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Sensor Applications

Measurement Offset Fault Detection Logic for PMSM Position Sensor

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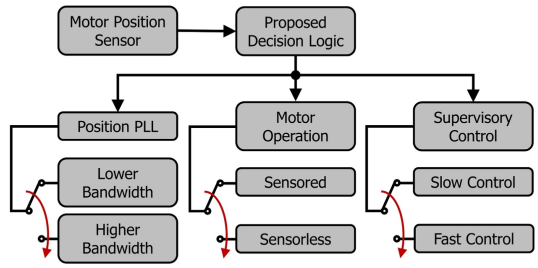

Abstract—High-performance control of permanent magnet synchronous motors (PMSMs) demands precise position information, but non-idealities and signal conversion issues may introduce a DC offset (DCO) in the motor position sensor output. This offset significantly degrades drive performance and efficiency. To address this, conventional state-machine-type algorithms adapt control bandwidths based on fault types. This letter introduces an intuitive decision logic (DL) for both forward and reverse (F&R) motor operations, offering simplicity and ease of implementation. In contrast to complex signal processing methods such as wavelet and Fourier transformation and neural network, the proposed lightweight DL can be efficiently implemented in a wide range of embedded devices. Experimental results using an industrial grade PMSM servo motor across diverse operating conditions validate the efficacy of the proposed DL over long short-term memory network-based counterpart.

Index Terms—Sensor applications, sensor signal processing, PLL, power grid, single-phase, DC offset, frequency ramp

I. INTRODUCTION

Position sensors are widely used for high-performance control of motors, *cf*. Fig. 1 in [1]. In the case of PMSMs, broadly speaking, a large number of existing PMSM position sensing technologies provide sin/cos signals with instantaneous phases corresponding to the actual position of the motor as discussed in [2]–[4]. Due to the presence of measurement noise and other nonlinear (e.g. harmonics) and non-ideal effects (e.g. measurement offset), signal processing methods such as the phase-locked loop (PLL) are often used for accurate position estimation. Tuning of the PLL parameters is accomplished as a trade-off between fast dynamic response and disturbance rejection properties. DC offset (DCO) is a common type of non-ideal effect that can significantly affect the performance of the PLL and consequently the PMSM position sensor. The DCO can come from the signal conversion process or the sensor itself. In the case of a low-cost sensor, it may reach up to 20% of the magnitude of the sin/cos signal as claimed in [5]. This will cause a significant position estimation error and result in inefficient operation of the motor drive. As such, mitigation of the DCO is essential for high-performance drives.

Numerous studies in the literature address DCO fault detection, emphasizing its significance. Many propose transitioning from position-sensored to position-sensorless operation upon fault detection, often employing simple threshold logic. For instance, as proposed in [6], a position estimator continuously monitors signal discrepancies, detecting faults when the difference surpasses a predefined threshold. However, a notable limitation is its reliance on a model-based approach, necessitating real-time execution of a complex estimator irrespective of fault presence. A similar methodology was explored in [7]. Additionally, deep-learning methods such as long short-term memory (LSTM) network also became prominent in recent time for detecting DCO in electrical signal is proposed in [8], albeit at the cost of significant real-time computational complexity.

In terms of not just detection but also DCO mitigation, three main solutions exist in the literature. The first involves using a high-pass filter (HPF), but it introduces phase deviation, necessitating real-time compensation through computationally expensive trigonometric functions. Additionally, the HPF has limitations in low-speed operations, struggling to differentiate between motor speed and DCO due to their very low frequencies. This poses issues, especially during motor startup and may even cause startup failure. To overcome these challenges, a variable time-step HPF in the angle domain, is proposed in [5]. This approach adjusts the angle integration-step ($\Delta\Theta$) based on the estimated frequency (ω_{est}). However, it is not suitable for reverse operation, as the required time-step becomes negative due to the estimated frequency being negative. In the second case, a neural network (NN) or another filter can be used to estimate the DCO-induced disturbance in the PLL as suggested in [9], [10]. Additional disturbance estimation techniques further increase the computational complexity, may require extensive training (e.g., for the NN case), and often come with slower dynamic response. Moreover, if the DCO is not prominent, then running an additional filter/NN in real-time will cause unnecessary computational burden. In the third case, extensive experimental testing-based calibration procedures are used as proposed in [11], which are applicable only for the motor for which the testing procedure is conducted, limiting wider applicability. To address these issues, in this letter, a simple signal processing-based decision logic (DL) is proposed, which can detect the presence of

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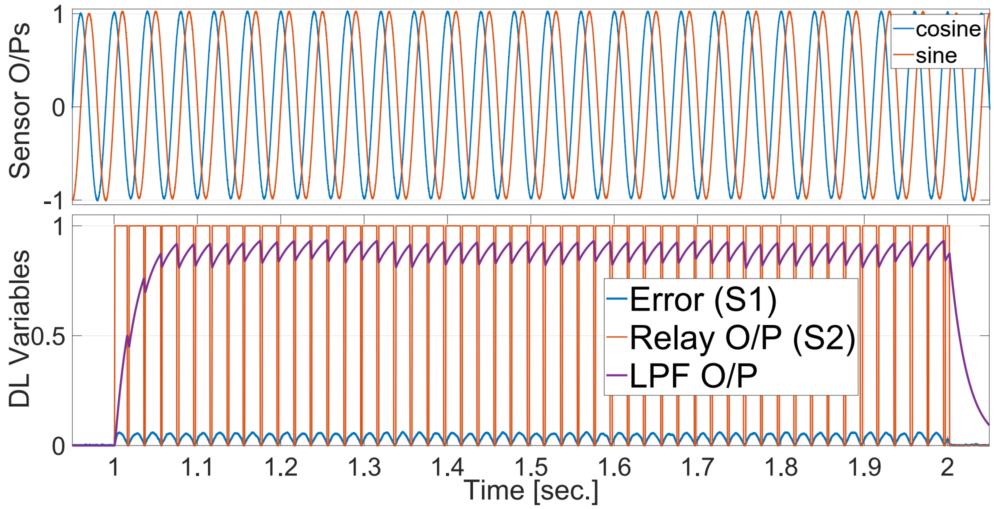

Fig. 1. Operation of the proposed DL.

TABLE 1. QUALITATIVE COMPARISON WITH EXISTING WORKS.

Method	Required Sensors		Speed Range		Compl-exity	Need PLL
	Position	Current	+(ve)	−(ve)		
[5]	✓	✗	✓	✗	Low	✓
[6]	✓	✓	✓	✗	High	✓
[7]	✓	✓	✓	✗	High	–
[9]	✓	✗	✓	✗	High	✓
[12]	✓	✓	✓	✗	High	✗
This Work	✓	✗	✓	✓	Low	✗

DCO in the sine/cosine signal. An overview of the proposed DL's application scenarios is given in the graphical abstract. An advantage of this approach is that it can trigger the activation of the disturbance mitigation block, such as NN. This will allow fast estimation of PMSM position with low computational cost when there is no DCO, whereas ensuring robust position estimation in the presence of DCO. Existing literature on fault-tolerant operation of PMSM switches from sensor to sensorless operation when there is a fault in the position sensor. The proposed approach can be easily integrated into such a solution *cf.* the method in [12], serving as the high-level DL, while the existing DL is based on computationally expensive real-time discrete Wavelet transformation. It is well known that a low bandwidth PLL can mitigate disturbances such as DCO. The proposed DL can also be used to switch between two different PLLs (fast and slow) to achieve fast operation when no DCO is present and vice versa. These application areas clearly highlight the proposed DL's versatility in the PMSM control application. A qualitative comparison of the proposed approach with the wider literature is provided in Tab. 1.

The remainder of this letter is organized as follows: Sec. II details the proposed DL, Sec. III offers real-time validation, and Sec. IV concludes the letter.

II. PROPOSED DECISION LOGIC

PMSM's position sensor signal vector (χ) can be written as:

$$\chi = V \begin{pmatrix} \cos(\theta) \\ \sin(\theta) \end{pmatrix} + \begin{pmatrix} \chi_{c0} \\ \chi_{s0} \end{pmatrix}, \tag{1}$$

where sensor signal amplitude, motor position, and DCOs are given by V, θ, χ_{c0}, and χ_{s0}, respectively. For further development, we assume that the sensor outputs are available in per unit (p.u.). Proposed DL can be summarized as:

$$\underbrace{\mathrm{DL} = \mathrm{LPF}\left(\underbrace{\left(\underbrace{\left|\mathrm{MAF}\left(\chi^T \chi\right) - 1\right|}_{\mathrm{S1}} \geq \epsilon_1 \right)}_{\mathrm{S2}} \right) \geq \epsilon_2}_{\mathrm{S3}}, \tag{2}$$

where MAF and LPF stand for simple moving average filter and low-pass filter, respectively, and the logical operations generate output 1 (satisfied) or 0. In normal operation, the amplitude of the sensor signal can be estimated by taking the squared sum of the vector χ, which should be equal to 1. Due to the presence of noise, a MAF (with a window length $N > 0$) is used to smooth out the noise in the signal $\chi^T \chi$ and provide protection against momentary measurement glitches. By subtracting the squared amplitude of the filtered estimated amplitude signal ($\hat{V}$) from the nominal value at step (S)1 (S1), an energy-type error signal ($e^2 = \hat{V}^2 - 1$) similar to the residual signal in fault detection literature is obtained. In the presence of DCO, the error/residual becomes an oscillatory signal. To further mitigate the noise effect in S2, a dead-band type threshold $\epsilon_1 > 0$ is used to pass the S1 output, acting as a relay. Theoretically, this should be sufficient to detect the presence of DCO. However, measurement noise and other non-idealities can lead to false alarms. Therefore, an additional LPF (cut-off frequency $\omega_l > 0$) is used to pass the relay output, providing memory effect and resilience from transient behavior. In S3, the LPF output is compared to another threshold $\epsilon_2 > 0$ to make the final decision about DCO's presence.

To illustrate the concept of the proposed DL, let's consider sensor signals with a frequency of 25 Hz; for a 2-pole PMSM, this corresponds to 750 revolutions per minute (rpm). Between 1.0 and 2.0 seconds, a DCO of ±0.02 [p.u.] is added to the sensor signals. The DL's operation can be observed in Fig. 1. Immediately after the introduction of DCO, the error signal (S1) started to oscillate as expected. This triggered

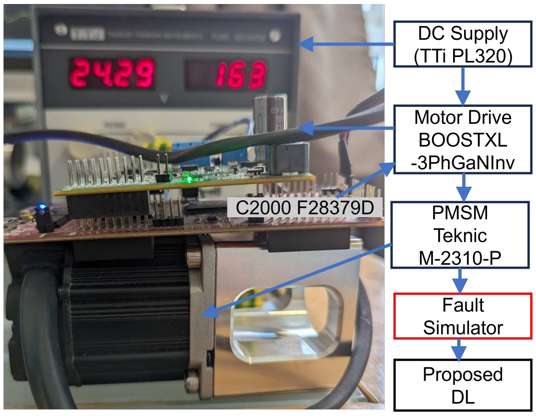

Fig. 2. Overview of the used experimental setup.

the relay (S2), resulting in a change in the output of the LPF. When the DCO is removed after 2.0 seconds, the LPF output also returns to 0, indicating the absence of DCO. The proposed DL is straightforward to implement and doesn't involve any complex computation or trigonometric function evaluation, making it suitable for computationally constrained embedded systems.

III. RESULTS AND DISCUSSIONS

An overview of the experimental setup used to validate the proposed work is shown in Fig. 2, where an industrial-grade three-phase 4-pole pairs Teknic servo motor (model M-2310P-LN-04K) is utilized, whose parameters can be consulted from [13]. The motor is controlled via field-oriented control (with 20kHz PWM) using a BOOSTXL-3PhGaNInv motor drive through a Texas Instruments C2000 F28379D micro-controller. Following the approach considered in existing literature such as [6, Fig. 6] and [10, Fig. 5], the motor output is employed for sensor emulation and subsequent fault injection. Results are exported to Matlab/Simulink for further processing and visualization. The proposed DL system is implemented with a 10 kHz sampling frequency. Parameters of the proposed DL are selected as: $N = 10$, $\epsilon_1 = 0.01$, $\epsilon_2 = 0.1$, and $\omega_l = 15\pi$. As a comparison method, LSTM network approach as proposed in [8] is considered. To train the LSTM network, the error signal from S1 is used as the input. This ensures a fair comparison, as both the proposed approach and the comparison method use the same input. The selected LSTM model has 32 hidden units for both the encoder and the decoder, and it uses DCO-free time-series data for training the DCO detector.

In the considered experiment, it is assumed that the motor is accelerating from 0 to +4000 rpm and then decelerating to -4000 rpm. Motor position, speed and phase currents signal of the motor drive can be seen in Fig. 3, where per unit values for the position and speed are considering with base values of 2π rad. and 4000 rpm, respectively. To emulate the position sensor fault, a DCO of ± 0.05 p.u. is added to the raw sensor signal during the acceleration (between 5 and 10 seconds), and a DCO of ∓ 0.05 p.u. during the deceleration (between 16 and 21 seconds).

Results with experimental data are presented in Fig. 4. Since the considered DCOs are asymmetric, sensor outputs in Fig. 4(a) show that under the presence of DCO, the symmetry between the sensor outputs (i.e. 90 degree phase difference) disappears. From Fig. 4(b), it can

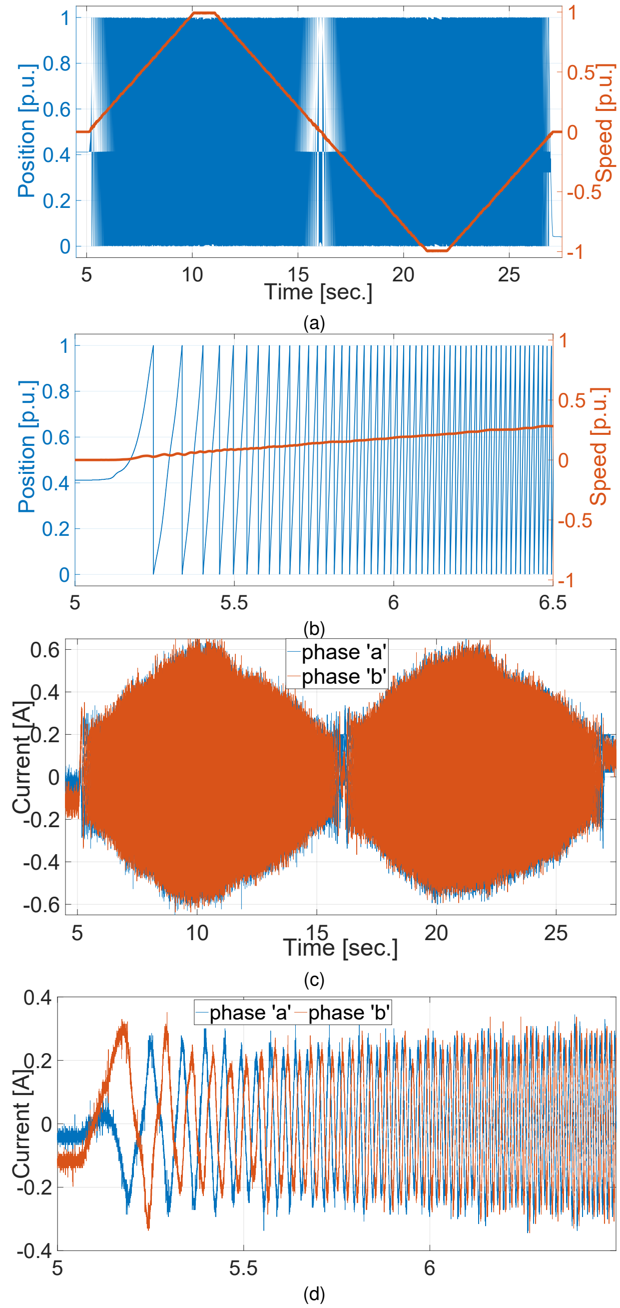

Fig. 3. Experimental results: (a) motor position & speed; (b) zoomed view of (a); (c) phase currents; (d) zoomed view of (c).

be noted that the proposed DL can easily differentiate between low-speed operation of the motor and the DCO. Results with experimental data demonstrate that the proposed method works under various operating conditions, including low and high speed, asymmetric DCO, acceleration (F&R), and deceleration (F&R). However, the same is not true for the LSTM network method, as can be seen in Fig. 4 (c). Despite having the same input as the proposed method, the LSTM struggles to differentiate between low-speed operation and DCO. As such, during the transient, several missed and false detections occurred, whereas the proposed method accurately detected the DCO without giving any false alarms. This demonstrates that the proposed method outperforms its computationally expensive advanced counterpart. Note that the proposed algorithm requires real-time evaluation of 2 multiplication, 2

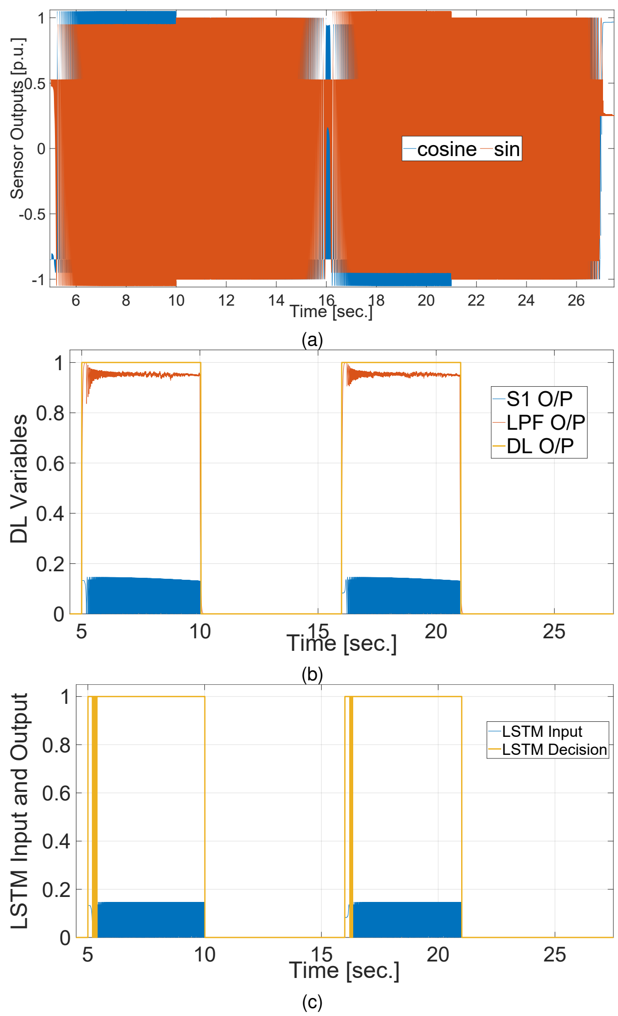

Fig. 4. Results with experimental data: (a) position sensor outputs; (b) evolution of the proposed DL variables; (c) output of the LSTM network.

addition/subtraction, 1 MAF, 1 LPF, and 2 comparator operations. This is very low-cost for implementation, even in entry-level embedded hardware.

IV. CONCLUSION AND FUTURE WORKS

This paper proposes a three-step DL for DCO fault detection in PMSM's sine/cosine-type position sensor. The DL involves simple filtering(MAF and LPF) and relay-type logic. Experimental results under various conditions demonstrate that the proposed DL can operate in a wide operating range, including both F&R motor operation. A qualitative comparison with the wider literature and a quantitative comparison with a deep learning-based method show that the proposed DL has a quick response time, is easy to implement without causing significant computational burden to the control computer, is signal processing-based, and doesn't require any information about the motor parameters, additional sensors (e.g., current), or estimators (e.g., PLL). These features demonstrate that the proposed DL is suitable for integration within the high-level supervisory controller of PMSM.

In this work, only DCO fault's presence is assumed, but other faults like amplitude mismatch and non-orthogonality may occur simultaneously, potentially limiting the DL's performance. Although the presence of MAF enhances the DL's immunity against measurement noise and harmonics, poor-quality instrumentation can significantly degrade sensor outputs. Hence, further measures are needed to enhance the DL's versatility against various sensor faults, For which statistical approach such as the method in [14] could be useful. Moreover, reduction of the offset will also an interesting future research direction.

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