Verification and validation of a FDD system for identification of aircraft control surface jamming ⋆

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Abstract: This paper presents verification and validation results of a model based *fault detection and diagnosis* (FDD) system for reliable detection and identification of aircraft control surface jamming at small deflections. Three main factors contributed decisively to a high reliability of the evaluated FDD system: (1) employing an accurate model of the surface-actuator dynamics in form of a linear parameter-varying model for the synthesis of the fault detection filter; (2) performing an integrated closed-loop tuning of the free parameters of the FDD system using multi-objective optimization techniques to guarantee the lack of false alarms and missed detections, as well as satisfactory detection time performance; and (3) employing numerically sound real-time signal processing techniques to perform fault identification. The verification of the FDD system has been done using standard Monte Carlo simulations, while for validation global optimization-driven worst-case search based robustness analysis has been employed. The final industrial validation has been performed on the AIRBUS actuator test bench and confirmed the satisfactory performance of the FDD system in a true industrial setting.

Keywords: Fault detection, fault identification, actuator jamming, verification and validation.

1. INTRODUCTION

The jamming (or lock-in-place failure) of an aircraft control surface creates a dissymmetry in the aircraft configuration, which must be compensated by appropriate deflections of other control surfaces. Therefore, the jamming leads to the degradation of the aircraft performance due to the increased drag, which depends on the amplitude and localization of the failure. For example, during a long time aircraft operation, a surface jamming may produce substantial drag which can lead to excessive fuel consumptions (with all associated negative environmental effects) and can even impede the fulfillment of the flight mission (i.e., the need for landing on a diverting airport for refueling). Therefore, the timely detection of jamming, especially of the primary control surfaces (e.g., elevator, ruder, ailerons), is important for both an economical and easy-to-handle operation of an aircraft.

To enhance the pilot situational awareness and consequently to perform, if possible, appropriate reconfiguration measures (e.g., passivation of the actuator and/or redistribution of control actions), the jamming must be not only robustly detected (i.e., in the presence of many flight related uncertainties), but also reliably identified. The task of fault identification is to confirm the occurrence of jamming and therefore is crucial for ruling out other type of faults (e.g., runaway, loss of efficiency, oscillatory fault), which require different handling. The jamming of a control surface at null deflection is a special case, which leads to additional challenges regarding its identification. For example, this case requires a special handling due to the difficulty of detecting this fault during cruise operations (i.e., straight level flight), when the intervening actuator input and output signals have very low (nearly zero) energy. For this reason, the detection of jamming at null deflection is only possible during maneuvers (e.g., turns), which involve a sufficiently high level of control activity.

In the framework of the European FP7 project ADDSAFE (Advanced Fault Diagnosis for Sustainable Flight Guidance and Control), the detection of actuator jamming at a small surface deflection, and in particular, the jamming in null position, were formulated as *fault detection and diagnosis* (FDD) benchmark problems. For the solution of some of these problems, new solutions have been developed which are described in (Alwi and Edwards, 2012; Henry et al., 2012; Vanek et al., 2012; Varga et al., 2011; Varga and Ossmann, 2012). In this paper, we additionally address the fault identification aspect, which was not part of the ADDSAFE benchmark formulation (Goupil and Marcos, 2011).

In the current industrial practice, threshold based signal monitoring schemes are widely used. An error signal is

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computed (generally as a function of the actuator command and the achieved surface deflection) which must be greater than a given threshold during a given time to confirm the detection of a surface jamming. The use of first order *linear time-invariant* (LTI) actuator models for model-based fault detection purposes has been also considered for the detection of actuator jamming failures. Because LTI models completely ignores the complex dependency between the actuator dynamics and the aerodynamics forces acting on the control surfaces, their use may raise difficulties in guaranteeing the lack of false alarms over a wide range of variation of flight parameters and in the presence of large parameter variations. Recently proposed advanced techniques based on the use of so-called *linear parameter varying* (LPV) models are therefore better suited for guaranteeing robustness of fault detection performance of flight actuator jamming (Varga et al., 2011; Alwi and Edwards, 2012; Henry et al., 2012; Vanek et al., 2012).

In this paper we present *verification and validation* (V&V) results of a model based *fault detection and diagnosis* (FDD) system for reliable detection and identification of flight actuator jamming at small surface deflections (including jamming at null deflection). For the detection of jamming we employ the discrete-time version of the LPV-model based fault detection approach of Varga et al. (2011), extended with the fault identification functionality. An integrated closed-loop tuning of the free parameters of the FDD system using multi-objective optimization techniques has been performed to guarantee the lack of false alarms and missed detections, as well as satisfactory detection time performance. The fault identification aspect has been addressed using numerically sound real-time signal processing techniques. The V&V of the FDD system has been done using both standard Monte Carlo based methods and advanced worst-case search based optimization-driven robustness analysis. Both analyses have shown the high robustness of the FDD system. The final industrial validation, performed on the AIRBUS actuator test bench, confirmed the satisfactory performance of the FDD system in a true industrial setting.

2. FDD SYSTEM SETUP

The FDD system in Fig. 1 for the detection and identification of actuator jamming must work in conjunction with a stable closed-loop flight control system, whose main components are the open-loop aircraft, the controller, the actuator and sensor blocks. The controller processes the pilot command vector $\underline{u}_p(t)$ used to perform various maneuvers and the measured outputs vector $\underline{y}_m(t)$ delivered by the sensors using the aircraft output vector $\underline{y}(t)$, and produces the actuator command vector $\underline{u}_c(t)$. The actuator output signals form the vector $\underline{u}(t)$ representing the corresponding surface deflections. The FDD system, whose detailed structure is presented in Fig. 2, processes a single actuator output signal $u(t)$ and the corresponding actuator command $u_c(t)$, which are selected via the selector block from the components of the actuator output vector $\underline{u}(t)$ and actuator command vector $\underline{u}_c(t)$, respectively. Additionally, the aircraft parameters $p(t)$ are used for gain scheduling purposes. The output of the FDD system is the confirmation signal $\eta(t)$, which indicates the presence or absence of actuator jamming.

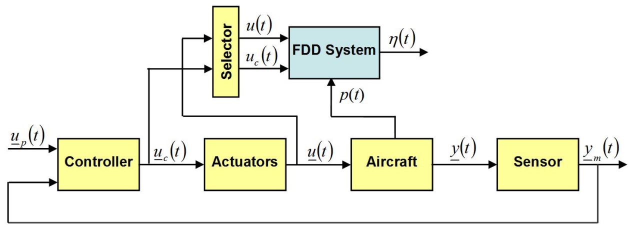

Fig. 1. Fault monitoring setup for FDD of jamming of a single actuator

The FDD system used to detect and identify actuator jamming is depicted in Fig. 2, where besides the residual generator, blocks for residual evaluation, decision making and fault identification are present. The fault identification involves the determination of the main characteristics of a surface jamming: the (mean) value u_{jam} of the control surface deflection angle and the corresponding variance σ, which in the case of jamming must be a value nearby to the variance of the measurement noise.

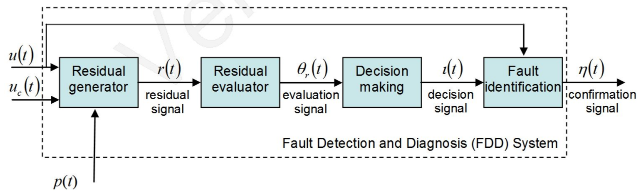

Fig. 2. FDD system for monitoring of jamming

The main components of the FDD system are now described with more details in what follows.

Residual generator: The fault detection filter (called also residual generator) generates the residual signal $r(t)$ using the measurable quantities $u(t)$ actuator output, $u_c(t)$ actuator command, and $p(t)$ a vector of measurable parameters. The function of the residual generator block is to produce a zero residual signal if there is no fault, and a non-zero residual signal when a fault is present. In practice, the presence of various uncertainties and measurement noise leads to nonzero residual signals even in the non-faulty case and therefore a suitable threshold on the magnitude of the residual signal is used to distinguish between nearly zero and nonzero signals.

The underlying model employed to describe the flight actuator and control surface dynamics can be approximated by a first order nonlinear differential equation model in a *quasi*-LPV form

$$\dot{u}(t) = K(u(t), p(t))(u_c(t) - u(t)), \qquad (1)$$

where $K(u,p)$ is the actuator gain, which depends on the surface deflection u and parameter vector p. Details of this model are available in (Goupil, 2010). It is shown in (Varga et al., 2011) that, with highly accuracy, $K(u,p)$ can be approximated as

$$K(u,p) = C_0(p) + C_1(p)\,\mathrm{sign}(\dot{u})(u + C_2(p)), \qquad (2)$$

where $C_0(p)$, $C_1(p)$ and $C_2(p)$ are affine approximations in the components of the parameter vector p. These components are the gain scheduling variables, which for this study have been chosen as the mass m, the position of center of gravity along x-axis X_{cg}, the calibrated air speed V_{cas} and the aircraft altitude h.

Using the transfer-function based expression developed in (Varga et al., 2011), the fault detection filter can be chosen in the *quasi*-LPV form

$$\begin{aligned} \dot{z}(t) &= -az(t) - \frac{aK(u(t),p(t))}{k_0}u_c(t) \\ &\quad + \frac{a(K(u(t),p(t))-a)}{k_0}u(t) \\ r(t) &= z(t) + \frac{a}{k_0}u(t). \end{aligned} \tag{3}$$

In (3), a is a free constant parameter which specifies the dynamics of the filter, while k_0 is a gain normalization factor (for example, a nominal value of the nonlinear gain $K(u,p)$).

For a discrete-time implementation with a sampling time T, we assume that the values of $u(t) = u(iT)$, $u_c(t) = u_c(iT)$ and $K(u(t),p(t)) = K(u(iT),p(iT))$ are constant on each sampling period for $t \in [\,iT, (i+1)T\,)$, for $i = 1, 2, \ldots$. The discretized fault detection filter can be implemented as

$$\begin{aligned} z((i+1)T) &= e^{-aT}z(iT) - \frac{(1-e^{-aT})K(u(iT),p(iT))}{k_0}u_c(iT) \\ &\quad + \frac{(1-e^{-aT})(K(u(iT),p(iT))-a)}{k_0}u(iT) \\ r(iT) &= z(iT) + \frac{a}{k_0}u(iT), \end{aligned} \tag{4}$$

For a discrete-time implementation of the gain (2), we can evaluate $\mathrm{sign}(\dot{u}(iT))$ as $\mathrm{sign}(u(iT) - u((i-1)T))$.

Typical values of the free parameters are: $T = 0.01 \div 0.04$sec, $a = 10 \div 20$ and $k_0 = 14 \div 30$.

Interestingly, the same residual generator can be used for the detection of different categories of faults, as jamming, runaway, oscillatory failure, surface angle sensor bias (liquid jamming) as suggested in (Varga et al., 2011; Varga and Ossmann, 2012).

Residual evaluator: The residual evaluator generates the evaluation signal $\theta_r(t)$ representing an approximation of the signal norm of $r(t)$. For decision making, an easy to compute measure of the residual signal energy $\|r(t)\|_2$ is necessary. For this purpose, the use of Narendra type fault evaluators is recommendable. These are first order filters of the form

$$\begin{aligned} \xi_r((i+1)T) &= \gamma_r \xi_r(iT) + |r(iT)| \\ \theta_r(iT) &= \xi_r(iT) + \alpha_r |r(iT)| \end{aligned} , \tag{5}$$

where α_r is a weight on the current residual values and γ_r is a suitable forgetting factor. Typical values of these free parameters are $\alpha_r = 0.1 \div 0.5$ and $\gamma_r = 0.995 \div 0.999$.

Decision making: The decision making block generates the decision signal $\iota(t)$ indicating the presence ($\iota(t) = 1$) or absence ($\iota(t) = 0$) of a fault using a simple threshold based logic

$$\iota(iT) = \begin{cases} 0, \text{ if } \theta_r(iT) < \tau \\ 1, \text{ if } \theta_r(iT) \geq \tau \end{cases} , \tag{6}$$

where τ is a suitable decision threshold.

Fault identification: The fault identification block generates the confirmation signal $\eta(t) = 1$, if jamming is confirmed or $\eta(t) = 0$, if jamming is not confirmed. The fault identification is triggered at time $t = t_d$, when the presence of a fault has been detected (i.e., the output of the decision block in Fig. 2 is $\iota(t) = 1$ for $t \geq t_d$). To confirm jamming at a constant deflection u_{jam}, the following computations are needed:

1. Collect n samples of the output variable $u(t)$: $u_1 = u(t_d + T'), \ldots, u_n = u(t_d + nT')$.
2. Compute u_{jam} as the mean of n samples: $u_{jam} = \frac{1}{n}\sum_{i=1}^{n} u_i$.
3. Compute the variance of n samples: $\sigma = \frac{1}{n-1}\sum_{i=1}^{n}(u_i - u_{jam})^2$.
4. If $\sigma \leq \tau_u$, then set $\eta(t) = 1$; else, set $\eta(t) = 0$.

Here, T' is the sampling period used to collect the n samples (usually $T' \leq T$) and τ_u is a threshold for zero (or negligible) variance. Typical values of the main parameters of the identification procedure are $T' = 0.01$, $n = 50 \div 300$ and $\tau_u = 0.01 \div 0.05$.

This computational approach requires the storage of n samples, which is not desirable for real time computations. Fortunately, it is possible to use recursive evaluation formulas of the mean and sample variance which avoid any additional storage needs and are based on a numerically stable computational method (Welford, 1962). The implementation of this algorithm starts with the initializations $m_1 = u_1$ and $s_1 = 0$, and recursively computes

$$\begin{aligned} m_k &= m_{k-1} + (u_k - m_{k-1})/k \\ s_k &= s_{k-1} + (u_k - m_{k-1})(u_k - m_k) \end{aligned}$$

for $k = 2, \ldots, n$. Then, $u_{jam} = m_n$ and $\sigma = s_n/(n-1)$. With this approach, the confirmation time t_c of a surface jamming is roughly equal to $t_c = t_d + nT'$.

The special case of jamming of a control surface at null deflection can alternatively be handled by computing the evaluation signals θ_{u_c} and θ_u for $t = 0, T, 2T, \ldots$ using Narendra-type filters similar as used in (5)

$$\begin{aligned} \theta_{u_c}((i+1)T) &= \gamma_{u_c}\theta_{u_c}(iT) + |u_c(iT)| \\ \theta_u((i+1)T) &= \gamma_u \theta_u(iT) + |u(iT)| \end{aligned} \tag{7}$$

The jamming at null deflection can be confirmed if the conditions for non-zero input $\theta_{u_c} \geq \tau_{u_c}$ and zero output $\theta_u < \tau_u$ are simultaneously fulfilled, where τ_{u_c} and τ_u are appropriate thresholds for nonzero and zero energy signals, respectively. A typical setting of the corresponding forgetting factors γ_{u_c} and γ_u must fulfill the condition $1 > \gamma_u > \gamma_{u_c}$ imposed by the signal transmission causality requirements.

3. TUNING OF FREE PARAMETERS

The free parameters of the fault evaluation and decision block can be determined in an optimal way, such that typical requirements as lack of false alarms and missed detections, as well as constraints on detection times are fulfilled. Multi-objective optimization based tuning strategies have been described, for example, in (Varga and Ossmann, 2012), where the term *integrated tuning* has been employed to emphasize that the FDD system runs with a robustly stable closed-loop system as shown in Fig. 1.

For the tuning of the FDD system, the values of the parameters α_r and γ_r of the residual evaluation block have been determined by maximizing the gap $\tau_d - \tau_f$, where τ_f is the *false alarm bound*, representing the largest magnitude of θ_r over all normal operation points of the aircraft, all relevant pilot maneuvers, all admissible variations of uncertain parameters (e.g., aerodynamical coefficients, measurements), for all relevant disturbances (e.g., typical wind spectra), while τ_d is the *detection bound*, representing the smallest amplitude of θ_r over all relevant fault cases. The maximization of $\tau_d - \tau_f$ has to be done such that the fault detection time satisfies $t_d \leq t_{detec}$, where t_{detec} is the maximum allowable detection time. Here, t_d stays for the maximum detection time over all uncertainties mentioned previously.

For the discrete-time fault detection filter in (4), we employed the typical values: $T = 0.01$sec, $a = 14$ and $k_0 = 14$. The optimal setting of the parameter of the residual evaluation filter (5) is $\alpha_r = 0.3$ and $\gamma_r = 0.998$ and the choice $\tau = 0.1$ of the detection threshold satisfies $\tau_f \leq \tau \leq \tau_d$. This leads to a completely satisfactory fault detection performance.

4. VERIFICATION AND VALIDATION

The determination of the threshold τ relies on worst-case search-based evaluations of the false alarm and detection bounds, and therefore its choice above guarantees the fulfillment of all basic performance requirements. To provide supplementary information on the robustness of the overall detection time performance of the FDD system, optimization-based search techniques have been used to determine the global worst-case detection time. The analysis itself relies on repeated simulations of the nonlinear model of the closed-loop aircraft including a nonlinear control law ensuring robust stability over the whole flight envelope (see Fig. 1). The main uncertainties are the flight conditions (altitude, speed) over the whole flight envelope and the full range of variations of the aircraft mass and center of gravity position. While the limits of the altitude h and the mass m are fixed, the limits of the center of gravity X_{cg} depend on the actual mass, while the limits of the calibrated airspeed V_{cas} depend on the actual mass and altitude. This leads to somewhat reduced bounds for these parameters depending on the concrete flight condition (Varga et al., 2011). Additionally, uncertainties in the aerodynamic database, in the measurements of altitude and velocity, and in the accuracy of the estimations of the mass and center of gravity have been considered.

4.1 Verification using Monte Carlo simulation

In the ADDSAFE Project, the *Functional Engineering Simulator* (FES) environment described in (Goupil and Marcos, 2012) has been used for the verification of the FDD designs. The FES is based on MATLAB-Simulink and built around the aircraft closed-loop nonlinear simulation benchmark model augmented with the designed FDD system as shown in Fig. 1. For randomly generated combinations of the uncertain parameters, the analysis tools implemented in FES evaluate several indicators which allow to assess the performance characteristics of the FDD system. In this section we summarize the results of an extensive industrial benchmarking of the designed FDD system obtained using the FES.

Within the validation campaign with FES a total of 1200 validated points in the flight envelope have been used to test the robustness of the designed FDD system in fault free cases during six demanding maneuvers (e.g., pitch protection and angle of attack protection maneuvers). None of these test points/maneuvers triggered any false alarms. To test the detection performance, the jamming at small deflections of the elevator during cruise and smooth turn maneuvers has been tested in 1000 different flight points. In particular, jamming at null deflection occurring in cruise had to be detected during turn maneuvers. Note that jamming at small deflections during smooth maneuvers poses challenges for the fault detection, due to the small amplitudes of the residual signals. The Monte Carlo analysis provided a mean detection and identification time of 3.57sec with a standard deviation of 0.92sec and a maximum detection time of 10.65sec. In Fig. 3 the histogram of the identification times determined by the Monte Carlo simulations are depicted. It can be observed that most of the 1200 fault cases are detected and identified nearly in minimum time of 3.01sec, and only a few ones are delayed. These delays are caused by the presence of very small control inputs and hence, small residuals, especially at high velocities in the flight envelope.

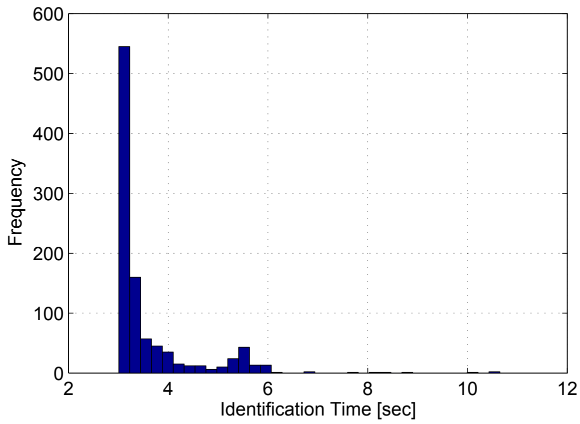

Fig. 3. Histogram of the fault identification times

4.2 Validation using worst-case search

While Monte Carlo simulation can be seen as a useful verification technique (e.g., well suited for rapid prototyping), for validation purposes it is necessary to use alternative approaches which are able to cover continuous uncertain parameter ranges, provide guarantees for lack of hidden weaknesses and determine worst-case parameter combinations to serve for design enhancements. Therefore, for the validation of the FDD design, a global optimization-based worst-case search is a suitable approach which fulfils all above requirements and delivers (usually in shorter times than with Monte Carlo simulation) accurate estimations of worst-case parameter combinations, for example, by maximizing the fault detection and identification time. The optimization environment MOPS (Multi-Objective Parameter Search) of DLR (Joos, 1999) provides an easy access to different optimization algorithms together with visualization tools of the computed results and even of the intermediary iterations. For the maximization of the fault detection and identification time, the *differential evolution* (DE) global search method has been employed (Storn and Price, 1997). This method allows to perform many function evaluations in parallel, which significantly contributes to alleviate the associated computational burden due to expensive simulation runs. The optimization has been performed on a Linux cluster with 16 CPUs at 2.6 GHz running MATLAB Parallel Toolbox. An optimization run, involving about 1500 function evaluations, took around 15 minutes.

The resulting worst case detection and identification time of the jamming for the designed FDD system was 18.09sec, which is still completely satisfactory for an industrial usage. Note that this time is about 40% higher than 10.65sec, the time found by Monte Carlo simulations. Fig. 4 depicts the search points in the normalized flight envelope and normalized weight-and-balance diagram, which have been generated by the DE method during the worst case optimization. Values of the identification time larger than 10sec are marked with red crosses, while values lower than 10sec are marked with blue circles. As it can be seen, the more critical region of the flight envelope from the point of view of a fast identification of the jamming corresponds to high velocities in combination with a more forward center of gravity position. This parameter combination makes the control task easier by needing smaller size inputs to steer the aircraft, but adversely affects the detection and identification times of the faults.

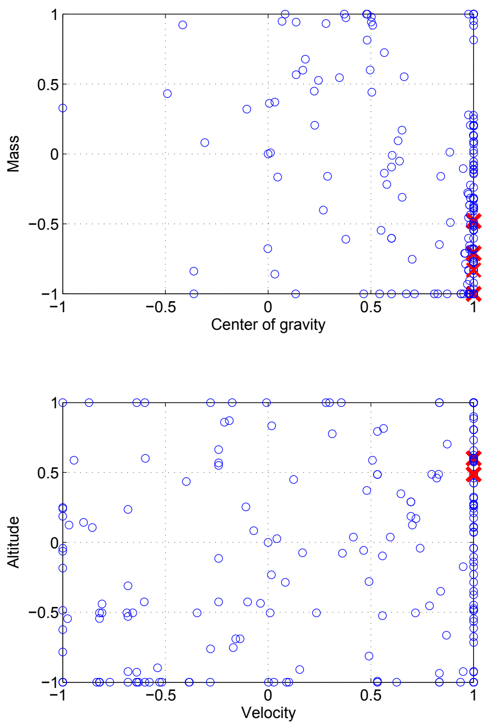

Fig. 4. Search points generated by the DE method

5. INDUSTRIAL EVALUATION

The industrial V&V activities that have been subsequently performed are part of a typical aircraft industrial development process. An important prerequisite for this is the implementation of the FDD system on the flight control computer of the fly-by-wire aircraft system environment. Code generation tools have been used for this purpose, which allow the automated generation of certifiable real-time codes. In a first step, a graphical tool has been used to specify the block diagram structure of the FDD system (computer aided-specification). In contrast to the equivalent Simulink-based block diagram modelling, only a limited set of certified elementary blocks (so-called graphical symbols) can be used to describe the functionality of the underlying fault detection and identification algorithms. Dedicated functional specification sheets have been used for this purpose. The FDD system specification is under the control of a configuration management tool, which allows a partially automated syntax checking too. In a second step, a code generation tool produces the associated code to be directly implemented in the flight control computer.

The industrial evaluation has been performed using hardware-in-the-loop simulations with a flight actuator test bench as the one presented in Fig. 5. The test bench is built around a real elevator actuator with simulated command inputs, aerodynamic forces and hydraulic pressures, providing continuous monitoring of computer internal variables. This bench offers the possibility to validate the FDD system in degraded configurations, as in the case of low hydraulic pressure and high loads on the control surface.

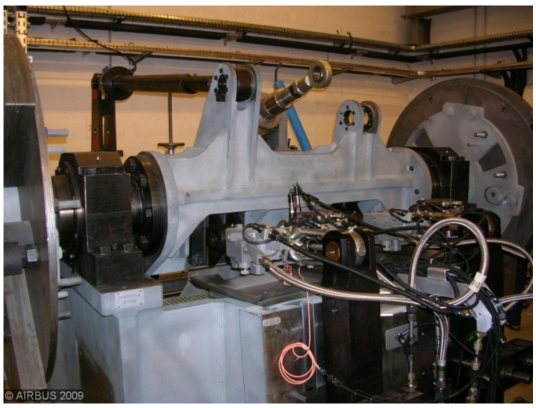

Fig. 5. Flight actuator test bench

The industrial validation campaign consisted of the assessment of the robustness (i.e., the lack of false alarms) and of the detection performance (i.e., the lack of missed detections and satisfactory detection time). The robustness of the FDD designs has been assessed during pure lateral manoeuvres, pure longitudinal manoeuvres and during mixed manoeuvres (combining lateral and longitudinal movement in the same manoeuvres). Both smooth and dynamic manoeuvres have been performed, as for example, auto-pilot manoeuvres, flight control checks, take-off and landing, certification manoeuvres, etc. The detection performances have been assessed by simulating the jamming failure scenario, during a classical flight and during specific manoeuvres. The results have shown a high degree of robustness of the designed FDD system for the whole range of tests and a highly satisfactory detection performance.

A typical detection result of a jamming at a surface deflection of $-2°$ is presented in Fig. 6.

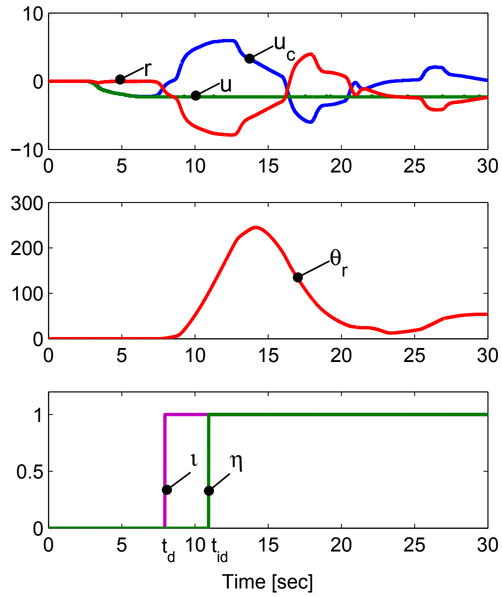

Fig. 6. Detection and identification of a jamming at $-2°$

In Fig. 7 we present an example for the detection of a jamming at a null surface deflection. As it can be observed, the dedicated identification scheme based on Narendra-type filters (7) has a significantly shorter identification time t_{id0} than the identification time t_{id} resulting when employing a general purpose fault identification method of jamming at arbitrary deflections.

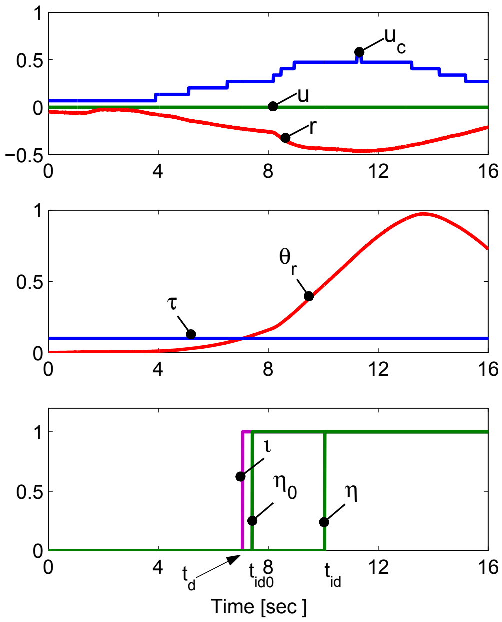

Fig. 7. Detection and identification of a jamming at $0°$

6. CONCLUSION

This paper clearly demonstrates via an extensive V&V campaign, that the methodology developed in (Varga et al., 2011; Varga and Ossmann, 2012) for the synthesis of FDD systems using LPV-model based synthesis can be successfully applied to develop a robust FDD system for the identification of the jamming of an elevator actuator. For this case, the strong requirements for no false alarms, no missed detections and short fault detection times can be completely fulfilled over the whole flight envelope and in the presence of significant parametric uncertainties and measurement noise. By performing a preliminary robustness assessment using either the Monte Carlo simulation based analysis or advanced global optimization-based worst-case search, substantial cost reductions of the final industrial V&V can be expected. The industrial V&V results show a good potential of the developed FDD system for industrial use.

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