

Diagnostics of electro-mechanical actuators based upon the back-EMF reconstruction

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# Diagnostics of Electro-Mechanical Actuators Based Upon the Back-EMF Reconstruction

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**Abstract.** Electrical systems are gradually replacing the more traditional hydraulic and pneumatic solutions for the transmission of secondary energy for onboard aircraft equipment. Therefore fault detection and health management strategies properly conceived for electrical devices are becoming a highly relevant topic for research and development in the aerospace disciplines. One possible practical implementation of these methodologies would be the identification of parameters for diagnostic and prognostic monitoring, which are highly sensitive to incipient faults but, at the same time, are less influenced by operating conditions (external loads, command input, temperatures, etc.). In this paper, the authors evaluated the effectiveness of counter-electromotive force (back-EMF) coefficient as a prognostic parameter, emphasizing a novel sampling approach that significantly lower the computational effort required while maintaining a good back-EMF coefficient curve reconstruction. The approach is virtual sensor-like, using only already available data for the correct operation of the BLDC motor. The proposed method was tested by evaluating the back-EMF coefficient reconstruction as a function of some progressive failures typical of EMA motors, such as inter-turn partial shorts and rotor static eccentricity. Its robustness to external disturbances has been tested by evaluating different actuation commands and operating conditions. As expected, the back-EMF signal shows a marked dependence on the considered failure modes and, at the same time, a suitable insensitivity to the other external factors.

## 1. Introduction

In recent years, the increasing adoption of *more electric* [1] and *all electric* [2] design philosophies thanks to the development of enabling technologies [3] has implied an increased interest in prognostics and diagnostics for electrical systems. In general, prognostics can be defined as a scientific discipline with the scope of determination of the failure time of a particular element or subsystem [4], usually referred to as Remaining Useful Life (RUL); prognostics can be viewed as being part of a more broad discipline, that is Prognostics and Health Management (PHM), which has the scope of determination of current system health status, i.e. evaluating system performance and actual capabilities and integrates with prognostics life estimation, usually with the scope of implementing a condition-based maintenance doctrine, as in [5], which can lead to increase safety and decreased operational costs [6]. On the other hand, diagnostics is the discipline that detect and identify faults of mechanical systems; diagnostics is often included in a broader discipline referred to as Fault Detection and Isolation (FDI); these definitions are based on [7, 8].

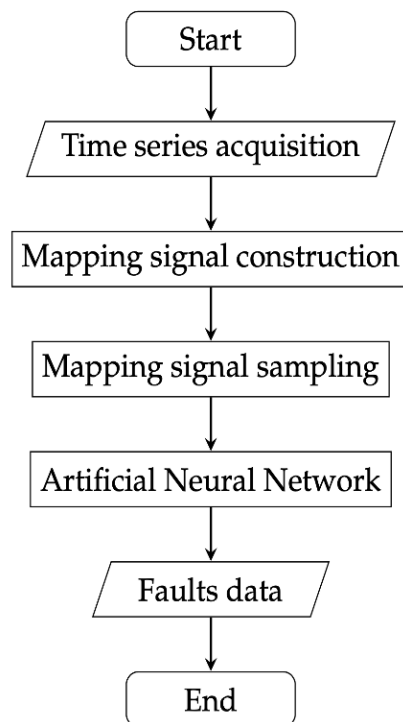


## 2. Methods and objectives

The main objective of the work has been to improve the algorithm presented in [9], to increase performance, shorten compute time and facilitate the implementation on limited-performance on-board computers (OBCs). In essence, the algorithm leverages a virtual sensor approach [10] to predict and quantify faults and current health status of an electromechanical actuator.

### 2.1. Algorithm overview

The algorithm will now be briefly described, including the modifications that have been made in order to strongly reduce computation difficulty and thus making execution much more rapid.



**Figure 1.** Algorithm overview

The first step is the acquisition of important data from sensors that are already present in the subsystem; such values are phase voltages, phase currents, motor angular position and motor angular velocity.

After having logged the aforementioned values, the following step is to create a relevant mapping signal, which in this case is the back-EMF coefficient. Mapping signal have the properties of being very sensitive to particular faults of interest while being not very much sensitive to either command signal and external disturbances. In this case, it has been shown [11] that back-EMF coefficient is strongly affected by electrical faults and is insensitive to external loads or command imposed.

Next step is to rewrite the back-EMF coefficient as function of angular position (back-EMF coefficient is originally a time function). In this case, it is useful to express the back-EMF as function of rotor position since it provides a direct correlation with eccentricity phase.

The back-EMF coefficient map, now a function of rotor angular position, is now sampled with a suitable number of relevant points distributed across the whole map; these points values will

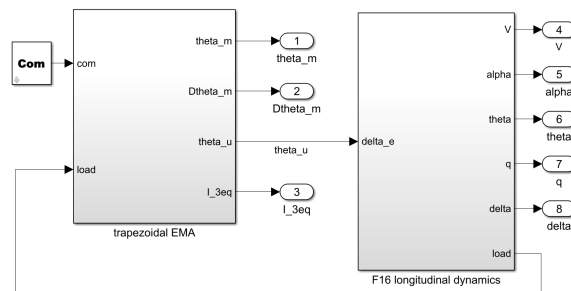
be the inputs for the artificial neural network used to perform a regression task on the sampled data and evaluate current system status and degradation.

One criticality that can be observed is the fact that for this particular application, only the back-EMF coefficient values of the sampled points are of interests; in fact, sampling the whole reconstructed back-EMF curve (*post-sampling*) can be substituted by *pre-sampling*, i.e. the value of the back-EMF coefficient can be evaluated only for the point chosen as inputs for the neural network, thus greatly reducing the points where the curve has to be reconstructed.

## 2.2. Model overview

In order to create a realistic data for the application of the algorithm, a MATLAB Simulink model has been adopted [12], modeling an F-16 flaperon actuation system. The model has been created without major assumptions, except for concentrated parameters, and it is detailed up to the component level.

In Fig. 2, the top-level view of the whole model can be observed. The two main subsystems are the *trapezoidal EMA* block, encompassing the whole system of interest, while the other block, *F16 longitudinal dynamics* includes a linearized state-space longitudinal dynamic response of the whole aircraft.



**Figure 2.** Model overview

In Fig. 3, a detail of the *trapezoidal EMA* subsystems can be observed. The main subsystems present are the *Control Electronics PID* which models a simple PID controller used to command the system as function of surface position, the *Hall sensors* subsystems modeling the fundamental rotor angular position sensor used for commutation logic control, the *Inverter Model* which includes Simscape Electrical transistors blocks and model the usual H-Bridge configuration used for driving the motor itself, the *BLDC electromagnetic model*, again modeled using Simscape Electrical components such as RL branches and finally the the motor transmission model which is a reducing gear train.

Further information can be found in [11].

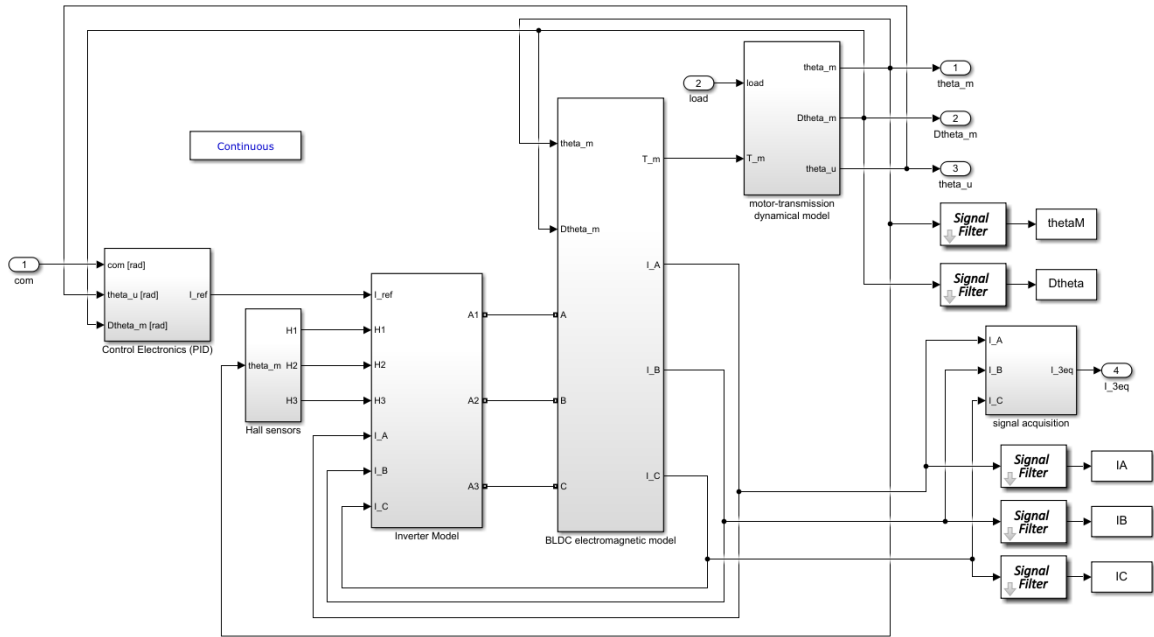
## 2.3. Back-EMF reconstruction and sampling

The first step necessary is the logging of the relevant signal for reconstructing the back-EMF: such values are the three phases voltages, the three phases currents, the rotor angular position and rotor angular velocity.

For each timestep, the following electrical equation holds:

$$V_j - e_j = V_j - k_{bemf,j} \dot{\theta}_m = R_m i_j + L_m \frac{di_j}{dt} \quad (1)$$

where  $e_j$  is the back-EMF voltage,  $R_m$  is the motor nominal resistance and  $L_m$  is the motor nominal inductance.



**Figure 3.** Trapezoidal EMA subsystem

It is now possible to express the back-EMF coefficient as function of the rotor angular position as such:

$$k_{bemf,j}(\theta_{m,k}) = \frac{1}{n} \sum_{l=1}^n k_{bemf,j,l}((\theta_{m,k} - \varepsilon) \leq \theta_m \leq (\theta_{m,k} + \varepsilon)) \quad (2)$$

which is a simple averaging of all the back-EMF coefficient points that have an angular position correspondent to a particular value ( $\theta_{m,k}$ ) plus or minus a small tolerance ( $\varepsilon$ ). The process is repeated for each of the three phases.

Finally, the equivalent single phase  $k_{bemf}$  is computed as such:

$$k_{bemf} = \sum_{j=1,2,3} |k_{bemf,j}| \quad (3)$$

The curves visible in Fig. 4 are reconstructed and sampled back-EMF coefficient curves seeded using random fault values.

### 3. Pre-sampling vs. post-sampling

Referring to Fig. 5, the top graph is obtained with the post-sampling approach, that is by first reconstructing the whole curve and then sampling the points of interest, while the bottom graph is obtained by using pre-sampling, that is reconstruction of the back-EMF coefficient only in the points of interest.

The main benefit of this approach is speed, given the fact that the average reconstruction and sampling time as presented in [9] is 0.228 s/curve, while using pre-sampling technique the average reconstruction and sampling time is reduced to 0.005 s/curve, thus achieving a speed-up factor greater than 42×.

On the other hand, the post-sampled curve (Fig. 5, top) is smoother (all curves are obtained assuming only a single phase partial short, with value increasing from blue curve to green curve), but the reconstructed shape is similar for both approaches.

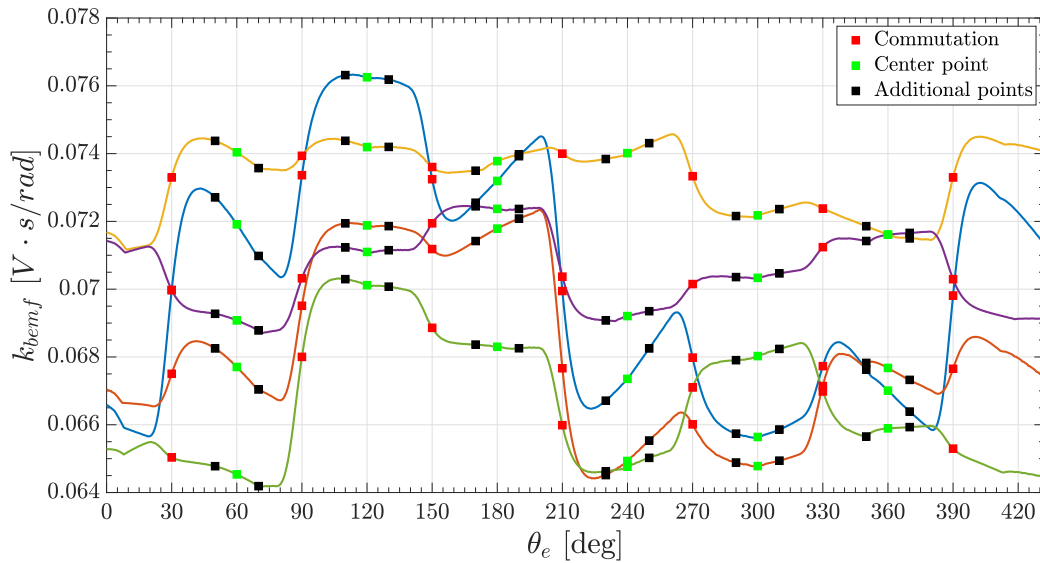


Figure 4. Reconstructed and sampled back-EMF coefficient curves [9]

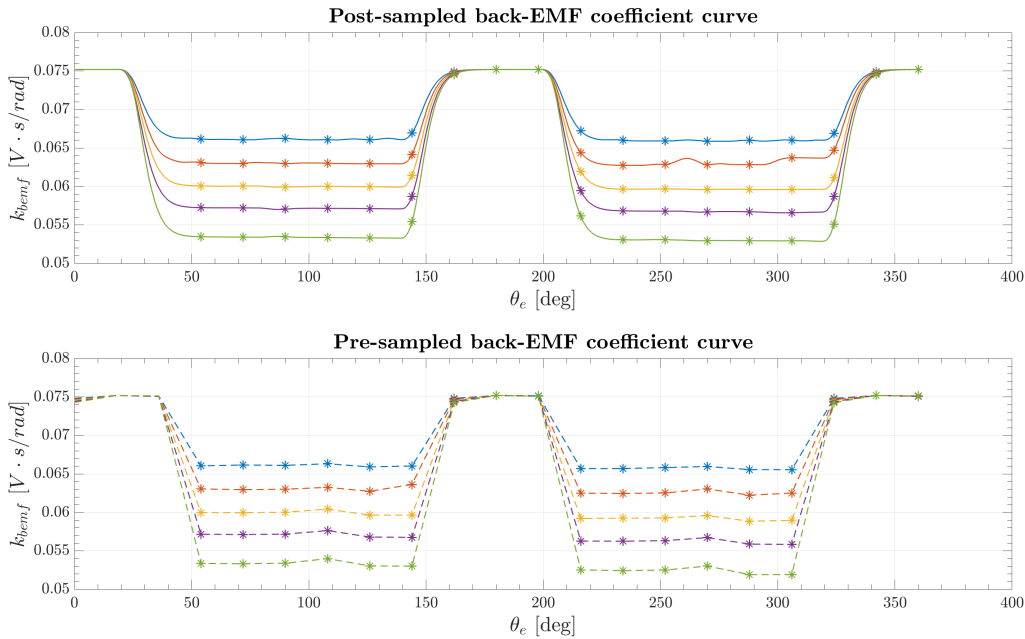


Figure 5. Comparison between post-sampling and pre-sampling approaches

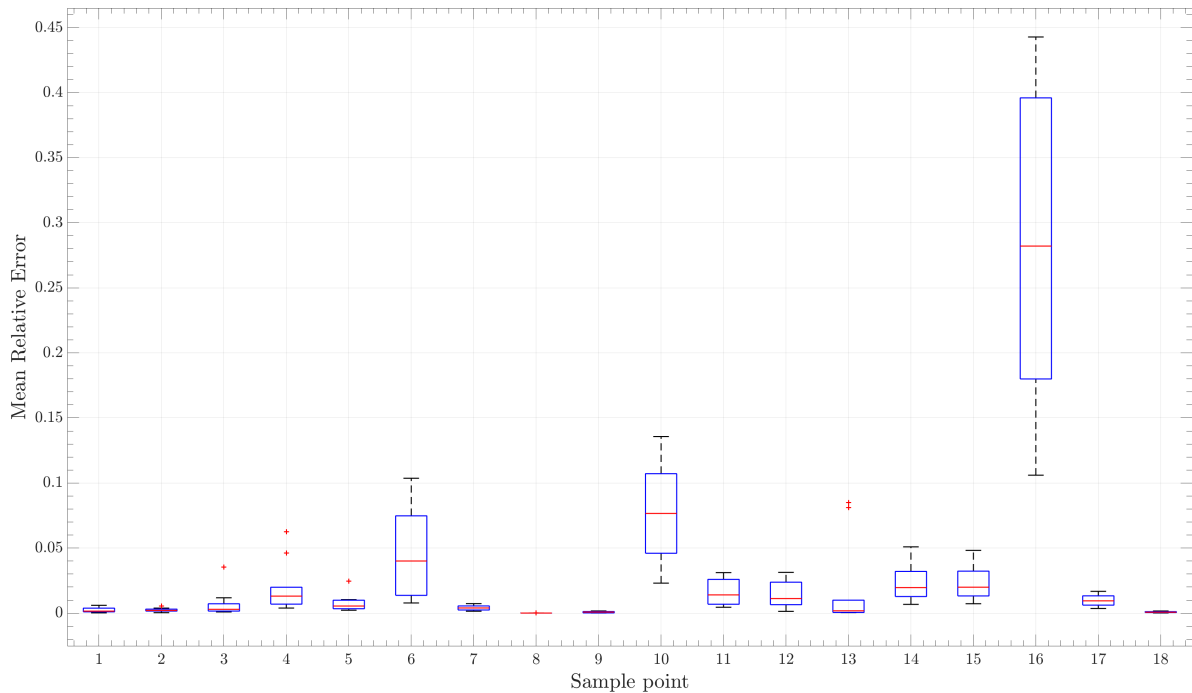
In both cases, 18 points have been sampled for each electrical revolution (i.e.  $180^\circ$  mechanical since a two-pole motor is considered), thus sampling 3 different points for each of the 6 electrical commutations present in a full electrical revolution.

It has to be noted that point 16 (third to last) assumes remarkably different values by switching to pre-sampling. In fact, referring to Fig. 6, it is clearly visible that the error on point 16 is disproportionately larger compared to the other points.

For all the sampled points, the average (calculated on 100 simulations) median error is 2.81%, the minimum median is 0.003% relative to point 8, while the maximum median error is 28.21% for point 16.

Standard deviation has an average value of 1.81%, minimum standard deviation is observed for point 8 with an average value of 0.003% and a maximum average standard deviation for point 16 with a value of 11.89%.

In general, the method is much faster and achieves very good global accuracy.



**Figure 6.** Box plot showing mean relative error between post- and pre-sampling logic

#### 4. Conclusions

As previously shown, using a pre-sampling approach can greatly reduce the computational cost and thus increase speed and it is a necessary step to allow the implementation on limited operational hardware on an aircraft, given the high computational limitation imposed by on-board computers.

A future work can be the optimization of the sample points choice in order to minimize error and variance for curves obtained by using different fault parameters and in particular by considering multiple faults at the same time; finally, the method has to be validated using neural networks as in [9] and then on real hardware before possible implementation on OBCs (On-board computers) of airworthy aircraft.

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