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Bearing fault detection of induction motor using wavelet and Support Vector Machines (SVMs)

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ABSTRACT

Condition monitoring of induction motors is a fast emerging technology in the field of electrical equipment maintenance and has attracted more and more attention worldwide as the number of unexpected failure of a critical system can be avoided. Keeping this in mind a bearing fault detection scheme of three-phase induction motor has been attempted. In the present study, Support Vector Machine (SVM) is used along with continuous wavelet transform (CWT), an advanced signal-processing tool, to analyze the frame vibrations during start-up. CWT has not been widely applied in the field of condition monitoring although much better results can been obtained compared to the widely used DWT based techniques. The encouraging results obtained from the present analysis is hoped to set up a base for condition monitoring technique of induction motor which will be simple, fast and overcome the limitations of traditional data-based models/techniques.

1. Introduction

Induction motors known as workhorse of modern industries are subjected to some undesirable stresses during their operating lifetime, causing some faults to develop leading to failures [5,16]. Heavy reliance of industry on these machines in critical applications makes catastrophic motor failures very expensive. Thus, finding an efficient and reliable fault diagnostic technique, especially for induction motors, is extremely important due to widespread use of automation and consequent reduction in direct man–machine interface to supervise the system operation. During the last decade different kinds of data-based models such as Neural Networks (NNs) have established a firm position in condition monitoring of electrical machinery.

Vibration analysis has been used in rotating machines fault diagnosis for decades [2–4,19,22]. In [4], it is claimed that vibration monitoring is the most reliable method of assessing the overall health of rotor system. Each fault in a rotating machine produces vibrations with distinctive characteristics that can be measured and compared with reference ones in order to perform the fault detection and diagnosis.

Traditional techniques like Fast Fourier Transform (FFT) used for analysis of the vibration signal is not appropriate to analyze signals that have a transitory characteristic. Moreover, the analysis is greatly dependent on the machine load and correct identification of very closed fault frequency components requires a very high-resolution data [10]. Wavelet a very powerful signal-processing tool can be used to analyze transients signal and thus eliminating load dependency. Variable window size allows the possibility to extract both low frequency as well as high frequency information as per requirement. Keeping these points in mind the investigation aims to design and develop an on-line monitoring and incipient fault detection scheme of induction motors by assessing the signature of the motor frame vibrations (g_{frame}) signals during start-up [4,11].

Continuous wavelet transform (CWT) used to extract the local information content of the data has several advantages over the more commonly used DWT [28,29] which uses a set of orthogonal wavelet bases to obtain the most compact representation of the data mainly useful for image compression. The CWT on the other hand uses a set of non-orthogonal wavelet frames to provide highly redundant information that is very good for detection of various types of faults. Wavelet coefficient at each analysis scale can be obtained allowing us to characterize the local information content. Moreover, CWT is easier to interpret since its redundancy tends to reinforce the traits and makes all information more visible which is especially true for very subtle information. Thus, CWT analysis gains in “readability” and in ease of interpretation, what it losses in terms of saving space, which is immaterial in signal processing technique where very important distinct informative feature extraction is the most important.

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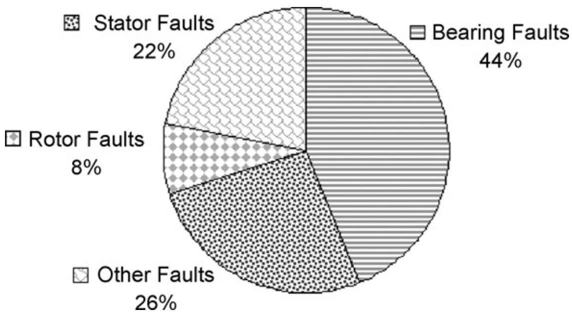

Fig. 1. Percentage occurrence of induction motor faults [1].

Among various motor faults the proposed investigation has been restricted to *bearing faults* only since motor reliability studies shows that bearing faults accounts for 44% of the faults occurring in an induction motor as shown in Fig. 1.

In recent years, Support Vector Machines (SVMs) have been found to be remarkably effective in many real-world applications. SVMs have been successfully applied in various classification and pattern recognition tasks, but in the area of fault diagnostics they have not been widely studied. SVMs are based on statistical learning theory and they specialize for smaller number of samples [13]. As it is hard to obtain sufficient fault samples in practice, SVMs have been applied for machinery fault diagnosis. It is believed that these techniques along with advanced signal processing tools like instantaneous power FFT, Park's transformation, bispectrum, wavelets will have significant role in electric drive system diagnosis. The current research works have obtained encouraging results by using Support Vector Machine (SVM) [18] as a fault classifier to identify the machine faults.

2. Proposed method

The schematic representation of the work is shown in Fig. 3. The scheme consists of four major parts, namely (i) simulation of different induction motor faults, (ii) data acquisition, (iii) signal processing and (iv) Post Processing and Diagnosis using SVM. For identifying the faults motor frame vibration (g_{frame}) signals at start-up are monitored and diagnosed.

Photograph of the experimental setup is presented in Fig. 2.

2.1. Simulation of faults

Machinery Fault Simulator (MFS), a tool for simulating various types of induction motor faults initially fitted with a healthy motor

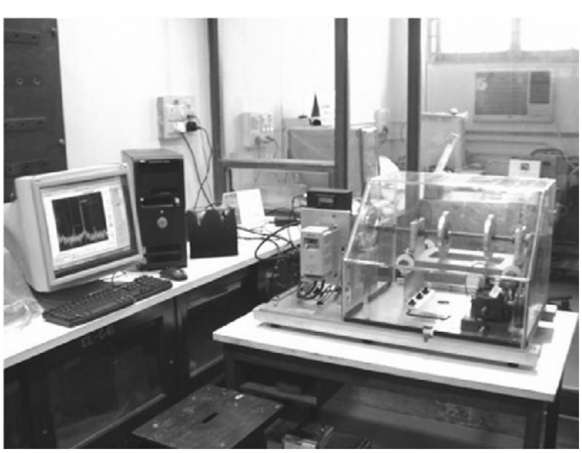

Fig. 2. Photograph of Machinery Fault Simulator (MFS).

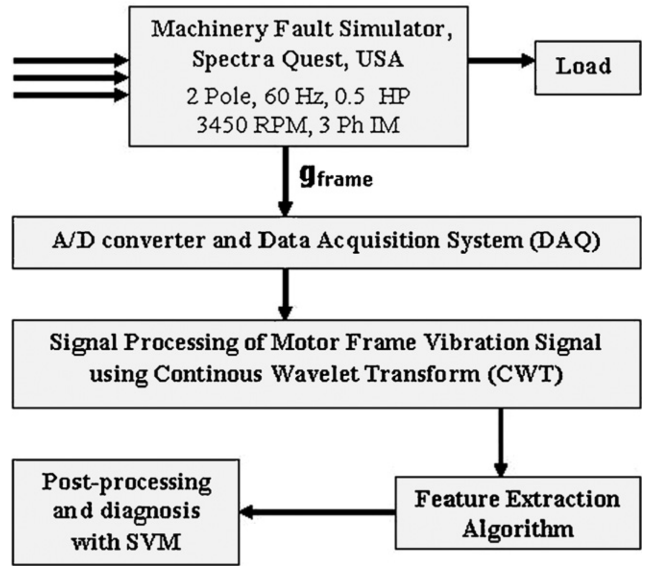

Fig. 3. Schematic diagram of the work.

and a motor with faulted bearings of same specification has been used for the fault simulation [24].

2.2. Data acquisition

The generated data corresponding to a particular motor condition were collected using an accelerometer probe, recorded and stored using a computer with four-channel data acquisition system (DAQ) [24]. The collection was done for both healthy motor and a motor with faulted bearings under the same running conditions. Time domain frame vibration signal for healthy motor and faulty motor with faulted bearing are shown in Fig. 4(a) and (b).

2.3. Signal processing

2.3.1. Continuous wavelet transform (CWT)

The *wavelet transform* or *wavelet analysis* is probably the most recent solution to overcome the shortcomings of the traditionally used Fourier transform [17,20,21]. Wavelets are well suited for approximating data with sharp discontinuities. Motor starting vibration contains numerous non-stationary or transitory characteristics: *drift*, *trends*, *abrupt changes*, and *beginnings and ends of events*. These characteristics are often the most important part of the signal, and traditional tools like Fourier analysis are not suited for analyzing non-stationary or transitory signals. Fourier analysis is only suitable for steady state analysis consisting of stationary signals – where only the signal's frequency content is needed. When looking at Fourier transform of a signal, it is impossible to tell when a particular event took place, since in transforming to the frequency domain, time information is lost. While in short time Fourier transform (STFT) compromises between time and frequency information can be useful, the drawback is that once a particular size time window is chosen, that window is the same for all frequencies. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In wavelet analysis, the scale plays a special role. Wavelet algorithms process data at different scales or resolutions. If we look at a signal with a large "window", we would notice gross features. Similarly, if we look at a signal with a small