Electromechanical Actuators Affected by Multiple Failures: Prognostic Method based on Wavelet Analysis Techniques

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Abstract: - Incipient failures of electromechanical actuators (EMA) of primary flight command, especially if related to progressive evolutions, can be identified with the employment of several different approaches. A strong interest is expected by the development of prognostic algorithms capable of identifying precursors of EMA progressive failures: indeed, if the degradation pattern is properly identified, it is possible to trig an early alert, leading to proper maintenance and servomechanism replacement. Given that these algorithms are strictly technology-oriented, they may show great effectiveness for some specific applications, while they could fail for other applications and technologies: therefore, it is necessary to conceive the prognostic method as a function of the considered failures. This work proposes a new prognostic strategy, based on artificial neural networks, able to perform the fault detection and identification of two EMA motor faults (i.e. coil short circuit and rotor static eccentricity). In order to identify a suitable data set able to guarantee an affordable ANN classification, the said failures precursors are properly pre-processed by means of Discrete Wavelet Transform extracting several features: in fact, these wavelets result very effective to detect fault condition, both in time domain and frequency domain, by means of the change in amplitude and shape of its coefficients. A simulation test bench has been developed for the purpose, demonstrating that the method is robust and is able to early identify incoming failures, reducing the possibility of false alarms or non-predicted problems.

Key-Words: - Artificial Neural Network (ANN), BLDC Motor Failures, Electromechanical Actuator (EMA), Fault Detection/Identification (FDI) Algorithm, Prognostics, Wavelet

1 Introduction

In the recent years, the electromechanical actuator (EMA) is becoming one of the most common types of augmented flight control systems in fly-by-wire architectures. In this scenario, prognostic studies results fundamental in order to reduce maintenance costs for preserving safety. Differently from mechanical fatigue, which can be predicted with a certain confidence level, EMA electrical failures, like partial stator phase short-circuit of rotor eccentricity, are hard to detect by the means of an external analysis: these faults are often caused by unexpected causes like current peaks or stresses, and their consequences are undetectable in a large scale, as system performance and response could remain almost constant, while the initial incipient damage could rapidly degrades into a severe damage which compromise the system correct working, causing the actuator failure. The ability to analyze the behavior of components to determine their degradation pattern is the main objective of the Prognostics and Health Management (PHM) [1-3].

Its goal is to provide real-time data of the current status of the system and to calculate the Remaining Useful Life (RUL) [1] before a fault occurs. The main advantages gained applying the PHM strategies are evident when comparing their results with those obtained with classical monitoring and maintenance concepts (e.g. based on overhaul or life-limited parts). By means of proper PHM strategies, the considered progressive faults could be managed in a more effective way, obtaining a substantial reduction of system redundancies, operating costs, maintenance interventions and, at the same time, improving the aircraft safety and reliability and simplifying logistics [2].

To these purposes, in this paper authors propose a new Fault Detection and Identification (FDI) technique [3], based on Artificial Neural Networks (ANNs), able to identify the failure precursors and evaluate the corresponding damage entity. In order to identify a suitable data set able to guarantee an affordable ANN classification, the said failures precursors are properly pre-processed by means of

Discrete Wavelet Transform (DWT) extracting several features: in fact, these wavelets result very effective to detect fault condition, both in time domain and frequency domain, by means of the change in amplitude and shape of its coefficients. The algorithm effectiveness has been evaluated by a dedicated MATLAB-Simulink® numerical model, able to analyze the EMA performance and the effects of different progressive faults; the so obtained results demonstrate that the method is robust and is able to early identify incoming failures, reducing the possibility of false alarms or non-predicted problems.

2 EMA Numerical Model

As previously mentioned, goal of this research is the proposal of a new technique able to identify precocious symptoms (usually defined as failure precursors) of EMA degradations. In order to assess the feasibility, the performance and the robustness of the aforesaid technique, a suitable simulation test bench has been developed in MATLAB/Simulink®. This numerical model, widely described in [4], is coherent with a typical EMA architecture [5].

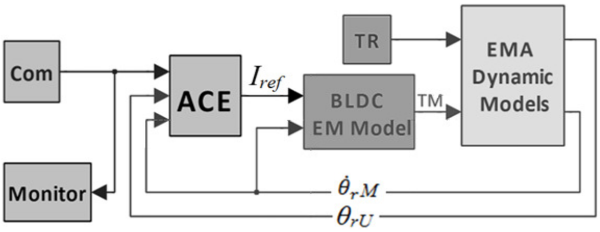

Fig. 1: Proposed EMA block diagram

It is composed by six different subsystems:

1. **Com**: input block that generates the different position commands.
2. **ACE**: subsystem simulating the actuator control electronics, closing the feedback loops and generating in output the reference current Iref.
3. **BLDC EM Model**: subsystem simulating the power drive electronics and the trapezoidal BLDC electromagnetic model, that evaluates the torque developed by the electrical motor as a function of the voltages generated by a three-phase electrical regulator.
4. **EMA Dynamic Model**: subsystem simulating the EMA mechanical behavior by means of a 2 degree-of-freedom (d.o.f.) dynamic system.
5. **TR**: input block simulating the aerodynamic torques acting on the moving surface controlled by the actuator.
6. **Monitor**: subsystem simulating the EMA monitoring system.

3 Considered EMA Failures

The employment of EMAs in aeronautics is quite recent, so statistics about their failures are not yet consistent. Anyhow, it is possible to refer to four main groups of failures: electronics (i.e. Controller) and sensors failures, electric motor, mechanical or structural failures. As shown in [5], main failures in BLCD motors are due to progressive stator coil short circuits (due to thermal effects that could compromise the insulation of the coil windings) and rotor static eccentricity (caused by bearing wears). Progressive short circuit (SC) usually starts between a few coils belonging to the same phase (turn-to-turn coil failure) and, then, spread to adjacent coils. In fact, in short-circuited coils the voltage remains almost the same and the resistance decreases; as a consequence, a high circulating current arises and generates a localized heating in phase conductors that facilitate the propagation.

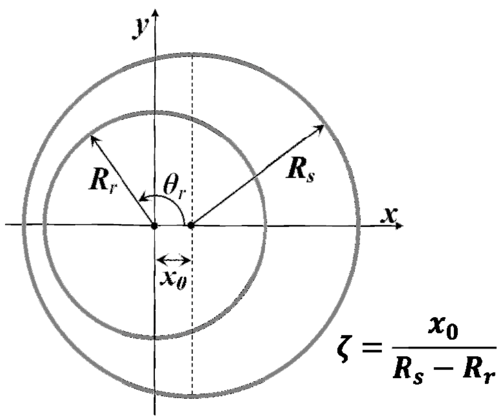

Fig. 2: BLDC Motor Rotor static eccentricity ζ: schematic of the reference system

Rotor static eccentricity (RE) consists in a misalignment between its rotation axis and the stator axis of symmetry. It is 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 schematically shown in Fig. 2) as a function of the rotor position ϑ_r:

$$g(\theta) = g_0(1 + \zeta\cos(\theta)) \quad where \quad \zeta = \frac{x_0}{g_0} \tag{1}$$

Taking into account coil short-circuit and rotor static eccentricity authors studied the consequences of faults on EMA performances [6] Failures and their effects on the electrical features of the BLDC motor (winding resistance, inductance and back-EMF) have been simulated through a simplified numerical model, according to [7].

In particular, the authors simulated the effects of faults affecting the magnetic coupling between stator and rotor varying values and angular modulations of the back-EMF coefficients [8]. Executed in the BLDC ElectroMec model block (Fig. 1), this method acts on the three back-EMF constants Ce_i (one for each branch) modulating their trapezoidal reference values Ke_i as a function of coil short circuit percentage, static rotor eccentricity ζ and angular position ϑ_r:

$$ke_i = Ke_i \cdot Ce_i \cdot (1 + \zeta \cdot cos(\vartheta_r)) \quad i = a, b, c \tag{2}$$

The so obtained constants (ke_a, ke_b, ke_c) are then used to calculate the counter-electromotive forces induced on the corresponding stator windings and, therefore, to evaluate the mechanical torque contributions generated by the three motor phases. As reported by [9, 10], the evaluation of precursors permits to adopt countermeasures despite quite fast propagation of sensors' and electrical components' failures. It must be noted that, with respect to other EM models available in literature, the numerical model shown in the previous sections is able to calculate the instantaneous value of each current phase (I_a, I_b, I_c) also in case of unbalanced electromagnetic system (e.g. partial short circuit on a stator branch or rotor static eccentricity); then, it is possible to correlate the progressive faults with the dynamic response of these signals (used as failure precursors) by means of an algorithm, based on the Wavelet analysis, that evaluates the filtered phase currents; for this purpose, each phase current is filtered by three low pass signal filter, in order to attenuate noise and disturbances [11].

4 Wavelet Neural Network

Wavelet analysis can decompose any signal through a wavelet family basis, expanded from a wavelet basis function and locally refinement the high and low-frequency details while retaining the characteristics of the original signal in time domain. So wavelet analysis has good time-frequency proprieties and can effectively identify non-stationary signals for fault diagnosis purposes [12].

4.1 Wavelet Analysis and Feature Extraction

Several simulations have been performed in order to estimate the system response in nominal and in faulty conditions. Every fault has been valued with one type of input: a step command at 1 radians. This command saturates the EMA controller so that it is possible to reach the maximum unloaded actuation speed of the motor.

In this regard, it is necessary to highlight that, by inhibiting the control logic, this type of command input allows detecting eventual failures by neglecting the controller influence (i.e. as long as it is in saturation conditions, the controller is not able to correct or attenuate the failure effects and, then, it makes faults visible). These results provide preliminary information for seeking a simple and effective prognostic method of BLDC motor faults. Current and speed signals from the two progressive fault cases are compared below with their wavelet analysis. Several wavelet families have been tested on every signal and then, after qualitative comparisons, it was carried out the best choice.

The orthogonal feature is a very important rule considered for selecting wavelet basis. A better orthogonal feature means larger rules coefficients, but the effect of mutations detection is worse. It is better to select wavelet basis with larger rules coefficients to reflect show the overall trend of the signal, then the coefficient with the rules of the wavelet function better.

This process is named "feature extraction" and, by an operatively point of view, it is a special form of dimensionality reduction. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately.

Since not all features that can be extracted from signals for a given classification problem need to be used, due to their redundancy, a further process is needed for redundancy reduction by retaining only an informative subset of them.

This stage of signal processing is typically named "feature selection".

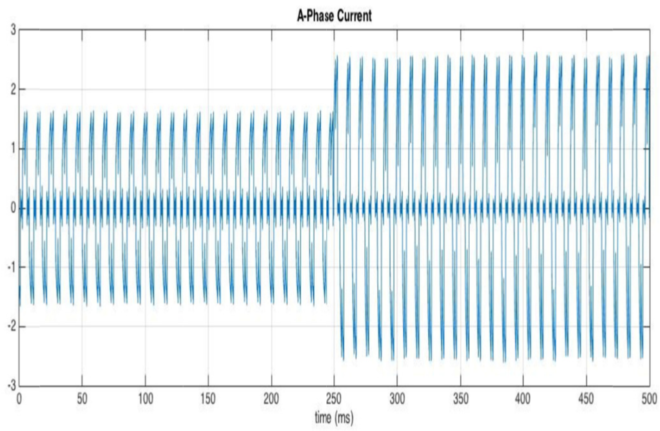

Fig. 3: Example of features for a stator phase current: NC vs. faulty condition (20% of coils short circuit

The selection of the type of mother wavelet suitable for analysis is dependent by the properties of the said mother wavelet or by the similarity between signal and mother wavelet [13].

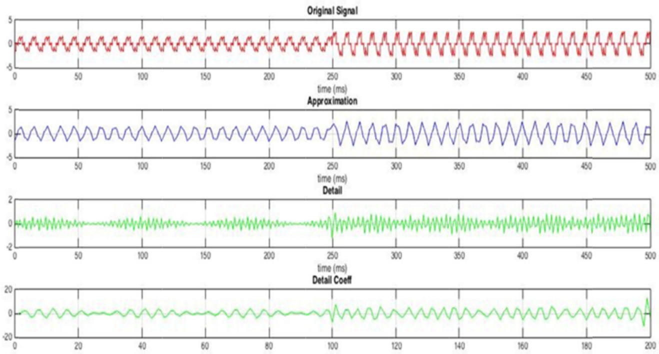

Fig. 4: Example of wavelet decomposition applied to the stator phase current shown in Fig.3

The same analysis was made for angular speed and is shown in Fig. 5, but in this case a *Db2* wavelet type [14] has been selected because it is more similar to the signal waveform.

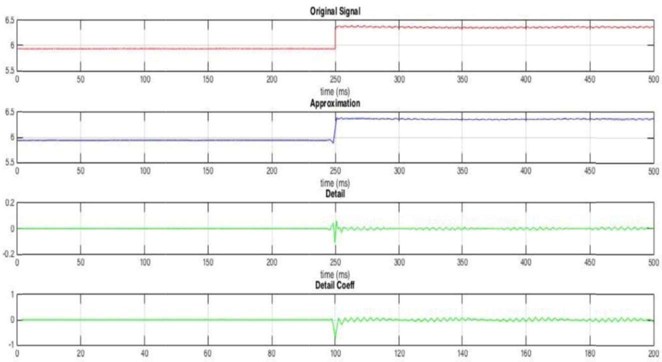

Fig. 5: Example of wavelet decomposition applied to BLDC Motor angular speed (*Db2* wavelet type)

This procedure was carried on for every fault signal. It must be noted that in this case, according to [12-14], the decomposition level was set at 7 and, then, DWT generates respectively the coefficient subsets at the seventh level approximation (cA7) and the first to the seventh level details (cD1, cD2, cD3, cD4, cD5, cD6, cD7). To investigate the usefulness of extracting features from individual wavelet components instead of extracting them from all the components, the reconstructed can be defined by the inversion of the subset dependence. For instance, in order to obtain the estimated signal from the approximation coefficient subset, the reconstructed signal (A7) is computed by using IDWT with the seventh-level approximation coefficients (cA7). The wavelet coefficient subsets (cD1-cD7, cA7) and the reconstructed signals (D1-D7, A7) are then used as features of the two progressive classes of fault. After implemented each feature in Matlab, they were evaluated for the two classes of progressive faults.

For instance, Fig. 6 shows the main Waveform Length features, calculated on A-phase current signal in case of progressive short circuit (SC) fault; bars represent a progressive growing fault.

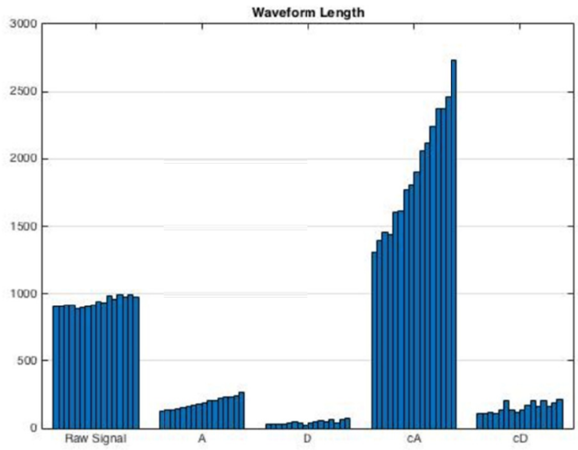

Fig. 6: Example of waveform length features: A-phase current with progressive short circuit

The next step is to choose, for two classes faults, the features and the related signal (e.g. raw signal, A7 approximation, D7 or cD7 detail coefficients) that represent the progressive fault in the best way. In fact, for example, as shown in Fig. 6, the wavelet component cD didn't show any relevant information about the fault degree, whereas wavelet components A and cA put in evidence a good correlation with the related SC failure magnitude.

5 ANN Fault Detection

The FDI neural network (ANN_1) has the task to perform the classification of the fault: it is able to distinguish a short circuit fault of the stator coils from a fault of the rotor eccentricity. The network was trained by the training vector K (inputs) and the target vector T. The training vector K consists of two section of 17 rows for 48 columns. Each row represents one of the features shown in the previous chapter and is characterized by the two classes of faults. Every column represents an increasing fault level of the three signals processed. The vector of the target T consists of 2 equal sections of 48 columns, one for 2 rows. In each column of the vector T it is associated with a column vector K. The first row represents the short-circuit fault of the stator winding, while the second row represents the failure of the rotor eccentricity. This target vector is initially composed by null values, but entering the value 1 in the proper column, it is able to indicate (to the neural network) the type of failure related to the corresponding column of training vector K.

The ANN_1 neural network is a network for pattern recognition of Multilayer Perceptron type and has been generated by Matlab tool and its architecture is shown in Fig. 7.

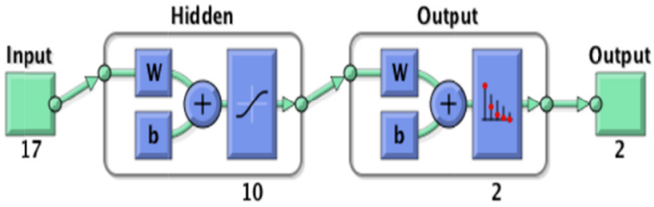

Fig. 7: Schematic of the proposed NN architecture

The network has the following characteristics:

- Layers: one hidden layer, one input layer, one output layer;
- Neurons: 10 perceptrons;
- Activation Function: log-sigmoid;
- Training Function: "*trainlm*" that updates ANN weights and bias according to Levenberg-Marquardt optimization [15-16];
- Performance Function: "*mse*" (mean square error), it measures the network's performance according to the mean of squared errors [16].
- Division Data: "*dividerand*", divide K into three sets using random indices following this percentages: 70% training samples, 15% validation samples, 15% testing samples [16].

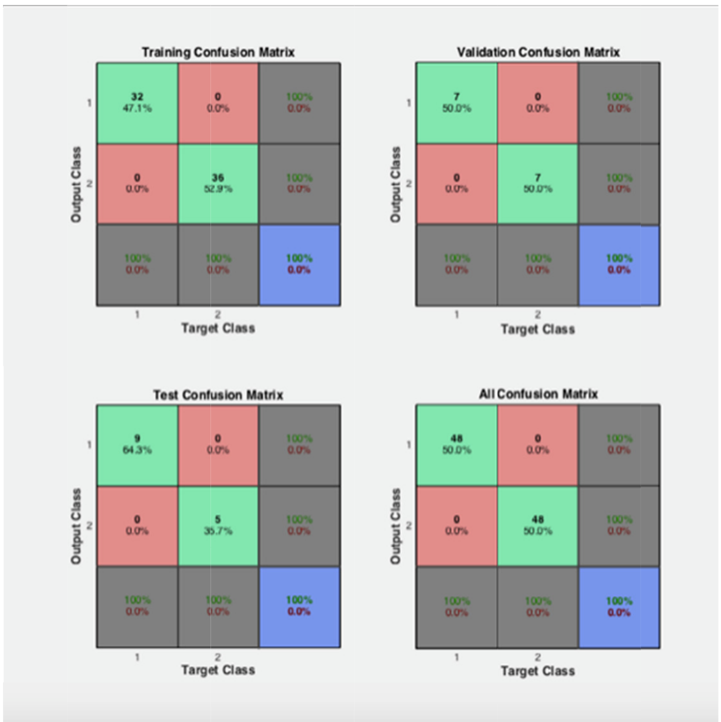

Fig. 8: SC Confusion Matrices for ANN_1

6 Conclusions

This work shows applicability of neural networks with supervised learning to prognostics and capability of wavelet transform to extract several features from outputs of a modeled BLDC Motor; this model, developed by a research group of Department of Mechanical and Aerospace Engineering of 'Politecnico Di Torino', is the starting point of this study and it can be seen as a test bench were faulty condition could be tested.

The principal issue, for neural network and more generally for prognostics, is to pre-process output signals from sensors, since the network needs a separable set of data to accomplish an affordable classification. In order to achieve this pre-processing, the Discrete Wavelet Transform seems to be a useful tool to elaborate the raw signals due to its time-frequency analysis: it is noticeable that the wavelet analysis easily detect fault condition and, like this case, a progressive one, both in time domain and frequency domain by change in amplitude and shape of its coefficients.

Hereafter, from transformed signals, features can be extracted using statistical definitions and trends come out, linkable to classes of progressive faults. This analysis operates similarity to the discrimination processes in our brain. The features of output signals is used as inputs of a Feedforward Neural Network and subsequently the network is trained to find a relationship that fit these inputs to targets, chosen to perform a specific non linear classification between two classes of defects and their degree.

This three-stage analysis presents as a first step, some advantages. First, the wavelet analysis is faster than a Fourier Analysis; as a matter of fact the wavelet transform has a computational cost of O(N) instead of O(NlogN) of the Fourier analysis. Second, use a neural network is a reliable approach for prognostics due to the large amount of data that can be collected and the increase of computer performance. The code used in this work needs the following amounts of time:

- BLDC Motor simulation: 17 seconds;
- Signal Processing using Wavelet: 2,82 seconds approximately;
- Network Training, Validation and Testing: 220 seconds approximately, this value can change from training to training because of the inductive method, but once trained, the network can be used as a predictor for other test inputs without other training operations.

Finally, the wavelet transform needs the raw signals and is not necessary to detect the changes in the outputs before this analysis.

It's the wavelet itself that detects changes in progressive faulty signals.

Future works could be carried out to increase the number fault classes or to improve the reliability of wavelet analysis and the ANN architecture. In order to achieve these objectives, a wavelet families choice can be done using a quantitative methods and not only by a similarity between the original signal and the wavelet family. Furthermore, an important challenge, according to Ockham Principle, is to simplify the network to prevent ovefitting:

- reduce the number of analyzed signals, taking into account only the current signals;
- reduce the number of neurons and hidden layers;
- reduce the number of useful features, by a selection during features extraction or by a selection after network training, based on a weight that the network gives at each feature.

Last but not least, in order to ensure the effectiveness and the robustness of the proposed FDI method, it's necessary to test the trained network with inputs related to several noise levels.

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