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

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***Abstract*—The objective of this study is the detection of oscillatory failure (unknown and bounded) that may affect the control system of a flight control surface (FCS) of an civil aircraft. Beside the fact that the failure may result in additional charges on the aircraft structure, it can excite a resonance phenomenon. Early detection of this type of failure is therefore a need for security as well as the controllability of the aircraft. From an analytical model of the flight control surface system, we can establish a so-called failure-free model translating the behavior of the system in the absence of failure, as well as failure models corresponding to system behaviors in the occurrence of different types of failure. This can then generate residual signals allowing the detection of failure.**

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

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 conventional steps of observation and monitoring must be assisted by a "smarter" step.

This step, often called supervision, uses all available information through an implicit or explicit model. In this study, the objective is the determination of oscillatory failures that may affect a flight control surface (FCS) of an aircraft, specifically an aileron. More generally, for this type of oscillatory failures, aviation regulations applied worldwide by all manufacturers require precaution designed to detect and to accommode these failure (see [3]). Software embedded on the Airbus A380, for example, is entirely complying with the current regulations. However, the improvement ([1], [2]) could be used for the next generation of aircrafts 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) intentionally caused by the pilot (see [7], [8]). In following, we propose some elements that led a methodology to detect such failures, which bases on existing sensors and on *soft sensors* (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 by the test of standard deviation. This problem is treated in the section V by the test of correlation. Some conclusion and perspectives end the paper.

II. MODELING OF STUDIED SYSTEM

The chosen principle is based on testing the adequacy of available measures of a FCS system 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 of failure must be analyzed to detect the presence of this failure as soon as possible. Regarding the model, we can establish a model called *failure-free* resulting system behavior in the absence of failure and *failure models* here corresponding to system behaviors in occurrence of two types of failure called "liquid failure" and "solid failure" as a disturbing signal is superimposed on or replace the control signal [1]. The probable sources of oscillatory failure are presented in figure 1.

In this application, the characteristic variables of FCS are given in the table I.

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

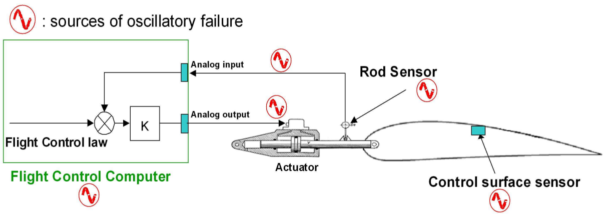

Fig. 1. The probable sources of oscillatory failure

x	position of the rod of FCS actuator (aileron)
u	position's order of FCS actuator
F_a	aerodynamic forces applied on the FCS
ΔP	difference of hydraulic pressure at the terminals of the FCS actuator
K_a	damping coefficient of adjacent actuator (in the case of 2 actuators for FCS)
ΔP_{ref}	pressure of reference
τ	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_d	position (in degrees) of the FCS

TABLE I
CHARACTERISTIC VARIABLES OF SYSTEM

$$M_b = \begin{cases} \dot{x}_b(t) = V_0(t)\sqrt{\dfrac{S\Delta P_i(t) + \mathrm{sign}(V_0(t))F_a(t)}{S\Delta P_{ref} + K_a(t)V_0^2(t)}} \\ V_0(t) = K(u(t) - x(t-\tau)) \\ \Delta P(t) = f_1(x_d(t)), \quad K_a(t) = f_2(x_d(t)) \\ F_a(t) = f_3(M_a(t), x_d(t), V_{av,x}(t)), \\ x_d(t) = f_4(x(t), \tau) \end{cases} \tag{1}$$

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:

$$M_s = \begin{cases} \dot{x}_s(t) = V_{0,s}(t)\sqrt{\dfrac{S\Delta P_i(t) + \mathrm{sign}(V_{0,s}(t))F_a(t)}{S\Delta P_{ref} + Ka(t)V_{0,s}^2(t)}} \\ V_{0,s}(t) = S_{def,s}(t) \end{cases} \tag{2}$$

$$M_\ell = \begin{cases} \dot{x}_\ell(t) = V_{0,l}(t)\sqrt{\dfrac{S\Delta P_i(t) + \mathrm{sign}(V_{0,\ell}(t))F_a(t)}{S\Delta P_{ref} + K_a(t)V_{0,\ell}^2(t)}} \\ V_{0,\ell}(t) = K(u(t) - x_\ell(t-\tau)) + S_{def,\ell}(t) \end{cases} \tag{3}$$

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 range of frequencies known.

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

III. Design of a soft sensor for the oscillatory failure detection

By integrating the equations related to the three modes of operation of FCS, we obtain the evolution of outputs noted respectively x_b, x_s and x_ℓ. One speaks in this case soft sensor, because the simulation provides information comparable to what given a physical sensor, under condition that the model is well representative of the system. This allows us to propose a diagnostic strategy summarized in the table (II).

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 $r_\lambda(t) = x(t) - x_\lambda(t)$, $\lambda = b, s, \ell$
E_4	Test of comparison residues to a threshold
E_5	Test of persistence over time the result of statistic tests
E_6	Take the decision of the occurrence of a failure

TABLE II
STRATEGY FOR FAULT DETECTION

The comparison of outcomes from these soft sensors with magnitudes measured by physical sensors results three residual signals allowing to determine the model the most representative of the behavior of the FCS and thus determine the type of failure which is potentially occurred. Note that one of the major difficulties in the implementation of this technics 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 $F_a(t)$ can not be identified simultaneously and they've choose to set $\Delta P(t)$ to its most likely value then identify $K_a(t)$ and $F_a(t)$. In our approach, taking 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. For example, with a representative flight scenario, we chose $\Delta P(t) = 187$, $K_a(t) = 0.22$ and $F_a(t) = -12000$. From equation (1), we establish the evolution of the output $x_b(t)$ as follows:

$$M_b = \begin{cases} \dot{x}_b(t) = V_0(t)\sqrt{\dfrac{S\Delta P_b + \mathrm{sign}(V_0(t))F_{ab}}{S\Delta P_{ref} + K_{ab}V_0^2(t)}} \\ V_0(t) = K(u(t) - x_b(t-\tau)) \\ \Delta P_b = 187; K_{ab} = 0.22; F_{ab} = -12000 \end{cases} \tag{4}$$

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.

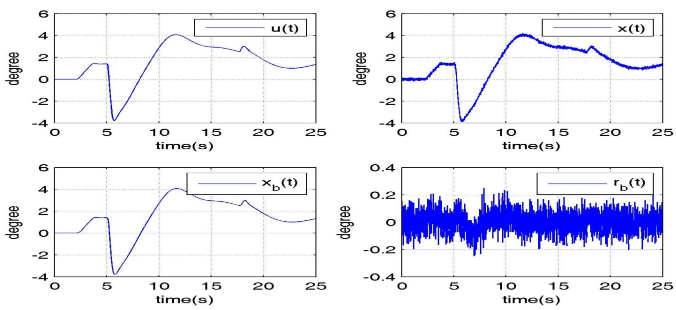

Fig. 2. Validation of simplified model

For the failure models of type solid and liquid (2 and 3), we also use fixed values:

$$\begin{array}{llll} M_s: & \Delta P_s = 193 & K_s = 0.22 & F_s = 0 \\ M_\ell: & \Delta P_\ell = 165 & K_\ell = 0.22 & F_\ell = -6000 \end{array} \quad (5)$$

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:

$$\begin{array}{ll} \text{For the solid failure:} & S_{def,s}(t) = 0.448 \sin(3\pi t) \\ \text{For the liquid failure:} & S_{def,\ell}(t) = 1.07 \sin(3\pi t) \end{array} \quad (6)$$

With the values (5) and the model of oscillatory failure signal (6) applied on the failure models (2 and 3), we can get the outputs to execute the proposed procedure of fault detection (table II). Note that the sampling step is 0.01 seconds.

IV. Fault Detection by Standard Deviation Test

A. Generation of residues

With the actual measurement of the position of the FCS and outputs corresponding with the modes of operation of the system, we can establish three residues as shown in figure 3.

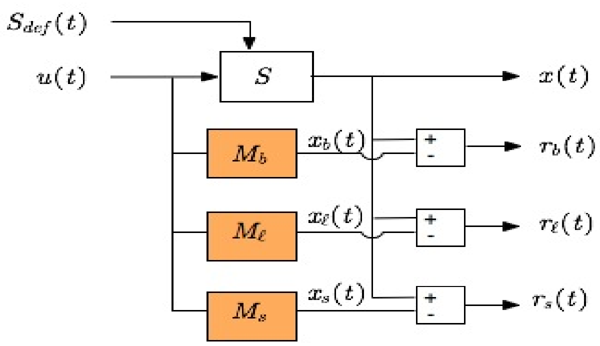

Fig. 3. Bank of residues for the detection of failure

Figure 4, represents residues $r_b(t)$, $r_s(t)$ and $r_\ell(t)$ in the case without failure. One observes without ambiguity, in the absence of failure, the amplitude of the residue $r_b(t)$ is limited to approximately 0.2 degree; however, residues $r_s(t)$ and $r_\ell(t)$ oscillate with a significantly greater amplitude.

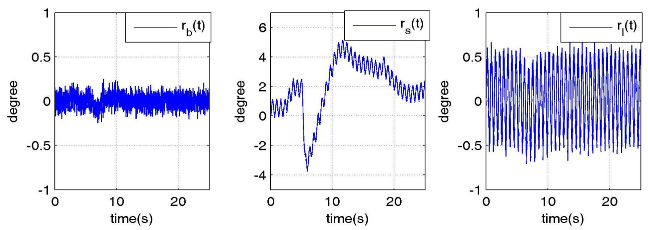

Figure 5 (*resp.* figure 6) represents the residues in the case of liquid failure (*resp.* solid failure). The failure is simulated between 5.3 and 15.3 seconds. There is an increase of the

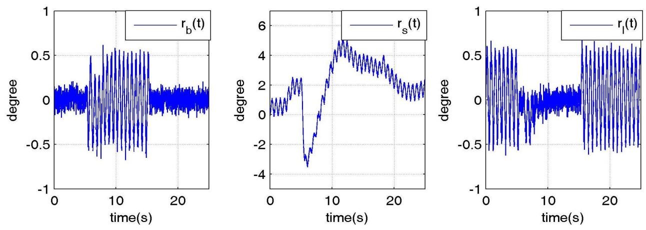

Fig. 5. Residues $r_b(t)$, $r_s(t)$ and $r_\ell(t)$: case of liquid failure

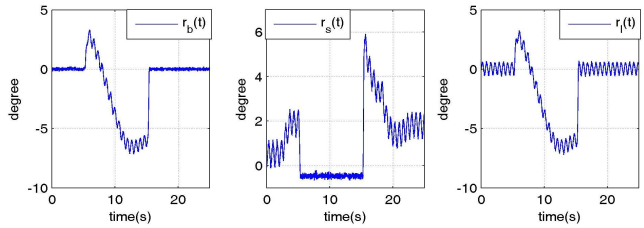

Fig. 6. Residues$r_b(t)$, $r_s(t)$ and $r_\ell(t)$: case of solid failure

variation of the residue $r_b(t)$ and a reduction in the variation of the residue $r_\ell(t)$ (*resp.* residue $r_s(t)$) in the presence of the liquid failure (*resp.* solid failure). These residues generating systems are quite capable of serving the fault detection and isolation procédure, 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 indication of failure

The standard deviation is a measure of dispersion of a set of data around its mean value and its variations are indicative of the occurrence or the disappearance of a failure. If there is a residue r of a temporal form, this deviation may be calculated over a sliding window of appropriate width N as follows:

$$\left\{ \begin{array}{lcl} \sigma_{r_\lambda}(k) & = & \sqrt{\frac{1}{N-1} \sum\limits_{m=k-N+1}^{k} (r_\lambda(m) - \overline{r}_\lambda(k))^2} \\ \overline{r}_\lambda(k) & = & \frac{1}{N} \sum\limits_{m=k-N+1}^{k} r_\lambda(m) \end{array} \right. \quad (7)$$

This assessment is carried out on residues (r_λ,$\lambda = b, s, \ell$) from failure-free model M_b and failure models M_s and M_ℓ.

C. Failure detection by standard deviation test

Thanks to deviation, the detection of the operational mode and therefore failure may be performed as summarizes 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 $\sigma_{r_b,0}$, $\sigma_{r_\ell,0}$ and $\sigma_{r_s,0}$.
2) Calculate the deviations $\sigma_{r_\lambda}(k)$ over sliding windows
3) Onset of failure: If the failure was not yet detected and that for a period of time $\sigma_{r_b}(k) \geq 2\sigma_{r_b,0}$,
   - If $\sigma_{r_\ell}(k) \leq 0.5\ \sigma_{r_\ell,0}$, we then declare the occurrence of the liquid failure.
   - If $\sigma_{r_s}(k) \leq 0.5\ \sigma_{r_s,0}$, we then declare the occurrence of the solide failure.
4) Disappearance of the failure: If a failure has already been detected and that for a period of time:
   - $\sigma_{r_b}(k) \leq 1.5\ \sigma_{r_b,0}$, $\sigma_{r_\ell}(k) \geq 0.75\ \sigma_{r_\ell,0}$ et $\sigma_{r_s}(k) \geq 0.75\ \sigma_{r_s,0}$

   we then declare the disappearance of the failure.

The result of failure detection by the algorithm 1 is illustrated by figures 7, 8 and 9 for the without failure, with liquid failure then with solid failure cases respectively.

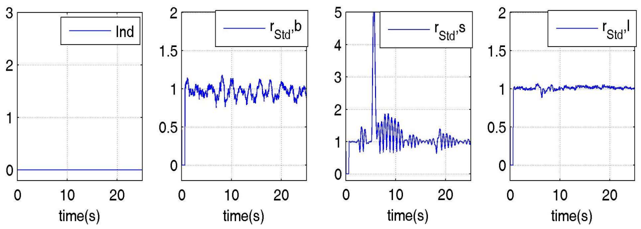

Fig. 7. Result of the detection: case without failure

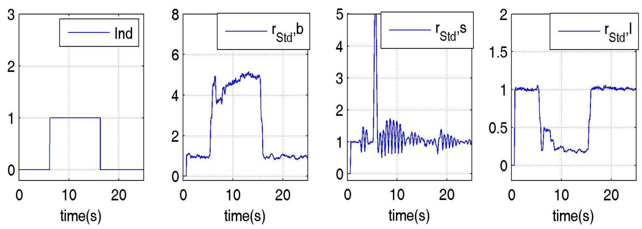

Fig. 8. Result of the detection: case of liquid failure

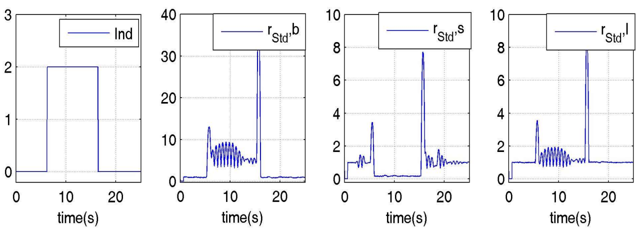

Fig. 9. Result of the detection: case of liquid failure

The failure flag noted `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_{Std}, b (*resp.* r_{Std}, s and r_{Std}, ℓ) is the ratio between the calculated deviation on $r_b(t)$ (*resp.* $r_s(t)$ and $r_\ell(t)$) and the initial standard deviation.

D. Discussion on failure detection by standard deviation test

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

If one focuses only on the failure detection (without isolation), then we can make only the test of standard deviation of the residue $r_b(t)$, 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 treated 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 we want to detect and isolate all failures that may appear in the control loop, we must increase the number of failure models described by equations (2) and (3) and therefore take into account different frequencies of oscillations. Each failure model whose parameters are fixed as in (5), is specific to a particular solid or liquid failure (of type (6)) that we want to identify. With the principle used by the algorithm 1, we can detect and isolate any solid and liquid failure on the frequency range $[0.5 \ldots 10.0]$ Hz and amplitude between 0.5 degree and 1.0 degree (or even lower) for many flight scenarios.

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

V. Fault detection by correlation test

The dysfunction models (2 and 3) allow us 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 on theses models, 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 residue $r_b(t)$ or output $x_(t)$ to detect and isolate the failure. Figure 10 shows the procedure to be implemented. The first residue $r_b(t)$ has already been defined. Signals $f_i(t)$ correspond to failures characterized by some specific frequencies (6) 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. We call such frequencies "selected" because we want to detect and isolate the failures of these frequencies. These signatures are then compared (by correlation over sliding windows) to the previously evaluated residue $r_b(t)$ or output $x(t)$. This principle applies to liquid and solid failure, model S_{MF} is then M_ℓ or M_s.

A. Generation of patterns

In this subsection we generate patterns for 0.5 Hz, 1.5 Hz and 7.0 Hz frequencies 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 degree. Each pattern is a sequence of length equal to two

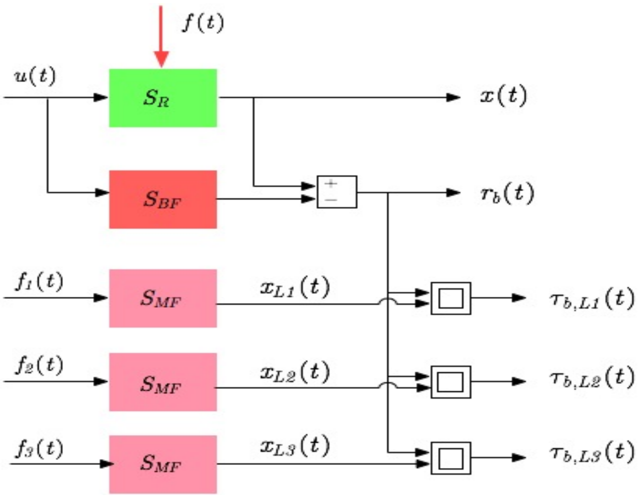

Fig. 10. Generation of residues for correlation test

periods of the failure of the same frequency. Our objective is to detect and isolate the failures of these three frequencies.

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

TABLE III
LIQUID FAILURES

Pattern	Sequence	Frequency
x_{L1}	400 points	0.5 Hz.
x_{L2}	135 points	1.5 Hz.
x_{L3}	28 points	7.0 Hz.

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 $r_b(t) = x(t) - x_b(t)$.

The patterns x_{L1}, x_{L2} and x_{L3} are the direct impacts of

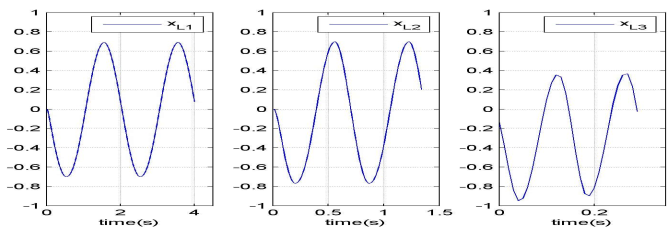

Fig. 11. Patterns x_{L1}, x_{L2} and x_{L3}

liquid failures (without the influence of the command) on the output of the system and they are comparable in some way with the residue $r_b(t)$ under the presence of a failure. Indeed, the difference $x(t) - x_b(t)$ reflects the impact of the failure on the output since the effect of the command on $x(t)$ and $x_b(t)$ is canceled by difference.

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

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 $x(t)$.

TABLE IV
SOLID FAILURES

Pattern	Sequence	Frequency
x_{S1}	400 points	0.5 Hz.
x_{S2}	135 points	1.5 Hz.
x_{S3}	28 points	7.0 Hz.

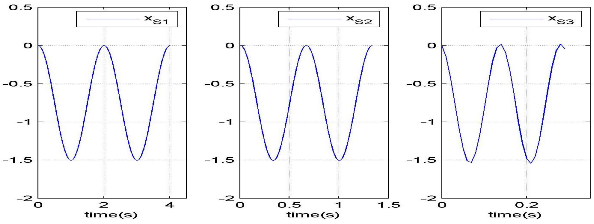

Fig. 12. Patterns x_{S1}, x_{S2} and x_{S3}

B. Generation of indication of failure

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 variable x and y is noted by $r_{x,y}$.

C. Fault detection by correlation test

With the correlation test, fault detection 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 $r_b(t)$ 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, we declare that a failure is detected.

Algorithm 2: Fault detection by correlation test

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 $V_s = 0.6$.
2) Perform calculations of linear correlation coefficients for each k^{th} sampling step:
   - Calculate $r_{r_{b(k-P(i)+1:k)}, x_{Li}}$ for $i = 1, 2, 3$.
   - Calculate $r_{x_{(k-P(i)+1:k)}, x_{Si}}$ for $i = 1, 2, 3$.
3) Evaluate the linear correlation coefficients by counting exceedances:
   - If a coefficient is greater than V_s or smaller than $-V_s$, we increase the number said *overruns* associated with this coefficient of a unit.
   - If no exceedance were observed within a limited time, we set the number of overruns to zero.
4) Onset of failure: If the failure has not yet detected and that one of the numbers of overruns is greater than or equal to 4:
   - We then declare the onset of failure.

- The nature of the failure (liquid or solid) as well as its frequency are indicated by the pattern x_{Li} or x_{Si} whose number of exceedances was observed with its correlation coefficient. If it is a pattern x_{Li}, the failure is liquid; if it is a pattern x_{Si}, 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
   - We then declare the disappearance of the failure.

The correlation coefficients calculated during the time is 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.

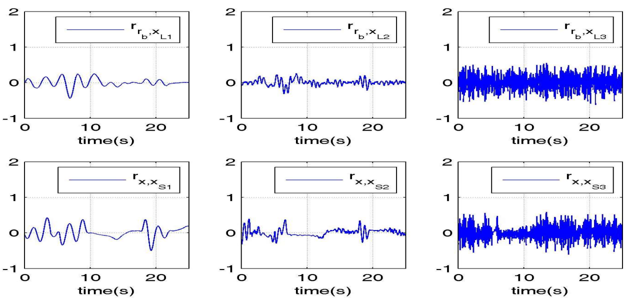

Fig. 13. Calculated correlation coefficients : case without failure

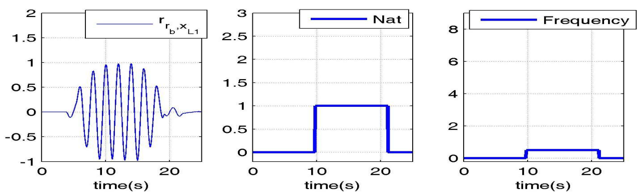

Fig. 14. Result of detection : liquid failure of 0.5 Hz frequency

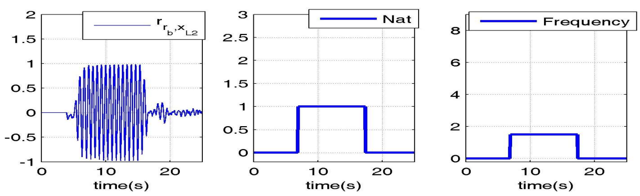

Fig. 15. Result of detection : liquid failure of 1.5 Hz frequency

The first column represents the correlation coefficient which led to the failure detection ($r_{r_b,x_{L1}}$, $r_{r_b,x_{L2}}$ and $r_{x,x_{S3}}$ respectively). The indicator of nature of the failure is noted by `Nat` in the second column. If `Nat` = 1, a liquid failure is detected,

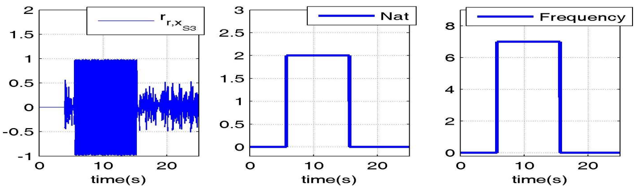

Fig. 16. Result of detection : solide failure of 7.0 Hz frequency

if `Nat` = 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 complying with the imposed 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 we can detect and isolate any solid and liquid failure of selected frequencies belonging to the frequency interval $[0.5 \ldots 10.0]$ Hz even at low amplitude (0.16 degree). However, this analysis does not identify the amplitude of the failure.

It should be noted that, in its current version, the algorithm 2 uses 6 correlation tests at every step of simulation (2 types of default, 3 selected frequencies). Although the calculations are simple and implement basic operators, it is possible to reduce substantially the volume of calculation taking account three points:

- The patterns x_{L1}, x_{L2}, x_{L3}, x_{S1}, x_{S2} and x_{S3} are determined by the type of failure. Their means and standard deviations over a window can be calculated offline and stored.
- Means, standard deviations of the output $x(t)$ and the residue $r_b(t)$ calculated over a window can be performed recursively when moving a step time of the observation window.
- The covariance between a reference pattern and a signal $x(t)$ or $r_b(t)$ over a window can also be calculated in recursive way.

Given these recurrences are easy to establish, so we can carry out the correlation tests with a small calculating volume.

VI. Conclusion

In this paper, we addressed the problem of detecting the oscillatory failure in the control system of a flight control surface of an civil aircraft. We have proposed two methods of fault detection based on a simplified model validated regarding the nonlinear models usually used. In the frequency range $[0.5 \ldots 10.0]$ Hz, we can detect any solid and liquid failure by standard deviation test, we can also detect and isolate 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). In the following, we extend these methods to other flight control surfaces (rudder or elevator), we will try to reduce the complexity as well as the number of failure models and we will try to improve the robustness of the correlation test for the failures of frequencies neighboring the selected ones.

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https://extranet.ims-bordeaux.fr/External/SIRASAS/

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