A New Prognostic Method Based on Simulated Annealing Algorithm to Deal with the Effects of Dry Friction on Electromechanical Actuators

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Matteo D. L. Dalla Vedova, Paolo Maggiore and Lorenzo Pace

***Abstract*—**In prognostics it is possible to apply several approaches with the aim to detect incipient failures, caused by progressive wear, of electromechanical actuators (EMA) in primary flight commands. The anticipation of a failure has to be performed through a correct interpretation of the degradation pattern, so to trig an early alert for maintenance and to properly schedule the servomechanism replacement. This paper proposes a prognostic approach based on the simulated annealing optimization method, able to identify symptoms of degradation before the behavior of the actuator becomes anomalous; friction failures are considered as the case study. The approach is validated through an experimental test bench, resulting in an adequate robustness and a high degree of confidence in the ability to early identify faults, with a low amount of false alarms or not annunciated failures.

***Keywords*—** Dry Friction, Electromechanical Actuator, Prognostics, Simulated Annealing Algorithm.

I. Introduction

An actuator is a device capable of operating the conversion of mechanical, electrical, hydraulic, or pneumatic power into mechanical power, to generate motion. In the aeronautics domain, actuators are commonly used for flight control surfaces and various utility systems, with the aim of indirect control and power gain. Flight control systems are considered flight critical and, although highly redundant, must meet tight reliability requirements; for example, in the military aircraft domain, they have to perform less than one catastrophic failure per 10^5 flight hours for F-18 and one per $18x10^6$ flight hours for F-35AB [1]. Unscheduled maintenance events are usually originated by unanticipated and extreme operating scenarios; these conditions may result into serious operational issues in terms of safety, mission completion and cost. A common situation is that a fault is registered without information regarding the real cause and effect relationship between the failure mode and failure itself.

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).

L. Pace is with the Department of Mechanical and Aerospace Engineering (DIMEAS), Politecnico di Torino, Corso Duca degli Abruzzi, 24 - 10129 - Torino, ITALY. (e-mail: lorenzo.pace@polito.it).

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).

The need for a robust health management solution is identified to go beyond the bare awareness of an occurred failure; such solution should be able to early detect faults and predict failures with good reliability, covering multiple failure modes for flight control actuators; this is called Prognosis and Health Management system (PHM) [2]. Electric actuators are more favorable to such kind of systems, as no additional sensors are required, for the same sensors used to the control scheme and system monitors can be used also for PHM [2]. For these reasons, the study presented in this paper considers electro-mechanical actuation systems. Huge benefit is expected with the advance of fault detection to failure prognosis for actuator systems, both from a maintenance and a logistic point of view, with subsequent economic profit; such advantages are foreseen as high Can Not Duplicate (CND - inability to replicate field failures during lower level maintenance assessment) rates still plague many aircrafts. From collected field analyses, CND failures can constitute more than 85% of all observed field failures in avionics, resulting in more than 90% of all maintenance costs [2-3]. These statistics can be attributed to a limited understanding of root cause failure characteristics of complex systems, inappropriate means of diagnosing the condition of the system and the inability to duplicate the field conditions in the lower level test environment [3]. Impact Technologies estimated that CND occurrences result in about a $30M/yr incurred cost for one particular aircraft. Moreover, their study showed that a $7M investment to develop a complete PHM solution would produce a ROI (Return On Investment) of 4 to 1 for a 5-year period considering just a 20% CND reduction. In other words, this means saving $30M in 5 years by spending just $7M initially. Moreover, in case the technology could produce a further CND cost reduction (e.g. 40%), the ROI would be of almost 10 to 1 in 5 years [2]. Since the prognostic activities typically involve systems having a complex non-linear multidisciplinary nature, the failure detection/evaluation strategies proposed in literature are various and extremely different each other. Model-based techniques based upon the direct comparison between real and monitoring system have been proposed in the recent past have been proposed [4], as well as methods based on the spectral analysis of well-defined system behaviors (typically performed by Fast Fourier Transform - FFT) [5], or appropriate combinations of the first two methods [6] or based on Artificial Neural Networks [7].

This paper reports the first results of a wider research activity focused on the diagnosis model-based approach and, in particular, on the parametric estimation task, having as a primary objective the design of a modern and fast damage estimator routine for a simple (but real) electromechanical actuation system, in order to prove its accuracy and reliability.

These objectives are pursued through the following steps:

1) define the optimization algorithm to be used for the parameter estimation task;
2) set up a real actuation system meeting as much as possible the aeronautical requirements and being capable of responding to different types of signals (step, sinusoidal, random sequence, ramp) as well as recording significant data (velocities, position, current);
3) build and validate a dedicated Matlab-Simulink numerical model of the considered actuation system (the aforesaid model, having to be run several times in the prognostic process, must represent a compromise between a satisfying representativeness of the actual EMA behaviors and the most reduced calculation effort);
4) simulate different fault conditions on the real actuation system (without damaging it);
5) test the damage estimator to evaluate its speed and reliability on the simulated faulty response of the system.

In particular, this paper shows the results obtained applying the proposed fault detection/evaluation method in case of EMA subjected to dry friction phenomena.

II. Aims of Work

The aims of this work are:

1) to propose a numerical algorithm able to perform the simulations of the dynamic behavior of a typical electromechanical servomechanism evaluating the global effects due to dry frictions acting on actuation system (e.g. rotor bearings, gear reducer, ball screw, gaskets);
2) to introduce an innovative fault detection/evaluation method, based on techniques derived from optimization methods, able to detect the EMA failure precursors and evaluate the corresponding failure entity.

The assessment of the robustness of the proposed techniques is done through an appropriate experimental test environment developed on the purpose; the effects due to the mentioned failures on the EMA behavior have been evaluated by means of several tests (related to different values of dry friction). These results have been compared with the ones provided by a corresponding numerical simulation model, in order to evaluate the differences and, by a proper algorithm based on simulating annealing, timely identify the failures and evaluate their magnitudes.

III. Optimization algorithm

Several optimization techniques are commonly used also for model parameter estimation tasks, which can be classified into two main categories: deterministic (direct or indirect) and probabilistic (stochastic, as Monte Carlo method, simulated annealing and genetic algorithms).

A large part of these methods are local minima search algorithms and often do not find the global solution. They are therefore highly dependent on a good initial setting. This is a viable solution in an off-line scenario, where initial guesses can be reiterated; on the other hand, these approaches are not suitable for an on-line automated identification process, because a good initial guess for one data set may not be such for the next identification. Local-minima approaches would not be robust and may provide a false indication of parameter changes in an on-line system. Alternatively, global search methods, such as genetic algorithms and simulated annealing, provide more promising options for on-line model identification [8-9]. However, as they are similar to simplex methods, genetic algorithms do not always find the global minima [10]. Simulated annealing methods are more effective at finding the global minima, but at the cost of a larger amount of iterations [2]. The simulated annealing method originates, as the name suggests, from the study of thermal properties of solids [11]. The procedure described in [11] was then an exact copy of the physical process which could be used to simulate a collection of atoms in thermodynamic equilibrium at a given temperature. In fact, the abstraction of this method in order to allow arbitrary problem spaces is straightforward. There is a significant correlation between the terminology of thermodynamic annealing process (the behavior of systems with many degrees of freedom in thermal equilibrium at a finite temperature) and combinatorial optimization (finding global minimum of a given function based on many parameters).

A detailed analogy of annealing in solids provides frame work for optimization. As reported in [12], Table 1 shows the key terms which are related with thermodynamic annealing, showing its association with an optimization process.

Table 1: Association between thermodynamic simulation and combinatorial optimization

Thermodynamic Annealing	**Combinatorial Optimization**
System State	Feasible Solutions
Energy of a State	Cost of Solution[1]
Change of state	Neighbor solution[2]
Temperature	Control parameter[3]
Minimum Energy	Minimum Cost

[1] The cost of a solution represents the corresponding objective function value (i.e. the function that the optimization algorithm attempts to minimize in order to identify the optimal solution).

[2] A new system solution calculated by the optimization algorithm and evaluated, with respect to the previous one, using the said cost functions.

[3] The system parameters iteratively modified by the optimization process so as to minimize its objective function.

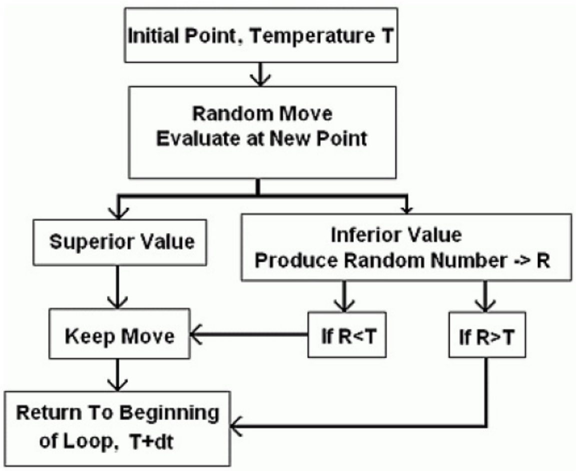

Fig. 1 Operating Logic of Simulated Annealing Method

At given temperature and energy, a new nearby geometry *i + 1* is generated in each iteration as a random displacement from the current geometry *i*. The energy of the resulting new geometry is then computed and the **energetic difference** ΔE is determined with respect to preceding energy as:

$$\Delta E = E_{i+1} - E_i \,. \tag{1}$$

The probability that this new geometry will be accepted is:

$$P(\Delta E) = \begin{cases} e^{-\Delta E/(k_b T)} & if\ \Delta E > 0, \\ 1 & if\ \Delta E < 0 \end{cases} \tag{2}$$

This means that, if the new nearby geometry has a lower energy level (successful iteration), the transition is accepted. Otherwise (unsuccessful iteration), a uniformly distributed random number larger or equal than 0 and lesser than 1 is drawn and the step will only be accepted in the simulation if it is lesser or equal the Boltzmann probability factor, i.e. $r \leq P(\Delta E)$. After a certain number of steps at the same temperature T, the latter is decreased following the specified cooling schedule scheme. It is worth noting that the temperature does not take part directly to the optimization itself, but it acts merely as an exploration parameter. As at high temperatures T the factor $P(\Delta E)$ is very close to 1, most likely many up-hill steps are accepted, even if they are unsuccessful. A wide exploration of the search space can be performed in this way, as one of the main valuable features of this algorithm. Subsequently, as the temperature falls off, the search is confined in a more limited space since Boltzmann factor $P(\Delta E)$ collapses to very low values, thus decreasing the acceptance probability in case of $\Delta E > 0$ (the algorithm becomes more selective). Finally, the global optimum should be found as soon as the temperature reaches its minimum value but, in practice, reannealing is performed, raising the temperature after a certain number of new points have been accepted so that the search starts again at the higher temperature. Basically, reannealing avoids getting caught at local minima.

The authors performed the abovementioned optimization analysis by means of the MATLAB Optimization Tool; in this case, the main annealing parameters are the following:

Annealing function: specifies the function used to generate new points for the next iteration:

- Fast annealing takes random steps, with size proportional to temperature
- Boltzmann annealing takes random steps, with size proportional to the square root of temperature using multivariate normal distribution.

Reannealing interval: is the number of points to accept before reannealing. Reannealing sets the annealing parameters to lower values than the iteration number, thus raising the temperature in each dimension. The annealing parameters depend on the values of the estimated gradients of the objective function in each dimension. The basic formula is:

$$k_i = \log\left(\frac{T_0}{T_i}\frac{\max(s_j)}{s_j}\right) \tag{3}$$

Where:

k_i = annealing parameter for component *i*.
T_0 = initial temperature of component *i*.
T_i = current temperature of component *i*.
s_j = gradient of objective in direction *i* times difference of bounds in direction *i*.

Temperature update function: specifies how the temperature will be decreased.

Initial temperature: is the temperature at the beginning of the run.

The **acceptance criterion** compares the function values between the current point and new point; the latter is kept or discarded depending whether it fits or not with the Boltzmann probability density distribution.

Specifically, MATLAB uses the following function:

$$P(\Delta E) = \frac{1}{1+e^{\Delta E/T}} \tag{4}$$

which ranges from 0 to 0.5 and therefore differs from (2).

IV. ACTUATION SYSTEM

Primary flight controls are typically proportional servomechanisms with continuous activation: they must return a force feedback related to command intensity and a high frequency response. Since their loss is a critical issue, their reliability must be very high. Their purpose is to control the dynamic of the aircraft by generating, by means of the rotation of the corresponding aerodynamic surfaces, unbalanced forces/couples acting on the aircraft itself. These controls are usually conceived to obtain the aircraft rotation around one of the three body axis when one control surface is activated, possibly minimizing the coupling effects. Depending on the actuation mode of the primary control surfaces, a flight control system can be classified as reversible or irreversible. The first type of system provides a direct mechanical linkage connection between the flight control surface and the control lever.

The pilot must compensate the hinge moment generating an adequate force: hinge moment is mainly related to primary surface sizes, to their deflection in airstream, to aircraft speed and it could be lowered by using proper aerodynamic compensation. Vice versa, irreversible flight control systems do not require a pilot's action to compensate the hinge moment and utilize command lines that can be mechanical, electrical (fly-by-wire) or optical (fly-by-light). Until a few years ago, the actuators mainly used in aeronautical applications were generally hydraulic and precisely hydromechanical or, more recently, electrohydraulic. This kind of actuator, because of its great accuracy, high specific power and very high reliability, is often equipped on current aircrafts, even if on more modern airliners electro-hydrostatic actuators (EHA) or electro-mechanical actuators (EMA) are installed. In EHA, highly-pressurized hydraulic fluid is maintained only near the actuator, whereas otherwise the hydraulic line is replaced by an electric signal, which allows a consistent weight reduction. In this case, the actuator usually consists of an electrical motor that converts electrical power into mechanical power, which is then transformed into hydraulic power by means of an axial piston pump. Finally, a linear or a rotary actuator can be employed, depending on the architecture. Even if the EHAs provides attractive benefits and represents an interesting alternative to traditional hydraulic controls, in the last years the trend towards the all-electric aircrafts brought to an extensive application of novel optimized electrical actuators, such as the electromechanical ones (EMA). To justify the fervent scientific activity in this field and the great interest shown by the aeronautical world, it must be noticed that, compared to the electrohydraulic actuations, the EMAs offer many advantages: overall weight is reduced, maintenance is simplified and hydraulic fluids, which is often contaminant, flammable or polluting, can be eliminated. For these reasons, the use of actuation systems based on EMAs is increasing in various fields of aerospace technology.

In the framework of the COVADIS project, an EMA has been developed and produced by Sagem and flew for the first time in January 2011, as the primary flight control for the aileron on an Airbus A320 commercial jet. EMAs have also become attractive candidates to replace hydraulic actuators for Thrust Vector Control (TVC) of launchers, thanks to an easier implementation and lower maintenance requirements. The TVC is a subsystem which controls the direction of gimballed nozzles of rocket engines, following the request/command from the launcher trajectory and attitude control system. In that case EMAs are currently under ESA development for the VEGA launcher and studied in the framework of the Future Launchers Preparatory Programme for Next Generation Launchers (NGL). Finally, Air Force Research Laboratory, AFRL/RQQM Mechanical & Thermal Systems Branch, has launched a program to develop a robust, thin-wing primary flight actuator, capable of achieving a high-duty cycle application (e.g. aileron) while fitting within the volume constraints, which is mandatory in future thin-wing aircraft design.

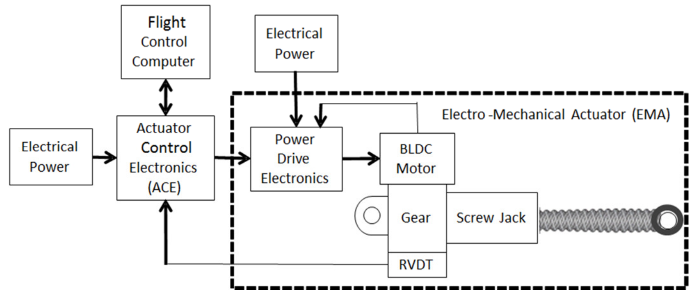

Fig. 2 Electromechanical Actuator Scheme

As shown in Fig. 2, a typical electromechanical actuator used in a primary flight control is composed of:

1) an **actuator control electronics** (ACE) that closes the feedback loop, by comparing the commanded position (FBW) with the actual one, elaborates the corrective actions and generates the reference current I_{ref};
2) a **Power Drive Electronics** (PDE) that regulates the three-phase electrical power;
3) an **electrical motor**, often BLDC (BrushLess Direct Current) type;
4) a **gear reducer** having the function to decrease the motor angular speed (RPM) and increase its torque to desired values;
5) a system that **transforms rotary motion into linear motion**: ball screws or roller screws are usually preferred to acme screws because, having a higher efficiency, they can perform the conversion with lower friction;
6) a **network of sensors** used to close the feedback rings (current, angular speed and position) that control the whole actuation system (reported in Fig. 2, as RVDT).

A proper experimental test-bench has been conceived with the aim to assess the behavior of the proposed prognostic method in case of EMA progressive failures,

After a tradeoff among available actuators, controllers and power supplies, the following components have been chosen to compose the case study shown in Fig. 3:

- MecVel ALI-2 (version M01) actuator, powered by a brushed DC (BDC) electrical motor and equipped with 24 VDC brake and encoder (Fig. 4);
- RoboteQ AX1500 controller (with encoder module);
- Acopian unregulated power supply (220 AC - 24 VDC, 23 A);
- RS-232 to USB converter.

Subsequently to a proper stage of setup and calibration of the EMA control logic (selection of the proper Proportional Integral Derivative - PID - gains and anti-windup filters), the actuation system was fully ready to operate.

The abovementioned controller logic closes the control loops feeding the EMA with various type of input meaningful for the parameter estimation process (sinusoidal with/without linear frequency sweep, ramp, step and external commands, all of them both in open and closed loop).

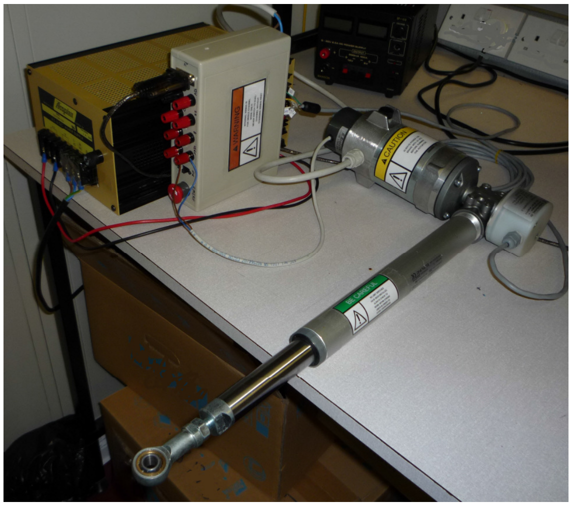

Fig. 3 Complete EMA actuation system

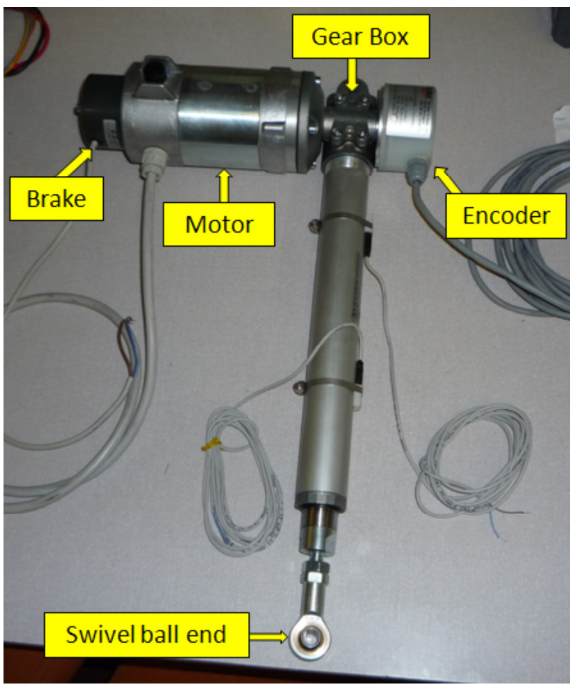

Fig. 4 Considered EMA actuator

Every significant datum (RPM, rod position, controller current, motor power level, PID actions) could have been recorded and exported to Microsoft Excel or even to Matlab: the following figures represent the response of the actuation system to a step command. An anti-windup (AW) control has been applied and the difference in the response with respect to the system without an anti - windup can be noticed.

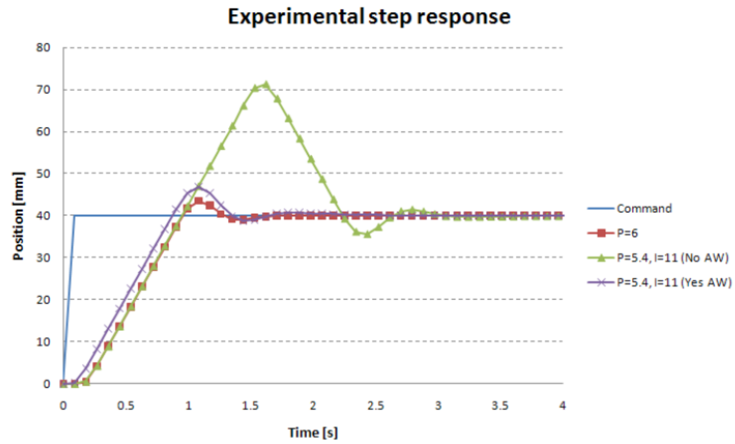

Fig. 5 Effect of PID controller on EMA Position

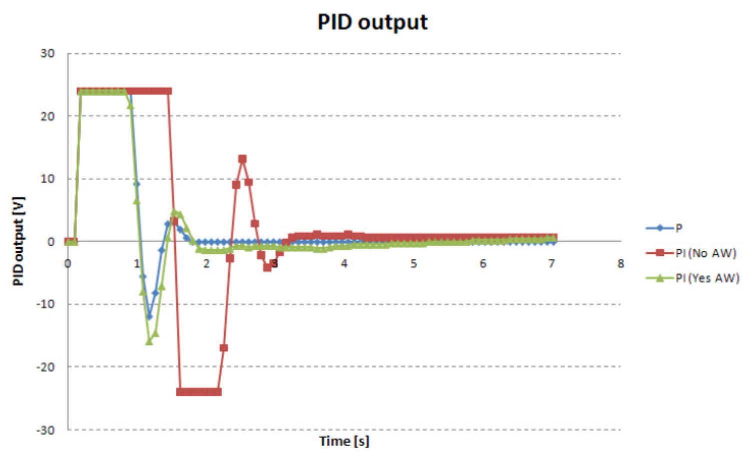

Fig. 6 Effect of PID controller on EMA Position

V. EMA Numerical Model

As previously reported, the subsequent step was to build an adequate Simulink model of the actuation system to be used as core of the damage estimator thus making it capable of recognizing the most representative actuator's failure modes according to some faulty experimental data achieved by the aforementioned software

In order to build an efficient model, two important (and often antithetical) aspects must be considered: the execution speed of the algorithm and the level of accuracy of the simulated results (with respect to the real ones).

Fundamentally, increasing one of them implies reducing the other. This is the main issue when dealing with models in general. In the present work, a parameter estimation task is involved (as shown in previous sections) meaning that the numerical model will go through an optimization problem and thus the speed aspect must be privileged. In fact the faster the model runs, the more iterations will be performed making the algorithm likely to find the parameters set which matches the experimental response (this is the primary goal of a damage estimator). If the model were very accurate (i.e. very slow), the optimization would be "stuck" on every iteration and the algorithm's convergence might also not be reached. This would then mean a totally useless damage estimator routine.

On the other hand, a fast model is generally equivalent to a simple one in the sense that not all the phenomena are taken into account. This brings to an unreliable simulated response which makes practically impossible the matching with experimental data (at least with sensed parameters). It is then clear that a compromise must be reached.

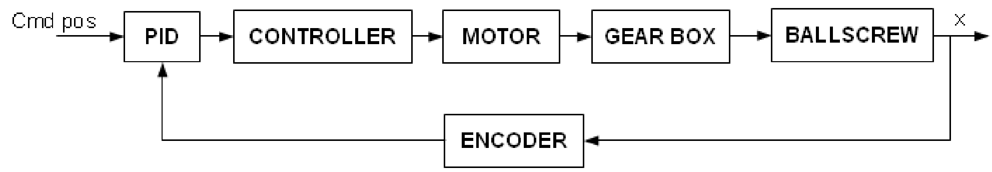

Fig. 7 Conceptual model's scheme

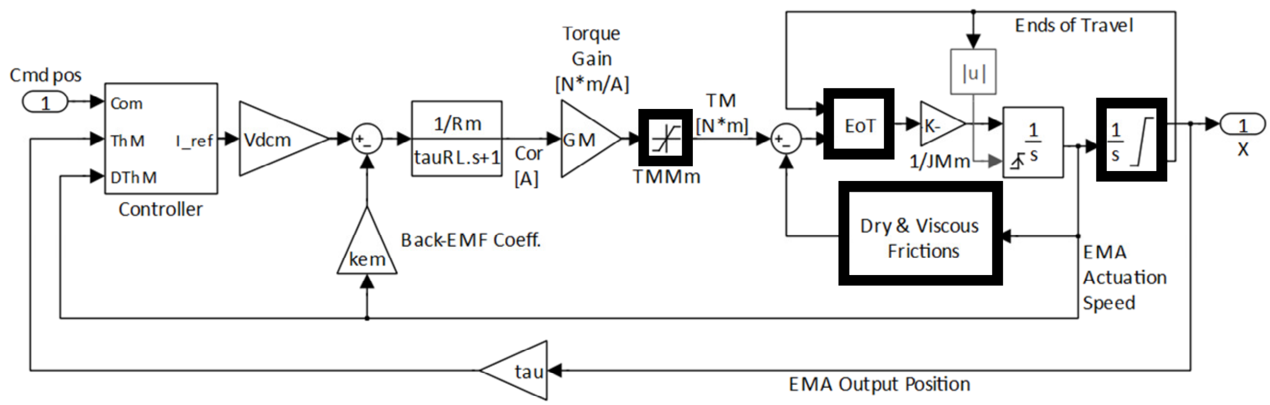

Fig. 8 Block Diagram of EMA numerical model: the blocks that implement the nonlinearities considered (saturation of the motor torque, friction phenomena and ends-of-travels acting on the final ballscrew actuator) are highlighted in the diagram by bold border.

The proposed numerical model is composed of six blocks representing the different, physical or functional, components of the actual EMA. Hence, the Simulink model includes:

- PID Control Logic (i.e. PID controller with saturated output and anti-windup);
- Controller (simulating the RoboteQ AX1500 controller);
- Motor (simplified electro-magneto-mechanical model of the considered DC motor);
- Gear box;
- Ball screw;
- Encoder.

As shown in [7], every block has been modelled starting from its basic electromechanical equations, but since the objective is to achieve a model capable of recognizing also some significant actuator failure modes (e.g. dry friction), it was decided to model the electromagnetic aspects in a suitably simplified way and focus instead on mechanical aspects.

The considered numerical model is developed from the monitoring model conceived by the authors for an EMA model-based prognostic application [4]. The electro-magneto-mechanical dynamics of the BDC motor is simulated by means of a classic resistive-inductive (RL) numerical model.

In particular, it is a 1st order linear model capable of calculating the moving torque TM as a function of the motor torque gain GM, of its power supply voltage (*Vdcm*I_ref*), of the back *emf*, of the dynamic characteristics of the RL circuit and of the saturation of magnetic induction flux. The dynamics of the mechanical actuation system (rotor of BCD motor, gear box and ball screw) is represented by a simplified 1 degree-of-freedom system (obtained assuming an ideal rigid transmission without elastic deformations or backlashes). According to [6], it is modelled by means of a 2nd order non-linear numerical model able to simulate the EMA behavior taking into account the global effects due to inertia, viscous damping, ball screw ends-of-travel and dry frictions.

The dry friction torques acting on the actuation system are simulated by a numerical algorithm which implements the classical Coulomb's model; in particular, the proposed algorithm has been developed by means of a lumped parameter model based on the Karnopp friction model [13] and suitably modified as shown in [14].

VI. Proposed Prognostic Algorithm

The outlined nonlinear third-order model can simulate the system response, taking into account the effects due to Coulomb friction, being then potentially able to reproduce seizure due to ball return jamming or bearing binding/sticking. Subsequently, its execution speed was tested in order to verify its suitability for optimization purposes. It must be noted that, despite being a relatively simplified numerical model, it shows a good accuracy, guaranteeing a satisfying correspondence with the experimental data (as reported in the following sections). The proposed prognostic algorithm performs the failure detection/evaluation by means of an optimization process implemented by means of simulated annealing algorithm; this process aims to minimize the value of appropriate objective functions (typically related to the magnitude of the error E(t) calculated comparing together experimental and numerical data) by acting on well-defined parameters of the numerical model. In particular, by means of simulated annealing algorithm, the optimization process modifies the parameter CSJ, representative of the dry frictions acting on the EMA numerical model, up to identify its value that minimizes the abovementioned objective functions.

It is clear that, in this case, the objective function of the optimization problem is the error generated, for a well-defined command input (*Cmd pos*), between the experimental data and the corresponding model output.

In this case the authors use the following function:

$$\bar{E}^2 = \begin{pmatrix} e_1^2 \\ \vdots \\ (y_{model} - y_{experim})_i^2 \\ \vdots \\ e_m^2 \end{pmatrix}$$

$$\Rightarrow E_{int} = \int_0^{t_m} E^2(t)dt \cong$$

$$\cong \sum_{i=1}^{m-1} \left[\frac{(\bar{E}_{i+1}^2 + \bar{E}_i^2) \cdot (t_{i+1} - t_i)}{2} \right] \qquad (5)$$

where E_{int} is the scalar value representing the "goodness" of the matching of the corresponding data. Before verifying the actual ability of the proposed prognostic method to identify and evaluate friction precursors, the calibration of the numerical model parameters has been performed.

The ideal values of these parameters have been identified by comparing the dynamic response of the real system in nominal conditions (NC: e.g. nominal dry friction level and no other failures) with that generated by the numerical model, then, identifying the corresponding objective function (E_{int}) and, at last, applying the proposed optimization process to the above parameters.

For instance, in Fig. 9 and 10 the experimental response of the EMA test bench is compared with the corresponding dynamic behaviors of the numerical model, putting clearly in evidence the best match that occurs (between experimental and simulated data) following of this calibration.

The model thus conceived and calibrated in NC was then used to estimate the global amount of the dry friction torques acting on the real EMA. The dynamic response of the real EM actuation system (subjected to a well-defined system of frictional actions) is compared with that produced by the simulation model and, by means of the abovementioned optimization method, it is calculated the value of the parameter CSJ that minimizes the error between real and simulated.

It should be noted that this parameter, dimensionally expressed in Newton·metre (Nm), is a global coefficient representing the equivalent static frictional torque acting on the whole EMA. The Simulated Annealing method used by the proposed prognostic routine to perform the fault estimation is implemented by means of **Matlab Optimization Tool**.

It must be noted that these optimizations have been carried out in condition of unloaded actuator since, within an operational scenario, these kinds of tests could be performed on the ground, without any aerodynamic loads, but rather just with the control surface weight, which is usually negligible compared to the actuator's capabilities.

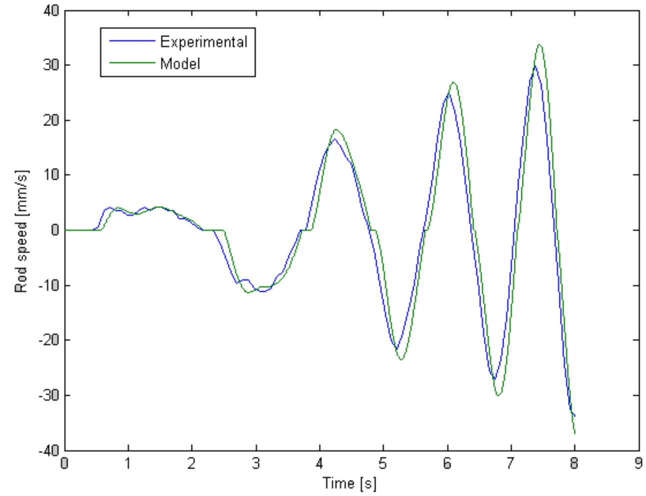

Fig. 9 EMA actuation speed before optimization

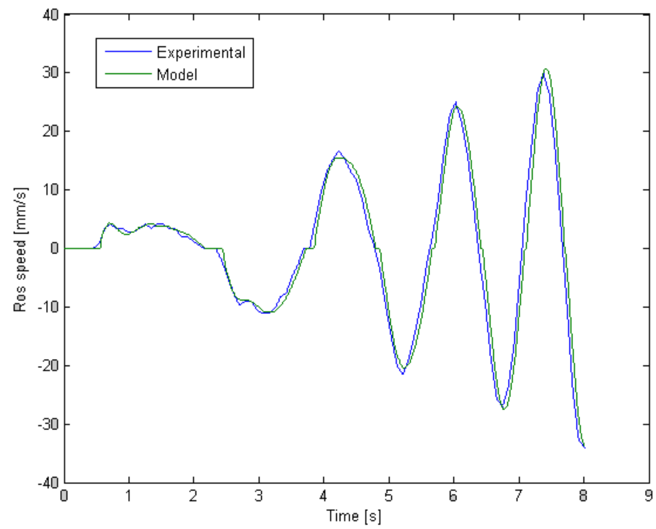

Fig. 10 EMA actuation speed after optimization

The problem of what type of signal should have been used to test the optimization algorithm has not a precise solution and depends strongly by the system's application. In the case here examined, a sinusoidal linear frequency sweep wave was chosen as standard input position signal for the parameter estimation process. In fact, such a signal allows testing, at one time, a wide range of system response frequencies.

For instance, in the low frequency range the stick-slip motion could be highlighted, enabling the optimization algorithm to finely tune the friction coefficients of the model and, at the same time, adapt the other parameters according also to the high frequency range, representing more significantly the system dynamic response. A simple step or ramp response could not comply with this necessity.

In order to obtain accurate results and assure a quick algorithm convergence, the static friction coefficient CSJ (varying during the optimization process in order to minimize the error between experimental data and corresponding numerical simulations) has been limited between a lower and an upper bound (respectively LB and UB).

In particular, CSJ can assume values from 0.01 Nm to 1.5 Nm which represent a quite large band given that its initial value is assumed equal to 0.12 Nm (NC dry frictional torque provided by motor datasheet) and the corresponding peak torque of the motor is worth 1.48 Nm.

In order to test the performance of the proposed method, different experimental tests have been conducted (with different time-history input and different levels of failure) that were then used as input to the optimization process performing the failure analysis.

For instance, the following section shows the results gained by the authors in case of experimental system affected by a friction torque of 0.779 Nm[4]. In this case, the considered input is a position command evolving like a sinusoidal linear frequency sweep wave.

Figures 11 and 12, comparing the dynamic response of the actual EMA with the corresponding numerical simulation before and after the optimization, allow evaluating immediately the effects that this optimization produces on the behavior of the simulated system. As shown in Fig. 11, before optimization the numerical model is not able to simulate the dynamic response of the real "faulty" system (i.e. affected by the fault in question) but, provided that the calibration of the model parameters is correct, approximates the real "healthy" system (i.e. in nominal conditions). The difference between the real position of the test case and the corresponding non-optimized numerical model is shown in Fig. 13 (blue curve).

Fig. 12 compares the trend of the instantaneous position of the experimental "faulty" system (blue line) with that of the optimized numerical model (green line). Compared to Fig. 11, Fig. 12 puts in evidence how the optimization process, realized by means of the Simulated Annealing algorithm, has significantly reduced the error between experimental and simulated data (as show in Fig. 13), increasing the accuracy of the numerical model with respect to the performance of the "faulty" test-bench. This means that the value of friction torque CSJ estimated at the end of the optimization process is reasonably close to the corresponding real and that, at least for the considered typology of fault, this approach can be satisfactorily used to identify / evaluate the failure. Finally, Fig. 14 shows the diagram of the temperature of the Simulated Annealing process concerning to the just described case.

[4] Of course, the actuator could not be damaged to quickly obtain "real" faulty data and even less there was enough time to carry out tests aimed at causing wear or seizure in the system. Hence, an expedient had to be found. As the MecVel actuator was equipped with an electric power-out safety brake mounted on the motor's shaft, the authors decided to lower its nominal voltage (24 V, i.e. brake not engaged) in order to increase the braking torque applied to the motor and obtain a sort of "seizure" simulation (i.e. a constant friction torque applied to the motor shaft which can alter its response). In fact, supplying the brake with 11 V by means of a separate power supply, a partial braking action is generated and, as a consequence, the BDC motor exhibits large sticking zones and a much higher delay in response. In this condition the braking torque applied should be theoretically equal to 11 V / 24 V ·1.7 Nm = 0.779 Nm, given that the maximum brake torque is 1.7 Nm. These behaviors could then be assimilated to an incoming failure like a bearing binding which implies an increase of the friction coefficients.

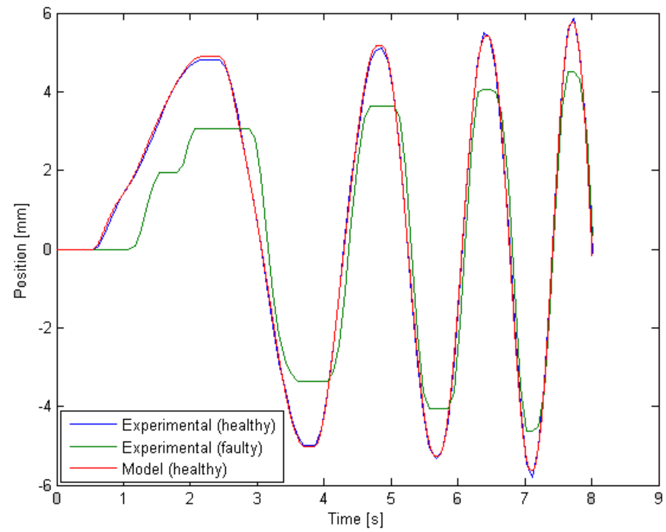

Fig. 11 Experimental vs simulated EMA position before optimization

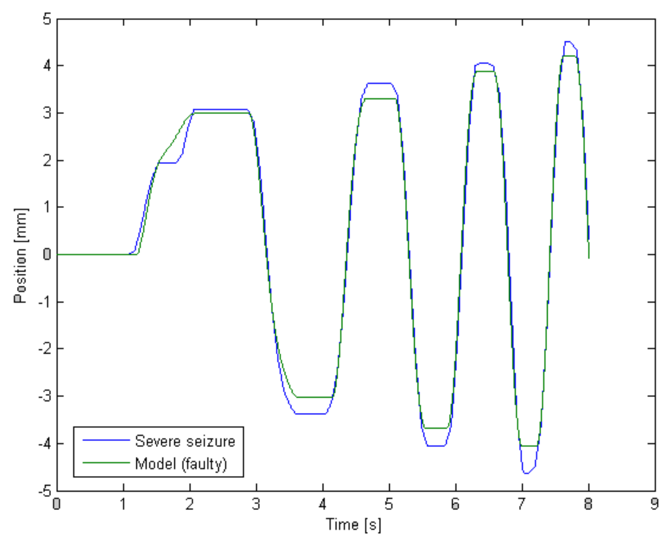

Fig. 12 Experimental vs simulated EMA position after optimization

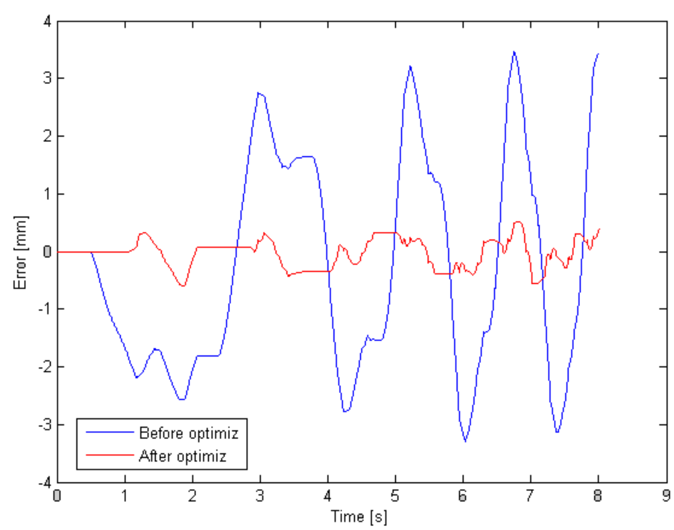

Fig. 13 Experimental vs simulated EMA position residuals before and after optimization

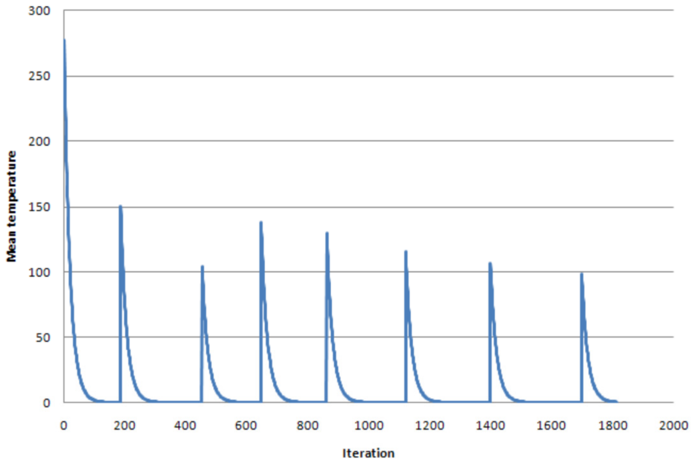

Fig. 14 Simulated annealing process temperature diagram

Comparing the results obtained with the proposed method it is possible to notice how, in this case, the Simulated Annealing algorithm has found a good solution, estimating a static friction coefficient CSJ equal to 0.7352 Nm (and, therefore, very close to the assumed experimental value of 0.779 Nm) and, therefore, a 5.6% of accuracy[5].

It is clear that the brake is heavily affecting the motor's motion causing a significant increase of the friction torque. This can be considered as a “limit" situation. Nevertheless, the simulated annealing algorithm has found a good solution even if starting from a totally different initial point. It can be further observed that the backlash increase is negligible with respect to CSJ and that the faulty CSJ is approximately half of the nominal brake torque (1.7 Nm). Specifically, the resultant 5.6% of accuracy has to be intended just as a rough estimate since it has been calculated supposing that the brake was applying 0.779 Nm but it is not an accurate datum. Finally, the dynamic friction coefficient has decreased by -53%. Additional investigations, performed taking into account also the effects due to electrical noises, analog to digital conversion (ADC) problems, signal transducers affected by offsets or electrical drifts or (reasonable) variations of the boundary conditions, have put in evidence the robustness and the accuracy of this algorithm.

VII. Conclusions

A model-based damage estimator for an electromechanical actuation system has been developed and tested under different operational conditions using the Simulated Annealing optimization algorithm with a MATLAB Simulink model capable of reproducing the effects of progressive growth of friction acting on mechanical devices (this is simulated properly modifying the static friction coefficient CSJ). An electromechanical system has been developed as a test bench for the purpose of producing experimental data useful to demonstrate the damage estimator capabilities.

This test-bench is able to feed the physical system with different type of signals (i.e. step, ramp, sinusoidal and generic external commands, both in open and closed loop mode), acquiring the position/speed response to a sinusoidal frequency sweep input which showed to be effective within the damage estimation process. The Simulated Annealing proved to be very effective, as its execution times were fairly acceptable (a few minutes) for an operational scenario. However, this method showed a strong dependence of the results on its initialization settings (i.e. initial temperature, function tolerance, reannealing interval) and also on the variables bounds which have to be chosen carefully, making, for example, some considerations regarding their physical limits. Anyway, there were no situations in which the algorithm remained trapped in a local minimum even if the starting point was far from the faulty experimental data. This happened instead for other deterministic methods like recursive-least-squares which gave worse results compared to the Simulated Annealing. Moreover, it has been proved that, with the provided model, the Simplex method failed after a few iterations as no constraints on the parameters could be specified and for this reason the dynamic friction torque overcame the static one causing the model to stop and return a fatal error. In view of the achieved results, this kind of damage estimator can be considered a very powerful tool for PHM applications. Hence its developing should be further improved.

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[5] It must be noted that the resultant 5.6% of accuracy, has to be intended just as a rough estimate since it has been calculated supposing that the brake was applying 0.779 Nm, but it is not an accurate datum because,at the moment, this value is only estimated.

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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 assistant researchers and PhD 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.

Lorenzo Pace graduated in Aerospace Engineering at Politecnico di Torino in 2008. Since 2008 to 2011, he worked as an assistant researcher, following studies about system experimental testing and modelization in the aerospace field, with a focus to energy saving techniques. Since 2012 to 2014 he completed a PhD in Aerospace Engineering at Politecnico di Torino, with the contribution of Thales Alenia Space, focused on the application of Model Based System Engineering to verification in the space industry.