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# Application of model-based LPV actuator fault estimation for an industrial benchmark

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ABSTRACT

To bridge the gap between model-based fault diagnosis theory and industrial practice, a linear parameter varying $\mathcal{H}_-/\mathcal{H}_\infty$ fault estimation approach is applied to a high fidelity nonlinear aircraft benchmark. The aim is to show how the fault estimation can provide robust early warning of actuator fault detection scenarios that can lead to abnormal aircraft flight configurations. The fault estimator state space solution is parameterised a priori using parameter-independent design freedom. Following this only constant free matrices are determined and the resulting affine linear parameter varying estimator has low computational load. The evaluation uses parametric simulation via an industry standard Monte Carlo campaign supported by a functional engineering simulator. The simulations are carried out in the presence of aerodynamic database uncertainties and measurement errors covering a wide range of the flight envelope.



## 1. Introduction

In the academic community, the methodologies of model-based fault detection and diagnosis (FDD) have been widely developed in last two decades (Bokor & Szabo, 2009; Chen & Patton, 1999; Ding, 2008; Gertler, 1998; Isermann, 1997, 2005; Korbicz, Koscielny, Kowalczuk, & Cholewa, 2004; Patton, Frank, & Clark, 1989, 2000; Witczak, 2014) and some of them have been successfully applied to aeronautical and aerospace missions (Edwards, Lombaerts, & Smaili, 2010) and have even been implemented in the Airbus industry practice to detect the oscillatory failure (Goupil, 2010; Lavigne, Zolghadri, Goupil, & Simon, 2011). Recently, the application of linear parameter varying (LPV) concepts to system modelling, control and FDD have also received much attention (Alwi & Edwards, 2014; Alwi, Edwards, Stroosma, Mulder, & Hamayun, 1995; Balas, 2002; Bokor & Balas, 2004; Chen, Patton, & Goupil, 2016; Hecker & Pfifer, 2014; Henry, 2008; Henry, Cieslak, Zolghadri, & Efimov, 2014; Ossmann & Varga, 2015; Rotondo, Nejjari, & Puig, 2015; Rotondo, Puig, Nejjari, & Romera, 2015; Sato, 2010; Vanek, Edelmayer, Szabo, & Bokor, 2014; Varga & Ossmann, 2014; Wei & Verhaegen, 2011a). Nevertheless, the technical demands of model-based FDD, especially for the FDD problem based on using LPV, are still quite limited and restrictive in the aerospace industry (Zolghadri, 2012).

As a leading-edge European aerospace FDD project, the EU-FP7 funded ADDSAFE (Advanced Fault Diagnosis for Sustainable Flight Guidance and Control) bridges a gap between the advanced model-based FDD being developed by the academic community and technical solutions demanded by the aerospace industry. The ADDSAFE project benchmark was provided to several academic and industrial partners involved in this project to evaluate the efficiency of their FDD approaches on various fault scenarios (Alwi & Edwards, 2014; Henry et al., 2014; Van Eykeren & Chu, 2014; Vanek et al., 2014; Varga & Ossmann, 2014). The benchmark model is highly representative of a generic twin engine civil commercial aircraft including the nonlinear rigid-body aircraft model with a full set of control surfaces, actuator models, sensor models, flight control laws and pilot inputs. The aim of the project is to highlight the link between commercial aircraft sustainability and fault detection, it can be demonstrated that improving the fault diagnosis performance in flight control systems facilitates the optimisation of the aircraft structural design (resulting in weight saving), which in turn helps to improve aircraft performance and to decrease its environmental footprint (e.g. fuel consumption and noise) (Goupil & Marcos, 2014).

In this paper, an LPV $\mathcal{H}_-/\mathcal{H}_\infty$ fault estimation approach is used to provide the technical solution for the industrial benchmark scenarios. This approach has been widely developed in the

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literature (Ding, Jeinsch, Frank, & Ding, 2000; Grenaille, Henry, & Zolghadri, 2008; Henry & Zolghadri, 2005; Henry, 2012; Li, Mazars, Zhang, & Jaimoukha, 2012; Wang, Yang, & Liu, 2007), based on the original work by Hou and Patton (1997). There have been a number of application studies on aircraft flight control involving the generation of FDD residuals which are robust against modelling uncertainty, gust and turbulence (Li et al., 2012; Marcos & Balas, 2005; Marcos, Ganguli, & Balas, 2005; Wei & Verhaegen, 2011b; Yang & Wang, 2010). The purpose of involving the $\mathcal{H}_-$ index in an $\mathcal{H}_\infty$ optimisation is to establish a trade-off between the fault sensitivity and the robustness of the residual (Hou & Patton, 1997). This paper extends the work in Li et al. (2012) into an LPV framework and proposes a specific $\mathcal{H}_-$ index which allows the fault estimation to be achieved in the presence of parametric uncertainties. The parameterisable solution of the fault estimator is then used to construct an $\mathcal{H}_\infty$ optimisation procedure.

The main motivation of the paper is to bridge the gap between the LPV $\mathcal{H}_-/\mathcal{H}_\infty$ approach and the technical solution required by the industry. The fault scenario 'Aircraft Abnormal Configuration' (Goupil & Marcos, 2014) is selected to be dealt with and the LPV fault estimation approach is implemented at both the local actuator model level and the global system level, to estimate various actuator jamming (also known as lock-in-place failure), those are 'liquid' jamming, 'solid' jamming and the control surface disconnection. The state space solution of the fault estimator is parameterised using a priori parameter-independent design freedom, and therefore only constant free matrices are computed. Compared with the polytopic LPV design approach, where gain matrices with respect to all vertices are required to be calculated and implemented, an affine LPV fault estimator can be implemented straightforwardly based upon using the free matrices, which largely reduces the computational load. Once the faults are estimated or detected in the presence of the parametric uncertainties caused by plant-model mismatch, aerodynamic database uncertainties, sensor noise and imperfect measurements of the scheduling parameters, the faulty actuator can be replaced by the adjacent redundant actuator at a very early stage of each fault development, and hence avoid the aircraft abnormal configuration. Furthermore, for the purpose of evaluating the design computational load, the fault estimator is recoded using the Airbus Flight Control Computer (FCC) software library. The fault estimation/detection results shown in this paper are evaluated based upon the parametric simulation and the Monte Carlo campaign supported by an industrial functional engineering simulator.

The remainder of the paper is outlined as follows: Section 2 introduces the selected ADDSAFE fault scenario to be solved. The LPV modelling encompasses both local and global levels, as discussed in Section 3. Section 4 outlines the LPV $\mathcal{H}_-/\mathcal{H}_\infty$ approach. In Section 5 the ADDSAFE project verification process and industrial limitations are discussed. The parametric and Monte Carlo verification results are given in Section 6.

### 1.1. Notation

For a matrix $X$, $X<0$ denotes that $X$ is negative definite. $X^T$, $X^{-1}$ and $X^\dagger$ denote its transpose, inverse and pseudo-inverse, respectively. $\mathrm{He}\{X\}$ denotes a shorthand notation for $X+X^T$ and $*$ denotes the symmetric entries of a matrix. Let an LPV system be denoted in boldface upper case, for example, a parameter dependent system $\mathbf{G}_{uy}(\rho)$: $u\mapsto y$ indicates $y(s)=G(s,\rho)u(s)$ where $\rho$ is the time-varying scheduling parameter. $\|v\|_2$ denotes the frequency domain 2-norm of the signal $v$. $\mathcal{L}_{2,\Omega}$ is the Lebesgue 2-space, wherein the signal is square integrable and norm bounded in a given finite frequency domain $\Omega$, given by

$$\mathcal{L}_{2,\Omega}=\{v:\ \|v\|_{2,\Omega}<\infty\} \tag{1}$$

where $\|v\|^2_{2,\Omega}=\frac{1}{2\pi}\int_\Omega v'(-j\omega)v(j\omega)d\omega$. The Lebesgue 2-space becomes infinite-horizon when $\Omega=[-\infty,\infty]$.

The frequency-domain $\mathcal{H}_\infty$ performance and $\mathcal{H}_-$ index for an LPV system $\mathbf{G}(\rho)$, appropriate to a given finite frequency range $\Omega$, are defined by

$$\|\mathbf{G}(\rho)\|_{\infty,\Omega}=\sup_{\forall\rho\in\Theta,\forall u\in\mathcal{L}_{2,\Omega}}\frac{\|\mathbf{G}(\rho)u\|_{2,\Omega}}{\|u\|_{2,\Omega}},\quad u\neq0 \tag{2}$$

$$\|\mathbf{G}(\rho)\|_{-,\Omega}=\inf_{\forall\rho\in\Theta,\forall u\in\mathcal{L}_{2,\Omega}}\frac{\|\mathbf{G}(\rho)u\|_{2,\Omega}}{\|u\|_{2,\Omega}},\quad u\neq0 \tag{3}$$

## 2. ADDSAFE benchmark

### 2.1. Fault scenario: aircraft abnormal configuration

The Aircraft Abnormal Configuration scenario is defined within the ADDSAFE benchmark, which concerns the detection of abnormal aircraft behaviour caused by an actuator or sensor fault in the control loop of a control surface, between the FCC and the appropriate moving surfaces. The possible locations of the actuator faults are listed in Fig. 1.

In this paper, three fault sub-scenarios are selected to be solved from the standpoint of rapid and robust fault detection, these are:

- 'Liquid' jamming: A bias fault occurs on the left inboard aileron rod sensor.
- 'Solid' jamming: The left inboard aileron control surface is jammed at a fixed position.
- The control surface of the left inboard aileron is disconnected: A mechanical breakage occurs between the control surface and the actuator rod. Furthermore, the control surface sensor of the left inboard aileron is not necessarily available on all types of the aircraft.

The above fault sub-scenarios all lead to a control surface stuck at a fixed position. In current industrial state-of-practice, if the fault is not detected, it will trigger abnormal aircraft configurations, followed by deflection of other control surfaces to compensate for the effects of the faults, leading to the possibility of excessive fuel consumption. In addition, the compensation commands, corrupted by the faults, also become unreliable. For instance, a control surface jamming occurring on a spoiler or an aileron (as shown in the left-hand side of Fig. 2 will result in constant sideslip and roll rates. This will then raise the deflections of other control surfaces to compensate the asymmetric aircraft motion (as illustrated in the right-hand side of Fig. 2).

The current AIRBUS state of practice is to use a dual active/passive scheme, i.e. an active actuator moving the control surface and adjacent passive actuator in a stand-by mode. So, if there exists a sufficiently early and precise fault estimation/detection, the faulty actuator can be switched off and the adjacent passive actuator becomes active. This provides an opportunity for the flight system to avoid the abnormal flight configuration.

In this work, 'liquid' and 'solid' jamming are modelled as additive sensor faults acting on the local aileron rod measurements, according to

$$\begin{cases} y=x & \text{fault-free case}\\ y=x+f_{liq} & \text{liquid jamming}\\ y=x+f_{sol}(x) & \text{solid jamming}\end{cases} \tag{4}$$

where $y$ are the outputs of the rod sensors and $x$ are fault-free rod