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Rotor Fault Detection of Induction Motors Using Stator Current Signals and Wavelet Analysis

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Abstract— A motor is the workhorse of our industry. The issues of preventive and condition-based maintenance, online monitoring, system fault detection, diagnosis, and prognosis are of increasing importance. Different internal motor faults (e.g., inter-turn short circuits, broken bearings, broken rotor bars) along with external motor faults (e.g., phase failure, mechanical overload, blocked rotor) are expected to happen sooner or later. This paper introduces the fault detection technique of induction motors based upon the stator current. The fault motors have rotor bar broken or rotor unbalance defect, respectively. The stator currents are measured by the current meters and stored by the time domain. The time domain is not suitable to represent the current signals, so the frequency domain is applied to display the signals. The Fourier Transformer is used for the conversion of the signal. After the conversion of the signals, the features of the signals have to be extracted by the signal processing methods like a wavelet analysis, a spectrum analysis, etc. The discovered features are entered to the pattern classification model such as a neural network model, a polynomial neural network, a fuzzy inference model, etc. This paper describes the fault detection results that use wavelet decomposition. The wavelet analysis is very useful method for the time and frequency domain each. Also it is powerful method to detect the features in the signals.

I. INTRODUCTION

The most popular way of converting electrical energy to mechanical energy is an induction motor. This motor plays an important role in modern industrial plants. The risk of motor failing can be remarkably reduced if normal service conditions can be arranged in advance. In other words, one may avoid very costly expensive downtime of plant by proper time scheduling of motor replacement or repair if warning of impeding failure can be obtained in advance. In recent years, fault diagnosis has become a challenging topic for many electric machine researchers.

The major faults of electrical machines can broadly be classified as follows [1]:

- Abnormal connection of the stator windings
- Broken rotor bar or cracked rotor end-rings
- Static and/or dynamic air-gap irregularities
- Bent shaft (akin to dynamic eccentricity)
- Shorted rotor field winding
- Bearing and gearbox failure

Faults in electric machines produce one of more of the following symptoms:

- Unbalanced air-gap voltages and line currents
- Increase torque pulsations
- Decreased average torque
- Increase losses and reduction in efficiency
- Excessive heating

The diagnostic methods to identify the above faults may involve several different types of fields of science and technology [1], [2]. Several methods are applied to detect the faults in induction motors as the following:

- Electromagnetic field monitoring
- Temperature measurements
- Infrared recognition
- Radio frequency (RF) emissions monitoring
- Noise and vibration monitoring
- Chemical analysis
- Acoustic noise measurements
- Motor current signature analysis (MCSA)
- Model, AI and NN based techniques

Although the Fourier transform is an effective method and widely used in signal processing and the transformed signal may lose some time domain information. The limitation of the Fourier transform in analyzing non-stationary signals lead to the introduction of time-frequency or time scale signal processing tools, assuming the independence of each frequency channel when the original signal is decomposed. This assumption may be considered as the limitation of this approach.

Wavelet transform is a method for time varying or non-stationary signal analysis, and uses a new description of spectral decomposition via the scaling concept. Wavelet theory provides a unified framework for a number of techniques, which have been developed for various signals processing applications. One of its feature is multi-resolution signal analysis with a vigorous function of both time and frequency localization. This method is effective for stationary signal processing as well as non-stationary signal processing. Mallat's pyramidal algorithm based on convolutions with quadratic mirror filters is a fast method similar to FFT for signal decomposition of the original signal in an orthonormal wavelet basis or as a decomposition of the signal in a set of independent frequency bands. The independence is due to the orthogonality of the wavelet function [3].

II. Fault Detection of Induction Motor

A. Bearing Faults

Though almost 4~50% of all motor failures are bearing related, very little has been reported in the literature regarding bearing related fault detection techniques. Bearing faults might manifest themselves as rotor asymmetry faults from the category of eccentricity related faults [4]. The vibration frequency of the fault is as follows,

$$f_1[Hz] = (f_r/2)f_r[1 - b_d \cos(\beta)/d_p] \tag{1}$$

where f_r is the rotational frequency, N is the number of balls, b_d and d_p are the ball diameter and ball pitch diameter respectively, and β is the contact angle of the ball. The following equation includes the vibration frequency and current spectrum.

$$f_{bng} = | f_1 \pm m.f_v | \tag{2}$$

where m=1, 2, 3, ... and f_v is one of the characteristic vibration frequency.

Artificial intelligence or neural networks have been researched to detect bearing related faults on line. And also adaptive, statistical time frequency method are studying to find bearing faults..

B. Broken rotor bar and end ring faults

Rotor failures now account for 5-10% of total induction motor failures. Broken rotor bars give rise to a sequence of side-bands given by:

$$f_b = (1 \pm 2ks)f \qquad k = 1,2,3,\ldots \tag{3}$$

where f is the supply frequency and s is the slip. Frequency domain analysis and parameter estimation techniques have been widely used to detect this type of faults.

In practice, the current side bands around fundamental may exist even when the machine is healthy [5]. Also rotor asymmetry, resulting from rotor ellipticity, misalignment of the shaft with the cage, magnetic anisotropy, etc. shows up at the same frequency components as the broken bars [6]. Therefore other features of this fault need to be investigated.

C. Eccentricity related faults

This fault is the condition of unequal air-gap between the stator and rotor. It is called static air-gap eccentricity when the position of the minimal radial air-gap length is fixed in the space. This maybe caused by the ovality of the stator core or by the incorrect positioning of the rotor or stator at the commissioning stage.

In case of dynamic eccentricity, the center of rotor is not at the center of rotation, so the position o minimum air-gap rotates with the rotor. This maybe caused by a bent rotor shaft, bearing wear or misalignment, mechanical resonance at critical speed, etc. In practice an air-gap eccentricity of up to 10% is permissible. Both static and dynamic eccentricities tend to exist in practice.

Using MCSA the equation describing the frequency components of interest is:

$$f\left[(kR \pm n_d)\frac{(1-s)}{p} \pm v\right] \tag{4}$$

where n_d=0 in case of static eccentricity, and n_d=1, 2, 3, ... in case if dynamic eccentricity f is fundamental supply frequency, R is the number of rotor slots, s is slip, p is the number of pole pairs, k is any integer and υ is the order of the stator time harmonics.

Other equations are also presented in the literature as low frequency components for mixed eccentricity [5]. As it is obvious, sometimes, different faults produce nearly the same frequency components or behave like healthy machine, which make the diagnosis impossible. This is the reason why new techniques must also be considered to reach a unique policy for distinguishing among faults. Park's vector based upon voltage and current has been proposed to detect the motor fault.

III. Wavelet Transformation

A wavelet is a function ψ belonging to $L^2(R)$ with a zero average. It is normalized and centered in the in the neighborhood of t=0. A family of time-frequency atoms is obtained by scaling ψ by a^j and translating is by b:

$$\psi_{a,b} = |a|^{\frac{-j}{2}}\psi\left(\frac{t-b}{a^j}\right) \tag{5}$$

These atoms also remain normalized. The wavelet transform of f belonging to $L^2(R)$ at the time b and scale a^j is:

$$Wf(b,a^j) = \langle f, \varphi_{b,a^j} \rangle = \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{a^j}}\varphi^*\left(\frac{t-b}{a^j}\right)dt \tag{6}$$

A real wavelet transform is complete and maintains an energy conservation as long as the wavelet satisfies a weak admissibility condition which is:

$$\int_0^{+\infty}\frac{|\Psi(w)|^2}{|w|}dw = \int_{-\infty}^{0}\frac{|\Psi(w)|^2}{|w|}dw = C_\psi < +\infty \tag{7}$$

When $Wf(b, a^j)$ is known only for $a<a_0$ to recover f we need a complement of information corresponding to $Wf(b, a^j)$ for $a<a_0$. This is obtained by introducing a *scaling function* ϕ that is an aggregation of wavelet at scales larger than 1. $\hat{\psi}(w)$ and $\hat{\varphi}(w)$ are Fourier transforms of $\psi(t)$ and $\varphi(t)$ respectively. $\psi(t)$ is a band pass filter, and $\varphi(t)$ is a low-pass filter. Taking positive

frequency into account $\hat{\varphi}(w)$ has information in [0, π] and $\hat{\psi}(w)$ in [π, 2π]. Therefore they both have complete signal information without any redundancy. Decomposition of the signal in [0, π] using Mallat's algorithm gives:

$$\begin{aligned} h(n) &= \langle 2^{-j}\varphi(2^{-1}t)\varphi(t-n)\rangle \\ g(n) &= \langle 2^{-j}\psi(2^{-1}t)\varphi(t-n)\rangle \end{aligned} \qquad j = 0,1,2,\ldots \tag{8}$$

Wavelet decomposition does not involve the signal in [π, 2π]. In order to decompose the signal in whole frequency band, wavelet packet can be used for this purpose. After decomposition for l times, we will get 2^l frequency bands each with the same bandwidth. That is:

$$\left[\frac{(i-1)f_n}{2}, \frac{if_n}{2}\right] \qquad i = 1,2,\ldots,2^j \tag{9}$$

where f_n is the Nyquist Frequency, in the i^{th} frequency band. Wavelet packet de-composes the signal into one low-pass filter $h(n)$ and 2^l-1 band-pass filters $g(n)$, provides diagnosis information in 2^l frequency bands.

Functions $h(n)$ and $g(n)$ can be obtained by inner product of $\psi(t)$ and $\varphi(t)$.

$$\begin{aligned} h(n) &= \langle 2^{-j}\varphi(2^{-1}t)\varphi(t-n)\rangle \\ g(n) &= \langle 2^{-j}\psi(2^{-1}t)\varphi(t-n)\rangle \end{aligned} \qquad t \in R, n \in Z \tag{10}$$

$$\begin{aligned} A_j(n) &= \textstyle\sum_k h(k-2n)A_{j-1} \\ D_j(n) &= \textstyle\sum_g g(k-2n)A_{j-1} \end{aligned} \qquad n = 1,2,3,\ldots \tag{11}$$

where $A_0(k)$ is the original signal and A_j is the low frequency approximation at the resolution j. D_j is called high frequency detail signal. After de-composition of j time, we can obtain one approximation signal A_j and D_1, D_2, …, D_j detail signals.

Wavelet packet decomposition is:

$$\begin{aligned} x_{2n}(t) &- \sqrt{2}\sum_k h(k)x_n(2t-k) \\ x_{2n+1}(t) &- \sqrt{2}\sum_k g(k)x_n(2t-k) \end{aligned} \tag{12}$$

where $x_1(t)$ is the original signal. Comparing (12) with (10), we can find that A_j in (10) is decomposed but also D_j in (10) is decomposed in (12).

Wavelet and wavelet packet decompose the original signal that is non-stationary or stationary into independent frequency bands with multi-resolution. Now we have an effective tool to monitor broken bar fault in the rotor.

IV. Experimental Results

A. *Current Signals and Data Preprocessing*

Motor rating applied in this paper is dependent on the electricity conditions. The rated voltage, speed, and horsepower are 220V, 3450RPM, and 0.5HP, respectively. And implemented motor specification includes the number of slot, the number of pole, slip, etc. The specification of used motor is 34 numbers of slots, 4 numbers of poles, and 24 numbers of rotor bars. The slip is determined by calculating an actual motor speed and a rated speed. And the current signals are measured under the fixed condition that considers the sensitivity of measuring signals that is, the output of the current probes. Each channel's sensitivity is 10mV/A, 100mV/A, and 100mV/A, respectively. The specification of measured input current signals under this condition consists of 16,384 sampling numbers, 3kHz maximum frequency, and 2.1333 measuring time. Therefore the sampling time is 2.1333 over 16,384. Applied fault types in this study are broken rotor, faulted bearing, bowed rotor, unbalance, and static and dynamic eccentricity case.

If the wavelet decomposition is implemented in the fault detection of induction motors, the unsynchronized current phase problem should influent the detection results much. As shown in Fig. 2, the comparing target signal are not synchronized each other, the unexpected results will appear in the wavelet decomposition. Therefore the signals are re-sampled by synchronizing the starting origin with phase 0 such as Fig. 3. The total re-sampled cycles of the signals are 64 cycles of 128 cycles. And the average value divided by one cycle signal is calculated to reduce the noise of original signals.

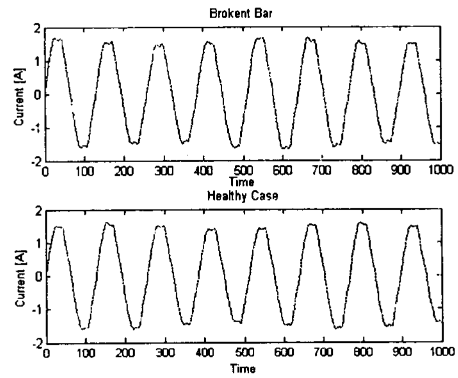


Fig. 1. Current signals under broken bar and healthy condition

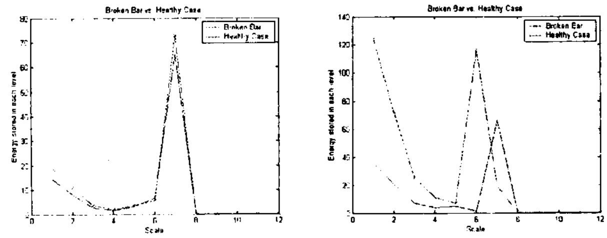


Fig. 2. Wavelet decomposition result under unsynchronized conditions.

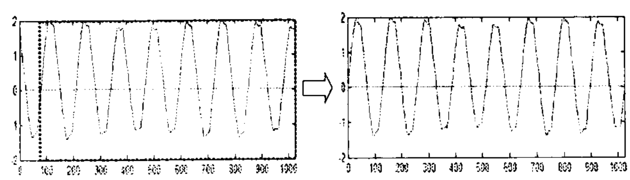


Fig. 3. Data re-sampling for the phase synchronizing.

B. Feature Extraction Using Fourier and Wavelet Transform

In this paper, two methods are considered to detection the faults of the induction motor. Fourier transform is applied in the full load condition. The FFT changes the original time domain signals into the frequency domain signals. In this conversion, some features to faults can appear but in out test, the case of broken rotor bar has a different feature that is a specific side-bend around supply frequency shown in Fig. 4.

But the other faults could not be classified by the FFT in this examination. Thus another approach is required to detect the motor faults. Wavelet transform is implemented for solution of this problem because the wavelet transform cannot lose the time information at the transforming time. And this method is very useful in the signal processing.

Energy value of decomposed wavelet has been applied to detect the broken bar fault in the past study. But this approach is not useful to detect several kinds of faults. Therefore in this paper, the specific scale of wavelet decomposition is considered in the fault detection as shown in Fig. 5. Because this detail scale contains most information of several faults, 6th decomposition scale of 12 scales is analyzed for the fault detection. And Coif-let wavelet function that is determined by the experimental experience for the better performance is used in the decomposition.

The features are extracted from the 6th decomposition. The collected features are a gradient value between the 3rd and 4th values and a peak value of 4th of the 6th decomposition result. Fig. 6 represents the results of wavelet analysis. From this result, it is possible that the wavelet decomposition is suitable for the fault detection in the induction motors.

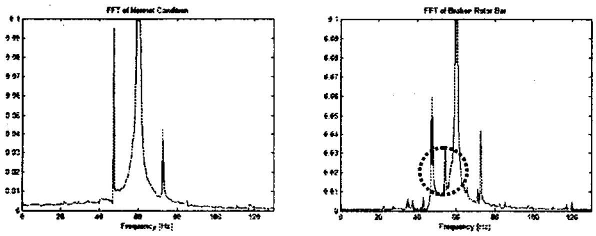


Fig. 4. FFT result of broken rotor bar and healthy case.

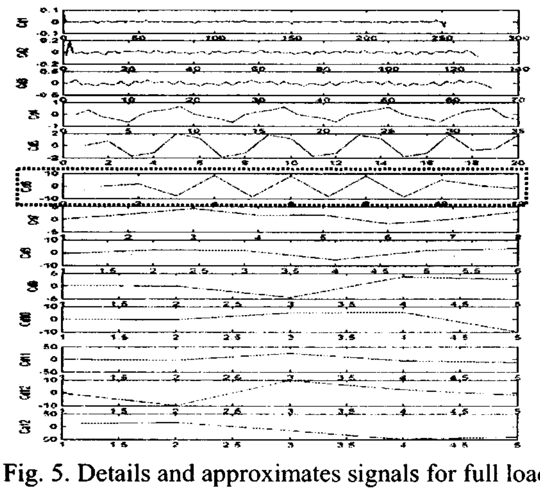
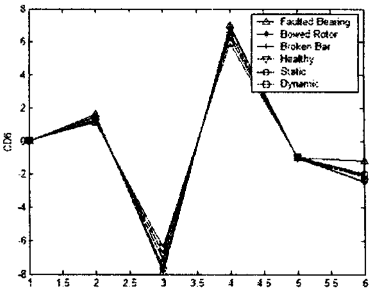
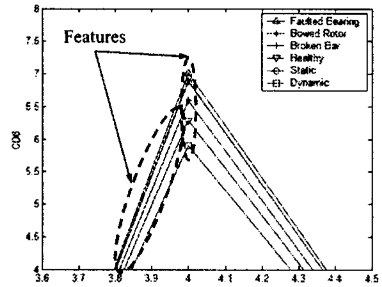


Fig. 5. Details and approximates signals for full load.



(a) 6th wavelet decomposition of important points.



(b) Zoom-in graph around the 4th values.

Fig. 6. Wavelet analysis in healthy and faulty motor.

V. CONCLUSION

The wavelet analysis is possible method to detect faults of induction motors except one mechanical fault like bearing bowed fault. The gradient and peak values of the 6th detail result of 12 scales of wavelet decomposition are applied.

In the wavelet analysis, features of broken rotor bar and static eccentricity are similar but the result of Fourier is much different. Therefore applying both of them together can separate the feature. In the future work, the classification model such as neural networks should be implemented to classify the fault kind automatically.

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