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DEMAGNETIZATION FAULT DETECTION METHOD IN BRUSHLESS DC MOTORS BASED ON FRACTAL DIMENSIONS

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Abstract. *BLDC motors (brushless direct current motors) have many advantages when compared to conventional motors. Despite this, they present an important negative point, the demagnetization failure, whose occurrence in some BLDC applications can cause severe financial loss and risk of death. The main objective of the work is to implement, validate and analyze a solution for the detection of demagnetization fault in BLDC motors. Current signals were obtained under normal and fault operating conditions at two different speeds. To cause the demagnetization failure of the motor, one of the permanent magnets was worn out. The use of the fractal dimensions method made the analysis simpler, since the demand for computational effort was lower since it was not necessary to involve transformations to other domains or complex operations in its calculations. The results were very positive, indicating that the methodology adopted is configured as a tool with good potential for analyzing other fault situations in BLDC.*

Keywords: *brushless dc motor; fractal dimensions; demagnetization; fault*

1. INTRODUCTION

In recent years, brushless direct current motors (BLDC) have gained a lot of attention in the electrical machinery industries for being more efficient and reliable. The main feature that makes these motors gaining this visibility is in their construction, as the absence of brushes reduces the overall dimensions and weight of the motor, and because of these benefits these motors are attracting the curiosity of several researchers (Kudelina et al., 2020). BLDC motors are widely used in domestic appliances, the main ones being washing machines, air conditioners, refrigerators, vacuum cleaners, freezers and others, and also on various industries such as automotive industries, pumping industries, and rolling industries (Mohanraj et al., 2022). In addition to being used in domestic appliances, we can find these engines in the automotive, aerospace, industrial automation equipment and instrumentation sectors (Yedamale, 2003).

According to Iakshmi and Ramesh (2015) BLDC motors have numerous benefits over brushed DC motors and induction motors, some of these benefits are better speed versus torque characteristic, high dynamic response, high efficiency, long operating life and silent operation.

As much as BLDC motors can be efficient and reliable, some operation failures can lead to serious problems, causing economic losses or fatal accidents (Veras et al., 2019). These faults can essentially be classified as mechanical faults, electrical faults and demagnetization faults (Kudelina et al., 2020).

There are many works in the literature that aim to identify dynamic eccentricity faults in various types of electrical machines, the most common methods are those that perform the acquisition of electrical signals from the motor. There are few works that address the identification and detection of demagnetization faults in BLDC motors using processing techniques based on chaos theory, thus being an area that is little explored by researchers (Veras et al., 2019).

2. THEORETICAL BACKGROUND

2.1 BLDC motors

BLDC motors are designed to overcome the problems caused by brushes. These motors are electronically commutated, and because of the absence of brushes, they do not produce sparks. This feature allows them to be used in applications where sparks can be hazardous (gas environment). Removing the motor brushes overcomes the problems associated with electrical erosion and mechanical friction. Brushless direct current motors are composed of a stator with three-phase armature windings and a rotor with permanent magnets(Iakshmi and Ramesh, 2015). The electrical equivalent circuit model of a BLDC can be seen in Figure 1. Based on this model, it is possible to obtain the following mathematical equations that describe its operation (Parveen and Muralidhar, 2015):

$$u_A = Ri_A + \frac{d}{dt}(L_A i_A + L_{AB} i_B + L_{AC} i_C) + e_A \tag{1}$$

$$u_B = Ri_B + \frac{d}{dt}(L_{BA} i_A + L_B i_B + L_{BC} i_C) + e_B \tag{2}$$

$$u_C = Ri_C + \frac{d}{dt}(L_{CA} i_A + L_{CB} i_B + L_C i_C) + e_C \tag{3}$$

Where:
u_x- phase voltage, where x represents phases A, B, and C;
i_x- phase current;
e_x- induced electromotive force in the phase;
R_x- Phase resistance for three symmetrical windings $R_A = R_B = R_C = R$;
L_x- phase self-inductance
L_{AB},L_{AC} – Mutual inductance of phase A with phase B and phase A with phase C, respectively.

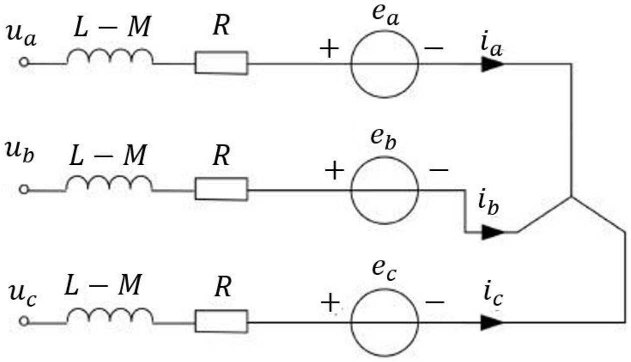


Figure 1. BLDC motor electrical circuit model.

The analysis of Eq. (1) - (3) shows that the equivalent circuit model of the BLDC motor consists of three non-linear coupled equations. As seen in Arrowsmith et al. (1990) and Wei (2006), a system whose behavior is described by three or more coupled nonlinear differential equations is subject to chaotic or nonlinear dynamics.

2.2 Main faults in BLDC motors

According to Kudelina et al. (2020), the failures that occur in BLDC motors can be classified as: mechanical failures (bearings and eccentricity), electrical failures (drive and winding failures) and magnetic failures (demagnetization). Almost 50% of motor failures are mechanical, with bearing failures being the most common.

Electrical faults usually start with a turn-to-turn short circuit and can grow to a phase-to-ground or phase-to-phase short circuit if there is no preventative maintenance that can be avoided (Da et al., 2011).

In BLDC motors, there is a risk of demagnetization due to permanent magnets. In these motors, the flux of the poles corresponds to the residual flux that is present in the magnets. If the armature current becomes higher, there is a risk that the magnetomotive force of the armature can demagnetize the poles, permanently reducing and otherwise orienting the residual flux that is present in them. Another way for this failure to occur is due to the temperature rise that can be caused by a shock (motor falling) or extended periods of overloads (Chapman, 2013).

Considering the application of BLDC motors in electric vehicles, elevators and in the aerospace area, the demagnetization failure is characterized as a serious problem, since its occurrence during the operation of certain equipment can cause risks to users or operators, as well as severe damage materials (Kim et al., 2014).

Demagnetization causes disturbance of the magnetic symmetry of the motor, which results in two changes in its mechanical operation (Fico et al., 2019): abnormal torque ripples that cause more localized vibrations and accelerations, and unbalanced rotor, if the demagnetization fault is caused by total or partial disintegration of the permanent magnet.

2.3 Fractal Dimensions

In the context of nonlinear or chaotic signal processing, some metrics can be used to estimate properties common to these types of signals, such as entropies, correlation, autocorrelation and fractal dimensions (Arjunan & Kumar, 2007). Fractal dimensions (FD) are cut-to-cut invariant metrics in time series, which enables them to be applied in pattern recognition algorithms (Parish, 1992).

Compared to other nonlinear methods that require a large amount of calculations, FD has a lower computational cost (Ahmad et al., 2014). The FD value gives a quantitative measure of an object's self-similarity (Layek, 2015), that is, how much a system is composed of smaller versions of itself. When dealing with time series, FD reveals how many times a pattern is repeated in the time series (Ahmadlou et al., 2010). The FD have been used in fault diagnosis methods for rotating machines (Soleimani and Khadem, 2015) and bearings (Yang et al., 2007), as well as in fault detection in combustion engines (Lima et al., 2021).

3. MATERIALS AND METHODS

3.1 Pattern Extraction Algorithm

The method used to calculate the FD of the BLDC motor current signals is the method proposed in (Petrosian, 1995), with its variations a, b and c. These variations consist of a binary representation of the time series prior to the calculation of the FD:

Averaging method – the value of the binary representation is assigned 1 if the time series sample value is above the signal mean and 0 otherwise.

Modified zone method – the value of the binary representation is assigned the value 1 if the time series sample value is outside the limits of the mean plus or minus the standard deviation and 0 otherwise.

"Differential" method – the sample of the binary representation receives the value 1 if the difference between two consecutive samples of the time series is positive and 0 if it is negative.

After the binary representations have been performed according to the methods described, the fractal dimension is calculated as:

$$FD_{Petrosian} = \frac{\log{(n)}}{\log(n) + log\left(\frac{n}{n + 0{,}4N\Delta}\right)} \tag{4}$$

Where:
n – Signal length;
NΔ - Number of signal changes in the binary sequence.

3.2 Preparation of the BLDC motor

A BLDC EMAX 2822 – 1200 KV motor was used to carry out the experiments, as can be seen in Figure 2a. The motor characteristics are operating voltage: 7.4 – 11.1 V, maximum current: 16 A – 10 sec., KV: 1,200 KV (revolutions per Volts).

To cause the demagnetization failure, the procedure of wearing out one of the permanent magnets was performed. The motor rotor, in its normal condition, has a weight of 20.62 g, as can be seen in Figure 2b.

With the aid of a micro grinder, a small portion of one of the permanent magnets was removed, as detailed in Figure 3a. After that, the rotor was weighed again and it was verified that it lost 50 mg, as can be seen in Figure 3b The engine operating conditions were adopted as follows:

- Normal, with a speed of 2690 RPM (Normal 1);
- Normal, with speed of 3850 RPM (Normal 2);
- With demagnetization fault, with speed of 2690 RPM (50 mg 1);
- With demagnetization fault, with speed of 3850 RPM (50 mg 2).

The engine rotation speeds were determined with the aid of a digital tachometer. As load, a 1045 propeller was used for all test scenarios.

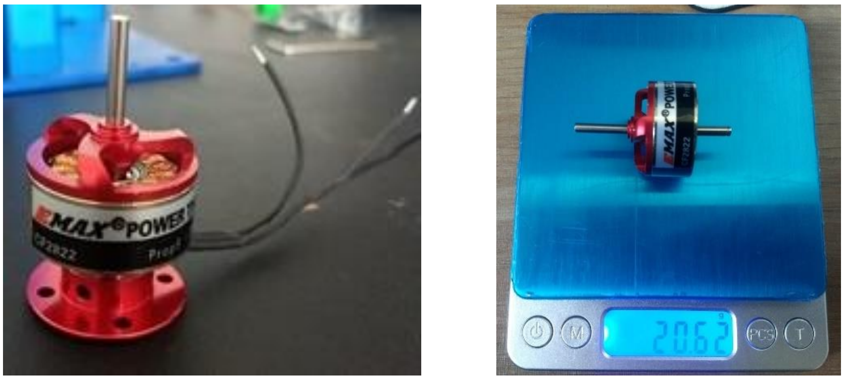


Figure 2. a) BLDC motor used. b) Rotor weighing under normal conditions.

Figure 3. a) Wear on a permanent magnet. b) Rotor weighing after permanent magnet wear.

3.3 Classification Algorithm and Test bench

For the classification task, the Neural Net Pattern Recognition tool (pattern recognition neural network - nprtool) of the MATLAB® software was used. This tool allows to create, visualize and train a two-layer feedforward ANN to solve data classification problems. The ANN training algorithm used in the application is the scaled conjugate gradient.

The next step is to determine the number of neurons present in the intermediate layer. In Heaton (2008) it is stated that the number of neurons in the hidden layer is empirically determined. However, the author suggests some approaches to determine this parameter. One is that the number of neurons in the hidden layer must be less than twice the number of neurons in the input layer. As the input layer has 3 neurons, a hidden layer with 5 neurons was adopted. The number of neurons at the input and output are set automatically. The three inputs correspond to each of the fractal dimensions calculated for the current signals. The outputs correspond to the four operating states of the motor:

Table 1. Representation of BLDC Functioning Classes.

Condition	N1 output	N2 output	N3 output	N4 output
Normal 1	1	0	0	0
Normal 2	0	1	0	0
50 mg 1	0	0	1	0
50 mg 2	0	0	0	1

Where Nx = Nth neuron of the output layer.

Then, the data separation was chosen, that is, how many samples will be considered for the training, validation and testing stages of the ANN algorithm. In total, 1180 samples were obtained for classification, each sample being composed of three values, Petrosian fractal dimensions a, b and c. 295 samples were considered for each operating condition. The following percentages were determined: 55% (649 samples) for training, 15% (177 samples) for validation and 30% (354 samples) for testing.

To carry out the tests, the experimental apparatus illustrated in Figure 4 was built. The bench consists of:

1 - A 12 V/30 switching power supply to feed the BLDC motor;
2 - NI-DAQ USB-6215 data acquisition board for signal acquisition, with 16-bit resolution and maximum acquisition rate of 250,000 samples per second;
3 - A 3.3V/5V DC power supply for the current sensor;
4 - A 30A ESC with internal 2A/5V BEC;
5 - ACS712 30 A current sensor;
6 - Support for BLDC motors Racerstar V3, with rotation speed control;
7 - 1045 propeller 1045;
8 - BLDC motor EMAX 2822.

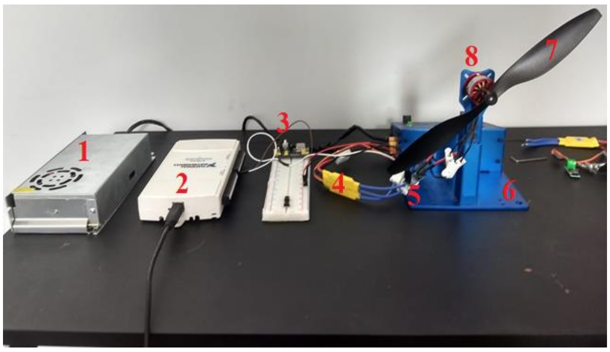


Figure 4. Test bench.

4. RESULTS AND DISCUSSSIONS

4.1 Acquired current signals

In Figures 5 and 6 the signals acquired for the 4 considered operating conditions can be seen.

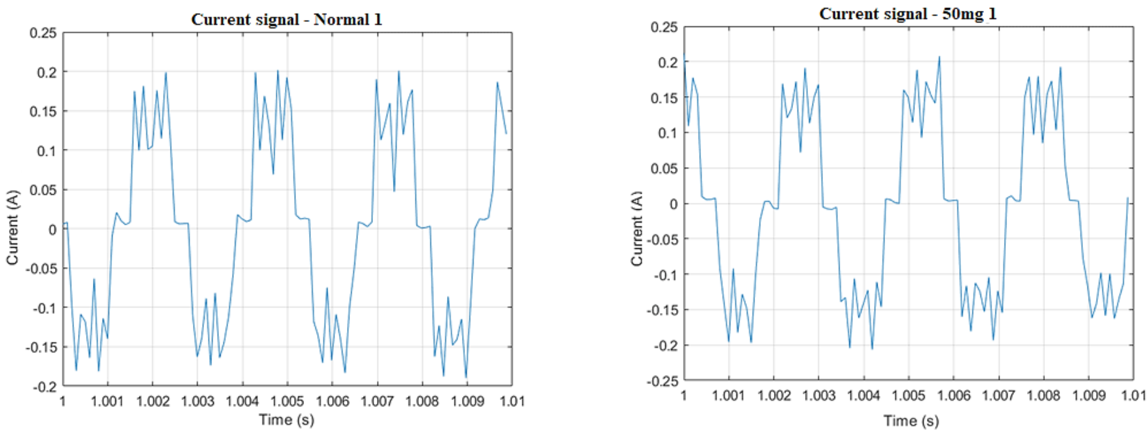


Figure 5. a) Current Signal – Healthy motor / 2960 RPM. b) Current Signal - Faulty motor / 2960 RPM.

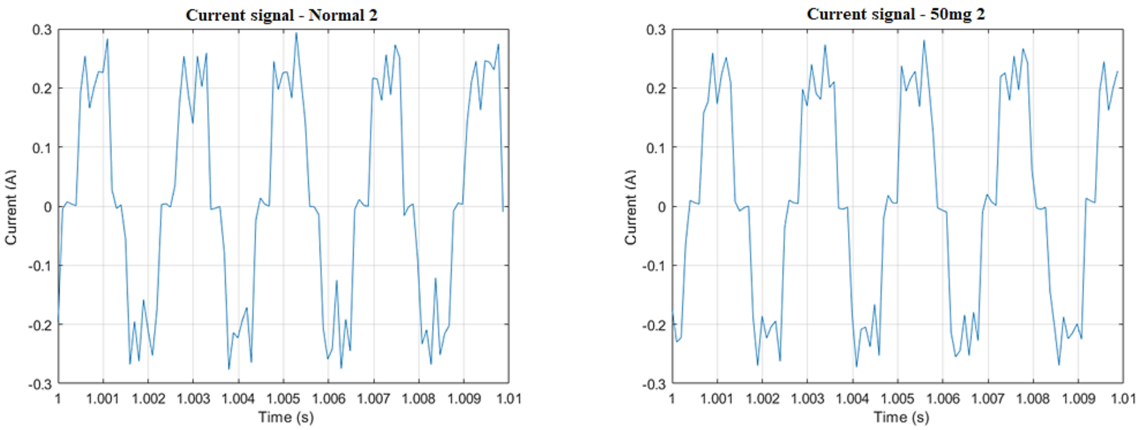


Figure 6. a) Current Signal – Healthy motor / 3850 RPM. b) Current Signal - Faulty motor / 3850 RPM.

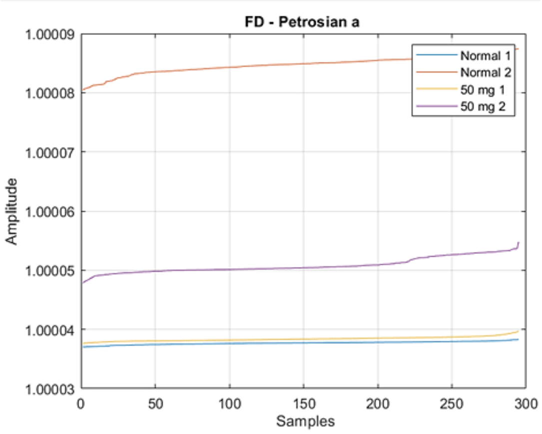
It is possible to verify that, in the time domain, the normal and fault signals are very similar, which makes the signal classification task unfeasible without the application of a suitable signal processing tool. It is worth noting that the analyzed samples were acquired at different times of the day, with no change in the behavior of the signals due to the variation in the time of acquisition.

4.2 Values of the extracted parameters

The values extracted for the fractal dimensions in the 4 signals under study are condensed in Table 2, in which their minimum, average and maximum values are exposed. In Figures 7 and 8 it is possible to observe the set of values for each fractal dimension obtained for the four signals considered in the present work.

Table 2. Minimum, average, and maximum values of the extracted parameters.

Signal	Parameter	Minimum	Average	Maximum
Normal 1	Petrosian a	1.000037038	1.000037700	1.000038325
	Petrosian b	1.000226594	1.000229176	1.000231469
	Petrosian c	1.000291834	1.000293550	1.000295103
Normal 2	Petrosian a	1.000080418	1.000084683	1.000087447
	Petrosian b	1.000145916	1.000148665	1.000151011
	Petrosian c	1.000280896	1.000282458	1.000283871
50mg 1	Petrosian a	1.000037619	1.000038391	1.000039692
	Petrosian b	1.000210734	1.000213728	1.000217438
	Petrosian c	1.000285965	1.000287732	1.000288984
50mg 2	Petrosian a	1.000047832	1.000050818	1.000054801
	Petrosian b	1.000148504	1.000151528	1.000153375
	Petrosian c	1.000282268	1.000283517	1.000285172



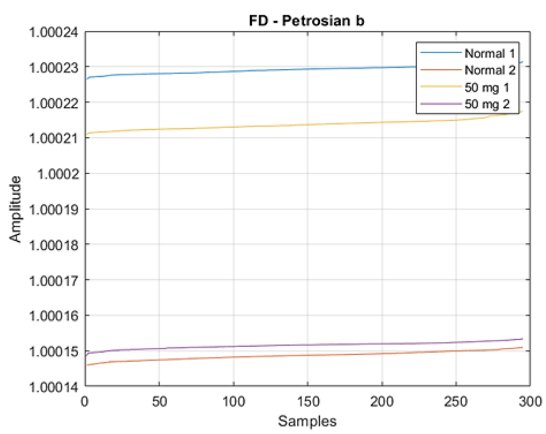


Figure 7. a) Petrosian's Fractal Dimension a b) Petrosian's Fractal Dimension b

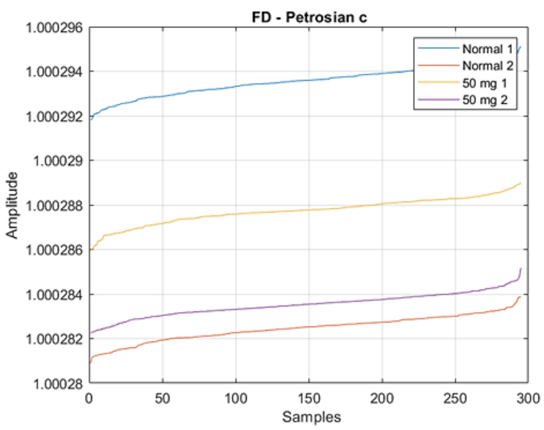


Figure 8. Petrosian's Fractal Dimension c

The analysis of Table 2 and from Figures 7 and 8 allows to conclude that, although the values in general are very close when considering each dimension (a, b and c) separately for the different failures, it is possible to notice that there is a sufficient separation for a classification system to obtain an excellent result in its task of predicting the process classes.

4.3 Classification Result

The overall result of the classification algorithm can be seen in Figure 9. It is possible to conclude that the performance of the algorithm was excellent, since for all steps its success rate was 100%. This fact is justified by the separation noted between the fractal dimensions extracted for the studied signals.

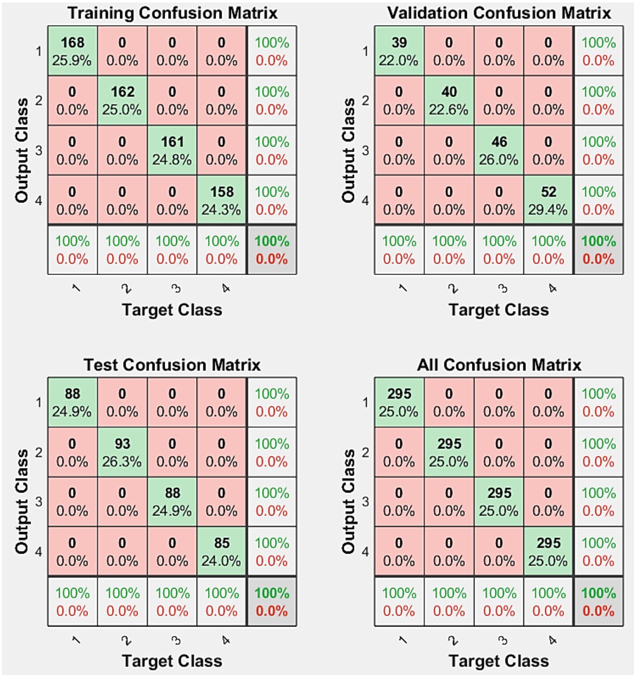


Figure 9. ANN confusion matrix.

5. FINAL CONSIDERATIONS

The present work dealt with the implementation of a method for detecting the demagnetization fault in BLDC motors based on fractal dimensions. In particular, two different operating speeds were considered for the normal and fault situation. As a differential, the work presented the assembly of the bench and the use of this non-linear processing technique to analyze this type of failure, which was not previously found in the literature.

It is worth mentioning that the use of fractal dimensions made the analysis simpler and with a low computational effort demand, since its calculations do not involve transformations to other domains or complex operations such as convolutions.

The performance of the classification algorithm was excellent, since the proposed classification task was not difficult, given the separation between the fractal dimensions calculated for each of the four studied signals.

As future work, it is proposed to increase the area removed from the magnet, as well as to wear out more than one magnet. Another possibility would be an overload analysis with the temperature measurement and a correlation with the Curie Temperature. In addition, it would also be interesting to analyze more speed conditions, in such a way that for a single fault, several speeds are considered to compose a single training set, thus overcoming one of the impediments of the current technique, that is, the need for training data for each operating speed and fault.

6. ACKNOWLEDGMENT

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