ISSN 1590-8844
International Journal of Mechanics and Control, Vol. 17, No. 02, 2016

A SMART ELECTROMECHANICAL ACTUATOR MONITOR FOR NEW MODEL-BASED PROGNOSTIC ALGORITHMS

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ABSTRACT

Prognostic algorithms able to identify precursors of incipient failures of primary flight command electromechanical actuators (EMAs) are beneficial for the anticipation of the incoming fault: an early and correct interpretation of the degradation pattern, in fact, can trig an early alert of the maintenance crew, who can properly schedule the servomechanism replacement. Given that very often these algorithms exploit a model-based approach (e.g. directly comparing the monitor with the real system or using it to identify the fault parameters by means of optimization processes), the design and development of appropriate monitoring models, able to combine simplicity, reduced computational effort and a satisfactory level of sensitivity and accuracy, becomes a fundamental and unavoidable step of the prognostic process. To this purpose, the authors propose a new simplified EMA Monitor Model able to accurately reproduce the dynamic response of the Reference Model in terms of position, speed and equivalent current, even with the presence of various incipient faults; its ability in reproducing the effects of several EMA faults is a good starting point for the implementation of a robust and accurate GA-based optimization, leading to a reliable and early fault isolation.

Keywords: aerospace, EMA, fault detection/identification, model-based, prognostics.

1 INTRODUCTION

Actuators are component responsible for moving or controlling a mechanism or system. They transfer power of various sources (mechanical, electrical, hydraulic, or pneumatic) into motion by means of gearings. With regard to flight commands, in the last years, actuators based on the hydraulic power have been replaced by Electromechanical Actuators (EMAs) because they offer more advantages: easier maintenance, reduced global weight, absence of hydraulic fluid that is often pollutant and inflammable. As some actuators are safety critical, in order to guarantee the system to always operate in safety conditions, it is necessary to schedule programs of maintenance and redundancy; nevertheless, even if, at present, they are the most common means to diminish the risks, in case of unpredicted and severe operative scenarios, they can be insufficient and it becomes necessary to forecast unscheduled maintenance.

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In this context, as described in [1-2], there is a discipline called Prognosis and Health Management (PHM) that, through the monitoring of functional parameters of the system involved, tries to predict failures at an early stage and to determine the source of irregular behaviours. In case of EMAs, the PHM can be applied in a more efficient way than in the case of hydromechanical or electrohydraulic actuators, because, on electrical systems, additional sensors are not required. In fact, the application of the PHM strategies normally entails the monitoring of a set of parameters in the form of electric signals and they often use the same sensors of the control scheme and system monitors. For this purpose, according to the "More-electric-aircraft" paradigm [3] and to the "All-electric-aircraft" [4], in this paper EMAs are considered. Concepts and results reported in this paper are related to the design of a reliable and fast prognostic Fault Detection and Identification (FDI) routines focused on the diagnosis model-based approach and, in particular, on the parametric estimation task: to this purpose, the design and development of appropriate EMA monitoring models, able to combine simplicity, reduced computational effort and a satisfactory levels of sensitivity

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and accuracy, becomes a fundamental and unavoidable step of the aforesaid prognostic process. To this purpose, in this paper authors propose a new simplified EMA Monitor Model (MM) able to accurately reproduce the dynamic response of the Reference Model in terms of position, speed and equivalent current, even with the presence of various incipient faults. For completeness it is however important to highlight that many different FDI strategies can be found in literature: e.g. model-based techniques centred on the direct comparison between real and monitoring system [5], on the spectral analysis of well-defined system behaviours performed by Fast Fourier Transform [6-7], on appropriate combinations of these methods [8] or on algorithms based on several architectures of Artificial Neural Network [9-13].

2 EMA REFERENCE MODEL

As previously mentioned, the goal of this research is the proposal of a new simplified numerical model able to simulate the behaviours of a real servomechanisms in order to perform an early identification of the symptoms (usually defined as failure precursors) of EMA degradations. First of all, in order to define the architecture of the MM and to evaluate the feasibility, the performances and the robustness of the aforesaid approach, a suitable simulation test bench has been developed in MATLAB/Simulink®. This numerical model, widely described in [13-14], is consistent with the EMA architecture shown in Fig. 1

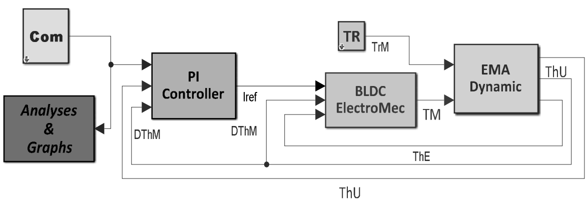

Figure 1 EMA Reference Model [13].

1. *Com*: generates input position commands.
2. *PI Controller*: simulates the actuator control electronics, closing position and speed feedback loops in and computing as output the reference current *Iref*.
3. *BLDC EM Model*: simulates the power drive electronics trough a SimScape model and the trapezoidal BLDC EM behaviour, evaluating torque as a function of three-phase current generated by an ideal H-bridge regulator.
4. *EMA Dynamic Model*: resolves the dynamic equation of mechanical behaviour by a 2 d.o.f. dynamic system.
5. *TR*: input block simulating the aerodynamic torques acting on the moving surface controlled by the actuator.
6. *Analyses & Graphs*: EMA monitoring system.

This numerical model simulates the behaviours of the real EMA taking also into account the effects of BLDC motor non-linearities [15-20], end-of-travels, compliance and backlashes acting on the mechanical transmission [21-22], ADC conversion of the feedback signals, electrical noise acting on the signal lines and electrical offset of the position transducers [5] and dry friction (e.g. acting on bearings, gears, hinges and screw actuators) [23].

3 EMA FAILURES AND DEGRADATION

Main failures in BLCD motors are due to rotor static eccentricity caused by progressive coil short-circuits or bearing wears. Short-circuits usually start between a few coils belonging to the same phase (coil-coil failure) and, then, spreading to adjacent coils. In fact, in short-circuited coils the voltage remains the same and the resistance decreases; as a consequence, a high circulating current arises and generates a localized heating in conductor that helps the propagation. Rotor static eccentricity consists in a misalignment between its rotation axis and the stator axis of symmetry: this usually occurs due to tolerances and imperfections introduced during motor construction or to gradual increase of wear of the rotor shaft bearings. Whenever it occurs, the motor, supposed to have more than one polar couple, generates a periodically variable magnetic flux, as the air gap varies during rotation as a function of the rotor angular position θ [13]. The authors, taking into account coil short-circuit and rotor static eccentricity, have studied the consequences of faults on the performances of the servomechanism [14]: their effects on the electrical features of the BLDC motor (e.g. winding resistance, inductance and back-EMF) are simulated by a simplified numerical model [24-26]. In particular, as reported in [27], authors simulated the effects of faults affecting the magnetic coupling between stator and rotor varying values and angular modulations of back-EMF coefficients. As regards the frictional effects acting on the mechanical transmission it must be noted that an increased dry friction, although does not cause the failure of the entire system, reduces the servomechanism accuracy and can influence the dynamic response of the system generating unexpected behaviour (stick-slip or limit cycles). Wear makes friction coefficients increase and reaction torque becomes higher so that the motor has to provide higher torques to actuate the control surface. Moving parts such as gears, hinges, bearings and particularly screw actuators can be affected by mechanical wear; it can generate backlashes that, acting on the elements of the mechanical transmission, reduce the EMA accuracy and can lead to stiffness and controllability problems [23].

4 EMA MONITOR MODEL

The EMA Reference Model reproduces the actual system dynamic response with the highest possible accuracy; however, its computational cost is not compatible with an iterative optimization method such as a Genetic Algorithm (GA). Then, a Monitor Model (MM) has been developed as a simplified representation of the considered EMA, yet detailed enough to simulate the effect of all the considered faults. In fact, during the optimization, the MM is executed several thousand times iteratively varying the fault parameters, until the MM response features a satisfying matching to the Reference response, which is used in place of the actual system for testing the FDI algorithm, and the quadratic error function, which compares the current signals of the two models, is minimized.

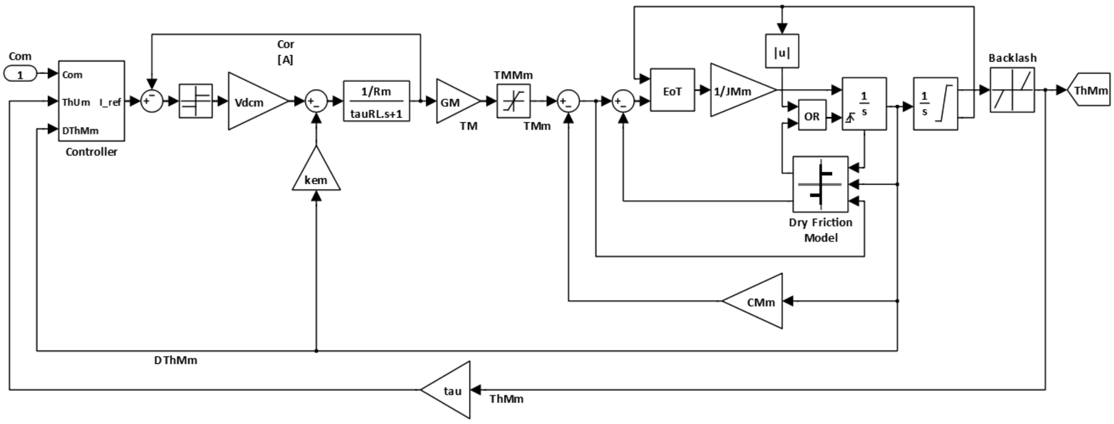

Figure 2 Simulink scheme of the Monitor Model (MM).

To achieve a good accuracy in fault isolation, the MM needs to reproduce the effect of faults with high accuracy: this way, when the same fault parameters are set to both the models, the error function returns a value near to zero, thus producing a well-defined global minimum which can be effectively detected by the genetic algorithm. Then, this paper focuses on the definition of the Monitor Model and in particular on the implementation of the BLDC electrical faults.The main simplification of the MM is the elimination of the three-phase trapezoidal control of the BLDC, replaced by a much simpler and computationally lighter single-phase equivalent scheme, which avoids the complex PWM current regulation an digital-to-analog conversion of signals (as shown in Fig. 2). This solution allows a much longer time step to be employed for the simulation, greatly reducing computing time; however, a complication arises for the simulation of electrical faults, which will be discussed in the following paragraphs.

4.1 MONITOR MODEL FAULT IMPLEMENTATION

The EMA mechanical branch is modelled with a nonlinear second order mechanical system, simulating effects of dry friction and backlash; then, the implementation of mechanical faults is quite straightforward and similar to that employed for the Reference Model. In fact, the Dry Friction fault is simulated by varying both the static and dynamic friction coefficient in the subsystem implementing the *Borello Friction Model* [23] (Fig. 2); in a similar way, the mechanical play is simulated modifying the dead band amplitude in the *Backlash* block from the Simulink libraries. Conversely, the electrical faults in the Reference Model are strictly related to the three-phase electromagnetic subsystem, not implemented in the Monitor. Reproduction of these damages thus requires a different approach. The short circuit fault is, as a first attempt, modelled with an averaged approach varying the electromagnetic parameters of the single-phase monitor electrical branch; as a first approximation, it is possible to define an equivalent N_{equiv}, which is valid for small fault entities, as:

$$N_{equiv} = \frac{N_A + N_B + N_C}{3} \tag{1}$$

where N_A, N_B and N_C are the fractions of working windings of each electrical phase. Then, the electrical parameters of the simplified model are corrected as reported below:

$$\begin{aligned} R_{equiv} &= N_{equiv} R_{equivNC} \\ L_{equiv} &= N_{equiv}^2 L_{equivNC} \\ k_{fcem} &= N_{equiv} k_{fcemNC} \\ G_{Mequiv} &= N_{equiv} G_{MequivNC} \end{aligned} \tag{2}$$

where the NC (Nominal Conditions) subscript specifies a quantity referred to a non-faulty condition.

This model does not allow to discriminate the fault in one phase from that in another, but only shows a net increase in equivalent[1] current and maximum actuating speed. Figure 3 shows the equivalent current trend resulting from a chirp command for the reference and monitor model, using the N_{equiv} approximation.

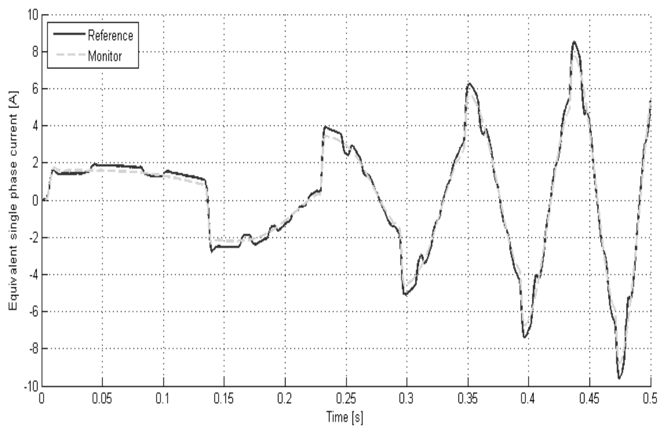

Figure 3 Response of the proposed Monitor Model with the N_{equiv} approximation.

1 Equivalent current refers to the current of the single-phase model for the Monitor; for the Reference Model, it is defined as the envelope of the three phase currents, computed as:

$$\mathrm{I_{ref}} = \frac{\mathrm{I_A} + \mathrm{I_B} + \mathrm{I_C}}{2} \cdot sign(\mathrm{T_M})$$

where T_M is the motor torque.

Moreover, the Rotor Static Eccentricity (RE) fault cannot be simulated with the same technique: unlike the Phase Short Circuit (PSC) fault, the RE has little-to-no effect on overall actuator performance intended as position and speed control, even in open-loop response. In fact, this fault causes the Torque Gain (*GM* gain in Fig. 2) and Counter Electromotive Force Gain (*kem*) to increase in some angular positions and to decrease in others so that the disturbance, averaged over one revolution, is null; the mechanical system characteristic time is significantly longer than the electromagnetic system one, so inertial effects of the rotor act as a low-pass filter over the torque signal, suppressing the high frequency noise in the angular velocity of the rotor, which does not differ appreciably from that of the nominal system. For these reasons, some modifications of the MM are required to better simulate the damages, improving the accuracy of optimization-based FDI techniques.

5 ENHANCED EMA MONITOR MODEL

To correctly replicate the Reference response to the electrical faults avoiding the costly simulation of the three-phase electromagnetic model, the MM needs to renounce a strict correlation to the physical phenomena generating the effect of the aforesaid faults on the EMA performance, as in the model-based approaches; the MM is indeed modified to produce the effect of PSC and RE regardless of their physical origin. This is achieved by the introduction of two shape functions used to modulate the electromagnetic parameters of the equivalent single-phase model as a function of fault magnitude and rotor angular position (schematically shown in Fig. 4).

5.1 MODULATING FUNCTION-BASED – PSC FAULT

The approach employed for the PSC fault consists in multiplying the stator resistance, torque gain and back-EMF coefficient by the fraction of windings working at each instant. Since two phases are active at a time, the modulating function is defined as:

$$f(\theta_m) = \begin{cases} \dfrac{N_b + N_c}{2}, & -\dfrac{\pi}{6} < \theta_e < \dfrac{\pi}{6} \\ \dfrac{N_c + N_a}{2}, & \dfrac{\pi}{6} < \theta_e < \dfrac{\pi}{2} \\ \dfrac{N_a + N_b}{2}, & \dfrac{\pi}{2} < \theta_e < \dfrac{5}{6}\pi \end{cases} \qquad (3)$$

where $\theta_e = P\,\theta_m$ is the normalized electrical rotor angle, limited in a range of amplitude π. This is equivalent to consider, for the evaluation of the equivalent short circuit parameter, only the two active phases for a given θ_m. Since this modulating function is difficult to express with a syntax compatible with the Simulink *Fcn* block, the subsystem shown in Fig. 5 is adopted. The non-normalized rotor position is fed in input, and the active phase computation block returns the integer values {1,2,3} depending on the active phases; subsequently, the multiport switch block commutates the corresponding constant value, which is returned as output.

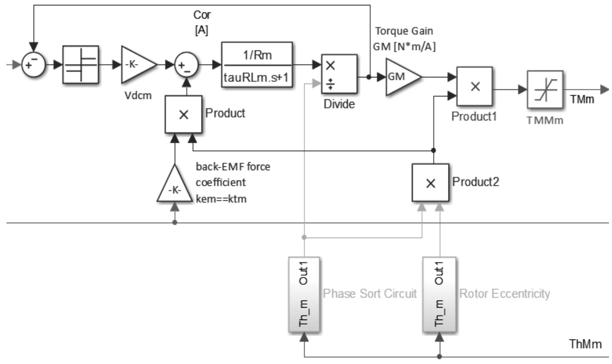

Figure 4 Modification of the Monitor Model to introduce the two shape functions.

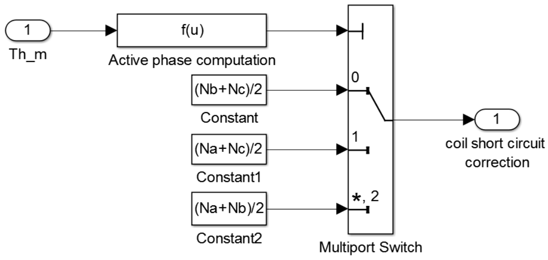

Figure 5 Short circuit subsystem.

The active phase computation block employs the function:

$$f(u) = floor\left[3\left(\frac{Pu}{\pi} + \frac{1}{6}\right) - 3floor\left(\frac{Pu}{\pi} + \frac{1}{6}\right)\right] \qquad (4)$$

where P is the number of pole-pairs and $u = \theta_m$ is the block input signal. A simpler alternative would be to call an external MATLAB function, but this would lengthen unacceptably the computing time, even in the Accelerator Mode. With this modification, the equivalent current waveform produced by a PSC is reproduced by the monitor model in a quite accurate way as shown in Fig. 6, allowing an improved recognition of the fault even when considered in combination with other damages. Moreover, the phase affected by PSC can be identified, even if this information may not have a great relevance for maintenance purposes.

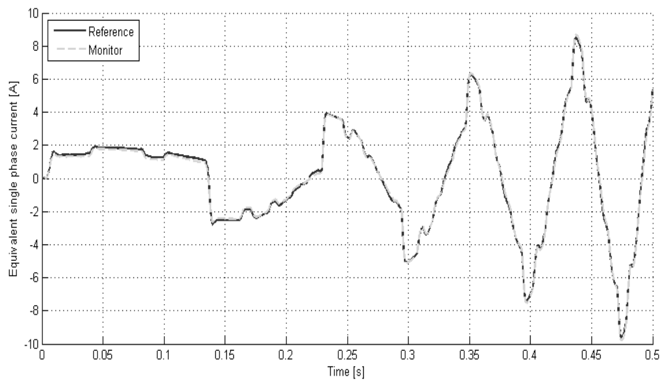

Figure 6 Response of the proposed Monitor Model with a 50% phase A short circuit.

5.2 MODULATING FUNCTION-BASED – RE FAULT

A similar approach to that described in Paragraph 5.1 is employed to model the effect of RE: a modulating function is used to multiply the torque gain (*GM*) and back-EMF coefficient (*kem*) to reproduce the Reference current signal. After some attempts, it is found that the correct waveform is accurately reproduced by using the correction:

$$K'_{fcem} = K_{fcem}\,(1 - Z(\cos(P\theta_m + \phi) + \text{sawtooth}(6P\theta_m - \pi)\sin(P\theta_m + \phi)) \quad (5)$$

This shape function has no physical meaning, but is an effective and computationally light solution for producing the effect of a rotor eccentricity on the Monitor current signal; the parameter Z represents the damage magnitude, since it multiplies the shape function. In order to find the correlation between Z and ζ some optimizations are performed using known values of ζ. For values of ζ ranging from 0 to 1 a value of Z is found to minimize the quadratic error between reference and monitor response, using a gradient-based method. As it can be seen in Fig. 7, a linear function of ζ can be used to accurately approximate the parameter Z. With a least squares method one can find:

$$Z = 0.42\,\zeta \quad (5)$$

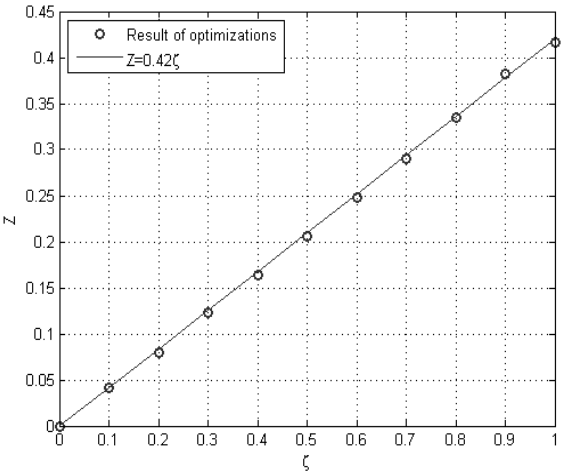

Figure 7 Linear fit of Z.

As shown in Fig. 8, this relation allows representing the correct waveform in a fairly accurate way, which reflects in improving the convergence of the genetic algorithm used for fault detection.

6 RESPONSE OF EMA MONITOR AND REFERENCE MODEL IN FAULTY CONDITIONS

Several combinations of commands and faults have been simulated to check for consistency of response between reference and monitor models. In fact, in order to perform a precise fault isolation, it is of critical importance that the monitor model is able to accurately reproduce the reference dynamic response, both in faulty and nominal conditions.

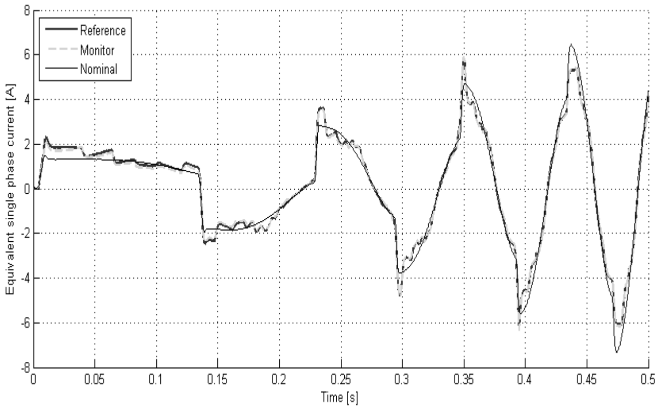

Figure 8 Response of the proposed Monitor Model with rotor eccentricity.

Figure 9 shows the response of Reference and Monitor models in nominal conditions. The proper setting of the MM parameters allows to exactly matching the Reference equivalent current: in this way, the error function returns a null value, ensuring convergence of the optimization. Figure 10 shows the behavior of the two models when multiple faults are introduced. It is possible to notice that the discrepancy between the two curves is small, and all the characteristic patterns produced by the incipient damages are correctly caught by the simplified model, meaning that the quadratic error function features a univocally located global minimum near the reference combination of faults. This should enable the GA optimization to effectively recognize the right damage levels, distributing the error variations among the four faults.

7 CONCLUSIONS

A simplified EMA Monitor Model has been developed to accurately reproduce the dynamic response of the Reference Model in terms of position, speed and equivalent current, even with the presence of various incipient faults. The high accuracy achieved in reproducing the effects of faults is a good starting point for the implementation of a robust and accurate GA-based optimization, leading to reliable and early fault isolation. The computing time for the simulation of a chirp command with the duration of 0.5 [s] is below one second[2] when using the Simulink *Accelerator Mode*. In this regard, it should be noted that the same simulation, performed with the Reference Model (more detailed and numerically burdensome) takes more than one minute: therefore, the computational cost is therefore compatible with a GA optimization for FDI performed during on-field pre-flight checks or scheduled maintenance.

2 The optimizations reported in this paper are performed on a desktop PC with Intel Core i5-3340 processor @ 3.10 GHz (6 MB Cache, up to 3.30 GHz) and 8 GB of RAM, running Windows 10 Home OS (64 bit architecture) and MATLAB R2012b.

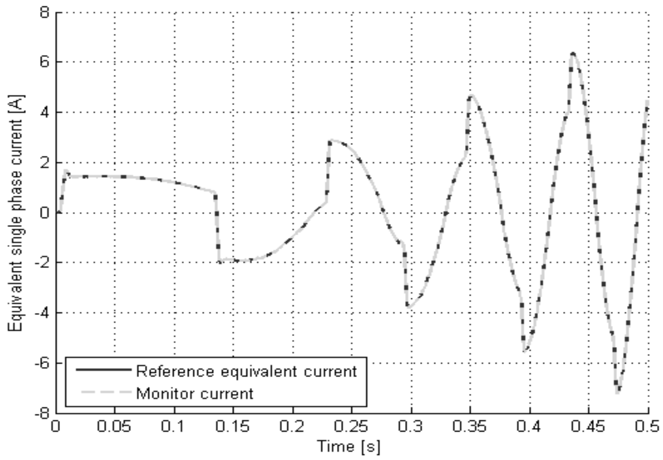

Figure 9 Response of Reference and Monitor models in Nominal Conditions.

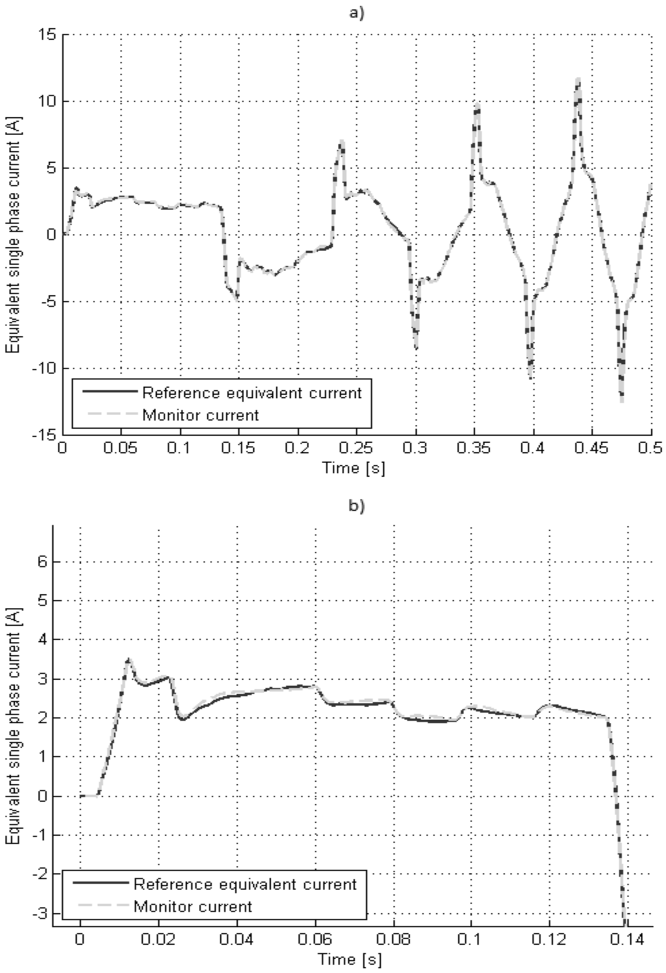

Figure 10 a) Response of the two models with multiple faults (180% of nominal friction, $4{\cdot}10^{-4}$ *rad* of backlash on the output shaft, 20% phase A PSC and RE of 20% the nominal air gap); b) Detail of the first 140 ms of response.

Real time in-flight monitoring is still impracticable, however, this solution would be excluded for other reasons, including regulation issues related to the non-deterministic nature of GAs and the technical difficulty of measuring aerodynamic loads to apply them to the Monitor Model. Future works will include the implementation and tuning of the GA optimization itself, the extension of the prognostic technique to a larger number of faults and possibly a further reduction of computing time, by simplifying the Monitor Model (for example pre-solving the controller current loop) or translating it in a lower level programming language.

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