HYDRAULIC ACTUATION LOOP DEGRADATION DIAGNOSIS AND PROGNOSIS

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Abstract:

Airplane engine hydromechanical components are used to adapt turbine geometry to achieve required engine performance. Degradation on those systems appears gradually with almost imperceptible trend. Diagnostic and fault detection is observable when the system is already failing. This paper proposes an improvement using diagnostic and prognostic techniques, identifying degradation indicators by means of life bench tests data analysis, with the advantage of not needing additional sensors.

1. INTRODUCTION

Civil airframe accessories removal policy is traditionally characterized by “on condition” maintenance and for some wear accessories advised constant TBO (Time Between Overhaul). This is the best approach when prior reliability knowledge is used. The renewal process may be improved with diagnosis (fault localization) and prognosis (fault prediction) techniques using information provided by health related indicators. This avoids non-necessary removals and operation costs and allows trouble shouting and stock size reduction.

The present study is devoted to health and aging indicators identification for local control loops. The studied case is an hydromechanical actuation control loop from civil aeronautical engines.

This system is first described and failures reported. Then, the prognostic methodologies state-of-the-art is introduced and some bench test data are analyzed as the basis for providing indicators which would lead to prognostic. Finally, trended-based prognosis method by means of parameter estimation defined and tested.

2. SYSTEM DESCRIPTION

The hydraulic actuation loop consists of two hydraulic actuators mechanically linked, two LVDT (Linear Variable Differential Transformer) position sensors and a servovalve. The servovalve transforms the electronic command into hydraulic power by means of fuel flow and pressure difference. This hydraulic power is used to change both actuator positions, which is measured by the LVDT providing the calculator the necessary information to command the engine variables.

2.1. Hydraulic actuator

A simulator has been used to identify the system operating points. An intensive analysis of the simulator model has been carried out. A brief description of the simulator inputs-outputs, achievable variables as well as simulation parameters are presented.
Inputs:

- Demand commanded
- Engine state variables

The inputs are introduced at transition between engine regimes to improve the engine performance when critical power is needed to accelerate either to decelerate the turbine.
The engine state variables affecting the actuator loop performance are the fuel flow, the high pressure turbine rotation speed and the combustion chamber pressure, which determine the inlet and outlet pressures working on the hydraulic actuator:
High pressure pump provides pump outlet pressure (actuator inlet pressure) in function of the engine thermodynamic variables and the fuel flow rate.

Hydraulic circuit contains the servovalve and the actuator models. Moreover, there is a redundant position LVDT (Linear Variable Differential Transformer) sensor, which provides the output of that block so as to be treated in the regulation control loop.

Control loop is a position sensor signal manipulation (interface) for subsequent utilization in the control loop itself. The control loop regulator consists of a PI regulator (Proportional- Integrator regulator) that loops a regulation signal into the hydraulic system, concretely into the servovalve, which controls de actuator position converting an electrical signal into a hydraulic one.

2.2. Differential model equations

A differential model study is proposed so as to have a better idea of the physical parameters mainly involved in the actuator dynamics. Since physical parameters are recognized to affect system performance, the validity of a parameter estimation method in actuator diagnostic would also be proved.

The differential equation which represents the actuator is taken from the resolution of the system dynamics. A basic scheme of the actuator is show in the figure below:

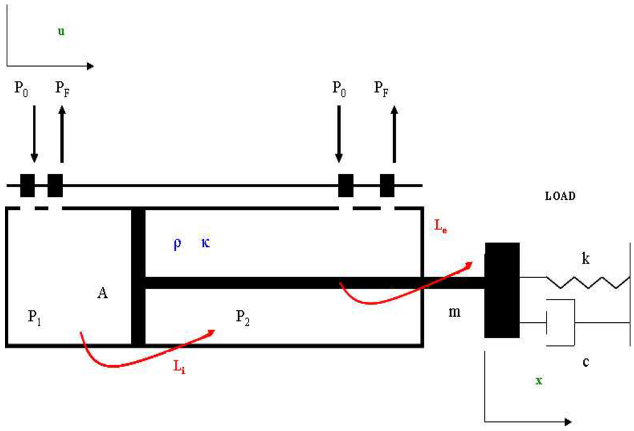

FIG 1. Actuator model scheme

This figure shows the most important variables involved in the actuator dynamics, which are described in table 1.

u	Servovalve displacement input
P_0	Supply pressure
P_F	Return pressure
P_1	Chamber one pressure
P_2	Chamber two pressure
V	Effective actuator volume (half of the total actuator volume)
A	Piston area
ρ	Fluid density
κ	Fluid Bulk modulus
L_i	Internal leakage constant
L_e	External leakage constant
m	Equivalent load mass
c	Load damping
K	Load stiffness
x	Actuator position response

TAB 1. Variables involved in the actuator differential model

The piston area is considered constant for both sides of the actuator [4]. Nevertheless, this is just an approximation since the area is smaller in the rod-side of the piston due to the rod area itself. The flow rate entering the actuator chamber can be expressed as function of the input signal of the servovalve (u) and the pressure difference between the two actuator chambers (P_2 et P1) [10] [11].

It should be remarked that as a first approximation only the internal leakage is taken in account since the external leakage is not modeled in literature, as considered avoided in hydraulic actuators [11] As an approximation, some authors don't consider the compressibility of the fluid in actuators [5]:

(1) $$\frac{\rho\cdot V\cdot m}{\kappa\cdot A}\cdot\dddot{x}+\left[\frac{\rho\cdot V\cdot c}{\kappa\cdot A}+\frac{(L+c_2)\cdot m}{A}\right]\cdot\ddot{x}+\left[A\cdot\rho+\frac{\rho\cdot V\cdot K}{\kappa\cdot A}+\frac{(L+c_2)\cdot c}{A}\right]\cdot\dot{x}+\frac{(L+c_2)\cdot K}{A}\cdot x=c_1\cdot u$$

The correspondent derivates appearing in this equation should be interpreted as the velocity of the piston (first derivate), the acceleration of the piston (second derivate) and the power (third derivate) Simplifying this expression above we find a third order differential equation expressed by the physical parameters of the system and the fluid itself, where *u* is the input of the system and *x* the piston position:

(2) $$a_3\cdot\dddot{x}+a_2\cdot\ddot{x}+a_1\cdot\dot{x}+a_0\cdot x=b\cdot u$$

Actuator system is considered in literature as an approximation of a second order response [5]. The third order derivate corresponding to the third parameter is found much smaller than the others and also non-observable [4]. In addition, the lack of desirable observable variables for diagnostic, as leakage *L*, in this third parameter of the equation makes us underestimate it. Consequently, the equation can be approximated as follows:

(3) $$a_2\cdot\ddot{x}+a_1\cdot\dot{x}+a_0\cdot x=b\cdot u$$

where all parameters are function of leakage. Therefore, we can assume that the model is directly affected by the leakage and that changes in this parameter would affect the model dynamics, linking that relation to system identification diagnostic methods.

(4) $$a_2, a_1, a_0 = f(L)$$

2.3. Hydraulic actuation loop failures

2.3.1. LVDT sensor

The LVDT position sensor is used to measure the actuator position. The main fault found in those sensors is the sensor position drift, caused particularly by:

- Intermittent contact at the electric wires
- LVDT sensor overheating

When a drifted position is provided to the aircraft calculator, it would probably lead to engine stun.

The intermittent contact has been reported to appear in the secondary winding of the sensor, so leading to a position drift. The intermittent contact can be found as well in the primary winding. However, this fault is easily detectable with the nowadays embarked diagnostic algorithm since its instantaneous effect in the global sensor performance surpasses largely the detection threshold. Moreover, the effects of the intermittent contact cause copper wires damage finally leading to electrical circuit permanent cut.

The LVDT overheating is due to the extreme thermic working conditions of the systems operating in the engine. Moreover, these conditions are combined with the phenomenon of cokefaction. The fuel, which is used as actuator fluid, is over heated due to actuator compression. To avoid this problem, a cooling diaphragm is used on the piston surface so as to generate a cooling flow between both actuator chambers. However, this diaphragm can be clogged by fuel cokefaction, so overheating the fuel and leading to sensor drift. The phenomenon of cokefaction responds hypothetically to an aging process.

2.3.2. Servovalve

The servovalve is the hydraulic loop subsystem in charge of converting the calculator command signal into hydraulic power. Therefore, a servovalve malfunction provides a bad conditioned input to the actuator thus affecting its dynamics and so the engine dynamics. The usual servovalve failures are associated to:

- flow and pressure curve hysteresis
- external leakage
- flow looses at minimum and maximum intensities
- Balance current drift corresponding to a null flow

Taking in account filed experience, the balance current drift is considered the main servovalve failure.

2.3.3. Actuator casing

Mechanic vibrations and actuation loop oscillations appear as a result of the actuation loop instability around the operating point associated to the cruise flight phase. This scenario leads to a casing wearing in the actuator cruise position, which is considered critical since it can change the actuator dynamic response. The figure below shows the actuator schema and the cruise position casing wearing location.

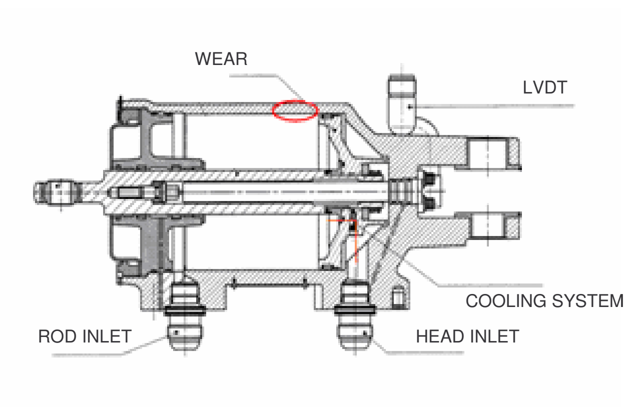

FIG 2. Actuator casing wear in cruise position

The casing wearing could lead to an internal leakage during the cruise flight phase, so changing the actuator dynamics. Consequently, the transfer function parameters set could be considered as an indicator or observable variable useful for model change detection. The 15% of replaced actuators show this phenomenon.

The table below sums up the failures described:

Causes	Effects	Failure	Observed symptom
Cooling diaphragm obstruction	Cokefaction	Overheating	LVDT sensor Drift
Engine Vibration Electrical circuit aging	Electric microcuts	Intermittent contact	
Component aging	Unbalanced intensities	Servovalve current drift	Biased zero point
Cruise mode oscillations	Casing wearing	Internal leakage	Model change

TAB 2. Cause-consequence for actuator casing wearing

3. PROGNOSTIC METHODOLOGIES

3.1. Prognostic aim

The aim of diagnostic is the knowledge and the identification of a system state or operation mode at a current instant. When monitoring a system with diagnostic purposes detecting and identifying failures and failing modes become critical tasks. In such situation, one could ask himself whether it would have been more appropriate to detect and identify failures before they occur. Therefore, prognostic could be defined as the need to predict a system state or an event over a system with enough time in advance so that the system could be readapt to ensured desired working conditions and efficiency. The failures and the failing modes as well as the desired working conditions and efficiency (performance) are part of a scenario that should be defined for each analyzed system.
Failures can be classed into hard failures and soft failures. The first ones are hard to predict due to its unexpected appearance, though they are evident in the whole system performance. Soft failures are related to a loss of performance that can be monitored by indirect indicators even not manifesting evidently [6]. The degradation is the process leading to a complete loss of performance.

Prognostics are inherently probabilistic or uncertainty in nature and can be applied to system component failure modes. On the other hand, like diagnostic algorithms, prognostic algorithms can be generic in design but specific in terms of application.

3.2. Background

Reliability lifetime tests are applied to systems considered identical by hypothesis based in production tolerance tests. However, these systems could be then submitted to different working environments variables in real life dynamics which would affect the observations and conclusions deduced in bench tests over the system reliability. Usually, the system design is carried out under the hypothesis of controlled working conditions that are known a priori and so used in the system conception. However, many systems are tested in identical bench conditions but then found not working in such conditions. Moreover, mobile systems as airplanes components are summated to variable working conditions, so their lifetime is relative not just to system conception but also to climatology, flight frequency, flight time, maintenance operations or landing and taking off conditions.

All methods used in reliability theory are based in static and off-line data analysis. The algorithms work with large amounts of data coming from bench tests, providing system degradation and reliability estimations by means of statistical techniques over a population. On the other hand, the aim is to provide on-line reliability for each single system in dynamic working conditions.

Some authors [2] establish the difference between permanent failure (PF) and intermittent failure (IF). By hypothesis, the aggregation of intermittent failures leads to a permanent failure: *Permanent failures* are understood as those who cause the permanent system malfunction, which can only be solved by repairing the faulty component, either replacing it. Therefore, they are the cause of high-level maintenance costs. *Intermittent failures* are failures who can be self-recovered by the own system or process dynamic, related to abnormal or non-desirable observations over the system (soft failures).

Furthermore, the intermittent failure definition can be extended to other events which, even not considered as a failure, degrade the system performance [9]. These events, included in the basic definition of intermittent failure could be no-desirable observations, abnormal outputs or instantaneous error detections in model based diagnostic which are considered under a critical threshold. In the example of the actuator, it can be an internal or external leakage which is only detected as a permanent failure, even their presence have been degrading the actuator since their existence. Following this reasoning, any degradation detected bigger than a threshold can be also considered an intermittent failure [6].
Once the intermittent failures for a system are defined, their observability must be ensured. IF's could be considered by hypothesis observable events, directly either indirectly. Then, each IF's could be defined by a causal relation with an indicator or a set of indicators that would provide IF's monitoring [2]. *Indicators* have been widely used for indirect degradation monitoring when considering them demonstrable of a change in system dynamics even not reaching hard failures [3] [14].

Consequently, the first hypothesis of causality between the IF's and the PF's suggests us that the design of the diagnosis method should be the first step towards the prognostic through a correct observation and treatment of the information obtained from the IFs dynamics.

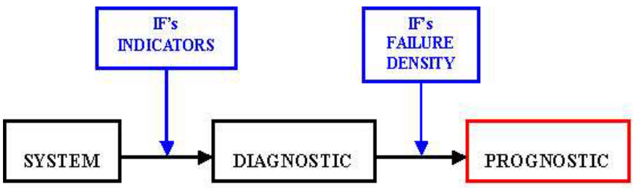

FIG 3. Schema of the interaction Diagnostic-Prognostic

The on-line system monitoring would provide information not just from the system state, but also this information would be useful for the estimation of a lifetime prognostic with a certain certitude interval. The reference to linking diagnostic and prognostic algorithms working in cooperation is proposed by some authors in terms of anomaly, diagnostic and prognostic technologies (A/D/P) [13] [14].

The model based diagnostics works with the hypothesis of time invariant models. The comparison between the model output and the real system output provides a criterion or a signature for fault detection and localization [12]. The time invariant models are found reasonable when making the diagnostic of system operating state, normal either failing. However, there is a lack of information when making the prognostic of system degradation, since the system degradation is not a failing state itself but a change in the system dynamics and performance. Therefore, the hypothesis of time variant model appears reasonable in such scenario thus the system dynamic changes despite that the system is not affected by any failure [13]. Following this reasoning, a level of degradation (or reliability loss) could be associated to a system submodel, so describing the system dynamics at a specified operating point. The submodels set would then be able to describe the system lifetime evolution in terms of degradation or reliability even if considering the system non failing in the classic concept of diagnostic.

3.3. Prognostic approaches

Various prognostics and health monitoring technologies (PHM) have been developed with the aim of detection and classification of system faults lifetime evolution. These technologies have been applied to different domains, as the aerospace and aeronautics one, so as to improve the conditioned based maintenance (CBM) operations in economic and security costs criteria [14].

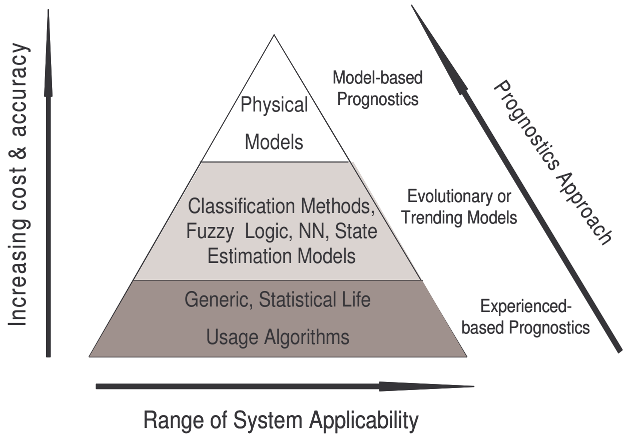

FIG 4. Hierarchy of prognosis technical approaches [15]

In the figure above, the different approaches are represented in three main groups, ranged by system applicability and costs/accuracy. The main characteristics of each group are briefly presented.

Statistical reliability and experienced-based approaches

This methods are used when insufficient sensor data is available or in face of poor system indicators network. This approach is the least complex and requires system component failure history. Typically, a system population is submitted to lifetime bench test to failure and a statistical distribution of failure data obtained is fitted after systems inspection. The Weibull distribution function is the most commonly recommended and used in those approaches (Groer 2000, Schomig, 2003). Even simplistic, this approach is used to carry out maintenance interval evaluation using the statistical MTBF (Mean time between failures) or MTTF (Mean time to failure) provided by the failure distribution. Moreover, the results obtained are worthy and provide useful a priori system knowledge and information to develop other more complex approaches. Trending-based approaches are usually based on those statistical methods for on-line degradation updating and for the identification of system aging indicators [6].

Physic-based approaches

The physic-based model is traditionally used to understand component failure mode progression. By integrating physical and stochastic modeling techniques, the model can be used to evaluate remaining useful system life as function of system physical properties and equations for a particular fault. The results from such model can be used for prognostic predictions with confidence bounds. This approach is rigid in terms of application, since is based in system physic equations. However, the fusion of system indicators if available could provide this approach of certain adaptability during system lifetime.

Trending-based approaches

Evolutionary prognostics may be implemented on systems that experience conditional or slow degradation faults related to loss efficiency. This approach requires sufficient data available and parametric conditions that would allow system performance mode identification [6]. The trend-based techniques use in measurable features or indicators extracted form sensed data that are identified to be correlated with faults or anomalies. Once these features are obtained, they can be tracked and trended over a system life so as to provide degradation information or remaining useful life estimation [15].

A key concept in this framework is the remaining useful life, represented by the probability distribution function (PDF). The PDF is a mathematical expression of the failing probability of a system. The most commonly PDF used are the Weibull distribution when expressing a failure probability model [7]. Furthermore, a PDF is actually a conditional PDF that changes at time advances. If not, the distribution function represents just the experienced-based methods approach. So, the conditional distribution function is recomputed at each current instant actualized with the information provided by system features tracking [8].

Among evolutionary techniques *the state estimator prognostics* is stressed since it is based on estimation and prediction techniques as the Kalman filter or the ARMAX models which are applied in section 4 after the previous analysis developed in the present section [17] [16]. These methods are used to monitor the system features related to the prediction of a failure mode progression, and so they are used in conjunction with the diagnostic algorithms [14]. State estimator prognostics are dependant on system model and noise that leads to algorithm covariance problems [13].

4. Airplane engine actuator loop prognosis

4.1. Endurance bench test data

The data sets used in this study are provided by airplane engines accelerated bench tests. The tests are applied over a whole engine and then data is stored to be analyzed afterwards. The variables involved in the bench tests are:

- N_1 (rpm) is the low pressure turbine rotation speed. The low pressure turbine provides a first compression stage to the air flow before the introducing it towards the high pressure turbine.
- N_2 (rpm) is the high pressure turbine rotation speed. This second compression stage provides the final air flow pressure before introducing it towards the combustion chamber. The inlet/outlet pressure ratio in the high pressure turbine is greater than the ratio in the low pressure turbine.

The turbine rotation speeds determine the engine flight phase performing. Moreover, the fuel pump rotation speed is proportional to the turbine rotation speed due to mechanical solidarity by means of a speed redactor. The fuel flow rate and the inlet combustion chamber fuel pressure are considered representative variables as well since the actuators are included in the fuel circuit and use fuel as actuator fluid, so being conditioned by fuel circuit flow and pressure.

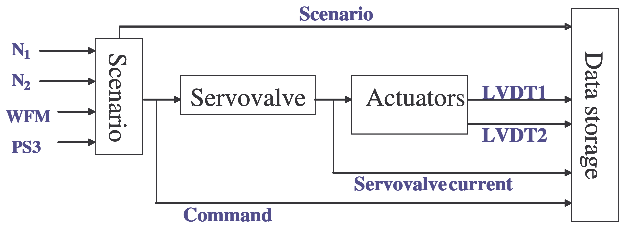

FIG 5. Data stored in bench tests for hydraulic actuator cycles

Figure 6 shows a typical airplane engine cycle for system testing and performance evaluation. The different cycle stages represented in the figure are defined by the engine speed:

- Idle, engine warming before taking off to reach appropriate engine conditions
- Acceleration (take off), transition state not represented in data.
- Cruise, after the taking off transitory represents the highest permanent rotation speed
- Ground, operations after landing transitory
- Grand idle, engine warm down
- Ground proceedings at lowest engine speed before turning off the engine

The times in the figure below are expressed in minutes and are considered proportional and significant for an engine normal operation cycle.

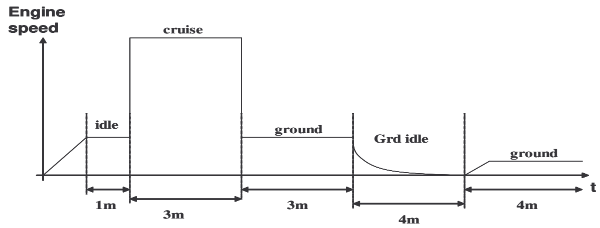

FIG 6. Typical airplane engine cycle in life tests

Figure 7 shows a sample of data recorded following the typical cycle in figure 6.

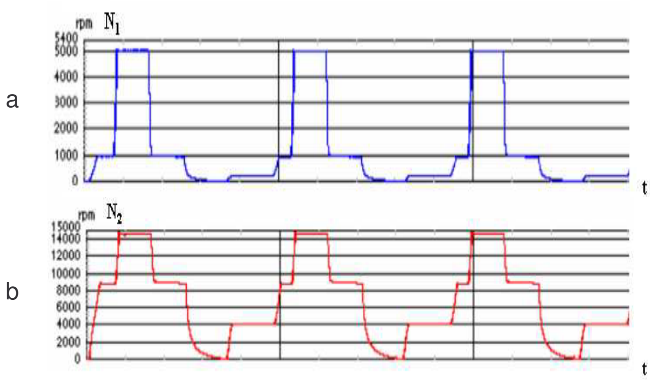

FIG 7. Life tests data, a) Low pressure turbine rotation speed, b) high pressure turbine rotation speed

The data to be stored is selected since it is considered to be representative of the actuator performance and degradation. Moreover, the study is developed taking in account the restriction of no-sensors added.

- Sensor 1/sensor 2, the output provided by the two redundant sensors.
- Command is the input provided from the calculator to the hydraulic actuator control loop.
- Servovalve current, is the input of the hydraulic system based on the command-output error
- Selected value is the output provided to the engine calculator which is used in engine regulation and control. When no fault is detected in one of the two sensors, the selected values is the mean value of the two sensor outputs.

The data sets used in this study correspond to the equivalent 2000 actuator cycles. Data sets are composed of 5 cycles each corresponding to different consecutive periods:

A	First endurance data from bench tests
B	First intermediate data from bench tests
C	Second intermediate data from bench tests
D	Last endurance data from bench tests

TAB 3. Data sources from endurance bench tests

4.2. Aging indicators and flight phase identification

4.2.1. Aging candidates

Using the data available provided by the installed sensors the table below sums up the possible aging indicators candidates:

∆Sens	Difference between signals provided by the redundant sensors
∆Com	Difference between input and output
SC	Servovalve current
SEL	Selected actuator position indication, usually the average value of the two redundant LVDT sensors

TAB 4. Indicators for system aging detection

The difference between redundant sensors is considered a candidate since the sensor drift has already been identified as a system failure (2.3). The discrepancy between the outputs provided by each sensor would be then a symptom of aging before reaching the failure. The servovalve current and the error between command and output would be considered a redundant indicator since the servovalve current is calculated using this error. However, both candidates will be evaluated since one of them would found to be more informative than the other one even easily to monitor. Moreover, the choice of servovalve current as a candidate is based on control theory, thus the more energy the system needs from the control loop to reach the desired input, the more incapable the system is to perform the command itself.

4.2.2. Flight phase selection

The study takes in account as well the most suitable flight phase for indicators monitoring. Therefore, the permanent flight phases (idle, ground cruise) are taken as candidates for aging monitoring to identify whether the flight phases have influence over the indicators. For that aim, a discrete events system (DES) is designed to recognize the flight phase at each current instant. The figure below corresponds to a dynamic schema describing the relations between flight phases:

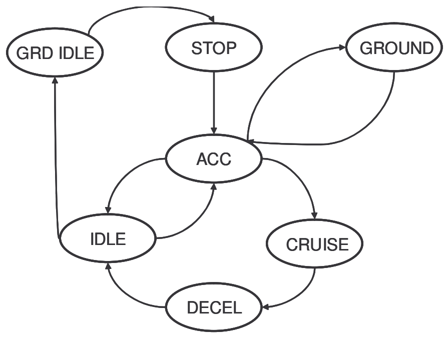

FIG 8. Discrete event system for flight phase detection

That automate provides us a criterion for bench test data analysis. Moreover, it would be useful when working on-line embarked on the motor to decide when to store the data that would be used afterwards on degradation analysis. Moreover, once the suitable flight phase would be identified, the DES would be used as input for the in-flight data storage criterion.

4.3. Aging indicators results

In section 4.2 indicator candidates have been proposed for the aging monitoring based in system a priori knowledge. Moreover, a method based in DES has been proposed for flight phase identification with two main objectives: to identify the most informative and appropriate flight phase for aging tracking, as well as to provide a criterion for in flight data storage.

The ANOVA method is applied to the data sets so as to identify the flight phase which provides us better information for aging or degradation observability. With that aim, the indicators showed in table 4 are compared between data sets described in table 3. As a result, this comparison would provide us a trend for each indicator evolution along flight cycles. Then, the ANOVA method would help us identify the most suitable flight phase to observe degradation. Moreover, another problem statement could be proposed identifying the most suitable indicator for each flight phase.

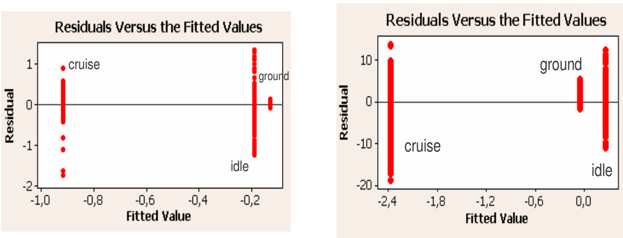

FIG 9. ANOVA results for a) selected output indicator b) servovalve current indicator

The figure above shows the main results for the ANOVA statistical analysis. The interpretation of those results confirm that the ground and cruise permanent flight phases are the most informative ones and so the most suitable for indicators monitoring. The whole results are summed up in the table below.

	ΔSensors		Selected output		Servovalve current	
	μ	σ	μ	σ	μ	σ
Idle	0,002	0,003	-0,20	0,26	0,25	2,5
Cruise	0,002	0,005	-0,92	0,18	-2,4	4,7
Ground	-0,007	0,003	-0,13	0,04	-0,06	0,8

TAB 5. Sum up table for mean and standard deviation from ANOVA flight phase results

As a result, the indicators performance during cruise flight phase. Cruise data corresponding to the four data sets available from bench tests cycles is analyzed. The data corresponding to each period is normal fitted, providing mean and standard deviation as a result for each cruise data set. The same operation is applied to each indicator to evaluate the most suitable one (or ones) for degradation monitoring. The indicator named Δcom has found not to be significant for prognostic objectives.

The figures below show the mean and standard deviation versus time corresponding to the redundant sensor difference. Both distribution parameters show an increasing tendency from initial cycles to the end of available data.

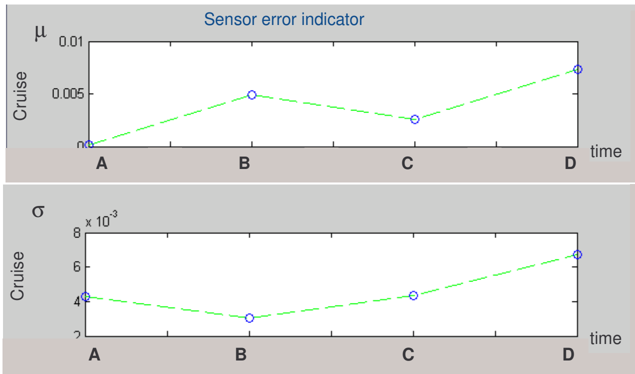

FIG 10. Sensor error indicator mean and standard deviation vs time

The same analysis is applied to the selected output indicator and the servovalve current. In the first case (Figure 11) the tendency observed in the first indicator analyzed is confirmed. Moreover, the μ-σ plot shows as well the indicator increasing along the observed time. On the other hand, in the case the servovalve current indicator (Figure 12) just the standard deviation shows the increasing tendency versus time while the other plotters μ-σ and μ-time are quite irregular and provide no information.

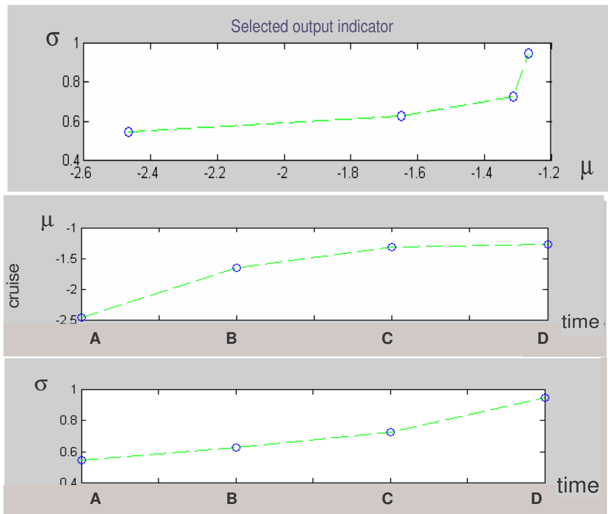

FIG 11. Selected output indicator mean and standard deviation vs time

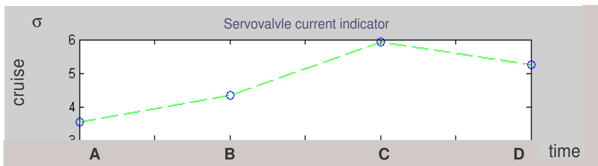

FIG 12. Servovalve current indicator standard deviation vs time

As a result, the output and the sensor outputs difference during the cruise flight phase would be used as indicators for the degradation and aging monitoring. In next section, the results and conclusions from the present one will be used to develop a methodology for aging prognostic based in the ARX estimation parameters as introduced in section 3.2 as part of the trending-based approaches.

5. ACTUATOR LOOP PROGNOSTIC USING ARX MODELS

This section is devoted to the description of a prognostic methodology as introduced previously. The method is in the framework of the trended-based approaches briefly described in section 3.2.

5.1. Algorithm EPI (Estimation by means of Pseudo-Inverse)

The bench life test data described in section 4.1 gives a set of data divided into cycles. A test on the information present in each cycle leads to the choice of the most representative cycles. In the application to real flight data this test enables to choose the most representative data for each flight phase. Therefore the indicator of device deterioration will be based on finite sets of data of a given duration, i.e. N samples.

The actuator dynamic system is modeled as a SISO system (Single Input Single Output) where the only working information available is online input-output y(t)-u(t). As a result, we can write the mathematical expression for the model corresponding as:

(5) $$\mathbf{y}(\mathbf{t}) = \sum_{\mathbf{i}=1}^{\mathbf{i}=\mathbf{ny}} \mathbf{a}_\mathbf{i}.\mathbf{y}(\mathbf{t}-\mathbf{i}) + \sum_{\mathbf{j}=1}^{\mathbf{j}=\mathbf{nu}} \mathbf{b}_\mathbf{i}.\mathbf{u}(\mathbf{t}-\mathbf{i})$$

The mathematical expression presented in equation (5) can also be expressed in a matrix version. This allows stocking and manipulating limited historical data useful for the estimation algorithm rather than using just data form the previous single time instant. According to equation (5) and the new mathematical representation, the equation can be rewritten as:

(6) $$\mathbf{y}(\mathbf{t}) = \mathbf{h}_\mathbf{y}(\mathbf{t}).\mathbf{a} + \mathbf{h}_\mathbf{u}(\mathbf{t}).\mathbf{b}$$

where,

$$\mathbf{h}_\mathbf{y}(\mathbf{t}) = [\mathbf{y}(\mathbf{t}-1) \quad \mathbf{y}(\mathbf{t}-2) \quad \dots \quad \mathbf{y}(\mathbf{t}-\mathbf{ny})]$$
$$\mathbf{h}_\mathbf{u}(\mathbf{t}) = [\mathbf{u}(\mathbf{t}-1) \quad \mathbf{u}(\mathbf{t}-2) \quad \dots \quad \mathbf{u}(\mathbf{t}-\mathbf{nu})]$$
$$\mathbf{a} = [\mathbf{a}_1(\mathbf{t}) \quad \dots \quad \mathbf{a}_{\mathbf{ny}}(\mathbf{t})]^\mathbf{T}$$
$$\mathbf{b} = [\mathbf{b}_1(\mathbf{t}) \quad \dots \quad \mathbf{b}_{\mathbf{nu}}(\mathbf{t})]^\mathbf{T}$$

Furthermore, regrouping first the input and output data, in a row vector $\mathbf{h}(\mathbf{t})$ and parameters in a single column θ, equation **(6)** becomes $\mathbf{y}(\mathbf{t}) = \mathbf{h}(\mathbf{t}) \cdot \theta$

(7) $$\mathbf{y}(\mathbf{t}) = \mathbf{h}(\mathbf{t}) \cdot \theta$$

By considering the finite sequence of data presenting N times equation $\mathbf{y}(\mathbf{t}) = \mathbf{h}(\mathbf{t}) \cdot \theta$, the following set of equations is obtained:

(8)
$$\begin{aligned} &\mathbf{y}(\mathbf{t}) = \mathbf{h}(\mathbf{t}) \cdot \theta \\ &\mathbf{y}(\mathbf{t}-1) = \mathbf{h}(\mathbf{t}-1) \cdot \theta \\ &\dots\dots\dots\dots\dots\dots\dots\dots \\ &\mathbf{y}(\mathbf{t}-\mathbf{N}+1) = \mathbf{h}(\mathbf{t}-\mathbf{N}+1) \cdot \theta \end{aligned}$$

or as well in a more compact form:

(9) $$\mathbf{Y}(\mathbf{t}) = \mathbf{H}(\mathbf{t})\theta$$

where the parameters vector θ is considered constant during the observation period. The corresponding elements of equation $\mathbf{Y}(\mathbf{t}) = \mathbf{H}(\mathbf{t})\theta$ are:

(10) $$\mathbf{Y}(\mathbf{t}) = \begin{bmatrix} \mathbf{y}(\mathbf{t}) \\ \mathbf{y}(\mathbf{t}-1) \\ \vdots \\ \mathbf{y}(\mathbf{t}-\mathbf{N}+1) \end{bmatrix} \qquad \mathbf{H}(\mathbf{t}) = \begin{bmatrix} \mathbf{h}_\mathbf{y}(\mathbf{t}-1) & \mathbf{h}_\mathbf{u}(\mathbf{t}-1) \\ \mathbf{h}_\mathbf{y}(\mathbf{t}-2) & \mathbf{h}_\mathbf{u}(\mathbf{t}-2) \\ \vdots & \vdots \\ \mathbf{h}_\mathbf{y}(\mathbf{t}-\mathbf{N}) & \mathbf{h}_\mathbf{u}(\mathbf{t}-\mathbf{N}) \end{bmatrix} \qquad \theta = \begin{bmatrix} \mathbf{a} \\ \mathbf{b} \end{bmatrix}$$

In the matrix formulation of the problem the system should be overdetermined, which means that the window length, *N*, should be strictly bigger than the number of variables, n_u and n_y, to be estimated,

(11) $$N > n_y + n_u$$

Forcing the system to be overestimated, the feasibility of applying the proposed algorithm can be assured; otherwise it would become mathematically incoherent.

Once the hypothesis and the equations are presented, the *a posteriori* error, or instantaneous error (IE) , *e*(*t*)*,* is given by equation (12).The IE is defined as the difference between the actual output and the estimated output issued from the parameters estimated at the same instant.

(12) $$\mathbf{e}(\mathbf{t}) = \mathbf{y}(\mathbf{t}) - \mathbf{h}(\mathbf{t}) \cdot \hat{\theta}(\mathbf{t}) \cdot$$

The parameters estimator $\hat{\theta}(\mathbf{t})$ is expected to minimise the square sum of the instantaneous errors [1]:

(13) $$J(t) = \frac{1}{N} \cdot \sum_{i=1}^{N} e(i)^2$$

Applying the above definitions and solving for the minimisation of the criterion equation the optimal estimator obtained is given by equation $\hat{\theta}(t) = H^{\#} \cdot Y(t)$, where $H^{\#}$ stands for Penrose pseudo inverse applied to equation **(13)**.

(13) $$\hat{\theta}(t) = H^{\#} \cdot Y(t)$$

As the initial problem is overdetermined, the *left pseudo-inverse* is defined as follows:

(14) $$H^{\#} = \left(H^T(t)H(t)\right)^{-1} H^T(t)$$

This pseudo-inversion introduces the problem of the inversion of matrix $\mathbf{H}^{\mathbf{T}}(\mathbf{t})\cdot\mathbf{H}(\mathbf{t})$ and its conditioning for a given historical data storage. This can be handled by conditioning indexes that reflect the information provided by $\mathbf{H}^{\#}$. If the matrix is bad conditioned, then the previous estimated parameters are hold as valid, $\hat{\theta}(\mathbf{t})=\hat{\theta}(\mathbf{t}-1)$.

5.2. Aging indicator monitoring by comparison to selected position indication

The EPI estimator is applied to three output sequences: LVDT1, LVDT2 and selected LVDT, with the input sequence pf the servovalve current (SC). The 3 parameters estimated by the EPI algorithm are 3 points in the space $\mathbf{R}^{(n_y+n_u)}$. In absence of failures the 3 points appear grouped, as shown in the left part of figure 13. For failures that affect only one of the LVDT sensors those distances appear to be dissymmetric, and the aged sensor would appear more apart, as shown the right part of figure 13.

The upper part of the figure above shows the distance between parameters sets in the $\mathbf{R}^{(n_y+n_u)}$ space, while the bottom part, for easier visualisation, shows the parameter representation in the plane of dynamic parameters $\mathbf{suy}=\sum_{\mathbf{i}=1}^{\mathbf{i}=\mathbf{ny}}\mathbf{a}_{\mathbf{i}}$ versus the gain parameters $\mathbf{suu}=\sum_{\mathbf{j}=1}^{\mathbf{j}=\mathbf{nu}}\mathbf{b}_{\mathbf{i}}$
The space suy-suu represents the addition of the dynamic parameters versus the gain (transfer function numerator) parameters for a more graphical comprehension of the plot, even the distance is calculated over the $\mathbf{R}^{(n_y+n_u)}$ space.

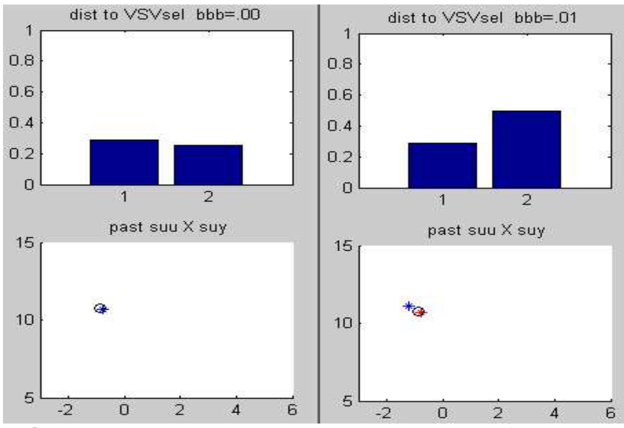

FIG 13. Aging indicator monitoring by means of estimated parameters space using selected output

5.3. Aging indicator monitoring by comparison to past data

The comparison with past data is used to detect a change in both sensors, which would indicated that a change in the model is found since both LVDT sensors are affected by the failure. Therefore, it is expected that the drift of the represented points in the parameters space will be similar for both sensors. Moreover, the three points in the parameter space may appear grouped since most of the time the selected value (LVDT selected) is the arithmetic mean of both sensor outputs. The application of this method is still possible by comparing the point obtained for two data sets such that, the first corresponds to data obtained in one early cycle, and the second when some effects of aging is expected in the form of failures as described in section 2.3. In the present work this has been experimented using data obtained from the first bench tests period, and a cycle corresponding the last cycles available from bench tests. In figure 14, the left image corresponds to data from initial cycles, assuming the system brand new. The figure shows the 3 points grouped, in the right image with the circle indicating the situation of the selected sensor in the initial data. In the right side of the figure the points correspond to the position of LVDT1 and LVDT2 for the data from an aged cycle.

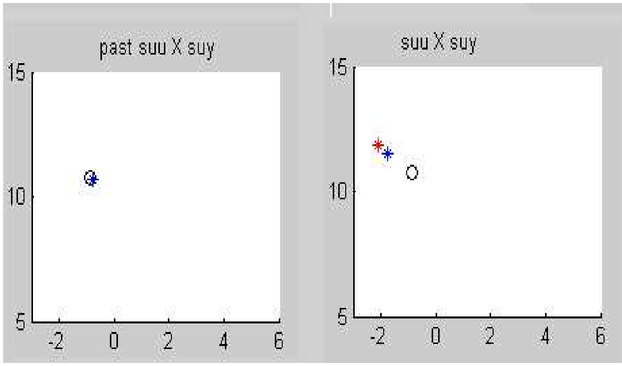

FIG 14. Aging indicator monitoring by means of estimated parameters space partition

6. CONCLUSIONS AND PERSPECTIVES

This work presents a methodology based on dynamic parameters estimation for failures diagnosis and prognosis with no additional sensors. The endurance bench test data analysis revels that the cruise permanent failure is an appropriate flight phase for aging tracking. Moreover, the aging indicators could have been identified to be used afterwards in aging monitoring. Linear ARX (Auto Regressive eXogeous) models have been used for system parameter estimation in the framework of trended-based prognosis approaches. Results show that the degradation of one redundant position sensor appears as a displacement of the failing sensor in the parameter space partition. Besides, degradation in the servovalve, which is common for both actuators; or the actuator casing wear, which affect both position sensors due to mechanical solidarity, impacts both position sensor ARX model parameters compared to reference parameter set. Therefore, diagnosis localization allows fault discrimination for each LRU (Line Replaceable Unit). The selected approach based in estimator parameters in the framework of trended-based prognostics provide satisfying results even if working with data sets corresponding to a short system life, so they could be extrapolated to more aged data cycles.

Future work should be done to improve indicators observability, over servovalve current above all. Moreover, other criteria for data selection are being studied based in information and entropy theory. Finally, the design of diagnosis and prognostic methods should be done in parallel, as said previously, in order to take profit one from each other. While diagnostics data could be used in prognostics, prognostics conclusions could also provide statements for a most accurate diagnostic of future data. As a result, system approach appears to be a key of prognostic for maintenance and operations costs savings.

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