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Prognostics of aerospace electromechanical actuators: comparison between model-based metaheuristic methods

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Abstract. Electro-Mechanical Actuators (EMAs) deployment as aircraft flight control actuators is an imperative step towards more electric concepts, which propose an increased electrification in aircraft subsystems at the expense of the hydraulic system. Despite the strong benefits linked to EMAs adoption, their deployment is slowed down due to the lack of statistical data and analyses concerning their often-critical failure modes. Prognostics and Health Management (PHM) techniques can support their adoption in safety critical domains. A very promising approach involves the development of model-driven prognostics methodologies based on metaheuristic bio-inspired algorithms. Evolutionary (Differential Evolution (DE)) and swarm intelligence (particle swarm (PSO), grey wolf (GWO)) methods are approached for PMSM based EMAs. Furthermore, two models were developed: a reference, high fidelity model and a monitoring, low fidelity counterpart. Several failure modes have implemented: dry friction, backlash, short circuit, eccentricity and proportional gain. The results show that these algorithms could be employed in pre-flight checks or during the flight at specific time intervals. Therefore, EMA actual state can be assessed and PHM strategies can provide technicians with the right information to monitor the system and to plan and act accordingly (e.g. estimating components Remaining Useful Life (RUL)), thus enhancing the system availability, reliability and safety.

1. Introduction

The More Electric Aircraft (MEA) concept, which involves a gradual replacement of EMA (ElectroMechanical Actuators) in place of hydraulic actuators and EHA (ElectroHydraulic Actuators) is leading to a large-scale change in aviation subsystem architectures. In fact, it is deemed that this paradigm shift will lead to substantial weight reductions, considerable LCC (Life Cycle Costs) cutbacks [1, 2], less impact on the environment and higher reliability of the whole aircraft system [3]. At the current state-of-the-art, flight control surfaces are actuated thanks to FBW (Fly-By-Wire) technologies and, as a result, the control surfaces are electrically controlled but hydraulically powered [4]. The core idea is targeting an all-in-one electrical solution able to satisfy the appropriate safety standards [5, 6].

However, still, some issues prevent a seamless substitution of hydraulic powered actuation systems [7, 6]. De facto, it is vital to assess what is involved in replacing a hydraulic device with an electric device in terms of usage, implementation, monitoring, and the equipment's reliability and safety. As far as hydraulic systems are concerned, a possible failure (e.g. a pressure decrease due to a leakage) can be identified well before a load is required.

On the other hand, electrical system failures pose new safety issues because no preventive mitigation strategy can be performed to minimize the effect of the fault itself if no extra auxiliary system is thought of. In other words, the system must be extremely fault-tolerant. This could be solved by adding hardware redundancies which, however, would lead to weight increases and also incompatibilities with actuation requirements [8], thus eliminating the benefits of MEA philosophies. The solution must be researched in other areas. This is when prognostics pays off. Prognostics and Health Management (PHM) strategies are conceived to identify malfunctions and hidden failures in their early stages, before they could instill hazardous or catastrophic consequences for the production cycle and the system's integrity and safety through their propagation. Prognostics is based on the monitoring of changes in operational parameters of a specific system during its regular operating cycle [9]. In this sense, prognostics can be seen as a powerful tool to support EMAs deployment in safety-critical applications. On the other hand, newer maintenance strategies (CBM and opportunistic maintenance [10, 11]) are seeing their light, exploiting data from PHM systems: the results are enhancements of mission readiness, improvements of RAMS capabilities and an overall contraction of LCC [12, 13]. Prognostics may be data-driven or model-based [14, 15]: in this paper we are focusing on a model-based approach to prognostics. After a general overview of the proposed methodology, a brief explanation of the employed algorithms and models is reported. A total of two different models are presented: an high fidelity one (RM-Reference Model) and a low fidelity counterpart (MM-Monitoring Model) which is the heart of the prognostic framework. This work continues the ongoing effort started in [16], where a similar strategy was applied on brushless BLDC trapezoidal motors: in this case the employed motor is a sinusoidal PMSM motor. Finally, the results and comparisons between the algorithms is reported.

2. FDI Overview and Concept of Operations

To enable a practical implementation of the presented methodology, a concept of operation is envisioned. The main idea is to perform a check routine in various moments on aircraft monitored subsystems. Prognostic checks can be carried out when the aircraft is at the gate, waiting for the passengers to arrive or during the walk-around or 24-hours checks. Furthermore, a test routine can be performed at specific time intervals during the flight phase. In this paper, a PHM strategy is presented, leveraging the MM, which can be run almost in real time [17, 18], and the signals coming from the hardware components of the system.

Due to the lack of extensive data-sets, in this study, data have been generated through the RM, intended as a Numerical Test Bench (NTB). The MM is characterized by a series of predefined Top Level Parameters (TLPs) which correspond to different failures: by changing

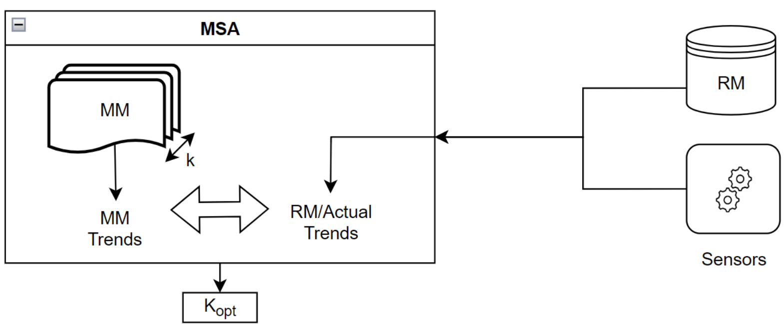


Figure 1: Methodology overview

these parameters the model will output trends with the specified failure injected. Both models have been validated in nominal conditions as well as in the presence of different failures and non linearities, confirming the models ability in estimating actual trends with high precision [19, 20].

In an operational scenario, the actual trends from the monitored component are logged in a Prognostic and Health Management Computer (PHMC). In this sense, a routine of typically used control laws can be applied as explained in [21]. In other words, during walk-around checks or even when flight surfaces functioning is checked while approaching the take off lane, a series of predefined signals can be sent to the flight control actuators (e.g. ramp, chirp, sinusoidal or square wave) to assess the actuators health status by analysing data coming from these tests.

During a prognostic check, the optimisation algorithms are then implemented to iteratively run the monitor model to find the monitoring TLPs that modify the MM outputs so as to minimise the error between the obtained trends and the actual one (real or simulated) as already presented in [22]. The running time, as better explained later on, is not negligible at all, and that is why a real-time implementation is not feasible. The error is defined by a suitable fitness function. In this way, when the optimization process is over, the result is a set of parameters thanks to which the output of the MM is very similar to the actual one. Once a good match has been found, the system's health is assessed by correlating the associated TLPs with the supposed increasing failures. By looking at TLPs it is hence possible to understand if a failure is happening and which kind of failure, thus performing a rough but effective FDI (Failure Detection and Identification) routine.

3. Employed Algorithms

The employed algorithms are Metaheuristic bio-inspired algorithms, a specific type of optimization algorithms. The main goal of optimization algorithms is to find the minimum or maximum of a function, called *objective or fitness function*, by varying the so-called *decision variables* (in our case the TLPs), which are limited by specific constraints [23]. Heuristic techniques' mission is to produce good solutions, or solutions that are near to the optimum, at a reasonable computing cost, but they cannot ensure the optimum itself. Metaheuristics methods, in particular, use several procedures to obtain good solutions to optimization problems within a large set of admissible solutions making few or no assumptions about the problem being optimized [24]. Moreover, they are bio-inspired since the algorithms have a biological origin. In fact, the natural phenomenon of adaptation or various animal behaviors can be interpreted as a form of optimization. In this work we are focusing on Evolutionary Algorithms (EA) and Swarm Intelligence (SI) ones.

3.1. Evolutionary Algorithms

Evolutionary Algorithms take inspiration from the evolution behaviour which can be found in nature. They present some main properties and parameters: *population* (which is initialized at the beginning of the process), *variety* (a population with different characteristics is pivotal to allow the exploration of a wide range of possible solutions [14,15]), *heredity* (i.e. ability to pass on a trait to their offspring) and *selection* (essential to guarantee that only the best solutions will be reproduced; for artificial algorithms selection must occur only in the desired direction. The individuals represent the various solutions to which a score called *fitness value* is attributed thanks to a mathematical expression (*fitness function*), determined by evaluating the phenotype (i.e. the characteristics) of the subjects in question.

The specific EA employed in this work is called Differential Evolution [25, 24]; it begins with a process called *mutation*. This occurs when two individuals (i.e. two parts of the population vector) are compared. The difference between these two vector is calculated and then added to a third vector. At this point the recombination or crossover phase starts: the mutated parameters of the initial vector are mixed with those of the so-called target vector to form the trial vector.

Trial and target vectors are evaluated during the selection process. If the trial's score is higher than the target, it will serve as the next target; if that is not the case, it will be discarded. The vector with the best fitness value will stay in the following generation.

Another widespread EA optimization strategy is represented by Genetic Algorithms (GA). An extensive analysis of the implementation of such algorithms on similar issues for PHM strategies has been carried out in [26, 16]. However, the algorithms presented in this paper outperform GA in every test case.

3.2. Swarm Intelligence Methods

These methods are inspired by intelligent behavior of biological swarms through the interaction of two or more individuals in certain environments. In fact, biological behaviours linked to the interaction of individuals lead to a form of optimization, thus generating a higher level structure, which an individual alone could never achieve, thanks to shared information. This type of phenomenon is not the result of a genetic process, but rather a collective one, driven by interaction. Another important feature of collective intelligence is the ability to voluntarily or involuntarily provide feedback or signal to individuals in the group. Two algorithms inspired by collective phenomena will be described below: Particle Swarm Optimisation (PSO) and Gray Wolf Optimisation (GWO).

3.2.1. Particle Swarm Optimization. PSO [27] is an optimization technique, inspired by the movement of organisms in a bird flock, which tries to improve the quality of various potential solutions (i.e. the swarm). It can solve issues by employing a population of possible answers (i.e., particles) and moving them around the search space. Each particle movement is influenced by its local best known position and the best known places in the search space, which are updated when other particles locate better positions. In this way, the swarm iteratively finds best solutions thanks to information sharing. The method require some initialization settings: the size of the population as well as the initial particle positions and speed must be set. On top of that, particles inertia must be selected too. At this point, each particle is assigned a random neighbourhood, and, by moving, the best neighbor is identified. The position and velocity associated with the best global position are updated so that other particles can respond appropriately. The intrinsic stochastic component in the velocities allows for an extensive investigation of the solution space [28].

3.2.2. Grey Wolf Optimization. The GWO [29] is inspired by Grey Wolf behavior: in this case, the research strategy is derived from the definition of a hierarchical scale among the grey wolf population individuals. The algorithm is initialized by ierarchizing a population of individuals. Once all of the individuals' positions have been defined for the first time, a hierarchy is used to identify the results that ensure the lowest fitness value among those found. This is accomplished by assigning a score to each solution: the lower the value of the error between the currents calculated with a specific vector k, the higher the score associated with the vector itself. Each wolf, in fact, is a solution to a specific problem. It is critical to determine the number of wolves in the pack, since the algorithm accuracy and execution time are both affected by this factor. Unlike the PSO, the various members of the population do not have the ability to communicate their position to the other members. As a result, an appropriate population initialization and search strategy for the pseudo-optimal solution must be chosen [30].

3.3. Fault Coefficients and Fitness Function

As presented in [22], the coefficients leveraged to find the minimum of the fitness function are the eight components k_i of a normalised vector k. Each value can vary between 0 and 1 to describe the different magnitudes of the possible faults.

$$k = [k_1; k_2; k_3; k_4; k_5; k_6; k_7; k_8]$$

- k_1: dry friction. When $k_1 = 1$, the friction is three times higher than the nominal value.
- k_2: backlash. When $k_2 = 1$, the backlash magnitude is one hundred times the nominal value.
- k_3, k_4, k_5: short circuit. The three coefficients correspond to the short-circuit fault entities in phases A, B and C respectively.
- k_6, k_7: static eccentricity. They represent the static eccentricity modulus and phase respectively. Under nominal conditions, the phase corresponds to 0 rad, so $k_7 = 0.5$.
- k_8: proportional gain. $k_8 = 0$ corresponds to a 50 per cent reduction in the nominal proportional gain, while $k_8 = 1$ refers to a 50 per cent increase. The nominal value corresponds to $k_8 = 0.5$.

The fitness fuction has been defined as:

$$e_{tls} = \sum_i \frac{(I_{MM,i} - I_{RM,i})^2}{\left(\frac{dI_{RM,i}}{dt}\right)^2 + 1} \cdot dt$$

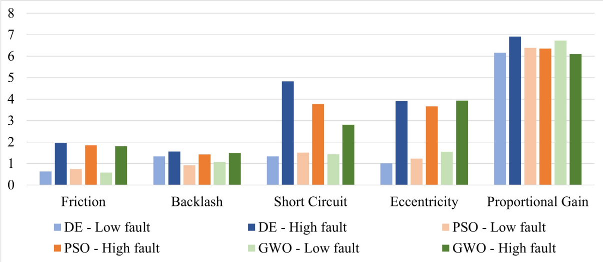
where $I_{MM,i}$ and $I_{RM,i}$ are the current outputs of the Monitoring Model and the Reference Model respectively at the instant time i. Further observation concerning the definition of the fitness function can be found in [31, 22].

4. Models

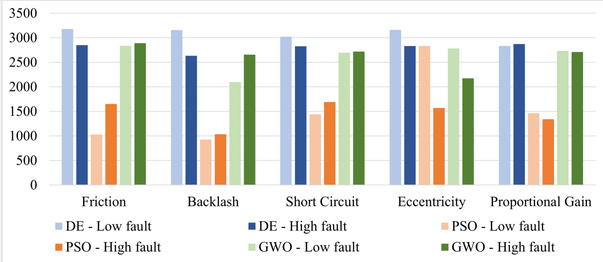
As total of two models have been designed, created in Simulink environment and then experimentally validated. The RF simulates the real behaviour of an electromechanical system and, de-facto, constitutes a virtual test bench. It is characterised by high performance so that the modelled physics is accurate on temporal and spatial scales. The behaviour of the individual components of the EMA is described by appropriate governing equations which are integrated into the modular elements of the system.

The MM, makes use of approximations of the parameters constituting the physics of the system in order to reduce the computational cost and allow a real time evaluation of the health status of the real system. The detailed description of both model is way beyond the scope of this work. The interested reader should refer to [32, 33] for the RF, Reference model and to [18, 17] for the MM. For the sake of clarity a brief explanation of the HF structure is reported below. It is characterised by four main blocks:

- Controller: a PID controller compares the desired position and signal with the user position and speed and outputs the reference current sent to the inverter;
- Inverter: it derives the three currents and voltages (one for each phase) for the PMSM motor and performs the corresponding PWM modulation;
- Sinusoidal BLDC motor: it receives as input position and angular velocity and supplies the required motor torque;
- Motor-transmission dynamics: it calculates the dynamics of the motor-transmission module (i.e. second-order dynamics and multiple non-linearities [19]).



(a) Mean Percentage Error



(b) Mean Computational cost

Figure 2: Comparison between different algorithms

5. Results

In order to find relevant potential failures to simulate and predict, a FMECA (Failure Mode Effect and Criticality Analysis) has been considered [7]. In this work we analyze the following failures (with medium high or high probability and/or criticality): dry friction, backlash, short circuit, eccentricity and proportional gain drift. Each failure has been injected in the RM and then predicted with two different levels of magnitude: an high level of failure ($k_i = 0.75$) and low one ($k_i = 0.25$). Moreover, a system affected by multiple low magnitude failure is simulated too. The interested reader should consider looking at [31, 20] for more details on failure implementations in the models as well as for the testing of each failure mode. For each algorithm, the mean percentage error and the mean computational cost related to each single fault have been considered and reported in Fig. 2. These data have been obtained through ten runs of each algorithm to have a minimal statistical relevance.

For low magnitude failures, the DE algorithm turns out to have a lower mean error. Conversely, the GWO method proves to be the most accurate for high magnitude failures (e.g. short circuit and proportional gain). Finally, the PSO algorithm provides higher accuracy for backlash faults of any magnitude, high static eccentricity and low proportional gain. With the exception of the static low eccentricity defect, for which the computational cost is equivalent to that incurred by the other two techniques, PSO is clearly the fastest algorithm, taking around 25 min on average to discover all types of faults. The GWO is slightly faster than the DE algorithm (about $44min$ versus $53min$) but the latter is more stable among the others as its standard deviation index is lower than the remaining two. Ultimately, a performance coefficient (PC) (first defined in [22]) was utilized to evaluate the quality of the approach on the basis of both computing cost and average error in order to determine which algorithm is superior than the others for each type of failure. The value of the computational cost and the average

Table 1: Different optimization algorithms outcomes with single failures.

Failures	DE			**PSO**			GWO		
	Time(s)	Err.(%)	PC(%)	Time(s)	Err.(%)	**PC**(%)	Time(s)	Err.(%)	PC(%)
Friction	3015	1.30	56.97	1342.5	1.30	**80.76**	2865.5	1.20	62.26
Backlash	2895	1.45	50.21	980.5	1.18	**86.28**	2378	1.28	63.49
Short Circuit	2925.5	3.08	52.32	1566	2.64	**78.12**	2709	2.13	69.54
Eccentricity	2995.5	2.46	62.30	2202	2.45	**72.45**	2479.5	2.75	65.24
Prop. Gain	2853	6.54	58.61	1403	6.38	**80.14**	2721.5	6.42	61.24
Total	2936.8	2.96	56.75	1498.8	2.79	**79.24**	2530.7	2.75	64.00

Table 2: Different optimization algorithms outcomes with multiple failures.

	Time(s)	Err.(%)	PC(%)
DE	1777.0	4.21	60.95
PSO	1131.4	3.37	**80.09**
GWO	1816.6	4.33	58.94

percentage error is obtained by averaging the high and low severity of each fault. As shown in Table 1, PSO shows the highest PC value for each fault implemented. This is mainly due to the lower computational cost, almost halved compared to the other two cases. The worst, however, turns out to be the DE algorithm which has the highest computational cost.
Table 2 shows the results involving a multiple failure (MF) condition [31]: PSO is again the best algorithm, showing good performances and lower error. It has to be noted that, unexpectedly, the MF condition results in a lower execution time than the single failure approach. This could be traced back to the algorithms' stochastic working principles. It is deemed that, being the k vector made up of random values and not only one component different from its nominal value, the algorithms reach the error tolerance quicker.

6. Conclusions

PSO is the algorithm that delivered the best outcomes for both single and multiple failures. This can be traced back to the nature of the algorithm itself, which enables information sharing and the exploration of nearby solutions not reached by any other particle: the likelihood that the next iteration leads to an improvement of the solution quality is very high. As far as the DE is concerned, the exploration of new solutions, is quite random indeed. Similarly, for the GWO algorithm, each individual in the population explores a defined space in a random and non-directional way, without exchanging information. This leads to high computational time and hence overall effort. On top of that, the implementation of the DE method is very challenging (e.g. parameter calibration). The most difficult failure to detect was the proportional gain fault: the proportional gain drift tends to replicate a generic electrical system breakdown inside the EMA. Therefore, the algorithm is not able to identify the specific issue properly. Overall, the obtained results are perfectly in line with the outcomes already collected in [16]. The main conclusion is that, despite different motor configurations, the best performing algorithm is still PSO.

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