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New Lumped Parameter Numerical Model For Monitoring Electromechanical Actuators

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Abstract

The increasing use of all-electric secondary power sources in onboard systems is leading to the increased use of Electro-Mechanical Actuators (EMAs) in the aerospace industry. However, ensuring acceptable levels of safety and reliability requires the development of new prognostic and diagnostic methods to detect faults early and prevent the degradation of EMA performance. Adopting a model-based approach proves beneficial to designing various algorithms tailored to specific purposes. These models range from simplified monitoring models that balance computational efficiency with precision, to high-fidelity models that accurately simulate system behavior. High-fidelity models are used to generate databases, create predictive algorithms, and train machine-learning surrogates. This study introduces a Simulink Medium Fidelity (MF) model for a 3-phase PMSM-driven (Permanent Magnets Synchronous Motor) aeronautical servoactuator. Positioned between the High Fidelity (HF) and Low Fidelity (LF) models in terms of structure, detail, and accuracy, the new model enables simulation of the operation of a three-phase PMSM motor without relying on the simplifications found in typical LF models. For example, it avoids reduction to an equivalent single-phase motor model or linearization of the stator circuit. Despite its lower computational cost, the Medium Fidelity (MF) model maintains consistency with High Fidelity (HF) models. It considers the mutual interaction between different phases and potential imbalances caused by saturation in an inverter H-bridge branch when solving the electromagnetic circuit of the stator. Despite these considerations, the MF model demonstrates commendable computational performance and accuracy.

Keywords: electromechanical actuator, lumped parameter, Matlab-Simulink, numerical simulation, PMSM, prognostics

1. Introduction

A trend observed in recent years is the push toward smart systems, i.e. a system capable of sensing, analyzing a situation and make decisions using the available data. Prognostics and Health Management (PHM) is the discipline analyzing the health status of a system and predicting the time left for safe operation, called Remaining Useful Life (RUL) (Baraldi et al., 2013; Zio, 2022). Two approaches are commonly found in PHM: data-driven (Tsui et al., 2015), where the system physics is considered unknown, or too complex to model, and machine-learning tools are used to infer relations regarding degradation trends, and physics-based (Daigle et al, 2012; Byington et al., 2004), where a degradation model of the system is explicitly included and is used to estimate the current (and future) status of the system. One tool used in physics-based prognostics is numerical modeling, which can simulate, with varying levels of fidelity, the behavior of the system in both nominal and faulted conditions. Models can be used to generate datasets when is not feasible to use real systems due to cost or complexity; such datasets can then be used as training for machine learning (ML) tools to extract health indexes and to estimate the Remaining Useful Life (RUL) for a component or system (Berri et al., 2021). Information regarding the RUL can be used to implement smart maintenance approaches, generally referred to as predictive maintenance (De Pater and Mitici, 2021; De Pater et al., 2022).

The case study used in this paper is an electromechanical actuator, which was described in several papers (Belmonte et al., 2015; Dalla Vedova and Berri, 2019), where an High Fidelity (HF) model has been presented and validated on a real system. Moreover, a reduced order model of the same system, called Low Fidelity (LF) has been described (Berri et al., 2017), where strong simplifying assumptions have been made, namely single-phase equivalent motor and lack of inverter. The usefulness of a much lower complexity model is the faster computation time which allows real-time monitoring of the real system, but only if the model is sufficiently descriptive of the system in both nominal and faulted conditions of interest. However, the two models have very different levels of fidelity, thus an effort to bridge the gap has been made, with the Enhanced Low Fidelity (ELF) (Quattrocchi et al., 2023), where the motor is now 3-phase, as in the HF, but the three phases are linearly independent and saturation effects are modeled in a simplified fashion. In this paper, the same system is modeled with an increased level of fidelity compared to the ELF, and is called Medium Fidelity (MF). Compared to the HF, the inverter is not modeled, which is one of the simulation bottlenecks given the characteristic times of the electronic components. It models the interactions between the three phases in voltage saturation conditions, even tough is still an ohmic model. However, the inductive characteristic is modeled with transfer functions.

2. Medium Fidelity model overview

As previously described, the MF model has been developed as an higher fidelity alternative to the ELF model, and thus the main improvement included is the voltage saturation description of the motor (which is a Permanent Magnet Synchronous Motor - PMSM). One assumption made is a corrected ohmic model, i.e. the three phases are considered as resistors (thus the lack of the inductive part), but the currents are filtered using a first order transfer function modeling a RL low-pass filter for each phase, with the following equation:

$$H_{j(s)} = \frac{1}{\tau_j s + 1} = \frac{1}{\frac{L_j}{R_j} s + 1} \tag{1}$$

where τ_j is the characteristic time of the phase, R_j, L_j are respectively the resistance and inductance of the phase in actual conditions, as they are both function of the healthy number of turns in the coil.

In this model, the equations applied are

$R_j = R_0 \cdot n_j$,

where R_j is the actual phase resistance, R_0 is the nominal value and n_j is the percentage of healthy turns in the phase and

$L_j = L_0 \cdot n^2$

for the inductance.

As shown in Figure 1, the overall layout of the model is similar to that of the HF model (Dalla Vedova et al, 2019), and the following main subsystems can be seen (from left to right): a *com* input, which is the desired output shaft position; a Control Electronic (PID) subsystem, which uses a two-loops nested PID control on speed and position, commanding a reference current i_{ref} (usually referred to as i_q^{ref}).

The Resolver subsystem simply computes the electrical angle from the mechanical angle; the Inverter Model subsystem which uses the i_{ref} and the electrical angle to determine the three-phases currents by using the inverse Clarke-Park transform; the PMSM electromagnetic model (Figure 2), which is the most complex subsystem, where the electromagnetic interaction is modeled, starting from the computation of the back-EMF (analogously to the HF), to the voltages and currents (*PMSM model*) and finally to the evaluation of the motor torque.

This subsystem is the main novelty of this paper and will be described in detail in the following section. Finally, the motor-transmission dynamical model is self-explanatory and is the same as the HF. It has been noted a difference of the back-EMF values between HF and MF and it has been corrected using a gain of 7.5%, as visible in Figure 2; the difference probably arises from the different modeling approach and simplifying assumptions made.

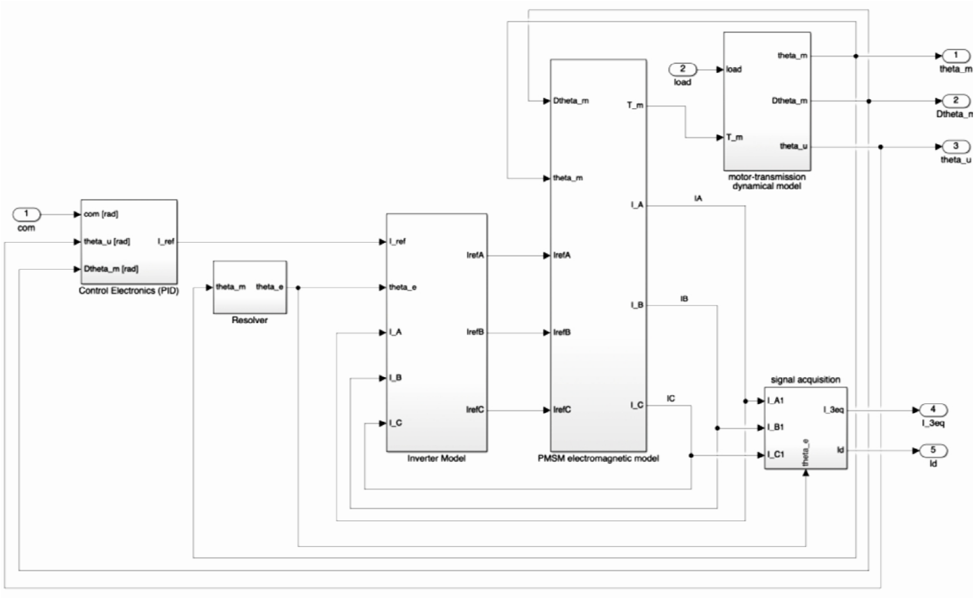

Fig. 1. Overview of the Medium Fidelity model.

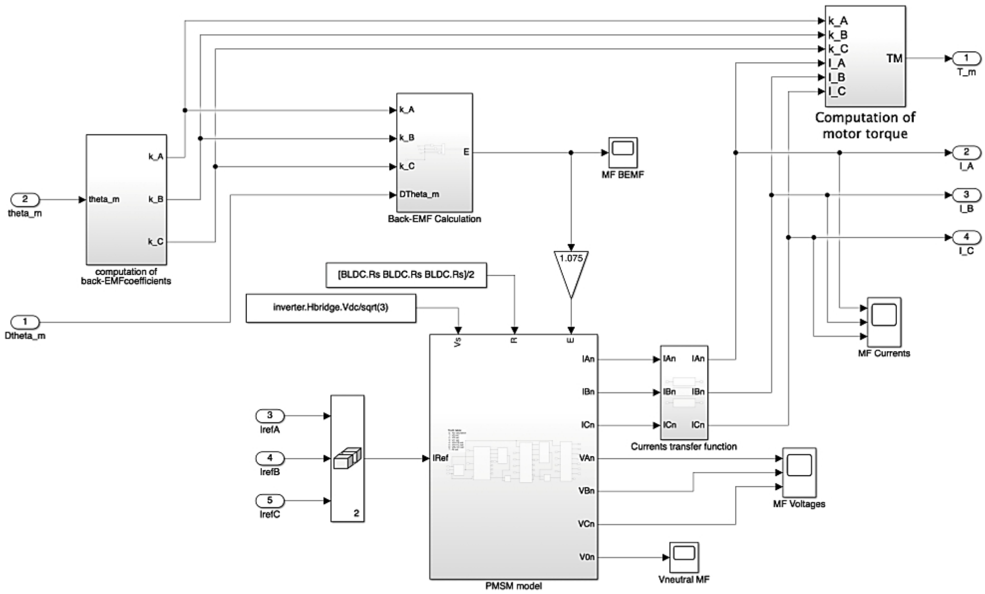

Fig. 2. PMSM subsystem.

3. PMSM model

In this work, the PMSM is modeled using a finite state machine to comply with conditions of voltage saturation where the ELF model would not accurately describe the system behavior. As visible in Figure 3, three evaluations are necessary to determine the total motor voltage saturation condition. Since the motor is current controlled, the three reference currents are used to calculate the three different control voltages:

$$V_j^{ref} = R_j \cdot i_j^{ref} + E_j = R_j \cdot i_j^{ref} + k_j \cdot \omega_m \qquad (2)$$

where V_j^{ref} and i_j^{ref} are the reference voltage and current for a phase, E_j is the phase back-EMF, k_j is the back-EMF coefficient and ω_m is the motor angular speed. However, these voltages are limited by the maximum supply voltage, V_s. It is thus possible to have a condition in which one or more phases are in voltage saturation, so that phase(s) have to be set equal to

$V_j = V_s \cdot sign(V_j^{ref})$.

After saturation are imposed, the electrical circuit is resolved obtaining currents and voltages for the three phases and the neutral voltage, being a wye-wound circuit. However, it is now necessary to re-evaluate the voltages obtained after the first step. It is possible that, after one phase becomes voltage-saturated, the system imbalance could push the other phases voltage above the supply value. The truth tables (*Case eval 1st stage*, *Case eval 2nd stage*) are used to compare the step output voltages to V_s, and a flag is used to determine which phases are in saturation. The direct lookup tables (*2nd step case selection*, *3rd step case selection*) are then used to select which set of equations the next step will use to solve the system. These tables are used to keep track of which phases have already been set to saturated in previous steps and add the newly saturated phases.

In particular, three different evaluations are needed since a condition that can occur is that only one phase is initially saturated; after system resolution, however, is found that a second phase is also in saturation; the final evaluation might show that even the third phase in saturation. Thus, only the last step currents and voltages are used as 'true' values outside of this subsystem For all the blocks in the subsystem, the truth table shown in Figure 3 is used to maintain consistency.

4. Comparison with HF model

In this section, a comparison with the HF model, same as in (Dalla Vedova et al., 2019), will be made for a single condition. The imposed command is a simple step command, starting at 0.05 s with an amplitude of 1 rad. The system has been set to nominal conditions, so no partial phase short (i.e. n_j = 1) or static eccentricity is present. In Figure 4, a comparison of the voltage, relative to phase A, is shown. A limited discrepancy between HF and MF is observable, especially in the maximum values obtained by the MF model, which is higher than those obtained using the HF model. However, there is a good match between the two models.

To remove high-frequency noise, arising from the transistors commutation (hysteresis control), a third-order low pass filter (realized by cascading three first-order low-pass filters, similar to equation (1)) has been applied to both systems, with a time constant of τ_F = 5 μs. Analogously, in Figure 5, a comparison of phase B current is shown.

A different phase has been graphed to show that different phases behave as expected and to avoid cherry-picking.

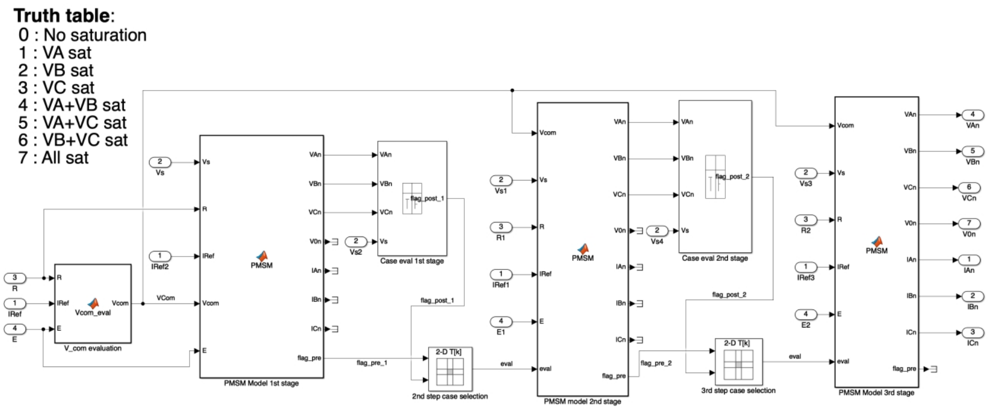

Fig. 3. Proposed PMSM implementation in Medium Fidelity model.

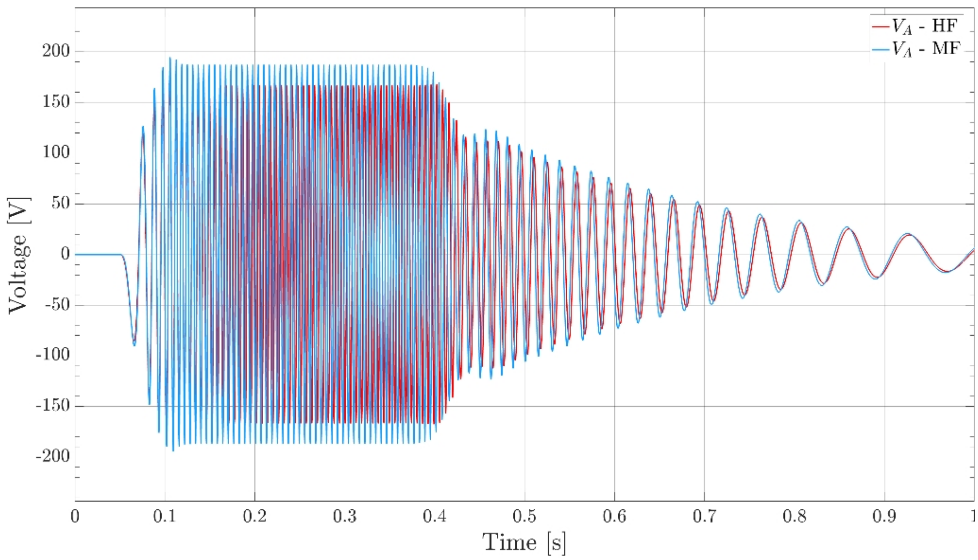

Fig. 4. Voltage comparison, Phase A, filtered.

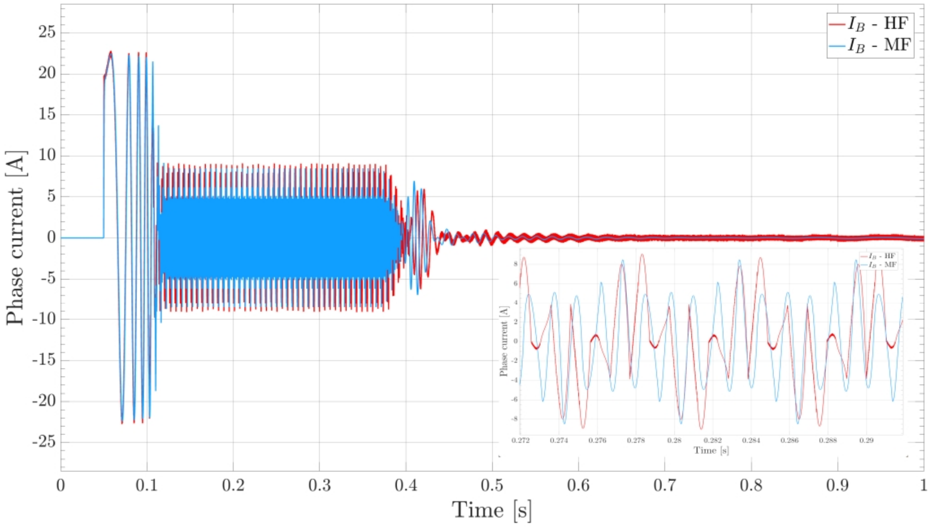

Fig. 5. Comparison of phase B current.

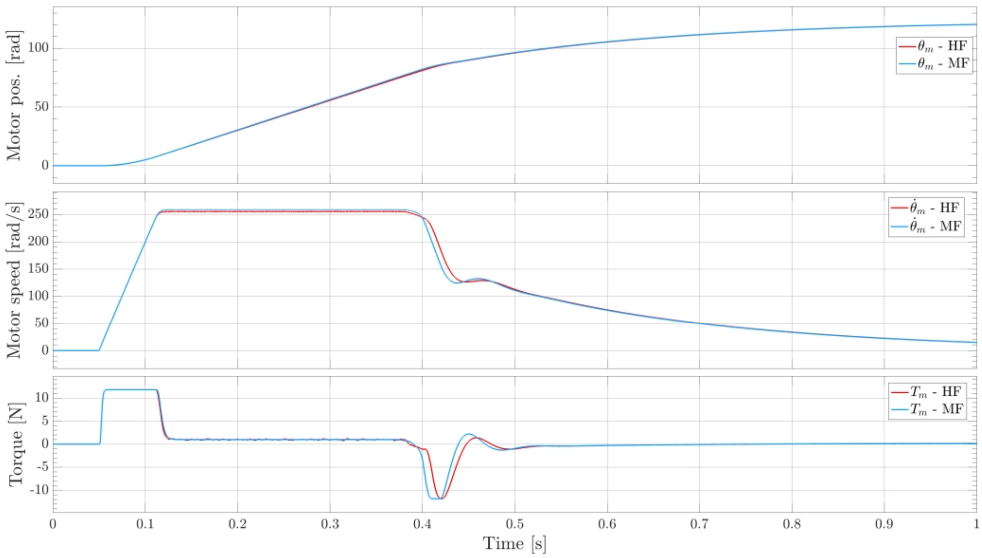

Fig. 6. Comparison of mechanical quantities.

The waveform is slightly different, especially in the constant speed regime (~ 0.1 – 0.4 s), as shown in the detail plot. The amplitude is similar, even though the signals are slightly out of phase; however, with more complex filtering, it should be possible to better match the phases. In Figure 6, mechanical quantities of interest are shown; in particular, motor position, motor speed and motor torque. For the mechanical quantities, there is a very good match between HF and MF models, especially for motor (and thus user) position.

A small but not insignificant discrepancy in the maximum actuation speed is observed: this phenomenon has been corrected with a slight increase of the back-EMF of 7.5%, however this value can be further optimized as to obtain a better match between the two models. In fact, the maximum speed is an important parameter since it changes the whole model behavior, as visible in the torque graph. Even though the maximum torque is the same, the HF model has a noticeable delay after the constant speed period, as visible in the (negative) peak at around 0.42 s. This is caused by the slight speed error that, when integrated over time, changes the dynamic response of the system.

5. Conclusions

In this paper, we have shown the structure of a new reduced-order MF model, called Medium Fidelity, of a PMSM-driven electromechanical actuator. The model was then compared to the previously used High Fidelity model at the component level. It has been shown that the MF model, even with the quite strong simplifying assumptions made, e.g. filtered ohmic circuit and lack of electronic driver, produces results in agreement with the reference model. Some numerical corrections have been made, in particular a 7.5% gain for the back-EMF has been implemented, as to better match the original HF model. Furthermore, the filtering coefficient for the first-order low pass filter used to model the inductive behavior have been directly obtained from the physics of the system. However, these values can still be optimized to achieve better accuracy. Finally, the Medium Fidelity model outperform the HF model for computation time, as the mean runtime for a 3 s simulation is 11.5 s as compared to 93.9 s on a 13” MacBook Pro 2020 (M1) with 16GB of RAM using Matlab R2021B in Normal mode, showing a great improvement. The proposed model could be used to generate datasets for prognostics when detailed data regarding the electrical components are not needed.

For future developments, it will be necessary to test the fidelity of the MF model simulation with different fault magnitudes and commands. Furthermore, the subsystem simulating the effects due to the saturation of the stator phases of the PMSM should be improved to increase its fidelity even in the presence of strong EM non-linearities.

References

Baraldi, P., F. Cadini, F. Mangili, E. Zio. 2013. Model-based and data-driven prognostics under different available information. Probabilistic Engineering Mechanics 32, 66-79.

Belmonte, D., M. D. L. Dalla Vedova, P. Maggiore. 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, 2365-2372.

Berri, P., M. D. L. Dalla Vedova, P. Maggiore, et al. 2017. On-board electromechanical servomechanisms affected by progressive faults: proposal of a smart ga model-based prognostic approach. Safety and Reliability - Theory and Applications - Proceedings of the 27th European Safety and Reliability Conference, ESREL 2017, 839-846.

Berri, P. C., M. D. L. Dalla Vedova, L. Mainini. 2021. Computational framework for real-time diagnostics and prognostics of aircraft actuation systems. Computers in Industry 132, 103523.

Byington, C. S., M. Watson, D. Edwards, P. Stoelting. 2004. A model-based approach to prognostics and health management for flight control actuators. 2004 IEEE aerospace conference proceedings (IEEE Cat. No. 04TH8720), 3551-3562.

Daigle, M., B. Saha, K. Goebel. 2012. A comparison of filter-based approaches for model-based prognostics. In 2012 ieee aerospace conference, IEEE, 1-10.

Dalla Vedova, M. D. L., P. C. Berri. 2019. Optimization techniques for prognostics of on-board electromechanical servomechanisms affected by progressive faults. International Review of Aerospace Engineering 12(4), 160-170.

de Pater, I., M. Mitici. 2021. Predictive maintenance for multi-component systems of repairables with remaining-useful-life prognostics and a limited stock of spare components. Reliability Engineering & System Safety 214, 107761.

de Pater, I., A. Reijns, and M. Mitici (2022). Alarmbased predictive maintenance scheduling for aircraft engines with imperfect remaining useful life prognostics. Reliability Engineering & System Safety 221, 108341.

Quattrocchi, G., M. D. L. Dalla Vedova, P. C. Berri. 2023. Lumped parameters multi-fidelity digital twins for prognostics of electromechanical actuators. Journal of Physics: Conference Series 2526(1), 012076.

Tsui, K. L., N. Chen, Q. Zhou, Y. Hai, W. Wang. 2015. Prognostics and health management: A review on data driven approaches. Mathematical Problems in Engineering 2015.

Zio, E. 2022. Prognostics and health management (phm): Where are we and where do we (need to) go in theory and practice. Reliability Engineering & System Safety 218, 108119.