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FDI Design and Verification using a High-Fidelity Industrial Airbus Nonlinear Simulator

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Abstract

This paper considers the problem of designing FDI algorithms for aircraft, within the scope of the FP7 RECONFIGURE project. Taking advantage of a high-fidelity AIRBUS industrial aircraft simulator (a key asset of the project), this paper provides an overview of the FDI design approach adopted by DEIMOS. A high-level description of the FDI synthesis procedures, including a global optimization-based approach to tuning, is provided. Finally, verification results, obtained with a Functional Engineering Simulator (FES) tailored for RECONFIGURE, and validation tests, performed at AIRBUS' facilities, are discussed.

1. Introduction

This paper considers the problem of designing Fault Detection and Isolation (FDI) algorithms for aircraft within the scope of the European Framework 7th project termed "REconfiguration of CONtrol in Flight for Integral Global Upset REcovery (RECONFIGURE)". RECONFIGURE[1] was a project co-funded by the European Commission, from 2013 to 2016, under the coordination of DEIMOS and with the participation of AIRBUS and several European universities and research institutes. The project aimed to support the investigation and development of advanced aircraft Guidance and Control (G&C) technologies that facilitate the automated handling of off-nominal and abnormal events, while simultaneously alleviating the pilots' task and optimizing aircraft performance. This automatism and optimization must be performed while maintaining the current aircraft safety level which is compliant with present-day regulations. In addition, anticipating more stringent future regulations, RECONFIGURE may also contribute to advance the current safety level - see [8]. Within the scope of this project, a series of aircraft fault scenarios is considered, assuming a myriad of types of sensor, actuator, and dynamics failures.

The problem of FDI has been extensively studied at both academic and industry levels. Since the early 1970's, the growing demand for safety and reliability bolstered a number of studies and research programs related to FDI - one of the first surveys on FDI and Fault Detection and Diagnosis (FDD) was presented in [13], and the theoretical basis for control reconfiguration appeared in [3]. Nevertheless, most of the reliability improvements of Flight Control Systems (FCSs), until the early 1980's, were attained by using hardware redundancy, which adds weight and volume to the aircraft, while also increasing the maintenance complexity and costs, and degrading flight performance.

Thanks to the use of Fly-By-Wire (FBW) approaches, a remarkable number of safety and performance improvements in terms of flight control were made possible. Nevertheless, new issues were also raised due to, for instance, the limited reliability of the onboard computers. To deal with these setbacks, different techniques were adopted by the industry. For instance, typical commercial airplanes have several onboard computers, each of which capable of operating the aircraft by itself. Each computer may be composed of independent units continuously monitoring each

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other. These units are composed of distinct hardware parts and execute software written in languages with different functionalities and architectures, thus reducing the likelihood of having the same error distressing all the computers – see [5], [7].

The idea behind modern FDI, however, is not to add redundant equipment, but rather to use a priori information regarding the plant (including, if available, the expected types of faults) to distinguish between nominal and faulty operation conditions, as described in the sequel.

Fault detection methods can typically be divided into two sets, according to their model-based or data-driven nature - see [9]. In general, model-based approaches are likely to attain higher levels of performance, whenever an accurate model of the plant (and faults) is available. Regarding data-driven methods, these are usually lighter in terms of model knowledge requirements, but their behavior under unpredicted conditions may be uncertain. It is important to stress that, despite of being referred to as *data-driven approaches*, some of these solutions require prior knowledge regarding the model of the system, although still avoiding the explicit derivation of a dynamic model. As an example, *limit checking* strategies require the nominal values of the variables/signals analyzed, that need to be obtained from flight data.

Driven by the stringent requirements of the RECONFIGURE benchmark, the FDI solution adopted by DEIMOS relies both on data-driven methods – for the detection of trivial but non-negligible faults, such as unrealistic step changes in the sensor measurements – and model-based approaches – for the detection of faults affecting, for instance, more than one redundant sensor (hence possibly not detected by voting schemes). Therefore, on the one hand, data-driven techniques were adopted to detect a large class of faults, thus allowing the overall FDI algorithm to attain the desired level of fault detection rate. On the other hand, model-based methods, complementary to those ones, were employed to improve the detection rate while also providing estimates of the corrected airspeed (VCAS) and Angle-of-Attack (AoA) in case of concurrent fault of all of the redundant sensors of the same type. In fact, the RECONFIGURE benchmark included the fault scenario in which all of the VCAS and/or AoA sensors were faulty, and required the very challenging estimation of VCAS and/or AoA, respectively, under those circumstances. It is also stressed that this benchmark includes a high-fidelity AIRBUS aircraft model as a key asset of the project, which ensured industrial representativity of the problem and of the results.

In terms of model-based approaches, techniques such as multiple-model methods typically aim to select the "best" model for the plant among a set of a priori plausible systems, while residual-based methods, such as H_∞ FDI, address the problem of synthesizing filters that estimate the fault signals or generate signals that are "large" under faulty conditions, and "small" under nominal operation. Although both methods were evaluated by DEIMOS within RECONFIGURE, this paper focuses on H_∞ FDI design and tuning, as this was the approach chosen for final testing on the AIRBUS facilities. A detailed discussion on the results obtained is provided.

1.1 RECONFIGURE's Design and V&V Approach

The design, verification, and validation approach adopted in RECONFIGURE is illustrated in Figure 1.

Figure 1. Design, verification, and validation steps in RECONFIGURE

The first high-level step of this process is the design of the FDI system. This step involves the selection of fault scenarios, the modeling of the aircraft dynamics in nominal and faulty conditions, and the synthesis of the FDI filters. This step also encompasses preliminary tradeoffs between algorithms and methodologies, to select the most promising approaches for verification.

The second step is performed by using the industrial, high-fidelity Functional Engineering Simulator (FES) described in [6]. A key output of this step is the assessment of the several approaches evaluated, so that a limited number of algorithms are tested in the subsequent phase.

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The final step of this process is the validation of the FDI algorithms at the AIRBUS' facilities, by using an even higher-fidelity simulator, allowing to put a human in the loop for typical industrial tests completed by the simulation of real event-inspired simulations.

1.2 Organization of the Paper

Taking advantage of the high-fidelity AIRBUS industrial aircraft simulator, this paper provides an overview of the FDI design approach adopted by DEIMOS within the scope of RECONFIGURE, by:

- describing the (Linear Fractional Transformation) **LFT modeling** approach – Section 2;
- giving an overview of the **FDI synthesis procedures**, including the proposition of a global **optimization-based approach to the selection of the tuning knobs** of the FDI filter – Section 3;
- describing the **preliminary verification** of the results with a Functional Engineering Simulator (FES) particularly tailored for the project – Section 4;
- evaluating the results of the **validation campaign** performed at the AIRBUS' facilities – Section 5.

Finally, the conclusions of the paper are discussed in Section 6.

2. Modeling Approach and Tradeoffs

2.1 Nonlinear Simulator

The high-fidelity industrial Airbus nonlinear simulator was implemented by using the architecture depicted in Figure 2. The FDI and control systems are implemented in the "Windows side", running Matlab/Simulink. The reference actuations are sent to the "Linux side", which implements the 6DoF nonlinear model of the aircraft. In addition, a set of parameters (flight point, wind, faults, etc.) is specified at the beginning of each simulation run.

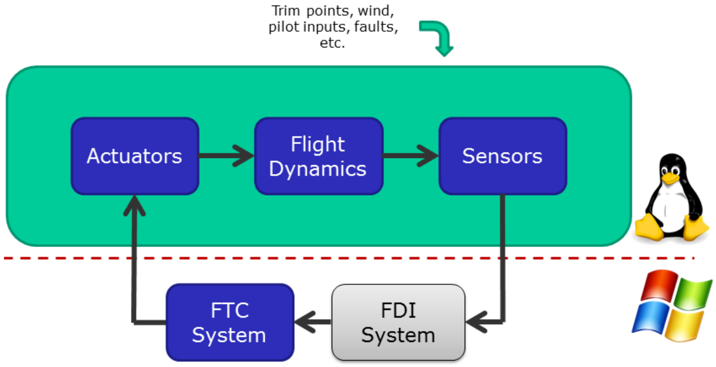

Figure 2. Nonlinear simulator implementation

The Functional Engineering Simulator (FES) described in [6] was developed for RECONFIGURE, implementing the aforementioned architecture and providing an industrial and common framework for simulation for all the partners in the consortium.

2.2 Model for FDI

Within the scope of RECONFIGURE, a set of 214 LTI models was provided by AIRBUS, corresponding to several flight conditions gridding the aircraft flight envelope. Each of these LTI models approximately describes the nonlinear dynamics implemented in the simulator, up to a level of accuracy that is typically deemed sufficient for control design purposes. However, FDI methods tend to be more susceptible to model mismatch, in the sense that false alarms can be issued due to inconsistencies between the simulator and model responses.

Thus, a thorough comparison between linear and non-linear models responses, as well as a derivation of a set of transformations that improve model matching and enhance the LTI-based model description (required for the subsequent tasks, in particular for the construction of the LFT model of the aircraft) was performed. The FDI designs

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described herein take advantage of those model enhancements and LFT-based realizations [12] to have a more accurate description of the aircraft.

2.3 Linear Fractional Transformation (LFT)

A Linear Fractional Transformation (LFT) model is a representation of a dynamic system using two matrix operators in a feedback interconnection: M = [M_{11} M_{12}; M_{21} M_{22}] and Δ. The operator M represents the nominal, known part of the model of the system, while Δ contains the time-varying, unknown, or uncertain components - see Figure 3. Although strictly not necessary, and without loss-of-generality, Δ is typically assumed norm-bounded by 1.

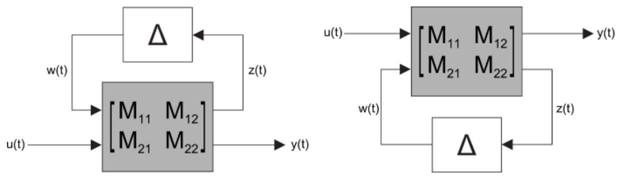

Figure 3. Lower and upper (left and right figures, respectively) LFT graphical representation

Assuming an uncertain model of the plant is available, the LFT formulation allows to completely decouple the nominal system from the uncertain part, and to reformulate the robustness requirements in terms of optimal control and, specifically, in terms of the H_∞ norm minimization from the exogenous inputs to the performance outputs.

Depending on the problem at hand, the blocks M and Δ can either be static or dynamic, or even time-varying. This allows the representations of a wide range of systems, which can include uncertain parameters, and frequency-dependent model uncertainty (such as uncertain time-delays), among others (cf. [14]).

Based on the enhanced LTI models derived, an LFT model covering the aircraft flight envelope was developed and validated. The LFT validation aimed to ensure that:

- One (or possibly more) LFT model covers the set of flight conditions considered with reasonable accuracy;
- The main characteristics of the LTI models are preserved within the LFT model, both in the frequency and the time domains;
- The LFT model contains the hull of the realizations of the dynamics of all the LTI models considered.

In order to validate the LFT model, time and frequency responses, as well as model parameters, have been compared against those of the LTI models. For instance, in Figure 4, the comparison of the normalized Mα derivative is shown for each LTI model and the corresponding instance of the LFT model. It can be seen that the approximation of Mα adequately matches, in general, the behavior of the LTI models over the several Flight Points (FP) considered. More importantly, the LFT model derivative appears to cover most of the LTI models values as the LFT parameters vary within the prescribed ranges.

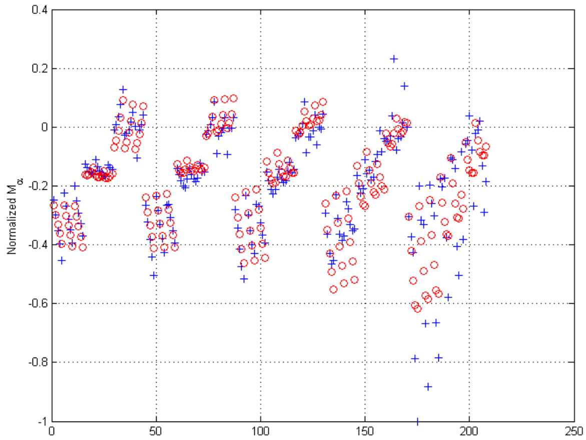

Figure 4. Mα approximation for the i-th flight point (FP) (blue: LTI, red: LFT)

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Concerning the time-domain analysis, the step responses of the LFT model were validated against those of the 214 LTI models in RECONFIGURE. In Figure 5(a-b-c), the mean relative errors between LTI and LFT responses over half of the slowest time-constant of the model are shown for each FP, respectively in terms of vertical acceleration (Nz), Angle of Attack (AoA), and pitch rate(q). As summarized in Table 1, the average error obtained is reasonably small, with mean errors in the range 5%-7%.

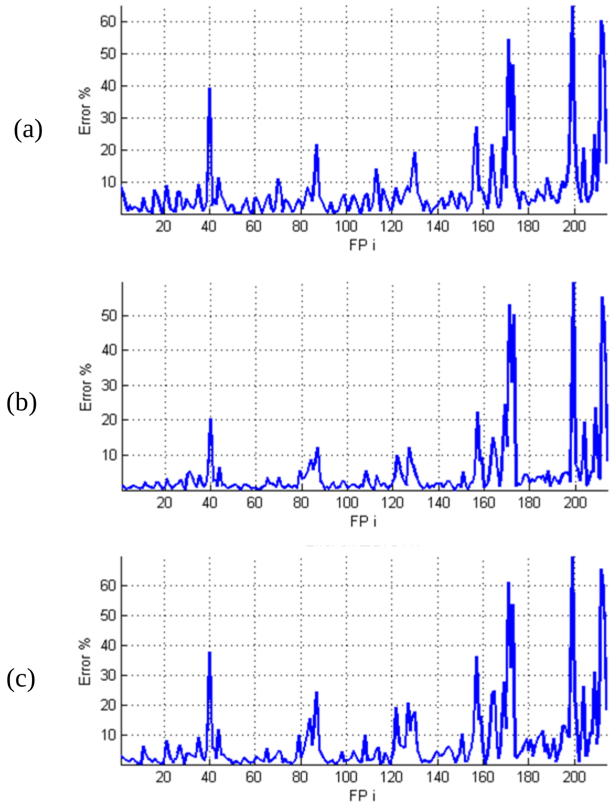

Figure 5: Mean percentage error of the step response:
vertical acceleration(a), AoA(b), pitch rate(c)

Table 1: Step response mean errors

Errors	Nz	AoA	q
Mean:	6.73%	4.43%	6.89%
Mean(Max_{FPi}):	11.12%	8.86%	14,17%

3. Model-based FDI Synthesis

This section describes the model-based FDI synthesis approach adopted in this work by DEIMOS and that was selected for the validation phase of RECONFIGURE, given its characteristics in terms of robustness, design simplicity, and performance, obtained in the verification phase.

The strategy followed is based on H_∞ and mixed-μ FDI filter synthesis, with an automated dynamic weight selector based on global optimization methods, to facilitate and systematize the design process and ultimately improve the quality of the results.

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3.1 H_∞/mixed-µ FDI Design

The synthesis of H_∞ and mixed-µ solutions for FDI is based on methods that explicitly address robustness-performance specifications. The main motivation for the use of H_∞ optimization is to obtain a fault estimation generator that is *robust*, in the sense that

- It reliably and accurately detects and isolate faults;
- It has reduced sensitivity to exogenous disturbances, noise and system uncertainty.

One of the distinguishing features of H_∞ filters is that they explicitly account for model uncertainty [1], [2], [4]. As such, they provide for a direct way to trade-off the level of robustness to uncertainty with the level of performance of the FDI filter. This is especially important in filtering problems, since it has a direct impact on the false alarm versus missed fault rates - which are critical for the practical applicability of an FDI filter and its industrial deployment.

In order to satisfactorily design an H_∞ FDI filter, attention must be paid to:

i. the selection of the *for-design* models, i.e. selection of operating conditions, input and output signals;
ii. correct and methodological weight definition;
iii. proper validation, namely using worst-case results given by robustness-performance analysis tools.

In the design of an H_∞ filter, the plant is augmented to include disturbances (such as wind) and to account for actuator and sensor faults. Uncertainties are included by means of LFTs, and frequency weights are introduced to shape the desired performance-robustness characteristics. This generates the so-called the *generalized plant* (actuators, sensors, and weighting functions are embedded in the plant description).

In the filter synthesis, the fault detection and isolation problem is defined as the problem of finding a filter F that maximizes the effect of the faults on the estimation errors, while minimizing the transfer functions from the disturbances to the errors. The optimization problem corresponds to that of solving an Algebraic Riccati Equation (ARE), for which well-known solvability conditions exist.

The µ-synthesis theory extends the H_∞ optimization results to the case where the uncertainties are structured, thus providing less conservative results. In these cases, the µ framework can significantly improve the performance of the synthesized FDI filter, at the cost of solving a more complex optimization problem, using the so-called D-K iterations for complex-valued uncertainties, and the D,G-K iterations for mixed real- and complex-valued structured uncertainties - see [1], [2]. In spite of the added computational complexity in solving the optimization problem, the resulting filter is an LTI system and hence as straightforward to implement as in the classical H_∞ design.

The essence of the model-based open-loop FDI problem is depicted in Figure 6 and can be formalized as: Given a model of the nominal system G_u and knowledge (measured or estimated) of the inputs u and outputs y of the system, determine a filter $F=[F_U\ F_Y]^T$ that provides a fault estimate[2] with information on the faults f entering the system (through G_f). This fault estimate can provide an indication of the fault's presence – *fault detection* – or provide as well an indication of the fault location/source – *fault isolation* [4]. Fault detection requires only a single signal (scalar), while fault isolation requires a set (vector) of fault estimates in order to be able to distinguish between faults.

[2] What is termed herein as a "fault estimate" is often also referred to as a "residual signal" in the general FDI community. We prefer to use the former term to distinguish it from the general concept of a residual, which is any signal formed by subtracting from a measured signal its ideal version, so that all effects not accounted for in the idealized signal (i.e. uncertainty, faults, noise, etc.) are shown in the residual.

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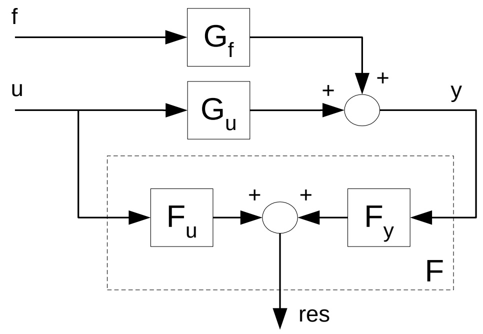

Figure 6. Basic FDI design architecture

The H∞ FDI technique has been assessed in the aeronautical and aerospace domains, including studies that consider high-fidelity nonlinear simulation models. The obtained results have shown that H∞ is an effective methodology to deal with the fault detection and isolation problem in aerospace vehicles. Moreover, in the FP7 European project entitled "Advanced Fault Diagnosis for Sustainable Flight Guidance and Control (ADDSAFE)", several H∞-based FDI schemes have been developed and shown to be valid up to a TRL of 5/6 in AIRBUS V&V benches [10].

3.2 Dynamic Weight Tuning with Global Optimizers

The selection of the dynamic weights, which can be interpreted as the tuning knobs of an H∞ filter, is one of the key tasks of the design process, typically requiring a substantial work effort and a large number of iterations. In this work, however, a Hybrid Differential Evolution (HDE) global optimization algorithm was adopted to perform this repetitive task. This methodology allows, in addition, pursuing time-domain requirements such as the maximum missed detections rate, as well as frequency-domain characteristics, such as reduced sensitivity to measurement noise, within the same framework. In particular, the algorithm illustrated in Figure 7 was used.

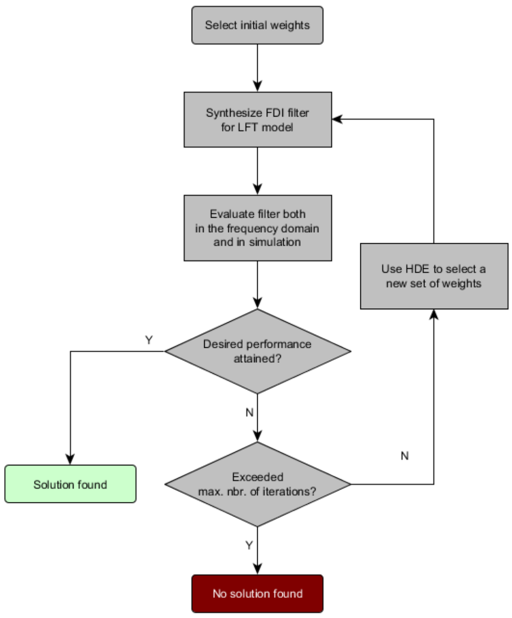

Figure 7. FDI filter synthesis dynamic weights optimization

4. Verification

As mentioned in Section 1.1, the overall RECONFIGURE industrial V&V is a two-step process that aims to evaluate the Technological Readiness Level (TRL) of the FDD/FTC (Fault Tolerant Control) designs and consists of:

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- Industrial verification: verification of the design in Matlab/Simulink environment with traditional Monte-Carlo analysis complemented by worst-case search tools.
- Industrial validation: validation of the designs in the AIRBUS V&V process, including tests with pilot-in-the-loop simulations using real flight code and avionics – Section 5.

As previously mentioned, a Functional Engineering Simulator (FES) was designed to support the industrial verification step providing a simulation environment to carry out the verification and benchmarking of the algorithms. This is based on a set of validation criteria (i.e. detection, estimation, control, reconfiguration, etc.) and their corresponding validation domains, which can be grids of operating points (parametric analysis) or sets of points randomly taken from the flight envelope (Monte-Carlo analysis).

The verification benchmark implemented in the FES allows testing the FDI techniques in fully realistic situations, considering several parameters:

- Flight point: defined by the set of calibrated airspeed, altitude, slat/flap configuration and landing gear position (i.e. up or down).
- Mass case: defined by the aircraft gross weight and the position of the center of gravity.
- Flight Control Unit (FCU) inputs: defined as a sequence of time-referenced selections of the flight controls used by the crew for engagement of auto-pilot and auto-thrust modes, guidance modes and selection of flight parameters (i.e. speed/ Mach, altitude, vertical speed/flight path angle, heading/track).
- Pilot inputs: defined by time-referenced actions on the sidestick, pedals, thrust lever, air brakes control, slat/flap control or landing gear control.
- Fault activation: a set of fault activation and configuration parameters that define the type of fault (i.e. freeze, noise, oscillation, bias, non-return-to-zero, runaway), the injection point (i.e. what sensor or actuator is the fault applied on) and the fault signal shape (e.g. magnitude, duration).
- Wind perturbations: defined as time-referenced wind speed components and turbulence components.

An extensive simulation campaign was carried out in the FES to cover all the abnormal and fault scenarios. It was additionally included a set of robustness scenarios, where no faults were considered in the system, to assess the algorithms' performance in nominal flight. The complete test campaign consisted of 27 simulation sets, for a total of 2106 runs in non-faulty conditions, and 2106 runs in faulty conditions. The results obtained for the H_∞ FDI designed are summarized in Table 2, grouped by robustness and faulty scenarios.

Table 2. Industrial verification results for the H_∞ FDI approach

Scenario	False alarms	Missed detections	True detections
Robustness	2.0%	N/A	N/A
Faulty	0.2%	<0.1%	99.7%

It can be seen that, for the faulty scenarios, the proposed FDI solution is characterized by good performance, with only 0.2% (4 out of 2106) false alarms, in addition to 1 missed detection situation. These cases were analyzed and the following conclusions were reached:

Table 3: False alarms and missed detections description

Case #	Applicable Scenarios	Description	Remarks/Possible solution
1	Double side-stick step inputs	**1 missed detection** The simulation ends 5 s after the fault occurrence.	The simulation stops given that the pilot's command would lead the aircraft too close to the ground. **Thus, the FDI system did not have enough time to operate properly.**
2	Double side-stick step inputs	**4 false alarms** The AoA fault detection threshold is barely crossed.	This problem can be easily solved by tuning of the fault threshold. **The solution is trivial.**

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On the other side, the relatively large number of false alarms observed in the robustness scenarios was caused by extreme conditions. These scenarios were investigated in detail, and the following conclusions were reached:

Table 4: False alarms description

Case #	Applicable Scenarios	Description	Possible solution
1	Extreme wind (head or rear)	The total of 36 false alarms in these scenarios was caused by the indistinguishability between VCAS sensor failures and wind disturbances. In other words, the FDI system is not able to distinguish between a ramp-like wind profile that increases to a very large magnitude (e.g. several dozens of kts), and a runaway type of fault in the three VCAS sensors.	Obtain a more accurate, high-fidelity model of the aircraft, Or Increase the threshold used to declare faults, at the cost of reducing the capability of the FDI system to quickly detect faults. **Both solutions are non-trivial.**
2	Double side-stick step inputs, AoA protection	The AoA fault detection threshold is barely crossed.	A small increase of the threshold potentially solves the problem without significantly degrading the missed detections rate. **The solution is considered trivial.**

As a general comment, it should be noticed that **the FDI system was tuned taking into account general objectives** (such as the tradeoff between robustness to model uncertainty and exogenous disturbances, and sensitivity to faults), **rather than the specific Monte-Carlo (MC) campaign**. This has the advantage of rendering the FDI system less tailored to the MC cases, and hence similar results would be obtained if a different set of simulation runs was selected. The drawback is that the optimal rate of true detections for the specific MC campaign is not obtained.

In terms of estimation error, the results obtained satisfy the requirements from AIRBUS, although a significant degradation was observed near the boundaries of the flight envelope. The exact figures are omitted for confidentiality.

5. Validation

To complement the FES verification campaign, an even more industry-oriented validation campaign was set up allowing to put a human in the loop for typical industrial tests completed by the simulation of real event-inspired simulations. In these real event-inspired tests, performed at AIRBUS' facilities, more than 20 families of tests were performed. Each family consisted of several test scenarios to be simulated in different flight and aircraft configurations and related to the scenario of interest, covering robustness and performances assessment.

The preliminary results (prior to FDI tuning) are summarized in the following table.

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Table 5. Validation results

Scenario	Preliminary Results	Final Results
Robustness 1.2		
Cruise, long – no variation of VCAS, AoA	**OK**	**OK**
Slow variation – VCAS	**OK**	**OK**
Slow variation – AoA	**OK**	**OK**
Change of slats/flaps configuration, 0-4	**OK**	**OK**
Cruise, airbrakes out/in	**OK**	**OK**
Take-off/low alt, erroneous mass	**OK**	**OK**
Medium alt, erroneous mass, no AP	**OK**	**OK**
In service winds		
In service wind 1	**False Alarm**	**OK**
In service wind 2	**False Alarm**	**OK**
In service wind 3	**False Alarm**	**OK**
In service wind 4	**OK**	**OK**
In service events		
In service event 1	**Missed detection**	**OK**
In service event 2	**Missed detection**	**OK**
In service event 3	**Missed detection**	**OK**
In service event 4	**OK**	**OK**
In service event 5	**OK**	**OK**

The preliminary FDI system, therefore, did not achieve the required levels of robustness and performance. As a consequence, the subset of scenarios where the algorithm did not perform as desired were analyzed and minor changes to the algorithm were implemented to minimize the number of false alarms and missed detections.

In particular, since the tuning of the adopted FDI algorithm revolves around the tuning of the filter and the appropriate selection of the residuals thresholds used to declare faults, the threshold was redefined as

$$th(t) = c_{th}(t) + g_{th}(t)|u(t)| \tag{1}$$

where $c_{th}(.)$ is a bias in the threshold to account for disturbances and measurement noise, and $g_{th}(.)$ relates the magnitude of the control input signal with that of the threshold. For the problem at hand, a constant $g_{th}(.)$ was deemed sufficient to attain the desired performance/robustness levels.

It was shown in RECONFIGURE that a **minor tuning** of the FDI algorithms proposed by DEIMOS can lead to substantially improved results for the AIRBUS validation scenarios proposed. In fact, all of the problematic cases were solved by this tuning step. I.e., **the results thus obtained were satisfactory in all the previously problematic cases**, leading to no missed detections and no false alarms in the validation scenarios.

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6. Conclusions

This paper considered the problem of designing Fault Detection and Isolation (FDI) algorithms for a large commercial aircraft, within the scope of the FP7 RECONFIGURE project. The methodology developed relies both on data-driven methods – for the detection of trivial but non-negligible faults, such as unrealistic step changes in the sensor measurements – and model-based approaches – for the detection of faults affecting, for instance, more than one redundant sensor. However, the focus of this paper is on the model-based part of the proposed FDI approach, as this is the one considered to pose more challenging design issues.

An H_∞/mixed-μ filter synthesis approach was adopted for that, applied to a Linear Fractional Transformation (LFT) model of the system, due to advantages in terms of robustness/performance tradeoffs selection, as well as to the capability to explicitly consider model uncertainty. A global-optimization-based method was proposed for the tuning of the dynamic weights required for the synthesis of the filter, which can be seen as the tuning knobs of the process. This solution significantly decreased the design effort of the filter, allowing for a systematic tuning of the FDI system when (or if) the aircraft model is updated.

Taking advantage of a high-fidelity AIRBUS industrial aircraft simulator (a key asset of the project), the results from the industrial verification have shown that, for the faulty scenarios, only 4 out of 2106 false alarms, in addition to 1 missed detection situation. For the robustness tests, however, a false-alarm rate of nearly 2% was obtained, which is a clear violation of the requirements. Nevertheless, such false alarms were observed in very extreme conditions only, which indicates that this figure would be substantially smaller in a Monte-Carlo (MC) campaigned centered in nominal scenarios.

The FDI system was tuned taking into account general objectives (such as the tradeoff between robustness to model uncertainty and exogenous disturbances, and sensitivity to faults), rather than the specific MC campaign, which, as previously mentioned, was not a typical one, as it was one of the key goals of RECONFIGURE to test the limits of state-of-the-art FDI technologies. Therefore, the FDI system was less tailored to the MC cases, and hence similar results would be obtained if a different set of simulation runs was selected. However, the optimal rate of true detections for the specific MC campaign was not obtained.

The FDI system was then evaluated at AIRBUS' facilities within the RECONFIGURE validation campaign. The preliminary results have shown that false alarms and missed detection cases occurred under specific configurations, related to extreme flight/environmental conditions. These issues were addressed by a minor tuning of the FDI threshold, leading to no missed detections and no false alarms in the validation scenarios

Acknowledgments

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References

[1] Balas, G., Chiang, R., Packard, A., Safonov, M., "Robust Control Toolbox v3.0", Mathwoks, 2006

[2] Balas, G.J., Doyle, J.C., Glover, K., Packard, A., Smith, R. "μ-Analysis and Synthesis Toolbox", Musyn-Mathworks, June 1998

[3] Beard, R.V., "Failure accommodation in linear systems through self-reorganization." PhD diss., MIT, 1971

[4] Chen, J., Patton, R.J. "Robust Model-based Fault Diagnosis for Dynamic Systems", Kluwer Academic Publishers: Dordrecht, 1999.

[5] Favre, C., "Fly-by-wire for commercial aircraft: The Airbus experience", International Journal of Control, 59(1), 139–157, 1994

[6] Fernández, V., Montaño, J., Recupero, C., Kerr, M., Rosa, P., Boada-Bauxell, J., & Dalbies, L., “A Tool for Industrial Verification and Benchmarking of FDD/FTC Designs”, IFAC SafeProcess’15, 48(21), pp. 1006-1011, 2015

[7] Goupil, P., “AIRBUS state of the art and practices on FDI and FTC in flight control system”, Control Engineering Practice 19, pp. 524-539, 2011a, DOI information: 10.1016/j.conengprac.2010.12.009, 2011

[8] Goupil, P., Boada-Bauxell, J., Marcos, A., Rosa, P., Kerr, M. and Dalbies, L., “An overview of the FP7 RECONFIGURE project: industrial, scientific and technological objectives”, IFAC SafeProcess’15, 48(21), pp.976-981, 2015

[9] Isermann, R., "Fault-diagnosis systems: an introduction from fault detection to fault tolerance," Springer, 2005

[10] Marcos, A., “Assessment on the ADDSAFE Benchmark Simulator of an H-infinity Fault Detection Design for Aircraft,” SAFEPROCESS 2012, Mexico, September 2012

[11] Puyou, G., Goupil, P. “Preliminary Benchmark Scenario Definition,” RECONFIGURE TN D1.1.2, version 3.0 April 2013.

[12] Rosa, P., Vasconcelos, J., Kerr, M., "A Mixed-μ Approach to the Integrated Design of an FDI/FTC System Applied to a High-Fidelity Industrial Airbus Nonlinear Simulator." IFAC SafeProcess’15, 48(21), pp. 988-993, 2015

[13] Willsky, Alan S., "A survey of design methods for failure detection in dynamic systems." Automatica 12.6 (1976): 601-611.

[14] Zhou, K., Doyle, J. C., Glover, K., "Robust and optimal control" (Vol. 40), Upper Saddle River, NJ: Prentice Hall, 1996

[15] Zolghadri, A., Castang, F., Henry, D., “Design of Robust Fault Detection Filters for Multivariable Feedback Systems,” International Journal of Modelling and Simulation, 26(1), 2006