A Fast FDI Approach for BLDC Motor using Phase Currents Normalization

Kareem Akeem Bayo[1], Tanvir Alam Shifat[2], and Jangwook Hur[3]

[1, 2, 3]*Department of Mechanical, Aeronautical and Electronic Convergence Engineering*
Kumoh National Institute of Technology
Gumi, Republic of Korea

20216004@kumoh.ac.kr
tanvir@kumoh.ac.kr
hhjw88@ kumoh.ac.kr

ABSTRACT

In modern industrial processes, fault detection and fault diagnosis of electrical machine and drive systems have critical importance. The significance of condition monitoring and fault diagnosis approach to improve the safety and reliability of electric motors in lieu of the widespread applications in the industry cannot be overemphasized. This is basically true for safety applications. Brushless DC motor do not use brushes for commutation, instead, they are electronically commutated. Unexpected failures in electrical motors can result in operation downtime, costly repairs and safety concerns. Brushless Direct Current (BLDC) motors are one of the motor types majorly gaining much popularity. Against the conventional brushed DC motors, BLDC motors are noiseless during operation, and have long operating life, high efficiency, high dynamic response, and better speed to torque ratio characteristics; however, there is need for continuous health monitoring. This study presents a fault diagnostic combining normalize model current analysis and machine learning algorithm. The experimental results demonstrate that the proposed diagnostic method can reliably separate different fault condition in BLDC motors.

Keyword – BLDC Motor, fault diagnosis, NMCA, KNN, LDA, fault visualization

1. INTRODUCTION

Condition Monitoring has gotten a lot of attention from experts and practical maintenance because it has such a major effect on industry. When it comes to system maintenance and process automation, machine condition monitoring is important. Condition monitoring is used in a number of industries to provide useful information on the health and maintenance needs of rotary machinery. Condition monitoring and diagnostic devices are generally used in machines that calculate vibration and technical parameters [1]. The mechanical status of equipment can be monitored using parameters such as vibration, temperature, lubricant quality, and acoustic emission. Fault diagnosis increases an existing system's reliability and availability. Since different faults degrade at different rates, fault diagnosis can be done at an early stage. It is important to note that machine fault diagnosis is becoming increasingly important in industry because of the need for highly reliable machinery [2]. Unfortunately, many of the traditional methods currently available necessitate a high degree of knowledgeable expertise in order to be effective.

To detect and estimate the form and severity of these faults in electric motors, a variety of methods have been used. Time domain methods, frequency analysis methods using the Fast Fourier Transform (FFT) [3], and time scale analysis methods using discrete and continuous wavelet transforms are all examples of these methods [4], [5]. Since it doesn't require any external connections or hardware, the motor signature current analysis (MSCA) is one of the most common online methods for fault detection.

In industrial applications, brushless DC motors (BLDC) are commonly used. A three-phase armature winding stator and permanent magnet rotor are common components of a BLDC motor. Commutation in BLDC motors is performed using power electronics in combination with rotor position input from hall sensors [6]. Unlike typical brushed DC motors, the BLDC does not have a mechanical commutator that can wear out and cause electric arcing. The BLDC motor's rotor contains rare earth magnets that generate a steady magnetic field, resulting in high efficiency and power factor [7]. Maintaining a desirable output in industrial processes, which often involve a number of faults, is a crucial challenge. Fault detection and diagnosis (FDD) is a critical control method for accomplishing this task among various process supervision techniques, since most industries expect to enhance their process efficiency by increasing their FDD capability.

The majority of permanent magnet motors in industries are powered by a three-phase current with the aid of an external motor. In these devices, the rotor is often a permanent magnet, and the stator is a set of coil windings that serve as an electromagnet. Electromagnets' pole positions are modified according to the polarity of permanent magnets by regulating the polarity and magnitude of phase currents. When a failure occurs in a single phase, all phase current components are affected because the stator coils are arranged in a "STAR" or "DELTA" configuration. The analysis of multiple step results, on the other hand, necessitates more computing resources and time. Furthermore, analyzing a single-phase current can result in an incorrect approximation. As a result, a normalized modal current computation is needed to ensure a stable CM system and fast decision making. The efficacy of a modal current computation approach for fault detection and diagnosis is validated in this paper using a machine learning algorithm that uses both K Nearest Neighbors (KNN) and Linear Discriminant Analysis (LDA) for dimension reduction.

2. PROPOSED METHOD

2.1. Normalized Modal Current Computation

The first step of the modal current computation is the amplitude normalization. Motor current magnitude changes drastically depending on the loads connected to it. Therefore, all three-phase currents need to be expressed in a normalized unit common to all. We have used simple signal processing technique to convert motor currents into per unit (pu) form given that the amplitude of the current signals (i) differs at different loads. This is actualized by dividing all samples to the peak current (I_{max}) using Eq. (1) [8].

$$I_{pu,(i)} = \frac{I_i}{I_{max}} \tag{1}$$

where i represent the phase current A, B and C. Next, the normalized signals are linearized using Eq. (2) to obtain the modal current equation.

$$I_M = \alpha I_{NA} + \beta I_{NB} + \gamma I_{NC} \tag{2}$$

where I_{NA}, I_{NB}, I_{NC} are normalized phase currents for phase A, B and C respectively while {α, β,and γ}∈{1, 2, and -3} are the modal current respectively [9, 10].

There is no simple subtracting or summation of two signals since the phases are multiplied by the different coefficients. As a result, the signals' transient behavior is guaranteed to be unchanged, and the modal signal retains all transient data in various conditions. Using the modal signal shortens the processing time and makes the proposed algorithm easier to construct. This will allow us to investigate the fault characteristics of each motor phase current without explicitly computing each phase separately.

2.2. K Nearest Neighbors (KNN)

It is one of the most fundamental and simplest classification methods. The easiest way to define KNN is the assumption that "similar things exist in close proximity". In this classification technique, similar data points are classified into a single group based on the distances among them. Initially, number of neighbors, K is determined and distances to other points are measured in an ordered collection [11]. K-NN is a well-known instance-based approach with advantages including better adaptability to unseen observation, fewer parametrization, high unsupervised learning efficiencies and significant learning capabilities for non-gaussian distribution.

2.3. Linear Discriminant Analysis (LDA)

LDA is a supervised algorithm that finds a linear transformation used to perform dimensionality reduction of the original data set by maximizing the classes' separability [12]. To perform this task, LDA uses two statistical information: the between-class scatter matrix S_b and within-class scatter matrix S_w defined in Eq. (3) and Eq. (4) as:

$$S_b = \frac{1}{N}\sum_{i=1}^{i} n_i(\mu i - \mu)T(\mu i - \mu) \tag{3}$$

$$S_w = \frac{1}{N}\sum_{i-1}^{i}\sum_{j=1}^{n_x}(X^i(j) - \mu_i)T(X^i(j) - \mu_i) \tag{4}$$

From these equations, it follows that the total-class scatter matrix S_t is obtained using Eq. (5):

$$S_t = S_b + S_w = \frac{1}{N}\sum_{j=1}^{N}(X(j) - \mu)T(X(j) - \mu) \tag{5}$$

3. EXPERIMENTAL TEST BENCH

We conducted the test using a conventional generator motor setup where the motor is coupled with the generator and some variable loading for balancing. At the other end of the BLDC Motor, we have attached an accelerometer as a sensor to measure the vibration signal. The data were continuously acquired using the DAQ module. Figure 1 shows the test bench setup for the BLDC motor test. Table 1 describes the BLDC motor parameters. A N1-9246 current module and a N1-9178 current module were used to continuously measure three-phase motor current. DAQ chassis at a rate of 5 kHz.

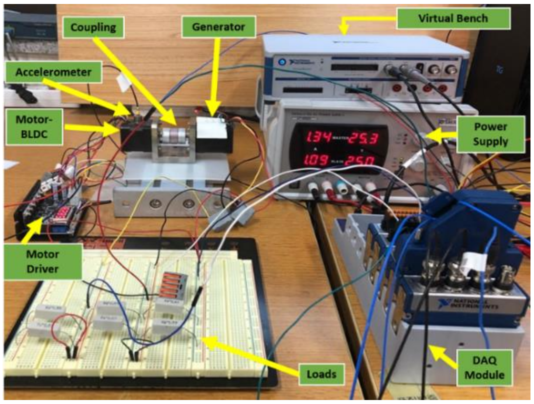

Figure 1. BLDC motor test experimental arrangement

Table 1. BLDC motor parameters

Parameter	Values
Model	BLS-24026N
Rated voltage	DC 24V
Rated torque	0.96 N.m.
Rated speed	4000 RPM ±10 %
Rated current	<2.5 A
Rated output	40 W
No load speed	5000 RPM ± 10 %
No load current	<0.6 A

4. RESULTS ANALYSIS AND DISCUSSION

The computed normalized modal current is shown in Fig. 2. The first diagram describes the sensor acquired motor current which represent the current raw current signals in three-phase form. The second diagram describes the computed modal current which signifies the normalized current from 3 phase to a single phase. The following methods (TSNE, LLE, and PCA) were deployed to classify the data derived from the normalized modal current. From Figure 3, TSNE showed a more effective data visualization but could not classify the detected fault as it is extremely applicable for image processing, NLP, genomic data and speech processing. To improve on the accuracy of the classifier [13]. LDA was utilized. LDA showed it is not just a reduction tool but a robust classification method. LDA has been able to present the data explicitly and it is a good reduction method for high dimensional data compared to the other algorithms. One can see that LDA enforces a clustering of the data that is virtually meaningful with a linear decision boundary despite the large reduction in dimension of the features and domain.

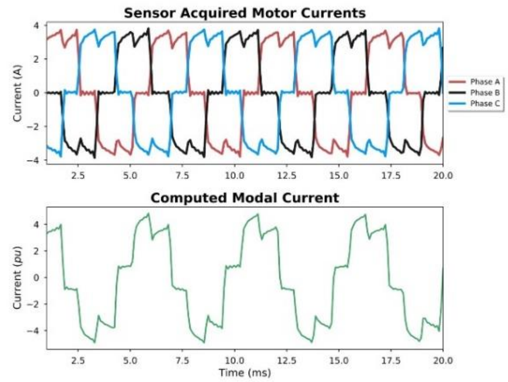

Figure 2. Frequency and time-frequency analysis of modal current.

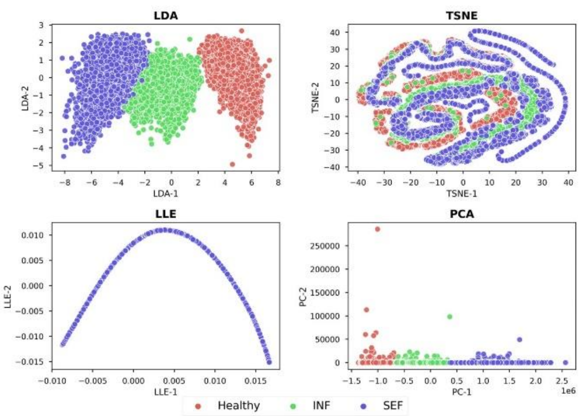

Figure 3. Performance of linear discriminant analysis (LDA) against other reduction model.

5. CONCLUSION AND FUTURE WORKS

In this paper, a fast condition monitoring approach of BLDC using phase currents normalization and supervised machine learning is presented. The fault characteristics of all three phases was taken into consideration when the dimensionality reduction took places. For future work, we would be looking into the RUL estimation method of BLDC motor by considering the INF fault and SEF fault**.**

REFERENCES

[1] A. Widodo and B.S. Yang, Review support vector machine in machine condition monitoring and fault diagnosis, Mechanical Systems and Signal Processing 21 (2007), 2560–2574.

[2] L. Zhang, G. Xiong, H. Liu et al., Bearing fault diagnosis using multi-scale entropy and adaptive neuro-fuzzy inference, Expert Systems with Applications 37 (2010),

6077–6085.

[3] Torkaman, H.; Afjei, E.; Yadegari, P., "Static, Dynamic, and Mixed Eccentricity Faults Diagnosis in Switched Reluctance Motors Using Transient Finite Element Method and Experiments," Magnetics, IEEE Transactions on , vol.48, no.8, pp.2254-2264, Aug. 2012
[4] Rosero, J.; Romeral, J.L.; Cusido, J.; Ortega, J.A.; Garcia, A., "Fault detection of eccentricity and bearing damage in a PMSM by means of wavelet transforms decomposition of the stator current," Applied Power Electronics Conference and Exposition, 2008. APEC 2008. Twenty-Third Annual IEEE, vol., no., pp.111-116, 24-28 Feb. 2008
[5] Georgakopoulos, I.P.; Mitronikas, E.D.; Safacas, A.N.; Tsoumas, I.P., "Detection of eccentricity in inverter-fed induction machines using wavelet analysis of the stator current," Power Electronics Specialists Conference, 2008. PESC 2008. IEEE, vol., no., pp.487-492, 15-19 June 2008.

[6] S. Nandi, H. A. Toliyat and X. Li, "Condition Monitoring and Fault Diagnosis of Electrical Motors—A Review," IEEE Transactions on Energy Conversion, vol. 20, no. 4, pp. 719-729, Dec. 2005.

[7] Jafari, Ahmad, Jawad Faiz, and Mohammad Amin Jarrahi. "A Simple and Efficient Current Based Method for Inter-Turn Fault Diagnosis of Brush-less Direct Current Motors." IEEE Transactions on Industrial Informatics (2020).

[8] Perera, Nuwan, A. D. Rajapakse, and T. E. Buchholzer. "Isolation of faults in distribution networks with distributed generators." IEEE transactions on power delivery 23.4 (2008): 2347-2355.

[9] Hu, Li-Yu, et al. "The distance function effect on k-nearest neighbor classification for medical datasets." SpringerPlus 5.1 (2016): 1304.

[10] R. Duin and M. Loog, "Linear dimensionality reduction via a heteroscedastic extension of lda: the chernoff criterion", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 26, no. 6, pp. 732-739, June 2004.

[11] I. Martin-Diaz, D. Morinigo-Sotelo, O. Duque-Perez, and R. Romero Troncoso, “Evaluation of intelligent approaches for motor diagnosis under changing operational conditions,” in Proc. 2017 IEEE 11th Int. Symp. Diagn. Elect. Mach., Power Electron. Drives, Sep. 2017, pp. 359–365.

[12] Fisher R. A., "The use of multiple measurements in taxonomic problems", Annals of Eugenics, vol. 7, no. 2, pp. 179-188, 1936.

[13] Van der Maaten L.J.P. and Hinton G.E. Visualizing High-Dimensional Data Using t-SNE. Journal of Machine Learning Research 9(Nov):2579-2605, 2008

BIOGRAPHIES

Kareem Akeem Bayo received the B.Sc. degree in mechanical engineering from University of Ilorin, Ilorin, Nigeria, in 2017. He is currently a Graduate Student at the Department of Mechanical System Engineering, Kumoh National Institute of Technology. He is also working as a full-time Graduate Research Assistance at the Defense Reliability and Maintainability Research Laboratory. He is primarily focused on the prognostics and health management of mechanical electrical and electronics systems. His research interests include reliability, maintainability, condition monitoring of rotary machinery and mechanical devices.

Tanvir Alam Shifat (Graduate Student Member, IEEE) received the B.Sc. degree in electrical and electronic engineering from East West University, Bangladesh, in 2016. He is currently a Graduate Student at the Department of Mechanical System Engineering, Kumoh National Institute of Technology. He is also working as a full-time Graduate Research Assistance at the Defense Reliability and Maintainability Research Laboratory. He is primarily focused on the advanced signal processing and machine learning techniques for the condition monitoring of electric motors. His research interests include reliability, maintainability, condition monitoring of rotary machinery, and electronic devices.

Jang Wook Hur received the Ph.D. degree in mechanical engineering from Tokyo Institute of Technology, Japan, in 1995. He is currently serving as a Professor at the Department of Mechanical Engineering, Kumoh National Institute of Technology, where he is the Director of the Defense Reliability and Maintainability Research Laboratory. He also served for Korean Army, and ranked Colonel, in 2011. His research interests include reliability, maintainability, and condition monitoring of various defense equipment.