Short-Circuit Detection by Means of Empirical Mode Decomposition and Wigner–Ville Distribution for PMSM Running Under Dynamic Condition

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Abstract—This paper presents and analyzes a method for short-circuit fault detection in a permanent-magnet synchronous motor (PMSM). The study includes steady-state condition and speed transients in motor operation. The stator current is decomposed by empirical mode decomposition (EMD), which generates a set of intrinsic mode functions (IMFs). Quadratic time–frequency (TF) distributions such as smoothed pseudo-Wigner–Ville and Zhao–Atlas–Marks are applied on the more significant IMFs for fault detection. Simulations and experimental laboratory tests validate the algorithms and demonstrate that this kind of TF analysis can be applied to detect and identify short-circuit failures in PMSM.

Index Terms—Electric machines, empirical mode decomposition (EMD), fault diagnosis, intrinsic mode function (IMF), motor diagnosis, permanent-magnet motors, Wigner–Ville distribution (WVD).

I. INTRODUCTION

THE PRIMARY function of a motor drive is to provide mechanical power, with a controlled torque at a specific speed. Failures of the drive can result in costly production downtime and mechanical damages and can even reduce human safety. For critical systems like avionics applications, a single-point fault must not provoke dangerous failures, and it is advantageous to assure the operation of the drive in the presence of a single failure. Such a drive is termed fault tolerant, and over the last several years, intensive research has been done on this subject [1]–[3]. The early detection of faults in the drive combined with a fault-tolerant control strategy can help avoid system shutdown and breakdown and can also avoid jeopardizing human safety.

Some of the more frequent faults or high-power-density permanent-magnet synchronous motor (PMSM) drives are short circuits in stator windings, which are usually related to insulation failure. In common parlance, they are generally known as phase-to-ground or phase-to-phase faults. It is strongly believed that such faults initiate as undetected turn-to-turn faults that finally grow and culminate into major ones [4], [5]. Although short-circuit current is limited to a rated value by designing the machine with a high phase inductance, short circuit between turns is the most critical fault in the machine and is quite difficult to detect and almost impossible to remove. In case of a short circuit in a PMSM, there is a risk of irreversibly demagnetizing the permanent magnets of the motor due to the strong opposing magnetic field from the short-circuit current. The high torque at a short circuit can also lead to mechanical failures of the machine, the shaft coupling, or the load [6].

There are a number of techniques used to detect turn-to-turn faults, with the majority of them being based on the analysis of stator voltages and currents, axial flux, and $d-q$ current and voltage components. The authors in [7]–[9] have very effectively examined the operation of induction motor drives under failure conditions, including shorted stator turns by using winding functions. However, they considered models that did not include flux saturation.

More frequently, the failure detection in a motor has been studied by analyzing the stator current harmonics by means of the well-known fast Fourier transform (FFT) [10]. Recently, this analysis has been extended to PMSM machines, which present the additional problem of the synchronism of the faulty frequencies regarding the motor speed[11].

Moreover, the FFT cannot be applied in nonstationary motor conditions that are more frequently and almost always present in advanced applications such as actuators in the aerospace and transportation industries. Fortunately, signal processing theories provide several algorithms for applications with nonstationary signals [12], in which the motor operates under conditions that rapidly vary with time.

Joint time–frequency (TF) analysis is a well-known tool in signal processing, and it is also considered as a promising approach in motor diagnosis applications. Short-time Fourier transform (STFT), wavelet transform, and Cohen-class quadratic distributions are the most usual TF techniques for fault diagnosis in industrial applications. The successful use of these techniques requires understanding of their respective properties and limitations.

The selection of a suitable temporal window size is required when computing the STFT to match with the TF resolution necessary for signal analysis, which is generally not known a priori.

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Wavelets are localized basis functions which are translated and dilated versions of some fixed mother wavelet. The wavelet transform consists of a correlation between wavelets functions and signal under analysis, obtaining a scaled time distribution. In the continuous wavelet transform, the dilation parameter of a wavelet can be any positive real value, and the translation can be an arbitrary real number. To improve computation efficiency, shift and scale parameters are often limited to some discrete values. This is then referred to as the discrete wavelet transform. A very appealing feature of the wavelet analysis is that it provides a different resolution for each scale, analyzing the signals at different frequencies with different resolutions. Wavelets [13], [14] and linear combination of the wavelet function [15] have been used as a feature extraction method for motor fault diagnosis.

Wavelets analysis allows different denoising approaches to enhance the measured signal. However, the noise present in the measurement device and the interferences generated by other frequencies present in the spectra often contaminate the signal and thus hinder condition-monitoring processes. This is particularly true when faults are at their early stages and the corresponding current signatures are very weak. Moreover, once the wavelet function is selected, one will have to use it to analyze all the data. Also, in a discrete wavelet with dyadic downsampling, frequency bands of scales are related to sampling frequency. Then, the quadrature mirror filters are fixed, and they predefine the analysis frequency bands at each decomposition stage. These bands cannot be changed, unless a new acquisition with different sampling frequency is made, and wavelet-based detectors cannot adapt themselves to the dynamic changes in motor operation.

Adaptive wavelets have been presented to improve the selection of a wavelet basis for a predetermined application. This adaptation is made by using intelligent algorithms. In [16], a genetic algorithm is used to choose the best wavelet to eliminate noises from signals, and compute the correlation function of the denoised signals as fault feature. In [17], a wavelet is derived from its filter coefficients, which are generated by optimizing a discriminate criterion based on a quadratic probability measure. Finally, in [18], a wavelet fuzzy neural network is proposed for fault diagnosis, which integrates the standard fuzzy inference and the learning concept of neural networks. The system does the tuning of wavelet functions that are used as membership functions.

These techniques, however, can show convergence problems if ranges of variables are not accurately defined, and also, they are penalized by a strong burden of calculation.

The Wigner–Ville distribution (WVD) is a quadratic TF representation part of the Cohen class of distribution. Due to this quadratic nature, the drawback of this transform is the presence of cross-terms in multifrequency signals.

Cross-term problems of quadratic transforms can be overcome by employing various approaches [19], although the removal of cross term (smoothing) also takes away some of the signal energy and reduces the joint TF resolution. Among these quadratic TF representations, the smoothed pseudo-WVD (SPWVD) not only presents high ability to suppress cross term but also results in being less affected by white noise. SPWVD has been successfully used in [20] for the detection of rotor faults in brushless dc (BLDC) motors operating under continuous nonstationarity. Another TF distribution for fault detection in motor drives that improves TF resolution while providing cross-term suppression is the Zhao–Atlas–Marks (ZAM) distribution [21]. ZAM has been recently proposed [22] for rotor fault detection in BLDC motors under rapid changes in motor operation. The authors of the proposals use an adaptive filter driven by a PLL to filter the fundamental frequency, because the fault frequency components are small and could be masked by it. Also, this filtering reduces the occurrence of cross-terms when using quadratic TF distributions.

Instead of filtering, to effectively construct the TF distribution of a signal that contains multiple-frequency components, empirical mode decomposition (EMD) can be used. EMD expands the signal into a set of functions defined by the signal itself, the intrinsic mode functions (IMFs), which are “monocomponent” signals [23]. Apart from hardware reduction, EMD is not restricted by a motor frequency operation to drive the PLL that obtains the motor base frequency; it extracts the oscillation modes contained in the signal, i.e., the IMFs, which are intrinsically defined by motor operation and motor fault frequencies. These IMFs have physical and mathematical meanings and can be considered as the simplest intrinsic mode oscillations of the original signal containing significant information.

Once the IMFs are obtained, an effective way to get the local information contained in the IMFs is to apply the Hilbert transform. The method, which is called Hilbert–Huang transform (HHT) [24], [27], has been applied to the analysis of mechanical and specific bearing-defect detection [26]. Although the Hilbert transform is a simple approach for instantaneous frequency calculation, in the presence of noise, the corresponding results may not be reliable. Furthermore, HHT is applied to each IMF, which is not always necessary for fault detection if fault frequency bands are known.

A new approach to extract fault frequencies for a nonstationary PMSM drive operation is proposed in this paper. The method uses SPWVD and ZAM applied to specific IMFs, which are selected to contain fault frequencies to detect. This paper shows that it is possible to identify short circuits in the windings of PMSM without using an external adaptive filter. The method was tested by simulation and experimental measurements of healthy and faulty PMSMs, which were operated at nominal torque with different speeds. Simulation and experimental results from healthy and faulty machines were discussed and compared.

This paper is organized into five sections. In Section II, a brief review of the signal processing techniques used in the work is provided. Section III presents the method proposed for fault diagnosis. Section IV describes a motor model for finite-element analysis (FEA) and also the experimental setup. Section V discusses simulation and experimental results for fault detection of short-circuited PMSM. Section VI summarizes and concludes this paper.

II. SIGNAL PROCESSING TECHNIQUES

This section is focused on describing the signal processing techniques that have been used in the development of the work,
The intention of signal processing is to isolate the information regarding fault condition from the whole signal. After fault signature extraction, a TF analysis will be applied for fault detection, even in nonstationary working conditions. To isolate the fault information, it is proposed to decompose the signal into the so-called IMFs by means of EMD. For TF analysis, both WVD and ZAM distributions are proposed.

### A. EMD

Given a signal \( x(t) \), the analytical signal \( z(t) \) could be defined as

\[
z(t) = x(t) + jy(t) = \alpha(t)e^{j\theta(t)}
\]

(1)

where \( y(t) \) is the Hilbert transform of \( x(t) \) given by

\[
y(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} d\tau
\]

(2)

\[
a(t) = [x^2 + y^2]^{\frac{1}{2}} \quad \theta(t) = \arctan \left( \frac{y(t)}{x(t)} \right)
\]

(3)

By this way, it is possible to define \( a(t) \) as the instantaneous amplitude and the derivative of \( \theta(t) \) as the instantaneous frequency. This could be a valid way for obtaining the TF distribution, but the problem is that it has only physical meaning if the signal is locally symmetric with respect to the zero mean level, and this is not a usual condition for stator current signals.

Instead, the EMD method is an easier way to decompose a signal in a set of IMFs for which the instantaneous frequency is well defined [24]. In other words, an IMF represents an oscillation mode embedded in the signal, and thus, the original signal is decomposed in a sum of characteristic oscillation modes. The IMFs satisfy two conditions. First, in the whole signal, the number of extremes and the number of zero crossings must be either equal or differ at most by one, and second, at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima has to be zero.

EMD is based on the so-designated sifting process, which extracts the IMFs by an iterating process in three steps, as shown in Fig. 1 and described in the following.

First, the upper and lower envelopes of the signal as the cubic spline interpolants of its local maxima and local minima, respectively, are found. Second, the mean envelope \( m_{10}(t) \) is computed as the average of the upper and lower envelopes previously found. Finally, the third step consists in subtracting the mean envelope to the signal, thus obtaining \( r_{10}(t) \).

Ideally, \( h_{10}(t) \) will be the first IMF, but usually, it does not fit the conditions. Then, the sifting process has to be repeated, taking \( h_{10}(t) \) as the new signal to decompose. In general, it is necessary to repeat this sifting procedure \( k \) times until \( h_{1k}(t) \) is an IMF, i.e., \( h_{1k}(t) = h_{1(k-1)}(t) - m_{1k} \).

Finally, we denote the first IMF as \( c_1(t) = h_{1k}(t) \). The stopping condition in order to determine if \( h_{1k}(t) \) is an IMF or not is given by

\[
\sum_{t=0} \frac{[h_{1k1}(t)h_{1k2}(t)]^2}{h_{1k1}^2(t)} < SD
\]

(4)

where \( h_{1k}(t) \) is the sifting result in the \( k \)th iteration for calculus of the first IMF, and SD is a standard deviation, which is typically set between 0.2 and 0.3.

The first IMF, \( c_1(t) \), contains the finest scale of the signal. The next IMFs, corresponding to larger scales, will be computed in a similar way with the first one but taking as the starting signal the residue given by (5) instead of the original signal

\[
r_{1}(t) = x(t) - c_{1}(t)
\]

(5)

Fig. 2 shows an example of the results obtained after an iteration of the sifting process.

The large-scale IMFs will be computed until the last residue \( r_{n}(t) \) has at most one local end. The residue \( r_{n}(t) \) characterizes the trend of the signal and is usually treated separately. Fig. 3 shows the decomposition in five IMFs of the stator current signal corresponding to a PMSM with 12 shorted turns running at 6000 r/min.
B. Cohen’s Class of Distributions

Cohen introduced a generalized form of TF distributions, from which all of them could be derived. They are the so-called Cohen’s class of distributions [27], given by

$$P(t, w) = \frac{1}{4\pi} \int \int e^{-j\theta t - j\tau w - j\theta u} \varphi(\theta, \tau) \cdot z^*(u - \frac{\tau}{2}) z(u - \frac{\tau}{2}) du d\theta$$

(6)

where \( \varphi(\theta, \tau) \) is an arbitrary function called the kernel. Setting the kernel to different values, different TF distributions could be obtained.

WVD is a quadratic joint TF distribution obtained by doing \( \varphi(\theta, \tau) = 1 \), which offers a high TF resolution. Given a time signal \( x(t) \), WVD is defined by

$$W(t, w) = \frac{1}{2\pi} \int_{-\infty}^{\infty} z(t + \frac{\tau}{2}) z^*(t - \frac{\tau}{2}) e^{-j\omega \tau} d\tau$$

(7)

where \( z(t) \) is the analytical signal corresponding to \( x(t) \) and \( z^*(t) \) is the complex conjugate of \( z(t) \).

WVD possesses a great number of good properties, and it has wide interest for fault detection with nonstationary signal analysis [28]. However, if the analyzed signal contains more than one frequency component, due to its quadratic nature, the WVD method suffers from cross-term interference, resulting in a difficult way of discriminating the actual frequency components.

There are several proposed techniques that try to suppress the cross-terms at the expense of the loss of TF resolution. A usual way is to use a windowed version of WVD obtaining the so-called pseudo-Wigner–Ville distribution (PWVD)

$$Wp(t, w) = \frac{1}{2\pi} \int_{-\infty}^{\infty} h(t) z(t + \frac{\tau}{2}) z^*(t - \frac{\tau}{2}) e^{-j\omega \tau} d\tau$$

(8)

where \( h(t) \), the time smoothing window, is a real and symmetric function. The effect of the temporal window is to reduce the cross-terms present in the original WVD, reducing the TF resolution, but, in fact, with a better performance than linear distributions, such as the STFT.

It is also possible to apply the smoothing in both time and frequency planes. In this way, SPWVD is obtained

$$W_s(t, w) = \frac{1}{2\pi} \int_{-\infty}^{\infty} L(t - t', w - w') W(t', w') dt' dw'$$

(9)

where \( L(t, w) \) is the chosen smoothing window applied to WVD, \( W(t, w) \). Several windows can be used, but the most usual is the Gaussian. Smoothing simultaneously in time and frequency planes results in a better suppression of the cross-terms, but of course, this is a cost of lost of frequency resolution.

On the other hand, a “cone kernel” intended to introduce finite-time support and reduce the cross-terms was proposed by Zao et al. [21], resulting in ZAM distribution. The expression of the kernel could be seen in

$$\varphi(\theta, \tau) = \varphi_1 \frac{\sin(\theta|\tau/a)}{\theta/2}$$

(10)

where \( \varphi_1(\tau) \) is a function, usually taken equal to one, and \( a \) is a parameter greater or equal to two.

ZAM distribution achieves a very good tradeoff between suppression of cross-terms and loss in TF resolution. For this reason, ZAM is a very promising technique to monitor fault condition in nonstationary working conditions, even if it has higher computational burden than simple WVD.

Even if estimating the computational burden of these algorithms to be embedded in online applications is out of the scope of this paper, the authors have proved previously that the computation of these TF distributions is possible with standard DSP [22], although it is clear that the amount of computation for doing correlations and TF distributions is not small. However, while the computational time for these distributions is larger than for conventional techniques such as the FFT or STFT, these quadratic TF distributions can be efficiently used because diagnosis does not need fast responses as control. Moreover, motor condition monitoring is performed over long periods.
Among the great consequences of an interturn short circuit, the loss of stator symmetry leads to the appearance of a negative sequence of the current in the stator windings [30], the unbalance due to short-circuit failure. They include also particularly the ninth harmonic of rotor speed that indicates any rotor speed. IMF1 and IMF2 contain the fault harmonics, particularly the ninth one, will be isolated by means of EMD. Five IMFs are then obtained from the stator current by using this decomposition. EMD is based on the sequential extraction of energy associated with various intrinsic time scales of the signal, starting from finer temporal scales (high-frequency modes) to coarser ones (low-frequency modes), as described in Section II. The major advantage of EMD is that the basis functions are derived from the signal itself. Hence, the analysis is adaptive, in contrast to traditional methods where basis functions are fixed. Moreover, no adaptive filter driven by an external PLL signal is needed to follow motor frequencies in case of nonstationary conditions. EDM adapts itself to frequency contents. Also, EDM is not restricted by phase lock delays in case of fast variations in motor operation, as other methods [20], [21] are.

The main part of the signal energy is concentrated on lower frequencies (last IMFs). High-frequency modes (first IMFs) contain the components due to faults at higher frequencies than the fundamental ones. For the 1.5-kHz bandwidth fixed by the LPF, EMD concentrates in IMF5, IMF4, and IMF 3 the lower frequencies, including the fundamental harmonic at any rotor speed. IMF1 and IMF2 contain the fault harmonics, particularly the ninth harmonic of rotor speed that indicates the unbalance due to short-circuit failure. They include also residual harmonics due to machine construction and possible subharmonics of modulating frequency.

Every motor has small unbalances and abnormalities due to manufacturing. To discard fault frequencies due to these asymmetries, in all the condition-based maintenance algorithms, base measurements are taken for a healthy motor prior to commissioning. Fault monitoring consists in tracking the amplitude of residual harmonics due to machine construction and possible subharmonics of modulating frequency, in all the condition-based maintenance algorithms, base measurements are taken for a healthy motor prior to commissioning. Fault monitoring consists in tracking the amplitude of residual harmonics due to machine construction and possible subharmonics of modulating frequency.
and IMF1 and IMF2 are added to obtain a signal that contains all the fault harmonics and, hence, those related to the short-circuit failure.

Once this grouped signal is obtained, either FFT or TF decompositions are applied depending on the motor state, stationary or transient, respectively. Two algorithms are proposed for TF decompositions—one based on SPWVD and the other on ZAM. The results of the machine with short circuit in stator windings are compared with those obtained from a healthy machine. A different fault metric can be used to classify faults through predetermined motor-operation-dependent thresholds, such as amplitude of the fault signals, root mean square of the instantaneous amplitudes of the fault ridges (local maxima of TF distribution), and others.

IV. SIMULATION PLATFORM AND EXPERIMENTAL WORKBENCH DESCRIPTIONS

A PMSM with three pairs of poles has been used in simulations and experiments. Motor characteristics are given in Table I. The motor was driven at nominal (6000 r/min), medium (3000 r/min), and low (1500 r/min) speeds. Also, fast-speed variations of ±500 r/min with a slope of 7.5 r/min/ms were introduced during testing to provoke dynamic conditions of operation. Only speed variations were considered for nonstationary conditions.

Simulations and experiments have been carried out for motors in healthy and faulty states. Faulty conditions were generated with a short circuit in the fourth, eighth, and twelfth stator winding turns. A special winding manufactured equal to the reference motor, but with external switches to provoke the damage, was used. The machine has 144 turns per stator phase winding.

Analysis and development of fault detection methods need, as a previous stage, good knowledge of the motor behavior under fault conditions. Compact parametric models of the motor are the usual tools for simulations if the motor is considered in healthy state, i.e., to calculate the efficiency, to obtain the torque–speed relationship, to analyze and develop control algorithms, etc.

However, it is difficult to model faults in specific parts of the motor by means of parameters, because parametric models usually assume symmetry in mechanics and electromagnetic fields, and this symmetry is missing in case of fault. To overcome this drawback, simulations by means of FEA can be done. For faulty conditions, coupling between the nonlinear magnetic effects and nonlinear electric circuits should be taken into account in order to determine the behavior of the electrical motor under fault [32]. FEA reveals itself as an accurate and easy method to determine the interaction between these nonlinear effects.

In this paper, PMSMs in a healthy state and with shorted turns are simulated at different operating points using the two-dimensional (2-D) FEA software FLUX 2-D [33], a CAD package for electromagnetic and thermal analysis. Electromagnetic

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**Fig. 5.** Flux density of a PMSM with short circuit.

**TABLE I**

<table>
<thead>
<tr>
<th>Model</th>
<th>ABB - 8C136020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voltage</td>
<td>380 V</td>
</tr>
<tr>
<td>Current</td>
<td>2.9 A</td>
</tr>
<tr>
<td>Speed</td>
<td>6000 rpm</td>
</tr>
<tr>
<td>Torque</td>
<td>2.3 Nm</td>
</tr>
<tr>
<td>Pair of poles</td>
<td>3</td>
</tr>
<tr>
<td>Resistance</td>
<td>2.6 Ω</td>
</tr>
<tr>
<td>Inductance</td>
<td>9.6 mH</td>
</tr>
<tr>
<td>Moment of Inertia</td>
<td>0.000235 kg m²</td>
</tr>
<tr>
<td>Back EMF Constant</td>
<td>57.6 V/krpm</td>
</tr>
<tr>
<td>Stator slots number (Z1)</td>
<td>18</td>
</tr>
</tbody>
</table>
Numerical simulations were developed with the combination of FLUX 2-D for the motor model and Matlab–Simulink for electronics and control. Both circuits have been coupled automatically by linking local variations in FLUX with the control circuit (Fig. 6).

The control of the drive is a vector control, with a current loop settled at $i_d = 0$. The control loops for speed and position are PI. Simulation results, i.e., motor currents, are used to check the behavior of the proposed fault detection method.

The analysis of the current signals has been made by means of software toolboxes; EMD was implemented by means of HHT Data Processing System NASA software [34], and the Rice University Time–Frequency analysis toolbox [35] from Matlab was used to compute FFT, WV, and ZAM distributions.

Simulations of the PMSM in stationary conditions at 1500 r/min are shown in Fig. 7, which shows the stator current harmonic content. All of the spectra have been normalized to a rotor frequency for the sake of readability. The graphic shows only the amplitude of the main harmonics, not the full spectra. Current harmonics, namely, 7th, 9th, 11th, and 13th, are higher for a faulty motor than for a healthy one, as it was expected after previous discussions in Section III.

As the amplitude of fault harmonics is quite small at low speed, discrimination is more difficult than that at nominal speed. However, fault detection is still possible if fault harmonics can be extracted from the stator current, which can be achieved by means of the previously discussed IMFs.

To emulate the real operation of the motor, an experimental workbench was built up at the laboratory. For the experiments, the motor was driven by an ABB power converter model DGV 700. The motor is loaded by an additional PMSM driven by a torque controller. A constant load of 2.3 N·m is considered for simulations and also imposed during the experiments.
A set of switches in the specially manufactured stator winding are used to provoke short circuits. The current has been measured by means of a Tektronix ac/dc current probe model A622. Current ranges are 0/100 mV/A, and the typical dc accuracy is $\pm 3\% \pm 50$ mA at 100 mV/A (50 mA to a 10-A peak). The frequency range goes from dc to 100 kHz.

Data acquisition is done by means of the DAQ NI PCI-6251, a multifunction board with 16 input channels, 16 bits of resolution, and 4000 samples of inner memory. The cutoff frequency of the LPF is 1.5 kHz, and the sampling frequency for the motor currents is 5 kHz.

V. SIMULATION AND EXPERIMENTAL RESULTS

A set of simulations and experiments have been performed. Motors were driven at nominal (6000 r/min), medium (3000 r/min), and low (1500 r/min) speeds, with nominal load in all cases. Both simulations and experiments were carried out under stationary and nonstationary conditions.

Analysis of the current and running of the algorithm are mainly done at low speed, i.e., for cases where classic methods of fault detection have lower performance.

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>AMPLITUDE DIFFERENCE IN NINTH ROTOR HARMONIC BETWEEN FAULTY AND HEALTHY PMSMs. STEADY STATE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed (rpm)</td>
<td>600</td>
</tr>
<tr>
<td>Difference</td>
<td>19 dB</td>
</tr>
</tbody>
</table>

A. Steady State (Constant Speed and Torque)

EMD allows extraction of the fault signature in an adaptive way, removing the rest of the information, such as fundamental harmonic of the power supply. In this way, the best resolution can be achieved in both steady state and transients of the motor.

As was explained in Section III, the addition of IMF1 and IMF2 contains the failure signature. In case of steady-state conditions, the FFT is enough to detect the short circuit. Fig. 8 shows the FFT of (IMF1 + IMF2) for 1500 r/min. Stator current has been acquired from the experimental setup. For this speed, the biggest harmonic of damaged motors is the third harmonic of fundamental (225 Hz), which is the ninth harmonic in rotor speed reference.
The main harmonic corresponding to power supply, which is always higher than the others when stator current is analyzed with standard motor current signature analysis methods, has been discarded from frequency decomposition.

The difference in decibels between amplitudes of the ninth harmonic—in rotor reference—for healthy and faulty motors is high enough to detect the fault and to activate the alarm circuit. This difference is even higher when the motor speed increases, as shown in Table II. The experimental results in the table are for healthy and faulty motors with 12 shorted turns.

Failure can also be detected by using the proposed TF distributions. Figs. 9 and 10 show ZAM distributions of the summation of IMF1 and IMF2 for healthy and faulty motors, respectively. The IMFs have been obtained from the stator phase current of the simulated motor. The TF distribution of harmonics is almost empty, and significant harmonics cannot be detected in the TF plane.

For the faulty motor, the ninth harmonic of rotor speed that is 900 Hz for 6000 r/min is clearly shown in the ZAM TF distribution (Fig. 10). Although, other harmonics like the 6th, 7th, and 12th ones can only be seen lightly. However, the amplitude difference is significant with respect to the stator current for the healthy motor. The fundamental component of the stator current has been removed by EMD and cannot be seen on IMF1 and IMF2 ZAM TF distributions. Thus, any fault metric algorithm can detect and track the fault frequencies with the best frequency resolution.

Results are also corroborated by experiments. Fig. 11 shows the ZAM TF distributions of IMF1 and IMF2 from the experimental setup. Stator currents were obtained from the damaged motor, and TF distribution is almost identical to that obtained from the simulated motor. In this way, the EMD plus ZAM algorithm demonstrates its ability to detect faults in steady-state motor operation. Similar results, which are not shown here for its repetitive character, confirmed also the performances and ability of SPWVD on IMF1 and IMF2 in detecting faults with the PMSM running in steady state.

B. Speed Change (Constant Torque)

To validate the effectiveness of the algorithm, PMSM is now operated in nonstationary operating conditions. More specifically, the speed operation of the motor is changed along the experiment, while the load torque remains constant at its nominal value. A linear speed change from 1500 to 1000 r/min, starting at 0.2 s and ending at 0.3 s, is considered.

Once again, the summation of IMF1 and IMF2 has been used for determining the fault condition, and SPWVD and ZAM TF
distributions are used to track the fault frequencies over time under these nonstationary conditions.

Fig. 12 shows an SPWVD TF distribution during the speed change in the simulated motor. A mains harmonic of 300 Hz has been removed from TF distribution by EMD, and fault harmonics seventh and, in particular, ninth in rotor-speed-based reference are tracked by the developed algorithm.

Most results are presented at low speeds, because the more difficult conditions to diagnose the fault are with the motor running at low speeds. Thus, validation of algorithms at low speed illustrates the ability of the proposed method to track and identify motor faults for the whole speed range.

Fig. 13 shows an SPWVD TF distribution for a healthy PMSM operating with a change of speed from 1500 to
1000 r/min. The graph is cut at 0.25 s for the sake of clarity and to avoid the numerical windowed effect. A speed change can be seen in 525 Hz that is the second stator-slot harmonic (seventh harmonic of fundamental), which is present even in the case of healthy motors. TF distribution, however, does not reflect any other significant harmonic, and a healthy state of the motor can be concluded. An SPWVD TF distribution for a faulty PMSM operated under these nonstationary speed conditions is shown in Fig. 14. The fault frequencies are now distinctly tracked over time. These frequencies correspond to the 9th, 12th, and 15th rotor speed harmonics, which are 225, 300, and 375 Hz, respectively. Frequencies correspond to unbalance due to short circuit (third harmonic of the fundamental stator frequency), to specific harmonic present in this motor and reinforced in case of fault (fourth harmonic of fundamental), and to the first stator-slot harmonic (fifth harmonic of fundamental). Among them, the frequency related to the unbalanced motor—the ninth harmonic in rotor speed reference—is the more evident one, and it is considered here as a fault indicator.

Similar results can be seen for IMF1 and IMF2 ZAM TF distributions (Fig. 15). Regarding frequency resolution, ZAM is not as good as SPWVD, but motor frequencies of 300 and 450 Hz can be better appreciated on the TF distribution.

Experiments match perfectly with the simulation. Figs. 16 and 17 show the TF distributions of IMF1 and IMF2 obtained by means of SPWVD and ZAM, respectively, for a twelfth shorted turn in the motor. Both distributions show clearly the motor fault harmonic (third harmonic of fundamental) and also other slots and motor harmonics. Although these harmonics are present in a healthy machine, they are reinforced in case of damage and contribute to the diagnosis of fault of the motor.

SPWVD shows better signal energy concentration than ZAM and also good cross-term suppression. ZAM TF, instead, has worse frequency resolution than SPWVD, but it shows richer harmonics.

Experiments demonstrate the viability of using the third stator current harmonic for detecting short circuit—in fact, motor unbalance. Experimental results validate the proposed method of fault detection by means of EMD decomposition and further analysis by using quadratic TF distributions, such as SPWVD and ZAM. Other than considering the third current harmonic, other motor harmonics that are increased due to fault can be considered as fault indicators into the TF distribution.

For a practical implementation of the method in real motor drives, some considerations must be done. Although stator faults develop faster than (mechanical) rotor faults, they are
usually related to insulation failure, which grows with thermal time constants [31].

These thermal constants are lower than mechanical ones, but they are large enough (hundreds of milliseconds or even seconds) to allow new 32-bit floating-point DSPs to carry out the full algorithm, as proposed in [22]. Even though EMD calculation burden is higher than SPVW or ZAM decomposition because of its iterative operation, new online fast EMD [36] requires only few iterations to extract a meaningful IMF.

In this way, the expected time to compute the full algorithm, i.e., EMD plus TF decomposition plus fault identification and metric, could be tens of milliseconds. It is higher than microseconds used in [34], but low enough to be tens of times faster than the fastest short circuit due to isolation fault, allowing detection of the fault when it is in its earlier stage.

VI. CONCLUSION

The use of TF distributions of the stator current has proved suitable for detecting faults in electric motors operating in steady-state and nonstationary conditions over the years. Quadratic TF distributions allow one to obtain much better frequency resolution and localization of energy than other classical linear TF distributions, such as the spectrogram.

However, the stator current would have to be filtered to remove the fundamental and other subharmonics prior to the applications of the fault detection algorithm. This filtering increases the resolution of TF distributions and makes easier the calculation of fault metrics.

Instead of using adaptive filters tuned at the motor speed, this paper describes the application of EMD as a classifier of stator current motor harmonics and, hence, as automatic tool for rejecting the main harmonic and concentrating the fault analysis in significant fault harmonics. Also, EMD avoids the use of extra electronics and does not compromise the fault detection process. Faulty frequencies in nonstationary motor states can be detected and tracked perfectly, as it has been demonstrated.

This paper presents the analysis and fault detection of a PMSM with shorted turns under steady-state and transient conditions. By means of the EMD of the stator current, IMFs are obtained, and SPWVD and ZAM TF distributions are applied to the summation of IMF1 and IMF2, which contain the failure signature. The method allows one to automatically reject the main power supply harmonic, concentrates the analyses on the failure signature, and maximizes the performance of fault detection in a PMSM.

SPWVD and ZAM distributions allow one to identify the fault within a short time of calculation. They do not need many...
samples to operate, and they obtain the fault signature independently of the speed variations. The featured signature differentiates between healthy and faulty conditions, as well as between different degrees of fault. As the method allows one to concentrate the analysis on the characteristic failure, it maximizes the relative fault metric value.

By means of FEA models and variable-speed drive, simulation and experimental results have been obtained, which match the expectations of theoretical analysis. Results also show the ability of the method to detect PMSM short-circuit faults in steady-state and nonstationary conditions.

The proposed method can be used in the industry for fault detection and diagnosis of such internal faults of PMSM at low speed and dynamic conditions, particularly for low- and medium-power applications, such as positioning, servomotors, electromechanical actuators, pick-and-place applications, and so on. Moreover, it is not limited to PMSM but could be applied to any other kind of three-phase alternative motors.

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REFERENCES


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