Effects of Mechanical Backlash on Linear Electromechanical Actuators: A Fault Identification Method based on the Simulated Annealing Algorithm

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Abstract: - Several approaches can be employed in prognostics, to detect incipient failures of primary flight command electromechanical actuators (EMA), caused by progressive wear. The development of a prognostic algorithm capable of identifying the precursors of an electromechanical actuator failure is beneficial for the anticipation of the incoming faults: a correct interpretation of the fault degradation pattern can trigger an early alert of the maintenance crew, who can properly schedule the servomechanism replacement. The research presented in this paper proposes a fault detection and identification technique, based on approaches derived from optimization methods, able to identify symptoms of EMA degradation before the actual exhibition of the anomalous behavior; in particular, the authors’ work analyses the effects due to progressive backlashes acting on the mechanical transmission and evaluates the effectiveness of the proposed approach to correctly identify these faults. An experimental test bench was developed: results show that the method exhibit adequate robustness and a high degree of confidence in the ability to early identify an eventual fault, minimizing the risk of false alarms or unrecognized failures.

Key-Words: - Mechanical Backlash, Electromechanical Actuator, Prognostics, Simulated Annealing Algorithm.

1 Introduction
Actuators are devices capable of operate conversion of mechanical, electrical, hydraulic, or pneumatic power into mechanical power. They are commonly used on aircraft for flight control surfaces and various utility systems. Flight control systems are considered flight critical and, as a consequence, they are both highly redundant and meeting strong reliability requirements [1]. A need is identified for a robust health management solution capable of accurate and reliable early fault detection and failure prediction, covering multiple failure modes for flight control actuators (this is typically known as Prognostic and Health Management system or, in short, PHM) [2]. Enormous economic (maintenance and logistics) benefit is expected with the advance of the state of fault detection to failure prognosis for actuator systems, as high Can Not Duplicate (CND - inability to replicate field failures during lower level maintenance assessment) rates still plague many aircrafts (CND failures can make up more than 85% of all observed field failures in avionics and account for more than 90% of all maintenance costs). 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]. 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. For instance, during these years have been proposed model-based techniques based upon the direct comparison between real and monitoring system [4], on the spectral analysis of well-defined system behaviors (typically performed by Fast Fourier Transform FFT) [5], on appropriate combinations of the first two methods [6] or on Artificial Neural Networks [7]. The present work reports the results of a 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 electromechanical actuation system. In particular, it is centered on the improvement of a developing method through the possibility to consider effectively the impact of mechanical backlash (BLK).
2 Aims of Work
The aim of this work is to improve the ElectroMechanical Actuator (EMA) Numerical Model developed by the authors [11] and develop it into a PHM approach able to consider the impact of backlash variations on the EMA behavior.

The results are then commented and the effectiveness of the approach is evaluated by a comparison between simulated and real data. The considered Optimization Algorithm and Actuation system are those already presented in [11].

3 EMA Numerical Model
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). In the present work, a parameter estimation task is involved (as shown in previous sections) meaning that the numerical model is going to be evaluated through an optimization problem and thus the speed aspect must be privileged. The proposed numerical model is composed of six blocks representing the different, physical or functional, components of the actual EMA (schematically shown in Fig. 1).

The proposed Simulink model (Fig. 2), is composed by the following blocks:

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

As shown in [7], every block has been modeled starting from its basic electromechanical equations, but since the objective is to achieve a model capable to recognize defined actuator faults (e.g. dry friction or mechanical backlash), it was decided to model in a suitably simplified way the electromagnetic aspects and focus instead on mechanical ones.

In particular, 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 ($V_{dcm \cdot I_{ref}}$), 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 [8] and suitably modified as shown in [9].

The effects of the backlashes affecting the mechanical transmission, evaluated according to [10], have been simulated, using a simplified approach\(^1\), by the "Backlash" Simulink block.

4 Proposed Prognostic Algorithm

The outlined nonlinear third-order model can simulate the system response, taking into account both Coulomb friction and backlash, being then potentially able to reproduce seizure due to ball return jamming or bearing binding/sticking as well as the appearance of backlash in case of balls excessive wear. 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 method performs the failure detection identification using an optimization process implemented by a 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 parameters CSJ and BKL, the former representative of the dry frictions, the latter of the mechanical backlashes globally acting on the EMA numerical model, in order to identify theirs values that minimize 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. Before verifying the actual ability of the proposed prognostic method to identify and evaluate failure precursors, the calibration of the numerical model parameters has been performed.

As shown in [11], 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 and mechanical backlash levels 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.

The aforesaid model, properly calibrated in NC, was then used to estimate the global amount of the mechanical backlash acting on the real EMA; the dynamic response of the real EM actuation system (subjected to a well-defined system of backlashes affecting the mechanical transmission) is compared with that produced by the simulation model and, by means of the abovementioned optimization method, the value of the parameter BLK\(^1\) that minimizes the error between real and simulated is calculated.

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. 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.

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\(^1\) It should be noted that the parameter BLK takes into account the global effects of the backlashes affecting the EMA mechanical transmission by means of a very simplified model; in fact, the dynamic interactions between the different elements interested to the above mentioned backlashes are neglected. Dimensionally speaking, BLK is expressed in millimetres and it is representing the equivalent mechanical backlash (calculated as a sum of the backlash affecting the components of the transmission) acting on the whole EMA.
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 and backlash 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 suitable speed of convergence of the algorithm, the mechanical backlash $B_{KL}$ (which varies during the optimization process 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)$^2$.

To this purpose, it is necessary identify some meaningful value regarding the aforesaid backlash phenomenon. By reading the MecVel ALI-2 maintenance handbook [12], it is possible to gain knowledge of the maximum acceptable backlash value of the ballscrew:

$$\Delta_b \leq 0.3 \cdot p = 1.5 \text{ mm}$$

(5)

where $p$ is the ballscrew pitch (5 mm). For higher values of $\Delta_b$, the ballscrew should be replaced. Therefore the afore calculated backlash value can be considered as limit value and clearly it is very far from the healthy value related to the actual system. In this case, BLK can assume values from 0 [mm] (LB) to 0.1 [mm] (UB), which represent a quite large band given that the authors’ goal is the proposal of a prognostic method (able to perform an early identification of the considered progressive faults) and the actual value of the mechanical backlash (in healthy conditions) is worth about 0.033 [mm]. Hence, it would be meaningful to increase the latter value by different percentage in order to test the algorithm's resolution and accuracy$^3$. To this purpose, this research evaluates three cases of backlash severity:

- High: 0.066 [mm];
- Moderate: 0.0495 [mm];
- Low: 0.04125 [mm].

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, Figures 3-5 show the results gained by the authors in case of experimental system affected by a high mechanical backlash. In this case, the considered input is a position command evolving like a sinusoidal linear frequency sweep wave. It must be noted that, in terms of speed or position dynamic response, the difference between experimental and simulated results are hardly detectable by the aforesaid figures (because the considered backlash values result very small compared to the corresponding amplitude of the EMA dynamic response).

Figure 5 shows the difference between the real position (experimental) of the test case and the corresponding numerical model: the blue curve reports the position residual calculated before optimization while the red curve 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, increasing the accuracy of the numerical model with respect to the performance of the “faulty” test-bench. This means that the value of mechanical backlash 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 detect/identify the fault. 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 global backlash value equal to 0.06613 [mm] (and, therefore, very close to the assumed experimental value of 0.066 [mm]).

Considering all the data collected during the tests, it must be noted that these results are rather satisfying and the algorithm is suitably able to estimate, with a small error, the varying parameters that represent the considered faults.

These considerations are synthesized in Fig. 6 by means of the diagnostic scalars$^4$ (i.e. a histogram representing the SA results performed in case of high, moderate and low backlash).

\[ \text{expression} \]

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$^2$ Similar considerations, regarding the friction coefficient $CSJ$, have been already developed by the authors in [11].

$^3$ Considering mechanical transmissions characterized to different fault magnitude (e.g. gears or screw suitably damaged) or modifying the experimental results in order to simulate the backlash effects.

$^4$ The diagnostic scalars compare each other the estimated and the actual values of the considered parameters (in this case the BLK and $CSJ$) putting in evidence the corresponding errors; these values are expressed as a percentage of the related nominal values (NC).
These results could be used as input for a prognostic early fault identification algorithm which, associated with dedicated evolution models able to represent the progressive growth of the considered faults, allow estimating the Remaining Useful Life (RUL) of the system. 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.

5 Conclusions
A model-based damage estimator for an electromechanical actuation system has been developed and tested under different operational conditions using the Simulated Annealing (SA) optimization algorithm with a MATLAB Simulink model capable of reproducing the effects of progressive growth of mechanical backlash acting on transmission devices (this is simulated properly modifying the corresponding backlash coefficient BLK). The experimental data useful to demonstrate the damage estimator capabilities have been achieved by means of an electromechanical system developed for this purpose. 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 SA 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.

The results encourage the extension of the proposed technique to investigate more challenging occurrences, such as the electrical and sensor failures. To this purpose the proposed actuator model should be further improved and detailed (e.g. improving the existing numerical model or developing new more detailed models simulating the behavior of different EMA subsystems). Combined failures should also be investigated.
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