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Demagnetization diagnosis in permanent magnet synchronous motors under non-stationary speed conditions

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ABSTRACT

Permanent magnet synchronous motors (PMSMs) are applied in high performance positioning and variable speed applications because of their enhanced features with respect to other AC motor types. Fault detection and diagnosis of electrical motors for critical applications is an active field of research. However, much research remains to be done in the field of PMSM demagnetization faults, especially when running under non-stationary conditions. This paper presents a time–frequency method specifically focused to detect and diagnose demagnetization faults in PMSMs running under non-stationary speed conditions, based on the Hilbert Huang transform. The effectiveness of the proposed method is proven by means of experimental results.

1. Introduction

Industry constantly demands products that are faster and more reliable. In this context, for some critical applications, permanent magnet synchronous motors (PMSMs) possess characteristics superior to induction motors. PMSMs are becoming widely applied in high performance positioning and variable speed applications because of their attractive features. Powerful rare earth magnet materials that are now cost-effective, such as Sm–Co and Nd–Fe–B, greatly enhance their properties. PMSMs possess a higher power density than induction motors with equivalent ratings. Advantages of PMSMs include high-speed operation, precise torque control, compactness, high power to weight ratio and high efficiency. Every day they are gaining ground in the automotive, robotics and aeronautical industries [1]. Additional applications of PMSM include gearless elevators in low- and high-rise buildings, centrifugation equipment, as well as the medical, chemical and semiconductor industries, among others.

Many of the applications where PMSMs are applied are critical, as their faults could potentially cause plant shutdown, huge economic loss and even human casualties. Hence, fault detection and diagnosis is one of the most serious areas of concern in the electric drives research field. Therefore, accurate diagnosis of incipient faults in critical applications where PMSMs play an important role can significantly improve system availability and reliability.

A new trend and challenge in the electric drives industry is the design of fault tolerant control systems which provide control algorithms capable of maintaining stability and performance of the controlled system despite the occurrence of faults. To meet this objective, fault detection and diagnosis of electric drives has become an essential tool in most fault tolerant control system designs.

In order to measure the impact of faults, the transient process of the machine under fault conditions must be studied, since this state usually reflects the worst case scenario that the machine designers may face [2]. While there is already a plethora of literature on the study of induction motors, it nevertheless continues to be a dynamic field of investigation [3–7]. Recently, Gritli et al. [8] conducted an interesting study to detect rotor faults on doubly fed induction machines due to unbalanced rotor phase windings. In this study Gritli et al. take advantage of the multiresolution analysis capabilities of the discrete wavelet transform when the machine operates under load-varying conditions and apply a multiresolution fault indicator based on the mean power at different resolution levels to perform a quantitative evaluation of the fault degree.

Conversely, in the case of permanent magnet synchronous motors – whether dc or ac brushless – both drive control and fault detection are relatively novel fields of investigation [1,9–13].

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This work presents a innovative method in order to diagnose the demagnetization fault in PMSMs. This fault can be due to an over current on the stator windings that creates a magnetic flux opposed to the natural flux of the magnet and leads to a demagnetization of the magnet. However, the major difficulty with PMSMs occurs at high speed when the induced eddy currents cause heating in the magnet. As the demagnetization curve of the material is highly temperature-dependent, heating effects may induce changes in magnetic properties of the material. In any case, the demagnetization of the permanent magnet results in a reduction of the torque production, generating torque pulsation, vibrations and excessive heat. Other faults that can occur in the motor are shorted turns, open turns, eccentricity and damaged bearings.

Different fault detection and diagnose methods have been applied to detect motor faults, the most common of which are motor current signature analysis (MCSA), vibration analysis and axial flux. Among them MCSA is one of the most popular as it is a non-invasive method, needing only to acquire the line currents of the motor and then to perform the fast Fourier transform (FFT).

It is well known that when the FFT is performed in a PMSM with a faulty rotor, different harmonics appear in the spectrum. They can be identified as [14–16],

$$f_f = f_e\left(1 \pm \frac{k}{P}\right) \tag{1}$$

where f_f is the fault frequency, f_e is the electrical fundamental frequency, k is an integer and P is the number of pole pairs.

In the study carried out in this work, healthy and faulty PMSMs with three pairs of poles are analyzed. The faulty motors studied have just one rotor pair of poles which are partially demagnetized. In this particular case, Eq. (1) can be rewritten as

$$f_f = f_e\left(1 \pm \frac{2k+1}{P}\right) \tag{2}$$

being $k = 0,1, 2, \ldots$ an integer.

Taking into account the number of pole pairs of the analyzed motors, in one electrical fundamental period 1/3 of a complete rotation of the rotor is produced. Thus, due to the damaged magnets, there is a pronounced change in the flux density curve around the rotor [15]. This results in an electrical frequency component at the rotating frequency of the rotor, that is, the odd harmonics such as 1/3 and 5/3 among others.

In case of non-stationary motor speed, faulty frequencies are not fixed and fault detection is not evident when using standard FFT. In this paper, a novel method for demagnetization fault detection of PMSMs under non-stationary speed conditions is presented, based on stator current signal decomposition using the Hilbert Huang transform (HHT).

This paper is divided into four sections. Following the introduction, Section 2 presents and discusses signal-processing methods for transient analysis. Section 3 introduces HHT and corresponding algorithms to obtain the time–frequency representation of a non-stationary signal. Experimental results are presented in Section 4, as well as feature extraction by means of energy content of the signal. Finally, conclusions are stated in Section 5.

2. Analysis methods for fault detection

Most of the signals obtained from natural phenomena and from measurements in industrial applications are of a transient nature. Therefore, these types of signals are essentially nonlinear and non-stationary, and traditional signal analysis methods such as Fourier transform fails when dealing with them [17]. Among them, the most likely applied method in industrial environments is based on the Fourier analysis of the steady-state stator currents and the study of the harmonic components that appear around the fundamental component. Fourier analysis of stator currents provides robust results when the machine operates under a certain load level and stationary regime, but has important drawbacks when applied to diagnose the condition of light-loaded machines or machines running under non-stationary load conditions [18].

The Fourier transform is not well suited for analyzing non-stationary signals since it projects the signal on infinite sinusoids which are completely delocalized in time. In dealing with non-stationary signals this is a very important drawback as it is essential to take into account both time and frequency variables. Consequently, a time–frequency representation (TFR) is needed. TFR can be understood as a two-dimensional view of a time-dependent signal represented over both time and frequency axes.

Several time–frequency analysis methods (some of them based on Fourier analysis) have been developed, although successful application of these techniques require a thorough understanding of their respective limitations. For example, the short-time Fourier transform (STFT) allows time–frequency analysis using the widely applied fast Fourier transform (FFT) algorithm. STFT implicitly assumes the signal behaves as stationary during the window interval of computation. The selection of a suitable window size is required to match with the specific frequency content of the signal, which is generally not known *a priori*. This provokes an inconsistent treatment at different frequencies due to the fixed length of the window. Therefore, its application for fault detection is limited to signals where frequency content changes very slowly over time.

Another widely applied time–frequency method is the wavelet transform (WT) which overcomes some of the limitations related to the STFT. WT allows decomposing the raw signal by means of a set of wavelets (basis functions) which are localized both in time and frequency [19]. However, WT presents a serious drawback due to the necessity of *a priori* knowledge about the kind of scale elements which are present in the signal for isolating and analyzing them. As pointed out by Antonino-Daviu et al. [18,20] the selection of the mother wavelet is somewhat arbitrary, since there is no clear rule for selecting the optimal mother wavelet for a specific application. Furthermore, the possible overlap between frequency bands associated with the wavelet signals or the dyadic frequency decomposition of the Mallat algorithm (especially when dealing with the discrete wavelet transform) can result in a limited resolution of some frequency components closer to the fundamental. Another drawback related with this method is the boundary distortion introduced by the WT that in some cases might make the identification of some frequency components difficult.

Some of the drawbacks related to the FT and the WT can be overcome by applying the HHT. HHT possesses advantages over WT because it avoids the selection of the mother wavelet. It also allows for a more valuable study of some frequency components closer to the fundamental as it does not perform the dyadic frequency decomposition of the Mallat algorithm.

3. Hilbert Huang transform

The HHT was proposed by Huang et al. [21] and it has been successfully applied in diverse areas such as geosciences and remote sensing applications [17], nonlinear structural dynamics [22], analysis of sea waves [23], analysis of electroencephalogram (EEG) signals [24], gear fault diagnosis [25], analysis of torsional shaft oscillations [26], analysis of electrical generator coherency [27] and detection of broken rotor bars in induction machines [18], among others.

However, as pointed out by Antonino-Daviu et al. [20] the patterns arising from the HHT appear less clear when compared with the DWT approaches. Furthermore, constraints such as the boundary distortion are not completely avoided. HHT performs the empirical mode decomposition (EMD) of the raw signal. This pro-