

Electrohydraulic actuators affected by multiple failures: proposal of an alternative model-based prognostic paradigm

M. D. L. Dalla Vedova, P. Maggiore, and F. Marino

Abstract—Onboard electrohydraulic actuator (EHA) applied to primary and secondary flight command, and in particular the servovalves (SVs) regulating their hydraulic power, are complex devices and can fail in several ways: servovalves are critical components of the hydraulic servos and their correct operation is mandatory to ensure the proper functioning of the controlled servosystem. For this reason, a continuous monitor is typically performed to detect a servovalve loss of operation, but this monitor falls short of recognizing other malfunctionings. Often, a progressive degradation of a servovalve occurs, which does not initially create an unacceptable behavior, but eventually leads to a condition in which the servovalve, and hence the whole servoactuator operation, is impaired. Developing a prognostic algorithm able to identify the precursors of a servovalve failure and its degradation pattern is thus beneficial for anticipating the incoming failure and alerting the maintenance crew such to properly schedule the servovalve replacement. This avoids a servovalve failure in service, thereby ensuring improved equipment availability and minimizing the impacts onto the logistic line. To this purpose, authors propose a new model-based fault detection and identification (FDI) technique able to perform an early detection of two of the most common types of SV progressive failures (dry friction acting on servovalve spool and contamination of the first stage filter). The robustness of the proposed technique has been assessed through a simulation test environment, built on the purpose. Such simulation has demonstrated that the methodology has adequate robustness; also, the ability to early identify an eventual malfunctioning has been proved with low risk of missed failures or false positives.

Keywords— Electrohydraulic servomechanism, flight command, numerical modeling, fault detection/identification, prognostics.

I. INTRODUCTION

PROGNOSTICS is a new discipline that aims to identify the progressive failure affecting a system and to predict the moment in which a specific component loses its functionality (and, then, it is not further able to meet desired performances).

P. Maggiore is with the Department of Mechanical and Aerospace Engineering (DIMEAS), Politecnico di Torino, Corso Duca degli Abruzzi, 24 - 10129 - Torino, ITALY. (e-mail: paolo.maggiore@polito.it).

F. Marino is with the Department of Mechanical and Aerospace Engineering (DIMEAS), Politecnico di Torino, Corso Duca degli Abruzzi, 24 - 10129 - Torino, ITALY. (e-mail: francesco.mrno@gmail.com).

M. D. L. Dalla Vedova is with the Department of Mechanical and Aerospace Engineering (DIMEAS), Politecnico di Torino, Corso Duca degli Abruzzi, 24 - 10129 - Torino, ITALY. (corresponding author phone: +390110906850; e-mail: matteo.dallavedova@polito.it).

It is based on knowledge and analysis of the possible failure modalities of the considered item and on the capability to individuate the initial symptoms of aging or wear; additionally, this discipline has the objective to assess the magnitude of such damage performing a fault detection and identification (FDI). Therefore, a dedicated failure propagation model uses these informations to evaluate any possible malfunction and its impact. Vachtsevanos et al [1-2] put in evidence as the use of this discipline in aeronautics, as in many other technological fields, could be very useful if applied to maintenance, since it lowers both costs and inspection time. In order to optimize these advantages, the discipline known as Prognostics and Health Management (PHM) originated: its purpose, as reported by Byington, Watson, Edwards, and Stoelting [3], is to provide real-time data on the current status of the system and to calculate the Remaining Useful Life (RUL) before a fault occurs or a component becomes unable to perform its functionalities at a desired level. The research presented in the paper, referring to the considerations reported by Borello, Dalla Vedova, Jacazio and Sorli in [4] and by Maggiore et al. in [5], is focused on the development of a fault detection/identification (FDI) method able to identify failure precursors (alerting that the system is degrading) and to evaluate the damage entity. Indeed, a progressive degradation of a system subsystem/component, which does not initially create an unacceptable behavior, often leads to a condition in which the efficiency of such component is impaired and hence the whole actuation system operation could be compromised. Developing a prognostic algorithm able to identify the precursors of an EHA failure and its degradation pattern is thus beneficial for anticipating the incoming failure and alerting the maintenance crew such to properly schedule the EHA replacement. This avoids a servomechanism failure in service, thereby ensuring improved equipment availability and minimizing the impacts onto the logistic line. The choice of the best algorithms able to detect and evaluate a particular kind of incipient failure is driven by their ability to detect the failure itself, so proper tests are needed. In order to develop the above mentioned research, a typical aircraft primary command electrohydraulic actuator (EHA) has been modelled in the MATLAB Simulink® environment and several sets of simulations (performed in nominal conditions or under various combinations and magnitude of failures) have been run.

The present work started with an extensive literature review, focused both on the most common EHA fault modalities and propagation models and on the techniques and algorithms allowing their detection and evaluation. Then, the numerical models, implemented in MATLAB Simulink® and used to analyze the progressive fault modes have been described. The first model, reported in Section 3, represents the typical electrohydraulic servomechanism, and allows simulating the effects due to the four different types of progressive faults previously mentioned. This model was coupled to the second one (Section 4), which represents a simplified model of the same EHA. Operatively speaking, the proposed approach aims to identify the health condition of the real EHA by comparing its dynamic response with the corresponding one provided by the said simpler monitoring model (i.e. calculated for the same command inputs and boundary conditions): the FDI algorithm identifies the value of appropriate coefficients of the monitor that minimize the quadratic error and, subsequently, allows to correlate them with the actual amount of the corresponding damages. In Section 5, the numerical modeling of the above-mentioned faults was discussed in detail, such as their effects on the system and the parameters allowing each fault to be detected. Sections 6, 7 and 8 show respectively the failure precursors, the proposed FDI method (describing the authors' algorithm and providing some explanatory results), the main conclusion and the directions for future works.

II. AIMS OF WORK

The aims of the work are:

- 1) The proposal of a detailed numerical model able to simulate the dynamic behavior of EHAs taking into account the effects due to two different types of progressive failures (dry friction acting on servovalve spool and contamination of the first stage filter).
- 2) The proposal of an innovative fault detection and evaluation method able to detect the EHA failure precursors and estimate the failures entity.

To assess the robustness of the proposed techniques, a dedicated simulation test environment has been developed; in particular, in order to evaluate the effects due to the above-mentioned failures on the EHA behavior, several simulations (related to different combinations of damages as well as different entity) have been performed. The results obtained from each simulation have been compared with the ones provided by a monitoring model (a simplified model that works in nominal conditions) to evaluate the differences and define an association with the corresponding failures.

III. EHA REFERENCE MODEL

The considered actuation system, schematically shown in Fig. 1, is a typical electrohydraulic position servomechanism (SM) widely used both in primary and secondary aircraft flight controls. As shown in [6-8], this servomechanism consists of three main subsystems, listed below:

- 1) Controller subsystem: the control electronics may be a computer, microprocessor or guidance system and creates a command input signal; the servo-amplifier (SA) provides a low power electrical actuating signal which is the difference between the command input signal and the feedback signal generated by the feedback transducer. The SA usually implements an embedded PID control logic (proportional-integral-derivative); it must be noted that it is possible to implement more simplified control logics. This work is referred to simple proportional control logic.
- 2) Electrohydraulic two stage servovalve (SV): responds to the SA low power electrical signal and controls the high pressure hydraulic fluid [9].
- 3) Hydraulic piston (symmetrical double acting linear cylinder subject to Coulomb friction) [10]: actuates the flight control surface closing the position feedback loop by means of a network of integrated position transducers.

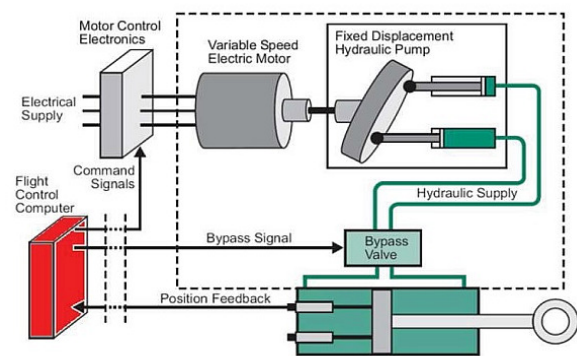


Fig. 1 schematic of EHA system layout

Wider descriptions of the servomechanism employed in this work and of its mathematical model are shown by Maggiore et al. in [11]; the scheme of the said logic is shown in Fig. 2.

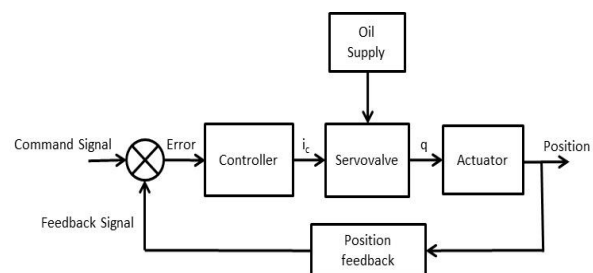


Fig. 2 schematic concept of EHA actuator

The aforesaid servomechanism belongs to the fly-by-wire paradigm: the pilot's command depends upon transducers that express the pilot wishes by an electric or a digital reference signal; this signal is continuously compared via a feedback loop with the actual position of the control surface generating the instantaneous position error as input to the control law. So, the error is processed and transformed into an electric current operating the electrohydraulic servovalve.

The servovalve drives an actuator that moves the control surface continuously pursuing, by a proper control law in order to obtain the reduction of the error between pilot's commanded position and flight surface actual position.

The servovalve is a high performance two-stage valve (Fig. 3); its second stage is a closed center, four-way, sliding spool, while the pilot stage is a symmetrical double nozzle and flapper, driven by a torque motor. Since its natural frequency is supposed to be orders of magnitude higher than the desired closed loop bandwidth of the whole servomechanism, only its orifices resistive effects were taken into account.

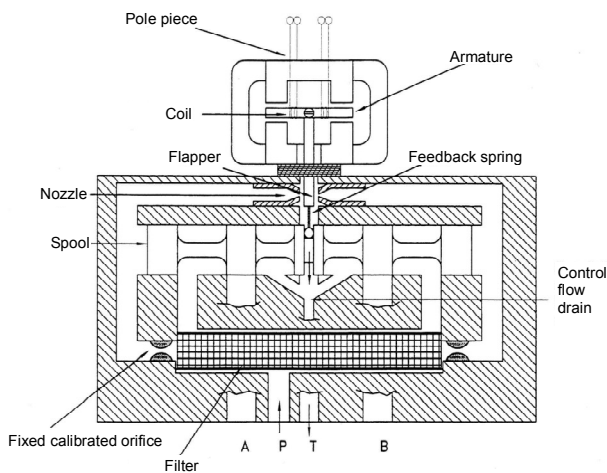


Fig. 3 schematic of the flapper-nozzle servovalve

Its behavior could be efficiently described, for the purpose of the paper, with a lumped parameter second order electro-mechanical model for the pilot stage (first stage) and a first order for the sliding spool (second stage) and the related feedback spring (Fig. 4).

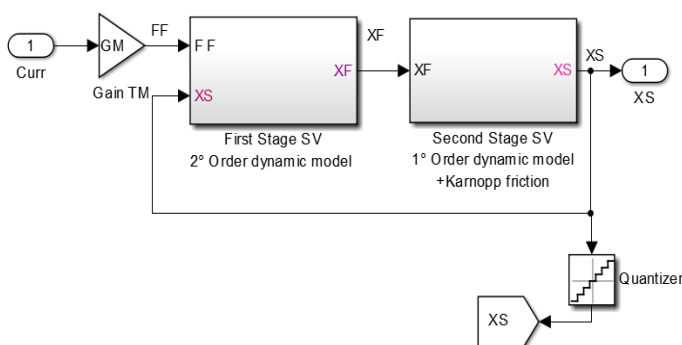


Fig. 4 proposed servovalve Simulink model

Moreover, in order to take in account, the feedback response between the second stage and the first one, we have modelled the saturation of the differential pressure itself as well as some other minor effects (e.g. oli leakage acting on the second stage SV spool).

The hydraulic linear actuator considered in the present paper is a double acting symmetrical one. It has been modelled considering inertia, dry friction (according to the dry friction Karnopp model shown in [12]), viscous friction and leakage effects through the piston seals developing a not working flow.

It is also able to take in account the effects due to its interactions with the mechanical ends of travel as well as the external (aerodynamic) loads acting on the flight surface.

A. EHA Analytical Model

In order to develop the abovementioned research, a typical aircraft primary command EHA has been mathematically modelled (according to considerations previously reported and widely explained in [11]) and, subsequently, implemented in MATLAB Simulink® numerical simulation environment.

This model has been used to simulate the dynamic behavior of a real actuator allowing to perform several sets of simulations (in nominal conditions or under several failures level). Its Simulink block diagram is shown in Fig. 5: the position error (Err), coming from the comparison of the instantaneous value of commanded position (Com) with the actual one (XJ), is processed by means of a PID logic giving the suitable current input (Cor) acting on the servovalve first stage torque generator; the aforesaid engine torque (expressed as a function of Cor through the torque gain GM), reduced by the feedback effect due to the second stage position (XS), acts on the first stage second order dynamic model giving the corresponding flapper position (XF) (flapper and spool positions are limited by double translational hard stops).

The above mentioned flapper position causes a consequent spool velocity and, by time-integrating, gives the displacement XS (limited by double translational hard stops $\pm XSM$); it must be noted that the second stage dynamics is modelled by means of a second order numerical model able to take into account the dry friction forces acting on the spool. From XS, the differential pressure P12 (pressure gain GP taking into account the saturation effects) effectively acting on the piston is obtained taking into account the pressure losses due to the flows through the hydraulic motors QJ (valve flow gain GQ).

The differential pressure P12, through the piston active area (AJ) and the equivalent total inertia of the surface-motor assembly (MJ), taking into account the total load (FR), the viscous (coefficient CJ) and dry friction force (FF), gives the assembly acceleration (D2XJ); its integration gives the velocity (DXJ), affecting the viscous and dry frictions and the linear actuator working flow QJ that, summed to the leakage one, gives the above mentioned pressure losses through the valve passageways, while velocity integration gives the actual jack position (XJ) which returns as a feedback on the command comparison element of the SM control logic.

It must be noted that the proposed numerical model is also able to take in account the effects of EMC (Electromagnetic Compatibility) phenomenon by considering the electrical noise acting on the signal lines and the disturbances generated by position transducers affected by electrical offset.

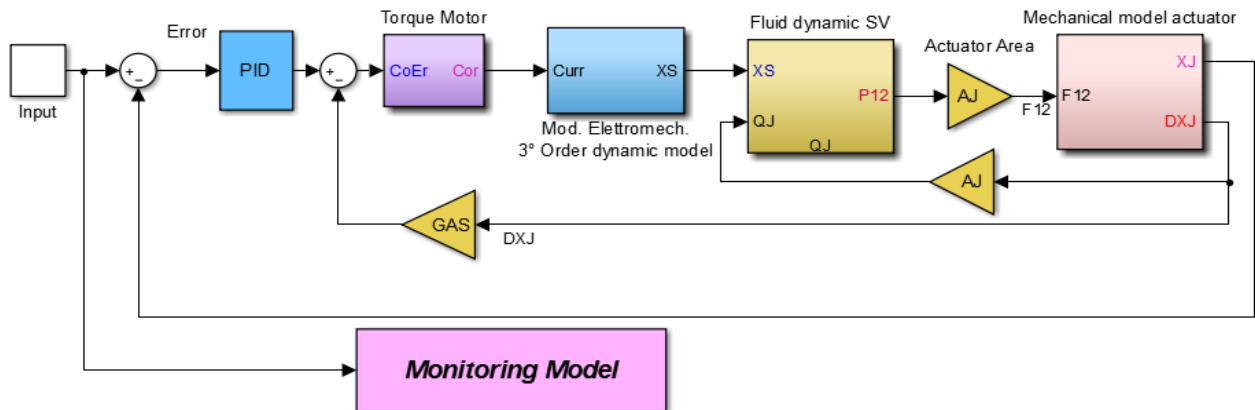


Fig. 5 Matlab-Simulink block diagram of the considered EHA

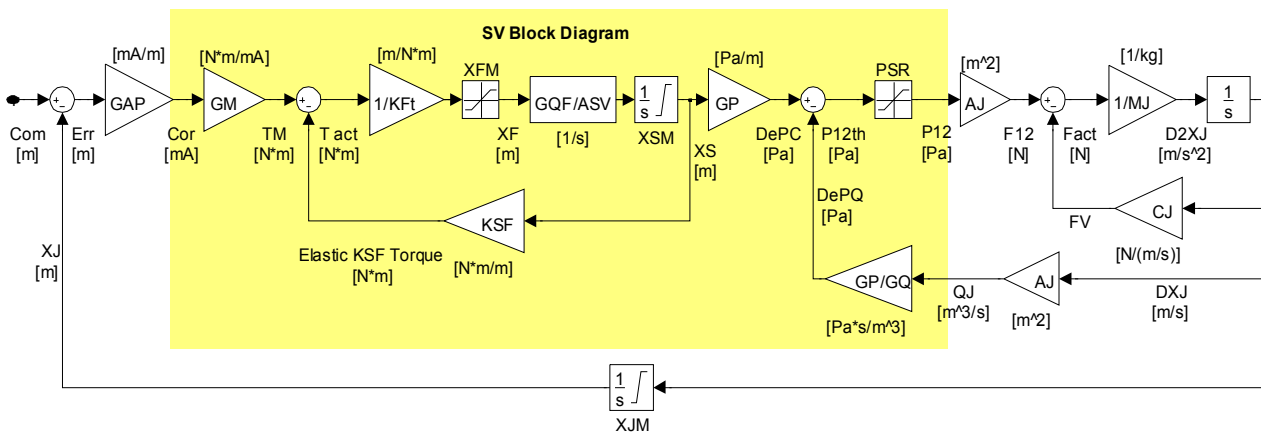


Fig. 6 Matlab-Simulink block diagram of the EHA monitoring model

IV. EHA MONITORING MODEL

The proposed detailed EHA Simulink model, as explained in the previous paragraphs, is able to simulate the dynamic behavior of an actual electro-hydraulic servomechanism taking into account the effects due to command inputs, environmental boundary conditions and several failures; therefore, it allows simulating the dynamic response of the real system evaluating the effects of different faults and testing new diagnostic and prognostic strategies. In order to conceive a smart system able to identify and evaluate the progressive failures, the authors propose a new method able to identify the health condition of the real EHA by comparing its dynamic response with the corresponding one provided by a simpler monitoring model properly designed: practically, the proposed FDI algorithm compares the two dynamic responses (EHA detailed model vs. monitor, calculated for the same command inputs and boundary conditions) identifying the value of appropriate coefficients of the monitoring model that minimize the quadratic error and, subsequently, correlates them with the actual amount of the corresponding damages.

To this purpose, on the basis of the algorithm shown in [11], a new EHA monitoring model has been developed. As shown in Fig. 6, this monitor represents a simplified version of the detailed EHA numerical model having the same logical and functional structure; such a model, with respect to the detailed one, is able to give similar performance (although less detailed) requiring less computational effort and more reduced computational time. The coefficients reported into the block diagram of Fig. 6 are defined in Table 1.

V. MODEL PROGRESSIVE FAILURES EFFECTS

As previously mentioned, the electrohydraulic actuators, and in particular the servovalves regulating their hydraulic power, are complex devices and can fail in several ways: according to the above considerations, in this work authors focused on some of the typical faults that affect the servovalve. It must be noted that a few servovalves failures are a sudden occurrence and there is at present no conceivable way of predicting them (e.g. some electrical failures of the SV first stage servo-amplifier or a feedback spring breaking).

Table 1: list of EHA Monitoring Model coefficients

Symbol	Definition
Com	Position command
Cor	Servovalve current
Err	Position error
F12	Hydraulic actuation force
FV	Actuator viscous force
P12	Actuator pressure differential
QJ	Actuator flow
s	Laplace variable
Tact	Net torque on flapper
TM	Servovalve motor torque
XF	Flapper position
XJ	Actuator position
DXJ	Actuator speed
D2XJ	Actuator acceleration
XS	Spool position
DXS	Spool speed
AJ	Actuator area
ASV	Spool end area
CJ	Actuator viscous resistance coefficient
GP	Servovalve pressure gain
GQ	Servovalve flow gain
GQF	1 st stage flow gain
GAP	Control law proportional gain
GM	Torque motor gain
KFt	1 st stage mechanical gain (spring stiffness)
KSF	Servovalve feedback spring stiffness
PSR	Maximum pressure differential
MJ	Actuator mass
XFM	Flapper max. displacement (half stroke)
XSM	Spool max. displacement (half stroke)
XJM	Actuator max. displacement (half stroke)

Failures of this type are the interruption of the electrical coils, the breaking of the internal feedback spring, the clogging of a nozzle or of the jet-pipe due to large size debris in the oil, a spool seizure resulting from a large metallic chip stuck in the radial clearance between spool and sleeve of the SV or erosive wear phenomenon [13]. However, as shown in [4,11], there are several other scenarios in which a progressive degradation of a servovalve occurs that does not initially create an unacceptable behavior; if undetected, these faults may lead to conditions in which the servovalve, and hence the whole EHA operation is impaired. As previously reported, the progressive SV faults considered in this work are the contamination of the first stage filter and the dry friction acting on servovalve spool.

A. Contamination of First Stage Filter

As dirt and debris accumulate in the SV first stage filter, its hydraulic resistance increases with a consequent reduction of the supply pressure available at the first stage and hence the pressure differential applicable to the spool: this progressive damage results in a slower response of the SV, with increased phase lag and reduction of the EHA stability margin (Fig. 7).

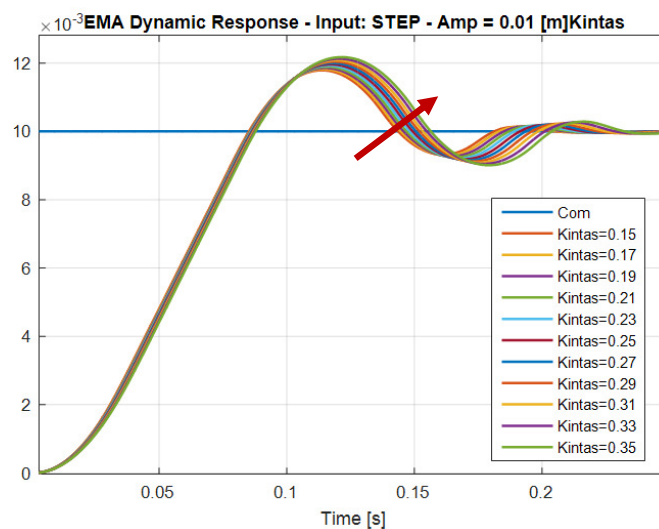


Fig. 7 EHA step position response in case of increasing first stage filter contamination

B. Dry Friction Acting on SV Spool

This growth of the dry friction force acting between spool and sleeve is due to a silting effect (associated either to debris entrained by the hydraulic fluid or to the decay of the hydraulic fluid additives which tend to polymerize when the fluid is subjected to high temperatures or large shear stresses - as they occur in the flows through small clearances): in this case, the progressive reduction of the spool positioning accuracy (due to the said friction), degrading the position accuracy and the stability of the valve (according to [14]), generates a corresponding decrease of the stability margin of the whole servomechanism, while, about the jack fault, the effects due to an increase of the friction force acting on the linear hydraulic actuator. This dissipative force, caused by the cylinder sealing and guiding elements, has been considered because of its influence on dynamic behavior of the actuation system [15]: in this case, dry friction produces a reduction of EHA position accuracy and degradation of its breakaway resolution (Fig. 8) and, at the limit, it could generate stick-slip.

For completeness, it should be noted that, in addition to these faults, the considered EHA system may also suffer electrical or electronic problems. Electrical and sensor failures are not less important than the others but, generally, their evolutions are usually very fast (if not instantaneous); then, the corresponding failure precursors are often difficult to identify and evaluate reasonably in advance on the onset of the corresponding fault.

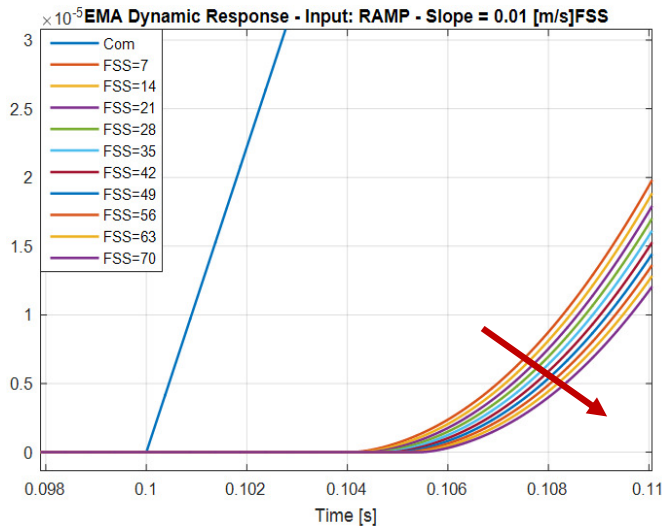


Fig. 8 EHA ramp position response for increasing spool friction

VI. FAILURE PRECURSORS

The proposed approach performs the fault detection and identification (FDI) analysis by means of an algorithm (based upon comparison between real system and its monitoring model) able to detect the progressive failures and predict their evolution¹. The health conditions of the real EHA are identified by comparing its dynamic response with the corresponding one provided by a simpler monitoring model properly designed. Operatively speaking, the proposed algorithm compares the two dynamic responses (generated by detailed model and by monitor, under the same command inputs and boundary conditions) in order to identify the value of appropriate coefficients of the monitoring model that minimize the quadratic error and, subsequently, to correlate the amount of the aforesaid coefficients with the actual level of the corresponding damages. It must be noted that, in order to limit costs, logistic problems and the reliability implications related to introduction of new components into the sensors network, this approach identifies potential system degradations without requiring any additional transducer. In conclusion, the proposed prognostic algorithm is based upon the detections of the precursor of degradations identified during the simulations: then now we are going to briefly explain what kind of result we have found during our analysis. In case of increased contamination of the first stage filter, we have observed a high correlation between this fault and the following parameters:

- 1) Amplitude of the first overshoot.
- 2) Time required for complete adjustment.

Figure 7 puts in evidence how the EHA dynamic response changes even with a small increasing of the servovalve filter contamination (simulated by means of a choking factor called Kintas), generating a measurable reduction of the stability margin of the whole system.

¹ This fact underlines a limit of prognostics: indeed, it could predict only failures which present a gradual growth and it is not able to detect sudden faults (or progressive faults having too rapid growth).

Indeed, evaluating higher value of filter contamination (shown by red arrows in Fig. 7), it is possible to verify how the EHA evidences a progressively reduced stability margin (with broader overshoots and longer settling times). As regards the increasing of the friction force acting between spool and sleeve, the authors found some difficulties in discern the effects attributable to static friction and dynamic one. Indeed, especially in the considered application, these two phenomena tend to be hardly discernible each other. About the dynamic friction acting on spool, three parameters are considered:

- 1) Breakaway resolution.
- 2) Average position error during slope actuation.
- 3) Frequency and amplitude of eventual stick-slip.

In order to identify increasing of dry friction, the most effective was the slope command input that could easily identify the previous three parameters. To ensure a better prognostic level of the incipient failure, evaluation parameters about time response and steady-state have been introduced.

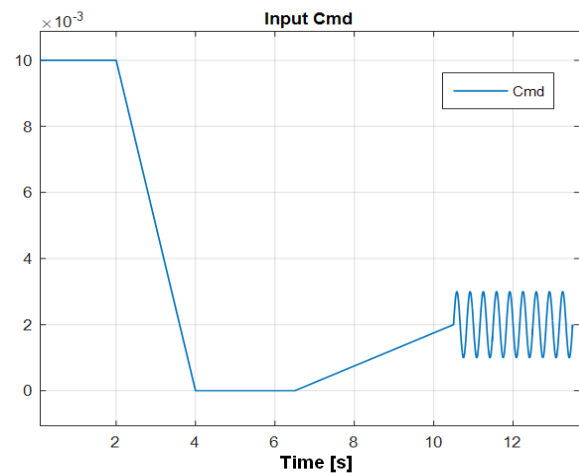


Fig. 9 command input used to perform the FDI analysis

VII. FAULT DETECTION AND IDENTIFICATION

The effects of the progressive faults on the characteristic parameters of the prognostic model have been firstly assessed separately, by considering the degradation of the single parameters, and then simultaneous degradations have been simulated to evaluate their effects. With the purpose to achieve a timely identification and evaluation of these failures, the authors have analyzed how the previous parameters evolve during the degradations of system: many scenarios have been evaluated and the so acquired know-how has been used to identify a suitable sequence of position command inputs (shown in Fig. 9) useful to perform with satisfactory accuracy the FDI of these progressive faults. The proposed prognostic procedure could be performed during the preflight checks (or the daily maintenance): the dynamic response produced by the real actuator as a consequence of the proposed command input will be acquired and, then, analyzed with post-processing software in which, by the comparison with the monitor, the EHA health status is esteemed.

In the first part of this paragraph we are going to consider single degradations (i.e. just one parameter). In order to perform a faster and more precise identification of the level of damage of the valve, the authors have considered responses within some predetermined band (as shown in Fig. 10, 11 and 12). This simple approach allows establishing if the actual performances of the SV are still acceptable and, moreover, in this way it is possible to provide a first identification of the failure level. The bands identification algorithm analyzes specific parts of the command input (Fig. 9) in order to use the most suitable command to identify the contamination of the first stage filter or the increasing of dry friction action on SV spool. In particular, as reported in paragraph 5.1 and 5.2, step position command input performs best in identification of first stage contamination; on the contrary, small amplitude slope ramp is best to identify dry friction. To ensure the identification of the prevailing failure, the algorithm compares the actual EHA response with a couple of “degraded” bands (Fig. 10-12); therefore, the algorithm is able to discern three failure levels:

- 1) Acceptable level (failures are barely distinguishable from measurement uncertainties and EM noise).
- 2) Maintenance required (Midband).
- 3) Non-nominal performance (MaxBand).

Finally, comparing the two classification levels assigned, the algorithm indicates which is the ruling (i.e. most probable) faults combination. In case of events of over bands, the algorithm is also able to evaluate these two main factors:

- 1) Number of events outside the band, in order to avoid false positive detections.
- 2) Time of entry and exit point of over band, in order to evaluate the health of the whole EHA.

To obtain suitable performance in classification of the failure level, it is important properly define the aforesaid bands; to this purpose, in order to assess the best FDI performance, the authors have performed several evaluations on the dynamic response of the real system under failures.

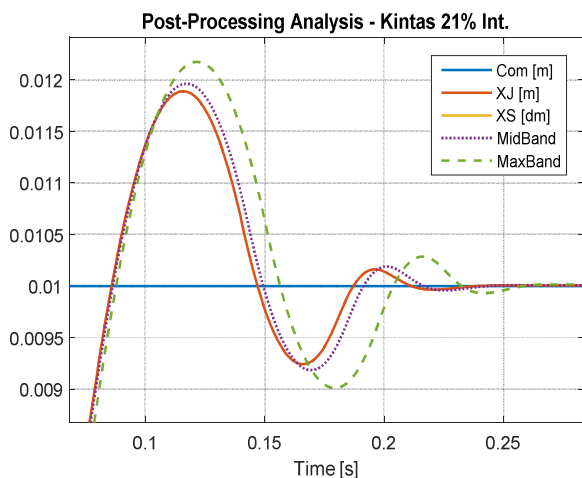


Fig. 10 particular of EHA response vs. command input: initial step section and related post-processing bands

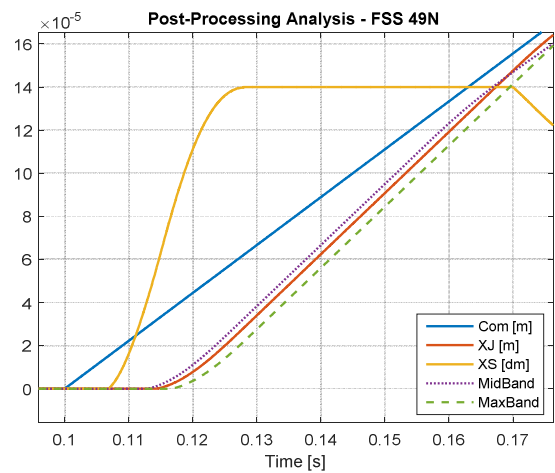


Fig. 11 particular of EHA response vs. command input: small slope section and related post-processing bands

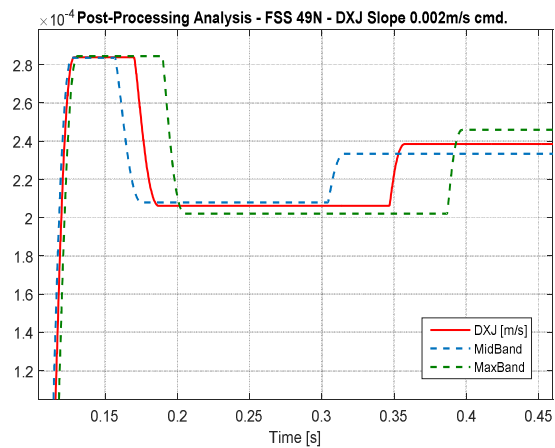


Fig. 12 particular of EHA actuation speed calculate for small slope section and related post-processing bands

It has been found that below the values reported as “mid band” in the Table 2, the performance of the EHA are still acceptable, so the identification is much harder and not always accurate; differently, within the two bands it is possible to operate a prognostic analysis in order to avoid a further increasing of the failure. In particular, the max band values represent an operational limit beyond which the performances of the actuation system are not still acceptable.

Table 2: definition of the bands failure level

Kintas [#]		FSS [N]	
MidBand	0.25	MidBand	35
MaxBand	0.35	MaxBand	70

It must be noted that, despite its simplicity, the proposed bands method performs properly the identification of a single failure and, in our tests, it has been always possible recognize a possible degradation.

Furthermore, a first coarse estimation of the failure presence could be directly performed by comparing the actual response with the band failure level. Anyways the algorithm is not able to estimate the actual degradation level, in fact, it operates a discrete identification and classification, this type of approach is quite common in prognostic algorithm even with more advanced ones (e.g. FDI algorithms based upon neural networks [16] or pattern recognition methods implemented by means of multinomial logistic regressions [17]). In case of multiple progressive degradations, an improvement of the prognostic method is required (in order to be able to discriminate between different combinations and levels of failure). To this purpose authors propose to use the monitoring model as a tracker of the response of the system: the health status of the real EHA (affected by a given combination of progressive failures) is evaluated comparing its dynamic response (generated by the command input shown in Fig. 9) with the corresponding output of the monitor. Indeed, as already shown in paragraph five, it is possible to evaluate the growth of the contamination of the SV first stage filter by means of a step command input as well as a low slope ramp command is the best way to evaluate the magnitude of the eventual dry friction acting on the servovalve sliding spool. In this way, minimizing the RMS error (1) calculated between the responses provided by EHA and monitoring model, it is possible estimate the value of the parameters considered.

$$RMS_{MONITOR} - RMS_{EHA} \tag{1}$$

The logic of proposed multi-failure FDI algorithm is depicted by the flowchart shown in Fig. 13.

The dynamic response calculated by the monitoring for the different combinations of faults is compared with that of the real system, so as to identify the possible couples of failure which minimize the RMS error. To avoid missing or incorrect failure identification and, at the same time, to allow a lighter computation cost, the possible combinations of faults are discretized obtaining the failure grid shown in Fig. 14.

Figures 14 and 15 show how the FDI algorithm evaluates the estimate combination of faults, starting from the two point of minimum RMS for each of the two commands then according to the distance from the first bisector is possible to compute a numerical weight, in order to compute a gravity center between these two points. Operatively speaking, the minimum RMS point, that is calculated by the step command (Fig. 10), has its maximum weight on the right side of the graph (Kintas = 0.35) whereas, on the contrary, for the ramp command (Fig. 11) the maximum weight is on the left side (Kintas = 0.15). Once identified this minimum area, it is then possible to implement a more accurate analysis using more refined methods (but more expensive in terms of time and power) such as deterministic optimization algorithms, Simulated Annealing or Genetic Algorithms².

² It should be noted that, compared to other most common model-based prognostic approaches (e.g. based on genetic algorithms, simulated annealing or more advanced optimization methods), the proposed method

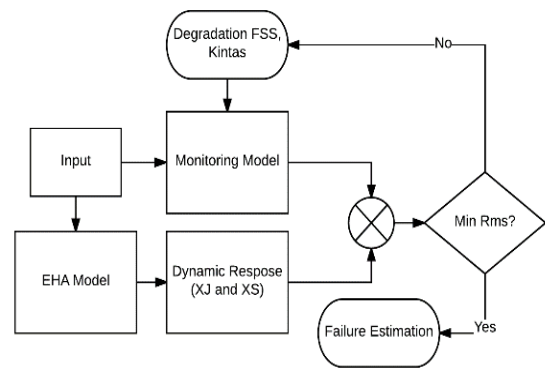


Fig. 13 schematic of the proposed multi-failure FDI algorithm

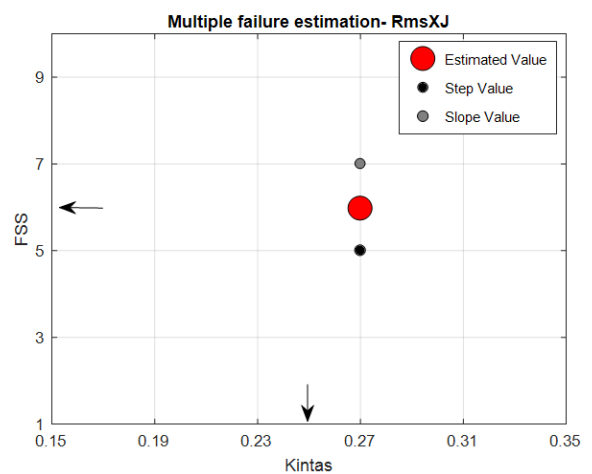


Fig. 14 schematic of FDI failure grid (Kintas=0.25; FSS=6·FSS_{NC}): black arrows identify the actual degradation level of the EHA

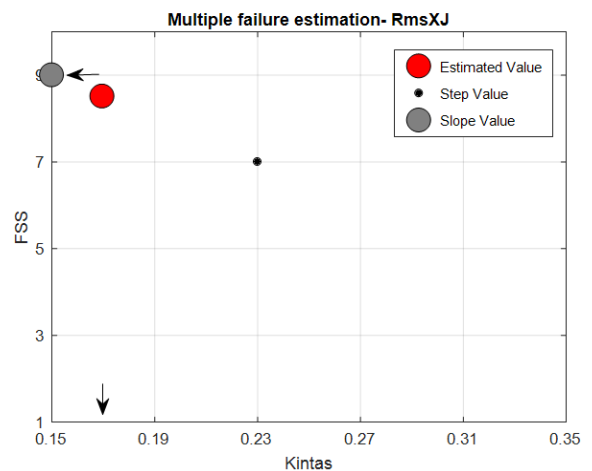


Fig. 15 schematic of FDI failure grid (Kintas=0.17; FSS=9·FSS_{NC}): black arrows identify the actual degradation level of the EHA

provides more coarse, and not necessarily unique, results but, as already mentioned in Section 7, it is not intended to be a standalone alternative to the most common FDI methods, but rather wants to provide a pre-assessment procedure, to foresee upstream of these FDI algorithms, that should be used as a startup step of the said prognostic process.

VIII. CONCLUSIONS AND FUTURE WORKS

This work analyses the effects of two progressive failures on the dynamic behavior of EHA in order to identify system-representative parameters which are suitable for prognostic activities and to propose a new model-based fault detection and identification (FDI) method. The study has been performed on a numeric test bench (simulating the real EHA) that implements several kinds of failure; by means of proper simplifications, the aforesaid numerical model was then reduced obtaining the monitoring model. The robustness of the proposed technique has been assessed through a simulation test environment, built for the purpose. Such simulation has demonstrated that the methodology has adequate robustness; also, the ability to early identify an eventual malfunctioning has been proved with low risk of missed failures or false positives. Overall the proposed algorithm demonstrates good statistical confidence in identification of the failure; furthermore, it could be used without any other additional sensors required and all the post-processing proposed could be executed to a common PC on the ground. In the authors' opinion, these aspects are more important, especially in order to improve the predictive maintenance of the analyzed component (i.e. prognostic analysis performed daily during the usual on-field operations). It is possible to conclude that this kind of damage estimator, while constituting a particularly simplified and coarse preliminary approach, can be considered a good approach for prognostics applications, even for combined failures. A broader evaluation of different study-cases is envisaged to assess the validity and the robustness of this method at all the possible different conditions.

ACKNOWLEDGEMENT

In conclusion, the authors wish to extend a heartfelt thanks to Professor Lorenzo Borello and to Dr. Licia Masoero for their essential support in the ideation, definition and development of these activities.

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Matteo D. L. Dalla Vedova received the M.Sc. and the Ph.D. from the Politecnico di Torino in 2003 and 2007, respectively. He is currently assistant researcher at the Department of Mechanics and Aerospace Engineering. His research activity is mainly focused on the aeronautical systems engineering and, in particular, is dedicated to design, analysis and numerical simulation of on board systems, study of secondary flight control system and conception of related monitoring strategies and developing of prognostic algorithms for aerospace servomechanism.

Paolo Maggiore is a professor at the Mechanical and Aerospace Engineering Department of Politecnico di Torino, that joined in 1992, where he teaches aerospace general systems engineering. Currently his students are involved in projects ranging from hydrogen fuel cell powered airplanes and UAVs, and health monitoring of flight controls, to multi-disciplinary design optimization of aerospace systems design.

Francesco Marino graduated in Aerospace Engineering at Politecnico di Torino in 2015. Since 2015 his research activities are mainly focused on modelization of servomechanisms, prognostics algorithms and predictive maintenance in aerospace applications. Since 2017 he is working at Lufthansa Technik, in collaboration with Politecnico di Torino, on the application of Model-Based System Engineering analysis.