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Induction machine bearing fault diagnosis based on the axial vibration analytic signal

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ABSTRACT

This paper deals with a new induction motor defects diagnosis using the Axial Vibration Analytical Signal (AVAS). The signal is generated by a bearing-defected induction machine. The calculation method may be divided into two main parts; the former is the Hilbert transform that consists in the first part normalization of the axial vibration and its comparison with the AVAS module. The second part consists in the extraction of feature vectors using the Signal Class Dependent Time Frequency Representation (TFR_{SCD}) based on the Fisher contrast design of the non parametrically kernel. The Particle Swarm Optimization (PSO) is used to optimize the feature vectors size. The vibration severity caused by the bearing fault is investigated for different loads. This last decreases with the increasing level of the load. The obtained results are experimentally validated on a 5500 W induction motor test bench.

Introduction

Powerful and reliable machine health monitoring schemes are being more and more developed in the field of fault diagnosis. The industry nowadays aims to develop and improve the performance and efficiency of industrial devices and apparatus while maintaining and improving reliability and safety. To avoid machine problems, great deal of expensive maintenance is performed in order to detect faults before they may end in catastrophic damages [1]. In this light, several monitoring techniques have been developed in order to detect induction machine fault problems. Amongst all of these, a great deal was given to the examination of the frequency component in the machine current spectrum, referred to as Motor Current Signature Analysis (MCSA) that has interested many researchers. Several approaches have been proposed and developed based on the vibration and torque profile analysis, acoustic noise measurement, magnetic field and temperature analysis [2–4]. These techniques require high level of sophisticated and expensive sensor monitoring systems, more electrical and mechanical equipments, and further operations of maintenance. In addition, recent techniques based on artificial intelligence approaches such as artificial neural networks [5–8], fuzzy logic [9], wavelets [10] gives good analysis of faulty machines although they do not require accurate models. They are cheaper, easy to extend or to modify and they give improved performance as well.

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Generally, diagnosis techniques use the analysis of the signal behavior either in time or frequency domain, whereas, our approach is based on the combination and the examination of time and frequency of the signal, in order to extract more substantial information. The time frequency examination of the motor current in the transform domain makes the signal properties, associated with fault detection, more obvious [11].

As main objective, the time frequency analysis, usually, attempts to describe a specified function representing the energy density of the signal in time and frequency domains to achieve classification purposes.

Indeed, such a representation may conflict with the objective of classification, generating a TFR that increases the separability of TFRs from different classes. It is quite advantageous to design TFRs that clearly emphasize differences between classes [12–14]. We aim to design by using the classifier directly in the ambiguity Doppler delay plane. Since all TFRs can be derived from the ambiguity plane, no a priori hypothesis is made about the smoothing necessary for precise classification. Therefore, the quadratic smoothing TFRs keep only the information that is essential for classification purposes.

This classification allows us to carry on an optimization procedure based on particle swarm optimization technique in order to find the suitable minimal feature vectors size and maintain only the pertinent information within the vectors. This helps to reduce consistently computer computation time.

The classification stage consists in the design of an optimized TFR from a time frequency ambiguity plane in order to extract the feature vector. The optimal length of the feature vectors is derived using the PSO algorithm [15]. The PSO approach exhibits the capacity of generating high quality solutions with reduced computing time and more stable convergence feature compared to other optimization stochastic techniques [16,17]. The quantification of the fault level is a key element in the domain of diagnosis of faults in induction machines. The severity of defects consists in the definition of a vibration factor linking the diagnosis index to the degree of the bearings deterioration.

In the present work, we aim to realize more reliable diagnosis system based on the analysis of the axial vibration signal caused by bearing faults in the induction machine. For this purpose, we use severity of defects as main indices for evaluating the vibration displacement and the vibration frequency based on experimental signal data of 5.5 kW asynchronous motor gathered throughout a 20,000 Hz signal acquisition system.

The paper is structured as follows. Section axial vibration analytic signal approach is dedicated to the description of the method of axial vibration analytic signal (AVAS) based on Hilbert transform and analytic signal. However, we discuss in a comprehensive manner the notion of the analytic signals and Hilbert transform. The severity of defects with respect to time and frequency as indices of the axial vibration levels is also presented. Section particle swarm optimization technique depicts the PSO algorithm used in optimization process. Section computation routine provides a description of computational routines. Section experimental investigation and results describes the experimental acquisition system and results. Finally, Section conclusion concludes the paper.

Axial vibration analytic signal approach

This approach consists in projecting a faulted signal on a reduced dimension time frequency representation TFR. The time-frequency quadratic representation may be defined simply by its characteristic function as the product of the signal ambiguity plane $A_x(\zeta,\tau)$ by the kernel function $\Phi(\zeta,\tau)$. By this, we focus the most on the kernels conception, which permits the minimization of the quadratic interferences. The proposed scheme mainly consists in the determination of a dispersion parameter ζ of the point cloud. However, as a feature design is of central meaning to all knowledge and classification, the dispersion parameter allows the TFR_{SCD} calculation and extraction of feature vectors [18].

Since the TFR_{SCD} does not allow us to reduce the dimension of the feature form, the particular swarm optimization technique is used here in to reduce these sizes, all without affecting the significance of the considered vectors. The AVAS method makes use of the principle of the analytical signal obtained by the application of the Hilbert transform.

Analytic signal and Hilbert transform

The concept of analytical signal provides a definition of the amplitude and the instantaneous frequency of a real signal. Furthermore, any complex function of a real variable whose real and imaginary components satisfy Hilbert transform pairs is called an analytic signal. The analytical signal of real valued function $S(t)$ is defined by the inverse Fourier transform of $S_a(f)$.

$$S_a(t) = \mathscr{F}^{-1}[S_a(f)] \tag{1}$$

$$S_a(t) = \mathscr{F}^{-1}[S(f) + sgn(f)\cdot S(f)] \tag{2}$$

$$S_a(t) = \mathscr{F}^{-1}[S(f)] + \mathscr{F}^{-1}[sgn(f)]*\mathscr{F}^{-1}[S(f)] \tag{3}$$

where

$$S(t) = \mathscr{F}^{-1}(S(f))$$

$$j\frac{1}{\pi\cdot t} = \mathscr{F}^{-1}(sgn(f))$$

So,

$$S_a(t) = S(t) + j\left[\frac{1}{\pi\cdot t}*S(t)\right] \tag{4}$$

$$S_a(t) = S(t) + j\mathscr{H}[s(t)] \tag{5}$$

$\mathscr{H}[s(t)]$ is the Hilbert transform of $s(t)$, j is the imaginary unit and $*$ is the convolution operator. In the field of electrical engineering, all signals generated are naturally, meaning that are real-valued. However, in several application we need to generate a complex signal from a real input. To do this, we use Hilbert transform.

The principle of Hilbert transform is to find a companion function for a real signal. Thus, the Hilbert transform of a signal $s(t)$ is given as follows: