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Design of a soft sensor for the oscillatory failure detection in the flight control system of a civil aircraft

Do Hieu Trinh∗, Benoît Marx∗, Philippe Goupil†, and José Ragot∗

∗Centre de Recherche en Automatique de Nancy
UMR 7039 – Nancy-Université, CNRS,
2 Avenue de la forêt de Haye, 54516 Vandœuvre, France
Email: {Do-Hieu.Trinh,Benoit.Marx,Jose.Ragot} @ensem.inpl-nancy.fr
†EDYC-CC Flight Control System, AIRBUS
316 route de Bayonne, 31060 Toulouse Cedex 09, France.
Email: Philippe.Goupil@airbus.com

Abstract—The objective of this study is the detection of oscillatory failure (unknown and bounded) that may affect the control system of a control surface (CS) of a civil aircraft. Beside the fact that the failure may result in additional loads on the aircraft structure, it can excite a resonance phenomenon. Early and robust detection of this type of failure is therefore a need for structural design objectives as well as for the controllability of the aircraft. From an analytical model of the actuator and its control loop, a so-called failure-free model translating the behavior of the system in the absence of failure is developed, as well as failure models corresponding to system behaviors in the occurrence of different types of failure. This allows generating residual signals for failure detection.

Index Terms—Soft sensor, Fault Detection and Isolation, Oscillatory Failure, Flight Control System

I. INTRODUCTION

The safe operation of a physical process can be harmed on the occurrence of faults, these faults may affect the process itself or its conduct bodies. This observation has naturally led to the implementation of surveillance systems whose objective is to be able at any moment, to provide operating status of the various organs constituting the system. When a fault occurs, it must be detected as soon as possible, even where all observed signals remain in their allowable limits. It must then be located and its cause identified. Thus, the steps of observation and monitoring must be assisted by a “smarter” step.

This step, called supervision, uses all available information through an implicit or explicit model. Here, the goal is the detection of oscillatory failures affecting a flight control system (FCS) -specifically an aileron- of an aircraft. For these oscillatory failures, airworthiness regulations applied worldwide by all manufacturers require precaution designed to detect and to accommodate these failures (see [3]). Software embedded on the Airbus A380, for example, is entirely compliant to the current regulations. However, improvements ([1], [2]) could be used for the next generation of aircraft from European manufacturer to accompany the future technological innovations and meet changing regulations. That is the purpose of this study. Examples of oscillatory failures detection in other areas can be found in [4], [5]. Note also that these oscillatory failures are different from Pilot-Induced Oscillations (PIO) caused by the pilot (see [7], [8]). In the following, some elements leading to a methodology to detect such failures are presented, which are based on existing sensors and on soft (or virtual) sensors capable of reconstructing some informations through a model.

The principle of supervision is presented in the section II and the design of a soft sensor for the oscillatory failure case detection in the section III. The section IV tackled the problem of fault detection and isolation (FDI) by the test of standard deviation. This problem is treated in the section V by the test of correlation. Conclusion and perspectives end the paper.

II. MODELING OF STUDIED SYSTEM

The chosen principle is based on testing the adequacy of available measures in a CS servo-loop towards its model. Thus, it is necessary to establish the model of the system, generating through this model and the available measures an indicator of failure. This indicator must be analyzed to detect the presence of this failure as soon as possible. A model called failure-free can be proposed simulating the system behavior in the absence of failure. Failure models corresponding to system behaviors in occurrence of oscillations can also be established. Two kinds of failures must be detected: “liquid failure” and “solid failure” as a disturbing signal is superimposed on or replaces the control signal [1]. The probable sources of oscillatory failure are presented in figure I. In this application, the characteristic variables of CS servo-loop are given in the table I.

The failure-free model $M_b$ is described structurally as follows:

$$
M_b = \begin{cases}
    x_b(t) = V_0(t) \sqrt{S∆P(t) + \text{sign}(V_0(t))F_a(t)} / S∆P_{ref} + K_a(t)V^2_0(t) \\
    V_0(t) = K_v(u(t) - x(t - τ)) \\
    ∆P(t) = f_1(x_a(t)), \ K_a(t) = f_2(x_a(t)) \\
    F_a(t) = f_3(M_a(t), x_a(t), V_{av,a}(t)) \\
    x_a(t) = f_4(x(t), τ)
\end{cases}
$$

(1)
Residual signals allowing to determine the most representative model of the behavior of the CS and thus to determine the type of the potentially occurring failure. Note that one of the major difficulties in the implementation of this technique is due to the fact that the physical system is subjected to hardly measurable disturbances ($\Delta P(t)$, $K_a(t)$ and $F_a(t)$). In [2], the authors have shown that $\Delta P(t)$ and $F_a(t)$ cannot be identified simultaneously and they have chosen to set $\Delta P(t)$ to its most likely value then identify $K_a(t)$ and $F_a(t)$. Taking into account the complexity of the estimation of $K_a(t)$ and $F_a(t)$ as well as the limited power of the flight control computer, the model was simplified by fixing the three perturbations $\Delta P(t)$, $K_a(t)$ and $F_a(t)$ with fixed nominal values$^1$. From equation (1), the corresponding evolution of the output $x_b(t)$ is:

$$M_b = \begin{cases} \dot{x}_b(t) = V_0(t) \left( \frac{S\Delta P_a + \text{sgn}(V_0(t))F_{ab}}{S\Delta P_{ref} + K_{ab}V_0^2(t)} \right) \\ V_0(t) = K(u(t) - x_b(t - \tau)) + S_{def,\ell}(t) \end{cases}$$

(4)

Figure 2 shows the output of the nonlinear model and that of its simplified model; the low amplitude of the difference between the two outputs justifies the use of simplified model.

Constant values are also chosen for the perturbations in the solid and liquid failure models (2 and 3) In following the isolation of an oscillation of 0.5 degree amplitude and 1.5 Hz frequency will be considered. This case corresponds to an oscillatory failure signal $S_{def} (t)$ described by:

For the solid failure: $S_{def,s}(t) = 0.448 \sin (3\pi t)$

For the liquid failure: $S_{def,\ell}(t) = 1.07 \sin (3\pi t)$

(5)

The FD procedure described in table II is applied, using the model of oscillatory failure signal (5) with the failure models (2 and 3) (the sampling period is 0.01s).

\begin{table}
\begin{tabular}{|c|c|}
\hline
$p$ & position of the rod of CS actuator (aileron) \\
$q$ & position’s order of CS actuator \\
$F_a$ & aerodynamic forces applied on the CS \\
$\Delta P$ & difference of hydraulic pressure in the input of the FCS actuator \\
$K_a$ & damping coefficient of adjacent actuator (in the case of 2 actuators per CS) \\
$\Delta P_{ref}$ & pressure of reference \\
$\tau$ & transmission delay of the sensor \\
$S$ & surface area of the actuator’s piston \\
$K$ & control gain \\
$V_0$ & speed computed by flight control computer \\
x_{def} & position (in degrees) of the CS \\
\hline
\end{tabular}
\end{table}

where the structure of functions $f_i(.)$ are not detailed here. The quantities $\Delta P(t)$, $K_a(t)$ and $F_a(t)$ play the role of disturbance of which one can know the domain of variation. Failure models of solid and liquid types take the following forms respectively:

$$M_s = \begin{cases} \dot{x}_s(t) = V_{0,s}(t) \left( \frac{S\Delta P_s(t) + \text{sgn}(V_{0,s}(t))F_{as}(t)}{S\Delta P_{ref} + K_{as}(t)V_{0,s}^2(t)} \right) \\ V_{0,s}(t) = S_{def,s}(t) \end{cases}$$

(2)

$$M_\ell = \begin{cases} \dot{x}_\ell(t) = V_{0,\ell}(t) \left( \frac{S\Delta P_\ell(t) + \text{sgn}(V_{0,\ell}(t))F_{a\ell}(t)}{S\Delta P_{ref} + K_{a\ell}(t)V_{0,\ell}^2(t)} \right) \\ V_{0,\ell}(t) = K(u(t) - x_\ell(t - \tau)) + S_{def,\ell}(t) \end{cases}$$

(3)

where the magnitudes of $\Delta P(t)$, $K_a(t)$ and $F_a(t)$ depend on flight scenario: $S_{def}(t)$ represents the oscillatory failure signal of unknown frequency, but characterized by a known frequency range.

The principle of supervision, which is therefore to determine at every moment, which mode of the system $M_b$, $M_s$ or $M_\ell$ is active, is the subject of Section III.

III. DESIGN OF A SOFT SENSOR FOR THE OSCILLATORY FAILURE DETECTION

The evolution of outputs noted respectively $x_b$, $x_s$ and $x_\ell$ are computed by integrating the equations related to the three modes of operation of CS. In this case, one speaks about soft sensor, because the simulation provides information comparable to what gives a physical sensor, under condition that the model is well representative of the system. This allows to propose a diagnostic strategy summarized in the table (II).

The comparison between the outputs of these soft sensors and the growths measured by physical sensors results in three

\begin{table}
\begin{tabular}{|c|c|}
\hline
$E_1$ & At time $t$, acquire the available measures \\
$E_2$ & Evaluate the outputs $(x_b(t), x_s(t), x_\ell(t))$ of three soft sensors \\
$E_3$ & Calculate the residues $r_{ab}(t) = x(t) - x_\lambda(t)$, $\lambda = b, s, \ell$ \\
$E_4$ & comparison between residuals and thresholds \\
$E_5$ & Test of persistence over time of the result of statistic tests \\
$E_6$ & Take the decision of the occurrence of a failure \\
\hline
\end{tabular}
\end{table}

\begin{table}
\begin{tabular}{|c|c|}
\hline
\end{tabular}
\end{table}

\begin{table}
\begin{tabular}{|c|c|}
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\end{tabular}
\end{table}

\begin{table}
\begin{tabular}{|c|c|}
\hline
\end{tabular}
\end{table}
IV. FAULT DETECTION BY STANDARD DEVIATION TEST

A. Residual generation

With the actual measurement of the CS position and outputs corresponding to the modes of operation of the system, three residuals are obtained as shown in figure 3.

Figure 4, represents the residuals $r_b(t)$, $r_s(t)$ and $r_l(t)$ in the case without failure. In the absence of failure, the amplitude of the residual $r_b(t)$ is clearly limited to approximately 0.2 deg; however, residuals $r_s(t)$ and $r_l(t)$ oscillate with a significantly greater amplitude.

Figure 5 (resp. figure 6) represents the residuals in the case of liquid failure (resp. solid failure). The failure is simulated between 5.3 and 15.3 s. There is an increase of the variation of the residue $r_b(t)$ and a reduction in the variation of the residue $r_l(t)$ (resp. residue $r_s(t)$) in the presence of the liquid failure (resp. solid failure). These residuals are used for the FDI procedure, the signatures of the residues being well differentiated according to the type of failure.

The previous qualitative visual study showed the ability of three residues to recognize the actual operational situation. In the next section, the quantitative analysis of residues confirms this study and shows how the recognition is processed from a numerical point of view.

B. Generation of failure indication

The standard deviation measures the dispersion of data set around its mean value, its variations indicate the occurrence or disappearance of a failure. For a residue $r(t)$, this deviation may be calculated over a sliding window of appropriate width $N$ as follows:

$$
\begin{align*}
\sigma_{r_b}(k) &= \sqrt{\frac{1}{N} \sum_{m=k-N+1}^{k} (r_b(m) - \bar{r_b}(k))^2} \\
\sigma_{r_s}(k) &= \sqrt{\frac{1}{N} \sum_{m=k-N+1}^{k} (r_s(m) - \bar{r_s}(k))^2} \\
\sigma_{r_l}(k) &= \sqrt{\frac{1}{N} \sum_{m=k-N+1}^{k} (r_l(m) - \bar{r_l}(k))^2}
\end{align*}
$$

This assessment is carried out on residuals ($r_b, r_s, r_l$) from failure-free model $M_b$ and failure models $M_s$ and $M_l$.

C. Failure detection by standard deviation test

Thanks to detection, the deviation of the operational mode and therefore failure may be performed as summarized in the algorithm 1. The principle of this algorithm is to evaluate the relationship between the calculated deviations over sliding windows of appropriate dimensions with the initial deviations (calculated in the absence of failure).

**Algorithm 1: Failure detection by standard deviation test**

1) Initialization : Calculate the initial deviations $\sigma_{r_b,0}$, $\sigma_{r_s,0}$ and $\sigma_{r_l,0}$.
2) Calculate the deviations $\sigma_{r_j}(k)$ over sliding windows
3) Onset of failure: If the failure was not yet detected and that for a period of time $\sigma_{r_j}(k) \geq 2\sigma_{r_j,0}$,
   - If $\sigma_{r_j}(k) \leq 0.5 \sigma_{r_j,0}$, then the occurrence of the liquid failure is confirmed.
   - If $\sigma_{r_j}(k) \leq 0.5 \sigma_{r_s,0}$, then the occurrence of the solid failure is confirmed.
4) Disappearance of the failure: If a failure has already been detected and that for a period of time:
   - $\sigma_{r_b}(k) \leq 1.5 \sigma_{r_b,0}$, $\sigma_{r_s}(k) \geq 0.75 \sigma_{r_s,0}$ and $\sigma_{r_l}(k) \geq 0.75 \sigma_{r_l,0}$
   then the disappearance of the failure is confirmed.

The result of failure detection by the algorithm 1 is illustrated by figures 7, 8 and 9 for the failure free case, the liquid case and the solid case respectively.

The failure flag noted $\text{Ind}$ is 1 if the liquid failure is detected, 2 if the solid failure is detected and 0 if no failure is detected. The quantity $r_{\text{Std},b}$ (resp. $r_{\text{Std},s}$ and $r_{\text{Std},l}$) is the ratio between the calculated deviation on $r_b(t)$ (resp. $r_s(t)$ and $r_l(t)$) and the initial standard deviation.
D. Discussion on failure detection by standard deviation test

The outcomes of algorithm 1 show that the failure is detected and identified at approximately 1.5 oscillation periods after its occurrence (0.89 s for the liquid failure case and 0.93 s for the solid failure case). This result is compliant with the required specifications.

If one focuses only on the failure detection (without isolation), then only the test of standard deviation of the residual \( r_b(t) \) is needed, without using failure models. In this case, the failure detection condition should be reduced to \( \sigma_{r_b}(k) \geq 1.75 \sigma_{r_b,0} \) for a period of time (algorithm 1). The different examples show that we can detect any solid and liquid failure on the frequency range \([0.5 \ldots 10.0]\) Hz even at very low amplitude (0.16 degree).

However, if the goal is to detect and isolate all failures that may appear in the control loop, the number of failure models described by equations (2) and (3) must be increased and therefore different frequencies of oscillations must be taken into consideration. Each failure model whose parameters are fixed is specific to a particular solid or liquid failure (of type (5)). With the principle used by the algorithm 1, any solid and liquid failure characterized by a frequency in \([0.5 \ldots 10.0]\) Hz and an amplitude in \([0.5 \ldots 1.0]\) deg can be detected and isolated for many flight scenarios.

To reduce the number of failure models, another approach is to use a correlation test that is developed in the next section.

V. FAULT DETECTION BY CORRELATION TEST

The dysfunction models (2 and 3) allow to study the behavior of the system in the presence of a failure. In the simulation of dysfunction models, by forcing the command to zero, the impact of the failure on the output can be directly identified and estimated. In this way, patterns of failures can be generated offline to be compared to the residual \( r_b(t) \) or output \( x(t) \) to detect and isolate the failure. Figure 10 shows the procedure to be implemented. The first residual \( r_b(t) \) has already been defined. Signals \( f_i(t) \) correspond to failures characterized by some specific frequencies (5) whose effect is assessed based on the failure models \( (M_s \) or \( M_l \)) thus generating signatures \( x_{Li}(t) \) or \( x_{Si}(t) \) specific to each of these frequencies. Such frequencies are called “selected” because this work aims at detecting and isolating the failures of these frequencies. These signatures are then compared (by correlation over sliding windows) to the previously evaluated residual \( r_b(t) \) or output \( x(t) \). This principle applies to liquid and solid failure, model \( S_{MF} \) is then \( M_s \) or \( M_l \).

A. Pattern generation

In this subsection patterns at 0.5 Hz, 1.5 Hz and 7.0 Hz are generated from models \( M_s \) and \( M_l \) by putting the command to zero. As the correlation test does not distinguish the amplitudes of sinusoidal signals, these patterns are generated so that they correspond with the oscillation of 0.75 deg. Each pattern is a sequence of length equal to two periods of the failure of the same frequency. The objective is to detect and to isolate these three failures.

1) Patterns of liquid failures: For the liquid failures, the three following patterns are generated (table III)

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Sequence</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x_{L1} )</td>
<td>400 samples</td>
<td>0.5 Hz</td>
</tr>
<tr>
<td>( x_{L2} )</td>
<td>135 samples</td>
<td>1.5 Hz</td>
</tr>
<tr>
<td>( x_{L3} )</td>
<td>28 samples</td>
<td>7.0 Hz</td>
</tr>
</tbody>
</table>

These three patterns \( x_{L1}, x_{L2} \) and \( x_{L3} \) are presented in figure 11. They are analyzed by correlation test with the signal \( r_b(t) \) defined previously by \( r_b(t) = x(t) - x_0(t) \).

The patterns \( x_{L1}, x_{L2} \) and \( x_{L3} \) are the direct impacts of...
liquid failures (without the influence of the command) on the output of the system and they are comparable in some way with the residue $r_0(t)$ under the presence of a failure. Indeed, the difference $x(t) - x_0(t)$ reflects the impact of the failure on the output since the effect of the command on $x(t)$ and $x_0(t)$ is canceled by difference.

2) **Patterns of solid failures:** For the solide failures, the three following patterns are generated (table IV).

![Fig. 11. Patterns $x_{L1}$, $x_{L2}$ and $x_{L3}$](image)

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Sequence</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_{S1}$</td>
<td>400 samples</td>
<td>0.5 Hz.</td>
</tr>
<tr>
<td>$x_{S2}$</td>
<td>135 samples</td>
<td>1.5 Hz.</td>
</tr>
<tr>
<td>$x_{S3}$</td>
<td>28 samples</td>
<td>7.0 Hz.</td>
</tr>
</tbody>
</table>

These three patterns $x_{S1}$, $x_{S2}$ and $x_{S3}$ are presented in figure 12. They are analyzed by correlation test with the actual output $x(t)$.

![Fig. 12. Patterns $x_{S1}$, $x_{S2}$ and $x_{S3}$](image)

### B. Failure indicator generation

The correlation between two or more variables is the intensity of the relation that may exist between these variables. A measure of this correlation is obtained by the calculation of the linear correlation coefficient. The linear correlation coefficient between two variables $x$ and $y$ is noted by $r_{x,y}$.

### C. Fault detection by correlation test

With the correlation test, FD can be performed as summarized in Algorithm 2. The principle of this algorithm is to compute the linear correlation coefficients over a sliding window, on the one hand between the residue $r_0(t)$ with signals $x_{L1}$, $x_{L2}$ and $x_{L3}$ which represent liquid failures; on the other hand between the output $x(t)$ with signals $x_{S1}$, $x_{S2}$ and $x_{S3}$ which represent solid failures. If one of these coefficients calculated over a sliding window exceeds a threshold a certain number of times within a limited time, a failure is detected.

![Fig. 13. Calculated correlation coefficients : case without failure](image)

The correlation coefficients calculated during the time are shown first in figure 13 for the case without failure. The result of failure detection by the algorithm 2 is shown in figures 14, 15 and 16. Figure 14 (resp. 15 and 16) represents the result obtained with the liquid failure of 0.5 Hz frequency (resp. the liquid failure of 1.5 Hz frequency and with the solid failure of 7.0 Hz frequency). Failures are simulated between 5.3 and 15.3 seconds.

![Algorithm 2: Fault detection by correlation test](image)

1) Initialization :  
- Read the patterns $x_{L1}$, $x_{L2}$, $x_{L3}$, $x_{S1}$, $x_{S2}$ and $x_{S3}$ from a file previously created.
- Define a table $P = [400, 135, 28]$ and one threshold $V_e = 0.6$.

2) Perform calculations of linear correlation coefficients for each $k^{th}$ sampling step:  
- Calculate $r_{x_0(k-P(i)+1:k)}x_{L1}$ for $i = 1, 2, 3$.
- Calculate $r_{x_0(k-P(i)+1:k)}x_{S1}$ for $i = 1, 2, 3$.

3) Evaluate the linear correlation coefficients by counting exceedances:  
- If a coefficient is greater than $V_e$ or smaller than $-V_e$, the number of so-called overruns associated with this coefficient is increased by one unit.
- If no exceedance were observed within a limited time, the number of overruns is set to zero.

4) Onset of failure: If the failure has not yet been detected and if one of the overruns is greater than or equal to 4; then:  
- the onset of failure is confirmed.
- The nature of the failure (liquid or solid) as well as its frequency are indicated by the pattern $x_{L1}$ or $x_{S1}$ whose number of exceedances was observed with its correlation coefficient. If it is a pattern $x_{L1}$, the failure is liquid; if it is a pattern $x_{S1}$, the failure is solid. The value of $i$ indicates the frequency of the failure.

5) Disappearance of the failure: If a failure has already been detected and no exceedance was observed within a limited time; then  
- the failure is declared to have disappeared.

The first column represents the correlation coefficient which led to the failure detection ($r_{x_0,x_{L1}}$, $r_{x_0,x_{L2}}$ and $r_{x_0,x_{S3}}$ respectively). The indicator of nature of the failure is noted by $Nat$ in the second column. If $Nat = 1$, a liquid failure is detected,
if $N_a = 2$, a solid failure is detected. The frequency of the failure is indicated in the third column. With this method, the detection and isolation of failure can be performed in less than three periods of the failure, which is in fact compliant with the required specifications.

**D. Discussion on the failure detection by correlation test**

Failure detection by correlation test has reduced significantly the number of failure models compared to deviation test. In fact, boarding only failure-free model in flight control computer to generate the residue $r_b(t)$ is sufficient. All the pattern of liquid and solid failures are generated in advance and stored. Different treated flight scenarios show that any solid and liquid failure characterized by frequencies in the frequency range $[0.5 \ldots 10.0] \text{Hz}$, even at low amplitude (0.16 degree). Future works will consist in extending these methods to other control surfaces (rudder or elevator), by trying to reduce the complexity as well as the number of failure models. The improvement of the robustness of the correlation test for the failures of frequencies neighboring the selected ones is also to be considered.

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These recurrences are easy to establish, so the correlation tests can be carried out with a reasonable computational load.

**VI. CONCLUSION**

This paper addresses the problem of detecting the oscillatory failure in the control system of a control surface of a civil aircraft. Two fault detection methods are proposed, based on a simplified model validated regarding the nonlinear models usually used. Any solid and liquid failure in the frequency range $[0.5 \ldots 10.0] \text{Hz}$ can be detected by standard deviation test, as well as any solid and liquid failure of selected frequencies by correlation test. Both methods have been successfully tested for a variety of flight scenarios, even with failures of low amplitude (0.16 degree). Future works will consist in extending these methods to other control surfaces (rudder or elevator), by trying to reduce the complexity as well as the number of failure models.