MODEL BASED FAULT DETECTION FOR AN AIRCRAFT ACTUATOR

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Abstract

A trend in actuator design leads to integrate the control into the unit itself so that the modern actuator includes an advanced electronic. This feature can be used to integrate fault diagnosis capabilities into the component. This paper deals with two analytical methods which allow a precise and comprehensive fault detection. The feasibility for a diagnosis tool will be proved with both methods and a comparison introduces some perspectives for the on-board application.

1 Introduction

The principal requirement for control systems in a modern aircraft is safety. To ensure a very low failure rate, redundant structures are used: duplex for mechanical,and triplex or even quadruplex for electrical devices because the latter are the most frequent causes for total failure. However, the conventional redundancy has disadvantages due to costs, weight, volume, energy consumption, failure rates and maintenance costs. In order to reduce the use of redundancy, fault detection and isolation schemes have to be introduced.

This paper deals with the use of analytical redundancy to improve the reliability of a primary flight control electro-hydraulic actuator. With analytical redundancy, the use of a plant model to generate a pseudo-sensor (redundancy) is understood. With this information on the plant-internal states, it is possible to decide on its safety. As consequence, a reliable and precise fault detection and diagnosis will enable "maintenance on demand" and therefore an improved system reliability.

To increase the precision of our diagnosis, two approaches for residual generation are combined. With an Extended Kalman Filter (EKF), some parameters of the system can be estimated. With the parity relation approach, on the other side, the possibility of state estimation is explored. A great challenge is then the combination of both of them in a comprehensive scheme.

After a brief introduction on the considered actuator and its typical faults, the EKF and the parity relations are introduced. For the parity space, several methods to improve the detectability of faults and the robustness of residuals are presented. Finally, the results are compared and a conclusion on the complementarity for the methods is given.

2 Faults in electrohydraulic Actuators

The plant, for which we developed the fault detection and diagnosis scheme, is an electro-hydraulic aircraft actuator. In contrast to servo concepts, the main control valve is directly driven by a quadruplex force motor. These actuators belong to the aircraft's primary control path and are therefore underlying strong safety demands. Any double fault in the system must not result in a total failure. Therefore the actuator is duplex redundant in its hydraulic components (supplied by two hydraulic systems) and quadruplex for all electric parts (see Fig. 1) including all position sensors.

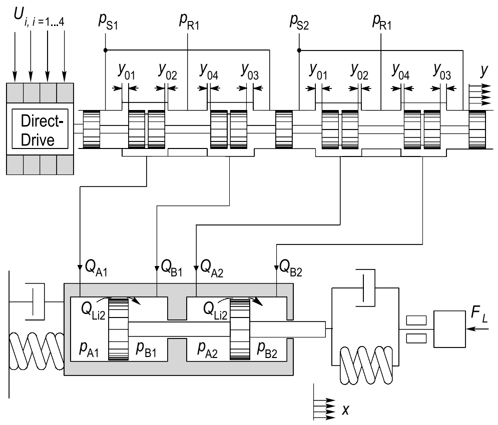

Fig. 1 Electro-hydraulic Actuator.

Relevant faults affecting the dynamic properties are:

- Sensor bias and scale factor faults
- Sensor hard faults (e.g. $0V$, $\pm 10V$)
- Force motor coil shortcut and break
- Increased valve friction
- Internal tandem cylinder leakage
- Increased valve edge wear (valve change necessary)

The results of the EKF have been proved with an actuator test rig which allows reversible implementation of all mentioned faults. For the parity space approach, we had to content ourselves with some simulated performance because a new test rig is under construction.

3 Model-based Diagnosis with EKF

3.1 System Model

To save numerical effort, the actuator model was split up into a 4th order tandem-cylinder model and a 7th order valve model.

For the direct drive valve (DDV) the inputs, states and outputs are:

$$\begin{aligned} \underline{u}_{DDV} &= [U_1 \quad \dots \quad U_4 \quad (p_S - p_R)] \\ \underline{x}_{DDV} &= [\psi_{C1} \quad \dots \quad \psi_{C4} \quad \psi_h \quad \dot{y} \quad y] \\ \underline{y}_{DDV} &= [i_1 \quad \dots \quad i_4 \quad y_{S1} \quad \dots \quad y_{S4}] \end{aligned} \tag{1}$$

where i_1 up to i_4 are the coil currents, y_{S1} up to y_{S4} the valve position sensor signals, ψ_{C1} up to ψ_{C4} the magnetic flow in each coil, ψ_h the main flow.

For one of the tandem cylinders the inputs, states and outputs are:

$$\begin{aligned} \underline{u}_{Cyl} &= [y_{DDV} \quad \dot{x}_{Cyl} \quad x_{Cyl} \quad (p_S - p_R)] \\ \underline{x}_{Cyl} &= [p_{A1} \quad p_{B1}] \\ \underline{y}_{Cyl} &= [p_{A1} \quad p_{B1}] \end{aligned} \tag{2}$$

3.2 Extended Kalman Filter

For the online estimation of the nonlinear system parameters an Extended Kalman Filter has been used. The dynamic states $\underline{x}_{dyn}$ are extended by the estimated parameters $\underline{x}_P$:

$$\underline{x} = \begin{bmatrix} \underline{x}_{\mathrm{dyn}} \\ \underline{x}_{\mathrm{P}} \end{bmatrix}, \tag{3}$$

The extended state-vector for the direct drive valve (DDV) model and ram model are given by:

$$\begin{aligned} \underline{x}_{DDV} = \; & [\psi_{C1} \dots \psi_{C4} \;\; \psi_h \;\; \dot{y} \;\; y \;\; R_{C1} \dots R_{C4} \\ & F_C \;\; D_{vis} \;\; Sb_1 \dots Sb_4 \;\; Skf_1 \dots Skf_4]^{\mathrm{T}} \end{aligned} \tag{4}$$

$$\begin{aligned} \underline{x}_{Cyl} = \; & \Big[p_{A1} \;\; p_{B1} \;\; K_{Li} \;\; \alpha_D \sqrt{\tfrac{2}{\rho}} \\ & E \;\; y_{01} \;\; y_{02} \;\; y_{03} \;\; y_{04} \Big]^{\mathrm{T}} \end{aligned} \tag{5}$$

where K_{Li} is the inner leakage coefficient, α_D the discharge coefficient, E the effective bulk modulus and y_{01} up to y_{04} the overlap lengths, R_{C1} up to R_{C4} the coil resistors, F_C the Coulomb friction, D_{vis} the viscous damping coefficient, Sb_j the bias and Skf_j the scale factors of each sensor j. Further details can be obtained from [7] and [10].

The extended Kalman-Filter [2] in continuous-discrete form has been used to perform parameter estimation. To improve stability and to achieve realtime capability the following modifications to the standard algorithms had to be employed:

- Calculation of the covariance: the transition-matrix $\underline{\Phi} = e^{\underline{F}T_S}$ from the Jacobian $\underline{F}$ is done with implicit Euler transformation and fast matrix inversion at each sampling step:

$$\underline{\Phi} \approx (\underline{I} - T_S \underline{F})^{-1}. \qquad (6)$$

- Due to numerical errors at each propagation the upper diagonal matrix of $\underline{P}$ is mirrored into the lower diagonal matrix to enforce symmetry. Positive semidefiniteness is not guaranteed by this measure but has never been critical with 32-bit floating point precision.

- For the adaptation of time-variant parameters the random walk approach [2] and [8] according to eq. (7) is chosen:

$$\underline{P}_p(t_{k+1}|t_k) = \underline{P}_p(t_k|t_k) + \underline{Q}_p(t_k), \qquad (7)$$

  For a longer period of missing excitation the update of the parameter error covariance is small. The approximately linear increase by eq. (7) has to be limited to physically sensible values by a first-order parameter-variance-model (state-variance-model still according to random-walk).

$$\begin{aligned} \dot{\underline{x}}_p(t) &= -T_{para}\,\underline{x}_p(t) + \underline{w}_p(t) \quad (8) \\ \underline{P}_p(t_{k+1}|t_k) &= (1 - \frac{T_A}{T_{para}})^2 \underline{P}_p(t_k|t_k) + \\ &\quad + \underline{Q}_p(t_k) \quad (9) \end{aligned}$$

  T_{para} denotes how long a missing input is tolerated. While input is missing, the covariance reaches a final value determined by $\underline{Q}$ and T_{para}. Therefore no surveillance layer like for a RLS algorithm [6] is necessary.

The described algorithms were implemented on a DSP realtime platform.The following sampling times including data acquisition have been achieved:

- Tandem-cylinder: 2 ms
- DDV model: 5 ms

The implementation proved detection and quantitative diagnosis for all relevant faults described in chapter 2 under the assumption that the system is enough excited. As an example, diagnosis of internal tandem cylinder leakage is shown in fig. 2.

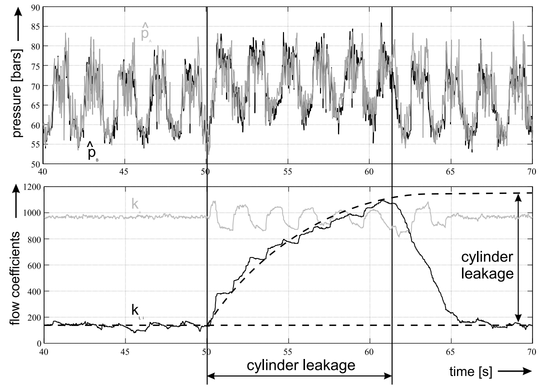

Fig. 2 Diagnosis of internal cylinder leakage.

4 Parity space for the DDV

4.1 Parity relations

With the parity space, a model is related to its plant without feedback. A fault is identified comparing the outputs of both systems, plant and model.

Please refer for further information into the classical development to [5].

Generally, some degrees of freedom exist the state elimination of the system equations. Further, they have been used to structure the parity relations, so that all equations are independent of one parameter or signal and to optimize the robustness of the residual.

Four suggestions to improve the residual have been considered:

- Filtering: The first proposition is to apply a low-pass filter on the residual in order to separate the noise from the signal. Some fault, typically time constant faults, are not located in low frequency range.

Therefore the squared residuum is filtered, so that a constant part appears in the signal's spectrum (for understanding, think of $sin^2(\omega t) = 1 - cos^2(\omega t)$). In order to reduce the numerical effort, a recursive calculation of mean value and variance for the parity relations is introduced.

- Linear transformation: With this design method, the sensibility for some parameters can be improved and the influence of the other parameters limited. For further developments, refer to [9],[1],[3].
- Design for a set of models: The idea of [9] is considered to suppress the influence of friction in the equations and to locate a faulty coil. For further developments on the theory, refer please to [11],[9].
- Nonlinear parity relation: According to the need for model accuracy, it is advantageous to avoid the loss of information due to linearization. Therefore two methods, which applies for nonlinear models, have been considered:
  - an analytical solution: local linearizing with partial derivatives [12],
  - an algebraical solution: using the elimination theory on a polynomial ideal (Groebner basis theory) [4].

  We refer also for the development of these methods on the literature.

4.2 System model

For this development we have considered only the DDV. This represents a first step for the design.

Furthermore several methods were explored which implies that the model structure had to be adapted to each experiment:

- For the primary residual, a linearized model was used with an equivalent coil instead of the four actual ones. Furthermore the sensor redundancy wasn't took into account. This order reduction enables a symbolic handling of the equations which means more insight in the design and facilities for decoupling of some influences. The model signals are:

$$\begin{aligned} \underline{u}_{DDV} &= [U_{eq} \quad (p_S - p_R)] \\ \underline{x}_{DDV} &= [\psi_C \quad \psi_h \quad \dot{y} \quad y] \\ \underline{y}_{DDV} &= [i_1 \quad y_{S1}] \end{aligned} \qquad (10)$$

- For the design of nonlinear parity relations, we came back to the original precise nonlinear model. Yet, the friction force discontinuity was approximated with an arctan-function. The order reduction to two electrical states is further applied for simplifying the design.
- The design with a set of models bases on numerical optimal decoupling. Therefore the full order model with four coils (see section 3.1) was taken again.

For this survey, we have taken three additive faults (coil voltage f_u as actor fault, coil current f_{yi} and valve position f_{yx} as measurement fault) and two parametric faults (resistor f_R and mechanical damping f_d) into account.

In the next section, only simulations of the parity relations for the DDV are presented. Each defect was simulated separately for one second as shown in figure 3.

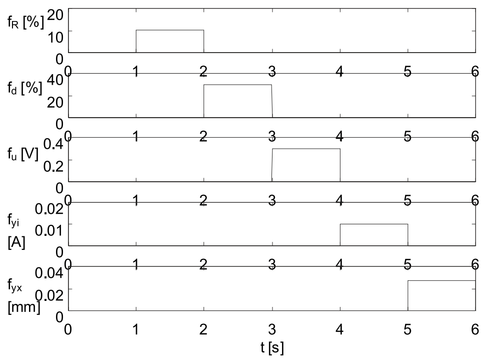

Fig. 3 Fault partition for the simulation

4.3 Results

- Primary linear residual: As first design, we consider the original method for linear model. The system matrix is 4×4 and the two outputs y_i and y_x are full observable, so that we expect to build 6 independent parity equations. Notice that it is not thought of sensor redundancy because of studying analytical and not hardware redundancy.

  With the available degrees of freedom, the equations were structured to get three of it. Each of them is independent of an external signal, actor or sensor. Then, the isolability of all additive faults is ensured. Furthermore, a sensibility analysis shows that these three residuals also react in consequence of parameter variations. In order to optimize these simple relations, a low-pass filter was already used to calculate mean value and variance of the residual.

  As result, the table 1 demonstrates that each fault will be isolated with this filter (μ: mean value; σ: variance):

	f_R	f_d	f_u	f_{yi}	f_{yx}
U independent		σ		μ	μ
y_x independent	μ,σ	σ	μ	μ	
y_i independent	μ,σ	σ	μ		μ

Table 1 Separation Table for the filtered Residuals

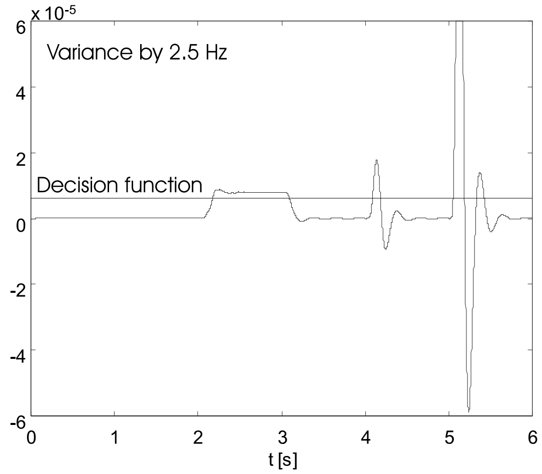

Fig. 4 Input independent residual

  As example, the filtered variance of the input independent equation shows that only a damping fault causes a permanent significant value (see fig. 4).

  In conclusion, the efficiency of our standard residuals is limited if disturbances increase. Therefore, we should improve the robustness of our equations.

- Secondary residuals: In order to structure the residuals, we propose a second method: the linear transformation. This transformation is applied on a new set of parity relations: a totally unstructured, but orthonormal space. Orthonormality provides the largest angle between each fault direction. The transformation is defined by optimizing the sensibility for one parameter in each equation. Note that some requirements are not realizable. Typically, an offset on input voltage will always be propagated to the sensor. Therefore, our separation is limited like shown in the table 2.

	f_R	f_d	f_u	f_{yi}	f_{yx}
Residual 1	X				
Residual 2		X			
Residual 3			X		X
Residual 4				X	X
Residual 5			X	X	

Table 2 Separation Table for Secondary Residuals

  The new residuals allow a faster FDI (no filtering is needed). Because of the orthonormality, the fault level is good approximated, as shown in figure 5 (R with 10% faulty). But the robustness is not improved as suggested by the high frequency peaks of figure 5.

- Nonlinear residuals Two important limits exist for the concrete application of these methods:

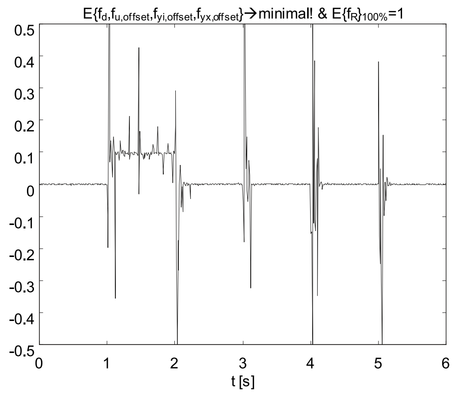

Fig. 5 Residual with linear transformation

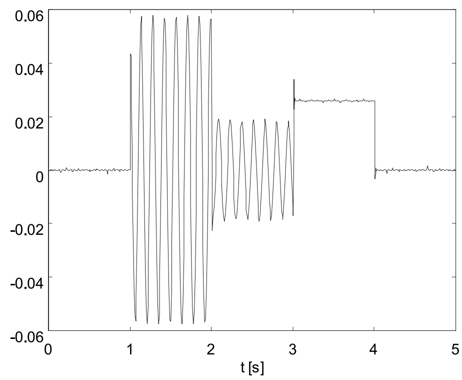

Fig. 7 Nonlinear residual

- both of them request a continuous nonlinearity, and the friction does not fulfill this condition at the origin,
- due to the high complexity, the design is very laborious and the common computer programs cannot solve this problem.

Though we can produce results as shown on figure 7. It shows the application of the analytical design method, exciting a residual with a nonlinear simulation. It should be compared to figure 6 where the standard residual for the linear model is also considered.

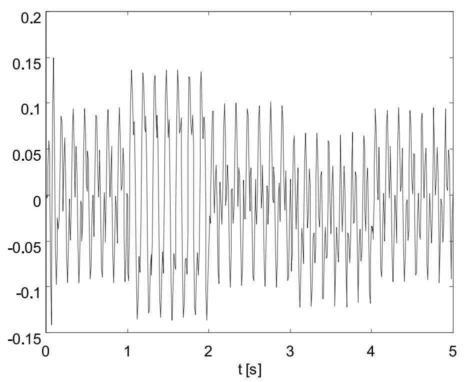

Fig. 6 Linear residual with nonlinear model

For this design, the friction was approximated with an arctan-function. Therefore, some inverse functions were not integrable and some parity equations must disappear. Due to this difficulty, the degrees of freedom are limited for the design. All residuals have the same fault sensibility and the isolation is not possible. Furthermore, the optimization against disturbances is also limited.

- Set of models: Due to the non-continuous friction, the damping coefficient is highly dependent of the valve speed. Therefore, damping faults are hard to detect and produce the major inaccuracy by using linear design methods for the plant. As a consequence, using the idea of Lou [9] linear models with a local valid damping coefficient are defined (see Fig. 8) and residuals are designed with Lou's method [9], [11]. Furthermore, due to the method based on an approximation, high order systems are needed to limit its influence. Therefore, the five (4+1) coils model is again considered. Resistance and sensor fault in each motor lane have to be isolated too. For the design, the damping is varied as shown on figure 8 and the four resistances are successive taken into the set $\{\frac{1}{2}R, \frac{7}{10}R, R, \frac{13}{10}R, \frac{3}{2}R\}$ to obtain a set of local valid models. Four residuals have been designed: each is robust for damping variation and for variation of a coil resistance, so that we can detect both coil and sensor fault. Figure

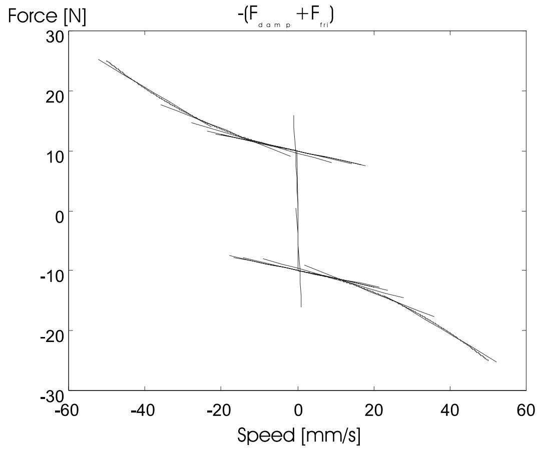

Fig. 8 Damping along speed range

	EKF	Parity Space
Property	-Parameter estimation -feedback -instability without input	-State or Output estimation -no feedback -stability
Appli-cation	-plant fault -off-line with enough excitation	-instrument fault -on-board

Table 3 Comparison of EKF and Parity Space Properties

9 shows such a residual stimulated with a nonlinear model. The fault in coil 2 and in sensor 1 are detected. The effect of damping is quite small and the residual is robust for coil 3 or coil 4 faults.

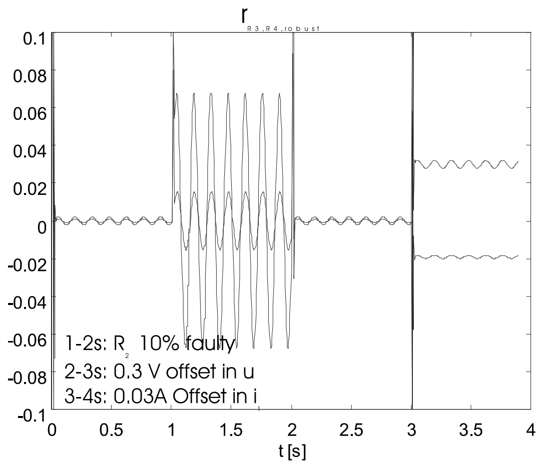

Fig. 9 Residual with a set of models

5 Comparison and perspective for both methods

As we have seen in the previous sections, the fault detection algorithms are efficient. We can detect relevant faults in actual conditions. But both methods are not totally equivalent so that we can show some complementarity (see table 3).

The comparison and the presented results demand a complementary use of both methods. EKF is not directly applicable for on-board detection but offers an high diagnosis depth. On the other side, although the parity space is quite efficient for additive faults, internal plant faults limit this detection approach. On the other hand, it is reliable in on-line application where we cannot influence the input signal.

The perspective is then to use the complementarity of both methods in the global diagnosis scheme. Therefore we can consider two approaches:

- a simple comparison of the results if both methods are independently applied,
- an adaptive scheme where the parameter of the parity space filter would be recovered from the EKF and the signal for the EKF ensured by the Parity Space.

The consequences of the transverse approach will be investigated in further works.

6 Conclusion

In this work two methods are introduced to allow a reliable fault detection in aircraft actuators. Therefore a contribution for improving the reliability of the surface control system was done.

We have shown that both methods allow an high detection depth and that they are complementary in their application field. For the future development of an on-board diagnosis scheme we propose two approaches for coupling both filters.

The next step will then be to prove the efficiency in an integrated diagnosis scheme on an actual system.

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