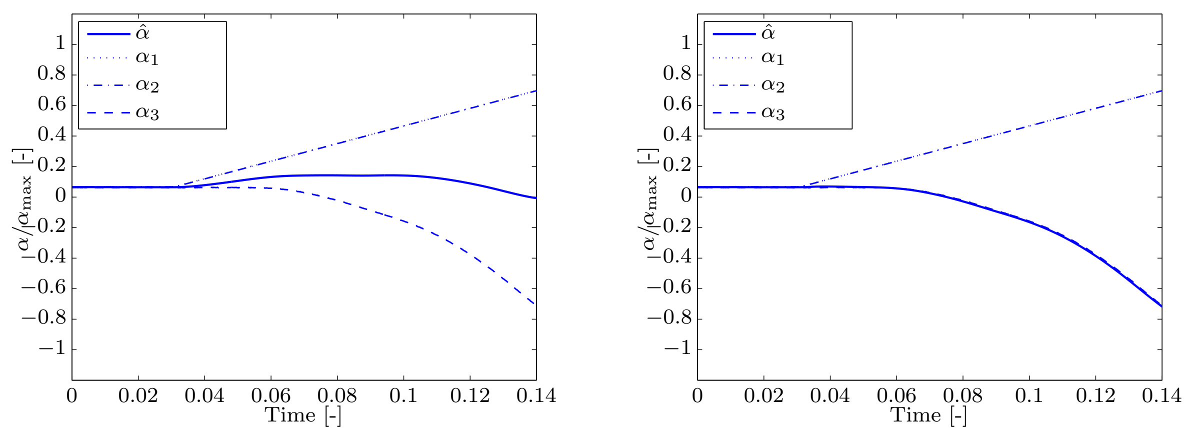
$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k \left(\mathbf{z}_m - \mathbf{h}(\hat{\mathbf{x}}_{k|k-1}) \right) \tag{24}$$

$$\mathbf{P}_{k|k} = \left[\mathbf{I} - \mathbf{K}_k\mathbf{H}\right] \mathbf{P}_{k|k-1} \left[\mathbf{I} - \mathbf{K}_k\mathbf{H}\right]^\top + \mathbf{K}_k\mathbf{R}\mathbf{K}_k^\top \tag{25}$$

where $\mathbf{K}$ is the Kalman gain, $\mathbf{H} = \frac{\partial \mathbf{h}(\mathbf{x})}{\partial \mathbf{x}} = \mathbf{I}$, and $\mathbf{R} = E\left[\mathbf{v}(t)\mathbf{v}^\top(t)\right]$ the measurement noise covariance matrix. Furthermore, from these equations we can define the innovation as $\mathbf{z}_{m_k} - \hat{\mathbf{z}}_k$ and the innovation covariance matrix as:

$$\mathbf{V}_{e_k} = \mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^\top + \mathbf{R} \tag{26}$$

This standard EKF can be applied to the system described in Sect. III with the triple measurement of, e.g. the angle-of-attack α augmented in the measurement vector. In this case, a simulation was chosen with a double runaway fault, i.e., sensor 1 and 2 experienced the same runaway fault at $t = 0.03$. In Fig. 3(a) the result of the estimated angle-of-attack $(\hat{\alpha})$ by the standard EKF can be seen compared to the three different measurements. As can be noticed, the estimated value of the angle-of-attack is in between the measured



(a) Regular EKF

(b) Adaptive fusion

Figure 3. $\hat{\alpha}$ compared with measurements for runaway fault of sensor 1 and 2 (equal fault value)

values. This is logical, as the assigned variances to the different sensors, through the matrix $\mathbf{R}$, are equal.

Therefore, each measurement of the same variable is equally weighted by the filter. From the figure it is clear that it cannot be decided on this information which sensor is failing, and which sensor is providing a correct value. In this we find a motivation to modify the algorithm such that FDI becomes possible by monitoring the performance of the sensors.

Instead of using all redundant measurements as separate observations in an adaptive EKF,[22] here is chosen to fuse the redundant measurements based on their performance. For this, an appropriate metric is the Mean Square Error (MSE) of the innovation which can indicate whether the sensor is failing or fault-free.

The MSE of an estimated or predicted variable, e.g. $\hat{\theta}$, is defined as:

$$\mathrm{MSE}(\hat{\theta}) = E\left[(\hat{\theta} - \theta)^2\right] \tag{27}$$

and as such depends on the unknown, real value of θ. In fact, the MSE is equal to the sum of the variance and the squared bias of the predictions:

$$\mathrm{MSE}(\hat{\theta}) = \mathrm{Var}(\hat{\theta}) + \left(\mathrm{Bias}(\hat{\theta}, \theta)\right)^2 \tag{28}$$

As can be noticed, the MSE does not represent a random value, but an expectation. For an EKF filtering measurements of a fault-free system, this value is known and equal to the innovation variance, as the EKF is an unbiased estimator. The theoretical innovation variances for the different measurements are equal to the diagonal values of the innovation covariance matrix, defined in Eq. (26). To evaluate the performance of the sensor, the MSE of each observed variable can be estimated online through:

$$\hat{\mathrm{MSE}}(\hat{\theta}) = \frac{1}{N}\sum_{i=1}^{N}(\theta_{m_i} - \hat{\theta}_i)^2 \tag{29}$$

where N represents the window width and $\theta_{m_i} - \hat{\theta}_i$ the innovation of the EKF. This estimated value can then be compared with the theoretical variance.

The estimation of the MSE is preferred over estimating the innovation variance, because also "constant" faults, e.g. a jamming or a bias, become detectable with one metric. For these types of faults, the estimated variance of the innovation would not increase, as only the mean would change due to the fault.

The reciprocal of the estimated MSE can also be used as weights to fuse the redundant measurements as long no fault is detected, e.g. θ:

$$\theta_c = \frac{1}{\sum_{i=1}^{3}\frac{1}{\hat{\mathrm{MSE}}(\theta_i)}}\sum_{i=1}^{3}\frac{1}{\hat{\mathrm{MSE}}(\theta_i)}\theta_i \tag{30}$$

As can be noticed, in the case one or two sensors give a bad measurement the faulty measurement will be given a lower weight. The detection and isolation signal will then be based on whether the value of $\hat{\mathrm{MSE}}$ will exceed a preset threshold T_θ. Once the threshold is exceeded, the faulty measurement(s) will be disregarded for the fusion process. The monitoring of the sensor will not stop and therefore if a faulty sensor becomes operational again, the MSE will decrease below the threshold and the measurement will be available again for the measurement fusion process.

Note that the method as presented here is limited to the detection of "output" measurement faults, i.e. signals in $\mathbf{z}$, as defined in Eq. (4). It is assumed that the "input" measurements $\mathbf{u}$ are fault-free.

V. Simulation Results

The method described above is applied to the system described in Sect. III. Simulations were run on the RECOVER benchmark model,[23] which is a detailed simulation of the Boeing 747 including actuator dynamics, wind models and turbulence models. Although the benchmark model was developed for the purpose of evaluating new fault tolerant flight control approaches, the model can easily be extended including sensor faults. The simulations were run at a specific point in the flight envelope; however as already mentioned, the method is valid over the whole flight envelope as the kinematic relations are independent of the flight parameters chosen.

Two main tuning parameters are required to be determined for the application of the filter for each observed variable:

1. The time window N, over which the estimate of the innovation covariance is calculated. This parameter depends on the system dynamics and the minimum required detection time. However, setting this parameter is trivial, and is done by trial and error.

2. The second tuning parameter is the threshold T_θ introduced in the previous paragraph. This parameter can be set based on the theoretical values of the innovation variances and the required FDI performance in terms of detection time and missed detection rate/false alarm rate which involves a trade-off.

Although the matrices $\mathbf{Q}$ and $\mathbf{R}$ can be considered as tuning variables, they are related to the performance of the sensors measuring the input and output vectors $\mathbf{u}$ and $\mathbf{z}$. Therefore, both matrices should be based on the real sensor performances which are considered to be known.

First, the method was applied to the same simulation as shown in Fig. 3(a). The result is shown in Fig. 3(b). As can be noticed, the estimated $\hat{\alpha}$ now follows the correct measurement α_3 and α_1 and α_2 are discarded. As the input measurements are assumed to be fault-free, the prediction of the output variables will be close to the real values. Therefore, if a fault occurs, the innovation and the MSE of the innovation as calculated by Eq. (29) will increase.

Typical results for the scenarios defined in Table 1 are shown in Figs. 4, 5, 6 and 7. In the left figures,

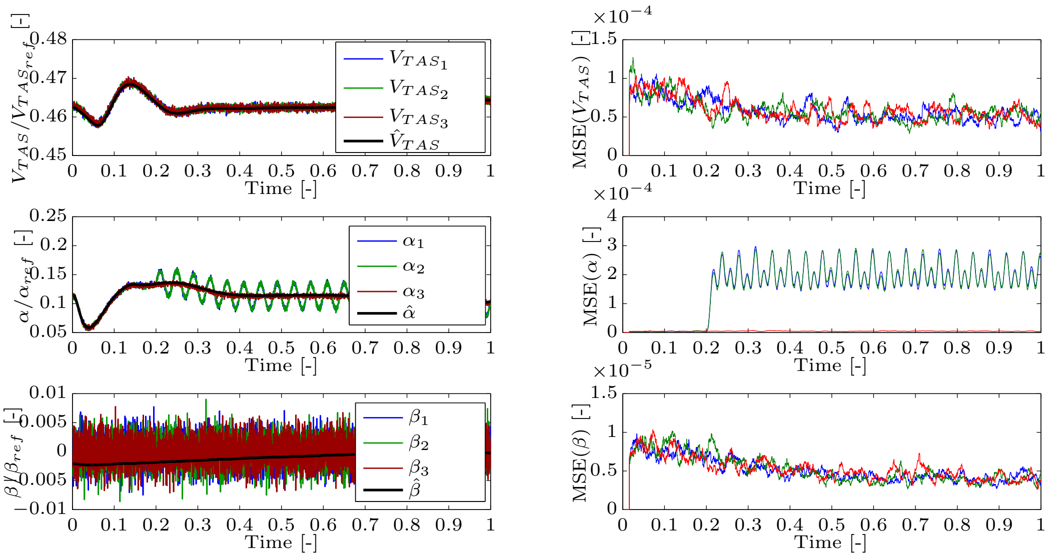


Figure 4. State estimates and MSEs of the observed signals for scenario 1

the measured signals are shown together with their corresponding estimate from the EKF. On the right, the corresponding MSEs can be found. As can be noticed, the algorithm is for every fault scenario capable of isolating the failing sensor and providing a correct estimate of the state. Furthermore, the estimated MSEs give a clear indication of the failing sensors. As mentioned in Sect. II, clear requirements in terms of FAR, MDR, etc. for FDD performance and a general benchmark model are not available in literature. This makes the comparison with other methodologies not possible.

In Fig. 8 the results are shown for a severe pitch-up/pitch-down maneuver during fault-free flight. Here again the algorithm provides a good estimate of the observed states, with low corresponding MSE values. However, some influence of sensor inaccuracies can be noticed, which could limit the detection of small faults. This could be resolved by applying an adaptive threshold for large maneuvers.

VI. Conclusion

This paper presented an algorithm based on an adaptive modification to the EKF that is capable of providing mathematical redundancy for the purpose of ADS fault detection. The main advantages of this method are the independence from the dynamics of the aircraft and it's low tuning complexity. In fact, the only aircraft

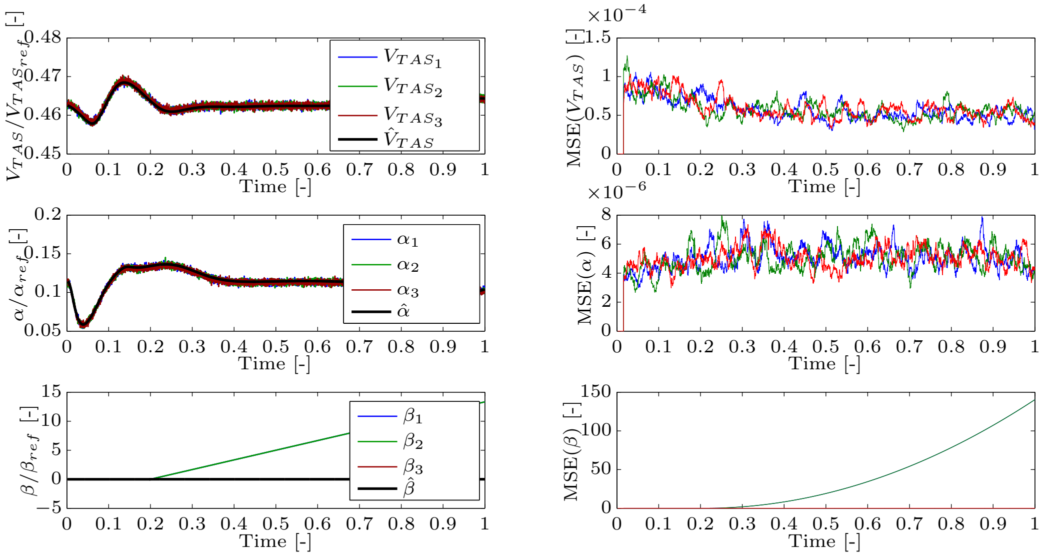


Figure 5. State estimates and MSEs of the observed signals for scenario 2

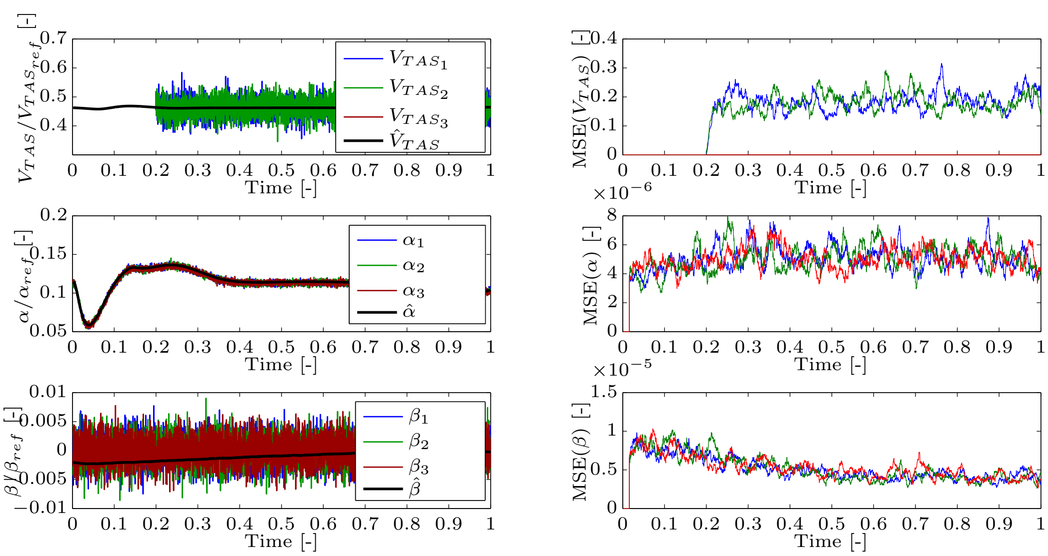


Figure 6. State estimates and MSEs of the observed signals for scenario 3

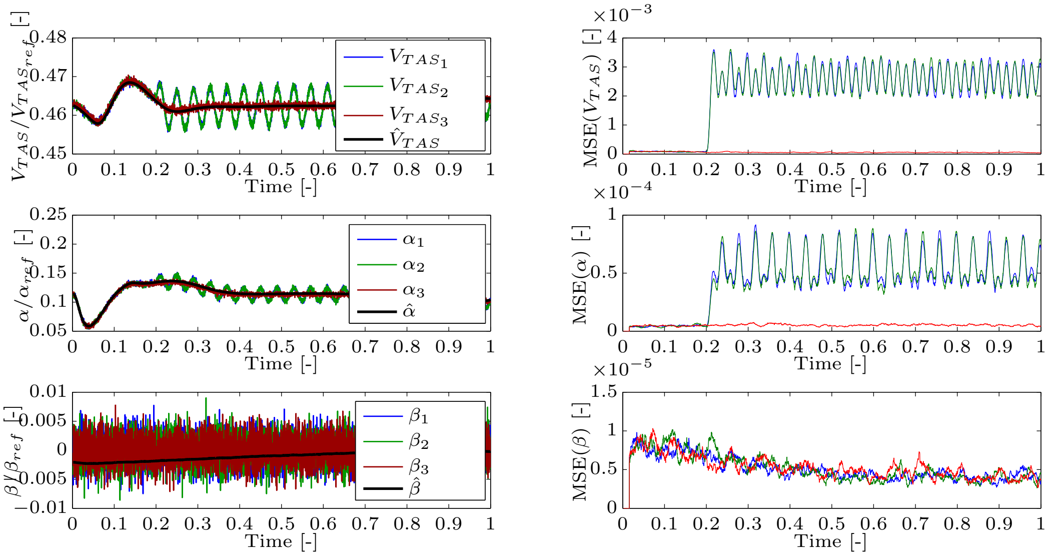


Figure 7. State estimates and MSEs of the observed signals for scenario 4

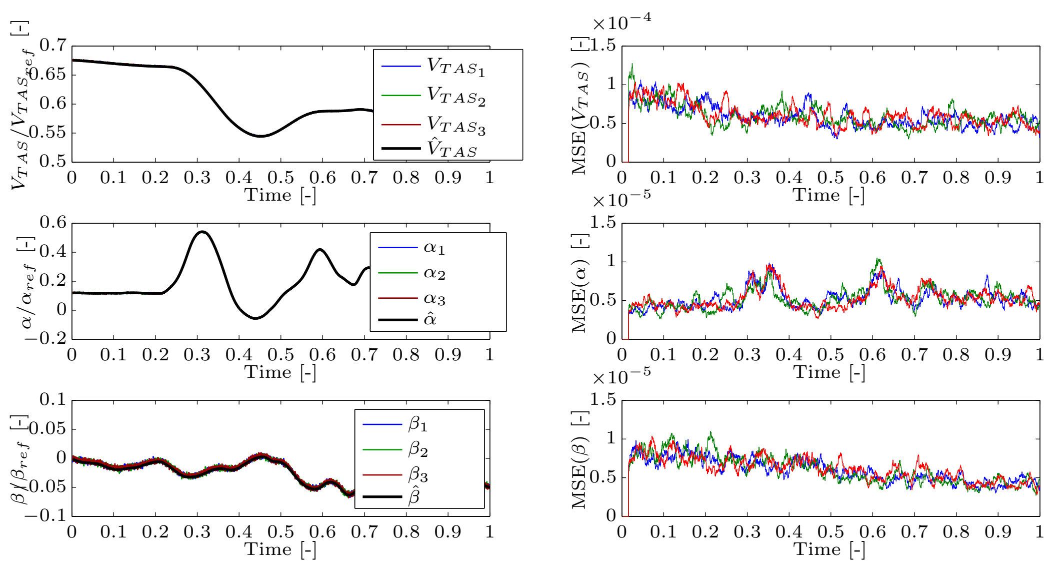


Figure 8. State estimates and MSEs of the observed signals for a fault-free maneuver

specific knowledge required is the exact location of the sensors and the sensor performance characteristics. Because only kinematic and no aerodynamic (forces and moments) relations are used, no special measures need to be taken to make the method valid over the whole flight envelope of the aircraft. This results in a very low tuning complexity, limited to setting a time window and a threshold for each observed variable. A last main advantage of the proposed algorithm is that is completely insensitive to actuator faults. In future work, FDI of the IRU will be covered to create a full FDI solution for ADIRS monitoring. Furthermore, the influence of atmospheric disturbances (turbulence and wind gusts) on the kinematics and the sensors will be investigated such that the method can cope with these disturbances.

References

[1]Traverse, P., Lacaze, I., and Souyris, J., "Airbus fly-by-wire: A total approach to dependability," *Proceedings of the 18th IFIP world computer congress*, Toulouse, France, 2004, pp. 191–212.

[2]Favre, C., "Fly-by-wire for commercial aircraft: the Airbus experience," *International Journal of Control*, Vol. 59, No. 1, 1994, pp. 139–157.

[3]Goupil, P. and Marcos, A., "Industrial benchmarking and evaluation of ADDSAFE FDD designs," *8th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes*, Mexico City, Mexico, 2012.

[4]RTCA, "Software Considerations in Airborne Systems and Equipment Certification, DO-178B," 1994.

[5]Houck, D. and Atlas, L., "Air Data Sensor Failure Detection," *17th Digital Avionics Systems Conference*, No. May 1979, AIAA/IEEE/SAE, 1998.

[6]Eubank, R. D., Atkins, E. M., and Ogura, S., "Fault Detection and Fail-Safe Operation with a Multiple-Redundancy Air-Data System," *AIAA Guidance, Navigation, and Control Conference*, No. August, Toronto, Canada, 2010, pp. 1–14.

[7]Cervia, F., Denti, E., Galatolo, R., and Schettini, F., "Air Data Computation in Fly-By-Wire Flight-Control Systems," *Journal of Aircraft*, Vol. 43, No. 2, March 2006, pp. 450–455.

[8]Freeman, P., Seiler, P., and Balas, G. J., "Robust Fault Detection for Commercial Transport Air Data Probes," *18th IFAC World Congress*, IFAC, Milan, Italy, 2011.

[9]Colgren, R., Frye, M., and Olson, W., "A Proposed System Architecture for Estimation of Angle-Of-Attack and Sideslip Angle," *AIAA Guidance, Navigation and Control Conference*, AIAA, 1999, pp. 743–750.

[10]Berdjag, D., Zolghadri, A., Cieslak, J., and Goupil, P., "Fault detection and isolation for redundant aircraft sensors," *2010 Conference on Control and Fault-Tolerant Systems (SysTol)*, No. 1, Ieee, Nice, France, Oct. 2010, pp. 137–142.

[11]Berdjag, D., Cieslak, J., and Zolghadri, A., "Fault diagnosis and monitoring of oscillatory failure case in aircraft inertial system," *Control Engineering Practice*, Vol. 20, No. 12, 2012, pp. 1410–1425.

[12]Grewal, M. S. and Andrews, A. P., "Applications of Kalman Filtering in Aerospace 1960 to the Present," *Control Systems Magazine, IEEE*, Vol. 30, No. 3, 2010, pp. 69–78.

[13]Del Gobbo, D., Napolitano, M., Famouri, P., and Innocenti, M., "Experimental application of extended Kalman filtering for sensor validation," *IEEE Transactions on Control Systems Technology*, Vol. 9, No. 2, March 2001, pp. 376–380.

[14]Jazwinski, A. H., *Stochastic Processes and Filtering Theory*, Academic Press, New York, 1970.

[15]Allerton, D. J. and Jia, H., "A Review of Multisensor Fusion Methodologies for Aircraft Navigation Systems," *Journal of Navigation*, Vol. 58, No. 03, Aug. 2005, pp. 405.

[16]Mehra, R. K. and Peschon, J., "An Innovations Approach to Fault Detection and Diagnosis in Dynamic Systems," *Automatica*, Vol. 7, 1971, pp. 637–640.

[17]Hajiyev, C., "Testing the covariance matrix of the innovation sequence with sensor / actuator fault detection applications," *International Journal of Control and Signal Processing*, Vol. 24, No. 9, 2010, pp. 717–730.

[18]Marzat, J., Piet-Lahanier, H., Damongeot, F., and Walter, E., "Model-based fault diagnosis for aerospace systems: a survey," *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering*, Vol. 226, No. 10, Jan. 2012, pp. 1329–1360.

[19]Chu, Q. P., Mulder, J. A., and Sridhar, J. K., "Decomposition of Aircraft State and Parameter Estimation Problems," *Proceedings of the 10th IFAC Symposium on System Identification, Vol. 3, Danish Automation Society, Copenhagen, Denmark*, 1994, pp. 61–66.

[20]Duke, E. L., Antoniewicz, R. F., and Krambeer, K. D., "Derivation and Definition of a Linear Aircraft model," Tech. rep., NASA, 1988.

[21]Lombaerts, T. J. J., *Fault Tolerant Flight Control, A Physical Model Approach*, Phd thesis, Delft University of Technology, 2010.

[22]Van Eykeren, L., Chu, Q. P., and Mulder, J. A., "Sensor Fault Detection and Isolation using Adaptive Extended Kalman Filter," *8th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes*, IFAC, Mexico City, Mexico, 2012, pp. 1155–1160.

[23]Smaili, H. M., Breeman, J., Lombaerts, T. J. J., and Joosten, D. A., *Fault Tolerant Flight Control - A Benchmark Challenge*, chap. 6, Springer-Verlag, 2009, pp. 171–212.