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A novel model-based metaheuristic method for prognostics of aerospace electromechanical actuators equipped with PMSM

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Abstract. The prior knowledge of incipient failures of primary flight command electromechanical actuators (EMAs) with prognostic algorithms can be very beneficial. Indeed, early and proper detection and interpretation of the deterioration pattern can warn for replacing the servomechanism before the actual manifestation of the abnormal behaviour. Furthermore, such algorithms often exploit a model-based approach established on the direct comparison between the actual (High Fidelity) and the monitor (Low Fidelity) systems to identify fault parameters through optimization processes. The monitor model allows the acquisition of accurate and precise results with a contained computational effort. The authors developed a new simplified monitor model capable of faithfully reproducing the dynamic response of a typical aerospace EMA equipped with a Permanent Magnet Sinusoidal Motor (PMSM). This digital twin senses mechanical and electrical faults: friction, backlash, coil short circuit, static rotor eccentricity, and proportional gain. Fault detection and identification task are performed by comparing the output signal of the reference system (real or simulated) with the one obtained from the monitor model. After that, the Genetic Algorithm is chosen as the optimization algorithm to match the two signals by iteratively changing the fault parameters to detect the global minimum of a quadratic error function. Once a suitable fit is obtained, the corresponding optimization parameters are correlated with the considered progressive failures to evaluate the system's health status. The high-fidelity reference models analysed in this work have been previously conceived, developed, implemented in Matlab-Simulink, and validated experimentally by researchers of the ASTRA group of the DIMEAS of Politecnico di Torino.

1. Introduction
Primary flight controls are a critical feature of an aircraft and hence designed with a conservative safe-life approach: components are replaced after a certain number of flight hours or operating cycles. When applying this approach, the actual condition of the components is not assessed, and maintenance is limited to the specific scheduled operation. Particularly, the safe life design criterion doesn't allow to assess initial defects, which could arise from the manufacturing process and escalate into a sudden fault that compromises the safety of the aircraft. The gradual degradation of a component, which initially does not present any unacceptable behavior, often leads to a condition in which the efficiency of such a component is weakened, and as a consequence the functionality of the whole system is compromised. In addition, the safe-life criterion does not allow the detection of the cause and location of the malfunction, whereas an accurate identification of the specific failed subcomponent could be effective in reducing maintenance inefficiencies and costs. New tools with a high grade of robustness have been developed to identify the most common of the flight control system before they start affecting its performance in terms of dynamical response, stability, stall force, or positioning accuracy.

These methodologies gave rise to the engineering discipline called Prognostics and Health Management (PHM) [1,2]; its primary purposes are the evaluation of the ongoing state of the system and the estimation of the Remaining Useful Life (RUL) [3]. The evaluation of the system's health is carried out by identifying and estimating the entity of faults, in the phase generally defined as fault detection and identification (FDI). Since PHM strategies are based on the analysis of the functional parameters of the system, acquired in the form of electrical signals, the use of electromechanical systems (and in particular electromechanical actuators or EMA) represents an advantage because no further signal conversions are needed and no additional sensors are required. Due to the complex and multidisciplinary nature of the monitored systems, the FDI task on EMA systems is particularly challenging, as different failure modes interact and acceptable accuracy is hardly achieved. A wide choice of FDI techniques is nowadays available in literature: direct comparison of the system response with an appropriate monitoring model [4,5], spectral analysis of system-specific behaviors [6-8], artificial neural networks [9-12], or several combinations of some of these methods [13,14]. Typically, model-based approaches are more computationally expensive and require proper system knowledge but often give more accurate results than data-driven methods. On the contrary, despite being computationally less costly, data-driven techniques approach the system as a black box. In these cases, all knowledge of the system behavior is acquired from the raw data and requires large experimental training data sets – unfortunately, rarely available [15-17]. By applying PHM strategies in aerospace systems, failure may be managed more effectively resulting in lower operating costs, less maintenance interventions, relaxed redundancy requirements, improvement of the aircraft safety and reliability, and simpler maintenance logistics [18]. Prognostic concepts, due to the variety of applications and the considerable impact they generate, have attracted great interest in the scientific and technological world and have been the subject of in-depth development and dissemination in scientific literature.

2. Aim Of The Work

Electromechanical actuators have been spreading widely in the aerospace sector in recent years. [19,20], but their use in safety-critical applications is still constrained by their limited reliability [21]. Then, PHM is often an enabler for the use of EMAs in the aerospace industry. This work proposes a new FDI method based on genetic algorithms (GAs), for EMAs equipped with a permanent magnet sinusoidal motor (PMSM). This algorithm was developed and validated through a numerical EMA test bench, previously designed and modelled for this purpose by the authors. The goal is to propose an algorithm with precision at least comparable to the existing ones and which, at the same time, does not require large data sets for the formation of automatic learning tools or excessive computational burden. In addition, differently from most work available in the literature [7,20,21], our methodology can address multiple fault modes. An evaluation time in the order of minutes is considered acceptable for detecting slow-progressing faults. The proposed technique is then tested in different failure conditions to assess its robustness and field of applicability. According to [13], we considered four progressive failure modes: partial PMSM coil short circuit, backlash, dry friction, and drift of the proportional gain of the PID (Proportional-Integrative-Derivative) position control. Those failures have progressive evolution and are common for EMAs [15].

3. EMA Architecture and Considered Fault Modes

In aircraft flight control systems, the current trend is to progressively replace traditional hydro-mechanical and electro-hydraulic actuators with EMAs, according to the "More Electric Aircraft" [22] or "All-Electric Aircraft "[23] system architectures. These technologies are already implemented on last-generation aircraft (B-787, A320, etc.) [24,25]. Still, they are generally relegated to secondary FCS non-safety critical applications, or to the FCS of small UAVs [26]. As shown in Figure 1, an EMA generally includes a PMSM generating the mechanical power to, drives the rotational or linear motion of the final user through a reduction gearbox. PMSMs are characterized by a wide range of speed control [27,28]. The magnets and the armature winding are arranged so that the back-EMF takes the form of a sine wave; therefore, the control system must supply engines with sinusoidal signal [29].
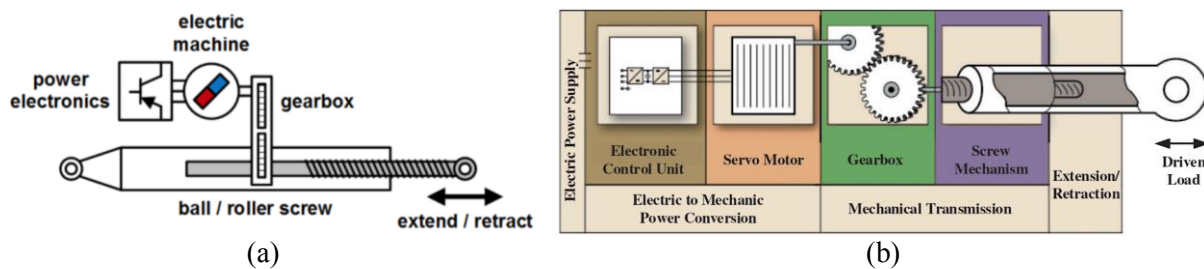
Figure 1: Simplified schematic (a) and diagram of the main components (b) of an EMA.

Currently, PMSMs are the preferred type of electric motor in servomechanism applications. These motors are highly efficient and, compared to the simpler brushless motors (BLDC) [30], they produce less noise and are more durable. A network of sensors (including position, velocity, phase current, temperature) and dedicated actuation control electronics (ACE) close the position control loop. The ACE output drives the Power Electronics that converts the electrical power supply into the required three-phase power for the PMSM, regulating the frequency and amplitude of the motor three-phase sinusoidal currents as a function of command input and rotor angular position. These systems have found recent applications in aerospace systems. Their reliability and the various failure modes are not yet characterized with a satisfactory confidence. In addition, some failure modes, potentially compromising the whole system's efficiency, represent a critical issue involving EMA safety. Therefore, intense work has been done in recent years to bridge these gaps and, at the same time, to develop robust and effective techniques for prognostics to improve the overall safety of operations.

3.1. EMA Degradations and Fault Modes
As already mentioned, EMAs cumulated flight hours are not enough to provide significant statistics about their most common failure modes. According to [31], the failure modes affecting EMAs can be typically summarized into four different categories: mechanical/structural failures, motor failures; control electronics failures, sensor failures. Unfortunately, not all the failure modes that can affect an electromechanical system can be faced with prognostic approaches. The types of faults characterized by sudden manifestations and extremely rapid evolution (e.g. breaking of a torsion bar of the flap transmission) do not allow identifying the incipient failure sufficiently in advance and, therefore, limit the typical benefits of the PHM approach. As suggested in [16], this study focuses on five particular progressive failure modes among the most likely in EMAs. In particular, we considered the effects of mechanical failures resulting from progressive wear, which manifests itself in an increase of backlash and friction, as well as two common PMSM motor failures, the coil-short circuits and the bearing gear generating rotor static eccentricity, together with a drift of the proportional gain of the controller. Indeed, electronic and sensor failures are no less relevant, although their failure precursors are often hard to identify and analyze as they usually occur very quickly, if not instantaneously [27].

4. Proposed EMA Digital Twins
This research proposes a prognostic tool able to identify early identifying degradation patterns of an EMA and esteem its actual health status. To evaluate the robustness and accuracy of this technique, the authors developed different multi-fidelity model types of the considered mechatronic system.

4.1. High Fidelity (HF) model
The authors have proposed the high fidelity model used as the digital twin of the considered EMA in [31]. This versatile numerical test-bench has been developed with the MATLAB/Simulink® platform. The reference model (depicted in Figure 2), already proposed by [13], and enhanced according to [32,33], presents a very high level of detail. It can simulate the dynamic response taking into account the effects of the aforesaid progressive failures. In addition, this model is also sensitive to the effects of the analog-to-digital conversion of signals and electrical noise on signal lines.

The three-phase RL stator circuit, hysteresis current control, and magnetic coupling between stator and rotor are implemented using a physical-based approach, obtaining lumped-parameter modeling of the components. The response of the mechanical transmission is simulated through a second-order dynamic model with one degree of freedom (neglecting the transmission compliance), which takes into account different non-linearities, such as dry frictions (modeled as proposed by [34] and evaluated in [35]), backlashes and the mechanical end-stops. While not adopting more expensive representations based on electromagnetic and mechanical FEM, this approach still allows a satisfactorily accurate simulation of the EMA. It has been validated using data available in the literature and obtained from an experimental test-bench expressly created by the authors (and described in details in [36-38]).

It should be noted that, despite having a reduced dimensionality and a lumped-parameter structure, the resulting HF model still requires quite heavy computational effort (in general two orders of magnitude above real-time) and, therefore, it is not suitable for iterative evaluation within FDI algorithms. This High Fidelity (HF) model represents the numerical reference model able to simulate the behavior of a real servomechanism in order to carry out an early identification of the symptoms that are considered to be the failure precursors of EMA degradations.

4.2. Low Fidelity (LF) model

The authors developed the proposed monitoring model (shown in Figure 3) to perform the prognostic analysis through a simplification of the HF model introduced in the previous section. The most significant assumptions introduced to simplify the model structure interest the implementation of the electromagnetic subsystem. These simplifications aim fundamentally to reduce its complexity and dimensionality, making it computationally lighter and faster. In detail, the three-phases architecture of the PMSM is modeled through a simplified equivalent single-phase motor [39], including a more straightforward first-order RL dynamical model based upon equivalent electrical and mechanical characteristics (calculated on the base of the electrical features of the actual system). As suggested in [40], the three-phases motor currents are adopted as a signal to perform the system FDI of the real system because it is sensitive to several fault modes. Due to the simplifications, the LF monitoring model does not calculate three-phase current signals but an equivalent single-phase. Therefore the authors devised a procedure to calibrate the LF model by comparing the equivalent single-phase current with the corresponding quadrature current of the PMSM (computed through the Clarke-Park transformation applied to the three measured currents signals provided by the HF model [41]).
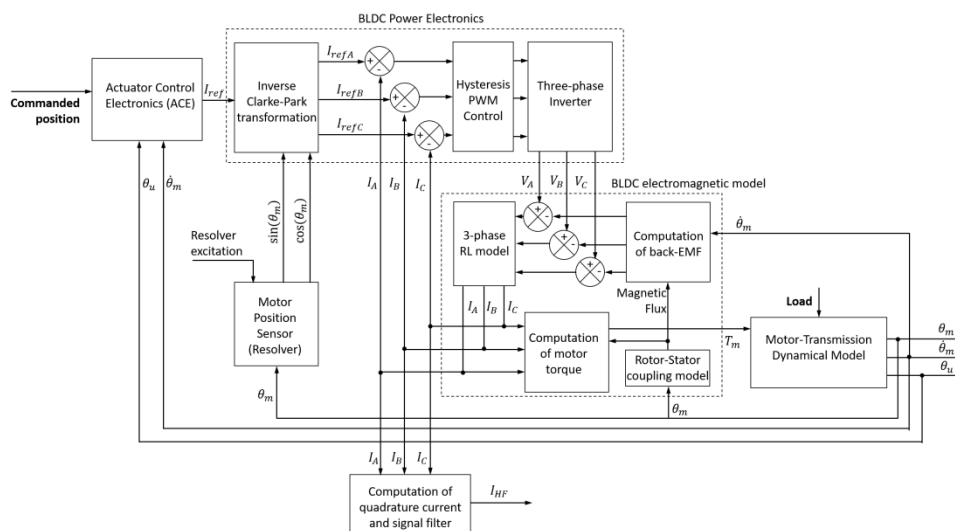

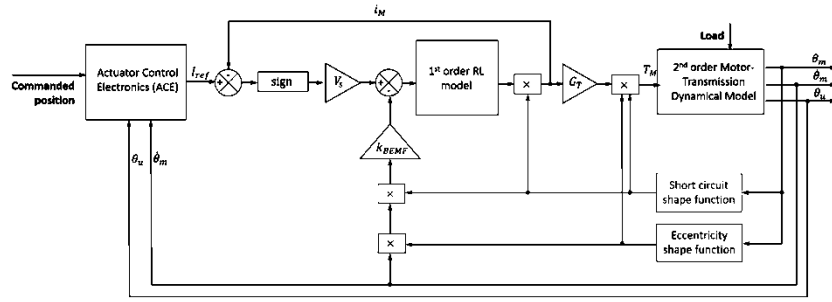Figure 2: Block diagram of the High Fidelity EMA digital twin [39].

Figure 3: Block diagram of the EMA monitoring model (LF) with relative positioning of the equivalent single-phase current loop and form functions for simulating electrical faults.

Indeed, both of these quantities are proportional to the torque of the motor. The complex modeling of PMSM and power electronics implemented in the HF model is replaced with a first-order one degree of freedom nonlinear model with a simplified hysteresis current loop. Electrical faults are simulated through a surrogate modeling approach. To this purpose, the authors introduced two shape functions [30] modulating equivalent stator phase resistance, motor back-EMF coefficient, and torque gain as a function of the rotor angular position. These shape functions do not represent a specific physical phenomenon. Still, they are designed to best approximate the behavior of the detailed model (but require a lower computational cost than the HF model). The two shape functions (related to eccentricity and short circuit failures affecting the real EMA) are a proper combination of sine waves dependent on failures magnitude, rotor angular position, and some calibration factors.

The short circuit (SC) shape function is defined as:

$$\varphi_{SC} = k_{FT} \{N_A [1 + k_{FS} \sin^2(\theta_e + \pi)] + N_B [1 + k_{FS} \sin^2(\theta_e + \pi/3)] + N_C [1 + k_{FS} \sin^2(\theta_e - \pi/3)]\} \qquad (1)$$

where N_A, N_B, N_C are the fractions of undamaged windings of each phase, k_{FT} and k_{FS} are the global and single contribution calibration coefficients, and θ_e is the rotor electrical angular position.

Instead, the shape function of static rotor eccentricity (ECC) [8] is formulated as follows:

$$\varphi_{ECC} = 1 - k_E \, \zeta \, [\cos(\theta_e + \phi_e)] \qquad (2)$$

where ζ and ϕ_e represent the amplitude and direction of the rotor static eccentricity, respectively, and k_E is an additional eccentricity calibration coefficient. It should be noted that the shape functions coefficients (i.e. the global and single contributions of the short circuit calibration coefficients, the eccentricity calibration one, the equivalent torque gain, and the back-EMF coefficient) are initially undefined. A calibration process based on a Genetic Algorithm (GA) asses the said coefficients; the related objective function is based on a Normalized Root Mean Square Error (NRMSE) algorithm comparing the Current signals of HF and LF models.
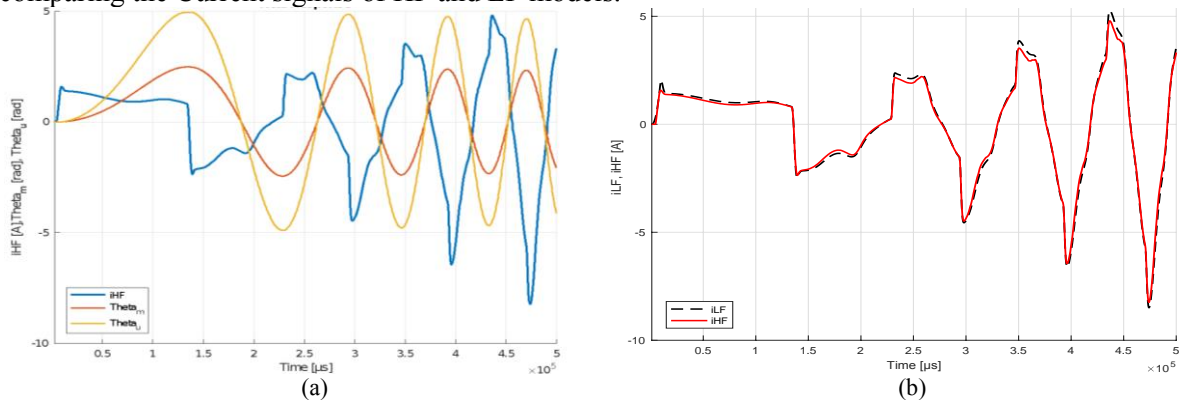

Figure 4: Dynamic response of the high-fidelity reference model for a chirp position command (a) and comparison of the equivalent HF and LF output currents before model calibration (b).

5. Proposed FDI Algorithm

To perform the FDI prognostic analysis, the authors use a metaheuristic model-based approach that compares the real EMA (affected by an unknown fault combination) with the related monitor [32]. The monitor model must run many times with different parameters combinations and select those closest to the reference model: these variations of the main features of the monitor model in each simulation are made by suitable optimization algorithms. The Genetic Algorithm (GA) has been chosen as the optimization algorithm for this work. At each calculation step, the FDI algorithm executes the monitoring model with a certain fault vector k (the values of the faults considered in the optimization). Then, based on an appropriate Fitness Function (FF), the *i-th* LF solution is compared with the reference HF one, and the values of the elements of the fault vector k are updated accordingly. The Fitness Function (FF) is then computed with a Modified Total Least Squares Method [30,42], which is tolerant to small phase lags cumulated between the two EMA models, even in presence of steep gradients and abrupt changes in the equivalent current. Therefore, the proposed FF is defined as:

$$err = \sum_t \frac{(I_1(t_0) - I_2(t_0))^2}{\sqrt{\frac{dI_1(t_0)^2}{dt} + 1}} = \sum_t \frac{(I_{HF}(t_0) - I_{LF}(t_0))^2}{\sqrt{\frac{dI_{HF}(t_0)^2}{dt} + 1}} \qquad (3)$$

where I_{HF} is the current of the HF model, I_{LF} is that of LF and t_0 is a generic instant of the simulation. The overall percentage error of the prognostic analysis is estimated using the following formula:

$$\%err = 100 \cdot \sqrt{\sum_{i=1}^{6} (k_i - \bar{k}_i)^2 + \bar{k}_6 \cdot (k_7 - \bar{k}_7)^2 + (k_8 - \bar{k}_8)^2} \qquad (4)$$

where k_i is the value of the *i-th* element of fault vector k evaluated by FDI algorithm and $\bar{k}_i$ is the actual value of the corresponding *i-th* fault parameter (applied to reference HF model). Typically, the system is simultaneously affected by several progressive failures (often of different entities). Therefore, we tested the proposed method in multiple fault conditions. The reference values of the failure vector are given randomly, and the results acquired are shown in the table below.

	k_1	k_2	k_3	k_4	k_5	k_6	k_7	k_8	
Ref.	0.2383	0.5003	$5.32 \cdot 10^{-7}$	0.4503	0.0404	0.0028	0.2785	0.5	$\%err$
1	0.2051	0.4727	$9.44 \cdot 10^{-4}$	0.4414	0.0445	0.0041	0.4334	0.4950	4.46
2	0.2192	0.4858	$5.59 \cdot 10^{-5}$	0.4421	0.0026	0.0067	0.1195	0.5096	4.67
3	0.2132	0.4732	0.0015	0.4466	0.0221	0.0010	0.0874	0.4962	4.16
4	0.2137	0.4813	$2 \cdot 10^{-4}$	0.4504	0.0021	0.0067	0.1402	0.4970	4.96
5	0.2123	0.4780	$2.59 \cdot 10^{-4}$	0.4660	0.0087	0.0009	0.6436	0.4978	4.93

Table 1: Example of prognostic analysis performed for multiple random error conditions
(given the heuristic nature of the method, the same FDI was evaluated five times)

6. Conclusions

A Genetic Algorithm solver-based Fault Detection and Identification technique has been suggested and verified. The results show that GA optimization is reliable and resilient when dealing with multi-variable, multimodal situations. The presented algorithm has been tested on various fault circumstances to determine its usefulness and performance in scenarios as near to field operations as feasible. Computational time is acceptable for FDI conducted during routine maintenance but not for real-time fault estimation. The findings of the tests had a high level of reproducibility. Because GA's optimization techniques are non-deterministic, two executions starting from identical conditions give different outcomes. The suggested approach, on the other hand, showed to be reproducible and robust since equivalent findings were observed on different runs for the same test case (both with and without noise on the measured signals). The study of larger failure modes sets, the extension to different system layouts (such as electrohydraulic actuation systems), better optimization of models and algorithms (to reduce the computational requirements of the FDI strategy), and experimental validation of the proposed models will all be part of future developments on this research.

References

[1]   Byington C S, Watson W, Edwards D and Stoelting P 2004 A Model-Based Approach to Prognostics and Health Management for Flight Control Actuators *Proceedings of the IEEE Aerospace Conference* (Big Sky, MT, USA)

[2]   Vachtsevanos G, Lewis F L, Roemer M, Hess A, and Wu B 2008 *Intelligent Fault Diagnosis and Prognosis for Engineering Systems* (John Wiley & Sons)

[3]   Berri P C, Dalla Vedova M D L and Mainini L 2021 Computational framework for real-time diagnostics and prognostics of aircraft actuation systems *Computers in Industry* (vol 132 n 103523) https://doi.org/10.1016/j.compind.2021.103523

[4]   Borello L; Dalla Vedova M D L, Jacazio G and Sorli M 2009 A Prognostic Model for Electrohydraulic Servovalves *Proceedings of the Annual Conference of the Prognostics and Health Management Society* (San Diego, CA, USA)

[5]   Dalla Vedova M D L, Germanà A, Berri P C and Maggiore P 2019 Model-based fault detection and identification for prognostics of electromechanical actuators using Genetic Algorithms. *Aerospace* (vol 6 n 9)

[6]   Dalla Vedova M D L, Maggiore P and Pace L 2014 Proposal of Prognostic Parametric Method Applied to an Electrohydraulic Servomechanism Affected by Multiple Failures *WSEAS Transactions on Environment and Development* (vol 10) pp 478–490

[7]   Bindu S and Thomas V V 2018 A Modified Direct-Quadrature Axis Model for Characterization of Air-Gap Mixed Eccentricity Faults in Three-Phase Induction Motor *International Review on Modelling and Simulations (IREMOS)* (vol 11 n 6) p 359

[8]   Belmonte D, Dalla Vedova M D L and Maggiore P 2015 Electromechanical servomechanisms affected by motor static eccentricity: Proposal of fault evaluation algorithm based on spectral analysis techniques *Safety and Reliability of Complex Engineered Systems - Proceedings of the 25th European Safety and Reliability Conference, ESREL 2015* (Zurich) pp 2365–2372

[9]   Battipede M, Dalla Vedova, M D L, Maggiore P and Romeo S 2015 Model based analysis of precursors of electromechanical servomechanisms failures using an artificial neural network *AIAA Modeling and Simulation Technologies Conference* (Kissimmee, FL, USA)

[10]   Elasha F, Shanbr S, Li X and Mba D 2019 Prognosis of a Wind Turbine Gearbox Bearing Using Supervised Machine Learning *Sensors* (vol 19 n 3092)

[11]   Chen J, Hu W, Cao D, Zhang B, Huang Q, Chen Z and Blaabjerg F 2019 An Imbalance Fault Detection Algorithm for Variable-Speed Wind Turbines: A Deep Learning Approach *Energies* (vol 12 n 2764)

[12]   Quattrocchi G, Berri P C, Dalla Vedova, M D L and Maggiore P 2020 Innovative actuator fault identification based on back electromotive force reconstruction *Actuators* (vol 9 n 3) p 50

[13]   Maggiore P, Dalla Vedova M D L, Pace L and Desando A 2015 Evaluation of the correlation coefficient as a prognostic indicator for electromechanical servomechanism failures *International Journal of Prognostics and Health Management* (vol 6 n 1) pp 1–13

[14]   Liu H, Qin C and Liu M 2019 A Rail Fault Diagnosis Method Based on Quartic C2 Hermite Improved Empirical Mode Decomposition Algorithm *Sensors* (vol 19 n 3300)

[15]   Balaban E, Bansal P, Stoelting P, Saxena A, Goebel K F and Curran S 2009 A diagnostic approach for electro-mechanical actuators in aerospace systems. *Proceedings of the 2009 IEEE Aerospace Conference* (Big Sky, MT, USA)

[16]   Balaban E, Saxena A, Goebel K, Byington C S, Bharadwaj S P and Smith M 2009 Experimental Data Collection and Modeling for Nominal and Fault Conditions on Electro-Mechanical Actuators *Proceedings of the Annual Conference of the Prognostics and Health Management Society* (San Diego, CA)

[17]   Balaban E, Saxena A, Narasimhan S, Roychoudhury I, Goebel K and Koopmans M 2010 Airborne Electro-Mechanical Actuator Test Stand for Development of Prognostic Health Management Systems. *Proceedings of the Annual Conference of the Prognostics and Health Management Society* (Portland, OR, USA)

[18]   Goebel K, Daigle M, Saxena A, Sankararaman S, Roychoudhury I and Celaya J 2017
         Prognostics: The Science of Making Predictions (CreateSpace Independent Publishing)
[19]   Garcia Garriga A, Govindaraju P, Ponnusamy S S, Cimmino N and Mainini L 2018 A
         modelling framework to support power architecture trade-off studies for More-Electric
         Aircraft *Transportation Research Procedia* (vol 29) pp 146-156
[20]   Fico V M, Rodríguez Vázquez A L, Martín Prats M Á and Bernelli-Zazzera F 2019 Failure
         Detection by Signal Similarity Measurement of Brushless DC Motors *Energies* (vol 12)
[21]   De Martin A, Jacazio G and Vachtsevanos G 2017 Windings fault detection and prognosis in
         electro-mechanical flight control actuators operating in active-active configuration
         International Journal of Prognostics and Health Management (vol 8 n 2)
[22]   Quigley R E J 1993 More electric aircraft *Proceedings of the Eighth Annual IEEE Applied
         Power Electronics Conference - APEC 93* (San Diego, CA, USA)
[23]   Howse M 2003 All-electric aircraft *Power Engineering* (vol 17) pp 35–37
[24]   Thalin P, Rajamani R and Maré J C 2018 *Fundamentals of Electric Aircraft* (SAE International)
[25]   Maré J C 2018 *Aerospace Actuators 2: Signal-by-Wire and Power-by-Wire* (Wiley & Sons)
[26]   Pozzuto G, De Martin A, Pispola G, Palmieri M and Gallorin M 2019 Electrical Flight Control
         for Load Control and Alleviation System *More Electric Aircraft* (Tolouse, France)
[27]   Bernatt J, Glinka T, Jakubiec M, Krol E and Rossa R 2007 Electric motors with permanent
         magnets with two-zone rotational speed control *Electrical Machines and Power Electronics*
[28]   Jarzebowicz L 2014 Indirect Measurement of Motor Current Derivatives in PMSM Sensorless
         Drives *Elektronika ir Elektrotechnika* (n 5) pp 23–26
[29]   Rudnicki T, Czerwinski R and Sikora 2015 A Examination of permanent magnet motor with
         sinusoidal back-EMF *IFAC-PapersOnLine* (vol 48 n 4) pp 170–173
[30]   Berri P C, Dalla Vedova M D L and Maggiore P 2016 A Smart Electromechanical Actuator
         Monitor for New Model-Based Prognostic Algorithms *International Journal of Mechanics
         and Control* (vol 17 n 2) pp 19–25
[31]   Gökdere L U, Chiu S L, Keller K J and Vian J 2005 Lifetime control of electromechanical
         actuators Proceedings of the IEEE Aerospace Conference Proceedings (Big Sky, MT, USA)
[32]   Dalla Vedova M D L and Berri P C 2019 Optimization techniques for prognostics of on-board
         electromechanical servomechanisms affected by progressive faults *International Review of
         Aerospace Engineering* (vo 12 n 4) pp 160–170.
[33]   Dalla Vedova M D L, Berri P C and Re S 2018 Novel Metaheuristic Bio-Inspired Algorithms
         for Prognostics of Onboard Electromechanical Actuators *International Journal of Mechanics
         and Control* (vol 19 n 2) pp 95−101
[34]   Borello L, Villero G and Dalla Vedova M D L 2009 New asymmetry monitoring techniques:
         Effects on attitude control *Aerospace Science and Technology* (vol 13 n 8) pp 475–487
[35]   Borello L, Villero G and Dalla Vedova M D L 2014 Flap failure and aircraft controllability:
         Developments in asymmetry monitoring techniques *Journal of Mechanical Science and
         Technology* (vol 28 n 11) pp 4593–4603
[36]   Boschetti V 2020 *Master's Thesis* Politecnico di Torino (Torino, Italy)
[37]   Sciandra P 2020 *Master's Thesis* Politecnico di Torino (Torino, Italy)
[38]   Boggio L 2021 *Master's Thesis* Politecnico di Torino (Torino, Italy)
[39]   Berri P C, Dalla Vedova M D L, Maggiore P and Viglione F 2019 A simplified monitoring
         model for PMSM servoactuator prognostics *MATEC Web of Conference*
[40]   Berri P C, Dalla Vedova M D L and Maggiore P 2018 A simplified monitor model for EMA
         prognostics *MATEC Web of Conferences* (vol 233 n 00016)
[41]   O'Rourke C J, Qasim M M, Overlin M R and Kirtley J L 2019 A Geometric Interpretation of
         Reference Frames and Transformations: dq0, Clarke, and Park *IEEE Transactions on Energy
         Conversion* (vol 34 n 4) pp 2070–2083
[42]   Markovsky I and S Van Huffel 2007 Overview of total least-squares methods Journal of Signal
         Processing (vol 10) pp 2283–2302.