

Fault Detection and Mitigation in a Multi-Stage Coreless Axial-Flux PM Motor System

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Abstract—Coreless Axial-Flux Permanent Magnet (CAFPM) Synchronous Machines offer unique advantages over conventional cored ones, due to their potential to achieve high efficiencies and power densities. However, the absence of core material leads to higher currents and overheating under fault conditions, resulting in the need for reliable fault detection algorithms. This paper presents the design of an Extended Kalman Filter (EKF) for estimating the electromagnetic torque produced by the faulty stage in a dual-stage Coreless Axial-Flux Permanent Magnet (CAFPM) motor for aerospace applications. The EKF exploits the measurements available from the healthy unit, as the information regarding the currents flowing in the faulty unit's stator is not available in case of an internal short-circuit. The estimation will serve an algorithm under development to determine whether the faulty unit is affected by an internal short-circuit, and to decide if it is necessary to stop the shaft or if continued operation can be guaranteed. The effectiveness of the proposed algorithm is proved by the simulation results.

Index Terms—axial-flux, multi-stage, coreless, fault detection, extended Kalman filter, aerospace propulsion

I. INTRODUCTION

Coreless Axial-Flux Permanent Magnet (CAFPM) Synchronous Machines (SMs) offer unique advantages over conventional cored ones [1]–[5]. Due to the lack of a magnetic core and its associated power losses, there is potential to achieve high efficiencies and power densities, making coreless machines well-suited for aerospace applications [6], especially in multi-stator or multi-motor drive configurations [7], [8]. The multi-stage motor configuration has already found application in aerospace, such as in [9].

A critical aspect of coreless technologies is the intrinsically low stator inductance caused by the lack of core material. In case of an internal stator fault, the high value of the fault current can cause severe damage due to unacceptable overheating. It follows that, among the faults that may affect a multi-stage propulsion system, the most critical one is represented by a short-circuit occurring in one module [7]. In this situation, a fault current flows as long as the shaft

rotates, and the faulty module will operate as a brake due to the constant PM excitation. Although this condition is common to any modular configuration [10], it is more severe for coreless machines, where the low stator inductance entails a higher fault current [11]. For this reason, the online detection of this fault and the monitoring of the faulty module is of key importance in critical applications.

State observers have been extensively used in electrical drives for fault detection and performance improvement purposes [12]–[15]. A state observer is a mathematical model that uses the available measurements of a system to reconstruct its unmeasured state variables. Among the different state observers that have been used in the literature [16]–[18], the Extended Kalman Filter (EKF) has proved to be suitable in applications involving nonlinear systems, parameter uncertainty, and unknown parameter estimation [15], [19].

In case in which the short-circuit is internal, the stator currents flowing in the faulty stage cannot be measured, so it is not possible to determine whether the fault currents are still flowing after the protection intervention. However, the faulty motor produces a characteristic braking torque that is function of the operating speed and fault typology. Since the two stages are connected in mechanical series, a state observer can be used to exploit the available measurements from the healthy units to reconstruct the unmeasured states in the faulty unit, thereby monitoring its state of health.

This work proposes an EKF for the online estimation of the electromagnetic torque produced by the faulty stage in a dual-stage CAFPM motor for aerospace applications. The EKF exploits the measurements available from the healthy unit, as the information regarding the currents flowing in the faulty unit's stator is not available in fault conditions, and it reconstructs the braking torque produced by it. The choice of the EKF as the state estimator is justified by its capability of estimating unknown quantities and its robustness against parameter uncertainty. Although it is applied to a coreless

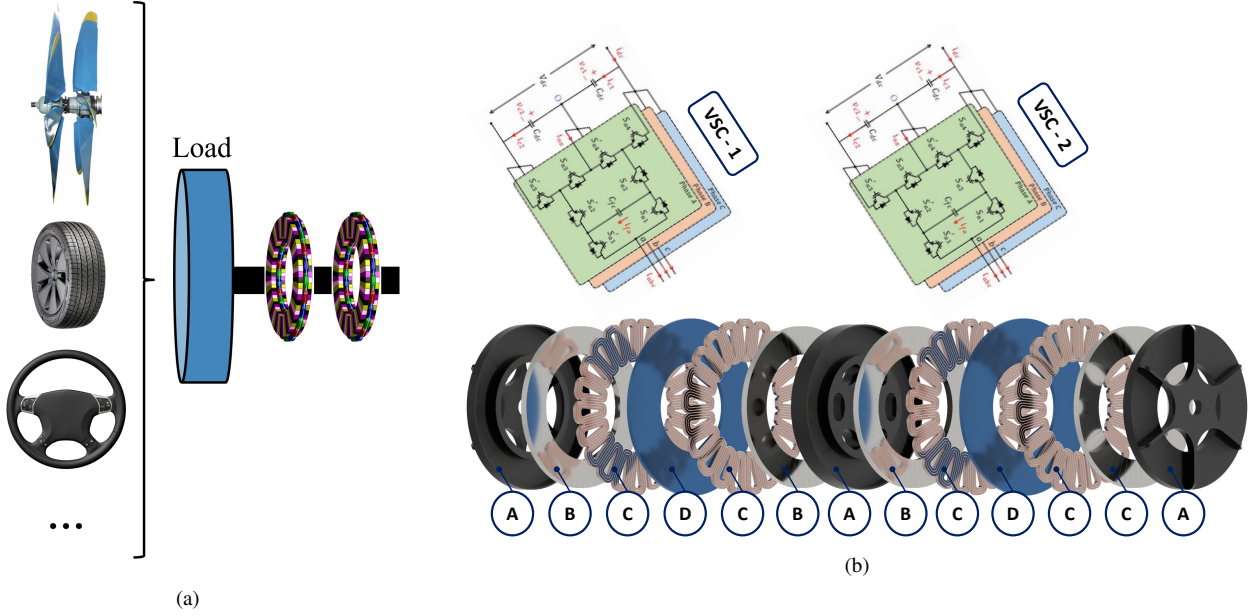


Fig. 1. Dual-stage CAFPM system: (a) overview of the system: in this work, a propeller is considered as a rotating load, but the analysis can be extended to other applications; (b) exploded view of the system with labeled components, comprising two stages with rotor holders (A), Halbach-array PM rotors (B), three-phase concentrated-coil winding (C), and cooling plates (D), each stage fed by a dedicated Voltage Source Converter (VSC).

drivetrain for aerospace applications, the proposed estimator can be applied to any multi-stage motor.

The estimation can be used by a dedicated fault-detection algorithm to determine whether the faulty unit is affected by an internal short-circuit, and to decide if it is necessary to stop the shaft in a multi-stage drivetrain. This is extremely important in critical applications, such as in aerospace [20], since this would prevent high fault current to flow inside the faulty stator, avoiding a potential hazard for the vehicle and the passengers. The paper is structured as follows: in Section II the dual-stage CAFPM is described and its analytical model is presented; Section III introduces the EKF algorithm and its design; in Section IV the estimation performance is discussed based on simulation results; the key findings of this paper are reported in Section V.

II. SYSTEM DESCRIPTION

The system under analysis is a dual-stage CAFPM drivetrain, consisting of two identical Halbach-array PM rotor three-phase CAFPM synchronous motors mounted on the same shaft and connected to a rotating load, as shown in Fig. 1a. Although this work considers the load to be a propeller for an aerospace application, the proposed study can be applied to any modular system.

Each stage is fed by a dedicated Voltage Source Converter (VSC), delivering half of the required power. The exploded view of the propulsion system is given in Fig. 1b. One EKF will be designed for each stage, its objective being the estimation of the electromagnetic torque produced by the other one. Since the state estimator relies on the state-space representation of the physical system, the electrical and mechanical models related to the single stage is defined. The

control model is not included, as the state observer estimates will not be used as feedback, hence they are independent of the system control dynamics. Both models are expressed on a per-unit (p.u.) basis. Since the two motors representing the stages are identical, the definition of each stage's EKF is identical.

A. Mechanical Model

The mechanical model in p.u. modeling the system is based on Newton's second law, hence:

$$\begin{cases} p\omega_m = \frac{t_{elm,u1}}{2H_m} + \frac{t_{elm,u2}}{2H_m} - \frac{t_{prop}}{2H_m} \\ p\theta_m = \Omega_b \omega_m \end{cases} \quad (1)$$

where: $p = d/dt$ is the derivative operator; ω_m and θ_m are the mechanical speed and angular position; $\Omega_b = \Omega_n$ is the base mechanical angular frequency; $t_{elm,u1}$ and $t_{elm,u2}$ are the electromagnetic torque produced by unit one and two; t_{prop} is the propeller torque; $H_m = 0.5J_{m,tot}\Omega_b^2/(T_b\Omega_b)$ is the propulsion system inertia constant, with $J_{m,tot} = J_{prop} + n_{stage} * J_m$ being the total drivetrain inertia, with $n_{stage} = 2$ for the dual-stage motor under investigation.

B. Electrical Model

The electrical model in p.u. related to the single CAFPM unit is based on the $\alpha - \beta$ stator voltage equations:

$$\begin{cases} pi_\alpha = -\frac{r_s\omega_b}{l_s}i_\alpha + \frac{\omega_b\hat{\psi}_{pm}}{l_s}\omega_m \sin(pp\theta_m) + \frac{\omega_b}{l_s}v_\alpha \\ pi_\beta = -\frac{r_s\omega_b}{l_s}i_\beta - \frac{\omega_b\hat{\psi}_{pm}}{l_s}\omega_m \cos(pp\theta_m) + \frac{\omega_b}{l_s}v_\beta \end{cases} \quad (2)$$

where: $i_\alpha, i_\beta/v_\alpha, v_\beta$ are the $\alpha - \beta$ stator currents and voltages; $\omega_b = pp\Omega_b$ is the base electrical angular frequency, with pp

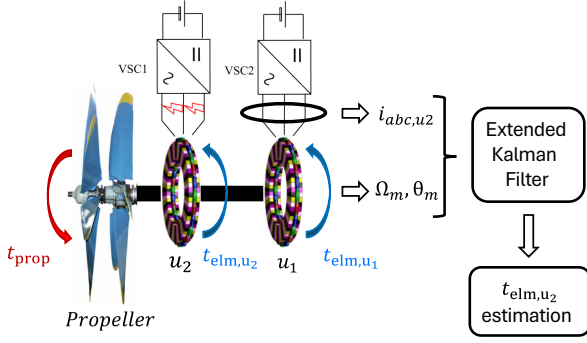


Fig. 2. Sketch representing the idea behind the state estimator: the EKF is used to estimate the torque produced by unit two u_2 , by processing the electrical and mechanical measurements of unit one u_1 .

being the motor pole-pair; r_s and l_s are the per unit stator resistance and synchronous inductance, and $\hat{\psi}_{pm}$ is the per unit PM flux linkage. The electromagnetic torque produced by the single CAFPM unit is given by:

$$t_{elm} = \hat{\psi}_{pm} i_\beta \cos(pp \theta_m) - \hat{\psi}_{pm} i_\alpha \sin(pp \theta_m). \quad (3)$$

The electrical and mechanical parameters are listed in Table II in the Appendix.

III. MUTUAL TORQUE ESTIMATION THROUGH EXTENDED KALMAN FILTER

Let us consider a generic discrete-time stochastic nonlinear process of the form [19]:

$$\begin{cases} \mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}) + \mathbf{w}_{k-1} \\ \mathbf{y}_k = \mathbf{h}(\mathbf{x}_k) + \mathbf{v}_k \end{cases}, \quad (4)$$

where $\mathbf{f}(\mathbf{x}, \mathbf{u})$ and $\mathbf{h}(\mathbf{x})$ are nonlinear functions modeling the system dynamics and observations, $\mathbf{x} \in \mathbf{R}^n$ represent the state variables of the system, $\mathbf{u} \in \mathbf{R}^p$ are the system inputs, $\mathbf{y} \in \mathbf{R}^q$ are the system observations, and $\mathbf{w}$ and $\mathbf{v}$ are additive noises representing the model and observation errors. Both $\mathbf{w}$ and $\mathbf{v}$ are zero-mean white noises, with covariance matrices $\mathbf{Q}$ and $\mathbf{R}$ respectively. The EKF works with nonlinear systems of differential equations, and it reconstructs the system state variables by means of a minimum variance estimation, based on a linear combination of the observation $\mathbf{y}_k$ and of the model forecast $\mathbf{f}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1})$ at each time step k . The workflow of the EKF is reported in Algorithm 1.

A. Preliminary Considerations

Let us focus on the design of the EKF applied to unit one u_1 and let us assume that a short-circuit fault occurs in unit two u_2 . It is worth mentioning that the same state estimator is implemented for both units, as they are identical, and the analysis is also valid if a fault occurred on u_1 .

The objective is the online estimation of the electromagnetic torque that is being produced by u_2 , relying only on the measurements related to u_1 . A sketch of the state estimator applied to the dual-stage CAFPM is shown in Figure 2. In

Algorithm 1 Pseudo-algorithm defining the EKF implementation step-by-step.

Initialization: $\mathbf{x}_0^A, \mathbf{P}_0^A, \mathbf{Q}, \mathbf{R}, k = 0$;

Inputs: $\mathbf{u}_k, \mathbf{y}_k$;

Output: Estimated state variables $\mathbf{x}_k^A$.

while ON **do**

$k = k + 1$

$\tilde{\mathbf{A}} = \frac{\partial \mathbf{f}}{\partial \mathbf{x}} \big|_{\mathbf{x}_{k-1}^A}$

$\tilde{\mathbf{B}} = \frac{\partial \mathbf{f}}{\partial \mathbf{u}} \big|_{\mathbf{u}_{k-1}}$

$\mathbf{x}_k^F = \tilde{\mathbf{A}} \mathbf{x}_{k-1}^A + \tilde{\mathbf{B}} \mathbf{u}_k$

$\mathbf{P}_k^F = \tilde{\mathbf{A}} \mathbf{P}_{k-1}^A \tilde{\mathbf{A}}^T + \mathbf{Q}$

$\mathbf{K}_k = \mathbf{P}_k^F \mathbf{C}^T (\mathbf{C} \mathbf{P}_k^F \mathbf{C}^T + \mathbf{R})^{-1}$

$\mathbf{P}_k^A = (\mathbf{I} - \mathbf{K}_k \mathbf{C}) \mathbf{P}_k^F$

$\mathbf{x}_k^A = \mathbf{x}_k^F + \mathbf{K}_k (\mathbf{y}_k - \mathbf{C} \mathbf{x}_k^F)$

end while

fact, if a short-circuit occurs in unit two, the measurement of the currents flowing inside its stator are not available anymore after the intervention of the protections. Moreover, if the short-circuit is internal, a fault current will flow as long as the shaft is rotating, due to the uncontrolled PM excitation.

The estimation will be required by a future fault-detection algorithm to determine whether u_2 is affected by an internal short-circuit, and to decide if it is necessary to stop the shaft. This is extremely important in aerospace application, since this would prevent high fault current to flow inside the faulty stator, avoiding a potential hazard for the vehicle and the passengers.

In [11], it is shown how the braking torque produced in case of a three-phase short-circuit in a CAFPM motor has a damped second-order dynamic with a constant steady-state value. Moreover, in healthy conditions, the electromagnetic torque produced by u_2 is constant in most of the system operating conditions. Thus, the EKF has to be designed to estimate a constant electromagnetic torque produced by unit two $t_{elm,u2}$, solving a problem referred to in the literature as system identification.

In particular, the unknown torque $t_{elm,u2}$ is considered as an unknown system parameter by the EKF. The observer treats it as an extended state variable, and a differential equation must be defined for it. Since it is a constant quantity and assuming there is no knowledge of its model, the differential equation is usually represented by the derivative of the unknown constant parameter to be equal to zero. This technique is the so-called state augmentation [19].

B. Extended Kalman Filter Design

Recalling (4), and considering (1), (2), and (3), one can define the following system of nonlinear differential equations

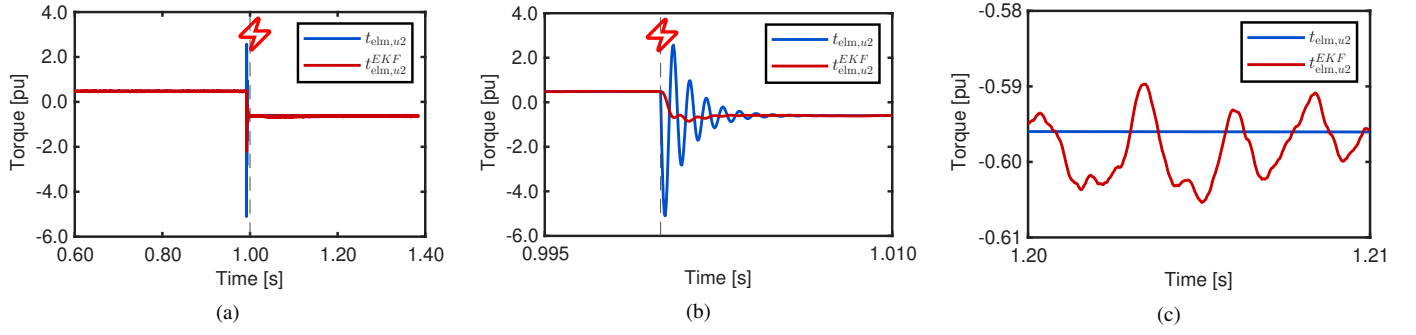


Fig. 3. Evaluation of the EKF estimation performance in case of a three-phase short-circuit affecting u_2 : (a) a panoramic view of the real and estimated values of $t_{elm,u2}$ throughout the simulation, showing how the EKF algorithm is stable both in healthy and faulty conditions; (b) a focus on the estimation of the fast second-order torque oscillation typical of three-phase short-circuit: the EKF struggles at reconstructing the oscillation, while it quickly converges to the constant steady-state solution; (c) steady-state performance of the EKF estimation in faulty conditions: it can be seen how the estimation error keeps low in value, while the oscillations are noises related to the EKF operation.

$p \mathbf{x} = \mathbf{f}(\mathbf{x}, \mathbf{u})$ for the EKF:

$$\begin{cases} p i_{\alpha,u1} = -\frac{r_s \omega_b}{l_s} i_{\alpha,u1} + \frac{\omega_b \hat{\psi}_{pm}}{l_s} \omega_m \sin(pp \theta_m) \\ \quad + \frac{\omega_b}{l_s} v_{\alpha,u1} \\ p i_{\beta,u1} = -\frac{r_s \omega_b}{l_s} i_{\beta,u1} - \frac{\omega_b \hat{\psi}_{pm}}{l_s} \omega_m \cos(pp \theta_m) \\ \quad + \frac{\omega_b}{l_s} v_{\beta,u1} \\ p \omega_m = \frac{\hat{\psi}_{pm}}{2H_m} i_{\beta,u1} \cos(pp \theta_m) - \frac{\hat{\psi}_{pm}}{2H_m} i_{\alpha,u1} \sin(pp \theta_m) \\ \quad + \frac{t_{prop}}{2H_m} + \frac{t_{elm,u2}}{2H_m} \\ p \theta_m = \Omega_b \omega_m \\ p t_{elm,u2} = 0 \end{cases}, \quad (5)$$

where the subscript u_1 denotes that the variables are referred to unit one, $\mathbf{x} = [i_{\alpha,u1}, i_{\beta,u1}, \omega_m, \theta_m, t_{elm,u2}]^T \in \mathbb{R}^n$ with $n = 5$ are the system state variables, $\mathbf{u} = [v_{\alpha,u1}, v_{\beta,u1}, t_{prop}]^T \in \mathbb{R}^p$ are the system input variables, with $p = 3$. The differential equations $p t_{elm,u2} = 0$ is added so that the EKF provides the estimation of the electromagnetic torque produced by unit two. Considering that they are needed for the closed-loop control of each unit, the measurements available from unit one are $\mathbf{y} = [i_{\alpha,u1}, i_{\beta,u1}, \omega_m, \theta_m]^T \in \mathbb{R}^q$ with $q = 4$.

The last step is to transform the system in discrete-time form for the EKF algorithm. Applying forward-Euler discretization to $p \mathbf{x} = \mathbf{f}(\mathbf{x}, \mathbf{u})$, the following can be obtained:

$$\begin{cases} \mathbf{x}_k = \mathbf{F}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}) + \mathbf{w}_{k-1} \\ \mathbf{y}_k = \mathbf{C} \mathbf{x}_k + \mathbf{v}_k \end{cases}, \quad (6)$$

where $\mathbf{w}_{k-1}$ and $\mathbf{v}_k$ are the model and observation errors, $\mathbf{F}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}) = \mathbf{x}_{k-1} + h_{step} * \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1})$, with h_{step}

being the integration time-step, and:

$$\mathbf{C} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \in \mathbb{R}^{q \times n}$$

is the output matrix.

The definition of the covariance matrices of the model and observation errors, i.e. $\mathbf{Q} \in \mathbb{R}^{n \times n}$ and $\mathbf{R} \in \mathbb{R}^{q \times q}$, is based on a trial-and-error approach, starting with a first guess obtained applying the method proposed in [21]. Both matrices are defined in a diagonal form, assuming the model errors to be uncorrelated, as well as the observation errors.

The initial conditions of the EKF algorithm has to be defined, i.e. the estimates of the state variables and the estimation error covariance matrix $\mathbf{P}_0^A \in \mathbb{R}^{n \times n}$ initial values. Concerning the initial conditions of the state estimates, they can be all set to zero, assuming no information is available prior to the start of the data acquisition. The variances related to the initial estimation errors, needed for the definition of $\mathbf{P}_0^A$, can be defined assuming the errors to have zero mean and uniform probability distribution ranging from the maximum and minimum value each state variable can assume in nominal operating conditions [21]. Starting from $i_{\alpha,u1}$, $i_{\beta,u1}$, and ω_m , they are expressed in per unit, so their values range between $[-1, 1]$ p.u., therefore $\sigma_{0,i_{\alpha,u1}}^2 = \sigma_{0,i_{\beta,u1}}^2 = \sigma_{0,\omega_m}^2 = 1/3$. Differently, θ_m ranges between $[-\pi, \pi]$, thus $\sigma_{0,\theta_m}^2 = \pi^2/3$. As for $t_{elm,u2}$, one can assume that the EKF algorithm starts operating when the system is in healthy conditions, thus its value can range between $[-1, 1]$ p.u.; therefore $\sigma_{0,t_{elm,u2}}^2 = 1/3$. Finally, $\mathbf{P}_0^A$ is defined as:

$$\mathbf{P}_0^A = \text{diag} \left[\sigma_{0,i_{\alpha,u1}}^2, \sigma_{0,i_{\beta,u1}}^2, \sigma_{0,\omega_m}^2, \sigma_{0,\theta_m}^2, \sigma_{0,t_{elm,u2}}^2 \right].$$

IV. RESULTS AND DISCUSSION

The estimation performance of the EKF designed for unit one to track the electromagnetic torque of unit two is tested

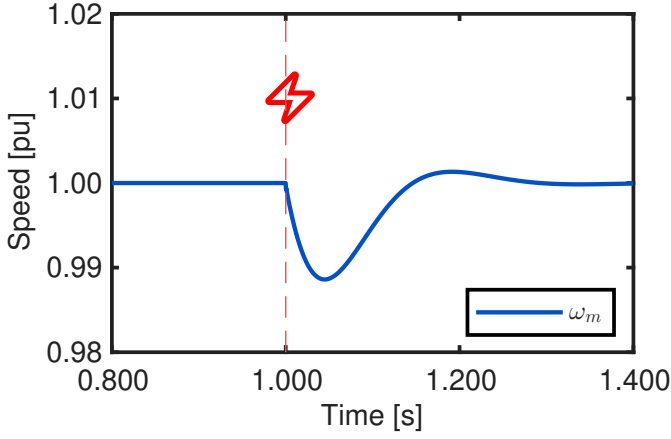


Fig. 4. Operating speed of the dual-stage CAFPM motor during the simulation: the speed decrement when a three-phase short-circuit occurs in unit two is limited by the high system inertia and torque response.

in a Matlab/Simulink environment. An aircraft cruise-mode operation is considered, where the dual-stage motor operates at nominal speed with each stage delivering half of the rated torque to move the propeller. A fault occurring during this operating condition represents the worst-case scenario, as the motor is operating at nominal speed and the aircraft cannot be stopped.

Each stage is fed by a dedicated VSC with Sinusoidal Pulse-Width Modulation (SPWM), operated with a constant switching frequency $f_{sw} = 50$ [kHz]. A high switching frequency is needed to limit current ripples due to the low stator inductance, typical of coreless motors [1]. The PI controllers and the EKF operate in discrete-time use an integration time step $h_{step} = 40$ [μ s].

It is assumed that the propeller torque t_{prop} can be measured or estimated, and its information is used as an input variable of the EKF; a uniformly distributed random noise ranging between $\pm 5\%$ of the nominal torque is added to it, to represent a more realistic case scenario. As for the $\alpha - \beta$ components of the stator voltages $v_{\alpha,u1}$ and $v_{\beta,u1}$ needed as the EKF inputs, the PI controllers' voltage references are used instead, since their measurement is not available in conventional drive systems. The speed and current PI control loop bandwidths are $f_{c,\Omega} = 10$ [Hz] and $f_{c,I} = 1000$ [Hz] respectively.

The values of the elements in $\mathbf{Q}$ and $\mathbf{R}$ used in the simulation can be found in the Appendix. The EKF estimation performance will be evaluated comparing the real and estimated electromagnetic torque produced by unit two $t_{elm,u2}$.

A. Three-Phase Short-Circuit Simulation

In this simulation, an internal three-phase short-circuit is introduced in unit two at 1 [s]. The speed of the motor during the simulation is shown in Figure 4. The speed decrement is limited by the high system mechanical inertia and by the fast torque response that characterizes CAFPM motors, as discussed in [11].

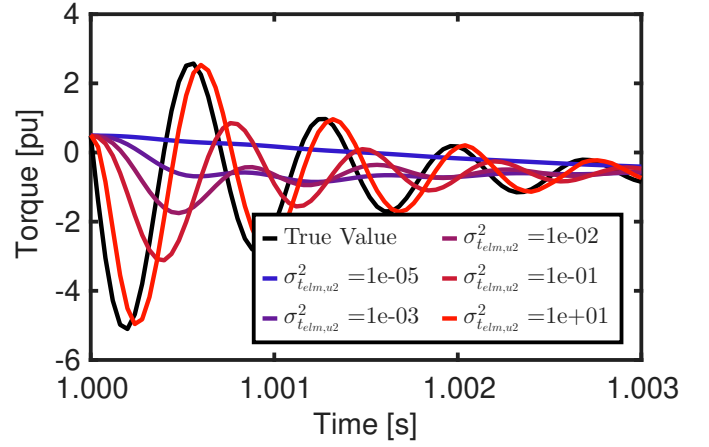


Fig. 5. Comparison of the EKF's ability to follow fast dynamics of $t_{elm,u2}$ at different selections of the variance of the model error of $t_{elm,u2}$, i.e. $\sigma_{t_{elm,u2}}^2$; it can be seen how the higher the value of $\sigma_{t_{elm,u2}}^2$, the better the tracking of the fast second-order torque oscillation.

The real and EKF-estimated value of $t_{elm,2}(t)$ are shown in Figure 3. Figure 3a provides a panoramic view of the EKF performance throughout the simulation, showing how the algorithm is stable and converges to an estimation both in healthy and faulty conditions. The EKF is not able to track the fast second-order transient oscillation that characterizes the three-phase short-circuit, as can be seen in Figure 3b. The estimation converges to the constant steady-state value in approximately 10 [ms], and it shows a limited steady-state error visible in Figure 3c. The proposed EKF is effective at estimating the braking torque related to an internal short-circuit occurring in the faulty unit. This information can be processed and used by a fault-detection algorithm to monitor the state-of-health of the units.

B. Impact of $t_{elm,u2}$ Model Covariance on Estimation Performance

To improve the dynamic response of the estimation, one may try to increase the variance of the model error of $t_{elm,u2}$, i.e. $\sigma_{t_{elm,u2}}^2 \in \mathbb{R}$. However, the EKF would be more sensitive to measurement noise and parameter uncertainties, so the estimation would be less robust.

To prove this, four different simulations are performed, each time changing the value of $\sigma_{t_{elm,u2}}^2$ in $\mathbf{Q}$, which is kept constant during the simulation. The estimation behavior of the EKF during transient conditions is shown in Figure 5, for the cases in which $\sigma_{t_{elm,u2}}^2 = [10, 10^{-1}, 10^{-2}, 10^{-3}, 10^{-5}]$. It is evident how by increasing the value of $\sigma_{t_{elm,u2}}^2$ the torque estimate's dynamics becomes faster, although the EKF keeps struggling to follow the fast second-order transient with any value of $\sigma_{t_{elm,u2}}^2$.

However, the speed of the estimation response must be evaluated alongside the variance of the estimation error, which serves as an indicator of the filter's accuracy. At a generic time step k , its value is given by the diagonal element of matrix $\mathbf{P}_k^A$ related to the state variable of interest. Let us

TABLE I
ESTIMATION STEADY-STATE UNCERTAINTY EVALUATION AT DIFFERENT
SELECTION OF THE VARIANCE OF $\sigma_{t_{elm,u2}}^2$

$\sigma_{t_{elm,u2}}^2$	10^{-5}	10^{-3}	10^{-2}	10^{-1}	10
$\sigma_{t_{elm,u2},SS}^{A^2}$	0.001	0.017	0.097	0.550	18.8
$\bar{\epsilon}_{t_{elm,u2},SS}$	0.002	0.004	0.005	0.007	0.015

define the variance of the estimation error of $t_{elm,u2}$ at step k as $\sigma_{k,t_{elm,u2}}^{A^2} \in \mathbf{P}_k^A$: this quantity is updated by the EKF at each integration step. Let us calculate its average value $\sigma_{t_{elm,u2},SS}^{A^2}$ at steady-state, so calculating the average of the values $\sigma_{k,t_{elm,u2}}^{A^2}$ from 1.5 [s] to 2.0 [s] simulation time; this quantity serves as an average value of the uncertainty related to the estimation of the state variable $t_{elm,u2}$ in a steady-state condition. The time interval used to calculate its mean was selected in order to capture a steady-state condition. Finally, let us define the average of the estimation error at steady-state $\bar{\epsilon}_{t_{elm,u2},SS}$, evaluated in the same time interval.

These variables are calculated for each selection of $\sigma_{t_{elm,u2}}^2$, and are listed in Table I. It can be seen that, by increasing the variance of the model error referred to $t_{elm,u2}$, the value of $\sigma_{t_{elm,u2},SS}^{A^2}$ increases exponentially, and so the uncertainty of its estimation at steady-state. By considering the estimation error to be zero-mean and with a Gaussian distribution, by choosing $\sigma_{t_{elm,u2}}^2 = 10$ one would obtain an estimation error with a standard deviation at steady-state $\sigma_{t_{elm,u2},SS}^A = 0.5 \sqrt{\sigma_{t_{elm,u2},SS}^{A^2}} = 0.5 \sqrt{18.8} = 2.2$ [pu]. It is clear how this range of uncertainty is unacceptable, and the estimation not reliable. As previously stated, the EKF estimation ability to track fast dynamics is directly proportional to $\sigma_{t_{elm,u2}}^2$: as shown in Fig. 5, the greater $\sigma_{t_{elm,u2}}^2$, the better the estimation of the braking torque's fast transient. Finally, the value of the average steady-state estimation error $\bar{\epsilon}_{t_{elm,u2},SS}$ shows a slight increase directly proportional to $\sigma_{t_{elm,u2}}^2$, however keeping always low in value.

C. On-Going Experimentation

The proposed algorithm is being tested on a laboratory test-bench comprising two CAFPMs connected in mechanical series on the same shaft, as shown in Fig. 6. One of the two motors is fed by a dedicated VSC, while the other one is connected through a mechanical switch to a low-impedance RL load. The mechanical and electrical time constants of the system are similar to the dual-stage motor considered in this paper for high-power aerospace applications. In this way, a controlled three-phase short-circuit can be inserted, and the proposed algorithm can be tested.

V. CONCLUSION

In this work, an EKF was designed for the online estimation of the electromagnetic torque produced by each unit of a dual-stage CAFPM for electrified propulsion. If an internal short-

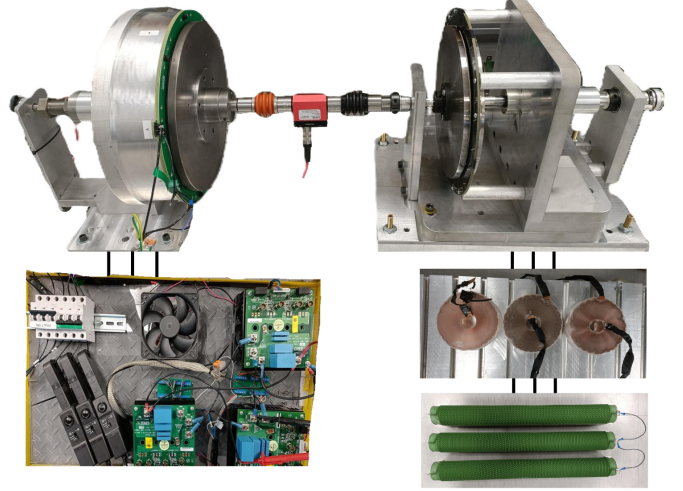


Fig. 6. Picture of the experimental setup on which the algorithm is being tested, comprising two CAFPM motors mounted on the same shaft. This test bench represents a scaled version of the high-power motor considered in this paper for aerospace application.

circuit occurs in one stage, its electrical measurements are not available, therefore it is not possible to verify whether the fault was effectively cleared after the tripping of the protections. Since the two stages are connected in mechanical series, a high fault current would flow as long as the shaft spins due the uncontrollable PM excitation, representing a potential hazard for the vehicle operation. This challenge is in common to any multi-modular motor topology, and it has to be addressed for ensuring safety operation in critical applications. Therefore, the idea is to equip each of the two units with an EKF that, in faulty conditions, exploits the measurements of the healthy unit to estimate the electromagnetic torque of the other one. The EKF is properly tailored to track the braking torque that results from a three-phase short-circuit.

The EKF estimation performance was evaluated through numerical simulations under healthy and three-phase short-circuit conditions, assuming an aircraft cruise-mode operation. The proposed design was proven to be effective at estimating the steady-state electromagnetic torque of the second unit in any conditions. The next steps will include an experimental validation, and a methodology to post-process the online torque estimation and to determine whether an internal short-circuit is occurring in the system.

APPENDIX

The covariance matrix of the model errors, i.e. $\mathbf{Q} \in \mathbb{R}^{n \times n}$, that was used for the presented EKF are:

$$\mathbf{Q} = \text{diag} [3.5e^{-3}, 3.5e^{-3}, 4.0e^{-13}, 1.0e^{-10}, 1e^{-3}] \in \mathbb{R}^{n \times n},$$

while the covariance matrix of the observation errors, i.e. $\mathbf{R} \in \mathbb{R}^{q \times q}$ is:

$$\mathbf{R} = \text{diag} [3.5e^{-4}, 3.5e^{-4}, 1.0e^{-8}, 1e^{-10}] \in \mathbb{R}^{q \times q}.$$

TABLE II
CORELESS AFPM MACHINE PARAMETERS (REFERRED TO A SINGLE
STAGE) USED FOR ANALYTICAL MODELING

Parameter	Symbol (Unit)	Value
Nominal power	P_n [MW]	1.0
Nominal speed	Ω_n [rpm]	4000
Pole pairs	pp	24
Rotor inertia	J_m [kg·m ²]	1.1
Propeller inertia	J_{prop} [kg·m ²]	12.3
Stator resistance	r_s [pu]	19.1×10^{-3}
Synchronous inductance	l_s [pu]	0.17
PM flux linkage	$\hat{\psi}_{pm}$ [pu]	0.97

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