An Alternative Approach for Condition Monitoring of Brushless DC Motor Drives

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***Abstract* -- In this study, an alternative approach based on redundant fault signatures is proposed for reliable condition monitoring of a Brushless DC motor drive in critical applications. To improve the fault detection and mitigation processes, a multi-source database is synthesized by redundant sensor signals. Focusing on Hall-effect position sensor-based drives, a data-driven approach for the unbalanced system operation diagnosis is presented, while the harmonic analysis with the Goertzel algorithm offers robust and fast fault detection. Thus, different configurations of misaligned position sensors are investigated to verify the effectiveness of the proposed fault signatures in identifying the defect and its severity. In addition, the position sensor breakdown fault can be detected, while the method can easily be expanded to sensorless drives for unbalanced operation detection. Finally, the reconstruction of the commutation signal and the required one-time commutation angle calibration are also feasible with the proposed monitoring scheme.**

***Index Terms* -- Brushless motors, Condition monitoring, Databases, Fault diagnosis, Frequency-domain analysis, Goertzel algorithm, Hall effect devices, Redundancy, Sensor fusion, Variable speed drives.**

I. Introduction

ELECTRICAL drive systems demanding high reliability can be found in both industrial and safety critical applications, such as automotive, aviation, and space industries, either due to potential extreme financial losses or life-threatening safety issues. In addition, Brushless DC (BLDC) motor drives are usually exploited in critical applications due to their high power density and efficiency in a wide speed range [1]–[4]. Motor faults, power electronics converter failures, and sensor faults can be distinguished among the potential faults of these drives, demanding the development of fault tolerant control systems [5]–[7].

Commonly, the fault diagnosis process is based on a single sensor for minimum implementation cost, but this approach either considers single fault types in the system, or neglects the possibility that the sensors utilized for the diagnosis can also fail. During the last years, multi-sensor control schemes are getting increasing attention for critical applications and, as a consequnce, more effective and reliable fault diagnosis, isolation and mitigation techniques can be developed [8]–[12]. More precisely, exploiting multiple sensors enables higher diagnostic accuracy through the redundant datasets, which are provided by sensors utilized to either measure the same quantity for noise and disturbance cancelation or integrate information from different aspects [9]. Thus, homogenous and heterogenous sensor configurations, either measuring the same quantity type (i.e. electrical or mechanical) or a different one, can be observed, respectively [10].

The unbalanced operation of a BLDC motor drive can be observed both in sensor-based and sensorless setups. The inaccurate placement of the Hall-effect position sensors, known as sensor misalignment defect, and the inevitable detection and processing errors in sensorless control systems are additional reasons for the observed increased torque ripple. It is worth noting that, the misalignment defect can be described by the relative commutation angle error (CAE), which is responsible for the unequal sectors during the electrical cycle, and the absolute error, which determines the negative or positive deviation from the ideal sensor position. These errors can be expanded in sensorless drives for the characterization of a leading or lagging commutation instant, i.e. a negative or positive CAE, respectively. Finally, in the case of sensor breakdown fault a constant sensor output signal will be observed and the control system has to identify the sensor as faulty. In the previous cases, unexpected stresses, either excessive or not, will occur on the system parts, negatively affecting the system reliability and stability, which in turn demands the development of a fault tolerant control technique for critical applications.

From the literature analysis, it can be concluded that there are three different approaches for the diagnosis of unbalanced operation and the commutation signal reconstruction. Thus, Back-EMF sensing [13]–[15], position sensor signals averaging and transition sequence estimation [16]–[19], current sensing [19]–[22], and their combinations can be exploited for the identification of the commutation angle error and the signal reconstruction. Nevertheless, the required low pass filters, the expected detection and processing errors of the sensed quantities, the speed dependent amplitude of the Back-EMF, and the speed controller interference along with motor parameters variation affects the accuracy of these techniques.

The frequency-domain analysis is an alternative approach, which offers a noise immune fault diagnosis in a qualitative manner. More precisely, the virtual third harmonic Back-EMF was exploited in [23], while the Discrete Fourier Transform (DFT) and the position sensor signals were investigated in [24]. Finally, current monitoring was selected in [25]–[27], since

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current sensors are commonly utilized in variable speed drives for closed loop control and safety features. However, both the control technique and the system operating point will partially affect the monitored signals and the accuracy of the method.

The development of a data-driven approach is proposed in this study, for the position sensor faults diagnosis. Exploiting multiple types of electrical sensors, accurate diagnosis and commutation signal reconstruction is feasible, counteracting the interference of the control technique and the system operating point. Instead of blindly placing sensors around the system, the candidate signals of the electronics controller input and output power are investigated and a new remedial strategy, based on partially redundant and complementary data, is proposed. The frequency-domain analysis is exploited for the diagnosis of both relative and absolute faults, while combined with the commutation signal reconstruction, an alternative solution for the overall misalignment fault is provided. Given the demand for a relatively fast and robust fault diagnosis, the second order Goertzel algorithm is selected for the frequency-domain analysis only in a narrow band around the online selected harmonic component of interest. Finally, early breakdown fault diagnosis can be performed, exploiting the previously established commutation signal.

II. Investigation of the Proposed Technique

A comparative analysis of the candidate signals' main features for the identification of reliable fault signatures under different types of position sensor faults will be presented in this section. For the selection of the final control scheme, different sensor signals are combined for a partially redundant and complementary implementation of the fault diagnosis.

A. System Overview and Theoretical Investigation

Hall-effect position sensors offer a simple solution to the required rotor position sensing in BLDC motor drives. The most common configuration is placing three sensors at 120 degrees apart in order to detect six sectors during the electrical cycle for the phase current commutations. Apart from their low cost and volume, these sensors are compatible with outrunner motor configurations, while under a hybrid commutation scheme [18], they could offer the required redundancy for a fault tolerant control technique with decoupled position sensor transitions and armature currents commutations. The block diagram of the investigated drive and the positions of all potential sensors is presented in Fig. 1.

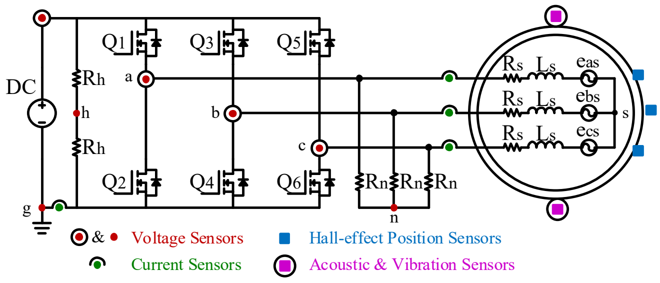

Fig. 1. Block diagram of a BLDC motor drive system with multiple sensors.

Multi-sensor systems have several advantages, such as the ability to verify every choice made by the control system, utilizing redundant and complementary data. Extending the number and type of the utilized sensors, additional information related to the unreliable behavior of the motor can be acquired introducing early fault diagnostic capabilities and possible identification of the fault type. Thus, the most common sensors in drive systems, apart from those for the electrical quantities monitoring, are internal and/or external magnetic flux, temperature, rotor speed and position, torque, and vibrations sensors.

Voltage sensors for the DC-link and the motor terminals could be selected in order to monitor voltages with respect to either the neutral point of a resistor network (n) or the negative rail of the DC-link (g) or the half of the DC-link (h). Sensors can also be considered for the DC-link and the armature currents. Moreover, acoustic emissions and vibration patterns could also be exploited for mechanical fault diagnosis [28]. Processing of the machine vibration signals is one of the earliest monitoring techniques and widely utilized to detect a variety of mechanical faults. Especially, regarding BLDC motor drives, an experimental analysis of vibration and acoustic noise is presented in [29], while a systematic approach for the identification of vibration and acoustic noise sources is developed in [30]. The suitability of acoustic measurements by consumer-grade sensors is presented in [31] for detection of unknown electrical nature current instabilities. However, for a more compact implementation, sensors only for the electrical quantities are considered in this study.

Considering a BLDC motor with concentrated windings and the motor neutral point (s), the terminal voltages and the Back-EMFs are expressed by (1) and (2):

$$\begin{bmatrix} V_{as} \\ V_{bs} \\ V_{cs} \end{bmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} * \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \\ + \begin{bmatrix} L_s - M & 0 & 0 \\ 0 & L_s - M & 0 \\ 0 & 0 & L_s - M \end{bmatrix} * \frac{d}{dt} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} e_{as} \\ e_{bs} \\ e_{cs} \end{bmatrix} \quad (1)$$

$$e_{xs} = K_e \omega_m f(\theta_r + \varphi) \quad (2)$$

where R, L_s, M, i_x (x=a, b, c), e_{xs}, K_e, ω_m, and $f(\theta)$ denote the phase resistance, self-inductance, mutual inductance, phase current, Back-EMF, Back-EMF constant, angular rotor speed, and a trapezoidal function, respectively.

Moreover, the phase currents and Back-EMFs can be analyzed with Fourier series as expressed in (3) and (4), respectively [23], [26].

$$i_x = i_{x1} + i_{x5} + i_{x7} + \ \dots \quad (3)$$

$$e_{xs} = e_{xs1} + e_{xs3} + e_{xs5} + e_{xs7} + e_{xs9} + \ \dots \quad (4)$$

where the number in the subscript denotes the harmonic order.

Furthermore, the mechanical dynamic model of the system and the produced electromagnetic torque T_e are expressed by (5) and (6), respectively.

$$\begin{cases} \dot{\theta}_m = \omega_m \\ \dot{\omega}_m = \frac{T_e - T_L - B\omega_m}{J} \end{cases} \quad (5)$$

$$T_e = \frac{1}{\omega_m}(e_{as}i_a + e_{bs}i_b + e_{cs}i_c) \quad (6)$$

where θ_m, T_L, B, and J are the rotor position, load torque, friction torque coefficient, and mechanical inertia, respectively.

It is worth noting that, a torque ripple is expected under normal operation, as the current waveform depends on the system inductances, resulting in a quasi-rectangular shape. However, the maximum and constant output torque demands the phase currents to be synchronized with the flat top of the Back-EMFs, which is not valid in case of erroneous commutation instants. Thus, increased torque ripple, vibrations, and acoustic noise are observed under unbalanced system operation, while even more excessive stresses are expected under a sensor breakdown fault.

B. Redundant Sensors and Fault Signature Selection

Since the common BLDC motor drives are not usually equipped with a torque sensor at the motor shaft, different approaches are considered here for the detection of the increased torque ripple due to the position sensor faults. Consequently, the estimation of the electromagnetic torque ripple by sensing different electrical quantities is investigated for a reliable diagnosis with partially redundant and complementary fault signatures.

To that end, a simulation model was built based on the parameters of a commercial BLDC motor, presented in Table I. For the simulation model a PWM frequency of 16kHz was selected along with a sampling frequency of 100kHz, a frequency resolution of 0.5Hz and the Hanning window. Furthermore, a defective configuration, initially presented in [14], with 11.2°, -7.6°, and 4.8° commutation angle errors (CAE) for the sensors A, B, and C was assumed, while the rated speed and torque were also selected as the system operating point.

The six-step commutation sequence of the motor controller and the interaction of the harmonic components of the armature currents and the Back-EMFs are responsible for the torque ripple and the high amplitude of 6th and 12th harmonic components in the electromagnetic torque frequency spectrum, even under the normal operating condition, as it is illustrated in Fig. 2. Despite the rich frequency spectrum of the electromagnetic torque, the increment of the second harmonic component (400Hz) could be a clear indicator of the defect.

TABLE I. PARAMETERS OF THE BLDC MOTOR

Parameter	Value
Rated Power	660 W
Rated Speed	3000 rpm
Rated Torque	2.1 Nm
Rated Voltage	48 V
Number of Pole Pairs	4
Phase Resistance	0.08 Ω
Phase Inductance	0.15 mH
Rotor Inertia	2400 g/cm²

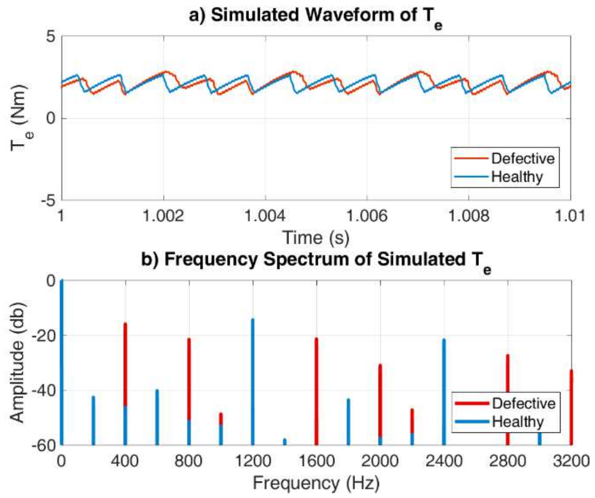

Fig. 2. Waveform and frequency spectrum of the simulated electromagnetic torque derived by the FFT analysis under the healthy and defective sensor configuration at the rated speed and torque.

A connection between the electromagnetic torque and the controller input and output power can be established for the investigation of multiple and redundant fault signatures. Considering the standard 120-degree commutation logic of a BLDC drive, e.g. in the sector where the phases A and B are energized and phase C is silent, the controller input and output power can be estimated, as it is described in (7):

$$\begin{cases} V_{AH} = -V_{BH} = \frac{V_{DC}}{2}, V_{CH} = e_{CS} \\ i_A = -i_B = i_{DC}, i_c = 0 \\ P_{out} = V_{AH}i_A + V_{BH}i_B + V_{CH}i_c \\ P_{in} = V_{DC}i_{DC} \\ T_e \approx \frac{P_{out}}{\omega_m} \approx \frac{P_{in}}{\omega_m} \end{cases} \quad (7)$$

where V_{xH} $(x=A, B, C)$ are the motor terminal voltages with respect to the half of the DC-link, V_{DC} is the DC-link voltage, i_{DC} is the controller input current, P_{in} is the controller input power, and P_{out} is the controller output power.

As it can be observed in Fig. 3 to Fig. 5, by approximating the Back-EMFs with the motor terminal voltages, motor and controller input power are candidate signals. By the close resemblance of their frequency spectrum with the one of the electromagnetic torque and the different sensors that are utilized for the estimation of each signal, the increment of the second harmonic component is a reliable fault signature. In addition, the diagnosis is independent of the DC-link current sensor position, i.e. after (Fig. 3) or before (Fig. 4) the input capacitor bank. Moreover, the low amplitude of this harmonic component under the healthy configuration enables the reliable fault detection. Although DC-link and motor currents can independently be utilized for the diagnosis, as it was presented in [26], the current work aims in investigation of both current signals as complementary signatures for redundant fault detection. Modifying this current approach for a control system with multiple sensors, the comparison of the DC-link current frequency spectrum with the one of the added armature currents will permit a redundant implementation of the diagnosis, based on the second harmonic component increment.

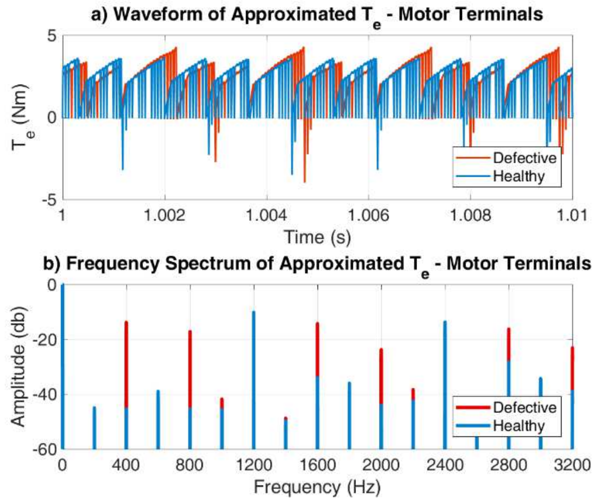

Fig. 3. Waveform and frequency spectrum of the approximated electromagnetic torque by the motor input power, derived by the FFT analysis under rated speed and torque.

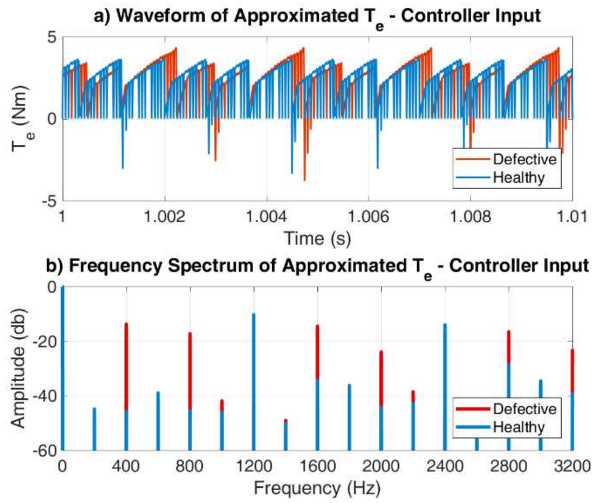

Fig. 4. Waveform and frequency spectrum of the approximated electromagnetic torque by the controller input power, including input capacitor current, derived by the FFT analysis under rated speed and torque.

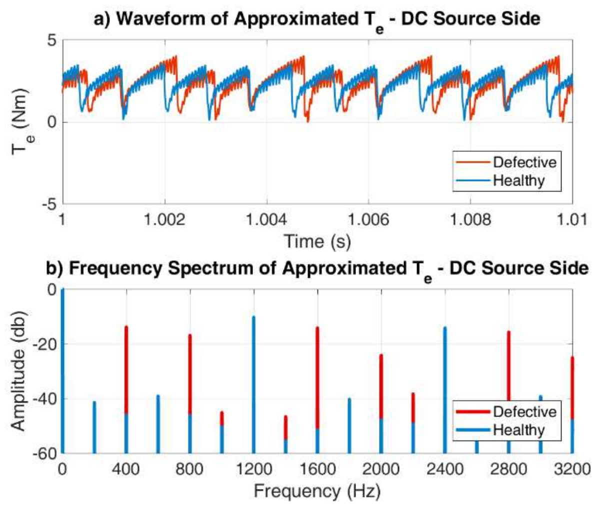

Fig. 5. Waveform and frequency spectrum of the approximated electromagnetic torque by the controller input power, without including the input capacitor current, derived by the FFT analysis under rated speed and torque.

On the other hand, the exploitation of the input power estimation improves the accuracy of the method, since potential fluctuations of the input voltage are also considered, and this is the main reason that it is selected in this study for further investigation. Finally, the breakdown fault can also be detected by the excessive increment of the second harmonic component and the highly enriched frequency spectrum of the monitored signals. Nevertheless, the observed system instability under a breakdown fault along with the required time for the harmonic analysis and the fault diagnosis limit the method usefulness for the breakdown fault diagnosis.

C. Harmonic Analysis and Fault Signature Detection

The fast and reliable detection of each fault signature should be an integral part of a robust sensor fusion scheme. However, the entire frequency spectrum is not required for the diagnosis and a single component is targeted with the proposed method. Therefore, the harmonic analysis can be performed in a narrow frequency band around the selected component, while both the investigated component and the frequency band can be determined online. Consequently, the Goertzel algorithm is preferable for the frequency-domain analysis of the monitored signals and the diagnosis of the fault.

The Goertzel algorithm is derived by the DFT, while it exploits the periodicity of the phase factor to reduce the computational complexity, as the FFT. However, it is more effective than the traditional FFT, when it comes for a small number of investigated frequencies, while it has a higher complexity for covering the entire frequency spectrum [32]. Since the first order difference equation contains a complex multiplication factor, the second order system expressed by (8), is preferred to save computational cost for the output $y_k[N]$ estimation [33].

$$\begin{cases} s[n] = x[n] + 2\cos\left(\frac{2\pi k}{N}\right) s[n-1] - s[n-2] \\ y_k[n] = s[n] - e^{-j\frac{2\pi k}{N}} s[n-1] \\ k = 0, \dots, N-1 \end{cases} \tag{8}$$

III. Development of Condition Monitoring and Remedial Strategy

Investigating the misalignment defect and breakdown fault in a unified manner improves both the diagnosis of the latter and the system postfault performance, while the redundant fault signatures enhance the expected effectiveness of the proposed technique. More precisely, the reconstructed commutation signal for the mitigation of the misalignment defect can also be exploited for the early breakdown fault diagnosis [18]. However, both relative and absolute errors should be identified and mitigated for an accurate solution in case of a more critical fault, such as the sensor breakdown.

This study extends the work presented in [18] from the diagnosis of relative and absolute errors' point of view. Therefore, the proposed technique consists of different processes in order to detect the unbalanced operation, reconstruct the commutation signal, and eliminate the absolute error. The outcomes of these processes are the reconstructed commutation signal with minimum commutation angle error and the decoupling of the position sensor transitions from the phase current commutations, which sequentially permits the early and reliable diagnosis of the breakdown fault.

A. Detection of Unbalanced System Operation

The first stage of the proposed method is a simple but reliable detection of the unbalanced system operation. The harmonic analysis of the monitored motor and controller input power permits the diagnosis of a single, double, and triple defect by the increment of the second harmonic component, as it was presented in the previous section. The identification of the exact value of each sensor commutation angle error is not the target of this stage, since this can be estimated by the reconstructed signal of the next stage. Consequently, a qualitive analysis is performed with the Goertzel algorithm.

B. Commutation Signal Reconstruction

The commutation signal reconstruction process is thoroughly presented in [18] and it is not included here due to space limitations. Averaging the sensor transitions, the speed and commutation instants can be estimated, while the relative errors can also be identified comparing the reconstructed signal with the one of the combined sensor transitions. Nevertheless, the absolute error cannot be defined at this stage and the reconstructed signal is highly affected by the selection of the reference sensor. As a result, the new signal may have a negative or positive commutation angle error because of the leading or lagging position of the reference sensor.

In other words, the system balancing process results in equal absolute errors for the virtual position sensors and a new diagnostic process must be implemented in the next stage for the calibration of the required reconstructed signal phase shift to minimize the absolute error. However, this is by far the most challenging defective case due to the system inductances, which affect the current slew rates and mask the leading reference sensor defect, demanding a sensitive and reliable monitoring approach.

C. Minimization of the Absolute Commutation Angle Error

To minimize the absolute commutation angle error the reconstructed signal should be shifted according to the deviation of the reference sensor from the ideal position. However, the real reference sensor position is unknown, which is translated into either a random first shifting of the reconstructed signal or the requirement of characterizing the reference sensor, as leading or lagging, before the first shift. It is worth noting that, even if a trial and error process seems to be fair enough, it may lead to system instability in case of a relatively high absolute error and a wrong default procedure that it has to be followed. Thus, a filtering stage is developed to detect an increased value of the monitored signal at the beginning or the end of a sector.

A low-power operating point is preferable for the reliable characterization of the reference sensor in these drives, since the freewheeling diode states can be clearly detected in the monitored signals and, depending on the position of these states in the investigated sectors, the reference sensor can be characterized. The low side diodes freewheeling states occur every two sectors in the electrical cycle due to the erroneous commutation instants. More precisely, in case of a leading position of the reference sensor an increased amplitude of the monitored signal is expected at the beginning of a sector identified by the failing edge of a position sensor signal. In case of a lagging reference sensor position, the indicator can be detected at the end of the sector before the falling edge of a position sensor signal. The above indicators can be detected under a clockwise operation, while a modified approach should be considered for the counterclockwise operation. Therefore, a simplified and rotation independent approach, based on the monitored power signal and a filtering process, is proposed for the characterization of the reference sensor.

By the reconstructed commutation pulsetrain transitions, two randomly selected consecutive sectors of the electrical cycle can be isolated, since an increased amplitude is expected in one of these sectors. To identify the exact position of the indicator in the investigated sectors, a filtering process is implemented to average the oversampled signal. Dividing this time interval into four subsectors, the overall mean value can be compared to the four different mean values and the leading or lagging case can be identified. In Fig. 6, the previous three different cases for the input power monitoring are illustrated under different defective configurations of the reference sensor. It is evident that, if the mean value of the first or third subsectors are higher than the overall mean value due to the freewheeling diode state, then the reference sensor has a negative commutation angle error, while the mean values of the even subsectors can highlight the lagging position of the reference sensor.

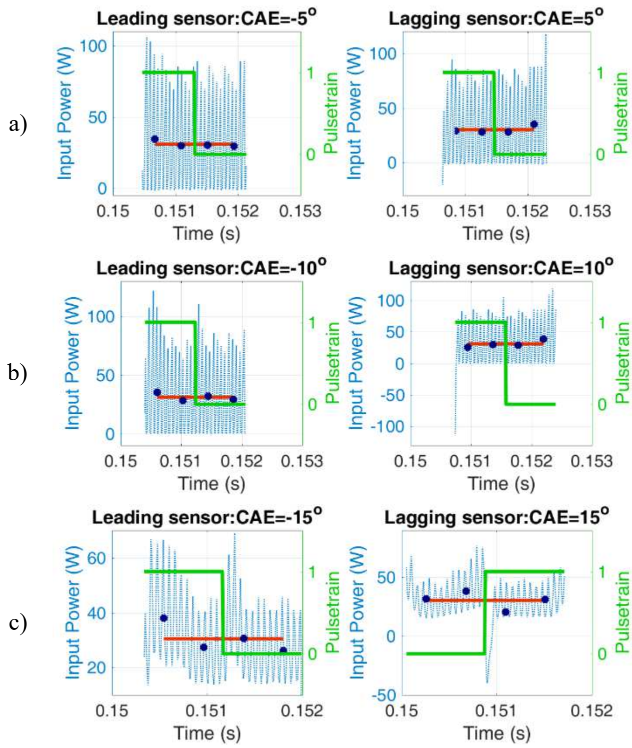

Fig. 6. Two randomly selected consecutive sectors of the electrical cycle of the monitored motor input power (a), controller input power including input capacitor current (b), and controller input power without including input capacitor current (c) under various negative or positive commutation angle errors (CAE).

After the characterization of the reference sensor by the filtering process, the reconstructed commutation signal can be shifted towards the ideal sensor position to minimize the absolute error, without risking the system stability. It is worth noting that, at this stage all sensors seem to have the same absolute error (which is not necessary zero) due to the balancing process, which further simplifies the identification of the real sensor positions. The proposed monitoring scheme enhances the effectiveness of the technique, since the required shifting of the commutation signal can be identified by different sensors and at different system operating points to cancel undesired noise and disturbances. The second order Goertzel algorithm is also exploited in the last stage for the reliable diagnosis of the absolute error fault signature by the harmonic analysis of the monitored signals.

As it is illustrated in Fig, 7, the amplitude of the ninth harmonic component, in case of input power monitoring, will highlight the severity of the absolute error and the need to shift the reconstructed signal. Since the fault signatures of the relative and absolute errors are detected at different harmonic components, an increased accuracy of the proposed method is expected, while the low amplitude of these harmonic components under the healthy operation further enhances the detectability of the technique. Thus, through a perturb and observe process, the minimum of the investigated harmonic component can be achieved by the shift of the reconstructed commutation signal, providing a complete solution to the unbalanced system operation.

In addition, one of the proposed technique advantages is the ability to verify every choice made by the control system, utilizing redundant and complementary data. Therefore, extending the work presented in [26], the armature current monitoring can be used in combination with the power monitoring, as it permits the reliable identification of the absolute error exploiting the second harmonic component. This component is also different from the relative error fault signature (third harmonic component was presented in [26]), and as a result of this it can be considered as a signature.

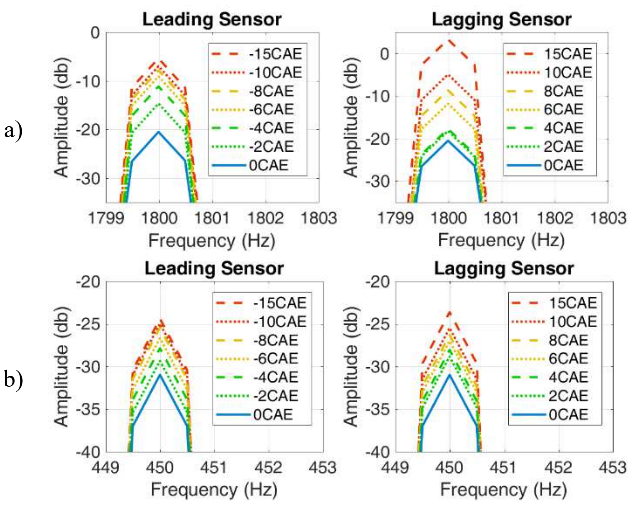

Fig. 7. Ninth harmonic component of the motor input power (a) and controller input power (b) frequency spectrum derived by the Goertzel algorithm, under the healthy, leading, and lagging positions of the reference sensor at no-load, 3000 rpm and 250 rpm, respectively.

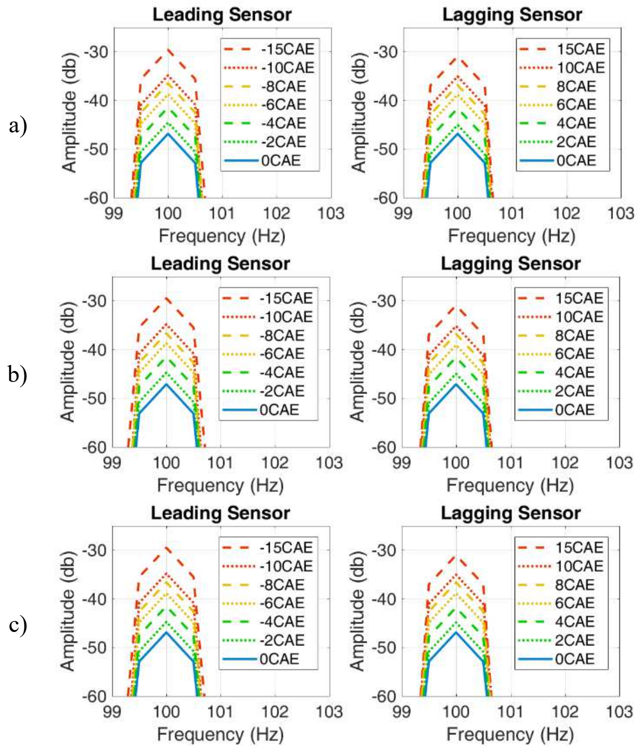

Fig. 8. Second harmonic component of the armature currents Ia (a), Ib (b), and Ic (c) frequency spectrum derived by the Goertzel algorithm, under the healthy, leading, and lagging positions of the reference sensor at 250 rpm and no-load.

IV. Conclusions

In this study, an alternative condition monitoring scheme for a BLDC motor drive for critical applications is proposed. This redundant data-driven approach aims to the identification of multiple faults and as a first target the position sensor faults have been targeted. Through the proposed technique a unified approach for misalignment and breakdown faults mitigation is developed, since with both relative and absolute misalignment errors been identified, early breakdown fault diagnosis can be performed, exploiting the previously reconstructed commutation signal. Apart from noise cancelation, the multiple sensor scheme offers the ability to detect faults at the utilized sensors for the fault diagnosis. Thus, the additional sensors where selected to provide mainly complementary information of the system condition and, as a result, the motor and controller input power monitoring were evaluated. Finally, the frequency-domain analysis using the Goertzel algorithm was preferred for reliable diagnosis of the relative and absolute errors, providing an overall solution.

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VI. Biographies

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