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Isolation and identification of dry bearing faults in induction machine using wavelet transform

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ABSTRACT

Any vibration signal obtained from electromechanical systems contains a level of random changes. These random changes in the measured signal may be due to the random vibrations that can be related to the health of the machine for some faults such as dry bearing fault or bearing ageing. The presence of dry bearing fault, which is caused by the lack of lubricant, increases the level of random vibrations as compared to those obtained in healthy bearing machine. If these random vibrations could be isolated from the measured signal, useful information about bearing health may be obtained. Therefore, in this paper, signals (three line to line voltages, three currents, two vibration signals, four temperatures and one speed signal) obtained from the monitoring system are treated and analyzed using wavelet transform to correlate it to the dry bearing faults in induction machine. In this study, on-line analysis of the acquired signals has been performed using C^{++}, while MATLAB has been used to perform the off-line analysis.

1. Introduction

The subject of machine condition monitoring is charged with developing new technologies to diagnose the machinery problems [1]. Different methods of fault identification have been developed and used effectively to detect the machine faults at an early stage using different machine quantities such as current, voltage, speed, efficiency, temperature and vibrations. One of the principal tools for diagnosing rotating machinery problems has been the vibration analysis. Through the use of different signal processing techniques, it is possible to obtain vital diagnostic information from vibration profile before the equipment catastrophically fails [2].

Recent study shows that more than 40% of induction motor failures are related to bearings [1]. Therefore, this type of fault must be detected as soon as possible to avoid fatal breakdowns of machines that may lead loss of productions [3,4]. Researchers have suggested many methods to identify the bearing faults at early stage [5–8]. Machine vibration signal is composed of three parts, stationary vibration, random vibration, and noise. Traditionally, Fourier transform (FT) was used to perform such analysis. If the level of random vibrations and the noise are high, inaccurate information about the machine condition is obtained. Noise and random vibrations may be suppressed from the vibration signal using signal-processing techniques such as filtering, averaging, correlation, convolution, etc. Sometimes random vibrations are also important because they are related to some types of machine faults hence; there is a need to observe these vibrations also.

Martin [9] has demonstrated the limitation of using FT approach for bearing damage monitoring. The traditional treatment of vibration spectrum fluctuations is the averaging, which results in suppression of some features of short duration. The author has presented the application of wavelet transforms of vibration signals for diagnosing the bearing faults. Paya et al. [10] have demonstrated its application for bearing and gearbox faults diagnosis. In this approach, the wavelet transform is used as a preprocessor for the vibration signals obtained from the experimental driveline. Dalpiaz and Rivola [11] have compared the effectiveness and the reliability of different vibration analysis techniques for fault detection. Al-Raheem et al have used the Laplace wavelet envelop power spectrum for rolling element bearing fault diagnosis [12]. From the literature survey [13–20], it is noticed that not much attention has been given to identify the dry bearing fault, which is caused by the lack of lubricant. The presence of dry bearing fault at an early stage introduces a small level of randomness in the vibration signal, and it is difficult to isolate these random vibrations by the traditional signal processing techniques. The difficulty in discovering such fault is that neither the variation in the vibration level nor additional

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spectrum components is detectable. Therefore, in this paper, a detailed experimental study has been carried out for isolation and identification of the dry bearing fault. For this purpose, signals (three line to line voltages, three currents, two vibration signals, four temperatures and one speed signal) obtained from the monitoring system are treated and analyzed using wavelet transform to correlate it to the dry bearing faults in induction machine. All the on-line analysis of the acquired signals has been performed using C++, while MATLAB has been used to perform the off-line analysis.

2. Signal processing techniques and wavelet transform

2.1. Digital signal processing technique

Electrical signals obtained from the physical systems by different type of transducers contain information about their conditions. The advancement in signal processing techniques and microprocessor technology has improved the extraction of information. There are two approaches used for processing the signal: time domain and frequency domain. In time domain approach, the discrete time signal is directly analyzed by one of the digital signal processing (DSP) techniques [21–23] such as, filtering, averaging, convolution, correlation, etc. In frequency domain approach, the signal is first transformed to the frequency domain using FT and then, different methods of analysis such as averaging, convolution; power spectrum, etc. can be applied.

2.2. Wavelet transform

Wavelet transform (WT) exhibits very attractive features that make it ideal for studying transient signals with more reliable discrimination than FT. In contrast to Fourier analysis, which averages frequency characteristics over time, wavelet decomposition localizes features both in time and in frequency. WT is a linear transformation that allows time localization of different frequency components of a given signals. Short Term Fourier transform (STFT) also achieves this same goal, but with a limitation of using a fixed width windowing function. As a result, both frequency and time resolution of the resulting transform will be fixed. In case of WT, the analyzing functions, which are called wavelets, having a finite duration in time, will adjust their time-widths to their frequency in such a way that higher frequency wavelets will be very narrow and lower frequency ones will be broader. This multi resolution property is particularly useful for analyzing fault transients, which contain localized high frequency components superimposed on original frequency [4,24,25].

WT decomposes a time domain signal into different frequency groups and provides an alternative to STFT for analyzing non-stationary signals [4,26–28]. The basic difference between STFT and WT is the basis function, where the STFT uses the windowed sinusoidal functions and uses windows of constant length in seconds; whereas WT uses a wide variety of functions specifying a certain mathematical property such as window length corresponding to a constant number of periods. The essential condition to satisfy in case of WT is that the basis functions must be located within the boundary of Hilbert space whose average is zero. The analysis of signal can be achieved through three distinct approaches: Multi-resolution, continuous wavelet transforms (CWT) and discrete wavelet transform (DWT). No attempt is made here to provide a complete description of wavelet theory.

2.2.1. Multiresolution analysis

The analysis of a practical signal by STFT may arise the effect of physical phenomena (the Heisenberg uncertainty principle). This is because of the time-bandwidth product of the window function used is lower bounded (the resolution in time and frequency can not be small). However, analysis of such signal can be achieved using multiresolution analysis approach. It provides a good frequency resolution and poor time resolution at low frequencies; and good time resolution and poor frequency resolution at high frequencies. This approach is appropriate for most practical applications especially when the signal has high frequency component for short duration and low frequency component for long duration. Multi-resolution analysis of a signal can be performed using a band pass filter with constant relative bandwidth. The multiresolution property is inherent in the WT, which decomposes a given signal into a coarse approximation and details. In multilevel decomposition, the approximation is decomposed further into lower frequency and detailed frequency, where the whole function space is decomposed into subspace. The wavelet multiresolution analysis can be adopted using two functions, $\varphi(x)$ (scaling function) and $\psi(x)$ (wavelet or mother function). These two functions can be expressed as:

$$\varphi(x) = \sum_{k \in z} l_k \cdot \varphi(2x - k) \tag{2.1}$$

$$\psi(x) = \sum_{k \in z} h_k \cdot \varphi(2x - k) \tag{2.2}$$

where, l_k and h_k is a sequence of real number.

However, for a given sequence of real number l_k there is unique $\varphi(x)$. The uniqueness of $\varphi(x)$ assured by:

$$\sum_{k \in z} l_k = 2 \tag{2.3}$$

More information about the scaling space and detail subspace is given in [29–31].

2.2.2. Continuous wavelet transform

A continuous wavelet transform (CWT) is an integral transform, in which a signal is represented in terms of a family of time and frequency localized basis functions. The WT basis functions are localized in both time and frequency. Since the basis functions are localized in time, it is necessary to translate them in time in order to cover the entire domain. Then, since the wavelet is localized in frequency, and to cover a wide frequency range, it is necessary to scale them in time, shifting them in frequency. The WT of a signal $f(t)$ can be obtained by convolution product:

$$W_s f(\tau) = \int_{-\infty}^{\infty} f(t) \psi_s(t - \tau)\, dt \tag{2.4}$$

where,

$$\psi_s(\tau) = \frac{1}{\sqrt{s}} \psi\left(\frac{\tau}{s}\right)$$

where, $\psi(\tau)$ is the wavelet basis function, τ translation factor and s ($s \in R^2$) the scaling factor. The time-frequency resolution of the WT involves sharp time of high frequency and sharp frequency at low frequency. The $\{1/\sqrt{s}\}$ is an energy normalization term that makes wavelets of different scales have the same amount of energy [31]. Therefore, any function $f(t)$ can be represented by its wavelet expansion:

$$f(t) = \int_r \int_k C_{r,k} \psi_{r,k}(t) \tag{2.5}$$

where, $C_{r,k}$ is the wavelet coefficient which can calculated from the following inner product:

$$C_{r,k} = \langle f, \tilde{\psi}_{r,k} \rangle \tag{2.6}$$