Detection of the Stator Inter-Turn Fault Using the Energy Feature of the Wavelet Coefficients Obtained by Continuous Wavelet Transform

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Abstract: This research aims to investigate a fault detection method applicable to the stator part of the Brush-Less DC motor (BLDC). Indeed, it is a concern to make sure the motor is operating in a healthy mode, and in any other case, it is of great importance to detect the fault as soon as possible to prevent the further ruin of the major system. Regarding this, a sub-branch method of the Wavelet Transform analysis, named Continuous Wavelet Transform (CWT), is utilized to observe the short-circuit fault in the stator coils. Thus, a novel simulator of the BLDC motor is developed by making an interconnection between ADAMS and MATLAB in which different electrical and mechanical components are included. Therefore, a close-to-reality model of the BLDC motor is achieved, leading to a more accurate evaluation of the proposed method. An energy-type feature will be suggested to characterize the fault happening. Through acquiring the normalized energy amount for one of the wavelet coefficient signals, obtained by the CWT, and comparing the energy with a predefined threshold amount of energy for that signal, it is feasible to detect the stator’s flawed performance. By conducting different simulations, the proposed method will be validated.

Keywords: BLDC motor, stator inter-turn fault, CWT, fault detection, ADAMS software.

1 Introduction

Due to their reliability and efficiency, brushless DC (BLDC) motors are known to be excellent choices to be applied in different application fields, including aerospace systems, chemical industry, and electric vehicles, to mention just a few [1–3]. The motor functioning in an unhealthy mode will undoubtedly lead to principal problems and issues, decreasing the efficiency, safety, or system reliability. Accordingly, prompt diagnosis of any defect existing in the system would be essential, having a prime impact on keeping the equipment operate in a reliable and safe mode.

Several fault diagnosis methods have been developed so far, not helping with detecting the actuator’s internal faulty parts. They are mainly based on control system modeling or data sets [4–6]. Regarding this issue, a different branch of works named signal-based methods has been developed, for module condition monitoring, based on measuring a crucial signal. Signal-based approaches work in time [7], frequency [8], or time-frequency [9] domains. The fault detection in a time-frequency domain is one of the approved methods as opposed to the ones based on time, in which the measured signal should have noticeable changes during its evolution in time. On the other hand, frequency-based algorithms may only be applied to stationary or periodic non-stationary signals. As the loading condition on the BLDC motor might be different such as with no load or changeable load, the system signals could be dynamic and have a transient part, in general. Therefore, the frequency spectrum might be changing with respect to time, and hence, each time or frequency algorithm cannot be very effective. Accordingly, recently, time-frequency approaches have been greatly applied to electrical machines as a practical means for fault detection, and several articles have been published in this field. Costa et al. [10] have studied two methods, i.e., Fast Fourier Transform (FFT) and wavelet, to detect the broken bars in induction motors. This research provides results showing the slight superiority of the Wavelet Transform (WT) method over FFT for fault detection purposes in this case. Moravej et al. [11] presented an algorithm for identifying a high impedance fault in which dual-tree complex WT has been utilized. Their results showed that the approach was highly dependable and secure. A novel approach using Discrete Wavelet Transform (DWT) and a recurrent neural network has been offered by Abed et al. in [12].

Defective stator windings in electrical motors happen to constitute a large percentage of the usual faults. The stator fault may start from unknown short-circuited turns in a coil, and thereby, it transfers to phase-to-phase or even phase-to-ground short circuits, causing tremendous and irreparable damage followed by a forced shut down of the system in each of both cases.

For this reason, obtaining fast and accurate information about any error in the stator windings is an important matter which has been extensively studied, such as the research done by Elbouchikhi et al. [13]. The authors of this paper proposed
a new approach for detecting stator faults in inverter-fed induction motor under closed-loop control. A flux-based approach has also been presented by Afrandideh et al. [14] for the online detection of stator defects in synchronous generators. Hu et al. [15] offer an inter-turn short circuit fault diagnosis technique for permanent magnet machines based on the current residual. Sá et al. [16] investigate a scheme to detect stator faults in the first moments, employing a classifier module based on a multilayer perceptron neural network and analyzing the stator electrical current patterns. Another approach is introduced by Shifat and Hur [17] to diagnose the insulation break in the stator winding through combining vibration and current signals collected from sensors. Akhil Vinayak et al. have researched a new real-time incipient Stator Inter-Turn Fault (SITF) diagnosis algorithm in [18] by applying DWT analysis on the stator current in inverter-fed induction machines.

In general, the systems operating in a stationary mode may be analyzed with the classic Fourier Transform (FT) techniques. However, FT analysis is not much help in a non-stationary system or one that undergoes a transient state. In these systems, time-frequency methods, such as Short-Time Fourier Transform, or time-scale algorithms, like WT, could be used. In this paper, a fault detection algorithm based on the Continuous Wavelet Transform (CWT) tool has been developed to detect the SITF. To this end, the Wavelet Coefficients (WC) signals are extracted from the stator phase current signal. As two parameters of position and scale- which are related to time and frequency, respectively- are involved in achieving WCs, the method works in a time-frequency domain with its advantages stated before. The work done in [19] covering diagnosing the short-circuit faults of the stator winding using CWT has researched fault diagnosis in electric motors using wavelet methods. Despite this paper and some other nearly related works, such as Zandi and Poshtan's [20], an energy-based approach towards the signals achieved from CWT is presented in our paper. Moreover, a more accurate model of the BLDC motor has been extracted with the help of MATLAB and ADAMS. In this regard, knowing the specific frequencies associated with the SITF, required WCs are obtained and analyzed in terms of their energy amount. There would be a higher cumulative energy amount in one or more of the WC signals in case of a fault occurrence, leading to the faulty situation determination. The calculation of the WC signals’ energies brings about a more distinct feature for fault detection than the criteria used in other research such as Frosini et al. [21], in which the shape and form of the WC signals are the base for the fault detection. A signal’s energy amount can render a numerical criterion that may be compared between different fault intensities and is more scientific than the mere shape of the signal itself. Therefore, the signal being under inspection for fault occurrence can be constantly and rapidly checked for any faults initiating in the system.

Many researchers use the standard BLDC motor model as a mathematical dynamic equation [3,22,23]. Although this model tries to consider as many aspects of the actual motor as possible, some elements are still not included in this model, such as the rotor’s static and dynamic imbalances. Here, the presented algorithm is done on the stator phase current obtained from an enhanced BLDC motor model simulated in MATLAB and ADAMS. Although the electrical and mechanical parts of the motor and their relations have been included in our mathematical model, there might still be some mismatches between the MATLAB model and the real BLDC motor. Consequently, a novel modeling methodology concerning MATLAB and ADAMS software has been proposed. ADAMS software plays a vital role in providing a closer-to-the-reality model of the motor. Only having MATLAB to make the model, one cannot closely model the mechanical parts and the affiliated imbalances, as it can be done with the help of ADAMS software. To be more precise, the rotor part is designed in the ADAMS software, and next, the ADAMS block is related to the stator and driver modules, already developed in MATLAB. Finally, this more detailed model provides a more accurate evaluation of the proposed algorithm.

The paper contributions are considered as follows. (1) The fault occurrence would be determined not only at the equipment level but also at the internal elements level. Hence, this method is superior to model-level approaches [4]. (2) As the method is not a data-based one, its performance does not rely on the existence of a rich dataset in comparison to the research done by Skowron et al. [24] and Maraaba et al. [25]. (3) Both the time and frequency features of the fault could be obtained, and as a result of not being a frequency-domain method as opposed to [8], our method can be implemented on the transient part of the signal as well as on its steady-state duration. (4) A novel characteristic will be developed to decide about the fault occurrence and its severity quickly. Using this feature, it is possible to precisely understand the intensity of the fault by a numerical value despite the works done by Zandi and Poshtan [20], Frosini et al. [21], and Rao et al. [26]. (5) The ADAMS simulator developed here is a tool that takes the classic MATLAB motor model to a higher level of accuracy in contrast with the studies done by Rao et al. [26] and Salehifar and Moreno-Equiliáz [22].

The paper structure is as follows. In section 2, a mathematical model for the BLDC motor is presented. In section 3, the fault and specific harmonics built in the stator current will be modeled. In section 3, our approach for the simulation of the system by both MATLAB and ADAMS is presented in detail. Section 4 contains information on the CWT method used in this paper and extracting the energy criteria as a tool for fault detection. Section 5 renders numerical and graphical presentations of the simulation results to validate the proposed method. Finally, the paper is concluded in section 6.

2 Problem statement

To diagnose a fault in a BLDC motor, a precise model of it is required. The model should be as close to the reality of the motor as possible. Thus, Matlab and ADAMS are utilized together in this paper for system modeling. ADAMS is responsible
for modeling the rotor and its static and dynamic imbalances, while Matlab is in charge of simulating other system parts. For giving a view of how Matlab and ADAMS work together for this model, it can be mentioned that in Matlab environment, the subtraction of the load torque from the electromagnetic torque is sent as an input to the ADAMS rotor model. The rotor (ADAMS) then, sends out the mechanical angle $\varphi_m$, the angular velocity $\omega$, as well as the motor imbalances (flywheel disturbance torque). In Matlab, the stator phase current signal is drawn out of the system to apply CWT. Then, WC signals are obtained through CWT, containing information about the current signal in some desired frequency bands. Knowing the nature of the fault (SITF), it is possible to recognize the fault frequencies. Therefore, WCIs are to be calculated based on those fault frequencies to monitor the current signal for SITF. Finally, the energies of the WCIs in a specific time span are calculated and used further to set a threshold for fault detection. This strategy is expected to detect the SITF in all the faulty scenarios with different load conditions.

3 BLDC motor model

To increase the accuracy of the simulations and the revelation of faults, a proper motor model is essential. In other words, the more precise the model is, the more real and exact the results will be. The phase-to-phase voltages of the brushless electric motor are given by [27,28]:

$$\begin{align*}
v_{ab} &= R(I_a - I_b) + L \frac{d}{dt}(I_a - I_b) + e_a - e_b \\
v_{bc} &= R(I_b - I_c) + L \frac{d}{dt}(I_b - I_c) + e_b - e_c \\
v_{ac} &= R(I_a - I_c) + L \frac{d}{dt}(I_a - I_c) + e_a - e_c
\end{align*}$$

(1)

(2)

(3)

where $L$ is the difference between self and mutual inductances of stator winding; $R$ is the resistance; $I_a$, $I_b$ and $I_c$ are stator currents of phases “a”, “b” and “c”; $v_{ab}$, $v_{bc}$, $v_{ac}$, $e_a$, $e_b$, and $e_c$ are phase to phase voltages and recursive electromotive forces (EMF) of each phase, respectively.

On the other hand, the relation between the mechanical and electrical position ($\varphi_m$ and $\varphi_e$) of the rotor for a BLDC motor with $p$ poles is as written below [26]:

$$\varphi_e = \frac{p}{2} \varphi_m$$

(4)

Also, $\tau_L$ (the load torque) is the sum of $\tau_{DB}$ (bearing disturbance torque) and $\tau_{DF}$ (flywheel disturbance torque), as written below:

$$\tau_L = \tau_{DB} + \tau_{DF}$$

(5)

where $\tau_{DB}$ is acquired through the following equation:

$$\tau_{DB} = \tau_{\text{viscouse}} + \tau_{\text{coulomb}} = C_v \omega + C_c \text{sign}(\omega)$$

(6)

Here, $\omega$ is the rotor’s velocity; $\tau_{\text{viscouse}}$ and $\tau_{\text{coulomb}}$ are respectively viscous and Coulomb frictions; $C_v$ is the viscous friction coefficient and $C_c$ is the Coulomb friction coefficient. The electromagnetic torque of a BLDC motor is derived as:

$$\tau_e = T_e \left( X(\varphi_e) I_a + X(\varphi_e - \frac{2\pi}{3}) I_b + X(\varphi_e + \frac{2\pi}{3}) I_c \right)$$

(7)

where $T_e$ is the torque constant, and $X(\theta)$ is a trapezoidal function that makes the trapezoidal shape of the flux density and the electromagnetic torque. Since flux density in brushless electric motors is trapezoidal, back EMF on stator windings and electric torque are trapezoidal; plus $X(\theta)$ is determined separately for each phase of brushless electric motor. The back EMF on the stator windings are obtained according to the following equations:
\[ e_a = K_e \omega X (\phi_e) \]  
(8)

\[ e_b = K_e \omega X (\phi_e - \frac{2\pi}{3}) \]  
(9)

\[ e_c = K_e \omega X (\phi_e + \frac{2\pi}{3}) \]  
(10)

where \( K_e \) is the induction electromotive constant. The result of sorting the dynamic-related relations would be the state-space model of the motor as follows:

\[
\begin{align*}
\frac{dI_a}{dt} &= \left( \begin{array}{ccc}
-R/L & 0 & 0 \\
0 & -R/L & 0 \\
0 & 0 & \omega
\end{array} \right) I_a + \left( \begin{array}{c}
2/(3L) \\
-1/(3L) \\
0
\end{array} \right) v_{ab} - e_{ab} \\
\frac{dI_b}{dt} &= \left( \begin{array}{ccc}
-R/L & 0 & 0 \\
0 & -R/L & 0 \\
0 & 0 & \omega
\end{array} \right) I_b + \left( \begin{array}{c}
1/(3L) \\
1/(3L) \\
0
\end{array} \right) v_{bc} - e_{bc} \\
\frac{d\omega}{dt} &= \omega - I_a + I_b \\
\frac{d\phi_m}{dt} &= \phi_m - \omega
\end{align*}
\]  
(11)

where \( f \) is the moment of inertia of the rotor and \( B \) is the damping coefficient due to friction; \( e_{ab} = e_a - e_b \) and \( e_{bc} = e_b - e_c \) are phase to phase back EMF of the electrical motor. Finally, the \( I_c \) current is as below:

\[ I_c = -(I_a + I_b) \]  
(12)

**Remark 1.** Equations (6) to (12) are to be modeled in the Simulink space in MATLAB. At the same time, the ADAMS software is used for the simulation of the rotor to model the static and dynamic imbalances based on mass-spring mechanisms. ADAMS outputs the mechanical angle, as well as the motor velocity, replacing their respective values, \( \phi_m \) and \( \omega \), in calculations. Besides, the two last state equations in (11) would be removed from the model as they are not used for the calculations of \( \phi_m \) and \( \omega \).

**4 Modeling the fault and fault frequencies**

A stator is a substantial component of an electrical motor. So, it is significantly crucial to diagnose and locate the stator fault before it inflicts serious harm to the motor's function. For which we represent an analysis approach, the fault is the most common one, SITF. SITF is illustrated in Figure 1, in which the fault has occurred within the coil of phase “a”. As it is shown, \( I_a \) is the stator current, as \( l \) implies the part of the healthy winding, and as \( s \) is the shorted windings. A circulating current, modeled here as \( I_f \), is induced in the shorted coils, which leads to an inverse air-gap flux density. Further, this flux is effective in the magnetic flux field.

To model SITF, we use a Simulink model displayed in Figure 2, comparing both healthy and faulty conditions of one of the three stator phases. In this figure, all of the stator phases’ inductances and all of the associated resistances are considered identical and equal to \( L \) and \( R \), respectively. \( e_a, e_b, \) and \( e_c \) imply back EMF. \( r_s \) is the resistance that models the winding turns that have been short-circuited. \( e_f \) is the back EMF derived from shorted circuit current, and \( \mu \) is the rate of shorted circuit turns to the whole number of turns in one phase [29]. The fault affects the stator current calculated by (11). The modified model of the stator phases accommodating any number of short-circuited turns on one phase is shown in Figure 2b. The inter-turn fault is illustrated by a set of elements, i.e., resistance, inductance, and back EMF. There grows a fault current around the short-circuited turns adding a state variable to the previous mathematical model. Based on the number of short-circuited turns, the fault makes the phase parameters change from normal values. The inductance \( L \) should change to \((1 - \mu^2)L\) and instead of \( R \), we should add \((1 - \mu)R \). In the normal operating mode of the motor, the parameter \( \mu \) is equal to zero, as shown in Figure 2a, and the faulty operation mode with a non-zero \( \mu \) would be as Figure 2b. In the case of two or three
faulty phases, rather than one, the same scenario repeats for modeling the faulty phase, but there could be different amounts 
for \( \mu \) in each phase [19].

Upon occurring SITF, some harmonics are constructed in the stator current with a pattern described as:

\[
f_{\text{fault}} = (2n-1)f_0
\]  

(13)

where \( f_0 \) is the fundamental frequency. In this equation, the main (or fundamental) frequency of \( f_0 = 20 \)Hz is obtained 
according to the nominal rotor’s speed of 400 rpm; accordingly, by considering six numbers of poles \( (P = 6) \), the main and 
side frequencies of failure would be 20, 60, 100, and 140Hz.

5 The interconnection between MATLAB and ADAMS software

In this section, the ADAMS software is used to simulate the rotor, which provides a precise model including the static 
and dynamic imbalances based on mass-spring mechanisms. ADAMS has been used as a means to find a model which is 
beyond theoretical mathematical formulations. This software takes some uncertainties, which are not included in the 
formulations, into consideration. An important difference between a model made in ADAMS and the one made in Simulink 
is that in ADAMS, some specifications of the rotor, such as the physical characteristics, are also considered and added. For 
instance, the rotor has been formed as a cylindrical shape with an appropriate cylindrical radius. These features cannot be 
easily added to the mass-spring model that one can build with Simulink. Furthermore, the entire configuration/form of the 
rotor can be easily set/edited in ADAMS, making it a suitable choice to model the mechanical subsystem of our system.

Figure 3 demonstrates the simulated rotor part in the ADAMS by taking into account the concerned imbalances. Figure 4 
exhibits the entire system model, including the ADAMS software or rotor and other motor parts, modeled in MATLAB.

Accordingly, this figure illustrates the proper way of applying (6) to (12) to the model created in ADAMS. Following this 
diagram, first the commands of \( v_{ab} \) and \( v_{ac} \) are yielded by the controller and the driver section. Having these voltages, \( I_a, I_b \) 
and \( I_c \) currents are acquired based on (11) and (12), inside the Stator Block1. In this block, the EMF \( e_a, e_b \) and \( e_c \) produced 
by the Stator Block3 ((8) to (10)), are given as inputs. The stator phase currents are the inputs for the Stator Block2 in addition 
to the load torque. As the output of this block, the electromagnetic torque \( \tau_e \) is derived through (7), which after subtracting 
the load torque \( \tau_L \) from it, is sent as an input to the ADAMS block, the rotor [26]. The rotor sends out the mechanical angle 
\( \varphi_m \), the angular velocity \( \omega \), as well as the motor imbalances (flywheel disturbance torque). These signals then return to the 
respective blocks in the MATLAB software. Equation (6) is covered in the Bearing Disturbance Torque block outputting 
\( \tau_{DB} \). For fault detection, the stator current of different phases gets faulty characteristics in the Stator Block1 as the way shown 
previously in Figure 2b. So, in this block, different models for healthy and faulty conditions have been implemented. The 
CWT block then evaluates the output currents explained in the next section of this paper, and the energy calculation process 
follows the CWT analysis.

The aforementioned series of connections between the stated software is to be used in the simulation subsection to 
investigate the validity of the designed algorithms.

6 CWT

In general, WT is a strong and relatively modern tool with broad applications in signal and image analysis. Wavelet 
analysis is done by first choosing a proper initial function, idiomatically named “the mother wavelet”. Multi-resolution and 
multi-scale are important features of this analysis approach, which means that the signal is studied in various scales and 
resolutions [15]. This paper offers the idea of detecting a fault using CWT, one of the most well-known sub-branches of WT.

To be more specific, CWT is defined through the WCs, according to the following equation [29]:

\[
WC(s, b) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t) \Psi \left( \frac{t - b}{s} \right) dt
\]  

(14)

in which the WCs are obtained from the convolution of a signal \( x(t) \) with a mother wavelet function \( \Psi(t) \) which is chosen by 
trial and error, depending a lot on the signal we are examining. Each WC contains information about the primary signal in a 
specific frequency band. In this paper, as Figure 4 illustrates, \( x(t) \) is the current of the phase “a” of the stator (it could be any 
of the 3 phases’ currents), and it is an input of the CWT block. \( \Psi(t) \) function is chosen “db3”, one of the functions in a 
particular mother wavelet functions set by the name of Daubechies, and it is the second input of CWT block in Figure 4.

Moreover, “\( b \)” is the parameter related to the time (or position) while “\( s \)” indicates the scale and has an inverse relation with 
the frequency, as below [30]:
\[ F = \frac{F_c}{sT_s} \]

Here, \( F \) depicts any frequency of the signal we wish to consider for fault detection, \( F_c \) is the central frequency of the chosen wavelet, which is 0.8Hz for db3, and \( T_s \) is the sampling period which has been considered \( 5 \times 10^{-6} \)s in this paper.

To avoid obtaining excess data, we only derive the WCs concomitant to the SITF specific frequencies. This way, the CWT calculation process would be optimized and efficient. Table 1 identifies WC signals for each of the fault frequencies already stated in part 2. Each of the four WCs is related to a specific frequency by the scale parameter and are shown by \( C_i \), \( i = 1:4 \). The scale that corresponds to each fault frequency is simply acquired through (15). According to (14), one can obtain \( C_i \) signals for a specific period and scale of the system. For our purpose, the four obtained WC signals differ in the frequency of the base signal \( x(t) \). In other words, each of these WCs evaluates \( x(t) \) in one particular frequency of \( x(t) \). The time period for which CWT is done should be considered identical among four WCs for abnormality detection at different frequencies.

In a glance at Figure 4, it is worth mentioning that the stator current of one particular faulty phase is to be perused by the CWT block to do further examinations and determine the defective situation. As the next step toward the detection, the energy of the WCs achieved by the CWT block would be calculated through the relation below:

\[ E_i = \frac{1}{N} \sum_{k=1}^{N} C_i(k)^2 ; i = 1:4 \]

wherein \( E_i \) is the calculated energy, and \( N \) is the total number of samples available from each \( C_i \) signal during the time. \( C_i \) implies the amplitude of this signal in each sample time. As will later be shown in the simulation section, the obtained \( E_i \) amounts corresponding to specific periods of the base signal (stator current) and different frequencies in that period are the fault detection criteria. These are to be compared to a consistent threshold proportional to the energy amounts of the healthy operation mode in those specific periods. Hence, the \( E_i, \text{healthy} \) are to be acquired. Based on the maximum \( E_i, \text{healthy} \) in the static state, \( E_{\text{threshold}} \) would be set with a proper margin. At last, the fault occurrence would be declared whenever the energy amounts rise higher than the threshold (\( \max(E_i, \text{faulty}) > E_{\text{threshold}} \)). It should be noted that it is best to consider \( \max(E_i, \text{faulty}) \) among all \( E_i, i = 1:4 \), that happens to be always and by far more than the others and is significantly affected by the fault. In other words, utilizing that \( \max(E_i, \text{faulty}) \) in different periods, the fault detection would be more clear and to the point.

**Remark 2.** The energy calculation method can be superior to using the \( C_i \) signals directly as a means to detect the abnormality in the stator current, in many ways. The occurrence of SITF will change the form of the \( C_i \) signals in terms of their amplitude and ripple density. Nevertheless, merely investigating the shape of a signal is not a proper way to discover the critical situation of a system [18]. Energy calculation gives a numerical value that can be compared with other faulty situations' energy results from the same or even other similar systems. The low or high amount of the energy expresses the severity of the fault, i.e., the higher the energy, the more severe the fault is. Also, a gradual increase in \( E_i \) can work as an alarm for the human operators to help prevent the system from complete shutdown or the damage of the expensive motor parts. Based on the fact that each \( C_i \) (and hence, each \( E_i \)), according to (16) is related to a certain frequency of the base signal (according to (14)), an energy-frequency criterion and diagram could also be achieved through the proposed method. Through this diagram, one can compare the intensity of the fault ripple in every related fault frequency and conclude which fault harmonic exists more on the system than the healthy situation.

In the next part, it is stated that how these energy amounts are used to determine the abnormal faulty situation.

### 7 Simulation results

In this section, the motor model is simulated with its corresponding parameters. Then, the healthy system is examined to obtain the numerical results for this mode of stator action so that this data can be used to detect the faulty condition. For finding an appropriate threshold for the fault detection criteria, which will be further discussed in detail, the healthy system under full-load torque is to be investigated. This approach will help with not confusing the load torque impact on the system with that of a fault. Afterward, the fault detection criteria of this research will be proposed based on the observations of the previous simulations. Table 2 includes some numerical information that is to be used in the related blocks of Figure 4 in MATLAB. Additionally, Table 3 presents the ADAMS software parameters related to our model. Figure 5 refers to the graphs of the EMF and the speed signals.
7.1 Healthy mode

For acquiring a proper perspective of fault occurrence and the subsequent fault detection, healthy mode evaluation is a must. The WCs $C_1$ to $C_4$ (obtained from the stator healthy current) are acquired from the MATLAB-ADAMS model and are shown in Figure 6. In this figure, CWT has been done on the stator current in the time of $t = 0$ to $t = 8$ (in 8 seconds, covering both transient and steady-state of the system, as shown in Figure 5), presented as an instance for a figurative view of CWT. The horizontal axis corresponds to the number of samples taken from the stator current for the CWT analysis. As will be shown later, through different periods, $C_4$ usually has the maximum energy amount among four WC signals in Table 1. This characteristic makes $C_4$ a better feature than the other WCs to consider singularly as the fault diagnosis criteria. By plotting the time-energy diagram of the $E(C_4)$, through 8 seconds of stator action, it is possible to notice the fault. Figure 7a and 7b show how $E(C_4)$ to $E(C_4)$ of healthy signal change in the first 8 seconds. These figures imply that $E(C_4)$ fluctuates more remarkable and significant than the three other energy amounts. The threshold energy amount for $C_4$, which has been considered $E_{\text{threshold}} = 5.0000$, that is about twice the $E(C_4)$ of the stator current in the static mode of the healthy full-load system. Note that this margin is for the purpose that small defects and transient conditions do not cause the occurrence of false alarms. Besides, Figure 8 presents a diagram containing the threshold amount at all times, and $E(C_4)$. This figure shows precisely how $E(C_4)$ of the healthy signal changes in the first 8 seconds in comparison to the threshold energy amount. The threshold is visible with red color and is fixed in the whole period of observation time. Table 4 gives numerical information related to the energy amounts of WCs for healthy operation mode and threshold energy amount. In this table, the duration of time in which each energy amount is calculated is equal to one second; for instance, $T_{\text{L}}=1\text{s}$ refers to the time between seconds 0 to 1; the specified energy amount is also related to that period.

The next step is to conduct different simulations so that we can validate the proposed fault detection algorithm. To this aim, the interconnection created before between the ADAMS and MATLAB software will be used to perform the following scenarios.

7.2 Fault scenarios

In this paper, we consider four faulty scenarios, which are described in Table 5.

- Scenario 1: a time-variable fault starting from $t = 1\text{s}$ and increasing with the initial value of 0 and the slope of 0.125, in the no-load condition
- Scenario 2: a constant fault with the consistent severity of $\mu = 0.25$ starting from $t = 4\text{s}$, through the load condition $\tau_L = 0.01 \text{ N.m}$.
- Scenario 3: two faulty phases involved, each with constant faults having the constant severities of $\mu = 0.5$ and 0.25, starting from $t = 0\text{s}$ and $t = 5\text{s}$, respectively, through the load condition $\tau_L = 0.01 \text{ N.m}$.
- Scenario 4: two faulty phases involved, each with constant faults having the constant severities of $\mu = 0.5$ and 0.25, starting from $t = 0\text{s}$ and $t = 5\text{s}$, respectively, through the load condition $\tau_L = 0.05 \text{ N.m}$ (full load).

7.2.1 Fault scenario no. 1

This fault scenario tests our algorithm for an increasing short-circuit fault in one phase of the stator, in the no-load system condition. Figure 9 is the stator’s current during the 8 seconds of action. Starting from $t = 1\text{s}$, while the system is still passing its transient state, the fault makes the current’s amplitude constantly rise as the fault grows itself into more and more stator phase winding turns. Figure 10 presents four diagrams of WCs, $C_1$ to $C_4$, achieved from the stator faulty current in the time of $t = 1\text{s}$ to $t = 8\text{s}$. Diagrams shown in Figure 10 can be compared to those related to the healthy mode illustrated in Figure 6, in terms of their amplitudes, to check the gradual fault impact. Figure 11a and 11b illustrate the time-energy diagram for $C_4$ as well as the threshold amount and show their contrast. This diagram proves the fact that $E(C_4)$ grows with time after the fault occurrence. As it was said before, each WC is related to a frequency of the signal, based on (15). By checking over Figure 11, it is interpreted that from the moment that fault started ($t = 1\text{s}$), which is in the transient state until the moment that steady state has begun and $E(C_4)$ is passed the threshold ($t = 2\text{s}$, based on Figure 9), it took 1 second for the algorithm to detect the fault. It must be pointed that $E(C_4)$ needs to be compared to the threshold only after the transient period of the system has passed to make the correct decision about fault occurrence. Hence, it can be stated that the fault detection algorithm made an immediate decision as soon as the transient mode finished.

With due attention to Table 1, the four scales are related to four fault frequencies. Hence, for the faulty stator current, it is also possible to obtain the frequency-energy diagram after the occurrence of the fault ($t = 1\text{s}$ and thereafter, the period when the fault initiates and grows). The concerned diagram is illustrated in Figure 12, showing a comparison between the energies of the four WCs from four frequencies of the stator current. The figure is obtained from four points with the coordinates (x, y) as follow: (20Hz, $E(C_4)$), (60Hz, $E(C_3)$), (100Hz, $E(C_2)$), (140Hz, $E(C_1)$), in the healthy and the faulty
mode in the pre-mentioned time. Also, the average amount of four $E_\mu$s ($E_{average}$) is calculated and shown in the diagram in the dotted line as a better tool for comparison between the healthy and faulty modes. The rise of the faulty mode $E_{average}$ of these WCs in comparison with the $E_\mu$s in the healthy mode is evident in Figure 12.

### 7.2.2 Fault scenario no. 2

This scenario deals with the occurrence of a fault on a BLDC motor under 0.01 N.m. load torque. As Figure 13 represents, it seems that the transient time of the stator current has extended over time, and the fault has had a greater impact on the stator compared with the no-load condition. Following Figure 13, the WCs’ diagrams are presented in Figure 14. Figure 15 shows $E(C_4)$ time variations in the first 8 seconds compared with the threshold energy amount. The frequency-energy diagrams in Figure 16 help with understanding the great effect of the fault on the stator current, specifically on the energy of one of the signal’s frequencies related to $C_4$.

Figure 15 shows that from the moment that fault started ($t = 4s$) until the beginning of the steady state, where $E(C_4)$ is passed the threshold ($t = 5.55s$), it took 1.55 seconds for the algorithm to detect the fault. The steady state can be tracked by observing the phase current in Figure 13.

### 7.2.3 Fault scenario no. 3

This scenario has to do with the fault occurrence in two stator phases (a and b), each having the constant severity of $\mu = 0.5$ and 0.25, starting from $t = 0s$ and $t = 4s$, respectively. The system's load torque is also equal to 0.01 N.m. The fault detection calculation results will be shown for only the phase a” current signal, per the previous scenarios. The current signals of two faulty phases are displayed in Figure 17. Figure 18 pictures the coefficient signals for the phase “a” current. Figure 19 shows $E(C_4)$ of the faulty stator phase “a” signal changes in 8 seconds as well as the time-invariable threshold amount. Figure 20 demonstrates the energies of each of the WCs in the period of $t = 0s$ to $t = 1s$ (phase “a”) in this scenario and compares them with those of the healthy operation mode.

Looking at Figure 19 and 17a, one can notice that from the moment the fault appeared ($t = 0s$) until the start of the steady state ($t = 7.10s$), it took 7.10 seconds for the algorithm to detect the fault, while through the passed seconds, the difference between the threshold and $E(C_4)$ was relatively high.

### 7.2.4 Fault scenario no. 4

The last scenario is presented to study the full-load system under the fault impact. The fault detection algorithm is applied to this system, similar to the previous scenarios. However, for conciseness, only the C4 time-energy diagram and the frequency-energy diagram for C1 to C4, related to the phase “a” stator current, are illustrated in Figures 21 and 22, respectively. It should be noted that the time span for fault detection in this scenario for phase “a” and phase “b” was 8 and 3 seconds, correspondingly. Table 6 is a summary of the fault scenarios, containing $E(C_4)$ at the fault detection moment, fault detection time span, and the load torque. It can be used to compare the cases.

To sum up, in section 7, four fault scenarios were investigated. Scenario number 1 was a gradually increasing fault with no load applied to the motor. The fault was applied to the system in $t = 1s$ in the transient state. As soon as the current enters its steady state, the detection is done. It takes 0.1 seconds for the fault in this scenario to be detected. The second scenario was a constant fault starting at $t = 4s$ in the transient state, and there was a 0.01 N.m. load applied to the system. The fault was detected in 1.55 seconds. Scenario 3 and 4 were the same fault types but happening in different 0.01 and 0.05 N.m. load conditions. The phase “a” fault was recognized after 7.10 and 8 seconds, and Phase “b” fault was detected after 2.10 and 3 seconds in scenarios number 3 and 4, respectively.

The proposed flaw detection algorithm has proved to act effectively in all of the scenarios studied in this paper, as was expected in section 2. Based on the proposed diagrams and data, one can interpret that the algorithm can be used successfully for fault detection. Each of the stator currents acquired from a faulty BLDC motor influenced by our fault scenarios showed a different behavior than the healthy mode. The variations in the energy amounts of WCs were compared to a threshold amount which led to fault detection.

### 8 Conclusions

A signal-based analysis approach was pursued in this paper for fault detection purposes. The algorithm was CWT which was applied to the BLDC motor model’s stator current. Part of the research’s novelty lies in the system model, which is acquired through MATLAB and ADAMS software to enhance the model in terms of its preciseness. Furthermore, an energy-based fault detection criterion was proposed. The faulty mode WC signal’s energy would be compared to a predefined energy threshold amount. For validating the approach, different fault scenarios were considered. According to the simulation results, it can be stated that the proposed fault detection algorithm may be of use in many conditions such as a delayed fault happening...
in the middle of the stator action, a fault already existing in the system from the first, a growing fault in one phase, the no-load as well as load condition, and having two flawed stator phases. The aforementioned process would help any operator to identify the inter-turn fault in the BLDC motor’s stator phases as early as possible. For further research in this field, it would be possible to achieve experimental results of a real BLDC motor under the short-circuit fault condition. Besides, one can take advantage of more recently developed WT's that might give more precise results in fault detection.

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Table 1.

| The wavelet coefficient | The fault frequency | The scale corresponding to the fault frequency |
|-------------------------|---------------------|-----------------------------------------------|
| $C_1$                   | 140                 | 1100                                          |
| $C_2$                   | 100                 | 1600                                          |
| $C_3$                   | 60                  | 2500                                          |
| $C_4$                   | 40                  | 8000                                          |

Table 2.

| Parameter                              | Value               | Symbol |
|----------------------------------------|---------------------|--------|
| Phase resistor                         | 8 $\Omega$          | $R$    |
| Phase inductance                       | $2 \times 10^{-3}$ H | $L$    |
| Short-circuit impedance                | $9 \times 10^{-2}$ $\Omega$ | $r_{i}$ |
| Moment of inertia                      | $0.66 \times 10^{-3}$ kg.m2 | $J$    |
| Damping coefficient                    | $2 \times 10^{-5}$ N.m.s/rad | $B$    |
| Induction electromotive coefficient    | 2 N.m/A             | $k_e$  |
| Brushless DC motor torque coefficient  | $13.689 \times 10^{-3}$ N.m/A | $K_T$  |
| Coulomb friction coefficient           | $10^4$ N.m          | $C_c$  |
| Viscous friction coefficient           | $2 \times 10^{-5}$ N.m.s/rad | $C_v$  |
| Sampling time                          | $5 \times 10^{-6}$ s | $T_s$  |

Table 3.

| Parameter                              | Value               | Symbol |
|----------------------------------------|---------------------|--------|
| Spring stiffness                       | $2.1 \times 10^7$ k | $k$    |
| Spring damper                          | 5067                | $c$    |
| Cylindrical thickness                  | $2 \times 10^{-2}$ m | $h$    |
| Cylindrical radius                     | $8 \times 10^{-2}$ m | $R$    |
| Dynamic imbalance mass                 | $3.125 \times 10^{-5}$ gr | $M_d$  |
| Static imbalance mass                  | $3.75 \times 10^{-6}$ gr | $M_s$  |

Table 4.

| Time | Energy | $E(C_1)$ | $E(C_2)$ | $E(C_3)$ | $E(C_4)$ | The assigned threshold for $E(C_4)$ |
|------|--------|----------|----------|----------|----------|-------------------------------------|
| $T=1$|        | 9.5764   | 18.9310  | 30.9249  | 183.7638 | 5.0000                              |
| $T=2$|        | 13.3293  | 24.2112  | 50.1505  | 1674.7942| 5.0000                              |
| $T=3$|        | 21.0947  | 40.7809  | 23.8932  | 3832.4821| 5.0000                              |
| $T=4$|        | 18.1181  | 35.9700  | 20.4967  | 3500.8622| 5.0000                              |
| $T=5$|        | 1.1084   | 1.9614   | 1.3931   | 5.8015   | 5.0000                              |
| $T=6$|        | 1.0509   | 1.8739   | 1.3163   | 4.6667   | 5.0000                              |
| $T=7$|        | 1.0967   | 1.8139   | 1.3098   | 4.6123   | 5.0000                              |
| $T=8$|        | 1.0421   | 1.8661   | 1.3956   | 4.6407   | 5.0000                              |
### Table 5.

| Fault scenario number | Feature | 1    | 2    | 3    | 4    |
|-----------------------|---------|------|------|------|------|
| Faulty phases         |         | a    | a    | a and b | a and b |
| Fault type            |         | Time-variable | constant | a: constant | b: constant |
| $\mu$                 |         | increasing with the initial value of 0 and the slope of 0.125 | 0.25 | $\mu_a = 0.5$, $\mu_b = 0.5$, | $\mu_a = 0.25$, $\mu_b = 0.25$ |
| Fault initiation time |         | $t = 1s$ | $t = 4s$ | $t_a = 0s$, $t_b = 5s$ | $t_a = 0s$, $t_b = 5s$ |
| Load torque           |         | 0 N.m. | 0.01 N.m. | 0.01 N.m. | 0.05 N.m. |

### Table 6.

| Fault scenario number | Feature | 1    | 2    | 3    | 4    |
|-----------------------|---------|------|------|------|------|
| $E(C_4)$ at the fault detection moment |         | 3359.7905 | 5773.3650 | 15713.8949 | 10000.3206 |
| Load torque           |         | 0 N.m. | 0.01 N.m. | 0.01 N.m. | 0.05 N.m. |
| Fault detection time span |         | 1s    | 1.55s | a: 7.10s, a: 8s, | a: 2.10s, b: 3s |
Figure 1.

Figure 2.
Figure 5.

Figure 6.
Figure 7.

(a) Transient state
(b) Steady state

Figure 8.

(a) Transient state
(b) Steady state
Figure 9.

Figure 10.

Figure 11.
Figure 15.

Figure 16.
Figure 17.

Figure 18.
Figure 22.