Sensor Applications

Stator Inter-Turn Fault Detection in BLDC Motors: A Signal-Processing Based Method

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Abstract—This paper develops a signal-processing-based method for stator inter-turn fault detection in brushless direct current (BLDC) motors. With the application of current probes as measurment sensors and using the Park transformation matrix, the proposed approach first transforms the current waveforms into a synchronous rotating reference frame (dq) axis. Then, the faults are identified through the Savitzky-Golay smoothing filter, the modified cumulative-sum method and a novel ratio-based index. In addition to being simple and efficient, the proposed technique is highly capable of functioning in different BLDC motor conditions without changing its threshold settings. Datasets from a laboratory BLDC motor setup are considered to assess the developed scheme. The results confirm the speed and high accuracy of the proposed technique. Moreover, to validate the efficiency of the suggested approach, it is compared with some other similar methods from various aspects.

Index Terms—BLDC Motors, Fault Detection, Savitzky-Golay Filter, Cumulative Sum, Signal Processing.

I. INTRODUCTION

Brushless Direct Current (BLDC) motors are widely used in transportation and industrial systems [1]. However, they face various protection challenges due to different types of faults, especially stator inter-turn faults (SITFs) caused by insulation defects, which can rapidly escalate and lead to motor failure. These faults impact current magnitude, waveform, and harmonic content, complicating detection and protection schemes. Therefore, the detection of SITFs in BLDC motors is a critical issue [2].

Numerous methods have been developed for detecting SITFs in BLDC motors, each offering distinct advantages and challenges [3]. Flux-based techniques using search coils or flux sensors provide high accuracy and speed but require expensive hardware, limiting their cost-effectiveness [4]. Input impedance methods, which monitor electrical parameters like current, voltage, and inductance, enable fast decision-making over a wide speed range but are complex to implement and struggle at low speeds, reducing their suitability for real-time diagnosis [5]. Parameter estimation approaches compare estimated motor parameters, such as resistance and back EMF, with measured values, offering good accuracy but at the cost of high computational demands and the need for multiple sensors, complicating real-time application [6]. Miscellaneous methods, while simpler and suitable for online detection with low computational burden, often sacrifice accuracy and speed, limiting their effectiveness for robust BLDC motor protection [7].

This paper proposes a signal-processing-based method for SITF detection using only current signals. The current waveforms are first transformed into dq quantities via Park transformation, then smoothed using a Savitzky-Golay (SG) filter. The root-mean-square (RMS) of the smoothed signals is used to detect faults. A modified cumulative sum (MCS) filter is applied to the RMS signals, with significant variations indicating fault occurrence. A fault detection index (FDI) based on these fluctuations is compared against a threshold to confirm faults. The method is validated through experimental testing, demonstrating high speed and accuracy compared to existing techniques. In summary, the main contributions of the proposed method are as follows:

1) Processing only one signal, reducing the computational burden.
2) Using simple current probes as current measurement sensors.
3) Simple implementation using basic mathematical operations.
4) Applicability across different BLDC motor load conditions.

II. THE PROPOSED FAULT DETECTION METHOD

The proposed SITF detection method includes five steps which capture phase current signals and process them using a combination of the MCS approach and a generalized index to detect faults. This current-based technique prevents issues existing in methods based on voltage or flux, offering an efficient solution for BLDC motor protection.

A. Step 1: Park Transform

In this method, the three-phase currents are transformed into a synchronous rotating reference frame using the abc–dq transformation (the so-called Park Transform) [8]. Hence, the direct and quadrature current from Park's vector components are obtained as follows:

$$\begin{bmatrix} i_d \\ i_q \end{bmatrix} = \begin{bmatrix} \sqrt{2/3} & \sqrt{1/6} & -\sqrt{1/6} \\ 0 & \sqrt{1/2} & -\sqrt{1/2} \end{bmatrix} \cdot \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} \tag{1}$$

where i_d and i_q are the direct and quadrature components, and i_a, i_b, and i_c represent the instantaneous current signals of the three phases. Since the calculation of dq components relies solely on the current (instantaneous) values of i_a, i_b, and i_c, previous samples or time-buffered data are unnecessary. This approach therefore reduces storage and computational requirements, as only the real-time values of i_a, i_b, and i_c at any given time t are needed for each calculation.

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B. Step 2: Smoothing Filter

The SG filter, introduced in 1964, smooths signals by fitting a polynomial to a moving window of data points, preserving key features while reducing noise. The filter works by fitting the polynomial to each window and using its coefficients to estimate the smoothed value at the center point. By adjusting the window size and polynomial degree, it finds a balance between noise reduction and signal preservation, making it highly effective for maintaining the shape of the original signal without compromising resolution [9].

In the proposed method, an SG filter with a one-fourth of a cycle moving window is applied to the dq components (i_d and i_q) obtained from the Park transform. These dq currents often contain unwanted harmonics and fluctuations, which can cause protection schemes to misinterpret normal conditions as faults. By applying the SG filter, these unwanted variations are smoothed out, enabling the detection process to operate more accurately, ensuring faults are identified without malfunctions during normal motor operation.

C. Step 3: Main Processed Signal

The smoothed i_d and i_q currents which can be named i_{ds} and i_{qs} have some unique features to be utilized in the process of the proposed method. However, using both of them would be difficult because of high complexity. So, to simplify the processing of digitally sampled signals in the fault detection unit and decrease the computation burden, a combination of i_{ds} and i_{qs} currents is suggested as i_m using the RMS concept. This signal is proposed as follows:

$$i_m = \sqrt{i_{ds}^2 + i_{qs}^2} \tag{2}$$

As eq. (2) shows, i_m has been defined as RMS instantaneous value of i_{ds} and i_{qs} which can be used for further analysis.

D. Step 4: MCS Filter

To detect changes in the i_m signal, a simple and efficient delta filter named MCS filter is used. This filter combines cycle-by-cycle comparison with the traditional cumulative sum approach. Each sample is compared to the corresponding sample from one cycle earlier, and the latest comparison value is added to the previous cumulative result [10]. The MCS formulation is as follows:

$$MSC(n) = |MSC(n-1) + \{i_m(n) - i_m\,(n - N_s)\}| \tag{3}$$

Here, N_s is the samples per cycle, and n represents the sample index. During normal operation, MCS value remains low, but it rises with the occurrence of SITF. This formulation, relying only on addition and subtraction, reduces complexity and is easy to implement in industrial drivers.

E. Step 5: Fault Detection Index

Having MCS signal from the last step, various algorithms can be defined to characterize the faults. In this paper, a novel ratio-based approach is suggested to generalize the proposed technique. Using this approach allows our method to be applicable in different BLDC motors with specifications and ratings. This unique index puts the variations of the computed MCS between 0 and 1 in all conditions so that it can be utilized in all conditions:

$$FDI(n) = 1 - \frac{1}{1 + |\beta * (MCS(n))|} \tag{4}$$

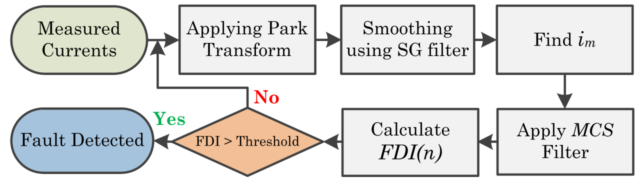

Fig. 1. Flowchart of the proposed method

The value of β in eq. (4) is considered 0.1 to balance the proposed FDI value. From eq. (4), it is evident that the possible range of the FDI is [0, 1]. In the normal operation of BLDC, FDI is very close to zero since the value of MCS would be very small. However, it increases to a higher value (near one) once MCS increases. Comparing the FDI with a predefined threshold, characterizes the occurrence of a fault. In this paper, a straightforward method named Otsu thresholding method is considered to set the threshold. More information about this method can be found in [2].

F. Implementation Flowchart

The flowchart of proposed method is depicted in Fig. 1. As it is observed, the method starts with sampling the stator current signals. Then, the Park transform should be applied to measured three-phase currents. The SG filter is then smoothed the i_d and i_q and makes them ready to be utilized to form the main processed signal i_m. After that, MCS filter is implemented on the i_m signal to find the variation of the i_m. Using the MSC filter output, FDI is calculated and compared with a pre-defined threshold. If FDI exceeds the threshold, the faulty condition is recognized, otherwise, this process keeps continuing.

III. EXPERIMENTATION AND RESULTS

A. Experimental Test Bench and Dataset

The developed approach was validated on an experimental test bench (Fig. 2) equipped with a BLDC motor, driver board, DC motor load, rheostats, power supply, current probes, and an oscilloscope. Current probes served as the primary sensors to capture real-time current waveforms from the BLDC motor, enabling accurate monitoring essential for fault detection. The driver board, configured with an inverter and a PI-controlled closed-loop system, adjusted motor speed using pulse-width modulation (PWM). The load was created with a 12 V DC motor, connected to rheostats to emulate varying loading conditions. To simulate faults, wires were welded to various coil turns without additional resistance, accurately replicating real-world SITF scenarios. During testing, the current probes collected waveform data at a 5 kHz sampling rate, recording motor responses under different operating conditions, including variable input voltages and load settings. The test setup included:

- BLDC motor: Three-phase, 370 W, 48 V, 10.5 A, 3000 rpm, 1.2 Nm torque.
- DC motor load: 12 V.
- Driver board: 48 V, 5 kHz PWM frequency.

A total of 36 test scenarios were conducted, covering four motor speeds, three current levels, and three fault severity levels, with current probes reliably capturing the data needed for robust SITF detection. This experimental setup highlights the simplicity and effectiveness of current sensors in diagnosing motor faults.

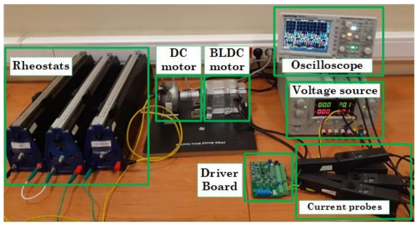

Fig. 2. Experimental Test Bench

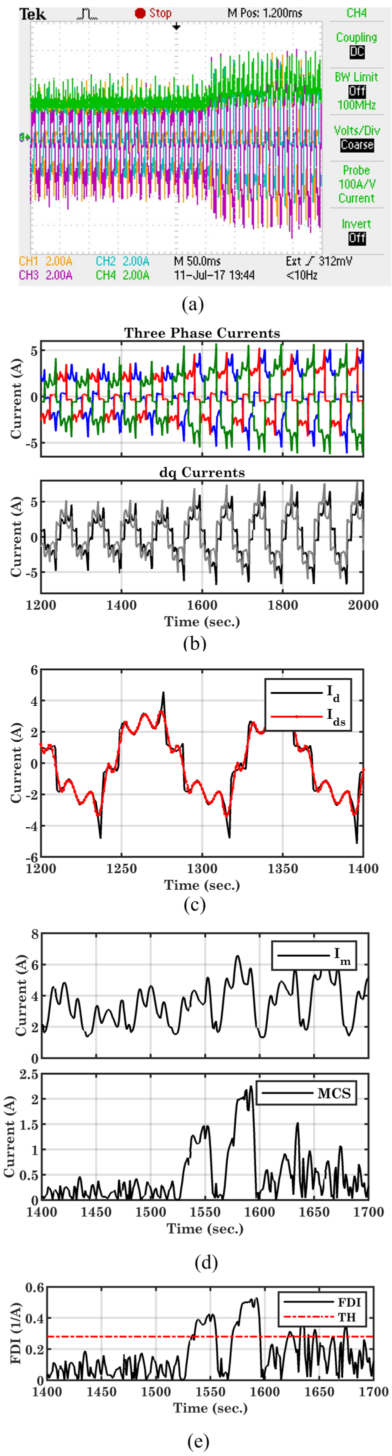

Fig. 3. Steps of the proposed method: (a) captured current, (b) step 1 & 2, (c) step 3, (d) step 4, and (e) step 5

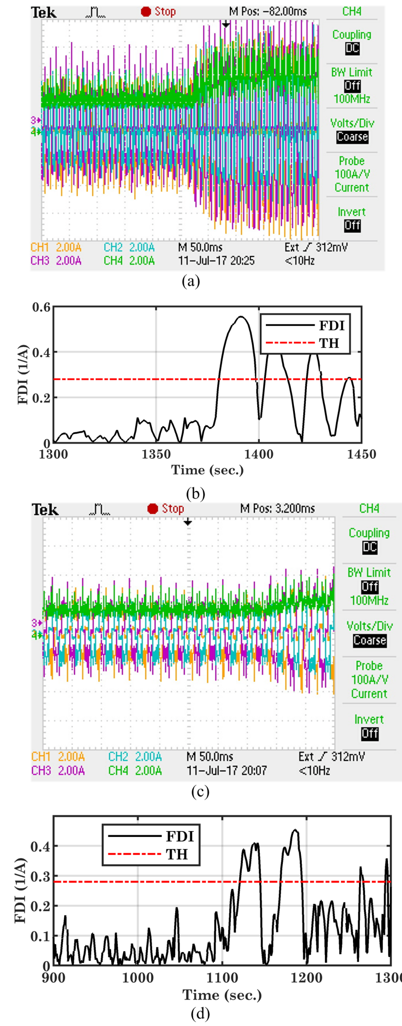

Fig. 4. Performance of the method in various severities fault: (a) captured current for high severity fault, (b) output of the method, (c) captured current for low severity fault, (d) output of the method

B. Results and Discussions

In this subsection, the proposed SITF detection method is evaluated using experimental data, and results are illustrated to showcase each processing step. Starting with a medium-severity fault example in Fig. 3, the three-phase currents are transformed into i_d and i_q components via the Park Transform. This preserves the signal's fluctuation characteristics, preparing it for further analysis. Next, an SG filter smooths the i_d component, effectively reducing noise while retaining the signal's overall shape, thus enhancing fault detection clarity. The main processed signal, i_m, is then derived, displaying regular fluctuations between positive limits. The MCS filter is applied to i_m to detect changes, as it identifies anomalies by comparing each sample to the prior cycle. Under normal operation, the filter output is stable, but with fault onset, it rises significantly, making fault moments apparent. The FDI index reflects this by exceeding the threshold shortly after the fault occurs, confirming reliable detection.

The method performance is then tested across two challenging fault severities. In Fig. 4 (a) and (b), a high-severity fault is detected quickly due to stronger waveform fluctuations, demonstrating the method's responsiveness to severe faults. In contrast, a low-severity fault, as shown in Fig. 4 (c) and (d), results in slower detection

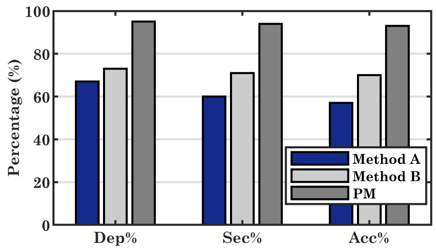

Fig. 5. Comparative study of the proposed method

due to more subtle fluctuations, but the FDI index still surpasses the threshold reliably. Interestingly, lower-severity faults exhibit minimal harmonic changes, whereas higher-severity faults show shifts in both amplitude and harmonics, reflecting the method's sensitivity to fault magnitude.

C. Comparative Study

To validate the effectiveness of the proposed framework, a comparison was conducted between the proposed method and two established techniques: A) a wavelet-based scheme [11] and B) a frequency-pattern-based technique [12]. For fairness, each method was assessed using the same experimental data, with settings optimized for peak performance. In this comparison, all approaches rely on current probes as the primary sensors for capturing BLDC motor data. Key performance factors considered in the analysis were:

- Dependability: Reflects the reliability of each method in accurately identifying fault conditions.
- Security: Measures the rate of false alarms, specifically non-fault cases mistakenly identified as faults.
- Accuracy: Indicates the overall performance in correctly classifying both fault and non-fault scenarios.

The evaluation used experimental data comprising 36 fault cases and 12 non-fault cases, totaling 48 test scenarios. These metrics were quantified for each method and are presented as bar charts in Fig. 5 for a visual comparison. As shown, the proposed method (PM), which utilizes straightforward current probes, outperforms the other techniques across all metrics, confirming its robustness in SITF detection for BLDC motors. This comparative study highlights the high sensitivity and reliability of the proposed approach, demonstrating its advantages in low-cost, accurate fault detection without the need for complex sensor infrastructure.

IV. CONCLUSION

This paper presents an accurate simple approach for detecting SITFs in BLDC motors, leveraging a current-based fault detection index across five stages. Experimental validation using a test bench confirms the method efficacy, particularly in detecting low-severity SITFs, demonstrating robust real-time capabilities. By utilizing only current sensors and applying signal-processing techniques, such as Park transform and SG filtering, this method avoids the need for voltage or flux-based sensors, significantly reducing hardware complexity and computational demands. The approach is well-suited for sensor-based applications, providing reliable, low-cost fault detection with high sensitivity and minimal latency. This efficient, easily implemented solution is promising for deployment in various BLDC motor applications, ensuring enhanced motor protection with minimal additional infrastructure.

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