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Stator fault analysis of three-phase induction motors using information measures and artificial neural networks

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ABSTRACT

The three-phase induction motors are considered one of the most important elements of the industrial process. However, in this environment, these machines are subject to electrical and mechanical faults, which may cause significant financial losses. Thus, the purpose of this paper is to present a pattern recognition method for the detection of stator windings short circuits based on measures of mutual information between the phase current signals. In order to validate the proposed patterns, feature vectors obtained from normal and faulty motors are applied to two topologies of artificial neural networks. The classification results presented accuracies over 93% even when the motors were subject to several conditions of load torque and power supply voltage unbalance.

1. Introduction

The three-phase induction motor (TIM) is one of the most common machines used to transform electrical energy into mechanical energy in industrial processes. This is mainly due to the low acquisition and maintenance costs, reliability, robustness to aggressive environments, as well as being easily adapted to several load conditions [1–3]. Despite these favorable characteristics, TIMs can present electrical or mechanical faults that may be caused by prolonged activity times, harsh operating conditions, voltage or current unbalance, among other factors. Even incipient faults can affect the motor performance, which may result in financial losses [4,5]. Therefore, the search for adequate diagnostic methods is a recurrent research topic in the past few years, aiming to detect the faults in an early stage and avoid unwanted production stops [6].

Among the electrical failures, up to 36% of the cases are due to stator winding faults [7]. Specifically regarding this kind of fault, in [8], Discrete Wavelet Transform (DWT) is used to obtain patterns from high frequency components that are classified using Artificial Neural Networks (ANN). Also, in [9], statistical measures of the stator current, such as mean, variance, skewness, and kurtosis, are used as inputs to a multilayer perceptron (MLP) ANN. Similarly, in [10], these measures are also used for rotor eccentricity faults along with stator winding inter-turn short circuit. In [11], the authors showed that Park vector modules combined with Hilbert Transform contain relevant information for detecting short circuit faults in TIM stator windings. In addition, in [12], wavelet transform was used for feature extraction of current signals for the identification of fault severity, even with the machine subject to different operating conditions.

A more recent approach of pattern recognition for motor fault detection is the use of information theory (IT) measures such as entropy. One example is presented in [13], in which TIM stator currents are analyzed using DWT and entropy estimations for fault diagnosis. Also, in [14], multiscale entropy estimations from current and vibration signals are used as patterns for stator fault detection. Similar entropy measures obtained from the stator current are presented in [15], where they are applied to an ANN for fault prediction. Entropy is also employed in [16], along with support vector machines (SVMs) and ANNs, for the detection of TIM faulty bearings and broken rotor bars. Finally, in [17], bearings faults are also the object of analysis, but using relative entropy and DWT of the TIM current signals.

Another IT measure that has recently being applied in fault diagnosis is mutual information (MI). It is a similarity measure used in feature extraction methods that has applications in many areas, such as in speech intelligibility prediction [18]. For motor fault detection, in [19], MI measurements of vibration signals

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in time-frequency domain are used to evaluate the condition of helicopter bearings and shafts. Similarly, in [20], MI is used to assess the correlation of diesel engine signals in order to obtain the most informative ones for fault diagnosis. One final example is [21], where the authors employed MI in the feature extraction step to select the most relevant and less redundant measurements from TIM current signals for eccentricity fault identification.

Considering this recent application of IT measures, the aim of this work is to present an alternative approach to the diagnosis of TIM stator windings short circuit. This method is based on the analysis of MI values obtained from delayed line currents of two TIM phases. Using this tool, it is possible to evaluate the common information of the signals, as well as verify the changes of MI values due to different TIM operating conditions.

The efficiency of the proposed feature extraction method is assessed using two ANN topologies, multilayer perceptron (MLP) and radial basis function (RBF), which are proved to be adequate for motor fault detection as shown in [9,10,22,23]. For that, we performed 814 experimental tests with two TIMs of 0.74 kW and 1.48 kW in steady state and under several operating conditions that are common in an industrial environment, such as variations of load torque and power supply voltage unbalance. It is worth pointing out that the technique has a characteristic of being low cost, therefore the current signals are acquired noninvasively, using Hall-effect sensors, and no frequency domain tools are employed.

This paper is structured as follows. Section 2 presents aspects related with TIM stator winding faults. In Section 3, the main concepts of MI are addressed. Section 4 presents aspects of the proposed methodology and experimental setup. The results are shown in Section 5, and finally, the conclusions in Section 6.

2. Stator faults

In this section, aspects related to TIM stator winding faults are presented, which are one of the main problems found in electric motors [4,7,24,25]. Also shown are brief descriptions of other researches addressing the identification of these faults at an early stage, aiming to avoid unscheduled downtime and reduce maintenance costs.

The most common defects associated with TIM stator are phase to ground, phase to phase, and coil to coil short circuits [26]. When there is a short circuit involving just a few coil turns, the stator insulation starts to deteriorate; this could rapidly develop into a more serious fault and affect the motor operation [4,7,27].

In order to monitor the TIM operating conditions and identify these faults, one must use a proper signal processing technique for the extraction and selection of relevant features of the signals. The motor current signature analysis is a commonly used method because it is simple, noninvasive, and can be automated [28]. This approach is focused on the current spectral analyses and has been widely used for TIM fault diagnosis [29–31].

In the literature of fault detection, there are other examples of signal processing techniques based on spectral decomposition using short-time Fourier transform and Wavelet transform [8,12,32–34]. In other papers, applications using these transforms with the Hilbert transform are presented [11,35]. Other authors propose methods for TIM fault diagnosis based on the analysis of vibrations [5,36], magnetic signals [5,37,38], active and reactive power [7], temperature [39], among other variables.

One disadvantage of most of these methods is the requirement for high-priced sensors, which increase the cost of the diagnostic system. In order to avoid that, some authors are looking for other noninvasive methods, in which measurements are provided by low cost sensors, and using time domain strategies. In [22], an alternative approach to the traditional intelligent systems methods was considered to diagnose stator faults. The TIMs were driven by three different types of frequency inverters and the currents amplitudes, in time domain, were used to classify stator fault severity. Also, in [23], the authors proposed an evaluation of several pattern classification methods, namely naive Bayes, *k*-nearest neighbors, support vector machines, ANNs, and decision trees, for multi-fault classification (rotor, stator, and bearings faults) using the TIM currents amplitudes in time domain.

It is noteworthy that intelligent systems methods are widely used for fault identification of electrical machines, mainly due to their ability to classify features without requiring complex mathematical models. The most usual methods are ANNs [22,40–42], SVMs [31,43], fuzzy logic [44,45], decision trees [46], and hybrid systems [30,47]. Thus, based on this, the features obtained with MI measures of the TIM current signals are classified using ANNs in this paper.

3. Mutual information

MI is a measure of how much information a random variable (RV) has over another one. In other words, it is the uncertainty reduction of a RV brought by information of the other [48]. This quantity describes the similarity between time series collected simultaneously from a system under study [49,50].

Thus, by estimating the MI between the TIM current signals, it is possible to quantify the association between them, allowing an efficient monitoring of the machine operating conditions. Considering two RV X and Y, the MI can be estimated using (1), where x and y are realizations of the RVs, $p(x)$ and $p(y)$ are the probability density functions (PDFs) of X and Y, respectively, and $p(x, y)$ is the joint PDF of the them.

$$I(X, Y) = \int_Y \int_X p(x, y) \log_2 \frac{p(x, y)}{p(x)p(y)} dxdy \quad (1)$$

In practice, the PDFs are approximated by the signals normalized histograms and the expected values are estimated by time averages.

Since the winding faults tend to present asymmetrical effects in the TIM line current signals and MI is a similarity measure, this quantity should reflect such variations. In this work, we analyzed the delayed MI of two TIM phase current signals. This quantity is dependent on a time shift of τ samples that is applied to one of the signals before estimation using (1). Delayed MI has been used in dynamic structural analysis of complex systems, due to its capacity of quantifying the dependence between RVs, seeking the similarity between them relative to the time delay τ [51–53].

In order to obtain a reasonable analysis of the TIM current variations caused by the stator faults, several MI values are estimated with shifted versions of the phase B current signal. As an example, Fig. 1(a) presents a part of a three-phase current acquired during 3 s on a normal TIM. The MI values obtained using the phase A current signal and 150 delayed versions of the phase B current signal are shown in Fig. 1(b).

In the next section, a detailed description of the methodology employed in this work is presented.

4. Proposed approach

As mentioned in the previous sections, the purpose of this work is to identify stator short circuit faults by using MI values of the TIM current signals. Fig. 2 presents a diagram of the proposed fault detection method explained in this section. In order to validate this approach, experimental tests were performed. Next, details are presented about the current signals acquisition, and feature analysis and classification using ANN.