Fault Detection and Identification Method Based on Genetic Algorithms to Monitor Degradation of Electrohydraulic Servomechanisms

(Article begins on next page)

Fault Detection and Identification Method based on Genetic Algorithms to Monitor Degradation of Electrohydraulic Servomechanisms

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***Abstract*—Electro Hydraulic Actuators (EHAs) keep their role as the leading solution for the control of current generation primary flight control systems: the main reason can be found in their high power to weight ratio, much better than other comparable technologies. To enhance efficiency and reliability of modern EHAs, it is possible to leverage the diagnostics and prognostics disciplines; these two tools allow reducing life cycle costs without losing reliability, and provide the bases for health management of integrated systems, in compliance with regulations. This paper is focused on the development of a fault detection algorithm able to identify the early signs of EHA faults, through the recognition of their precursors and related degradation patterns. Our methodology provides the advantage of anticipating incoming failures, triggering proper alerts for the maintenance team to schedule adequate corrective actions, such as the replacement of the degraded component. A new EHA model-based fault detection and identification (FDI) method is proposed; it is based on deterministic and heuristic solvers able to converge to the actual state of wear of the tested actuator. Three different progressive failure modes were chosen as test cases for the proposed FDI strategy: clogging of the first stage of the flapper-nozzle valve, spool-sleeve friction increase, and jack-cylinder friction increase. A dedicated simulation model was created for the purpose. The results highlighted that the method is adequate in robustness, since EHA malfunctions were identified with a low occurrence of false alarms or missed failures.**

Keywords- EHA; aeronautical servomechanism; numerical modeling; fault detection/identification; FDI; prognostics; genetic algorithm

I. Introduction

A. *Airworthiness of Servo Actuators*

Servo actuators are aimed to the transformation of one or several power sources (which can be mechanical, electrical, hydraulic or pneumatic, depending on the system architecture), into a controlled motion of mobile surfaces of the aircraft for the actuation of primary commands, or to fulfil other operative needs. As a consequence, an onboard servo actuator is extremely critical in the capability of the aircraft to operate its mission and guarantee adequate levels of safety. Such safety, which is strictly linked to reliability, is obtained to a strict maintenance and inspection schedule, programmed in compliance to standards which are essential to certify airworthiness. Such maintenance program considers nominal operations and can be complemented with unscheduled actions in case of unexpected operative scenarios, out-of-nominal flight conditions and defective parts. Airworthiness requires high costs and time consuming maintenance activities. Monitoring the functional parameters of the system can help increasing the efficiency of maintenance programs, assessing the state of health of the system through the observation of the deviation of system response w.r.t. nominal behavior; this can reduce scheduled (i.e. not solicited) maintenance actions, while triggering additional maintenance when an anomalous behavior is identified. To achieve such objective, the monitoring system must be highly reliable [1].

B. *Prognostics and Health Management*

Prognostics is the practice of monitoring and analyzing the response of a system (through sensors), to provide an assessment of the fault and its evolution in time. The final purpose of prognostics is the prediction of the failure of a certain component, intended as loss of functionality and the inability to meet the desired performances. Prognostics are based on analysis and knowledge of failure modes that a component can experience, and on the capability to recognize the first signs of wear; beyond the qualitative recognition (what is degrading and how), prognostics must also be able to assess the magnitude of such degradation; this task is called fault detection and identification (FDI). The data acquired are then used as input of a proper failure propagation model. Vachtsevanos et al [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 would lead to both costs and inspection time savings. In order to maximize such 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.

Prognostics is typically best suited for the application to mechatronic systems, which have a complex non-linear multidisciplinary behavior; in this field, literature proposes a wide range of FDI strategies.

Among these, it is worth mentioning model-based techniques centered on the direct comparison between real and monitoring system [4][5], on the spectral analysis of well-defined system behaviors performed by Fast Fourier Transform [6][7], on appropriate combinations of these methods [8] or on algorithms based on several architectures of Artificial Neural Networks [9] to [13].

The advantages gained with PHM strategies are evident in the comparison of a traditionally designed system and one designed according to PHM principles. Primary flight controls are a critical feature of aircraft and are designed with a conservative safe-life approach: components are replaced after a pre-determined number of flight hours or operating cycles (scheduled maintenance) or after a certain lapse of time (calendar maintenance).

This approach cannot account for possible initial flaws, e.g. undetected manufacturing defects that could generate a sudden fault. In addition, safe-life approach requests the replacement of still functional components at the end of their expected life, leading to inefficiencies and avoidable costs. Instead, in a system suitably conceived taking into account the PHM strategies, failures could be managed in a more efficient way, obtaining the following advantages:

- lower operating costs;
- reduced and faster maintenance interventions;
- reduced system redundancy;
- improved safety and reliability of the aircraft;
- reduction of corrective maintenance interventions.

The research presented in this paper, referring to the considerations reported by Borello et al. [4] and by Maggiore et al. [14], is focused on the development of a FDI method able to identify failure precursors (alerting that the system is degrading) and to evaluate damage entity on a Electro Hydraulic Actuator (EHA). In fact, a progressive degradation of a 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 jeopardized.

In order to develop this research, a typical aircraft primary command electro hydraulic actuator has been modelled in the MATLAB Simulink® environment and several sets of simulations (in nominal conditions or with various failures) have been run.

C. Aim of Work

The aim of this paper is to propose an effective approach to perform the diagnosis of an electro-hydraulic servo-actuator with flapper-nozzle valve. To this purpose, a new FDI method based on the Genetic Algorithms (GA) is designed, optimized and then validated through the comparison between the behavior of the real system (affected by progressive faults) and the corresponding numerical EMA virtual test-bench, conceived and modeled for this purpose. The proposed method merges deterministic and GA algorithms together, to guide the iterative combination of simulated faults to the one that represents the actual heath state of the actuator.

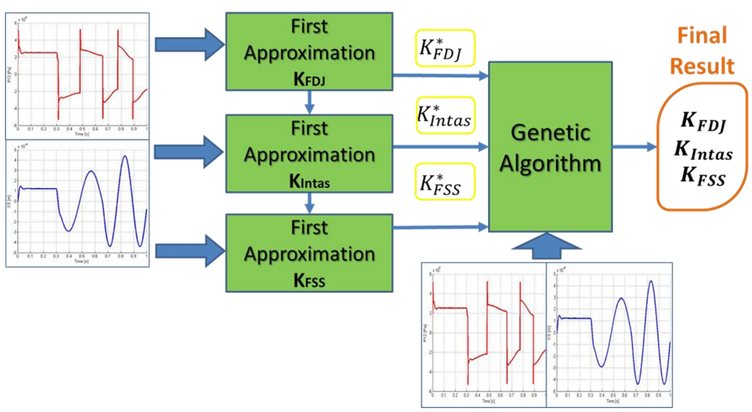

Figure 1. Overall logic of the proposed FDI method.

In order to evaluate the accuracy of the prediction at the different conditions and to assess the field of validity of this method, several combinations of progressive faults have been considered. According to hypothesis reported in [15], the following progressive faults have been assessed:

- clogging of the SV first stage ($\boldsymbol{K_{intas}}$);
- dry friction acting between second stage sleeve and spool of the SV ($\boldsymbol{K_{FSS}}$);
- dry friction acting on the linear actuator ($\boldsymbol{K_{FDJ}}$).

The proposed FDI procedure follows two phases (as shown in Figure 1):

- in the first phase, the solver finds a first approximation of the system health condition by minimizing several objective functions, computed through the analysis of the actuator dynamic response to different test commands
- in the second phase, this approximated solution is used to initialize the heuristic process.

The objective function measures the discordance between the reference response and the one provided at each iteration by a monitoring model. The parameters representing the amount of the considered faults are normalized in order to vary linearly from zero (original healthy or ideal condition) to one (extreme, fully damaged condition). In this paper, Section 2 describes the simulation models used for the study: in particular, a detailed model used as a simulated test bench and a computationally simpler monitoring model intended to be executed iteratively within the FDI algorithm. Section 3 presents the considered EHA fault modes and their effects; Section 4 is the description of the proposed FDI method, and Section 5 shows the results of the investigation.

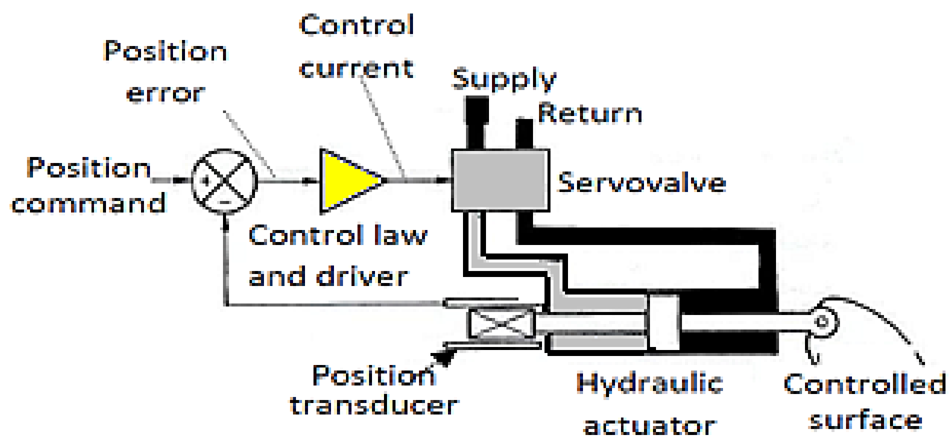

Figure 2. Scheme of the considered EHA.

II. Reference EHA Numerical Models

The examined system, as shown in Figure 2, is a typical electrohydraulic position servomechanism (SM) widely used both in primary and secondary aircraft flight controls. This SM consists of a three main subsystems briefly described in the following. The controller subsystem is made of a control electronics and a servo amplifier (SA); the control electronics may be a computer, microprocessor or guidance system and creates a command input signal; the SA provides a low power electrical signal which depends on the difference between the command input signal and the feedback signal generated by a position transducer. The SA usually implements an embedded PID (Proportional-Integral-Derivative) control logic; for this work, Integrative and Derivative gains are set to zero, to obtain a pure Proportional control law. The second component is an electrohydraulic SV that amplifies the low power electrical input regulating a high power flow of hydraulic fluid to the actuation element. The last element is a hydraulic piston (symmetrical double acting linear cylinder subjected to Coulomb friction [16]): it is the EHA actuating component to produce the forces needed to position the controlled device. Details of the considered system and its mathematical model are provided in [4, 15]. The aforesaid servomechanism is designed for a fly-by-wire control architecture: the pilot's command is converted in an analog or digital electronic signal; this 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. The error is processed and transformed into an electric current operating the electrohydraulic servo valve. The valve drives in turn an actuator that moves the control surface continuously to reduce the position error. The servo valve is a high performance two-stage valve (Figure 3); its output 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 the first stage 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 SV behavior can be accurately described, for the purpose of this paper, with a lumped parameters second order dynamical model for the pilot stage (first stage) and one for the second stage sliding spool.

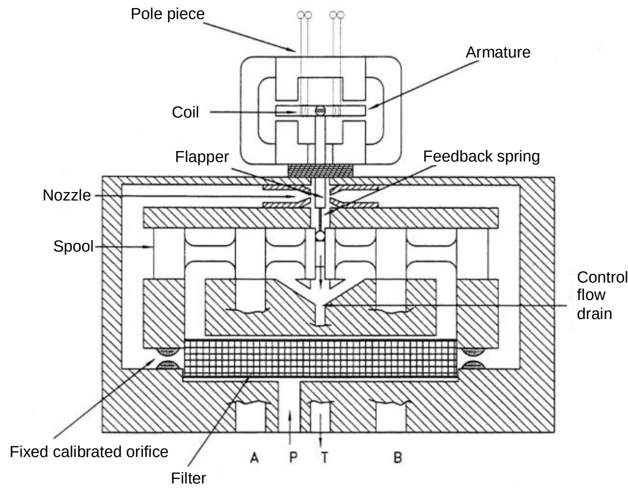

Figure 3. Schematic of the flapper-nozzle servo valve.

The second-stage dynamic model accounts for the effects due to the Coulomb friction forces acting on the spool (by means of the numerical model proposed in [4]). Moreover, a feedback from the second stage toward the first one, a saturation of the second stage output differential pressure and the effect of working flow and leakage on the differential pressure itself were considered; the abovementioned model is conceived to take into account the effect of time-dependent supply pressure. The hydraulic linear actuator considered in the this paper is a double acting symmetrical actuator: its model includes inertia, Coulomb and 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 load acting on the flight surface. This type of simulation algorithm, widely explained in [15], is also able to evaluate the dry friction force effects, taking into account its dependency on mechanical actuator efficiencies and on external loads acting on the EHA.

A. Analytical Model of the EHA

The considered EHA is modelled by means of the Simulink block diagram shown in Figure 4. As described in [17], the position error (*Err*), coming from the comparison of the instantaneous value of commanded position (*Com*) with the actual position (X_J), is processed by means of a PID logic. The controller generates the suitable current input (*Cor*) acting on the servo valve first stage torque generator. Such torque (expressed as a function of *Cor* through the torque gain G_M), reduced by the feedback effect due to the second stage position (X_S), acts on the first stage second order dynamic model, to compute the flapper position (X_F). The flapper position, limited by double translational hard stops, causes a spool velocity and, by time-integrating, gives the displacement X_S, limited by double translational hard stops $\pm X_{SM}$. Second stage dynamics is modelled with a second order numerical model taking into account the dry friction forces acting on the spool.

For a given X_S, the differential pressure P_{12} effectively acting on the piston is computed according to the flow through the hydraulic jack Q_J, with a two-gains linear-saturated model. The jack acceleration D^2X_J is computed accounting for the differential pressure P_{12} (acting on the piston active area A_J), the equivalent total inertia of the surface-motor assembly (M_J), the total load (F_R), viscous friction (coefficient C_J) and dry friction force (F_F). The integration of D^2X_J gives the velocity (DX_J), needed to compute the linear actuator working flow Q_J that, summed to the leakage one, is fed to the SV model to evaluate the pressure losses through the valve passageways. A further integration gives the actual jack position (X_J), which returns as a feedback signal to the control logic. The proposed numerical model is also able to simulate the effects due to conversion of the feedback signals from analogic to digital (ADC), electrical noise acting on the signal lines and position transducers affected by electrical offset.

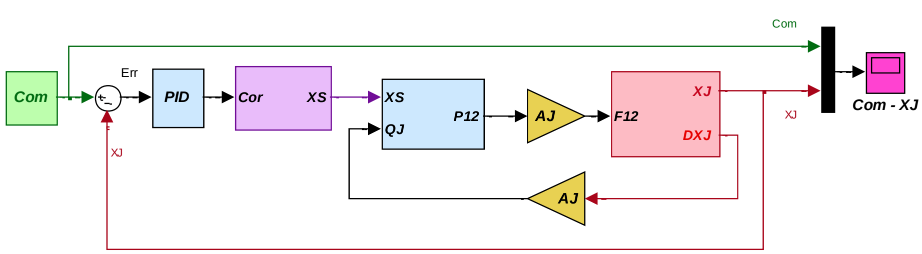

Figure 4. Simulink block diagram of the considered EHA.

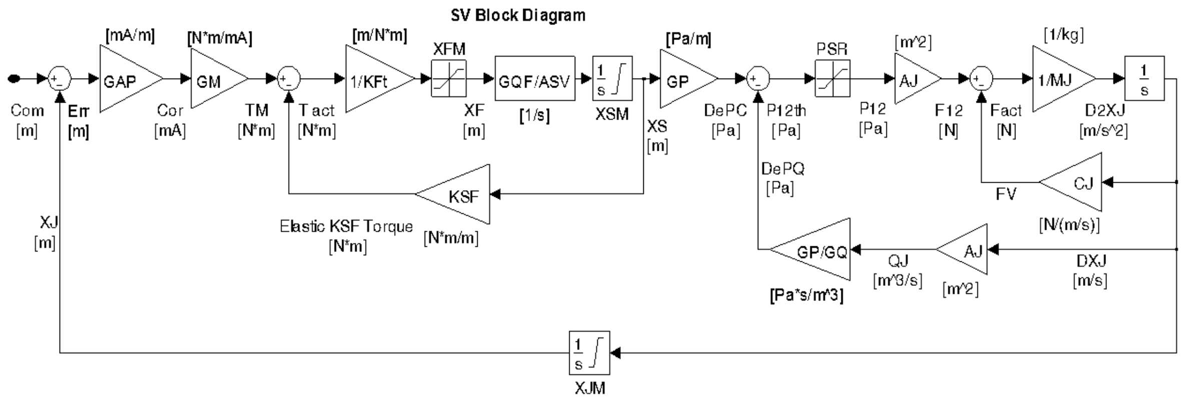

Figure 5. Block diagram of the EHA mathematical model used for the prognostic algorithm.

B. EHA Monitoring Model

The proposed detailed EHA Simulink model is able to simulate the dynamic behavior of an actual EHA taking into account the effects due to command inputs, environmental boundary conditions and several failures. This model allows to simulate the dynamic response of the real system to evaluate the effects of different faults and designs, and to analyze and test different diagnostic and prognostic monitoring strategies. In order to develop a smart system able to identify and evaluate the progressive failures, the detailed model is used as a simulated test bench, and its response is considered as a surrogate of data measured from a real, physical system. A simpler model is developed for health monitoring; this is intended to be executed iteratively, so its computational time shall be kept as low as possible; at the same time, the monitoring model is able to mimic the response of the detailed model, even in presence of faults. As shown in Figure 5, this model represents a simplified version of the detailed EHA numerical model having the same logical and functional structure.

Figure 6 shows the comparison between the dynamic response of the detailed model and the monitoring model in case of a step command in nominal conditions. The small discrepancy between the two models is due to the simplifications characterizing the mathematical model of the monitoring system (e.g. the friction forces on the SV spool, which introduce a certain response delay, and some nonlinearities are neglected).

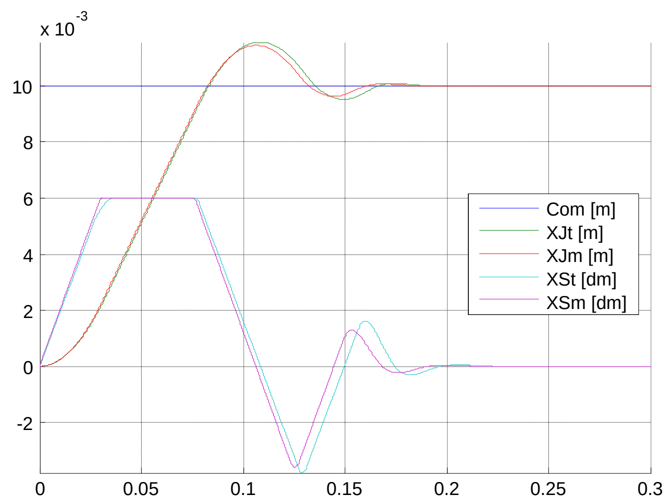

Figure 6. Comparison between the dynamic responses of the considered Electro Hydraulic Actuators (green line - XJt) and related monitoring model (red line - XJm) in case of step position command.

III. EHA FAILURES AND DEGRADATIONS

The electrohydraulic actuator, and in particular the servo valves regulating their hydraulic power, are complex devices and can fail in several ways. Some SV failures are sudden occurrences and, at the moment, there is no conceivable way of predicting them.

Among these 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, or a spool seizure caused by metallic chips stuck in the radial spool-sleeve clearance. All these failures are addressed by a diagnostic monitoring logic which removes the hydraulic power supply from the servo valve and inhibits any further operation. According to these considerations, some of the typical faults affecting SVs with a progressive degradation have been used as case studies.

The first progressive fault considered is the clogging of the servo valve first stage filter: the first stage pressure gain and flow gain decrease, and the spool moves slower to reach the desired position. The maximum differential pressure available downstream the filter is reduced, and this results in a longer settling time. As proved by the failure mode analysis, the maximum spool velocity and the initial overshoot peak are measurable parameters strongly influenced by this fault mode, so they are considered as terms of comparison useful to lead the first approximation evaluation of the state of health of the SV filter. The second progressive fault analyzed in this work is the increase of the friction coefficient of the sliding contact between spool and sleeve, due to the wear of their contact surfaces. Such deterioration determines an increase of the static and dynamic friction forces, which anyway maintain a constant ratio to each other. High friction often results in non-linear phenomena such as stick-slip and limit cycles. The task of the fault analysis in this context evidenced that the limit cycle is extremely, and quite exclusively, representative of the friction state. In particular, as the sliding contact increases its wear, the period and the amplitude of the steady state oscillation due to limit cycle tends to rise too. An alternative way to estimate the friction condition is to measure the standstill time, which is directly proportional to the friction coefficient.

The third fault mode analyzed is the progressive increase of the friction forces acting on the sliding contact of the hydraulic linear actuator, between jack and cylinder. 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: it results in a loss of position accuracy and resolution; extreme friction values can eventually generate stick-slip conditions. The relevant parameter monitored to estimate a first approximation of the cylinder-jack friction is the average differential pressure with the jack moving at low constant velocity. The amount of pressure needed is approximately proportional to the friction force, provided that the viscose contribution is unaltered. Then, the three considered failure mode can be robustly estimated analyzing two relevant signals: second stage spool position and actuator differential pressure.

IV. Fault Detection and Identification

The Fault Detection and Identification phase is performed as a model parameter estimation task, with an approach similar to [17,18]. The problem can be addressed with several optimization techniques, usually classified into two main categories: deterministic (direct or indirect) and probabilistic (stochastic, as Monte Carlo method, simulated annealing and genetic algorithms).

As reported in [7], a large part of these methods are local minima search algorithms and often do not find the global solution (i.e. they are highly dependent on good initial settings of the process parameters). Local-minima approaches would not be robust and may provide a false indication of parameter changes in an on-line system (i.e. a wrong selection of starting settings could determine the failure to convergence on the global minimum). As reported in [19][20], global search methods, such as genetic algorithms [21] and simulated annealing, provide more promising options for on-line model identification. Genetic Algorithms (GAs) have been used in science and engineering for solving design optimization problems in multiple disciplines, such as structural optimization, fluid dynamic design of rotating equipment, or robust control strategies [22-26]. In recent years the application of GAs in the development of diagnostic systems based on numerical models has met wide interest in the scientific world and has led to several technical applications. In particular, in the field of mechatronics and electromechanical systems, many researches have been published about new diagnostic and prognostic algorithms, which integrate GAs optimization and model-based approach [27]. For example, Raie and Rashtchi in [19] proposed a GA-based parameter identification approach (i.e. a parameter identification method applied to a simplified fault-sensing model), able to detect and evaluate the magnitude of progressive stator turn-to-turn coil faults.

The FDI procedure compares the dynamic response of the physical system, affected by faults (replaced by the detailed model for the purpose of this study), with the one computed by the monitoring model. An objective function is defined as the cumulative difference between the two signals. As summarized in the flow chart of Figure 7, the optimization algorithm iteratively varies the fault parameters of the monitoring model, in order to minimize the objective function. When the algorithm converges on the function minimum, the solution of the optimization is taken as an estimate of the faults affecting the physical system.

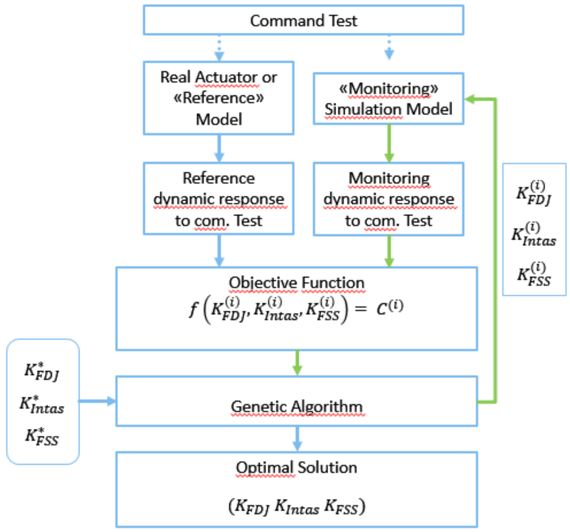

Figure 7. Logic of the proposed FDI procedure.

The parameters that represent the amount of the considered progressive faults (K_{FDJ}, K_{intas}, K_{FSS}) are normalized to the maximum wear compatible with operative conditions, and vary linearly from zero (original fully integral condition) to one (extreme fully damaged condition). The effectiveness of the diagnostic procedure highly depends on several aspects, such as the definition of the test command time-history, the susceptibility to the external disturbances and the robustness of the optimization tool chosen. Deterministic solvers have been often used for this kind of tasks, but in recent years the application of GAs in diagnostic systems based on numerical models has met wide interest, thus leading to several technical applications. Indeed, deterministic optimization algorithm perform poorly on multimodal problems, where several local minima are present; depending on the initialization, a deterministic algorithm will likely converge in a local minimum near the starting point, without exploring the whole search space. As the number of considered fault modes increases, the objective function becomes ever more irregular and the deterministic search loses in reliability. Heuristic solvers provide a suitable solution for this problem: they are less accurate in finding the optimal solution than the deterministic approach, but, on the contrary, they are considerably more robust, thus decreasing the probability of falling into a local minimum of the fitness function.

As for every optimization method, the performance of GAs in terms of robustness, accuracy and computational cost is strongly dependent on the correct parameter settings and algorithm initialization. In particular, for the proposed FDI procedure we make use of the information provided by the first approximation analysis, consisting in a preliminary evaluation of the condition of fault of the actuator (as shown in Figure 1). This initial step of the FDI procedure provides an approximate value of the fault state with deterministic methods. The approximation is used in the initialization of the first population of the GA.

A. Genetic Algorithm Tuning

In the genetic algorithm, a population of eligible solutions (referred to as individuals) is generated iteratively in order to evolve towards the optimal solution [19-21]. Each eligible solution has a set of properties, corresponding to the genotype, which can be mutated and altered. Usually, solutions are represented in binary as strings of zeros and ones, but other encodings are also possible. At each iteration, the new population is assembled by selecting the best individuals of the previous one, and generating new individuals by crossover (i.e. recombining the genomes of existing individuals) or mutation (i.e. randomly modifying the genome of an existing individual). Focusing on the EHA problem, the specific response of an actuation system, in terms of characteristic parameters in the time and frequency domains, depends on the intrinsic state of the wear of the actuator. Therefore the damage parameters represent the genotype and the features of the response represent the phenotype. The aim of the GA diagnostic procedure is to find the correct combination of faults (genotype), taking dynamic response (phenotype), as a term of comparison. In order to build a well-conditioned search and make it effective from a numerical point of view, the strategy of using the first approximation solution was followed as the initial data to feed the solver with.

This section of the document deals with the devices used to adapt genetic algorithm to the problem of finding the exact state of fault of an actuation system. By default, the optimization tool is set up to apply the rank scaling function. It consists in ordering the raw scores in their rank independently from the score obtained through the objective function. This approach on the fitness score of individuals guarantees to the least fit elements a great probability of being selected for the reproduction process. The rank scaling is very conservative because it tends to be cautious in eliminating the influence of the least fit individuals. On the one hand, getting a less strict selection of the individuals, makes it possible to preserve the genetic heritage provided by elements that, though being lacking in fitness value, are equipped with a precious portion of genetic pool. On the other hand, the process is slower in excluding the wrong solutions that do not provide any significant contribute.

The initialization of the first population near the expected solution allows to avoid the rank scaling to increase the convergence rate, while retaining a high accuracy and robustness. The effectiveness of this device is demonstrated by the evolution of the best fitness value and the mean fitness value during the process initialization. The genetic algorithm with the proportional fitness scaling function is faster in seeking fit solutions, as evidenced in the table below, showing the mean and best values of the objective function after 5 and 10 minutes of optimization.

TABLE I. MEAN AND BEST VALUES OF THE OBJECTIVE FUNCTION CALCULATED IN 5 AND 10 MINUTES RUNS.

	Elapsed Time			
	5 min		10 min	
	Rank	**Prop**	**Rank**	**Prop**
Best value	4,2	3,36	3,37	1,11
Mean value	304,6	130,9	15,8	5,9

B. Hybrid Function

Due to the complexity of the EHA problem, a deterministic process would be unable to detect a reasonable way to minimize the objective function just passing through the information supplied by the calculation of the gradient. On the other hand, the solution of the genetic algorithm solver could not be accurate enough. Of course, as the solver runs for a longer time, the solution error would approach zero. Conversely, the genetic algorithm is unable to further refine the solution once it has reached a competitive fitness value while satisfying a halt criterion.

The deterministic search methods provide a convenient approach to the refining task. The results of the genetic algorithm are used as starting point for a local deterministic optimization, which is able to converge in the exact minimum in a fraction of the time needed by heuristic methods.

TABLE II. RESULTS OF THE PROPOSED FDI PROCEDURE

Test Case	**Fault Parameters**		**Reference Value**	**First Approx. Result**	**GA Result**	**Error of First Approx. Result**	**Error of GA Result**	**Error Reduction**
1	K1	K_{intas}	0,3	0,294778	0,300862	0,00522175	0,00086175	
	K2	K_{FSS}	0,6	0,468279	0,59343	0,13172150	0,00657039	
	K3	K_{FDJ}	0,3	0,299984	0,300004	0,00001572	0,00000369	
					Average Error	**0,04565299**	**0,00247861**	**0,04317437**
2	K1	K_{intas}	0,3	0,295537	0,302905	0,00446328	0,00290502	
	K2	K_{FSS}	0,3	0,361526	0,294117	0,06152644	0,00588263	
	K3	K_{FDJ}	0,6	0,599992	0,599997	0,00000837	0,00000272	
					Average Error	**0,02199936**	**0,00293012**	**0,019069240**
3	K1	K_{intas}	0,6	0,679822	0,597723	0,0798223	0,00227672	
	K2	K_{FSS}	0,6	0,525945	0,607861	0,07405464	0,00786098	
	K3	K_{FDJ}	0,3	0,300042	0,300002	0,00004237	0,00000221	
					Average Error	**0,05130644**	**0,00337997**	**0,047926468**

V. RESULTS OF THE FDI PROCEDURE

We assess the FDI procedure using the detailed model as a simulated test bench. The model computes the actuator response in presence of a given set of fault parameters, then the spool position and differential pressure signals are analyzed to estimate the value of the fault parameters. In the first phase of the FDI algorithm an approximated estimation is found deterministically, by analyzing the stick-slip, overshoot and standstill time of the spool, as well as the differential pressure peak at the jack starting. Then, in the second phase of the FDI, the results are refined by the GA solver, which computes the optimal fault parameters to match the detailed model reference response with the monitoring model.

The command time-history plays an essential role in the achievement of a good FDI analysis, since a proper selection of these command inputs could produce a more accurate and efficient evaluation of the EMA health conditions. Specifically, the test command shall have characteristic such to highlight the effect of the considered fault modes.

The test command employed for this study consists in three sections: a ramp command, a low frequency sine wave, and a high frequency sine wave. The first part of the signal is intended to achieve a constant actuation speed, with a steady spool position, which can be used for the deterministic approximation of the system health condition. The other two parts are analysed within the GA to find the actual value of the fault parameters. The sine wave command uses two different frequencies to reduce the chance of two distinct fault combinations producing similar effects. In fact, it can happen that two fault combinations get the same gain and phase of system response for a given frequency of sinusoidal input. However, it is much more unlikely, given the nonlinear behavior of the system, that the two combinations have the same effect for two different input frequencies.

Table 2 shows the test results for three different fault combinations. The absolute errors are reported, since the fault parameters are already normalized and their range of variation is bound between 0 and 1. The last column reports the error reduction from the initial approximate estimation to the final GA result. The first approximation estimate often has still a high error. This is the case of the third simulation where first approximation solver overestimates the K_{intas} parameter and underestimates the K_{FSS} parameter. This is due to the deterministic approximation evaluating each fault individually and neglecting the combined effects of multiple faults. In the application on a physical system, this error would be probably worsened by measurement uncertainty and noise. The second FDI step leveraging the GA solver, conversely, uses a model-based approach inherently considering the fault combination effects; then, the final error is usually at least one order of magnitude smaller than that of the first approximation. All the diagnostic simulations led to a satisfying solution, able to find a final solution affected by an average error less than 1%

VI. CONCLUSIONS

The main goal of this work was to realize a reliable procedure to perform the partial diagnosis of an electro-hydraulic actuator (EHA) with a flapper-nozzle valve.

The proposed method allows finding the current state of wear in three of the fundamental causes of faults in an electro-hydraulic servo-actuator. The diagnosis procedure has reached a high robustness; future developments will include the modelling of additional fault modes like the electrical hysteresis in the first stage torque motor, or the modification of the geometry of the elements due to wear, e.g. with a variation of the backlash between the spool and the feedback spring sphere. The study will be repeated with variable environmental conditions, such as variation of physical characteristics of the considered hydraulic fluid

(due to temperature changes) and fluctuations of the hydraulic supply pressure (due to the activation of other users). The study has been performed on a numerical test bench that implements several failure modes; by means of proper simplifications, the aforesaid numerical model was then reduced obtaining the monitoring model. The experimental data shows that the amount of mean error in a general diagnostic test is less than 1%. It is an acceptable value, considering the complexity of the problem. Accuracies are all over 90%, which means that the method shows adequate convergence. Even if the method is probabilistic, every simulation converges at the same result almost in every attempt, making the method suitable in terms of repeatability. Starting from the analysis of fault modes effect on the actuator response, it was necessary to find a robust way to keep a valid approximation of the fault states. At the current advancement, these first approximation results approach the actual fault combination with insufficient precision, 5% in the worst case. The first approximation results were therefore considered as initial conditions for the next step, consisting in the Genetic Algorithm optimization task. The results proved the approach to be accurate and effective, thus being worth of refinement for the introduction in PHM applications.

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