Optimization algorithms for prognostics of electrohydraulic on-board servomechanisms

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Abstract—This paper studies the response of an electrohydraulic actuator (EHA) subjected to three different progressive failures (demagnetization of the torque motor, increment of the jack static friction and presence of backlash); in particular, it is focused on the identification of failure precursors able to give an early identification of progressive failures affecting the system, in order to provide tools that can be used to predict its remaining useful life. This kind of analysis belongs to a new discipline, called Prognostics and Health Management (PHM), that focuses on predicting the time at which a system or a component will no longer perform its intended function, estimating its Remaining Useful Life (RUL) and, then, providing an effective diagnostic tool that allows them to exploit a component until it is safe, saving money. In order to conceive an effective prognostic algorithm authors studied the failures effects on the system behaviors, identifying some details in the monitored time-history signals that exclusively got evidence of a particular failure, avoiding confounding each other and allowing pointing out the fault level of the system. For this purpose, the authors developed a new EHA Monitor Model able to reproduce the dynamic response of the actual system in terms of position, speed and equivalent current, even with the presence of incipient faults. Starting from this Monitor Model, the authors propose a new model-based fault detection and identification (FDI) method, based on Genetic Algorithms (GAs) optimization approach and parallelized calculations, investigating its ability to timely identify symptoms alerting that a component is degrading.

Keywords—Electrohydraulic actuator, fault detection algorithm, genetic algorithm, prognostics.

I. INTRODUCTION

THE actuation system is one of the most important on an aircraft. It effects the deflection of movable surfaces to the position commanded by the pilot, ensuring the controllability and maneuverability of the aircraft. The servoactuators convert the source of power (mechanical, electrical, hydraulic or pneumatic depending on the general concept of design) into a controlled motion that enables the motion of the surfaces in order to meet operative needs. As it can be easily noticed, this task is crucial and requires high reliability. Right now, the solution to guarantee an adequate level of reliability is delivered to the scheduling of a maintenance program.

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This should guarantee that an actuation system continues to operate in the normal range of safety conditions. This approach, however may show ineffective since it doesn't take count of the effective state of health of the system but only of predictions. In fact, it can lead on one hand to an underestimation of the problem in order to save money or on the other to overestimate it wasting resources. An alternative strategy could consist in monitoring the functional parameters of the system and to determine its state of health by observing the deviation of its response from the original one. This practice of monitoring and analyzing the system's response and make an evaluation of the evolution of the fault is the purpose of the so called Prognosis and Health Management (PHM): in general, PHM aims to predict failures at an early stage through the monitoring of functional parameters of the system involved and it permits to determine the source of irregular behaviors [1]. The application of the PHM strategies typically requires the monitoring of a set of parameters in the form of electric signals so its application is preferred on electrical systems where no additional sensor is required. In literature, different Fault Detection and Identification (FDI) strategies are proposed: model-based techniques based upon the direct comparison between real and monitoring system [2-7], on the spectral analysis of well-defined system behaviors performed by Fast Fourier Transform [8-9], on combinations of these methods [10] or on Artificial Neural Networks [11-14].

II. AIMS OF WORK

The aim of this paper is to propose two different algorithms able to perform the diagnosis of an electrohydraulic servoactuator with flapper-nozzle valve. Both the procedures are able to esteem the real state of damage of the system returning a plausible damage condition that consists in three dimensionless parameters corresponding to the three fault modes studied (demagnetization of the torque motor, increment of the jack static friction and presence of backlash). While the first procedure uses a deterministic approach, the second one makes use of a genetic solver. Both the methods, however, work following the same philosophy. The prognostic analysis in fact is carried out by comparing the response provided by the reference model and the one given by the monitoring model using a well-defined command sequence.

The parameters of the monitoring model are iteratively modified in order to make its response matching up the reference response.
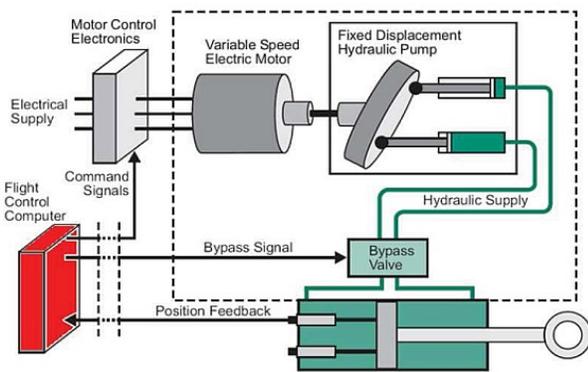
Fig. 1 Schematic of the considered EHA layout

Fig. 2 Schematic of the flapper-nozzle servovalve

The combination of parameters that accomplishes this task indicates the extent of damage of the system. The parameters that represent the amount of damage of the specific fault mode (respectively K_{GM}, K_{FSJ}, K_{BKL}) are normalized to the border state of usage in operative condition, therefore, vary linearly from zero (original fully functioning condition) to one (limit damaged condition considered). The considered actuation system (consistent with the schematic shown in Fig. 1) is a typical electrohydraulic position servomechanism (SM) widely used both in primary and secondary aircraft flight controls. According to [15], the EHA consists of three main subsystems:

1) Controller: it 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, in several applications, 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 [16-17].

3) Hydraulic piston (symmetrical double acting linear cylinder subject to Coulomb friction): actuates the flight control surface closing the position feedback loop by means of a network of position transducers.

Wider descriptions of the servomechanism employed in this work and of its mathematical model are shown in [9]; this 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. This valve drives an actuator that moves the control surface continuously pursuing the reduction of the error between pilot's commanded position and flight surface actual position.
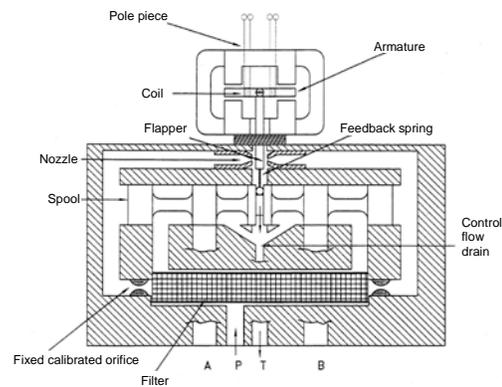
The servovalve is a high performance two-stage four-ways valve (as shown in Fig. 2); its second stage is a closed center, four-way, sliding spool, while the pilot stage is a symmetrical double nozzle and flapper, driven by a torque motor. Since its natural frequency is supposed to be orders of magnitude higher than the desired closed loop bandwidth of the whole SM, only its orifices resistive effects were taken into account.

The hydraulic linear actuator considered in the present paper is a double acting symmetrical one. It has been modelled considering inertia, viscous friction, dry friction (according to [18-19]) and leakage effects through the piston seals developing a not working flow. It is also able to take into account the effects due to its interactions with the mechanical ends of travel as well as the aerodynamic loads acting on the flight surface [20].

III. EHA COMPUTATIONAL MODELS

In recent years computational modeling has provided an important tool for the evaluation of the state of health and behavior of systems, during both the test and the operational phases. As explained in the overview, this paper uses two different simulation models that both simulate the behavior of the EHA. While the first one, proposed in [9], has a level of accuracy higher and it's used to get the reference data, the second one it's quicker and less demanding and it's used to make the iterative process of optimal solution research. Both models used in this paper are developed on the platform MATLAB-Simulink® 2016b release.

A. EHA Reference Model

Figure 3 represents the detailed Simulink numerical model used in the following EHA failure analysis (described in chapter 4) and to get the reference data during the optimization task (chapter 5). This numerical model takes into account several details that contribute to the deterioration of the actuation chain, like, in particular, the effect of the clogging of the first stage filter of the SV and the rising progressive loss gain on the torque motor. In addition, it is also able to simulate the effect of disturbing noises provoked by external electro-magnetic sources that interfere with the command input signal from the control module to the valve.
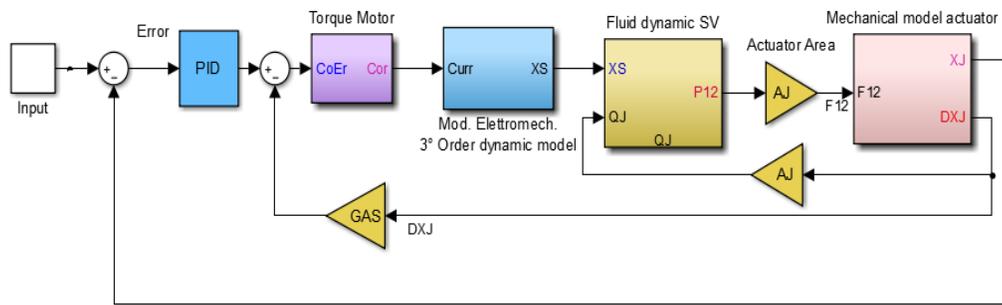
Fig. 3 Simulink block diagram of the considered EHA

The proposed Simulink model is made up of several parts:

1) The Input block, used to define the time history of the input (reference position in close-loop test and command to valve in open-loop test).
2) The PID block, simulating the behavior of the servomechanism controller.
3) The Torque Motor model calculates the mechanical torque acting on the SV first stage.
4) The third order dynamic model that reproduces the dynamic response of the flapper-nozzle valve.
5) The fluid-dynamic SV block, which for a given spool position and flow rate returns the amount of differential pressure to the chambers of the actuator, using the linearized theory (Jacazio and Borello, 1987).
6) The second order block simulating the dynamic response of the linear actuator.

The general view of the model reflects the block diagram of a closed loop controlled system. In fact, the external loop of the scheme supplies the instantaneous position of the jack that has to be subtracted to the input signal (standard or given by the user), allowing to calculate the error signal that represents the true input to the system. This signal is processed by the PID controller that it's responsible to stabilize the dynamic of the response. This signal, once substracted the result of the multiplication of the actual value of velocity by the gain of the control GAS (second closed loop), enters the hysteresis block.

This block provides the possibility of introduce a contribution of contrived electrical current, dependently on the previous value of current in output; going on, the so obtained input current is supplied to the valve. The task of this block, divided into two elements representing the two stages of the flapper-nozzle servo-valve, is to simulate the third order dynamic of the valve. The spool position is used as input in the following Fluid dynamic SV block to estimate the amount of differential pressure supplied from the valve. In fact, the Fluid dynamic SV block reproduces the dynamic of the fluid that concerns the opening of the orifices that feed the actuator; through the internal closed loop, this block receives also the value of the fluid's flow rate corresponding to the previous step analysis. This is provided multiplying the calculated velocity of the jack with its surface. This operation doesn't take care of the negligible effect of the system compressibility (i.e. pipelines and hydraulic connections, hydraulic fluid).

The differential pressure just obtained is multiplied by the jack's surface area and supplied to the second order module that reproduces the dynamic of the actuator. This block takes into account the effects of ends-of-travels and dry friction acting on the final actuator, making cinematic evaluations. Results regarding different signals calculated within this model are delivered to the MATLAB® workspace in order to proceed with further calculations and tasks. The main aim of the proposed model is to simulate the dynamic response of the EHA for different health conditions (i.e. various combinations of SV first stage torque motor gain loss and dry frictions or backlashes). To this purpose, the authors developed a new detailed numerical model able to simulate its dynamic response, taking into account the effects of the said failures. Its dynamic fluid model (which calculates the delivery differential pressure regulated by the SV as a function of the spool position and the oil flow disposed of through the valve) has been conceived according to numerical models proposed in [21] and validated by comparing with experimental, analytical and numerical results found in literature [22-27].

B. EHA Monitoring Model

The proposed detailed EHA reference 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 proposed in [9], a new EHA monitoring model has been developed.

It must be noted that 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 main difference between the two models however is the implementation of the valve, in particular the block representing the first stage. This stage in fact has been represented from an external point of view without considering the real physics events, but considering the first stage as a second order dynamic system.

IV. EHA FAILURES ANALYSIS

While in perfect conditions an original component responds ideally, when there's a failure the response may change even drastically, affecting the performance of the system. The deterioration of the response can be evaluated by looking at characteristic parameters of the dynamic response in the domain of time and frequency. Of all the different failures that can manifest on EHA, this paper analyzes three of them: demagnetization of the torque motor [28], increment of the jack static friction [9] and presence of backlash [19-20].

At the beginning every fault has been studied singularly, commanding different command sequences (step, ramp, sinusoidal) and analyzing different output signals (position of the jack XJ, velocity of the jack DXJ, position of the spool XS, differential pressure P12 and current Cor) varying the adimensional coefficients K_{GM}, K_{FSJ}, K_{BKL}. Once identified one or more combinations of command-signals able to point out the presence of each fault, it has been carried out a complete analysis in which the three faults have been superimposed (taking also into account the effects of eventual mutual interactions between these failures).

This study has been necessary since the three faults can appear simultaneously on the real system, making fundamental to consider their mutual influence. Through this analysis, it was possible to verify the effectiveness of the thresholds of the prognostic parameters obtained by the study of the aforesaid single failures.

A. SV Torque Motor Demagnetization

The study of the demagnetization of the torque motor has been led working on the torque motor gain GM, varying it between its nominal value and a maximum failed condition in which it is reduced by 50%. The obtained numerical results show that the step command is the most effective in the prognosis of this failure. Among all the parameters analyzed the most efficient results to be the jack position, in particular its overshoot; in fact, the overshoot decrease significantly in magnitude when K_{GM} grows as it can be observed in Fig. 4, where this detail has been pointed out. It must be noted that, in case of progressive demagnetization of EHA torque motor, the response of the system becomes slower and this is due to the motor that, being unable to give a sufficient torque, seals the SV orifices partially, reducing the differential pressure on the spool and making the system slower and more damped.
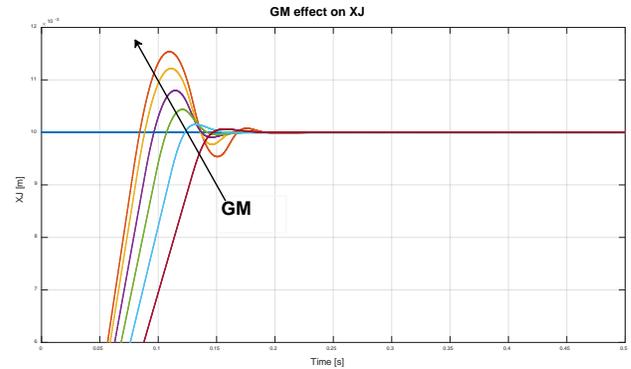
Fig. 4 Particular of EHA step position response
in case of progressive torque motor gain loss GM
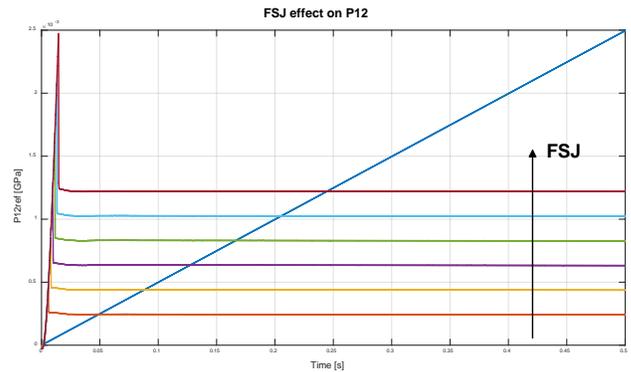
Fig. 5 Particular of the P12 differential pressure response
(due to a ramp position command in case of dry friction FSJ)
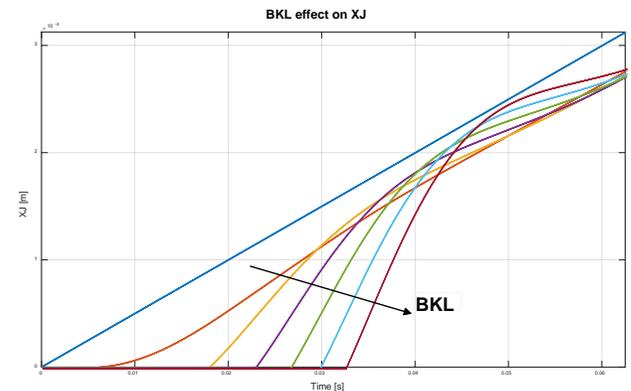
Fig. 6 Particular of the EHA ramp position response
parametrized for increasing backlash BKL

B. Dry Friction acting on Linear Actuator

In EHA the static friction force is typically produced by the wear of the sliding surfaces of the cylinder which provokes the rise of the corresponding amount of friction that acts on the jack. Numerical results show that, in this case, the ramp command is the most effective input. As shown in Fig. 5, among all the effects caused by the rise of FSJ, such as the delay of the cue of XJ or the increase of the peak of DXJ, the most significant is the increase of differential pressure P12 acting on the linear hydraulic actuator during the said ramp actuation.

It must be noted that, in the differential pressure diagram (Fig. 5), this phenomenon causes both the increase of the P12 peak during the breakaway and the increase of its stationary value (i.e. when the actuator reaches the commanded speed).

C. Backlash

EHAs are often affected by another progressive failure, typically due to mechanical wear phenomenon, called "backlash" (although, machining tolerances and mounting errors may determine an initial value of such mechanical play): this fault, allowing a discrepancy between motor and user position, is characteristic of the mechanical cinematic transmission which connects the linear hydraulic actuator with the final user (e.g. aerodynamic surfaces) and plays an important role in the stability and accuracy of the whole servomechanism. Among all the command sequences used, the ramp shows the most significant results even if, differently from the other faults, different possible prognostic parameters have been identified. The presence of this little dimensional difference between the two coupled elements causes a delay in the response of the system that affects several output signals. It can be noticed in the XJ graph, for example, how the system starts moving increasingly later as the backlash grows up (as shown in Fig. 6). Also the time interval between the peak of pressure that should move the jack and the effective cue becomes greater because there is a bigger free space that has to be routed before the motion could be transmitted; similarly the DXJ gives evidence of this behavior presenting an increasing value of the peak as the backlash grows up. Another important feature that must be considered is the peak of current: in fact, as shown in Fig. 7, the current peak generated during the system breakaway becomes higher and delayed; this is due to the increased delay in the EHA time response.
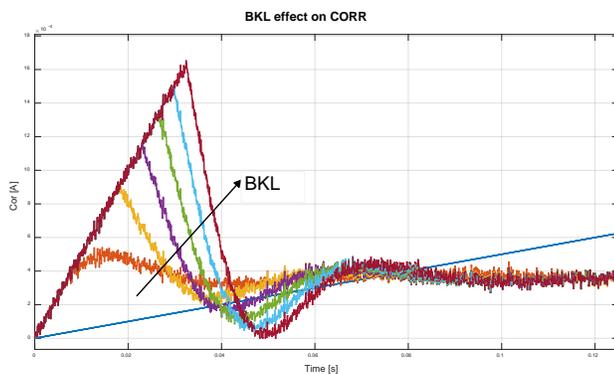
Fig. 7 Particular of the breakaway EHA peak current in case of ramp command and increasing backlash

D. Combined Faults

Given that the three progressive failures analyzed in the previous paragraph may appear simultaneously on the real system, it is necessary to consider their mutual influence and their effects on the effectiveness of prognostic algorithms. For this reason the previous analysis must be completed considering simultaneously all the three faults.

In this paragraph will be presented the method used to have a first, rough, indication of the real state of damage. This procedure gives a valuation of which faults are present in the component by using the prognostic parameters presented above. This first evaluation, even if very low in precision since it points out only the presence of a fault and not its magnitude, will be useful in the following optimization task carried out by the algorithms presented in chapter 5. The command sequence used in this analysis is a combination of ramp and step commands, those that have shown the most interesting results in the previous study. In order to discriminate the case in which the prognostic value starts giving evidence of the presence of a fault, it's necessary to identify a threshold for each parameter. These thresholds have been chosen on the basis of results gained by simulations with a 20% of damage.

Choosing a value slightly smaller than the one calculated in those simulations assures to point out situations where the fault has a magnitude big enough to start giving problems.

V. EHA FAULT DETECTION AND IDENTIFICATION

In this chapter all the knowledges and results obtained will be used to create two reliable procedures able to esteem the real state of health of the electro-hydraulic servo actuator with flapper-nozzle valve. The first method will use a deterministic approach while the other a heuristic one. The general logic followed by these two procedures, however it's the same.

The proposed procedures are model-based and evaluate the EHA health status by comparing the dynamic responses of the two MATLAB-Simulink® models described in chapter 3. The detailed model will provide the reference response and will be considered as real system: it will be run implementing different combinations of faults in order to verify the procedure for different conditions. The simplified model, on the other hand, will be processed by the optimization tool in order to esteem the faults' conditions actually implemented in the previous one; being executed many times as it's requested by the iterative process carried out by the optimization algorithms, the second model must be lighter than the other, as already pointed out earlier. Given that the final purpose of this paper is to propose a new FDI automatic procedure that, confronting the responses of these two models, identifies the faults in the aforesaid monitoring MATLAB-Simulink® model (in order to obtain the corresponding amount of the real faults constants), it's crucial to find a feasible approach to evaluate each progressive fault independently.

For this reason the considerations reported in chapter 4 regarding the different ways in which each fault influences the response of the system, will be now resumed to create the fitness functions that will be minimized by the optimization algorithms. Monitoring the details of the response that discriminate the presence of one fault, the algorithm, through its iterative process, can provide a reliable esteem of the magnitude of the faults that are present or not.

The general logic followed by the used optimization algorithms can be resumed by the following figure:
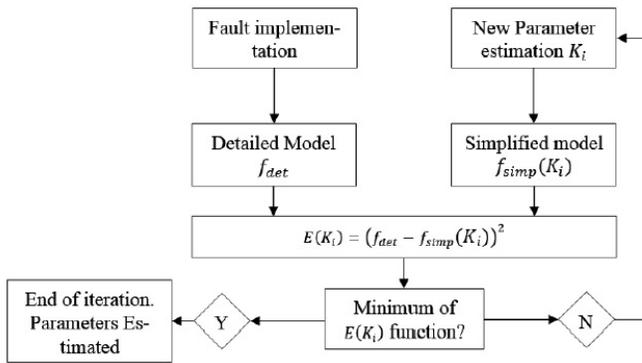
Fig. 8 Flowchart of the proposed GA based prognostic algorithm

Varying the three constants of damage K_i (i.e. numerical parameters K_{GM}, K_{FSJ}, K_{BKL} suitably implemented into the EHA monitoring model in order to simulate the effects of the considered progressive failures), the optimization algorithm aims to minimize the fitness functions related to examined faults; once responses of the reference and simplified models match well, the algorithm has ended its task and, through the values of the said constants of damage (used to accomplish this result), it is possible to esteem the actual EHA health status. This algorithm is implemented by MATLAB−Optimtool®. As already stated in chapter 4, not all the commands give the same evidence of a physical phenomenon: for this reason, the FDI process will be carried out commanding to the MATLAB-Simulink® models the particular sequence of commands shown in Fig. 9.
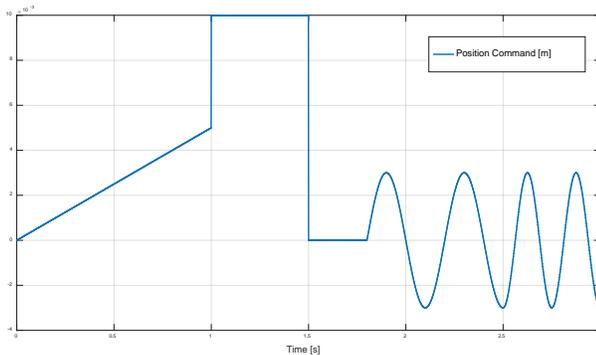
Fig. 9 Position Command input used to perform the FDI analysis

Each section of this sequence has a precise purpose and utility in the prognostic analysis. The first half of the command time-history (from 0 to 1.5 seconds) it's the same already discussed in chapter 4 and it's the part intended to point out the presence of the three faults evaluated in this paper.

This section of the command history is in turn composed of two parts The first part is a ramp command with a slope of 5 mm/s that starts at 0 second and ends after 1 second: it is used to identify and quantify FSJ and BKL faults. The second part, on the other hand, it's a step command that reaches the magnitude of 0.01 m and allows identifying the presence of demagnetization of the torque motor.

The second half of the time history command (from 1.5 seconds to the end of the simulation), is composed of a step command at 1.5 seconds that bring back the system to the initial condition and a sinusoidal command at variable frequencies that starts at 1.8 seconds: from 1.8 to 2.5 seconds the frequency is 2.5 Hz, so (from that moment until the end of the simulation) it grows up to 4 Hz. These sinusoidal inputs are implemented to improve the results of the proposed FDI genetic based algorithm; further details about this choice will be provided later in the corresponding section.

A. Deterministic Algorithm FDI Method

The deterministic technique works calculating in specific point the corresponding fitness value, starting from a point provided by the user. This method test different points in the around of the instantaneous reference point and, considering the variation of the fitness value, evaluates the gradient of the fitness function along the possible variables. This process is very suitable for fitness functions without significant discontinuity, marked relative minima and too many variables.

Firstly, each part of the complete algorithm has been verified controlling its effectiveness; the separate analysis of each fault has been carried out taking advantage of the results obtained in the previous chapters. In fact, the fitness functions elaborated by the proposed FDI algorithm use the EHA response characteristics that showed the most interesting results (i.e. peak of P12 for FSJ, peak of XJ for GM, peak of DXJ for BKL), searching them in the sections of the command where they have the greatest impact (i.e. ramp command for FSJ and BKL, and step for GM). The task to find the minimum of the fitness functions is entrusted to the *Fminsearch* optimization method in the FSJ and GM analysis and to *Fmincon* in the BKL case [29-30]. While *Fminsearch* doesn't require bounds, but only an initial point x_0, *Fmincon* is a constrained method; it must be noted that, especially in case of backlash nominal condition ($K_{BKL}=0$), these constraints results very helpful, avoiding to assign negative values to the backlash (values that have no physical sense since it would mean that the mechanical elements interpenetrate). For instance, Table 1 shows the results obtained by the proposed preliminary FDI analysis for different test cases.

Table 1: FDI results in case of a single fault conditions (preliminary deterministic procedure)

Real K_{FSJ}	Estimate K_{FSJ}	Real K_{GM}	Estimated K_{GM}	Real K_{BKL}	Estimated K_{BKL}
0,0	0,00084	0,0	0,02094	0,0	0,00000
0,4	0,40083	0,4	0,40269	0,4	0,39891
0,6	0,60081	0,6	0,60213	0,6	0,60365
1,0	1,00080	1,0	1,00240	1,0	0,99000

As it can be seen, the percent errors calculated between the values estimated by the algorithms and the ones implemented in the reference model are always less than 1%, being very accurate in the FSJ case (less than 0,1 %).

All these considerations confirm the effectiveness of the procedure and allow to move forward to the following step, the creation of the complete procedure. Instead of running each algorithm on its own now it's necessary to make them cooperate since the actuator can perform all three faults simultaneously. For this reason the three algorithms work in series, running one after another. Doing this way it's possible to use what already found by one algorithm to improve the effectiveness of the following. Not only the results, but also the time spent on accomplishing the prognostic task improve step by step; in fact, the evaluation of the final fault results less demanding than the first one. The complete procedure starts from the evaluation of FSJ. Since the control is made in close loop the command of the valve is an error signal that directly derives from the instantaneous discordance between the commanded position and the real position of the jack. This is deeply influenced by FSJ that, for this reason, must be analyzed firstly. After that, using the K_{FSJ} just found, the procedure calculates the GM and finally, using all these results, estimates BKL. This fault has been analyzed lastly, since it's the most difficult to evaluate, as already pointed out in chapter 4. In fact, BKL acts similarly to FSJ and this make its prognostic very demanding; therefore it is suitable to calculate it when the algorithm has already information about the other faults. The results of the complete deterministic procedure can be seen in the following chapter.

B. Genetic Algorithm FDI Method

The proposed FDI prognostic algorithm is based on a heuristic method that applies Darwin's evolutionary theory to optimize processes. Operatively speaking, the Genetic Algorithm (GA) technique iteratively generates a population of eligible solutions in order to evolve its individuals toward a better solution; each eligible solution (fault combination) has a set of properties, corresponding to the genotype, which can be mutated and altered. Traditionally, solutions are represented in binary as strings of 0 and 1, but other encodings are also possible. The fittest individuals of the last generation are stochastically selected, and each individual feature is modified by recombining the genome (crossover) or by randomly mutating (mutation) to create a new generation.

$$FF = \sum_i (XJ_{i\_Monitor} - XJ_{i\_EHA})^2 \tag{1}$$

The fitness function (1), in addition to comparing the details of the signal responses shown in previous chapters, also calculates the quadratic difference of the XJ responses provided by the reference and monitoring models during the second half of the simulation, where a double frequency sinusoidal input is commanded, in order to avoid that the genetic algorithm finds a "twin cases" in which different combinations of fault cause the same dynamic response: in fact, using a double frequency sinusoidal input instead of a simpler monochromatic harmonic input, the risk to declare false positive o twin cases decreased drastically (avoiding false EHA warnings or, vice versa, undetected incoming failures).

Before showing the results obtained during this analysis, it's useful to look to the settings of the genetic algorithm. Unlike what happens in the case of the Matlab Fminsearch method, GAs approach requires to declare the starting point (set to 0.5) of the different constants of damage K_i and, in addition, the values of their bounds. It has been chosen to study the complete field of the solutions giving 0.0 as lower bound and 0.99 as upper bound. These bounds, giving a huge range in which GAs can search the solution, ensure the validity of the algorithm. The *gaoptimset* offers also other features where the user can personalize its algorithm: Table 2 summarizes them and shows the parameters chosen in this work.

Table 2: Proposed *gaoptimset* features

gaoptimset feature	Description	Parameter implemented
Stall Generation Limit	The procedure stops if the average relative change in the best fitness function value over the entire process is less than or equal to the function tolerance	10
Tolfun	The algorithm stops if the average relative change in the best fitness function value over the generations set by the user is less than or equal to the function tolerance	0,0001
Initial Population Data	Sets the point in the field of the solutions where the algorithm starts its research	0.5
Population Size	This parameter sets the number of individuals considered during the analysis	20
FitnessScalingFcn	Allows the user to choose the function that scales the values	Proportional scaling factor
Number of Generations	This parameter sets how many generations the procedure will consider	20
Hybrid function	Through this parameter it's possible, after the last step of the genetic process, to use a deterministic algorithm	Fmincon

The promising results obtained in this phase allow to proceed to the next step, the complete analysis. Unlike the aforesaid deterministic routine, the proposed GA method simultaneously analyzes the three progressive failures using a new fitness function that, fundamentally, constitutes the synthesis of the three previously developed objective functions. In fact, this fitness function sums the three different parameters that identify the three faults: the absolute difference between the peaks of differential pressure P12 (used to identify FSJ), the absolute difference between the peaks of the dynamic response of the jack position XJ (GM) and the absolute difference between the peak of actuation speed DXJ (BKL).

This fitness function takes into account also the quadratic difference, calculated between the corresponding EHA actual positions, obtained during the sinusoidal actuation commanded in the second half of the proposed input sequence. This is due to the necessity of discriminate "twin cases" in which different combinations of faults lead to the same response.

As in the deterministic procedure, the results of the complete analysis are shown in chapter 6. Table 3 shows the results obtained by the proposed genetic FDI method considering the single failure conditions.

VI. FDI TESTING

In order to verify the robustness of the proposed FDI prognostic algorithms and their effectiveness in case of combined faults, a series of tests were implemented. The values of the progressive faults used to test the behavior of the proposed FDI algorithms have been arbitrarily chosen so as to cover all possible fault conditions (both single and combined ones) related to the prognostic application field (i.e. the failures range within which the proposed prognostic algorithms must be able to correctly detect and evaluate these progressive faults). The robustness of the proposed algorithms have been tested not only using realistic combinations (such as those where the constants of damage have values of 0.4 or 0.6) but also in extreme and "unrealistic" conditions, such as the ones with the constants equal to 0.0 (ideal condition) or 1.0 (maximum amount of damage). In fact, in order to provide a wider evaluation of the robustness of the proposed FDI algorithms, the authors considered also results obtained in the case of ideal conditions (K_{GM}, K_{FSJ} and K_{BKL} equal to 0.0 – i.e. the system is not affected by faults) and for EHA completely corrupted (all constants equal to 1.0). The results obtained in both cases (i.e. calculated using deterministic and GA-based methods) are reported in tables 4 and 5.

In order to evaluate the effectiveness of these procedures, it's been necessary to calculate the percent errors of each constant of damages and the mean error of each case. The percent error (*% err*) of the i-th constant of damage is calculated by means of the following expression:

$$\% \, err_i = \frac{\left(K_i - K_{i \, \text{ESTIMATED}}\right)}{K_i} \quad (2)$$

Therefore, according to Eq. (2), a negative percentage error indicates an overestimation of the i-th constant of the damage, while a positive one is equivalent to its underestimation.

The average percentage error (*Mean % err*) is calculated as:

$$Mean \, \% \, err = \frac{\left|\% \, err_{GM}\right| + \left|\% \, err_{FSJ}\right| + \left|\% \, err_{BKL}\right|}{3}$$

3)

Table 3: FDI results in case of single fault conditions (proposed GA based procedure)

Real K_{FSJ}	Estimated K_{FSJ}	Real K_{GM}	Estimated K_{GM}	Real K_{BKL}	Estimated K_{BKL}
0,0	0,00084	0,0	0,00539	0,0	0,00047
0,4	0,40094	0,4	0,40428	0,4	0,40415
0,6	0,60105	0,6	0,60373	0,6	0,60503
1,0	0,99000	1,0	0,99000	1,0	0,99000

Table 4: FDI results in case of combined fault conditions (preliminary deterministic procedure).

Case	K_{GM}	K_{FSJ}	K_{BKL}	Estimated K_{GM}	Estimated K_{FSJ}	Estimated K_{BKL}
1	0,0	0,0	0,0	0,02075	0,00084	0,00000
2	0,4	0,4	0,4	0,40944	0,40083	0,40612
3	0,4	0,4	0,6	0,40944	0,40075	0,60851
4	0,6	0,4	0,4	0,60775	0,40058	0,40561
5	0,4	0,6	0,4	0,41300	0,60088	0,40794
6	0,6	0,4	0,6	0,60781	0,40067	0,60719
7	0,6	0,6	0,4	0,61056	0,60061	0,40835
8	0,4	0,6	0,6	0,41306	0,60076	0,60939
9	0,6	0,6	0,6	0,61056	0,60067	0,60811
10	1,0	0,0	0,0	1,00230	0,00053	0,00516
11	0,0	1,0	0,0	0,07963	1,00080	0,00543
12	0,0	0,0	1,0	0,02081	0,00071	0,99000
13	1,0	1,0	0,0	1,01060	1,00030	0,00701
14	1,0	0,0	1,0	1,00240	0,00864	0,99000
15	0,0	1,0	1,0	0,07956	1,00080	0,99000
16	1,0	1,0	1,0	1,01060	1,00000	0,99000

Table 5: FDI results in case of combined fault conditions (proposed GA based procedure).

Case	K_{GM}	K_{FSJ}	K_{BKL}	Estimated K_{GM}	Estimated K_{FSJ}	Estimated K_{BKL}
1	0,0	0,0	0,0	0,00531	0,00084	0,00003
2	0,4	0,4	0,4	0,41154	0,40083	0,39830
3	0,4	0,4	0,6	0,41214	0,40076	0,59807
4	0,6	0,4	0,4	0,60985	0,40058	0,39765
5	0,4	0,6	0,4	0,41546	0,60089	0,39724
6	0,6	0,4	0,6	0,60925	0,40066	0,59761
7	0,6	0,6	0,4	0,61303	0,60062	0,39657
8	0,4	0,6	0,6	0,42636	0,60077	0,63025
9	0,6	0,6	0,6	0,62888	0,60066	0,59008
10	1,0	0,0	0,0	0,99000	0,00053	0,00070
11	0,0	1,0	0,0	0,04776	0,98997	0,00192
12	0,0	0,0	1,0	0,01980	0,00041	0,92500
13	1,0	1,0	0,0	0,99000	0,99000	0,01869
14	1,0	0,0	1,0	0,99000	0,00001	0,99000
15	0,0	1,0	1,0	0,04350	0,99000	0,99000
16	1,0	1,0	1,0	0,99000	0,99000	0,99000

In conclusion, Table 6 summarizes the mean percent error obtained in both cases by applying the proposed FDI method:

Table 6: FDI deterministic procedure vs FDI GA-based procedure

FDI Procedure	K_{FSJ} % error	K_{GM} % error	K_{BKL} % error	Mean % error
Deterministic	< 0.21 %	< 2.5 %	< 2.0 %	< 1.8 %
GA-based	< 0.21 %	< 4.0 %	< 1.0 %	< 1.6 %

Referring again to Table 6, it should be noted that, in terms of percentage error, the deterministic method generally provides a better result (compared to the heuristic method); in fact, by comparing each other the maximum values of the percent error module calculated with these two methods, the latter is more accurate only in the estimate of the fault coefficient due to the backlash (i.e. K_{BKL}). However, as reported in Tables 4 and 5, the GA-based method generally provides a more accurate estimate of the overall health of the system, resulting in lower average percentage errors. As it will be more widely pointed out in the next chapter, it's authors' opinion that both these methods provide adequate results in terms of FDI analysis. The deterministic procedure is faster and requests a lower computational effort, but the GA-based method is overall more reliable, generates lower average percentage errors and is less sensitive to the negative effects due to discontinuities or local minima of the fitness functions.

VII. CONCLUSIONS AND FUTURE PERSPECTIVES

The principal goal of this paper was to use the optimization tool provided by MATLAB® in order to realize reliable procedures to perform the partial diagnosis of an electro-hydraulic actuator with flapper-nozzle valve. For this purpose, the authors examined the dynamic response of the system subjected to the three faults implemented (demagnetization of the torque motor, static friction in the jack-cylinder contact, backlash in the mechanical linkage between the jack and the mobile surfaces) in order to find details that could point out the presence of one of these faults. On the base of these results, the authors developed two different procedures: deterministic and heuristic. As these methods are based on different approaches, the development of a new FDI procedure, based on comparing the corresponding results, is reliable, robust and adequately accurate. Both the deterministic and heuristic procedures proposed in this paper therefore allow finding the current state of wear in three fundamental causes of faults in an electro-hydraulic servoactuator. It could be interesting to extend the investigation by considering other faults. However, this development would require some attention. In fact, even if in this document both procedures guarantee good results, in the event that the problem should become more complicated, the deterministic procedure could manifest convergence problems. In fact, since it is not able to solve functions characterized by strong discontinuity or affected by local minima, the aforementioned deterministic procedure could provide incorrect solutions (significantly compromising the accuracy of the method). On the other hand, genetic algorithms can easily overcome these criticalities due to their intrinsically heuristic nature. However, genetic algorithms may show other problems, e.g. be rather slow or, if not set correctly, give inaccurate results. For this purpose, in the proposed work, the performances of the aforementioned GAs have been improved by acting on some settings, as an appropriate formulation of the fitness function and the proportional scaling of the fault parameters implemented in it.

It may be interesting to further integrate both procedures (deterministic and heuristic) together in order to achieve a robust approach in which the two approaches compensate each other (i.e. the weak points of one method are compensated by the strengths of the other, and vice versa). For example, it might be useful to evaluate the use of the deterministic procedure to perform a first (coarse) evaluation of the system health status and, therefore, adopt this data set as initial population of the optimization algorithm based on genetic algorithms, in order to accelerate the convergence of this heuristic procedure. Another measure that the authors intend to adopt in order to increase system performance consists in parallelizing the calculation; in fact, by subdividing the computational effort on the different processors, it is possible to fully utilize the potential of the computer and, therefore, perform multiple optimizations simultaneously, significantly reducing the overall computational time of the genetic algorithm. In conclusion, it is the authors' opinion that the proposed approach provides an adequate tool for identifying and assessing in good time the health status of an electrohydraulic servomechanism and, therefore, it can constitute a valid prognostic method.

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